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MACHINE LEARNING BASED ARTIFICIAL NEURAL NETWORKS FOR FINGERPRINT RECOGNITION

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Abstract

Fingerprint identification relies on computations and classification models based on images to identify individuals at their most basic level. For feature extraction, several image preprocessing approaches are used, and image locality bifurcations of different kinds are used for classification. For feature extraction and classification, artificial neural networks (ANNs) are proposed. ANN machine learning method and Gabor filter are introduced in this paper for feature extraction and classification respectively. Artificial Neural Networks and Gabor filtering features are used to create the feature vector. An algorithm based on the extracted features was developed to create a multiclass classifier. Special Database - NIST SD4 served as the basis for evaluation in this research. The Error matrix led to the discovery that, in terms of accuracy, the approach was superior to many traditional machine learning algorithms like Support Vector Machine, Random Forest, Decision Tree and KNN.

Keywords:

Artificial Neural Network (ANN), Gabor Filter, Machine Learning, Feature Extraction, Classifiers

1. INTRODUCTION

Individual identities are determined by their physical or behavioral characteristics through biometrics [1]. Today, security concerns are becoming more serious and complex as a result of an increasing number of threats. Protection is needed by organizations, educational institutions, political and government agencies when it comes to dealing with extortion and personality issues. Biometrics prevents illegal access to vital information systems when a new threat emerges. It is a routine practice for every organization to implement and update security programmes on a regular basis, Our daily lives have become increasingly dependent on biometric recognition [2].

It is interesting to consider how to authenticate an individual in a safe and reliable manner, and as the value of personal security rises, it becomes more pertinent in many facets of daily life. The use of biometric technologies can facilitate the identification of individuals. With the aid of these approaches, a client can prove ownership of a specific trademark. Because of its richness and uniqueness, biometrics is now an undeniable aspect of human life.

Taking into account the biometric highlights, each individual is evidently in need of a different strategy and system for user identification and control. A biometric identification system electronically verifies our identities by using a variety of body characteristics [3].

Various physical elements and individual characteristics make up biometric systems. Digital evidence comes in many different forms, including fingerprints, signatures, keystrokes, voice, ears, and DNA.

A greater emphasis has been given to security systems for personal checks considering biometric innovations. Biometrics are provided in compliance with technological and safety requirements. Keeping data secure frequently requires the use of biometrics.

In the field of computer vision and processing of images, the Gabor attributes are widely acknowledged to be an extremely pragmatic tool [4]. As recently as 1990s, Gabor filters have been successfully used for segmenting textures and classifying them, identifying characters and targets, identifying edges, interpreting text, managing textures, analyzing images, and compressing them.

Several factors led to ANN's selection. Namely, In addition to storing network information, it organizes it. A few bits of data may be lost from one location, but the ANN as a whole continues to operate. It makes a good option for deep learning because of its capacity to handle incomplete data, fault tolerance, parallel data processing, and ability to handle limited datasets. The qualities lead us to choose ANNs for our investigation even though they were ancient models.

Grayscale images of randomly selected fingerprints can be found in the Database NIST, served as the foundation for the research. The database will be distributed in order to test automated fingerprint categorization methods on a shared collection of images. Using customized lossless compression methods and by using the IHead raster data format from NIST, fingerprints are encoded on the CD. A white space of 32 rows is situated at the bottom of each print, and its dimensions are 512x512 pixels.

An architecture for fingerprint recognition combining Gabor-based fingerprint preprocessing and machine learning algorithms such as ANN is proposed in this paper. The results show that the accuracy of the suggested framework is superior by 97.95% to that of the most recent algorithms of machine learning.

2. RELATED WORKS

Samuel [5] presents a method for cloud user interface authentication based on chaotic patterns. For the purpose of successfully verifying the assertion of a user who appears authentic, the proposed method utilizes an N-stage Arnold Transform as a property. An examination of the foreground and backdrop patterns of an image was made by Hany S. Khalifa, et al. [6] It is necessary to extract deceptive minutiae from background noise, distortion, and instability in order to extract significant facts.

