Real Fingerprint Detection System (RFDS) Based on Image Quality Measures and Six Classifiers

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We certify that we have read this thesis and that in our opinion it is fully adequate in scope and quality as a thesis for the degree of Master of Science in Computer Engineering.

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ABSTRACT

Fingerprint detection in biometrics is an important field of study in our new modern world, many forensic departments around the world use fingerprints as the key to detect criminals and bring them justice. To improve the accuracy of fingerprint detection system we implemented a Real Fingerprint Detection System (RFDS) that has high performance level of detecting real and fake fingerprint images. In this thesis, we present an RFDS system based on image quality measures (IQM’s) to detect real fingerprint images and fake fingerprint images. We performed different RFDS experiments with 25, 10, 15, and 5 IQM’s; they showed sufficient quality of real and fake fingerprint images detection. We compared our RFDS using 25, 15, 10, and 5 IQM’s with RFDS that has used 25 IQMs. Based on the comparison in this thesis we can conclude that the best result from all these RFDS is the one with 25 IQMs, because it’s HTER score is the minimum one with 0.3%, and the worst RFDS is the one with the 15 IQMs which has the maximum HTER score with 14.8%.

Keywords: Biometrics, Image Quality Measure, Real and Fake Fingerprint Image, Classifier.

ÖZ

Biyometride parmak izi tespiti, yeni modern dünyamızda önemli bir çalışma alanıdır, dünyadaki birçok adli departman, suçluları tespit etmek ve adalet getirmek için parmak izi kullanmaktadır. Parmak izi algılama sisteminin doğruluğunu artırmak için, gerçek ve sahte parmak izi görüntülerini algılamada yüksek performans seviyesine sahip bir Gerçek Parmak İzi Algılama sistemi (RFDS) uyguladık. Bu tezde, gerçek parmak izi görüntülerini ve sahte parmak izi görüntülerini tespit etmek için görüntü kalitesi ölçümlerine (IQM'ler) dayanan bir RFDS sistemi sunuyoruz. 25, 15, 10 ve 5 IQM'lerle farklı RFDS deneyleri gerçekleştirdik; yeterli kalitede gerçek ve sahte parmak izi görüntüleri algılama özelliği gösterdiler. 25, 15, 10 ve 5 IQM kullanarak RFDS'imizi 25 IQM kullanan RFDS ile karşılaştırdık. Bu tezdeki karşılaştırmaya dayanarak, tüm bu RFDS'lerden en iyi sonucun 25 IQM'ye sahip olduğu sonucuna varabiliriz, çünkü HTER puanı % 0.3 ile en düşük olanıdır ve en kötü RFDS ise %14.8 HTER puanı ile 15 IQM'ye sahip olanıdır.

Anahtar Kelimeler: Biyometri, Görüntü Kalitesi Ölçüsü, Gerçek Ve Sahte Parmak Izi Görüntüsü, Sınıflandırıcı.

DEDECATION

To My Family

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I would like to thank my supervisor (Assoc. Prof. Dr. Alexander Chefranov) who gave me the golden opportunity to do this wonderful project on the topic (Real Fingerprint Detection System (RFDS) Based on Image Quality Measures and Six Classifiers), which also helped me in doing a lot of research and I came to know about so many new things, I am thankful to him.

Secondly, I would like also to express my special thanks of gratitude to my parents and friends who helped me in finalizing this project within the limited time frame

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LIST OF ABBREVIATIONS

ACE	Average Classification Error
AD	Average Difference
FAR	False Accept Rate
FFR	False Fake Rate
FFR	False Fake Rate
FLR	False Living Rate
FR	Full Reference
FR-IQA	Full Reference Image Quality Assessment
GME	Gradient Magnitude Error
GPE	Gradient Phase Error
HTER	Half Total Error Rate
IQM	Image Quality Measures
LDA	Linear Discriminant Analysis
LMSE	Laplacian Mse
MAS	Mean Angle Similarity
MD	Maximum Difference
MSE	Mean Squared Error
NAE	Normalized Absolute Error
NCC	Normalized Cross Correlation
NR	No Reference
NR-IQA	No Reference Image Quality Assessment
PSNR	Peak Signal To Noise Ratio

QDA	Quadratic Discriminant Analysis
RAMD	R-Averaged Md
RFDS	Real Fingerprint Detection System
SC	Structural Content
SME	Spectral Magnitude Error
SNR	Signal To Noise Ratio
SPE	Spectral Phase Error
TCD	Total Corner Difference
TED	Total Edge Difference

Chapter 1

INTRODUCTION

Biometric recognition system is a mixture of hardware and software means used to differentiate and identify individuals [1]. Biometric recognition system obtains data such as fingerprint image of an individual, and then applies comparison to the image against the stored fingerprint images in the database. If the input fingerprint image matches one of the available images in the database, the system will accept it as **Real** image, otherwise it will be considered as **Fake** and will be rejected by the system. A biometric recognition system offers a natural and consistent solution to the problems of individual identification [1].

We can categorize the biometric methods used by biometric systems into two classes [2]:

1. Physiological-based methods use face, fingerprint, voice, retinal, DNA analysis, and measure the physiological characteristics of a person.

2. Behavior-based methods use signature, key stroke analysis and measure behavioral characteristics.

Biometric recognition systems can work in two modes:

▪ **Identification Mode:** The system recognizes a person searching a large database of registered ones for a match.

▪ **Verification Mode:** The system confirms a person's claimed identity from his previous registered pattern.

1.1 Definition of Common Biometric Terms [3]

▪ **Enrollment or Registration:** The individual’s biometric data are obtained, processed and saved as a template for ongoing usage in a biometric system; this is known as enrollment, or registration process. The template will be used for identification or verification in further stages.

▪ **Biometric Data:** Any data related to the physiological and behavioral characteristics of an individual is known as biometric data, which can also be referred as raw biometric data.

▪ **Presentation:** In this procedure, the individual presents his or her biometric data to the hardware that is used to gather data. For example, placing your finger on a biometrical sensor.

▪ **Feature Extraction:** The procedure of finding and encoding unique characteristics from biometric data in order to produce a template is known as feature extraction. Feature extraction takes place during enrollment and verification stage.

▪ **Image Quality Measures (IQM’s):** Mathematical measures applied to identify the quality of the image such as its color accuracy, noise, and sharpness, the results we get from the iqms assist us to identify or verify if the image is real or fake [4].

▪ **Classification:** A saved template will be compared with other templates during identification or verification stage. Based on the comparison we can classify if the individual is verified or not.

1.2 Fingerprint Detection Systems

Fingerprint is unique for every individual; they are mainly used for identifying individuals. Real fingerprint detection systems (RFDS) are one of the most known biometric systems used in many applications such as border control and forensic department. RFDS are systems that identify or verify any fingerprint image fed to the system as real or fake image. Rfds systems are described in [6], [18], [19], [20], and [21]. RFDS performance is very critical, any failure can cause harm to individuals and governments. For example, detecting the innocent individual's fingerprint as the criminal, or passing the border control of a country with another individual's fingerprint, and system will detect it as true and make you pass the border control. These kinds of problems shouldn't occur as they will cause injustice and security problems to individuals and the governments. Based on this major problem, we chose RFDS as our main area of study in this thesis. We will show different RFDS algorithms and implement the best of them, in which we will try to reduce the amount of wrong fingerprint detection as minimum as possible.

1.3 Key Terms Used in Fingerprint Images Analysis

1. Ridge ending: the point, at which the ridge terminates, shown in figure 1, a.

2. Ridge bifurcation: when one ridge splits in-to two or more ridges, shown in figure 1, b.

3. Minutiae: major features of a fingerprint like ridge endings and ridge bifurcations.

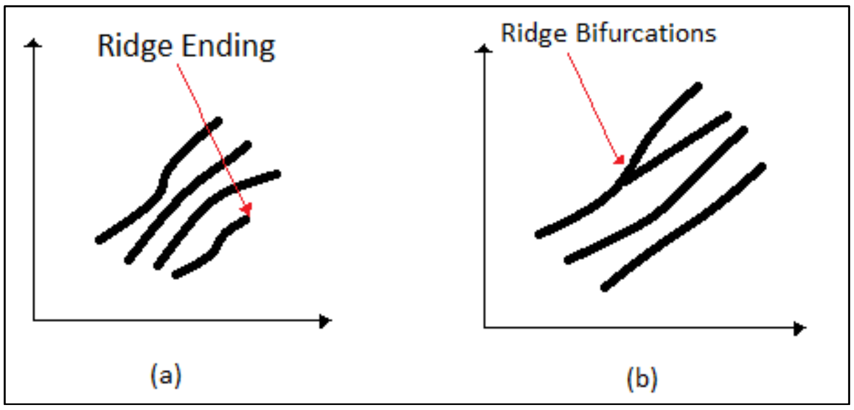


Figure 1: Fingerprints ridge ending (a) and ridge bifurcation (b) [5].

1.4 Summary

In this thesis, we implement a real fingerprint detection system (RFDS) using feature extraction and classification algorithm to classify the registered or enrolled fingerprint image. In Chapter 2, we review known fingerprint detection systems and define the problems. In Chapter 3, we show the general diagram of the RFDS, its implementation, classification algorithm used, and defining the best 10 and 5 IQMs. In chapter 4, we describe the experiments conducted on RFDS, steps taken for applying these experiments, and the results obtained. Chapter 5 contains the conclusion of the thesis and future work.

Chapter 2

ANALYSIS F KNOWN RFDS AND PROBLEM DEFINITION

In this chapter, we analyze some known rfds and list their experimental results. We also list the problems to be analyzed and tested in this thesis.

2.1 Analysis of Known RFDS

2.1.1 Image Quality Assessment for Fake Biometric Detection: Application to Iris, Fingerprint, And Face Recognition [6]

In RFDS, they input images and extract their features using 25 IQMs; then, these images will be classified on **Real**/ **Fake**. The details of how RFDS works are as follows [6]:

1. Training model should be created by feeding in to the system with good amount of real and fake biometric images of users. The images fed to system for creating the training model are known as the training data. The explaniation of how the training model is created is in Chapter 3, section 3.2.3. Once the training model is created, it is exported to the system making the system ready to predict between real and fake images based on the training model.

2. Image enrolment, input some (Real or Fake) gray scale image to the system for identification.

3. Features of the input image will be extracted by the system using the IQM's.

Classification of the input image, the system will classify if the fingerprint image is real or fake image based on the training model exported to it. Steps of the classification implementation are in 3.2.4. Image quality measures in [6].

In RFDS [6], 25 image quality measures have been used split into two parts: 21 of the measures are full reference image quality measurements (image quality measure that requires a reference of similar biometric image type to determine the quality level of the image fed to the system), and 4 are no reference image quality measures (they don't require a reference of similar biometric image type to determine the quality level of an image). Full reference image quality measures to extract the quality features of the original image and enhanced image (original image with adjusted noise is known as enhanced image); no reference image quality measures evaluate the state of the original image inputted to the system. Next we describe the 25 image quality measures used.

2.1.2 Full Reference (FR) Image Quality Measures Used In [6]

1. Mean Squared Error (MSE): It calculates the sum of squared difference (error) between the original image (I) and the enhanced image (Ī). The mean squared error formula (2.1) [7].

$$\text{MSE}\ (\text{I}.\ \bar{\text{I}}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(I_{i,j} - \bar{\text{I}}_{i,j})^2. \tag{2.1}$$

Where **m, n** is the number of columns and rows original image has.

2. Peak Signal-To-Noise Ratio (PSNR): It calculates the ratio between the signal power and distortion noise. The peak signal to noise ratio formula (2.2) [8,9].

$$\text{PSNR}\ (\text{I}, \bar{\text{I}}) = 10\ log_{10}(\frac{\text{Max}\ (I^2)}{MSE(I,\bar{\text{I}})}). \tag{2.2}$$

3. Signal-To-Noise Ratio (SNR): Calculates the ratio of power in the input signal to the ration of the noise power, SNR can be defined as the ratio of wanted information to unwanted. Signal-To-Noise Ratio formula (2.3) [10].

$$\text{SNR}\ (\text{I}, \bar{\text{I}}) = 10\ log_{10}\ \left(\frac{\sum_{i=1}^{N}\sum_{j=1}^{M}(\text{I}_{i,j})^2}{N\cdot M.MSE(\text{I},\bar{\text{I}})}\right). \qquad (2.3)$$

4. Structural Content (SC): Calculates the sum of the original image (I) pixel values squared divided by the sum of the enhanced image pixel values (Ī) squared. Structural content formula (2.4) [11].

$$\text{SC}\ (\mathbf{I},\bar{\mathbf{I}}) = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M}(\text{I}_{i,j})^2}{\sum_{i=1}^{N}\sum_{j=1}^{M}(\bar{\text{I}}_{i,j})^2}\ . \qquad (2.4)$$

5. Maximum Difference (MD): Calculates absolute maximum difference of the original image (I) pixel values subtracted with enhanced image (Ī) pixel values. Maximum difference formula (2.5) [11].

$$\text{MD}\ (\text{I},\bar{\text{I}}) = \text{Max}\ |\mathbf{I}_{i,j} - \bar{\text{I}}_{i,j}|. \qquad (2.5)$$

6. Average Difference (AD): Calculates sum of difference of original image (I) subtracted with enhanced image (Ī) divided with total pixels amount the image has. The average difference formula (2.6) [11].

$$\text{AD}\ (\text{I}, \bar{\text{I}}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(I_{i,j} - \bar{\text{I}}_{i,j}). \qquad (2.6)$$

7. Normalized Absolute Error (NAE): Calculates sum of absolute difference of the original image (I) subtracted with the enhanced image (Ī) and divided with sum of absolute pixel values of the original. The normalized absolute error formula (2.7) [11].

$$\text{NAE}\ (\text{I}, \bar{\text{I}}) = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M}|I_{i,j}-\bar{\text{I}}_{i,j}|}{\sum_{i=1}^{N}\sum_{j=1}^{M}|I_{i,j}|}\ . \qquad (2.7)$$

8. R-Averaged Maximum Difference (RAMD): Calculates the maximum difference summation of **R** between the between the original image (I) and the enhanced image (Ī) averaged by **R** value. The R-averaged maximum difference formula [7] (2.8).

RAMD (I, Ī,r)= $\frac{1}{R}\sum_{r=1}^{R} max_r |I_{i,j} - \bar{I}_{i,j}|$. (2.8)

Where the value of **R** is the number of times we iterate and select the maximum difference between the pixel of the original and enhanced images.

9. Normalized Cross Correlation (NCC): Calculates the sum of multiplying the original image (I) and the enhanced image (Ī), divided by the sum squared of the original image (I). the normalized cross correlation formula (2.9) [11].

NCC (I, Ī) = $\frac{\sum_{i=1}^{N}\sum_{j=1}^{M}(I_{i,j}.\bar{I}_{i,j})}{\sum_{i=1}^{N}\sum_{j=1}^{M}(I_{i,j})^2}$. (2.9)

10. Total Edge Difference (TED): Calculates the total sum of absolute value of edge difference between the original image (I) pixel values and the enhanced image (Ī) pixel values, averaged by total number of pixels in the image. Total edge difference formula (2.10) [12].

TED (I, Ī) =$\frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M} |I_{Ei,j} - \bar{I}_{Ei,j}|$. (2.10)

Where $\mathbf{I_{Ei,j}}$ is total number of corners in the original image **(I),** $\bar{I}_{ei,j}$ is total number of corners in the enhanced image **(Ī).**

11. Total Corner Difference (TCD): Calculates the total sum of absolute value of corner difference between the original image (I) pixel values and the enhanced image (Ī) pixel values, and then averaged by the maximum number of corners in the image. The total corner difference formula (2.11) [12]

TCD (I, Ī) = $\frac{|N_{cr} - \bar{N}_{cr}|}{\text{Max}\,(N_{cr}, \bar{N}_{cr})}$. (2.11)

Where NCR is total number of corners in the original image **(I),** $\bar{N}_{cr}$ is total number of corners in the enhanced image **(Ī).**

12. Spectral Phase Error (SPE): Calculates the sum of phase error between the original image (I) and the enhanced image (Ī) squared in the fourier transform and divided by the total number of pixels in the image. Fourier transform transforms original/enhanced image to the fourier domain, where each point represents a particular frequency contained in the image [13]. The spectral phase error formula (2.12) [14].

$$\text{SPE}\ (\text{I}, \bar{\text{I}}) = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} |\ \text{Arg}(F_{i,j}) - \text{arg}\ (\bar{F}_{i,j})|^2. \quad (2.12)$$

Where $arg(\text{f}_{\text{I,j}})$ is the phase of the original image, and $arg(\bar{F}_{i,j})$ is the phase of the enhanced image.

13. Spectral Magnitude Error (SME): Calculates the total sum of absolute value of the difference between the original image (I) and the enhanced image ($\bar{I}$) in the fourier transform averaged by the total number of pixels in the image. The spectral magnitude error formula (2.13) [14].

$$\text{SME}\ (\text{I}, \bar{\text{I}}) = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} (|F_{i,j}| - |\bar{\text{F}}_{i,j}|)^2. \quad (2.13)$$

Where (|fi, j|-|$\bar{\text{f}}$i, j|) is the absolute value of difference between two vectors of the original image **(I)** and enhanced image**(Ī)** in the fourier transform.

14. Gradient Phase Error (GPE): Calculates the sum of phase error between the original image (I) subtracted from the original image (Ī) squared in the gradient transform and divided by the total number of pixels in the image. Gradient phase error formula (2.14) [15].

$$\text{GPE}\ (\text{I}, \bar{\text{I}}) = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} |\ \text{Arg}(G_{i,j}) - \text{Arg}(\bar{G}_{i,j})\ |^2. \quad (2.14)$$

Where $arg(g_{I,j})$ is the gradient phase of the original image **(i),** $arg(\overline{G}_{I,j})$ is the gradient phase of the enhanced image **(Ī)**.

15. Gradient Magnitude Error (GME): Calculates the total sum of absolute value of the difference between the gradient of the original image (I) and the gradient of the enhanced image (Ī) averaged by the total number of pixels in the image. Gradient magnitude error formula (2.15) [15]:

$$\text{GME}\ (I, \bar{I}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(|G_{i,j}| - |\bar{G}_{i,j}|)^2. \qquad (2.15)$$

Where **gi, j** is the gradient of the original image, and **'gi, j** is the gradient of the enhanced image.

16. Mean Angle Similarity (MAS): The mean angle that calculates the similarity between the original image (I) and the enhanced image (I). The mean angle similarity formula (2.16) [7]:

$$\text{MAS}\ (I, \bar{I}) = 1 - \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(\alpha_{i,j}). \qquad (2.16)$$

Where $\boldsymbol{\alpha_{i,j}}$ the angle of the original/enhanced image.

17. Mean Angle Magnitude Similarity (MAMS): The mean angle calculates the magnitude similarity between the original image (I) and the enhanced image (I). The mean angle magnitude similarity formula (2.17) [7]:

$$\text{MAMS}\ (I, \bar{I}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(1 - [1 - \alpha_{i,j}][1 - \frac{||I_{i,j} - \bar{I}_{i,j}||}{255}]). \qquad (2.17)$$

18. Laplacian Mean Squared Error (LMSE): Calculates the sum of ratio between the original image(I) and the enhanced image (I) to the original image squared, $h(ii, j) = ii + 1, j + ii - 1, j + ii, j + 1 + ii, j - 1 - 4ii$. The laplacian mean squared error formula (2.18) [11]:

$$\text{LMSE}\,(\text{I}, \bar{\text{I}}) = \frac{\sum_{i=1}^{N-1}\sum_{j=2}^{M-1}(h(\text{I}_{i,j}) - h(\bar{\text{I}}_{i,j}))^2}{\sum_{i=1}^{N-1}\sum_{j=2}^{M-1} h(\text{I}_{i,j})^2}\,. \tag{2.18}$$

19. Structural Similarity Measures (SSIM): It’s a quality measure when one single image is contrasted and the other image is still with its original quality, SSIM is an upgrade widespread index.
(Available in [16] and implemented in [17]).

20. Visual Information Fidelity (VIF): Considers that the real images are on scenes defined as natural and according to this the type of properties should be the same.
(Available in [18] and implemented in [17]).

21. Reduced Reference Entropy Difference (RRED): It’s a quality measure that extracts some local information of a given sample by processing as a wavelet. Speculation of the sample can’t be seen in samples in nature.
(Available in [19] and implemented in [17]).

22. High Low Frequency Index (HLFI): Concerned with sharpness and functions by the estimation of the power between the low and up frequency actions of a fourier spectrum.
(Available in [20] and implemented in [17]).

23. Jpeg Quality Index (JQI): Evaluation of the distorted image qualities by a known closed artificial initiated comparing algorithm at a decreased number of bit rate like jpeg.
(Available in [21] and implemented in [17]).

24. Blind Image Quality Index Measures (BIQI): The basic idea of this measure is that clear original images present some common properties if calculated accurately, divergence of the uniformity in the given statistics in nature is able to estimate the given image quality. BIQI is used for the train image in the past.
(Available in [22] and implemented in [17]).

25. Natural Image Quality Evaluator (NIQE): This quality measure evaluates the blind image quality feature when extracting the features of statistics associated to many alterations producing quality information.
(Available in [23] and implemented in [17]).

2.1.3 Classifiers Used in [6] and Our RFDS

Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) are used in [6] to classify fingerprint images if they real or fake.

- **Linear Discriminant Analysis** (**LDA**): a method used in statistics, pattern recognition and machine learning to find a linear combination of features that characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier or, more commonly, for dimensionality reduction before later classification [24].

- **Quadratic Discriminant Analysis** (**QDA**): QDA is closely related to linear Discriminant Analysis (LDA), where it is assumed that the measurements are normally distributed. Unlike LDA however, in QDA there is no assumption that the covariance (the measure of how much two or more random variables differ) of each of the classes is identical. To estimate the parameters required in quadratic discrimination more computation and data is required than in the case of linear discrimination [25].

▪ **Linear Support Vector Machine** (**LSVM**): use 3 or 4 support vectors to obtain the optimum boundary between features. For example, we will use 3 support vectors s1, s2, and s3.

$\hat{S}1=\begin{pmatrix}2\\1\\1\end{pmatrix}$, $\hat{S}2=\begin{pmatrix}2\\-1\\1\end{pmatrix}$, And $\hat{S}3=\begin{pmatrix}4\\0\\1\end{pmatrix}$.

Find 3 parameters α1, α2, and α3 based on the following 3 linear equations:

$A_1\hat{S}_1.\,\hat{S}_1 + A_2\hat{S}_2.\,\hat{S}_1 + A_3\hat{S}_3.\,\hat{S}_1 = -1\ (-negative\ class)$

$A_1\hat{S}_1.\,\hat{S}_2 + A_2\hat{S}_2.\,\hat{S}_2 + A_3\hat{S}_3.\,\hat{S}_2 = -1\ (-negative\ class)$

$A_1\hat{S}_1.\,\hat{S}_3 + A_2\hat{S}_2.\,\hat{S}_3 + A_3\hat{S}_3.\,\hat{S}_3 = +1\ (+postive\ class)$

Substitute the values for ŝ1, ŝ2, and ŝ3 in the above equations, after simplification of the quations above we get:

$6\alpha_1 + 4\alpha_2 + 9\alpha_3 = -1$

$4\alpha_1 + 6\alpha_2 + 9\alpha_3 = -1$

$9\alpha_1 + 9\alpha_2 + 17\alpha_3 = +1$

Simplifying the above 3 simultaneous equations we get:

$\alpha_1 = A_2 = -3.25\ and\ \alpha_3 = 3.5.$

Now we will get the boundary using these three parameters. The boundary between two classes is called hyper plane(ŵ), it discriminates the positive class form the negative class.

$\hat{w} = \sum_i \alpha_i \hat{S}_i$.

$\hat{W} = (-3.25).\begin{pmatrix}2\\1\\1\end{pmatrix} + (-3.25).\begin{pmatrix}2\\-1\\1\end{pmatrix} + (3.5).\begin{pmatrix}4\\0\\1\end{pmatrix} = \begin{pmatrix}1\\0\\-3\end{pmatrix}$.

The vectors are augmented with a bias; we can equate the entry in $\hat{\boldsymbol{w}}$ as the hyper plane with an offset ***b***, therefore the separating hyper plane equation, x and y points on co-ordinate axis (x1, y1) (x2, y2).

$$Y = wx + b. \tag{2.19}$$

$W = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$ and offset $b = -3$. This is the expected decision boundary for the linear svm.

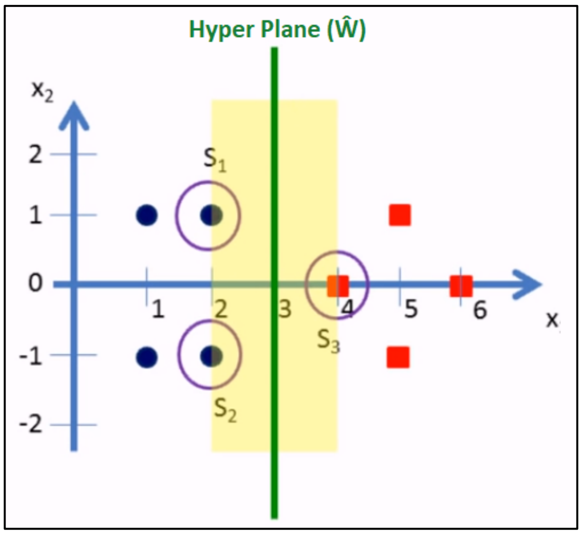


Figure 2: The boundary between two classes (Hyper Plane(Ŵ)).

▪ **Logistic Regression**: Logistic regression predicts whether something is **True** or **False**, instead of predicting something continuous like size. Logistic regression doesn't fit a line to the data, instead it fits an "s" shaped "logistic function", where the "s" curve goes from 0 to 1, which means the curve tells us the probability that a fingerprint is **Fake** or not based on its **IQM** result.

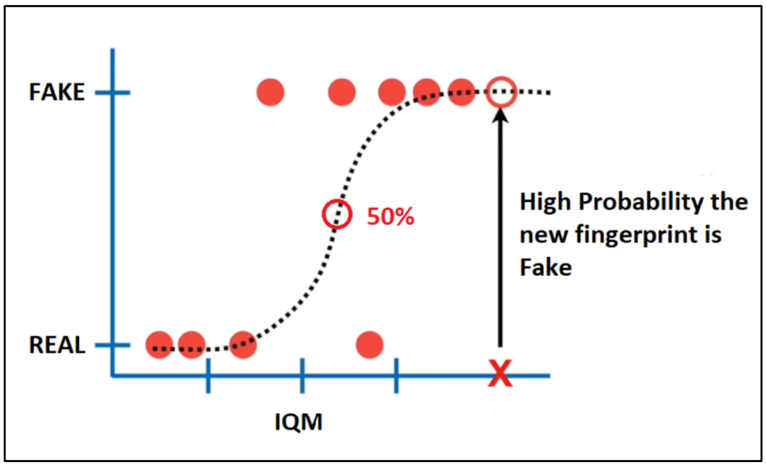


Figure 3: 'S' shaped logistic function.

If the probability a fingerprint is fake is above 50% then we classify it as fake, otherwise we will classify it as real.

▪ **Fine KNN (K-Nearest Neighbors):** Fine KNN is a simple way to classify data, if you already had a lot of data that classify the fingerprint, we could use fine KNN to decide which type of class the new fingerprint image(New Cell) belongs to, to be more clear here is an example:

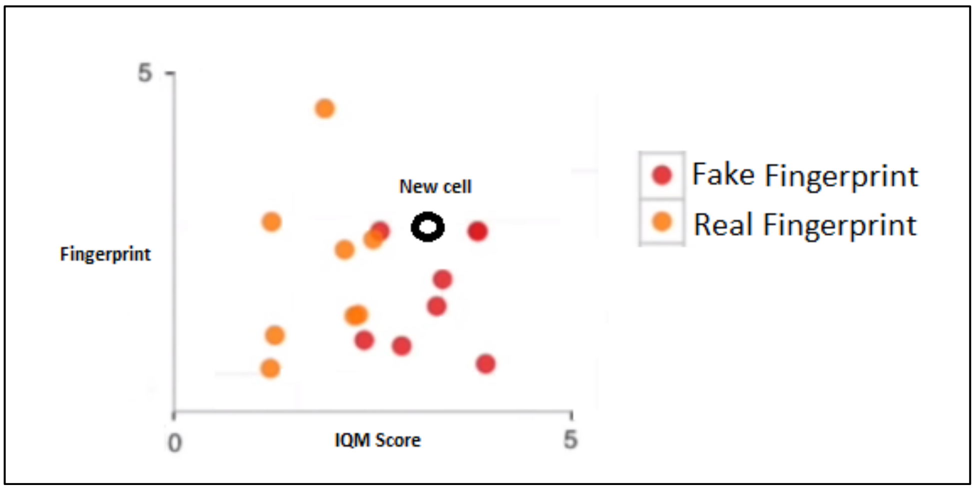


Figure 4: A new cell (fingerprint image) with unknown category to classify.

In figure 4, we added a new cell with unknown category, and we want to classify this new cell. We want to figure out what cell it's most similar to it, then we are going to call it that type of cell. In fine KNN, the new cell will be classified by looking at its nearest neighbors. If "k" in "K-Nearest Neighbors" is equal to 1, then we only use the nearest neighbor to define the category, and in our example the category is red for the new cell because the nearest neighbor is also red.

2.1.3.1 RFDS Experiments In [6]

Experiment was implemented on a system with 64-bit operating system, Windows 7 PC, 3.4 GHz processor, RAM of 16GB, and MATLAB r2012b. LivDet09 [26] was the database used in the fingerprint detection experiment. LivDet09 [26] has above 18,000 samples obtained from more than 100 different fingers.

Three sensors used in [6] are Biometrika, Crossmatch, and Identix. The overall error rate using biometrika sensor was 12.8%, crossmatch 10.7 %, and identix 1.2%, all shown in Table 1.

Table 1: RFDS [6] results using three different type of fingerprint sensors.

	Comparative Results: Fingerprints-LivDet09								
	Biometrika			**Crossmatch**			**Identix**		
	FFR	**FGR**	**HTER**	**FFR**	**FGR**	**HTER**	**FFR**	**FGR**	**HTER**
IQA-Based	14.0	11.6	12.8	8.6	12.8	10.7	1.1	1.4	1.2

Description of the measures used in Table 1:

False Fake Rate (FFR) refers to the number of real images that were considered as fake in the system.

$$\text{FFR}=\frac{\text{FFR}}{\text{TOTAL NUMBER OF REAL IMAGES}}\ . \qquad (2.20)$$

False genuine rate (FGR) refers to number of fake images that were considered as real in the system:

$$\text{FGR}=\frac{\text{FGR}}{\text{TOTAL NUMBER OF FAKE IMAGES}}\ . \qquad (2.21)$$

Half Total Error (HTER) refers to the number of real images that were considered as fake in the system summed with the number of fake images that were considered as real in the system divided by 2,

$$\text{HTER}=\frac{\text{FGR+FFR}}{2}\ . \qquad (2.22)$$

2.1.4 Fingerprint Liveness Detection Based on Quality Measures [27]

In [27], the RFDS uses image quality measures for a Software-Based solution in fingerprint image detection. The main purpose of [27] is to counter the direct attacks implemented against the fingerprint recognition systems.

Direct attacking methods present artificial fingerprints to the sensors so that the sensor will identify them as real fingerprints inserted to the system, and thus access is granted. To prevent direct attacking occurrence, a new live detection system was proposed in this paper with 3 types of image quality measures, ridge strength, ridge continuity, and ridge clarity. The new live detection system proposed in [27] includes the steps that are explained below:

Input: Once the fingerprint image gets inserted into the system, it will be immediately segmented (Image is Easier to Analyze) in the background.

Feature Extraction: Image quality measures will be extracted, the image quality measures with the best performance only will be selected from the all the available ones. After selecting the best image quality measures, we reach the final stage, cclassification of the fingerprint image. Linear discriminant analysis (LDA) (described in subsection 2.1.1) is used in [27] to classify whether the inserted fingerprint image is Real or Fake.

2.1.4.1 RFDS Experiments In [27]

Database used in [27] is provided in the fingerprint liveness detection competition, livdet 2009, containing over 18,000 real and fake samples of fingerprint images generated with different materials and captured with different sensors. Three sensors were used in [27]: biometrika, crossmatch, and identix.

The proposed new liveness detection system result was on average (7.58% hter) in identifying real or fake sample of fingerprint images. The results of [27] for each sensor are shown in Table 2.

Table 2: The results for each sensor [27].

	Fgr(%)	**Ffr(%)**	**Hter(%)**
Bionetrika	2.12	1.54	1.83
Crossmatch	12.48	12.32	12.40
Identix	6.40	10.67	8.53
Average	7.00	8.17	7.58

2.1.5 A High-Performance Fingerprint Liveness Detection Method Based on Quality Related Features [28]

A software-based fingerprint liveness detection approach using image quality measures is proposed in [28]. The system was tested by using two different databases and five different sensors.

The proposed system starts with inserting a fingerprint image and, the type of sensor used for getting the fingerprint image. After inserting the sensor type and the fingerprint image, segmentation will be applied to the fingerprint image, and then three different types of image quality measures will be extracted from the fingerprint image: ridge strength, ridge continuity, and ridge clarity.

After applying extraction to the fingerprint image and obtaining the results of every single image quality measurement, selection of the ones with the best results from the image quality measures will be done, and the rest will be excluded for the classification of the image stage. Classification is done using LDA (defined in 2.1.1) to classify if the fingerprint image is real or fake.

2.1.5.1 RFDS Experiments In [28]

In [28], two databases were used: LivDet DB and ATVS DB. ATVS database contains three different datasets of real and fake fingerprints captured each by three different sensors: Biometrika, Precise, and thermal Yubee. LivDet database contains also three different datasets of real and fake fingerprints captured each captured by three different sensors, Namely, Biometrika, Crossmatch, and Identix.

Experiments results in [28] with both ATVS DB and LivDet show overall around 10% of error in identifying real and fake fingerprint images in the liveness detection system. The results for both databases with five different sensors are listed in Table 3, FGR_1, FFR_1, and HTER_1 REFER to the ATVS db, and FGR_2, FFR_2, and HTER_2 refer to the LivDet.

Table 3: Performance result of the two databases used in [28].

	Performance Results In %			
	$\mathrm{FGR}_1/\mathrm{FGR}_2$	**$\mathrm{FFR}_1/\mathrm{FFR}_2$**	**$\mathrm{HTER}_1/\mathrm{HTER}_2$**	**Hter**
Biomet.Ld	3.1/9.8	71.8/21.5	37.4/15.6	26.5
Crossmatch	8.8/16.7	20.8/6.8	14.8/11.7	13.2
Identix	4.8/8.0	5.0/9.1	4.9/8.5	6.7
Biomet.Atvs	9.4/0.4	1.5/11.8	5.5/6.1	5.8
Precise	3.1/0.4	13.7/0.4	8.4/0.4	4.4
Yubee	2.7/1.6	6.3/13.0	4.5/7.3	5.9
Average	5.3/6.1	19.8/10.4	12.5/8.2	10.4

2.1.6 Fingerprint Identification in Biometric Security Systems. International Journal of Computer and Electrical Engineering [29]

In [29], two software based matching algorithms (algorithms that match fingerprints against a database of known and unknown fingerprint) are discussed. The first algorithm is developed at the Hong Kong Baptist University; the second matching algorithm is developed at the michigan state university in usa. Two of the algorithms were downloaded and tested with a common database.

The Hong Kong Baptist University fingerprint identification system uses a traditional minutia matching algorithm, while the Michigan State University uses filter-based algorithm in their system.

The Hong Kong baptist university fingerprint identification system is based on three steps:

1. Preprocessing: The inserted fingerprint image is enhanced using fourier transform (conversion of the image from space domain to frequency domain) and histogram equalization (modify the intensity and contrast of the fingerprint image), after that binarization is applied to the image which will change it from pixel image to a binary image using threshold for each block in the image.

2. Minutiae Extraction: The extraction is done by thinning the inserted fingerprint image and marking any minutiae that exists in the image.

3. Post-Processing: In this stage, all false minutiae (major features of a fingerprint such as ridge ending and bifurcation) are removed.

Michigan State University method uses filter-bank based matcher: the proposed filter-bank based algorithm uses more than one filter to capture details in a fingerprint as a compact fixed length feature vector. The fingerprint matching is based on the euclidean distance between the two corresponding vectors.

2.1.6.1 RFDS Experiments In [29]

The database used in [29] is NIST special database 4 which is publicly available; it contains 8-bit gray scale image fingerprints distributed for development and testing of fingerprint identification systems.

For 25 pairs of fingerprints with high quality inserted into the software using filter-based algorithm, the results are as follows: 8% FAR and 4% FFR.

In [29], they concluded that both of the algorithms are equal in performance and none of them can be considered as better than the other in general sense.

2.1.7 Fingerprint Spoof Detection Using Quality Features [30]

In [30], three stages are considered for fake fingerprint detection:

1. Feature Extraction: The inserted fingerprint image is divided into blocks and the features are extracted from each block. There is a total of 7 features which will be get extracted from the input fingerprints image.

2. Features Selection: The features with optimal performance will be selected; the ones that are not effective, will be excluded.

3. Classification: After feature extraction and selecting the best extracted features, classification of the fingerprint image is implemented to identify if the inserted fingerprint image is real or fake.

2.1.7.1 RFDS Experiments In [30]

The database used in [30] is provided in the fingerprint liveness detection competition LivDet 2009 [26] with three data sets of real and fake fingerprint images all captured with different kind of optical sensors: Biometrika, Identix, and Crossmatch.

Experiment results in [30] are considered overall as a good RFDS to use, the results in Figure 5 show that if all features are used at once without excluding any one of them, better results will be obtained.

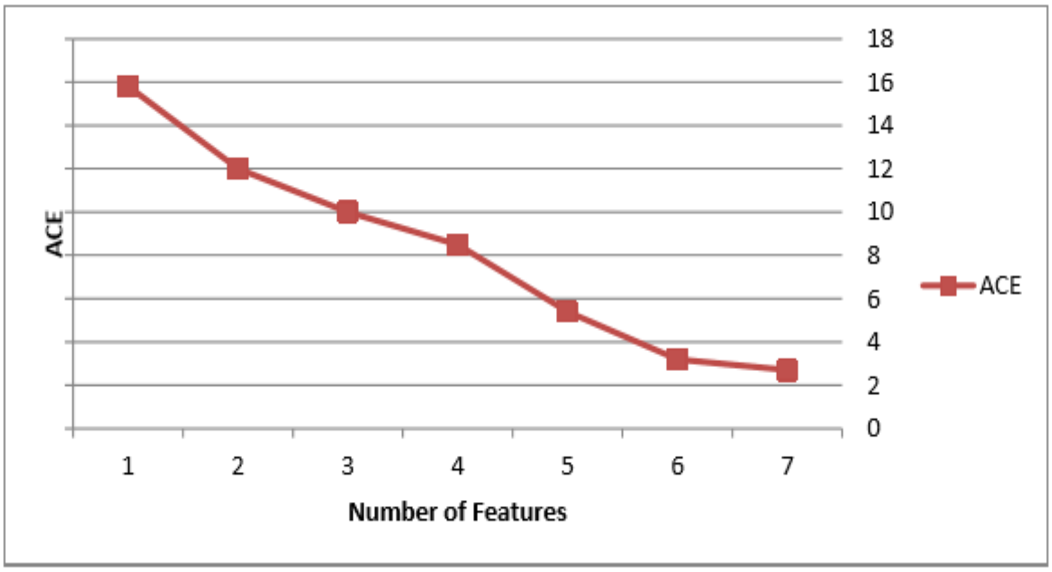


Figure 5: Average classification error (ACE) results in [30].

2.2 Problem Definition

We have observed [6], [18], [19], [20], and [30], but we will mainly compare our RFDS to be developed with RFDS [6]. The list of problems considered in this thesis is:

1. Implement and test a real fingerprint detection system (RFDS) similar to [6].

2. Repeat experiments on RFDS implemented as in [6].

3. Compare our RFDS with [6].

4. Find the best 5, 10, and 15 iqms in our RFDS.

5. Modifying thesis [31] the distinction from our RFDS and thesis [31] is that we used 10 more IQMs and 6 classifiers. Thesis [31] was implemented for face detection while ours is for fingerprints.

2.3 Summary

In this chapter, we have done a literature review from the reading and analysis of [6], [27], [28], [29], and [30]. We conclude that some of the presented RFDS use similar image quality features and classification algorithms and some use different. The experiment results on these systems were gathered using different databases, all these results obtained still didn’t reach 100% accuracy of detecting fingerprint spoof attacks. The features to be built in our RFDS is to find the best 5, 10 and 15 IQM’s automatically calculating the FFR, FAR, and HTER of the RFDS. We define our thesis problem as: implementation and testing of real fingerprint image detection system (RFDS).

Chapter 3

DESIGN AND IMPLEMENTATION OF RFDS

In this chapter, we show the design of our RFDS, implementation of the feature extraction in our system as well as the classification process. We implemented the Gaussian filter as explaned in subsection 3.2.1, feature extraction stage for the fingerprint images as explaned in subsection 3.2.2 using 25 image quality measures. The training structure was implemented and explaned in subsection 3.2.3, classification process in subsection 3.2.4, method of defining the best IQMs in subsection 3.2.5, and the method of defining the best IQMs was implemented and tested as described in subsection 3.2.

3.1 Design of RFDS

Figure 6 shows the design of our RFDS. Basically, our system contains two structures:

1. Training Structure (as shown at the top of figure 6)
2. Detection Structure (as shown at the top of figure 6).

The top of Figure 6 shows our RFDS training structure where (I) refers to the original fingerprint image and (‘I) refers to the enhanced image. Images will be input in our RFDS training structure. In block 1, each single image will be filtered using gaussian filter (see subsection 3.2.1) with 3*3 kernel to reduce the noise of the image. By filtering the input images (I), we get the enhanced fingerprint image (I’). In block 2, we will apply feature extraction process to both of the fingerprint images by extracting image quality measures (see subsection 3.2.2), we then create a table and list the results of the fingerprint images and their IQM. In block 3, we import the table with all the results to classification learner application, which is a user-friendly application that we use in MATLAB software to create our training model (block number 4) and classify images (see subsection 3.2.3). From this we move to the classification stage where all the fingerprint images will be classified as either real or fake images.

The bottom of Figure 6 shows our RFDS detection structure. All input images will be classified on real or fake depending on the trained model created in the "training structure" shown in figure 6.

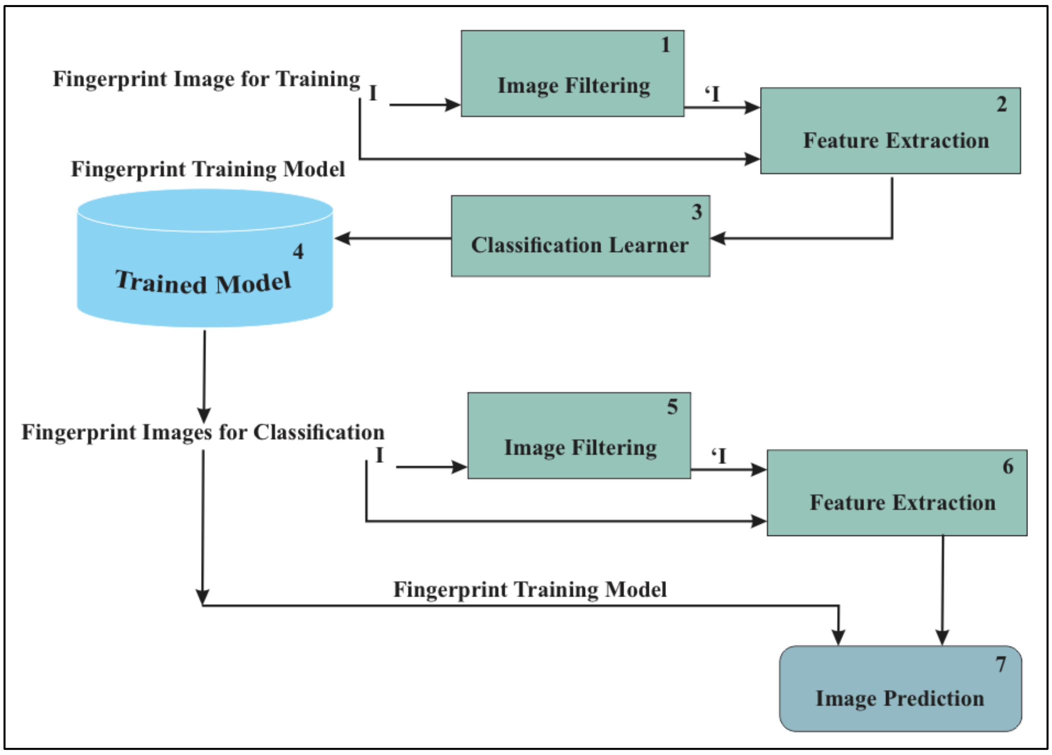
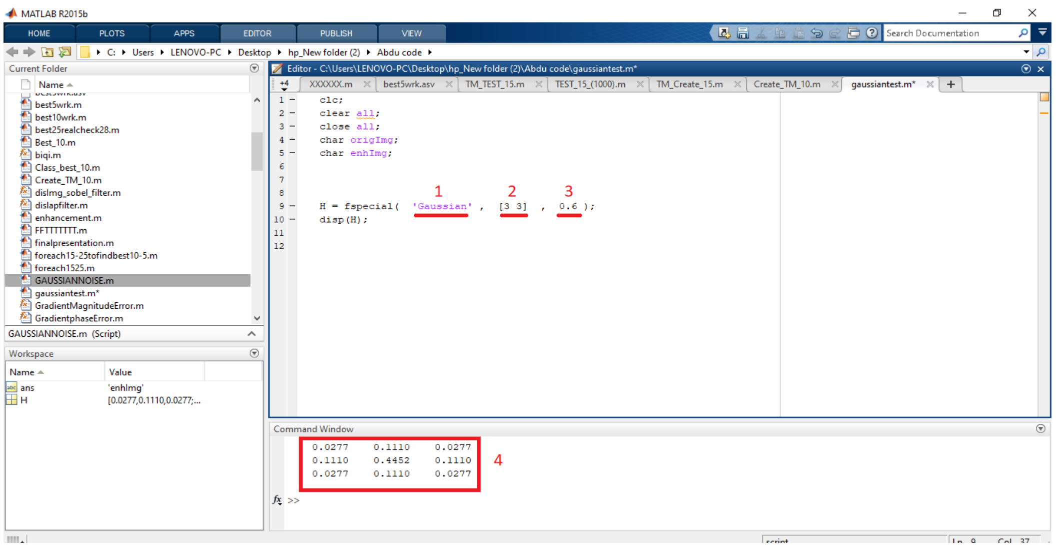


Figure 6: RFDS training and detection structure.

3.2 Implementation of RFDS

3.2.1 Implementation and Testing of Gaussian Filter

Gaussian filter is a filter whose impulse response is a Gaussian function (or an approximation to it). Gaussian filters have the properties of no overshoot to a step function input while minimizing the rise and fall time [32]. For our RFDS implementation and testing, we used MATLAB 2015 in this thesis. For implementation of Gaussian filter, we used a ready MATLAB function “Gaussian” to enhance and reduce the noise of the image. All we had to do was to call the function by typing “Gaussian” which is shown below in Figure 7, and highlighted with number 1. Then, we set the value of the Gaussian kernel as “3x3” highlighted and numbered 2 in the screenshot, and set the standard deviation as “0.6” (0.6 was selected just as an example) highlieghted and numbered 3 in Figure 7. By these three values, we set our RFDS system that gives us a Gaussian filter with the values shown in number 4 of the screenshot below.



```
clc;
clear all;
close all;
char origImg;
char enhImg;


H = fspecial( 'Gaussian' , [3 3] , 0.6 );
disp(H);
```

```
    0.0277    0.1110    0.0277
    0.1110    0.4452    0.1110
    0.0277    0.1110    0.0277
```

Figure 7: Gaussian filter code and the Gaussian filter obtained from it.

