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Palm-print recognition based on deep residual networks

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Abstract: A palmprint is a tiny portion of the palm flat that carries extra information that may be utilized in authentication systems. It also has the quality of permanence, meaning that it will not change throughout time. Extracting meaningful characteristics from palm prints is crucial. The majority of newly developed approaches rely on primary lines, wrinkles, and creases, which are insufficient to discriminate between two people owing to their proximity. Deep learning approaches are increasingly used for extracting deep properties, such as texture. A deep residual neural network (ResNet) built for safe authentication using palmprint images is proposed. The Chinese Academy of Sciences Institute of Automation (CASIA), IIT Delhi Touchless, and Sapienza University Mobile (SMPD) Palm-Print databases were used for the experiments. Accuracy and an F1 score were used to grade the results. The suggested model was highly accurate, scoring 99.75%, with an F1 score of 99.54% and precision scoring of 99.37%. This approach for palmprint authentication is efficient and effective.

Keywords: Palm print, Biometric, Deep Learning, Convolutional Neural Network (CNN), Authentication, ResNet, Accuracy.

1. Introduction

Undoubtedly, palm print recognition plays a crucial role in authentication processes across various fields, including both civilian and military, thanks to its numerous unique features that make it safer and more accurate than traditional methods. Traditional methods have encountered vulnerabilities in recent years. The rise in fraud and scams in recent years has highlighted the necessity of security and surveillance. Traditional access control systems, such as passwords and PINs, have proven vulnerable to breaches. In today's environment, addressing these risks requires a greater emphasis on information security and privacy. Biometric recognition, including fingerprints, iris, and faces, is crucial for ensuring privacy and security. As a result, this technology is employed in a variety of different applications to improve security. During the recognition process, a feature such as a fingerprint is digitized and turned into a biometric pattern, which represents a biometric template the Using computational algorithm method, we create a unique pattern that can be accurately identified by comparing it to other templates [1]. d by comparing it to other templates [1]. This study recommends the use of palmprints for authentication due to their broad scope, independence from age, and high user acceptance.

Therefore, it is crucial to understand the characteristics and traits of a dataset, as well as palmprint authentication techniques [2]. Palm prints are a fascinating physiological biometric with many distinctive characteristics. It is located on the inside surface of a hand, between the wrist and the fingers. This surface has many textures, including main lines, wrinkles, and ridges [2, 3]; see Figure 1. These textures are easy to identify; Tarawneh et al. [4] demonstrated pre-trained Convolutional Neural Networks (CNNs) for palm-print identification. The low-quality photos are used to train several CNN models, including AlexNet, VGG16, and VGG19.

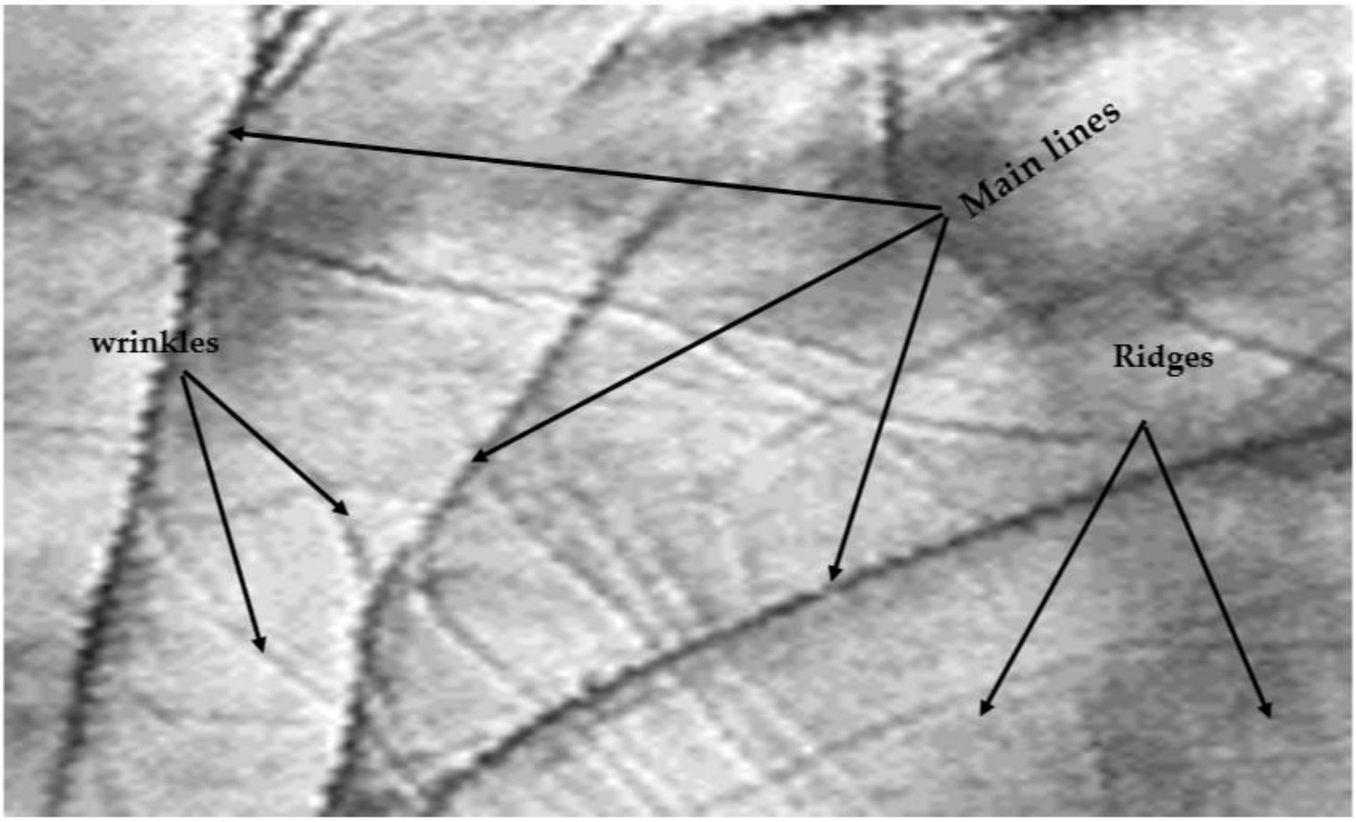

Figure 1. The main lines or ridges in the palmprint.

Palm print is a recognized biometric technique, alongside face, fingerprint, iris, and vein. [5]. This little area of The palm surface is ideal for personal authentication due to its durability and ability to remain constant throughout time [6]. Palmprint authentication is ideal for real-world applications due to its low-cost image-gathering equipment, compatibility with high- and low-resolution photos, and ability to distinguish characteristics like grooves and crinkles [7]. The outdated biometric identification and verification technique has security and privacy concerns [8]. Biometric templates are vulnerable to theft and cannot be changed, making them dangerous. The authors identified an additional danger that may be addressed in systems using traditional identification or authentication. By making biometric database templates public, applications and systems that rely on users' biometrics may be readily targeted, resulting in cross-matching and cross-application invariance. This allows for simple user tracking. Data imbalance in some of the available palm print datasets is a common problem in machine learning, with one class having many more or fewer examples than others [8, 9]. Unbalanced data distribution can impede deep learning algorithms by favoring the majority over the minority. This can lead to suboptimal performance in the minority class, such as decreased accuracy or sensitivity [10, 11]. There are several ways available to resolve data imbalances in some of the accessible palm print datasets. One method is to oversample the minority class by creating synthetic or duplicate cases. Another technique is to sample the majority class and delete specific cases [12, 13].

