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Motion Tolerant Finger Vein Authentication using Deep Learning Techniques

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Abstract: Finger vein authentication offers enhanced security due to the unique and internal nature of vein patterns. However, real-world applications encounter significant issues from motion artifacts and varying image capture conditions, impacting performance and reliability. This study addresses these challenges by utilizing image labelling, dataset augmentation, and a motion-tolerant deep learning architecture. Pixel-wise labelling of finger vein images enhances the model's sensitivity to vein patterns, facilitating data augmentation at the pixel level and improving robustness to environmental variations. The data is enhanced using extensive data augmentation techniques. The proposed methodology combines "Convolutional Neural Networks (CNN)" and "Long Short-Term Memory (LSTM)" for feature extraction and handling motion artifacts. CNN effectively captures spatial features while the LSTM processes temporal information, making the model more resilient to motion artifacts. The model is designed to adapt to different lighting conditions and handle variations in finger positioning, ensuring accurate recognition. This comprehensive approach significantly improves the reliability and performance of finger vein authentication systems in diverse real-world environments.

Keywords: *Dataset Augmentation, Finger Vein Authentication, Finger Vein Image Labelling, LSTM, VGG16*

1. Introduction

Biometric authentication is a critical field focused on ensuring robust security and precise identity verification systems. Traditional methods like fingerprint, facial recognition, and iris scanning are widely adopted but encounter issues such as susceptibility to spoofing, sensitivity to environmental conditions, and variability in user cooperation. In contrast, finger vein authentication has emerged as a promising alternative within biometrics due to the unique and internal nature of vein patterns, which are inherently resistant to forgery and alteration. However, implementing finger vein authentication in real-world scenarios presents challenges, particularly concerning motion artifacts and variations in image capture conditions, which can compromise system performance and reliability. To mitigate these challenges, this study investigates the application of image labelling, dataset augmentation techniques, and the development of a motion-tolerant deep learning architecture. Using these approaches, finger vein authentication can be made more robust and accurate, thereby improving their effectiveness in diverse and dynamic operational environments. [1-3].

The proposed methodology uses the VGG16 architecture, a well-established CNN model, for feature extraction [4]. LSTM networks, known for their capability in handling sequential data and learning temporal dependencies, are incorporated to mitigate the impact of motion artifacts [5-7].

Finger vein image labelling involves identifying and marking specific patterns within the images that correspond to the vein structure. During the labelling process, each pixel is categorized as either vein or background. This detailed labelling allows the deep learning model to capture the intricate complexities of finger vein patterns. It enhances the model's sensitivity to subtle changes in vein patterns, which is critical for applications requiring high accuracy, such as biometric authentication. In pixelwise labelling, the model learns features that are unique to the vein and background regions, improving robustness to variations in lighting, pose, and other environmental factors. It facilitates the application of data augmentation techniques at the pixel level. Augmenting labelled images with variations in pixel values (e.g., brightness, contrast, or rotation) helps models generalize better to data that is unknown. Labelled images reduce ambiguity during training, leading to faster convergence and enhanced model performance [8-9].

To address the limited availability of finger vein images per individual, extensive data augmentation techniques are applied. We have used conventional transformations and deep learning-based augmentation techniques to enhance the existing dataset [10-14].

The proposed model is designed to adapt to different lighting conditions and other environmental factors that affect the quality of the vein images. It also handles variations in the movement or positioning of the user's finger during the scanning process, ensuring accurate recognition even if the finger is not perfectly still [15]. VGG16 is used to extract features, followed by Time Distributed, LSTM, and a dense layer.

The paper is further structured as follows. The research emphasizing the need for image labelling, augmentation, and motion-tolerant deep learning models for precise recognition is reviewed in section 2. The proposed model is discussed in Section 3 followed by the results obtained from various configurations in section 4. Section 5 gives the conclusion.

