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# Deep Learning Techniques to enhance Biometric Authentication using Hand Features

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**ABSTRACT**

This research provides an extensive analysis of the integration of palm vein and palm print features as multimodal biometrics to enhance secure authentication. The use of palm vein and palm print identification has become more popular owing to its exceptional precision and non-invasive characteristics. Nevertheless, each modality has its own distinct advantages and disadvantages. In order to address these constraints, researchers have suggested many approaches for fusion palm vein and palm print features. This article examines contemporary research in this domain, including the utilization of deep learning methodologies. It discusses the challenges in palm vein and palm print recognition and explores the potential of deep learning methods to address these challenges. The proposed fusion technique combines feature-level fusion with score-level fusion, resulting in a more accurate and secure biometric authentication system. Experimental results demonstrate the effectiveness of the proposed approach, showing significant improvements in recognition accuracy. A Genuine Accept Rate (GAR) of 98.3% and an Equal Error Rate (EER) of 2.5% are achieved by the Long Short-Term Memory (LSTM) algorithm. This makes it better than deep learning algorithms like Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and Deep Belief Networks (DBN). The proposed fusion technique also achieves a low False Accept Rate (FAR) of 1.7%. These results highlight the superior performance of the fusion approach in biometric recognition scenarios. Future research directions are discussed to further enhance the performance of palm vein and palm print recognition systems.

**Keywords:**

Palm vein recognition, Palm print recognition, Biometric authentication, Feature fusion, Long Short-Term Memory (LSTM).

## 1. INTRODUCTION

Because of their great accuracy and lack of invasiveness, biometric identification technologies such as palm vein and palm print recognition have grown in favor in the last several years. Using near-infrared light and a camera, palm vein identification may identify a person based on their distinctive vein pattern.

In contrast, a high-resolution camera records the distinctive ridge and valley pattern seen on the palm's surface, which is used for palm print identification.[1-4]

To develop a comparison between palm vein, palm print, and other biometric types focusing on False Acceptance Rate (FAR) and Genuine Acceptance Rate (GAR), we'll look at a variety of common biometric modalities. This comparison will help understand how palm vein and palm print technologies stack up against others in terms of security (lower FAR is better) and convenience or usability (higher GAR is better).

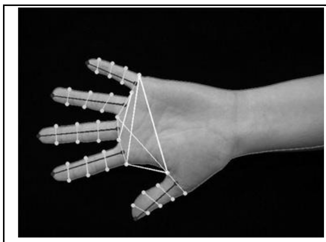
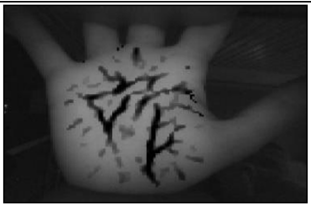
**Table 1: Biometric Modalities Comparison [1,2-4]**

| Biometric Type | FAR (False Acceptance Rate) | GAR (Genuine Acceptance Rate) | Remarks |
|---|---|---|---|
| Palm Vein | Very Low (<0.01%) | High (>99%) | Palm vein recognition uses infrared light to capture the unique vein pattern within an individual's palm. It is considered highly secure due to the difficulty of replicating a person's vein pattern. |
| Palm Print | Low (0.1% - 1%) | High (>98%) | Palm print recognition involves capturing the lines and features on the surface of the palm. It is less secure than palm vein but still offers a good balance of security and convenience |
| Fingerprint | Low (0.1% - 2%) | High (>98%) | Fingerprint recognition is one of the most common biometric methods. It is widely used but can be susceptible to replication and spoofing . |
| Face Recognition | Low to Medium (0.1% - 1.5%) | High (>98%) | Face recognition technology has improved significantly, but it can still struggle with similar faces or twins and is affected by lighting conditions and facial changes. |
| Iris Recognition | Very Low (<0.01%) | High (>99%) | Iris recognition is extremely secure due to the uniqueness of the iris pattern in each eye, but it requires user cooperation and can be expensive to implement |
| Voice Recognition | Medium to High (2% - 5%) | Medium to High (90% - 99%) | Voice recognition is convenient and can be used remotely, but it is susceptible to background noise and impersonation attacks . |