In addition to being distinctive, Hemalatha S [7], describes Fingerprint as a simple, straightforward strategy for clients. Organizing significant details, singularities, and minutiae is an effective way of categorizing and recognizing desirable traits, according to Hemad Heidari Jobaneh [8], The statistical properties of two processes based on Markov chains and kernel smoothing are presented.

Zhang Rui and Zheng Yan [9] emphasize several capabilities that protect security and privacy. Among the vulnerabilities mentioned by [9] are privacy invasion, duplication assaults, synthetic fingerprinting methods, and replay attacks. It has been demonstrated that two fingerprints can be correlated completely using a linear classifier by Kittiya Khongkraphan [10], A criterion for shortening inventory was developed by Javad Khodadoust and Ali Mohammad Khodadoust [11] to enhance the efficiency of identification and offer an environmentally friendly indexing system.

Using fusion-based approaches [12], the input sample's many frequency domain properties are integrated, and similar fusion techniques have been demonstrated in studies and experiments on medical imaging. It has been reported that Weixin Bian, et al. [13] have devised a novel method for evaluating fingerprint orientation fields. A weighted aggregate assessment and an orientation drift are used to replicate FOF. An environmentally friendly approach of recognizing fingerprints was suggested by Subba Reddy Borra, et al. [14], Three components form the proposed system: In order to promote development, morphological operators such as elongation and region opening are the most prevalent forms of imperialization. Third method of categorizing images is achieved by utilizing the AGNN. Data is collected by IoT users and transmitted to a control station via a variety of terminals, but during this process, it is susceptible to attack.

C. Xie and Kumar [15] pioneered the implementation of light convolutional neural networks in Deep Neural Networks. Using deep representative features as a method, H Qin and M A El-Yacoubi [16] proposed a method. As a preliminary step in creating foreground segmentation images, fingerprint images were initially segmented into foreground and background. CNN algorithms determine if a foreground pixel contains vein points or non-vein points. The missing veins were found by combining the segmented images with a convolutional neural network.

Criminals and trespassers at borders must be identified to stop international crimes. To circumvent security measures, a criminal may alter his fingerprint, A study was carried out by Shehu Y I, et al. [17] with the goal of identifying altered fingerprints. A new database named the Coventry Fingerprints Dataset (CovFingDataset) is made public as part of this work.

An estimated 55,249 images were artificially altered, including those that used Z-Cut, obliteration, and center rotation. Fingerprints can be classified according to their type and modified fingerprints can be separated from the real fingerprints. On actual images, the approach achieved 100% recall and precision when compared to the pre-trained ResNet approach, which achieved 98.55% accuracy.

The DTCWT method was suggested by Pradeep N.R and Ravi J [18] for identifying fingerprints. Using a three-stage DTCWT technique, 2^x x 2^y images are finally sized according to their specifications. The performance terms have been strengthened in comparison to contemporary algorithms. Time resolution and accuracy are exceptional in the framework proposed. On the basis of the HOG feature extractor, A effective technique for pixel recognition is presented by Pradeep and Ravi [19]. They provide gradient intensities in pixel form as a histogram. The method persists even when the shade and light are changed. The computation was time-consuming. As a result, authors predicted using deep learning and artificial intelligence in place of HOG soon.

A combination of deep CNN-extracted network of deep features and customized features for concealable biometrics was presented by Abdellatef E, et al. [20]. A multi- biometric system was developed that combines biometrics from face, iris, ear, and palm prints. A number of meticulous techniques were applied during the process, including Local Binary Patterns (LBPs), Oriented Rotated Briefs, Speeded-Up Robust Features (SURF), Scale-Invariant Feature Transform (SIFT), and Histograms of Oriented Gradients (HOG). In order to align with deeper features, the handcrafted features were further decomposed using independent component analysis. With an F1-score of 95.4%, recall of 95.94%, precision of 94.88%, specificity of 96.77%, and accuracy of 96.69%, For fingerprint recognition using the CASIA Fingerprint dataset, the proposed method provided the best results utilizing SIFT and ICA.