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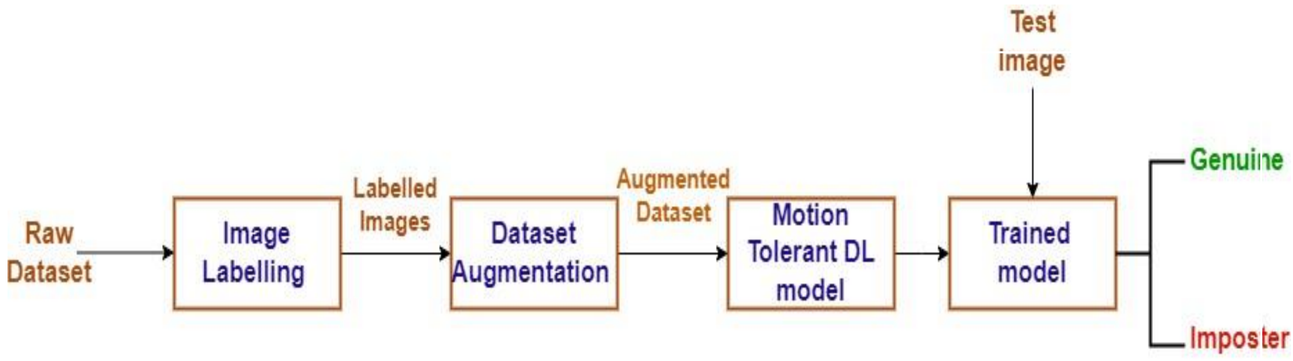


Fig 1. Overview of the motion tolerant finger vein recognition model

2. Related Work

The authors of [16] investigated the use of CNNs for feature learning in finger vein authentication, highlighting that while CNNs are effective, they require substantial computational resources and sufficient training data, posing challenges in their practical application.

The research conducted in [17] using CNN with a stochastic diagonal Levenberg- Marquardt algorithm found that CNNs robustness to noise and misalignments in the acquired images, which enhances their effectiveness for biometric identification. In [18] CNNs are used for labelling and training while the missing vein patterns are recovered using a Fully Convolutional Network (FCN). However, their approach struggled with imbalanced local illumination, presenting a significant challenge for accurate finger-vein verification.

The finger-vein recognition using CNNs with data augmentation was explored in [19], specifically using translation techniques for augmentation. They found that relying solely on translation for augmentation was insufficient, indicating the need for more diverse augmentation strategies to improve recognition performance.

In a study involving deep fully convolutional neural semantic segmentation networks for finger vein recognition, automatic labels significantly increased the network's recognition accuracy, demonstrating the importance of quality training data for model performance [20].

A two-stream convolutional network learning proposed in [21] identified that the limited number of training samples hindered effective training for learning invariant features. Additionally, they noted that preprocessing steps failed to adequately address the change in angles and positioning of fingers, further complicating the training process.

Multimodal biometric recognition by fusing finger-vein and finger-shape data, based on a deep CNN was examined in [22]. They found that most false rejection cases were due to improper alignment of finger-vein images, caused by position changes of fingers during enrollment and recognition phases, highlighting a critical issue in practical biometric systems.

The research in [23] demonstrated that GAN-generated synthetic images can significantly improve the classification accuracy of CNNs by providing additional training examples that capture the variability of real medical images. The authors found that the augmented dataset improved the network's generalization ability, leading to better performance on unseen data than traditional augmentation techniques. The study findings in [24] underscore the potential of GANs to address data scarcity issues which contribute towards improving the robustness and performance of deep models in diverse applications.

The researchers in [25] introduced a method for real time verification of finger-vein biometrics using CNNs and LSTM networks. Their study demonstrated that this approach effectively handles variations in finger movement or positioning during scanning, thereby developing an accurate and robust system.

3. Proposed Method

After extracting the region of interest from the raw dataset, a hybrid algorithm is used to label the dataset. The labelled images are then used to augment the dataset. Conventional transformations and GAN based augmentation are used to expand the database. Deep learning models become more robust and generalizable with augmentation by providing it with a more diverse set of training examples. Using the augmented dataset, a motion-tolerant deep learning model is trained. This model is designed to handle variations and inconsistencies in the input images that might arise from motion, ensuring reliable performance even when the fingers are not perfectly still. A new image, which is not used for training or augmentation, is provided to the trained model for evaluation. The model then can be used to authenticate or reject a person. classifies it as genuine, authentic person or imposter.

3.1 Dataset

The experimentation is conducted with two datasets and the details are given in Table 1. The first dataset is sourced from the "SDUMLA-HMT" database, compiled by Shandong University. A total of 3816 images were scanned from 106 persons. Images of three fingers from both the hands, excluding thump and small finger were captured six times. These images are sized at 320x240 pixels [26]. The second dataset is from "THU-FVFDT1" [27] comprising images from 220 individuals. Each individual has two images, with a resolution of 720x576 pixels for the raw images.

