A Novel Contactless Middle Finger Knuckle Based Person Identification Using Ensemble Learning*

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***Abstract*— In Modern times, automated security for identifying a person is one of the main concerns. There is a significant need for a trustworthy and secure identity verification solution. A reliable way to identify someone can be using a biometric identification system. The finger knuckle pattern offers excellent discriminatory features for biometric identification with indirect touch, including the advantages of long-range visibility. Existing models are failing to handle the depth information in finger knuckles that are highly relevant to understand the identification patterns. Therefore, we elaborate on the significance of utilizing the middle finger knuckle for biometric identification. We propose an ensemble approach that appropriately captures the rich features to identify a person based on their finger knuckle. The proposed model performance is evaluated on a standard dataset (HKPolyU 3D photometric stereo knuckle image dataset). Experimental results illustrate that the proposed model outperforms the existing results. Further, this approach would be advantageous in forensic investigations, security, and surveillance.**

***Keywords*— Ensemble Learning, Finger Knuckle Recognition, Biometrics, Personal Authentication**

I. INTRODUCTION

Automatic methods for personal identification are a crucial issue for academic research and businesses due to their use across all fields, including law enforcement security and e-commerce [1]. Automation using machine learning and deep learning techniques is sought after many applications like vision, text and in healthcare [2], [3]. Likewise, numerous industries have focused on automating Biometrics in recent years. In the context of security applications involving physical or logical access control systems, the recognition of identity data through diverse physiological traits like the face, signature, iris, fingerprint, finger knuckle print, palm print, voice, and hand geometry introduces a unique challenge in managing extensive biometric data for individuals. Automated biometric authentication has several significant features because they increase the reliability and security of e-commerce trades. These benefits frequently outperform the privacy risks underlying their consumption or deployment [4]. However, it isn't easy to readily integrate the palm print recognition system for current security applications. It is also more expensive than other biometric systems. Research focusing on hand characteristics, fingerprints, and finger knuckle prints has experienced notable growth and emergence due to their diverse features. This procedure [5] is also utilized in forensics applications, where psychological variables, rotational and transformational variant images are used to identify the individual. It is simple to capture finger knuckle images with inexpensive tools. Hand attributes contain incredibly recognizable aspects that enable identity information. It was collected without physical contact and demonstrated outstanding accuracy and speed, so it received a high user approval rate. The distinct information embedded in the valley pattern between the middle and proximal phalanges of fingers, the skin crease, and the finger knuckle pattern can be observed from a distance and captured alongside other hand biometrics.

Yet, it may be quite challenging to extract knuckle curves and wrinkles from 2D images. The intensity data may be considerably impacted because of illumination variations brought on by uneven reflections off nearby 2D knuckle surfaces, as the 3D information is not anticipated to alter with changes in illumination. Moreover, spoofing attacks can be more successful against 2D than 3D images. By displaying printed pictures, one individual can duplicate another.

Several experiments have been carried out to develop identification systems that consider knuckle pictures for identifying people. In the early stages of knuckle identification systems, researchers relied on manual techniques to extract distinctive information from knuckle images. These methods involved handcrafting feature extraction approaches to derive feature vectors containing relevant discriminative details. Subsequently, a Traditional classifier was employed to compare and classify the acquired feature vectors, enabling the identification of individuals based on specific patterns and characteristics. Its low capability is the limitation of such 3D knuckle recognition. Recent studies on convolutional neural networks (CNNs) performance for image categorization have been quite promising [6]. It integrated feature extraction and classification into a unified end-to-end model, allowing for a seamless process of extracting relevant features and performing classification simultaneously. This method's applicability has been addressed in various biometric identification challenges, including Recognition of faces, iris patterns, and fingerprint recognition. The current models are unable to effectively address the depth information inherent in finger knuckles, which plays a significant role in comprehending the identification patterns essential for accurate analysis. To mitigate overfitting, a common problem in machine learning, training deep convolutional neural networks (CNNs) requires substantial data. However, the utilization of deep CNNs for finger knuckle identification has been limited due to the scarcity of publicly available extensive datasets. One of the key strategies to address these limitations is to apply aggressive data augmentation techniques. Also, there is a

*This work was not supported by any organization

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convincing reason to employ different CNN models and various ensemble methods to enhance the recently developed 3D middle finger knuckle recognition system. This study incorporates these cues and implements an ensemble learning technique that utilizes four distinct CNN models. This approach aims to enhance the performance of finger knuckle recognition systems by leveraging the combined strength of multiple models.

