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RESEARCH PAPER

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A FINGERPRINT BASED GENDER DETECTOR SYSTEM USING FINGERPRINT PATTERN ANALYSIS

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Abstract: Humans have distinctive and unique traits which can be used to distinguish them thus, acting as a form of identification. Biometrics identifies people by measuring some aspect of individual's anatomy or physiology such as hand geometry or fingerprint which consists of a pattern of interleaved ridges and valleys. The aim of this research is to analyse humans fingerprint texture in order to determine their gender, and correlation of RTVTR and Ridge Count on gender detection. The study is to analyze the effectiveness of physical biometrics (thumbprint) in order to determine gender in humans. Humans have distinctive and unique traits which can be used to distinguish them thus, acting as a form of identification. Biometrics identify people by measuring some aspect of individual's anatomy or physiology such as hand geometry or fingerprint which consists of a pattern of interleaved ridges and valleys. This work developed a system that determines human gender using fingerprint analysis trained with SVM+CNN (for gender classification). To build an accurate fingerprint based model for gender detection system using fingerprint pattern analysis, there are certain steps that must be taken, which include; Data collection (in conducting research, the first step is collecting data in the form of a set of fingerprint image), Pre-processing Data (before entering the training data, pre-processing data is performed, which is resize the fingerprint image 96x96 pixels). Training Data (in this processing the dataset will be trained using the Convolutional neural network and Support vector machine methodology. This training data processing is a stage where CNN + SVM are trained to obtained high accuracy from the classification conducted). Result Verification (after doing all the above process, at this stage, we will display the results of gender prediction based on fingerprint images in the application that has been making). SOCOFing database is made up of 6,000 fingerprint images from 600 African subjects. It contains unique attributes such as labels for gender, hand and finger name as well as synthetically altered versions with three different levels of alteration for obliteration, central rotation, and z-cut. The values for accuracy, sensitivity and precision using the CNN classifier at threshold 0.25 were 96%, 97.8% and 96.92% respectively. At threshold 0.45 the values were 96.3%, 97.6% and 97.6% respectively. At threshold 0.75 the values were 96.5%, 97.3% and 97.9% respectively. In case of the SVM classifier, at threshold 0.25 were 94.3%, 96.6% and 95.8% respectively. At threshold 0.45 the values were 94.5%, 96.4% and 96.2% respectively. At threshold 0.75 the values were 94.8%, 97.3% and 96.8% respectively. From the 600 fingerprints classified, it was observed that a total of 450 fingerprints were detected for male and 150 for female. Results were obtained for gender accuracy, sensitivity and precision through several thresholds to compare the two classifiers. However, it should be verified that the results obtained showed that the CNN classification yielded better accuracy, sensitivity and precision than SVM.

Keywords: Security, GSM Module, Voice recognition module, Microcontroller, Access control system, Arduino

I. INTRODUCTION

The technology of using human body for identification purpose is known as Biometrics. The word was derived from the Greek word meaning Bio for "*life*" and Metric for "*Measurement*", the authentication of biometrics for personal identification is extremely and more reliable compared with something you know which can be forgotten like password, registration numbers or what you have like identity card, physical lock, smart card which can be misplaced compared with something you are or parts of your body.

Biometrics measures the unique physical or behavioural characteristics of individual as a means to recognize or authenticate their identity. The earliest documented use of systematic biometric methods as a means to distinguish one individual from another can be traced back to 14th century China. Chinese merchants were known to stamp children's inked palm and footprints on paper in order to tell them apart. In western culture, the earliest documented distinction made of a biometric property was that done by the English botanist Nehemiah Grew, who in 1684, published a paper reporting the distinct characteristics of ridge, furrow and pore structures in human fingerprints.

A Fingerprint is the representation of the epidermis of a finger; it consists of a pattern of interleaved ridges and valleys. Fingertip ridges evolved over the years to allow humans to grasp and grip objects. Like everything in the human body, fingerprint ridges form through a combination of genetic and environmental factors. This is the reason why even the fingerprint of identical twins is different.

Personal recognition or identification is very important in our daily lives. We always have to prove our identities for getting access to bank account, entering protected sites, drawing cash from Automated Teller Machines, logging in to computers, etc. Generally, we identify ourselves and gain access by physically carrying passports, keys, access cards or by remembering passwords, secret codes and personal identification numbers (PINs). Conventional personal identification techniques could either be knowledge-based technique (password, PIN, etc.) or token-based technique (driver's license, passport, identity card, etc.) The problem with the former is that it is prone to fraud, as passwords may be guessed; secret codes and PINs can easily be forgotten, compromised, shared, or observed; while the latter could be lost, cloned or stolen. Biometric solves the problem faced at the level of both the token-based and knowledge-based identification approaches as it attempts to answer the questions: "who are you?" and "are you who you claim to be?" It is a unique, measurable characteristic or trait of a human being for automatically recognizing or verifying identity. Biometric characteristics are generally more difficult to duplicate and they are naturally present with the user without extra memorization or storage efforts. It is the science of measuring physiological and behavioral characteristics that uniquely identify individuals. Instances of physiological traits include face, iris, fingerprint, vascular images, and hand geometry; while that of behavioral traits include voice pattern, signature dynamics, gait pattern, keystrokes, etc. All these traits are captured by specialized devices and converted through sophisticated algorithms into mathematical representations or templates, which are used as references against which an individual's identity is verified.

Based on the varieties of the information available from the fingerprint we are able to process its identity along with gender. Fingerprints have some important characteristics that make them invaluable evidence in crime scene investigations; It is unique to a particular individual, and no two fingerprints possess exactly the same set of characteristics, it does not change over the course of person's lifetime (even after superficial injury to the fingers. The patterns can be classified, and those classifications then used to narrow the range of suspects.

The fingerprint technology, a physiological biometrics technology is an Artificial Neural Network concept. It is the representation of the epidermis of a finger, and consists of pattern of interleaved ridges and valleys. Its evidence is undoubtedly the most reliable and acceptable forensics evidence till date, even in the court of law. Now, this technology is being used in several other applications such as access control for high security installations, credit card usage verification and so on. However, due to the unique nature of fingerprints, it has become increasingly popular for personal identification and verification. In this work, we investigate gender determination methods based on finger related features such as ridge arrangement, fingerprint patterns and the most predominant minutiae features that exist in a particular gender in Nigeria. A novel work of this nature will help the country to march up with other developed nations of the world in data collection of her citizens. This will assist and improve her security challenges, and also helps in electoral forensic investigations.

In various fields of practical application, grouping of gender is a composite problem for identification of a person. For example, by using demographic information for seeking worthy consumer statistics in shopping centre, a robust gender classification system can provide a base or foundation for performing passive surveillance, through which performance of biometric systems can also be improved like authentication and recognition.

In biometric, majority of studies are based on face recognition since it provides important clues with visual information from human faces for gender classification. On the basis of various information obtained from the fingerprints the identity along with gender can be processed. By noticing differences in match scores, image quality and texture the impact of gender in fingerprints images is checked first then automatic gender estimators for fingerprints is proposed.