Example of how Gaussian filter is implemented using a 4*4 matrix image:

Original Image			
0	1	7	3
4	2	8	10
0	2	1	6
6	3	5	4

3x3 Gaussian Kernel		
0.0277	0.1110	0.0277
0.1110	0.4452	0.1110
0.277	0.1110	0.0277

Let's select the pixel in 2nd row 3rd column of the original image and apply Gaussian filter to it:

0	1	7	3
4	2	8	10
0	2	1	6
6	3	5	4

*

0.0277	0.111	0.0277
0.1110	0.4452	0.111
0.0277	0.111	0.0277

=

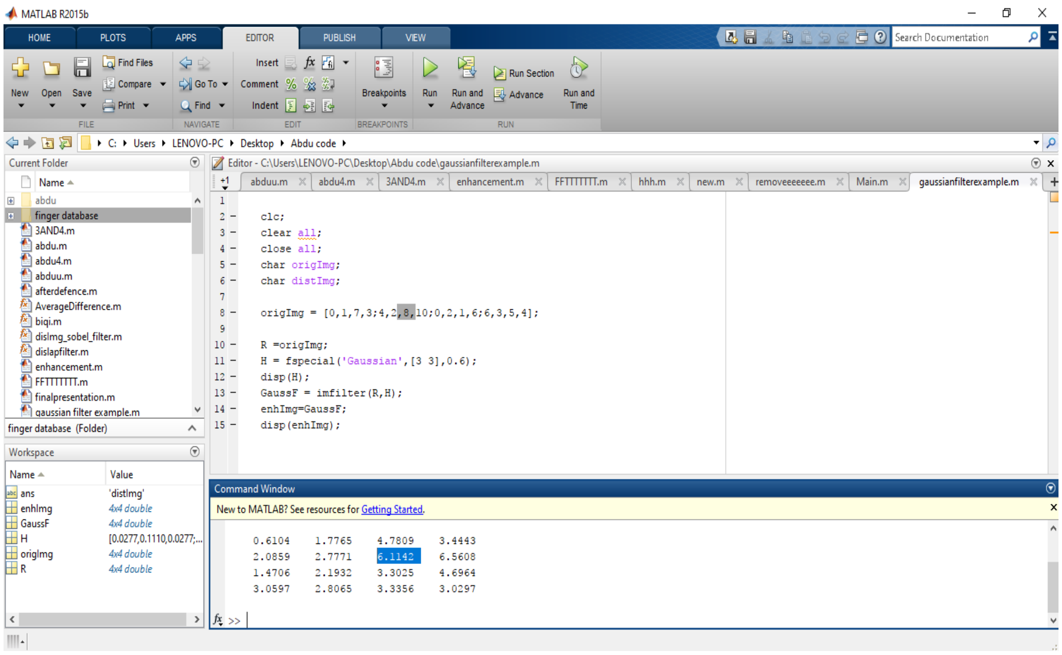
0.0277	0.777	0.0831
0.222	3.5616	1.11
0.0554	0.111	0.1662

Add the values in the vector: 0.0277 + 0.777 + 0.0831 + 0.222 + 3.5616 + 1.11 + 0.0554 + 0.111 + 0.1662 = 6.114

Final result of the original image after Gaussian filter as.

0.610	1.776	4.780	3.444
2.085	2.777	6.114	6.560
1.470	2.193	3.302	4.696
3.059	2.806	3.335	3.029

To check if our manual calculation of the Gaussian filter applied to the original image is correct or not, we ran our MATLAB code and took a screenshot of the result shown below in figure 8, the result of the original image with Gaussian filter applied to it is the same as (3.1).



```
clc;
clear all;
close all;
char origImg;
char distImg;

origImg = [0,1,7,3;4,2,8,10;0,2,1,6;6,3,5,4];

R =origImg;
H = fspecial('Gaussian',[3 3],0.6);
disp(H);
GaussF = imfilter(R,H);
enhImg=GaussF;
disp(enhImg);
```

```
    0.6104    1.7765    4.7809    3.4443
    2.0859    2.7771    6.1142    6.5608
    1.4706    2.1932    3.3025    4.6964
    3.0597    2.8065    3.3356    3.0297
```

Name	Value
ans	'distImg'
enhImg	4x4 double
GaussF	4x4 double
H	[0.0277,0.1110,0.0277;...
origImg	4x4 double
R	4x4 double

Figure 8: Result of the original image with Gaussian filter applied to it.

3.2.2 Implementation and Testing of Feature Extraction

To test the implementation of our RFDS, we use 4x4-sized (for ease of calculation) two gray scale images, one named original image (I) with matrix elements: (0, 1, 7, 3), (4, 2, 8, 10), (0, 2, 1, 6), (6, 3, 5, 4) and the second one named enhanced image (‘I) (original image with Gaussian filter applied to it) with matrix elements: (2, 5, 10, 4), (0, 1, 5, 1), (3, 6, 2, 3), (1, 3, 10, 0).

Original Image (I)			
0	1	7	3
4	2	8	10
0	2	1	6
6	3	5	4

Enhanced Image (‘I)			
2	5	10	4
0	1	5	1
3	6	2	3
1	3	10	0

For each of the 25 IQMs we will do the following (our MATLAB code is provided in Appendix A and the IQM function in Appendix B).

For 4x4-sized of the enhanced and original image, we will take screenshots of every IQM result in MATLAB.

3.2.2.1 Implementation and Testing of MSE (2.1)

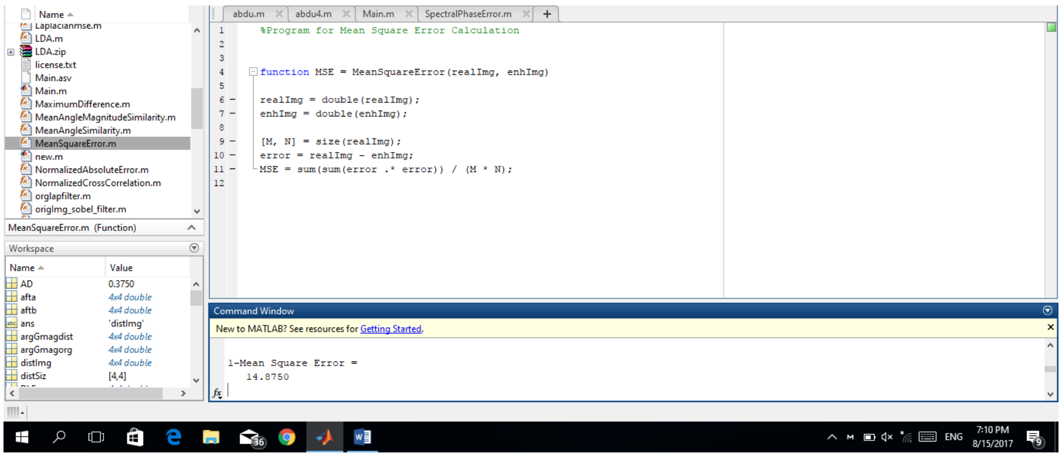
Explanation of MSE code given in (Appendix A-1):

Line 1: MSE function has two inputs: rel_img refers to the real image, and enhcd_img to the enhanced image. Line 4: [m n] is defined where m is the number of rows and n is the number of columns the real image has. Line 5: difference between real and enhanced images is calculated. Line 6: using (2.1), MSE is calculated.

Testing example of MSE calculation for I and ‘I:

MSE = 1/16 *((0-2) ^2 + (1-5) ^2 + (7-10) ^2 + (3-4) ^2 + (4-0) ^2 + (2-1) ^2 + (8-5) ^2 + (10-1) ^2 + (0-3) ^2 + (2-6) ^2 + (1-2) ^2 + (6-3) ^2 + (6-1) ^2 + (3-3) ^2 + (5-10) ^2 + (4-0) ^2) = 1/16*(238) = 14.875 (3.2)

The result of MSE calculation shown in Figure 9 is equal to our manually calculated result (3.2).



```
%Program for Mean Square Error Calculation


function MSE = MeanSquareError(realImg, enhImg)

realImg = double(realImg);
enhImg = double(enhImg);

[M, N] = size(realImg);
error = realImg - enhImg;
MSE = sum(sum(error .* error)) / (M * N);
```

```
1-Mean Square Error =
   14.8750
```

Figure 9: MATLAB result of MSE calculation.

3.2.2.2 Implementation and Testing of PSNR (2.2)

Explanation of the PSNR code (Appendix A-2):

Line 1: PSNR function with two inputs rel_img and enhcd_img refers to the real and enhanced image, respectively. Line 4: [m n] is defined, where m and is the number of rows and columns the real image has. Line 5: difference between real image and enhanced image will be calculated. Line 6: using (2.1), MSE is calculated. Line 7: using (2.2), PSNR is calculated. Line 8: we set PSNR value as 99 if MSE is zero.

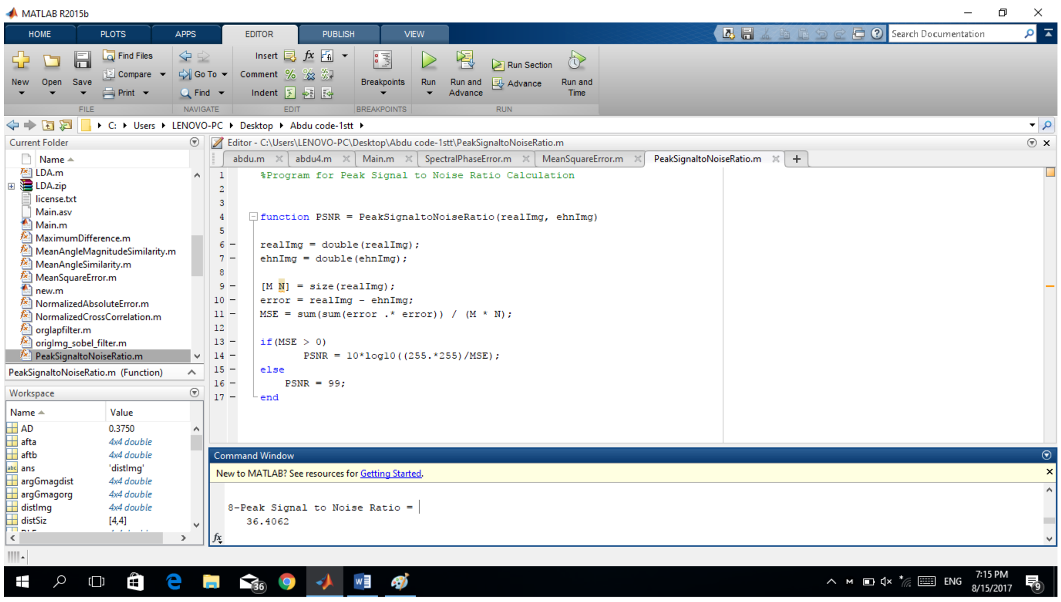
MSE = 14.875 (Obtained from Figure 9).

Max _I = 255 (max pixel value in grayscale image).

PSNR= $20log_{10}255 - 10log_{10}MSE$

= $20log_{10}255 - 10log_{10}14.875$ = 48.13 – 11.72= 36.40 (3.3)

The result of PSNR calculation shown in Figure 10 is equal to our manually calculated result (3.3).



```
%Program for Peak Signal to Noise Ratio Calculation


function PSNR = PeakSignaltoNoiseRatio(realImg, ehnImg)

realImg = double(realImg);
ehnImg = double(ehnImg);

[M N] = size(realImg);
error = realImg - ehnImg;
MSE = sum(sum(error .* error)) / (M * N);

if(MSE > 0)
       PSNR = 10*log10((255.*255)/MSE);
else
    PSNR = 99;
end
```

```
8-Peak Signal to Noise Ratio =
   36.4062
```

Figure 10: MATLAB result of PSNR calculation.

3.2.2.3 Implementation and Testing of SNR (2.3)

Explanation of the SNR code (Appendix A-3):

Line 1: SNR function with two inputs: rel_img and enhcd_img refer to the real and enhanced image, respectively. Line 4: [m n] is defined, where m and n are the number of rows and columns of the real image. Line 5: difference between real image and enhanced image is calculated. Line 6: using (2.1), MSE is calculated., Line 7: using (2.3), SNR (2.3) is calculated. Line 8: we set SNR to 99 if MSE is zero.

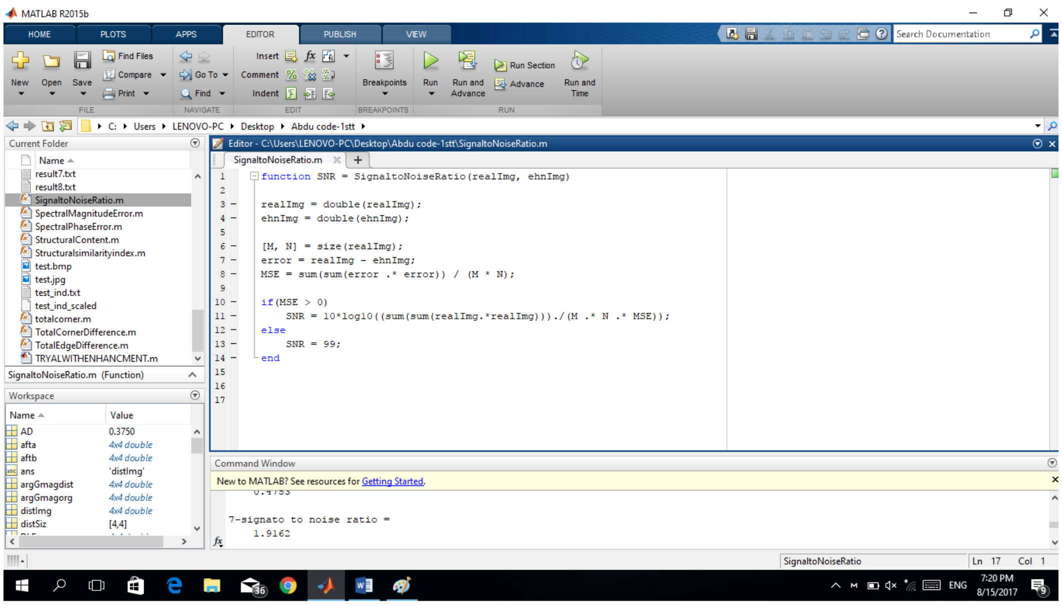
MSE = 14.875 (obtained from Figure 9)

SNR Calculation:

SNR = 10 Log10 (0^2 + 1^2 + 7^2 + 3^2+4^2 + 2^2 + 8^2 + 10^2 + 0^2 + 2^2 + 1^2 + 6^2 + 6^2 + 3^2 + 5^2 + 4^2) / 4 * 4 * 14.875

SNR = 10 Log10 370/238 = 10 Log10 1.55 = 1.91 (3.4)

The result of SNR calculation shown in Figure 11, is equal to our manually calculated result (3.4).



Editor - C:\Users\LENOVO-PC\Desktop\Abdu code-1stt\SignaltoNoiseRatio.m

```
function SNR = SignaltoNoiseRatio(realImg, ehnImg)

realImg = double(realImg);
ehnImg = double(ehnImg);

[M, N] = size(realImg);
error = realImg - ehnImg;
MSE = sum(sum(error .* error)) / (M * N);

if(MSE > 0)
    SNR = 10*log10((sum(sum(realImg.*realImg)))./(M .* N .* MSE));
else
    SNR = 99;
end
```

Command Window

New to MATLAB? See resources for Getting Started.

```
     0.4753

7-signato to noise ratio =
     1.9162
```

Figure 11: MATLAB result of SNR calculation.

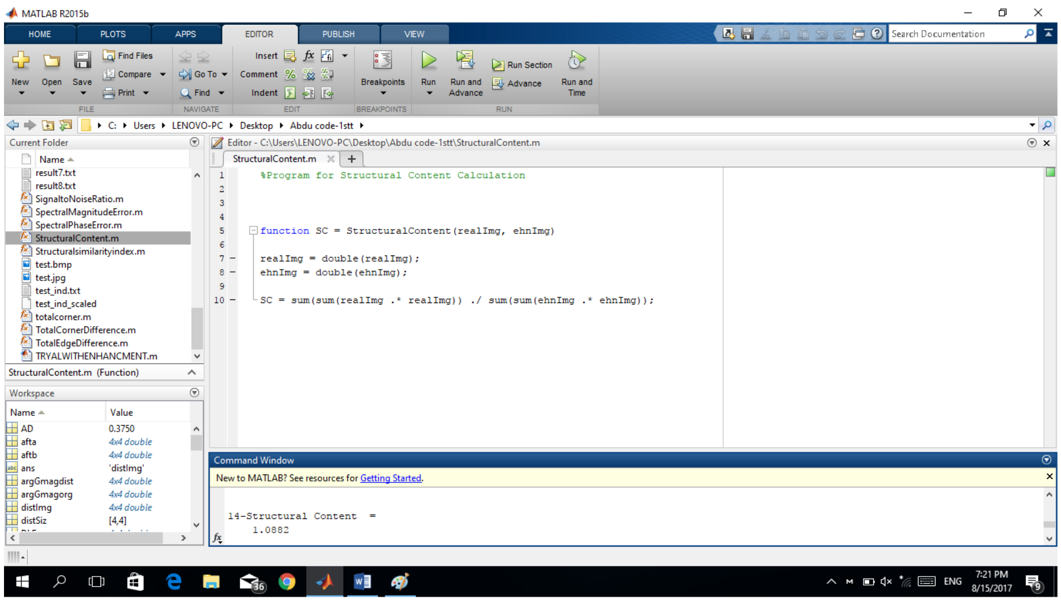
3.2.2.4 Implementation and Testing of SC (2.4)

Explanation of the SC code (Appendix A-4):

Line 1: SC function with two inputs rel_img and enhcd_img refers to the real and enhanced image. Line 4: using (2.4), SC is calculated.

SC = (0^2 + 1^2 + 7^2 + 3^2+4^2 + 2^2 + 8^2 + 10^2 + 0^2 + 2^2 + 1^2 + 6^2 + 6^2 + 3^2 + 5^2 + 4^2) / (2^2 + 5^2 + 10^2 + 4^2 + 0^2 + 1^2 + 5^2 + 1^2 + 3^2 + 6^2 + 2^2 + 3^2 + 1^2 + 3^2 + 10^2 + 0^2) = 370/340 = 1.0882. (3.5)

The result of SC calculation shown in Figure 12, is equal to our manually calculated result (3.5).



```
%Program for Structural Content Calculation



function SC = StructuralContent(realImg, ehnImg)

realImg = double(realImg);
ehnImg = double(ehnImg);

SC = sum(sum(realImg .* realImg)) ./ sum(sum(ehnImg .* ehnImg));
```

```
14-Structural Content  =
    1.0882
```

Figure 12: MATLAB result of SC calculation.

3.2.2.5 Implementation and Testing of MD (2.5)

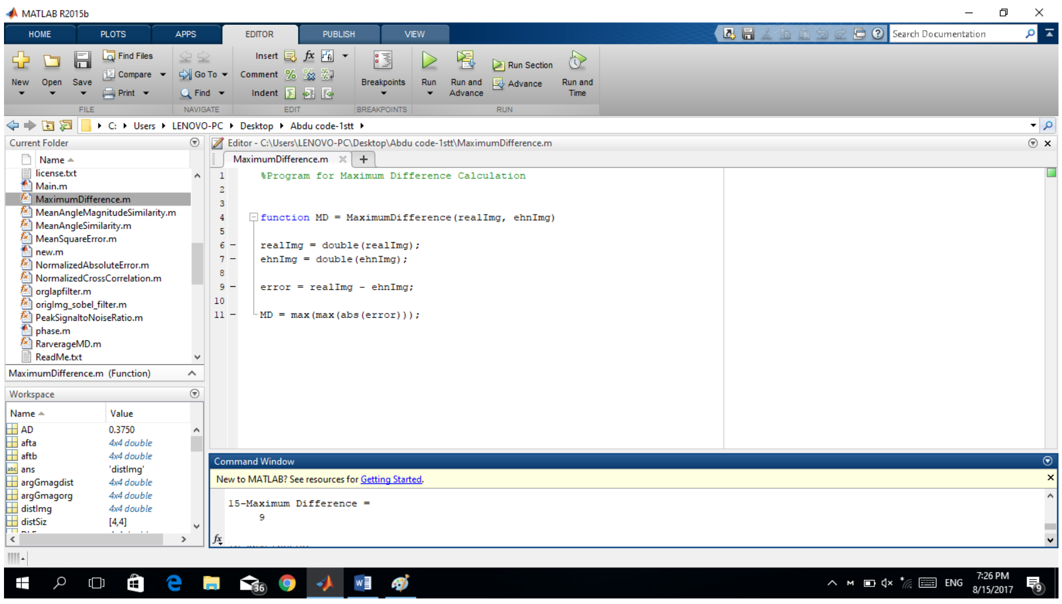
Explanation of MD code (Appendix A-5):

Line 1: MD function with two inputs: rel_img and enhcd_img refer to the real and enhanced image. Line 4: the difference between the real image and the enhanced image will be calculated. Line 5: using (2.5), MD will be calculated.

$$
\begin{aligned}
&P1 = 0 - 2 = -2 && P9 = 0 - 3 = -3 \\
&P2 = 1 - 5 = -4 && P10 = 2 - 6 = -4 \\
&P3 = 7 - 10 = -3 && P11 = 1 - 2 = -1 \\
&P4 = 3 - 4 = -1 && P12 = 6 - 3 = 3 \\
&P5 = 4 - 0 = 4 && P13 = 6 - 1 = 5 \\
&P6 = 2 - 1 = 1 && P14 = 3 - 3 = 0 \\
&P7 = 8 - 5 = 3 && P15 = 5 - 10 = -5 \\
&P8 = 10 - 1 = 9 && P16 = 4 - 0 = 4
\end{aligned}
\tag{3.6}
$$

$$Md = 9$$

The result of MD calculation shown in Figure 13 is equal to our manually calculated result (3.6).



```
%Program for Maximum Difference Calculation


function MD = MaximumDifference(realImg, ehnImg)

realImg = double(realImg);
ehnImg = double(ehnImg);

error = realImg - ehnImg;

MD = max(max(abs(error)));
```

```
15-Maximum Difference =
      9
```

Figure 13: MATLAB result of MD calculation.

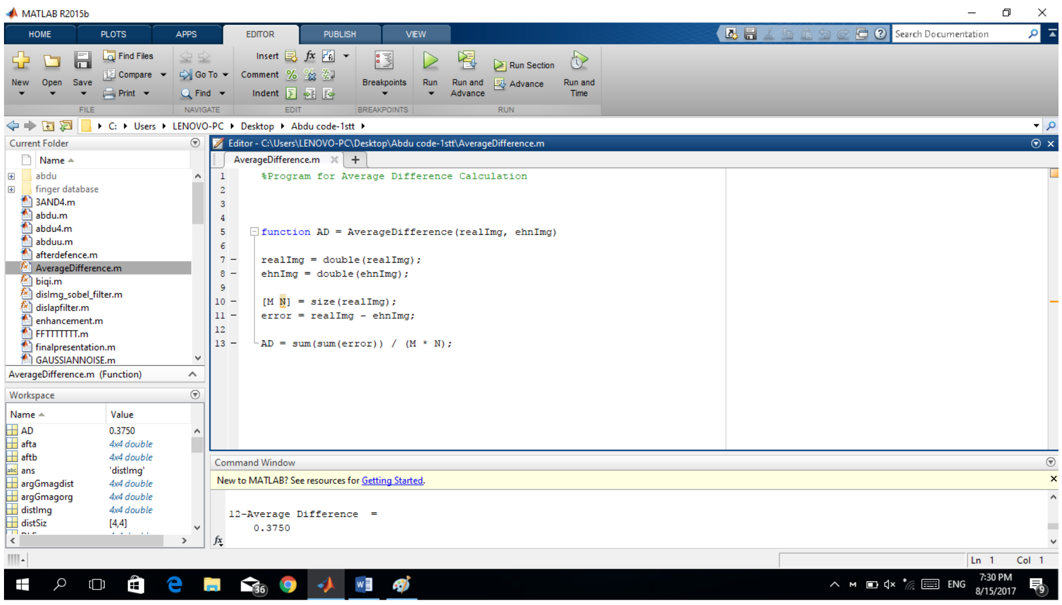
3.2.2.6 Implementation and Testing of AD (2.6)

Explanation of the AD code (Appendix A-6):

Line 1: AD function with two inputs: rel_img and enhcd_img refer to the real and enhanced image, line 4: [m n] is defined, where m and n is the number of rows and columns of the real image. 5: difference between real image and enhanced image will be calculated. Line 6: using (2.6), ad will be calculated.

AD = 1/16((0-2) + (1-5) + (7-10) + (3-4) + (4-0) + (2-1) + (8-5) + (10-1) + (0-3) + (2-6) + (1-2) + (6-3) + (6-1) + (3-3) + (5-10) + (4-0))=1/16(-2-4-3-1+4+1+3+9-3-4-1+3+5+0-5+4) = 6/16 = 0.375 (3.7)

The result of ad calculation shown in Figure 14 is equal to our manually calculatedresult (3.7).



Name	Value
AD	0.3750
afta	4x4 double
aftb	4x4 double
ans	'distImg'
argGmagdist	4x4 double
argGmagorg	4x4 double
distImg	4x4 double
distSiz	[4,4]

```
%Program for Average Difference Calculation


function AD = AverageDifference(realImg, ehnImg)

realImg = double(realImg);
ehnImg = double(ehnImg);

[M N] = size(realImg);
error = realImg - ehnImg;

AD = sum(sum(error)) / (M * N);
```

```
12-Average Difference  =
    0.3750
```

Figure 14: MATLAB result of AD calculation.

3.2.2.7 Implementation and Testing of NAE (2.7)

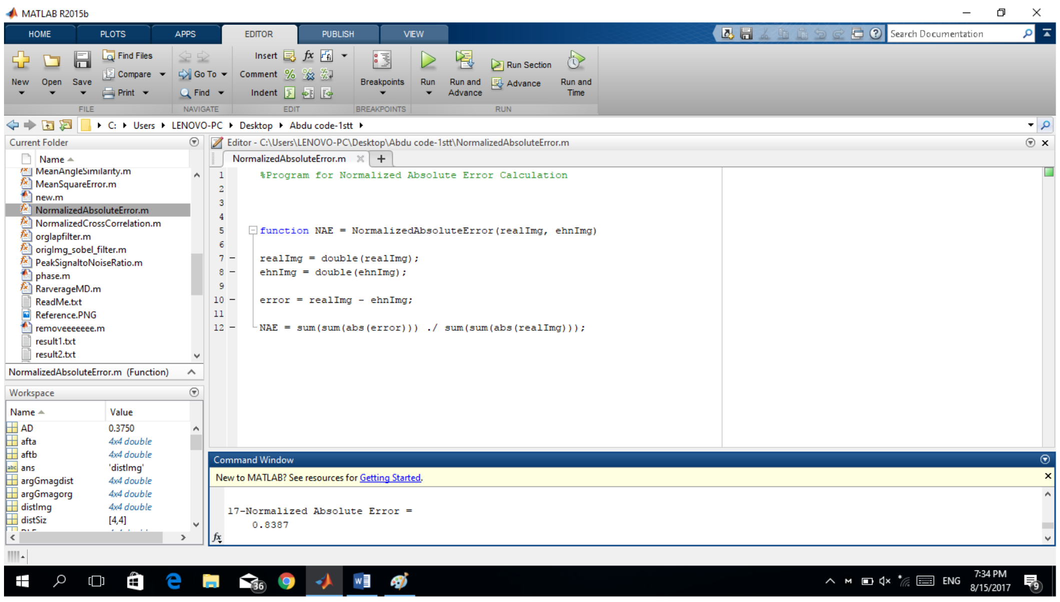
Explanation of NAE code (Appendix A7):

Line 1: NAE function with two inputs: rel_img and enhcd_img refer to the real and enhanced image. Line 4: the difference between the real and enhanced image will be calculated. Line 5: using (2.7), NAE will be calculated.

NAE = [(0-2) + (1-5) + (7-10) + (3-4) + (4-0) + (2-1) + (8-5) + (10-1) + (0-3) + (2-6) + (1-2) + (6-3) + (6-1) + (3-3) + (5-10) + (4-0)]

Nae = [2+4+3+1+4+1+3+9+3+4+1+3+5+0+5+4] = 52/62 = 0.8387 (3.8)

The result of NAE calculation shown in figure 15 is equal to our manually calculated result (3.8).



```
%Program for Normalized Absolute Error Calculation



function NAE = NormalizedAbsoluteError(realImg, ehnImg)

realImg = double(realImg);
ehnImg = double(ehnImg);

error = realImg - ehnImg;

NAE = sum(sum(abs(error))) ./ sum(sum(abs(realImg)));
```

```
17-Normalized Absolute Error =
     0.8387
```

Figure 15: MATLAB result of NAE calculation.

3.2.2.8 Implementation and Testing of RAMD (2.8)

Explanation of the RAMD code (Appendix A-8):

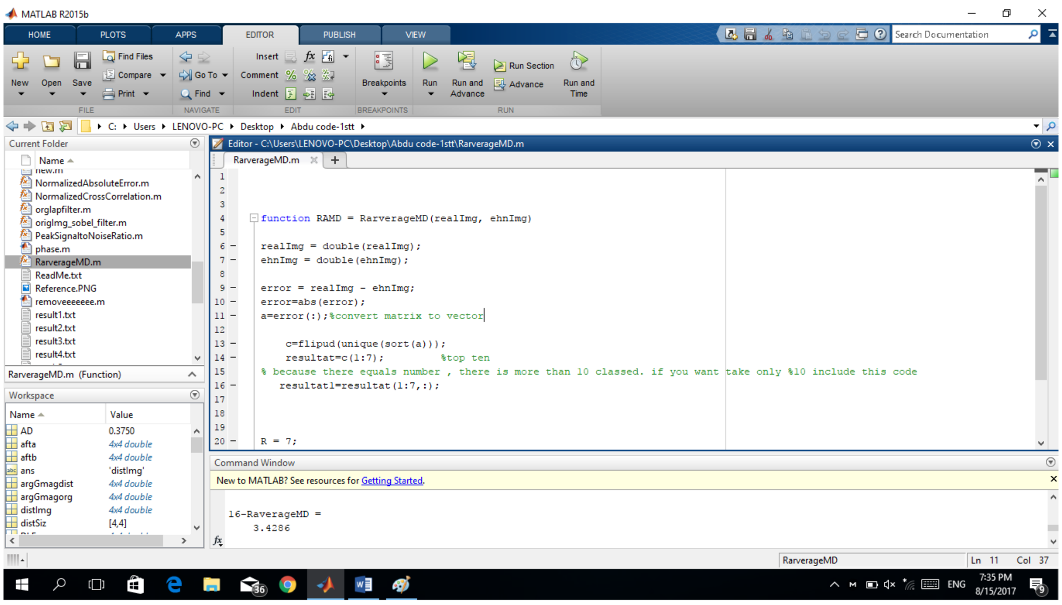
Line 1: RAMD function with two inputs: rel_img and enhcd_img refer to the real and enhanced image. Line 4: the difference between the real and enhanced image is calculated. Line 5: the variable 'eror' will have the absolute value of error. Line 6: we convert matrix to vector, then we order the numbers by descending order (using flipud a ready MATALAB function) without having repeated numbers, all numbers should be unique. Line 7: select top ten from the vector. Line 8: using (2.8), RAMD is calculated.

R = 7 (we select the maximum 7 differences between the image I and 'I and divide over 7, in the main code r=10, but for the testing case we set R=7 because if we set R=10 the 8th, 9th, and 10th values will be equal to zero).

P1= 0 – 2 = -2	P9 = 0 – 3 = -3	
P2 = 1 – 5 = -4	P10 = 2 – 6 = -4	
P3 = 7 – 10 = -3	P11 = 1 – 2 = -1	
P4 = 3 – 4 = -1	P12 = 6 – 3 = 3	(3.9)
P5 = 4 – 0 = 4	P13 = 6 – 1 = 5	
P6 = 2 – 1 = 1	P14 = 3 – 3 = 0	
P7 = 8 – 5 = 3	P15 = 5 – 10 = -5	
P8 = 10 – 1 = 9	P16= 4 – 0 = 4	

RAMD = 1/7 | 9 + 5 + 4 + 3 + 2 + 1 | = 24/7 = 3.428

The result of RAMD calculation shown in Figure 16 is equal to our manually calculated result (3.9).



```
function RAMD = RarverageMD(realImg, ehnImg)

realImg = double(realImg);
ehnImg = double(ehnImg);

error = realImg - ehnImg;
error=abs(error);
a=error(:);%convert matrix to vector

    c=flipud(unique(sort(a)));
    resultat=c(1:7);          %top ten
% because there equals number , there is more than 10 classed. if you want take only %10 include this code
   resultat1=resultat(1:7,:);



R = 7;
```

```
16-RaverageMD =
    3.4286
```

Figure 16: MATLAB result of RAMD calculation with R=7.

3.2.2.9 Implementation and Testing of NCC (2.9)

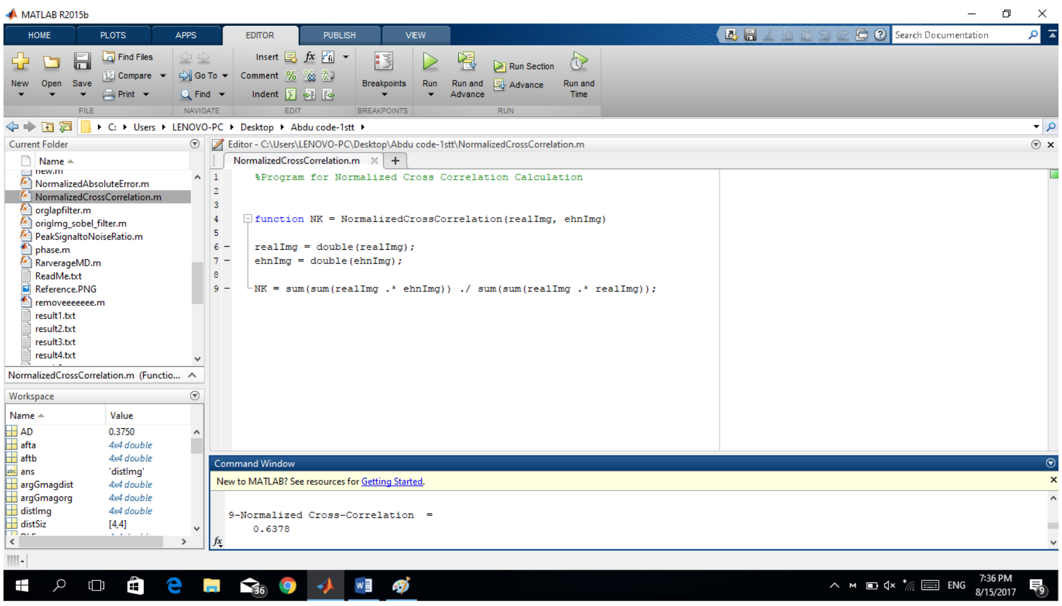
Explanation of NCC code (Appendix A-9):

Line 1: NCC function with two inputs: rel_img and enhcd_img refer to the real and enhanced image. Line 4: using (2.9) NCC will be calculated.

NCC = ((0*2) + (1*5) + (7*10) + (3*4) + (4*0) + (2*1) + (8*5) + (10*1) + (0*3) + (2*6) + (1*2) + (6*3) + (6*1) + (3*3) + (5*10) + (4*0) / (0^2 + 1^2 + 7^2 + 3^2+4^2 + 2^2 + 8^2 + 10^2 + 0^2 + 2^2 + 1^2 + 6^2 + 6^2 + 3^2 + 5^2 + 4^2) =

NCC = 236 / 370 = 0.637 (3.10)

The result of NCC calculation shown in Figure 17 is equal to our manually calculated result (3.10).



```
%Program for Normalized Cross Correlation Calculation


function NK = NormalizedCrossCorrelation(realImg, ehnImg)

realImg = double(realImg);
ehnImg = double(ehnImg);

NK = sum(sum(realImg .* ehnImg)) ./ sum(sum(realImg .* realImg));
```

```
9-Normalized Cross-Correlation  =
    0.6378
```

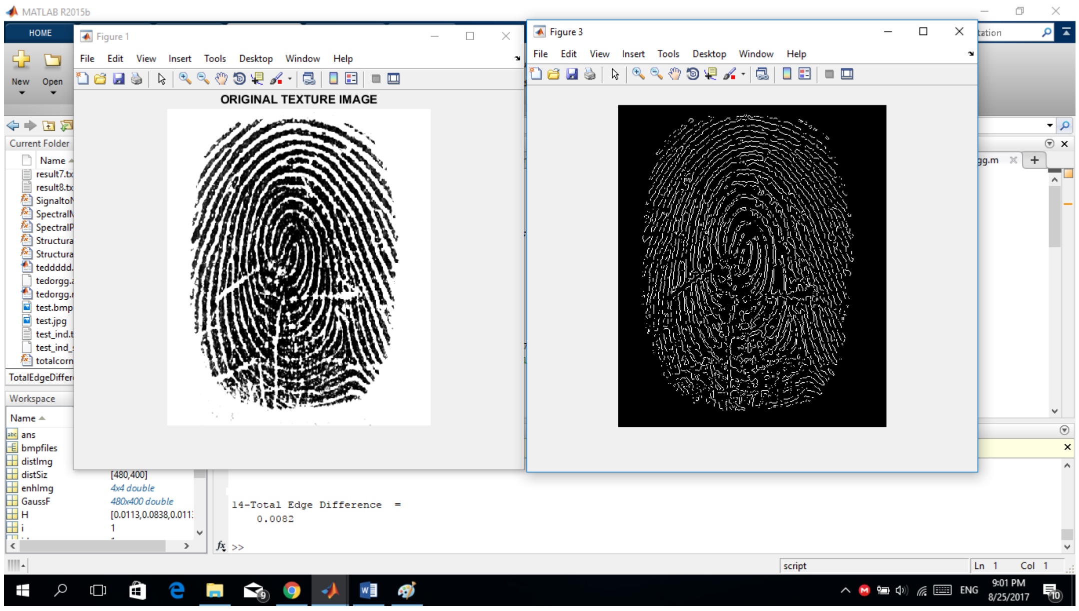
Figure 17: MATLAB result of NCC calculation.

3.2.2.10 Implementation and Testing of TED (2.10)

Explanation of TED code (Appendix A10):

Line 1: TED function with two inputs: rel_img and enhcd_img refer to the real and enhanced image. In Line 2, ready MATLAB function (edge) is used to detect the edges of the real image. In Line 3, all edges that were detected by the MATLAB function will be displayed. In Line 5 and 6 the same process is done as in lines 2 and 3 but this time for the enhanced image. Line 8: [m n] is defined, where m is the number of rows and n is the number of columns the real image has. Line 9: difference between real image and enhanced image will be calculated and saved in ‘eror’ variable. Line 10: using the formula provided in (2.10) TED will be obtained.

We didn’t apply manual calculation to test TED because in our code we use ready MATLAB function “edge (image)” to automatically find the image total edge difference of any image inserted to the RFDS, so we feed a fingerprint image to our system and took a screenshot of the result shown below in figure 18.



```
14-Total Edge Difference  =
    0.0082
```

Figure 18: Matlab result for calculating TED of fingerprint image.

3.2.2.11 Implementation and Testing of TCD (2.11)

Explanation of the TCD code (each line number corresponds to its code in Appendix A-15):

Line 1: TCD function with two inputs rel_img which refers to the real image and enhcd_img refers to the enhanced image, line 4 we use a ready MATLAB function called “detectharrisfeatures” to detect corners of the real image, Line 5: we plot the corners in the real image using a MATLAB function called “plot”, Line 6: we will get the sum of corners of the real image using ready MATLAB function called “length”, Line 7 we will detect corners of the enhanced image, Line 8: we plot the corners of the enhanced image same as we did to the real image, Line 9: we will get the sum of corners in of the enhanced image using the same function we applied to the real image, Line 10: we will set the value of variable “max1” either as the number of corners of the real or enhanced image depending on which one has th maximum number of corners detected, Line11: using the formula provided in (2.11) TCD will be calculated.

Ncr = Number of Corners in The Original Image.

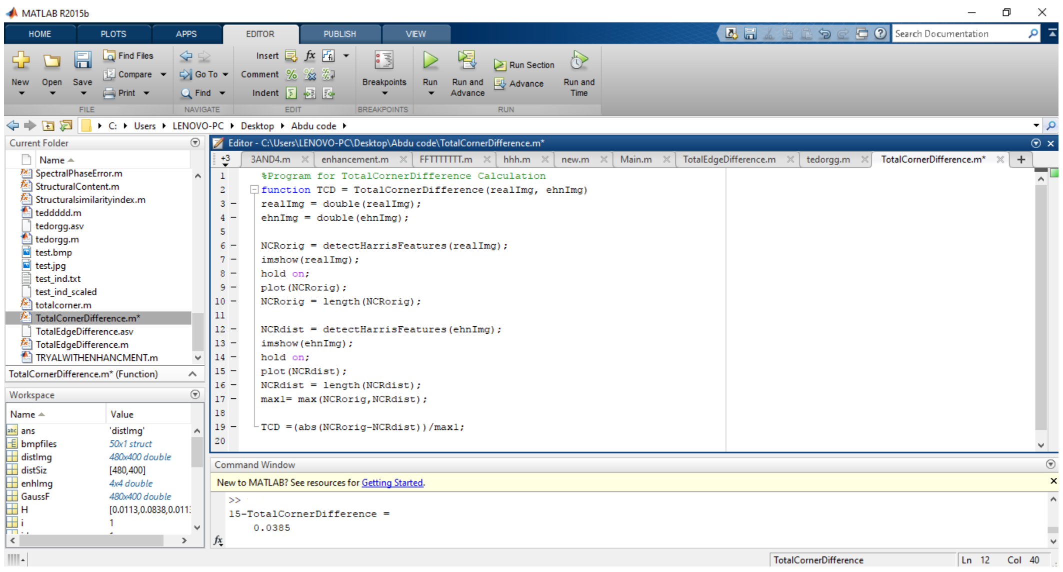
‘**Ncr** = Number of Corners in The Enhanced Image.

Ncr= 2496

‘**Ncr**= 2400

Tcd = |2496-2400| / 2496 = 0.0385 (3.11)

The result of TCD calculation shown in Figure 19 is equal to (3.11).



Current Folder

Name
SpectralPhaseError.m
StructuralContent.m
Structuralsimilarityindex.m
teddddd.m
tedorgg.asv
tedorgg.m
test.bmp
test.jpg
test_ind.txt
test_ind_scaled
totalcorner.m
TotalCornerDifference.m*
TotalEdgeDifference.asv
TotalEdgeDifference.m
TRYALWITHENHANCMENT.m

TotalCornerDifference.m* (Function)

Workspace

Name	Value
ans	'distImg'
bmpfiles	50x1 struct
distImg	480x400 double
distSiz	[480,400]
enhImg	4x4 double
GaussF	480x400 double
H	[0.0113,0.0838,0.011
i	1

Editor - C:\Users\LENOVO-PC\Desktop\Abdu code\TotalCornerDifference.m*

3AND4.m | enhancement.m | FFTTTTTTT.m | hhh.m | new.m | Main.m | TotalEdgeDifference.m | tedorgg.m | TotalCornerDifference.m*

```
1    %Program for TotalCornerDifference Calculation
2    function TCD = TotalCornerDifference(realImg, ehnImg)
3 -  realImg = double(realImg);
4 -  ehnImg = double(ehnImg);
5
6 -  NCRorig = detectHarrisFeatures(realImg);
7 -  imshow(realImg);
8 -  hold on;
9 -  plot(NCRorig);
10 - NCRorig = length(NCRorig);
11
12 - NCRdist = detectHarrisFeatures(ehnImg);
13 - imshow(ehnImg);
14 - hold on;
15 - plot(NCRdist);
16 - NCRdist = length(NCRdist);
17 - max1= max(NCRorig,NCRdist);
18
19 - TCD =(abs(NCRorig-NCRdist))/max1;
20
```

New to MATLAB? See resources for Getting Started.

```
>>
15-TotalCornerDifference =
    0.0385
```

TotalCornerDifference   Ln 12   Col 40

Figure 19: MATLAB result of TCD calculation.

3.2.2.12 Implementation and Testing of Spectral Phase Error (SPE)

Original Image			
0	1	7	3
4	2	8	10
0	2	1	6
6	3	5	4

Explanation of the SPE code (each line number corresponds to its code in Appendix B-14):

Line 1: SPE function with two inputs rel_img which refers to the original image and enhcd_img refers to the enhanced image, Line 4: we use a ready MATLAB function "fft" to transform the original and enhanced image to the frequency domain, Line 5: [m n] where m is amount of row the real image has and n is amount of columns the real image has; Line 6: difference between real image and enhanced image will be calculated, Line 7: using the formula provided in (2.12) spe will be calculated.

FFT Original Image			
62 +0i	-11+15i	0+0i	-11-
2-6i	1+3i	10+4	-13+7i
-22+0i	-5-3i	-8+0i	-5+3i
2+6i	-13-7i	10-4i	1-3i

Distorted Image			
2	5	10	4
0	1	5	1
3	6	2	3
1	3	10	0

FFT Distorted Image			
56+0i	-21-7i	10+0i	-21+
7+7i	-6-2i	7+5i	-12-6i
14+0i	7-1i	-12+0i	7+1i
7-7i	-12+6i	7-5i	-6+2

Argument (Original Image)			
0	2.2035	0	- 2.2035
-1.2490	1.2490	0.3805	2.6477
3.1416	-2.6012	3.1416	2.6012
1.2490	-2.6477	- 0.3805	-1.2490

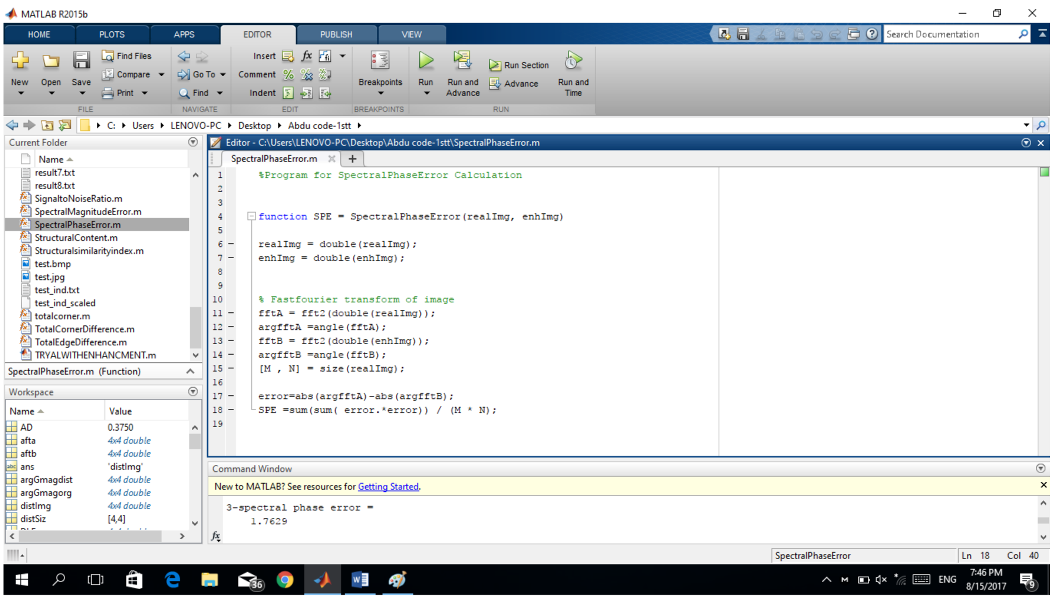
Argument (Enhanced Image)			
0	-2.8198	0	2.8198
0.7854	-2.8198	0.6202	-2.6779
0	-0.1419	3.1416	0.1419
-0.7854	2.6779	-0.6202	2.8198

Original – Enhanced			
0	-0.6163?	0	-0.6163
0.4636	-1.5708	-0.2397	-0.0303
3.1416	2.4593	0	2.4593
0.4636	-0.0303	-0.2397	-1.5708

SPE = 1/16 (0^2 + 0.6163^2 + 0^2 + 0.6163^2 + 0.4636 ^2 + 1.5708 ^2 + 0.2397^2 + 0.0303^2 + 3.1416^2 + 2.4593^2 + 0^2 + 2.4593^2 + 0.4636^2 + 0.0303^2 + 0.2397^2 + 1.5708^2) =

SPE = 28.20703848/16 = 1.7629 (3.12)

The SPE result calculation shown in Figure 20 is equal to (3.14).