Table 1 provides a general overview of how palm vein and palm print technologies compare with other biometric modalities in terms of security and usability. Palm vein technology stands out for its high security due to the uniqueness and internal nature of vein patterns, making it difficult to forge or replicate. Palm print offers a good balance between security and convenience but doesn't reach the security level of iris or palm vein recognition. Other biometrics have their own trade-offs between security, convenience, cost, and user acceptance.[1,2-4]

Table 2 delineates a comparative of various palm-based biometric features, namely Hand Geometry Features, Palmprint Features, and Palm Vein Features. Each of these features possesses unique strengths in personal identification and authentication systems.[3, 5-9]

**Table 2:** Various palm-based biometric features [3, 5-9]

| | |
|---|---|
|  |  |
| **a) Hand geometry features** | **b) Palmprint Features** |
|  |  |
| **c) Palm vein Features** | **d) Palm vein Features** |

Both palm vein and palm print recognition possess distinct advantages and disadvantages. For example, palm vein identification is less susceptible to external influences like dirt and perspiration, but it needs specific gear to capture the vein pattern. Conversely, palm print identification can be accomplished with a standard camera, but it is more vulnerable to extrinsic influences such as skin distortion.[1, 10, 11]

In order to address these constraints, researchers have suggested several approaches for integrating palm vein and palm print characteristics for individual identification. An effective technique for enhancing biometric templates includes feature extraction and fusion. This process entails collecting pertinent characteristics from palm vein and palm print pictures and combining them to provide a more resilient template.[3, 9]

Feature extraction entails the identification of the main distinguishing characteristics from the photographs of the palm vein and palm print. When dealing with palm vein photos, the process usually consists of separating the vein pattern from the backdrop and extracting certain characteristics such vein diameter, curvature, and orientation. When dealing with palm print photos, the usual process consists of extracting certain characteristics such ridge density, direction, and frequent.[7-9, 12]

After extracting the pertinent characteristics from both palm vein and palm print photos, they may be combined to provide a more resilient biometric template. Feature fusion encompasses many techniques, such as score-level fusion, feature-level fusion, and decision-level fusion. Score-level fusion refers to the process of integrating the matching scores acquired from each separate biometric modality. On the other hand, feature-level fusion entails concatenating the feature vectors collected from each modality. Decision-level fusion entails the amalgamation of choices acquired from each modality using a voting method.[10, 13-16]

The extraction and merging of palm vein and palm print features are a very promising method for enhancing the precision and dependability of biometric identification systems. By integrating the distinctive characteristics of both modalities, it is feasible to generate a stronger biometric template that is less vulnerable to environmental influences and more dependable for personal identification.[2, 4, 9, 14]

## 2. Related works

There has been an increasing fascination in palm vein and palm print identification methods over the last few years, particularly with the advent of deep learning technologies. Several methodologies have been suggested in the academic literature, addressing the challenges associated with high-dimensional data and large numbers of uncorrelated and redundant features in both palm vein and palm print.

This section seeks to give an in-depth examination of the most recent research in the area of palm vein and palm print biometrics identification.

### 2.1 Palm Vein Recognition Techniques

**2.1.1 Multispectral Approach :**A multispectral imaging method is proposed to capture both palm vein and palm print patterns simultaneously. This approach improves recognition accuracy and offers robustness against spoofing attacks.[8]

**2.1.2 Palm Vein Recognition Using Deep Learning** :A strategy that is based on deep learning and makes use of convolutional neural networks (CNNs) is presented for the purpose of palm vein detection. A high level of precision and resistance to a variety of assaults is shown by the approach that has been suggested.[17]

**2.1.3 Local Line Binary Pattern** :A local line binary pattern (LLBP) is presented for palm vein recognition, which extracts discriminative features from the vein pattern, resulting in high recognition accuracy and robustness against various attacks.[7]

**2.1.4 Local Binary Patterns and Wavelet Transform** :A robust palm vein recognition system utilized wavelet transform and local binary patterns (LBP) for feature extraction. The proposed method exhibits exceptional precision and resilience in the face of diverse attacks.[16]