The CNN network proposed by N R Pradeep and J Ravi [21], performs exceptionally well in contrast to deep learning networks. The fact that CNN's rotation is not reliable presents another difficulty. Despite CNN's own discussion of the Gabor filter, this inquiry puts it in a very simple form. CNN that is built on the Gabor filter, produces well regarded data effectiveness, and is rotation-invariant. The suggested strategy for 64 epochs was successful with a validation accuracy of 99.33% for training accuracy of 100%. The results are substantially more accurate than the results from the same dataset that were previously reported.

Special Database NIST was used by Pradeep N R and Ravi J [22], A confusion matrix further supported these findings, and when comparing the suggested method with more recent Machine Learning techniques like RF, KNN, SVM, and DT, it performed better in terms of accuracy.

2.1 PROBLEM IDENTIFICATION

Most traditional fingerprint matching algorithms, according to the survey findings, do not save the retrieved feature information, cannot handle partial data, cannot perform more than one computational function at once, and haven't been sufficiently examined or classified. Researchers have been attracted to ANNs due to their ability to quickly process complex computations.

3. MODEL

This section includes discussions on performance indicators, models, datasets, and classifiers.

3.1 DEFINITIONS

Consistency is evaluated using the characteristics of precision, sensitivity, accuracy, specificity, and F Score.

True Positive (TP): A measure of how many positive cases the model correctly classified.

True Negative (TN): Indicator of how many locations were properly classified as not falling into a certain category. It is equivalent to a straight denial.

False positive (FP): It is comparable to a false alarm because it is a type-1 error. Essentially, It's an indicator of how many false positives the model has found.

False Negative (FN): An error of type-1 is synonymous with a missing value. The statement emphasizes the number of false negatives reported by the model.

Precision [23]: Taking the sum of true positives and false positives and dividing it by the true positives. This accuracy metric measures how well the model classifies positive data.

$$\text{Precision}=TP/(TP+FP) \quad (1)$$

Sensitivity [24]: It evaluates the model's ability to recognize positive samples. With increased sensitivity, more samples are discovered to be positive. The most common method for calculating it is to take the sum of true positives and false negatives and dividing it by the number of true positives.

$$\text{Sensitivity}=TP/(TP+FN) \quad (2)$$

Accuracy [23]: This result is obtained by dividing the total number of observations by the number of accurately anticipated observations.

$$\text{Accuracy}=(TP+TN)/(TP+FN+FP+TN) \quad (3)$$

Specificity [24]: As a percentage, it represents the true negatives projected as real negatives.

$$\text{Specificity}=TN/(TN+FP) \quad (4)$$

F_Measure or F_Score [24]: The harmonic mean of Sensitivity and Precision makes up the statistic known as the F Score, which measures a model's consistency on a dataset. As the F_Score increases, the model's performance improves.

$$\text{FScore}=(2*(\text{Sensitivity}*\text{Precision}))/((\text{Sensitivity}+\text{Precision})) \quad (5)$$

3.2 MODEL SUGGESTED

The block diagram for the suggested approach, which makes use of ANN after integrating Gabor-based features to identify a person using the Special data base NIST more accurately, is shown in Fig.1.

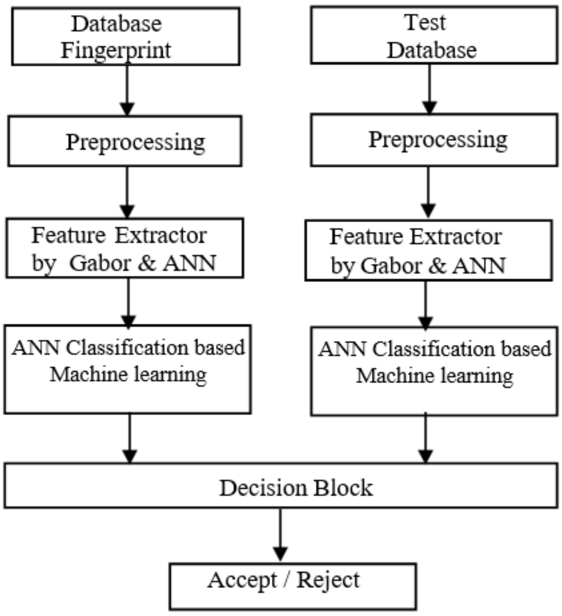

Fig.1. Machine learning classification using Gabor-based feature extraction and ANNs

3.2.1 NIST Special Database 4:

Located in database data is a collection of 8-bit grayscale images of fingerprints. The images are encoded and delivered as a CD-ROM [25] in ISO-9660 format, containing 1.1 Gigabytes of uncompressed memory and 636 Megabytes of compressed memory.