II. Related Work

The technique that automatically detects a person's identification is known as biometrics, and it is a prominent research field with significant implications for everyday use [7], [8]. For instance, practically every nation uses biometrics for immigration checks due to its dependability, efficiency, and ease of collecting biometric images. Access to resources and authentication for online transactions are two further uses for consumer apps. Physiological properties for accurate biometric recognition include the face, iris, ear, fingerprint, palmprint, and finger knuckle patterns. So far, each biometric identification has advantages and disadvantages. For instance, a person's cosmetics may change how their face looks, while sweat and grime can make fingerprint images look less apparent. The biometric indicators selection is contingent upon the application's requirements. For a biometric system to be considered adequate, it must fulfill the prerequisites of precise and appropriate recognition.

The fingerprint is one of the most frequently used biometric traits out there. Nevertheless, developing fingerprint-based biometric identification involves significant difficulties. At first, fingertip deformations, lingering dirt, moisture, sweat, and cuts can reduce the accuracy of fingerprint identification. Poor-quality fingerprints for automated identification can be harmful to a large number of workers and elderly people. According to a NIST report [9] given to the US Congress, 2% of the population's fingerprints are of insufficient quality. Following another UIDA research [10], 1.9% of the general population cannot be verified using fingerprints. Finger knuckle layouts may be obtained synchronously with fingerprint pictures and are less prone to distortion since they come into touch with objects less often during daily activities. In contrast to a fingerprint, a finger knuckle may be easily obtained from a distance since the main ridges and valley patterns are clear to see. For this reason, adding finger knuckle patterns to only fingerprints might help address some issues and offer more dependable biometric recognition solutions.

Many studies have examined the distinctiveness and dependability of finger knuckle patterns for human identities [11]–[16], wherein discriminative information has been studied using 2D photos of finger knuckle patterns. The authors [17] presented a unique biometric approach for feature extraction using a unique Riesz transform-based feature identification method and compressed it using a 6-bit coding scheme. The author [18] examined experimental results on several main and minor knuckle patterns using a publicly accessible database. This approach may be a benchmark for assessing performance using 2D finger knuckle photographs. Research [19] that looked at discriminative information from 3D creases and curves also revealed significant information. Furthermore, emerging 3D imaging systems is necessary to replace conventional 2D imaging systems. For instance, one example [20] employed a fast camera with the addition of a modified projector for capturing 3D fingers, while another reference [21] used five cameras. Fine 3D texture patterns may be recovered with great precision using the photometric stereo technique. To discover distinct 3D features and, more precisely, identify 3D finger knuckle patterns, authors [22] looked at the 3D information of finger knuckle patterns and developed a novel feature descriptor architecture. The same year, authors [23] created a more effective matching approach for the problem using the surface key points retrieved from the 3D knuckle surface. The authors [24] additionally acknowledged the difficulties encountered in constructing biometric systems, including the limited availability of training data and the substantial variability between training and testing samples observed in real-world implementations. For contactless 3D finger knuckle identification, they provided an advanced deep neural network-based technique. For contactless 3D forefinger knuckle identification, they provided a novel deep neural network-based method. The authors [25] also researched the possibility of utilizing 3D middle finger knuckle patterns for biometric verification. In order to detect 3D finger-knuckle patterns, the study introduces a newly developed deep convolutional neural network model that is designed to be user-friendly and has undergone recent training. The testing results were remarkably positive, suggesting a promising potential for employing the 3D middle finger knuckle layout in various biometric technologies. Our work has thus concentrated on thoroughly investigating 3D middle finger knuckle outline detection utilizing complex neural networks and different ensemble learning techniques.

