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CLASSIFICATION ALGORITHMS BASED ON RECOGNITION TO IMPROVE THE ACCURACY AND ERROR RATE

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Master's Thesis

Supervisor

Asst. Prof. Dr. Sefer KURNAZ

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This thesis titled CLASSIFICATION ALGORITHMS BASED ON RECOGNITION TO IMPROVE THE ACCURACY AND ERROR RATE prepared by ALI MUSTAFA SHAKIR and submitted on 9/08/2022 has been **accepted unanimously** for the degree of Master of Science in Electrical and Computer Engineering.

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I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Ali Mustafa AL-METWALI

Signature

DEDICATION

To my Parents, the reason of what I become today. To my sister & brothers. A special thanks to Asst. Prof. Dr. Sefer KURNAZ for his support, worth notes and close follow up.

ABSTRACT

CLASSIFICATION ALGORITHMS BASED ON RECOGNITION TO IMPROVE THE ACCURACY AND ERROR RATE

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Computer vision technology have a significant role in the human being's daily life due to, the expansion of visual surveillance system as well as the interaction systems between humans and computer machines. In the recent few years' gender recognition and identification get a vast amount of attention as a part of the computer vision systems. Biometric identification and recognition systems are becoming increasingly significant, due to its capable of providing more efficient and reliable abilities of identity verification based on many biometrical characters of a human beings such as fingerprints, face, eye, voice, iris, etc. conventional classification algorithms not recommended in with the biometrical systems since it has a large number of features that can help in classification and recognition of human beings. In this thesis two important biometrical charterers of human are used in order to accomplish the identification and recognition of human being. The facial images as well as, voice wave signals of persons are used in order to recognize the person whether it was a female or a male in this study. Three powerful classification algorithms are used in this study (NB, SMO, J48) and gives an accuracy more than 99% in both facial images and voice signals as well as the proposed work in this study considered to be fast in the concept of speed and the recognition of male from the female is performed in accurate manner.

Keywords: Gender Recognition, Preprocessing, Feature Extraction, Classification, Machine Learning

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ABBREVIATIONS

STD: Standard Deviation

STA: Short Term Autocorrelation

LPC: Linear Predictive Coding

DFT: Discrete Fourier Transform

MRA: Multi Resolution Analysis

CWT: Continuous Wavelet Transform

DWT: Discrete Wavelet Transform

MFCC: Mel Frequency Cepstral Coefficients

VQ: Vector Quantization

LDA: Linear Discriminates Analysis

KNN: K-nearest Neighbor

LVQ: Learning Vector Quantization

SMO: Sequential Minimal Optimization

NB: Naïve Bayes

MAE: Mean absolute error

RMAE: Root mean s

1. INTRODUCTION

In the last few years, biometrics methods that involve gender, age and ethnicity get a huge attention due to their ability in increasing the performance of the different application like access control, surveillance, and online advertisements. In the current inextricable world of visual systems and technologies gender identification of a person is a demanding and advanced research subject [1]. Various techniques have been developed in order to recognize person gender such as hand shape, voice, iris, face and gait style, therefore, researchers try to discover the most distinctive features for using it in gender recognition. Recognizing gender based on voice get the researcher's attention because it's considered as a type of the major common biometrics' features. The human individual's voice is unique in many aspects such as: prosodic, articulation, depth and the frequency which will be necessary in recognizing procedure. Facial images used and gained much interest in gender recognition and have many interesting in multiple fields like, machine learning society and computer vision due to the multiple features that exists around the eyes, mouth, and cheeks which can be vigorous declarative way of either it is a male or a female face [2].
This thesis presents a gender recognition system based on two important biometric features those human beings have. Voice and facial images are used to recognize male from female in this thesis. Machine learning technique are used after multistep performed on both voice signals and facial images of human to classify and recognize male from female in best accuracy and in minimum error rate as possible as can.

1.1 PROBLEM DIFINITION

Many and several problems rise when trying to build a human gender recognition system due to the large number of biometrics that the human has, so it will be difficult to choose which one will give an accurate result. The accuracy and the ability to recognize the male from the female problem is the most important one that gender recognition systems suffer from. The use of face images in recognition process has several problems due to illumination variations and facial expression changing in these images. Gender recognition system that based on human voice also has a number of limitations such as, background noise, instrumentation noise, the accuracy of recordings and the in a circumstance of recording; for instance, one of the samples could be a yelling and the other is whispering.

1.2 AIM OF THE STUDY

In this study, we aim to design as well as, building a robust gender recognition system based on two important biometrics for the verification purpose which adaptive by many online and offline applications. The main idea in this thesis is focused on building a system that uses to important biometrics that human being has to get a high result of accuracy in classification process and to get know and separate the male from the female in an easy way. The features in voice signal and face image will be used in this thesis to recognize the human gender because of the powerful features that these biometrics provide. The system uses the facial images to recognize the person as a second procedure to verify the person and get sure of his gender.

1.3 PREVIOUS WORKS OVERVIEW

Selvam, I.R.P et al. [3] in 2017, propose a system to identify the gender using face images by finding the face region location in which the inputted image is partitioned into blocks that are overlapped subsequently Gabor features will be extracted with dissimilar orientations and scales. The improved features are produced using serial of standard deviation, mean, and deviation of Gabor features which are attained from every block. The mentioned features will have passed and used within the classifier in order to perform the detecting of face regions. The reinforced local binary patterns are utilized in order to reproducer the person facial native features to recognize the gender. The selection as well classification of the distinctive features is performed using Ad boost algorithm to recognize the person weather it is as male or a female. The Face detection depending on Gabor features gives accuracy 98, 98.5 and 96.5% as well as, 97.08% accuracy is achieves with the reinforced local binary patterns attained for the classification of the person's gender. Yan, C. [4] in 2011, presents a new algorithm for gender recognition depending on facial images. The features extraction from the person face is accomplished using 2-D Gabor transform. To reduce the dimensions of Gabor, transform output new method is put forwards for accelerating the training of the SVM; at last recognizing the person's gender is accomplished within the SVM classifier. In spite of the low low-resolution and the large scales that the facial image that is used suffer from the performance of the individuals gender classification was good. Ghojogh, B. et al. [5] in 2018, present a fusion-based method for gender recognition that utilizes as input the facial images. First of all, the significant milestones of face is obtained using the preprocessing method as well as, a landmark detection technique. Afterword, four dissimilar frameworks are presented which are inspired by state-of-the-art recognition systems for gender. The first framework elicits features by the Principal Component Analysis (PCA) and Local Binary Pattern (LBP), and accomplish back propagation neural network. The next second framework utilizes Gabor filters, kernel Support Vector Machine (SVM), and PCA. Third framework uses lower sections of faces as input and uses kernel SVM to classify them. The Linear Discriminant Analysis (LDA) is used at the fourth framework to perform the side outline of the face's outlines classification. The final step, by using the weighted voting the four decisions of frameworks will be fused. The advantage of both geometrical and texture information is taken in this work. For this study, the two predominant kinds of information are obtained in facial gender recognition. The power and efficiency for this work are described in the experimental results in which recognition rate obtains 94% accuracy for neutral facial images', H. et al. [6] in 2008, presents a method for real-time gender recognition known as pixel-pattern-based texture feature (PPBTF) is. The inputted grayscale image is converted into a map of patterns where lines and edges to use them for characterizing the information texture. The basis of the pattern map is the Q44, the vector of feature contains the numbering of the pixels that owned by every pattern. The principal component analysis (PCA) is used for the basic functions of the image that attained as the pattern's equivalent templates. The feature properties are extensively analyzed to perform gender recognition by a unique application. For the selection of the most exceptional feature subset the Ad boost is utilized, and for the classification the support vector machine (SVMs) utilized. The experiential results shows that features obtained by PPBTF have more efficiency than the features acquired from Gabor in recognition time as well as, computing time also the accuracy that achieves in this work is above 90%.Buyukyilmaz, M. et al. [7] in 2016, present a deep learning model that named as Multilayer Perceptron (MLP) for recognizing and identify gender based on voice that utilizes a technique called backpropagation which it is supervised learning for training the network and include a set of input layers. To train the model Nadam optimization algorithm in Keras has been obtained. The presented work has a slow learning but it prevents from any missing due to, the choosing of minimum learning rate which equal to 0.001. On the testing dataset the model achieves accuracy equal to 96.74% Ghosal, A. et al. [8] in 2014 present an audio speech signal novel simple scheme that classify signals into speech of men and speech of women. The identification of person gender depending on the signal of the speech is a challenging task in the state of content-based multimedia indexing. Some famous important time-domain acoustic features with low level that are related very close to the physical characteristics of origin audio signal like, short time energy (STE) along with spectral flux, zero crossing rate (ZCR), a frequency domain feature with low level which are attained for this distinguishing. The classifier in this proposed work is RANSAC and Neural-Net. The strength of the features that presented in this work is highlighted in which the Neural-Net gives accuracy equal to 85.5% in another hand the RANSAC gives much better result in which the accuracy of classification rate is 92.5%. Herb, H et al. [9] in 2003 introduces a general audio classifier using a novel gender identification approach. The audio signals is classified using the presented classifier models which it works by the first arrangement spectrum's statistics in windows and utilizes for classification a group of neural networks. The classification results attain 92% accuracy.

Al Suleiman, M. et al. [10] in 2012 propose a technique that measures the voice intensity of the talking through computing the area that under the curve. The curve is attained by performing a normalizing procedure to the cubic polynomial prepared by the peaks. When dividing each frame of the utterance into parts of 20 milliseconds the peaks will be obtained. To compute the area that exist under the curve the Simpson's rule is utilizes and the SVM attain this region to classify the person genders. The classification rate of gender into male and female achieves 98.27%.

1.4 THESIS LAYOUT

In addition to the First Chapter, that provide an introduction about the proposed system that depends on two biometric feature of the human and what are the problem that we will face and the aim of this thesis in trying to solve these problems as well as, an acceptable number of previous works are presented, there is four chapters more that helps to get the goal of this thesis and organized as follow:

Chapter Two: which provide a whole review of the theoretical background of the introduced techniques and system in this thesis.

Chapter Three: will present a description about the developed system in this thesis in details and the utilized techniques and algorithms as well as, both of gender recognition systems that based on facial images and voice signals phases will be introduced.

Chapter Four: will exhibit the enforcement of the presented system of this thesis and execution environment will be introduce as well as, some performance measurements results is illustrated in this chapter and discussed.

Chapter Five: which presents the set of conclusions attained from the proposed system implementation and what are the recommendations for the upcoming work.

2. LITRITURE REVIEW

This chapter contains the overview of all the approaches and mechanisms which have been implemented in the proposed Multi-modal gender recognition based on human biometrics. In the last few years' human biometrics get an attention in the popular media and became an important element in the identification procedure. Biometrics handle with recognition of persons depending on their biological or behavioral properties they have.

2.1 HUMAN SOUND PRODUCTION MECHANISM

Sound is a form of energy which makes us hear. It travels in the form of wave. Rarefactions and compressions related to air molecules which come from the movement of the individual's anatomic structure because an acoustic pressure that denoted as sound. The primary parts related to the speech. Production system of the individual are the lips, teeth, tongue, hard palate (allow consonant articulation), velum or soft palate (permit the air to be passed via the nose), nasal cavity (nose), larynx or its major part vocal cords (responsible for voice production), trachea (windpipe) and the lungs (during speech, the lungs are the source of air). Articulators, is the term used for all these parts by speech experts, different sounds are produced when moving to different places. Sounds of speech could be divided to consonants, unvoiced and voiced bowels according to their production. Technically speaking, it is helpful to consider the system of speech production with regard to acoustic filtering operation which impacts the air originated from lungs. The main acoustic filter is comprised via three major cavities which are pharyngeal, oral and nasal cavities [11]. Forming the output of the system and changing its properties is caused by the articulators. Vocal tract is defined as the combination of these articulators and cavities, it is basic acoustic model is demonstrated in the figure below.

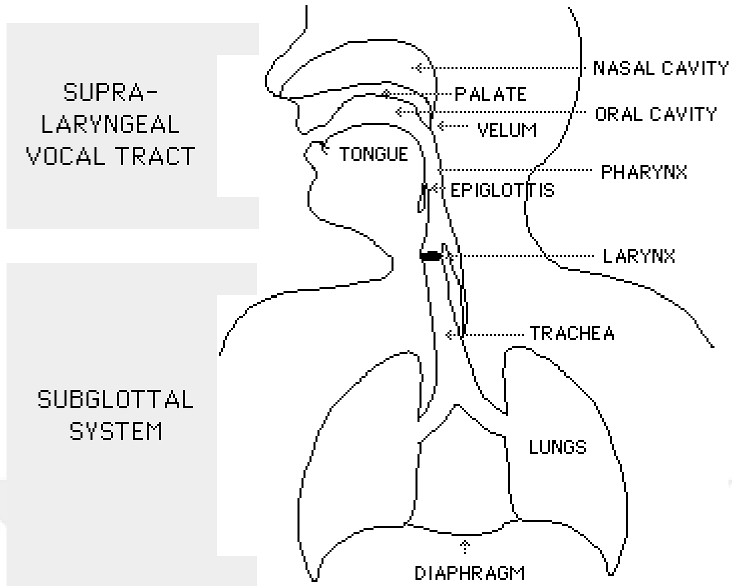

Figure 2. 1: Demonstration of The Model of Vocal Tract [11]

Based on their excitation mode, three different classed are used to classify speech sound [12]: -

I. Voiced sounds can be created via pushing the air past the glottis with the adjustment of vocal cords‟ tension in order to make them vibrate in relaxation oscillation, thus creating quasi-periodic air pulses that excite the vocal tract.
II. Fricative or un-voiced sounds are emanating when starting a pressure in the vocal tract (typically in the direction of the end of the mouth) and pushing the air through constriction at proper velocity for producing turbulence.
III. Plosive sounds triggered by the creation of an entire lock (usually towards the vocal tract), pressure after the locking and then sudden release. [13].