This research focuses on the commonly used method of palmprint identification using deep learning-based CNNs. CNN Unlike conventional approaches, which require manual feature extraction (e.g., edges, textures), CNNs automatically learn hierarchical features from raw data. Lower layers catch basic patterns (like edges), whereas deeper layers capture complex structures (such as objects or faces) [14].

After the introduction, this paper is provided as follows. Materials, methods, and ROI for recognizing the procedure are described in Section 2. A revolutionary palm-print recognition methodology is proposed and discussed. Section 3 presents the results of employing residual networks in palm print authentication. Section 4 highlights the most essential conclusions.

2. Literature Review.

Several recent research studies investigated palmprint authentication using various approaches. Kumar and Premalatha [15] developed a process that uses both local and global data. By preserving phase information through linear frequency scaling, the discrete orthonormal Stockwell transformation proves valuable for palm-print image analysis. Additionally, extending the discrete orthonormal transformation to infinity allows for the capture of global features. It also provides additional information about spectra that is not accessible from locally referenced phase data. The approach was evaluated on databases from Poly U, COEP, and the data sets called IIT Delhi, and the combination of local and global attributes generated positive results.

Fei et al. [16] developed a simple technique that uses two half-orientations for identifying features and palm print authentication. Fei et al. [16] developed a simple method that uses two half-orientations to identify features and authenticate palm prints. A class of "half-Gabor" filters is defined in their approach for palmprint half-orientation extraction. Palmprints have multiple half-orientations, which better reflect their overall orientation than the binocular dominant pattern. Additionally, Z. Yang and L. Leng [17] proved that the latent correlation of coding-based palmprint templates may be determined. In particular, we look at six coding-based palmprint representations and come up with a good cross-database attack method that uses hidden statistical links between them. The attack exploits the target users' palmprint templates to infer the templates stored in other databases, although the coding methods used are different. In some circumstances, using public datasets, our cross-database assault achieves a 100% success rate. This shows that palmprint identification systems that use coding-based representation are vulnerable to cross-database attacks and invasions of privacy.

H. Wang and V. Y. Mariano [18] in this research devised a method that was able to shine a light on the limits of the identification process utilizing fingerprints and offered A novel coding approach, LOC, that combines the benefits of LLDP and sequential codes while improving identification accuracy by utilizing the ordinal aspect of linear coding. Furthermore, a linear control factor was created to linearly regulate the size of the coding feature to minimize the dimension without sacrificing accuracy, significantly reducing matching time and allowing for large-scale real-time manual retrieval. For Poly U multispectral datasets were utilized to evaluate the effectiveness of the proposed technique, with positive results.

Verma and Chandran [19] offer a palmprint verification model using Sobel Edge Detection, a 2D Gabor Filter, and Principal Component Analysis (PCA). The model is verified on the IITD palmprint database, and the findings were 99.5% correct. Morales [20] found that using Scale-Invariant Feature Transform for feature extraction led to improved results for contactless palmprint identification than standard approaches. However, mismatched points may still impair the recognition outcome.

Xie and Kumar [21] describe a system that utilizes CNN and discrete hashing. Several CNN architectures are also studied and compared to the suggested model. The strategy produces superior outcomes while also reducing the template dimensions. Pranav and Manikandan [22] created a CNN-based real-time face recognition system, with the CNN parameters tweaked to improve the performance system by square measurement. They proposed a model to enhance the system's performance. Maximum recognition accuracies of 98.75% and 98.00% are obtained.

Wang et al. [23] sought to produce high-quality palmprint pictures using an improved Deep Convolution Generative Adversarial Net (DCGAN) with swapping. The authors implemented the convolution transpose layer with linear upsampling. It incorporates the Structure Similarity Index (SSIM). Enter the loss function. The results of our experiment on three publicly available datasets, Poly U, IIT Delhi, and CASIA palm databases, demonstrate the effectiveness of the suggested technique. We present a palmprint authentication model that combines deep convolutional neural networks (CNNs) and deep residual networks to obtain high accuracy using deep features, building on recent research on the importance of deep learning models.
Çalışkan and Ö. Türk suggested a model with various phases. In the first stage, raw photos were obtained from the Poly U database, and then preprocessing procedures were carried out to identify ROI regions. The second stage involved extracting deep ROI characteristics from preprocessed photos using deep learning techniques. In the last step, the deep features that were collected were put into groups using a hybrid deep convolutional neural network and support vector machine models. It was found that the suggested system worked very well, with a total accuracy of 99.72% when using a hybrid technique [24].

3. Materials and Methods.

This section describes the picture datasets utilized in the investigation. Next, we will prepare and process the data. The feature extraction approach is based on a descriptor often used in computer vision and palm print picture analysis. Following this, the proposed methodology begins with pre-processing to improve image quality. The Region of Interest (ROI) is a portion of the palm extracted from the original hand images, as discussed in [25]. Figure [2] shows the steps for ROI extraction. First, the palm image is converted to a binary image (black and white), with the region of the palm turning white and the background turning black. The hand boundary is then determined. Next, we present the classification strategies. Finally, we establish measures for evaluating results and compare them to current methodologies. As it appears in the suggested model, it is explained in the following subsections.

3.1 Proposed Methodology.

This paper offered multiple uses of ResNet features to improve classification results. The features derived from the ROI picture are fed into the ResNet with the image itself. This model has been tested on a variety of data sets, and the results have been quite accurate. Figure 3 shows the steps of the proposed model. When tested on the API model by using the Postman application, the results were truly astounding. They made no mistakes in classifying the data sets that were tested with it and Figure 4 shows the proposed model for the API block diagram.

The Application programming interference (API) model, tested via the Postman application, demonstrated reliability and functionality for image classification tasks. With further optimizations for validation, security, and performance, the API can be scaled for deployment in real-world applications.