Table 1. Details of dataset

Dataset	No. of classes or Individual	No. of fingers per individual	No. of images per finger	Total images
SDUMLA- HMT	106	6	6	3816
THU FV	220	1	2	440

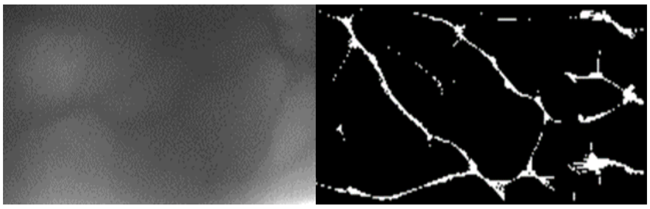
3.2 Finger Vein Image Labelling

Labelling finger vein images involves identifying and marking distinct patterns within the images that correspond to the vein structure. Each pixel in the image is labelled as either vein or background. This allows the deep learning (DL) model to learn the intricate characteristics of the finger vein patterns and enhances the model's sensitivity to subtle changes in vein patterns, which is crucial in applications where high accuracy is required, such as biometric authentication. Pixel-wise labelling ensures that the model learns features specifically related to the vein and background regions, making it more robust to variations in lighting, pose, and other environmental factors. It also facilitates the application of data augmentation techniques at the pixel level; augmenting labelled images by introducing variations in pixel values (e.g., brightness, contrast, or rotation) which helps the model to predict images with variations in enrolled images. Labelled images help reduce ambiguity during training, leading to faster convergence and improved model performance.

We have used automated labelling, which assigns labels or annotations to data automatically without manual intervention. This approach reduces the time and effort required for manual labelling, which is crucial when dealing with vast amounts of data. It is also cost-effective and ensures consistency across the dataset, as the algorithms or rules used to assign labels are applied uniformly.

After extracting the vein region from the original image, a hybrid algorithm that integrates the "Local Maximum Curvature" algorithm, the "Wide Line Detector" algorithm, and the "Repeated Line Tracking" algorithm is used to label the images in the pixel level [6].

The resultant images contain more features compared to those produced by each individual algorithm alone. Sample ROI image and the final labelled image are displayed in Fig. 2.



(a) (b)

Fig 2. (i) ROI extracted FV image (ii) Labelled FV image

3.3 Finger Vein Dataset Augmentation

Most finger vein image databases consist of images from different subjects with few images per person. The number of images used for training per person significantly impacts the verification performance of the model. To capture the variability in vein patterns among individuals, a larger dataset is required. A diverse dataset can improve generalization by making the model more robust to different conditions such as rotation, displacement, and lighting variations.

The dataset has been augmented using two strategies. First, using conventional transformations like rotation, shifting, brightness variations, and zooming. Secondly using Generative Adversarial Networks (GAN). Conventional transformations rely on predefined rules and geometric operations, while GANs are deep learning-based methods that require more computational power and complex implementation but can create highly realistic and diverse images. Combining both methods can enhance the dataset for the effective training of deep learning models. Among the transformation methods, systematic rotation helped in creating images at various angles and aids in recognizing images at different angles due to slight variations in finger positioning.