2.2 SOUND WAVE FEATURES

A viable collection of identifiable features is the key problem in the production of sound waves. There are usually two kinds of sound characteristics: both auditory and physical characteristics. Physical features mean that mathematical quantities are directly determined by the sound wave and detailed described in Figure 2.2.

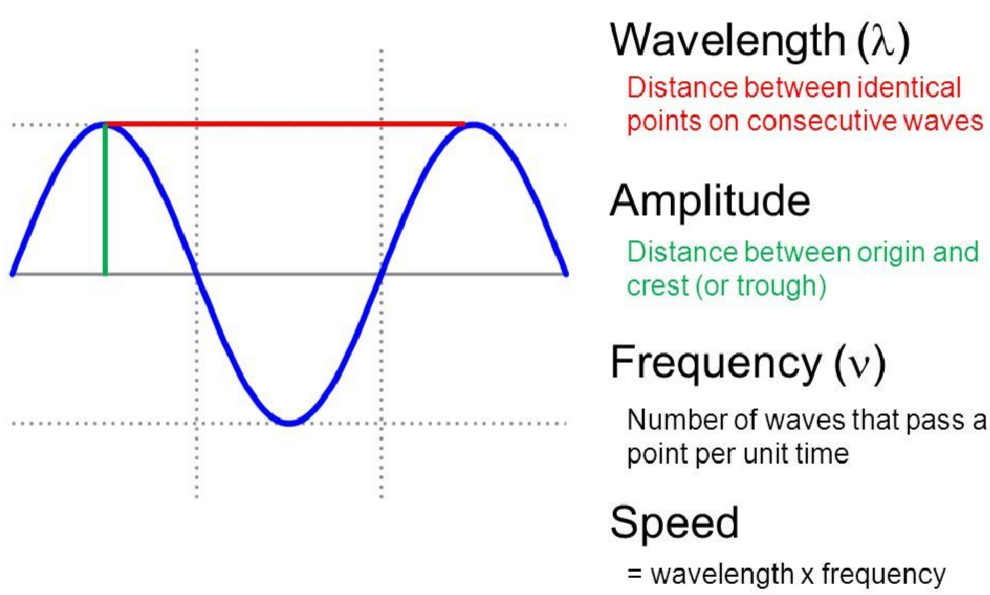

Figure 2. 2: The Physical Characters of Sound Wave

On the other side the perceptual features of sound wave are the subjective idioms that are related to the human being's perception sounds, which include [14]:

I. Loudness: used for describing how intense the sound is perceived, the loudness or volume is specifying based on the amplitude of a sound wave. A louder sound refers to larger amplitude, and vice versa the smoother sound means the amplitude have a small value.

II. Pitch: refers to the sense of the sound having a tone, what the ear understands and deals with is the sound wave's frequency. The high the frequency value was meaning the pitch is also high and the low pitch means the sound frequency is also low so the relationship is direct between the frequency and the Pitch values.

III. Timbre: it shows the nature of the sound, it is the quality of the sound and its shows how waves can have the same frequency and amplitude, but can have a different shape.

2.2.1 The Preprocessing of Sound Wave Signal

The preprocessing stage includes Sampling, Framing, and Windowing processes:

Sampling: The speech signal is sampled with suitable sampling rate to convert it from analog to digital. Giving the items an equal chance without bias is the intent of all sampling methods [15].
Framing: Because of the physical limitations, the shape of the vocal tract changes quite slowly as time goes by and have a tendency to be quite constant throughout short gaps (about 10–20 milliseconds). Therefore, a sensible approximation is to examine the speech signal to frames" sequence, as each frame will be signified via singular vector of feature depicting the average spectrum for short intervals. Each part of the signal will be multiplied by tapered windows before analyzing any frequency [16].
Hamming or Henning window: This kind of windowing is needed for reducing the discontinuity at the edges of particular region that might result in some issues for the analysis of the subsequent frequency via introducing spurious high frequency ingredients for the spectrum. For giving the needed time resolution, the length of all analysis window should be short, also the window should be long enough due to the analysis procedure is usually performed at a steady time interval, throughout the voiced speech so that it has no sensitivity to a specific position that related to the glottal cycle (i.e., there needs to constantly be leastwise one consummate glottal cycle in the fundamental partition of the window). The advantage of long windows is the smoothing out of some random temporal disparity that happens in unvoiced sounds like fricatives, but at the cost of blurring is expeditious events like the releases of the stop consonants [17].
In the applications of Speech Processing and Digital-signal processing, window techniques are widely applied. A mathematical function of zero- value outside the selected interval is considered as window function [18]. In the temporary domain, a point wise multiplication of the frame and the window function can be defined.
Describes the window. The hamming windows it the most utilized windows that is defined in the equation below [19]: Eq. (2.1)

$$x(n) = x(n)\, w(n) \qquad 00 \leq n \leq N-1 \tag{2.1}$$

A plot of the hamming windows is displayed in Figure (2.3). The window is proper selection for implementing windowing on the frames because of the smooth transitions at the start and the end of a window [20].

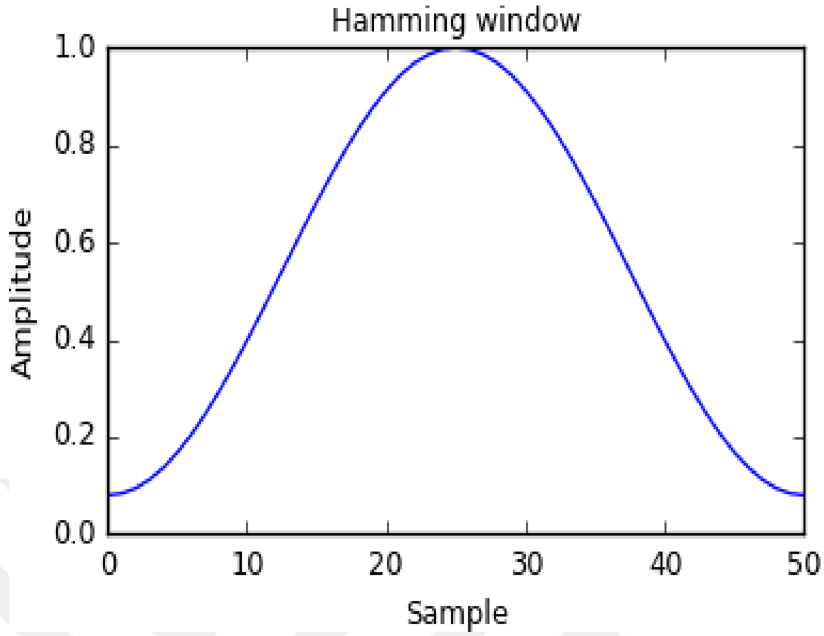

Figure 2. 3: Hamming Window

Restricting the start and end of the talk signal can be done using such strategies as for example:

I. Mean: It represents an average value between distinct collections of numbers that is group of variables that divided by the total numbers of variables. The arithmetic computations are nearly matching to the calculations of population's statistical data and the sample's mean, with insignificant differences in the utilized variables [21].

$$x' = \frac{1}{N}\sum_{i=1}^{N} xi \tag{2.2}$$

Where: -

x': - describe the mean

N: - refers to the numbers of variables,

Xi: - is the location of the element in the array.

II. Standard Deviation (STD): It is considered as a commonly utilized method for measuring the diversity or variability applied in probability and statistics theory. It displays the amount of variation occurs from mean (average). High standard deviation specify that data points are distributed over a wide range of values, while the low standard deviation indicates that data points are below the average. Standard Deviation (STD) of random variable, dataset, the statistical population or the probability distribution is considered as the square root of its variance [22]. The variance of data set can be attained by obtaining the arithmetic mean of squared distinction among the mean value and each value. It is algebraically plainer, yet not as much robust than average absolute deviation. A valuable feature of the Standard Deviation (STD) is that, in contrast to variance, it is represented in the same units as data. The standard sample difference and the mean of the sample in each frame is shown in the equations (2.3) and (2.5) [23].

$$x' = \frac{1}{N}\sum_{i=1}^{N} xi \tag{2.3}$$

Where: -

(n): - State the sample number in each of the frames.

Xi: - shows the signal value.

M': - is the Mean sample of the signal

2.2.2 Feature Extraction of Sound Wave Signal

The dimensionality of the measurement is decreased via the process of extraction the features through taking out the distinctive features, this process must be fast and easy to compute, and this process could operate in either frequency domain or in time-domain. Feature Extraction in Time Domain Short Term Autocorrelation (STA), Through the process of offering various time slowness for the series and calculated with the specific sequence like a reference, auto-correlation could be achieved [24] [25].

Linear Predictive Coding (LPC), For the storage and effective transmission, compressing the signal is a main requirement. To utilize channels effectively on the media that is wireless [26], the signal that its type is digital will be squeezed prior to the process of transmission. Linear Predictive Coding (LPC) is utilized average for the medium or low bitrate coder [27]. A power spectrum of the signal is calculated via Linear Predictive Coding (LPC) [28].

Entropy, the uncertainty of the random experiment's outcome is measured quantitatively by the process of Entropy. The uncertainty of entropy could be demonstrated via two examples [29]. One random experiment with high uncertainty result is throwing a fair dice, due to the fact that each side of the dice could turn up equally likely. Thus, the outcome will be high entropy (less certainty). At the same time, some random experiment is biased and offers the same result almost always, the outcome will be low entropy (more certainty). This approach of calculating the uncertainty of a random experiment is widened to discrete time random signal through notion of prediction. Shannon's entropy is suitable for metric for measuring information and organization sources of the signal [30].

Short-Time Energy, the energy that related to the short speech piece is referred to as the short-time energy. One of the most efficient and simple categorizing parameters for silent and acoustic segments is the short-time energy [31]. Also, identifying end-points of utterance is achieved via the energy [32].

Amplitude can be defined as the maximal displacement of points on a wave, which could be described as the amount or intensity of change. This maximal displacement is measured from the position of the equilibrium. The image bellow depicts an illustration of a sine wave. It depicts the amplitude and the wave-length, which is the distance between a couples of consecutive points on a wave. Wave-length is like the distance between a couple of neighboring peaks or valleys. In other words, wave-length is the time which is needed for completing a full wave cycle.

A sound's acoustic intensity or energy is directly associated to amplitude. Each of the intensity and the amplitude are related with the power of the sound [35]

$$s(t) * \cos wct = s(t) \cos wct \tag{2.4}$$

Where: -

(t): denotes the information carrier.

Cos wct: denotes a carrier wave and a sine wave (Cos ct).

The amplitude is determined by the force in a certain region. The Newton's / square meter (N/2) is an ideal public force unit that supports a learning audio region [36].

Feature extraction concerning speech in frequency domain includes transformation, the process of transformation might be described as the method of converting information from signal's spatial domain and translate it to another domain. This approach separates the approximation information (that characterize the intelligent information) from details (that comprises the noise), for example, Wavelet Transform (WT) and Fourier Transform (FT).

model was combined with the epochal features. Gradual spectral variations are captured using 12 Mel Frequency Cepstral Coefficients (MFCCs) obtained from speech signal. The speech signal is separated to frames by length of sentence, as each of the frames is overlapped by 50 ms with the neighboring frame [42]. 12 cepstral frequency (MFCC) functions are obtained for each frame. The Hamming Fenster is superimposed on each frame section to reduce the spectral distortion at the end and the start of each structure. From these photos, the features of Mel Frequency Cepstral Coefficients (MFCC) are achieved by using the MFCC algorithm. Cutting the cepstral mean and the normalization variance of Mel frequency cepstral coefficients (MFCCs) at utterance level counteract record variations. The graph of the feature obtaining and retrieving and transforming proposed is shown in Figure (2.4) [43].