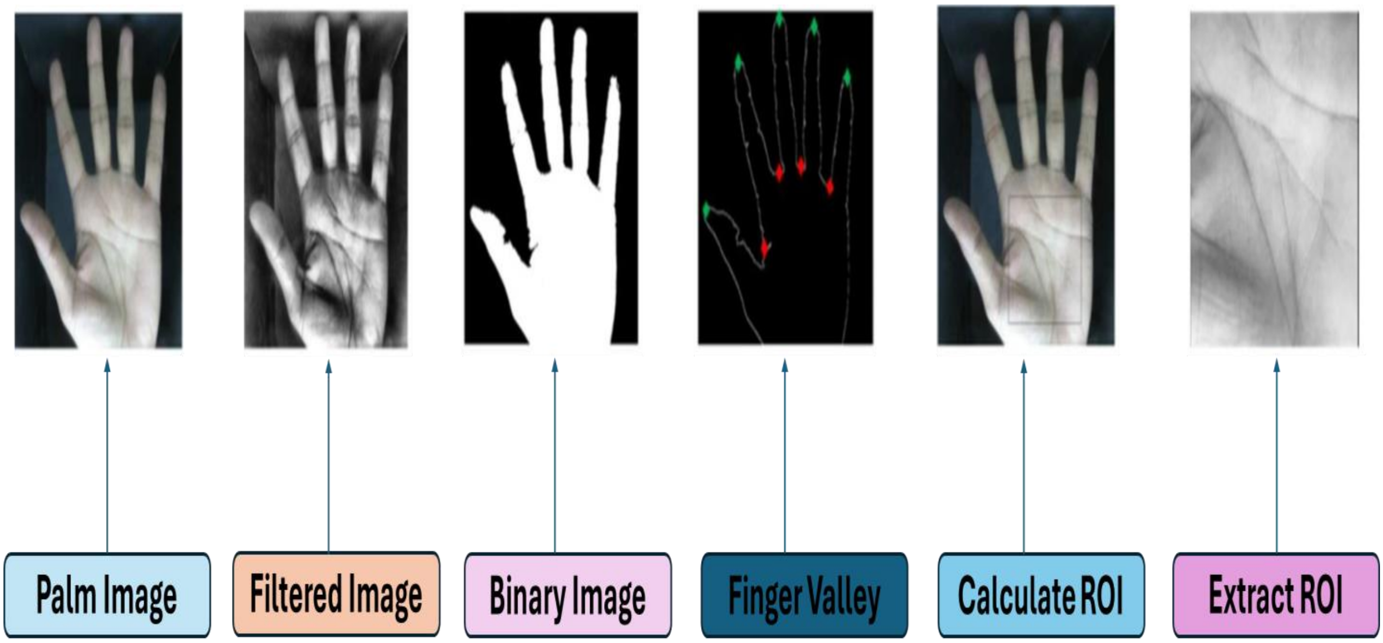

Figure 2. ROI recognizing the technique.

3. 1.1 Palmprint databases.

Palm print databases are critical for enhancing biometric recognition systems. These datasets include a variety of images samples, allowing researchers to create and test effective palm print identification algorithms. When used with machine learning models like SVM or deep learning architectures like ResNet, the accuracy and dependability of palm print-based identification systems are improved. Some of these techniques are noise reduction, feature extraction (e.g., Gabor filters or PCA), and noise reduction. High-quality datasets make these systems scalable, efficient, and adaptable to real-world biometric applications. As appears in Table 1, it describes some of the most frequent palmprint datasets released online for research purposes.

3. 1.2 Data Preparation and Preprocessing.

Pre-processing is a fundamental step in building biometric systems for identification or verification, as it minimizes noise and refines the data. In palmprint recognition, pre-processing improves scan quality and effectiveness by isolating critical details from the palm's Region of Interest (ROI), which is a rectangular section of the palm surface. Figure 5 outlines the primary steps in palmprint pre-processing. To standardize image dimensions, palmprint images are resized to a specific resolution or aspect ratio, then converted to greyscale, enhanced, and binarized, identifying borders along with key reference, extreme, and valley points. The ROI is subsequently scaled and cropped. Several techniques exist for ROI extraction from palmprint images, including direct cropping without algorithms [29],[30]. In our study, the dataset was randomly divided, with 80% used for training and 20% for testing.

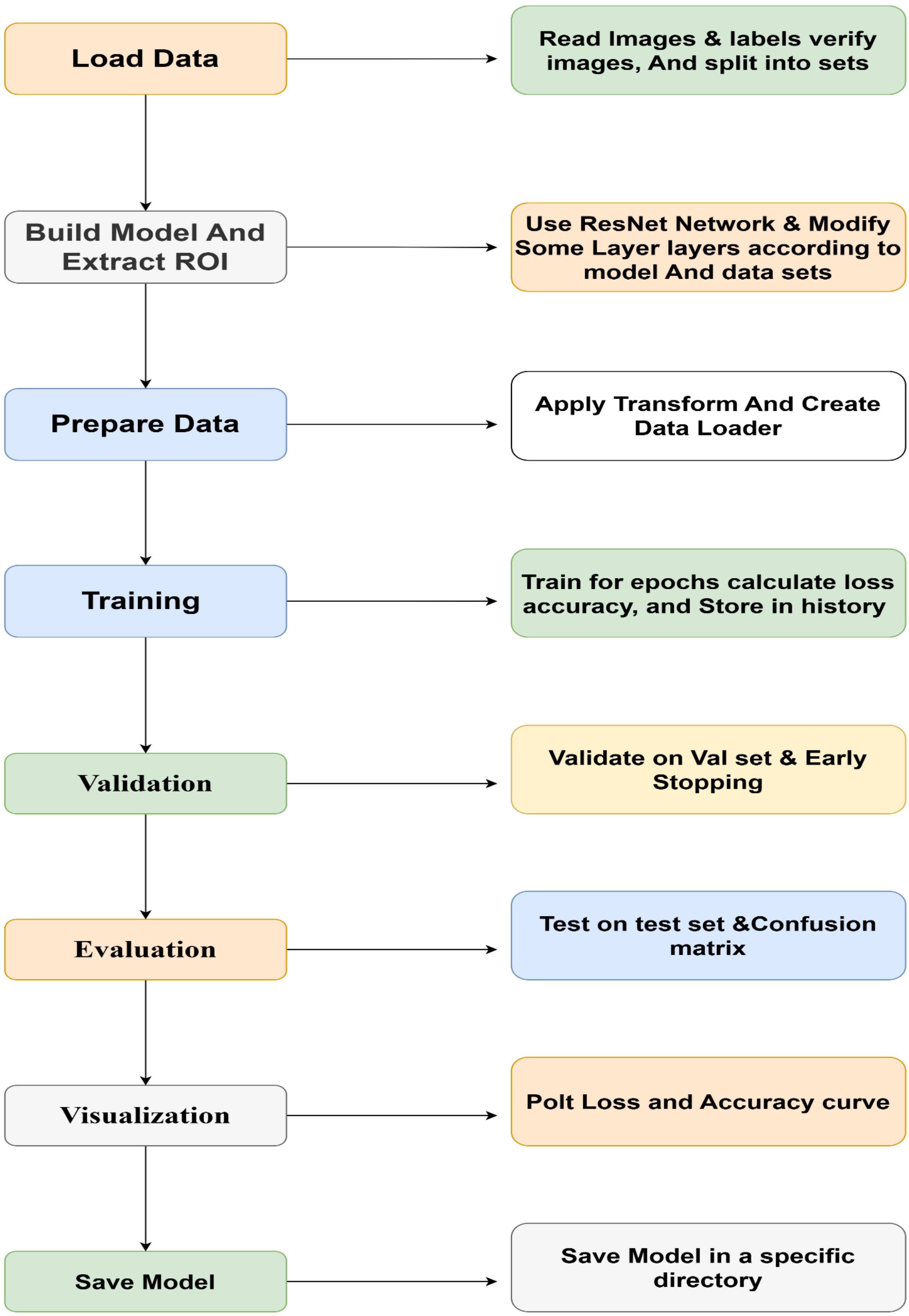

Figure 3. Block diagram the proposed model.

