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FUSION OF MULTIMODAL UNCONSTRAINED BIOMETRIC AUTHENTICATION USING MACHINE LEARNING TECHNIQUE

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Abstract – The term "biometric identification" pertains to the use of physiological and behavioural attributes for the purpose of distinguishing and verifying the identity of a person. The reliability of biometric identification surpasses that of older techniques. This paper presents a comprehensive review of the identification process, including a concise explanation of the functioning of biometric systems, the rationale behind its efficacy as a viable substitute for conventional identification methods, and the evaluation of biometric systems in terms of their performance. In this work, a novel bag of classifiers approach is proposed. Accuracy, specificity, sensitivity, F1-score, MCC, and AUC measurements are used for performance comparison. The performance of the proposed method is found to be considerable over the other methods.

Keyword: Biometric Identification, Feature Selection, Feature Fusion, Machine Learning, Multimodal, Biometric Authentication

1. Introduction

A biometric authentication system employs one or more biometric traits or data modalities to verify the identity of a user by either accepting or rejecting their claim. The following is a standard architectural framework for such a system [1]:

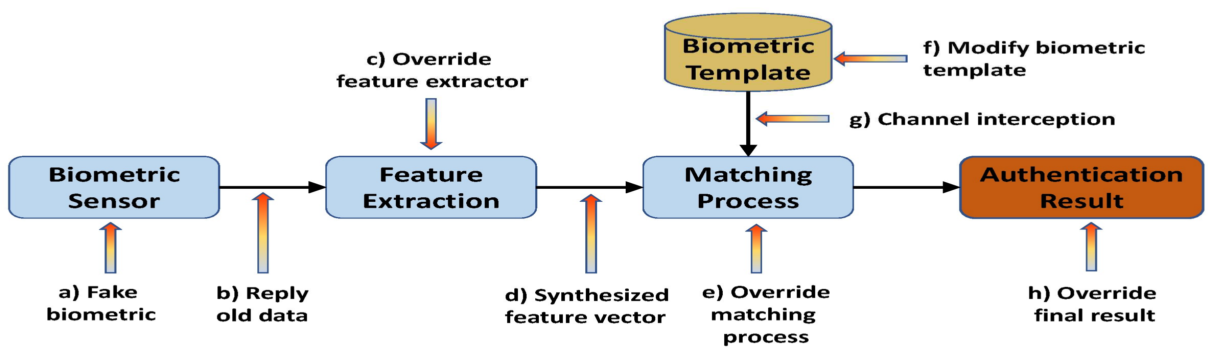

Figure 1: Biometric (image/signal) processing pipeline [2]

Just by replacing the sensor with a Camera/sensor that captures images and then each module in the above pipeline (Figure 1) working on the biometric images, the above general biometric recognition (authentication) pipeline turned into a Biometric Recognition BR) system or method. The factors (or challenges) to consider in general recognition methods are- viewpoint variations, scale variations, illumination variations, occlusions, deformations, intra-class variations, and background clutter [2]. In real-time, the source of a person's biometric can have different views (i.e. orientation/rotation in multiple dimensions), can be with different scales (small/medium/large size), and can be taken in different lighting conditions (light, dark). Some garments/ornaments can hide the source (occlusion). Some internal deformations in the source surface structure may be present which can be difficult to detect and/or remove. The same person's biometric data can have intra-class variations. The biometric data has to be detected from a very noisy background (background clutter). Hence, having a good recognition method that performs well and with great accuracy in the presence of these variations is the ultimate research goal in this field. How much such variations are dealt with in the recognition method is the determining factor in classifying it as **constrained or unconstrained**[3].

Biometrics is an automated mechanism designed to authenticate and verify the identity of an individual [4]. Its objective is to replicate the very efficient identification process seen in human beings. The cognitive process of pattern recognition plays a crucial role in the human capacity to identify familiar faces, voices, and unique walking styles. This process involves the initial capture and storage of certain characteristics pertaining to the observed individual, which can be subsequently retrieved within a reasonable timeframe when necessary [5] [6]. Biometrics, as a field, not only facilitates the acceleration of the identification process but also introduces novel modalities such as iris, Biometrics offers significant advantages over traditional human recognition methods in terms of efficiency, speed, and variety.

