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A NEW BIOMETRIC SYSTEM USING DEEP LEARNING: ANALYSIS OF PALMPRINT IMAGES

Mohammed Jaafar Rashid AL-MAJMAIE

Master's Thesis

Supervisor

Asst. Prof. Dr. Mesut ÇEVİK

Istanbul, 2022

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The thesis titled A NEW BIOMETRIC SYSTEM USING DEEP LEARNING: ANALYSIS OF PALMPRINT IMAGES prepared by MOHAMMED JAAFAR RASHID AL-MAJMAIE and submitted on 09/12/2022 has been **accepted unanimously** for the degree of Master of Science in Electrical and Computer Engineering.

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I hereby declare that this thesis meets all format and submission requirements of a Master's thesis.

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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.

Mohammed Jaafar Rashid AL-MAJMAIE

Signature

PREFACE

I would like to extend our thanks and appreciation to Asst. Prof. Dr. Mesut ÇEVİK who are doing everything they can to support us during the research period. And thanks and appreciation And thanks and appreciation to my parents who supported me and brought me to this stage God bless us all.

ABSTRACT

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Rapid developments in technology can affect humanity both positively and negatively. Especially with the increase in crimes committed in cyber environments, important security studies on information security have been made in the world. For this reason, today, many companies and institutions take advantage of biometric recognition systems and use these devices in order to protect their security.

In this study, new method based convolutional neural network pretrained model AlexNet and wavelet transform applied to recognize the humans. The proposed method extracted new and effective features from hand images and wired the extracted features to the ensemble learning classifier that classified the features into multiclass that are represented the 72 human. The obtained results 99.14 which is remarkable when compared with state of art studies.

Keywords: AlexNet, Deep Learning, CNN, Ensemble Learning, Hand Geometry.

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ABBREVIATIONS

RNN	:	Recurrent Neural Network
DBN	:	Deep Belief Network
DL	:	Deep Learning
CNN	:	Convolutional Neural Network
SVM	:	Support Vector Machine
KNN	:	K-Nearest Neighbour Algorithm
EL	:	Ensemble Learning
DT	:	Decision Tree
PCA	:	Principal Component Analysis
DNA	:	Deoxyribo Nucleic Acid
WT	:	Wavelet Transform
LDA	:	Linear Discriminant Analysis
TRTSR	:	Two-Phase Test Sample Representation
RoI	:	Return on Investment
Ml	:	Machine Learning
HG	:	Hand Geometry
RBF	:	Radial Basis Function
DCNN	:	Diffusion-Convolutional Neural Networks

1. INTRODUCTION

For many years, people have known each other from their characteristic features such as face, posture, gait and voice. Taking this situation as an example a century ago, Alphonse Bertillon came up with the idea of using body measurements in catching criminals and tested its usability.[1] Thus, the first step was taken in the formation of biometric-based recognition systems. Biometric recognition systems; are pattern recognition systems that enable identification using distinctive physical and/or behavioral features such as fingerprint, face, iris, and posture. Today; The increase in identity fraud indicates that traditional information and token-based identification systems are insufficient. Therefore, the necessity of using biometric technology in identification applications has gained importance. Since biometric-based systems use personal features, they provide the solution of various security risks. Since biometric identifiers cannot be shared or copied, they are considered more reliable identification tools than password and information-based systems. The fact that biometric recognition systems are more secure than other systems, eliminating the necessity of memorizing information such as passwords and user names and carrying documents such as IDs makes them more preferred systems compared to traditional methods. For this reason, studies on biometric systems have been carried out for many years. Fingerprint, face, iris, posture, hand geometry, DNA, signature and voice are the main biometric determinants used in biometric applications. Since the face is one of the characteristics that people use most to recognize each other, it is one of the biometric identifiers with high acceptance. However, it is quite difficult to create a system that will perform the recognition process by taking into account the changes of the face caused by make-up, beard, old age and the shooting angle of the face picture. This is an issue that needs much development. Iris recognition systems are systems that work very fast and have a high recognition rate, but their costs are high. Fingerprint recognition systems, on the other hand, are systems with very low cost and high recognition rates. Biometric systems are divided into two main groups according to their authentication and identification processes. In the first group, the identity of the person is compared with the biometric identity, and the system checks whether they match. The system determines whether the person has the claimed identity by making a one-to-one comparison.

The result is positive or negative. In the second group, the system tries to find out who the person is by comparing their biometric features with other biometric features in the previously stored database. As a result, either the person is identified or the person being compared is not in the current database. In these systems, one biometric feature is compared with more than one biometric feature. Biometric systems have some basic working principles according to their groups, regardless of the biometric identifier used. In the systems in the first group, the person gives his/her name or an introductory feature such as a password to the system, biometric characteristics are taken with the help of a scanner or camera, the features are converted into digital format and the feature is extracted, the extracted features are checked by comparing them with the previously extracted features of the user whose password or name is entered. In the systems in the second group, biometric characteristics are obtained and features are extracted without the need for password or name entry, and it is tried to find out who the person is by comparing them with all the biometric features registered in the database. Biometric Systems can be designed online or offline. In online systems, the biometric feature of the user is obtained with the help of a scanner and results are expected quickly without any action from anyone. In these systems, besides the reasonable recognition rate, the feature of fast processing comes to the fore. In offline systems, some biometric identifiers that were previously stored in the database are compared, pre-processes can be applied to increase the quality of the biometric identifier, and it is considered normal to reach the result in a longer time compared to online systems [2].

Regardless of the biometric identifiers used in biometric systems, all of them must have certain characteristics. These; to be in every human being; universality, not changing over a period of time; permanence, distinctiveness, collectability, acceptability, difficulty in imitation, fast and acceptable recognition rate; is good performance. Fingerprints contain the features that should be in biometric identifiers in a balanced way. Fingerprints remain distinctive despite injury, cuts, skin disorders or skin condition. Thanks to the fingerprint scanners, fingerprints of the desired quality are scanned and there is no problem of removing fingerprints from the background. Fingerprint-based biometric systems are inexpensive and perform very well thanks to small sensors.

Fingerprints were one of the first biometric markers used in catching criminals after they were determined to be personal. While the characteristic features of fingerprints were researched and compared by experts in the past, it was necessary to start the fingerprint recognition process with the help of a computer due to reasons such as the growth of the fingerprint database and the prolongation of the comparison times. For nearly half a century, a wide variety of research has been done on this subject. Therefore, there has been a misconception that the issue of fingerprint recognition is a completely resolved issue. On the contrary, fingerprint recognition still remains a challenging issue that needs research [3].

In order to identify the perpetrator of the crime, there is a need for crime proof tools, that is, evidence. By using these proof tools; It has become even more important today to be able to stay one step ahead of the criminals, to reveal the crime, to be able to identify the criminals with material evidence as well as confessions and personal statements. In this respect, evidence is accepted as the most basic element of the trial in our legal system. Today's modern understanding of law and human rights approaches require that in order for any suspect to be accused of committing a crime, that person's involvement with the crime event should be based on concrete evidence/evidence and take into account that the suspects (defendants) are innocent unless their connection with the crime is proven concretely (www.adli). Bilimler.net, 2015). The means that carry parts of a lived, finished, past event to the present and give an idea about how this event took place are called evidence. Evidence must be of such a nature as to make the person who will use it or benefit from it live today, right now, yesterday. Things that are in the middle today and that shed light on yesterday are evidences (Bıçak, 2013:423). As it can be understood from the definition, a connection is established between the event and the perpetrator by means of evidence. Evaluation and interpretation of evidence is needed to establish this connection. The evaluation and interpretation in question is made by experts on the subject upon the request of the judicial authorities. Parallel to the developments in science and technology, progress is made day by day in the fight against crime and criminals. In the events that took place, the evidences are examined by the expert, within the framework of scientific and technical methods. The common framework of the fields of science, in which these scientific examination methods are included, is defined as "Forensic Sciences" [4].

Currently, there are many individuals or institutions serving the field of forensic sciences. The crime scene, which has been the subject of any judicial or administrative crime, is examined by specially trained personnel. As a result of the examination, the evidences that are considered to be able to establish the event-perpetrator relationship are collected and kept under protection. The said evidences, upon the request of the relevant authorities; official experts (Forensic Medicine Institute, Gendarmerie Criminal Laboratories, Police Criminal Laboratories, Forensic Physicians, Higher Education Institutions, High Health Board and Central Bank), other natural or legal persons in the expert list, science and arts professions required to be known for the examination. It is subject to examination by those who acquire it and those who are officially authorized to do the necessary profession for the examination. Although palmprint recognition is a less popular method than other biometric recognition systems, interest in this branch of biometrics has been increasing in the last 10 years. Palmprint has advantages over other biometric attributes. Since the palm print surface is wider, its distinctiveness is high. In addition, the required database can be collected easily and at low cost, and it does not cause any deterioration in the images. Generally, by minimizing the free movement of the biometrics, contact 2D palm print recognition systems have been developed, which can be advantageous in restriction or segmentation, but also bring hygiene problems. Another disadvantage is that 2D palm print images can be easily copied and imitated, which reduces system reliability. In addition, the inclusion of skin-like objects on the back of the hand makes segmentation difficult and distorts the palm print information [5].

1.1 BIOMETRIC SYSTEMS

Biometrics is the science of verifying the identity of an individual by analyzing biological data, that is, a personal quality or behavior of an individual. Biometric-based verification, which is of great importance in our lives, is a powerful method for reliable authentication. Biometrics is becoming more and more popular nowadays. The biometric system scans an individual's attribute or behavior and compares it with the previously created record. This system must be extremely sensitive as it examines an individual's fingerprint, hand, palm, retina or voice. While measuring the anatomical or physiological characteristics of the individual, accurate and repetitive measurements should be made [6].

1.2 THE HISTORY OF BIOMETRICS

The understanding and application of the basic principles of biometric systems, which is a product of information technologies that have left their mark on our century, actually dates back to a long time ago. Thousands of years ago, people living in the Nile Valley used biometric identification routinely during many day-to-day work. In the 19th century, criminology researchers' investigations of whether physical features and characteristics have anything to do with criminal tendencies increased the interest in this field. As a result of these researches, many measuring instruments have been produced and many data have been collected. Although the results are not conclusive, measuring the physical characteristics of individuals has been accepted and fingerprinting has become an international method used by the police for identification [7].

1.3 PURPOSE OF BIOMETRICS

The general aim of biometrics practitioners is to replace any information they need to keep in mind in order to verify their identities, or tools such as cards, keys, which they have to carry with them, not lose or forget; to enable them to use features that are impossible to copy or imitate. In biometric systems, since the identification process is carried out based on the physical or behavioral characteristics of the individuals, it is not possible to transfer it to someone else, forget it or lose it. It has much less risk than other methods. However, some standard measures should be used in order to create biometric systems. There is an international standard created by INCITS (International Committee for Information Technology Standards) for the use of these measures, called biometric measures, in passwords [8].

1.4 FACE RECOGNITION SYSTEMS

Automatic face recognition is a relatively new concept. The first semi-automated facial recognition systems were developed in the 1960s and required a rendering engine to locate the eyes, ears, nose, and mouth in a photograph, record the calculated distances and proportions of 13 common points, and compare them to lines. Base. . Data from the 1970s by Lesk et al.

They used features like hair color and lip thickness to automate the recognition process. The problem with these first two solutions is that you have to manually calculate the sizes and positions. Principal component analysis (PCA), a standard method in linear algebra, was implemented by Kirby and Sirovich in 1988. This is an important step because it shows that at least 100 values are needed to properly encode and align an image. and standardized images. . When Turk and Pentland used the PCA algorithm with Eigenfaces, they found that this bug can now be used to detect faces in images, allowing real-time face detection. Although the approach is limited by environmental factors, it has generated significant interest in the development of automatic face recognition technologies. This approach was tested by capturing surveillance footage at the USA SUPER BOWL soccer championship in January 2001 and then compared to a digital database. Today, face recognition is used in various fields. The field of security remains the main field of application. In this area, recognition faces are required for identification and authentication. A good example of this use is the airport in Frankfurt (Germany), where it is known for automating passenger control. Analysis of videos captured by external camera systems managed by cities is another example, a suspect can be identified. Advertising agencies develop attractive billboards thanks to the recognition of the faces of people who adapt to the displayed content. Google and Facebook have applied algorithms to identify people in their photo databases. In October 2013, Facebook abandoned facial recognition in Europe following technology criticism. Detecting people's faces in photos is prohibited, this jeopardizes their privacy. In the United States, this technology continues to evolve, even being used by government agencies (FBI) or private companies. In Brazil, the police prepared for the 2014 World Cup in their own way: they wore glasses equipped with a camera capable of taking 400-14 images per second and compared them to a digital database of 13 million photos. The innovation in face recognition is the introduction of new three-dimensional (3D) type cameras. These photographic camera work improved than traditional cameras. Since they take over a three-dimensional view point of each one face [9].

1.5 FINGERPRINT

Fingerprint contains the basic features that should be found in biometric identifiers in a very balanced way. These; It can be found in everyone except people who have lost their hands, it is distinctive and permanent, it can be collected by scanners, and biometric systems using fingerprints are acceptably fast and have a high recognition rate. Fingerprints consist of an elevation called a line line or a line and the pits between these elevations. The different shapes of the fingerprint lines in the skin papillae and the fingerprint details that change in each person make the fingerprint a very complex combination of shapes. No two fingerprints are alike, as the details in a fingerprint are found in different numbers and in different places in each fingerprint. However, fingerprint lines form certain shapes called loops, deltas, and spirals. Depending on these shapes, fingerprints are divided into different classes. Fingerprint types are based on deltas, spirals and loops, which are the main shapes formed by fingerprint lines. Delta is defined as the area left between two lines running side by side, diverging from each other.

In other words, the delta shown in Figure 2.1 is the triangular shape formed when two fingerprint lines diverge and meet a third line. Basically, fingerprint types are determined based on the number of deltas in the fingerprints. However, in addition to deltas, spiral and loop shapes also play a role in the determination of fingerprint types. The helix is the circular region inside the curves formed by the fingerprint lines. The loop is the shape formed by one or more lines that start on one side of the fingerprint, bend by cutting the virtual line between the delta and the core point, and end or tend to end where it started. Fingerprints are divided into three main groups as shown in Figure 1.1, the loop consisting of a delta and a loop (right or left loop), a spiral consisting of one or more deltas and a spiral, an arc type that does not have any of the delta, helix or loop shapes.

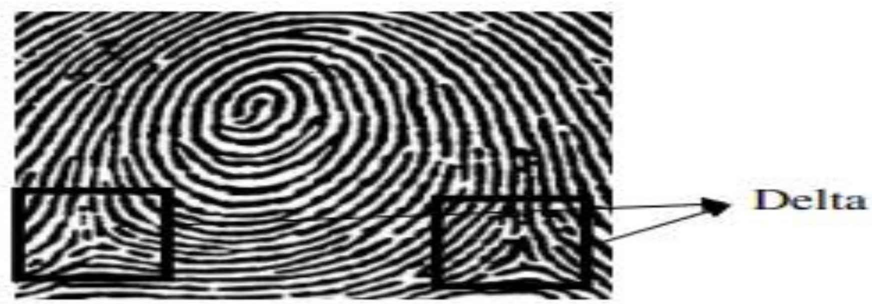

Figure 1.1: Delta shape in fingerprint.

Figure 1.2: Fingerprint types.

Spiral, loop and arc classes are also divided into subgroups within themselves. According to this; spiral fingerprint; simple, central pocket, double loop and random helix, loop type; ulnar and radial loop, arc type; It is divided into subclasses called simple and t-arc. Apart from these, there are fingerprints that cannot be included in any group.

In spiral-type fingerprints, the lines are arranged circularly around the middle region of the fingerprint. They generally consist of two deltas and a spiral shape. Around 25-35% of fingerprints consist of this type of fingerprints. [10] Spiral fingerprints are divided into four subgroups as simple, central pocket, double loop and random, respectively.

A simple spiral fingerprint consists of lines or lines that form a circle or try to form a circle, intersected by the virtual line drawn between two deltas in the innermost pattern area. Central pocket spiral type fingerprints are fingerprints in which the virtual line drawn between the two deltas does not cut the circle or lines within the innermost pattern area. In this type of fingerprint, the lines can be full circle, spiral, oval, circular or any variant of the circle. The double-loop helix consists of two independent circular formations, two distinct shoulders and two deltas. A random spiral fingerprint consists of two different types of patterns, including two or more deltas or an undefined pattern structure. Loop fingerprints are the most common type of fingerprint. Approximately 60-70% of fingerprints contain a loop shape. In these fingerprints, one or more lines enter by cutting or contacting the virtual line advancing from the delta to the core point, bending backwards, forming a loop and ending in the region where it enters. Each loop fingerprint consists of a delta and a loop shape and is divided into two subgroups as radial and ulnar. The radial and ulnar loops are named after the two long bones that make up the forearm skeleton and are parallel to each other. Of these bones, the one on the outer side of the thumb is called the radius (rotating bone), the one on the inner side and the one on the little finger side is called the ulna (elbow bone). In the radial loop, the flow direction of the loop formed by the fingerprints is towards the thumb in the direction of the rotating bone (radius). This type of fingerprints are very rare 8 and are usually seen on the index fingers. In the ulnar loop, the flow direction of the loop formed by the fingerprints is in the direction of the ulna bone, towards the little finger. In order to understand whether any loop fingerprint is of the defined radial or ulnar type, it is first necessary to know which hand it belongs to. If the fingerprint in Figure 2.4 belongs to the right hand, according to the definition; Since the direction of the loop shape formed by the lines will be towards the thumb, if the radial loop belongs to the left hand, the direction of the loop formed by the lines will be towards the little finger, so it falls into the ulnar loop fingerprint category.

Since it is not known which hand all the fingerprints collected in practice belong to, it is very difficult to make this distinction. In this respect, the concepts of right loop and left loop are used instead of radial and ulnar definitions in some sources. According to this nomenclature, which is determined according to the starting and ending regions of the lines forming the loop, it can be determined which loop type the fingerprints belong to, without knowing which hand they belong to.

In the left loop, the lines forming the loop start from the left part of the fingerprint in a slanting manner, curl on themselves in the middle, and then return to the direction they came from and end in the starting zone. In the right loop; The lines start from the right part of the fingerprint and proceed as in the left loop and end in the starting region. the lines start to rise from one side of the fingerprint and end up arching in the middle and descending to the other side. In this type of fingerprint, the lines form an arch-like shape on top of each other, but there are no shapes such as delta, loop, spiral and core point. About 5% of people have this type of fingerprint. In some sources, they are also called belt-type fingerprints.

1.6 HAND GEOMETRY RECOGNITION

Hand geometry recognition is a method that has been used in the United States for 20 years and is especially preferred in airports and nuclear power stations. As shown in Figure 1.32, in this method, the geometric structure of the hands or two fingers of the individuals is analyzed. The length, width, width and twisting places of the fingers are used as distinguishing features. Although hand geometry recognition is a method with high accuracy, it has disadvantages in terms of cost and usage due to the large and heavy reading device.

The long time taken to take the picture is also a factor that makes the system slow. In addition, the performance of the system decreases due to tools such as rings, band-aids, injuries, loss of fingers, gout or calcification, and the system cannot be used at all due to the rapid growth and development of the hands in children [11].

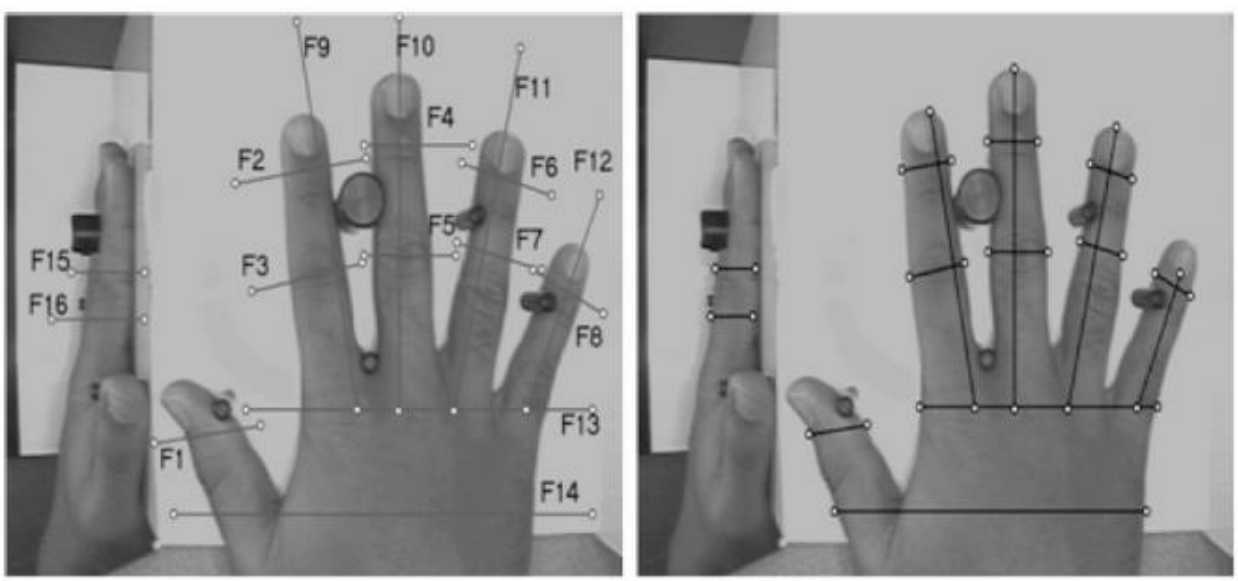

Figure 1.3: Hand geometry sample.

1.7 VOICE RECOGNITION

In a voice recognition application, signals must first be expressed correctly in order to be recognized. In other words, the elements of the sound that the examined audio signal contains and which are only targeted to be recognized are determined by applying various digital signal processing techniques one after the other. Then the determined elements need to be expressed with a feature vector. With these attributes, a voice recognition database is created. The pattern presented to the system by the user during the data request is tried to be matched with one of the records in the database. The result of the matching process is transferred to the final decision mechanism of the system and the authorization request is determined positively or negatively.