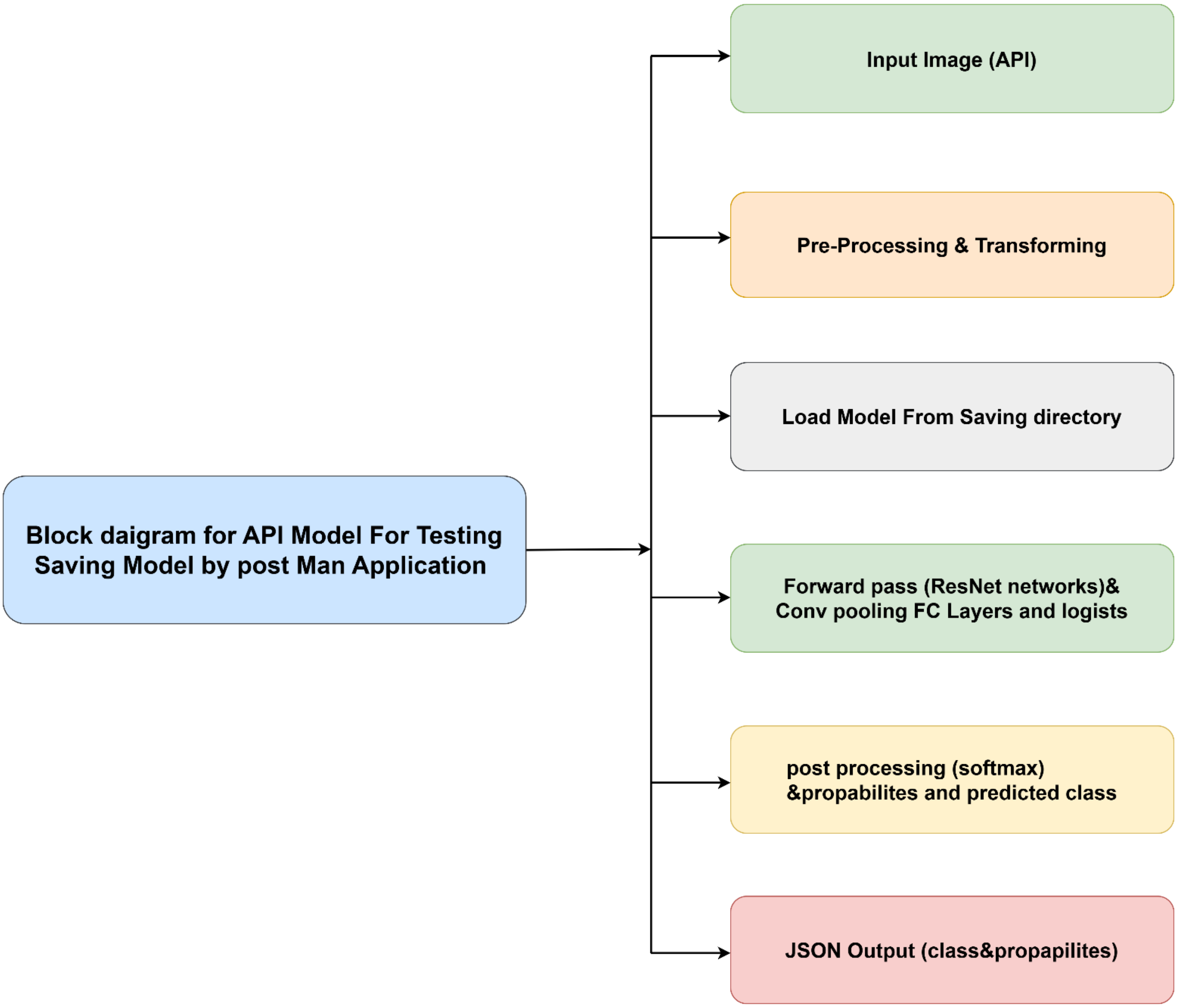

Figure 4. The block diagram of the proposed steps for the API.

Ref.	Datasets	NO. of palm	Image sizes(pixel)	Characterization
[26]	IIT Delhi Touchless Palmprint Database	3290	150x150 and 800x600	The Bitmap photos consist of 3290 palms from 235 participants, each with 14 samples
[27]	CASIA Palmprint Image Database	5505	640x480	An 8-bit grayscale picture of 5505 palms from 312 participants
[28]	Sapienza University Mobile Palmprint Database (SMPD)	7354	3264x2448	The color images include 6000 palms gathered from 250 people, each with 24 samples.

Table 1. Palmprint Databases [2].

3. 1.3. Build model and Extract features.

Building models and extracting features with deep learning and transfer learning has significantly expedited the construction of high-performance models, particularly in scenarios with little data. Transfer learning uses expertise from pre-trained models, which are often acquired on large datasets, to extract important characteristics and adapt them to new tasks. This strategy reduces training time and computer resources while frequently enhancing model performance through robust, generalizable feature representations. Deep neural network feature extraction layers also enable transfer learning, which is the process of adapting pre-trained models to new tasks with minimum training. Overall, deep learning provides a versatile and effective method for extracting and using characteristics, accelerating progress in domains such as computer vision, NLP, and bioinformatics [23].

Transfer learning is particularly successful in fields such as computer vision and natural language processing, where pre-trained models capture complex, domain-specific patterns that may be fine-tuned for specific tasks. Deep learning, which combines model construction, feature extraction, and transfer learning, can produce accurate models rapidly, making it an attractive choice for practical applications across sectors.

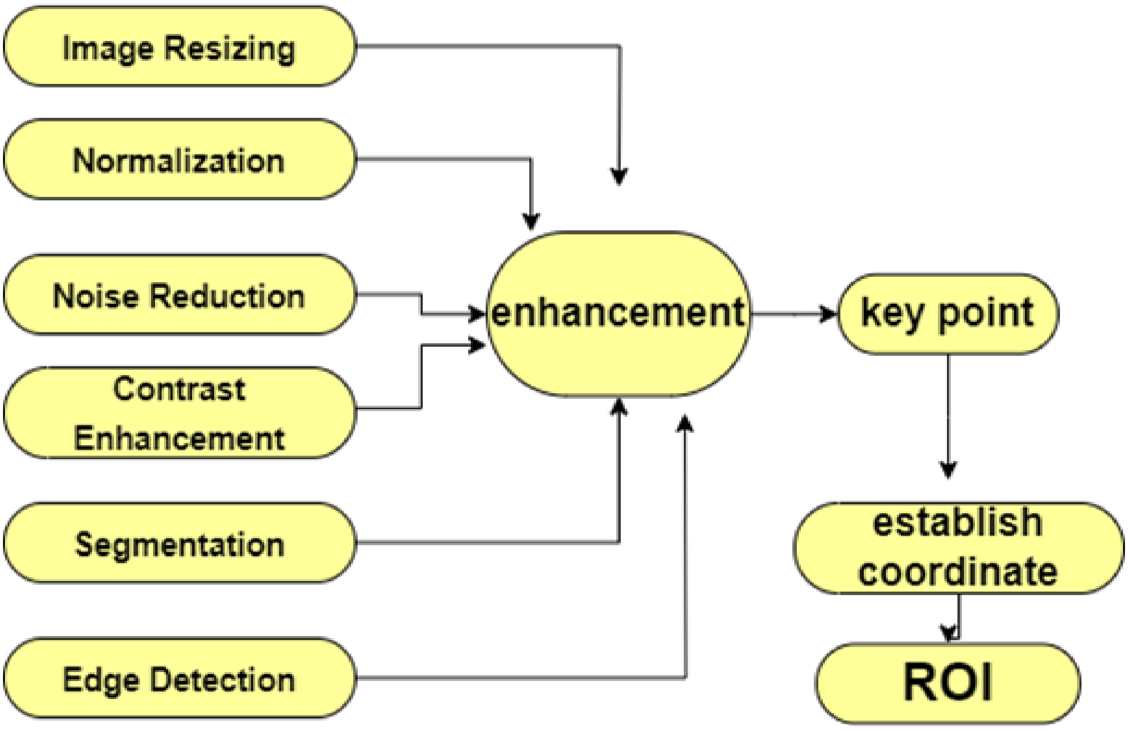

Figure .5. General steps of the preprocessing.