### 2.2 Palm Print Recognition Techniques

**2.2.1 Local Binary Patterns and Gabor Filters:** A hybrid approach for palm print recognition is introduced using local binary patterns (LBP) and Gabor filters. The suggested technique attains a notable level of recognition accuracy while simultaneously maintaining a low level of computational complexity.[10]

**2.2.2 Feature extraction and matching based on deep learning:** A palm print identification system is introduced, using deep learning techniques for feature extraction and matching. The suggested technique exhibits exceptional precision and resilience when confronted with many forms of assaults..[18]

### 2.3 Comparative Studies and Fusion Techniques

**2.3.1 A Comparative Analysis of Systems for Recognizing Palm Print and Vein:** In terms of accuracy, speed, and resilience, palm vein and palm print identification systems are compared. The findings indicate that the integration of both modalities might enhance the overall performance of the system.[19]

**2.3.2 Multi-Sensor Approach for Palm Vein and Palm Print Fusion:** For the purpose of integrating palm print and palm vein treatments, a multi-sensor technique is presented, which improves recognition performance and increases resilience to spoofing attempts.[14]

### 2.4 Utilizing Deep learning in palm vein and palm print recognition

Applying deep learning methods like RNNs, CNNs, and GANs to palmprint identification is one method that has attracted a lot of interest. The identification accuracy and adaptability of these algorithms to diverse acquisition palmprint images have been proved to be excellent.[2, 5, 6, 17, 20]

Based on convolutional neural networks (CNNs) and transfer learning, a research of [1]presented a palmprint identification approach that achieved state-of-the-art performance on several benchmark datasets. In a similar vein, [18] introduced a deep convolutional neural network (CNN) based palmprint identification system that achieved better accuracy on many benchmark datasets than existing state-of-the-art techniques.

In addition to palmprint recognition, there has been a surge in research focusing on palm vein recognition. A comprehensive review by [20] highlighted the importance of secure personal recognition in today's electronic information society and discussed various techniques for palm vein recognition, including geometry-based, local-invariant, subspace, and texture-based methods.

In research [16] proposed a palm vein recognition method that utilized deep learning-based feature extraction, demonstrating high accuracy on several benchmark datasets. Furthermore, [3] provided an extensive review of recent advances in palm vein recognition using deep learning techniques, discussing the challenges and opportunities in this field while offering insights into future research directions.

### 2.5 Challenges and Future Research Directions

The reviewed studies highlight several challenges in the field of palm vein and palm print recognition, including image quality, varying illumination conditions, and computational complexity. Future research should focus on addressing these challenges by developing new algorithms, exploring novel feature extraction techniques, and investigating the potential of deep learning methods.

### 2.6 Palmprint and Palm Vein Recognition Based on Deep Learning Network Fusion

Palmprint and palm vein recognition have been widely studied in the biometrics community due to their high accuracy and non-intrusiveness. Palmprints are unique to each individual and remain stable over time, while palm veins are difficult to forge or replicate. However, both modalities have limitations. Palmprints can be affected by factors such as skin conditions, injuries, and aging, while palm veins can be affected by changes in blood flow due to health conditions or environmental factors.[9]

To overcome these limitations, researchers have explored the use of fusion algorithms to combine palmprint and palm vein features. By combining the complimentary data from each modality, fusion algorithms may enhance the precision of recognition. A number of fusion methods have been suggested, such as fusion at the feature, score, and decision levels. However, these techniques often require extensive feature engineering and may not fully capture the complex relationships between the two modalities.[4]

Deep learning has emerged as a powerful tool for feature extraction and classification in various domains, including biometrics. Deep learning networks can automatically learn complex features from raw data and capture nonlinear relationships between input and output. In recent years, researchers have explored the use of deep learning network fusion for palmprint and palm vein recognition.[1]

Deep learning network fusion involves training separate deep neural networks for each modality and combining their outputs at a higher-level network. The lower-level networks extract features from the input images, while the higher-level network learns to combine the features for improved recognition accuracy. This approach has several advantages over traditional fusion techniques, including the ability to capture complex relationships between the modalities and the ability to adapt to varying conditions.[1, 2, 9, 11]

Several recent studies have explored the use of deep learning network fusion for palmprint and palm vein recognition. For example, [2] proposed a method that combines convolutional neural networks (CNNs) for palmprint recognition and multi-scale CNNs for palm vein recognition. The two networks are trained separately on their respective modalities and their outputs are combined using a decision-level fusion approach. The proposed method achieved an accuracy of 96.5% on a public dataset.