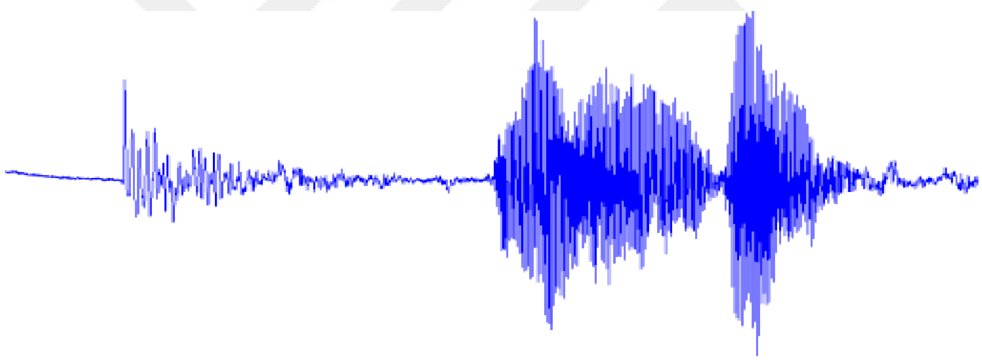

Figure 1.4: Voice recognition.

1.8 KEYSTROKE

One of the biggest disadvantages of other biometric systems is that they require extra hardware to be used in all terminals, and the most basic feature that distinguishes typing rhythm systems from other biometric systems is that they do not need any special hardware. The only input device needed to design a Typing Rhythm system is simply the keyboard. There is no reason why a biometric system with such an advantage should not be used in real life. Especially in many places such as universities, such a system can be easily used both scientifically and technically. Because there is a great similarity between the keyboard typing styles of people, as well as their handwriting. Indeed, when a person starts typing something on the keyboard, the keyboard naturally leaves a mark on the computer.

In other words, the user's navigating the characters on the keyboard actually corresponds to a typing rhythm movement that he or she does quite regularly. Theoretically, when you want to write a word to an editor on the computer using the keyboard, the time it takes to write the letters in the word is equal to each other. A user was asked to write their surname and the time spent in writing was determined.

While the user loses a lot of time between t and e characters, they can switch between n and s or s and o characters very quickly. It is tried to determine the typing rhythms of the users by measuring the time elapsed between two characters entered from the keyboard. In fact, this is the value that has been measured and tried to be evaluated in many studies on writing rhythm. One of the most important disadvantages of typing rhythm systems is that the data required for decision-making can only be obtained from a single parameter, namely the delay time between two keys. Detection of not only the key spacing, but also the elapsed time while pressing the keys will increase the reliability rate in typing rhythm studies [12].

2. RELATED WORKS

2.1 LITRETURE REVIEW

There are many studies in the literature for hand geometry biometric systems, contactless and unrestricted recognition systems. Of those who may have all the websites reviewed here, it would be helpful to mention some of the recent ones here.

Jain (1999) and they took out and aligned their fingers from images from different angles. They have developed a system according to the way the fingers are aligned. They extracted clusters of elements with the length and length of the fingers in these regions, and they work on a database of 352 images taken over 53 [3].

Unlike classifying, grouping is an unsupervised/untrained method. There is a target variable in the classification and part of the dataset is reserved for training, which allows the model to learn. According to this learning, it is expected into which class a new object with the same properties will be included. There is no target variable in assembly, so there is no class. whereas the purpose of classification is to place similar items in the same class; The purpose of grouping is to group similar objects in the same group. For example; The people of city are here, the psychopaths are here, the idiots are on the other side. There are actually idiots in the classification and they share similar common characteristics, such as: B. stilan system is developed from the model in Sanchez-Riello's (2000) study, a 97% project was not selected [4].

Kumar (2003) and tried-and-true hand geometry and fingerprinting suggested combining these features. The individual and combined performances of these features were examined. They used a database of 100 people and when they combined the features it was a 99% coincidence [5].

Yuan Jing (2004) have suggested experiments have individuals not recognized by a person using DCT and truth discrimination. These are the bands that can be applied to a distinctive extent from 2B, which can be designed appropriately by selecting D from all the high bands applied in this class. Then with the use of Fisherface, they extracted the distinctive features and did what they did with the closest proximity. Emphasized meanings in determining the characteristics of choosing to care [6].

Hennings (2004) et al. applied correlation filter classifiers, which had previously been applied to other biometric features, to palm print and achieved 100% success on a database of 50 people [7].

Wu (2004) et al. suggested DLEF (Directional Line Energy Feature) as an alternative to features such as palm line structure and thickness. DLEF refers to the sharpness of palm lines in different directions at different positions in the palm region. In other words, it contains line structure and thickness together. As a result, they obtained the best performance as 97.2% using 6 different directions [8].

Wu (2005) et al obtained a new feature by combining phase information and direction information using 2D Gabor filters [9].

Amayeh (2006) et al. used high-level Zernike moments to express the hand geometry, so that the rotation, translation and scaling-independent properties of the hand in the image plane were tried to be extracted [10].

Ekinci and Aykut (2007, 2008) used Gabor-Based and Wavelet-based Core Principal Components Analysis to extract the distinctive features of the palmprint region using the PolyU Palmprint database, and used the Nearest Neighborhood and Support Vector Machines methods for classification. As a result of these studies, they achieved a recognition success of 99.654% [11, 12].

Cui (2011) et al. extracted 3-dimensional palm print features using the view-based Linear Discrimination Method (LDA). In addition, by examining the relationship between the recognition accuracy and the resolution of the 3D palm print image, they observed that the recognition was better in 16x16 and 32x32 resolution images [13].

Zheng (2007) et al. focused on the mathematical representation of biometric features that are not only discriminatory but independent of projective transformations. Unlike other existing hand geometry technologies, they propose a geometric model that uses projective invariants of the hand. Thus, palmprint recognition was performed using a single image of the hand, regardless of the perspective [14].

Zhang (2008, 2009) and colleagues obtained 3D palmprint information using a structured light source. They used curvature-based feature extraction algorithms to extract features such as mean curvature, Gaussian curvature and surface type of the region of interest they obtained. They used fast feature matching and score level fusion in classification. They examined the recognition and validation results on a 3D palmprint database consisting of 600 images of 260 people [15, 16].

Li (2009) et al. extracted position and direction information from the average curvature features of the 3D palmprint information they obtained using a structured light source. A score-level fusion of these two features was used in the classification. High recognition and validation results were obtained with the fusion of these two features and these features on the database consisting of 8000 images taken from 200 people [17].

Li (2010) et al. obtained palmprint features such as shape, outline and texture by using 2D information as well as 3D information they obtained. They observed a significant increase in validation results on a 2D+3D palmprint database of 6000 images taken from 200 people [18].

Kanhangad (2011) and his colleagues observed an increase in performance by using the 3D features they obtained with the 3D Digitizer, considering that the 2D hand geometry features have limited discriminating information in identification. They also proposed a new comparison method called SurfaceCode in classification and analyzed the results on a database of 177 people. In addition, they observed an increase in performance by using 5 biometric features: 2D and 3D palm print, finger texture, 2D and 3D hand geometry [19].

Iula (2013) et al. used the developed ultrasound technique to obtain 3D information [20]. Cui (2014) et al. used 2D and 3D palmprint features together in recognition. They used the TPTSR (Two-Phase Test Sample Representation) method, which is very effective in face recognition, during the recognition phase, and previously they used the PCA (Principal Component

Analysis) method to extract the 2D and 3D palm print global features, and they had satisfactory recognition performance on the PolyU2B+3D palm print database. they have reached [21]. The production of 3D information with structured light still requires a high cost, although not as much as 3D scanners. Cost and speed problems are seen as an obstacle to the widespread use of palm print recognition systems.

2.2 TRADITIONAL TECHNIQUES USED IN HAND GEOMETRY BIOMETRIC SYSTEMS

In previous studies there are several traditional techniques used in the biometric systems. In this section we will presented these techniques. The detail advantages and disadvantages of these techniques are presented below:

2.2.1 Principle Component Analysis (PCA)

PCA, Principal Component Analysis, is a valuable numerical method utilized in the playing field of image identification, image categorization, and image density. It is a method whose primary goal is to obtain the dataset with the greatest variation of high-dimensional data, but at the same time provide a reduction in dimensionality. Find common ground in big data by reducing the number of dimensions and compressing data. Certainly, some functions are lost when downsizing; However, the fact is that these leak panels have not enough data around the population. This technique mixes extremely associated variable quantity to create a lesser set of duplicate variable quantity known as "principal components" that represent the greatest diversity in the data point [23].

PCA is a very useful technique to remove relevant information from data. The goal of PCA is to represent multidimensional data with less varying quantity and to capture the most important characteristics of the data.

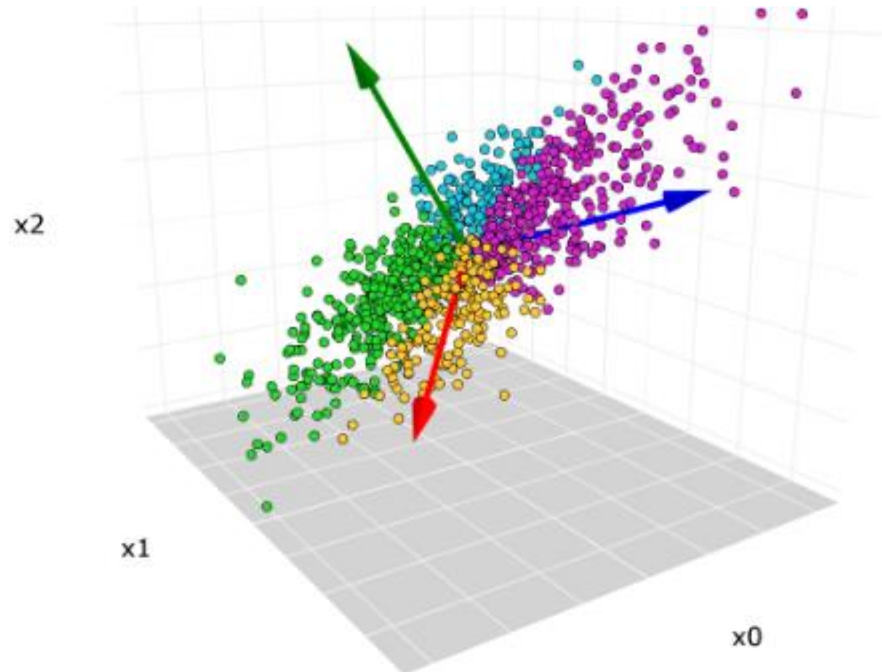

Figure 2.1: PCA.

2.2.2 Fisher Reagent Analysis

Fisher Reagent Analysis; It is based on the logic of projecting data into a new feature space that will maximize the separability of the classes to which they belong. This approach, first proposed by Fisher, basically tries to maximize the distance between the mean of each class and minimize the spread within the classes themselves. The Fisher Reagent Analysis is in several studies the process of the Fisher Reagent Analysis presented in Figure 2.2.

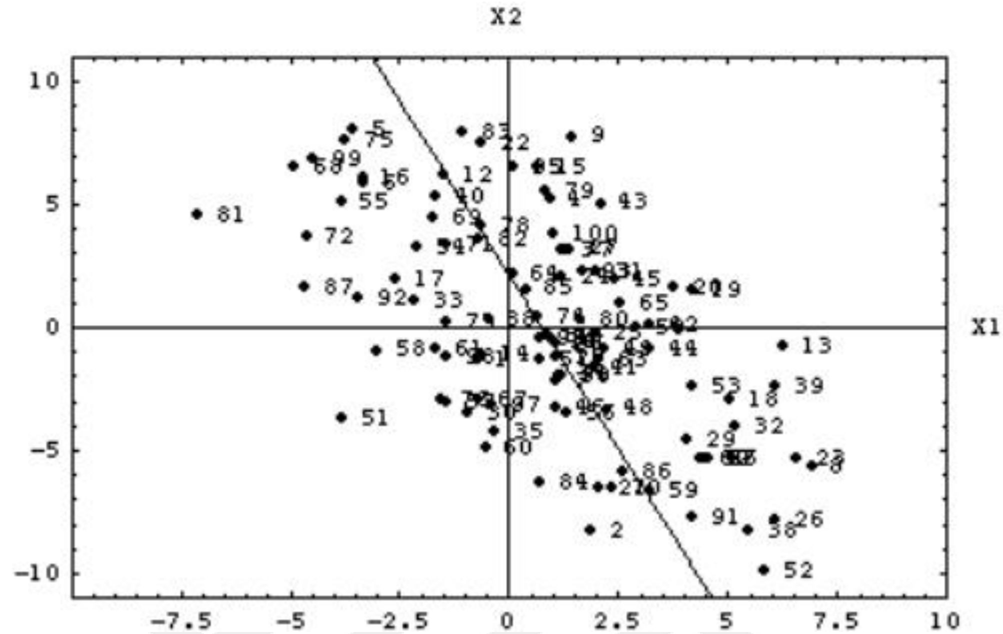

Figure 2.2: Fisher reagent analysis.

2.2.3 Similarity Measurement

The mappings of the feature vectors were made by considering the EYK. This classification method uses distance criteria for matches. Distance criteria are used to determine whether two numbers (or lists of numbers) are similar or different. Numerous similarity measures have been developed, but in our study, we considered three well-known and frequently used metrics. These; Euclidean, Manhattan, and Cosine metrics.

2.2.4 Local Feature-Based Approaches

Local Feature-Based Approaches These are the techniques used to make the basic lines and wrinkles more prominent in the palm print. While various edge detection methods are used in some studies in this class, there are also studies that highlight these lines with the help of Gaussian Derivative. One of the most interesting approaches that fall into this class is palmprint coding. Palmprint coding techniques; They offer significant advantages in terms of matching ease, computation time and memory usage.

These techniques, which are especially preferred in multi-user and real-time verification systems, are generally created by passing the ROI region through a filter bank. Kong first applied coding techniques in palmprint biometrics during his doctoral study. In fact, this coding was inspired by IrisCod, a well-known technique proposed by Dougman] in iris recognition. This coding technique, called PalmCode, was developed by applying a 45 degree Gabor filter on the pattern. In the same study, the technique known as FusionCode was proposed by taking different angles of the Gabor filter.

2.2.5 K-Mean

First of all, let's take a look at where and for what purposes this algorithm can be used. In my opinion, before we start to examine an algorithm, knowing what it serves increases our working efficiency.

i. Document Classification Groups documents into various categories based on the tags, topics, and content of the documents. This is a very standard classification task and the k-mean tool is suitable for this purpose.

ii. Identification of Crime Locations, the crime-associated information offered in certain regions of a town, criminality classification, criminality zone, and the connection among the two can offer value data on crime-prone regions in a town or area.

iii. Customer Segmentation, Clustering services vendors improve their client support, go to work in focus regions, and portion consumers established on buying record, concerns or interest tracing. Category helps the firm focus on individual client sets for particular promotions.

iv. Player Analysis, Aanalysing actor data has constantly been a crucial component of the sporting realm, and with growing rivalry, machine learning has a vital role to work here [33,34].

The simple process of the K-mean presented in the Figure 2.3.

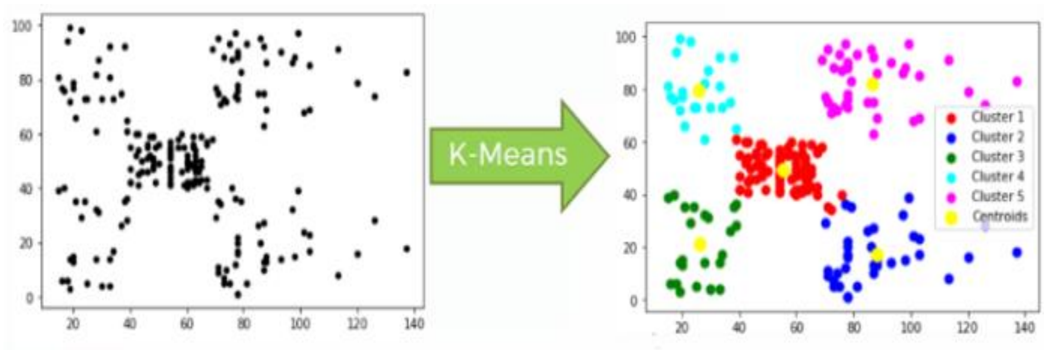

Figure 2.3: K-Mean.

2.2.6 Support Vector Machine (SVM)

If the problem to be solved belongs to one of the controlled binary classifications, SVM (Support Vector Machine) can be used. That is, we can use SVM algorithms when we want to separate new invisible objects (an unknown category) into two distinct groups based on their properties and a set of known instances already classified. A good example of this system is the classification of a series of new documents into groups as positive or negative based on other documents that were previously classified as positive or negative. Or, similarly, we can classify incoming emails as spam or non-spam based on a large collection of documents that people have already marked as spam or not. SVMs are very useful algorithms for such situations. The support vector machine models the situation by creating a feature field, which is a finite-dimensional vector field whose size represents a "property" of a particular object. In the context of spam or document classification, each "feature" refers to the prevalence of a particular word or the importance of that word. The purpose of SVM is to create a model that classifies new invisible objects. It tries to do this by creating a linear partition of the feature space into two categories. Depending on the characteristics of the new invisible objects (eg: documents or emails), you can place the category (eg: spam or not spam) "above" or "below" the multiple separation plane (hyperplane). "locations.

This would be an example of a non-probabilistic linear classifier. This is unlikely because the features of the new objects determine their exact location in the feature space [35]. The figure 2.4 represented the SVM process.

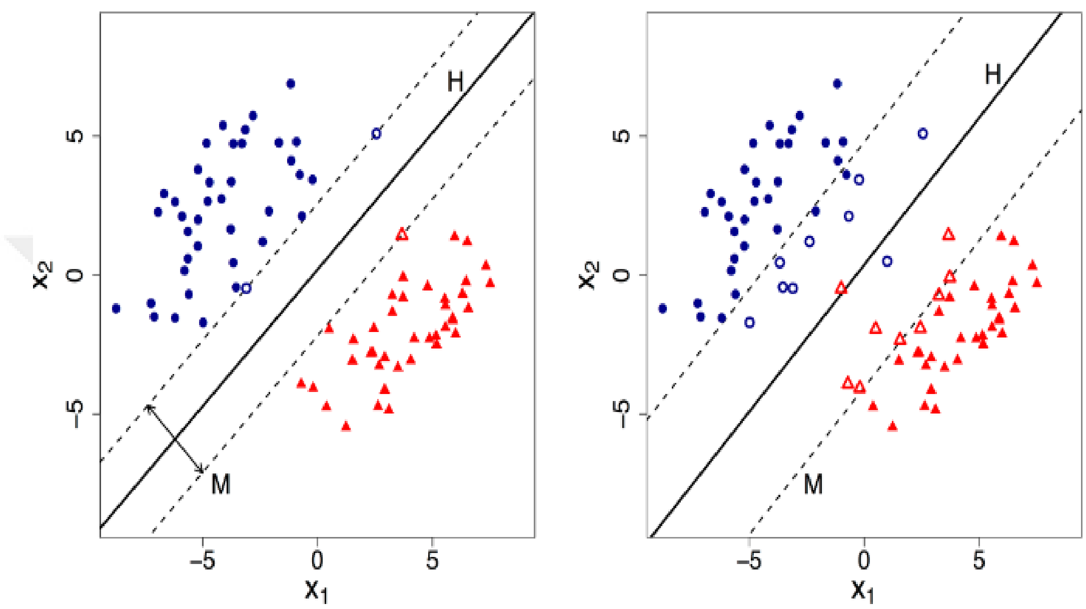

Figure 2.4: SVM.

2.2.7 Decision Tree (DT)

According to Aggarwal, decision trees are a classification methodology in which the classification process is modeled by a series of hierarchical decisions about feature variables organized in a tree structure. According to Sharma, Bhargava and Mathuria, a decision tree is a decision support system that uses graphical decision trees and potential outcomes (consequences of random events, resource costs and benefits, etc.). Decision trees or classification trees are used to examine classifiers that assign values of dependent attributes (variables) as values of independent (input) features (variables). A decision tree is composed of nodes that form a root tree. That is, H is a linear tree with no front edge at the node called "root". All other nodes have exactly one leading edge. Nodes with prominent edges are called internal nodes or test nodes. All other nodes are called leaves (also called terminal nodes or decision nodes).

In a decision tree, each interior node divides the sample space into two or more subregions based on other properties of the input attribute values. In the simplest and most common case, each test examines an attribute, so the sample space is divided into attribute values. For numeric attributes, the condition is in scope [36] .

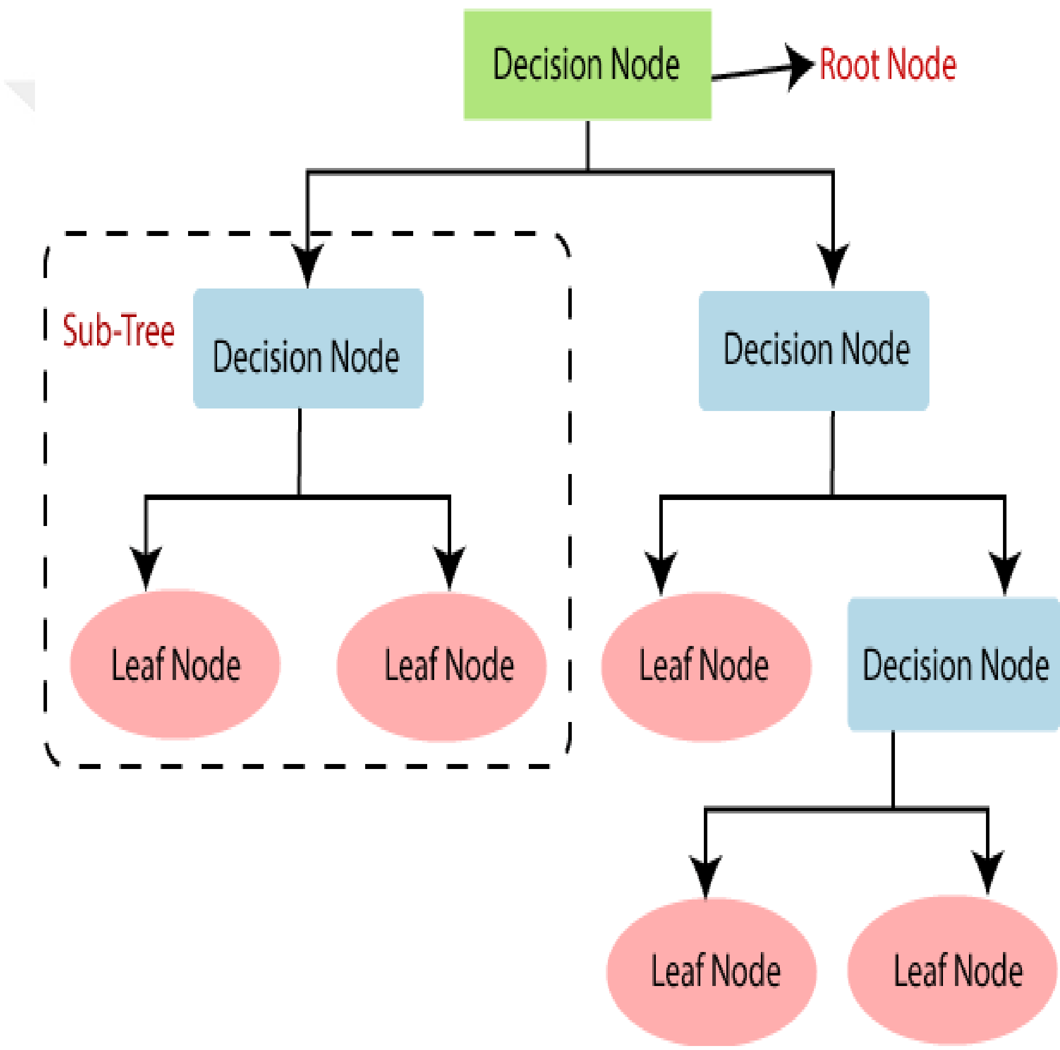

Figure 2.5: DT.