- **ResNet**

  ResNet, an artificial neural network, was launched in 2015 [31]. It is constructed utilizing skip connections (double or triple layers). ResNet presents a new residual layer that combines the input and output from a convolutional layer [31]. Figure 6 shows the basic ResNet architecture. These skip connections enable more efficient feature extraction. This paper covers a single implementation of five different ResNet architectures:

ResNet-18, ResNet-34, ResNet-152, ResNet-101, and ResNet-50. Each of these topologies uses a unique number of convolutional layers and a final fully connected layer. Figure 7 displays the main residual blocks of ResNet architecture. Where X is the input data fed into the block, weight layers are typically convolutional layers, where the input is processed. There are usually two layers, each followed by an activation, which is applied to introduce non-linearity. Skip Connection (x identity) uses the original input and is added directly to the output of the weight layers and Addition (F(x) + x) consists of the output of the weight layers (F(x)) being added to the input (x) before applying the ReLU function again. The enhanced ROI images are put through the ResNet layers, and the results are produced. Our model focused on developing it using ResNet34 for feature extraction, which is an effective approach for image recognition applications. ResNet34's deep residual architecture captures complicated patterns while avoiding difficulties like vanishing gradients, making it ideal for extracting rich information from photos. Using its pre-trained weights and fine-tuning the network on a given dataset, the extracted features can considerably enhance the performance of classification or recognition systems. This approach offers great accuracy, resilience, and generalization in a variety of applications, including biometric recognition and object detection. "The architecture is trained with a single GPU."

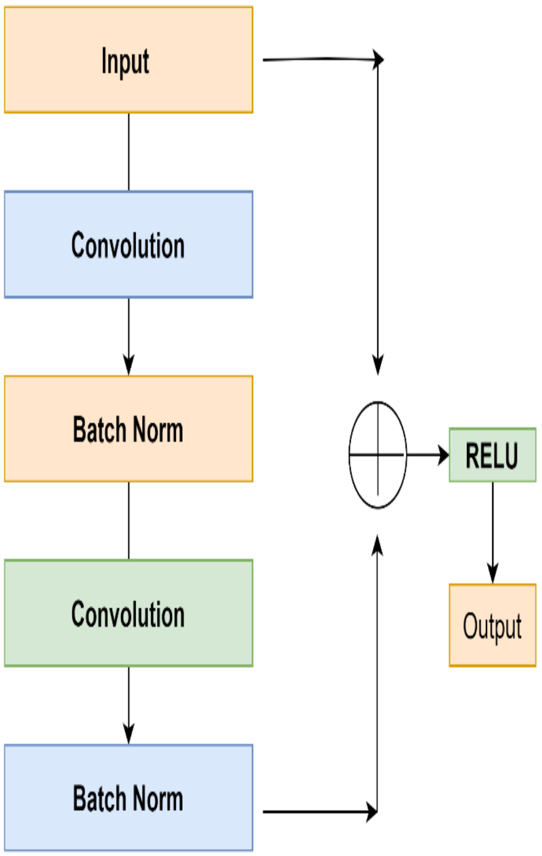

Figure 6. Basic residual blocks of Res Net architecture

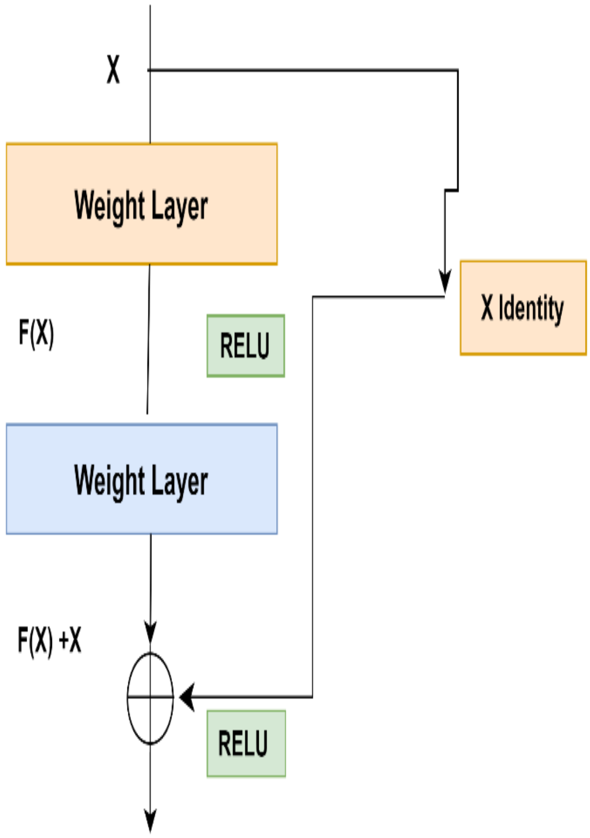

Figure 7. Building blocks of residual network

3.1. 4. Performance Evaluation Metrics Parameters.

The model accurately classified positive values. Classifiers that correctly predict negative samples out of a total of negative samples demonstrate specificity. The F1 score is the harmonic average of accuracy and recall scores. The Matthews correlation coefficient (MCC) [32] is a composite estimate statistic that considers both sensitivity and specificity. As a correlation coefficient, it falls between 1 and +1. The correlation coefficient is +1 for perfect prediction, 0 for average random prediction, and -1 for inverse prediction. The classification success index (CSI) [33] measures the efficacy of a classification model by calculating the proportion of properly categorized samples among all samples.

Classification Error (CE) is the proportion of inaccurate predictions. It is sometimes referred to as the misclassification rate. Equations 1–8 provide formulas for accuracy, precision, recall, specificity, F1 score, MCC, CSI, and CE.

The confusion matrix is a powerful tool for evaluating the performance of the palm print recognition model, as it provides detailed insights into how well the model distinguishes between different classes, revealing misclassification patterns. Furthermore, visualizing the model's predictions allows for a more intuitive interpretation of its accuracy and reliability, enabling researchers to identify specific cases where the model excels or struggles. This dual approach not only enhances understanding of model performance but also facilitates informed decisions for future improvements, ultimately leading to more effective deployment in real-world applications. These four outcomes are described below:

- True Positive (TP) indicates that the actual and expected values are the same
- True Negative (TN): The number of times the classifier accurately classified the negative class as negative.
- False Positive (FP): A negative class predicts a positive one.
- False Negative (FN): Positive instances were misclassified into other classifications.