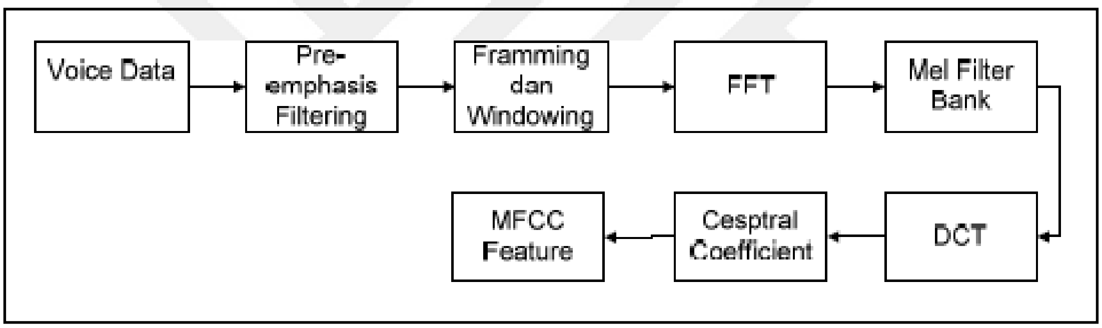

Figure 2. 4: The Block Diagram of the Mfcc Processor [44]

There are various implications in the process of altering the illustration of dimension from one (scalar) to multiple (vectors). To begin with, vector quantization doesn't inevitably resemble rounding the values of data to coarse levels. Indices are produced by the vector quantization step, these indices representing the vector produced via grouping the samples. The output integer index has no or slight physical association with the vector that it represents, which is produced through grouping complex or real valued samples. Identical vectors are being represented by using the same index is the source of the word "quantization" in vector quantization term. So, a large number of separated vectors that are on multi-dimensional space are being specified to a single vector which is showed through the index. Every one of these indexes resembles a formerly-decided vector. Therefore, the number of quantization levels is defined by the number of separate indices. Reasonably, it is possible to say that the quantization index of data vector must be chosen based on the closest vector in the set of the vectors that are formerly-decided (that is referred to as Vector Quantization (VQ) codebook) [46].

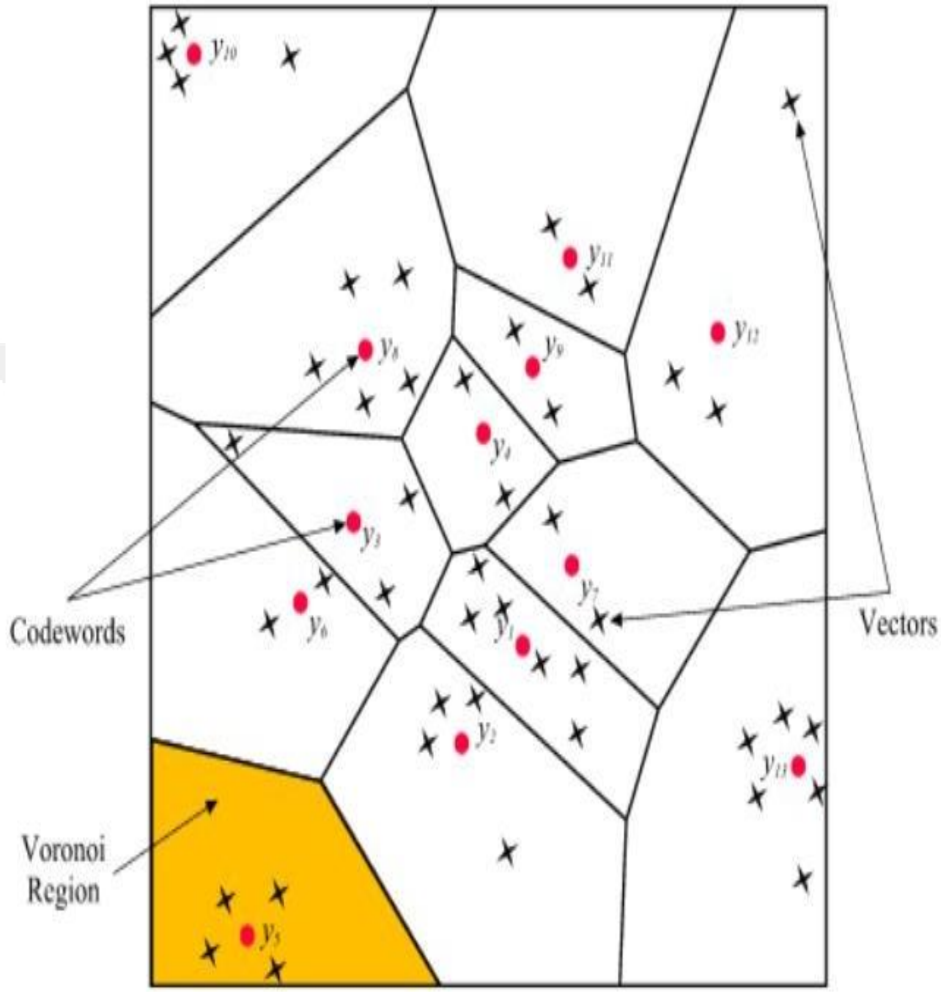

Figure 2. 5: The code words in a 2-D space. (X) Are the entered vectors, (red circles) is the words, and the boundary lines for isolating the Voronoi regions

2.2.3 Voice Feature Selection

It is also known as attribute selection or selection of variable [47]. Information gain is one of the most popular features choosing methods to analyze sentiment, which computes the quantity of information that achieved after being aware of the feature's worth. The following equation demonstrates the large information gain that is utilized to differentiate between several classes:

$$H(C) = -\sum^{m} p(c_i) \log_2 p(c_i) \qquad (2.5)$$

The m represents the number value of classes: C = {c1, c2, cm}, and P (ci) is the probability of the number of documents in the class ci [29].

2.3 HUMAN FACIAL IMAGES

As well as Facial images of human beings are very important and can be used to give an accurate recognition and identification results due to the large number of details and features that can be provided from it [48].

2.3.1 Facial Image Preprocessing

The pre-processing operation involves: transformation the facial images from the colored image to the one with a greyscale coloring space, enhancing the facial image by adjusting the contrast through histogram equalization, and finally, the improved facial images will be taking a new resizing measurement from 320x240 to 20x20 pixels in order to compensate for the different resolution across the databases. Facial images Feature Extraction, the Feature selection and obtaining is a distinctive term of dimensionality stenography. The conversion of input data into a collection of features is named as feature extraction. Large numbers of algorithms are utilized for this process as well as, a set of acceptable filters are obtained for feature extraction such as median filter [53], Gabor filter which they are attained in order to extract the features without noise and distortion mean.

2.4 CLASSIFICATION ALGORITHMS OVERVIEW

Predicting a particular outcome according to a specified input is what classification means. For predicting the outcome, a training set is processed by the algorithm, this set contains a group of attributes and the respective outcome, is typically referred to as the prediction attribute or the goal. The algorithm attempts to determine relations between the attributes which might make predicting the outcome possible. Afterwards, a set of data which have not been seen before they will be given to the algorithm, referred to as the prediction set, that involves the same group of attributes, apart from the prediction attribute which is not yet identified. The input is analyzed by the algorithm, then the algorithm will produce a prediction. The efficiency of the algorithm is defined by the accuracy of prediction [56].

3. METHODOLOGY

Gender recognition is important in human being’s social life, in this chapter all the procedures and processes that have been used and applied to get a successful gender recognition system depending on both person’s voice and facial images. The algorithms, an explanation of each step and why it's crucial to achieve the aim, numbers, and a full description of all the stages that have been employed in the proposed gender recognition system will be presented.

3.1 PROPOSED GENDER RECOGNITION SYSTEM DESIGN

Proposed system design is essential to attain thesis goal in recognizing the male from the male due to its importance in many applications nowadays. The proposed gender recognition system recognizes and classify gender basically deals and based on two important biometrics features in human which include voice signal and facial images Figure (3.1), which presents the suggested system of the block diagram design for the speech signals dataset, illustrates this. A dataset of male and female voice signals as well as, the suggested method takes input from face pictures. The results of the gender recognition are obtained using the two data sets, which are then compared for verification purposes. Figure (3.2) show the proposed gender recognition followed steps that based on facial images as well as figure (3.3), exhibit the resulted recognition procedure from both facial images and voice signals in order to compare them to perform the verification process.