The aim of this work is to develop a fingerprint gender detector system using fingerprint pattern analysis trained with Convolutional Neural Network (CNN) and Support Vector Machine (SVM) for gender classification.

II. LITERATURE REVIEW

a. Pattern Recognition

Pattern recognition is the automated recognition of patterns and regularities in data. Pattern recognition also is the classification of data based on knowledge already gained or on statistical information extracted from patterns or their representation. One of the important aspects of the pattern recognition is its application potential. P**attern recognition,** in computer science, involves the imposition of identity on input data, such as speech, images, or a stream of text, by the recognition and delineation of patterns it contains and their relationships. Stages in pattern recognition may involve measurement of the object to identify distinguishing attributes, extraction of features for the defining attributes, and comparison with known patterns to determine a match or mismatch. Pattern recognition has extensive application in astronomy, medicine, robotics, and remote sensing by satellites.

b. Identification and Classification of Pattern

Fingerprint identification and verification are one of the most significant and reliable identification methods. It is virtually impossible that two people have the same fingerprint, having a probability 1 / 1.9 X 1015 (Hong *et. al.,* 2000). In fingerprint identification and verification applications world-wide, a large volume of fingerprints was collected and stored for a wide range of applications, including forensics, civilian, commercial and law-enforcement applications. Automatic identification of humans based on fingerprints requires the input fingerprint to be matched with a large number of fingerprints in a database. To reduce the search time and computational complexity, it is desirable to classify the database into accurate and consistent classes so that input fingerprint is matched only with a subset of the fingerprints in the database.

The nature of each application will determine the degree of accuracy required. For example, a criminal investigation case may require higher degree match than access control case systems. Automatic fingerprint classification methods rely on point patterns in fingerprints, which form ridge endings and bifurcation unique to each person.

Traditionally, activities to solve a pattern recognition task are twofold; first, a set of features has to be found describing the object(s) being classified. Second, after a set of features has been found, a classification mechanism is chosen and optimized. These two steps are highly interdependent, since the choice of features influences the conditions under which a classifier operates, and vice versa. With the advent of neural networks however, more and more problems are solved by simply feeding large amounts of raw data (e.g. images, sound signals, stock market index ranges) to a neural network. This approach, however, is not feasible in fingerprint classification, which are highly susceptible to noise and elastic distortions. Therefore, it is desirable to extract features from the images that are invariant to such distortions. During training the classification, network learns the association and significance of features. An attempt has been made previously to study fuzzy logic and artificial neural network techniques in fingerprint identification (Mohamed *et. al.*, 2000).

c. Types of Fingerprint Pattern

There are three basic approaches that pattern recognition algorithms utilize:

i. **Statistical:** This approach is based on statistical decision theory. Pattern recognizer extracts quantitative features from the data along with the multiple samples and compares those features. However, it does not touch upon how those features are related to each other.

ii. **Structural:** This approach is closer to how human perception works. It extracts morphological features from one data sample and checks how those are connected and related.

iii. **Neural:** In this approach, artificial neural networks are utilized. Compared to the ones mentioned above, it allows more flexibility in learning and is the closest to natural intelligence.

d. Importance of MATLAB for Artificial Intelligence

There are many different programming languages of various applications such as data science, machine learning, signal optimization, web development, signal processing. MATLAB users have deployed thousands of applications for predictive, maintenance, sensor analytics, finance and communication electronics. Statistics and machine learning techniques toolbox makes the hard parts of machine learning easy with apps for training and comparing models, advanced signal processing and feature extraction, classification, regression, and clustering algorithms for supervised and unsupervised learning. In this case we will be considering MATLAB for this project and building a fingerprint detector of age and gender software.

Machine Learning Techniques

Machine learning systems are concerned with building fixable algorithms or techniques that their performance is automatically improved with experience (training). Machine learning system is first trained with source data, and following, it is used to perform required operations according to its acquired experience. The problem of machine learning techniques is related to their sensitivity to the training data and the training parameters as they may produce different results by changing the training data. However machine learning includes many techniques such as Artificial Neural Networks, Support Vector Machine, Principal Component Analysis, and Genetic Algorithms.

i. Artificial Neural Networks

Artificial Neural Networks is the most widely used algorithm of the machine learning system (Sivanandam, 2009). The quality assurance of the acquired fingerprint image is an important process before the feature extraction. Xie and Qi (2010) designed a supervised back propagation neural network that uses the gray scale fingerprint image for continuous image quality estimation. The problems of this method are the lack of evaluation as it has been evaluated for small fingerprint images from Fingerprint Verification Competition 2002 (Maio, 2002). Moreover, the fingerprint image needs to be divided into blocks which are computationally expensive process before running the proposed method. Zhu *et. Al.* (2005) used the neural network for quality estimation of the fingerprint images using fingerprint ridge orientation. The correct ridge orientation is estimated using the trained neural networks. Labati *et. al.* (2010) proposed the usage of neural network for image quality measurement in contactless fingerprint acquisition. They discovered a set of new features for contactless images and designed a neural network to extract the complex features for future fingerprint matching. The bottleneck of this method is the computational complexity as it needs 1.5 to 3.7 seconds for the implementation of the region of the interest needed for that method. Feature extraction is another application of neural networks in fingerprint identification. Liu *et. al.* (2010) used back propagation neural network for singular point detection from the gray scale fingerprint images. The problem of this method is the image division process as the image needs to be divided into small blocks (35×35 pixels) which are time consuming operation, and the location of the detected singular point is not accurate. Bartunek *et. al. (2006)* used the back propagation natural networks for extracting minutiae points (ridge termination and bifurcation) from thinned fingerprint images. A sliding (5×5 pixels) window has been used to access the whole fingerprint image searching for minutia points. The problem with this method is the huge processing time to get the thinned image. Yang *et. al.* (2005) used the fuzzy neural networks for minutiae extraction from the gray scale image with high invariant to rotation and gray level changes. Fingerprint classification is an important process for reducing the identification time. Sarbadhikari *et. al.* (1998) proposed two-stage fingerprint classifier. In the second stage, Multi-Layer Perceptron (MLP) feed forward neural network was used to classify the directional Fourier image. The achieved classification accuracy was around 84%. Mohamed and Nyongesa (2002) proposed the usage of fuzzy neural networks as a classification mechanism due to its ability to work as an adaptive filter in order to produce reliable results. They constructed a feature vector using five different parameters including number of core points, number of delta points, directional image, core point direction, and the position of delta point. The algorithm achieved 85.0% for classifying the Left Loop class, and 98.35% for classifying the Whorl class. Kumar and Vikram (2010) used multidimensional ANN (MDANN) for fingerprint matching using minutiae points. The algorithm achieved a maximum recognition rate as 97.37%. Kristensen *et. al.* (2007) presented a comparative study on different neural networks and support vector machine. They implemented four types of neural networks including Multi-Layer Perceptron (MLP), Bidirectional Associative Memory (BAM), Hopfield and Kohonen neural networks, as well as the support vector machine. They concluded that MLP neural network achieved the best performance with an overall accuracy as 88.8% for the $5-$ *class* problem. Support vector machine came in the second rank with classification rate about 87.0%, but both classifiers failed to classify most of Tented Arches class. In general, the other three classifiers could not perform well compared to multi-layer perceptron and support vector machine.