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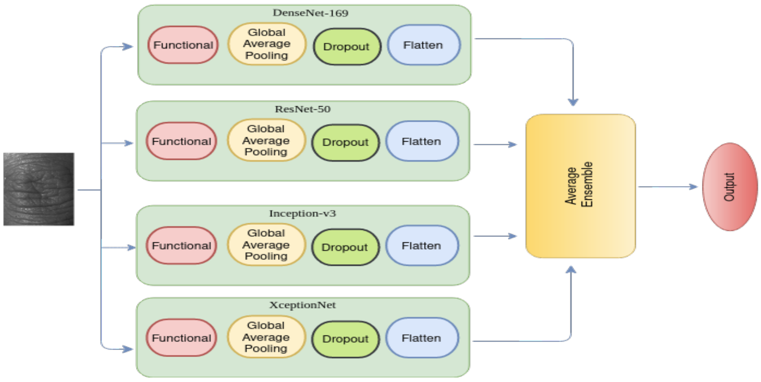

Fig. 1: Architecture Diagram of Ensemble Deep Learning for Middle Finger Knuckle Identification.

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III. Proposed Model

We proposed a deep learning architecture based on ensemble learning techniques. The developed model aims to learn and extract textual and depthwise information from the middle finger knuckle using well-known CNN models such as DenseNet169, ResNet50, InceptionV3, and XceptionNet. As shown in Figure 1, the input images are first fed to Four different models—Resnet50, Densenet169, Inceptionv3 and XceptionNet —which classify them using the same dataset. After the prediction, we used the average predictions to combine the predictions and create ensemble models. After that, this model is fed to the same test data, which is session two data, and has improved accuracy. The CNN models, such as Resnet50, Densenet169, Inceptionv3 and XceptionNet were fine-tuned on the Imagenet dataset.

A. Inception-v3

It employed 1×1, 3×3, and 5×5 convolution layers simultaneously in the inception module, fused these three outputs, and transferred them to the next module. As a result, various scales of information are processed simultaneously with the support of a more comprehensive network. It also reduces parameters by using a small convolution kernel size and splitting the module channel-wise and spatial-wise.To lower the parameters while retaining the receptive field and improving representational abilities, the Inception-v3 substituted a convolution with a kernel size of 5×5. with two convolutions with a kernel size of 3×3.

B. Resnet-50

To solve the issue of disappearing or expanding gradients, Resnet was developed. ResNet consists of multiple residual blocks, each consisting of a convolution layer, a ReLU layer, and a batch normalization layer. Additionally, the input and output of each residual block were connected directly through an identity connection to facilitate residual learning. While deep networks are being trained, this primary feature addresses gradient issues. ResNet50 is constructed by sequentially stacking multiple residual blocks until the total number of network layers reaches 50.

C. Densenet

Similar to Resnet, Densenet is utilized to solve the vanishing gradient issue. But did not consist of a residual block to achieve the goal. It used dense block and the input of dense block *n-th* layers concatenated with all prior *n-1* layers. For this, it is possible to maximize the use of the characteristics of earlier layers while carrying out a related action on the *n-th* layer. This kind of reuse feature method can be helpful for better feature work while reducing the number of parameters.

D. XceptionNet

Xception employs depth-wise separable convolutions. There are a total of 36 convolutional stages. The Xception model performs the sequential convolution as the initial step, followed by the spatial convolution applied across channels. For Xception, there is no intermediate activation. Due to this, it has the best accuracy compared to other methods.

E. Ensemble Learning

The two methods frequently used to ensemble multiple networks are the weighted average and averaging. An ensemble learning approach called weighted average ensemble combines the predictions from many models, with each model's contribution being weighed according to its proficiency or competence. The average is computed by summing the outcomes of multiple networks, where each network carries equal weight and exerts an equal impact on the final output. The following formula for ensemble learning,

1) Average Ensemble::

$$Y_{avg} = \frac{Y_1 + Y_2 + Y_3 + Y_3 + Y_4}{4} \quad (1)$$

In the average ensemble, Y_1, Y_2, Y_3, Y_4 represent different model, respectively.