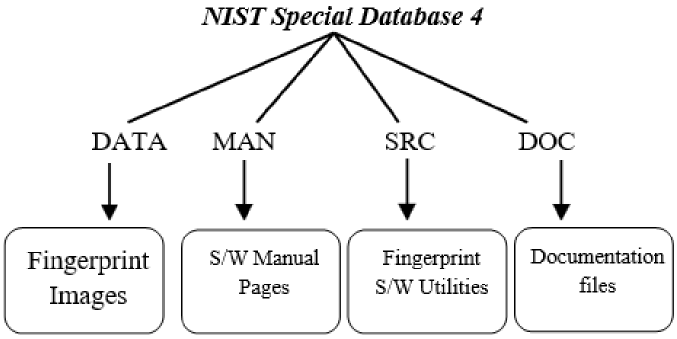

Fig.2. An overview of NIST Special Database 4 at the top level [22]

Documents, source files, man files, and data files are listed in order of importance in the file hierarchy. The image data decompression and access code is stored in the src directory. For the source code, man pages are kept in the man folders. Information on the CD-ROM is available in the doc directory. For faster access, the data directories fingerprint images are stored in 8 sub-directories. Each subdirectory stores 250 fingerprint combinations (the same fingerprint rolled twice). A fingerprint file [22] with the ".pct" extension is named with two letters, four numbers, two more digits, and a letter. The first and second fingerprint rolls are identified in the filename by the letters "f" or "s," respectively. In order of their appearance, the final two numbers represent the finger number, while the next four (i.e., 0001-2500) stand for the impression number.

3.2.2 Preprocessing of Fingerprint:

The fingerprint image will first be divided into sections that can be recovered and those that cannot be recovered before being used to generate the area mask. An accepted image is used for the filtering stage. The best combined spatial and frequency resolution is achieved by gabor filters, which are distinguished by their frequency and orientation. With gabor filters, true valley features are preserved while band-pass noise can be reduced efficiently.

Enhanced greyscale images are converted to binary images through binarization. The binarized image is given a morphological thinning. Dilating images until there is no further change is a morphological process.

3.2.3 Gabor based Fingerprint Features:

Using the Gaussian function as a multiplier of the harmonic function, the Gabor filter is able to produce an impulsive response [26]. A major objective of Gabor's is to enhance the peaks while flattening the valleys. Computer vision, imaging, and model recognition are among the areas where Gabor is widely used. An image with a Gabor filter is robust to changes in contrast and luminosity as well as spectral spatial information, Eq.(6) provides the general form of the Gabor filter.

$$G_{(\delta,f,\theta)}\left(S_1,S_2\right)=e^{-\left(\frac{\left[(S_1)^2+(S_2)^2\right]}{\left[2\delta^2\right]}\right)}\begin{Bmatrix}\cos\left(2\pi f\left(s_1\right)\right)\\ +j\sin\left(2\pi f\left(s_1\right)\right)\end{Bmatrix} \tag{6}$$

where, S1=S1cosθ + S2sinθ and S2=S2cosθ – S1sinθ, along the S1 and S2 axes, on the x-axis, f represents the sinusoidal plane frequency, 'θ' x-axis orientation of the Gabor Filter, An envelope with Gaussian shape has a width of δ. Setting the variables (δ, f and θ) is required before filtering [26]. with an 1800 rotation the Gabor filter according to the predicted filter direction corresponds to a 00 rotational angle. Symmetrical features characterise Gabor filters. Calculating the filter orientations (θ_n) using Eq.(7):

$$\theta_n = \pi(n/k), \text{ where } n = [0................(k\text{-}1)] \tag{7}$$

There are k filter directions and θ_n directions of orientation. Eight filter orientations are therefore computed with values of 0°, 22.5°, 45°, 67.5°, 90°, 112.5°, 135°, and 157.5°.