Editor - C:\Users\LENOVO-PC\Desktop\Abdu code-1stt\SpectralPhaseError.m

```
%Program for SpectralPhaseError Calculation


function SPE = SpectralPhaseError(realImg, enhImg)

realImg = double(realImg);
enhImg = double(enhImg);


% Fastfourier transform of image
fftA = fft2(double(realImg));
argfftA =angle(fftA);
fftB = fft2(double(enhImg));
argfftB =angle(fftB);
[M , N] = size(realImg);

error=abs(argfftA)-abs(argfftB);
SPE =sum(sum( error.*error)) / (M * N);
```

```
3-spectral phase error =
    1.7629
```

Figure 20: MATLAB result of SPE calculation.

3.2.2.13 Implementation and Testing of SME (2.13)

Explanation of the SME code (each line number corresponds to its code in Appendix A13):

Line 1: SME function has two inputs rel_img which refers to the original image and enhcd_img refers to the enhanced image, Line 4: we use a ready matlab function "**fft**" to transform the real image to the frequency domain, Line 5: shows the real part of the original image Line 6: shows the imaginary part of the original image Line 7: we take the SQRT of the real part summed with imaginary part of the original image, Line 8: shows the real part of the enhanced image, Line 9: shows the imaginary part of the enhanced image Line 10: we take the sqrt of the real part summed with imaginary part of the enhanced image Line 11: using the formula provided in (2.13) SME will be calculated.

Fourier Transform [13]:

Original Image			
0	1	7	3
4	2	8	10
0	2	1	6
6	3	5	4

FFT Original Image			
62 +0i	-11+15i	0+0i	-11-15i
2-6i	1+3i	10+4	-13+7i
-22+0i	-5-3i	-8+0i	-5+3i
2+6i	-13-7i	10-4i	1-3i

Distorted Image			
2	5	10	4
0	1	5	1
3	6	2	3
1	3	10	0

FFT Distorted Image			
56+0i	-21-7i	10+0i	-21+7i
7+7i	-6-2i	7+5i	-12-6i
14+0i	7-1i	-12+0i	7+1i
7-7i	-12+6i	7-5i	-6+2i

FFT (Original Image) Gradient:

Sqrt 62^2 + 0^2 = 62.

Sqrt -11^2 + 15^2 = Sqrt 121+225 = Sqrt 346 = 18.6011.

Gradient (Original Image)			
62	18.6011	0	18.6011
6.3246	3.1623	10.7703	14.7648
22	5.8310	8	5.8310
6.3246	14.7648	10.7703	3.1623

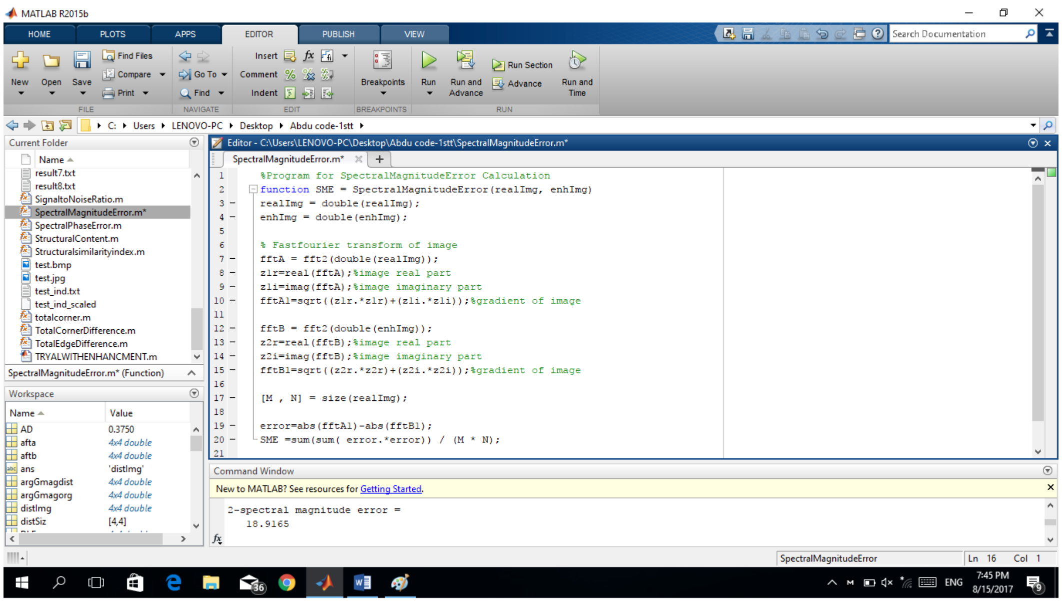
Gradient (Distorted Image)			
56	22.1359	10	22.1359
9.8	6.3246	8.6	13.4164
14	7.0711	12	7.0711
9.8	13.4164	8.6	6.3246

Original – Distorted			
6	-3.534	-10	-3.534
-3.574	-3.162	2.168	1.348
8	-1.24	-4	-1.24
-3.574	1.348	2.168	-3.162

SME= (6^2 - 3.534^2 - 10^2 - 3.534^2 - 3.574^2 - 3.162^2 + 2.168^2 + 1.348^2 + 8^2 - 1.24^2 - 4^2 - 1.24^2 - 3.574^2 + 1.348^2 + 2.168^2 - 3.162^2) /16

SME = 295.795364/16 = 18.9 (3.13)

The result of SME calculation shown in Figure 21 is equal to our manual calculation result (3.13).



```
%Program for SpectralMagnitudeError Calculation
function SME = SpectralMagnitudeError(realImg, enhImg)
realImg = double(realImg);
enhImg = double(enhImg);

% Fastfourier transform of image
fftA = fft2(double(realImg));
z1r=real(fftA);%image real part
z1i=imag(fftA);%image imaginary part
fftA1=sqrt((z1r.*z1r)+(z1i.*z1i));%gradient of image

fftB = fft2(double(enhImg));
z2r=real(fftB);%image real part
z2i=imag(fftB);%image imaginary part
fftB1=sqrt((z2r.*z2r)+(z2i.*z2i));%gradient of image

[M , N] = size(realImg);

error=abs(fftA1)-abs(fftB1);
SME =sum(sum( error.*error)) / (M * N);
```

```
2-spectral magnitude error =
   18.9165
```

Figure 21: MATLAB result of SME calculation.

3.2.2.14 Implementation and Testing of Gradient Phase Error (GPE)

Explanation of the GPE code (each line number corresponds to its code in Appendix A-14):

Line 1: GPE function has two inputs rel_img which refers to the real image and enhcd_img refers to the enhanced image, Line 4: the gradient 2 of the original image will be calculated, Line 5: transfer gradient values of the original image to complex number, Line 6: angle of complex of the original image will be calculated, Line 7: the gradient of the enhanced image will be calculated, Line 8: transfer gradient values of the enhanced image to complex, Line 9: angle of complex of the enhanced image will be calculated Line 10: [m n] where m is amount of row the real image has and n is amount of columns the real image has; Line 11: difference between real image and enhanced image will be calculated and saved in 'eror' variable, Line 12: using the formula provided in (2.14) GPE will be calculated.

Gradient of The Original Image:

Fx1			
1	3.5	1	-4
-2	2	4	2
2	0.5	2	5
-3	-0.5	0.5	-1

Fy1			
4	1	1	7
0	0.5	-3	1.5
1	0.5	-1.5	-3
6	1	4	-2

Z =			
1+4i	3.5+1i	1+1i	-4+7i
-2+0i	2+0.5i	4-3i	2+1.5i
2+1i	0.5+0.5i	2-1.5i	5-3i
-3+6i	-0.5+1i	0.5+4i	-1-2i

F =			
3-2i	4-4i	-0.5-5i	-6-3i
1+0.5i	2.5+0.5i	0-4i	-4-0.5i
3+0.5i	-0.5+1	- 1.5+2.5i	1-0.5i
2-2i	4-3i	-1.5+8i	-10-3i

Arg Original (Angle(Z))			
1.3258	0.2783	0.7854	2.0899
3.1416	0.2450	-0.6435	0.6435
0.4636	0.7854	-0.6435	-0.5404
2.0344	2.0344	1.4464	-2.0344

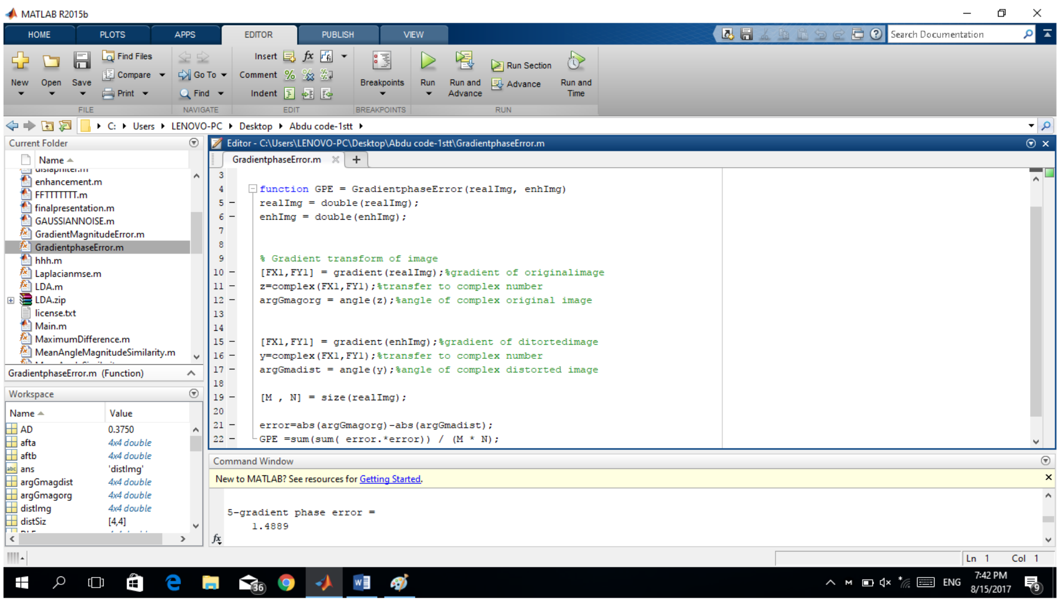
Arg Distorted (Angle(F))			
-0.5880	-0.7854	-1.6705	-2.6779
0.4636	0.1974	-1.5708	-3.0172
0.1651	2.0344	2.1112	-0.4636
-0.7854	-0.5880	1.7561	-2.8501

Arg Original – Arg Distorted			
0.7378	-0.5071	-0.8851	-0.5880
2.6779	0.0476	-0.9273	-2.3737
0.2985	-1.2490	-1.4677	0.0768
1.2490	1.4464	-0.3097	-0.8157

GPE = 1/16 (0.7378 ^2 -0.5071^2 -0.8851 ^2 -0.5880 ^2 + 2.6779 ^2 +0.0476 ^2 -0.9273 ^2 -2.3737 ^2 + 0.2985^2 - 1.2490 ^2 -1.4677 ^2 +0.0768 ^2 +1.2490 ^2 +1.4464 ^2 -0.3097 ^2 -0.8157^2) =

GPE = (11.46483746+12.50639178)/16 = 1.48 (3.14)

The result of GPE calculation shown in figure 22 is equal to our manual calculation result (3.14).



```
Editor - C:\Users\LENOVO-PC\Desktop\Abdu code-1stt\GradientphaseError.m

function GPE = GradientphaseError(realImg, enhImg)
realImg = double(realImg);
enhImg = double(enhImg);


% Gradient transform of image
[FX1,FY1] = gradient(realImg);%gradient of originalimage
z=complex(FX1,FY1);%transfer to complex number
argGmagorg = angle(z);%angle of complex original image


[FX1,FY1] = gradient(enhImg);%gradient of ditortedimage
y=complex(FX1,FY1);%transfer to complex number
argGmadist = angle(y);%angle of complex distorted image

[M , N] = size(realImg);

error=abs(argGmagorg)-abs(argGmadist);
GPE =sum(sum( error.*error)) / (M * N);
```

```
5-gradient phase error =
    1.4889
```

Figure 22: MATLAB result of GPE calculation.

3.2.2.15 Implementation and Testing of Gradient Magnitude Error (GME)

Explanation of the GME code (each line number corresponds to its code in Appendix A-15):

Line 1: GME function with two inputs rel_img which refers to the real image and enhcd_img refers to the enhanced image, line 4: using a ready MATLAB function the gradient (shows directional change in the intensity or color in an image) of the real image will be calculated, then the gradient magnitude is calulcated and saved in "gamgorg" variable, same steps will be applied for the enhanced image, Line 5: [m n] where m is amount of row the real image has and n is amount of columns the real image has; Line 6: difference between real image and enhanced image will be calculated and saved in "eror" variable, Line 7: using the formula provided in (2.15) GME will be calculated.

For testing our gme function used in our RFDS we will calculate manually the GME of one pixel only, which is the matrix element with value equal to (2).

Original Image (I)			
0	1	7	3
4	2	8	10
0	2	1	6
6	3	5	4

Gradient of Pixel (2,2)

Fx1 = (Df/Dx) = (8 – 4)/ 2

4 / 2 = 2

Fy1 = (Df/Dx) = (2 – 1) /2

1 / 2 = 0.5

Sqrt 2^2 + 0.5^2 = Sqrt 4.25 = 2.061

Fx1			
1	3.5	1	-4
-2	2	4	2
2	0.5	2	5
-3	-0.5	0.5	-1

Fy1			
4	1	1	7
0	0.5	-3	1.5
1	0.5	-1.5	-3
6	1	4	-2

Orignal Image I			
4.123	3.640	1.414	8.062
2	2.061	5	2.5
2.236	0.707	2.5	5.831
6.708	1.118	4.031	2.236

Distorted Image ‘I			
3.605	5.656	5.024	6.708
1.118	2.549	4	4.031
3.041	1.118	2.915	1.118
2.828	5.408	8.139	10.440

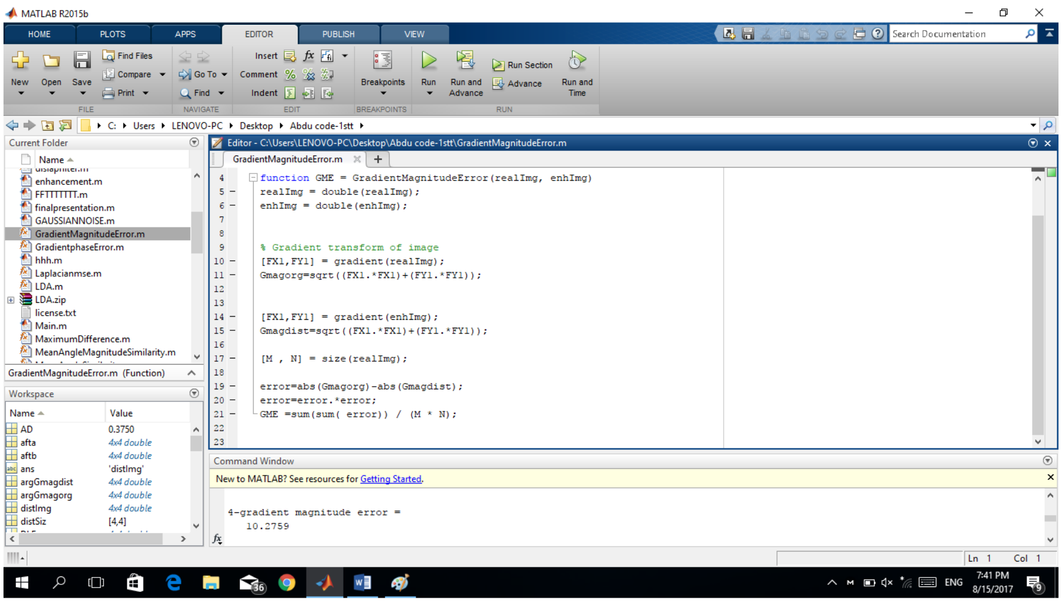
Original – Distorted			
0.517	-2.016	-3	1.354
0.882	-0.488	1	-1.531
-0.805	-0.41	-0.415	4.712
3.879	-4.29	-4.1	-8.2

1/16 (0.517^2 + -2.016^2 + -3.610^2 + 1.354^2 + 0.882^2 + -0.488^2 + 1^2 + -1.531^2 + -0.805^2 + -0.41^2 + -0.415^2 + 4.712^2 + 3.879^2 + -4.29^2 + -4.1^2 + -8.2^2)

GME = 1/16 (0.2673 - 4.0643 -13.0321+ 1.8333 + 0.7779 - 0.2381 + 1 - 2.3440 - 0.6480 - 0.1681 -0.1722 + 22.2029 + 15.0466 -18.4041 -16.8100 + -67.2400)

GME = 164.2489/16 = 10.27 (3.15)

The result of GME calculation shown in figure 23 is equal to our manual calculation result (3.15).



Editor - C:\Users\LENOVO-PC\Desktop\Abdu code-1stt\GradientMagnitudeError.m

```
function GME = GradientMagnitudeError(realImg, enhImg)
realImg = double(realImg);
enhImg = double(enhImg);


% Gradient transform of image
[FX1,FY1] = gradient(realImg);
Gmagorg=sqrt((FX1.*FX1)+(FY1.*FY1));


[FX1,FY1] = gradient(enhImg);
Gmagdist=sqrt((FX1.*FX1)+(FY1.*FY1));

[M , N] = size(realImg);

error=abs(Gmagorg)-abs(Gmagdist);
error=error.*error;
GME =sum(sum( error)) / (M * N);
```

Command Window

New to MATLAB? See resources for Getting Started.

```
4-gradient magnitude error =
   10.2759
```

Workspace

Name	Value
AD	0.3750
afta	4x4 double
aftb	4x4 double
ans	'distImg'
argGmagdist	4x4 double
argGmagorg	4x4 double
distImg	4x4 double
distSiz	[4,4]

Figure 23: MATLAB result of GME calculation.

3.2.2.16 Implementation and Testing of Mean Angle Similarity (MAS)

Explanation of the MAS code (each line number corresponds to its code in Appendix B-16):

Line 1: MAS function with two inputs rel_img which refers to the original image and enhcd_img refers to the enhanced image, line 4: we use a ready MATLAB function “dot” to get the scalar dot of the real image and enhanced image, we also use another ready MATLAB function “acosd” which returns the inverse cosine of the element of the real; Line 5 : we take the sum of the variable “alfa2” ; Line 6: using the formula provided in (2.16) MAS will be calculated.

Original Image			
0	1	7	3
4	2	8	10
0	2	1	6
6	3	5	4

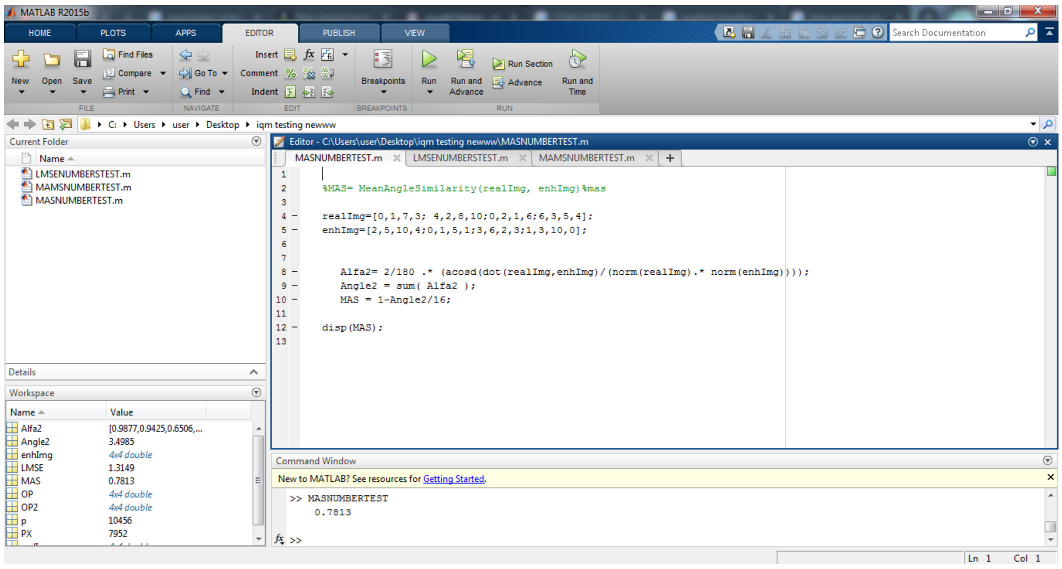
Distorted Image			
2	5	10	4
0	1	5	1
3	6	2	3
1	3	10	0

Alfa2 (Original Image, Distorted Image) = 0.9877, 0.9425, 0.6506, 0.9178

Angel2= Sum (Alfa2) = 3.4985

MAS= 1-(3.4985/16) = 0.7813 (3.16)

The result of MAS calculation shown in Figure 24 is equal to (3.16).



Editor - C:\Users\user\Desktop\iqm testing newww\MASNUMBERTEST.m

```
%MAS= MeanAngleSimilarity(realImg, enhImg)%mas

realImg=[0,1,7,3; 4,2,8,10;0,2,1,6;6,3,5,4];
enhImg=[2,5,10,4;0,1,5,1;3,6,2,3;1,3,10,0];


  Alfa2= 2/180 .* (acosd(dot(realImg,enhImg)/(norm(realImg).* norm(enhImg))));
  Angle2 = sum( Alfa2 );
  MAS = 1-Angle2/16;

disp(MAS);
```

Name	Value
Alfa2	[0.9877,0.9425,0.6506,...
Angle2	3.4985
enhImg	4x4 double
LMSE	1.3149
MAS	0.7813
OP	4x4 double
OP2	4x4 double
p	10456
PX	7952

Command Window

```
>> MASNUMBERTEST
   0.7813
```

Figure 24: MATLAB result of MAS calculation.

3.2.2.17 Implementation and Testing of Mean Angle Similarity (MAMS)

Explanation of the MAMS code (each line number corresponds to its code in Appendix A-17):

Line 1: MAMS function with two inputs rel_img which refers to the original image and enhcd_img refers to the enhanced image, Line 4: we use a ready MATLAB function “dot” to get the scalar dot of the real image and enhanced image, we also use another ready MATLAB function “acosd” which returns the inverse cosine of the element of the real; Line 5 :” ; Line 6 : using the formula provided in (2.17) MAMS will be calculated and assigned to variable “x”; Line 7: we take the sum of the variable “x; Line 8: we divide the sum and assign the result to variable ”MAMS”.

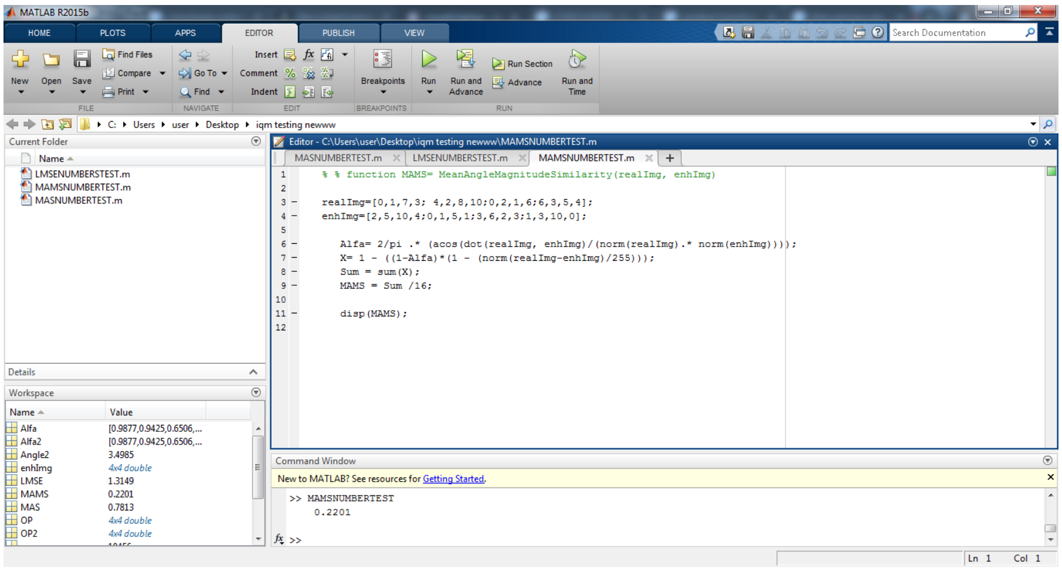
Alfa (Original Image, Distorted Image) = 0.9877, 0.9425, 0.6506, 0.9178

X= 1-(1-Alfa) *(1-(Original Image-Distorted Image/255)) = 0.9883, 0.9452, 0.6667, 0.9215

SUM = Sum(X) = 3.5216

MAMS = (3.5216/16) = 0.2201 (3.17)

The result of MAMS calculation shown in Figure 25 is equal to (3.17).



Editor - C:\Users\user\Desktop\iqm testing newww\MAMSNUMBERTEST.m

```
1       % % function MAMS= MeanAngleMagnitudeSimilarity(realImg, enhImg)
2
3  -    realImg=[0,1,7,3; 4,2,8,10;0,2,1,6;6,3,5,4];
4  -    enhImg=[2,5,10,4;0,1,5,1;3,6,2,3;1,3,10,0];
5
6  -       Alfa= 2/pi .* (acos(dot(realImg, enhImg)/(norm(realImg).* norm(enhImg))));
7  -       X= 1 - ((1-Alfa)*(1 - (norm(realImg-enhImg)/255)));
8  -       Sum = sum(X);
9  -       MAMS = Sum /16;
10
11 -       disp(MAMS);
12
```

Workspace

Name	Value
Alfa	[0.9877,0.9425,0.6506,...
Alfa2	[0.9877,0.9425,0.6506,...
Angle2	3.4985
enhImg	4x4 double
LMSE	1.3149
MAMS	0.2201
MAS	0.7813
OP	4x4 double
OP2	4x4 double

Command Window

```
>> MAMSNUMBERTEST
   0.2201
```

Figure 25: MATLAB result of MAMS calculation.

3.2.2.18 Implementation and testing of Laplacian Mean Squared Error (LMSE)

Explanation of the LMSE code (each line number corresponds to its code in Appendix A-18):

Line 1: LMSE function with two inputs: rel_img which refers to the real image, and enhcd_img refers to the enhanced image;, line 4: [m n] where m is amount of row the real image has and n is amount of columns the real image has; Line 5& Line 6: we use a ready MATLAB function “del2” to calculate the second derivavtive of the real image and distorted image; Line 7: using the formula provided in (2.18) LMSE will be calculate.

Original Image			
0	1	7	3
4	2	8	10
0	2	1	6
6	3	5	4

Del2 Original Image			
-6	2	-37	-49
12	7	-12	-27
-2	-2	17	17
41	8	27	4

Original Image			
0	1	7	3
4	2	8	10
0	2	1	6
6	3	5	4

Del2 Original Image			
-6	2	-37	-49
12	7	-12	-27
-2	-2	17	17
41	8	27	4

Distorted Image			
2	5	10	4
0	1	5	1
3	6	2	3
1	3	10	0

Del2 Distorted Image			
30	28	-18	-9
19	12	-6	-14
-24	-15	16	12
12	-20	3	-54

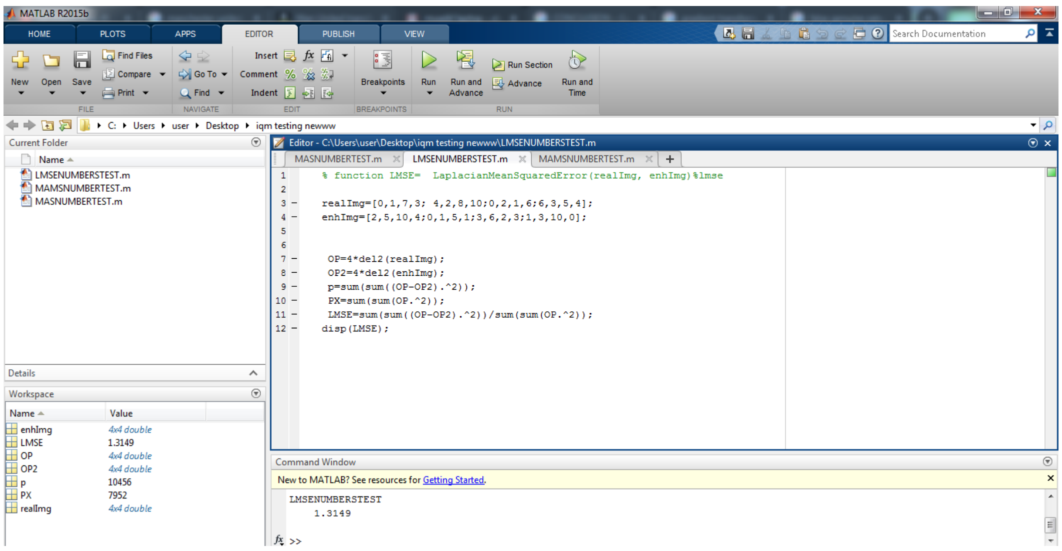
Del2 Original Image - Del2 Distorted			
-36	-26	-19	-40
-7	-5	-6	-13
22	13	1	5
29	28	24	58

sum(sum(op-op2).^2)= 10456

sum(sum(op.^2))= 7952

LMSE = 10456/7952 = 1.3149. (3.18)

The Result of LMSE calculation shown in Figure 26 is equal to (3.18).


Editor - C:\Users\user\Desktop\iqm testing newww\LMSENUMBERSTEST.m

```
% function LMSE=  LaplacianMeanSquaredError(realImg, enhImg)%lmse

realImg=[0,1,7,3; 4,2,8,10;0,2,1,6;6,3,5,4];
enhImg=[2,5,10,4;0,1,5,1;3,6,2,3;1,3,10,0];


 OP=4*del2(realImg);
 OP2=4*del2(enhImg);
 p=sum(sum((OP-OP2).^2));
 PX=sum(sum(OP.^2));
 LMSE=sum(sum((OP-OP2).^2))/sum(sum(OP.^2));
disp(LMSE);
```

Name	Value
enhImg	4x4 double
LMSE	1.3149
OP	4x4 double
OP2	4x4 double
p	10456
PX	7952
realImg	4x4 double

```
LMSENUMBERSTEST
    1.3149
```

Figure 26: Matlab result of LMSE calculation.

For the rest of the IQMs (SSIM, VIF, RRED, HLFI, JQI, BIQI, AND NIQE) we implemented the following:

1. Downloaded ready implemented code from:

"live.ece.utexas.edu/research/quality/index_algorithms.htm" Texas University [17].

We added the function files of every IQM to our thesis code folder. Then in our main.m file we call all the IQM functions. Input and output we get from these functions:

2. VIF

Input: (1) Img1: the reference image as a matrix. (2) Img2: the distorted image (Order Is Important).

Output: (1) VIF the visual information fidelity measure between the two images.

3. NIQE

Input: A test image loaded in an array.

Output: A quality score of the image. higher value represents a lower quality.

4. JPEG

Input: A test 8bits/pixel grayscale image loaded in a 2-d array.

Output: A quality score of the image. the score typically has a value. between 1 and 10 (10 represents the best quality, 1 the worst).

5. BIQI

Input: A test 8bits/pixel grayscale image loaded in A 2-D array.

Output: A quality score of the image. the score typically has a value. between 1 and 10 (10 represents the best quality, 1 the worst).

6. RRED

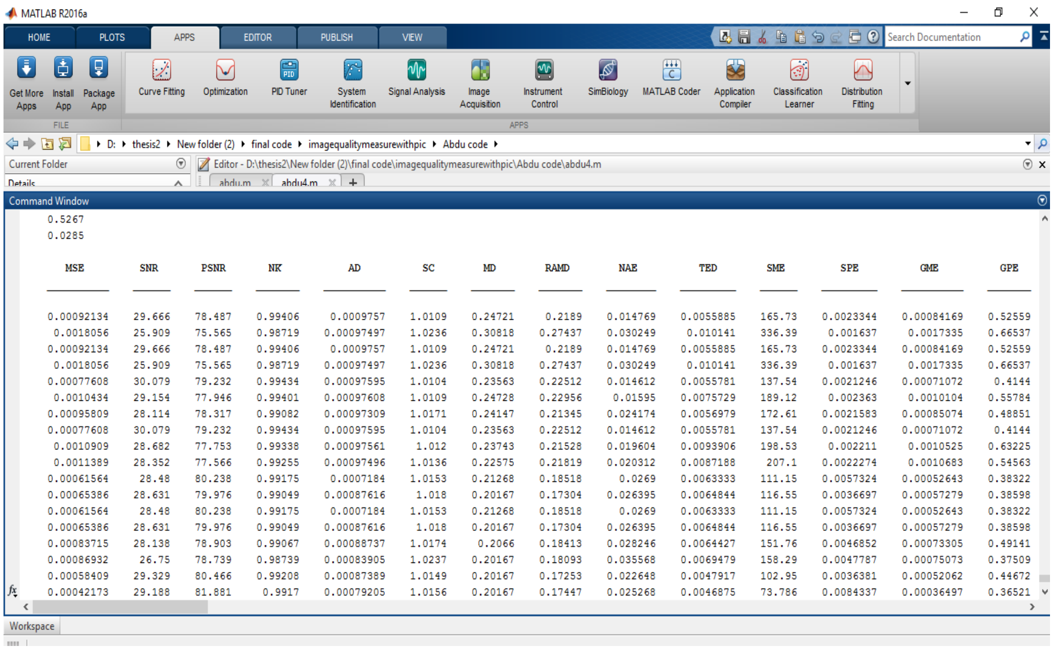
Input: A test 8bits/pixel grayscale image loaded in a 2-d array.

Output: Estimated entropy at different locations and the local spatial/temporal ('spatial' and 'temporal' refer to the spatial and temporal scaled entropy information for different blocks in the subband).

3.2.3 Implementation of Training Structure

MATLAB 2015 provides a classification learner application that can be used to import tables from the work space. The application is very simple to use. It automatically extracts predictors (our IQM’s) and observations (real or fake image), also has more than one classification algorithm such as LDA and QDA which are used for classifying the extracted samples of an image.

In order to use classification learner application, the results have to be arranged in a table and displayed in the workspace. The results displayed in workspace will be all imported to the classification learner application, then we select the table which has all the fingerprint image results of IQM’s, after that we select the response (Real/Fake) and predictors (Quality Measures). The steps of implementing our classifier using the classification learner application are shown in Figures 27-31.



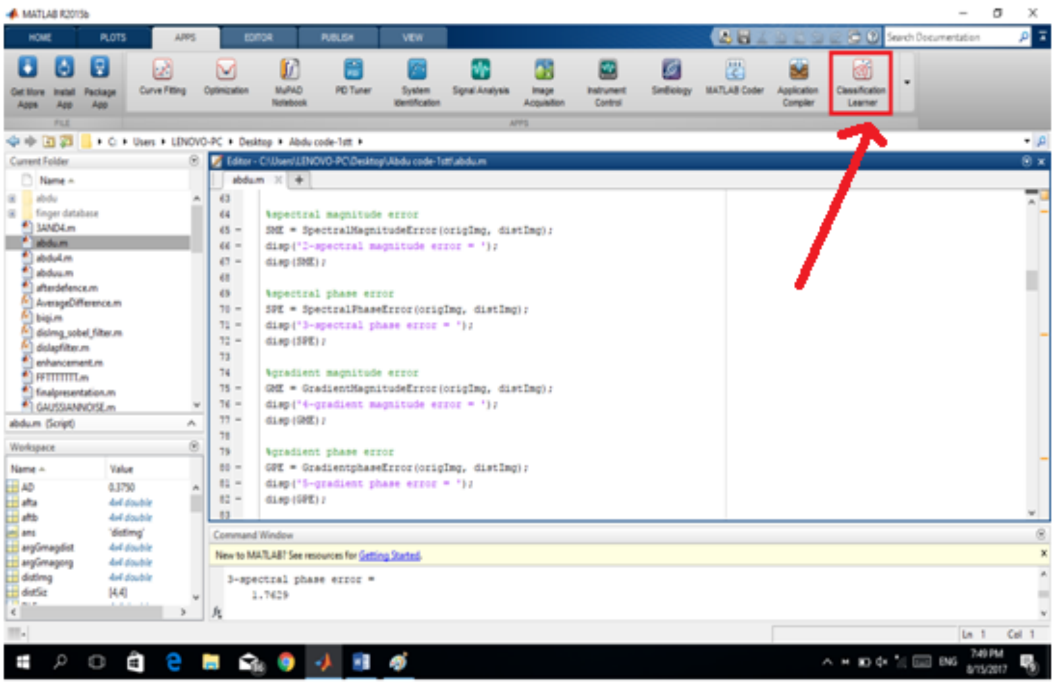
```
    0.5267
    0.0285

       MSE         SNR      PSNR      NK           AD          SC        MD        RAMD       NAE          TED         SME        SPE          GME          GPE
    __________    ______    ______    _______    __________    ______    _______    _______    ________    _________    ______    _________    __________    _______

    0.00092134    29.666    78.487    0.99406     0.0009757    1.0109    0.24721     0.2189    0.014769    0.0055885    165.73    0.0023344    0.00084169    0.52559
     0.0018056    25.909    75.565    0.98719    0.00097497    1.0236    0.30818    0.27437    0.030249     0.010141    336.39     0.001637     0.0017335    0.66537
    0.00092134    29.666    78.487    0.99406     0.0009757    1.0109    0.24721     0.2189    0.014769    0.0055885    165.73    0.0023344    0.00084169    0.52559
     0.0018056    25.909    75.565    0.98719    0.00097497    1.0236    0.30818    0.27437    0.030249     0.010141    336.39     0.001637     0.0017335    0.66537
    0.00077608    30.079    79.232    0.99434    0.00097595    1.0104    0.23563    0.22512    0.014612    0.0055781    137.54    0.0021246    0.00071072     0.4144
     0.0010434    29.154    77.946    0.99401    0.00097608    1.0109    0.24728    0.22956     0.01595    0.0075729    189.12     0.002363     0.0010104    0.55784
    0.00095809    28.114    78.317    0.99082    0.00097309    1.0171    0.24147    0.21345    0.024174    0.0056979    172.61    0.0021583    0.00085074    0.48851
    0.00077608    30.079    79.232    0.99434    0.00097595    1.0104    0.23563    0.22512    0.014612    0.0055781    137.54    0.0021246    0.00071072     0.4144
     0.0010909    28.682    77.753    0.99338    0.00097561     1.012    0.23743    0.21528    0.019604    0.0093906    198.53     0.002211     0.0010525    0.63225
     0.0011389    28.352    77.566    0.99255    0.00097496    1.0136    0.22575    0.21819    0.020312    0.0087188     207.1    0.0022274     0.0010683    0.54563
    0.00061564     28.48    80.238    0.99175     0.0007184    1.0153    0.21268    0.18518      0.0269    0.0063333    111.15    0.0057324    0.00052643    0.38322
    0.00065386    28.631    79.976    0.99049    0.00087616     1.018    0.20167    0.17304    0.026395    0.0064844    116.55    0.0036697    0.00057279    0.38598
    0.00061564     28.48    80.238    0.99175     0.0007184    1.0153    0.21268    0.18518      0.0269    0.0063333    111.15    0.0057324    0.00052643    0.38322
    0.00065386    28.631    79.976    0.99049    0.00087616     1.018    0.20167    0.17304    0.026395    0.0064844    116.55    0.0036697    0.00057279    0.38598
    0.00083715    28.138    78.903    0.99067    0.00088737    1.0174     0.2066    0.18413    0.028246    0.0064427    151.76    0.0046852    0.00073305    0.49141
    0.00086932     26.75    78.739    0.98739    0.00083905    1.0237    0.20167    0.18093    0.035568    0.0069479    158.29    0.0047787    0.00075073    0.37509
    0.00058409    29.329    80.466    0.99208    0.00087389    1.0149    0.20167    0.17253    0.022648    0.0047917    102.95    0.0036381    0.00052062    0.44672
    0.00042173    29.188    81.881     0.9917    0.00079205    1.0156    0.20167    0.17447    0.025268    0.0046875    73.786    0.0084337    0.00036497    0.36521
```

Figure 27: Table which has all the fingerprint image results of IQMS we used.

Figure 27 shows the table created in the workspace with 100 fingerprint images, 50 fake and 50 real images. To create table to display our RFDS results we had to set a variable for every single IQM, each variable contains results calculated for one single IQM, then we used a ready MATLAB function called "table" for creating tables with our IQM variables in it. The table is imported to the classification learner application. Table is not completely shown in figure 27 due to screenshot limitation.



```
%spectral magnitude error
SME = SpectralMagnitudeError(origImg, distImg);
disp('2-spectral magnitude error = ');
disp(SME);

%spectral phase error
SPE = SpectralPhaseError(origImg, distImg);
disp('3-spectral phase error = ');
disp(SPE);

%gradient magnitude error
GME = GradientMagnitudeError(origImg, distImg);
disp('4-gradient magnitude error = ');
disp(GME);

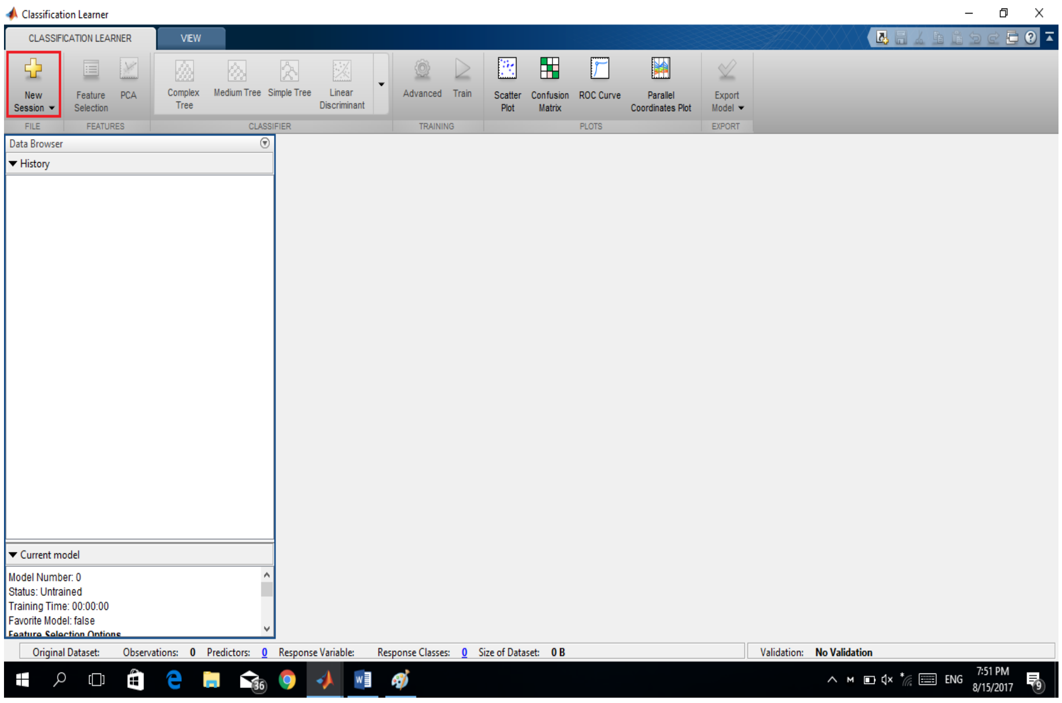
%gradient phase error
GPE = GradientphaseError(origImg, distImg);
disp('5-gradient phase error = ');
disp(GPE);
```

```
3-spectral phase error =
    1.7629
```

Name	Value
AD	0.3750
afta	4x4 double
aftb	4x4 double
ans	'distImg'
avgGmagdist	4x4 double
avgGmagorg	4x4 double
distImg	4x4 double
distSiz	[4,4]

Figure 28: The arrow shows a button used to call the classification learner app in MATLAB.

Figure 28 shows all the apps provided in MATLAB 2015; to access the classification learner app in MATLAB click on apps, select classification learner app.

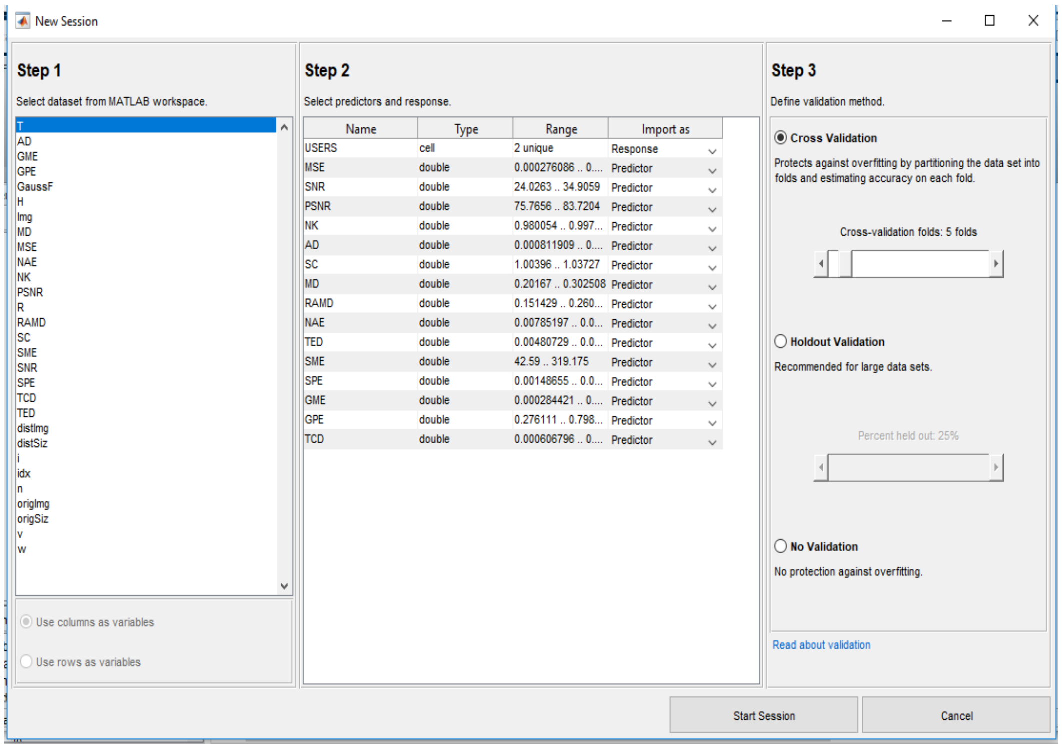


Model Number: 0
Status: Untrained
Training Time: 00:00:00
Favorite Model: false

Original Dataset: Observations: 0 Predictors: 0 Response Variable: Response Classes: 0 Size of Dataset: 0 B Validation: No Validation

Figure 29: Start new session to import results.

Figure 29 shows classification learner first page, click new session to import all datasets from the recent work space.


New Session

Step 1

Select dataset from MATLAB workspace.

T
AD
GME
GPE
GaussF
H
Img
MD
MSE
NAE
NK
PSNR
R
RAMD
SC
SME
SNR
SPE
TCD
TED
distImg
distSiz
i
idx
n
origImg
origSiz
v
w

Use columns as variables

Use rows as variables

Step 2

Select predictors and response.

Name	Type	Range	Import as
USERS	cell	2 unique	Response
MSE	double	0.000276086 .. 0....	Predictor
SNR	double	24.0263 .. 34.9059	Predictor
PSNR	double	75.7656 .. 83.7204	Predictor
NK	double	0.980054 .. 0.997...	Predictor
AD	double	0.000811909 .. 0....	Predictor
SC	double	1.00396 .. 1.03727	Predictor
MD	double	0.20167 .. 0.302508	Predictor
RAMD	double	0.151429 .. 0.260...	Predictor
NAE	double	0.00785197 .. 0.0...	Predictor
TED	double	0.00480729 .. 0.0...	Predictor
SME	double	42.59 .. 319.175	Predictor
SPE	double	0.00148655 .. 0.0...	Predictor
GME	double	0.000284421 .. 0....	Predictor
GPE	double	0.276111 .. 0.798...	Predictor
TCD	double	0.000606796 .. 0....	Predictor

Step 3

Define validation method.

[✓ Cross Validation]

Protects against overfitting by partitioning the data set into folds and estimating accuracy on each fold.