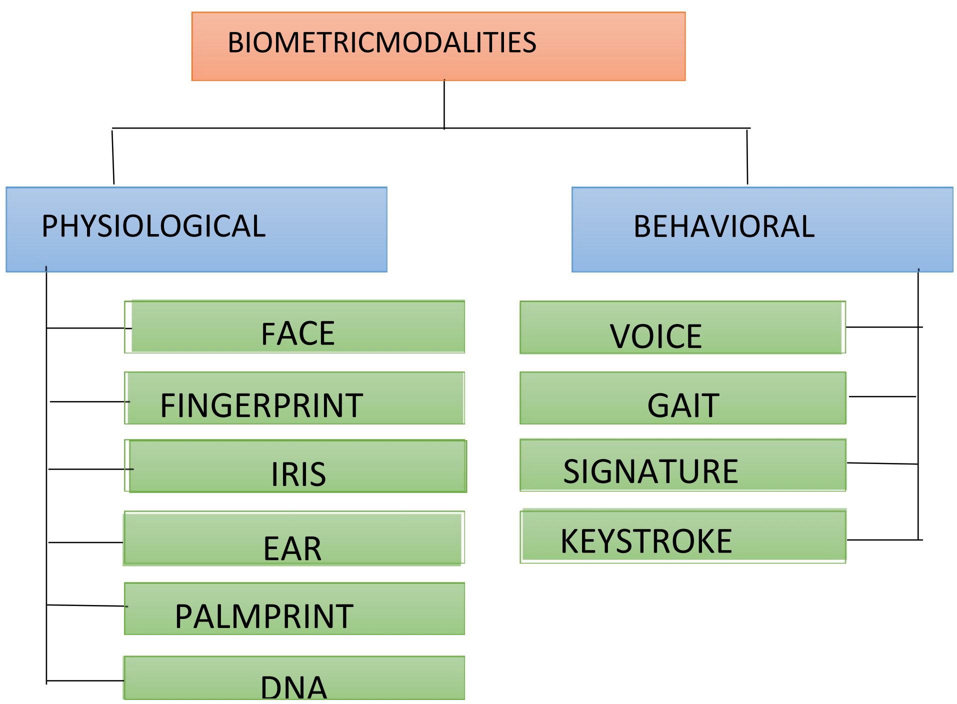

Figure 2: Basic Biometric Modalities

In figure 2, attributes, sometimes known as "identifiers" or "traits," are indicative of certain qualities. Physical characteristics include several features such as the face, iris, fingerprints, palm print, ear, and so on. In contrast, behavioural traits include attributes such as Signature, Voice, Keystroke dynamics, and so on.

1.1 Unimodal Biometrics

Authentication, such as the use of a single fingerprint or face, is a unimodal method that serves as a source of information. There are several techniques that effectively address counterbalance concerns [7].The presence of noise in sensed data may be attributed to several factors, such as the fingerprint sensor being malfunctioning due to accumulated dirt or scratches on the fingerprint image, or the sensor being held improperly. In this particular scenario, it seems that the use of fingerprint or voice verification methods may not be seen as an optimal means of self-identification.

1.2 Multi Modal Biometrics

An new concept in biometrics is multimodal biometric authentication, which combines two or more biometric types or biometric systems (such face, finger print, and iris recognition) to enhance performance [8].Whenever the user wants to use multiple identity markers, the system determines that high security is necessary. This system makes it much difficult for an intruder to fool the system as various fake identifiers would need to be provide details at the same time. For example, the biometric system combining facial and iris characteristics for biometric identification is considered a multimodal system, irrespective of whether the same or different imaging devices capture the face and iris images. Also, the measures need not be mathematically combined in anyway. This system allows users to be verified using modality

1.3 Feature Selection in Bioinformatics

The design of the supervised learning framework is based on the biometric system when the assessment of the function is of significance. The existing body of literature indicates that the practical value of contemporary biometrics research has not been assessed. Feature subset selection is a technique used to identify and eliminate redundant characteristics that are superfluous. The assumption of a modest feature set size has the effect of reducing the space required for implementation and is a crucial factor in the successful deployment of online personal authentication systems [10].

The process of biometrics authentication often takes place when there is a determined measure of similarity between the identity verification rights and the feature vector provided to the system by the feature vector stored in the database [11]. Figure 3 is shown in the next section.

The choice is determined by predetermined thresholds. Nevertheless, the first characteristics lack distinctive information. Hence, the potential for confusion arises when attempting to differentiate between samples from different individuals, thereby diminishing the overall accuracy of the verification system [12]. The verification issue was categorized as a problem belonging to a single class or a class with a variable number of elements denoted as (1 + X). The process of feature selection involves identifying certainattributes that differentiate a person from other users based on their feature vectors. The identification of a distinctive characteristic pertaining to a certain person posed a challenge. Discriminate analysis has been used in several applications, including face recognition, multi-class text classification, and content-based picture retrieval.