ii. Support Vector Machine

Support Vector Machine is a training algorithm for linear classification, regression, principal component analysis and for non-linear classifications. The idea behind the support

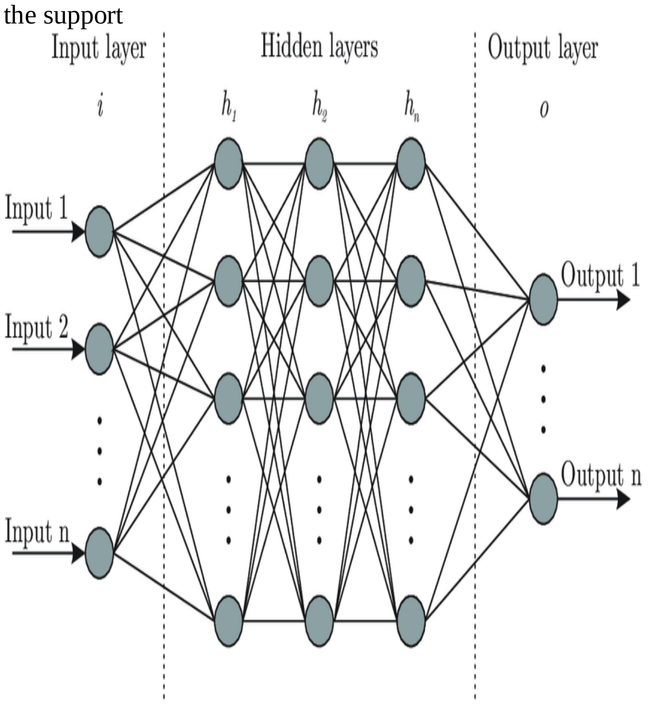


Figure 1: ANN architecture (Facundo Bre *et. al.,* 2017)

vector machine is to maximizing the margin between the training patterns and the decision boundary. Machine Learning Techniques for Fingerprint Identification 529 Liu *et. al.* (2008) used the support vector machine technique with five features vector length to determine the fingerprint image quality. Fingerprint has been classified into high, medium and low quality images with the accuracy of 96.03%. The problem with Liu's method is the long processing time of the feature extraction step. Zhao *et. al.* (2008) implemented support vector machine for fingerprint image segmentation as it is an important step before feature extraction. They divided the image into (12 × 12 pixels) blocks, and five features have been used to construct the feature vector. These features are grey mean, grey variance, contrast, coherence and the main energy ratio. The proposed method is considered as robust for small scale evaluation. From the other side, Liu *et. al.* (2008) used the support vector machine for fingerprint classification into $5-$ *classes* with total achieved accuracy 93.5% with a combination of singular points and orientation image. However, using the orientation coefficients only produced 87.4% and using singular point only produced 88.3% at maximum.

iii. Principal Component Analysis (PCA)

PCA is a statistical procedure that uses an orthogonal transformation that converts a set of correlated variables to a set of uncorrelated variables. PCA is the most widely used tool in exploratory data analysis and in machine learning for predictive models. Moreover, PCA is an unsupervised statistical technique used to examine the interrelations among a set of variables. It is also known as a general factor analysis where regression determines a line of best fit.

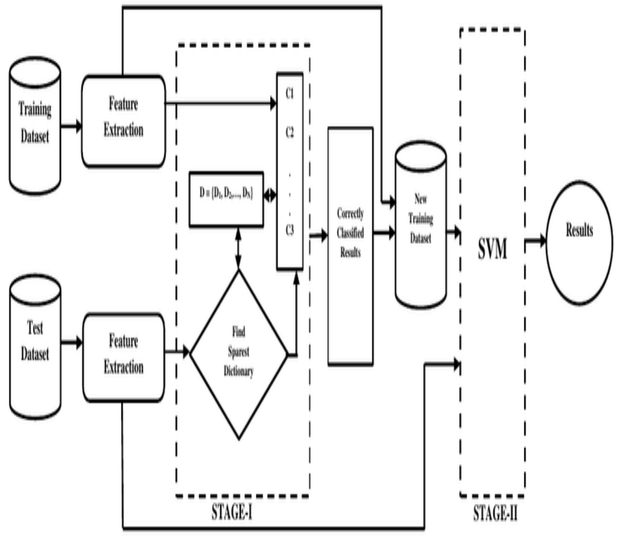


Figure 2: Block diagram of the proposed Multi-level classification technique using support vector machine based classification approach (Mettu 2015).

iv. Genetic Algorithms

Genetic Algorithms are promising machine learning techniques for solving fingerprint related problems. Mao *et. al.* succeeded to use genetic algorithm for singular point extraction.

They presented a new definition for core point location and orientation which is used as fitness function for the genetic algorithm. The challenge of this method is processing time is become higher with increased accuracy (1×1 pixels with 10◦ accuracy). Tan *et. al.* (2006). implemented genetic algorithm for fingerprint matching process using optimized minutiae transformation. However the genetic algorithm achieves promising matching results, the required times are 15 and 8 seconds for genuine and imposter matching, respectively. Therefore, an optimization process is become a crucial need. Tan *et. al.* (2006) developed a classification algorithm based on some new learned features. In the proposed approach, they tried to find unconventional primitives from the orientation images using the Genetic Programming (GP) technique. The learned features might never be imagining by humans experts. Then, a Bayesian classifier was used for conducting the actual classification process. The proposed method was evaluated over the NIST-4 database. The first 2000 images were used for the training process, and the second 2000 were used for the evaluation purposes. The total Percentage of Correct Classification (PCC) was about 93.3% and 91.6% for the 4 − *class* and the 5 − *class* classification problems, respectively.

e. Components of Fingerprint Identification System

Every machine learning-based pattern recognition algorithm includes the following steps.

i. **Input of data -** Large amounts of data enter the system through different sensors.

ii. **Pre-processing or segmentation-** At this stage, the system groups the input data to prepare the sets for future analysis.

iii. **Feature selection (extraction) -** The system searches for and determines the distinguishing traits of the prepared sets of data.

iv. **Classification -** Based on the features detected in the previous step, data is assigned a class (or cluster), or predicted values are calculated (in the case of regression algorithms).

v. **Post processing -** According to the outcome of the recognition, the system performs future actions.

f. Types of Fingerprint Pattern

Before computerization replaced manual filing systems in large fingerprint operations, manual fingerprint classification systems were used to categorize fingerprints based on general ridge formation (such as the absence or presence of circular patterns in various fingers).

The three basic patterns of fingerprint ridges are arch, loop and whorl.

Arch is a pattern where the ridges enter from one side of the finger, rise in the center forming an arc, and then exit the other side of the finger.