Cross-validation folds: 5 folds

Holdout Validation

Recommended for large data sets.

Percent held out: 25%

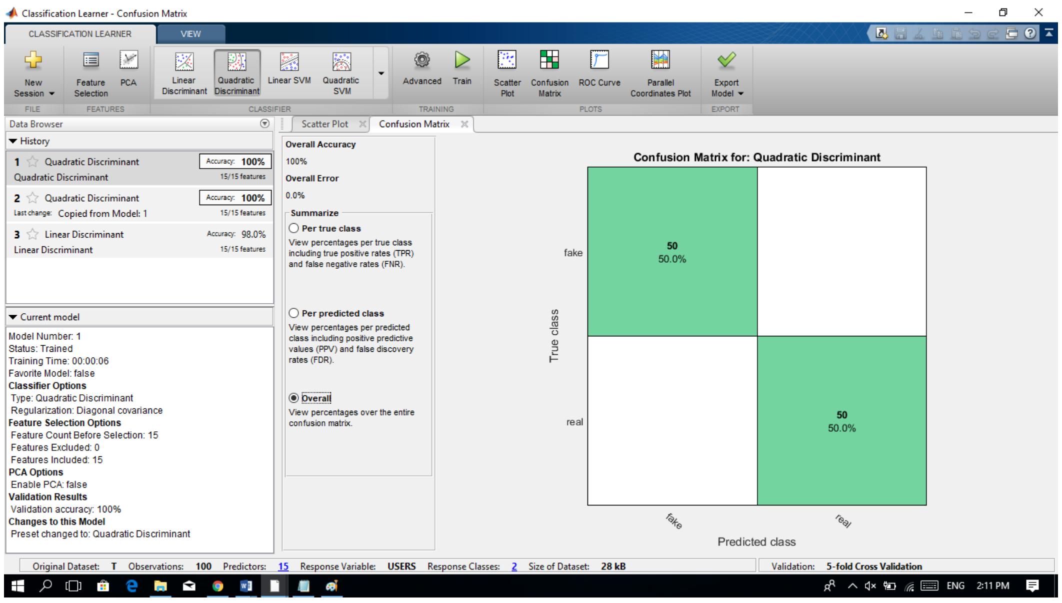
No Validation

No protection against overfitting.

Read about validation

Figure 30: Selection of our dataset, predictors and response in MATLAB.

Figure 30 shows the imported datasets from the works space which includes table t, the one we created, response (Real/Fake), and the predictors which is the image quality measures.



History

1 Quadratic Discriminant — Accuracy: 100%
Quadratic Discriminant — 15/15 features

2 Quadratic Discriminant — Accuracy: 100%
Last change: Copied from Model: 1 — 15/15 features

3 Linear Discriminant — Accuracy: 98.0%
Linear Discriminant — 15/15 features

Current model

Model Number: 1
Status: Trained
Training Time: 00:00:06
Favorite Model: false
Classifier Options
Type: Quadratic Discriminant
Regularization: Diagonal covariance
Feature Selection Options
Feature Count Before Selection: 15
Features Excluded: 0
Features Included: 15
PCA Options
Enable PCA: false
Validation Results
Validation accuracy: 100%
Changes to this Model
Preset changed to: Quadratic Discriminant

Overall Accuracy
100%
Overall Error
0.0%

Summarize
( ) **Per true class**
View percentages per true class including true positive rates (TPR) and false negative rates (FNR).
( ) **Per predicted class**
View percentages per predicted class including positive predictive values (PPV) and false discovery rates (FDR).
[✓ **Overall**]
View percentages over the entire confusion matrix.

Confusion Matrix for: Quadratic Discriminant

True class \ Predicted class	fake	real
fake	50 50.0%	
real		50 50.0%

Original Dataset: T Observations: 100 Predictors: 15 Response Variable: USERS Response Classes: 2 Size of Dataset: 28 kB
Validation: 5-fold Cross Validation

Figure 31: Selection of the classifier for our table imported and training result.

Figure 31 shows the classifiers that can be selected on the left-side of the screenshot, in our case we selected LDA classifier shown on the left corner of the figure, we then clicked train button to start the classification process for the fingerprint images which were selected for training. The right-side of Figure 29 shows the result of training 50 real and 50 fake fingerprint images, the training result had classified them all correctly. This training result obtained is considered as our training model, Figure 30 shows how to use and export the training model.

3.2.4 Implementation of The Classification Process

The training model we got from training on 100 fingerprint images is required for classification process. We input 1000 images from the fingerprint database for RFDS to classify the images on real and fake. There are four stages to implement classification process.

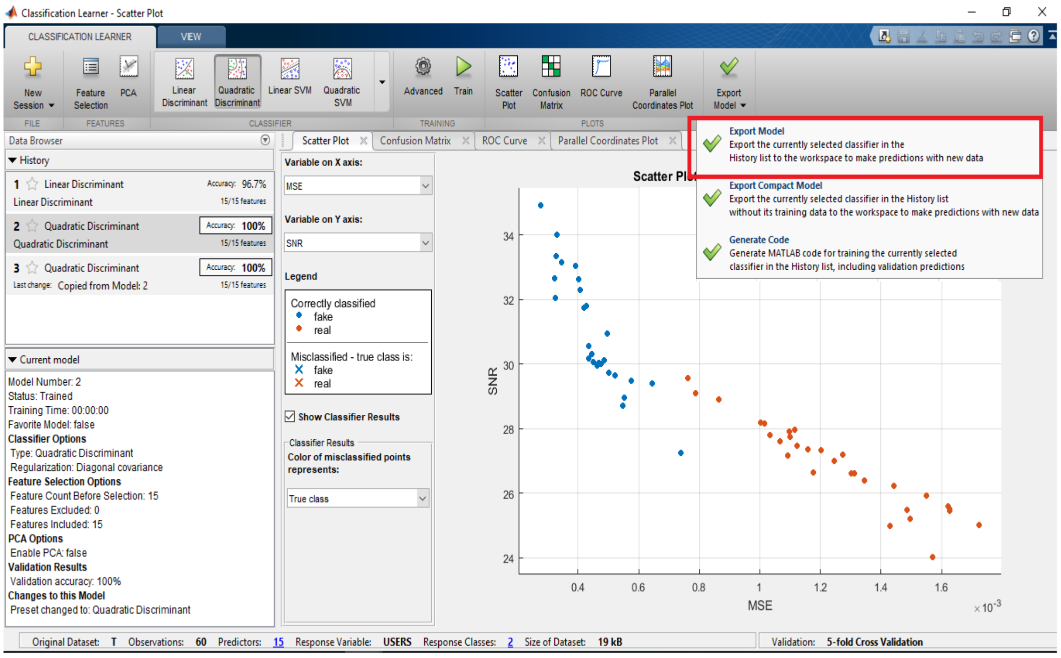
1. Export model of the classifier to the workspace to classify fingerprint images. Figure 30 shows how to use and export the training model

2. To classify the fingerprint images using the training model obtained from the classification learner app, we need to call a ready MATLAB function ”yfit = trainedclassifier.predictfcn(t)” and insert it after the table creation code, because this function will predict the fingerprint images if they are real or fake using a table with all the IQM results listed in it, in our case the function will predict table ‘T’ results real or fake based on the training model we obtained.

3. 1000 fingerprint images were used for classification. (Appendix C2) shows results of the 1000 images classification.

4. Run and classify.

The steps that show how the classification process works are shown in Figures 32-35: Click on the rectangle highlighted on the top right corner of Figure 32 to export the training model of 100 real and fake fingerprint training images, we export this model to our work space for the classification process. We enter then random images of fingerprints from different users and let our training model classify if the images FED to the RFDS are real or fake. For exporting the model click on the top right button “export model” and select the first option export model”, by this, the training model will be exported to the workspace.



Export Model
Export the currently selected classifier in the History list to the workspace to make predictions with new data

Export Compact Model
Export the currently selected classifier in the History list without its training data to the workspace to make predictions with new data

Generate Code
Generate MATLAB code for training the currently selected classifier in the History list, including validation predictions

Data Browser

History

1 Linear Discriminant — Accuracy: 96.7% — Linear Discriminant — 15/15 features

2 Quadratic Discriminant — Accuracy: 100% — Quadratic Discriminant — 15/15 features

3 Quadratic Discriminant — Accuracy: 100% — Last change: Copied from Model: 2 — 15/15 features

Current model

Model Number: 2
Status: Trained
Training Time: 00:00:00
Favorite Model: false
Classifier Options
Type: Quadratic Discriminant
Regularization: Diagonal covariance
Feature Selection Options
Feature Count Before Selection: 15
Features Excluded: 0
Features Included: 15
PCA Options
Enable PCA: false
Validation Results
Validation accuracy: 100%
Changes to this Model
Preset changed to: Quadratic Discriminant

Variable on X axis: MSE

Variable on Y axis: SNR

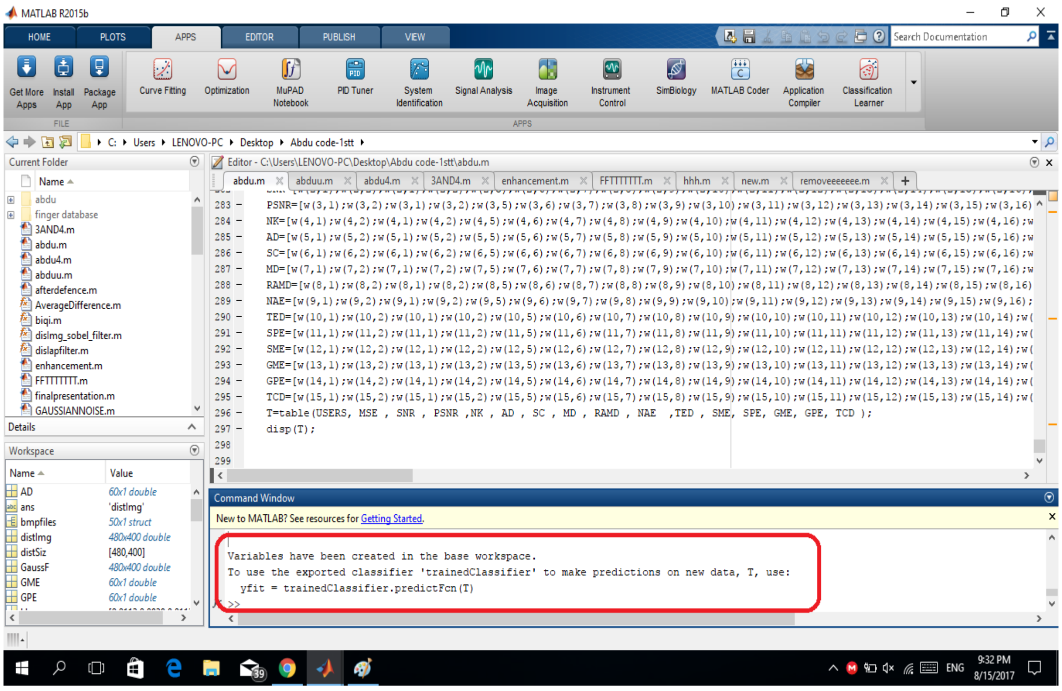
Legend
Correctly classified
● fake
● real
Misclassified - true class is:
✕ fake
✕ real

[✓] Show Classifier Results

Classifier Results
Color of misclassified points represents: True class

Original Dataset: T Observations: 60 Predictors: 15 Response Variable: USERS Response Classes: 2 Size of Dataset: 19 kB Validation: 5-fold Cross Validation

Figure 32: Exporting training model of 100 real and fake fingerprint images.



Editor - C:\Users\LENOVO-PC\Desktop\Abdu code-1stt\abdu.m

```
PSNR=[w(3,1);w(3,2);w(3,1);w(3,2);w(3,5);w(3,6);w(3,7);w(3,8);w(3,9);w(3,10);w(3,11);w(3,12);w(3,13);w(3,14);w(3,15);w(3,16)
NK=[w(4,1);w(4,2);w(4,1);w(4,2);w(4,5);w(4,6);w(4,7);w(4,8);w(4,9);w(4,10);w(4,11);w(4,12);w(4,13);w(4,14);w(4,15);w(4,16);w
AD=[w(5,1);w(5,2);w(5,1);w(5,2);w(5,5);w(5,6);w(5,7);w(5,8);w(5,9);w(5,10);w(5,11);w(5,12);w(5,13);w(5,14);w(5,15);w(5,16);w
SC=[w(6,1);w(6,2);w(6,1);w(6,2);w(6,5);w(6,6);w(6,7);w(6,8);w(6,9);w(6,10);w(6,11);w(6,12);w(6,13);w(6,14);w(6,15);w(6,16);w
MD=[w(7,1);w(7,2);w(7,1);w(7,2);w(7,5);w(7,6);w(7,7);w(7,8);w(7,9);w(7,10);w(7,11);w(7,12);w(7,13);w(7,14);w(7,15);w(7,16);w
RAMD=[w(8,1);w(8,2);w(8,1);w(8,2);w(8,5);w(8,6);w(8,7);w(8,8);w(8,9);w(8,10);w(8,11);w(8,12);w(8,13);w(8,14);w(8,15);w(8,16)
NAE=[w(9,1);w(9,2);w(9,1);w(9,2);w(9,5);w(9,6);w(9,7);w(9,8);w(9,9);w(9,10);w(9,11);w(9,12);w(9,13);w(9,14);w(9,15);w(9,16);
TED=[w(10,1);w(10,2);w(10,1);w(10,2);w(10,5);w(10,6);w(10,7);w(10,8);w(10,9);w(10,10);w(10,11);w(10,12);w(10,13);w(10,14);w(
SPE=[w(11,1);w(11,2);w(11,1);w(11,2);w(11,5);w(11,6);w(11,7);w(11,8);w(11,9);w(11,10);w(11,11);w(11,12);w(11,13);w(11,14);w(
SME=[w(12,1);w(12,2);w(12,1);w(12,2);w(12,5);w(12,6);w(12,7);w(12,8);w(12,9);w(12,10);w(12,11);w(12,12);w(12,13);w(12,14);w(
GME=[w(13,1);w(13,2);w(13,1);w(13,2);w(13,5);w(13,6);w(13,7);w(13,8);w(13,9);w(13,10);w(13,11);w(13,12);w(13,13);w(13,14);w(
GPE=[w(14,1);w(14,2);w(14,1);w(14,2);w(14,5);w(14,6);w(14,7);w(14,8);w(14,9);w(14,10);w(14,11);w(14,12);w(14,13);w(14,14);w(
TCD=[w(15,1);w(15,2);w(15,1);w(15,2);w(15,5);w(15,6);w(15,7);w(15,8);w(15,9);w(15,10);w(15,11);w(15,12);w(15,13);w(15,14);w(
T=table(USERS, MSE , SNR , PSNR ,NK , AD , SC , MD , RAMD , NAE  ,TED , SME, SPE, GME, GPE, TCD );
disp(T);
```

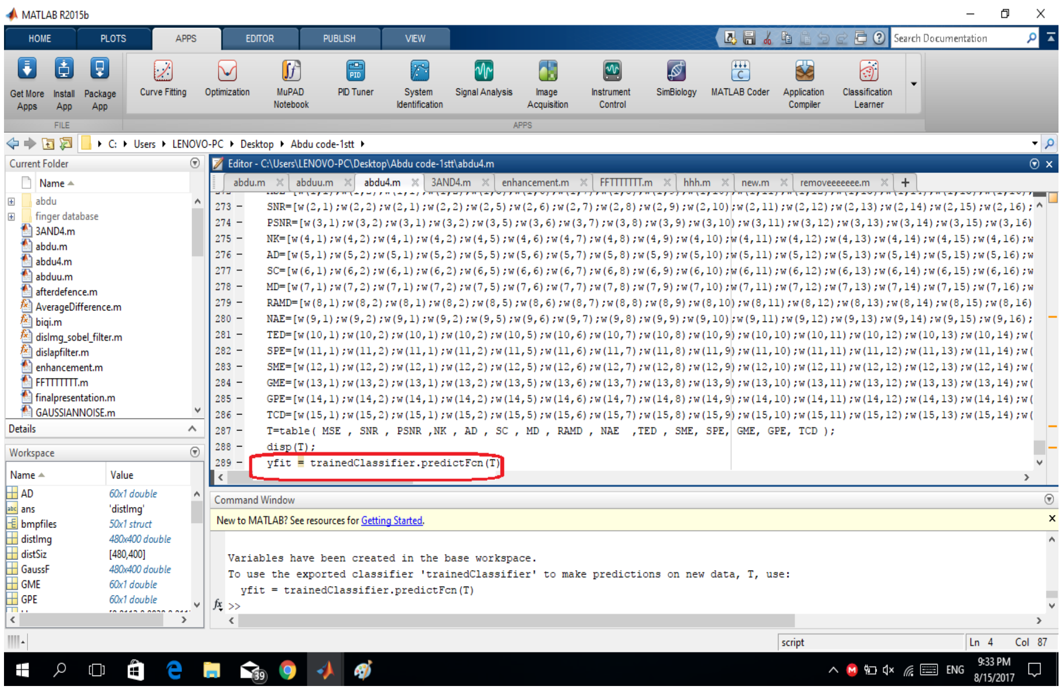
Workspace

Name	Value
AD	60x1 double
ans	'distImg'
bmpfiles	50x1 struct
distImg	480x400 double
distSiz	[480,400]
GaussF	480x400 double
GME	60x1 double
GPE	60x1 double

```
Variables have been created in the base workspace.
To use the exported classifier 'trainedClassifier' to make predictions on new data, T, use:
  yfit = trainedClassifier.predictFcn(T)
>>
```

Figure 33: After exporting the training model, we can use it to make prediction by the code provided in the command window highlighted with a rectangle.

Figure 33, shows that our training model has been exported to the works space, as it can be seen clearly in the command window. If this highlighted rectangle message doesn’t appear in the command window, it means, the training model wasn’t exported successfully.

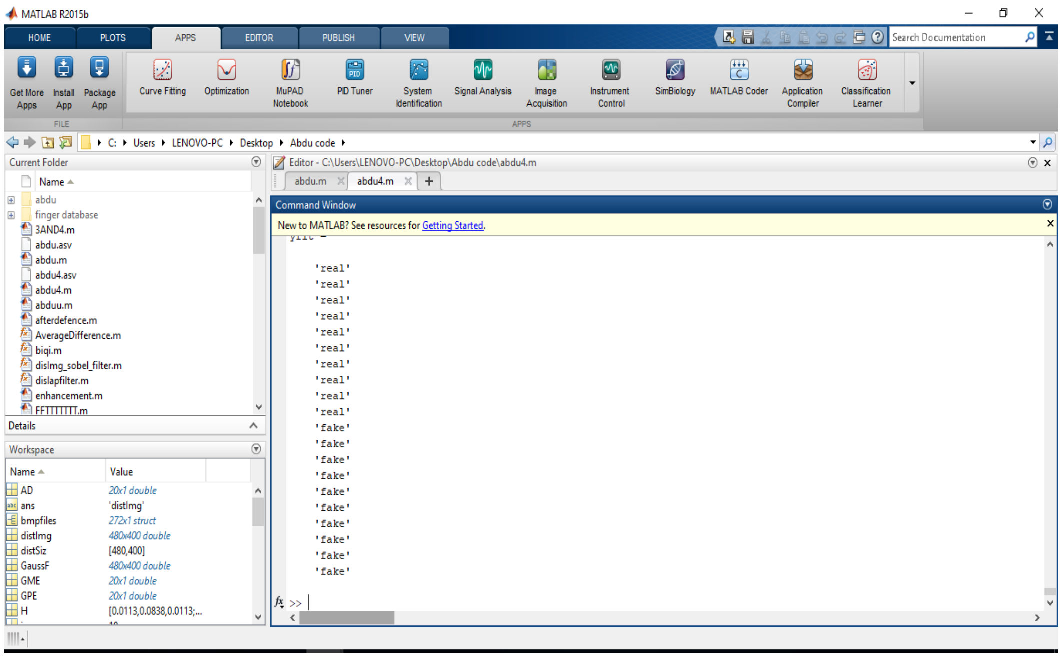


```
SNR=[w(2,1);w(2,2);w(2,1);w(2,2);w(2,5);w(2,6);w(2,7);w(2,8);w(2,9);w(2,10);w(2,11);w(2,12);w(2,13);w(2,14);w(2,15);w(2,16);
PSNR=[w(3,1);w(3,2);w(3,1);w(3,2);w(3,5);w(3,6);w(3,7);w(3,8);w(3,9);w(3,10);w(3,11);w(3,12);w(3,13);w(3,14);w(3,15);w(3,16)
NK=[w(4,1);w(4,2);w(4,1);w(4,2);w(4,5);w(4,6);w(4,7);w(4,8);w(4,9);w(4,10);w(4,11);w(4,12);w(4,13);w(4,14);w(4,15);w(4,16);w
AD=[w(5,1);w(5,2);w(5,1);w(5,2);w(5,5);w(5,6);w(5,7);w(5,8);w(5,9);w(5,10);w(5,11);w(5,12);w(5,13);w(5,14);w(5,15);w(5,16);w
SC=[w(6,1);w(6,2);w(6,1);w(6,2);w(6,5);w(6,6);w(6,7);w(6,8);w(6,9);w(6,10);w(6,11);w(6,12);w(6,13);w(6,14);w(6,15);w(6,16);w
MD=[w(7,1);w(7,2);w(7,1);w(7,2);w(7,5);w(7,6);w(7,7);w(7,8);w(7,9);w(7,10);w(7,11);w(7,12);w(7,13);w(7,14);w(7,15);w(7,16);w
RAMD=[w(8,1);w(8,2);w(8,1);w(8,2);w(8,5);w(8,6);w(8,7);w(8,8);w(8,9);w(8,10);w(8,11);w(8,12);w(8,13);w(8,14);w(8,15);w(8,16)
NAE=[w(9,1);w(9,2);w(9,1);w(9,2);w(9,5);w(9,6);w(9,7);w(9,8);w(9,9);w(9,10);w(9,11);w(9,12);w(9,13);w(9,14);w(9,15);w(9,16);
TED=[w(10,1);w(10,2);w(10,1);w(10,2);w(10,5);w(10,6);w(10,7);w(10,8);w(10,9);w(10,10);w(10,11);w(10,12);w(10,13);w(10,14);w(
SPE=[w(11,1);w(11,2);w(11,1);w(11,2);w(11,5);w(11,6);w(11,7);w(11,8);w(11,9);w(11,10);w(11,11);w(11,12);w(11,13);w(11,14);w(
SME=[w(12,1);w(12,2);w(12,1);w(12,2);w(12,5);w(12,6);w(12,7);w(12,8);w(12,9);w(12,10);w(12,11);w(12,12);w(12,13);w(12,14);w(
GME=[w(13,1);w(13,2);w(13,1);w(13,2);w(13,5);w(13,6);w(13,7);w(13,8);w(13,9);w(13,10);w(13,11);w(13,12);w(13,13);w(13,14);w(
GPE=[w(14,1);w(14,2);w(14,1);w(14,2);w(14,5);w(14,6);w(14,7);w(14,8);w(14,9);w(14,10);w(14,11);w(14,12);w(14,13);w(14,14);w(
TCD=[w(15,1);w(15,2);w(15,1);w(15,2);w(15,5);w(15,6);w(15,7);w(15,8);w(15,9);w(15,10);w(15,11);w(15,12);w(15,13);w(15,14);w(
T=table( MSE , SNR , PSNR ,NK , AD , SC , MD , RAMD , NAE  ,TED , SME, SPE, GME, GPE, TCD );
disp(T);
yfit = trainedClassifier.predictFcn(T)
```

```
Variables have been created in the base workspace.
To use the exported classifier 'trainedClassifier' to make predictions on new data, T, use:
  yfit = trainedClassifier.predictFcn(T)
>>
```

Figure 34: The highlighted rectangle shows the code used to classify images according to our exported training model.

Figure 34, Shows the code used for classifiying the images “yfit = trainedclassifier.predictfcn(t)”. As we mentioned before this code has to be added after creating a table with all the results of the IQMS listed in it, so that we can classify the fingerprint images as real or fake. In our case we created a table named ‘T’ with all the results saved, then we added the function “yfit = trainedclassifier.predictfcn(t)” in our code to classify images results from the table ‘T’ according to our exported training model.



Editor - C:\Users\LENOVO-PC\Desktop\Abdu code\abdu4.m

```
    'real'
    'real'
    'real'
    'real'
    'real'
    'real'
    'real'
    'real'
    'real'
    'real'
    'fake'
    'fake'
    'fake'
    'fake'
    'fake'
    'fake'
    'fake'
    'fake'
    'fake'
    'fake'

>>
```

Name	Value
AD	20x1 double
ans	'distImg'
bmpfiles	272x1 struct
distImg	480x400 double
distSiz	[480,400]
GaussF	480x400 double
GME	20x1 double
GPE	20x1 double
H	[0.0113,0.0838,0.0113;...

Figure 35: Results of 10 real and fake images classified correctly using the classification code.

Figure 35 shows the results obtained from fingerprint images after running the classification code (Appendix A). In this run we had 10 real images and 10 fake all were classified correctly. The fingerprint images used were obtained from fingerprint database atvs-ffp db [33]. Figure 36 shows a screenshot of one real and fake fingerprint image sample we used in our experiments. Real and fake finger print images were read from directory" c:\users\lenovo-pc\desktop\hp_new folder (2)\abdu code\finger database\abdu\1biometrika\tm real". Appendix A. Line 3. Shows the code we used for reading the directory of the fingerprint images.

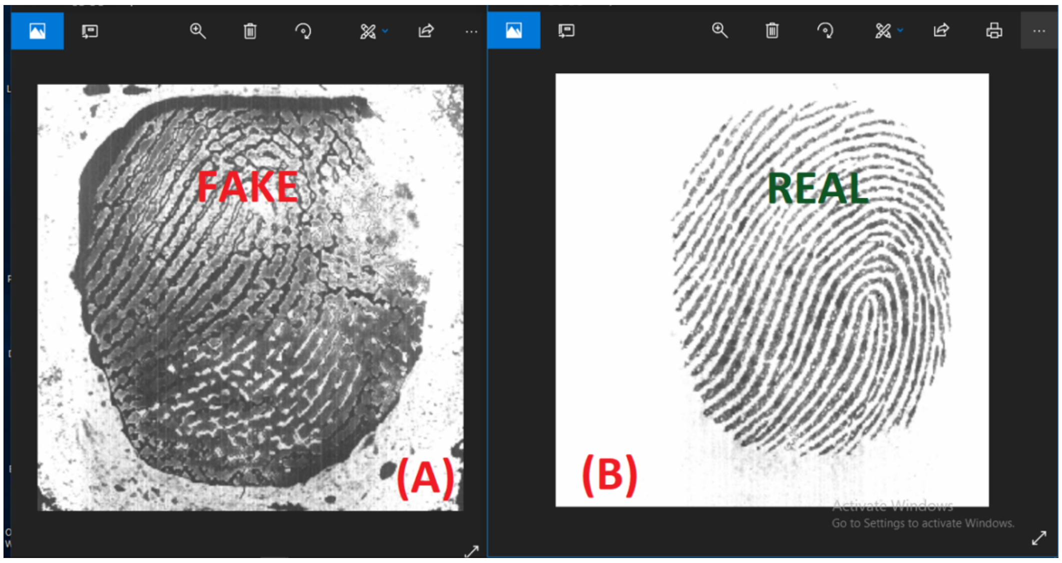


Figure 36: Fingerprint images used in our expirments, (A) fake fingerprint image from the file" U01_F_Fc_Li_01.Bmp", (B) real fingerprint image form the file" U01_O_Fc_Li_01.Bmp".

3.3 Development of A Method of Defining the Best IQMs

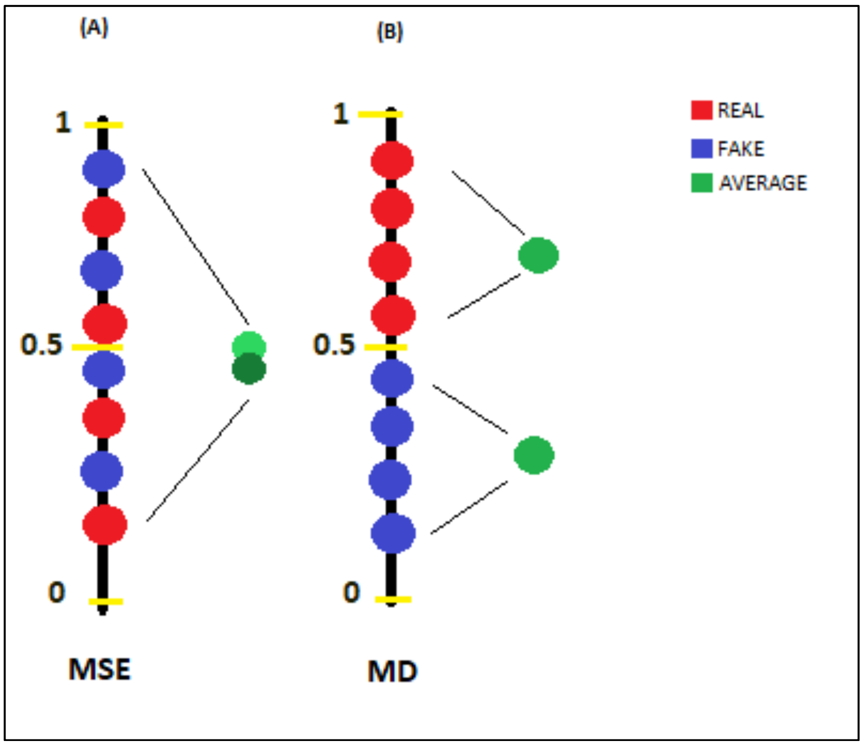


Figure 37: Numerical axis for MSE (A) And MD (B), showing MSE of fake (real) fingerprint images. And the respective averages calculated by (3.16) and (3.17).

Figure 37, shows a drawing that will help you to understand our basic idea behind finding the best 5 and 10 IQMs ,as you can see in Figure 34 there are two graphs (A) for MSE and (B) for MD, both of the graphs have red dots which represent the values of MSE and MD in real fingerprint images, the blue dots which represent the fake fingerprint image values of MSE and MD, and the green dots represent the average of MSE and MD in real fingerprint images (red dots) and fake fingerprint images (blue dots) calculated by (3.16) and (3.17) . Figure 34 has two scenarios: let's start with (A), the MSE red points are close to the blue points which means that the real and fake points in MSE are very close to each other and makes it difficult for us to distinguish between both of the points, in (A) the average point of the real points of MSE and the average point of the fake points of MSE are very close, in other words, it means that the real and fake points are very near to each other and it's hard to differentiate between them. In (B) the MD red and blue points are well separated from each other, so that means the real points and fake points can be well distinguished from each other, we can also see that in (B) the average points for the real and fake images are far away from each other, so (B) is far better than (A) in distinguishing real and fake fingerprint images, from these two cases we can say that MD is a better IQM than MSE. The IQM which will have the highest absolute value of the difference between the green dots representing averages will be set as the best in the list of the IQM sorted by the difference (3.18) in the descending order.

1. To find the best 5 and 10 IQM of our RFDS we need to apply the following steps for every measurement.

Find the IQM average of real fingerprint images ($\bar{x}r$).

$$\bar{x}r = \frac{\sum_{i=1}^{N} x_i^r}{Nr} \qquad (3.16)$$

Where x_i^r is the value of IQM in one single real fingerprint image, NR is number of real fingerprint images FED to the system.

2. Find the IQM average of fake fingerprint images (x̄f).

$$\bar{x}f = \frac{\sum_{j=1}^{N} x_j^f}{Nf} \qquad (3.17)$$

Where x_i^r is the value of iqm in one single fake fingerprint image, nf is number of fake fingerprint images fed to the system.

3. Find the difference between real ($\bar{x}r$) and fake fingerprint images ($\bar{x}f$).

$$\Delta X = |\bar{x}r - \bar{x}f| \qquad (3.18)$$

Apply these three steps for every single IQM, then sort them from maximum to minimum difference value which is found in step 3. The best IQM will be the one with the maximum distance value. $\bar{x}r$.

$\boldsymbol{Sort} = max(\Delta Xr \ldots . \Delta Xn)$

Where n is the number of iqm used in the system

3.3.1 Implementation and Testing of The Method of Defining the Best IQMs

The code for the defining the best IQMs was implemented using MATLAB. The complete code is shown in Appendix B.

Explanation of defining the best IQMS code (Appendix B-1):

Line 1: We set the results of the IQM from 1-500 as real values. Line 2: we set the results of the IQM from 501-1000 as fake values. Line 3: we take the average of the real values of the IQM. Lines 4 and 5: display the average of the real values of the IQMs. Line 6: we take the average of the fake values of the IQM. Lines 7 and 8: display the average of the fake values of the IQM; line 9: displays the difference of the averages of real values and fake values of the IQMs. Line 10: we take the absolute value of the difference calculated. Line 11: we display the result.

Explanation of ranking the best IQMs code (Appendix B-2):

Line 1: We list the names of all IQMs in one array. Line 2: we list the difference of the averages of real and fake values of every IQM in one array. Line 3: we create a table with "title" and "best 15" as its fields. Line 4: we sort the table rows in descending order.

3.3.1.1 Calculation of Defining the Best 5 IQMs

1. For MSE

Real fingerprint image values of the MSE: 0.0017764, 0.0016535, 0.0016386, 0.00163, 0.0016254

Fake fingerprint image values of the MSE: 0.0015887, 0.0015395, 0.0015314, 0.0014846, 0.0014052

Average of the real fingerprint image values of MSE: (0.0017764 + 0.0016535 + 0.0016386 + 0.00163 + 0.0016254)/ 5 = 0.0017

Average of the fake fingerprint image values of MSE: (0.0015887 + 0.0015395 + 0.0015314 + 0.0014846 + 0.0014052)/ 5 = 0.0015

Difference between the average of real fingerprint image values of MSE and average of the fake fingerprint image values of MSE: |0.0017 - 0.0015| = 0.0001549

2. For SNR

Real fingerprint image values of the SNR: 32.608, 31.179, 30.719, 30.149, 30.149

Fake fingerprint image values of the SNR: 29.958, 29.674, 29.664, 29.584, 29.674

Average of the real fingerprint image values of SNR: (32.608 + 31.179 + 30.719 + 30.149 + 30.149) / 5 = 30.9608

Average of the fake fingerprint image values of SNR: (29.958 + 29.674 + 29.664 + 29.584 + 29.674) / 5 = 29.7108

Difference between the average of real fingerprint image values of SNR and average of the fake fingerprint image values of SNR: |30.9608 - 29.7108| = 1.2500

3. For PSNR

Real fingerprint image values of the PSNR: 81.171, 81.106, 80.41, 79.938, 79.541

Fake fingerprint image values of the PSNR: 79.142, 79.142, 78.689, 78.668, 78.522

Average of the real fingerprint image values of PSNR: (81.171 + 81.106 + 80.41 + 79.938 + 79.541) / 5 = 80.4332

Average of the fake fingerprint image values of PSNR: (79.142 + 79.142 + 78.689 + 78.668 + 78.522) / 5 = 78.8326

Difference between the average of real fingerprint image values of psnr and average of the fake fingerprint image values of PSNR: |80.4332-78.8326| =1.6006

4. For NK

Real fingerprint image values of the NK: 0.99731, 0.99604, 0.99542, 0.99542, 0.9948

Fake fingerprint image values of the NK: 0.99453, 0.99447, 0.99417, 0.99409, 0.994

Average of the real fingerprint image values of NK: (0.99731 + 0.99604 + 0.99542 + 0.99542 + 0.9948) / 5 = 0.9958

Average of the fake values of NK: (0.99453 + 0.99447 + 0.99417 + 0.99409 + 0.994) / 5 = 0.9943

Difference between the average of real fingerprint image values of NK and average of the fake fingerprint image values of NK: |0.9958 - 0.9943| = 0.0015

5. For AD

Real fingerprint image values of the AD: 0.00097608, 0.00097608, 0.00097608, 0.00097608, 0.197608

Fake fingerprint image values of the AD: 0.297608, 0.07608, 0.208, 0.1608, 0.397608

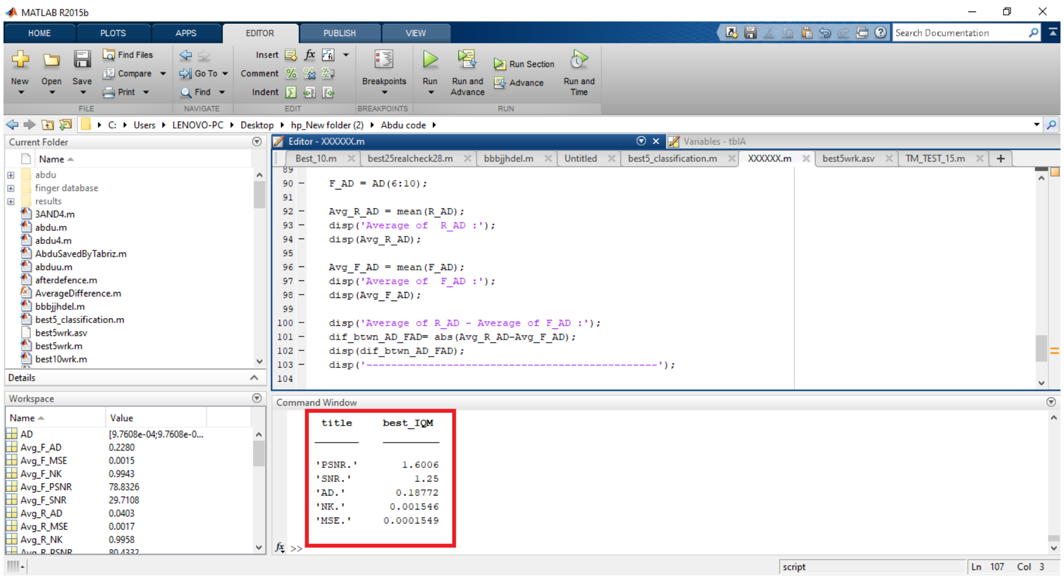
Average of the real fingerprint image values of AD: (0.00097608 + 0.00097608 + 0.00097608 + 0.00097608 + 0.00097608 + 0.197608) / 5 = 0.0403

Average of the fake fingerprint image values of AD: (0.297608 + 0.07608 + 0.208 + 0.1608 + 0.397608) / 5 = 0.2280

Difference between the average of real fingerprint image values of ad and average of the fake fingerprint image values of AD: |0.0403 - 0.2280| = 0.1877

The best IQM is the one with the fake fingerprint image values. The rank of the best 5 IQMs will be:

SNR	1.6006
SNR	1.25
AD	0.18772
NK	0.001546
MSE	0.0001549



```
F_AD = AD(6:10);

Avg_R_AD = mean(R_AD);
disp('Average of  R_AD :');
disp(Avg_R_AD);

Avg_F_AD = mean(F_AD);
disp('Average of  F_AD :');
disp(Avg_F_AD);

disp('Average of R_AD - Average of F_AD :');
dif_btwn_AD_FAD= abs(Avg_R_AD-Avg_F_AD);
disp(dif_btwn_AD_FAD);
disp('---------------------------------------------');
```

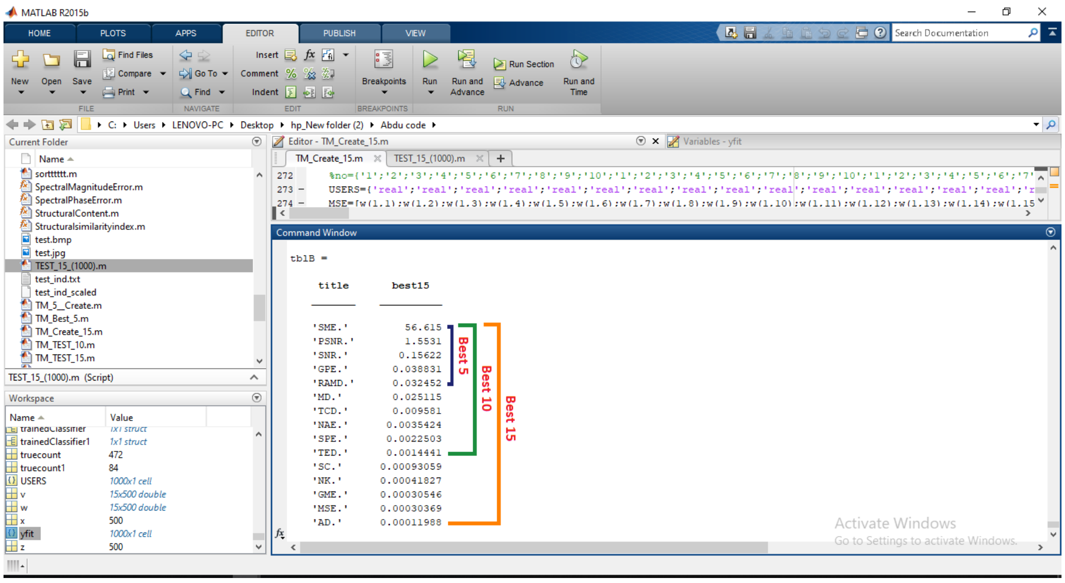
```
 title      best_IQM
_______    __________

'PSNR.'        1.6006
'SNR.'           1.25
'AD.'         0.18772
'NK.'        0.001546
'MSE.'      0.0001549
```

Name	Value
AD	[9.7608e-04;9.7608e-0...
Avg_F_AD	0.2280
Avg_F_MSE	0.0015
Avg_F_NK	0.9943
Avg_F_PSNR	78.8326
Avg_F_SNR	29.7108
Avg_R_AD	0.0403
Avg_R_MSE	0.0017
Avg_R_NK	0.9958
Avg_R_PSNR	80.4332

Figure 38: The list of the best IQMs (in the red rectangle).

Figure 38 shows a screenshot with the list of the best IQMs. Using MATLAB, we inserted the same values used for every IQM in the manual calculation above and applied the same steps of calculation, which generated expected results at the end. For our RFDS expirment we used the same method explained above to define our best 15, 10, and 5 IQMs. Figure 38 shows a screenshot of our best 15, 10, and 5 IQMs generated by our code which is available in Appendix B. The MATLAB screenshot in Figure 39 shows our IQMs listed as follows: for **best 10 IQMs**: SME, PSNR, SNR, GPE, RAMD, MD, TCD, NAE, SPE, and SC, and the first five of them are the **Best 5 IQMs**.



```
%no={'1';'2';'3';'4';'5';'6';'7';'8';'9';'10';'1';'2';'3';'4';'5';'6';'7';'8';'9';'10';'1';'2';'3';'4';'5';'6';'7'
USERS={'real';'real';'real';'real';'real';'real';'real';'real';'real';'real';'real';'real';'real';'real';'r
MSE=[w(1,1);w(1,2);w(1,3);w(1,4);w(1,5);w(1,6);w(1,7);w(1,8);w(1,9);w(1,10);w(1,11);w(1,12);w(1,13);w(1,14);w(1,15
```

```
tblB =

      title        best15
    _________    __________

    'SME.'           56.615
    'PSNR.'          1.5531
    'SNR.'          0.15622
    'GPE.'         0.038831
    'RAMD.'        0.032452
    'MD.'          0.025115
    'TCD.'         0.009581
    'NAE.'        0.0035424
    'SPE.'        0.0022503
    'TED.'        0.0014441
    'SC.'        0.00093059
    'NK.'        0.00041827
    'GME.'       0.00030546
    'MSE.'       0.00030369
    'AD.'        0.00011988
```

Figure 39: List of our best 15,10,5 IQMs used in our RFDS expirments.

3.4 Summary

In this chapter we have presented the implementation of our RFGS, including Gaussian Filter, Feature Extraction, Measurnment of Traning Strcture, Classification Process and the best IQMs using MATLAB r2015b as showen in (Appendices A- C).

Chapter 4

EXPERIMENTS ON RFDS

4.1 Experimental Setup

The experiment was implemented on a PC with Windows 10 pro, 64-bit operating system, CPU Intel Core I7 2.50 Ghz, 8 Gb Ram, and MATLAB r2015b.

4.2 Database Used

ATVS fingerprint database [33] contains two datasets of fingerprint images with bmp file format:

1. Dataset 1: fake samples were captured from gummy fingers generated with the cooperation of the user. It contains fingerprint samples of the middle and index finger of both hands of 17 users, which means in total 68 (17x4=68) different fingers. Four samples of each fingerprint (Fake and Real) were captured in one acquisition session with the use of three sensors, so the dataset consists of 68 x 4 x 3 =816 real image samples and as many fake images.

The three types of sensors are used in the dataset:

- Biometrika Sensor.
- Thermal Sensor.
- Flat Capacitive Sensor.

2. Dataset 2: ds_withoutcooperation fake samples were captured from gummy fingers generated with the cooperation of the user. It contains fingerprint samples of the middle and index fingers of both hands of 16 users, which means in total 64 (16x4) different fingers. Four samples of each fingerprint (Fake and Real) were captured in one acquisition session with the use of three sensors, this way the dataset comprises 768 (64 x 4 x 3 =816) real image samples and as many fake images.

In all the experiments we ran on the RFDS we used 50 real and 50 fake images for training stage, while in the classification stage we used 500 original fingerprint images and 500 fake fingerprint images a total of 1000 fingerprint images. Three different types of experiments on the RFDS were conducted: RFDS training and classification with 25 IQMs, RFDS training and classification with best 15 IQMs, RFDS training and classification with the best 10 IQMs, RFDS training and classification with the best 5 IQMs.

4.3 Classification Methods Used

- LDA (Linear Discriminant Analysis)
- QDA (Quadratic Discriminant Analysis)
- Linear SVM, Quadratic SVM
- Logistic Regression, and fine KNN.

4.4 Code Parts for Experiments Conducting

The experiment code is divided into three parts:

- Input the Fingerprint Image and Filtering Code.
- Feature Extraction Code.
- Classification Process.

In the first part of the code (Appendix A, lines 1-29), we input the fingerprint images and convert them from RGB to grayscale image. Then, we convert the image to double, and apply a 3*3 Gaussian filter to it; we resize both the original and fake fingerprint image to an equal size.

In the second part of the code (Appendix A, Lines 30-80), 25 image quality measures are implemented and each of them has a function for calculation, using the two inputs, real and enhanced fingerprint image. Each image quality measure function provided in the code was successfully tested. For training, 50 real fingerprint images and 50 fake fingerprint images with their 25 image quality measures calculated will be gathered all in a vector and arranged in a table to be able to import them to the classification learner application for training process.

In the third part which is the classification process, we use a user-friendly MATLAB application called "Classification Learner Application" to classify fingerprint images to real and fake images using six classifiers.

4.5 Experimental Results

4.5.1 Experiments on the RFDS Training and Classification with 15 IQMs

Table 4: Training results with 15 IQMs.

15 IQMs SME, PSNR, SNR, GPE, RAMD, MD, TCD, NAE, SPE, SC, TED, NK, MSE, GME, AND AD; ATV Database, 50 Real And 50 Fake Fingerprints.			
Classifier/Sample No.	**FFR**	**FGR**	**HTER**
Lda/1000 Images	4%	30%	17%
Qda/100 Images	4%	24%	14%
Linear Svm/100 Images	2%	2%	2%
Quadratic Svm/100 Images	0%	0%	0%
Logistic Regression/100 Images	0%	0%	0%
Fine Knn/100 Images	0%	0%	0%

The results listed in Table 4, are generated from ATV database. There were 50 real and 50 fake fingerprint images input to the system to train, the detailed results of the 100 samples of fingerprints using 15 IQMs and 6 classifiers are shown in Appendix C-1, Figures 38-43.

Table 5: Classification results with 15 IQMs.

15 IQMs SME, PSNR, SNR, GPE, RAMD, MD, TCD, NAE, SPE, SC, TED, NK, MSE, GME, AND AD; ATV Database, 500 Real And 500 Fake Fingerprints			
Classifier/Sample No.	**FFR**	**FGR**	**HTER**
LDA/1000 Images	5.4%	21.6%	13.5%
QDA/1000 Images	12.4%	17.2%	14.8%
Linear SVM/1000 Images	8.4%	7.6%	8%
Quadratic SVM/1000 Images	1.6%	10%	5.8%
Logistic Regression/1000 Images	8%	9%	8.5%
Fine KNN/1000 Images	2.6%	13.6%	8.1%

Table 5, shows the classification results with 15 IQMs for 500 real and 500 fake fingerprint images inputted to the system to classify, the detailed results of the 1000 samples of fingerprints for classification are shown in Appendix C-2, Figures 44–49.