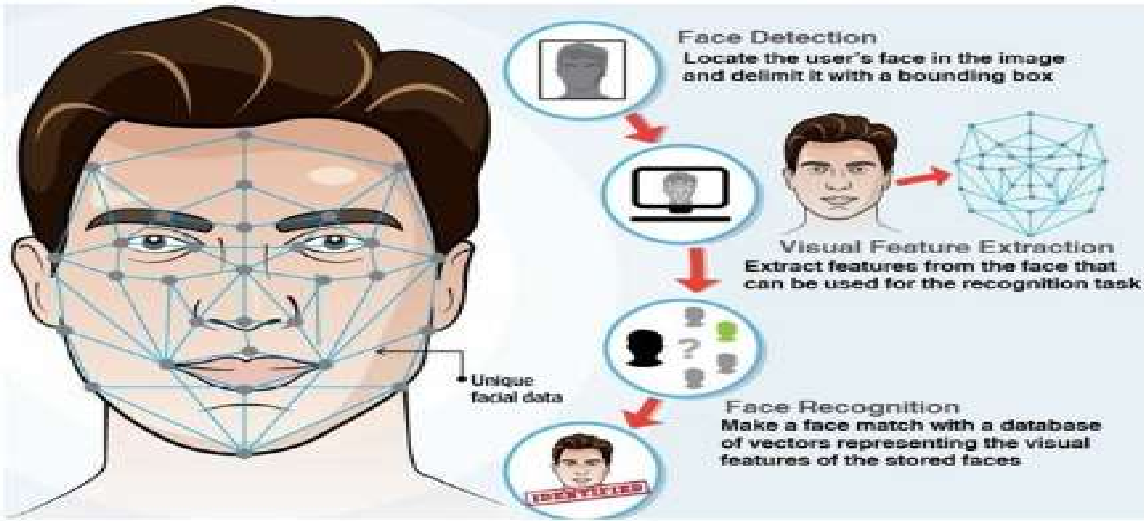

Figure 3: Face Feature Extraction [13]

The incorporation of the hand shape's functionality into the new area serves to augment the original functionality of user identification.

Nevertheless, it is essential that the transformation be executed in a manner that ensures the feature vector specified by the user is distinct from the feature vectors present in other databases. Discrimination must exhibit a prejudiced inclination towards the specified identity.

In order to preserve the integrity of the identity vector inside the transform space, it is necessary to minimize the influence of features originating from other classes. This may be achieved by pushing these features away from the desired identity. Additionally, clustering the features is essential to evaluate the effectiveness of the tightly k-nearest neighbor approach.

1.4 Machine Learning Approaches in Bioinformatics

Machine Learning (ML) is a subfield of Artificial Intelligence that acquires knowledge and skills via the analysis and interpretation of data, rather than relying only on explicit programming. Machine learning methods rely on training data to construct accurate models [14]. During the training phase, the model creates output based on the provided data. Subsequently, following the completion of training, the model is capable of providing anticipated output by leveraging the input data. Prior to deployment, machine learning (ML) allows the models to undergo training using datasets [15]. Given its repetitive nature, this technique enhances the quality of linkages among various data pieces. These small-scale interactions are very minute and, owing to their diminutive size and intricate nature, are imperceptible via human gaze. The trained model may be effectively used in real-time scenarios to enhance accuracy and enable automation [16]. ML models have several applications that are implemented online and used in a continual manner. Machine learning approaches have been shown to enhance the precision of prediction models. Machine learning (ML) may be classified into many categories based on its nature, the kind and amount of data used, and the specific issue being addressed. The individuals in question are [17-19].

Supervised learning is a machine learning technique used to classify patterns within data during the process of data analytics. The pattern data comprises the labelled characteristics that serve to determine the pattern class. Some examples of biometric technologies are face identification, biometric attendance tracking systems, and handwriting matching.

Unsupervised learning is a kind of learning that is used when dealing with a substantial volume of unlabeled data in a given task. For instance, social media platforms such as Instagram, Twitter, Snap chat, and others. Additionally, it is used in electronic mail systems to identify and filter out unsolicited and potentially harmful communications often referred to as spam.

Reinforcement learning is a kind of learning that is rooted in the principles of behavioral learning. The model utilizes data analysis to gather input and provide guidance to the user, ultimately leading to the optimal conclusion. The learning process involves a series of trials and errors.

Deep learning is a learning approach that employs neural networks organized in several layers to facilitate the learning process [20]. The use of unstructured data patterns is advantageous. For instance, the use of image recognition and computer vision applications might be cited as examples.

1.5 Motivation of Research

This study primarily focuses on both modalities: finger and palm print. As far as we can determine, there is no existing research that explores the integration of various modalities. The primary rationale for choosing finger and palm print as the biometric elements for constructing a heterogeneous biometric system is that,

- The finger has been used for personal identification and it is mostly used in daily applications for a long time.
- The palm region exhibits a greater size, allowing for the recording of a greater number of unique features in comparison to fingerprints.

So,thesemodalitiesmakeitevenmoresuitableinidentificationsystemsthanothers.In the present study, the person identification is performed with multimodalbiometric traits. There are several biometric traits: Finger and palm print. The proposed system usesthe rough set approach for increasing the accuracy with the help of the Eigenfeatures.