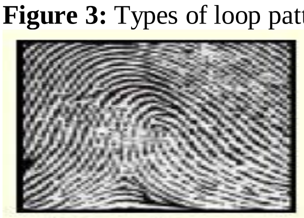
Loop is a pattern where the ridges enter from one side of a finger, from a curve, and tend to exit from the same side enter

Whorl is a pattern where ridges form circulatory around a central point on the finger. Scientists have found that family members often share the same general fingerprint patterns, to the belief that these patterns are inherited.

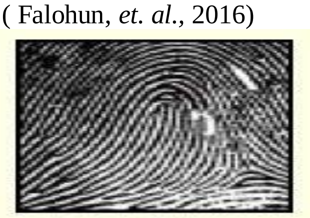
Plain arch pattern

Tented arch pattern

Figure 3: Types of loop pattern (Falohun, *et. al.,* 2016)



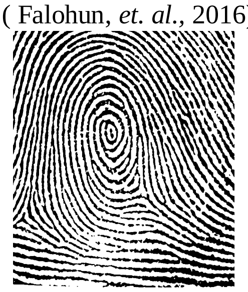
Ulnar loop pattern



Radial Loop pattern

Figure 3: Types of loop pattern (Falohun, *et. al.,* 2016)

Plain whorl pattern



Central pocket pattern

Double Loop pattern

Accidental Whorl Pattern

Figure 4: Types of whor; pattern (Falohun, *et. al.,* 2016)

III. RELATED WORKS

Fingerprint Based Gender Classification Using Local Binary Pattern. Acree, *et. al.* (2007), has presented a study whose aim is to determine if women have significantly higher ridge density, hence finer epidermal ridge detail, than men by counting ridges that occur within a well-defined space. If significant gender differences do exist then the likelihood of inferring gender from given ridge densities will be explored. Their study focused on 400 randomly picked ten - print cards representing 400 subjects. The demographic composition of this sample population represents 100 Caucasian males, 100 African American males, 100 Caucasian females and 100. African American females all within the age range of 18 - 67. Results show that women tend to have a significantly higher ridge density than men and that this trend is upheld in subjects of both Caucasian and African American descent ($F = 81.96$, $P < 0.001$). Application of Bayes' theorem suggests that a given fingerprint possessing a ridge density of 11 ridges/25 mm 2 or less is most likely to be of male origin. Likewise a fingerprint having a ridge density of 12 ridges/25 mm 2 or greater is most likely to be of female origin, regardless of race.

Gender Classification from Fingerprint Based on Wavelet Transform (DWT) and Singular Value Decomposition (SVD). Gnanasivam *et. al.* (2012) proposed a method for Gender Classification from Fingerprint based on discrete wavelet transform (DWT) and singular value decomposition (SVD). The classification is achieved by extracting the energy computed from all the sub-bands of DWT combined with the spatial features of non-zero singular values obtained from the SVD of fingerprint images. K nearest Neighbor (KNN) used as a classifier. This method is experimented with the internal database of 3570 fingerprints finger prints in which 1980 were male fingerprints and 1590 were female fingerprints. They obtained Finger wise gender classification which is 94.32% for the left hand little fingers of female persons and 95.46% for the left hand index finger of male persons. Gender classification for any finger of male persons tested is obtained as 91.67% and 84.69% for female persons respectively. Overall classification rate is 88.28% has been obtained.

Fingerprint Based Gender Identification using Frequency Domain Analysis**.** Ritu *et.al.*, (2012) have worked on fingerprint based gender identification using frequency domain analysis. The classification is achieved by analyzing fingerprints using Fast Fourier transform (FFT), Discrete Cosine Transform (DCT) and Power Spectral Density (PSD). A dataset of 220 persons of different age and gender is collected as internal database. Frequency domain calculations are compared with predetermined threshold and gender is determined. They obtained results of 90%, and 79.07% for female and male samples respectively. Rijo, *et. al.*, have proposed a method for Fingerprint Based Gender Classification through frequency domain analysis to estimate gender by analyzing fingerprints using 2D Discrete Wavelet Transforms (DWT) and PCA. A dataset of 400 persons of different age and gender is collected as internal database. They have used minimum distance method for classification and achieve overall success rate in gender classification of around 70%. Gnanasivam, *et. al.*, 2012 have proposed a method for Gender Identification Using Fingerprint through Frequency Domain Analysis to estimate gender by analyzing fingerprints using fast Fourier transform (FFT), discrete cosine transform (DCT) and power spectral density (PSD). A dataset of 400 persons of different age and gender is collected as internal database. Frequency domain calculations are compared with predetermined threshold and gender is determined. They obtained the results of 92.88 % and 94.85 % for male and female respectively.

Gender Classification using Fingerprints Based on Support Vector Machine (SVM) with 10-Cross Validation Techniques. Gornale, *et. al.*, (2015) have worked on gender classification using fingerprints based on support vector machine (SVM) with 10-cross validation techniques. Support Vector Machine (SVM) is a new classification technique based on the statistical learning theory pro-posed by Vapnik (1995). It is a binary classifier it abstracts a decision boundary in multidimensional space using an appropriate sub set of the training set of vectors; the elements of this sub set are the support vectors. Geometrically SVM are those training patterns that are closest to the decision boundary. It is useful to understand linear discriminant functions and neural networks. An 89% and 91% classification rate is achieved for DWT using SVM (RBF sigma) and SVM (polynomial) using SVM classifier respectively.

Gender Classification from Fingerprints. Manish, *et. al*. (2008) have proposed a method for Gender classification from fingerprints. Features extracted were; ridge width, ridge thickness to valley thickness ratio (RTVTR), and ridge density. SVM is used for the classification. This method is experimented with the internal database of 400 fingerprints in which 200 were male fingerprints and 200 were female fingerprints. They found male - female can be correctly classified up to 91%. Jen, *et. al.*, (2008) has worked on gender determination using fingertip features. He obtained fingerprints from 115 normal healthy adults in which 57 were male fingerprints and 58 were female fingerprints. They have used ridge count, ridge density, and finger size features for classification. However, the ridge count and finger size features of left little fingers are used to achieve a classification. The best classification result of 86% accuracy is obtained by using ridge count and finger size feature together. Ahmed, *et al*, (2006) proposed a Gender classification from fingerprints, which is an important step in forensic anthropology in order to identify the gender of a criminal and minimize the list of suspects search. A dataset of 10 - fingerprint images for 2200 persons of different ages and gender (1100 males and 1100 females) was analyzed. Features extracted were; ridge count, ridge thickness to valley thickness ratio (RTVTR), white lines count, and ridge count asymmetry, and pattern type concordance. Fuzzy - C Means (FCM), Linear Discriminate Analysis (LDA), and Neural Network (NN) were used for the classification using the most dominant features. They obtained results of 80.39%, 86.5%, and 88.5% using FCM, LDA, and NN, respectively.