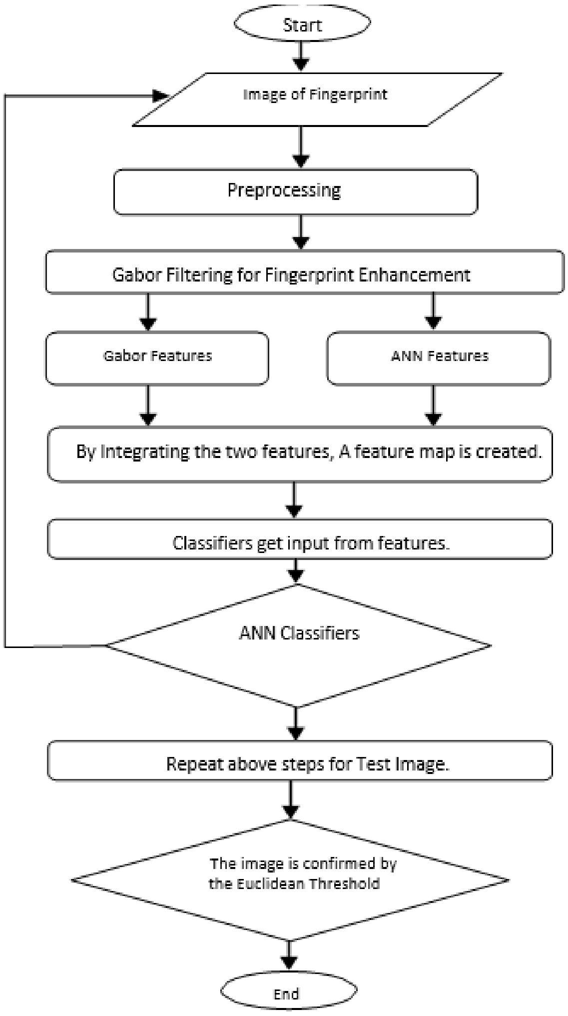

Fig.3. Framework for Fingerprint Identification in a Proposed ANN Model

3.2.4 ANN Framework:

In addition to generalization and fault tolerance, artificial neural networks can also learn adaptively. The proposed framework of ANN is depicted in Figure 3.

The Database fingerprint images are processed through a Gabor filter and a neural network to extract statistical information. ANN and Gabor features are sent to classifiers as vectors. Input images of fingerprints were used in this model, and classification was performed as an output. The special database 4 of NIST is used in this study. A method for improving and segmenting images using morphological processes was implemented in MATLAB 2017b.

3.2.5 Layers of Neural Networks:

An artificial neural network (ANN) is a technology derived from the brain and nervous system as it is made up of layers of neurons, much like the neurons in the brain. Several factors determine how input is processed for each neuron in the network, including the weight of the neuron, or a numerical value. As new values are acquired, they leave neurons and circulate throughout the network. The following are the functions of each layer:

Input Layer: There is no information flowing into input neurons unlike neurons in lower layers. The distribution of weights is random.

Latent or Hidden Layer: Latent layers transform the inputs of the network nonlinearly. It transforms and converts a probabilistic input signal into an output signal.

Output Layer: Using its neurons, the output layer computes the output based on the input from the layers preceding it.

We define:

K: No. of output layer units.

I: No. of units (without bias) at input layer.

J: No. of units (without bias) at latent layer.

(*U*1... *UI*): Input patterns, *UI*+1 =1: Bias unit.

W: Neural Network's matrix weight.

(*S*1… *SK*): A categorization output vector.

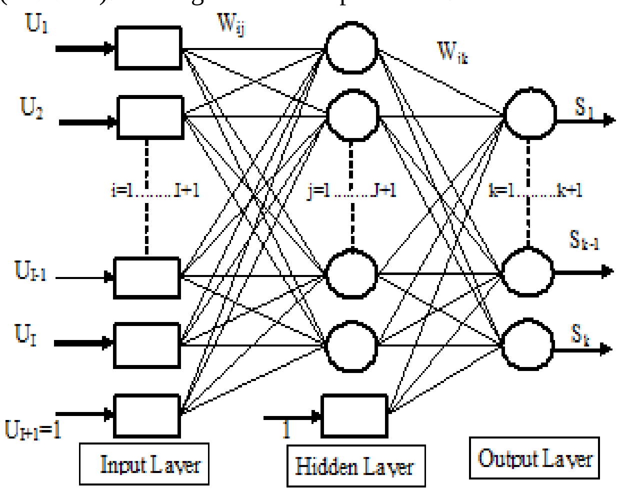

Fig.4. Representing a Neural Network Schematically [27].