1.6 Research Objective

The main objective of the research is “To design and develop

MultimodalBiometricIdentificationSystemwithmoreaccuracywhencomparedtotheunimodal BiometricSystems."

Toachievethisobjective,somesub-objectivesaretobeachieved,whichareshownbelow:

- Conceptualstudyof Finger recognition and palm printrecognition,theirmethods
- Collecting Dataset
- Designing anddeveloping abiometric Finger identification system
- Designinganddevelopingabiometricpalm printidentificationsystem.
- Studyofexisting multimodalbiometricsystemsandmethods.
- Designing and developing the multimodal biometric systems using differentmodalities atfeaturelevelfusion
- Comparingtheresultsomultimodal Biometricsystems(Finger andPalm print).

In this study, biometric images are gathered and subjected to feature extraction in preparation for further processing at a higher level. A comprehensive set of 152 significant characteristics is retrieved from every fingerprint picture and then compiled into a database. The database is afterwards categorized via the use of strong algorithms in order to provide accurate classification outcomes. This thesis has seven chapters, each of which presents essential information pertaining to our study.

2. Literature Survey

In this section, we have extensively studied the contributions of different researchers in the field of Biometrics, Fingerprint and Palm print Image Recognition, and the potential applications of different machine learning techniques in Biometrics recognition. This chapter is organized as follows.

Heidari, H. et al. (2022), introduced a deep learning approach for verifying the identity of individuals by analysing the features of the back of their hands. The suggested technique utilises the fingernail (FN) and fingerprint (FP) obtained from the fingers. The suggested approach was assessed using a collection of 1090 hand pictures, with 10 photos from each of the 109 individuals. The images were subjected to hand skin identificationand a strategy for extracting both finger joint and nail. The suggested system incorporates a multimodal biometric method to enhance authentication performance and increase resistance against spoofing attacks. The applied method utilises a convolutional neural network (CNN), depending on deep learning principles. The scientists used normalisation and fusion approaches to integrate various information collected from hand photographs at different levels. The experimental findings showcase the superior effectiveness, resilience, and dependability of the suggested biometric system in comparison to current alternatives. As a result, it has the potential to be used in several practical applications.

Devi, R. et al. (2022),authenticated and identity pose significant challenges in our everyday lives. A biometric system enables the automated identification of a person by analysing their behavioural or physiological characteristics. This study utilises multimodal biometric features, namely finger print and iris. The characteristics underwent pre-processing using a Wiener filter and performing certain morphological procedures. The biometric features that had undergone pre-processing were divided and combined using three specific algorithms: discrete wavelet transform (DWT), principal component analysis (PCA), and gradient pyramid (GP). The integration of many biometric variables via genetic programming yields superior outcomes while preserving the essential data. The process of extracting features and classifying data was conducted using grey scale co-occurrence matrices (GLCM) and support vector machine (SVM). The accuracy of authentication using fused biometric features is 83.75%, whereas the effectiveness using just fingerprint is 73.75% and using only iris is 78.48%.

Ammour, N. et al. (2023), suggested unimodal biometric methods depend on a solitary source or distinct human biological characteristic for measurement and analysis. Fingerprint-based biometric technologies are widely used, however they may be compromised via presentation assaults or spoofing, which include the display of a counterfeit fingerprint to the scanner. In order to tackle this problem, we suggest an improved biometric system that relies on a multimodal approach including two distinct kinds of biological characteristics. Our proposal involves integrating fingerprint and Electrocardiogram (ECG) data in order to counteract spoofing attempts. We have developed a specialised deep learning framework that can process both fingerprints and ECG data. This framework combines the feature vectors from both inputs utilising stacking and channel-wise techniques. The architectural feature extraction foundation relies on transformers that are efficient in handling data. The experimental findings illustrate the potential of the suggested strategy in improving the system's resilience against presentation assaults.

The introduction of existing studies and comparative analysis of biometric system's benefits and downsides have been covered thus far. The subsequent chapters have been grouped into numerous categories and focus on recommended approaches.The objective of the proposed study is to develop a safe, multimodal biometric system with low mistake rates and a high rate of recognition that is optimal for personal authentication.

3. Methodology

3.1 Dataset Collection

The work that was proposed, the experimental setup, the performance measures, and the findings that were acquired are discussed in this part. For the purpose of the study that is being suggested dataset has 90 individuals, and each subject includes 74 sample photos, for a total of 6660 sample images in the dataset. We make use of the dataset that is open to the public and can be found at (www.comp.polyu.edu.hk /csajaykr/ IITD/Database Palm). This dataset pertains to the palm modality. This particular dataset is referred to by us as the IITD dataset. There are 230 individuals, and for each participant, there are 7 sample photographs of both the left and right hand [25]. This results in a total of 3220 sample images. We also use CASIA dataset, as referenced by [26], is widely recognized as the preeminent publicly accessible resource for biometric pictures. A total of 200 individuals participated in two sessions, during which their biometric data was collected, resulting in a total of 4800 photographs being generated and The dataset GPDS100[27] comprises a collection of 1000 photographs capturing 100 distinct palm trees throughout a single session.