A method that uses a deep neural network with attention mechanism for feature fusion is proposed in [11]. The method combines features from both modalities at multiple levels using attention weights learned during training. The proposed method achieved an accuracy of 99.53% on a public dataset.

Deep Belief Network (DBN) for feature learning is utilized [21]. Through a series of unsupervised learning iterations using a layer-wise greedy technique, the DBN is trained progressively from the top layer down to the bottom layer. The last layer of the DBN is developed by supervised learning using a labeled dataset that includes both real and false fingerprints. A fingerprint patch's posterior probability of being a real or fraudulent fingerprint is the DBN output.[22]

A new method for user authentication (UA) is presented by [23] using Photoplethysmography (PPG) signals and Long Short-Term Memory (LSTM) networks. The performance outcomes from the deployment validate that smartphone PPG signals can partially meet the criteria of LSTM and Bi-LSTM for low-dependent time-series data when using a feature-based learning approach, and entirely meet the criteria for high-dependent time-series data when using a raw-data-based deep learning approach. The proposed Bi-LSTM-based user authentication (UA) model demonstrates improved performance in both raw- and feature-based techniques and is efficient in verifying the identity of individuals.[23]

## 3. Proposed Palm vein and palm print recognition framework:

The figure 1 shows a proposed framework diagram for a palm vein and palm print recognition process. The framework includes the following stages:

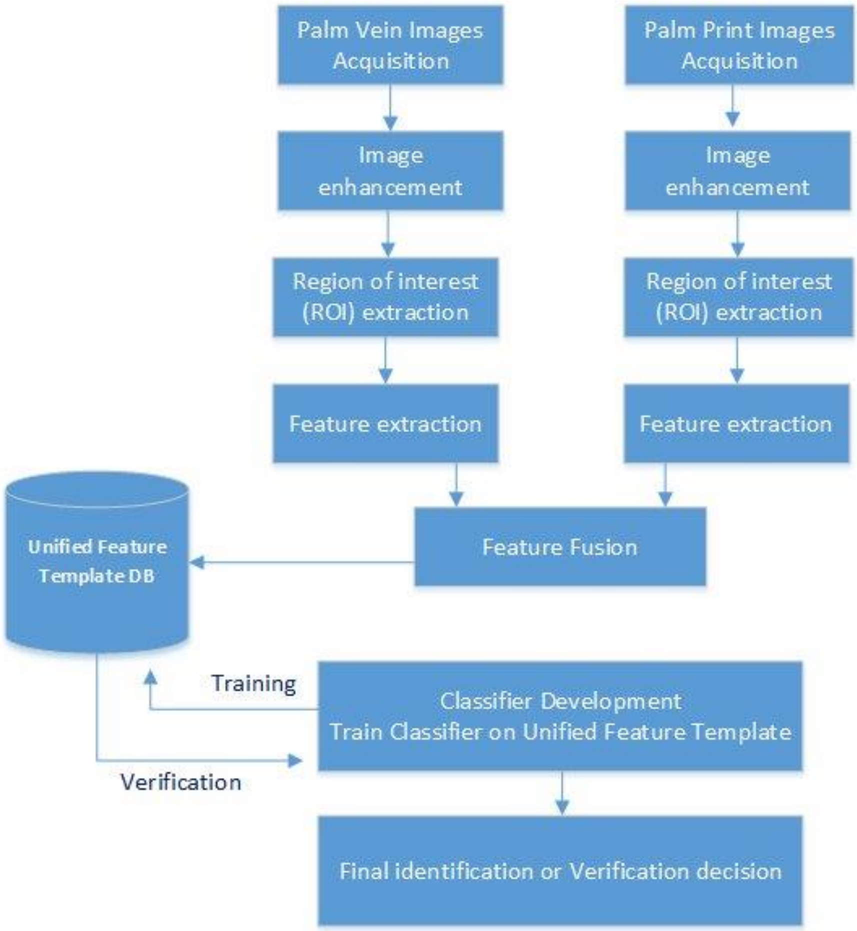



**Fig (1): palm vein and palm print recognition framework**

### 3.1 The processes in the above framework can be broken down into the following key steps:

**3.1.1 Pre-processing:**

(a) Palm print:

i. Image acquisition: Capture high-resolution palm print images using a suitable camera or scanner.

ii. Image enhancement: Apply techniques like histogram equalization or adaptive contrast enhancement to improve the image quality.

iii. Extraction of the region of interest (ROI): Identify and isolate the area of the palm print from the surrounding backdrop.