The objective of ANN is to identify distinctive fingerprint images as belonging to particular individuals. As soon as the algorithm has collected all the necessary information, it will be able to identify an image. Information is propagated both forward and backward through a neural network, as shown in figure 4. Neural networks using this technology are widely used. It can be utilized for a wide range of purposes. The terminology "feed forward" is used to characterize this neural network operation.

Only forward connections between neurons can be made in a feed-forward neural network. There is an interconnection between neurons in each layer. But there are no back linkages. "Back propagation" is another term for the process in which neural networks are trained. Through an iterative weight-adjusting technique, errors are transmitted backwards from neural networks by changing their weights [27].

The hidden layers were set to 1, and the range J was set from 2 to 120. Evaluation of neural network performance is based on the number of hidden units. When a particular input is applied to a neuron, its activation function determines its output.

3.2.6 Matching:

Calculation of fingerprint matching relies on determining Euclidean distance between prominent vectors.

$$d(r,s)=d(s,r)=\sqrt{(r_1-s_1)^2+...+(r_n-s_n)^2} \quad (8)$$

where 'r' = Features of Test image and 's' = Features of Database image.

The Euclidean distance between two vectors is less than a certain threshold, both images come from the same finger between two vectors. Otherwise, two images are acquired from different fingers.

4. ALGORITHM

Individuals can be successfully identified by using the Gabor and ANN specific feature extraction algorithm.

4.1 PROBLEM DEFINITION

The characteristics of an individual's fingerprint are extracted from the fingerprint image using Gabor and ANN- specific algorithms.

It is possible to evaluate the correctness of an ANN model by examining the confusion matrix, this displays the efficiency of the algorithm.

5. EXPERIMENTAL RESULTS

Video/image analysis using computer-aided software requires selecting the right features. For this investigation, having access to standard data is essential. Any image classification algorithm is determined by its training dataset. Over 5000 fingerprint images were used in our investigation in order to get a good result. According to the recommended method, 1000 images were selected for testing and 4000 images for training. A combination of ANN and Gabor filters was applied to the training dataset to extract features. By combining those features, a dimensionality reduction technique was used. We trained the ANN classifier by combining the collected features. As soon as the fingerprints were sent through the classifier for the test, the attributes were obtained. The classification result is investigated to determine if it is accurate.

Table.1. An Algorithm that recognizes individuals uses Gabor and ANN Features

Input: An image of fingerprint.

Output: A classification model based on Gabor and ANNs for identifying individuals.

Step 1: Based on fingerprint databases, Images were created.

Step 2: The image is scaled down to 2x x 2y.

Step 3: Image quality is improved with fingerprint enhancement.

Step 4: An image is binarized from grayscale.

Step 5: The ridges are scaled back to the size of a pixel.

Step 6: An algorithm based on Gabor is being implemented to extract features.

Step 7: Using Eq.(6) and Eq.(7), Determine features f, δ and θ .

Step 8: An algorithm for extracting ANN features is implemented.

Step 9: The feature map is created by considering every aspect of Gabor & ANN.

Step 10: Gabor and ANN features along with their labels are loaded.

Step 11: Create equal number of images for each category.

Step 12: Load Pre-trained ANN.

Step 13: Assess the proposed ANN model's accuracy using a confusion matrix.

Step 14: Calculate precision, sensitivity, accuracy, specificity and F-score.

Step 15: Repeat steps 1 to 14 for a test image.

Step 16: The Euclidean threshold value for image verification.