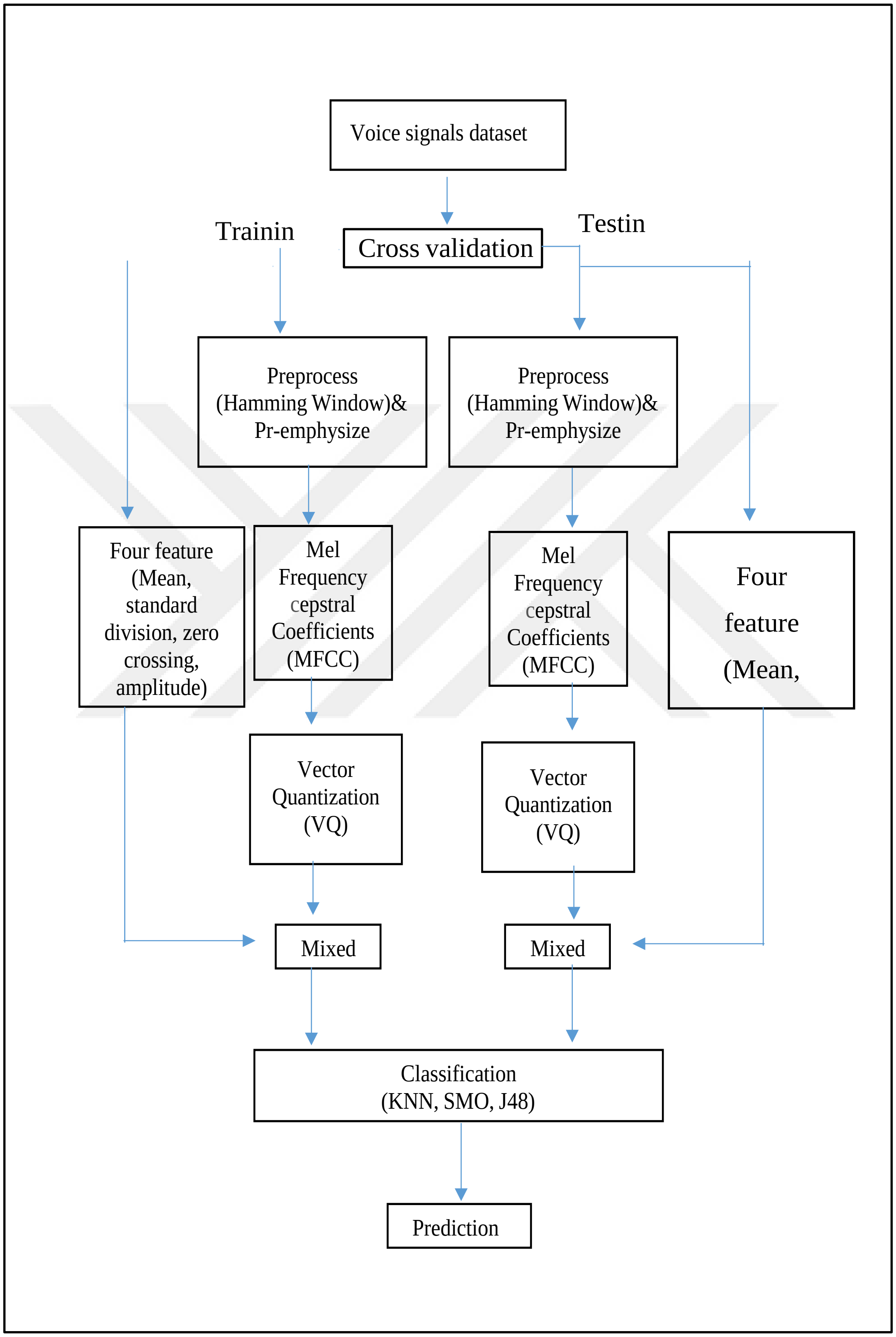

Figure 3. 1: Gender Recognition System Based on Voice Signals

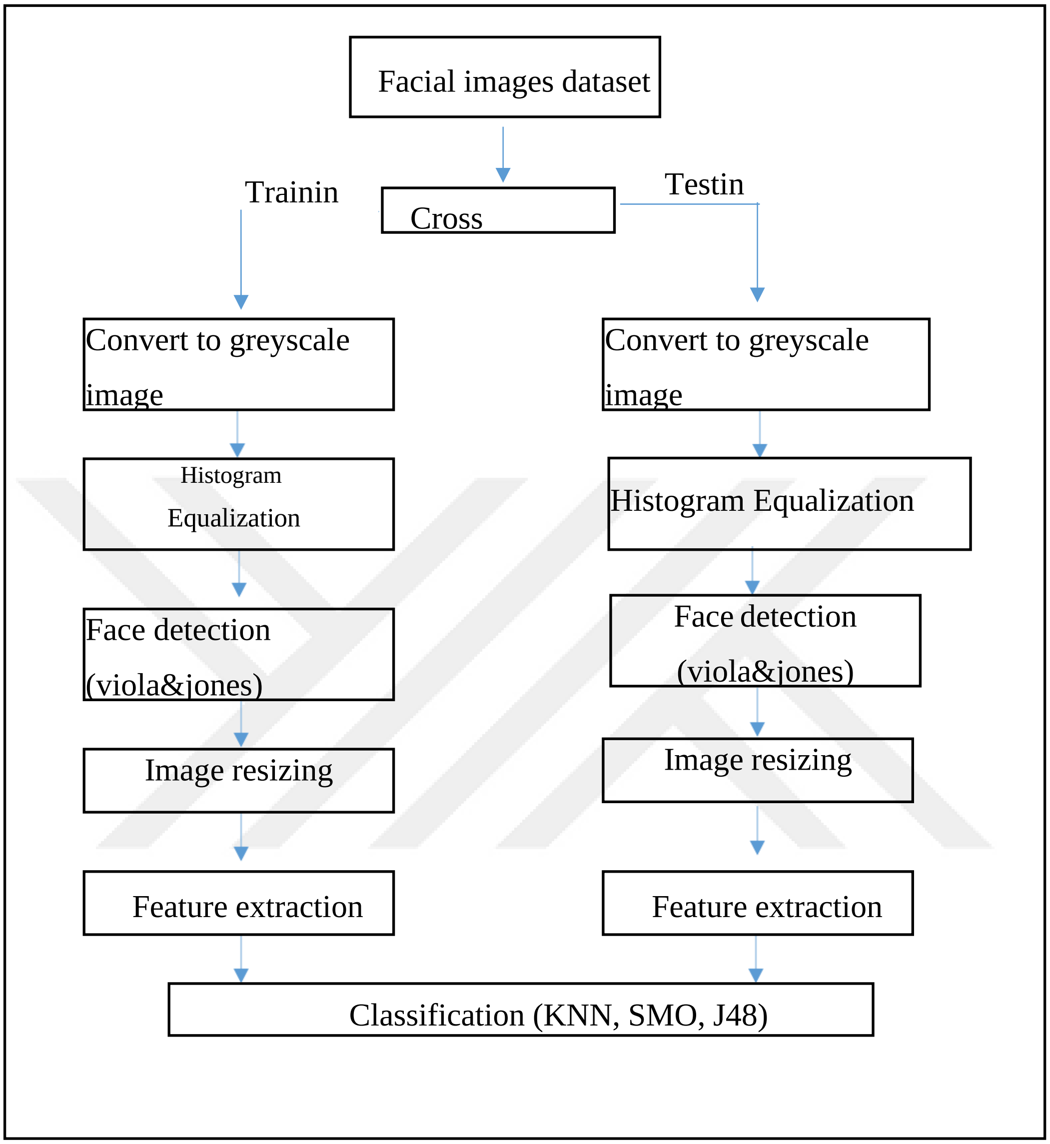

Figure 3. 2: Gender recognition system based on facial images

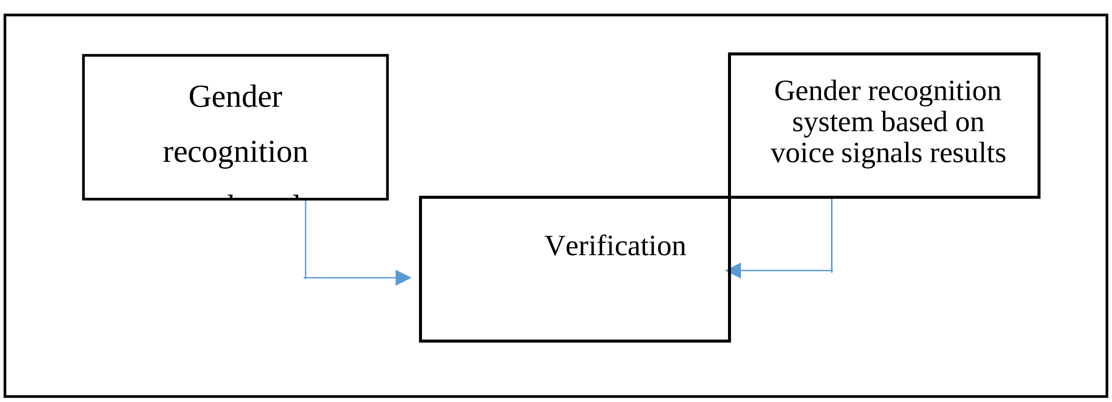

Figure 3. 3: Verification proposed system block diagram

3.2 VOICE AND FACIAL IMAGES DATASET

The utilized dataset in this thesis for gender identification that depends on voice signals and facial images will be describe in this section. The voice signals that used in this thesis to recognize male from female consist from two folders one for male voice signals and the other for female. Each folder contains a set of voice signals which used in the proposed gender recognition system based on voice signal, in which the one of male folder contain 1138 voice signal and the female folder have 1132 inside it which can be found in [71]. This dataset of voice signals for both male and female will be used in the proposed system, and will be pass across multi levels and through many algorithms to attain a superior result in gender recognition. 946 colored face photos of both men and women were included in the data set utilized for gender identification. The facial image dataset will undergo multiple changes in order to be used in the proposed gender recognition system, which is based on 946 images that were obtained from [72]. The datasets that is used in both voice, and facial images are completely balanced, since both the training and the test set are composed of equal numbers of samples.

3.3 K-FOLD CROSS-VALIDATION

Voice signals and face picture data are randomly divided into k almost equal-sized test and train partitions that are mutually exclusive. To choose the hypothesis that will be tested on the partition itself, only the cases that are not present in the test partition are used. The cross-validated error rate is the mean value of the error across all k partitions.

Algorithm (3.1): K- fold cross validation

Input: word processing file

Output: divide the data into learning and test sets.

Initial:

For I = 1 To K

Calculated the prediction error of fitted M when predicting the I of the data

Next I

End

3.4 GENDER RECOGNITION SYSTEM BASED ON VOICE SIGNALS

The Automatic detecting the speaker gender possess multiple potential applications that are important in human being's life. This part of thesis illustrates all procedures and steps performed on the voice signals data set to make them appropriate for the classification processes and algorithms in order to make the gender recognition success and provide the ability to separate the male from the female using only their voice signals.

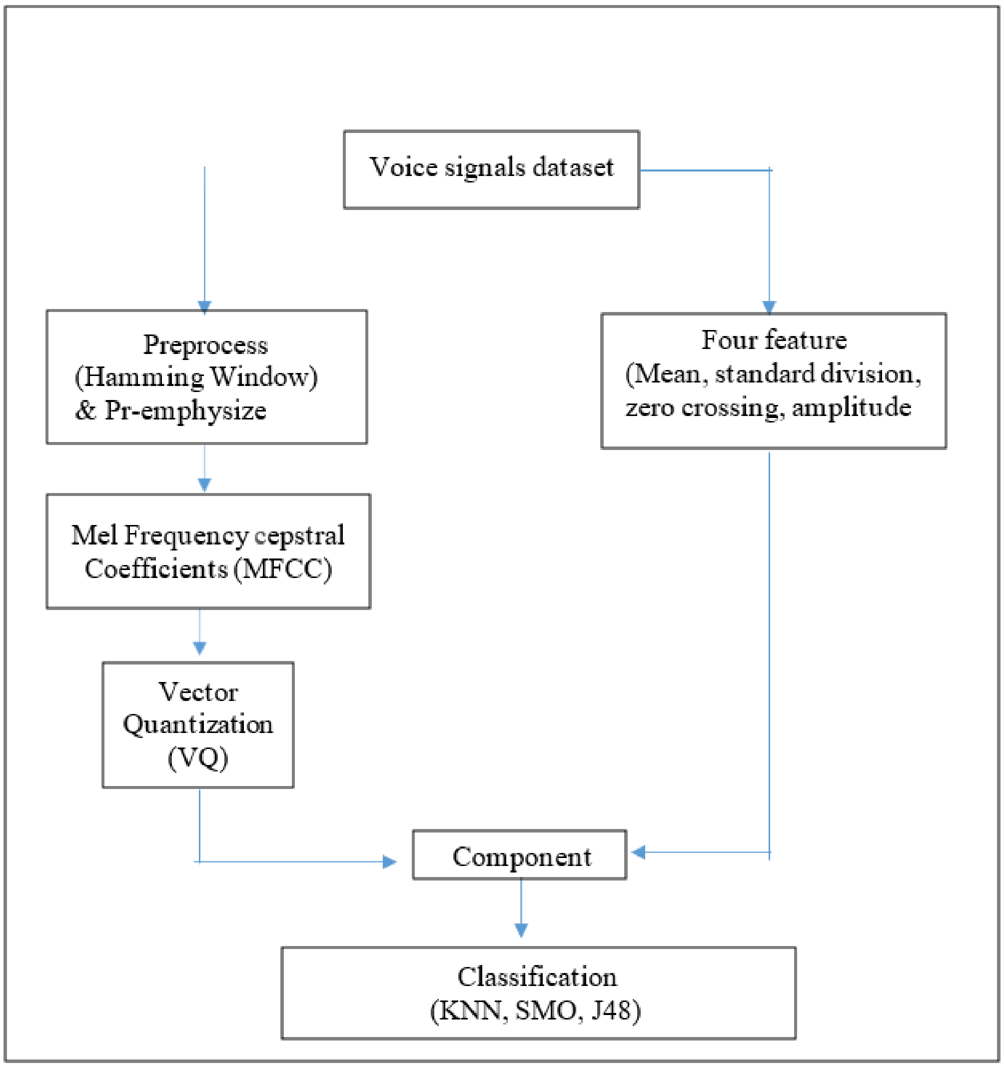

Figure 3. 4: The followed steps in both training and testing phase in voice recognition system

3.4.1. Voice Signals Preprocessing Phase

One major benefit of the preprocessing stage is that it helps organize the data in a way that makes the recognition task easier. Preprocessing is the term used to describe all actions taken on audio signals, and it will be thoroughly explained.

Hamming Window, it is used for the purpose of deleting noise from the data set, used in the system and was one of the important stages in this field before the extraction of the characteristics of the data used

3.4.2 Voice Signals Feature Extraction

The feature extraction process is worked on both testing and training groups and offers a set of features by following some steps on the voice signal. Feature extraction in ASR is calculating a set of vectors of feature that offers a tight impersonation of a certain signal of a speech.

I. Mean This is the second of the methods used to feature extraction the characteristics of the data and one extract was extracted and merged with Mel Frequency Cepstral Coefficients (MFCC). The results were introduced in several algorithms to show the correspondence between the sounds.

II. Standard Deviation This is the third of the methods used to extract the properties of the data set. One extract was extracted and merged with the Cepstral frequency Coefficients (MFCC) results. The results were introduced in several algorithms to show the correspondence between the sounds.

III. Amplitude It is third of the methods used to feature extraction the characteristics of the dataset, one extract was extracted and merged with Mel Frequency Cepstral Coefficients (MFCC). The results were introduced in several algorithms to show the correspondence between the sounds.

IV. Zero Crossing It is fourth of the methods used to feature extraction the characteristics of the dataset, one extract was extracted and merged with Mel Frequency Cepstral Coefficients (MFCC). The results were introduced in several algorithms to show the correspondence between the sounds.

V. Mel Frequency Cepstral Coefficients (MFCC) It is a main method in the thesis was compared with four tools that are used to feature extraction of the data used the first 12 feature coextraction, which are specific to the sound and merged the results feature extraction from the above four feature extraction with the results extracted from Mel Frequency Cepstral Coefficients (MFCC).

VI. Vector Quantization (VQ) It was attained to convert the binary matrix generated from MFCC to a one row matrix until it was collected with the resulting matrices from the other tools. The result of this collection process is to enter several matrices to extract the best accuracy

3.5 GENDER RECOGNITION SYSTEM BASED ON FACIAL IMAGES

The proposed recognition system for person's gender is a paradigm of a biometric consistency which, accomplishes the techniques of recognition of the pattern depending on human facial images. Facial images recognition system consists of four phases. These are:

3.5.1 Facial Images Training and Testing Stage

The training of the dataset, which will be generated from the cross validation as in the speech signal that was previously mentioned, is the first stage of the gender realization system that is now being presented and that depends on a dataset of face photos. The second stage of the system proposed is the test phase which processes the remaining face images, which also result from the cross-validation process. The training and testing facial images datasets will pass across multi phases which include preprocessing by converting them into grey scale and contrast enhancement and then viola and jones algorithm will be applied for face discovery after all the resizing of image will be performed and then, feature extraction phase will be applied .The values that introduced from these phases that performed previously on the facial images datasets will be prepared for the classification using the algorithms (KNN, SMO, and J48) such as in voice signals dataset.

3.5.2 Facial Images Preprocessing Phase

The requirement for the preparation step arises from the requirement for the entered photos to be upgraded and infectious, as well as from the preprocessing improving. The input image removes any extraneous information from the subsequent phases of the willingness value. Three stages are the ingredients of the image preprocessing phase that includes: scaling the picture, histogram equalization, viola & jones face detection, and creating a grayscale version of the entered image. The suggested preprocessing technique is depicted in Figure (3.5).