4.5.2 Experiments on The Rfds Training and Classification with Best 10 IQMs

Table 6: Training results with best 10 IQMs.

Best 10 IQMs SME, PSNR, SNR, GPE, RAMD, MD, TCD, NAE, SPE, AND SC			
Classifier/Sample No.	**FFR**	**FGR**	**HTER**
LDA/100 Images	4%	24%	14%
QDA/100 Images	4%	12%	8%
Linear SVM/100 Images	2%	0%	1%
Quadratic SVM/100 Images	0%	0%	0%
Logistic Regression/100 Images	0%	0%	0%
Fine KNN/100 Images	0%	0%	0%

The results listed in Table 6, are generated with the use of 10 IQMs, there were 50 real and 50 fake fingerprint images inputted to the system to train, the detailed results of the 100 samples of fingerprints using 6 classifiers are shown in Appendix C-3, Figures 50-55.

Table 7: Classification results with best 10 IQMs.

Best 10 IQMs: SME, PSNR, SNR, GPE, RAMD, MD, TCD, NAE, SPE, AND SC			
Classifier/Sample No.	**FFR**	**FGR**	**HTER**
LDA/1000 Images	9%	18.8%	13.9%
QDA/1000 Images	13.4%	13.6%	13.5%
Linear SVM/1000 Images	8.8%	7.4%	8.1%
Quadratic SVM/1000 Images	3%	9.4%	6.2%
Logistic Regression/1000 Images	14.6%	12.2%	13.4%
Fine KNN/1000 Images	3.8%	13.2%	8.5%

Table 7, shows the classification results with 10 IQMs for 500 real and 500 fake fingerprint images inputted to the system to classify. The results of the 1000 samples of fingerprint classification are shown in Appendix C-4, Figures 56–61.

4.5.3 Experiments on The RFDS Training and Classification with Best 5 IQMs

Table 8: Training results with best 5 IQMs.

Best 5 IQMs: SME, PSNR, SNR, GPE, AND RAMD			
Classifier/Sample No.	**FFR**	**FGR**	**HTER**
LDA/100 Images	4%	16%	10%
QDA/100 Images	4%	6%	5%
Linear SVM/100 Images	2%	0%	1%
Quadratic SVM/100 Images	2%	0%	1%
Logistic Regression/100 Images	0%	0%	0%
Fine KNN/100 Images	0%	0%	0%

The results listed in Table 8, are obtained with the use of 5 IQMs, there were 50 real and 50 fake fingerprint images inputted to the system to train, the detailed results of the 100 samples of fingerprint using 6 classifiers are shown in Appendix C-5, Figures 62-67.

Table 9: Classification results with best 5 IQMs.

Best 5 Iqms: SME, PSNR, SNR, GPE, AND RAMD			
Classifier/Sample No.	**FFR**	**FGR**	**HTER**
LDA/1000 Tested Fingerprint Images	10.4%	14.6%	12.5%
QDA/1000 Images	13.8%	9.2%	11.5%
Linear SVM/1000 Images	8.8%	6.4%	7.6%
Quadratic SVM1000 Images	7.8%	6.2%	7%
Logistic Regression/1000 Ima+Ges	6.2%	6.8%	6.5%
Fine KNN/1000 Images	6.4%	8.6%	7.5%

Table 9, shows the classification results with 5 IQMs for 500 real and 500 fake fingerprint images inputted to the system to classify, the detailed results of the 1000 samples of fingerprints tested for classification are shown in Appendix C-6, Figures 68-73. 4.3.4.

4.5.4 Experiments on The RFDS Training and Classification With 25 IQMs

Table 10: Training results with 25 IQMs.

25 IQMs SME, PSNR, SNR, GPE, RAMD, MD, TCD, NAE, SPE, SC, TED, NK, MSE, GME, AD, LMSE, MAS, MAMS, HLFREQIQ, BIQI, SSIM, RRED, JPEG, VIF, AND NIQE			
Classifier/Sample No.	**FFR**	**FGR**	**HTER**
LDA/100 Images	4%	20%	12%
QDA/100 Images	2%	0%	1%
Linear SVM/100 Images	0%	2%	1%
Quadratic SVM/100 Images	0%	0%	0%
Logistic Regression/100 Images	0%	0%	0%
Fine KNN/100 Images	0%	0%	0%

The results listed in Table 10 are generated from ATV database for 50 real and 50 fake fingerprint images inputted to the system to train. The detailed results of the 100 samples of fingerprints using 25 IQMs using 6 classifiers are shown in Appendix C-7, Figures 74 -78.

Table 11: Classification results with 25 IQM's.

25 IQMs SME, PSNR, SNR, GPE, RAMD, MD, TCD, NAE, SPE, SC, TED, NK, MSE, GME, AD, LMSE, MAS, MAMS, HLFREQIQ, BIQI, SSIM, RRED, JPEG, VIF, AND NIQE			
Classifier/Sample No.	**FFR**	**FGR**	**HTER**
LDA/1000 Images	5.4%	0%	2.7%
QDA/1000 Images	19%	0%	9.5%
Linear SVM/1000 Images	2.6%	0%	1.3%
Quadratic SVM/1000 Images	0.6%	0%	0.3%
Logistic Regression/1000 Images	1%	0%	0.5%
Fine KNN/1000 Images	1.2%	0%	0.6%

Table 11, shows the classification results with 25 IQM's for 500 real and 500 fake fingerprint images inputted to the system to classify. The detailed results of the 1000 samples of fingerprints for classification are shown in Appendix C-8, Figures 79-84.

4.5.5 Comparsion of the RFDS Performance With 5, 10, 15, And 25 Iqms Used

Table 12: Result of comparison HTER (%) between our RFDS and RFDS [6].

Result of Comparison For 5, 10, 15 And 25 IQMs						
Classifiers						
RFDS	**FINEKNN**	**QDA**	**LDA**	**QSVM**	**LSVM**	**LOGREG**
25	N/A	12.8%	N/A	N/A	N/A	N/A
25 IQMs	0.6%	9.5%	2.7%	0.3%	1.3%	0.5%
15 IQMs	8.1%	14.8%	13.5%	5.8%	8%	8.5%
10 IQMs	8.5%	13.5%	13.9%	6.2%	8.1%	13.4%
5 IQMs	7.5%	11.5%	12.5%	7%	7.6%	6.5%

Table 11, shows the comparison between RFDS performances with the usage of 25, 15, 10, 5 IQMs. We can clearly see that performance of our RFDS with 25 IQMs has better performance than the rest of the RFDS. Table 11, also shows that 10 and 15 IQMs RFDS are very similar to each other, their hter results are very close not like the RFDS with 5 IQMs where the result of its HTER has minmum 12% gap from the other RFDS. From Table 11, we can say that the best performance from the RFDS in the list is the one with 25 IQMs, because it's HTER score is the minimum one with 0.3%, and the worst RFDS is the one with the 5 IQMs which has the maximum HTER score with 29.7%.

4.6 Summary

We show the experiment setup of our RFDS, we also compared four of our RFDS using 5, 10, 15, and 25 IQMs with RFDS [6] which has used 25 IQMS. Our RFDS experiment was implemented using atv database [33], 100 fingerprint images were used for training process, and 1000 fingerprints were used for detection process. With the exclusion of our RFDS that used 5 IQMs, we can summarize that with less IQMs than RFDS [6], our system still managed to give us better results, listed all in table 11.

Chapter 5

CONCLUSION

In our thesis we analyzed similar to the “State-of-The-Art” RFDS systems; some of them used different image quality measures (IQMs), and also different types of classification process. The results of these RFDS systems in detecting fake fingerprint images still had errors and were not 100% accurate. These existing errors of detecting fingerprint image made us interested in implementing a RFDS system with high performance and fewer errors. In our studies we explained step by step procedure of how to implement our RFDS, implementation of Gaussian filter to the input image, implementation of the IQMs, implementation of the classification process, and implementation of the method of defining the best IQMs. All these implementations were done using MATLAB r2015b. We also show our experimental setup used for investigation of our RFDS. We compared our RFDS (using 5,10, 15, and 25 IQMs) with state of the art RFDS (using 25 IQMs). Our best RFDS hter result is 0.3% using 25 IQMs, and state oft he art RFDS hter was 12.8% using also the same 25 IQMs, which indicates that our RFDS performance is overall much better than the state of the art” RFDS even though in some experiments we used a smaller number of IQMs in our system compared to the state of the art RFDS.

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APPENDICES

Appendix A: Feature Extraction Code:

1. MSE Function

```
Function Iqm_Mse = Mean_Sqr_Error(Rel_Img, Enhcd_Img)
Rel_Img = Double(Rel_Img);
Enhcd_Img = Double(Enhcd_Img);
[M N] = Size(Rel_Img);
Eror = Rel_Img - Enhcd_Img;
Iqm_Mse = Sum(Sum(Eror .* Eror)) / (M * N);
```

2. PSNR Function

```
Function Iqm_Psnr = Pk_Signalt_Nse_Ratio(Rel_Img, Enhcd_Img)
Rel_Img = Double(Rel_Img);
Enhcd_Img = Double(Enhcd_Img);
[M N] = Size(Rel_Img);
Eror = Rel_Img - Enhcd_Img;
Iqm_Mse = Sum(Sum(Eror .* Eror)) / (M * N);
If(Iqm_Mse > 0)
 Iqm_Psnr = 10*Log10((255.*255)/Iqm_Mse);
Else
 End
```

3. SNR Function

```
Function Iqm_Snr = Signal_Nse_Ratio(Rel_Img, Enhcd_Img)
Rel_Img = Double(Rel_Img);
Enhcd_Img = Double(Enhcd_Img);
[M, N] = Size(Rel_Img);
Eror = Rel_Img - Enhcd_Img;
Iqm_Mse = Sum(Sum(Eror .* Eror)) / (M * N);  If(Iqm_Mse > 0)
Iqm_Snr = 10*Log10((Sum(Sum(Rel_Img.*Rel_Img)))./(M .* N .* Iqm_Mse)); Else
Iqm_Snr = 99; End
```

4. SC Function

```
 Function Iqm_Sc = Struct_Cntnt(Rel_Img, Enhcd_Img)
Rel_Img = Double(Rel_Img);
Enhcd_Img = Double(Enhcd_Img);
Iqm_Sc = Sum(Sum(Rel_Img .* Rel_Img)) ./ Sum(Sum(Enhcd_Img .* Enhcd_Img));
```

5. MD Function

```
Function Iqm_Md = Max_Diff(Rel_Img, Enhcd_Img)
Rel_Img = Double(Rel_Img);
Enhcd_Img = Double(Enhcd_Img);
Eror = Rel_Img - Enhcd_Img;
Iqm_Md = Max(Max(Abs(Eror)));
```

6.AD Function

```
Function Ad = Avrge_Diff(Rel_Img, Enhcd_Img)

Rel_Img = Double(Rel_Img);

Enhcd_Img = Double(Enhcd_Img);

[M N] = Size(Rel_Img);

Eror = Rel_Img - Enhcd_Img;

Iqm_Ad = Sum(Sum(Eror)) / (M * N);
```

7. NAE Function

```
Function Iqm_Nae = Normalized_Abs_Error(Rel_Img, Enhcd_Img)

Rel_Img = Double(Rel_Img);

Enhcd_Img = Double(Enhcd_Img);

Eror = Rel_Img - Enhcd_Img;

Iqm_Nae = Sum(Sum(Abs(Eror))) / Sum(Sum(Abs(Rel_Img)));
```

8. RAMD Function

```
Function Iqm_Ramd = Ravg_Md(Rel_Img, Enhcd_Img)

Rel_Img = Double(Rel_Img);

Enhcd_Img = Double(Enhcd_Img);

Eror = Rel_Img - Enhcd_Img;

Eror=Abs(Eror);

A1=Eror(:);
```

```
B=Flipud(Unique(Sort(A1)));

Resultatt=B(1:10);

Resultat_1=Resultatt(1:10,:)

R  = 10;

Iqm_Ramd = Sum((Abs(Resultat_1)))/R;
```

9. NCC Function

```
Function Iqm_Ncc = Normalized_Crs_Correlation(Rel_Img, Enhcd_Img)

Rel_Img = Double(Rel_Img);

Enhcd_Img = Double(Enhcd_Img);

Iqm_Ncc = Sum(Sum(Rel_Img .* Enhcd_Img)) ./ Sum(Sum(Rel_Img .* Rel_Img));
```

10. TED Function

```
Function Iqm_Ted = Total_Edg_Dif(Rel_Img, Enhcd_Img)

Rel_Img=Edge(Rel_Img,'Sobel');

Figure, Imshow(Rel_Img)

Rel_Img = Double(Rel_Img);

Enhcd_Img=Edge(Enhcd_Img,'Sobel');

Figure, Imshow(Rel_Img)

Enhcd_Img = Double(Enhcd_Img);

[M, N] = Size(Rel_Img);

Eror = Rel_Img - Enhcd_Img;

Iqm_Ted = Sum(Sum(Abs(Eror))) / (M * N);
```

11.TCD Function

```
Function Iqm_Tcd = Total_Crner_Diff(Rel_Img, Enhcd_Img)

Rel_Img = Double(Rel_Img);

Enhcd_Img = Double(Enhcd_Img);

Ncr_Orig = Detectharrisfeatures(Rel_Img);

Imshow(Rel_Img);

Hold On;

Plot(Ncr_Orig);

Ncr_Orig = Length(Ncr_Orig);

Ncr_Dist = Detectharrisfeatures(Enhcd_Img); Imshow(Enhcd_Img);  Hold On;

Plot(Ncr_Dist);

Ncr_Dist = Length(Ncr_Dist);

Max_1= Max(Ncr_Orig,Ncr_Dist);

Iqm_Tcd =(Abs(Ncr_Orig-Ncr_Dist))/Max_1;
```

12. SPE Function

```
Function Iqm_Spe = Spectral_Ph_Error(Rel_Img, Enhcd_Img)

Rel_Img = Double(Rel_Img);

Enhcd_Img = Double(Enhcd_Img);

Fft_A = Fft2(Double(Rel_Img));

Argfft_A =Angle(Fft_A);

Fft_B = Fft2(Double(Enhcd_Img));

Argfft_B =Angle(Fft_B);
```

```
 [M , N] = Size(Rel_Img);

Eror=Abs(Argfft_A)-Abs(Argfft_B);

Iqm_Spe =Sum(Sum( Eror.*Eror)) / (M * N);
```

13. SME Function

```
Function Iqm_Sme = Spectral_Mg_Error(Rel_Img, Enhcd_Img)

Rel_Img = Double(Rel_Img);

Enhcd_Img = Double(Enhcd_Img);

Fft_A = Fft2(Double(Rel_Img));

Z1rr=Real(Fft_A);

Z1ii=Imag(Fft_A);

Fft_A1=Sqrt((Z1rr.*Z1rr)+(Z1ii.*Z1ii));

 Fft_B = Fft2(Double(Enhcd_Img));

Z2rr=Real(Fft_B);

Z2ii=Imag(Fft_B);

Fft_B1=Sqrt((Z2rr.*Z2rr)+(Z2ii.*Z2ii));

 [M , N] = Size(Rel_Img); Eror=Abs(Fft_A1)-Abs(Fft_B1);

Iqm_Sme =Sum(Sum( Eror.*Eror)) / (M * N);
```

14. GPE Function

```
Function Iqm_Gpe = Gradient_Ph_Eror(Rel_Img, Enhcd_Img)

Rel_Img = Double(Rel_Img);

Enhcd_Img = Double(Enhcd_Img);
```

```
 [Fx1,Fy1] = Gradient(Rel_Img);
Zz=Complex(Fx1,Fy1);
Arggmagorig = Angle(Zz);
[Fx1,Fy1] = Gradient(Enhcd_Img);
Yy=Complex(Fx1,Fy1);
Arggma_Dist = Angle(Yy);
[M , N] = Size(Rel_Img);
Eror=Abs(Arggmagorig)-Abs(Arggma_Dist);
Iqm_Gpe =Sum(Sum( Eror.*Eror)) / (M * N)
```

15. GME Function

```
Function Iqm_Gme = Gradient_Mg_Error(Rel_Img, Enhcd_Img)
Rel_Img = Double(Rel_Img);
Enhcd_Img = Double(Enhcd_Img);
 [Fx1,Fy1] = Gradient(Rel_Img);
Gmgorig=Sqrt((Fx1.*Fx1)+(Fy1.*Fy1)); [Fx1,Fy1] = Gradient(Enhcd_Img);
Gmgdis=Sqrt((Fx1.*Fx1)+(Fy1.*Fy1));
[M , N] = Size(Rel_Img);
Eror=Abs(Gmgorig)-Abs(Gmgdis);
Eror=Eror.*Eror;
Iqm_Gme =Sum(Sum( Eror)) / (M * N)
```

16. MAS Function

```
Function Mas= Meananglesimilarity(Realimg, Enhimg)%Mas

[M N]= Size(Realimg);

Alfa2= 2/180 .* (Acosd(Dot(Realimg,Enhimg)/(Norm(Realimg).* Norm(Enhimg))));

Angle2 = Sum( Alfa2 );

Mas = 1-Angle2/(M*N);

End
```

17. MAMS Function

```
Function Mams= Meananglemagnitudesimilarity(Realimg, Enhimg)

[M N]= Size(Realimg);

Alfa= 2/Pi .* (Acos(Dot(Realimg, Enhimg)/(Norm(Realimg).* Norm(Enhimg))));

X= 1 - ((1-Alfa)*(1 - (Norm(Realimg-Enhimg)/255)));

Sum = Sum(X);

Mams = Sum / (M*N);

End
```

18. LMSE Function

```
Function Lmse=  Laplacianmeansquarederror(Realimg, Enhimg)%Lmse

[M N]= Size(Realimg);

Op=4*Del2(Realimg);

Op2=4*Del2(Enhimg);
```

```
Lmse=Sum(Sum((Op-Op2).^2))/Sum(Sum(Op.^2));

End
```

19. SSIM Function

```
Function Ssim= Structuralsimilarityindex(Realimg, Ehnimg)

Img1=Double(Realimg);

Img2=Double(Ehnimg);

K = [0.01 0.03];

Window = Fspecial('Gaussian', 11, 1.5);

L = 255;

Ssim = Ssim_Index(Img1, Img2, K, Window, L);
```

20. VIF Function

```
Function Vif=Vifvec(Imorg,Imdist);

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%Visual Information Fidelity (Vif) Measure (May Also Be Known As The Sheikh

%-Bovik Index) Between Two Images. Please Refer

%To The Following Paper:

```
%H. R. Sheikh And A. C. Bovik "Image Information And Visual Quality"
%Ieee Transactios On Image Processing, In Publication, May 2005.
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%Publications Link
%This Implementation Is Slightly Differnet From The One Used To Report
%Results In The Paper Above. The Modification Have To Do With Using More
%Subands Than Those Used In The Paper, Better Handling Of Image Boundaries,
%And A Window That Automatically Resizes Itself Based On The Scale.
%Report Bugfixes And Comments To Hamid.Sheikh@Ieee.Org
%----------------------------------------------------------------
% Prerequisites: The Steerable Pyramid Toolbox. Available At
% Http://Www.Cns.Nyu.Edu/~Lcv/Software.Html
%Input : (1) Img1: The Reference Image
%        (2) Img2: The Distorted Image (Order Is Important)
%Output: (1) Vif Te Visual Information Fidelity Measure Between The Two Images
%Default Usage:
%   Given 2 Test Images Img1 And Img2, Whose Dynamic Range Is 0-255
%   Vif = Vifvec(Img1, Img2);
%Advanced Usage:
%   Users May Want To Modify The Parameters In The Code.
%   (1) Modify Sigma_Nsq To Find Tune For Your Image Dataset.
%   (2) Mxm Is The Block Size That Denotes The Size Of A Vector Used In The
%   Gsm Model.
%   (3) Subbands Included In The Computation
%=====================================================
M=3;
Subbands=[4 7 10 13 16 19 22 25];
Sigma_Nsq=0.4;
% Do Wavelet Decomposition. This Requires The Steerable Pyramid. You Can
% Use Your Own Wavelet As Long As The Cell Arrays Org And Dist Contain
% Corresponding Subbands From The Reference And The Distorted Images
% Respectively.
[Pyr,Pind] = Buildspyr(Imorg, 4, 'Sp5filters', 'Reflect1'); % Compute Transform
Org=Ind2wtree(Pyr,Pind); % Convert To Cell Array
[Pyr,Pind] = Buildspyr(Imdist, 4, 'Sp5filters', 'Reflect1');
Dist=Ind2wtree(Pyr,Pind);
% Calculate The Parameters Of The Distortion Channel
[G_All,Vv_All]=Vifsub_Est_M(Org,Dist,Subbands,M);
% Calculate The Parameters Of The Reference Image
[Ssarr, Larr, Cuarr]=Refparams_Vecgsm(Org,Subbands,M);
% Reorder Subbands. This Is Needed Since The Outputs Of The Above Functions
% Are Not In The Same Order
Vvtemp=Cell(1,Max(Subbands));
Ggtemp=Vvtemp;
For(Kk=1:Length(Subbands))
Vvtemp{Subbands(Kk)}=Vv_All{Kk};
Ggtemp{Subbands(Kk)}=G_All{Kk};
End
% Compute Reference And Distorted Image Information From Each Subband
For I=1:Length(Subbands)
```

```
Sub=Subbands(I);

G=Ggtemp{Sub};

Vv=Vvtemp{Sub};

Ss=Ssarr{Sub};

Lambda = Larr(Sub,:);,

Cu=Cuarr{Sub};

% How Many Eigenvalues To Sum Over. Default Is All.

Neigvals=Length(Lambda);

% Compute The Size Of The Window Used In The Distortion Channel Estimation,
And Use It To Calculate The Offset From Subband Borders

% We Do This To Avoid All Coefficients That May Suffer From Boundary

% Effects

Lev=Ceil((Sub-1)/6);

Winsize=2^Lev+1; Offset=(Winsize-1)/2;

Offset=Ceil(Offset/M);

% Select Only Valid Portion Of The Output.

G=G(Offset+1:End-Offset,Offset+1:End-Offset);

Vv=Vv(Offset+1:End-Offset,Offset+1:End-Offset);

Ss=Ss(Offset+1:End-Offset,Offset+1:End-Offset);

%Vif

Temp1=0; Temp2=0;

For J=1:Length(Lambda)

Temp1=Temp1+Sum(Sum((Log2(1+G.*G.*Ss.*Lambda(J)./(Vv+Sigma_Nsq))))); %
Distorted Image Information For The I'th Subband
```

```
Temp2=Temp2+Sum(Sum((Log2(1+Ss.*Lambda(J)./(Sigma_Nsq))))); % Reference
Image Information
End
Num(I)=Temp1;
Den(I)=Temp2;
End
% Compuate Vif
Vif=Sum(Num)./Sum(Den);
```

21. RRED Function

```
Function Rred=Rred_Out(Realimg, Enhimg)
% Total = 5;
Original=Realimg;
Fake= Enhimg;
Rredoutput= Extract_Info(Original, Fake);
[X Y] = Size(Rredoutput);
Sumoutput=0;
For I=1 :X
For J=1:Y
Sumoutput = Sumoutput + Rredoutput(I,J);
End
End
Rred=Norm(Sumoutput);
% End
```

22.HLFI Function

```
Function Hlfreqiq=  High_Low_Freq_Index(Realimg)

[R,C]=Size(Realimg);

N = C;

Imgfft =Fft(Fft2(Realimg));

Colhalf = (Round(N / 2));

Freqsel = 0.15;

Freqcol = Round(Freqsel * N);

Lowfreqcolhalf = (Round(Freqcol / 2.0));

Fftres = Imgfft;  %R# Np.Fft.Fft2(Image)

Fftmag = Abs(Fftres);

Totalenergy = Sum(Sum(Fftmag));

%# Print(Totalenergy)

Lowidx = Colhalf - Lowfreqcolhalf;

Hiidx = Colhalf + Lowfreqcolhalf;

Lowfreqmag = Fftmag(:, Lowidx:Hiidx);

Lowfreqmagtotal = Sum(Sum(Lowfreqmag));

Fftmag(:, Lowidx:Hiidx) = 0;

Highfreqmagtotal =Sum( Sum(Fftmag));

Hlfreqiq = Abs(Lowfreqmagtotal - Highfreqmagtotal) /(Totalenergy);

End
```

23. JQI Function

```
Function [Score B A Z] = Jpeg_Quality_Score(Img)

%==================================================

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% Author  : Zhou Wang

% Version : 1.0

% Modified: Anush Krishna Moorthy

% Version: 1.Buqi

%The Authors Are With The Laboratory For Image And Video Engineering

%(Live), Department Of Electrical And Computer Engineering, The

%University Of Texas At Austin, Austin, Tx.

%
```

```
%Kindly Report Any Suggestions Or Corrections To Zhouwang@Ieee.Org
%===========================
%This Is An Implementation Of The Algorithm For Calculating The Quality
%Score Of Jpeg Compressed Images Proposed By Zhou Wang, Hamid R. Sheikh
%And Alan C. Bovik. Please Refer To The Paper: Zhou Wang, Hamid R. Sheikh
%And Alan C. Bovik, "No-Reference Perceptual Quality Assessment Of Jpeg
%Compressed Images," Submitted To Ieee International Conference On Image
%Processing, Sept. 2002.
%You Can Change This Program As You Like And Use It Anywhere, But Please
%Refer To Its Original Source (Cite Our Paper And Our Web Page At
%Http://Anchovy.Ece.Utexas.Edu/~Zwang/Research/Nr_Jpeg_Quality/Index.Html)
%
%Input : A Test 8bits/Pixel Grayscale Image Loaded In A 2-D Array
%Output: A Quality Score Of The Image. The Score Typically Has A Value
%       Between 1 And 10 (10 Represents The Best Quality, 1 The Worst).
%Usage:
%1. Load The Image, For Example
%   Image = Imread('Testimage.Jpg');
%2. Call This Function To Calculate The Quality Score:
%   Quality_Score = Jpeg_Quality_Score(Image)
%===================================
If (Nargin > 1)
Score = -1;
Return;
End
```

```
[M N] = Size(Img);

If (M < 16 | N < 16)

Score = -2;

Return;

End

X = Double(Img);

% Feature Extraction:

% 1. Horizontal Features

D_H = X(:, 2:N) - X(:, 1:(N-1));

B_H = Mean2(Abs(D_H(:, 8:8:8*(Floor(N/8)-1))));

A_H = (8*Mean2(Abs(D_H)) - B_H)/7;

Sig_H = Sign(D_H);

Left_Sig = Sig_H(:, 1:(N-2));

Right_Sig = Sig_H(:, 2:(N-1));

Z_H = Mean2((Left_Sig.*Right_Sig)<0);

% 2. Vertical Features

D_V = X(2:M, :) - X(1:(M-1), :);

B_V = Mean2(Abs(D_V(8:8:8*(Floor(M/8)-1), :)));

A_V = (8*Mean2(Abs(D_V)) - B_V)/7;

Sig_V = Sign(D_V);

Up_Sig = Sig_V(1:(M-2), :);

Down_Sig = Sig_V(2:(M-1), :);

Z_V = Mean2((Up_Sig.*Down_Sig)<0);

% 3. Combined Features

B = (B_H + B_V)/2;
```

```
A = (A_H + A_V)/2;
Z = (Z_H + Z_V)/2;
% Quality Prediction
Alpha = -927.4240; Beta = 850.8986;Gamma1 =235.4451 ;Gamma2 =
128.7548;Gamma3 =-341.4790;
Score = Abs(Alpha +
Beta*(B.^(Gamma1/10000))*(A.^(Gamma2/10000))*(Z.^(Gamma3/10000)));
```

24. BIQI Function

```
Function [Score B A Z] = Blinimagequalityindex(Rimg)
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%World Wide Web At Http://Www.Fsf.Org.
%
% Author  : Zhou Wang
% Version : 1.0
% Modified: Anush Krishna Moorthy
% Version: 1.Buqi
%
%The Authors Are With The Laboratory For Image And Video Engineering
%(Live), Department Of Electrical And Computer Engineering, The
%University Of Texas At Austin, Austin, Tx.
%
%Kindly Report Any Suggestions Or Corrections To Zhouwang@Ieee.Org
%
%==============================================
%This Is An Implementation Of The Algorithm For Calculating The Quality
%Score Of Jpeg Compressed Images Proposed By Zhou Wang, Hamid R. Sheikh
%And Alan C. Bovik. Please Refer To The Paper: Zhou Wang, Hamid R. Sheikh
%And Alan C. Bovik, "No-Reference Perceptual Quality Assessment Of Jpeg
%Compressed Images," Submitted To Ieee International Conference On Image
%Processing, Sept. 2002.
%
%You Can Change This Program As You Like And Use It Anywhere, But Please
%Refer To Its Original Source (Cite Our Paper And Our Web Page At
%Http://Anchovy.Ece.Utexas.Edu/~Zwang/Research/Nr_Jpeg_Quality/Index.Html)
%Input : A Test 8bits/Pixel Grayscale Image Loaded In A 2-D Array
%Output: A Quality Score Of The Image. The Score Typically Has A Value
%       Between 1 And 10 (10 Represents The Best Quality, 1 The Worst).
%Usage:
%1. Load The Image, For Example
%   Image = Imread('Testimage.Jpg');
%2. Call This Function To Calculate The Quality Score:
%   Quality_Score = Blinimagequalityindex(Image)
%===========================================
If (Nargin > 1)
Score = -1;
Return;
End
[M N] = Size(Rimg);
If (M < 16 | N < 16)
Score = -2;
Return;
End
X = Double(Rimg);
% Feature Extraction:
% 1. Horizontal Features
D_H = X(:, 2:N) - X(:, 1:(N-1));
B_H = Mean2(Abs(D_H(:, 8:8:8*(Floor(N/8)-1))));
A_H = (8*Mean2(Abs(D_H)) - B_H)/7;
```

```
Sig_H = Sign(D_H);

Left_Sig = Sig_H(:, 1:(N-2));

Right_Sig = Sig_H(:, 2:(N-1));

Z_H = Mean2((Left_Sig.*Right_Sig)<0);

% 2. Vertical Features

D_V = X(2:M, :) - X(1:(M-1), :);

B_V = Mean2(Abs(D_V(8:8:8*(Floor(M/8)-1), :)));

A_V = (8*Mean2(Abs(D_V)) - B_V)/7;

Sig_V = Sign(D_V);

Up_Sig = Sig_V(1:(M-2), :);

Down_Sig = Sig_V(2:(M-1), :);

Z_V = Mean2((Up_Sig.*Down_Sig)<0);

% 3. Combined Features

B = (B_H + B_V)/2;

A = (A_H + A_V)/2;

Z = (Z_H + Z_V)/2;

% Quality Prediction

Alpha = -927.4240; Beta = 850.8986;Gamma1 =235.4451 ;Gamma2 =
128.7548;Gamma3 =-341.4790;

Score = Abs(Alpha +
Beta*(B.^(Gamma1/10000))*(A.^(Gamma2/10000))*(Z.^(Gamma3/
10000)));
```

NIQE Function

```
Function  Quality = Computequality(Im,Blocksizerow,Blocksizecol,...
Blockrowoverlap,Blockcoloverlap,Mu_Prisparam,Cov_Prisparam)
```

```
% Input
% Im - Image Whose Quality Needs To Be Computed
% Blocksizerow - Height Of The Blocks In To Which Image Is Divided
% Blocksizecol - Width Of The Blocks In To Which Image Is Divided
% Blockrowoverlap - Amount Of Vertical Overlap Between Blocks
% Blockcoloverlap - Amount Of Horizontal Overlap Between Blocks
% Mu_Prisparam - Mean Of Multivariate Gaussian Model
% Cov_Prisparam - Covariance Of Multivariate Gaussian Model
% For Good Performance, It Is Advisable To Use Make The Multivariate Gaussian
Model
% Using Same Size Patches As The Distorted Image Is Divided In To
% Output
%Quality      - Quality Of The Input Distorted Image
% Example Call
%Quality = Computequality(Im,96,96,0,0,Mu_Prisparam,Cov_Prisparam)
% ------------------------------------------------------------
%Number Of Features
% 18 Features At Each Scale
Featnum      = 18;
%------------------------------------------------------------
%Compute Features
If(Size(Im,3)==3)
Im              = Rgb2gray(Im);
End
Im              = Double(Im);
```

```
[Row Col]        = Size(Im);
Block_Rownum     = Floor(Row/Blocksizerow);
Block_Colnum     = Floor(Col/Blocksizecol);
Im               = Im(1:Block_Rownum*Blocksizerow,1:Block_Colnum*Blocksizecol);
[Row Col]        = Size(Im);
Block_Rownum     = Floor(Row/Blocksizerow);
Block_Colnum     = Floor(Col/Blocksizecol);
Im  = Im(1:Block_Rownum*Blocksizerow, .
1:Block_Colnum*Blocksizecol);
Window          = Fspecial('Gaussian',7,7/6);
Window          = Window/Sum(Sum(Window));
Scalenum        = 2;
Warning('Off')
Feat = [];
For Itr_Scale = 1:Scalenum
Mu = Imfilter(Im,Window,'Replicate');
Mu_Sq = Mu.*Mu;
Sigma  = Sqrt(Abs(Imfilter(Im.*Im,Window,'Replicate') - Mu_Sq));
Structdis              = (Im-Mu)./(Sigma+1);
Feat_Scale = Blkproc(Structdis,[Blocksizerow/Itr_Scale Blocksizecol/Itr_Scale],
[Blockrowoverlap/Itr_Scale Blockcoloverlap/Itr_Scale], ...
@Computefeature);
Feat_Scale              = Reshape(Feat_Scale,[Featnum ....
Size(Feat_Scale,1)*Size(Feat_Scale,2)/Featnum]);
Feat_Scale              = Feat_Scale';
```

```
If(Itr_Scale == 1)

Sharpness = Blkproc(Sigma,[Blocksizerow Blocksizecol], ...

[Blockrowoverlap Blockcoloverlap],@Computemean);

Sharpness = Sharpness(:);

End

Feat = [Feat Feat_Scale];

Im =Imresize(Im,0.5);

End

% Fit A Mvg Model To Distorted Patch Features

Distparam = Feat;

Mu_Distparam = Nanmean(Distparam);

Cov_Distparam = Nancov(Distparam);

% Compute Quality

Invcov_Param = Pinv((Cov_Prisparam+Cov_Distparam)/2);

Quality = Sqrt((Mu_Prisparam-Mu_Distparam)* ...

Invcov_Param*(Mu_Prisparam-Mu_Distparam)');
```

Appendix B: Code for Ranking IQM's

1. Mean Squared Eror

```
R_Mse = Mse(1:500);

F_Mse = Mse(501:1000);

Avg_R_Mse = Mean(R_Mse);

Disp('Average Of  R_Mse :');

Disp(Avg_R_Mse);

Avg_F_Mse = Mean(F_Mse);

Disp('Average Of  F_Mse :');

Disp(Avg_F_Mse);

Disp('Average Of R_Mse - Average Of F_Mse :');

Dif_Btwn_Mse_Fmse= Abs(Avg_R_Mse-Avg_F_Mse);

Disp(Dif_Btwn_Mse_Fmse);

Disp('-----------------------------------------------');
```

Note: Apply The Same Code For Every Iqm

2. Ranking the Best 15 IQMs

```
Title={'Mse.'; 'Snr.'; 'Psnr.'; 'Nk.'; 'Ad.'; 'Sc.'; 'Md.'; 'Ramd.'; 'Nae.'; 'Ted.'; 'Spe.'; 'Sme.';
'Gme.'; 'Gpe.' ;'Tcd.'};
Best15=[Dif_Btwn_Mse_Fmse;Dif_Btwn_Snr_Fsnr;Dif_Btwn_Psnr_Fpsnr;Dif_Btw
n_Nk_Fnk;Dif_Btwn_Ad_Fad;Dif_Btwn_Sc_Fsc;Dif_Btwn_Md_Fmd;Dif_Btwn_R
amd_Framd;Dif_Btwn_Nae_Fnae;Dif_Btwn_Ted_Fted;Dif_Btwn_Spe_Fspe;Dif_Bt
wn_Sme_Fsme;Dif_Btwn_Gme_Fgme;Dif_Btwn_Gpe_Fgpe;Dif_Btwn_Tcd_Ftcd];
Tbla = Table(Title,Best15)
```

```
Disp('------------------Best 15 Iqm Rank (Classification)---------------------');

Tblb = Sortrows(Tbla,{'Best15'},{'Descend'})
```

3. Calculating FGR, FFR, And HTER Of The RFDS

```
Yfit = Trainedclassifier1.Predictfcn(T)

Truecount=0;

Fakecount=0;

Truecount1=0;

Fakecount1=0;

%Real Images Count

Z=500;

For B=1:Z;

If Isequal(Yfit{B},'Real')

Truecount=Truecount+1;

Else Isequal(Yfit{B},'Fake')

Fakecount=Fakecount+1;

End

End

%500 Fake Images Count

M=1000;

For Q=501:M;

If Isequal(Yfit{Q},'Real')

Truecount1=Truecount1+1;

Else Isequal(Yfit{Q},'Fake')

Fakecount1=Fakecount1+1;
```

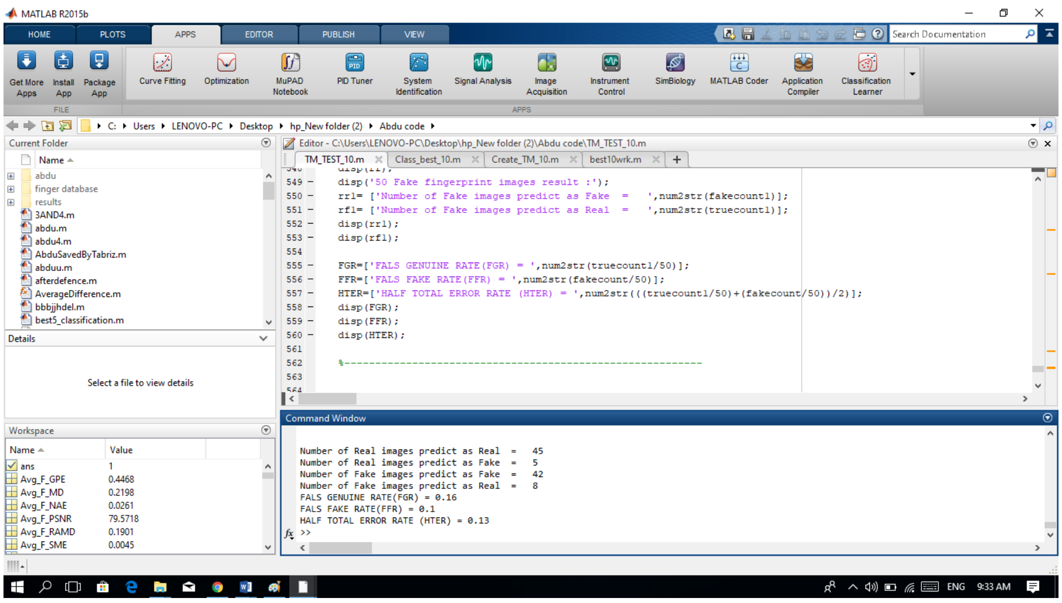
```
End
End
Disp('500 Real Fingerprint Images Result :');
Rr= ['Number Of Real Images Predict As Real  =   ',Num2str(Truecount)];
Rf= ['Number Of Real Images Predict As Fake  =   ',Num2str(Fakecount)];
Disp(Rr);
Disp(Rf);
Disp('500 Fake Fingerprint Images Result :');
Rr1= ['Number Of Fake Images Predict As Fake  =   ',Num2str(Fakecount1)];
Rf1= ['Number Of Fake Images Predict As Real  =   ',Num2str(Truecount1)];
Disp(Rr1);
Disp(Rf1);
Fgr=['Fals Genuine Rate(Fgr) = ',Num2str(Truecount1/500)];
Ffr=['Fals Fake Rate(Ffr) = ',Num2str(Fakecount/500)];
Hter=['Half Total Error Rate (Hter) =
',Num2str(((Truecount1/500)+(Fakecount/500))/2)];
Disp(Fgr);
Disp(Ffr);
Disp(Hter);
```

Appendix C: Screenshots and Tables of Our Rfds Results

1. Table and Screenshot of Training Results For 100 Fingerprint Images Using 15 IQMs

The following are the screenshots providing results of a dataset with 50 real and fake fingerprint images, with 15 image quality measures calculated for each fingerprint image. Table d.1 shows he result of 15 image quality measures of 50 real fingerprint images and 50 fake fingerprint images used for training. 100 fingerprint images with 15 IQMs results using 6 classifiers.

1. LDA



```
disp('50 Fake fingerprint images result :');
rrl= ['Number of Fake images predict as Fake  =   ',num2str(fakecount1)];
rfl= ['Number of Fake images predict as Real  =   ',num2str(truecount1)];
disp(rrl);
disp(rfl);

FGR=['FALS GENUINE RATE(FGR) = ',num2str(truecount1/50)];
FFR=['FALS FAKE RATE(FFR) = ',num2str(fakecount/50)];
HTER=['HALF TOTAL ERROR RATE (HTER) = ',num2str(((truecount1/50)+(fakecount/50))/2)];
disp(FGR);
disp(FFR);
disp(HTER);

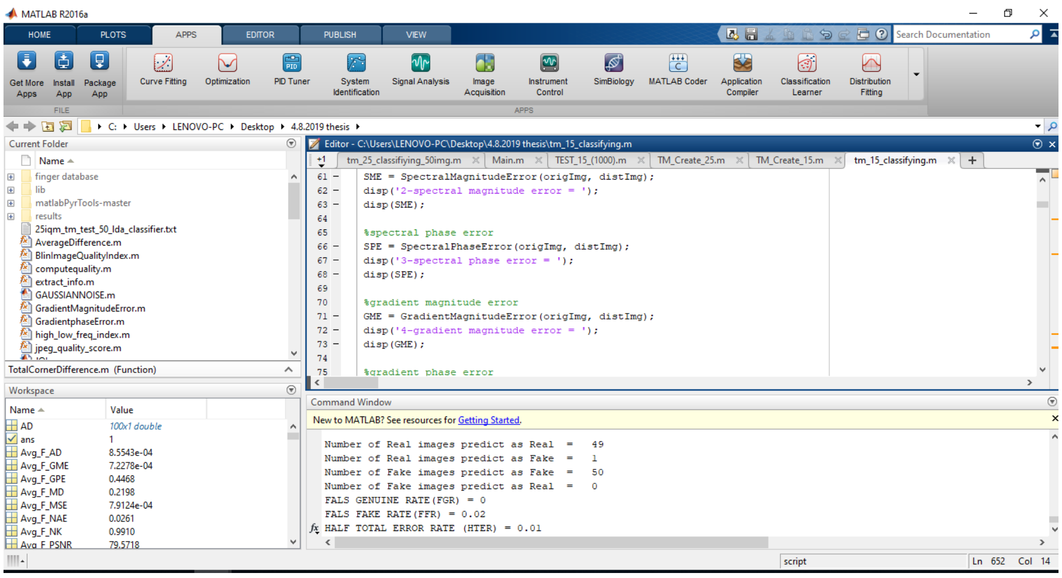
%----------------------------------------------------------
```

```
Number of Real images predict as Real  =   45
Number of Real images predict as Fake  =   5
Number of Fake images predict as Fake  =   42
Number of Fake images predict as Real  =   8
FALS GENUINE RATE(FGR) = 0.16
FALS FAKE RATE(FFR) = 0.1
HALF TOTAL ERROR RATE (HTER) = 0.13
>>
```

Name	Value
ans	1
Avg_F_GPE	0.4468
Avg_F_MD	0.2198
Avg_F_NAE	0.0261
Avg_F_PSNR	79.5718
Avg_F_RAMD	0.1901
Avg_F_SME	0.0045

Figure 38: LDA training result of 100 fingerprint images using 15 IQMs.

2. QDA



```
finger database
lib
matlabPyrTools-master
results
25iqm_tm_test_50_lda_classifier.txt
AverageDifference.m
BlinImageQualityIndex.m
computequality.m
extract_info.m
GAUSSIANNOISE.m
GradientMagnitudeError.m
GradientphaseError.m
high_low_freq_index.m
jpeg_quality_score.m
TotalCornerDifference.m (Function)
```

```
SME = SpectralMagnitudeError(origImg, distImg);
disp('2-spectral magnitude error = ');
disp(SME);

%spectral phase error
SPE = SpectralPhaseError(origImg, distImg);
disp('3-spectral phase error = ');
disp(SPE);

%gradient magnitude error
GME = GradientMagnitudeError(origImg, distImg);
disp('4-gradient magnitude error = ');
disp(GME);

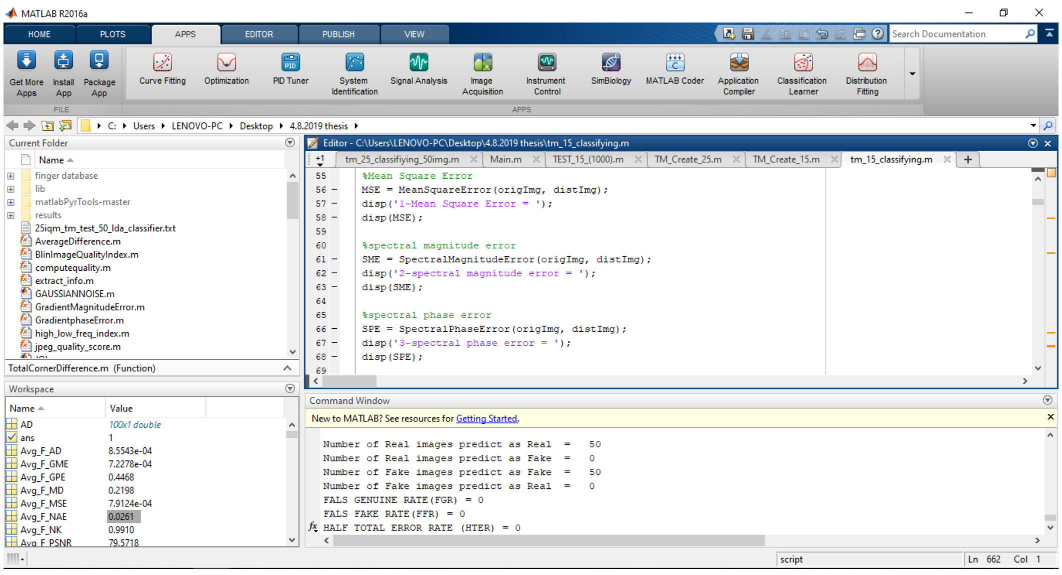
%gradient phase error
```

Name	Value
AD	100x1 double
ans	1
Avg_F_AD	8.5543e-04
Avg_F_GME	7.2278e-04
Avg_F_GPE	0.4468
Avg_F_MD	0.2198
Avg_F_MSE	7.9124e-04
Avg_F_NAE	0.0261
Avg_F_NK	0.9910
Avg_F_PSNR	79.5718

```
Number of Real images predict as Real  =   49
Number of Real images predict as Fake  =   1
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
FALS GENUINE RATE(FGR) = 0
FALS FAKE RATE(FFR) = 0.02
HALF TOTAL ERROR RATE (HTER) = 0.01
```

Figure 40: QDA training result of 100 fingerprint images using 15 IQMs.

3. Linear SVM



```
finger database
lib
matlabPyrTools-master
results
25iqm_tm_test_50_lda_classifier.txt
AverageDifference.m
BlinImageQualityIndex.m
computequality.m
extract_info.m
GAUSSIANNOISE.m
GradientMagnitudeError.m
GradientphaseError.m
high_low_freq_index.m
jpeg_quality_score.m
TotalCornerDifference.m (Function)
```

```
%Mean Square Error
MSE = MeanSquareError(origImg, distImg);
disp('1-Mean Square Error = ');
disp(MSE);

%spectral magnitude error
SME = SpectralMagnitudeError(origImg, distImg);
disp('2-spectral magnitude error = ');
disp(SME);