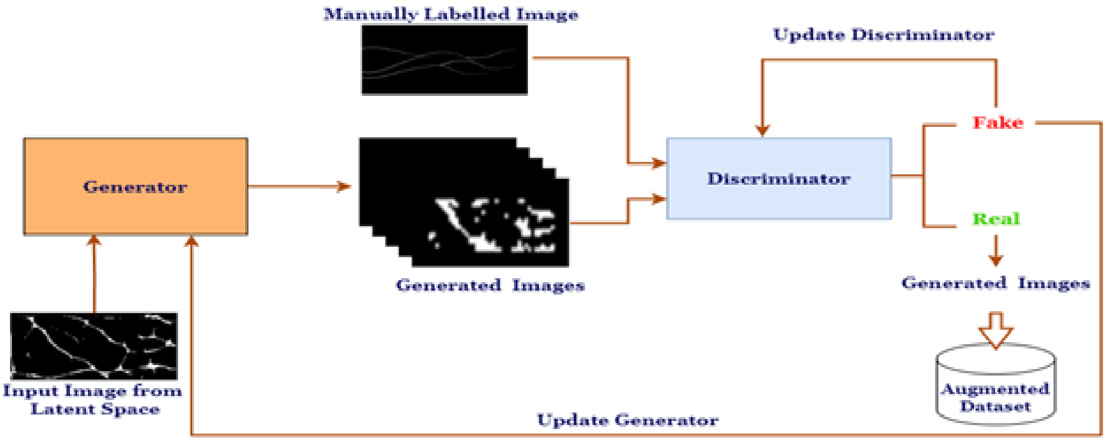


Fig 3. Architecture of cGAN for finger vein dataset

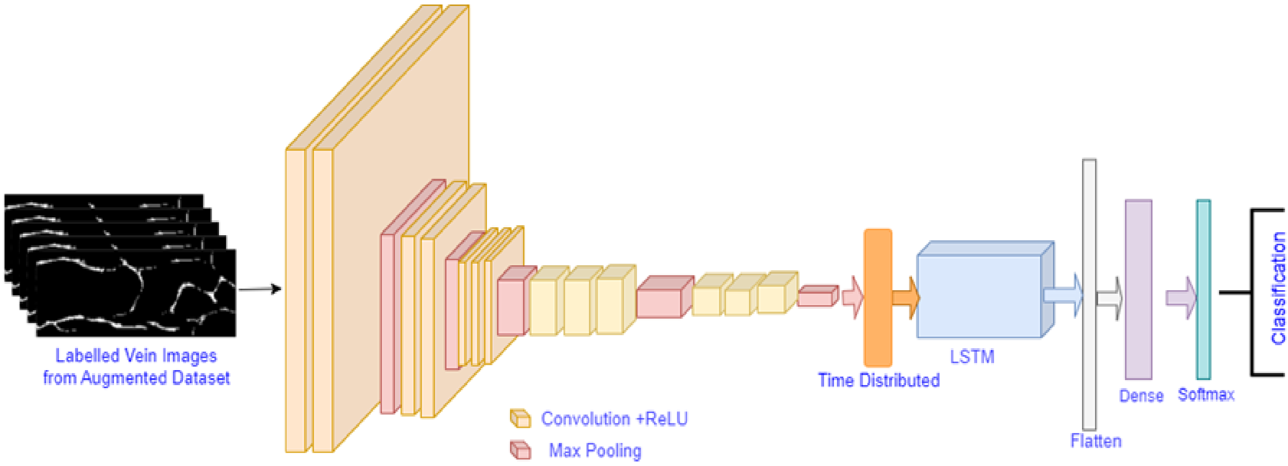


Fig 4. Architecture of motion tolerant deep learning model for finger vein authentication

Shifting helps in making the system less sensitive to small positional shifts of the finger within the capture device. Brightness variations reflect adaptability to different lightning conditions. Zooming helps when the finger may appear at varying distances from the camera. For augmenting using GANs, we employed conditional GANs (cGANs) [28-30]. In cGANs, additional information is provided to the generator and discriminator during training. Manually labelled vein images are given as additional information to the discriminator, helping to maintain the semantic meaning. This approach creates new samples based on the learned features of the dataset, capturing more intricate and complex features of the data distribution, resulting in more realistic and diverse augmented samples. Figure 3 illustrates the architecture of cGAN implemented for finger vein dataset augmentation. The labelled image is inputted as latent vector to the generator. The generator then generates fake images initially and gradually real images after upon training with the feedback from discriminator. The discriminator is also provided with manually labelled images as additional information. If the discriminator output is ‘fake image’, the feedback is fed to generator and discriminator for training, otherwise the image is added to the dataset.

Algorithm1: Finger Vein Image Dataset Augmentation

Start Algorithm

1. Load Original Dataset:

1.1 Load the original dataset

2. Apply Conventional Augmentation:

2.1 For each image I in the dataset:

2.1.1 Apply rotation transformations to generate images at various angles: I_rot = rotate (I, θ) for θ in A

A: Set of angles used for rotating the images

2.1.2 Apply shifting transformations to generate images with positional shifts:

I_shift = shift (I, δx, δy) for (δx, δy) in S

S: Set of shift values for x and y directions.

2.1.3 Apply brightness variations to simulate different lighting conditions:

I_bright = adjust_brightness (I, β) for β in B

B: Set of brightness adjustment factors

2.1.4 Apply zooming transformations to simulate varying distances:

I_zoom = zoom (I, z) for z in Z

Z: Set of zoom factors.