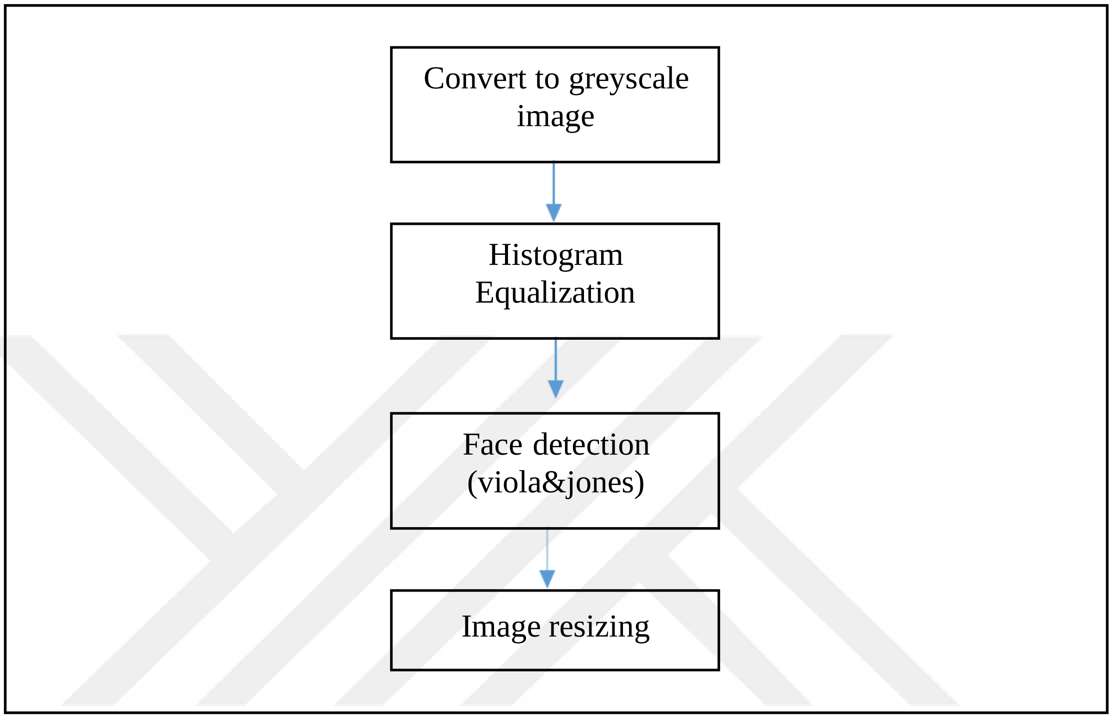

Figure 3. 5: The block diagram of proposed pre-processing method

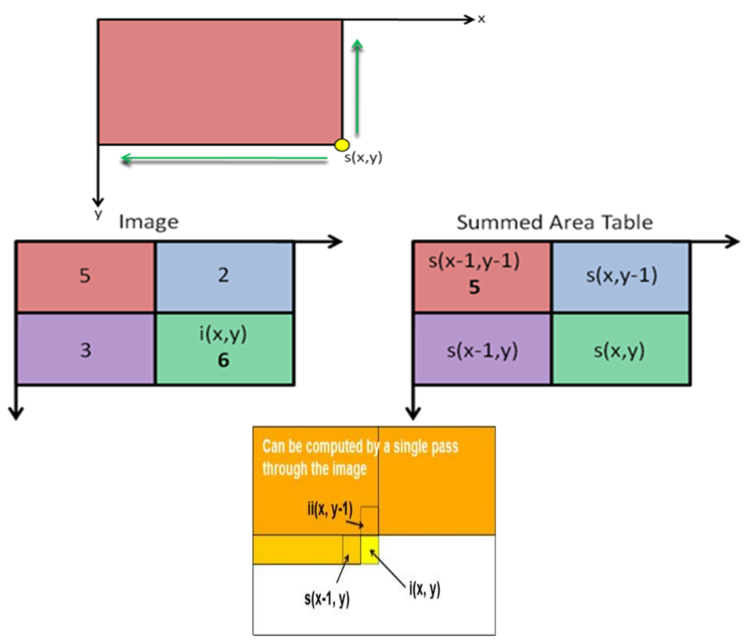

Figure 3. 6: Image of Integral Value

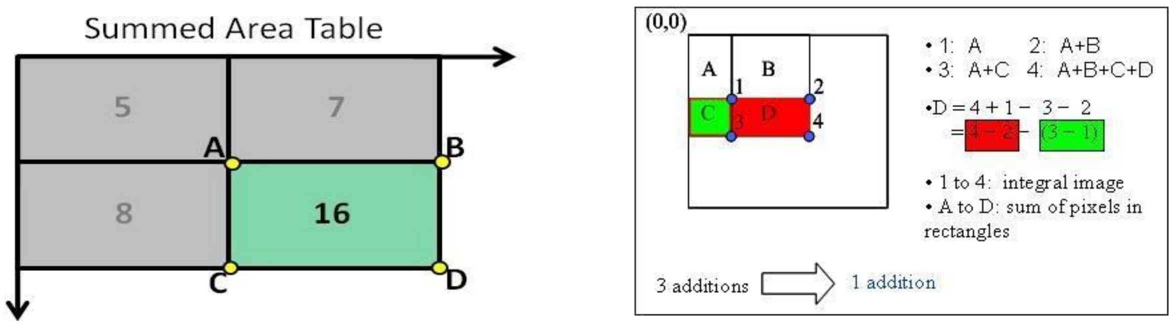

Figure 3. 7: Calculation of Integral Image

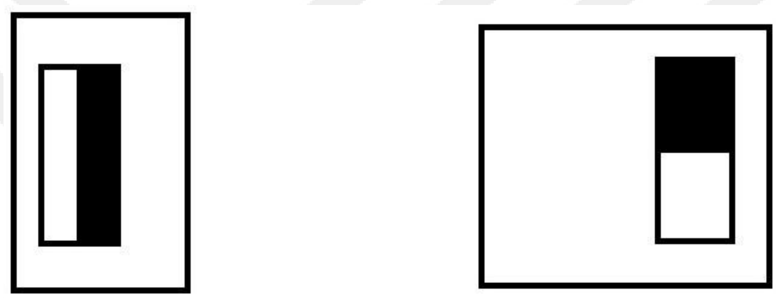

Figure 3. 8: Calculation of Haar Like Features (The Pixels Sum Lying Inside the White Rectangle Are Subtracted from Pixels Sum in The Grey Rectangle)

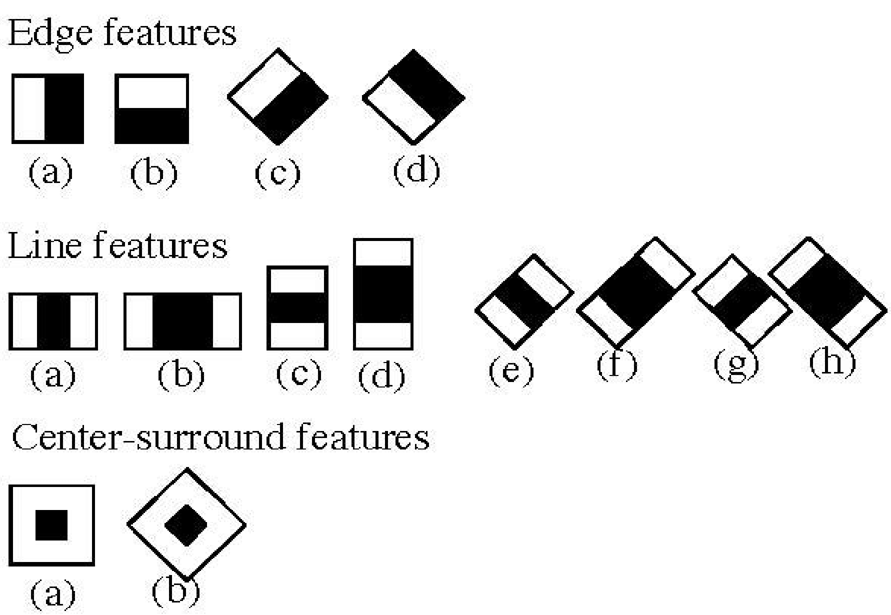

Figure 3. 9: Examples of Haar-like features

3.5.3 Facial Image Feature Extraction

Feature extraction is the afterward phase that comes after processing the entered images in mode of transforming it into the grayscale color and improve their disparity utilizing the Cumulative Histogram Equalization algorithm. Feature disarmament is an important stage for images classification, in which this phase is obtained for improving the influence of the classification for the digital facial image. In the proposed system in this thesis, the feature extracted is accomplished using Linear Discriminant Analysis.

3.6 K-NEAREST NEIGHBOR (KNN) IMPLEMENTED CLASSIFIER

This algorithm is a famous machine learning algorithms that utilized in the proposed identification system and compared with the results of other algorithms that accomplished in this thesis to obtain the best accuracy in recognition and identification of individuals. KNN is a lazy limitless learning algorithm. The KNN limitless appears in that there is no hypothesis for the distribution of underlying data. In other sense, the model framework obtained from the dataset so, it will be very useful in practicing due to, most of popular effective real-world datasets do not attain mathematical theoretical assumptions steps. Because the KNN method does not require any training data points, it is a lazy algorithm for creating models. The testing phase uses all of the training data, which makes the training phase quicker. In contrast, the testing phase is slower and more memory and time intensive than the training phase. The KNN algorithm in the worst case, require more time for scanning all data points and so, more memory space will be needed for keeping the training data. The KNN algorithm is obtained for both regression and classification problems. figure (3.10) illustrates the KNN classification steps in more clarified manner.

3.6.1 J48 Implemented Classifier

The classification is implemented using one of the famous decision tree algorithms on the extracted features from both facial images and voice signals. The construction of decision trees using J48 is presented in algorithm (3.2).

Algorithm (3.2): J48

Input: feature set, a

Output: accuracy evaluation matrices

Begin

R={}

D= feature set

If (D is “pure”)and (other stopping criteria met) then get rid of All attribute a € D

Obtain impurity function criteria if we split on a

a best = beat attribute according above compute to above obtained criteria 7 R= Generate a decision node which tests a best in the root

DV= Obtain sub-datasets from D based on a best

For all Dv do Begin

Rv = J48 (Dv)

Connect Rv to the corresponding branch of R End

Return R

End

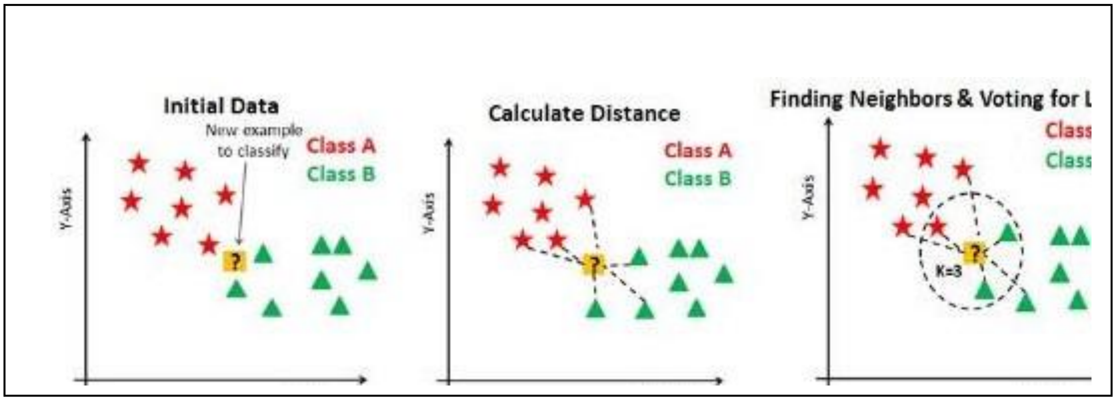

Figure 3. 10: KNN Steps: (A) Initial Stage, (B) Second Stage, (C) Final Stage

3.6.2 Naive Bayes Implemented Classifier (NB)

This partition describes the execution of the Naive Bayes algorithm with its related training and testing procedures. The Naive Bayesian algorithm is implemented with the list of characteristics (facial images and voice signals) as one of the classifier inputs in the Bayesian classifiers, the probability p (d | c) for each characteristic is determined by measuring the number of times these characteristics appear in the class list. After completion of the instruction, the test phased is carried out to prophesize the user class in which the testing cycle begins from the unmarked vector of the software and carries out preprocessing and extraction. Afterward this set of the features is entered into the prediction section of NB to perform the unlabeled class's classification within the right class prediction. The mentioned procedures are listed in details in the algorithm (3.3).

algorithm: k-nearest neighbor

Input: group of training features for every one of the classes
Output: Class label.
Begin **Step1: For** i=1 to the number of classes // **Training phase** **Begin** - Calculate posterior likelihoods of every one of the classes using - Calculate the probability of features taking in account Class using $P\ (d \mid c)$. End **Step2:** Compute the previous probability of predictor. **Step3**: compute the follow up possibility $P\ (\mathrm{C}\|d)$ of class (i.e. target). // **Testing phase** For i =1 to Number of classes Attain the class that has the maximal subsequent possibility, eq.(2.21) End Loop **End.**

3.6.3 Sequential Minimal Optimization (SMO) Implementation

This algorithm is a development algorithm, which it is important and rapid algorithm for a classification used in the current system and compared with other algorithms and showed us high results. As entrance to a Sequential Minimal Optimization Classifier, identical features used for inputs for KNN and naive classificatory are also achieved. It is possible to introduce SMO as an algorithm used in support of vector equipment where the database is broken down into a concatenation of binary classes, which are then analytically solved as shown in an algorithm (3.4).