A Fingerprint-based Age and Gender Detector System using Fingerprint Pattern Analysis. Falohun, *et. al.* (2016) developed a system that determines human age-range and gender using fingerprint analysis trained with Back Propagation Neural Network (for gender classification) and DWT+PCA (for age classification). A total of 280 fingerprint samples of people with various age and gender were collected. 140 of these samples were used for training the systems Database; 70 males and 70 females respectively. This was done for age groups 1-10, 11-20, 21-30, 31-40, 41-50, 51-60 and 61-70 accordingly. In order to determine the gender of an individual, the Ridge Thickness Valley Thickness Ratio (RTVTR) of the person was put into consideration. Two studies revealed that the males have higher ridge count than the females. It was also shown that both males and females have higher rightward directional asymmetry in the ridge count, with the asymmetry being higher in males than females and higher incidence of leftward asymmetry in females. Female's fingerprints are significantly of lower quality than male fingerprints. The findings of establishing that the females fingerprint is characterized by a high Ridge Thickness Valley Thickness Ratio, while the males fingerprint is characterized by low Ridge Thickness Valley Thickness Ratio, with the exception of small percentage of males fingerprints having high Ridge Thickness Valley Thickness Ratio, and females fingerprints having low Ridge Thickness Valley Thickness Ratio. This presented a model towards the determination of gender through the fingerprint information using Multi-Layer Perceptron (MLP) technique. Result showed 80.00 % classification accuracy for females and 72.86 % for males while 115 subjects out of 140 (82.14%) were correctly classified in age.

Analysis, Design and implementation of Human Fingerprint Patterns System Towards Age and Gender Determination, Ridge Thickness to Valley Thickness Ratio and Ridge Count on Gender Detection. In this research, the authors Omidiora, *et. al.* (2012) proposed Analysis, design and implementation of human fingerprint patterns system towards age and gender determination, ridge thickness to valley thickness ratio & ridge count on gender detection. The aim of this research is to analyse humans fingerprint texture in order to determine their Age & Gender, and correlation of RTVTR and Ridge Count on gender detection. The study is to analyse the effectiveness of physical biometrics in order to determine age and gender in humans. An application system was designed to capture the finger prints of sampled population through a fingerprint scanner device interfaced to the computer system via Universal Serial Bus, and stored in Microsoft SQL Server database, while back-propagation neural network will be used to train the stored fingerprint. The fingerprints of two hundred individual was collected, one hundred male and one hundred females for different age groups. The age group was divided in series of five years (i.e. 0-5, 6-10, 11-15, 16-20, 21-25…….). The captured fingerprint was stored in a Microsoft SQL Server database through an interfaced fingerprint reader. It was observed that the percentage accuracy of the model for age is 33.3% while that of gender is 80%.

Estimation of Age through Fingerprints Using Wavelet Transform and Singular Value Decomposition. (Gnanasivam, 2012). In this paper discrete wavelet transform (DWT) and the singular value decomposition (SVD) has been used to estimate a person's age using his/her fingerprint, the most robust K-nearest neighbour (KNN) used as a classifier. The evaluation of the system is carried on using internal database of 3570 fingerprints in which 1980 were male fingerprints and 1590 were female fingerprints. Tested fingerprint is grouped into any one of the following five groups: up to 12, 13-19, 20-25, 26-35 and 36 and above. By the proposed method, fingerprints were classified accurately by 96.67%, 71.75%, 86.26%, 76.39% and 53.14% in five groups respectively for male and by 66.67%, 63.64%, 76.77%, 72.41% and 16.79% for female. Finger-wise and Hand-wise results of age estimation also achieved.

Gender Detection and Classification from Fingerprints Using Pixel Count (Anju, 2019). Gender detection from the fingerprint helps to catalogue the data and to analyze it easily. In this work we tried to implement a system to detect the gender of the particular fingerprint. In this proposed system, time domain approach is used to find out the gender of a particular fingerprint obtained using systematic pixel counting. Fingerprints consist of many different features. In this work, Pixel ratio can be used as a feature. Pixel ratio can be determined by using these three steps. Initially, we need the count of white pixels within the valley area and the count of black pixels within the same area. Finally calculate the ratio between white pixels and black pixels. After performing gender detection in scoffing dataset, methodology is applied to the collected latent fingerprint data set. Then accuracy is found to be 73.5%. From the result we found that this method is not much applicable to the case of latent fingerprints. It was found that female fingerprints have more ridges and male fingerprints possess more valleys. The results showed that the gender identification using systematic pixel counting have 90.2% classification accuracy for females and 96.4% for males.

Fingerprint Based Gender Classification using ANN (Sudharshan, 2019). A unique finger pattern is epidermis of finger comprise of the example of interleaved edges and valleys. The endpoint and bifurcation points of edges are called ridges. Fingerprint minutiae details examples of edges are resolved as one of the kind through the mix of hereditary and condition features. They proposed a technique for classifying the gender based on feature extraction. The related feature to be removed and differentiate the gender is Gabor filters and Minutiae extraction and ROI. The extracted feature is used to train artificial neural network based on the extracted data.

According to above literature reviews, it is observed that numerous researchers have worked on fingerprint based age and gender classification using different approaches and forecasted some promising results with their dataset. In this work fingerprint will be use to determine the age and gender of people. This will be more precise and appropriate for most of implementation to increase the rate of classification.

IV. METHODOLOGY

a. Fingerprint Based Model

To build an accurate fingerprint based model for gender detection system using fingerprint pattern analysis. There are certain steps that must be taken and this chapter provides an extensive explanation to the steps involved. They include;

1. Data Collection - In conducting research, the first step is collecting data in the form of a set of fingerprint image.
2. Pre-processing Data - Before entering the training data, pre-processing data is performed, which is resize the fingerprint image 96x96 pixels.
3. Training Data - In this processing the dataset will be trained using the Convolutional neural network and Support vector machine methodology. This training data processing is a stage where CNN + SVM are trained to obtained high accuracy from the classification conducted.
4. Result Verification - After doing all the above processes, at this stage, we will display the results of gender prediction based on fingerprint images in the application that has been made.

b. Fingerprint acquisition/Data Collection

The first step is collecting data in the form of a set of fingerprint image. This dataset is useful as an input that will process on the system. As per our knowledge there is no separate standard database for male and female fingerprints. The experiment is carried out on acquired fingerprints which are obtained from Sokoto Coventry Fingerprint Dataset (SOCO-Fing), a biometric fingerprint database designed for academic research purposes. SOCOFing is made up of 6,000 fingerprint images from 600 African subjects. There are 10 fingerprints per subject and all subjects are 18 years or older. SOCOFing contains unique attributes such as labels for gender, hand and finger name as well as synthetically altered versions with three different levels of alteration for obliteration, central rotation, and z-cut. The dataset is freely available for non-commercial research purposes at Kaggle. Moreover, synthetically altered versions of these fingerprints are provided with three different levels of alteration for obliteration, central rotation, and z-cut using the STRANGE toolbox.

c. Pre-processing

Solving gender prediction problems require overcoming some main difficulties, such as differing image dimensions and qualities, varying levels of luminosity, choosing appropriate database for each problem, and employing sufficient number of images in each experiment. Therefore, we should apply some important pre-processing techniques such as segmentation, histogram equalization converting colour image into binary image etc. before processing the system to provide accurate and robust ways of solving these problems. After collecting fingerprint samples in bitmap format, they are pre-processed. For computer efficiency, the colour image is converted into binary image.

d. Conversion from RGB to gray scale

The fingerprints acquired from the dataset were gotten in the RGB format and it was needed for the images to be converted to the gray scale representations. The main reason why grayscale representations are often used for extracting descriptors instead of operating on color images irectly is that grayscale simplifies the algorithm and reduces computational requirements.