2) Weighted Average Ensemble::

$$Y_{wavg} = W_1Y_1 + W_2Y_2 + W_3Y_3 + W_1Y_3 + W_4Y_4 \quad (2)$$

In the weighted average ensemble, W_1, W_2, W_3, and W_4 represent the weights assigned to each model, respectively. The process of assigning weights manually involves utilizing existing knowledge.

IV. Experimental Result

A. Dataset

The HKPolyU 3D finger knuckle image dataset, previously released to the public, was used in this research to evaluate the model performance [26]. It offers a dual-stage dataset with both two-dimensional and three-dimensional images of knuckles. This dataset for imaging techniques was collected using a photometric stereo technique. The biometric photography equipment comprises a camera, seven evenly distributed lights, a control circuit, and a computer system. The dataset was collected from 228 individuals, out of which 190 participants volunteered for the second data-gathering session. Each session for every subject included six photographs of the forefinger and six photographs of the middle finger. For each 3D image, there are seven corresponding photometric stereo images. Consequently, each subject in each session has 42 images of the forefinger and 42 images of the middle finger.

This 3D finger knuckle database contains complex images that might illustrate the real reality circumstances, where photographs from the second session were captured using various imaging settings, imaging lenses, and lighting [24]. The authors [26] stated that using forefinger pictures can result in better performance than using middle finger knuckle images.

By proposing a convolutional neural network model for assessing middle fingers, the author [25] aims to reduce the impact of the middle finger knuckle problem. As a result, just the middle finger was employed in the investigation. The approach demonstrates a reasonably commendable solution With a 71% accuracy rate.

In this study, we employed ensemble learning techniques to produce a more precise accuracy for identifying 3D middle finger images. As a result, only the 3D middle finger images of 190 subjects were included in the study. We used different data augmentation techniques such as blurred images, soft edges, noisy images, flip, and brightness increase and decrease in session one image. For each participant, there were 294 images; as a result, 55860 images from session one were utilized for training the model. In session 2, 7980 images were employed for testing. The efficiency and excellence of the proposed network were assessed using a total of 63840 images.

B. Model Evaluation

1) Experimental Setup: The network was built on this machine, which has an Intel Xeon CPU and 64 GB of RAM, using the Python package and the Linux operating system. The training settings for models have been specified, with the batch size 1 set to 128, and a 50-epoch limit was imposed.

2) Classification Metrics: The measures listed below were used to measure the model's effectiveness. For instance, Accuracy (Accu), Precision (Pr), Recall (Re), F1 Score (F1sc), True positives (TrPs), True negatives (TrNe), False positives (FaPs), False negatives (FaNe):

$$F1sc = \frac{1}{N}\sum_{c=1}^{k}\frac{2 \times Pr_c \times Re_c}{Pr_c + Re_c} \quad (3)$$

In this formula, *k* represents the number of classes, and *N* represents the number of samples.

The False Reject Rate (FRR) refers to the rate at which a biometric system incorrectly rejects or fails to authenticate a valid user or sample.

$$FRR = \frac{FaNe}{TrPs + FaNe} \quad (4)$$

The False Acceptance Rate represents the rate at which a biometric system incorrectly accepts an impostor or unauthorized individual as a genuine match.

$$FAR = \frac{FaPs}{FaPs + TrNe} \quad (5)$$

The Equal Error Rate is a performance metric used to evaluate the accuracy and balance of a biometric system's False Acceptance Rate (FAR) and False Reject Rate (FRR).

$$EER = \frac{FAR + FRR}{2} \quad (6)$$

3) Result: The primary dataset is divided into training as session one images and testing as session two images. Table I shows the classification results without augmentation; the models Densenet121, Inceptionv3, Resnet50, DenseNet201, DenseNet169, XceptionNet and ResNet101 give a prediction of accuracy 49.91%, 52.84%, 53.27%, 54.27%, 55.84%, 57.62% and 60.23%. Table II shows the classification results with augmentation; the models Densenet121, Resnet101, Inceptionv3, ResNet50, XceptionNet, DenseNet201 and DenseNet169 give a prediction of accuracy 65.16%, 71.72%, 71.64%, 72.37%, 75.28%, 81.96% and 82.03%. We obtained 88.85% for the average ensemble method after applying the ensemble learning approach for the combination of DenseNet169 + ResNet50 + InceptionV3 + XceptionNet.