The relevant performance terms were measured. True positive, true negative, false positive, and false negative results are denoted, respectively, by the letters TP, TN, FP, and FN. Based on the classification accuracy, the classifier's complete performance is evaluated. Negative data are found more quickly with a classifier that has high specificity. As a key indicator of classification success, the F Score determines the level of positive data.

5.1 ERROR MATRIX

Error matrices, also referred to as confusion matrices, are frequently used to illustrate statistical categorization issues, An algorithm's effectiveness is displayed in a certain table format in machine learning. There were 4000 images acquired in total, including 33 false positives, 49 false negatives, 1969 true negatives and 1949 true positives.

Table.2. Confusion Matrix for Performance Evaluation

No. of images in total 4000	True Positives (TP) 1949	True Negatives (TN) 1969
	False Negatives (FN) 49	False Positives (FP) 33

Table.3. Evaluation Parameters for Analysis

Parameter Name	Values (%)
Precision	98.33
Sensitivity	97.54
Accuracy	97.95
Specificity	98.35
F_Score	97.49
False Detection Rate	1.66
Miss Detection Rate	2.45

Table.4. Comparative Analysis of Different Machine Learning Algorithms

Evaluation Matrices	Machine Learning Methods [24]				
	KNN% [28]	Decision Tree% [29]	Proposed ANN %	SVM% [30]	Random Forest % [30]
Precision	95.65	92.83	98.33	93.9	91.54
Sensitivity	94.54	88.24	97.54	95.89	92.67
Accuracy	92.37	89.65	97.95	97.86	95.47
Specificity	96.9	84.06	98.35	94.71	92.95
F_Score	95.09	90.47	97.49	97.76	87.95

Table.5. Comparison Between KNN and Proposed ANN

Evaluation Matrix	Precision	Sensitivity	Accuracy	Specificity	F_Score
KNN (%)	95.65	94.54	92.37	96.9	95.09
ANN (%)	98.33	97.54	97.95	98.35	97.49
Improvement (%)	2.68	3	5.58	1.45	2.4

Table.6. Comparison between DT and proposed ANN

Evaluation Matrix	Precision	Sensitivity	Accuracy	Specificity	F_Score
DT (%)	92.83	88.24	89.65	84.06	90.47
ANN (%)	98.33	97.54	97.95	98.35	97.49
Improvement (%)	5.5	9.3	8.3	14.29	7.02

Table.7. Comparison between SVM and proposed ANN

Evaluation Matrix	Precision	Sensitivity	Accuracy	Specificity	F_Score
SVM (%)	93.9	95.89	97.86	94.71	97.76
ANN (%)	98.33	97.54	97.95	98.35	97.49
Improvement (%)	4.43	1.65	0.09	3.64	-----

Table.8. Comparison between RF and proposed ANN

Evaluation Matrix	Precision	Sensitivity	Accuracy	Specificity	F_Score
RF (%)	91.54	92.67	95.47	92.95	87.95
ANN (%)	98.33	97.54	97.95	98.35	97.49
Improvement (%)	6.79	4.87	2.48	5.4	9.54

Table.9. Comparison of FDR and MDR of different methods for NIST special database with proposed ANN model.

Approach	Database	FDR %	MDR %	Avg. %
Ridge Orientation and frequency computation [31]	NIST SD	47.99	14.78	31.38

Adaptive Total Variation [32]	NIST SD	26.13	14.10	20.12
K-means Clustering [33]	NIST SD	26.06	4.77	15.42
Fractal Dim & WELM [34]	NIST SD	18.7	9.22	13.96
Proposed ANN	NIST SD	1.66	2.45	2.055

The Table.3 describes the values and their information of evaluation parameters for analysis. Performance of the suggested ANN algorithm in comparison to other Machine Learning algorithms currently in use:

Several competing fingerprint classification methods, including k-Nearest Neighbor [28], Decision Tree [29], Support Vector Machine [30], and Random Forest [30], were compared with the suggested ANN Model.

Comparisons of a number of classification methods with the suggested model are performed based on evaluation measures such as precision, specificity, accuracy, and F Score. A comparison of the proposed metrics and those used by existing classifiers is shown in Figure 5.