Figure 5: Male gender fingerprint

Figure 6: Female gender fingerprint

e. Image Cropping

Separating the fingerprint area from the background is useful to avoid extraction of features in noisy areas of the fingerprint and background. Since fingerprint images are always striated patterns, using a global or local thresh-holding technique does not allow the fingerprint area to be effectively isolated. In fact, what really discriminates foreground and background is not the average image intensities but the presence of a striped and oriented pattern in the foreground and of an isotropic pattern (i.e., which does not have a dominant orientation) in the background. If the image background were always uniform and lighter than the fingerprint area, a simple approach based on local intensity will be very effective for discriminating foreground and background; in practice, the presence of noise (such as that produced by dust and grease on the surface of live-scan fingerprint scanners) requires more robust segmentation techniques. (Maltoni *et. al*., 2003)

f. Image Enhancement

The performance of minutiae extraction algorithms and fingerprint recognition technique relies heavily on the quality of the input fingerprint images. Since the fingerprint images acquired from sensors or other media are not assured with perfect quality; In practice, due to skin conditions (e.g. wet or dry, cuts and bruises), sensor noise, incorrect finger pressure, and inherently low quality fingers (e.g. elderly people, manual workers), a significant percentage of fingerprint images is of poor quality. The importance of fingerprint enhancement algorithm is to improve the clarity of the ridge structures in the recoverable region and mark the unrecoverable region for further processing. Here, Histogram equalization was employed.

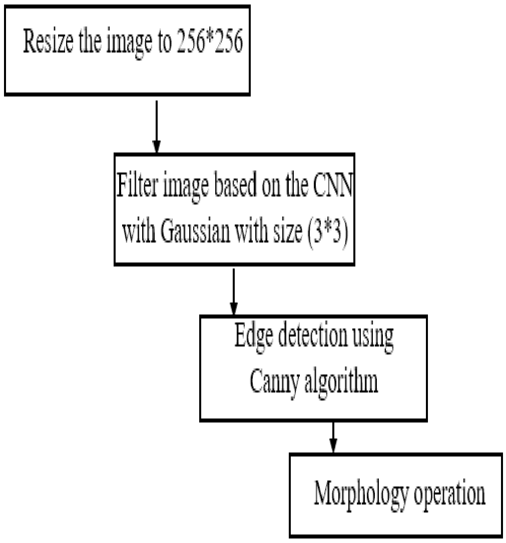


Figure 7: Fingerprint image Pre-Processing (Dibya *et. al., 2020*).

g. Feature Extraction (PCA+CNN)

i. Feature and dimensionality reduction by PCA

After feature extraction by CNN-based method, the features can contain higher dimensional that lead to higher computation and information redundancy. Therefore, we adopt a principal component analysis (PCA) (Moon and Phillips, 2001) to reduce the noise and the feature dimension before recognizing faces. PCA is a statistical method for finding correlations between features and reducing the dimensions of data and is used to reduce the number of components while keeping the information characterizing the object to be analyzed. The idea behind PCA is to project the CNN features to a lower dimensional subspace in order to improve the performance SVM classifiers, by mapping the data points to a lower dimensional space we can categorize data into a set number of classes. Experiments have shown that in selecting only a few dimensions of the PCA feature space produces comparable fingerprint recognition rates to those of the original space. It is a very interesting property of CNN-learned features, because low dimensionality can significantly reduce memory and computation (Mohammed, 2017).

ii. Feature extraction via CNN

CNN is a multi-layered neural network that has the ability to perform both feature extraction and classification. The input layer receives normalized images with the same sizes. Then the image is convolved with multiple learned kernels using shared weights. CNN is composed of a stack of convolutional layers; a convolutional layer is parameterized by the number of maps. CNNs apply a number of filters to the raw pixel data of an image to extract and learn features, which the model can then be used for classification. After this convolution layer, we apply a nonlinear layer (activation layer) ReLU function and we apply a pooling layer to reduce the size or downs ample the image data extracted by the convolutional layers in order to decrease processing time. There are also several options in this pooling layer corresponding to max-pooling, mean-pooling, or stochastic-pooling, over non-overlapping, but max-pooling being the most popular, which extracts sub-regions of the feature map to its maximum value. Convolutional layer and pooling layer compose the feature extraction part. Afterwards, it becomes the fully connected layers which perform classification on the extracted features by the convolutional layers and the pooling layers. These layers are similar to the layers in Multilayer Perceptron (MLP) (Mohammed, 2017).

h. Classification (SVM + CNN)

i. Support Vector Machine (SVM)

Support Vector Machine is a training algorithm for linear classification, regression, principal component analysis and for non-linear classifications. The idea behind the support vector machine is to maximizing the margin between the training patterns and the decision boundary. The support vector machine (SVM) was developed by Vapnik (Vapnik et. al., 1995) for binary classification. It is a powerful discriminative classifier and has been widely exploited with good performance for many pattern classification and face recognition (Wright *et al.*, 2009). The SVM was trained on the deep features extracted from our CNN. In our system, the input of SVM is the facial features of the output layer in CNN after reduction by PCA. The input training dataset and the testing dataset of SVM are the output features of the training dataset and the testing dataset of CNN, respectively. The training label and the testing label of SVM are respectively same to the training label and the testing label of CNN. Its objective is to find the optimal hyperplane f (w, x) = w · x + b to separate two classes in a given dataset, with features $x \in R^m$. SVM learns the parameters w by solving an optimization problem (Eq. 1)

$$\min 1/p w^T w + C \sum \max(0, 1 - y_i(w^T x_i + b) \qquad (1)$$

where wTw is the Manhattan norm (also known as L1 norm), C is the penalty parameter (may be an arbitrary value or a selected value using hyper-parameter tuning), y′ is the actual label, and wT x + b is the predictor function. Eq. 1 is known as L1-SVM, with the standard hinge loss. Its differentiable counterpart, L2-SVM (Eq. 2), provides more stable results (Yichuan Tang. 2013).

$$\min 1/p \|w\| + C \sum \max(0, 1 - y_i(w^T x_i + b)^2 \qquad (2)$$

where $\|w\|_2$ is the Euclidean norm (also known as L2 norm), with the squared hinge loss (Abien, 2019).

ii. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a class of deep feed-forward artificial neural networks which is commonly used in computer vision problems such as image classification. The distinction of CNN is its usage of convolutional layers,