3.2 Design Parameter

This investigation has two objectives:

• Assessment of the effectiveness of unimodal palm identification on the IITD palm and finger dataset.
• Assessment of the effectiveness of multimodal finger and palm identification using scoring rank fusion.
The datasets are partitioned into training and testing databases in order to generate batches of photographs including 50, 100, 150, and 200 sampling images of 10 virtual personalities obtained from these datasets. To illustrate, in order to generate a set of 50 sample shots, one can utilise ten virtual identities, each consisting of three facial images and two palm print images (one for the left palm and one for the right palm) [27].
The study includes three classifiers that were trained and evaluated: Random Forest (RF), Support Vector Machine Classifier (SVM), and Artificial Neural Network (ANN). Additionally, the k-nearest neighbour technique (kNN), Bagging, and Boosting were also utilised. The selection of these six classifiers was motivated by the aim to identify a more efficient approach for addressing supervised multiclass classification issues. Support Vector Machines (SVM) are highly effective at separating hyperplanes in multidimensional data. Random Forest (RF) is a promising ensemble technique for extracting features. Artificial Neural Networks (ANN) have the ability to automatically acquire enhanced features. The integration of the most beneficial components of multimodal systems enhances their overall efficiency.
In order to fully utilise the Python tool, it is necessary to convert all the photographs together with their corresponding labels into the SCV file format. Subsequently, it is important to transform these files into the arif format as stipulated by the python tool.

3.3. Working Mechanism

The working mechanism of work is described as follows:
Input: m - size, C_1 and C_2 set classes for interacting and non-interacting Biometric Authentication
Output: Get output score for Interacting and non-interacting target indication.
Step-1: The software reads Dataset and saves them in SequenceSet objects.
Step-2: Convert quantify raw and modified sequences with a single value.
Step-3: The beginning of the algorithm for the number of features from 1 to the total number of features .Check each feature one by one (until the end of the feature)
Step-4: Use feature class objects that encompass conversion mappings and quantification measures, making chaining simple.
Step-5: Define matrix m_{ij} to calculate the pairwise score. No score is computed less than 62% for a size by calculate BLOSUM.
Step-6: Calculate the pairwise score for row vector and compare in two-dimensional feature space that measured by quantitative property of sequence.
Step 7: If the query's features are not the same as the previous one, but are larger than zero, the query is considered successful.
Adding up the interacting pair
Alternatively, count the non-interacting pair.

Step 8: Calculation of Interacting and non-interacting sequence row vector and their classification in two sets C_1, and C_2.