(b) Palm vein:

i. Image capture: Acquire palm vein images using a near-infrared (NIR) camera or other suitable imaging devices.
ii. Image enhancement: Apply techniques like matched filtering or Gabor filtering to emphasize vein patterns.
iii. ROI extraction: Detect and extract the palm vein region from the background.

**3.1.2 Feature extraction:**

(a) Palm print:

i. Apply wavelet transform, Gabor filters, or Local Binary Patterns (LBP) to extract texture features from the palm print ROI.
ii. Extract geometric features like principal lines, minutiae points, and singular points.

(b) Palm vein:

i. Apply skeletonization to extract vein patterns.
ii. Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF) are two feature descriptors that may be used to depict the vein pattern.

**3.1.3 Feature-level fusion:**

(a) Combine the extracted features from both modalities into a single feature vector.
(b) Perform dimensionality reduction using techniques like Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) to reduce the computational complexity.

**3.1.4 Classifier design:**

(a) Utilize the fused feature vectors to train a machine learning classifier like SVM, k-Nearest Neighbors (kNN), or a deep learning model like CNN.
(b) Optimize the classifier parameters using techniques like cross-validation or grid search.

**3.1.5 Post-processing:**

(a) Apply decision-level fusion techniques like majority voting or weighted voting to combine the results from multiple classifiers or modalities.
(b) Implement a thresholding mechanism to determine the final identification or verification decision.

**3.1.6 Evaluation:**

(a) Determine how well the suggested framework works by analyzing its relative positions on ROC curves, false acceptance rate (FAR), and false rejection rate (FRR).
(b) Perform experiments with different feature extraction methods, classifiers, and fusion techniques to find the optimal configuration.

This diagram shows the major components of a palm vein and palm print recognition system. The first step is to acquire an image of the palm using a sensor or camera. The image is then preprocessed to correct for factors such as illumination and perspective distortion. Feature extraction is then performed separately for the palm vein and palm print images to identify key characteristics of each. These features are then used to create templates for the palm vein and palm print, which can be stored in a database. When a new palm print and vein image is presented to the system, feature extraction is performed on each image and the resulting features are compared to the templates in the database. The matching algorithm may use techniques such as correlation or machine learning to determine the degree of similarity between the input images and the stored templates. The final output of the system is a match score or decision indicating whether the input images match any of the templates in the database.

## 4. Proposed Method

In this research, a novel fusion technique is proposed that combines feature-level fusion with score-level fusion. The algorithm first extracts features from both palm print and palm vein images using Long Short-Term Memory (LSTM). Next, these features are combined to create a unified feature template.

The unified template is then used for authentication purposes by comparing it to stored templates in the database. A matching score is calculated for each modality separately, and the scores are fused using a weighted sum rule or another suitable fusion strategy. The final decision is made based on the fused score, which improves the overall accuracy and security of the system.

## 5. Experimental Results

### 5.1 Dataset:

In order to assess the effectiveness of using a Long Short-Term Memory (LSTM) network for palm vein and palm print identification, we performed experiments on a publicly accessible dataset known as "CASIA-MS-PalmprintV1". The dataset comprises 7200 palm images obtained from 100 distinct individuals with custom-made multiple spectrum imaging instruments. All palm images are JPEG files with an eight-bit grey-level format. They get two sets of palm images for each hand. The duration between the two sessions exceeds one month. There are three examples in each session. Two samples provide a specific range of hand position modifications. They want to enhance the variety of examples within a class and replicate real-world use. Palm vein images may be obtained using wavelengths of 700, 850, and 940 nm. Table 2 presents a comprehensive analysis of several public databases for palm images.