In conclusion, calculating training and evaluation metrics is critical for developing a robust palm print recognition model, as it effectively assesses the model's learning capabilities and generalization to unseen data. By meticulously analyzing these metrics, researchers can identify strengths and weaknesses in the model, allowing for targeted improvements that enhance performance and reliability in practical applications. Ultimately, a well-evaluated model boosts accuracy and instills confidence in its deployment in real-world scenarios.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \quad (1)$$

$$\text{Precision} = \frac{(\text{TP})}{(\text{TP} + \text{FP})} \quad (2)$$

$$\text{Recall} = \frac{(\text{TP})}{(\text{TP} + \text{FN})} \quad (3)$$

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

$$\text{F1 Score} = \frac{2 * (\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (5)$$

$$\text{Matthews Correlation Coefficient (MCC)} = \frac{[(TP * TN) - (FP * FN)]}{\text{sqrt}[(TP + FP)* (TP + FN)* (TN + FP)* (TN + FN)]} \quad (6)$$

$$\text{Critical Success Index (CSI)} = \frac{TP}{(TP + FN + FP)} \quad (7)$$

$$\text{Classification Error (CE)} = \frac{(FP + FN)}{(TP + TN + FP + FN)} \quad (8)$$

4. Experimental results and discussion.

The studies are carried out on three palm print datasets, IIT-Delhi [26], CASIA [27], and SMPD [28]. The trials drawn are conducted in the Python environment. Five images were randomly chosen for training during the experiment, All the results were obtained based on the hyperparameters as shown in Table 2, while the remaining images were used for testing. After acquiring the feature matrix, the next step is to train a classifier to identify the data as imposter or real. ResNet achieves this with its last fully connected layer. The characteristics extracted from the training data are then used to train the classifier. The aspects of the test results (precision, recall, specificity, F1-score, MCC, CSI, and CE) are then analyzed to confirm the identity and accuracy of one of the different ResNet architectures (ResNet34), as shown in Tables 3 and 4. The accuracy plot displays the performance of ResNet 34 architectures. The performance of various ResNet architectures is conducted on various palm datasets named SMPD, IIT-Delhi, and CASIA. These are shown in Figures 8–13. ResNet-34 achieves maximum accuracy. Table 5 compares the findings with several known approaches. F. M. Bachay [34] used a convolutional neural network with local coding to obtain 97.55% accuracy. The suggested model outperforms traditional methods.

Hyper-Parameters	**Value**		
LR	.0001		
Loss Function	Cross Entropy Loss ()		
optimizer	Adam		
Weight Decay	(1e-4)		
Batch Size	32		
Early Stopping	(Patience: 3, Min Delta: 0.001)		
Number of epochs	40		
ResNet 34 structure			
Layer/Stage	NO. of Blocks	Total Conv layer	Output Size
Conv 1(7*7,64, stride =2)	1	1	112*112
Stage 2	3 Blocks (64 filters).	6	56*56
Stage 3	4 Blocks (128 filters).	8	28*28
Stage4	6 Blocks (256 filters).	12	14*14
Stage5	3 Blocks (512 filters).	6	7*7
Fully Connected	-	1	Equal to the number of classes

Table .2. Hyperparameters and structure of the proposed model.

Datasets	**Method**	**Accuracy**		**loss**		**F-score**	**precision**	**Recall**
		Validation	**Test**	**Validation**	**Test**			
SMPD Dataset	ResNet34	98.49%	98.86%	0.0062	0.0166	98.86%	98.49%	99.24%
IIT-Delhi Dataset		99.62%	99.81%	0.0124	0.0064	99.81%	99.62%	100%
CASIA Dataset		99.71%	99.68%	0.0061	0.0164	99.68%	99.71%	99.80%

Table 3. The result of using the residual network.

Metrics	**Datasets**		
	SMPD	**IIT-Delhi**	**CASIA**
Specificity	98.48%	99.60%	99.54%
MCC	97.72%	99.62%	99.36%
CSI	97.75%	99.63%	99.4%
CE	0.0114	0.0019	0.0032

Table 4. shows specificity, CSI, and CE for the proposed model with some datasets.

Reference	**Method**	**Accuracy**
F. M. Bachay [34]	Deep convolutional neural networks	97.55%
Miura et al. [35]	Using maximum curvature points	86.01%
Yang et al. [36]	Convolutional neural network with local coding	90.33%
Van et al. [37]	Discriminant orientation feature	92.50%
Proposed model	Residual network with different design	**99.8%**

Table 5. Comparison with existing methods.

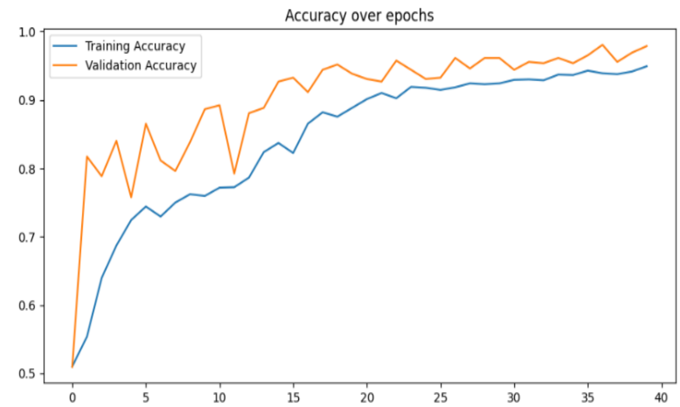

Figure 8. Training and validation loss curves for SMPD.

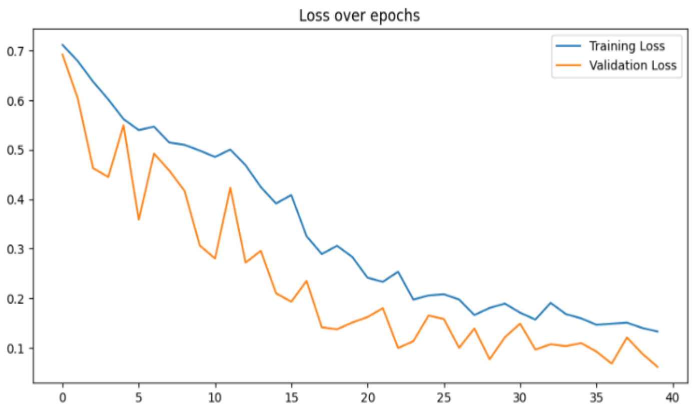

Figure 9. Training and validation curves loss for SMPD.

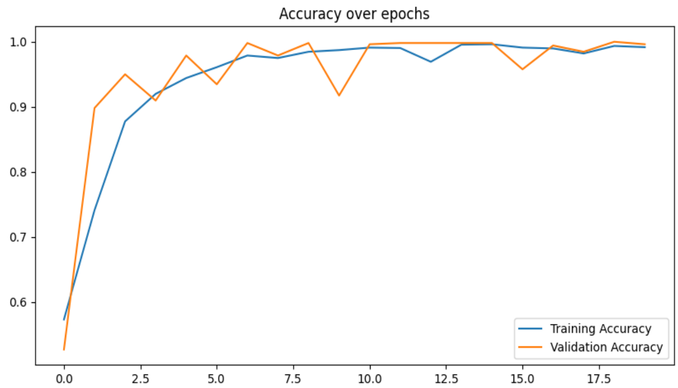

Figure 10. Training and validation accuracy curves for IIT-Delhi

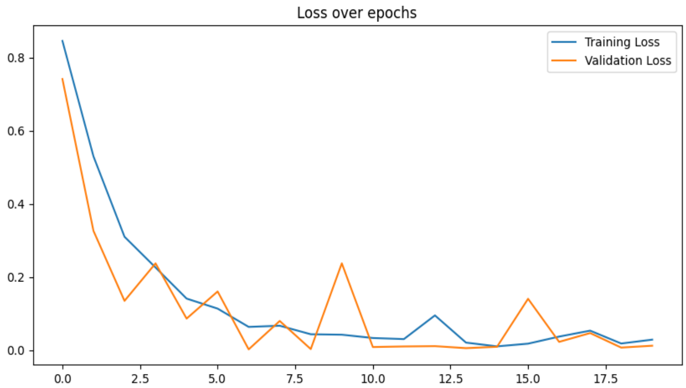

Figure 11. Training and validation loss curves for IIT-Delhi.