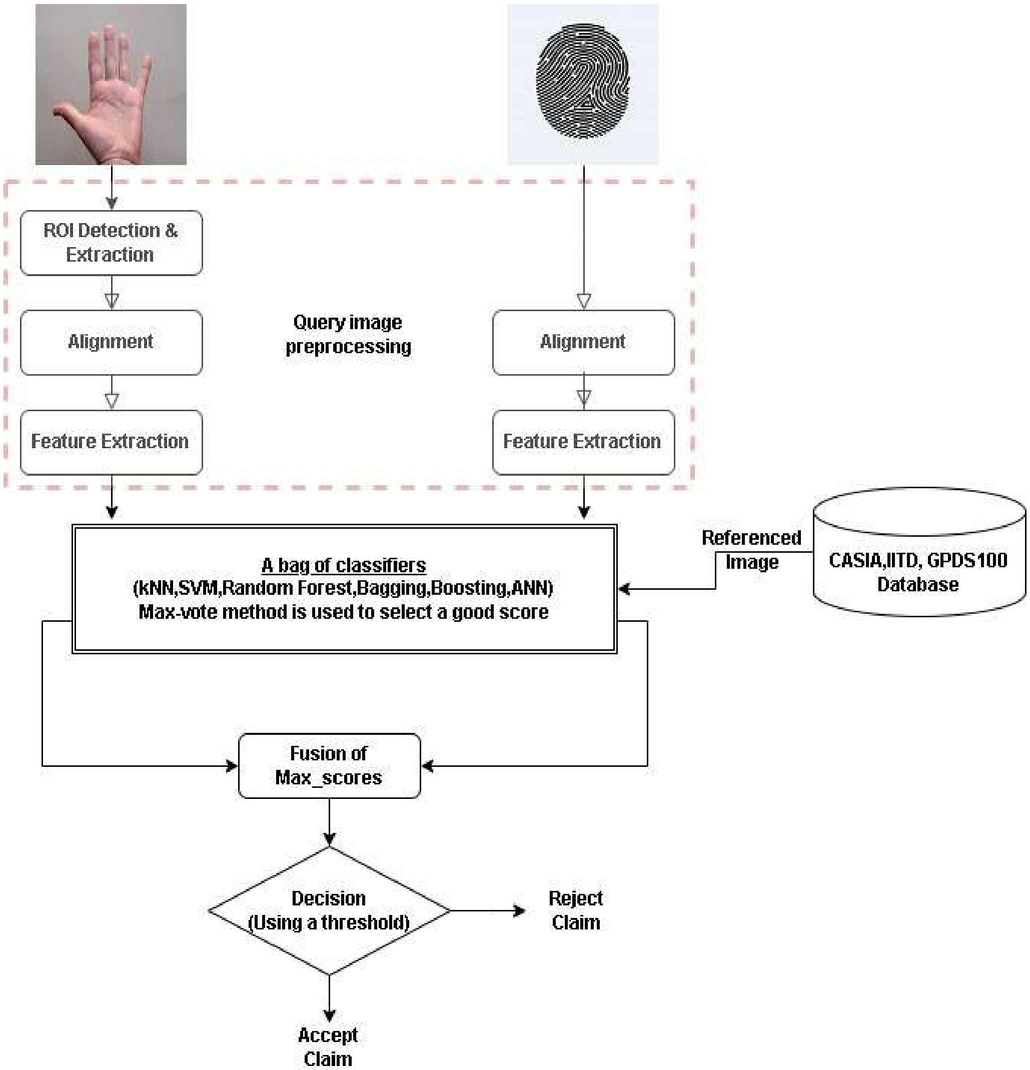

Figure 4. An outline of the proposed methodology

4 Result and Discussion

AlltheexperimentationisperformedasoutlinedinFigure 4.Whilerealizingthe pipeline (Figure 4) for different cases (as discussed below), some sort offlexibility is used. The first step, as always is palm ROI detection. Palm/finger alignment isan important pre-processing step done after detection. Usually for fingers no such requirement for the ROI extraction. The size and aspectratio of each detected palm/finger is constant for all these experiments. Gray imagesareusedallthetimeforefficiency.The palm/finger detection is achieved by implementing the method proposed in [27].

Exp-1#palm recognition on CASIA, IITD, and GPDS100

The three kinds of popular methods are – line-based, subspace-based, and deep feature-based [5]. The first category methods look for three principal lines- the heart line, the headline, and the lifeline. These include well-known edge detectors or new ones. We use canny edge detectors for this category#1. In the second category#2, i.e. subspace-based, PCA and LDA are popular for dimensionality reduction or feature extraction. The EigenPalm and FisherPalm, are chosenas the representative methods of category#2 relying on PCA and LDArespectively. In the third category#3, the trending methods include CNN, fuzzy sets, and dictionarylearning. Here, we emphasized more on CNN and obtained 128-d face embedding using pre-trained ResNet architecture [5].

Exp-2# finger recognition on CASIA, IITD, and GPDS100

Like palm, finger recognition supports – minutiae points, subspace, and deep features. The first category of methods looks for minutiae points. In the second category#2, i.e. subspace-based, PCA and LDA are used for global feature extraction.In the third category#3, the CNN features i.e. 128-d face embedding using pre-trained ResNet architecture are utilized.

Exp-3# multimodality recognition on CASIA, IITD, and GPDS100

The multimodality is achieved using the architecture outlined in Figure 2. The individual experiments as discussed in Exp-1 and Exp-2 are carried out once and the scores after the classification stage are used for fusion. The max policy is used to decide on the final score. The best dataset and the best score combination resulted in Exp-1 and Exp-2 for palm and finger respectively utilized for the experimentation in Exp-3.

4.1 Evaluation Criteria for Performance Measurement

A confusion matrix is obtained, and various performance metrics are calculated using the components of the confusion matrix- TP, TN, FP, and FN. TP refers to the number of correct/true instances which are predicted correct/true. TN refers to the number of incorrect/false instances which are predicted as incorrect/false. The cross-reference between true and false instances gives a notion to FP and FN. In this work, the confusion matrix is used to evaluate all metrics including- *Accuracy, Precision, TPR/Recall/Sensitivity, F1-Score, MCC, and ROC-AUC*.

The accuracy (*Accuracy*) represents the accurate classification done and is calculated mathematically through confusion matrix components as given in Equation 4.