The assessment matrices for our work and different machine learning techniques [24] are compared in Table.3. The suggested method clearly outperformed current state-of-the-art classification methods for all performance matrices when the results were compared. Comparing ANN model accuracy with SVM, RF, KNN, and DT, the accuracy of ANN model increased by 0.09%, 2.48%, 5.58%, and 8.30%, respectively. As can be seen from the basic performance matrices, ANN appears to be the most effective strategy compared to the other strategies. In comparison to the ANN's accuracy (97.95%), the SVM and RF classification accuracy were lower, at 97.86% and 95.47%, respectively. As stated, SVM and proposed model differ in accuracy by 0.09%, SVM, however, has a problem with parallelization, whereas ANNs have a built-in parallel processing capability. Structured data is usually better served by RF classifiers [30], but unstructured data is better served by ANN classifiers.

The effectiveness of applying machine learning approaches (KNN and ANN) in the creation of models for fingerprint recognition has been demonstrated by this comparative comparison. At the conclusion of the experiment, ANN outperformed KNN with an accuracy of 97.95% compared to 92.37%. ANN proved to be a more effective method when applied to the same datasets and platform. The Percentage improvement in accuracy is 5.58%.

Due to their complexity at handling partial and missing data, Artificial Neural Networks are frequently viewed as the machine learning ultimate, all-knowing, all-encompassing solution. However, because of how straightforward they appear, tree-based approaches are rarely given the same reverence and adulation. This has been proved once again from Table.6 with ANN yielding an accuracy of 97.95% against DT's accuracy of 89.65%. The Percentage improvement in accuracy is 8.3%.

The benefit of ANN is that we can aprioristically limit a network's size and the number of layers it contains. This indicates that by arbitrary placing a particular restriction on the network size, we can assist in resolving the problem of dimensionality for machine learning models. That is impossible for SVMs with non-linear kernels. Instead, as they use more support vectors, the number of their parameters grows linearly. The general speed with which neural networks make predictions after training is the second benefit. This is due to the fact that a neural network only requires as many computations of activation functions and weight matrix multiplications as there are layers. Since matrix multiplications are frequently performed in parallel, they can be computed quickly. This has been demonstrated from Table.7 with ANN yielding an accuracy of 97.95% against SVM's accuracy of 97.86%. The Percentage improvement in accuracy is 0.09%.

In contrast to Artificial Neural Networks, which may be used with several data types, Random Forests can only be utilised with tabular data. Creating Random Forests requires no missing values or category data, and category values must be converted to numerical values. On the other hand, ANN works effectively with missing and partial data. This has been demonstrated at Table.8 with ANN yielding an accuracy of 97.95% against RF's accuracy of 95.47%. The Percentage improvement in accuracy is 2.48%.

To rate classification accuracy, two metrics are used: the Missed Detection Rate (MDR) and the False Detection Rate. The average number of foreground pixels that are erroneously classified as background is known as MDR, FDR, on the other hand, is described as the average proportion of background pixels that are erroneously labelled as foreground. Based on the NIST SD database, Table.9 shows the average FDR and MDR values of the proposed ANN algorithm as well as those of other contemporary algorithms. There was a significantly lower false rate for proposed ANN than other algorithms, at 2.055% on average.

6. CONCLUSION

It is quick, simple, safe, and trustworthy to identify and verify individuals using their fingerprints. With the aid of a Gabor and ANN model, we investigated fingerprint feature extraction and fingerprint identification. Validation of the algorithm is performed using Database NIST.

It is possible to generate a biometric password utilising body component. In this work, ML-based fingerprint recognition is described with a preprocessing stage, a Gabor and ANN-based feature extractor, and an ANN classification stage.

Precision (98.33%), Sensitivity (97.54%), Specificity (98.35%), F Score (97.49%), FDR (1.66%), and MDR (2.45%) were among the performance measures that outperformed any conventional machine learning method. Based on the results, ANN outscored any combination of feature extraction and classifier.

A larger data set would be trained and evaluated for future studies. Using machine learning architectures, future research is focused on creating multimodal biometric identification systems, which combine fingerprint and keystroke features with signatures, iris patterns, and facial characteristics to identify individuals. This will enable the creation of biometric recognition systems that are more trustworthy.

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