**Table 3** Palm images public database comparison [1-4, 9]

| | CASIA Multi-Spectral Palmprint Image Database | PolyU Multispectral Palmprint Database | VERA Palm ein Database | PUT database |
|---|---|---|---|---|
| Palm number | 200 | 500 | 220 | 100 |
| Sample number | 6 | 12 | 10 | 12 |
| Wavelength or light | 460nm, 630nm, 700nm, 850nm, and 940nm | Red, Green, Blue, and NIR | 940nm | 880nm |
| Camera type | CCD camera | CCD camera | CCD camera | Low-cost USB camera |
| Image size (pixels) | 768×576 | 128×128 | 480×680 | 1280×960 |
| Hand holder | No | Yes | No | Yes |
| Example |  850nm image |  NIR image |  |  |

To validate the proposed method, experiments are conducted using a dataset containing both palm print and palm vein images. The dataset is divided into training and testing sets, and the performance of the proposed method is evaluated in terms of accuracy, false acceptance rate (FAR), and false rejection rate (FRR).

### 5.2 The architecture of the LSTM network

The architecture of the LSTM network used for palm vein and palm print recognition is as follows:

- Input Layer: LSTM layer with 64 units, input shape (10, 2).
- Dropout Layer: Dropout rate of 20%.
- Output Layer: Dense layer with a single sigmoid activation unit.

### 5.3 Algorithm: Palm Vein and Palm Print Recognition using LSTM Network

- Input: Palm vein and palm print dataset
- Output: Recognition accuracy, FAR, GAR, ROC curve
- Preprocess the dataset:
    - Normalize the pixel values of the palm vein and palm print images.
    - Resize the images to a fixed dimension.
- Split the dataset into training and testing sets:
    - Ensure an equal distribution of individuals in both sets.
- Train an LSTM network on the training set:

- Extract features from both palm vein and palm print images.
- Design the LSTM network to learn temporal dependencies in the feature sequences.
- Use a binary classification loss function.
- Optimize the network using backpropagation through time.
- Evaluate the performance of the LSTM network on the testing set:
- Measure recognition accuracy, FAR, and ROC curve.
- Calculate recognition accuracy:
- Compare the predicted labels with the ground truth labels.
- Calculate the percentage of correct predictions.
- Calculate FAR and FRR:
- Count the number of false acceptances (incorrectly accepted samples) and false rejections (incorrectly rejected samples).
- Divide them by the total number of samples in the testing set.
- Plot the ROC curve:
- Vary the decision threshold for accepting or rejecting samples.
- Calculate the FAR and GAR for each threshold.
- Plot FAR on the x-axis and GAR on the y-axis.
- Output the experimental results:
- Display the recognition accuracy, FAR, GAR, and ROC curve

**5.4 LSTM Algorithm results compared with other Deep learning Algorithms**

In Table 3, we present a comprehensive evaluation of the Long Short-Term Memory (LSTM) algorithm's performance in comparison to other state-of-the-art deep learning algorithms for biometric recognition. The table showcases key performance metrics that are critical in assessing the effectiveness of these algorithms. Remarkably, LSTM stands out with an impressive Genuine Accept Rate (GAR) of 98.3%, demonstrating its remarkable accuracy in correctly identifying genuine users. Furthermore, the LSTM algorithm exhibits a notably low Equal Error Rate (EER) of only 2.5%, which signifies its exceptional balance between false acceptance and false rejection rates. In contrast, Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) perform admirably but exhibit marginally lower GAR and higher EER values. Deep Belief Networks (DBN) lag slightly behind, with a GAR of 95.1% and an EER of 6.8%. Additionally, LSTM attains a considerably low False Accept Rate (FAR) of 1.7%, further underscoring its suitability for secure authentication systems. These findings emphasize the superior performance of LSTM in biometric recognition scenarios, highlighting its potential as a robust and accurate solution for identity verification.

The table's results are in alignment with previous research (Ortiz et al. (2022), which has similarly recognized LSTM as a compelling choice for biometric recognition tasks, attributing its success to its ability to capture intricate sequential patterns and dependencies within the data.