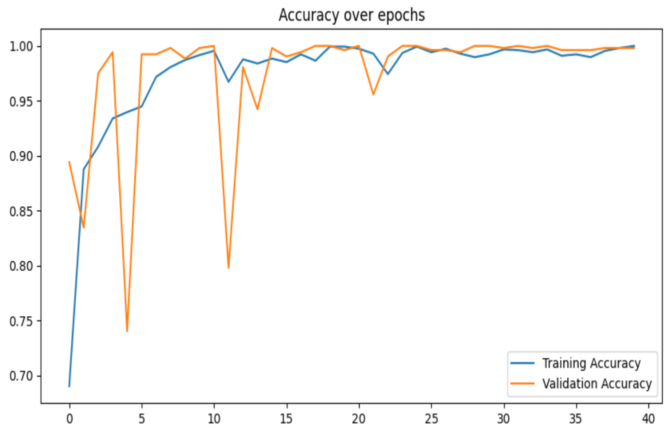

Figure 12. Training and validation accuracy curves for CASIA.

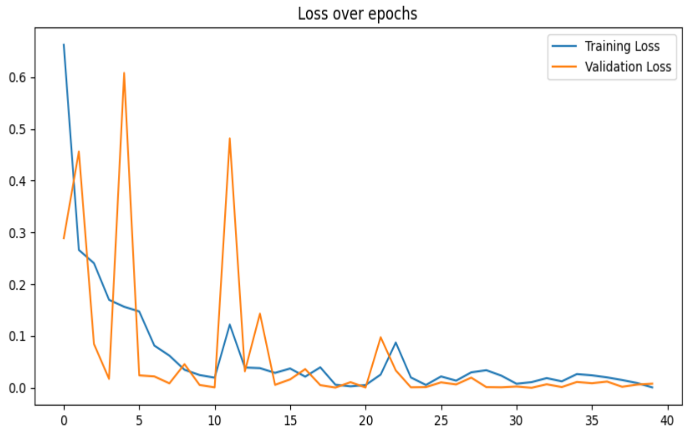

Figure 13. Training and validation loss curves for CASIA.

4.1. Confusion Matrix And Visualize some Predictions For Training Models.

The confusion matrix not only aids in determining overall accuracy, but also allows for the computation of key performance measures such as precision, recall, and F1 score. These measures are critical in situations where the cost of false positives or false negatives varies dramatically, such as medical diagnosis or fraud detection. Visualizing predictions is an effective approach for understanding model performance beyond numerical measurements. Examining situations and comparing predicted vs. real labels provides vital insights into how and why a model makes certain mistakes. It aids in discovering patterns of misclassification, recognizing bias toward specific classifications, and detecting outliers or noisy data

4.1.1. Confusion Matrix

The suggested system's efficacy was determined by generating a confusion matrix based on the model's accurate and faulty predictions. confusion matrices plots for one of the different Res Net architectures (Res Net 34) are shown in Figures 14 to 16 with available palm datasets (SMPD, IIT-Delhi, and CASIA).

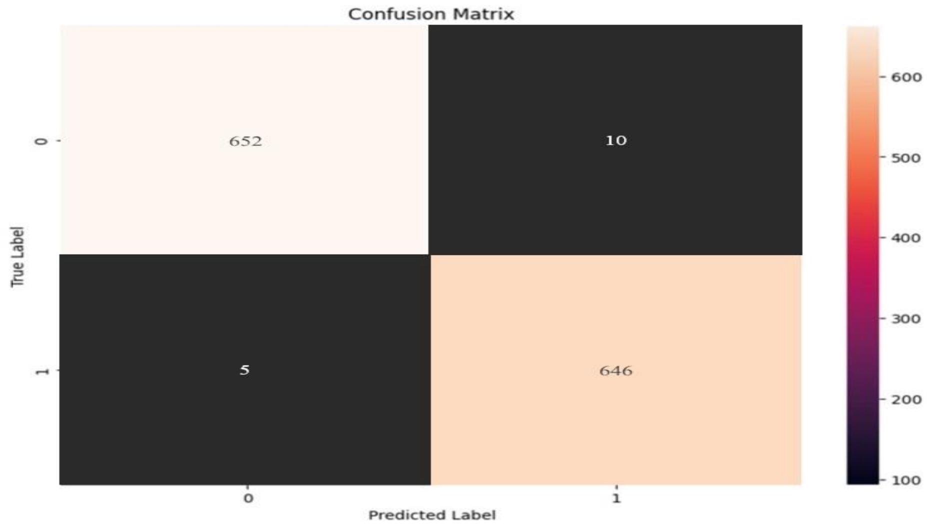

Figure 14. Confusion matrix for SMPD palm print dataset.

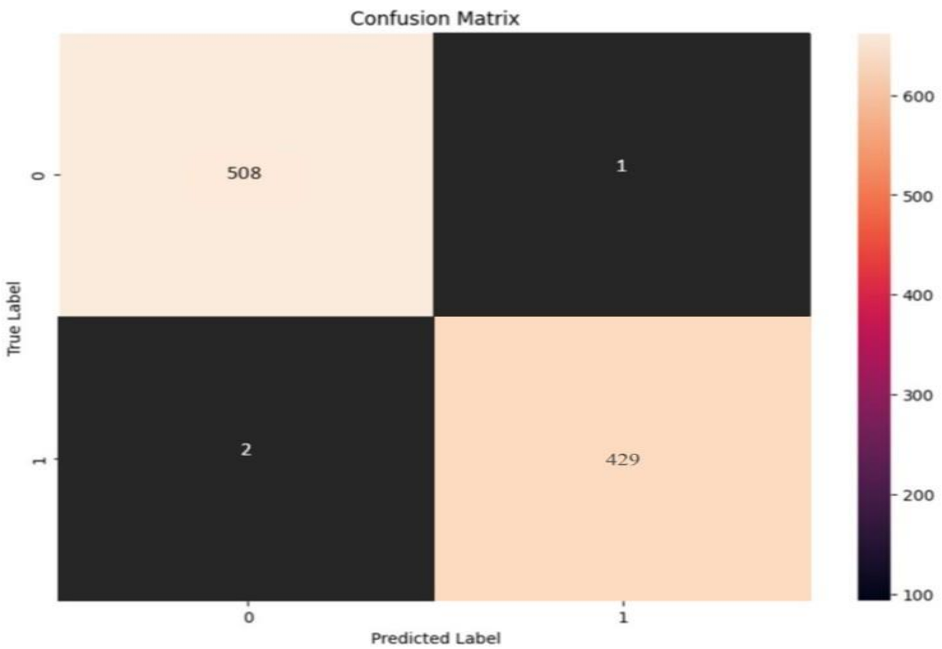

Figure 15. Confusion matrix for CASIA palm print dataset.