The precision of positive predictions, as defined by Equation 3, refers to the level of accuracy (Geron, 2019). The recall is a measure that quantifies the proportion of correctly predicted positive instances out of all the actual positive instances (Geron, 2019). The F-1 score is calculated as the harmonic average of accuracy and recall. An elevated F-1 score will be achieved when both precision and recall exhibit high values (Geron, 2019). A Receiver Operating Characteristic (ROC) curve is a graphical representation that illustrates the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR). The false positive rate (FPR) represents the proportion of negative cases that are erroneously identified as positive. The formula is expressed as 1 minus the ratio of True Negative Rate (TNR) to Specificity (Geron, 2019). The ROC-AUC curve quantifies the degree of accuracy in distinguishing between the classes. A high AUC indicates that the model has a strong capacity to correctly identify true classes as true and false classes as false. TNR/specificity refers to the proportion of negative events that are accurately identified as negative.

The metrics Sensitivity, Specificity, and F1 Score are described mathematically in terms of confusion matrix components as given in Equations 1-5, respectively.

$$Precision = \frac{TP}{TP+FP} X\ 100\% \quad (1)$$

$$Accuracy = \frac{TN+TP}{TP+FP+FN+T} X\ 100\% \ (2)$$

$$Sensitivity = \frac{TP}{TP+FN} X\ 100\% \ (3)$$

$$Specificity = \frac{TN}{FP+TN} X\ 100\% \ (4)$$

$$F1\ Score = \frac{2\ XTP}{2\ X\ TP\ X\ FP\ X\ FN} X\ 100\% (5)$$

The Mathew's correlation coefficient (MCC) is a statistic utilised to forecast the classifications score within the range of -1 to +1. The numbers +1, -1, and close to zero correspond to the optimal, incorrect, and arbitrary forecasts, respectively (Equation 6).

$$MCC = \frac{TP\ X\ TN - FP\ X\ FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} X\ 100\% \quad (6)$$

4.2 Multimodal Recognition

The saved classifier model along with hyperparameters and datasets for which maximum accuracy is obtained is utilized for multimodal configuration. The three strategies are used for fusion in multimodal configuration – feature fusion, score fusion, and decision fusion. Here, all these fusion levels are implemented and tested for improved performance. Our proposed score fusion outperforms all other fusion levels as well as individual recognition systems. The metric measurements are summarized in Tables 8, 9, and 10.

Table 1. Performance measurement of multimodal fusion on the CASIA dataset

Recognition Method	**Accuracy**	**Specificity**	**Sensitivity**	**MCC**	**F1**	**AUC**
Feature fusion	64.2857	97.4658	66.6667	0.6280	0.6651	0.6903
Decision fusion	80.9524	98.641	82.2222	0.7993	0.8067	0.7915
Proposed (Score fusion)	88.0952	99.1453	88.8889	0.8782	0.7061	0.8831

Table 2. Performance measurement of multimodal fusion on the IITD dataset

Method	**Accuracy**	**Specificity**	**Sensitivity**	**MCC**	**F1**	**AUC**
Feature fusion	49.6377	99.6241	48.6949	0.4931	0.4859	0.6903
Decision fusion	11.9565	99.3429	12.0811	0.1131	0.1179	0.1042
Proposed (Score fusion)	71.3768	99.7863	70.6173	0.7121	0.8911	0.7092

Table 3. Performance measurement of multimodal fusion on the GPDS100 dataset

Method	Accuracy	Specificity	Sensitivity	MCC	F1	AUC
Feature fusion	59.6377	99.4341	58.6949	0.5931	0.5459	0.7319
Decision fusion	41.9565	99.3429	52.0811	0.4531	0.5279	0.5112
Proposed (Score fusion)	79.3768	99.8863	76.6173	0.7521	0.7461	0.7316

Best Performing Model: Ultimately on all the datasets CASIA, IITD, and GPDS100, our proposed method (Score fusion with Max vote) gives the best of all performance. The accuracy achieved is <= 88.0952 %> on CAISA dataset. The other metrics have promising values for *<specificity, sensitivity, MCC, F1>* as *<GPDS100-99.8863%, CASIA-88.8889%, CASIA-0.8782, CASIA-0.8911>*. In summary, the metrics measurements are best described in Figures 5 and 6 also.