3. MATERIAL AND METHODS

3.1 DEEP LEARNING

Deep learning (DL) is a subset of machine learning (ML) and was inspired by the processing of information in the human brain. In deep learning, there is no need for a pre-determined rule by humans. Deep learning method needs a lot of data for the relationship between labeled data instead of a predetermined rule. In order to establish this relationship, deep learning uses multiple artificial neural network algorithm layers, each of which is fed from the output of the previous layer and then different interpretations are made [37]. In machine learning, feature extraction, feature selection, learning and classification processes are performed respectively to perform a classification task. The feature extraction and selection operations greatly affect the performance of this method. Here, the misguided feature selection due to human influence affects the machine learning method in the wrong direction and may reduce the correct classification ability. On the contrary, deep learning has the ability to automatically learn the attributes of the data. Because of these developments, DL is one of the most popular learning methods when working with big data.

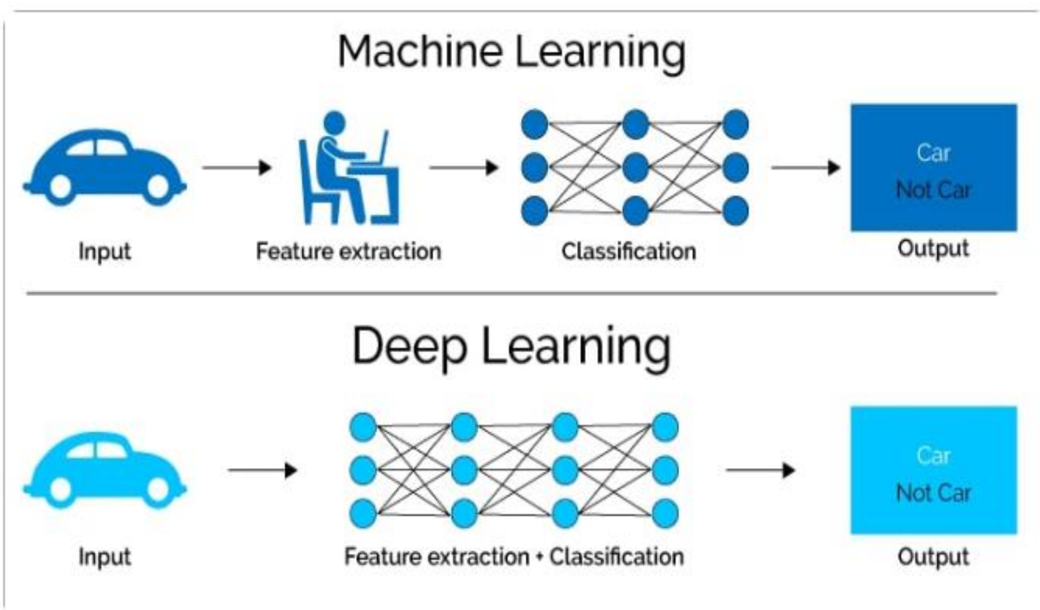

Figure 3.1: Deep Learning vs Machine Learning.

Deep learning, which is used in many research branches such as segmentation, classification, speech recognition and natural language processing; It is defined as a machine learning method that performs the learning process based on concept hierarchies by making decisions similar to humans. The biggest advantage of this method is that the computer can acquire the features/attributes that it will use for learning purposes on its own. In classical methods, this process is carried out by the operator and there is a long process such as the analysis of the data set to be used. However, deep learning significantly shortens this process with its automatic feature/feature extraction capability. Deep learning architectures, which are divided into two as supervised and unsupervised methods; It is used for segmentation, classification and object detection. AE (Automatic Encoders), SSAE (Sparse Stacked Auto Encoders) etc. methods can be given as an example of unsupervised deep learning methods. U-Net, V-Net, FractalNet, SegNet, DenseNet, ResNet, etc. architectures are also among the supervised deep learning architectures; KSA, R-CNN, FCN, etc. based on architectural types.

3.1.1 Convolutional Neural Network (CNN)

Convolutional Neural Networks Convolutional neural networks (CNN) are one of the most popular and widely used methods of DL networks. CNN networks are used extensively in a range of tasks including computer vision, image classification, speech recognition, face recognition. The structure of CNN networks was inspired by the study of the visual cortex in human and animal brains, similar to artificial neural networks. Each CNN method trained with data is called a model. CNN is basically a mathematical modeling consisting of 3 typical layers. These layers are; convolution and pooling and the fully connected layer. From these layers, the convolution and pooling layers perform the feature extraction process to establish the necessary relationship for training the model. The fully connected layer classifies the extracted features [38].

The convolution layer is one of the key components of the CNN architecture that performs feature extraction consisting of convolution operation and activation function. In image processing, convolution is the processing of a matrix by another matrix called kernel (filter, mask, kernel).

Considering a 3 x 3 core, the rendered matrix will be the image matrix, so the 3 x 3 core matrix will repeatedly examine each pixel across all positions where the image fits. This review usually starts in the upper left corner and continues to the right. For each pixel examined in the convolution process, the values of this pixel and the 8 pixels around it are multiplied by the value corresponding to the core, and then these values are summed up and this result is written to the examined pixel address in the output matrix. The convolution layer, on the other hand, is the layer where kernels of various sizes are applied to the input matrix called tensor with convolution logic in order to determine which regions of the input data are important in terms of the feature map. The nuclei are shifted along the width, height and depth of the tensor on the tensor and calculations are made at this time. A two-dimensional feature map matrix is obtained from the results after shifting the kernel on the tensor in this way and point-based calculations are completed (Figure 3.2). Therefore, different kernels can be considered as different feature extractors [39].

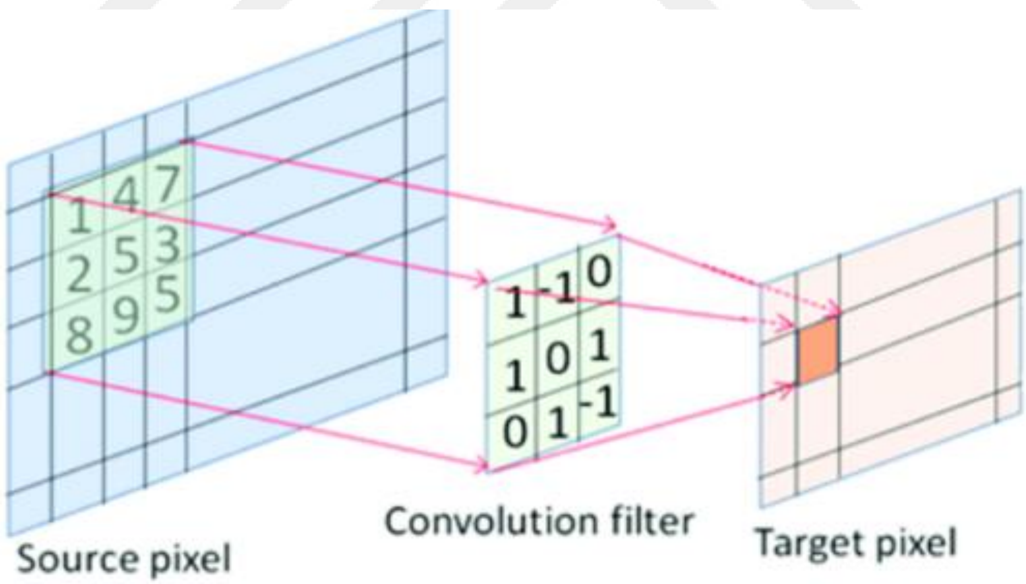

Figure 3.2: Convolution layer.

With the number of steps (stride), it is decided how many pixels to shift the core. If the number of steps is one, the kernel is shifted one pixel at a time along the input tensor. The number of steps affects the size of the data output at the end of the convolution process.

If the number of steps is large, the number of data obtained is less and the network is easier to train. However, this may cause losses in the information obtained from the data. Sometimes the kernel cannot fully scan the input tensor when shifted by the desired number of steps along the input tensor. In some cases, it cannot transfer enough information to the feature matrix. Therefore, it may be necessary to make adjustments to the size of the input tensor.

The key feature of a convolution operation is weight sharing. Cores are shared with all image locations. Weight sharing allows local feature models to be invariant in convolution operations, shifting across all image and input tensors of the kernel, and detecting new patterns. For CNN to understand complex structures, it needs to be generalized. For this, it is necessary to add a non-linear activation function to the deep learning network. Thus, by deciding whether to enable the output tensor where the operation takes place, the CNN is generalized in a way that it can understand complex structures. Activation functions used in CNN and other deep learning networks; They are Sigmoid, Tanh, Parametric Linear Units, ReLU, Leaky ReLU, Noisy ReLU (Figure 3.3). The most widely used of these enable functions is ReLU (Rectified Linear Unit) [40].

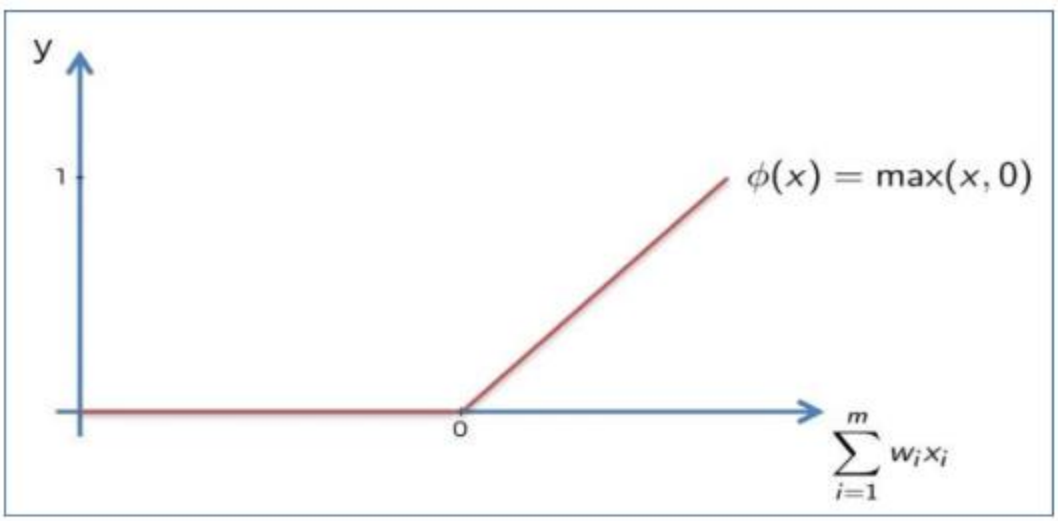

Figure 3.3: Rectified linear unit layer.

Pooling Layer The Pooling Layer reduces the size of the feature matrix by downsampling to reduce distortions during learning and the number of learnable parameters.

In the pooling layer, as in the convolution layer, although there are parameters such as number of steps, kernel size and padding, there are no learnable parameters. The reason for this is the subsampling in this layer. Three different pooling methods are used in the pooling layer, which is one of the basic layers of the CNN network, which is one of the DL networks. These are Maximum Pooling, Average Pooling, and Global Average Pooling. In the Maximum Pooling method, m x m sized pieces are taken on the n x n size feature matrix used as input, and the largest element in this piece is written to the new feature matrix as output. Since no operation is applied to the feature matrix that will reduce the depth dimension, the height and width dimensions of the feature matrix are subsampled using the Maximum Pooling layer, while the depth remains constant. On the feature matrix of size n x n used as input in the Average Pooling method, m x m pieces are taken so that n > m, all the values in this piece are summed and then divided by m^2 and written to the new feature matrix as output. Similarly, in the Average Pooling method, while there is no decrease in the depth dimension, there is a decrease in the width and height dimensions of the feature matrix, resulting in subsampling (Figure 4.6).

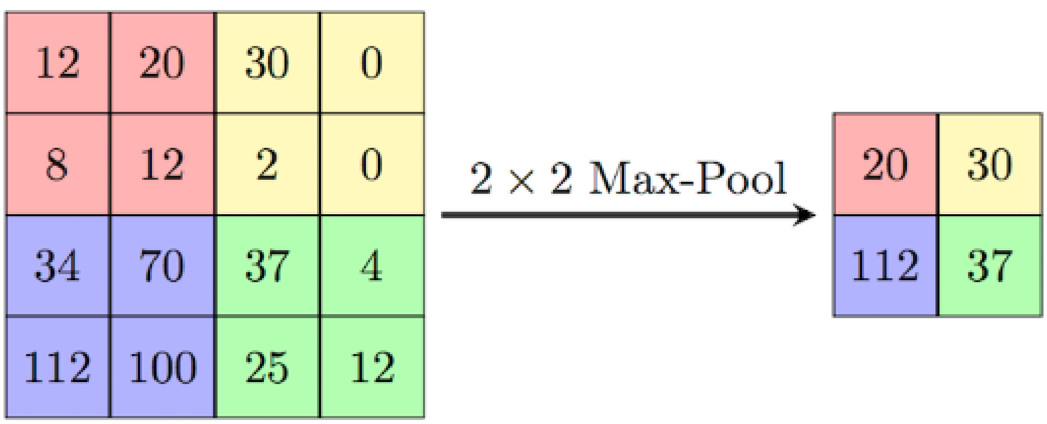

Figure 3.4: Max pooling.

In the Global Average Pooling method, the average of all the elements in each depth region of the n x n feature matrix used as input is written to the new feature matrix of 1 x 1 size as output [48].

Similarly, in the Global Average Pooling method, while there is no decrease in the depth dimension, an extreme reduction in the width and height dimensions of the feature matrix occurs, resulting in a subsampling of 1 x 1 dimension (Figure 3.4).

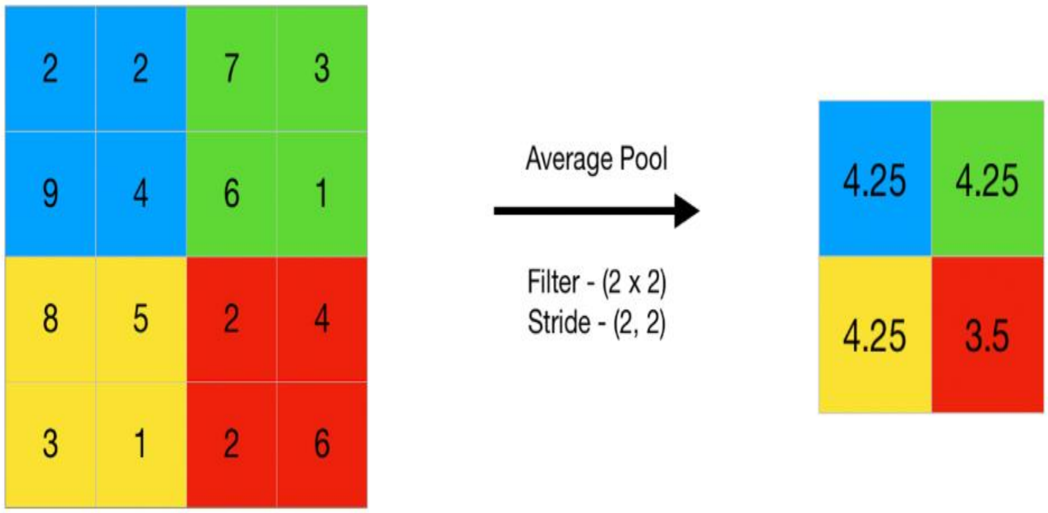

Figure 3.5: Average pooling.

Then, the fully connected layer comes after the convolution and pooling layers, which are the first part of the CNN network. In the fully connected layer, the feature matrix obtained as a result of the first convolution and pooling layers is converted into a one-dimensional array of numbers (Figure 3.6). In this part, each input sequence in more than one fully connected layer is connected to the output with a learnable weight [41]. Thus, the outputs of the CNN network for each class become clear. So the size of the output array of the last fully connected layer in the CNN should be the same as the number of classes.

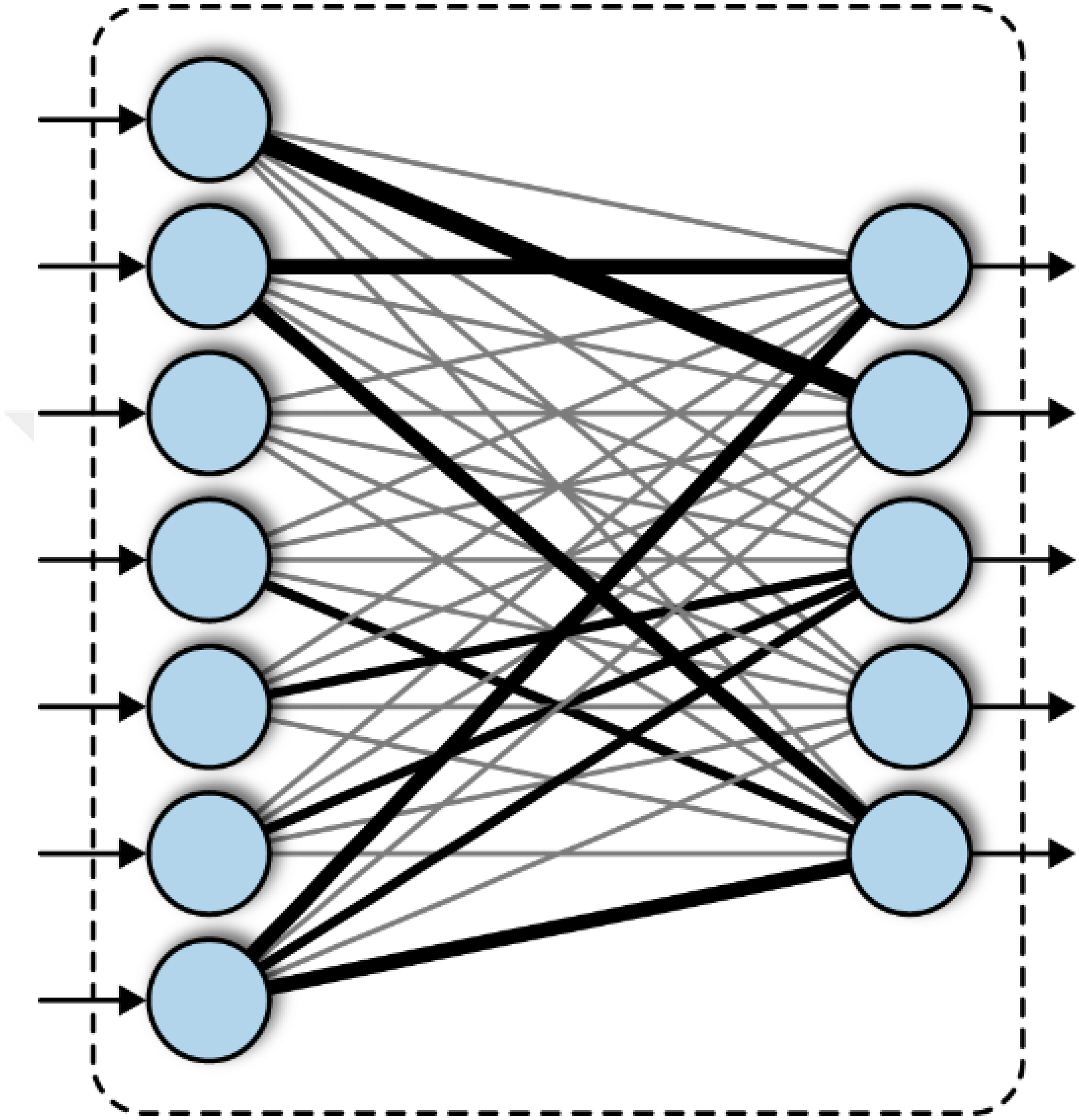

Figure 3.6: Fully connected layer.

3.1.2 AlexNet

AlexNet was developed in 2012 by Krizhevsky et al. presented in the article "ImageNet Classification with Deep Convolutional Neural Networks" [42]. The AlexNet network includes 8 layers, 5 convolution layers and 3 fully connected layers. Since the AlexNet network was originally designed for the ILSVRC competition, 227 x 227 images are used as input.

The output of the network is 1000 x 1, which is the number of classes in the ImageNet dataset. The AlexNet model trained on ImageNet has a total of 58 million parameters. In AlexNet network, multiple convolution layers are used to extract features from images. The first two convolution layers are followed by the maximum pooling layer. The third 31 and fourth convolutional layers are directly connected to the next layer. The fifth convolutional layer is followed by the maximum pooling layer. Flattening is then applied and bonded to fully bonded layers. The second fully connected layer feeds the softmax classifier and the softmax classifier determines the weights for 1000 classes (Figure 3.7). In the AlexNet network, ReLU is used as the enable function. ReLU is used after each convolution and fully connected layer. Maximum pooling is often used for subsampling. In this way, the width and height dimensions of the tensors are reduced, while the depth dimension remains constant. During maximum pooling, the pooling window is 3 x 3 and 2 is used as the number of steps to scroll this window.