Algorithm (3.4): Sequential Minimal Optimization (SMO)

Input: feature set

Output: accuracy evaluation matrices, b

Begin

Divide sample in to two different clustering 3 Initialize: $\alpha i = 0$, $fi = -yi$

Calculate: bhigh, Ihigh, blow, Ilow

Upgrade αIhigh and αIlow 6 Repeat

Upgrade fi

Calculate: bhigh, Ihigh, blow, Ilow 9 Upgrade αIhigh and αIlow

IF blow $\leq$ bup + 2t

then save the new α1 and α2 values

Upgrade weight vector w if SMO is linear 13 End

4. EXPERIMANTAL RESULTS

In this chapter a group of an experimental results will be implemented to test and show the success of the two biometric recognition system which presented in chapter three that based on facial images and voice wave signals to show their power and accuracy in recognize male from female. First of all, an environment description where the system implemented is introduced which include all the used programing languages and platforms.

4.1 PROPOSED SYSTEM IMPLEMENTATION ENVIRONMENT DESCRIPTION

When assessing the proposed system's behavior and performance, it's crucial to describe the implementation environment. The proposed system's implementation will be described in this section along with accompanying charts. The new Java 8 programming language is used in conjunction with the NETBEANS IDE version 8.2 software and Visual Studio 2013 to implement the proposed system function. On a Lenovo laptop with a CORE i7 processor, all suggested system procedures are carried out. The seventh generation has a 16 GB RAM capacity, an NVIDIA GTX 6G screen cart, an SSD hard drive, and Windows 10 64-bit as its operating system. The proposed recognition system's information and results are displayed through a graphical user interface. The primary interfaces of the proposed system are shown in Figures (4.1) and (4.2) for voice signals and facial images, respectively.

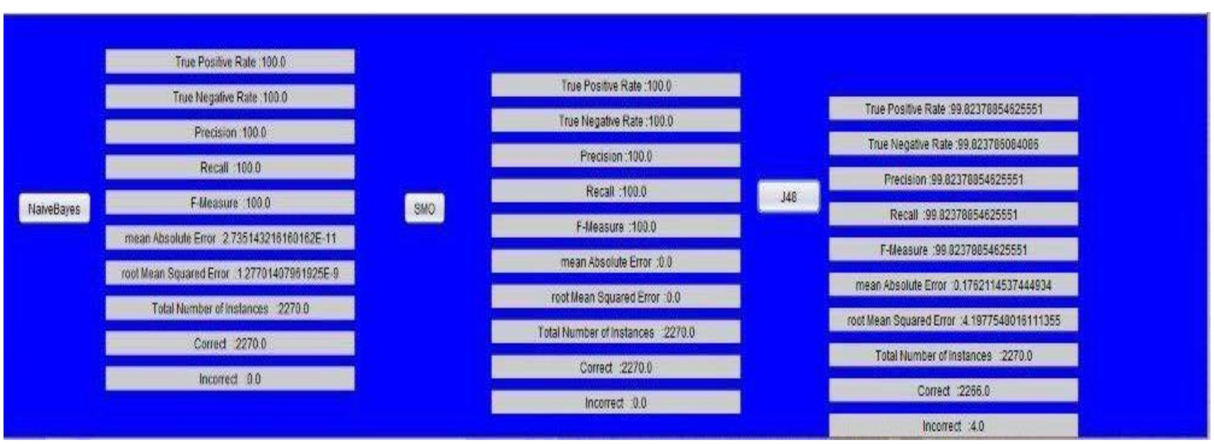

Figure 4. 1: Sound Wave Recognition System Main Interface

Figure 4. 2: Facial Image Recognition System Main Interface

4.2 VOICE WAVE SIGNALS RECOGNITION SYSTEM RESULTS

In this section of thesis, a detailed description about the recognition system that based on voice wave signals behavior and a set of measures will be explained and implemented in order to show its success. By using the MFCC plus Amplitude, zero crossing, Mean, and Standard Division in order to extract features of sound waves with a set of classification algorithms which include: Naive Bayes, SMO, and J48. Each one will be tested using True positive rate, True negative rate, Precision, Re Call, F-Measure, mean Absolute Error, Root Mean Squared Error, Total number of Instances, Correct, Incorrect. Figure (4.3), (4.4), (4.5) and (4.6) show the different values of these measures using the different classification algorithms.

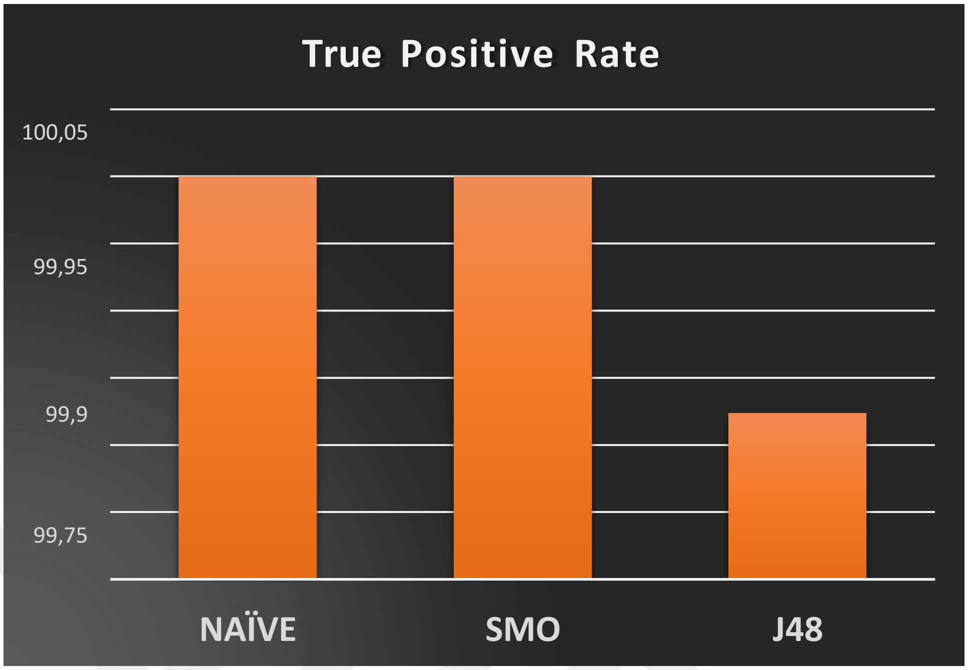

Figure 4. 3: The True Positive Rate Chart of Voice Signals Using Multi Classification Algorithms

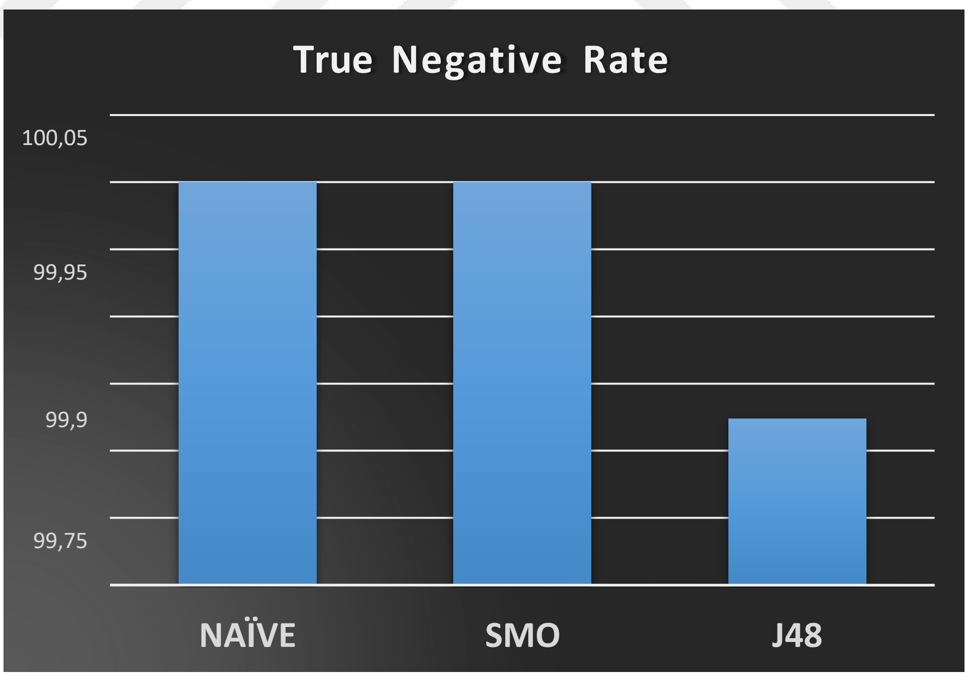

Figure 4. 4: The True Negative Rate Flow Chart of voice signals using multi classification algorithms

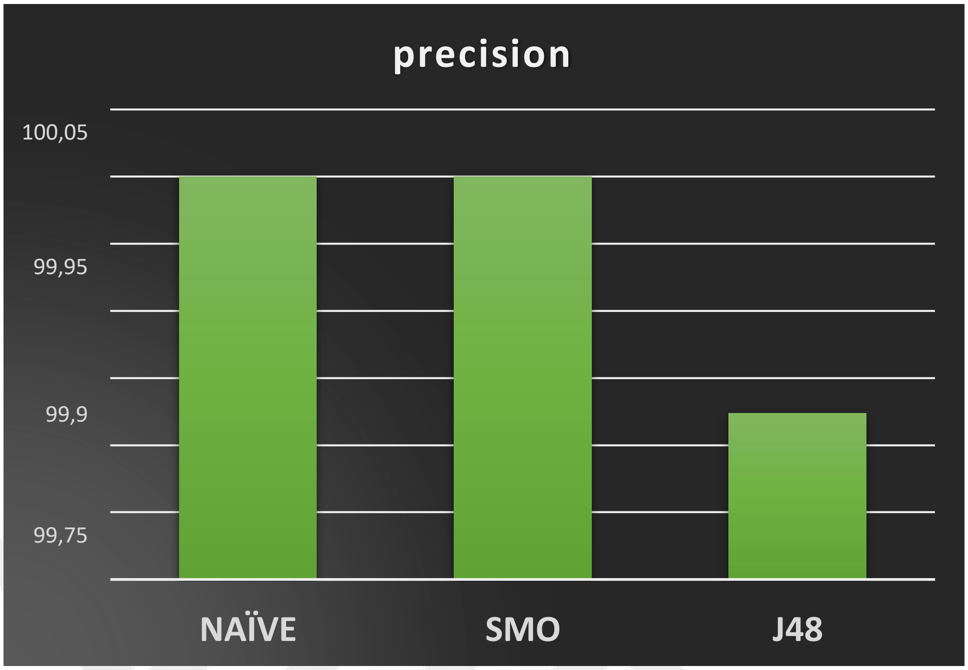

Figure 4. 5: The Precision Flow Chart of Voice Signals Using Multi Classification Algorithms

As shown in figure (4.3), and (4.4) the true positive rate and the true negative rate, and precision for the classification algorithm which gives values 100,100, and 99.823 for naïve Bayes, SMO, and J48 sequentially. The next figures will present the flow chart for the Recall and F-Measure for these classification algorithms.

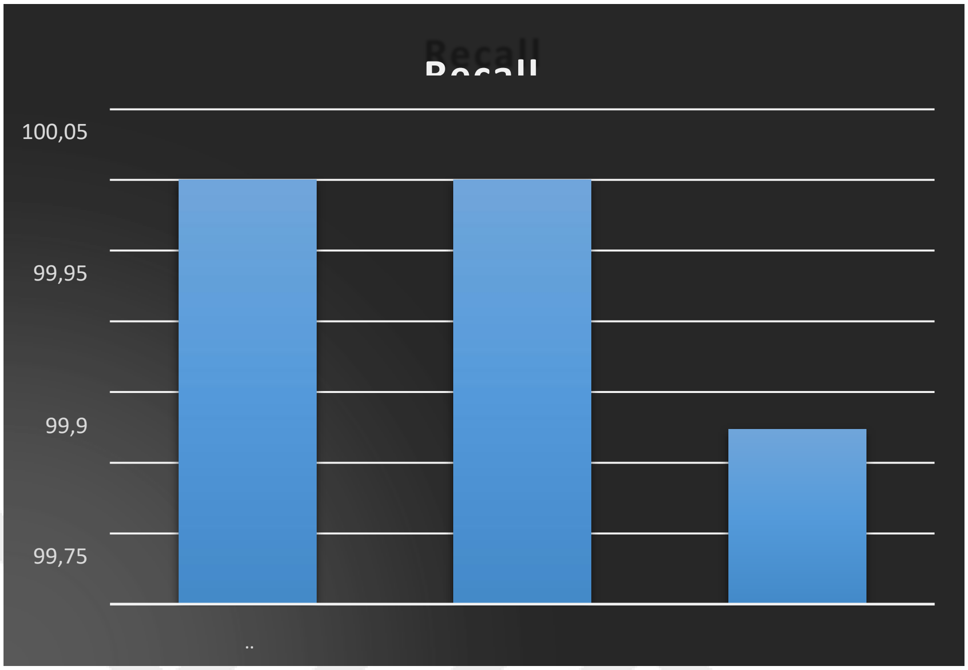

Figure 4. 6: The Recall Flow Chart of Voice Signals Using Multi Classification Algorithms