Combine the augmented images to form D_conv

3. Apply Augmentation using cGANs:

3.1 Initialize cGAN model components:Generator G, Discriminator D

3.2 For each image I labelled as L in the dataset:

3.2.1 Input labelled image L as latent vector to generator G

3.2.2 Generator G generates initial fake image I_fake

3.2.3 Provide labelled image L to discriminator D

3.2.4 Discriminator D evaluates generated image:

output = **D** (I_fake, L)

3.2.5 If output is ‘fake image’:

3.2.5.1 Provide feedback to G and D for further training

3.2.6 Otherwise if output is ‘real image’:

3.2.6.1 Add I_fake to D_cGAN

4. Combine Augmented Datasets:

Combine D_conv and D_cGAN to form the final augmented dataset D_aug

End Algorithm

3.4 Proposed Deep Learning Model

The proposed model uses finger vein image sequences for classification. The dataset is pre-processed with image labelling and augmentation techniques. Each sequence groups finger vein images of a single individual. The features are extracted using a VGG16 model, retaining only the convolutional layers of the model. As the fully connected layers are removed, the model becomes lighter and more computationally efficient and focuses solely on feature extraction, without being constrained by the specific task of classification. These layers generate fixed-size feature vectors for each input image. A Time Distributed layer with flattening incorporates temporal information. It processes each image in the sequence independently, reshaping the data for a successive LSTM layer. LSTM layer, with 32 hidden units, learns the relationships between these feature vectors across the sequence. Finally, the sequence is classified by a dense layer with neurons matching the count of classes and a softmax activation function. Fig. 4 shows the architecture of the motion tolerant model.

Algorithm 2: Proposed Deep Learning model

Start Algorithm

1. Data Pre-processing:

1.1. Group the labelled and augmented images into sequences Sj for each individual j: Sj= {Ij,1, Ij, 2…,Ij,T} ,
T : count of images in the sequence
Ij,t : t^{th} image in the sequence of the jth individual

2. Feature Extraction using pre-trained VGG16:

2.1. Initialize the pre-trained VGG16 model.
2.2. Remove the fully connected layers from the VGG16 model.
2.3. For each image Ij,t in sequence Sj:
Fj,t=VGG16_Conv(Ij,t)

3. Incorporate Temporal Information:

3.1. Apply a Time Distributed layer with flattening to each feature vector
Fj,t′=Flatten(Fj,t)

4. Learn Temporal Relationships using LSTM:

4.1. Initialize an LSTM layer with U=32 hidden units.
4.2. For each sequence Sj with flattened feature vectors {Fj,1', Fj,2′…,Fj,T:
Hj=LSTM ([Fj,1′, Fj,2′…,Fj,T′])

5. Classification:

5.1. Initialize a dense layer with c neurons and a SoftMax activation function. (c:number of classes)
5.2. For each hidden state sequence Hj, classify the sequence:
yj=Softmax (WHj+b)

6. Model Training and Evaluation:

6.1. Compile the model with the loss function categorical cross-entropy and Adam Optimizer.
6.2. Train the model on the pre-processed and augmented dataset:
model.fit(sequences, labels, validation_split =0.2, epochs = num_epochs)
6.3. Evaluate the performance on a validation set: model.evaluate (validationset)

End Algorithm

4. Results and Discussion

Different approaches are adopted to assess the model performance on the SDUMLA and THUFV databases. The first approach utilized the VGG16 model with the original dataset. The second approach involved the VGG16 trained on a labelled dataset. The third approach uses the labelled and augmented dataset, to improve model robustness and accuracy. Lastly, the proposed model was evaluated using the labelled and augmented dataset to compare its performance against the VGG16 configurations. These approaches assess the impact of labelling, data augmentation, and model architecture on training time and accuracy.

Table 2 compares performance metrics across different configurations of models trained on two datasets, SDUMLA and THUFV. The results highlight that while augmentation increases training time, the proposed model effectively utilizes labelled and augmented datasets to achieve significantly higher accuracy with reduced training times compared to VGG16, showcasing its robustness and efficiency in finger vein authentication applications.