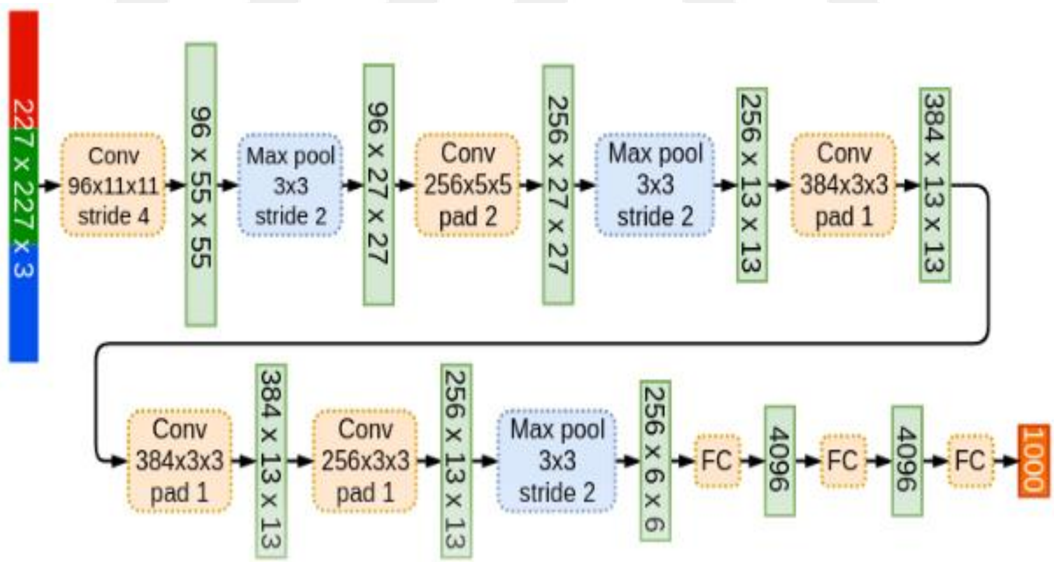

Figure 3.7: AlexNet structure.

3.2 PROPOSED CNN BASED BIOMETRIC SYSTEM

In this study, new method based CNN and wavelet transform based ensemble learning applied for human identification. The proposed method applied CNN for features extraction.

The aim of using CNN that the CNN extracted high level features in minimum execution time. This lead to enhance the performance of the classifiers that are used in classification. The AlexNet which is CNN transfer learning-based technique applied for features extraction instead of classic CNN. The AlexNet is pretrained model trained to with millions of images and the saved optimal weights and basis assist in enhancing the performance of the proposed method.

The main contribution of this study is applying wavelet transform to reduce the features size that are extracted by AlexNet. The extracted features size by the AlexNet are 4094, and the Wavelet transform reduce it to 2048. This mean great gain in the processing time of the model. Then, the extracted features by the wavelet transform wired to the ensemble classifiers that are applied for classification issue. The flowchart of the proposed method presented in Figure 3.7.

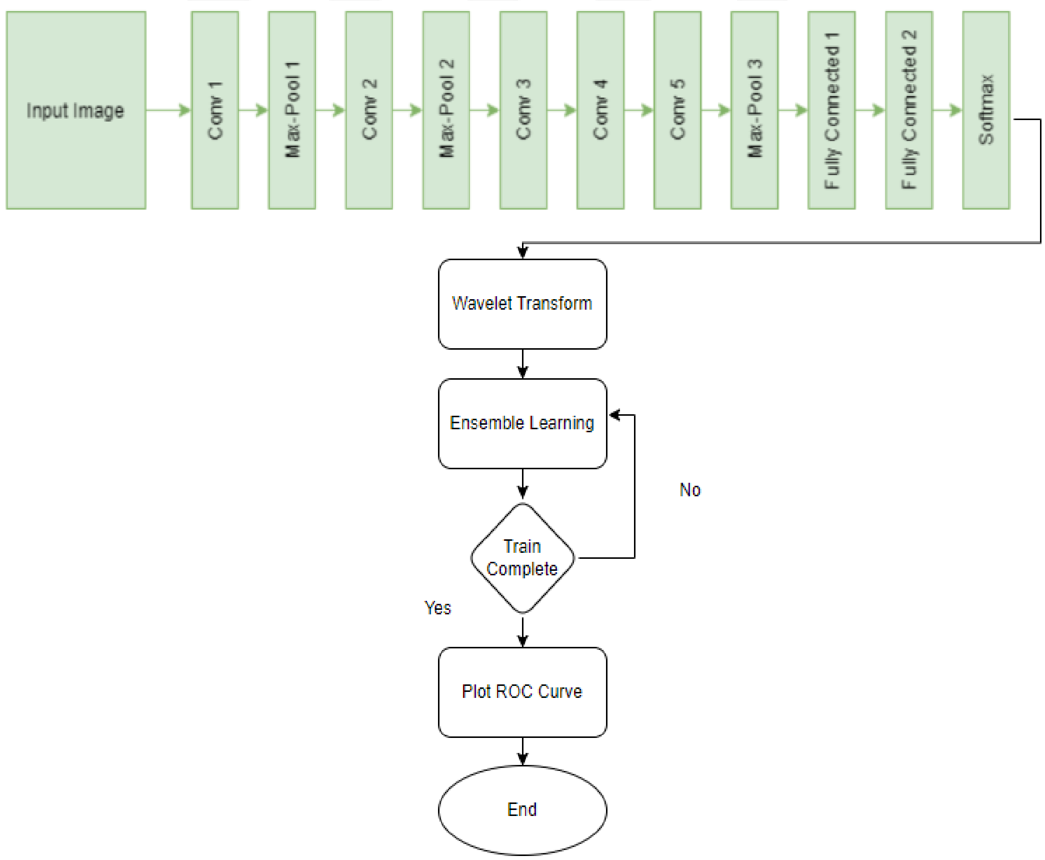

Figure 3.8: Proposed Biometric System.

4. EXPERIMENTS AND DISSCUSION

4.1 RESULTS

In this section the proposed method executed and the results presented according to the classifiers and the training and testing ratio to evaluate the method performance.

4.1.1 Support Vector Machine (SVM) Results

In this section the results of the SVM presented according to the training ratio to evaluate the performance of the method according to the various test ratios. The MATLAB script of the classifier presented in the Figure 4.1.

```
figure;

tic

  svmMd = fitcecoc(featuresTrain,YTrain);
  svmPredicate = predict(svmMd,featuresTest);

svmaccuracy = mean(svmPredicate == YTest)

  SVMtimeElapsed = toc
  YTestplotroc = grp2idx(YTest);
svmPredicateplotroc= grp2idx(svmPredicate);
P=plotroc(YTestplotroc,svmPredicateplotroc);

```

Figure 4.1: SVM MATLAB script.

As shown in the Figure 4.1, 4.2,4.3

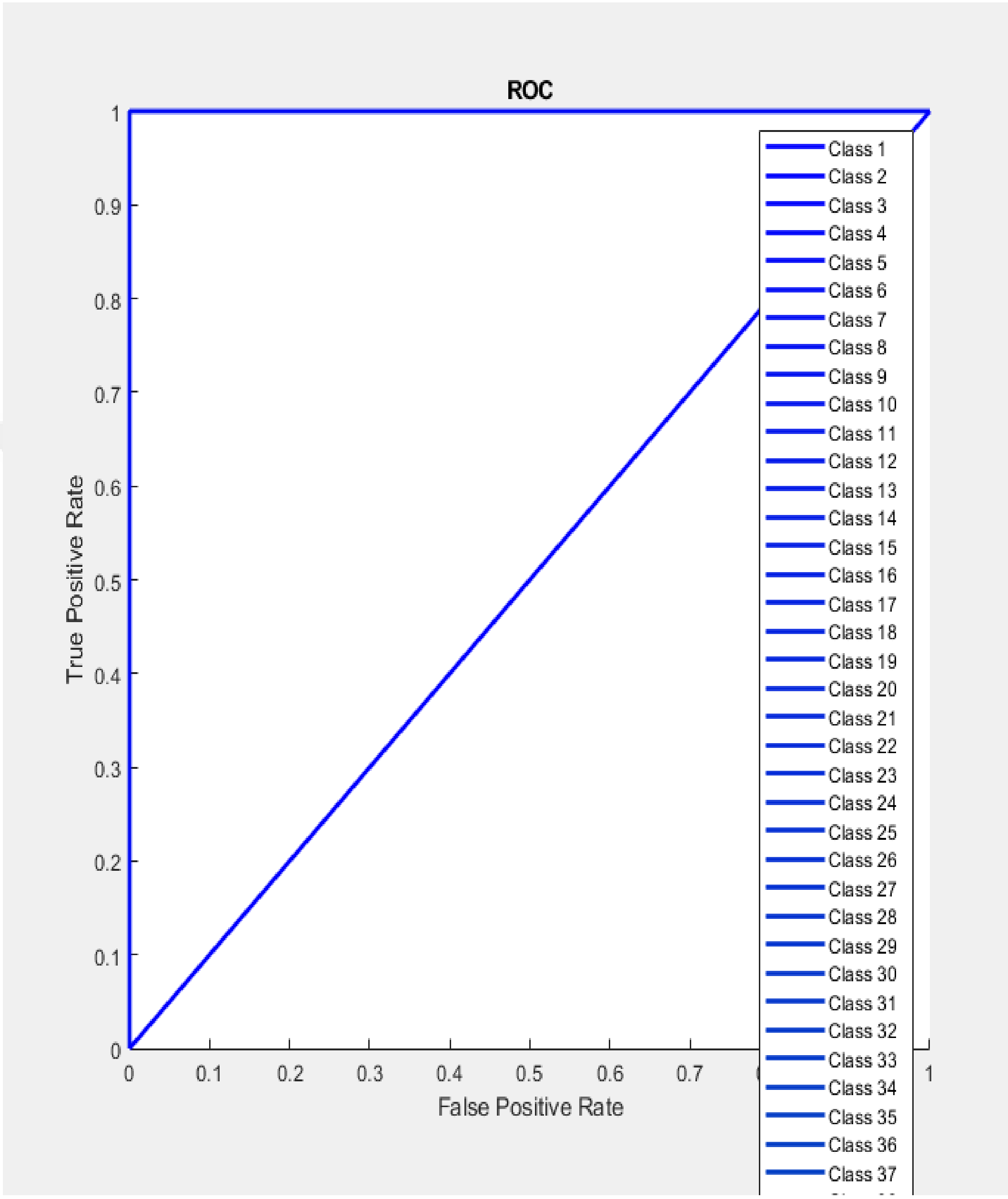

Figure 4.2: SVM with 90% training.

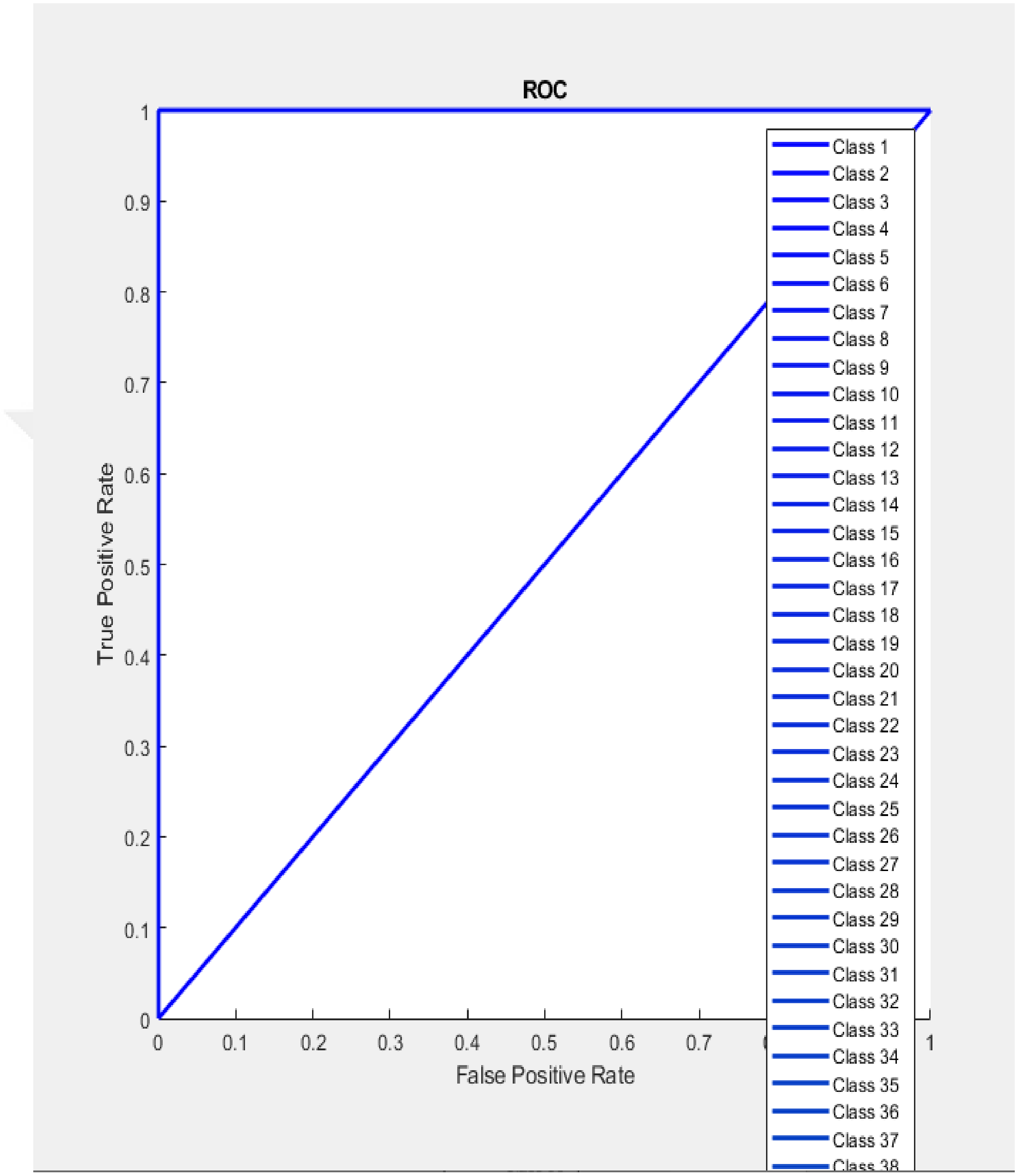

Figure 4.3: SVM with 80% training.

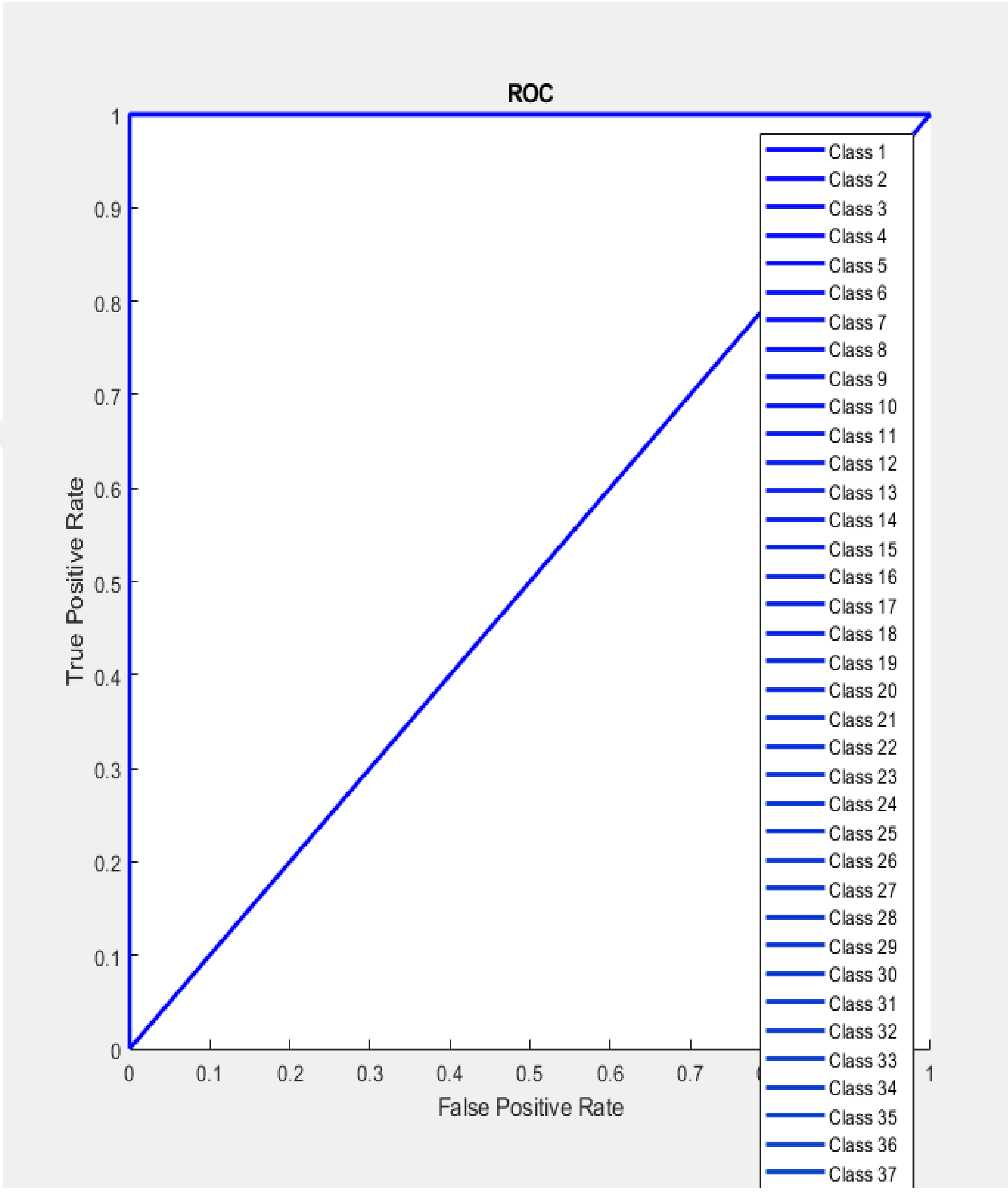

Figure 4.4: SVM with 70% training.

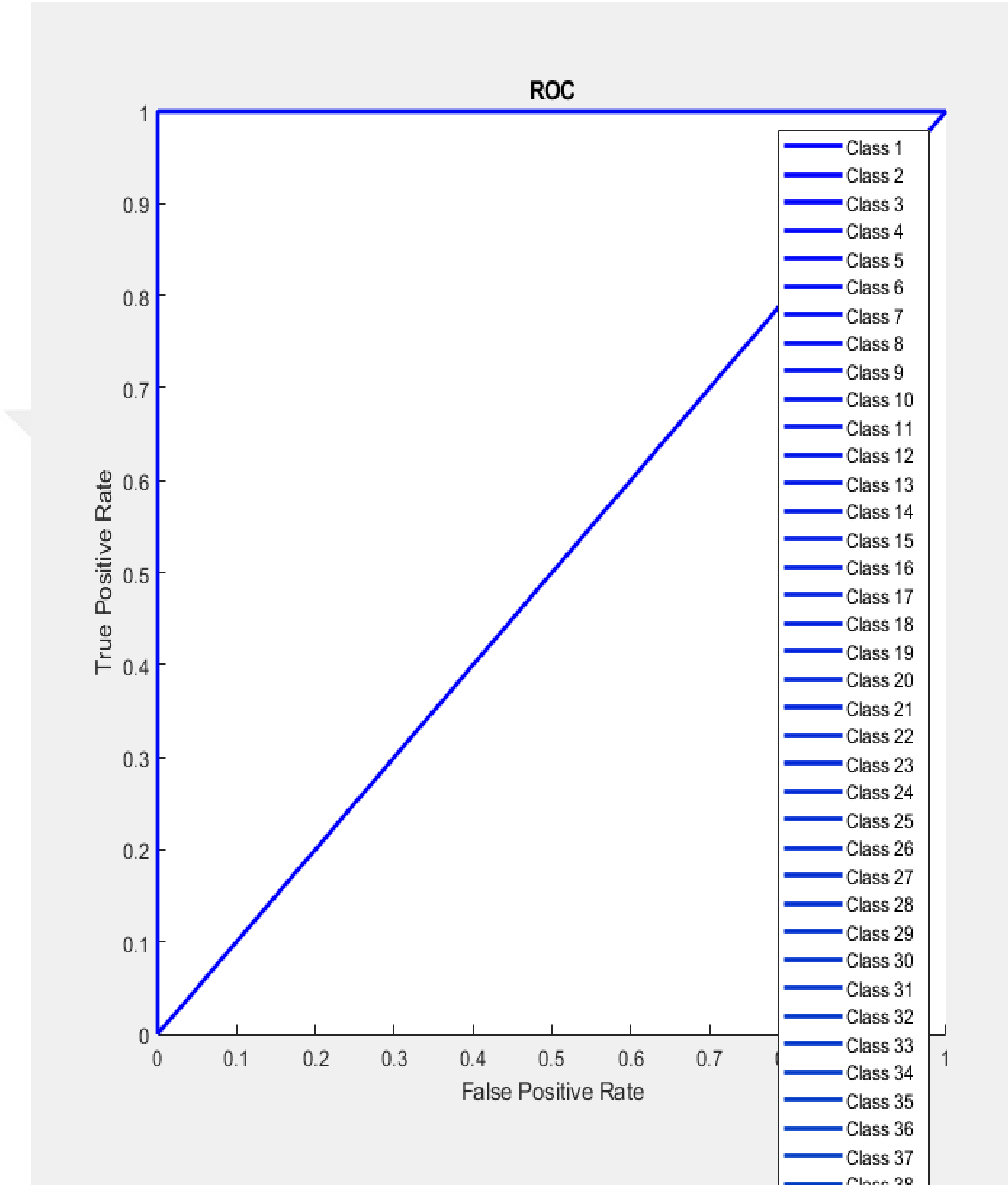

Figure 4.5: SVM with 60% training.