%spectral phase error
SPE = SpectralPhaseError(origImg, distImg);
disp('3-spectral phase error = ');
disp(SPE);

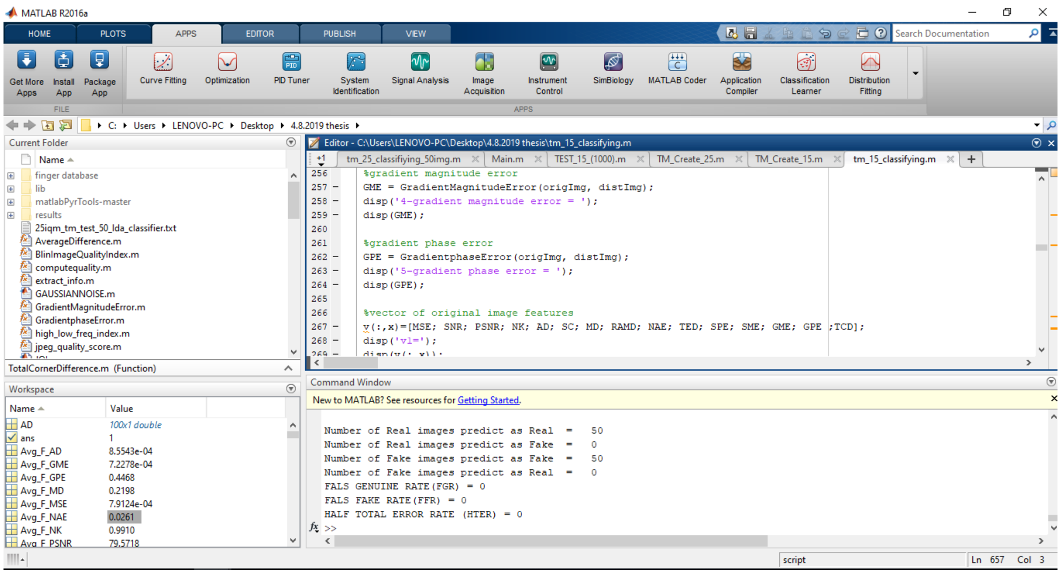
```

Name	Value
AD	100x1 double
ans	1
Avg_F_AD	8.5543e-04
Avg_F_GME	7.2278e-04
Avg_F_GPE	0.4468
Avg_F_MD	0.2198
Avg_F_MSE	7.9124e-04
Avg_F_NAE	0.0261
Avg_F_NK	0.9910
Avg_F_PSNR	79.5718

```
Number of Real images predict as Real  =   50
Number of Real images predict as Fake  =   0
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
FALS GENUINE RATE(FGR) = 0
FALS FAKE RATE(FFR) = 0
HALF TOTAL ERROR RATE (HTER) = 0
```

Figure 41: Linear SVM training result of 100 fingerprint images using 15 IQMs.

4. Quadratic SVM



Editor - C:\Users\LENOVO-PC\Desktop\4.8.2019 thesis\tm_15_classifying.m

```
%gradient magnitude error
GME = GradientMagnitudeError(origImg, distImg);
disp('4-gradient magnitude error = ');
disp(GME);

%gradient phase error
GPE = GradientphaseError(origImg, distImg);
disp('5-gradient phase error = ');
disp(GPE);

%vector of original image features
v(:,x)=[MSE; SNR; PSNR; NK; AD; SC; MD; RAMD; NAE; TED; SPE; SME; GME; GPE ;TCD];
disp('v1=');
```

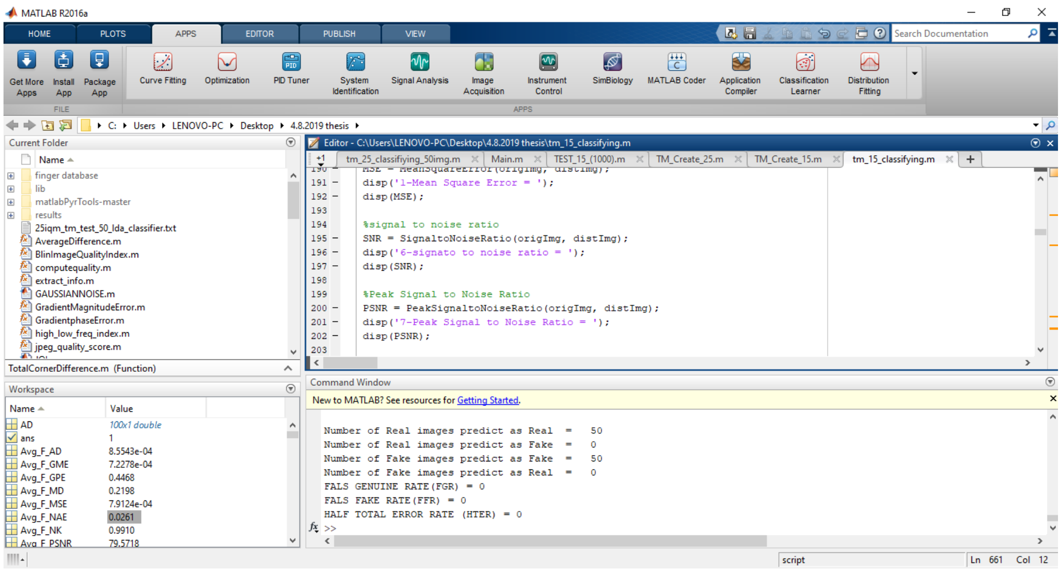
Command Window

```
Number of Real images predict as Real  =   50
Number of Real images predict as Fake  =   0
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
FALS GENUINE RATE(FGR) = 0
FALS FAKE RATE(FFR) = 0
HALF TOTAL ERROR RATE (HTER) = 0
>>
```

Name	Value
AD	100x1 double
ans	1
Avg_F_AD	8.5543e-04
Avg_F_GME	7.2278e-04
Avg_F_GPE	0.4468
Avg_F_MD	0.2198
Avg_F_MSE	7.9124e-04
Avg_F_NAE	0.0261
Avg_F_NK	0.9910
Avg_F_PSNR	79.5718

Figure 42: Quadratic SVM training result of 100 fingerprint images using 15 IQMs.

5. Fine KNN



Editor - C:\Users\LENOVO-PC\Desktop\4.8.2019 thesis\tm_15_classifying.m

```
disp('1-Mean Square Error = ');
disp(MSE);

%signal to noise ratio
SNR = SignaltoNoiseRatio(origImg, distImg);
disp('6-signato to noise ratio = ');
disp(SNR);

%Peak Signal to Noise Ratio
PSNR = PeakSignaltoNoiseRatio(origImg, distImg);
disp('7-Peak Signal to Noise Ratio = ');
disp(PSNR);
```

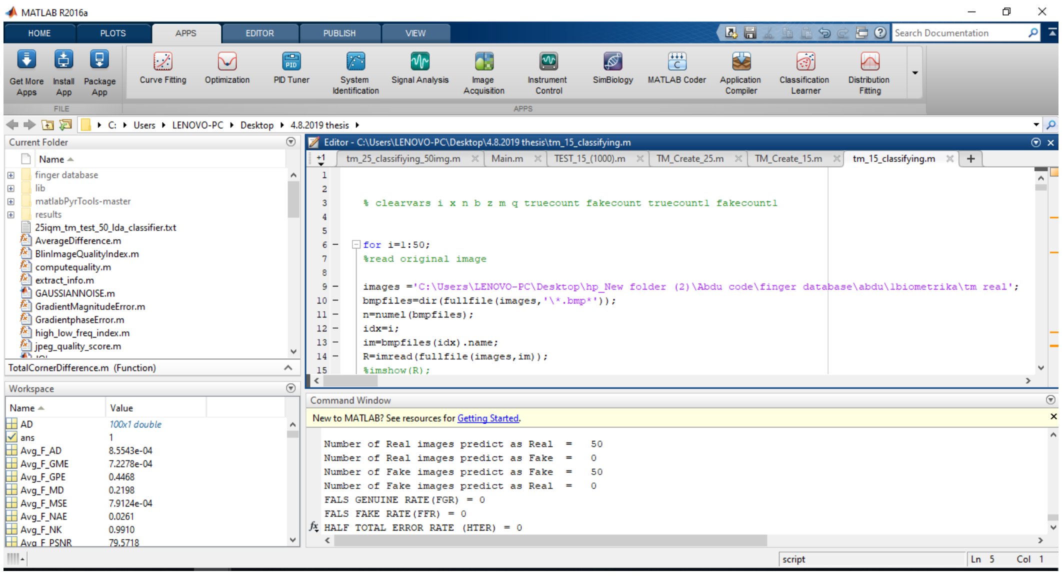
Command Window

```
Number of Real images predict as Real  =   50
Number of Real images predict as Fake  =   0
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
FALS GENUINE RATE(FGR) = 0
FALS FAKE RATE(FFR) = 0
HALF TOTAL ERROR RATE (HTER) = 0
>>
```

Name	Value
AD	100x1 double
ans	1
Avg_F_AD	8.5543e-04
Avg_F_GME	7.2278e-04
Avg_F_GPE	0.4468
Avg_F_MD	0.2198
Avg_F_MSE	7.9124e-04
Avg_F_NAE	0.0261
Avg_F_NK	0.9910
Avg_F_PSNR	79.5718

Figure 43: Fine KNN training result of 100 fingerprint images using 15 IQMs.

6. Logistic Regression



Editor - C:\Users\LENOVO-PC\Desktop\4.8.2019 thesis\tm_15_classifying.m

```
% clearvars i x n b z m q truecount fakecount truecount1 fakecount1


for i=1:50;
%read original image

images ='C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\finger database\abdu\1biometrika\tm real';
bmpfiles=dir(fullfile(images,'\*.bmp*'));
n=numel(bmpfiles);
idx=i;
im=bmpfiles(idx).name;
R=imread(fullfile(images,im));
%imshow(R);
```

Workspace

Name	Value
AD	100x1 double
ans	1
Avg_F_AD	8.5543e-04
Avg_F_GME	7.2278e-04
Avg_F_GPE	0.4468
Avg_F_MD	0.2198
Avg_F_MSE	7.9124e-04
Avg_F_NAE	0.0261
Avg_F_NK	0.9910
Avg_F_PSNR	79.5718

Command Window

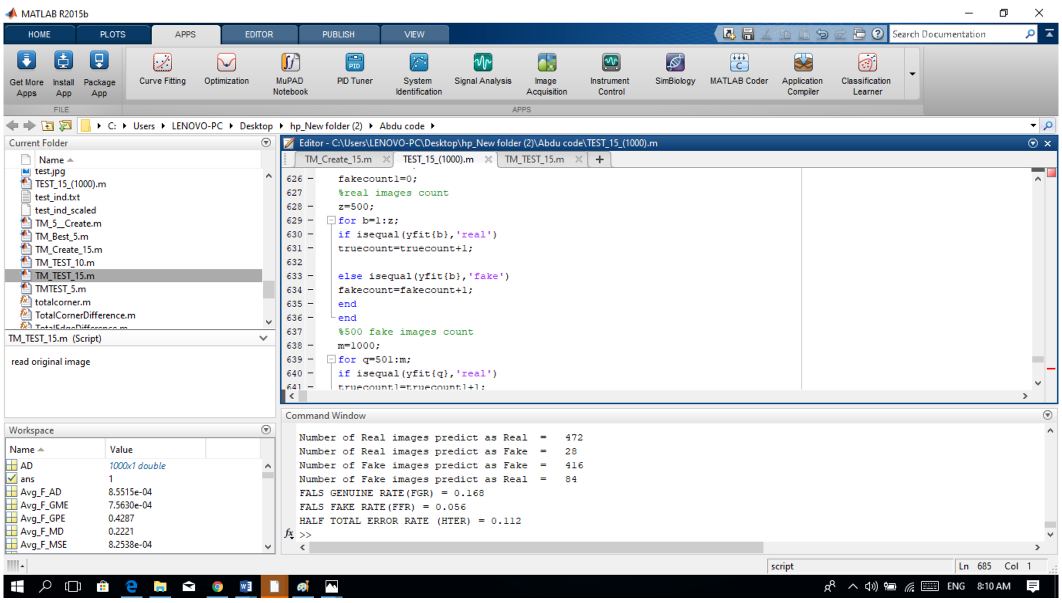
```
Number of Real images predict as Real  =   50
Number of Real images predict as Fake  =   0
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
FALS GENUINE RATE(FGR) = 0
FALS FAKE RATE(FFR) = 0
HALF TOTAL ERROR RATE (HTER) = 0
```

Figure 44: Logistic Regression training result of 100 fingerprint images using 15 IQMs.

2. Table and Screenshot of Classification Results For 1000 Fingerprint Images Using 15 IQMs

1000 fingerprint images with 15 IQMs results using 6 clasifiers.

1. LDA



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\TEST_15_(1000).m

```
fakecount1=0;
%real images count
z=500;
for b=1:z;
if isequal(yfit{b},'real')
truecount=truecount+1;

else isequal(yfit{b},'fake')
fakecount=fakecount+1;
end
end
%500 fake images count
m=1000;
for q=501:m;
if isequal(yfit{q},'real')
truecount1=truecount1+1;
```

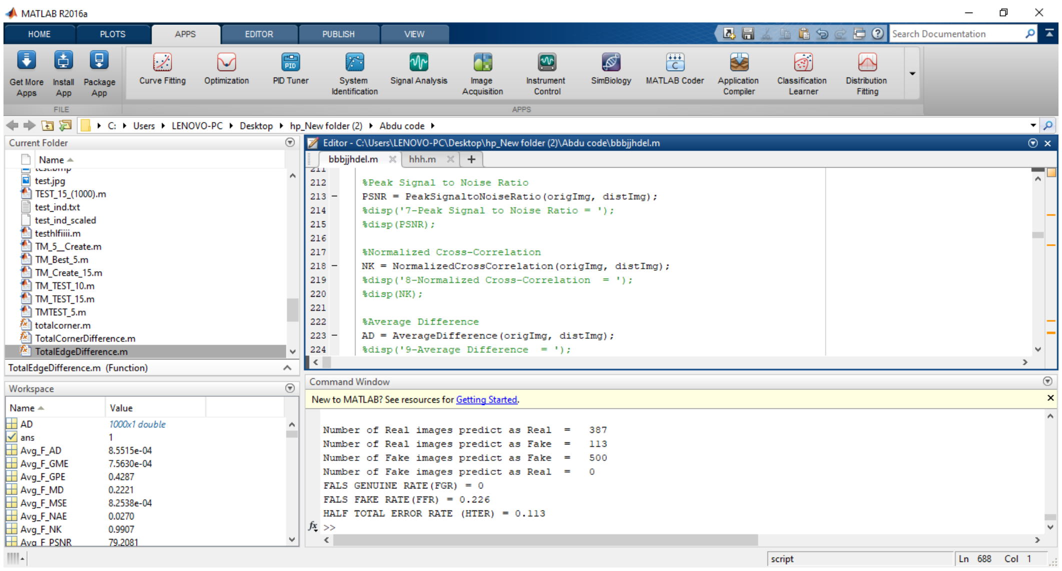
Command Window

```
Number of Real images predict as Real  =   472
Number of Real images predict as Fake  =   28
Number of Fake images predict as Fake  =   416
Number of Fake images predict as Real  =   84
FALS GENUINE RATE(FGR) = 0.168
FALS FAKE RATE(FFR) = 0.056
HALF TOTAL ERROR RATE (HTER) = 0.112
>>
```

Name	Value
AD	1000x1 double
ans	1
Avg_F_AD	8.5515e-04
Avg_F_GME	7.5630e-04
Avg_F_GPE	0.4287
Avg_F_MD	0.2221
Avg_F_MSE	8.2538e-04

Figure 45: LDA classification result of 1000 fingerprint images using 15 IQMs.

2. QDA



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\bbbjjhdel.m

```
%Peak Signal to Noise Ratio
PSNR = PeakSignaltoNoiseRatio(origImg, distImg);
%disp('7-Peak Signal to Noise Ratio = ');
%disp(PSNR);

%Normalized Cross-Correlation
NK = NormalizedCrossCorrelation(origImg, distImg);
%disp('8-Normalized Cross-Correlation  = ');
%disp(NK);

%Average Difference
AD = AverageDifference(origImg, distImg);
%disp('9-Average Difference  = ');
```

Command Window

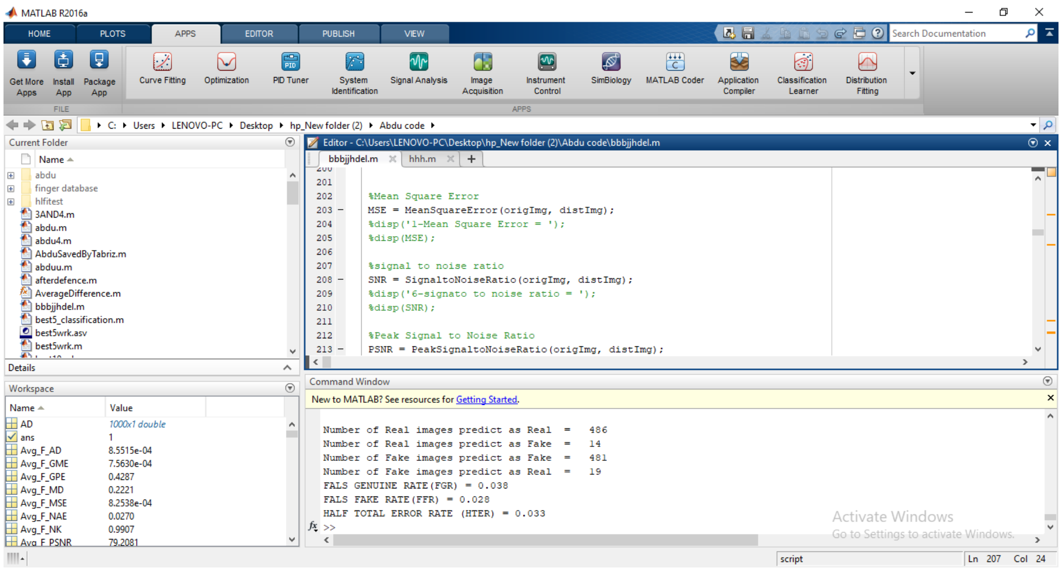
New to MATLAB? See resources for Getting Started.

```
Number of Real images predict as Real  =   387
Number of Real images predict as Fake  =   113
Number of Fake images predict as Fake  =   500
Number of Fake images predict as Real  =   0
FALS GENUINE RATE(FGR) = 0
FALS FAKE RATE(FFR) = 0.226
HALF TOTAL ERROR RATE (HTER) = 0.113
>>
```

Name	Value
AD	1000x1 double
ans	1
Avg_F_AD	8.5515e-04
Avg_F_GME	7.5630e-04
Avg_F_GPE	0.4287
Avg_F_MD	0.2221
Avg_F_MSE	8.2538e-04
Avg_F_NAE	0.0270
Avg_F_NK	0.9907
Avg_F_PSNR	79.2081

Figure 46: QDA classification result of 1000 fingerprint images using 15 IQMs.

3. Linear SVM



```
%Mean Square Error
MSE = MeanSquareError(origImg, distImg);
%disp('1-Mean Square Error = ');
%disp(MSE);

%signal to noise ratio
SNR = SignaltoNoiseRatio(origImg, distImg);
%disp('6-signato to noise ratio = ');
%disp(SNR);

%Peak Signal to Noise Ratio
PSNR = PeakSignaltoNoiseRatio(origImg, distImg);
```

New to MATLAB? See resources for Getting Started.

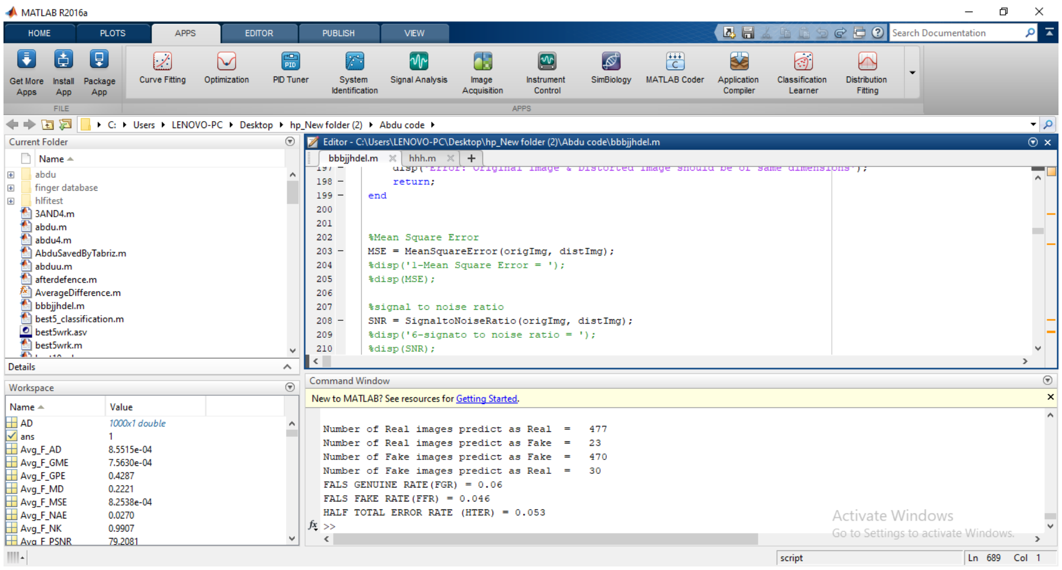
```
Number of Real images predict as Real  =  486
Number of Real images predict as Fake  =  14
Number of Fake images predict as Fake  =  481
Number of Fake images predict as Real  =  19
FALS GENUINE RATE(FGR) = 0.038
FALS FAKE RATE(FFR) = 0.028
HALF TOTAL ERROR RATE (HTER) = 0.033
fx >>
```

Name	Value
AD	1000x1 double
ans	1
Avg_F_AD	8.5515e-04
Avg_F_GME	7.5630e-04
Avg_F_GPE	0.4287
Avg_F_MD	0.2221
Avg_F_MSE	8.2538e-04
Avg_F_NAE	0.0270
Avg_F_NK	0.9907
Avg_F_PSNR	79.2081

Current Folder: abdu, finger database, hlftest, 3AND4.m, abdu.m, abdu4.m, AbduSavedByTabriz.m, abduu.m, afterdefence.m, AverageDifference.m, bbbjjhdel.m, best5_classification.m, best5wrk.asv, best5wrk.m

Figure 47: Linear SVM classification result of 1000 fingerprint images using 15 IQMs.

4. Quadratic SVM



```
    disp('Error: Original Image & Distorted Image should be of same dimensions');
    return;
end

%Mean Square Error
MSE = MeanSquareError(origImg, distImg);
%disp('1-Mean Square Error = ');
%disp(MSE);

%signal to noise ratio
SNR = SignaltoNoiseRatio(origImg, distImg);
%disp('6-signato to noise ratio = ');
%disp(SNR);
```

New to MATLAB? See resources for Getting Started.

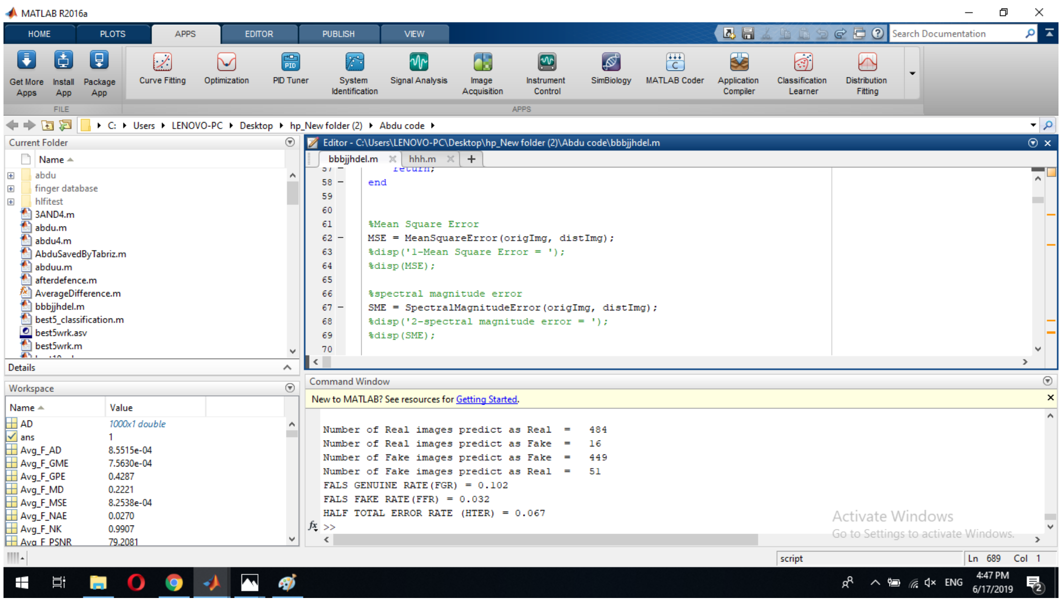
```
Number of Real images predict as Real  =  477
Number of Real images predict as Fake  =  23
Number of Fake images predict as Fake  =  470
Number of Fake images predict as Real  =  30
FALS GENUINE RATE(FGR) = 0.06
FALS FAKE RATE(FFR) = 0.046
HALF TOTAL ERROR RATE (HTER) = 0.053
fx >>
```

Name	Value
AD	1000x1 double
ans	1
Avg_F_AD	8.5515e-04
Avg_F_GME	7.5630e-04
Avg_F_GPE	0.4287
Avg_F_MD	0.2221
Avg_F_MSE	8.2538e-04
Avg_F_NAE	0.0270
Avg_F_NK	0.9907
Avg_F_PSNR	79.2081

Current Folder: abdu, finger database, hlftest, 3AND4.m, abdu.m, abdu4.m, AbduSavedByTabriz.m, abduu.m, afterdefence.m, AverageDifference.m, bbbjjhdel.m, best5_classification.m, best5wrk.asv, best5wrk.m

Figure 48: Quadratic SVM classification result of 1000 fingerprint images using 15 IQMs.

5. Fine KNN



```
end


%Mean Square Error
MSE = MeanSquareError(origImg, distImg);
%disp('1-Mean Square Error = ');
%disp(MSE);

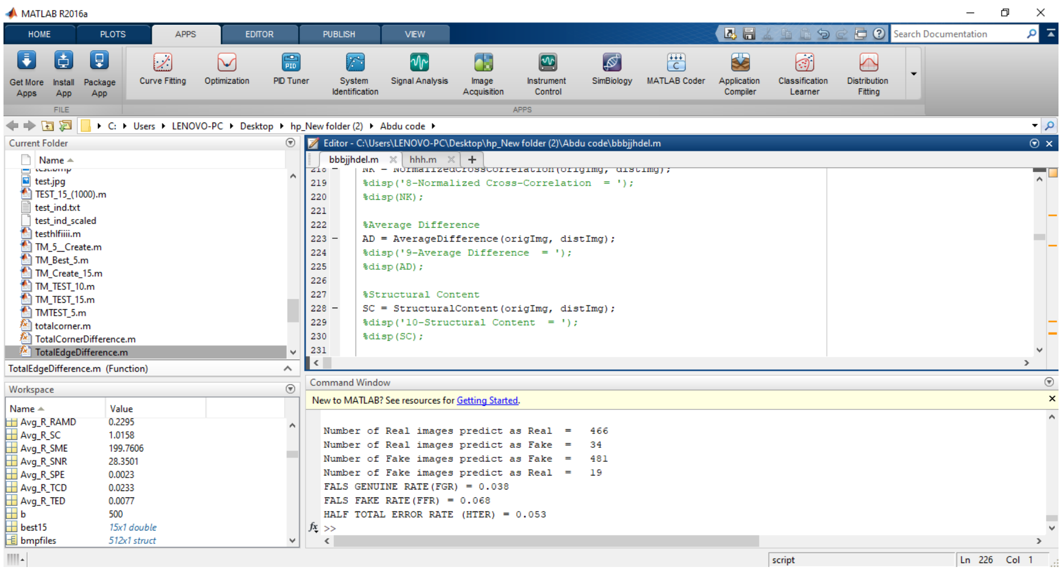
%spectral magnitude error
SME = SpectralMagnitudeError(origImg, distImg);
%disp('2-spectral magnitude error = ');
%disp(SME);
```

```
Number of Real images predict as Real  =   484
Number of Real images predict as Fake  =   16
Number of Fake images predict as Fake  =   449
Number of Fake images predict as Real  =   51
FALS GENUINE RATE(FGR) = 0.102
FALS FAKE RATE(FFR) = 0.032
HALF TOTAL ERROR RATE (HTER) = 0.067
>>
```

Name	Value
AD	1000x1 double
ans	1
Avg_F_AD	8.5515e-04
Avg_F_GME	7.5630e-04
Avg_F_GPE	0.4287
Avg_F_MD	0.2221
Avg_F_MSE	8.2538e-04
Avg_F_NAE	0.0270
Avg_F_NK	0.9907
Avg_F_PSNR	79.2081

Figure 49: Fine KNN classification result of 1000 fingerprint images using 15 IQMs.

6. Logistic Regression



```
%disp('8-Normalized Cross-Correlation  = ');
%disp(NK);

%Average Difference
AD = AverageDifference(origImg, distImg);
%disp('9-Average Difference  = ');
%disp(AD);

%Structural Content
SC = StructuralContent(origImg, distImg);
%disp('10-Structural Content  = ');
%disp(SC);
```

```
Number of Real images predict as Real  =   466
Number of Real images predict as Fake  =   34
Number of Fake images predict as Fake  =   481
Number of Fake images predict as Real  =   19
FALS GENUINE RATE(FGR) = 0.038
FALS FAKE RATE(FFR) = 0.068
HALF TOTAL ERROR RATE (HTER) = 0.053
>>
```

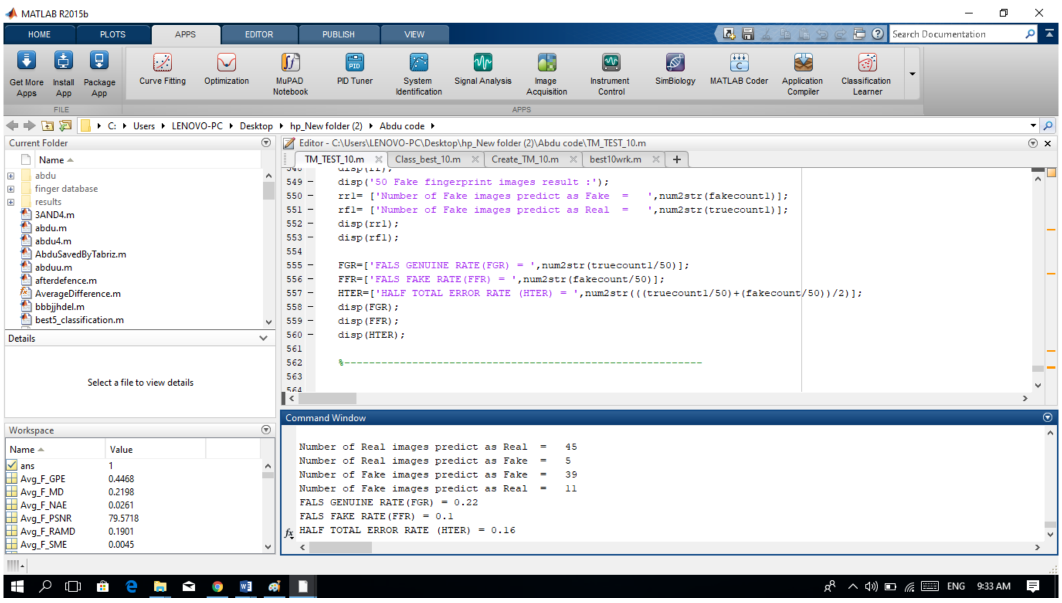
Name	Value
Avg_R_RAMD	0.2295
Avg_R_SC	1.0158
Avg_R_SME	199.7606
Avg_R_SNR	28.3501
Avg_R_SPE	0.0023
Avg_R_TCD	0.0233
Avg_R_TED	0.0077
b	500
best15	15x1 double
bmpfiles	512x1 struct

Figure 50: Logistic Regression classification of 1000 fingerprint images using 15 IQMs.

3. Table and Screenshot of Training Results For 100 Fingerprint Images Using 10 IQMs

100 fingerprint images with 10 IQMs result using 6 classifiers.

1. LDA



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\TM_TEST_10.m

```
disp('50 Fake fingerprint images result :');
rrl= ['Number of Fake images predict as Fake  =   ',num2str(fakecountl)];
rfl= ['Number of Fake images predict as Real  =   ',num2str(truecountl)];
disp(rrl);
disp(rfl);

FGR=['FALS GENUINE RATE(FGR) = ',num2str(truecountl/50)];
FFR=['FALS FAKE RATE(FFR) = ',num2str(fakecount/50)];
HTER=['HALF TOTAL ERROR RATE (HTER) = ',num2str(((truecountl/50)+(fakecount/50))/2)];
disp(FGR);
disp(FFR);
disp(HTER);

%---------------------------------------------------------
```

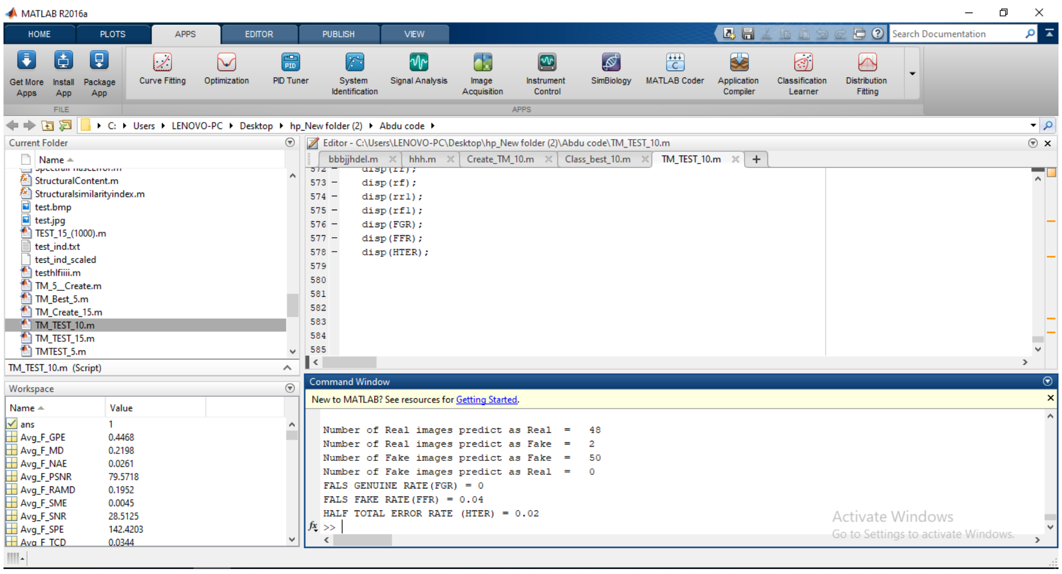
Command Window

```
Number of Real images predict as Real  =   45
Number of Real images predict as Fake  =   5
Number of Fake images predict as Fake  =   39
Number of Fake images predict as Real  =   11
FALS GENUINE RATE(FGR) = 0.22
FALS FAKE RATE(FFR) = 0.1
HALF TOTAL ERROR RATE (HTER) = 0.16
```

Name	Value
ans	1
Avg_F_GPE	0.4468
Avg_F_MD	0.2198
Avg_F_NAE	0.0261
Avg_F_PSNR	79.5718
Avg_F_RAMD	0.1901
Avg_F_SME	0.0045

Figure 51: LDA training result of 100 fingerprint images using 10 IQMs.

2. QDA



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\TM_TEST_10.m

```
disp(rf);
disp(rrl);
disp(rfl);
disp(FGR);
disp(FFR);
disp(HTER);
```

Command Window

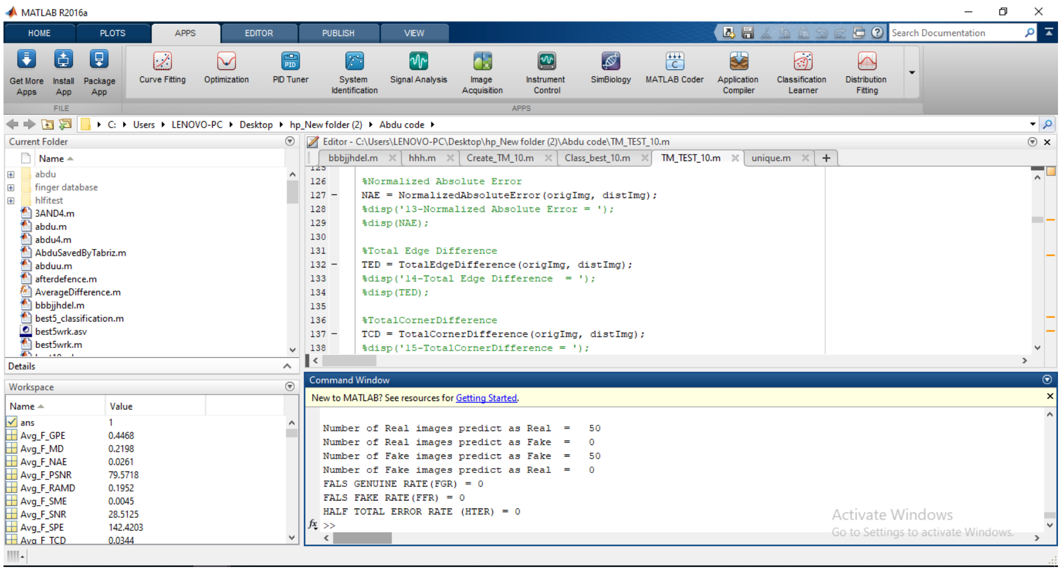
New to MATLAB? See resources for Getting Started.

```
Number of Real images predict as Real  =   48
Number of Real images predict as Fake  =   2
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
FALS GENUINE RATE(FGR) = 0
FALS FAKE RATE(FFR) = 0.04
HALF TOTAL ERROR RATE (HTER) = 0.02
>>
```

Name	Value
ans	1
Avg_F_GPE	0.4468
Avg_F_MD	0.2198
Avg_F_NAE	0.0261
Avg_F_PSNR	79.5718
Avg_F_RAMD	0.1952
Avg_F_SME	0.0045
Avg_F_SNR	28.5125
Avg_F_SPE	142.4203
Avg_F_TCD	0.0344

Figure 52: QDA training result of 100 fingerprint images using 10 IQMs.

3. Linear SVM



MATLAB R2016a

Current Folder:

abdu
finger database
hlfitest
3AND4.m
abdu.m
abdu4.m
AbduSavedByTabriz.m
abduu.m
afterdefence.m
AverageDifference.m
bbbjjhdel.m
best5_classification.m
best5wrk.asv
best5wrk.m

Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\TM_TEST_10.m

```
%Normalized Absolute Error
NAE = NormalizedAbsoluteError(origImg, distImg);
%disp('13-Normalized Absolute Error = ');
%disp(NAE);

%Total Edge Difference
TED = TotalEdgeDifference(origImg, distImg);
%disp('14-Total Edge Difference  = ');
%disp(TED);

%TotalCornerDifference
TCD = TotalCornerDifference(origImg, distImg);
%disp('15-TotalCornerDifference = ');
```

Workspace

Name	Value
ans	1
Avg_F_GPE	0.4468
Avg_F_MD	0.2198
Avg_F_NAE	0.0261
Avg_F_PSNR	79.5718
Avg_F_RAMD	0.1952
Avg_F_SME	0.0045
Avg_F_SNR	28.5125
Avg_F_SPE	142.4203
Avg_F_TCD	0.0344

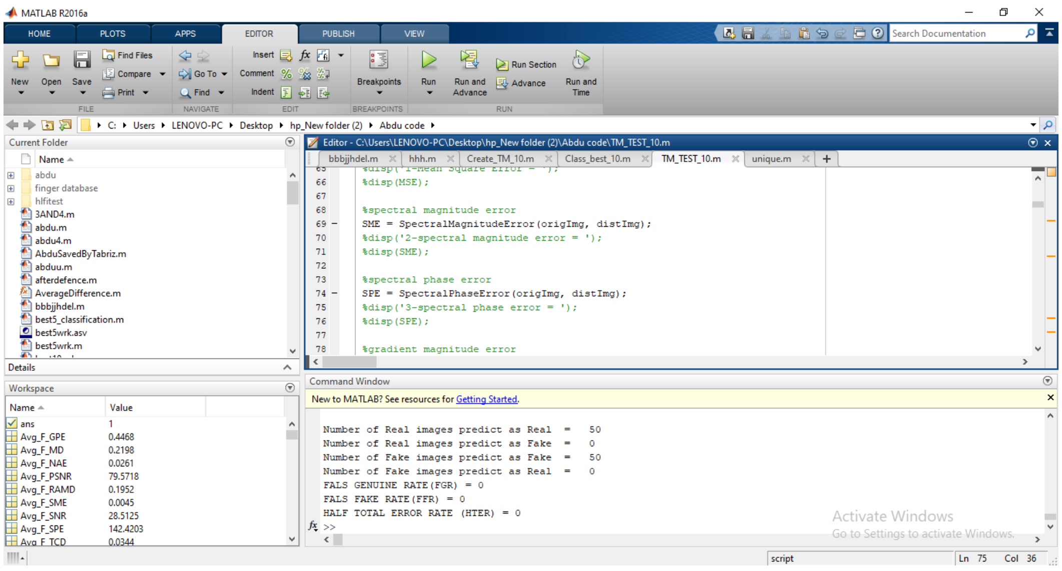
Command Window

New to MATLAB? See resources for Getting Started.

```
Number of Real images predict as Real  =   50
Number of Real images predict as Fake  =   0
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
FALS GENUINE RATE(FGR) = 0
FALS FAKE RATE(FFR) = 0
HALF TOTAL ERROR RATE (HTER) = 0
>>
```

Figure 53: Linear SVM training result of 100 fingerprint images using 10 IQMs.

4. Quadratic SVM



MATLAB R2016a

Current Folder:

abdu
finger database
hlfitest
3AND4.m
abdu.m
abdu4.m
AbduSavedByTabriz.m
abduu.m
afterdefence.m
AverageDifference.m
bbbjjhdel.m
best5_classification.m
best5wrk.asv
best5wrk.m

Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\TM_TEST_10.m

```
%disp(MSE);

%spectral magnitude error
SME = SpectralMagnitudeError(origImg, distImg);
%disp('2-spectral magnitude error = ');
%disp(SME);

%spectral phase error
SPE = SpectralPhaseError(origImg, distImg);
%disp('3-spectral phase error = ');
%disp(SPE);

%gradient magnitude error
```

Workspace

Name	Value
ans	1
Avg_F_GPE	0.4468
Avg_F_MD	0.2198
Avg_F_NAE	0.0261
Avg_F_PSNR	79.5718
Avg_F_RAMD	0.1952
Avg_F_SME	0.0045
Avg_F_SNR	28.5125
Avg_F_SPE	142.4203
Avg_F_TCD	0.0344

Command Window

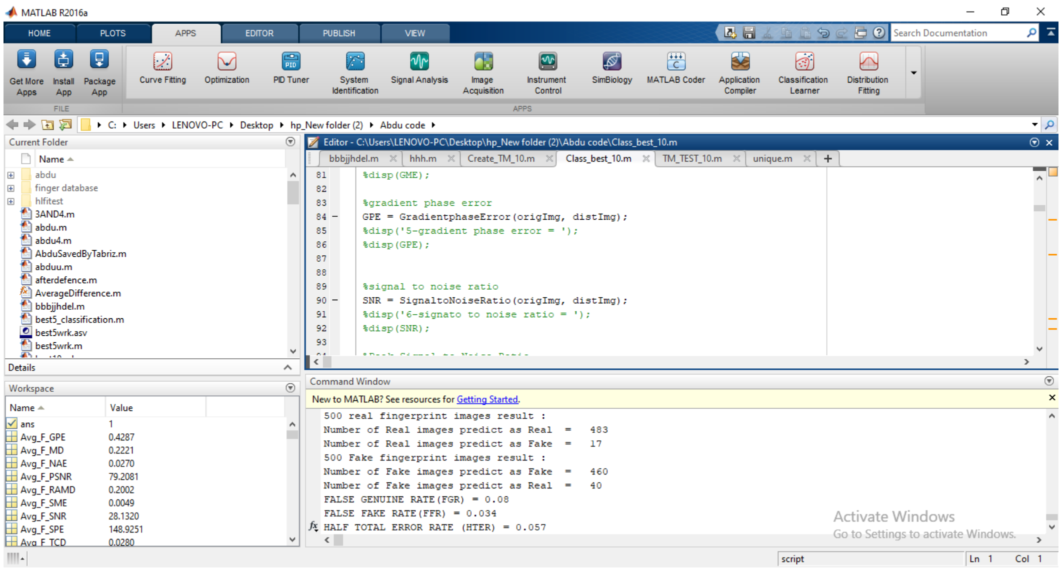
New to MATLAB? See resources for Getting Started.