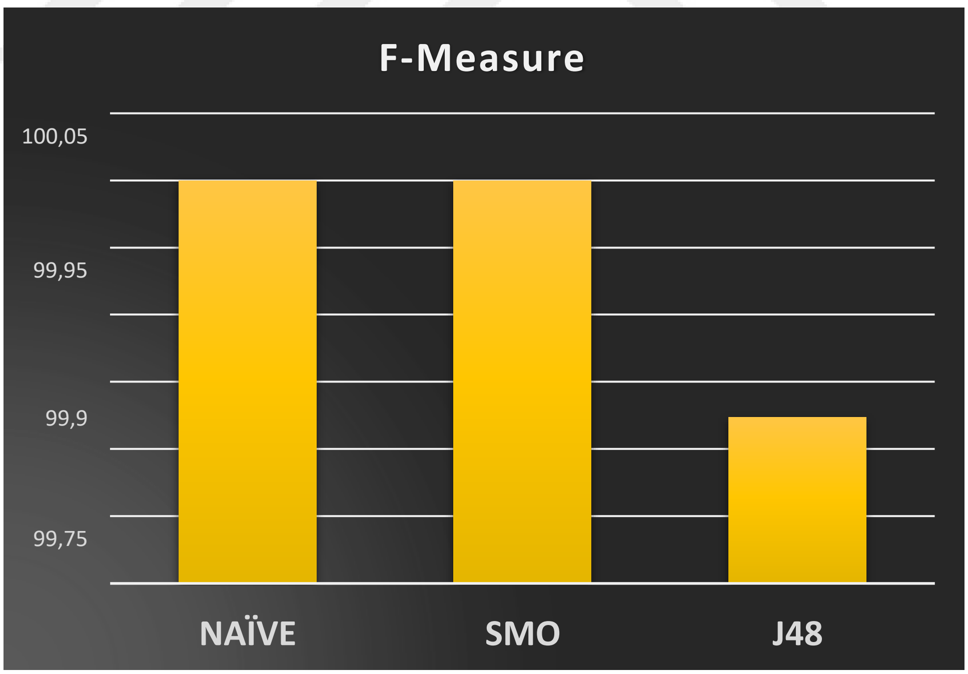

Figure 4. 7: The F-Measure flow Chart of voice signals using multi classification algorithms

The results of the implementation of the suggested system are showed in table (4.1) which the values that are calculated based on the use of the classification algorithm are introduced.

Table 4. 1: The experimental results of the implementation of three classification algorithms on voice signals

	Naïve Bayes	SMO	J48
True positive rate	100.0	100.0	99.8237
True negative rate	100.0	100.0	99.8237
Precision	100.0	100.0	99.8237
Recall	100.0	100.0	99.8237
f-measure	100.0	100.0	99.8237
MAE	2.735	0.0	0.176
RMSE	0.0	0.0	4.198
Total no. of instances	2270.0	2270.0	2270.0
Correct	2270.0	2270.0	2266.0
Incorrect	0.0	0.0	4.0

The MAE for the three classification algorithms shows the difference between them, figure 4.8 and 4.9 present the flow chart of MAE and the correct percentage of the classification procedure using these three algorithms

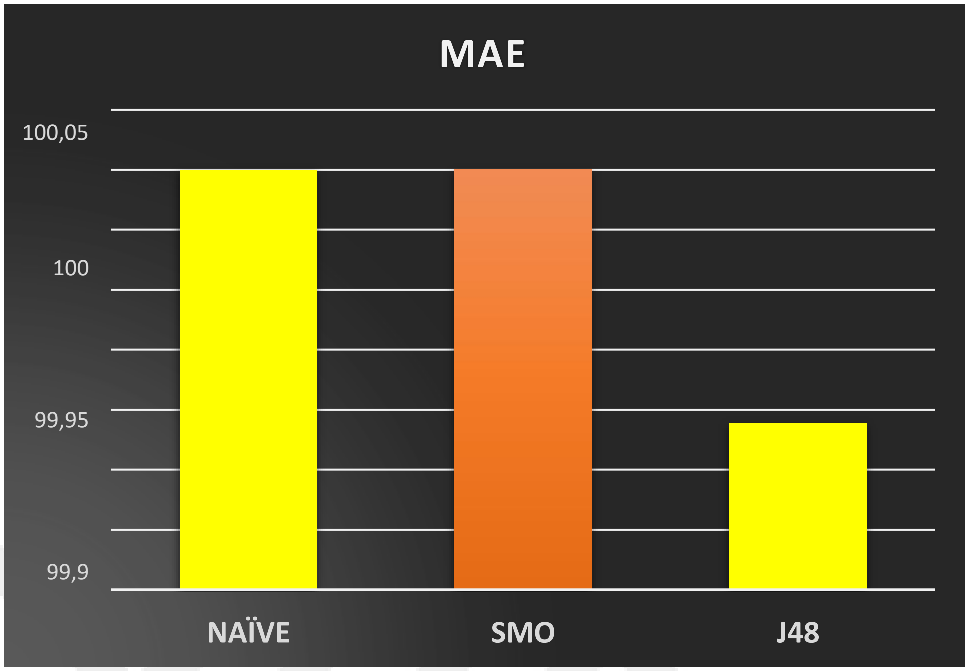

Figure 4. 8: The MAE flow Chart of voice signals using multi classification algorithms

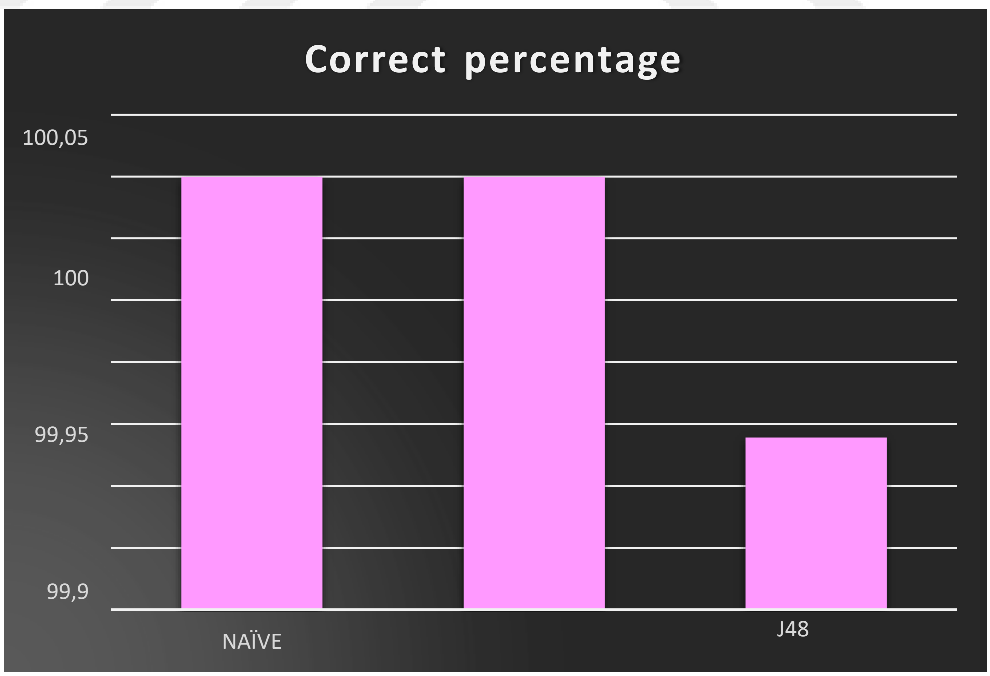

Figure 4. 9: The correct percentage flow Chart of voice signals using multi classification algorithms

4.3 FACIAL IMAGES RECOGNITION SYSTEM RESULTS

The facial images recognition system consists of multi stages and each one gives us a resulted image. The preprocessing stage is the first one that the face pictures go through, and it entails a number of stages to give us a precise, ideal facial image to work with in the classification stage. Preprocessing includes the following:

Grey Scale Image Stage, the first move was to turn a digital face picture of the RGB color, using the weighted technology, into a one with a grey color. Figure (4.10), show samples of male and female facial-colored images and how they look like after converting them into grey scale images.

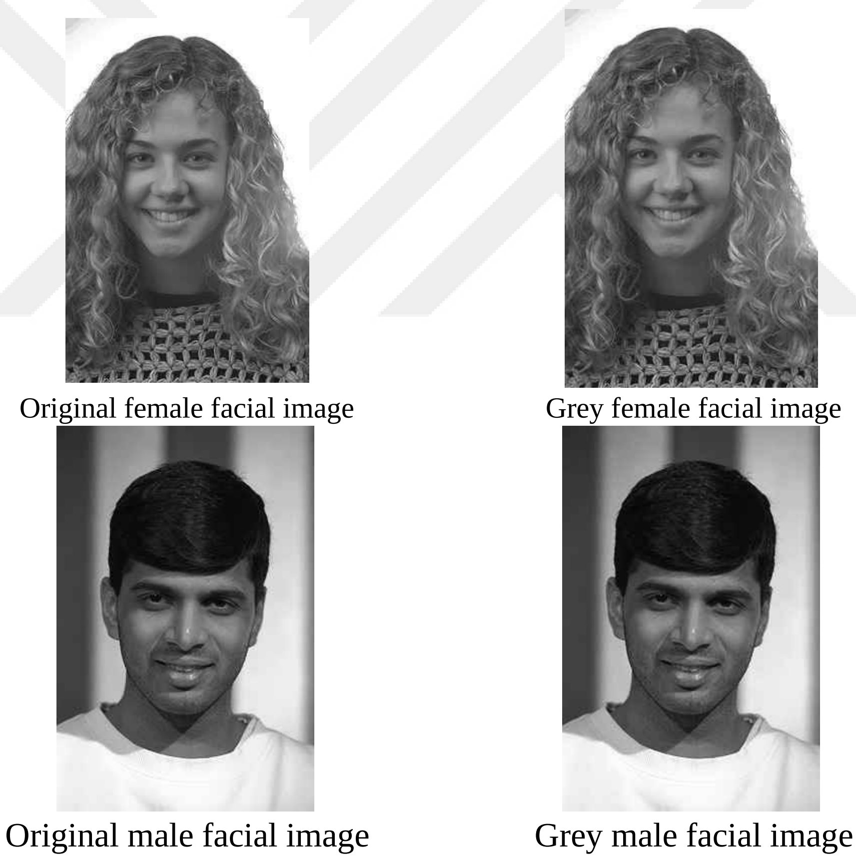

Figure 4. 10: Samples of Male and Female Colored Images Converted to Greyscale Image.

Histogram Equalization Stage, after image transformation from the colored into grey scale, the second stage attained in applying the histogram equalization technique. Figure (4.11), describe the normal digital facial image histogram and the resulted image and its histogram after Accomplishment histogram equalization algorithm.

Figure 4. 11: The Facial Image After Applying Histogram Equalization

Face Detection Using Viola & Jones, in this stage viola & jones detection method is obtained after applying Adaboost machine learning to detect the important details in the facial images and to remove all unwanted details from the images. Figure (4.12), show two samples about the detection mechanism

.

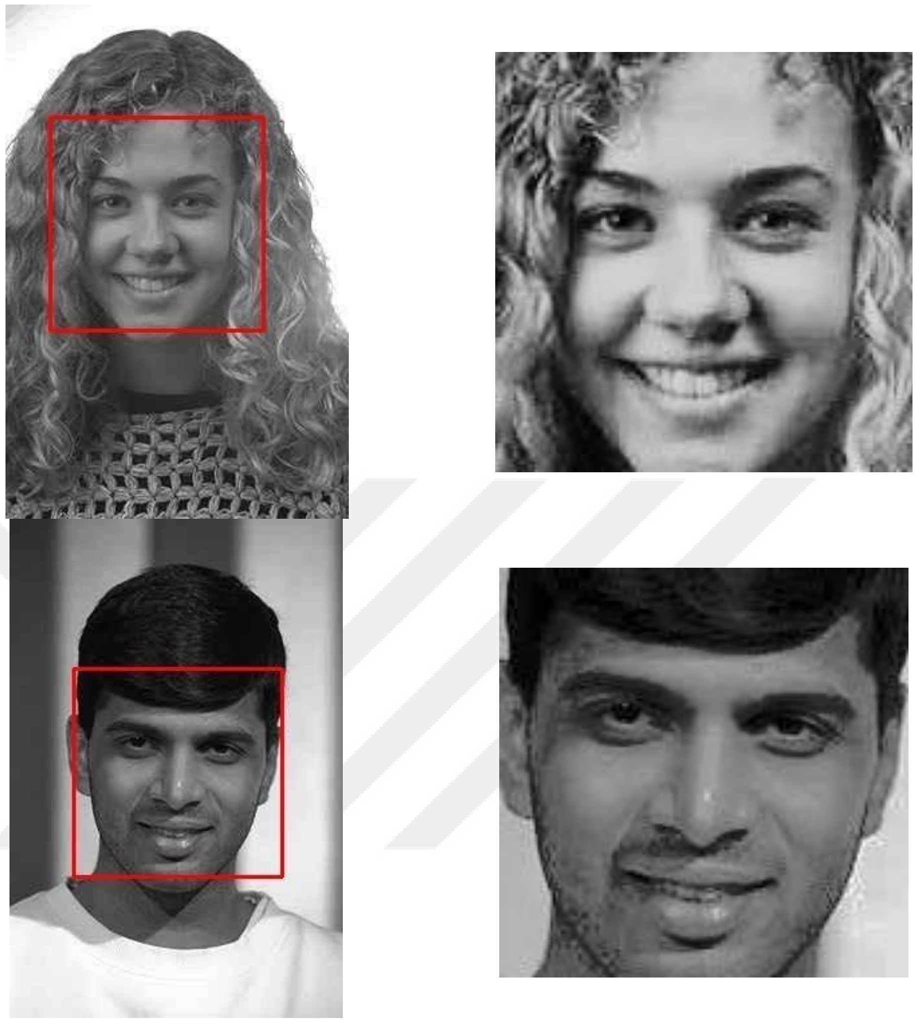

Figure 4. 12: Face Detection Resulted Facial Image

Figure 4. 13: Resized Facial Images

4.3.1 Facial Images Classification Results

Three machine learning techniques were utilized for the training and testing of features since classification is a key component of the system that was described in this thesis. For the extraction of features with three algorithms in classification, the linear discrimination analysis (LDA) algorithms are obtained in this process. NB, SMO, and J48. The NB classifier as well as SMO, and J48 was used in the proposed system with LDA and some results about their accuracy were obtained and show in figure (4.14), (4.15), (4.16), (4.17), (4.18) and (4.19) that describes the true positive rate, the true negative rate, precision, recall, f-measure, and MAE different values for these classification algorithms.