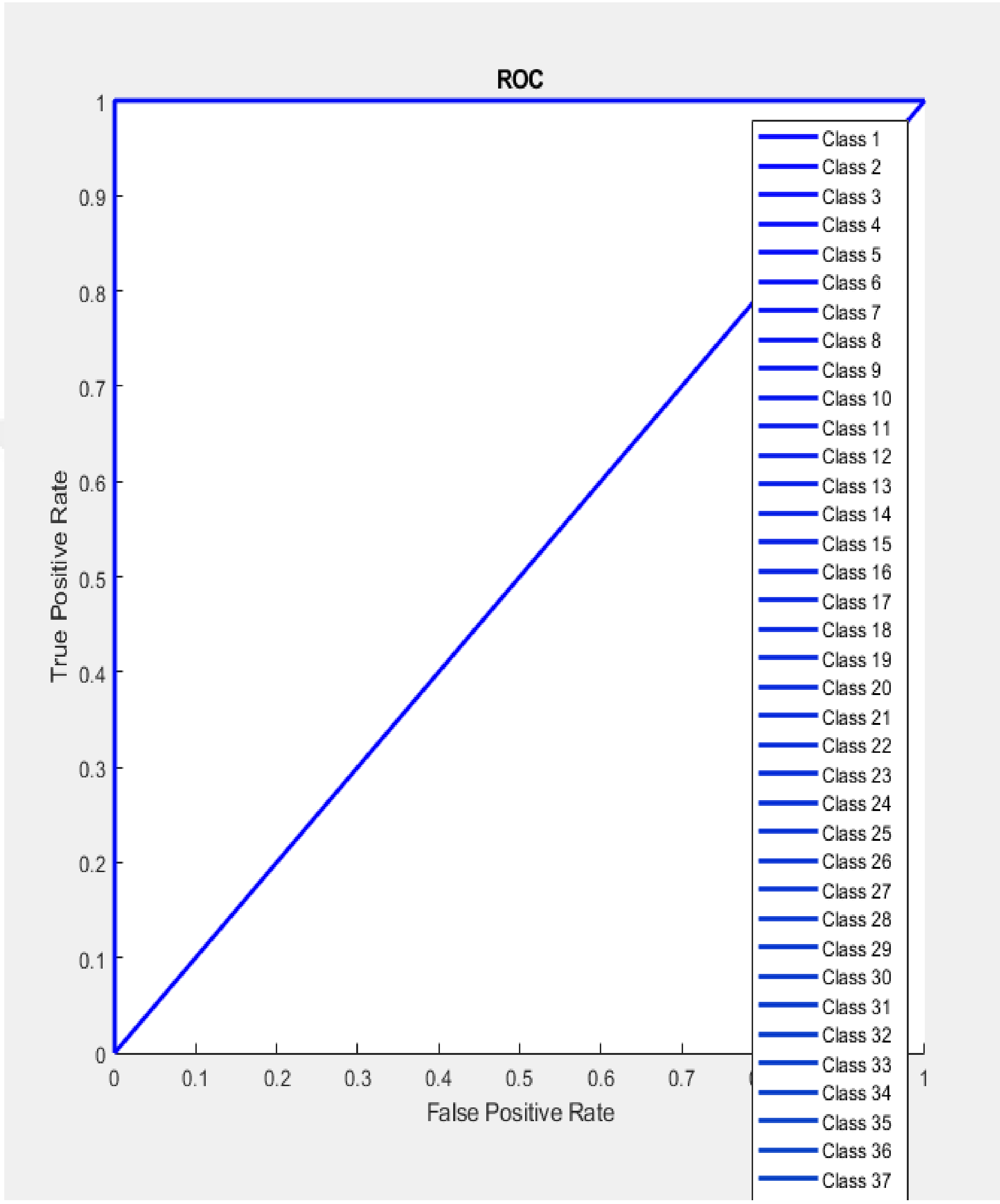

Figure 4.6: SVM with 50% training.

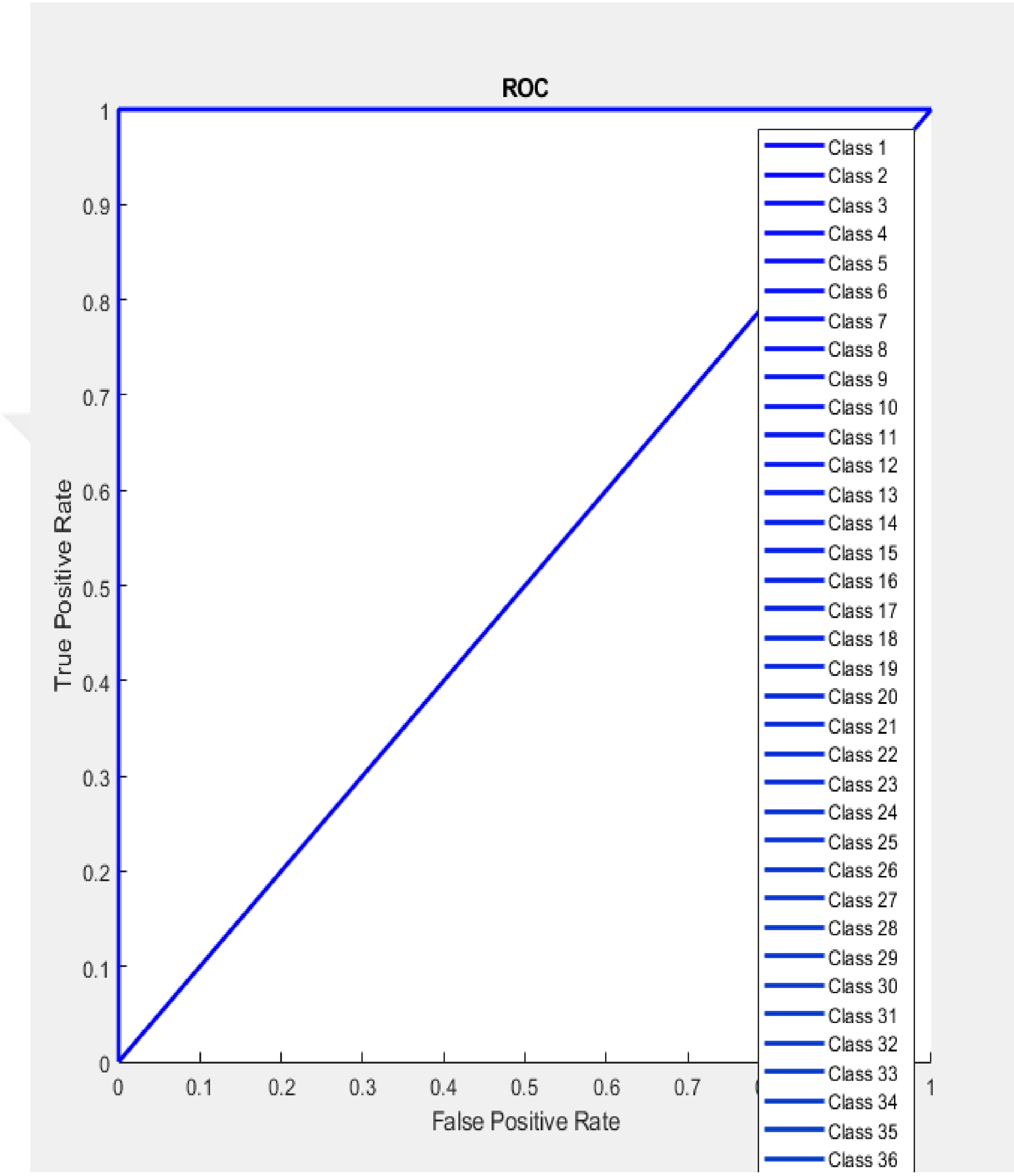

Figure 4.7: SVM with 40% training.

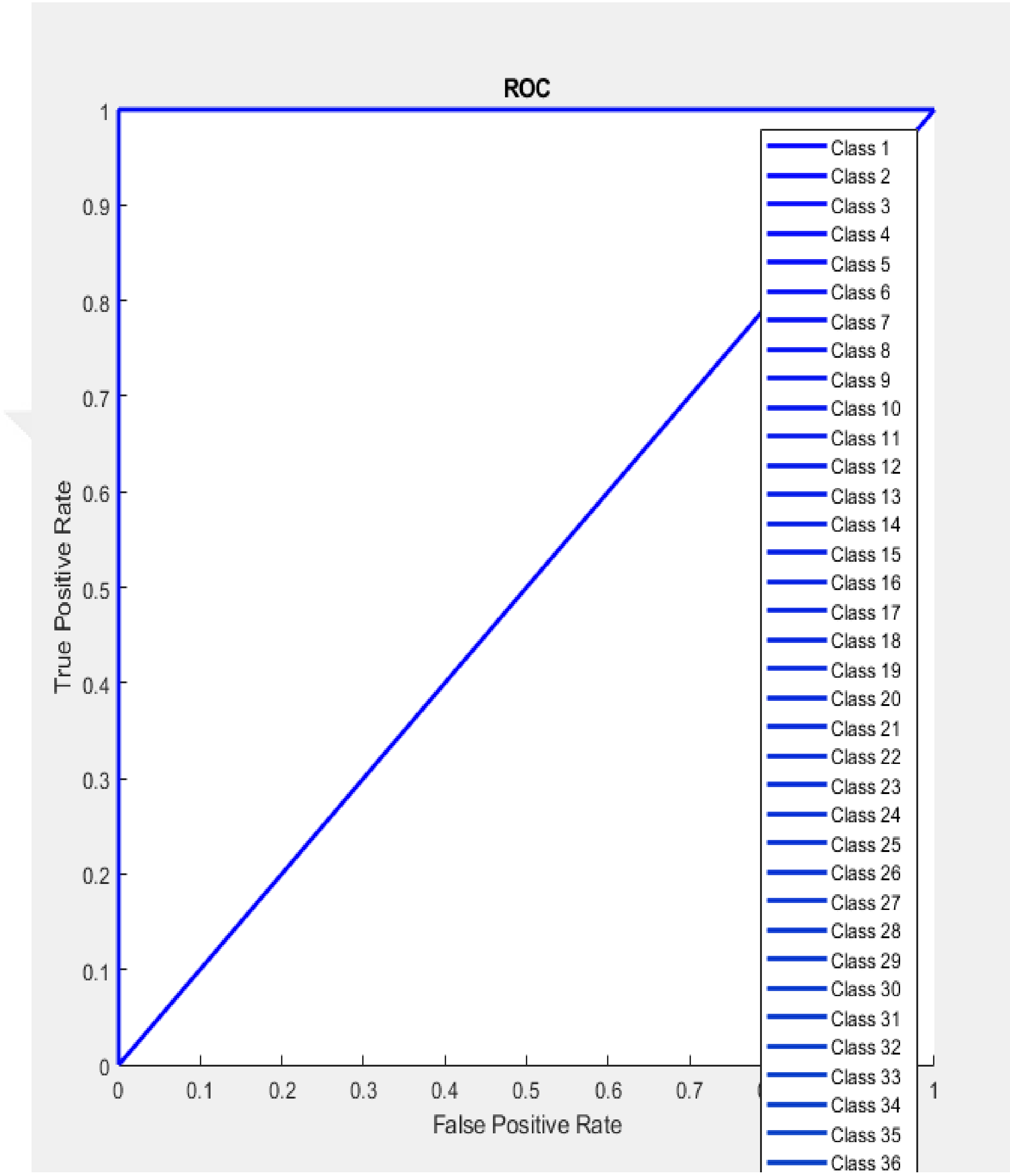

Figure 4.8: SVM with 30% training.

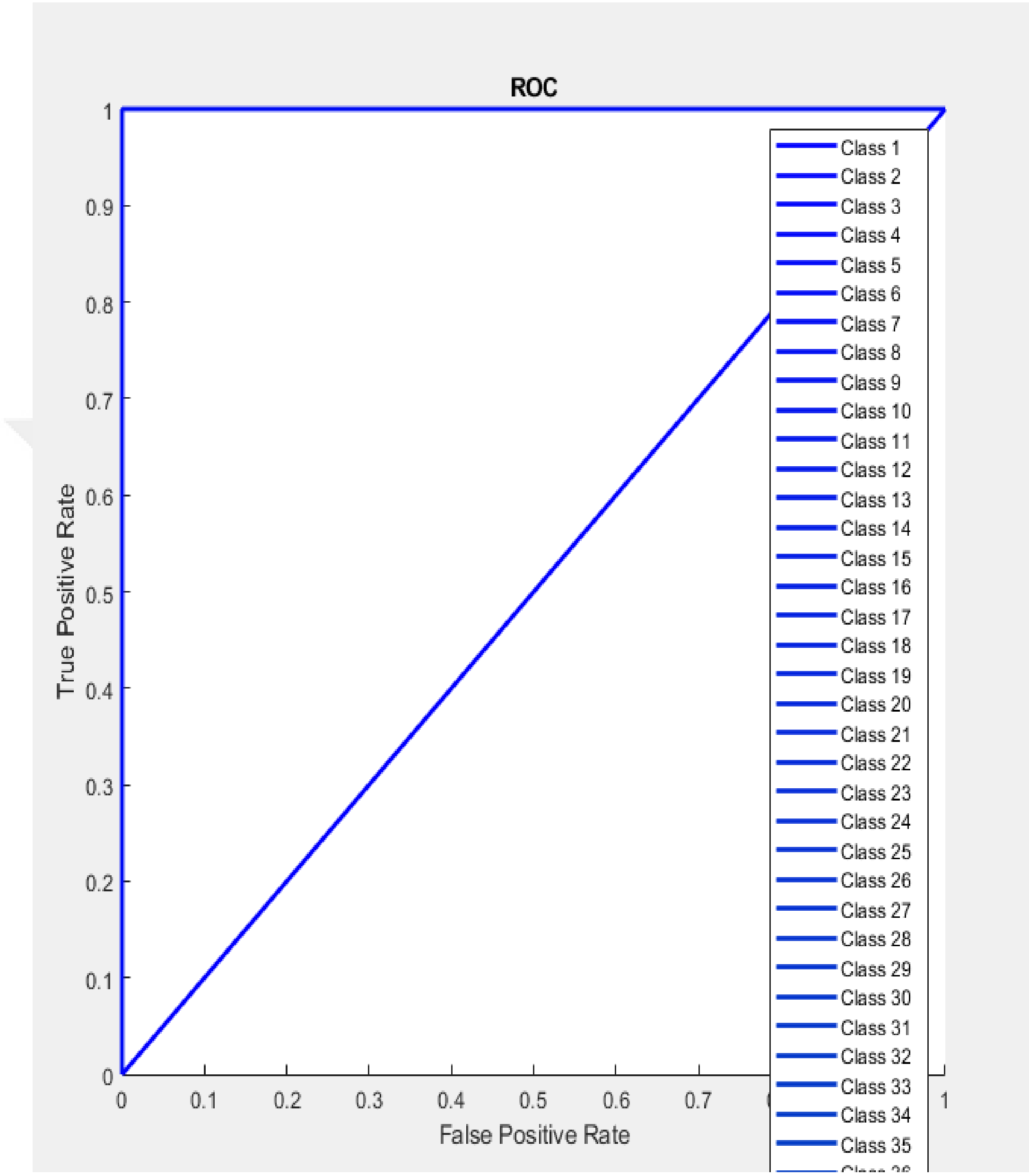

Figure 4.9: SVM with 20% training.

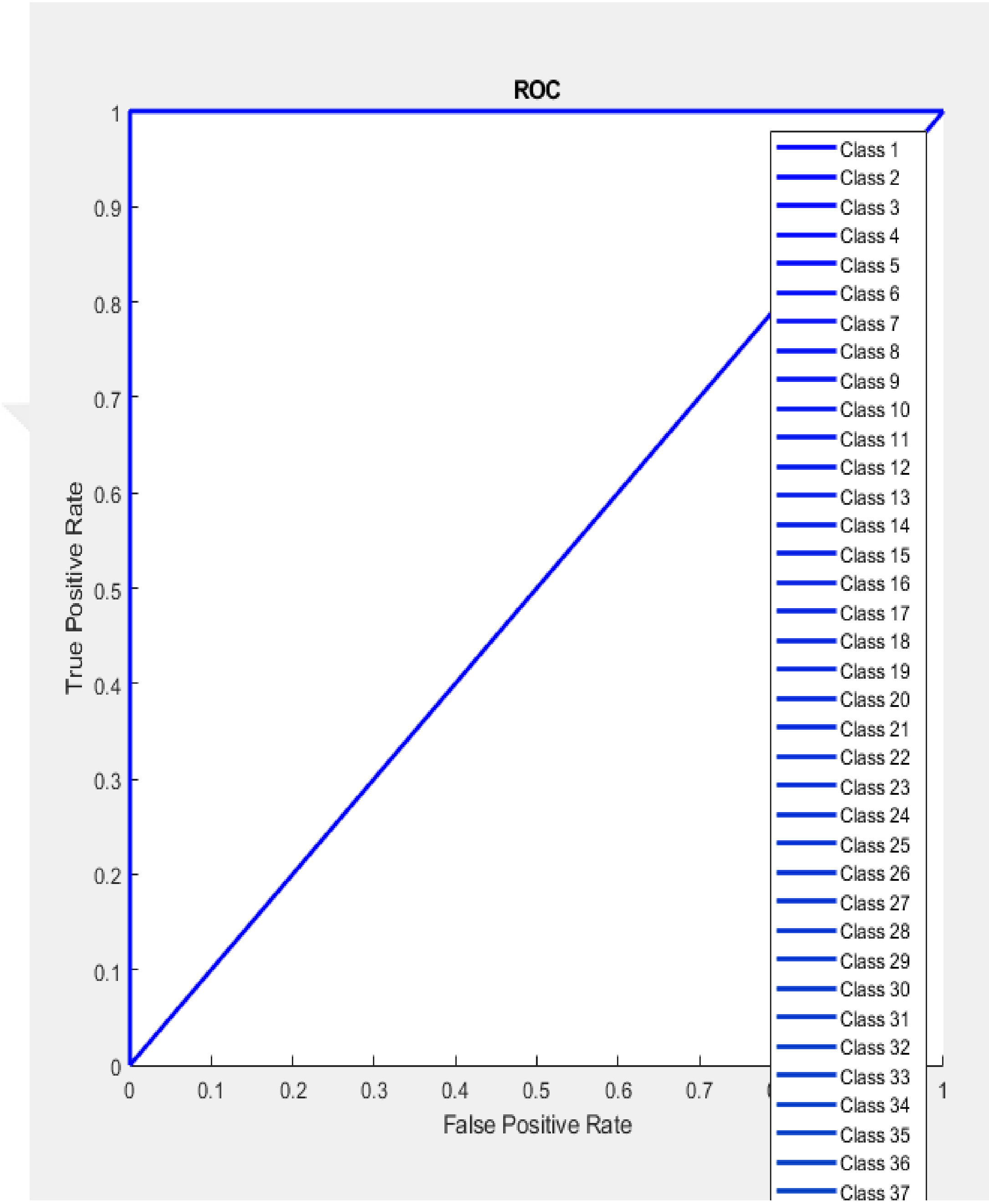

Figure 4.10: SVM with 10% training.

4.1.2 K-Nearest Neighbour Algorithm (KNN)

The KNN is the second classifier used in this study and the script of this KNN presented in below figure 4.11.

```
figure;

tic

  knnMd = fitcknn(featuresTrain,YTrain);   % KNN Training

  knnPredicate = predict(knnMd,featuresTest);   % KNN Testing
  knnaccuracy = mean(knnPredicate == YTest)   % find KNN classification accuracy
  KNNtimeElapsed = toc

%save handgeometry
knnPredicateplotroc= grp2idx(knnPredicate);

V=plotroc(YTestplotroc,knnPredicateplotroc);
```

Figure 4.11: KNN MATLAB script.

The results of the all training ratios presented in the figures below.

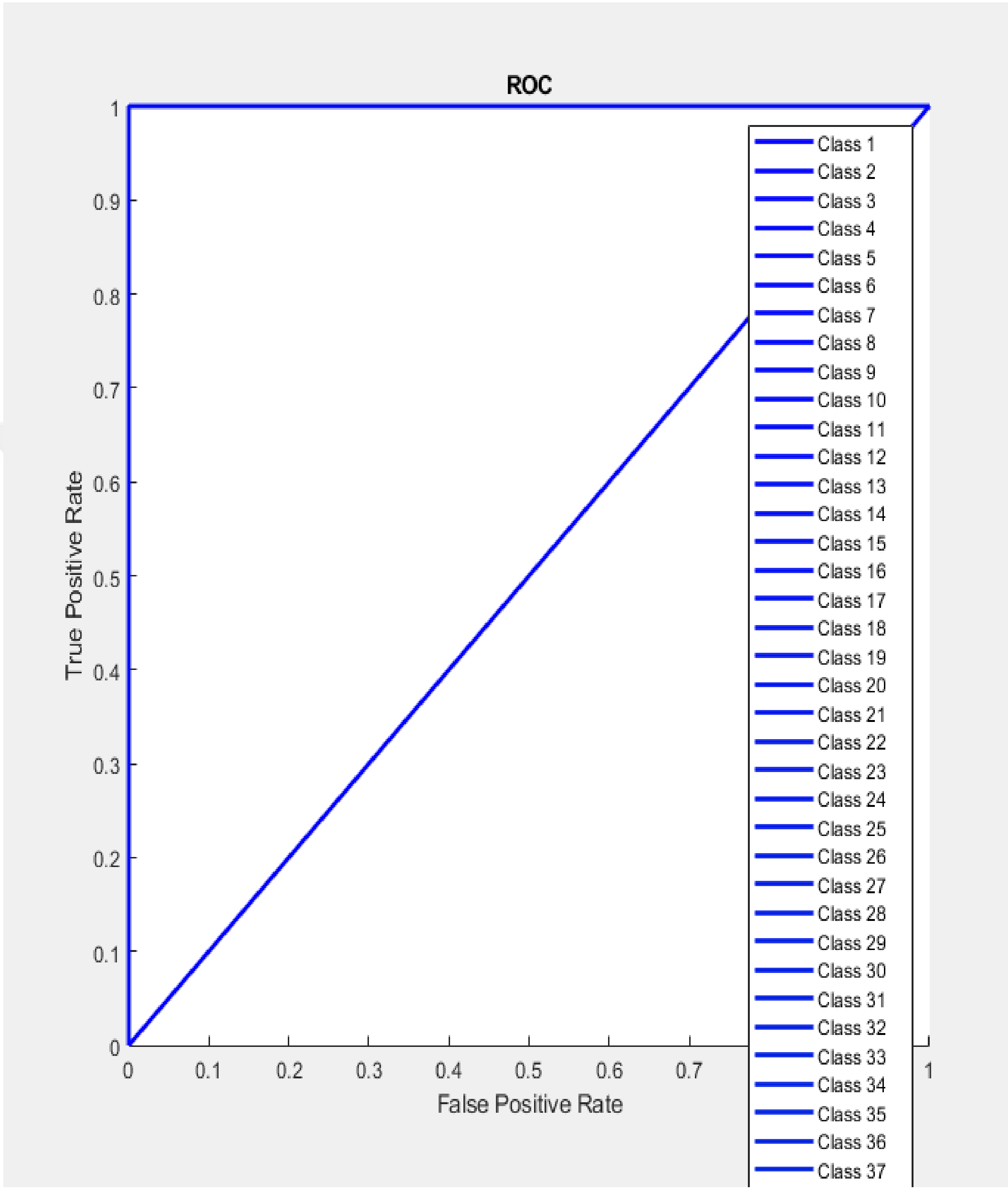

Figure 4.12: KNN with 90% training.