```
Number of Real images predict as Real  =   50
Number of Real images predict as Fake  =   0
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
FALS GENUINE RATE(FGR) = 0
FALS FAKE RATE(FFR) = 0
HALF TOTAL ERROR RATE (HTER) = 0
>>
```

script   Ln 75   Col 36

Figure 54: Quadratic SVM training result of 100 fingerprint images using 10 IQMs.

5. Fine KNN


Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\Class_best_10.m

```
    %disp(GME);

    %gradient phase error
    GPE = GradientphaseError(origImg, distImg);
    %disp('5-gradient phase error = ');
    %disp(GPE);


    %signal to noise ratio
    SNR = SignaltoNoiseRatio(origImg, distImg);
    %disp('6-signato to noise ratio = ');
    %disp(SNR);
```

Command Window

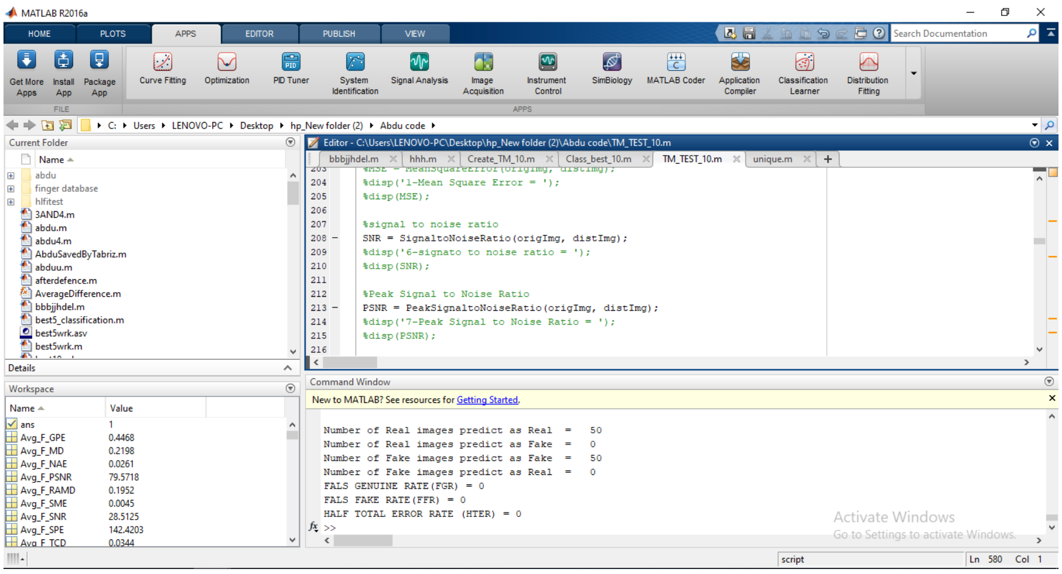
```
500 real fingerprint images result :
Number of Real images predict as Real  =   483
Number of Real images predict as Fake  =   17
500 Fake fingerprint images result :
Number of Fake images predict as Fake  =   460
Number of Fake images predict as Real  =   40
FALSE GENUINE RATE(FGR) = 0.08
FALSE FAKE RATE(FFR) = 0.034
HALF TOTAL ERROR RATE (HTER) = 0.057
```

Workspace

Name	Value
ans	1
Avg_F_GPE	0.4287
Avg_F_MD	0.2221
Avg_F_NAE	0.0270
Avg_F_PSNR	79.2081
Avg_F_RAMD	0.2002
Avg_F_SME	0.0049
Avg_F_SNR	28.1320
Avg_F_SPE	148.9251
Avg_F_TCD	0.0280

Figure 55: Fine KNN training result of 100 fingerprint images using 10 IQMs.

6. Logistic Regression


Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\TM_TEST_10.m

```
    %disp('1-Mean Square Error = ');
    %disp(MSE);

    %signal to noise ratio
    SNR = SignaltoNoiseRatio(origImg, distImg);
    %disp('6-signato to noise ratio = ');
    %disp(SNR);

    %Peak Signal to Noise Ratio
    PSNR = PeakSignaltoNoiseRatio(origImg, distImg);
    %disp('7-Peak Signal to Noise Ratio = ');
    %disp(PSNR);
```

Command Window

```
Number of Real images predict as Real  =   50
Number of Real images predict as Fake  =   0
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
FALS GENUINE RATE(FGR) = 0
FALS FAKE RATE(FFR) = 0
HALF TOTAL ERROR RATE (HTER) = 0
>>
```

Workspace

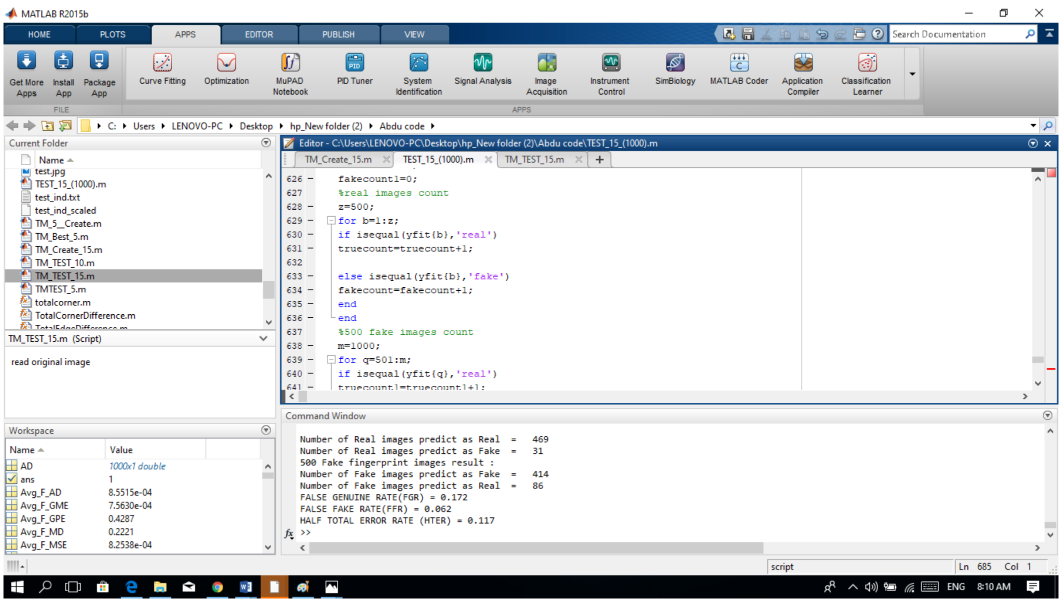
Name	Value
ans	1
Avg_F_GPE	0.4468
Avg_F_MD	0.2198
Avg_F_NAE	0.0261
Avg_F_PSNR	79.5718
Avg_F_RAMD	0.1952
Avg_F_SME	0.0045
Avg_F_SNR	28.5125
Avg_F_SPE	142.4203
Avg_F_TCD	0.0344

Figure 56: Logistic Regression training result of 100 fingerprint images using 10 IQMs.

4. Table and Screenshot of Classification Results For 1000 Fingerprint Images Using 10 IQMs

1000 Fingerprint images with 10 IQMs result using 6 classifiers:

1. LDA



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\TEST_15_(1000).m

```
    fakecount1=0;
    %real images count
    z=500;
  for b=1:z;
    if isequal(yfit{b},'real')
    truecount=truecount+1;

    else isequal(yfit{b},'fake')
    fakecount=fakecount+1;
    end
    end
    %500 fake images count
    m=1000;
  for q=501:m;
    if isequal(yfit{q},'real')
```

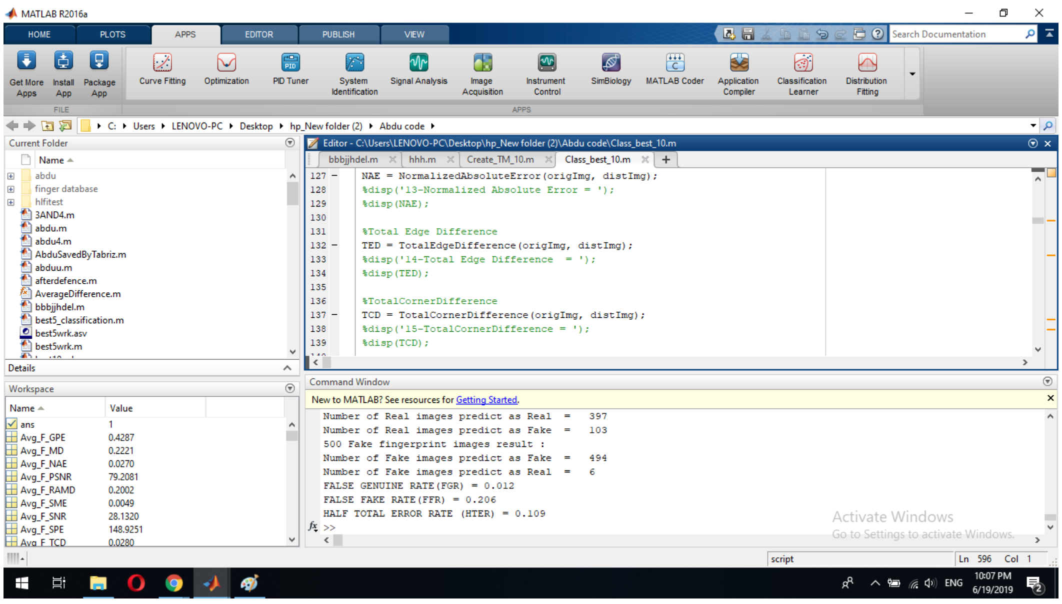
Command Window

```
Number of Real images predict as Real  =   469
Number of Real images predict as Fake  =   31
500 Fake fingerprint images result :
Number of Fake images predict as Fake  =   414
Number of Fake images predict as Real  =   86
FALSE GENUINE RATE(FGR) = 0.172
FALSE FAKE RATE(FFR) = 0.062
HALF TOTAL ERROR RATE (HTER) = 0.117
>>
```

Name	Value
AD	1000x1 double
ans	1
Avg_F_AD	8.5515e-04
Avg_F_GME	7.5630e-04
Avg_F_GPE	0.4287
Avg_F_MD	0.2221
Avg_F_MSE	8.2538e-04

Figure 57: LDA Classification result of 1000 fingerprint images using 10 IQMs.

2. QDA



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\Class_best_10.m

```
    NAE = NormalizedAbsoluteError(origImg, distImg);
    %disp('13-Normalized Absolute Error = ');
    %disp(NAE);

    %Total Edge Difference
    TED = TotalEdgeDifference(origImg, distImg);
    %disp('14-Total Edge Difference  = ');
    %disp(TED);

    %TotalCornerDifference
    TCD = TotalCornerDifference(origImg, distImg);
    %disp('15-TotalCornerDifference = ');
    %disp(TCD);
```

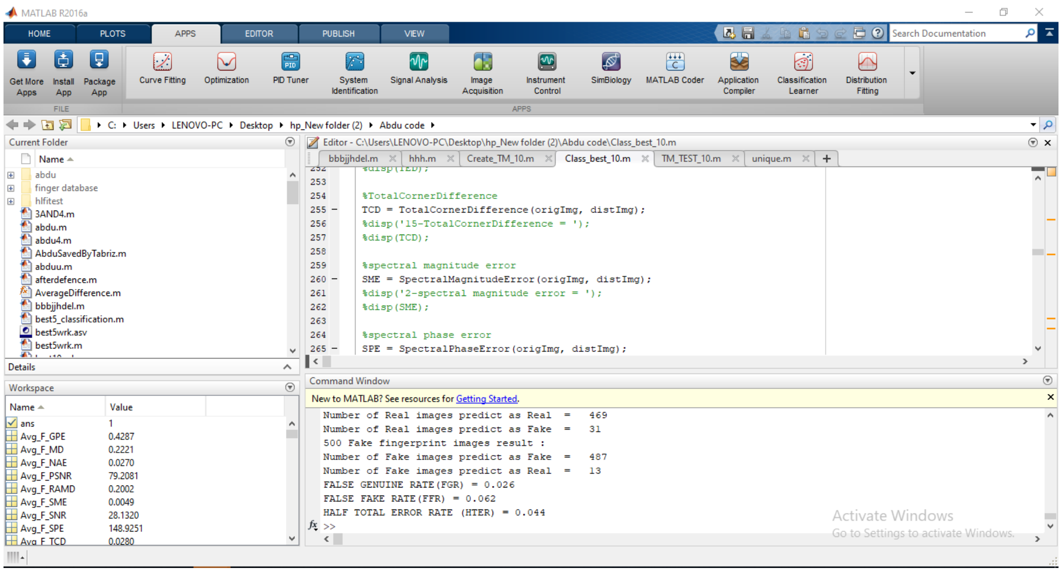
Command Window

```
Number of Real images predict as Real  =   397
Number of Real images predict as Fake  =   103
500 Fake fingerprint images result :
Number of Fake images predict as Fake  =   494
Number of Fake images predict as Real  =   6
FALSE GENUINE RATE(FGR) = 0.012
FALSE FAKE RATE(FFR) = 0.206
HALF TOTAL ERROR RATE (HTER) = 0.109
>>
```

Name	Value
ans	1
Avg_F_GPE	0.4287
Avg_F_MD	0.2221
Avg_F_NAE	0.0270
Avg_F_PSNR	79.2081
Avg_F_RAMD	0.2002
Avg_F_SME	0.0049
Avg_F_SNR	28.1320
Avg_F_SPE	148.9251
Avg_F_TCD	0.0280

Figure 58: QDA Classification Result of 1000 Fingerprint Images Using 10 IQMs.

3. Linear SVM



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\Class_best_10.m

```
%TotalCornerDifference
TCD = TotalCornerDifference(origImg, distImg);
%disp('15-TotalCornerDifference = ');
%disp(TCD);

%spectral magnitude error
SME = SpectralMagnitudeError(origImg, distImg);
%disp('2-spectral magnitude error = ');
%disp(SME);

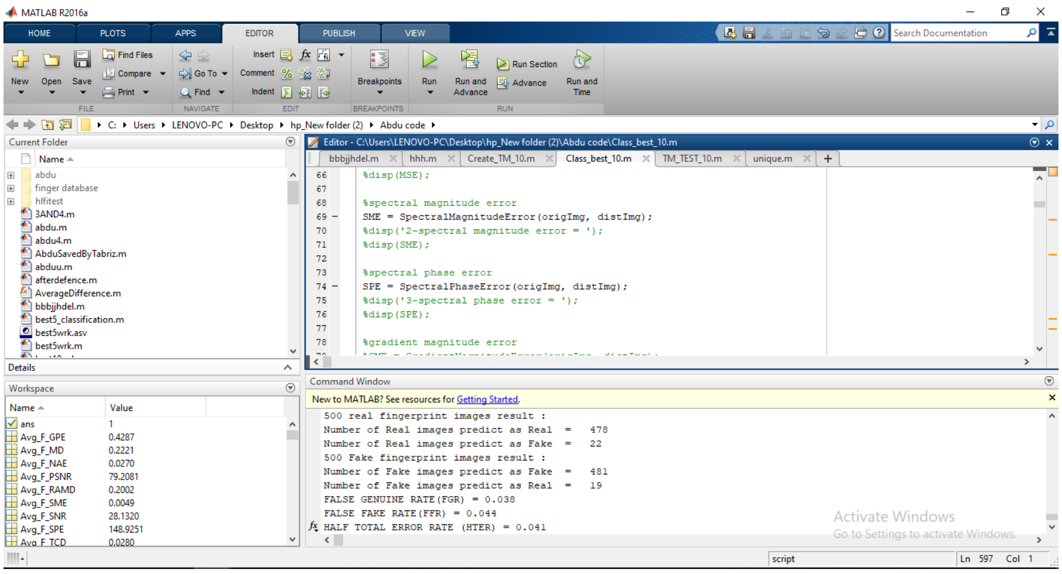
%spectral phase error
SPE = SpectralPhaseError(origImg, distImg);
```

```
Number of Real images predict as Real  =   469
Number of Real images predict as Fake  =   31
500 Fake fingerprint images result :
Number of Fake images predict as Fake  =   487
Number of Fake images predict as Real  =   13
FALSE GENUINE RATE(FGR) = 0.026
FALSE FAKE RATE(FFR) = 0.062
HALF TOTAL ERROR RATE (HTER) = 0.044
>>
```

Name	Value
ans	1
Avg_F_GPE	0.4287
Avg_F_MD	0.2221
Avg_F_NAE	0.0270
Avg_F_PSNR	79.2081
Avg_F_RAMD	0.2002
Avg_F_SME	0.0049
Avg_F_SNR	28.1320
Avg_F_SPE	148.9251
Avg_F_TCD	0.0280

Figure 59: Linear SVM classification result of 1000 fingerprint images using 10 IQMs.

4. Quadratic SVM



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\Class_best_10.m

```
%disp(MSE);

%spectral magnitude error
SME = SpectralMagnitudeError(origImg, distImg);
%disp('2-spectral magnitude error = ');
%disp(SME);

%spectral phase error
SPE = SpectralPhaseError(origImg, distImg);
%disp('3-spectral phase error = ');
%disp(SPE);

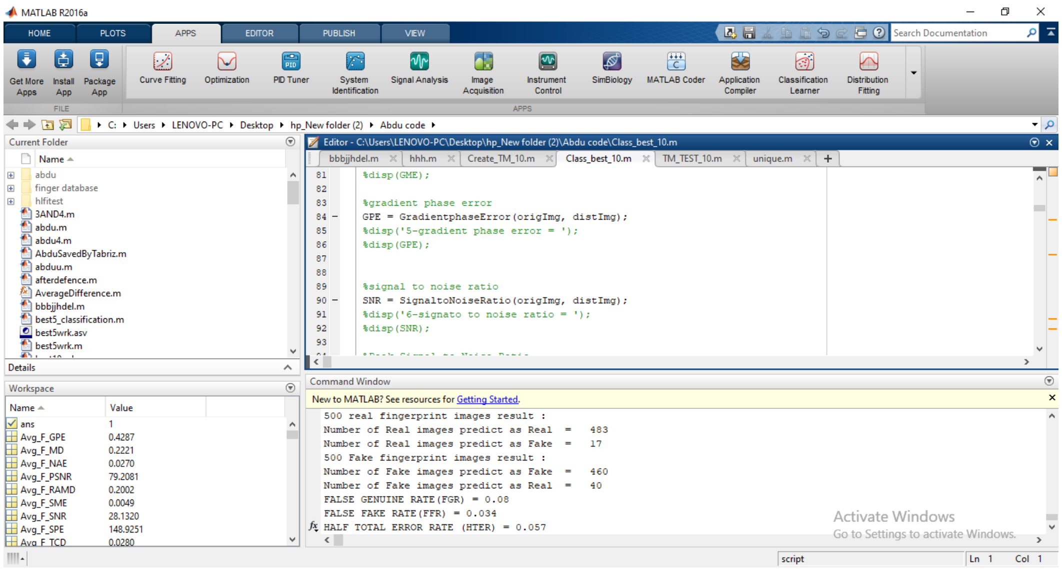
%gradient magnitude error
```

```
500 real fingerprint images result :
Number of Real images predict as Real  =   478
Number of Real images predict as Fake  =   22
500 Fake fingerprint images result :
Number of Fake images predict as Fake  =   481
Number of Fake images predict as Real  =   19
FALSE GENUINE RATE(FGR) = 0.038
FALSE FAKE RATE(FFR) = 0.044
HALF TOTAL ERROR RATE (HTER) = 0.041
```

Name	Value
ans	1
Avg_F_GPE	0.4287
Avg_F_MD	0.2221
Avg_F_NAE	0.0270
Avg_F_PSNR	79.2081
Avg_F_RAMD	0.2002
Avg_F_SME	0.0049
Avg_F_SNR	28.1320
Avg_F_SPE	148.9251
Avg_F_TCD	0.0280

Figure 60: Quadratic SVM classification result of 1000 fingerprint images using 10 IQMs.

5. Finee KNN



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\Class_best_10.m

```
%disp(GME);

%gradient phase error
GPE = GradientphaseError(origImg, distImg);
%disp('5-gradient phase error = ');
%disp(GPE);


%signal to noise ratio
SNR = SignaltoNoiseRatio(origImg, distImg);
%disp('6-signato to noise ratio = ');
%disp(SNR);
```

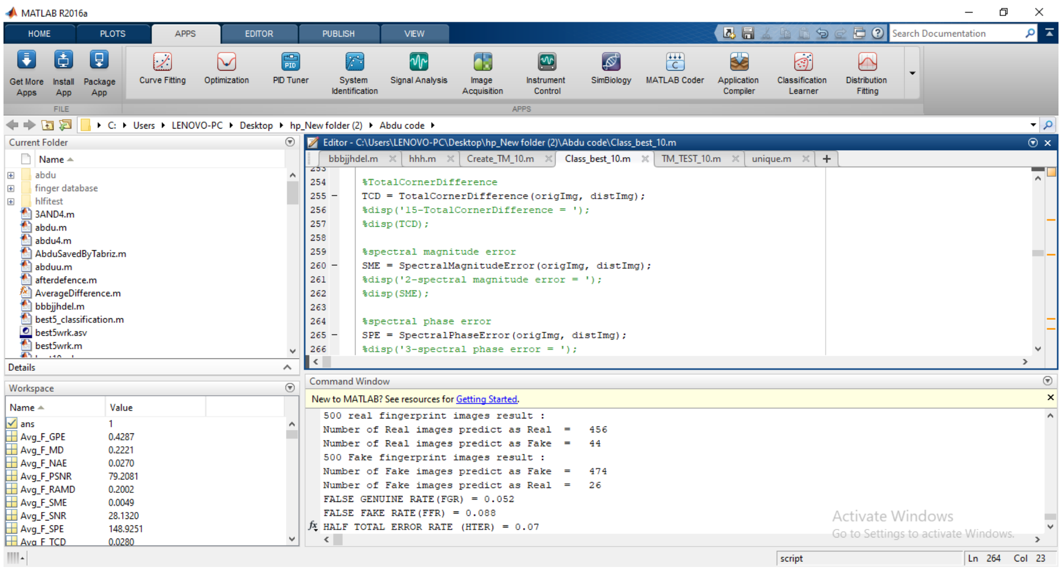
Command Window

```
500 real fingerprint images result :
Number of Real images predict as Real  =   483
Number of Real images predict as Fake  =   17
500 Fake fingerprint images result :
Number of Fake images predict as Fake  =   460
Number of Fake images predict as Real  =   40
FALSE GENUINE RATE(FGR) = 0.08
FALSE FAKE RATE(FFR) = 0.034
HALF TOTAL ERROR RATE (HTER) = 0.057
```

Name	Value
ans	1
Avg_F_GPE	0.4287
Avg_F_MD	0.2221
Avg_F_NAE	0.0270
Avg_F_PSNR	79.2081
Avg_F_RAMD	0.2002
Avg_F_SME	0.0049
Avg_F_SNR	28.1320
Avg_F_SPE	148.9251
Avg_F_TCD	0.0280

Figure 61: Fine KNN classification result of 1000 fingerprint images using 10 IQMs.

6. Logistic Regression



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\Class_best_10.m

```
%TotalCornerDifference
TCD = TotalCornerDifference(origImg, distImg);
%disp('15-TotalCornerDifference = ');
%disp(TCD);

%spectral magnitude error
SME = SpectralMagnitudeError(origImg, distImg);
%disp('2-spectral magnitude error = ');
%disp(SME);

%spectral phase error
SPE = SpectralPhaseError(origImg, distImg);
%disp('3-spectral phase error = ');
```

Command Window

```
500 real fingerprint images result :
Number of Real images predict as Real  =   456
Number of Real images predict as Fake  =   44
500 Fake fingerprint images result :
Number of Fake images predict as Fake  =   474
Number of Fake images predict as Real  =   26
FALSE GENUINE RATE(FGR) = 0.052
FALSE FAKE RATE(FFR) = 0.088
HALF TOTAL ERROR RATE (HTER) = 0.07
```

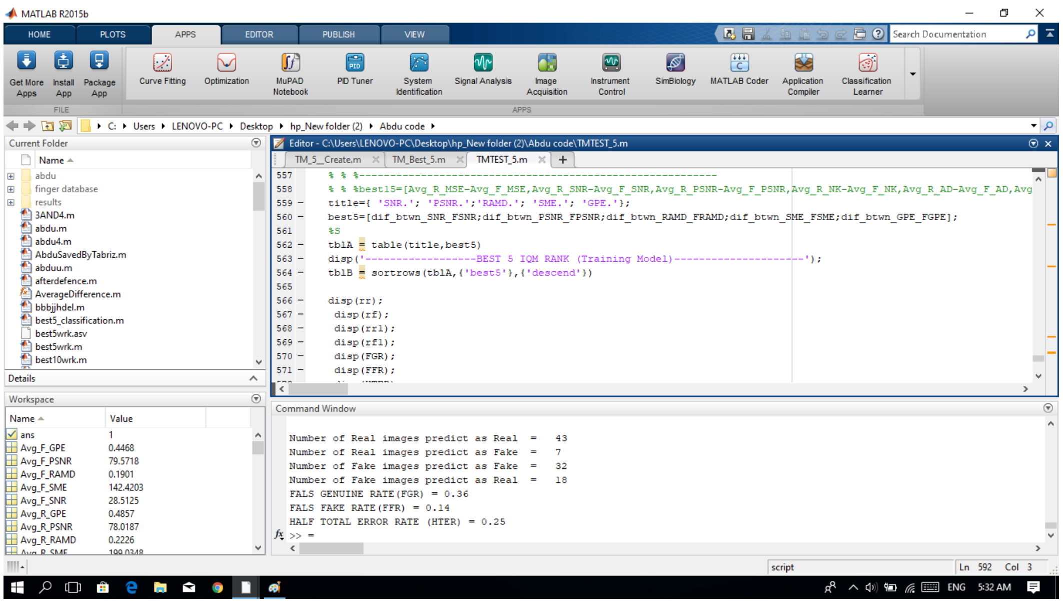
Name	Value
ans	1
Avg_F_GPE	0.4287
Avg_F_MD	0.2221
Avg_F_NAE	0.0270
Avg_F_PSNR	79.2081
Avg_F_RAMD	0.2002
Avg_F_SME	0.0049
Avg_F_SNR	28.1320
Avg_F_SPE	148.9251
Avg_F_TCD	0.0280

Figure 62: Logistic Regression classification result of 1000 fingerprint images using 10 IQMs.

5. Table and Screenshot of Training Results For 100 Fingerprint Images Using 5 IQMs

100 fingerprint images with 5 IQMs result using 6 classifiers:

1. LDA



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\TMTEST_5.m

```
% % %-------------------------------------------------------
% % %best15=[Avg_R_MSE-Avg_F_MSE,Avg_R_SNR-Avg_F_SNR,Avg_R_PSNR-Avg_F_PSNR,Avg_R_NK-Avg_F_NK,Avg_R_AD-Avg_F_AD,Avg
title={ 'SNR.'; 'PSNR.';'RAMD.'; 'SME.'; 'GPE.'};
best5=[dif_btwn_SNR_FSNR;dif_btwn_PSNR_FPSNR;dif_btwn_RAMD_FRAMD;dif_btwn_SME_FSME;dif_btwn_GPE_FGPE];
%S
tblA = table(title,best5)
disp('------------------BEST 5 IQM RANK (Training Model)---------------------');
tblB = sortrows(tblA,{'best5'},{'descend'})

disp(rr);
 disp(rf);
 disp(rr1);
 disp(rf1);
 disp(FGR);
 disp(FFR);
```

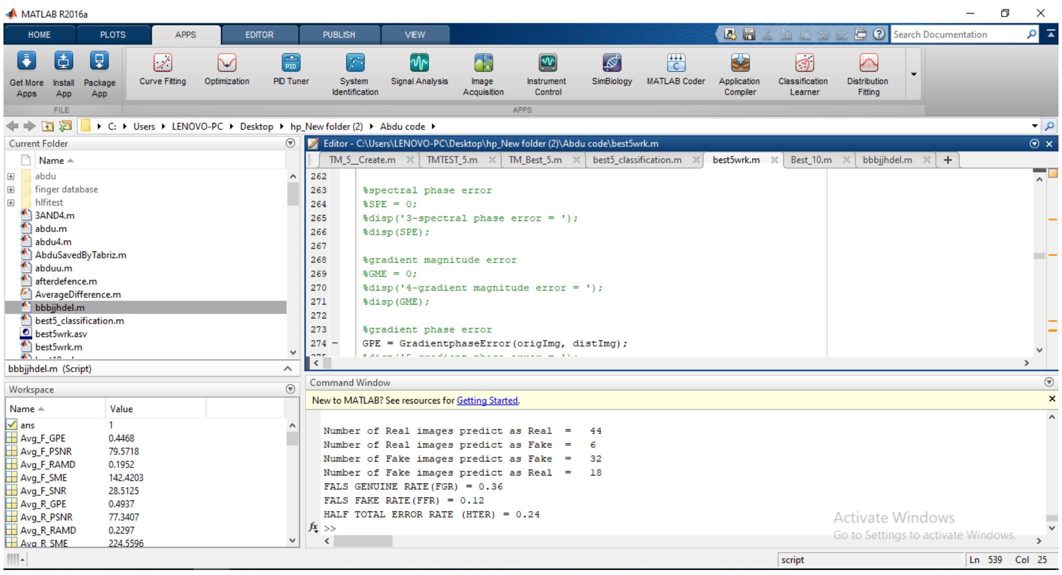
Name	Value
ans	1
Avg_F_GPE	0.4468
Avg_F_PSNR	79.5718
Avg_F_RAMD	0.1901
Avg_F_SME	142.4203
Avg_F_SNR	28.5125
Avg_R_GPE	0.4857
Avg_R_PSNR	78.0187
Avg_R_RAMD	0.2226

Command Window

```
Number of Real images predict as Real  =   43
Number of Real images predict as Fake  =   7
Number of Fake images predict as Fake  =   32
Number of Fake images predict as Real  =   18
FALS GENUINE RATE(FGR) = 0.36
FALS FAKE RATE(FFR) = 0.14
HALF TOTAL ERROR RATE (HTER) = 0.25
>> =
```

Figure 63: LDA training result of 100 fingerprint images using 5 IQMs.

2. QDA



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\best5wrk.m

```
%spectral phase error
%SPE = 0;
%disp('3-spectral phase error = ');
%disp(SPE);

%gradient magnitude error
%GME = 0;
%disp('4-gradient magnitude error = ');
%disp(GME);

%gradient phase error
GPE = GradientphaseError(origImg, distImg);
```

Name	Value
ans	1
Avg_F_GPE	0.4468
Avg_F_PSNR	79.5718
Avg_F_RAMD	0.1952
Avg_F_SME	142.4203
Avg_F_SNR	28.5125
Avg_R_GPE	0.4937
Avg_R_PSNR	77.3407
Avg_R_RAMD	0.2297
Avg_R_SME	224.5596

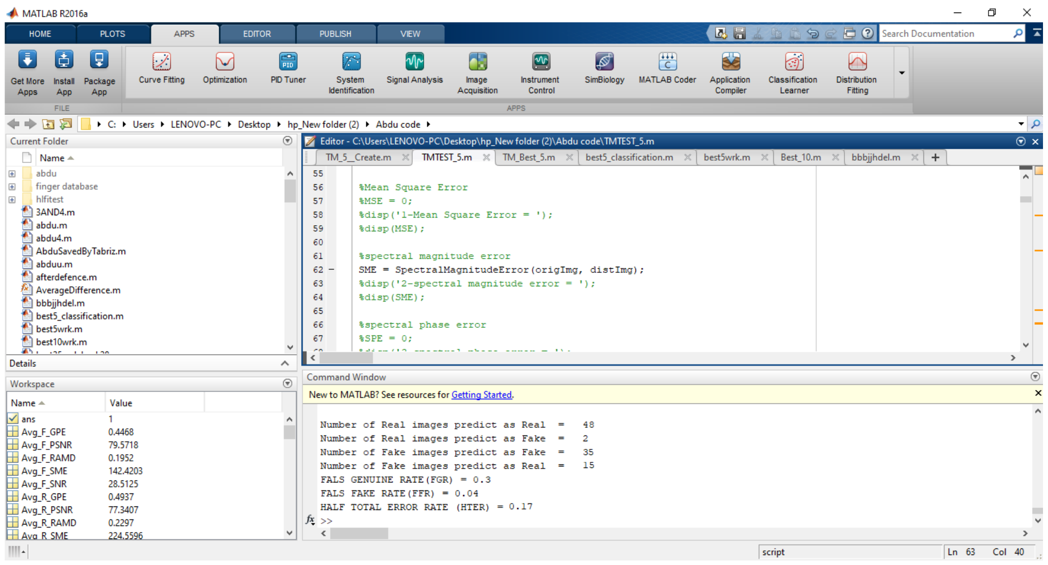
Command Window

New to MATLAB? See resources for Getting Started.

```
Number of Real images predict as Real  =   44
Number of Real images predict as Fake  =   6
Number of Fake images predict as Fake  =   32
Number of Fake images predict as Real  =   18
FALS GENUINE RATE(FGR) = 0.36
FALS FAKE RATE(FFR) = 0.12
HALF TOTAL ERROR RATE (HTER) = 0.24
>>
```

Figure 64: QDA training result of 100 fingerprint images using 5 IQMs.

3. Linear SVM



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\TMTEST_5.m

```
%Mean Square Error
%MSE = 0;
%disp('1-Mean Square Error = ');
%disp(MSE);

%spectral magnitude error
SME = SpectralMagnitudeError(origImg, distImg);
%disp('2-spectral magnitude error = ');
%disp(SME);

%spectral phase error
%SPE = 0;
```

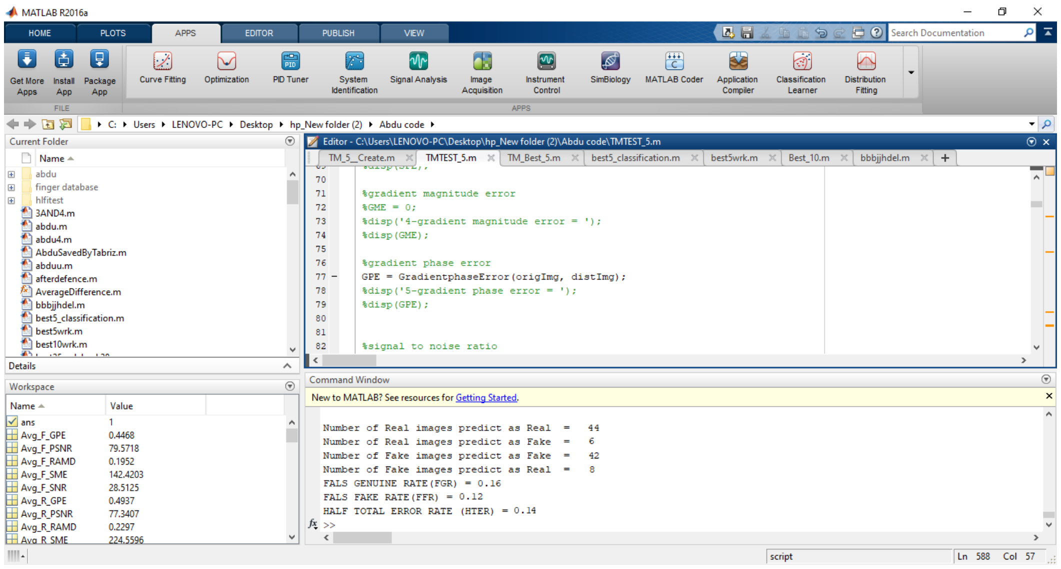
Command Window

```
Number of Real images predict as Real  =   48
Number of Real images predict as Fake  =   2
Number of Fake images predict as Fake  =   35
Number of Fake images predict as Real  =   15
FALS GENUINE RATE(FGR) = 0.3
FALS FAKE RATE(FFR) = 0.04
HALF TOTAL ERROR RATE (HTER) = 0.17
>>
```

Name	Value
ans	1
Avg_F_GPE	0.4468
Avg_F_PSNR	79.5718
Avg_F_RAMD	0.1952
Avg_F_SME	142.4203
Avg_F_SNR	28.5125
Avg_R_GPE	0.4937
Avg_R_PSNR	77.3407
Avg_R_RAMD	0.2297
Avg_R_SME	224.5596

Figure 65: Linear SVM training result of 100 fingerprint images using 5 IQMs.

4. Quadratic SVM



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\TMTEST_5.m

```
%gradient magnitude error
%GME = 0;
%disp('4-gradient magnitude error = ');
%disp(GME);

%gradient phase error
GPE = GradientphaseError(origImg, distImg);
%disp('5-gradient phase error = ');
%disp(GPE);


%signal to noise ratio
```

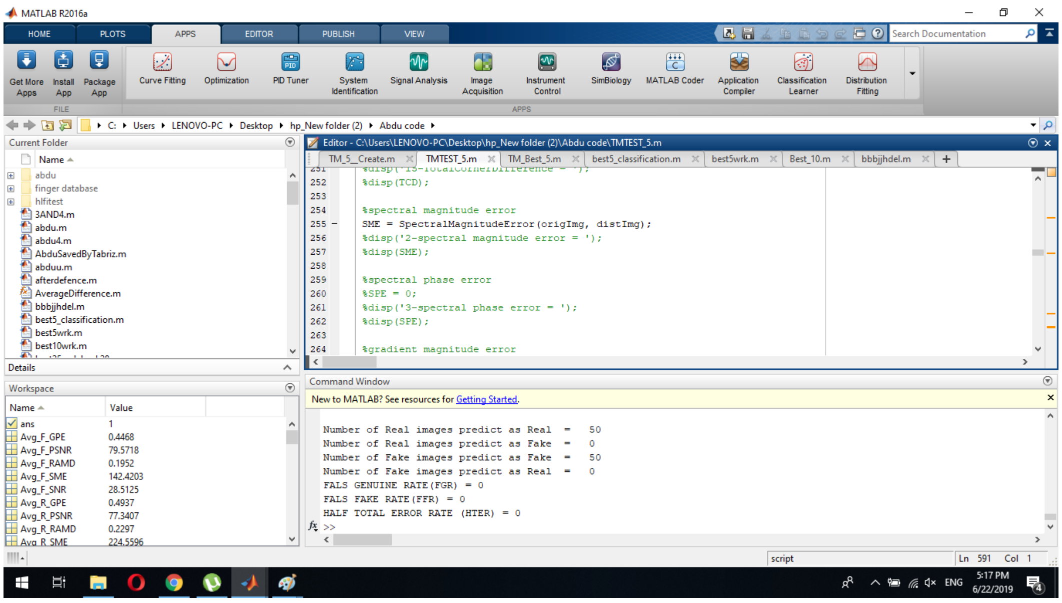
Command Window

```
Number of Real images predict as Real  =   44
Number of Real images predict as Fake  =   6
Number of Fake images predict as Fake  =   42
Number of Fake images predict as Real  =   8
FALS GENUINE RATE(FGR) = 0.16
FALS FAKE RATE(FFR) = 0.12
HALF TOTAL ERROR RATE (HTER) = 0.14
>>
```

Name	Value
ans	1
Avg_F_GPE	0.4468
Avg_F_PSNR	79.5718
Avg_F_RAMD	0.1952
Avg_F_SME	142.4203
Avg_F_SNR	28.5125
Avg_R_GPE	0.4937
Avg_R_PSNR	77.3407
Avg_R_RAMD	0.2297
Avg_R_SME	224.5596

Figure 66: Quadratic SVM training result of 100 fingerprint images using 5 IQMs.

5. Fine KNN



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\TMTEST_5.m

```
%disp(TCD);

%spectral magnitude error
SME = SpectralMagnitudeError(origImg, distImg);
%disp('2-spectral magnitude error = ');
%disp(SME);

%spectral phase error
%SPE = 0;
%disp('3-spectral phase error = ');
%disp(SPE);

%gradient magnitude error
```

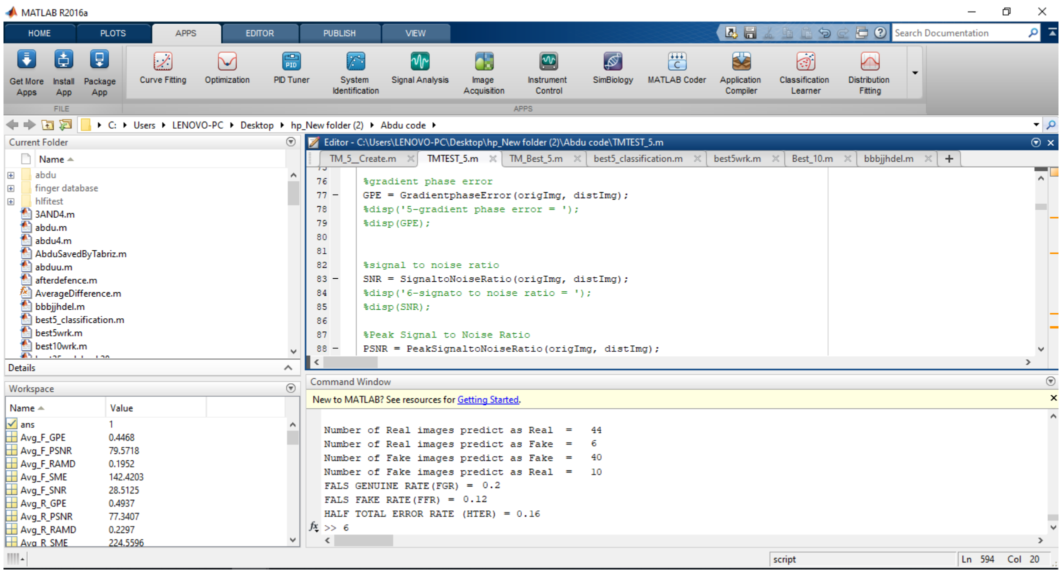
Command Window

```
Number of Real images predict as Real  =   50
Number of Real images predict as Fake  =   0
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
FALS GENUINE RATE(FGR) = 0
FALS FAKE RATE(FFR) = 0
HALF TOTAL ERROR RATE (HTER) = 0
>>
```

Name	Value
ans	1
Avg_F_GPE	0.4468
Avg_F_PSNR	79.5718
Avg_F_RAMD	0.1952
Avg_F_SME	142.4203
Avg_F_SNR	28.5125
Avg_R_GPE	0.4937
Avg_R_PSNR	77.3407
Avg_R_RAMD	0.2297
Avg_R_SME	224.5596

Figure 67: Fine KNN training result of 100 fingerprint images using 5 IQMs.

6. Logisitc Regression



Editor - C:\Users\LENOVO-PC\Desktop\hp_New folder (2)\Abdu code\TMTEST_5.m

```
%gradient phase error
GPE = GradientphaseError(origImg, distImg);
%disp('5-gradient phase error = ');
%disp(GPE);


%signal to noise ratio
SNR = SignaltoNoiseRatio(origImg, distImg);
%disp('6-signato to noise ratio = ');
%disp(SNR);

%Peak Signal to Noise Ratio
PSNR = PeakSignaltoNoiseRatio(origImg, distImg);
```

Command Window

```
Number of Real images predict as Real  =   44
Number of Real images predict as Fake  =   6
Number of Fake images predict as Fake  =   40
Number of Fake images predict as Real  =   10
FALS GENUINE RATE(FGR) = 0.2
FALS FAKE RATE(FFR) = 0.12
HALF TOTAL ERROR RATE (HTER) = 0.16
>> 6
```

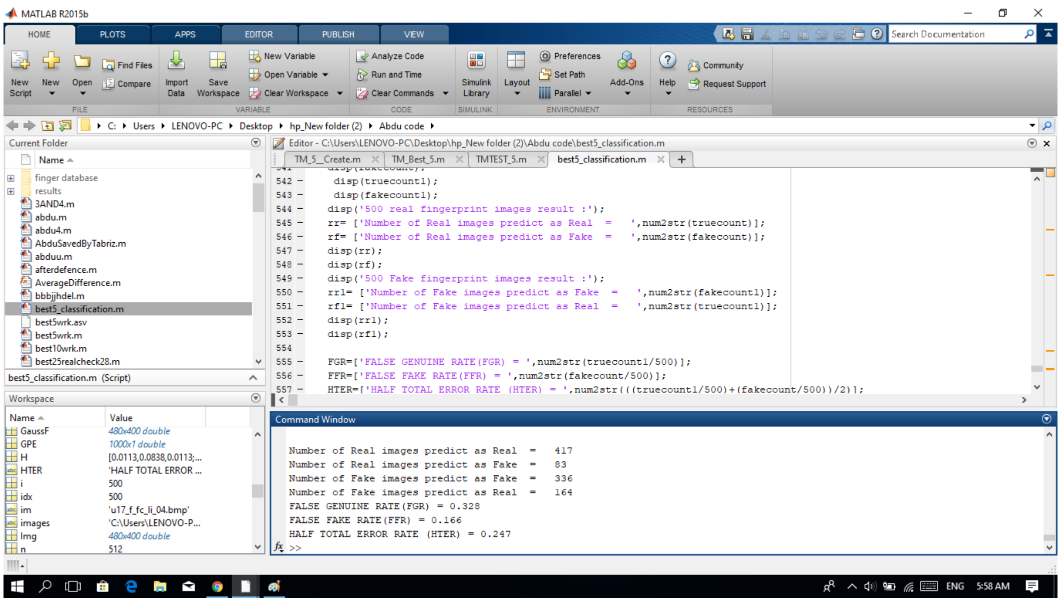
Name	Value
ans	1
Avg_F_GPE	0.4468
Avg_F_PSNR	79.5718
Avg_F_RAMD	0.1952
Avg_F_SME	142.4203
Avg_F_SNR	28.5125
Avg_R_GPE	0.4937
Avg_R_PSNR	77.3407
Avg_R_RAMD	0.2297
Avg_R_SME	224.5596

Figure 68: Logistic Regression training result displayed for 100 fingerprint images using 5 IQMs.

6. Screenshot of Classification Results For 1000 Fingerprint Images Using 5 IQMs:

1000 fingerprint images with 5 IQMs result using 6 classifiers:

1. LDA



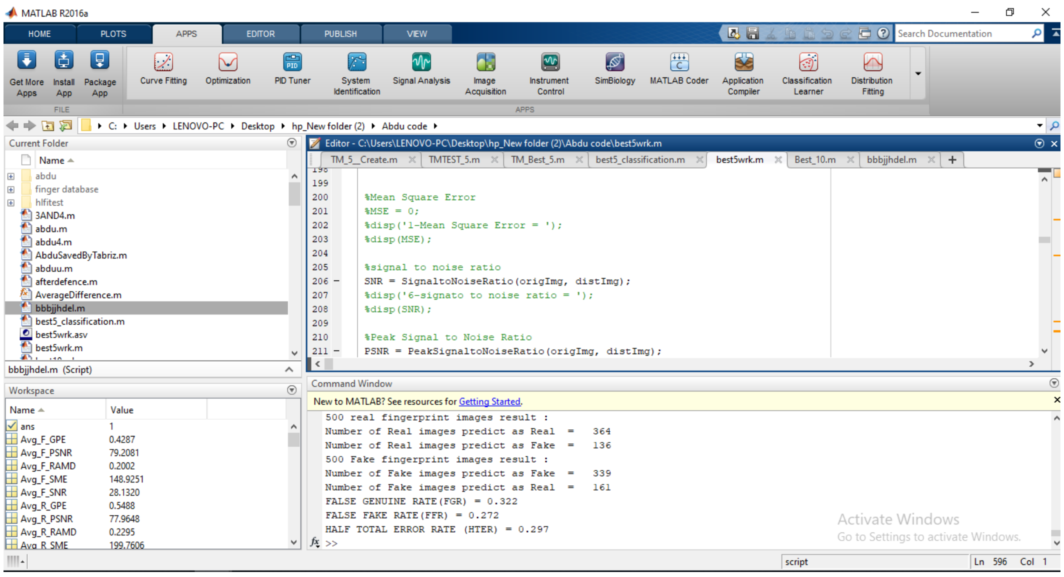
```
disp(truecount1);
 disp(fakecount1);
disp('500 real fingerprint images result :');
rr= ['Number of Real images predict as Real  =   ',num2str(truecount)];
rf= ['Number of Real images predict as Fake  =   ',num2str(fakecount)];
disp(rr);
disp(rf);
disp('500 Fake fingerprint images result :');
rr1= ['Number of Fake images predict as Fake  =   ',num2str(fakecount1)];
rf1= ['Number of Fake images predict as Real  =   ',num2str(truecount1)];
disp(rr1);
disp(rf1);

FGR=['FALSE GENUINE RATE(FGR) = ',num2str(truecount1/500)];
FFR=['FALSE FAKE RATE(FFR) = ',num2str(fakecount/500)];
HTER=['HALF TOTAL ERROR RATE (HTER) = ',num2str(((truecount1/500)+(fakecount/500))/2)];
```

```
Number of Real images predict as Real  =   417
Number of Real images predict as Fake  =   83
Number of Fake images predict as Fake  =   336
Number of Fake images predict as Real  =   164
FALSE GENUINE RATE(FGR) = 0.328
FALSE FAKE RATE(FFR) = 0.166
HALF TOTAL ERROR RATE (HTER) = 0.247
>>
```

Figure 69: LDA classification result of 1000 fingerprint images using 5 IQMs.

2. QDA



```
%Mean Square Error
%MSE = 0;
%disp('1-Mean Square Error = ');
%disp(MSE);

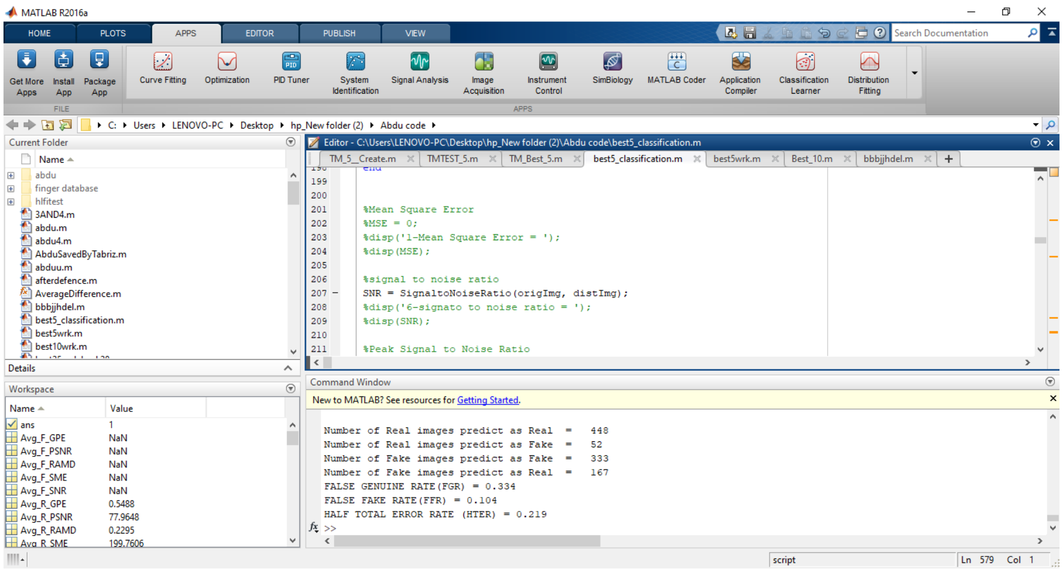
%signal to noise ratio
SNR = SignaltoNoiseRatio(origImg, distImg);
%disp('6-signato to noise ratio = ');
%disp(SNR);