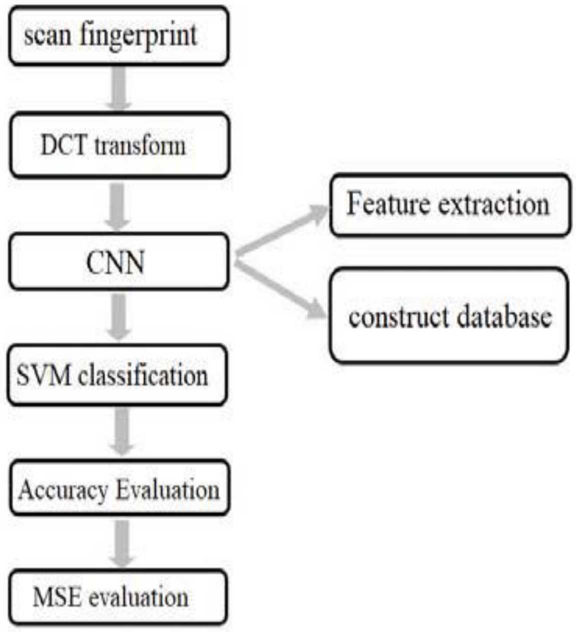


Figure 8: Proposed SVN + CNN method (Abdullahi *et. al*., 2020)

pooling, and non-linearities such as tanh, siдmoid, and ReLU. The convolutional layer (denoted by CONV) consists of a filter, for instance, 5 × 5 × 1 (5 pixels for width and height, and 1 because the images are in grayscale). The CONV layer is used to slide through the width and height of an input image, and compute the dot product of the input’s region and the weight learning parameters. This in turn will produce a 2-dimensional activation map that consists of responses of the filter at given regions. Consequently, the pooling layer (denoted by POOL) reduces the size of input images as per the results of a CONV filter. As a result, the number of parameters within the model is also reduced called down-sampling. An activation function is used for introducing non-linearities in the computation. Without such, the model will only learn linear mappings. The commonly-used activation function these days is the ReLU function because it accelerates the convergence of stochastic gradient descent compared the other two functions (Abien, 2019).

For the training of a convolutional neural network it is important to capture information that adequately represents the pattern that is trying to be recognized for the creation of characteristic vectors. In the case of the current project, it was decided to use three different characteristic vector schemes for the generation of databases for the training of neural networks that can adequately represent images. The three schemes used are listed below:

1. Image
2. Discrete Cosine transform

Discrete wavelet transform

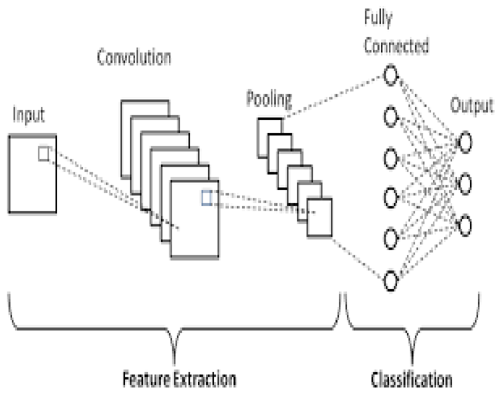


Figure 9: Convolutional Neural Network (Dibya, *et al 2020*).

Once the different schemes for the characteristic vectors were chosen, a treatment was carried out to adapt them to the training of neural networks. It is necessary that the information used to train the convolutional neural networks is representative of the sample that is trying to be recognized and that the information administered to it is the most important (Abdullahi *et. al.*, 2020).

V. IMPLEMENTATION, RESULTS AND DISCUSSION

a. Dataset

The experiment is carried out on acquired fingerprints which are obtained from Sokoto Coventry Fingerprint Dataset (SOCO-Fing), a biometric fingerprint database designed for academic research purposes. SOCOFing is made up of 6,000 fingerprint images from 600 African subjects. There are 10 fingerprints per subject and all subjects are 18 years or older. SOCOFing contains unique attributes such as labels for gender, hand and finger name as well as synthetically altered versions with three different levels of alteration for obliteration, central rotation, and z-cut. The dataset is freely available for non-commercial research purposes at: https://www.kaggle.com/ruizgara/socofing. Moreover, synthetically altered versions of these fingerprints are provided with three different levels of alteration for obliteration, central rotation, and z-cut using the STRANGE toolbox. STRANGE is a novel framework for the generation of realistic synthetic alterations on fingerprint images. Alterations were done using easy, medium and hard parameter settings in the STRANGE toolbox over 500dbi resolution images. Therefore we provide a total of 17,934 altered images with easy parameter settings, 17,067 with medium settings, and 14,272 with hard parameter settings. Note that in some cases some images did not meet the criteria for alteration with specific settings using the STRANGE toolbox, hence the unequal number of altered images across all three alteration categories.

All original images were acquired based on impressions collected with Hamster plus (HSDU03PTM) and SecuGen SDU03PTM sensor scanners. SOCOFing consists of a total of 55,273 fingerprint images combined. All file images have a resolution of 1 × 96 × 103 (gray × width × height). The developed algorithm has been tested using the MATLAB.

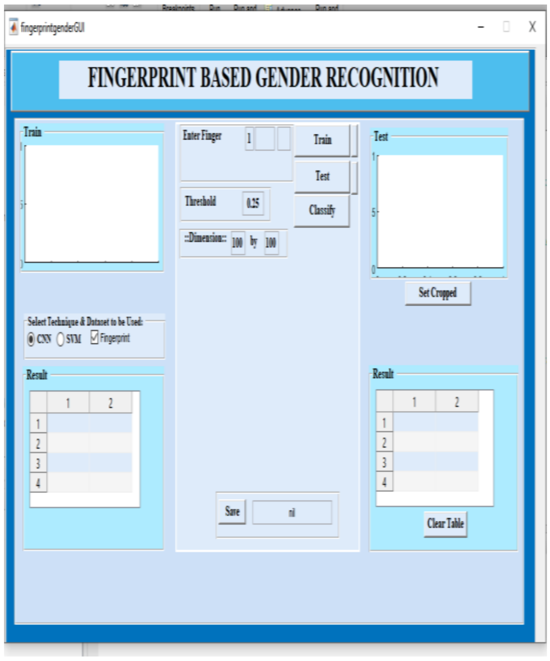


Figure 10: Graphical User Interface (GUI) of the model

Figure 11: Sample of five left hand fingerprints belonging to the same subject.