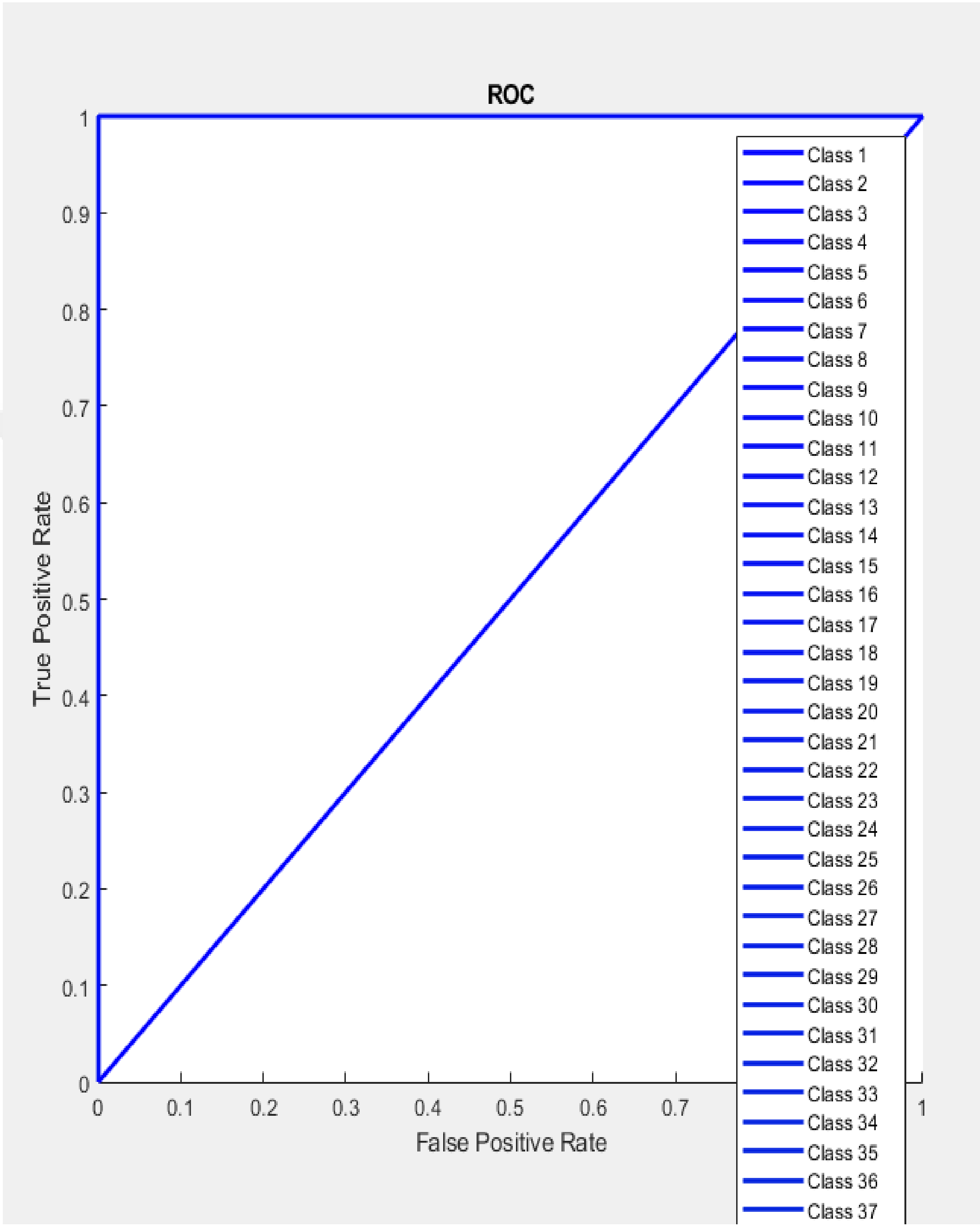

Figure 4.13: KNN with 80% training.

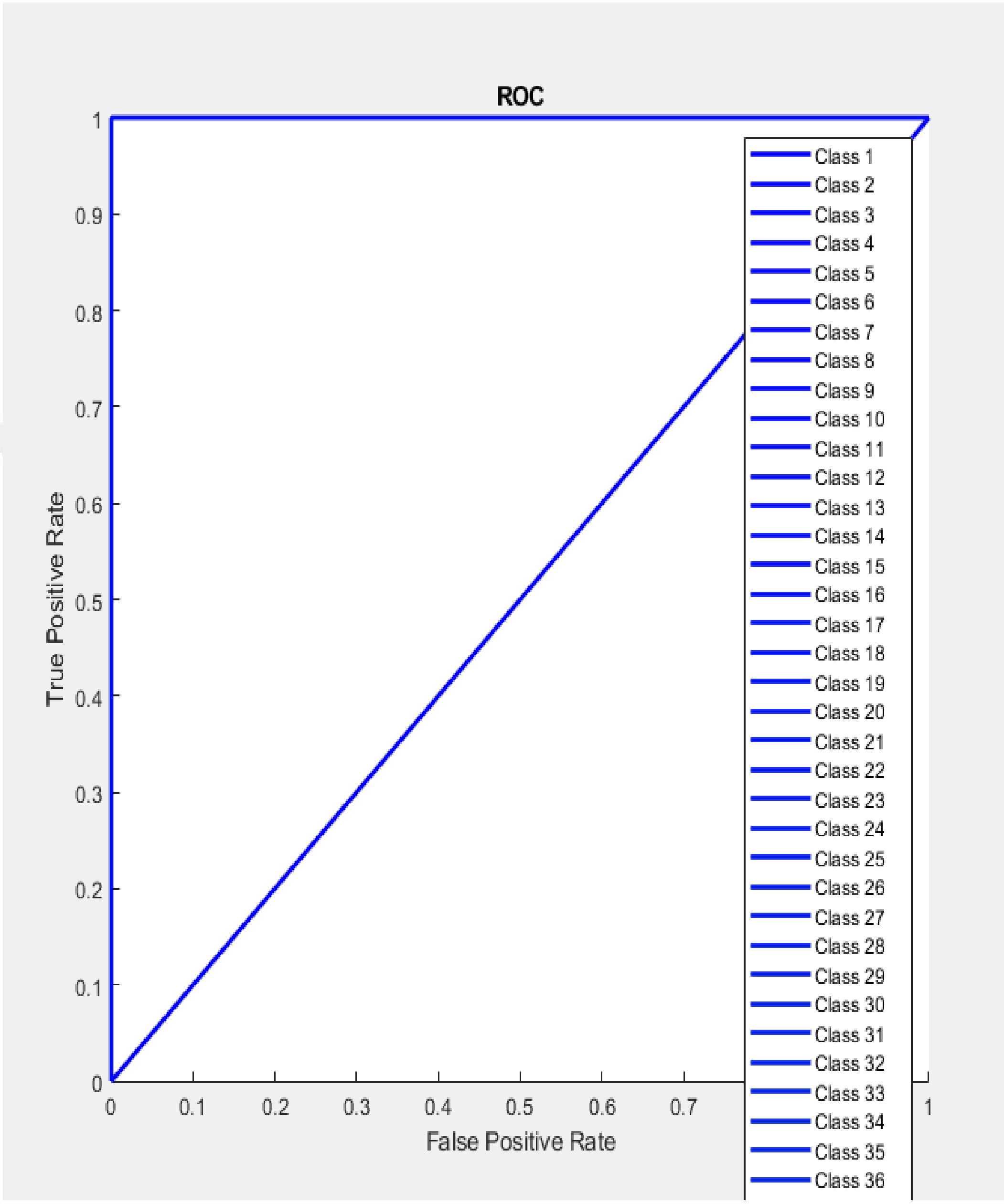

Figure 4.14: KNN with 70% training.

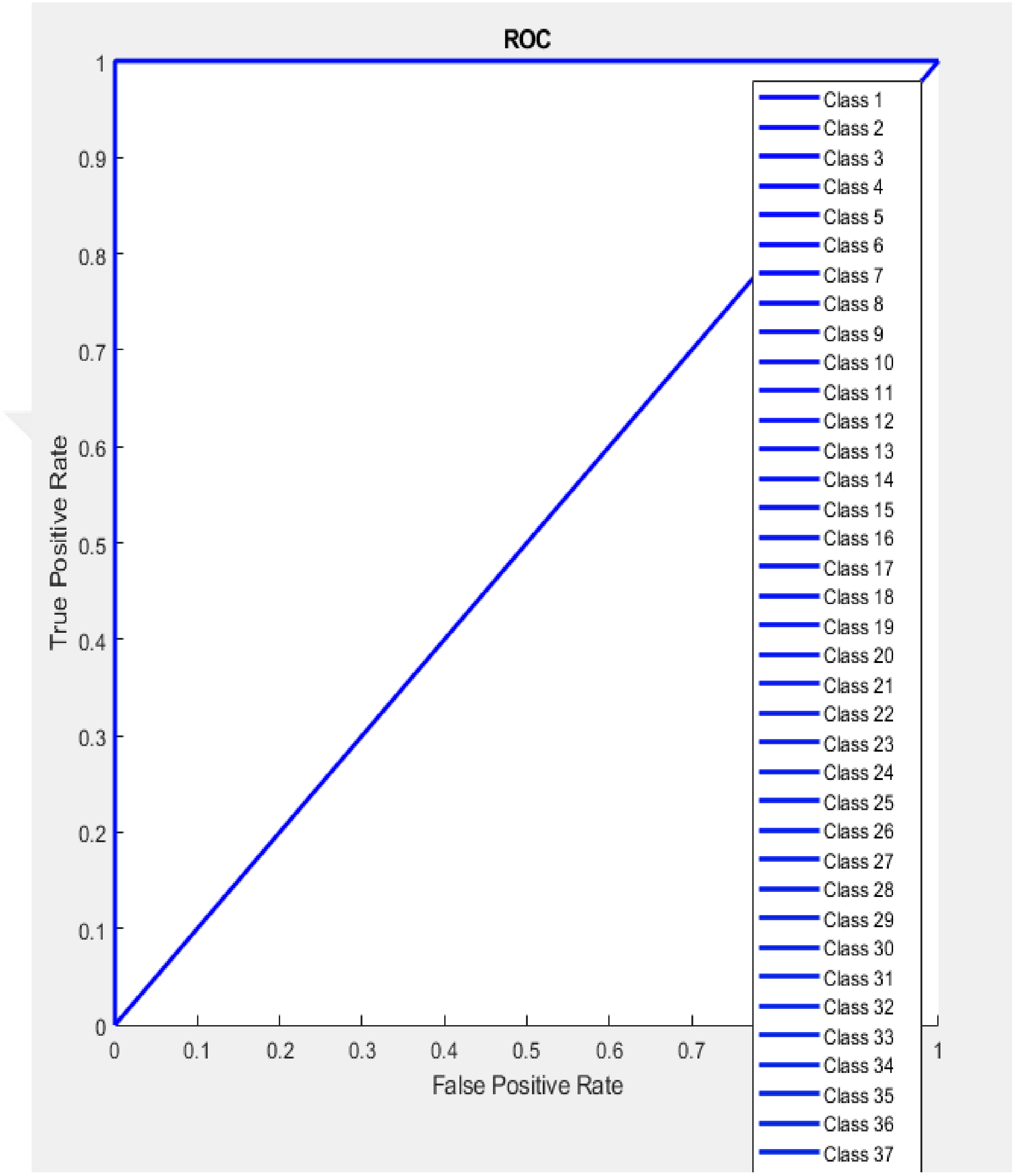

Figure 4.15: KNN with 60% training.

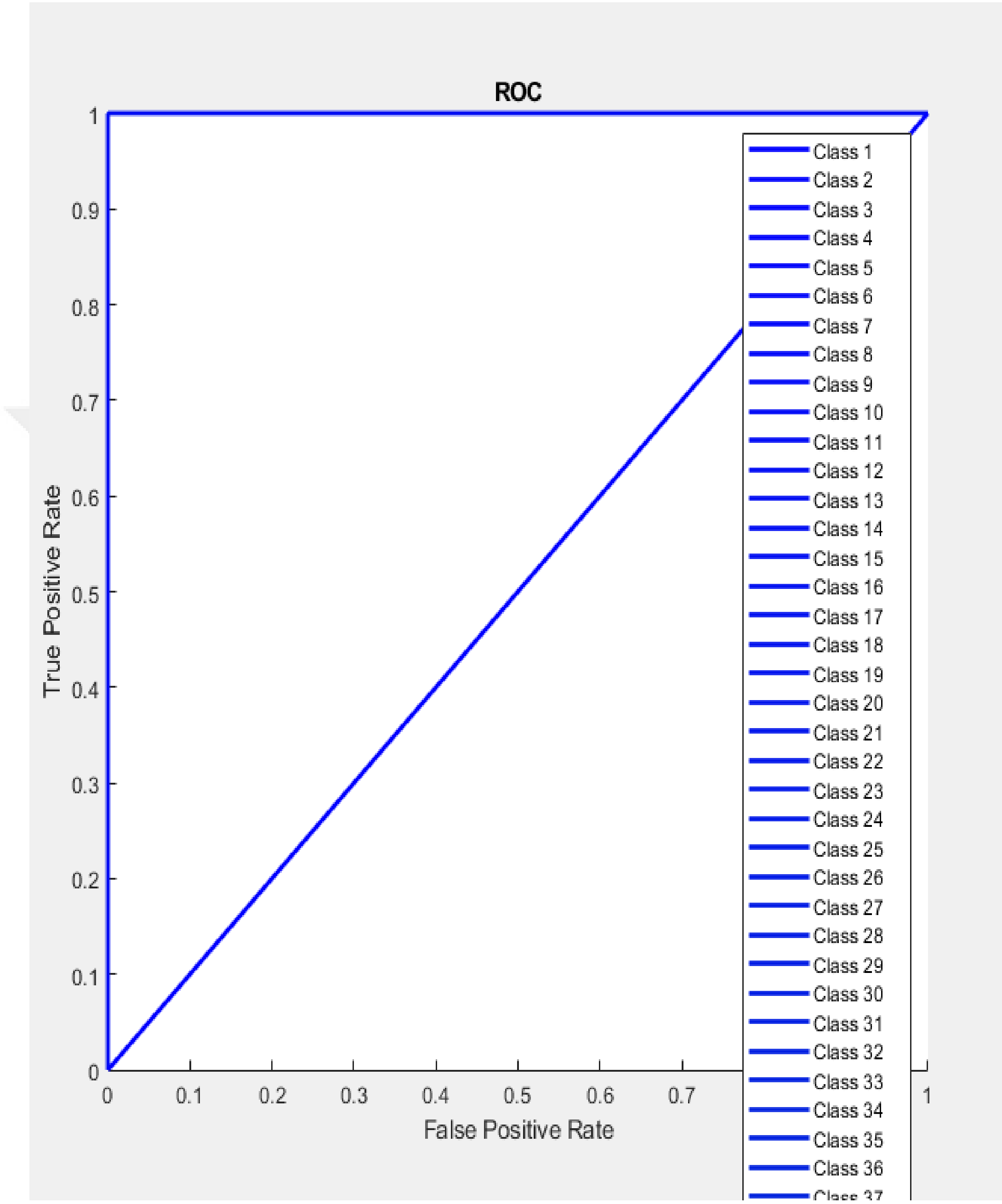

Figure 4.16: KNN with 50% training.

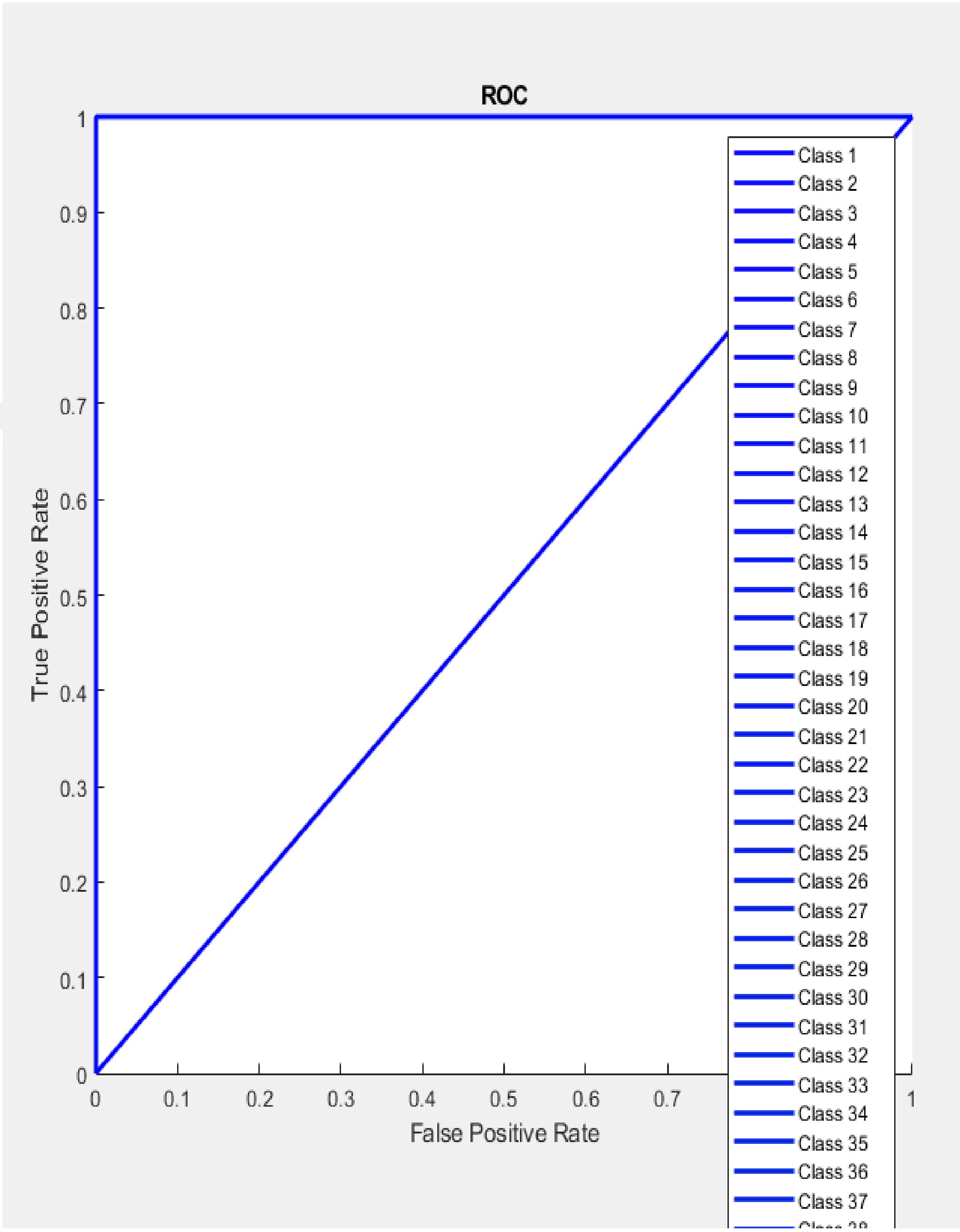

Figure 4.17: KNN with 40% training.

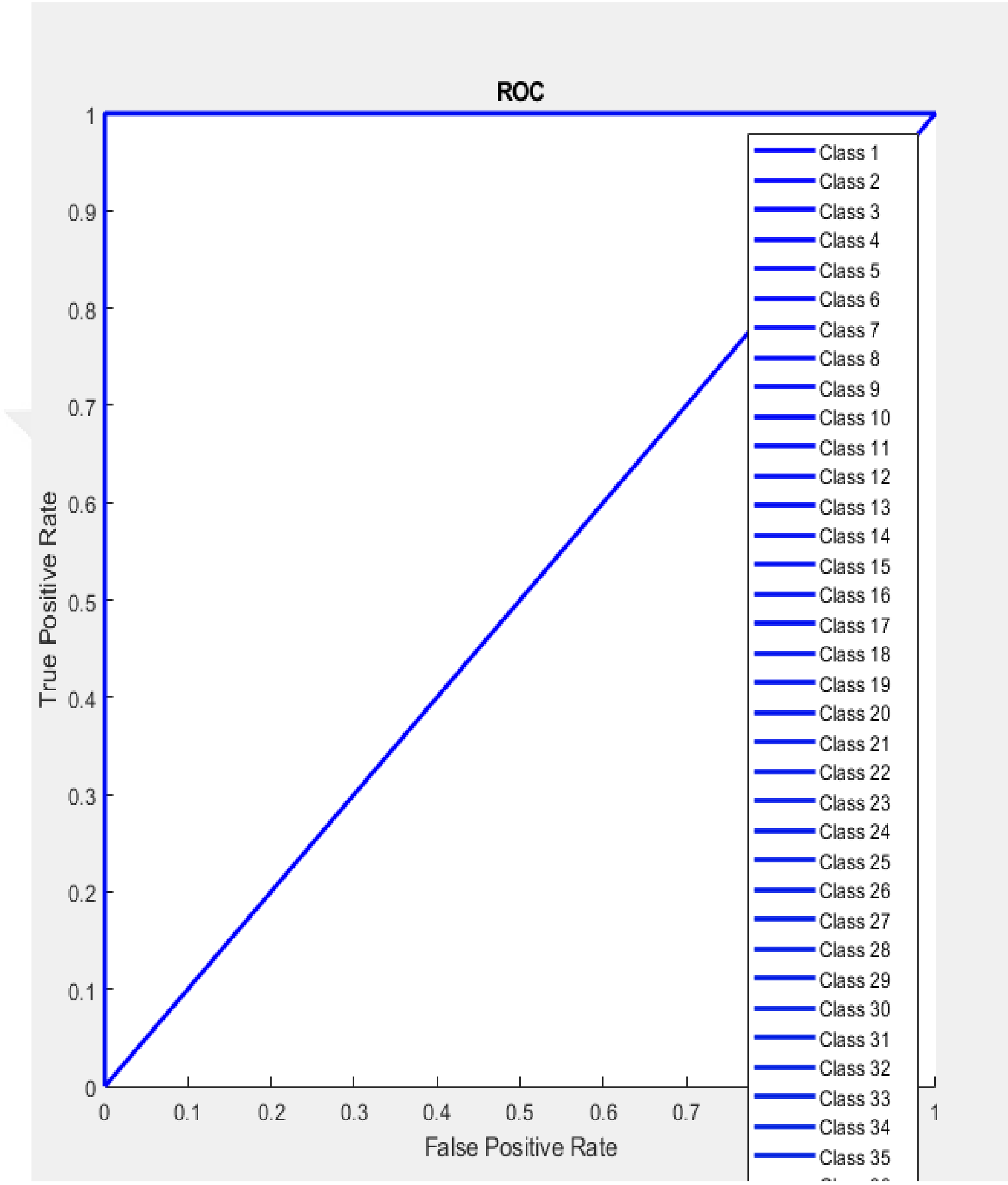

Figure 4.18: KNN with 30% training.