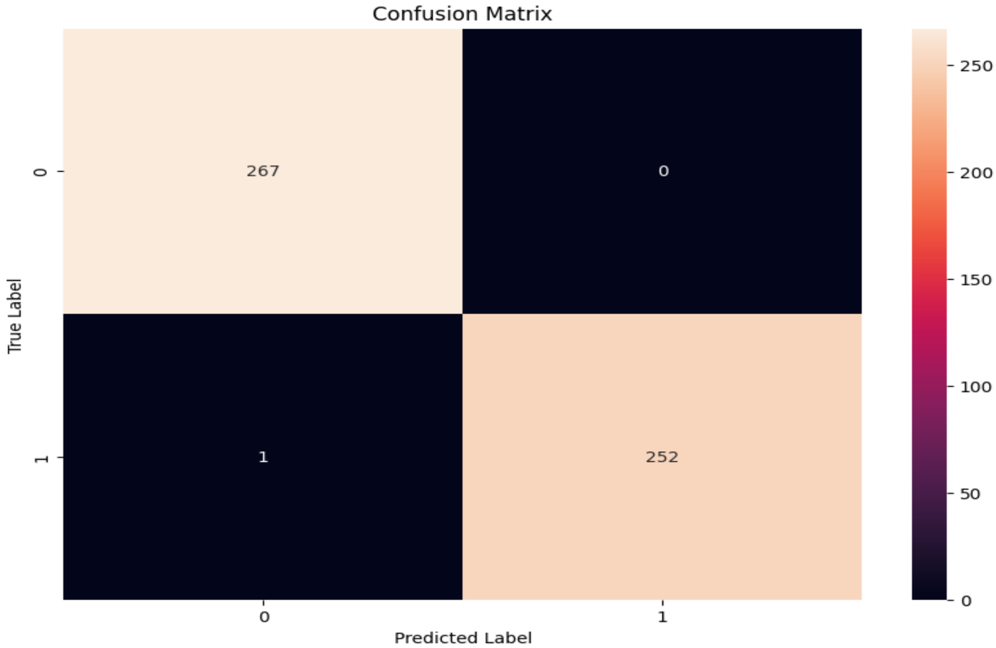

Figure 16. Confusion matrix for IIT-Delhi palm print dataset.

4.1.2. Visualizing Predictions for Training Models.

Visualizing predictions is an essential step in model evaluation, providing deeper insights into a model's performance beyond traditional metrics. Figures 17 to 19 showing examining specific examples, such as correct and incorrect predictions, one can identify patterns in model behavior, such as biases towards classes, sensitivity to certain features, or common misclassification patterns.

Visualization helps highlight areas where the model may need improvement, whether through adjusting data preprocessing, refining architecture, or enhancing training data. Additionally, tools like confusion matrices, heatmaps, and sample image annotations allow for a more intuitive understanding of model strengths and weaknesses, guiding informed adjustments for further training. Overall, visualizing predictions transforms raw model output into actionable insights, improving model interpretability and effectiveness.

Figure 17. Visualize some predictions for the SMPD palm print dataset.

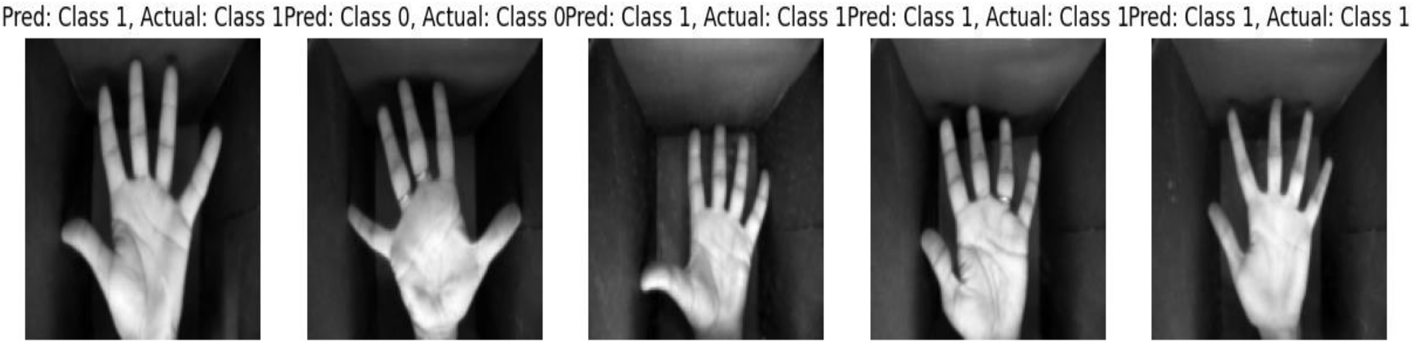

Figure 18. Visualize some predictions for the IIT-Delhi palm print dataset.

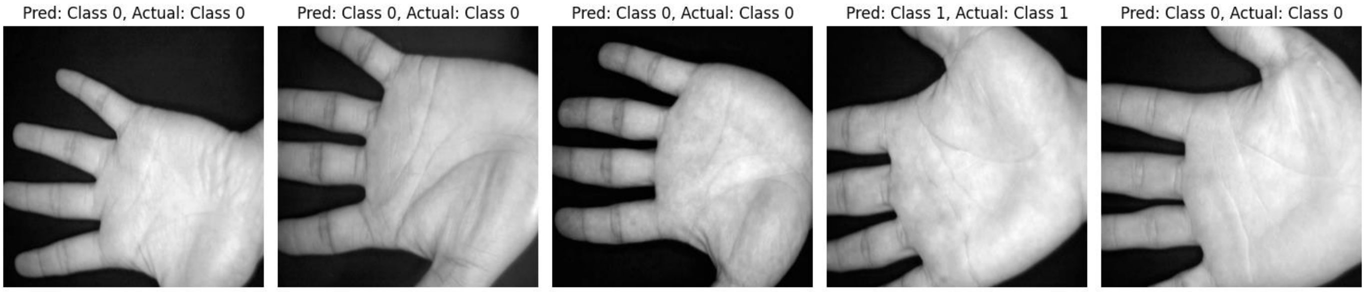

Figure 19. Visualize some predictions for the CASIA palm print dataset.

5. Conclusions

In this paper, a palm-print verification through deep learning, especially leveraging a residual network approach, is proposed. As outlined in this research, the core objective of palmprint image authentication is to extract deep features that yield reliable authentication outcomes. The training process is refined across three publicly available datasets, conducting several experiments to examine how the parameters of different layers in the ResNet 34 model are affected. Our suggested model successfully extracts deep features from the ResNet 34 model, achieving impressive verification results with a small set of images, a common challenge for deep learning models. Our model demonstrated adaptability across diverse palmprints, yielding excellent authentication performance. The highest recorded accuracy was 99.98%, with an F1 score of 99.63%. Future research should investigate incorporating deep learning networks at every stage of palmprint authentication technology, from Region of Interest (ROI) extraction to final matching. Our findings also suggest that not all deep learning models require extensive image datasets to produce meaningful results

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