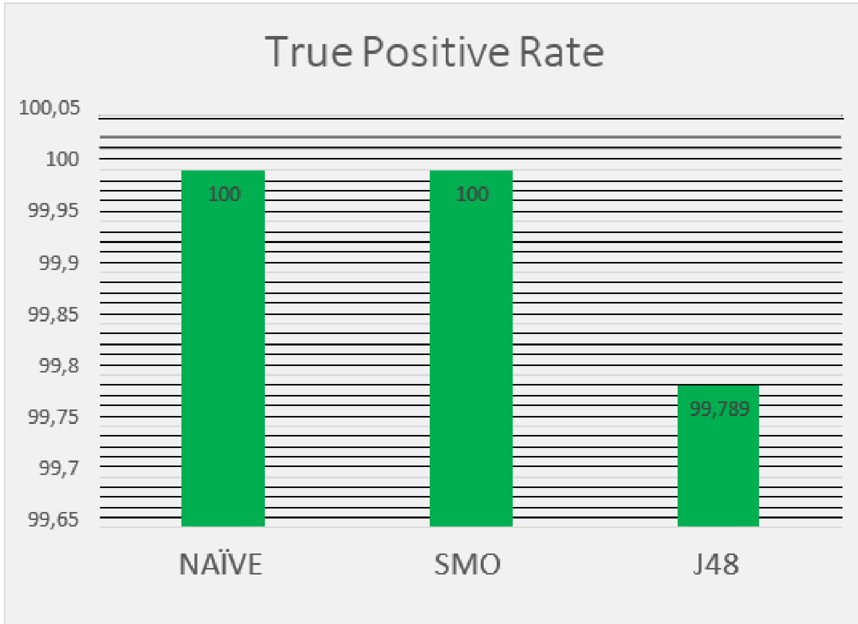

Figure 4. 14: The true positive rate for using three classification approaches for facial images with LDA

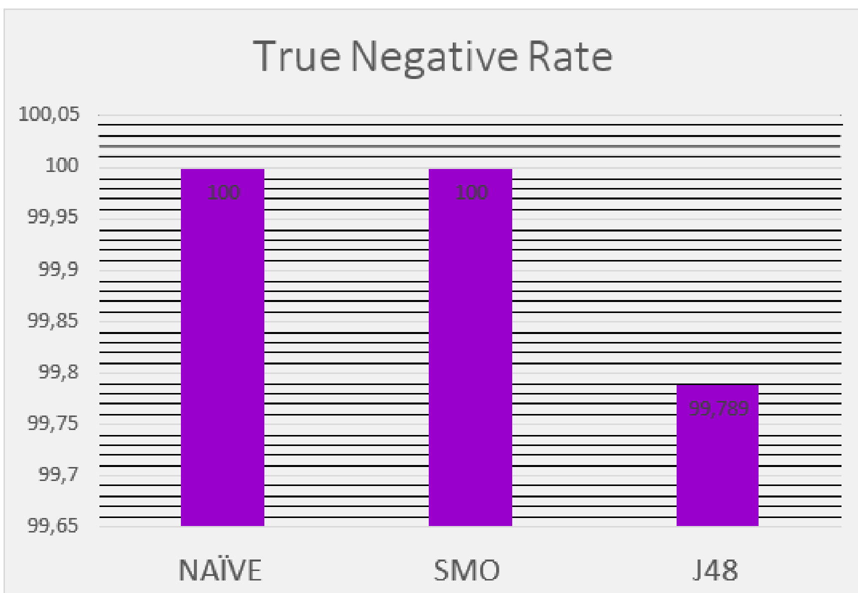

Figure 4. 15: The true negative rate for using three classification approaches for facial images with LDA

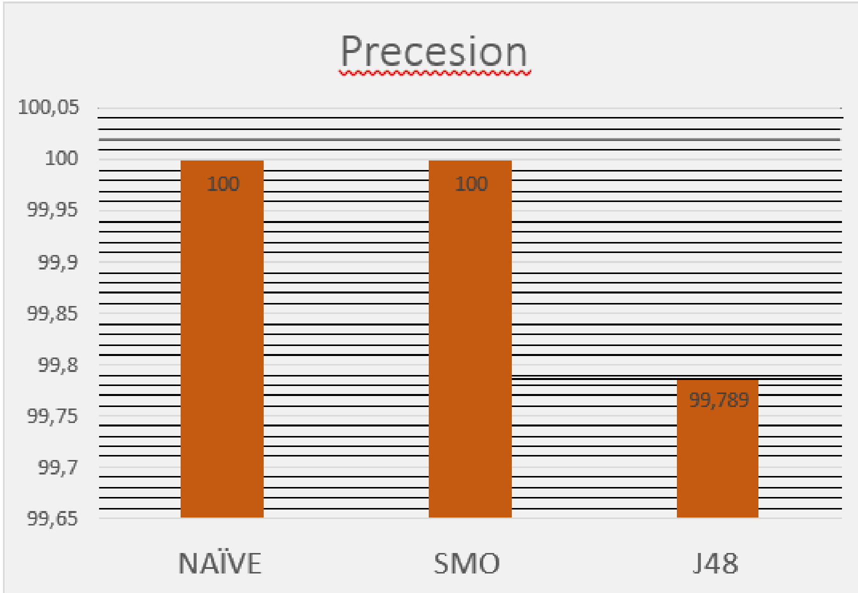

Figure 4. 16: The precision for using three classification approaches for facial images with LDA

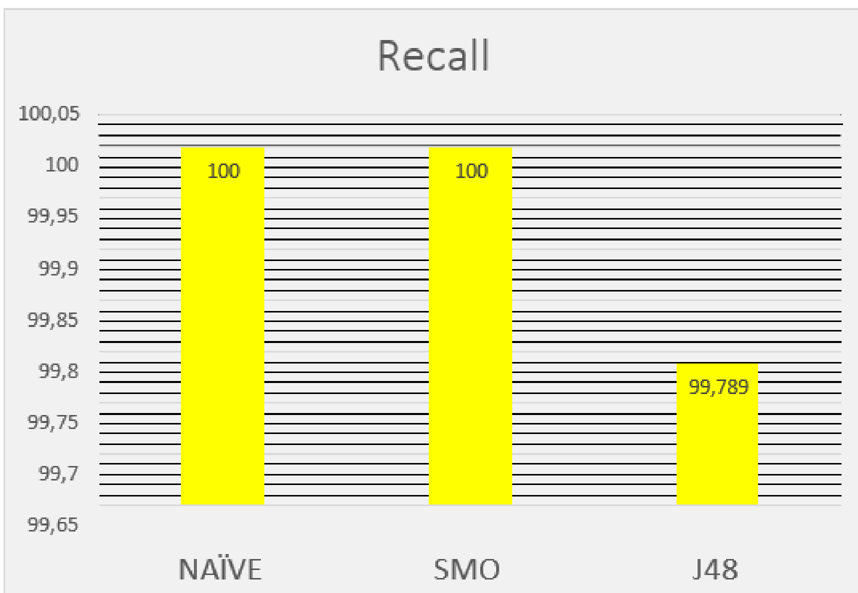

Figure 4. 17: The recall for using three classification approaches for facial images with LDA

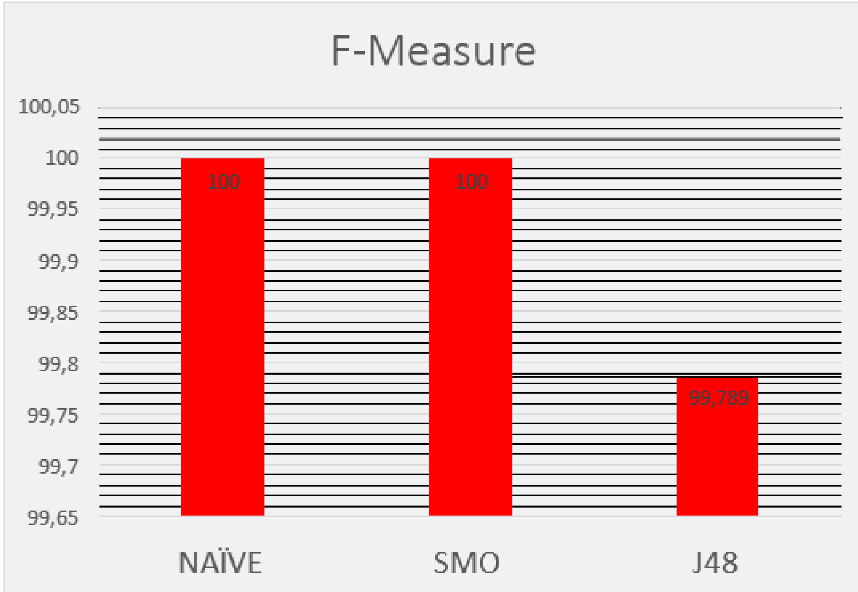

Figure 4. 18: The F-measure for using three classification approaches for facial images with LDA As shown previously a set of measures that describe the different of using each classification algorithm with LDA. In Table (4.2), all the values that obtained from applying these algorithms will be show in more detail.

Table 4. 2: The test results of the three classification algorithms combined with LDA in face pictures

	SMO	Naïve Bayes	J48
True positive rate	100.0	100.0	99.789
True negative rate	100.0	100.0	99.789
Precision	100.0	100.0	99.789
Recall	100.0	100.0	99.789
f-measure	100.0		99.789
MAE	0.0	2.735	0.210
RMSE	0.0	0.0	4.593
Total no. of instances	474.0	474.0	474.0
Correct	474.0	474.0	473.0
Incorrect	0.0	0.0	1.0

5. CONCLUSIONS

A large number of systems calls for a reliable powerful personal recognition mechanism either for ensuring or determining the identity of the persons that obtaining their services. The cause of such techniques is to determine that a particular service is admittance only within the allowed and authorized user, and not through anyone else. An assortment of s such systems and frameworks that requires authenticity such as, computer systems access, the secure entry for buildings, laptops usage protection as well as the cellular phones and ATMs machines utilization. Any behavioral and/or physiological of human being's characteristic can be obtained as a biometric characteristic identifier like eyes, face, iris, sound, and gait style etc. A biometric system usually means a pattern recognition system that uses biometric data from a individual and then extracts a collection of data features from them and compares the collection with the mold set stored in the database.

In this study, two important human's beings' biometric characters are used to recognize and identify the person whether it was a male nor female. The sound wave signal of individuals are used as well as facial images in this study for the reason of recognition of the person gender. The data set used in the sound wave signals recognition system is a universal dataset that known as CMU_ARCTIC databases that consist of two folders male and female as well as the facial image data set also known as FERET data set. These two universal datasets are used in the proposed recognition system that based on three famous classification algorithms. The two biometrics are passes through multi phases in order to pass through the classification algorithms. Both of naive Bayes and SMO classification algorithms gives an accuracy result of 100% which means it is a perfect and without any error, while the j48 have given a less accuracy with little difference from the two other classification algorithms in which it was 99%. The j48 classification algorithm also considered a success classification algorithm because the different between the two other classification algorithm is very few and have almost no effect on the classification and recognition procedure. The classification procedure that accomplished by the three algorithms is very fast in the testing phase of the system and takes a second or a part of a second and this is one of the system power points. The proposed system has no loss and it is considered perfect to use due to the remarkable results obtained in both voice signals and, facial images.

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