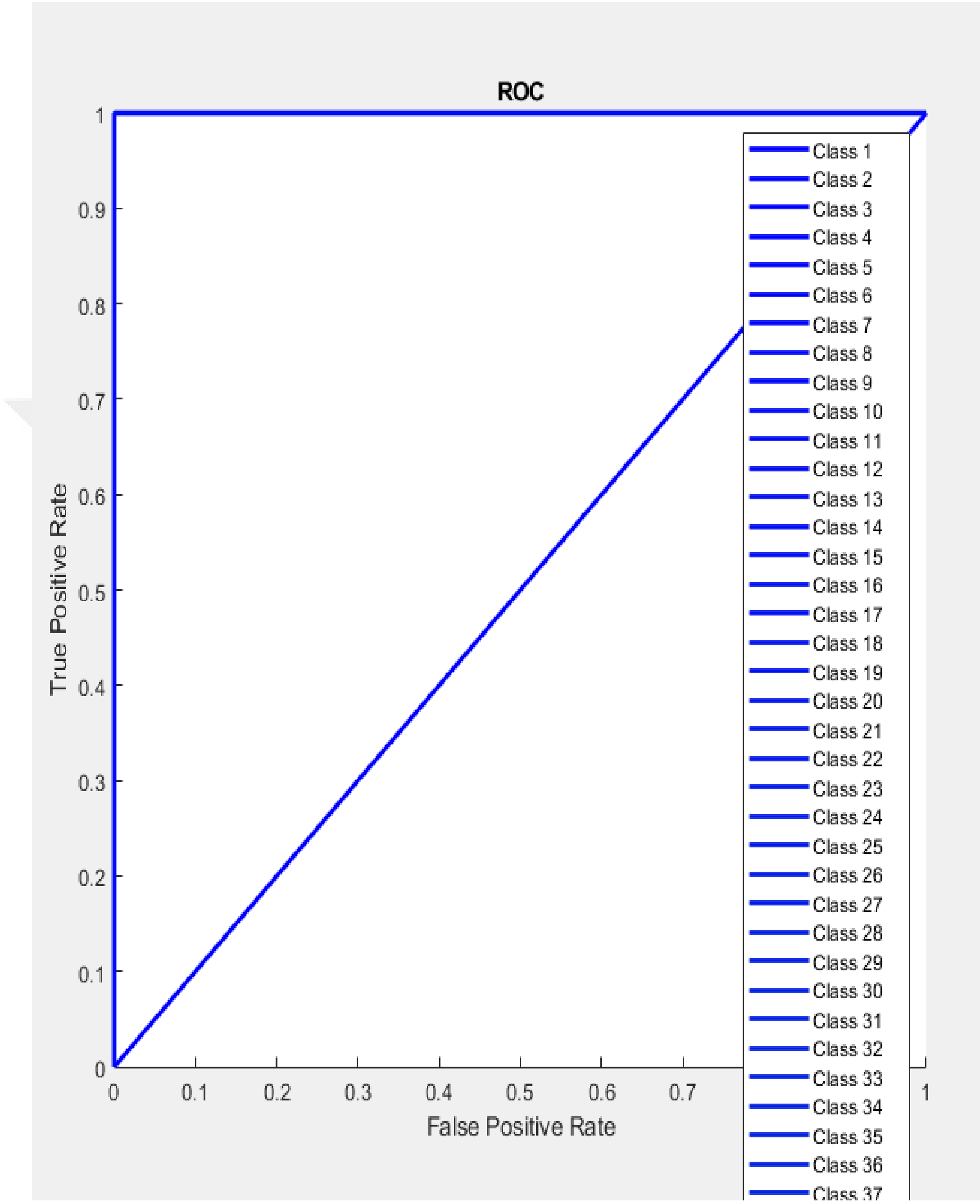

Figure 4.19: KNN with 20% training.

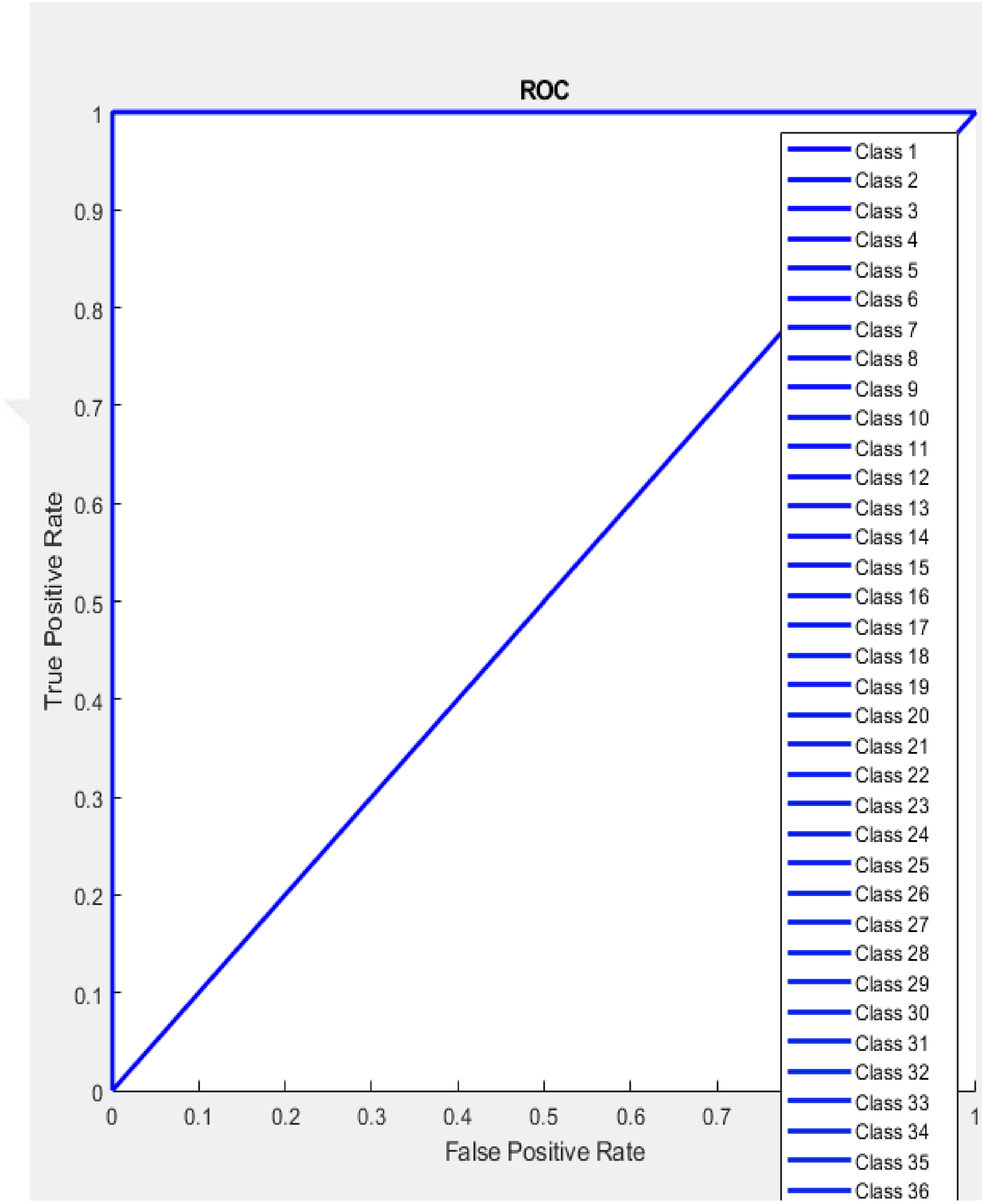

Figure 4.20: KNN with 10% training.

4.1.3 Ensemble Learning (EL)

Ensemble learning is the machine learning techniques that applied all techniques and select the best classification rate. This is more robust machine learning approach that can applied in classification problems. In this study the script of ensemble learning presented in the figure 4.20.

```
figure;
ensembleMd = fitcensemble(featuresTrain,YTrain);
ensemblePredicate = predict(ensembleMd,featuresTest);
 YTestplotrocensen = grp2idx(YTest);
ensPredicateplotroc= grp2idx(ensemblePredicate);
P=plotroc(YTestplotroc,ensPredicateplotroc);
```

Figure 4.21: EL MATLAB Script.

The results of this techniques presented in the figures below.

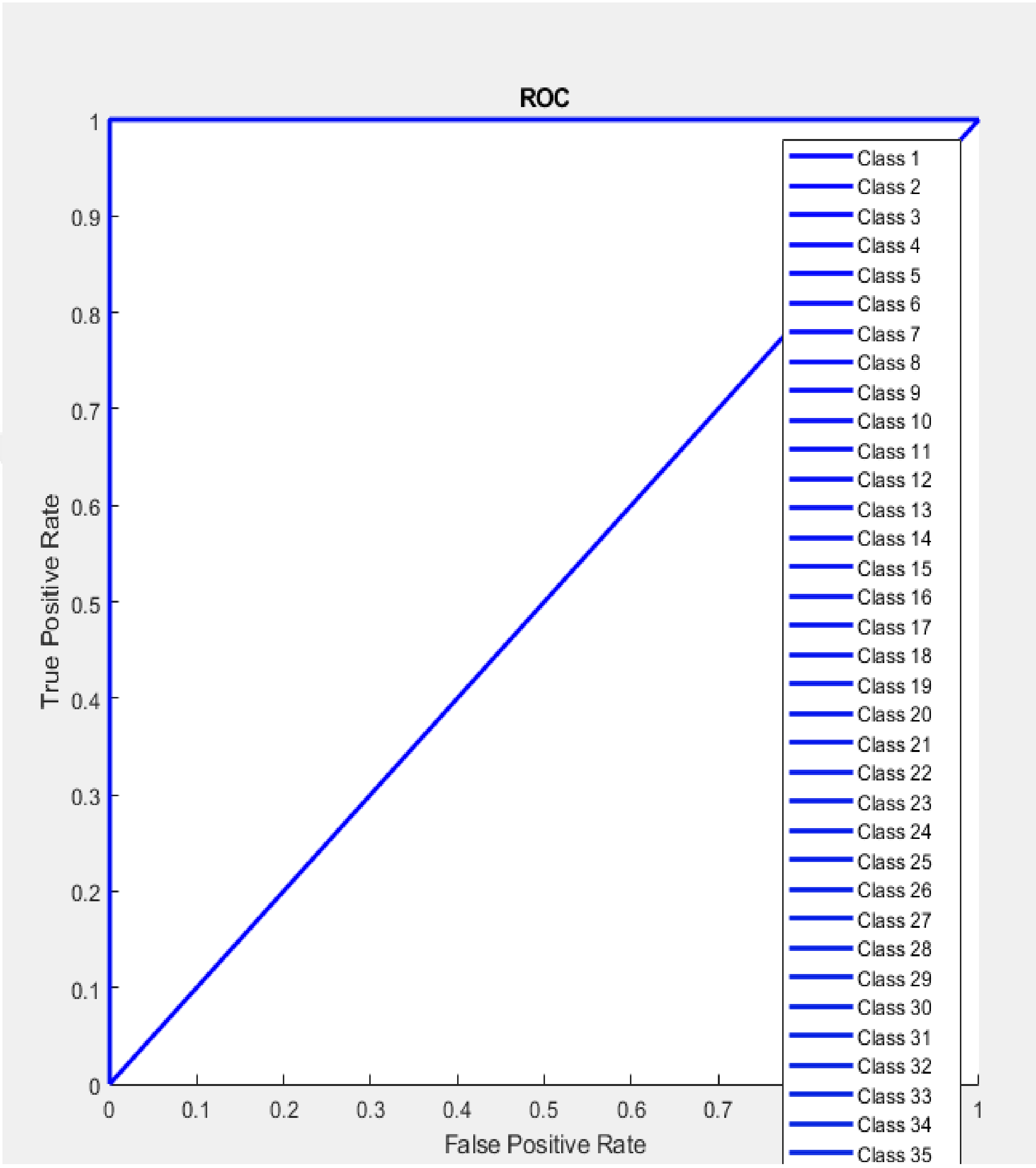

Figure 4.22: EL with 90% training.

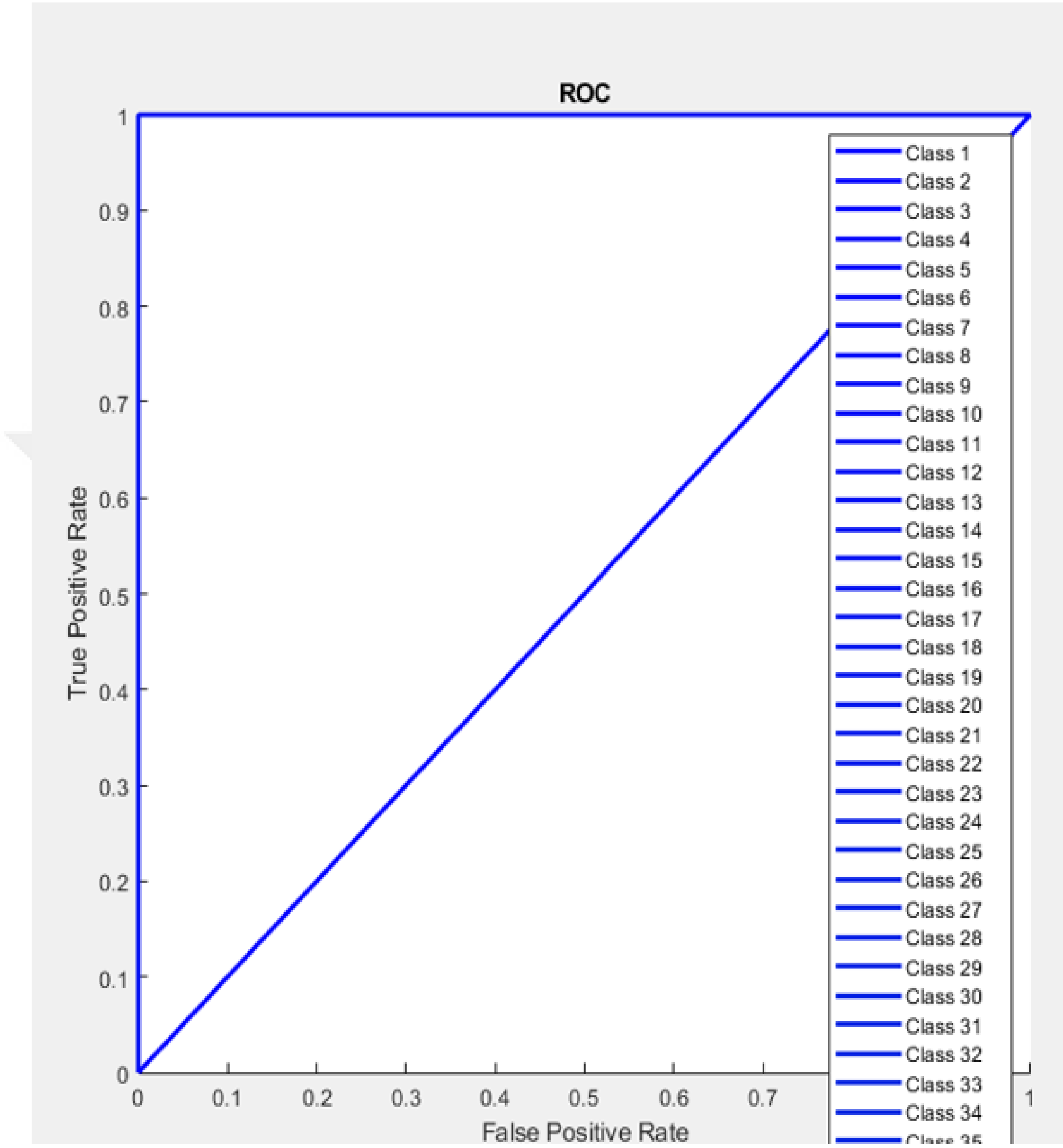

Figure 4.23: EL with 80% training.

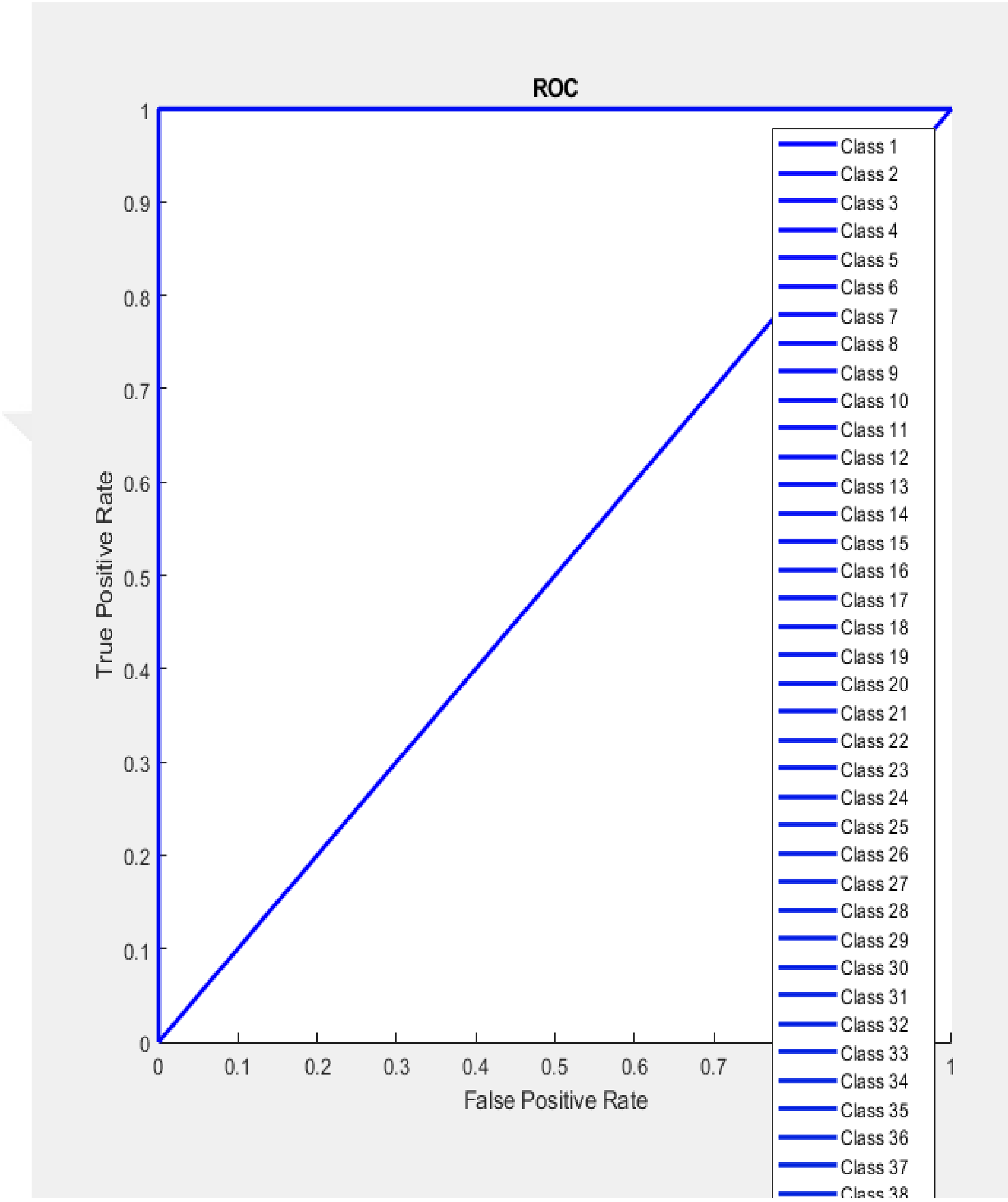

Figure 4.24: EL with 70% training.

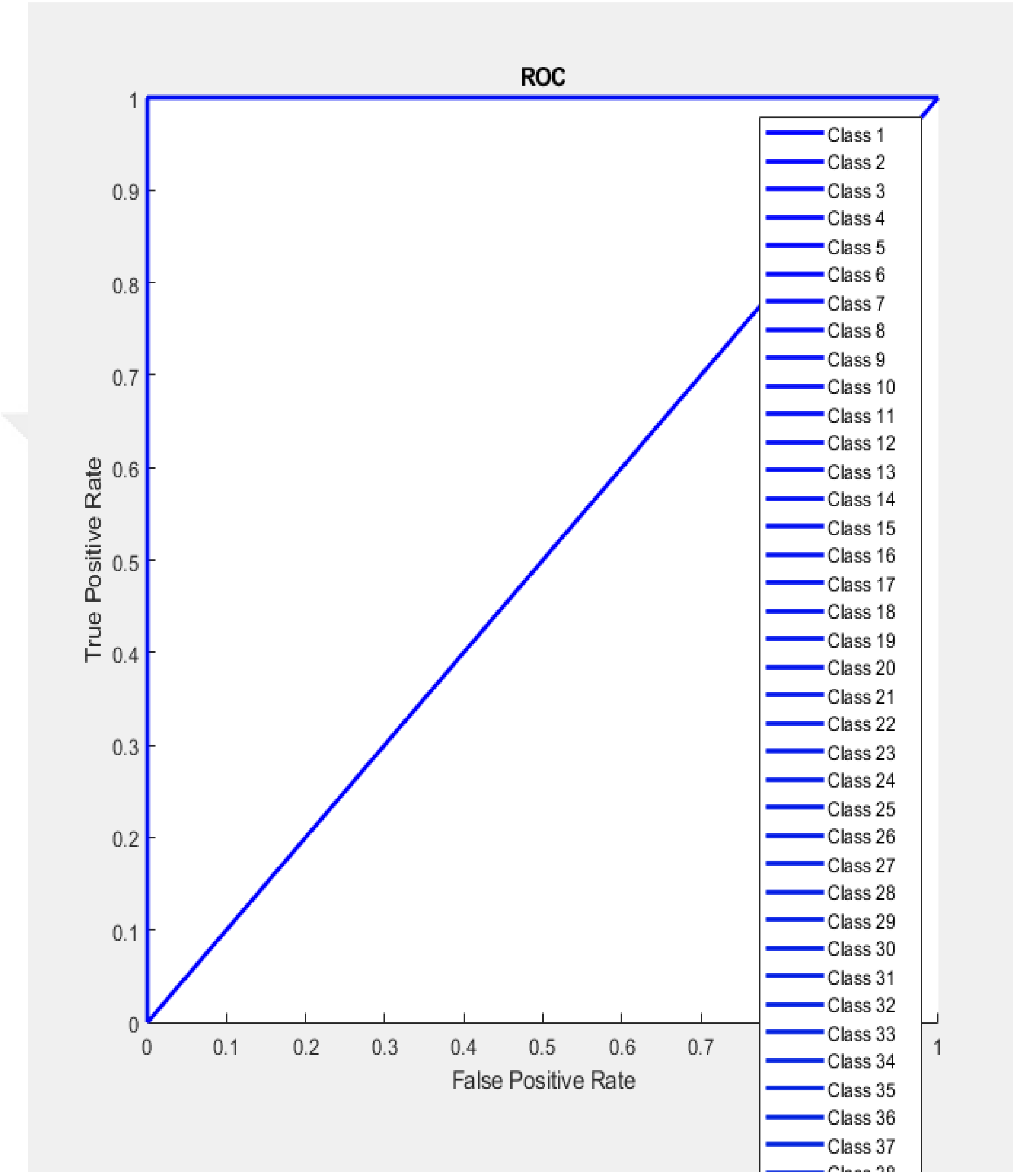

Figure 4.25: EL with 60% training.