Table 2. Comparison of performance for various approaches

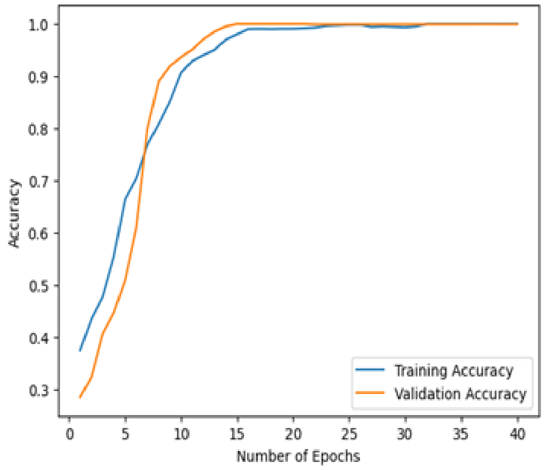
Data base	**Comparison Factor**	**VGG16 + Original Dataset**	**VGG16 + Labelled Dataset**	**VGG16 + Labelled and Augmen -ted Dataset**	**Proposed Model + Labelled and Augment-ed Dataset**
SDUMLA	Training Time (min)	54	36	110	72
	No. of images	424	424	16960	16960
	Accuracy	94.30%	95.45%	97.11%	99.76%
THUFV	Training Time (min)	35	25	85	56
	No. of images	220	220	8800	8800
	Accuracy	92.50%	96.34%	98.60%	99.89%

Comparison of accuracy for various approaches is shown in Table 3. For the "SDUMLA" dataset the accuracy of VGG16 on the initial dataset was 94.30%, which improved to 95.45% with the labelled dataset. With the labelled and augmented dataset, the accuracy further increased to 97.11%. The proposed model achieved 99.76% accuracy with the labelled and augmented dataset, indicating superior performance. For the THUFV dataset the accuracy of VGG16 on the original dataset was 92.50%, improving to 96.34% with the labelled dataset. Using the labelled and augmented dataset, the accuracy increased to 98.60%. The proposed motion tolerant model achieved an accuracy of 99.89% on the labelled and augmented dataset, demonstrating the best performance among all configurations.

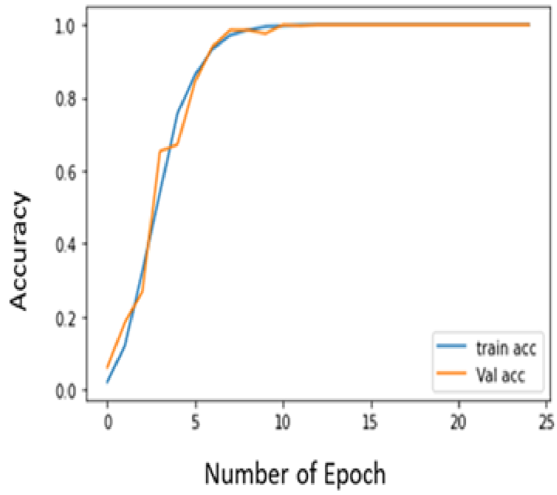
Table 3. Accuracy obtained on SDUMLA and THUFV Database

Database	**VGG16 + Original Dataset**	**VGG16 + Labelled Dataset**	**VGG16 + Labelled and Augment ed Dataset**	**Proposed Model + Labelled and Augmented Dataset**
SDUMLA	94.3%	95.45%	97.11%	**99.76%**
THUFV	92.5%	96.34%	98.6%	**99.89%**

Figure 5 shows the accuracy graphs for the proposed model trained on the THUFV dataset over 40 epochs and the SDUMLA dataset over 25 epochs. For the THUFV dataset, the model's accuracy began to stabilize around the 20th epoch, showing a clear trend towards convergence. By the end of training, the model achieved a remarkable accuracy of 99.89%. Similarly, on the SDUMLA dataset, the model's convergence was observed slightly earlier, starting to stabilize around the 10th epoch. Despite a shorter training duration of 25 epochs, the model attained a high accuracy of 99.76%. This underscores the robustness of the proposed motion tolerant model architecture and its capability to handle variations in finger vein patterns across different datasets. This indicates that the model effectively learned the intricate patterns within the finger vein images from both the dataset, showing its ability to generalize and make accurate predictions.