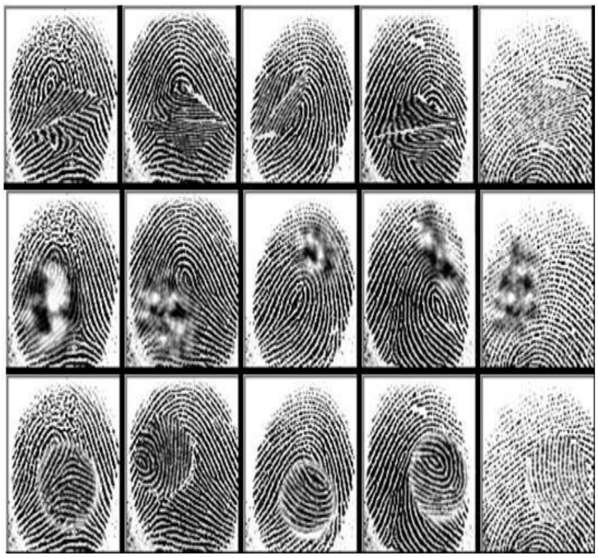


Figure 12: Images from Figure 4.1 after being altered into z-cut, obliteration and central rotation.

b. Analysis of Results

The two classifiers used in this project (CNN and SVM) were used for the training and testing of the dataset to compare which is a better classifier than the other. For the training and the testing of the model created, the thumb image of the dataset which consists of 600 images was used for the process. The 600 images were used for testing and after been tested it was also used for training. This method is referred to as K-fold cross-validation method, which requires that the total number of data used for training is also used for testing. To determine the accuracy, precision, and sensitivity of the each classification method, the following formulas were utilized;

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FN + FP + TN)} \times 100\%$$

$$\text{Sensitivity} = \frac{TP}{TP + FN)} \times 100\%$$

$$\text{Precision} = \frac{TP}{(TP + FP)} \times 100\%$$

i. Result of using the CNN and SVM classifier

Table 1 and Table .2 defined the performance analysis of the developed technique analyzed using the Convolutional Neural Network (CNN) and Support Vector Machine(SVM) classification with the accuracy, sensitivity and precision as earlier stated at several threshold. The values for accuracy, sensitivity and precision using the CNN classifier at threshold 0.25 were 96%, 97.8% and 96.92% respectively. At threshold 0.45 the values were 96.3%, 97.6% and 97.6% respectively. At threshold 0.75 the values were 96.5%, 97.3% and 97.9% respectively. In case of the SVM classifier, at threshold 0.25 were 94.3%, 96.6% and 95.8% respectively. At threshold 0.45 the values were 94.5%, 96.4% and 96.2% respectively. At threshold 0.75 the values were 94.8%, 97.3% and 96.8% respectively. From the 600 fingerprints classified, it was observed that a total of 450 fingerprints were detected for male and 150 for female.

TABLE 1: Performance evaluation of the system using CNN classifier

Technique	Data	Threshold	Accuracy	Sensitivity	Precision
CNN	Fingerprint	0.25	96%	97.8%	96.92%
CNN	Fingerprint	0.45	96.3%	97.6%	97.6%
CNN	Fingerprint	0.75	96.5%	97.3%	97.9%

TABLE 2: Performance evaluation of the system using SVM classifier

Technique	Data	Threshold	Accuracy	Sensitivity	Precision
SVM	Fingerprint	0.25	94.3%	96.6%	95.8%
SVM	Fingerprint	0.45	94.5%	96.4%	96.2%
SVM	Fingerprint	0.75	94.8%	97.3%	96.8%

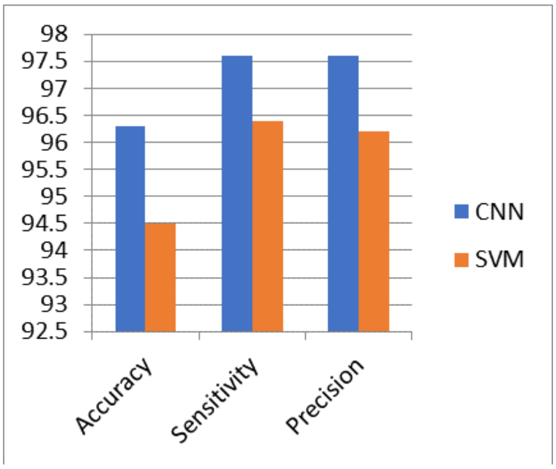


Figure 13: Histogram of CNN and SVM at threshold 0.25

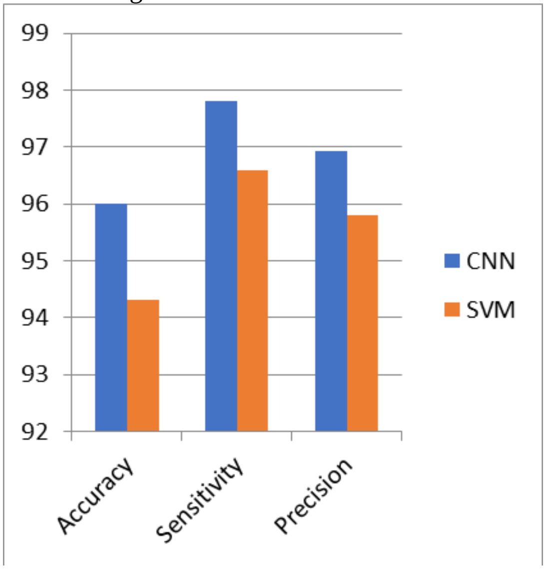


Figure 14: Histogram of CNN and SVM at threshold 0.45

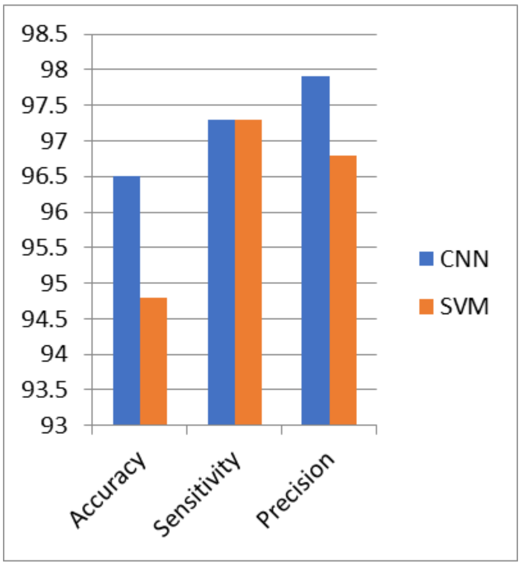


Figure 15: Histogram of CNN and SVM at threshold 0.75

VI. CONCLUSION AND RECOMMENDATION

Conclusion

This work demonstrates the feasibility of recognizing minutiae with the use of convolutional neural networks and an easily achievable hardware implementation. The use of support vector machine classification to increase the bases gave the network robustness by introducing different patterns. Results were obtained for gender accuracy, sensitivity and precision through varied thresholds to compare the two classifiers. However, the results obtained showed that the CNN classification yielded better accuracy, sensitivity and precision than SVM. Inaccuracies due to the observed wrong classifications in gender could be because some people have much larger growth (body sizes) than their counterparts in sex group. This study proves the increased potential of deep learning techniques over the traditional machine learning techniques. Convolutional Neural Networks (CNNs) are similar to the standard neural networks in that they are made up of hidden layers consisting of neurons with learnable parameters and introduce the usage of Support Vector Machine (SVM) in artificial neural network architecture.

Recommendation

Future research that will combine DNA analysis with the fingerprint ridge. This information might yield a better accuracy of gender classification as well as develop a much better feature extraction approaches that can reliably and consistently extract features that provide rich information to paternalism and so on.

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