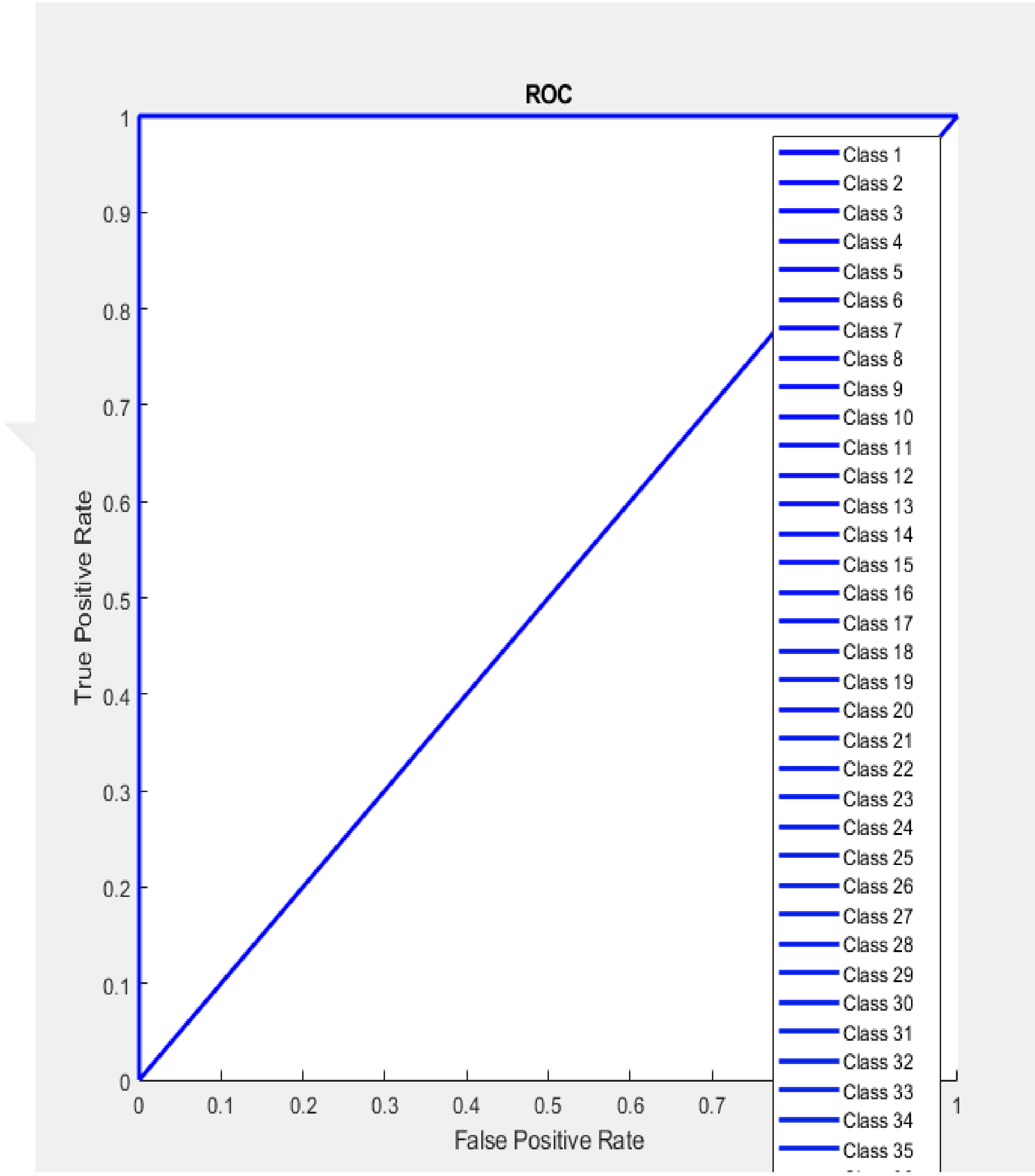

Figure 4.26: EL with 50% training.

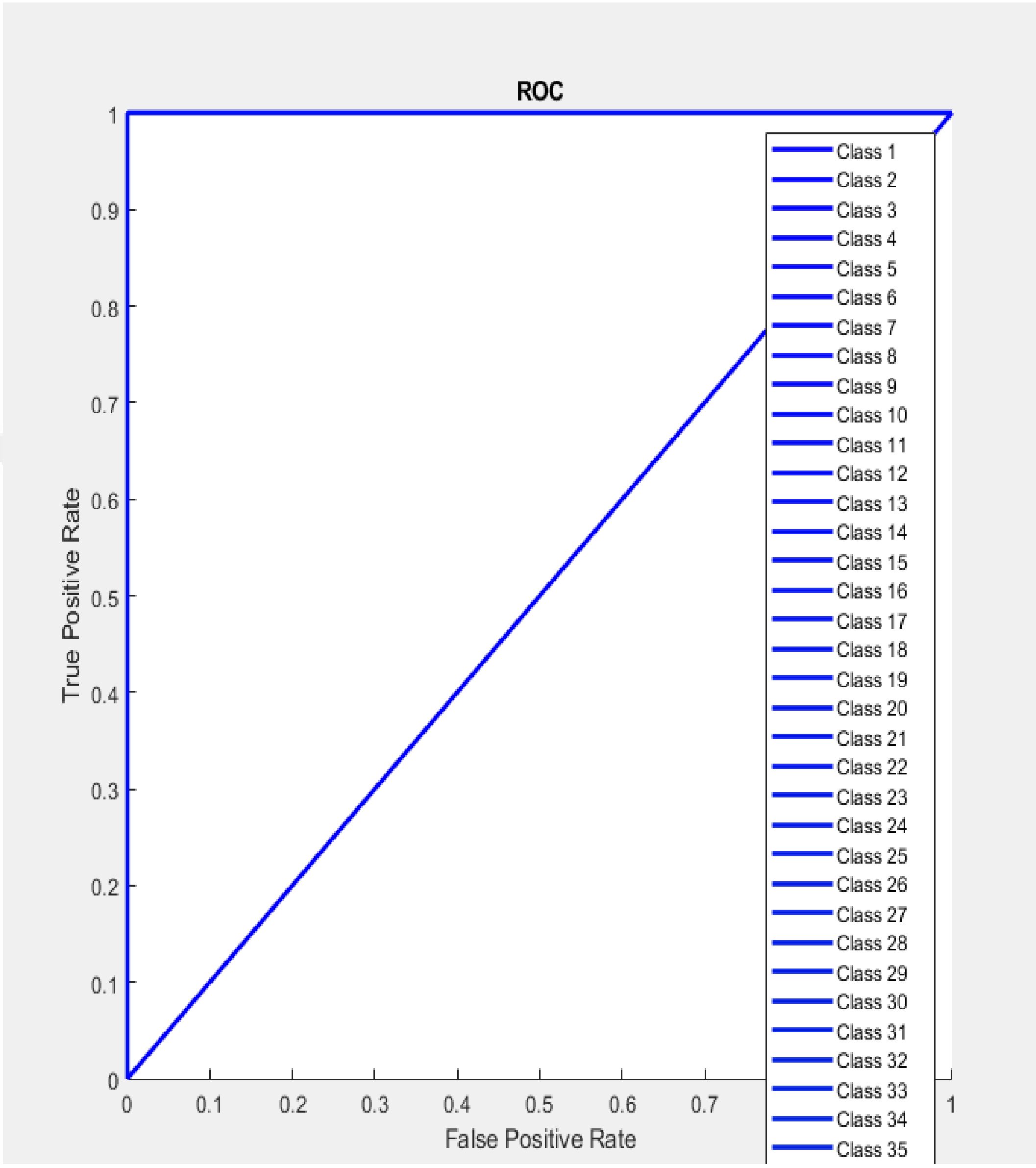

Figure 4.27: EL with 40% training.

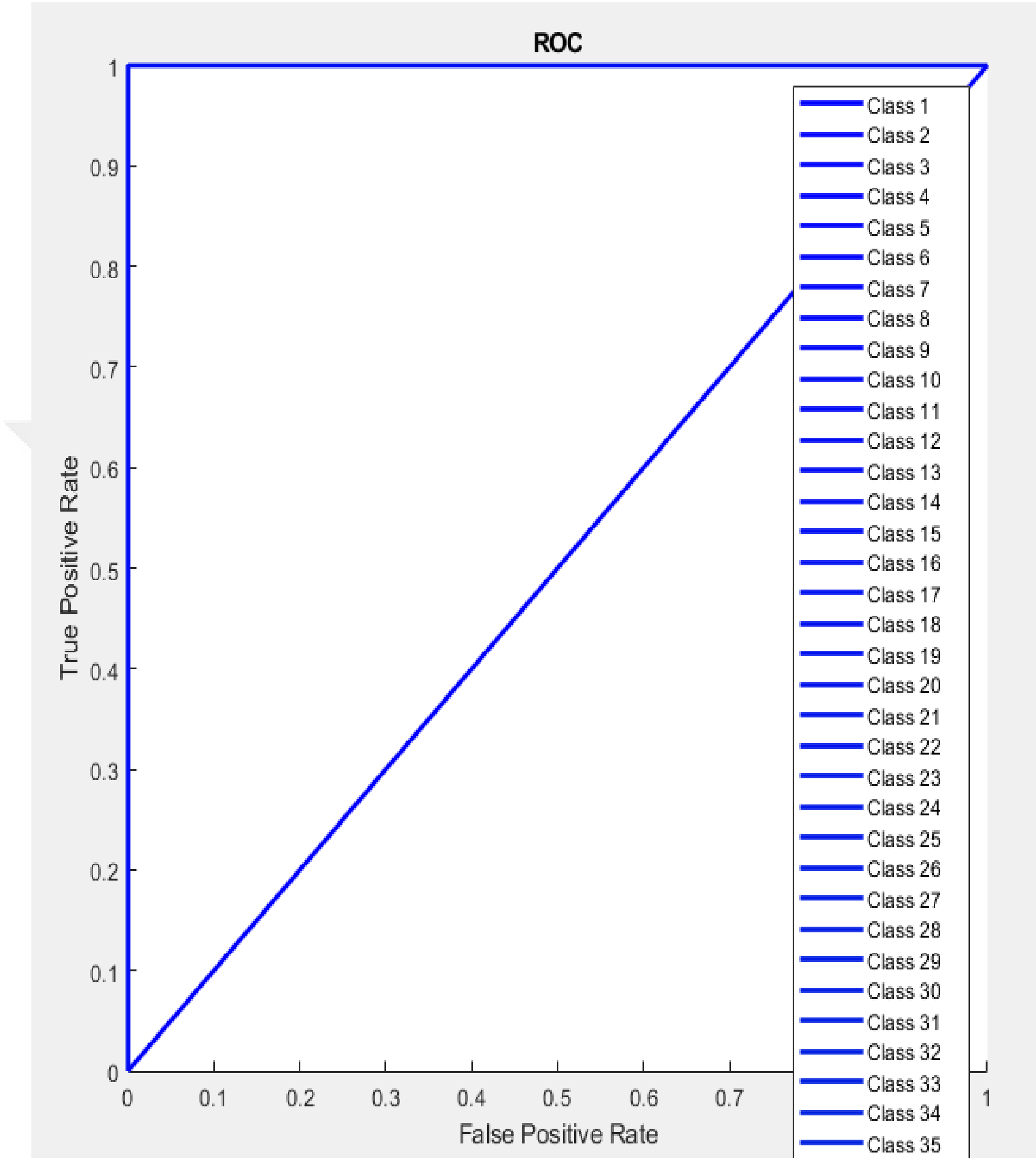

Figure 4.28: EL with 30% training.

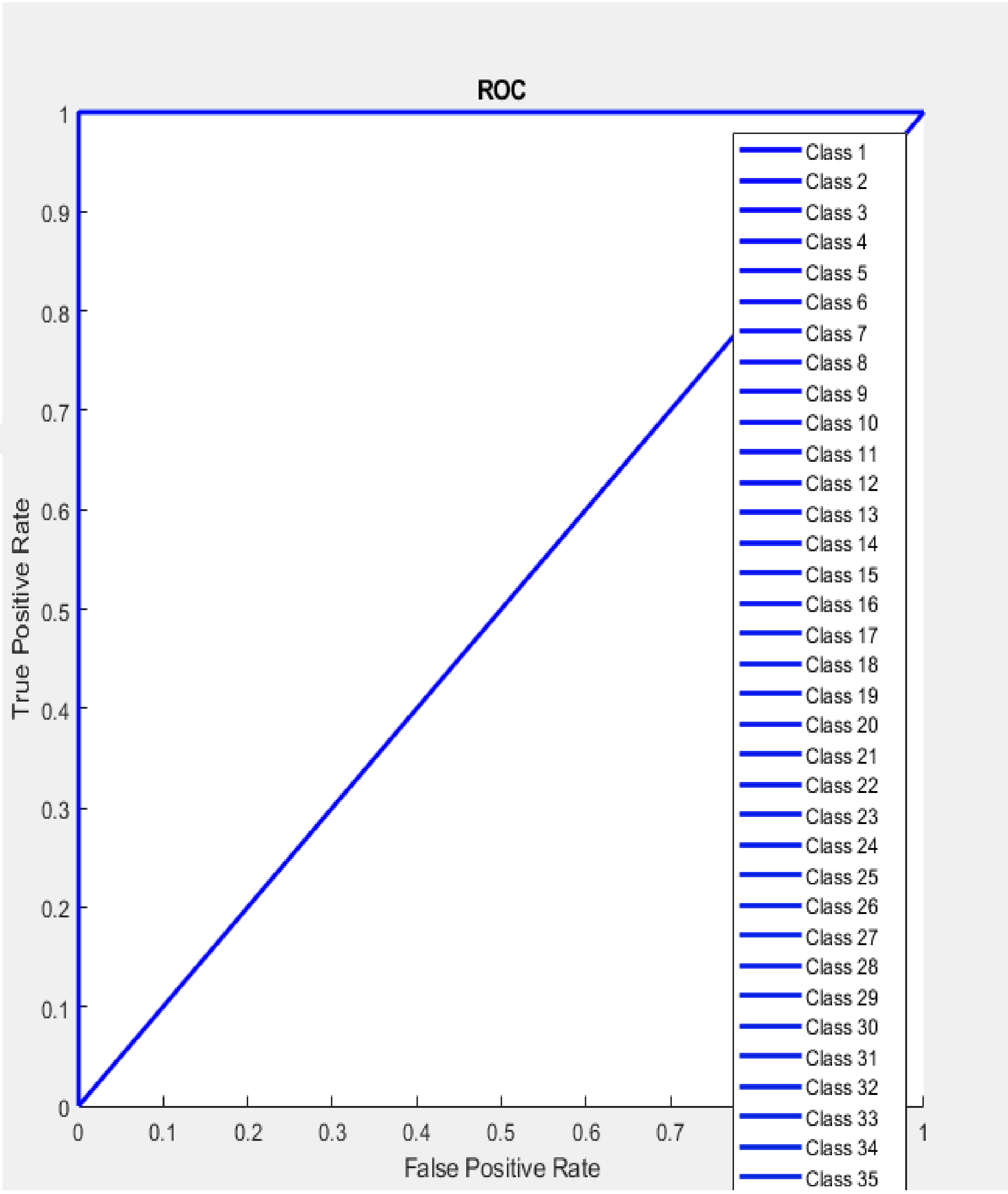

Figure 4.29: EL with 20% training.

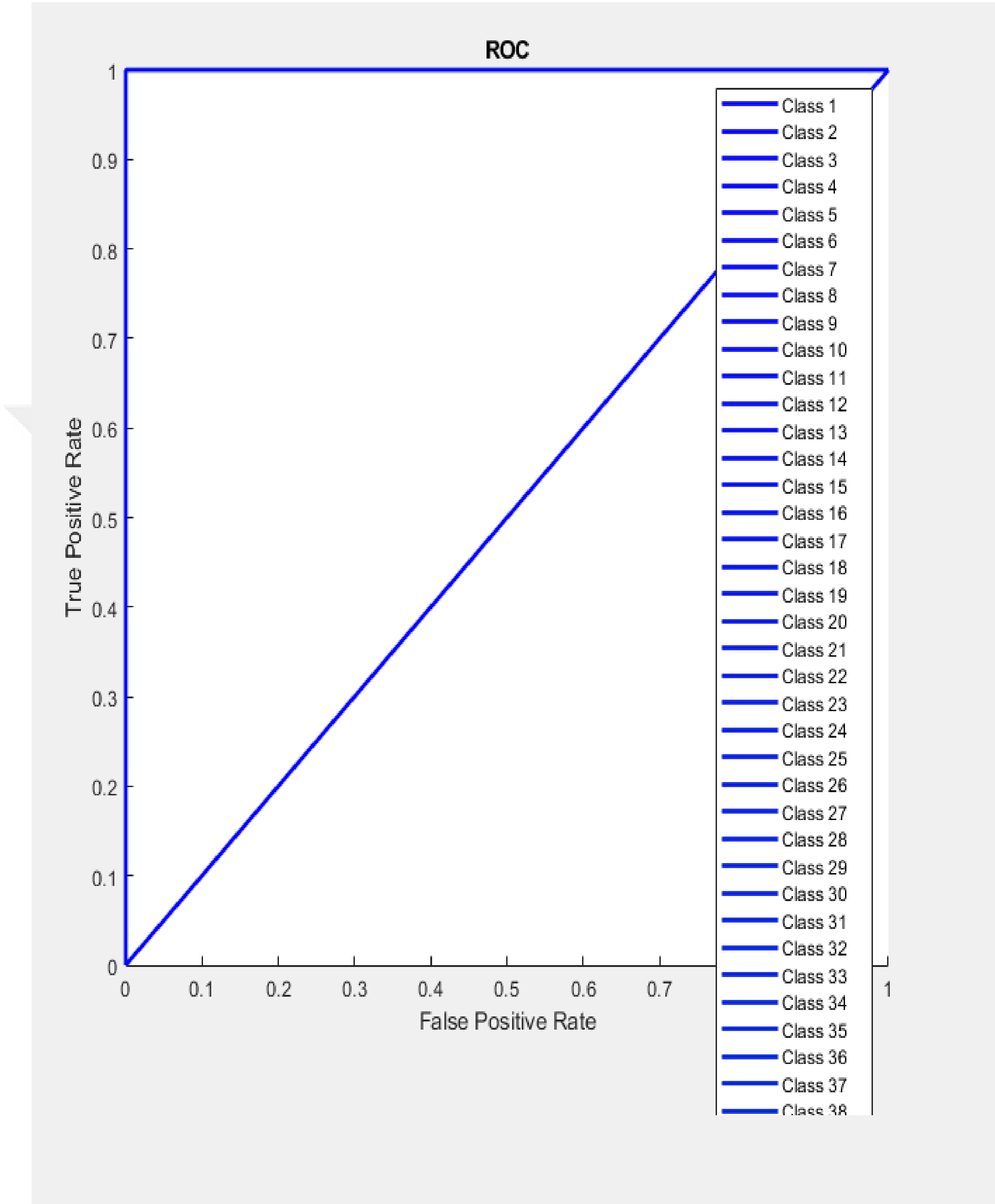

Figure 4.30: EL with 10% training.

4.2 DISCUSSIONS AND COMPARISONS

From analysing of the proposed method, we can prove that the classifiers not effect the performance of the model. This is because that the features selection combination of the CNN with wavelet is extract high level features that assist the classifiers to presented best performance. The results show that the classifiers presented results above 99% in most cases. Furthermore, we applied ensemble learning techniques which can automatically select the best classifier model. This assist the researchers to easily find the best classifiers without extra efforts. The proposed method also compared with several state of art studies that are presented in previous studies and show that our method is best as shown in the Table 4.1.

Table 4.1: Comparison with state of art.

Reference	Method	Accuracy (%)
[43]	Energy map based classifiers	98,83
[44]	Two stage classifier method	94
[45]	Radial basis function (RBF)	98
[46]	DCNN	98
[47]	Features vector based radial basis function (RBF)	97.6
Our Method	CNN(AlexNet)+WT+ Ensemble Learning	99.14

Our method presented best results than previous studies that are presented in the [43-47]. This is because the proposed method combined the CNN features that are presented effective features to the wavelet transform that extracted also effective and sensitive features to the classifiers.

5. CONCLUSION

Within the scope of the thesis, an offline system was created, software and hardware adjustments were made, a database was created, and various results were obtained by applying different methods in order to develop a palmprint-based identification system in an unrestricted environment. In the study, new method based convolutional neural network pretrained model AlexNet, presented for human identification. The dataset first read by the MATLAB and the dataset arranged in the form that can be analyzed by the CNN.

In the second stage, the signal processing technique applied to extract features from input images. The signal processing techniques used in several studies as features extraction model which presented remarkable results when compared with traditional techniques. The aim of applying wavelet transform is to reduce the features size and try to presented effective features that can easily classified by the classifiers.

In the last stage, the classifiers applied to classify the features that are extracted by the AlexNet and the classifiers. The classification in this study is very complex and need fitting the classifiers in optimum face. The complex of this study is that the problem is multiclass which this lead to reduce the performance of the classifiers.

Then, several classifiers are applied to classify the extracted features and present remarkable classification performance which are more than 99% in most of cases. furthermore, several senarios are applied to evaluate the performance of the model which training rate differ between 90%-10%. This mean that the proposed method can adapt to low size and high size datasets.

In future works, we can advise the researchers to applied our method with some enhancements such as : applying optimization algorithms to train the classifiers, applying other signal processing techniques to present new results compared to this study. on the other hand, other datasets can also tested using these methods.

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