(a)



(b)

Fig. 5. The accuracy graph for the proposed motion tolerant model using labelled and augmented dataset (a) THUFV Dataset (b) SDUMLA Dataset

Figure 6 shows the plot of Receiver Operating Characteristic (ROC) plotted at varying threshold settings to evaluate the model's performance. "Equal Error Rate (EER)" represents the point where false rejection and acceptance rates are equal, indicating when positives and negatives are equally likely. "Area Under the Curve (AUC)" is a measure of how well the model differentiates between positive and negative classes. The ROC for the proposed model using labelled and augmented dataset is depicted in Fig. 6. The EER for SDUMLA and THUFV dataset are 1.73% and 1.42% respectively. The area under the curve for SDUMLA and THUFV are 0.993 and 0.991 respectively, which are close to 1. Both the EER and AUC metrics indicate a highly effective classification system for both databases.

Table 5. EER and AUC vales for SDUMLA and THUFV Database

Database	*EER*	*AUC*
SDUMLA	1.73%	0.993
THUFV	1.42%	0.991

The proposed model also demonstrates better efficiency in training time compared to VGG16 under similar conditions which is detailed in table 4. For the SDUMLA database, training the VGG16 model on the original dataset took 54 minutes, while using the labelled dataset reduced this time to 36 minutes. Training on the labelled and augmented dataset increased the time to 110 minutes. The proposed model with the labelled and augmented dataset required 72 minutes. Similarly, for training original THUFV database on VGG16 took 35 minutes, and on the labelled dataset, it reduced to 25 minutes. Training on the labelled and augmented dataset took 85 minutes, while the proposed model with the labelled and augmented dataset needed 56 minutes. Overall, while augmentation increases training time, the proposed model offers a balance with improved performance over the VGG16 with labelled and augmented datasets.

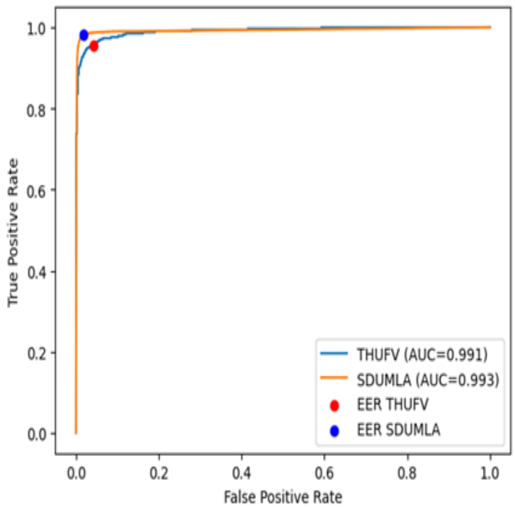


Fig 6. ROC for the proposed motion tolerant model using labelled and augmented dataset for SDUMLA Dataset and THUFV Dataset

Table 4. Training time (in minutes) on SDUMLA and THUFV Database

Database	**VGG16 + Original Dataset**	**VGG16 + Labelled Dataset**	**VGG16 + Labelled and Augmented Dataset**	**Proposed Model + Labelled and Augmented Dataset**
SDUMLA	54	36	110	72
THUFV	35	25	85	56

5. Conclusion

The study demonstrates that finger vein authentication systems can significantly benefit from image labelling, data augmentation, and advanced model architectures to improve performance and robustness. Evaluations on the SDUMLA and THUFV databases reveal that while the VGG16 model performs well on original datasets, its accuracy substantially improves with labelled datasets and further with labelled and augmented datasets. The proposed model, incorporating a combination of VGG16 and LSTM networks, achieves the highest accuracy and demonstrates superior performance over VGG16 configurations, achieving 99.76% accuracy on SDUMLA dataset and 99.89% accuracy on THUFV dataset. Moreover, the proposed model exhibits better training efficiency, balancing increased training time due to augmentation with enhanced accuracy and robustness. The ROC and AUC metrics confirm the high effectiveness of the proposed system, underscoring its potential for reliable biometric authentication in real-world applications.

Overall, the integration of labelling, augmentation, and a motion-tolerant deep learning architecture represents a significant step in the development of secure and accurate finger vein authentication systems.

Author contributions

Amitha Mathew (Corresponding author): Developing an original draft, studying methodology, conceiving and designing the study, reviewing and editing it, analysis and interpretation of results

***Dr.* P. Amudha:** Concept development, Reviewing and editing.

Conflicts of interest

The authors declare no conflicts of interest.

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