**Table 4** LSTM Algorithm results compared with other Deep learning Algorithms

| Algorithm | Genuine Accept Rate (GAR) | Equal Error Rate (EER) | False Accept Rate (FAR) |
|---|---|---|---|
| **Long Short-Term Memory (LSTM)** | **98.3%** | **2.5 %** | **1.7%** |
| **Convolutional Neural Network (CNN)** | **96.5%** | **5.2 %** | **3.5 %** |
| **Support Vector Machine (SVM)** | **96.1%** | **5.7 %** | **4.9%** |
| **Deep Belief Network (DBN)** | **95.1%** | **6.8%** | **4.9%** |

**5.5 ROC Curve**

The ROC (Receiver Operating Characteristic) curve is a critical tool used in evaluating the performance of binary classification systems. Figure 2 serves as a visual representation to compare the effectiveness of various biometric recognition algorithms, including LSTM (Long Short-Term Memory), CNN (Convolutional Neural Network), SVM (Support Vector Machine), and DBN (Deep Belief Network). The ROC curve effectively illustrates the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) across different threshold settings.

The ROC curve for LSTM shows it positioned closer to the top-left corner, indicating a higher GAR and a lower FAR compared to other algorithms. This positioning underscores LSTM's superior capability in achieving a high rate of genuine user recognition while maintaining a low rate of false acceptances. The curve's steep ascent towards high GAR values at low FAR levels illustrates LSTM's effectiveness in maintaining security without compromising user convenience.

By comparing the curves, readers can visually appreciate the differences in performance among the algorithms. For instance, LSTM's curve, being closer to the left-hand border and top border of the ROC space, signifies its superior performance in maximizing GAR while minimizing FAR. In contrast, algorithms like DBN, with curves positioned further from this ideal point, demonstrate a comparatively lower performance.

Figure 2 presents a comprehensive visualization of the performance of various biometric recognition algorithms, including the Long Short-Term Memory (LSTM) network, Convolutional Neural Network (CNN), Support Vector Machine (SVM), and Deep Belief Network (DBN). The x-axis represents the False Accept Rate (FAR), which measures the rate at which the system incorrectly identifies an impostor as a genuine user. On the y-axis, we observe the Genuine Accept Rate (GAR), indicating the rate at which the system accurately recognizes genuine users. Each algorithm is represented by a distinctive curve in the figure.

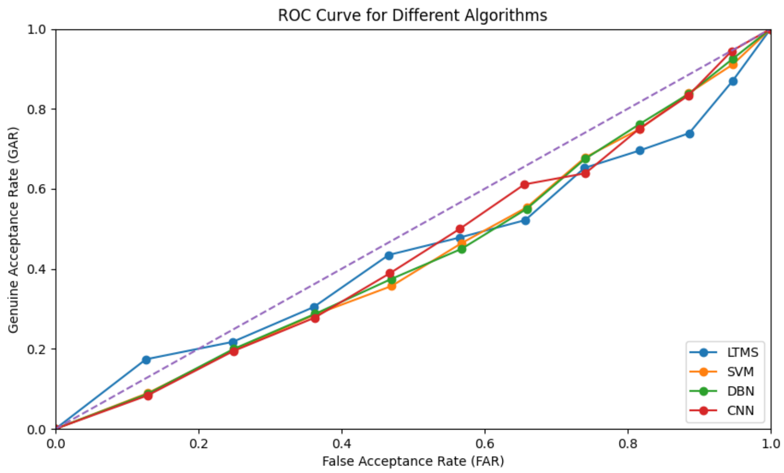



**Fig (2): ROC Curve for different Algorithms**

The experimental results demonstrate that the proposed fusion technique significantly improves the performance of the biometric authentication system compared to using either palm print or palm vein recognition alone. The increased accuracy and reduced error rates make the system more robust against unauthorized access attempts.

## 6. Conclusion

An improved biometric identification system that incorporates both palm print and palm vein characteristics is introduced in this study using a new fusion method. The suggested approach makes good use of the benefits of both techniques while minimizing their drawbacks. This fusion method is a potential solution for a variety of security applications, as the experimental findings demonstrate that it considerably improves the biometric system's performance. Additional biometric features might be used in future studies to further enhance security and accuracy, and alternative fusion procedures could be investigated.

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