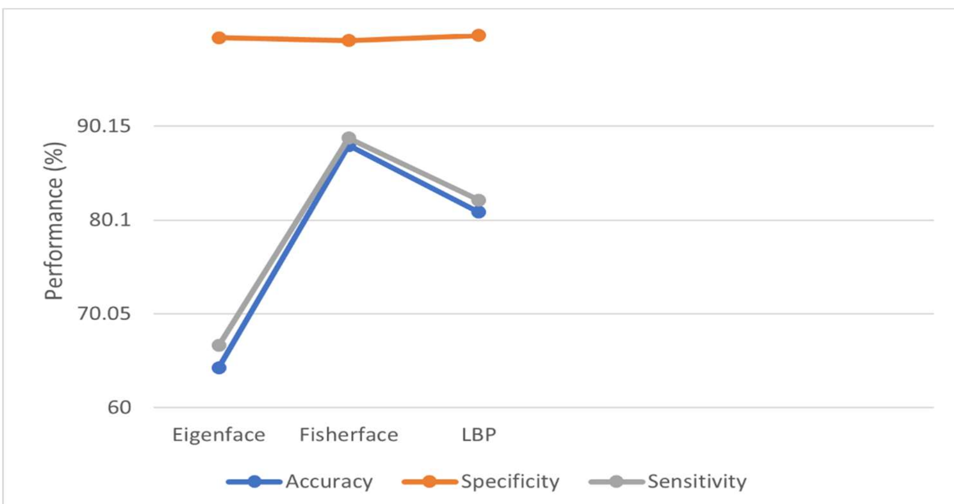

Figure 5. Overall *accuracy, specificity, and sensitivity* achieved over all datasets in the multimodality

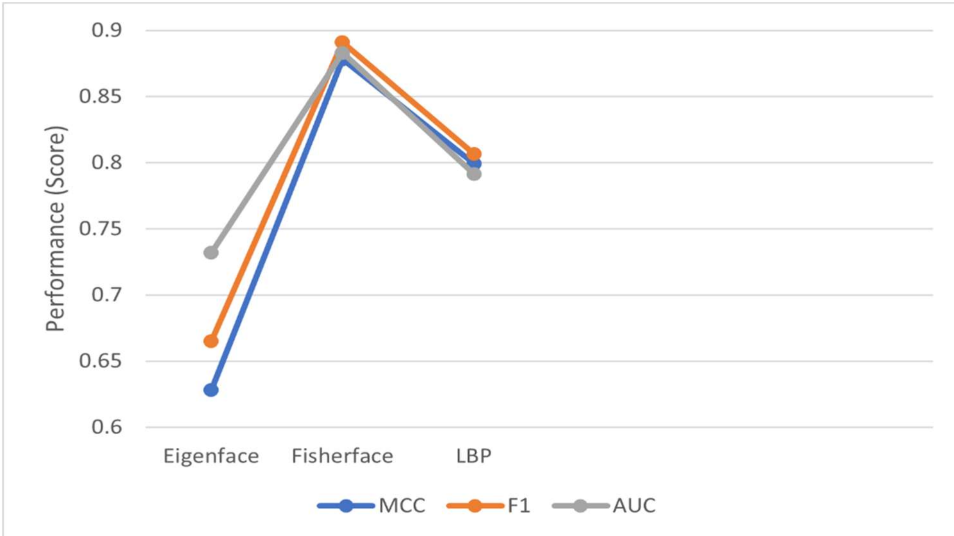

Figure 6. Overall *MCC, F-1 Score, and AUC* achieved over all datasets in the multimodality

5. Conclusion and Future Scope

Palm and finger recognition is still a challenging task for researchers as we go closer to the real worldandmoreunconstrainedenvironmentswehave.Thisworkanalyzesthebench-markedpalm recognitionworkalongwiththeunconstrainedenvironmenttheysupportbefore proposing a robust and efficient solution to fit the gap. The study favorsthe categorization of palm recognition methods into three- line-based, ML/subspace-based,andCNN feature-based.

Tohaveavarietyofunconstrained environments three popular datasets are chosen including CASIA, IITD, and GPDS100As the dataset's size grows, more support for unconstrained challenges growsand results in a considerable decrease in performance if classical methods aretaken. For ML/subspace and CNN methods, as usual, performance improvement wasachieved. With the experimentations, the palm detection methods, also, havean impact on performance as the modified palm detector has a performance advantage. A wide vector of performancemetrics including *<accuracy, specificity, sensitivity, MCC, AUC>*is utilized toperfectlymeasureofmethod'sperformanceeventofourdecimaldigitsprecision after a decimal point. The results obtained in experiments are visualizedwith detailed tables and figures and advocate the maximum accuracy achievedby Proposed (Score fusion with max_vote, *accuracy=88.0952%)*, by PCA (RF, *accuracy=76.1905%)*,andbyCNN(*accuracy=79.3768%)*onCASIA, IITD, and GPDS100 respectively.

The multimodal configuration has outperformed all the fusion techniques including – feature fusion and decision fusion. To achieve this performance rigorous experimentation is done with a novel bag of classifier approach where most of the time Random Forest (RF) performs well. The individual pipeline performances and compared with the multimodal performance at last and found very good over these. In the future, a novel shape-based palm extractionmethodisproposedwhoseperformanceiscomparedtothesetbenchmarkachievedinthis presentwork. The work can be extended to include (finger, palm) to have a more robust biometric authentication pipeline. Also,morelargedatasetscanbeusedtoperformasimilaranalysiswithpopularCNNarchitectures forpalm recognition

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