%Peak Signal to Noise Ratio
PSNR = PeakSignaltoNoiseRatio(origImg, distImg);
```

```
500 real fingerprint images result :
Number of Real images predict as Real  =   364
Number of Real images predict as Fake  =   136
500 Fake fingerprint images result :
Number of Fake images predict as Fake  =   339
Number of Fake images predict as Real  =   161
FALSE GENUINE RATE(FGR) = 0.322
FALSE FAKE RATE(FFR) = 0.272
HALF TOTAL ERROR RATE (HTER) = 0.297
>>
```

Figure 70: QDA Classification of 1000 Fingerprint Images Using 5 IQMs.

3. Linear SVM



```
end


%Mean Square Error
%MSE = 0;
%disp('1-Mean Square Error = ');
%disp(MSE);

%signal to noise ratio
SNR = SignaltoNoiseRatio(origImg, distImg);
%disp('6-signato to noise ratio = ');
%disp(SNR);

%Peak Signal to Noise Ratio
```

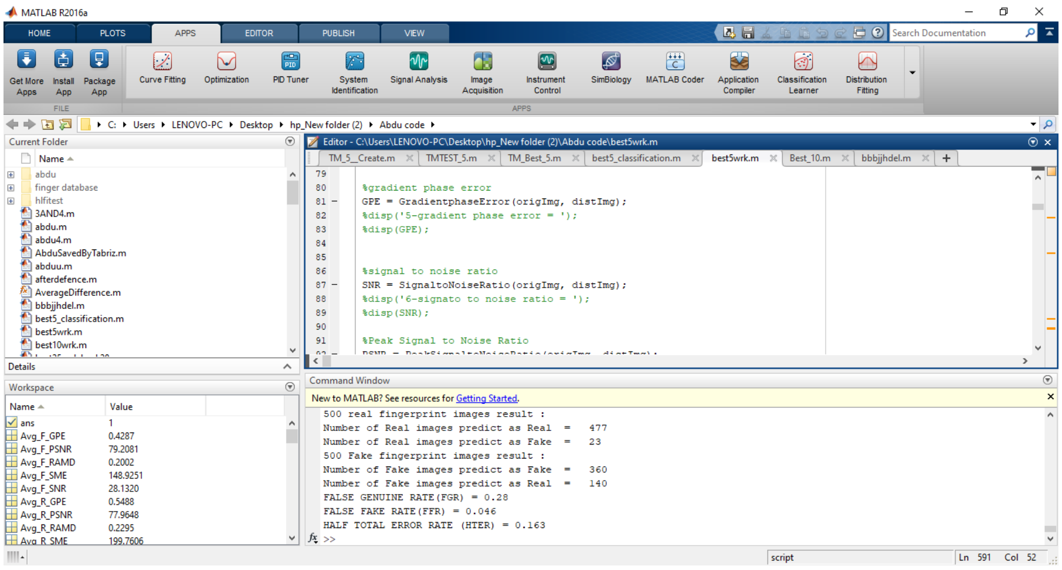
```
Number of Real images predict as Real  =   448
Number of Real images predict as Fake  =   52
Number of Fake images predict as Fake  =   333
Number of Fake images predict as Real  =   167
FALSE GENUINE RATE(FGR) = 0.334
FALSE FAKE RATE(FFR) = 0.104
HALF TOTAL ERROR RATE (HTER) = 0.219
>>
```

Workspace

Name	Value
ans	1
Avg_F_GPE	NaN
Avg_F_PSNR	NaN
Avg_F_RAMD	NaN
Avg_F_SME	NaN
Avg_F_SNR	NaN
Avg_R_GPE	0.5488
Avg_R_PSNR	77.9648
Avg_R_RAMD	0.2295
Avg_R_SME	199.7606

Figure 71: Linear SVM LDA classification result of 1000 fingerprint images using 5 IQMs.

4. Quadaratic SVM



```

%gradient phase error
GPE = GradientphaseError(origImg, distImg);
%disp('5-gradient phase error = ');
%disp(GPE);


%signal to noise ratio
SNR = SignaltoNoiseRatio(origImg, distImg);
%disp('6-signato to noise ratio = ');
%disp(SNR);

%Peak Signal to Noise Ratio
```

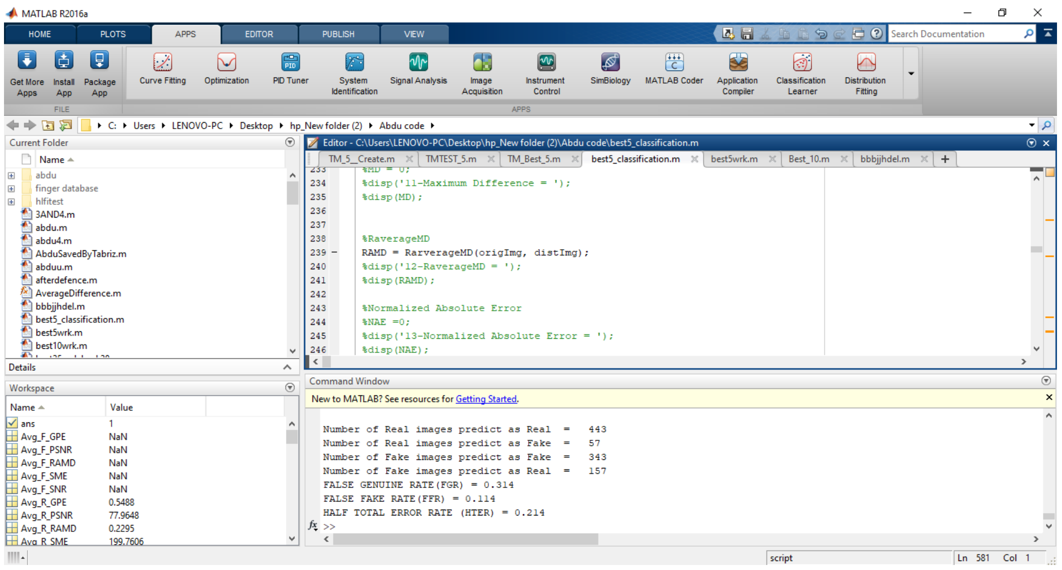
```
500 real fingerprint images result :
Number of Real images predict as Real  =   477
Number of Real images predict as Fake  =   23
500 Fake fingerprint images result :
Number of Fake images predict as Fake  =   360
Number of Fake images predict as Real  =   140
FALSE GENUINE RATE(FGR) = 0.28
FALSE FAKE RATE(FFR) = 0.046
HALF TOTAL ERROR RATE (HTER) = 0.163
>>
```

Workspace

Name	Value
ans	1
Avg_F_GPE	0.4287
Avg_F_PSNR	79.2081
Avg_F_RAMD	0.2002
Avg_F_SME	148.9251
Avg_F_SNR	28.1320
Avg_R_GPE	0.5488
Avg_R_PSNR	77.9648
Avg_R_RAMD	0.2295
Avg_R_SME	199.7606

Figure 72: Quadaratic SVM classification result of 1000 fingerprint images using 5 IQMs.

5. Fine KNN



```
%MD = 0;
%disp('11-Maximum Difference = ');
%disp(MD);

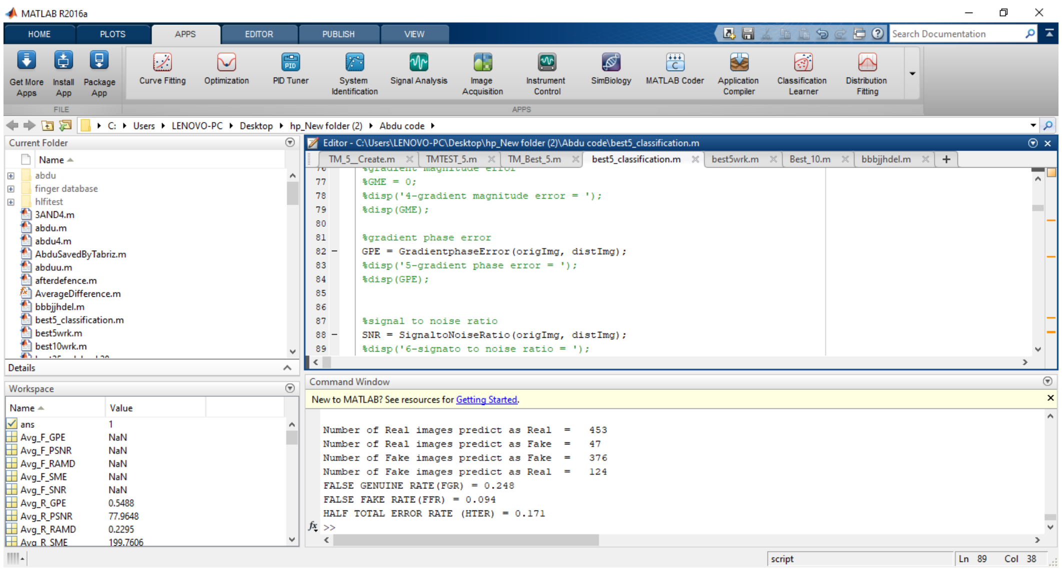

%RaverageMD
RAMD = RarverageMD(origImg, distImg);
%disp('12-RaverageMD = ');
%disp(RAMD);

%Normalized Absolute Error
%NAE =0;
%disp('13-Normalized Absolute Error = ');
%disp(NAE);
```

```
Number of Real images predict as Real  =   443
Number of Real images predict as Fake  =   57
Number of Fake images predict as Fake  =   343
Number of Fake images predict as Real  =   157
FALSE GENUINE RATE(FGR) = 0.314
FALSE FAKE RATE(FFR) = 0.114
HALF TOTAL ERROR RATE (HTER) = 0.214
>>
```

Figure 73: Fine KNN classification result of 1000 fingerprint images using 5 IQMs.

6. Logistic Regression



```
%GME = 0;
%disp('4-gradient magnitude error = ');
%disp(GME);

%gradient phase error
GPE = GradientphaseError(origImg, distImg);
%disp('5-gradient phase error = ');
%disp(GPE);


%signal to noise ratio
SNR = SignaltoNoiseRatio(origImg, distImg);
%disp('6-signato to noise ratio = ');
```

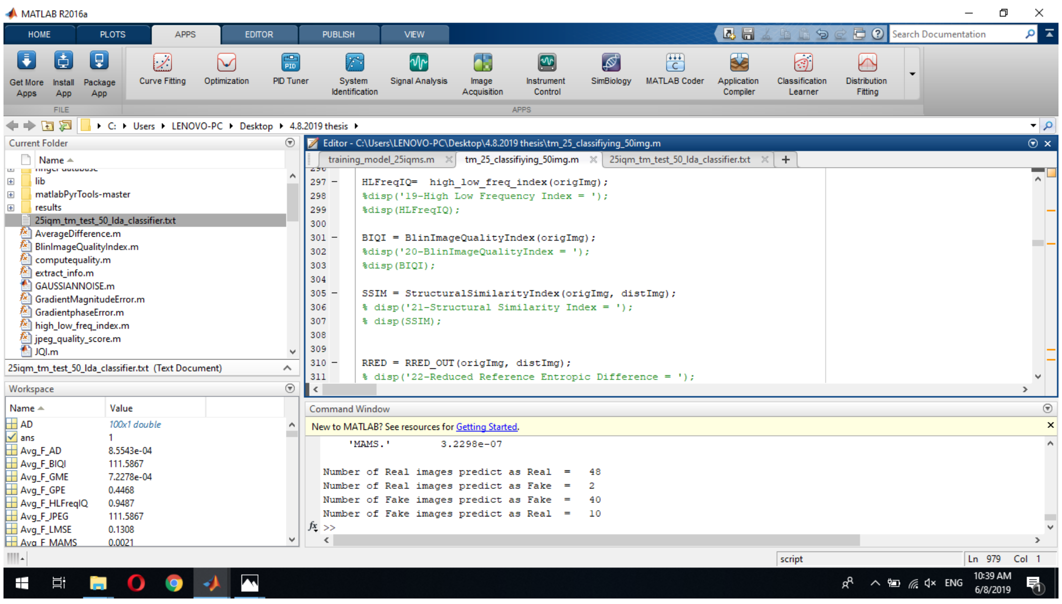
```
Number of Real images predict as Real  =   453
Number of Real images predict as Fake  =   47
Number of Fake images predict as Fake  =   376
Number of Fake images predict as Real  =   124
FALSE GENUINE RATE(FGR) = 0.248
FALSE FAKE RATE(FFR) = 0.094
HALF TOTAL ERROR RATE (HTER) = 0.171
>>
```

Figure 74: Logistic Regression classification result of 1000 fingerprint images using 5 IQMs.

7. Table and Screenshot of Training Results For 100 Fingerprint Images Using 25 IQMs:

100 Fingerprint Images With 25 IQMs Result Using 6 Classifiers:

1. LDA



Editor - C:\Users\LENOVO-PC\Desktop\4.8.2019 thesis\tm_25_classifiying_50img.m

```
HLFreqIQ=  high_low_freq_index(origImg);
%disp('19-High Low Frequency Index = ');
%disp(HLFreqIQ);

BIQI = BlinImageQualityIndex(origImg);
%disp('20-BlinImageQualityIndex = ');
%disp(BIQI);

SSIM = StructuralSimilarityIndex(origImg, distImg);
% disp('21-Structural Similarity Index = ');
% disp(SSIM);


RRED = RRED_OUT(origImg, distImg);
% disp('22-Reduced Reference Entropic Difference = ');
```

Command Window

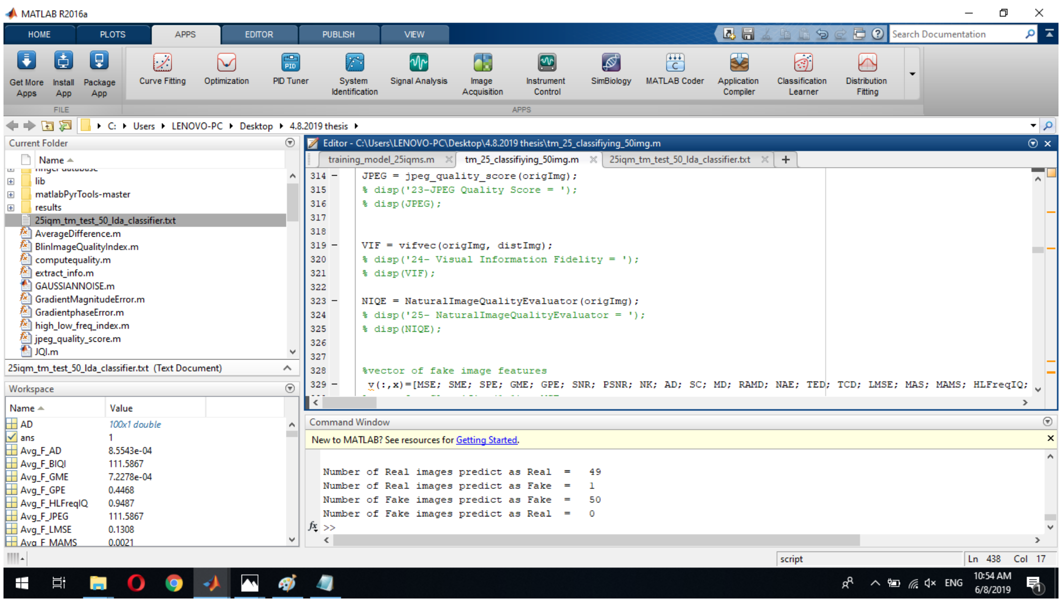
```
    'MAMS.'        3.2298e-07

Number of Real images predict as Real  =   48
Number of Real images predict as Fake  =   2
Number of Fake images predict as Fake  =   40
Number of Fake images predict as Real  =   10
>>
```

Name	Value
AD	100x1 double
ans	1
Avg_F_AD	8.5543e-04
Avg_F_BIQI	111.5867
Avg_F_GME	7.2278e-04
Avg_F_GPE	0.4468
Avg_F_HLFreqIQ	0.9487
Avg_F_JPEG	111.5867
Avg_F_LMSE	0.1308
Avg_F_MAMS	0.0021

Figure 75: LDA training result of 100 fingerprint images using 25 IQMs.

2. QDA



Editor - C:\Users\LENOVO-PC\Desktop\4.8.2019 thesis\tm_25_classifiying_50img.m

```
JPEG = jpeg_quality_score(origImg);
% disp('23-JPEG Quality Score = ');
% disp(JPEG);


VIF = vifvec(origImg, distImg);
% disp('24- Visual Information Fidelity = ');
% disp(VIF);

NIQE = NaturalImageQualityEvaluator(origImg);
% disp('25- NaturalImageQualityEvaluator = ');
% disp(NIQE);


%vector of fake image features
 v(:,x)=[MSE; SME; SPE; GME; GPE; SNR; PSNR; NK; AD; SC; MD; RAMD; NAE; TED; TCD; LMSE; MAS; MAMS; HLFreqIQ;
```

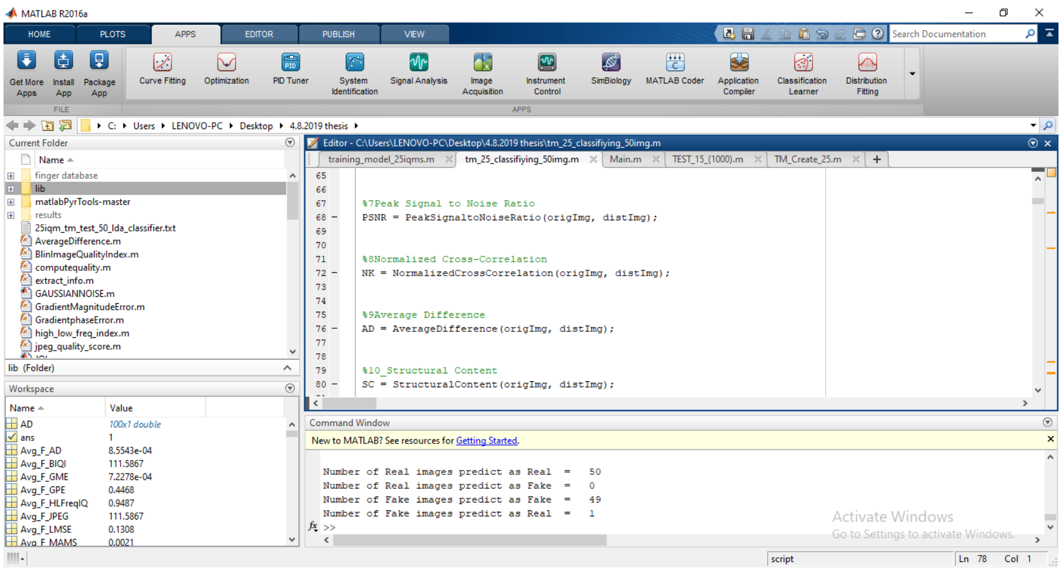
Command Window

```
Number of Real images predict as Real  =   49
Number of Real images predict as Fake  =   1
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
>>
```

Name	Value
AD	100x1 double
ans	1
Avg_F_AD	8.5543e-04
Avg_F_BIQI	111.5867
Avg_F_GME	7.2278e-04
Avg_F_GPE	0.4468
Avg_F_HLFreqIQ	0.9487
Avg_F_JPEG	111.5867
Avg_F_LMSE	0.1308
Avg_F_MAMS	0.0021

Figure 76: QDA Training Result of 100 Fingerprint Images Using 25 IQMs.

3. Linear SVM


Editor - C:\Users\LENOVO-PC\Desktop\4.8.2019 thesis\tm_25_classifiying_50img.m

```
%7Peak Signal to Noise Ratio
PSNR = PeakSignaltoNoiseRatio(origImg, distImg);


%8Normalized Cross-Correlation
NK = NormalizedCrossCorrelation(origImg, distImg);


%9Average Difference
AD = AverageDifference(origImg, distImg);


%10_Structural Content
SC = StructuralContent(origImg, distImg);
```

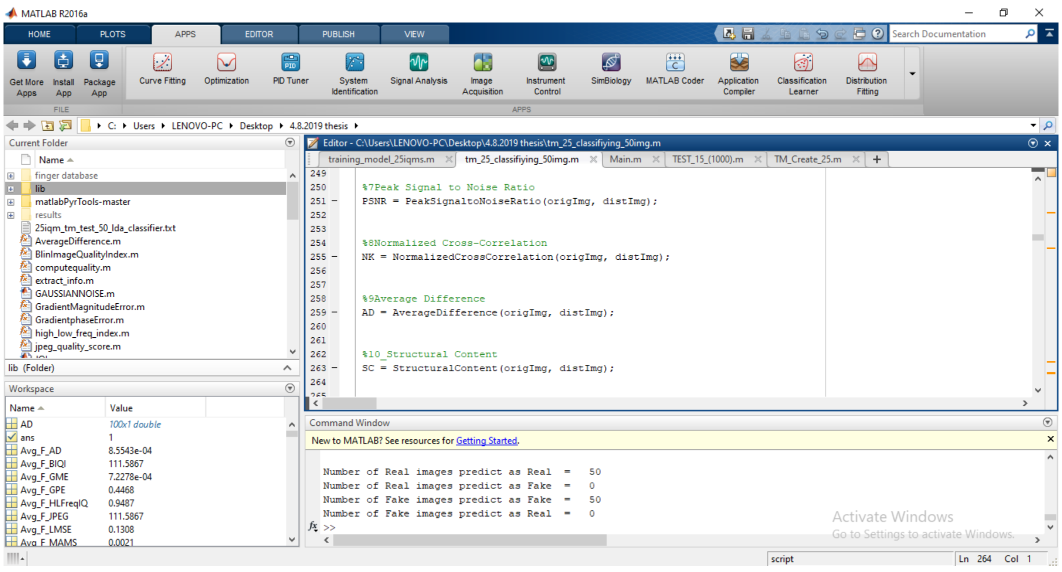
Command Window

```
Number of Real images predict as Real  =  50
Number of Real images predict as Fake  =  0
Number of Fake images predict as Fake  =  49
Number of Fake images predict as Real  =  1
>>
```

Name	Value
AD	100x1 double
ans	1
Avg_F_AD	8.5543e-04
Avg_F_BIQI	111.5867
Avg_F_GME	7.2278e-04
Avg_F_GPE	0.4468
Avg_F_HLFreqIQ	0.9487
Avg_F_JPEG	111.5867
Avg_F_LMSE	0.1308
Avg_F_MAMS	0.0021

Figure 77: Linear SVM training result of 100 fingerprint images using 25 IQMs.

4. Quadaratic SVM


Editor - C:\Users\LENOVO-PC\Desktop\4.8.2019 thesis\tm_25_classifiying_50img.m

```
%7Peak Signal to Noise Ratio
PSNR = PeakSignaltoNoiseRatio(origImg, distImg);


%8Normalized Cross-Correlation
NK = NormalizedCrossCorrelation(origImg, distImg);


%9Average Difference
AD = AverageDifference(origImg, distImg);


%10_Structural Content
SC = StructuralContent(origImg, distImg);
```

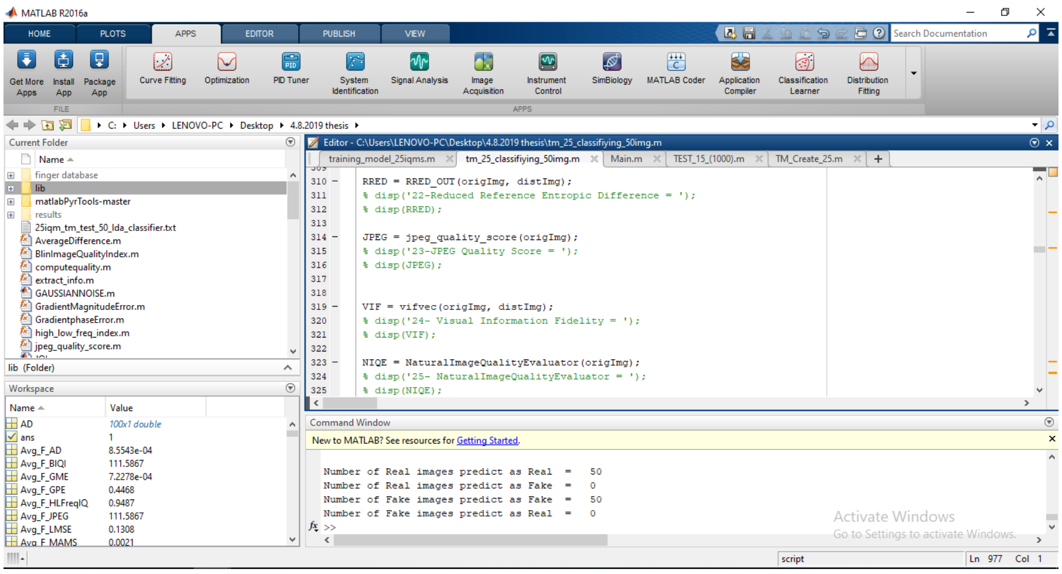
Command Window

```
Number of Real images predict as Real  =  50
Number of Real images predict as Fake  =  0
Number of Fake images predict as Fake  =  50
Number of Fake images predict as Real  =  0
>>
```

Name	Value
AD	100x1 double
ans	1
Avg_F_AD	8.5543e-04
Avg_F_BIQI	111.5867
Avg_F_GME	7.2278e-04
Avg_F_GPE	0.4468
Avg_F_HLFreqIQ	0.9487
Avg_F_JPEG	111.5867
Avg_F_LMSE	0.1308
Avg_F_MAMS	0.0021

Figure 78: Quadaratic SVM training of 100 fingerprint images using 25 IQMs.

5. Fine KNN



MATLAB R2016a

Editor - C:\Users\LENOVO-PC\Desktop\4.8.2019 thesis\tm_25_classifiying_50img.m

```
RRED = RRED_OUT(origImg, distImg);
% disp('22-Reduced Reference Entropic Difference = ');
% disp(RRED);

JPEG = jpeg_quality_score(origImg);
% disp('23-JPEG Quality Score = ');
% disp(JPEG);


VIF = vifvec(origImg, distImg);
% disp('24- Visual Information Fidelity = ');
% disp(VIF);

NIQE = NaturalImageQualityEvaluator(origImg);
% disp('25- NaturalImageQualityEvaluator = ');
% disp(NIQE);
```

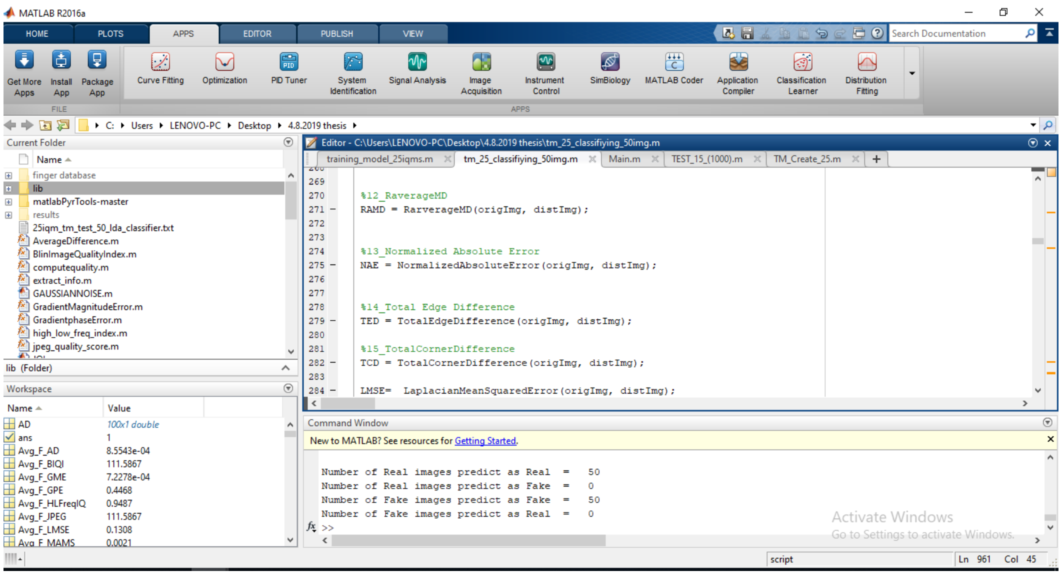
Command Window

```
Number of Real images predict as Real  =   50
Number of Real images predict as Fake  =   0
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
>>
```

Name	Value
AD	100x1 double
ans	1
Avg_F_AD	8.5543e-04
Avg_F_BIQI	111.5867
Avg_F_GME	7.2278e-04
Avg_F_GPE	0.4468
Avg_F_HLFreqIQ	0.9487
Avg_F_JPEG	111.5867
Avg_F_LMSE	0.1308
Avg_F_MAMS	0.0021

Figure 79: Fine KNN training result of 100 fingerprint images using 25 IQMs.

6. Logistic Regression



MATLAB R2016a

Editor - C:\Users\LENOVO-PC\Desktop\4.8.2019 thesis\tm_25_classifiying_50img.m

```

%12_RaverageMD
RAMD = RarverageMD(origImg, distImg);


%13_Normalized Absolute Error
NAE = NormalizedAbsoluteError(origImg, distImg);


%14_Total Edge Difference
TED = TotalEdgeDifference(origImg, distImg);

%15_TotalCornerDifference
TCD = TotalCornerDifference(origImg, distImg);

LMSE=  LaplacianMeanSquaredError(origImg, distImg);
```

Command Window

```
Number of Real images predict as Real  =   50
Number of Real images predict as Fake  =   0
Number of Fake images predict as Fake  =   50
Number of Fake images predict as Real  =   0
>>
```

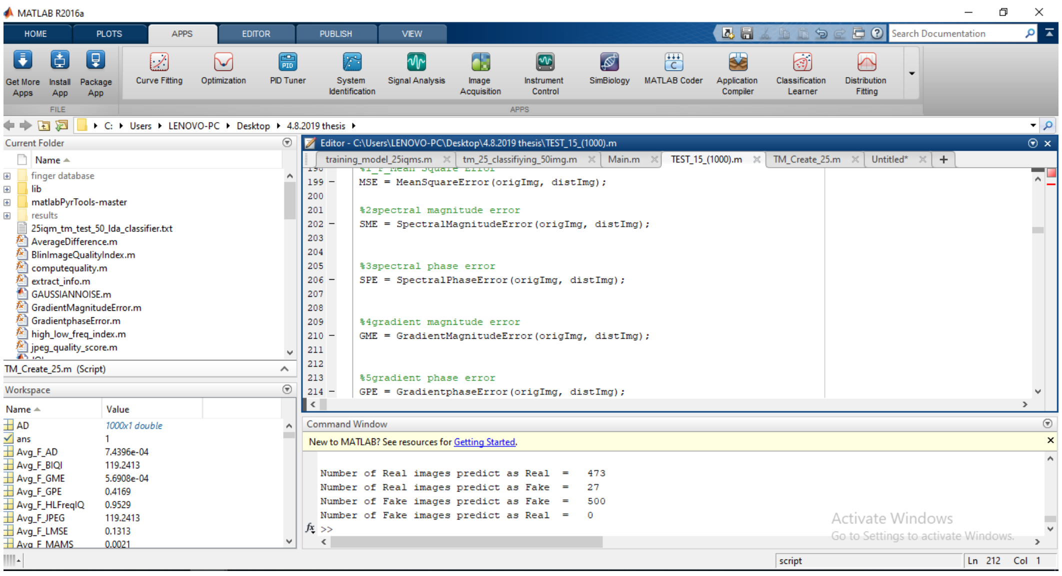
Name	Value
AD	100x1 double
ans	1
Avg_F_AD	8.5543e-04
Avg_F_BIQI	111.5867
Avg_F_GME	7.2278e-04
Avg_F_GPE	0.4468
Avg_F_HLFreqIQ	0.9487
Avg_F_JPEG	111.5867
Avg_F_LMSE	0.1308
Avg_F_MAMS	0.0021

Figure 80: Logistic Regression training result of 100 fingerprint images using 25 IQMs.

8. Screenshot of Classification Results For 1000 Fingerprint Images Using All 25 IQMs

1000 Fingerprint images with 25 IQMs result using 6 classifiers:

1. LDA



```
MSE = MeanSquareError(origImg, distImg);

%2spectral magnitude error
SME = SpectralMagnitudeError(origImg, distImg);


%3spectral phase error
SPE = SpectralPhaseError(origImg, distImg);

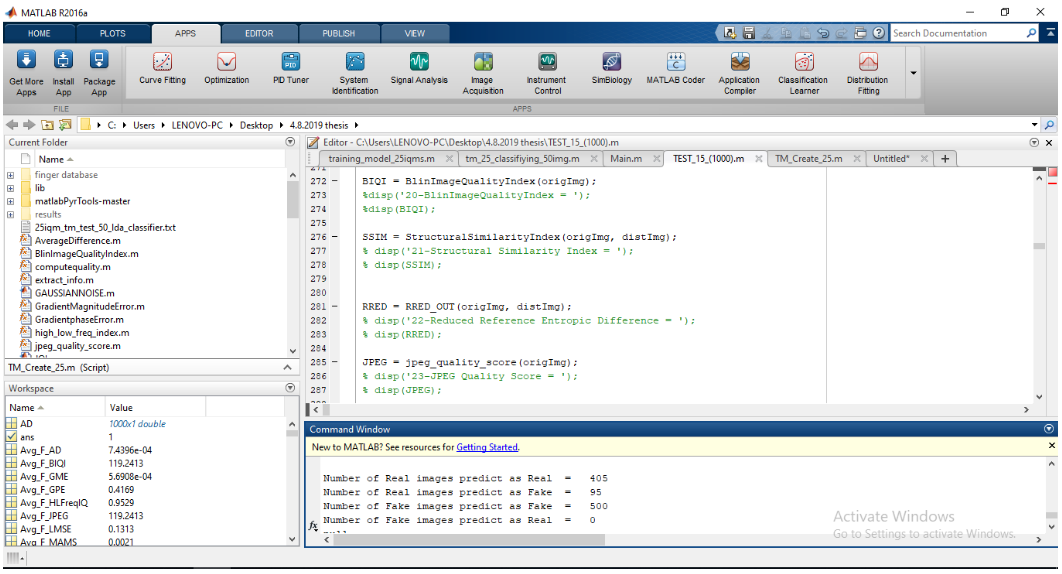

%4gradient magnitude error
GME = GradientMagnitudeError(origImg, distImg);


%5gradient phase error
GPE = GradientphaseError(origImg, distImg);
```

```
Number of Real images predict as Real  =   473
Number of Real images predict as Fake  =   27
Number of Fake images predict as Fake  =   500
Number of Fake images predict as Real  =   0
```

Figure 81: LDA classification result of 1000 fingerprint images using 25 IQMs.

2. QDA



```
BIQI = BlinImageQualityIndex(origImg);
%disp('20-BlinImageQualityIndex = ');
%disp(BIQI);

SSIM = StructuralSimilarityIndex(origImg, distImg);
% disp('21-Structural Similarity Index = ');
% disp(SSIM);

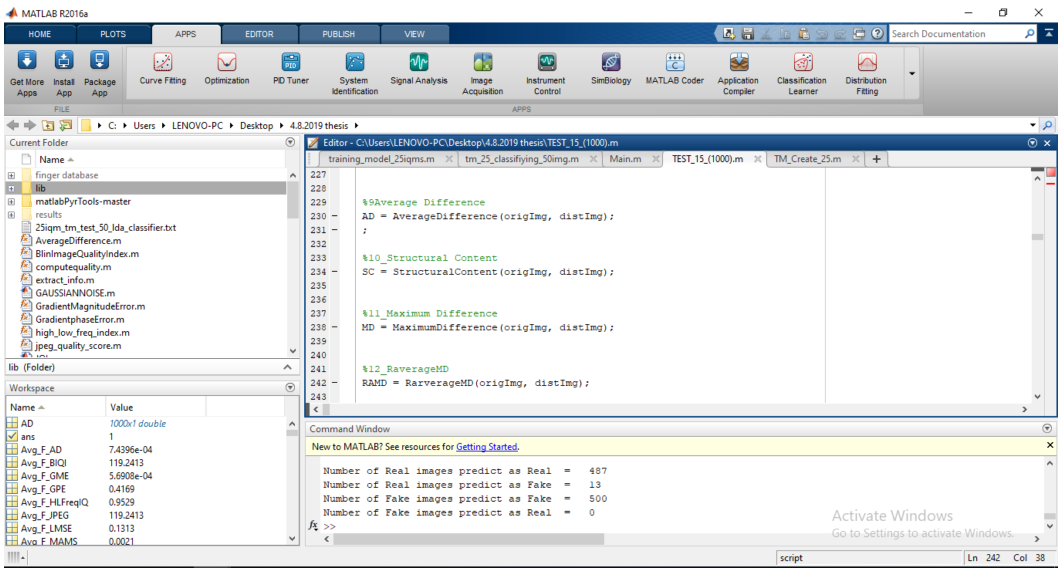

RRED = RRED_OUT(origImg, distImg);
% disp('22-Reduced Reference Entropic Difference = ');
% disp(RRED);

JPEG = jpeg_quality_score(origImg);
% disp('23-JPEG Quality Score = ');
% disp(JPEG);
```

```
Number of Real images predict as Real  =   405
Number of Real images predict as Fake  =   95
Number of Fake images predict as Fake  =   500
Number of Fake images predict as Real  =   0
```

Figure 82: QDA classification result of 1000 fingerprint images using 25 IQMs.

3. Linear SVM



```
%9Average Difference
AD = AverageDifference(origImg, distImg);
;

%10_Structural Content
SC = StructuralContent(origImg, distImg);

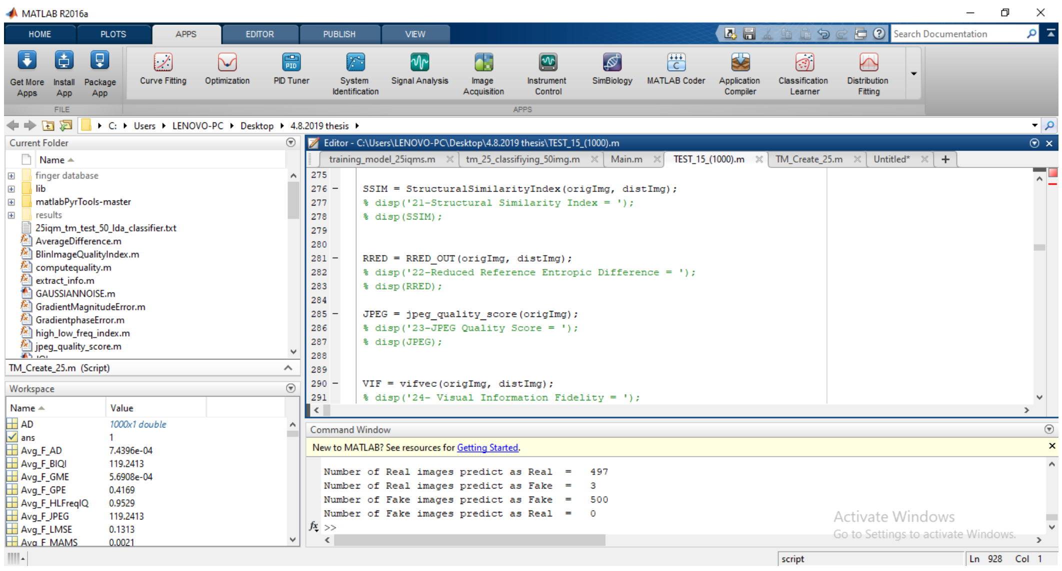

%11_Maximum Difference
MD = MaximumDifference(origImg, distImg);


%12_RaverageMD
RAMD = RarverageMD(origImg, distImg);
```

```
Number of Real images predict as Real  =   487
Number of Real images predict as Fake  =   13
Number of Fake images predict as Fake  =   500
Number of Fake images predict as Real  =   0
>>
```

Figure 83: Linear SVM classification result of 1000 fingerprint images using 25 IQMs.

4. Quadaratic SVM



```
SSIM = StructuralSimilarityIndex(origImg, distImg);
% disp('21-Structural Similarity Index = ');
% disp(SSIM);


RRED = RRED_OUT(origImg, distImg);
% disp('22-Reduced Reference Entropic Difference = ');
% disp(RRED);

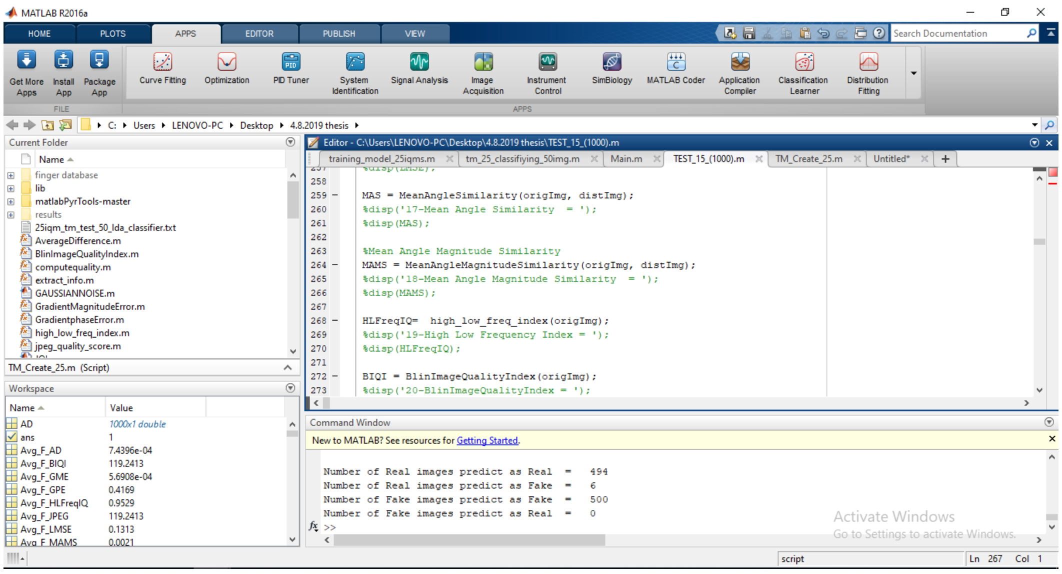
JPEG = jpeg_quality_score(origImg);
% disp('23-JPEG Quality Score = ');
% disp(JPEG);


VIF = vifvec(origImg, distImg);
% disp('24- Visual Information Fidelity = ');
```

```
Number of Real images predict as Real  =   497
Number of Real images predict as Fake  =   3
Number of Fake images predict as Fake  =   500
Number of Fake images predict as Real  =   0
>>
```

Figure 84: Quadaratic SVM classification result of 1000 fingerprint images using 25 IQMs.

5. Fine KNN



Editor - C:\Users\LENOVO-PC\Desktop\4.8.2019 thesis\TEST_15_(1000).m

training_model_25iqms.m | tm_25_classifiying_50img.m | Main.m | TEST_15_(1000).m | TM_Create_25.m | Untitled*

Current Folder: finger database, lib, matlabPyrTools-master, results, 25iqm_tm_test_50_lda_classifier.txt, AverageDifference.m, BlinImageQualityIndex.m, computequality.m, extract_info.m, GAUSSIANNOISE.m, GradientMagnitudeError.m, GradientphaseError.m, high_low_freq_index.m, jpeg_quality_score.m

TM_Create_25.m (Script)

Name	Value
AD	1000x1 double
ans	1
Avg_F_AD	7.4396e-04
Avg_F_BIQI	119.2413
Avg_F_GME	5.6908e-04
Avg_F_GPE	0.4169
Avg_F_HLFreqIQ	0.9529
Avg_F_JPEG	119.2413
Avg_F_LMSE	0.1313
Avg_F_MAMS	0.0021

```
MAS = MeanAngleSimilarity(origImg, distImg);
%disp('17-Mean Angle Similarity  = ');
%disp(MAS);

%Mean Angle Magnitude Similarity
MAMS = MeanAngleMagnitudeSimilarity(origImg, distImg);
%disp('18-Mean Angle Magnitude Similarity  = ');
%disp(MAMS);

HLFreqIQ=  high_low_freq_index(origImg);
%disp('19-High Low Frequency Index = ');
%disp(HLFreqIQ);

BIQI = BlinImageQualityIndex(origImg);
%disp('20-BlinImageQualityIndex = ');
```

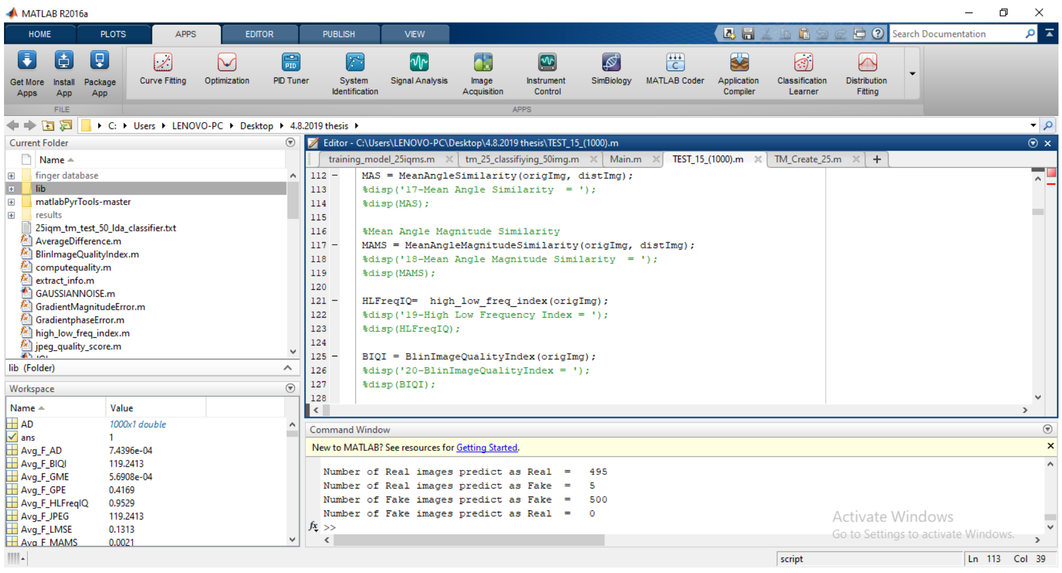
New to MATLAB? See resources for Getting Started.

```
Number of Real images predict as Real  =   494
Number of Real images predict as Fake  =   6
Number of Fake images predict as Fake  =   500
Number of Fake images predict as Real  =   0
>>
```

script | Ln 267 | Col 1

Figure 85: Fine KNN classification result of 1000 fingerprint images using 25 IQMs.

6. Logistic Regression



Editor - C:\Users\LENOVO-PC\Desktop\4.8.2019 thesis\TEST_15_(1000).m

training_model_25iqms.m | tm_25_classifiying_50img.m | Main.m | TEST_15_(1000).m | TM_Create_25.m

Current Folder: finger database, lib, matlabPyrTools-master, results, 25iqm_tm_test_50_lda_classifier.txt, AverageDifference.m, BlinImageQualityIndex.m, computequality.m, extract_info.m, GAUSSIANNOISE.m, GradientMagnitudeError.m, GradientphaseError.m, high_low_freq_index.m, jpeg_quality_score.m

lib (Folder)

Name	Value
AD	1000x1 double
ans	1
Avg_F_AD	7.4396e-04
Avg_F_BIQI	119.2413
Avg_F_GME	5.6908e-04
Avg_F_GPE	0.4169
Avg_F_HLFreqIQ	0.9529
Avg_F_JPEG	119.2413
Avg_F_LMSE	0.1313
Avg_F_MAMS	0.0021

```
MAS = MeanAngleSimilarity(origImg, distImg);
%disp('17-Mean Angle Similarity  = ');
%disp(MAS);

%Mean Angle Magnitude Similarity
MAMS = MeanAngleMagnitudeSimilarity(origImg, distImg);
%disp('18-Mean Angle Magnitude Similarity  = ');
%disp(MAMS);

HLFreqIQ=  high_low_freq_index(origImg);
%disp('19-High Low Frequency Index = ');
%disp(HLFreqIQ);

BIQI = BlinImageQualityIndex(origImg);
%disp('20-BlinImageQualityIndex = ');
%disp(BIQI);
```

New to MATLAB? See resources for Getting Started.

```
Number of Real images predict as Real  =   495
Number of Real images predict as Fake  =   5
Number of Fake images predict as Fake  =   500
Number of Fake images predict as Real  =   0
>>
```

script | Ln 113 | Col 39

Figure 86: Logistic Regression classification result of 1000 fingerprint images using 25 IQMs.