Table III presents the evaluation results of the ensemble methods. The metrics used for evaluation include precision, recall, F1-score, and test accuracy. The Voting method achieved a precision of 89.07%, recall of 84.80%, F1-score of 83.20%, and test accuracy of 84.80%. The Weighted Average method improved the precision to 89.95%, recall to

TABLE I: The Performance Comparison of Proposed Model with State-of-the-Art Models (without Augmentation).

Model	Precision(%)	Recall(%)	F1-Score(%)	Test Accuracy(%)
DenseNet121	44.91	49.91	41.38	49.91
InceptionV3	63.28	52.84	47.71	52.84
ResNet50	50.18	53.27	45.59	53.27
DenseNet201	50.54	54.27	46.31	54.27
DenseNet169	52.28	55.84	48.30	55.84
XceptionNet	60.14	57.62	52.62	57.62
ResNet101	63.28	60.23	54.60	60.23
Proposed Method	**65.31**	**64.07**	**57.69**	**64.07**

TABLE II: The Performance Comparison of Proposed Model with State-of-the-Art Models (with Augmentation).

Model	Precision(%)	Recall(%)	F1-Score(%)	Test Accuracy(%)
DenseNet121	72.72	65.16	61.56	65.16
ResNet101	77.02	71.72	69.53	71.72
InceptionV3	78.08	71.64	69.52	71.64
ResNet50	77.97	73.37	69.65	72.37
XceptionNet	81.51	75.28	72.64	75.28
DenseNet201	86.60	81.90	80.30	81.96
DenseNet169	86.51	82.03	80.21	82.03
Proposed Method	**91.07**	**88.85**	**87.76**	**88.85**

TABLE III: The Performance Comparison of Different Ensemble Methods for Middle Finger Knuckle Identification.

Method	Precision(%)	Recall(%)	F1-Score(%)	Test Accuracy(%)
Voting	89.07	84.80	83.20	84.80
Weighted Average	89.95	87.63	86.51	87.63
Stacking	90.64	88.58	87.38	88.58
Average	**91.07**	**88.85**	**87.76**	**88.85**

87.63%, F1-score to 86.51%, and test accuracy to 87.63%. Stacking further enhanced the performance with a precision of 90.64%, recall of 88.58%, F1-score of 87.38%, and test accuracy of 88.58%. The Average ensemble method outperformed all others, achieving a precision of 91.07%, recall of 88.85%, F1-score of 87.76%, and test accuracy of 88.85%.

TABLE IV: The False Reject Rate (FRR), False Acceptance Rate (FAR) and Equal Error Rate (EER) values for models are listed below. The model with the lowest FRR, FAR and EER is indicated in bold.

Model	FRR	FAR	EER
DenseNet121	0.3483	0.00184	0.1751
ResNet101	0.2828	0.00149	0.1424
InceptionV3	0.2834	0.00149	0.1416
ResNet50	0.2764	0.00146	0.1389
XceptionNet	0.2473	0.00130	0.1243
DenseNet201	0.1808	0.00095	0.0908
DenseNet169	0.1796	0.00095	0.0903
Voting Ensemble	0.1520	0.00080	0.0764
Weighted Average Ensemble	0.1236	0.00065	0.0621
Stacking Ensemble	0.1156	0.00061	0.0581
Average Ensemble	**0.1115**	**0.00059**	**0.0560**

Table IV presents the False Reject Rate (FRR), False Acceptance Rate (FAR), and Equal Error Rate (EER) values for different models used in the study. The table includes several popular deep learning models, such as DenseNet121, ResNet101, InceptionV3, ResNet50, Xception, DenseNet201, and DenseNet169. It also includes the performance of ensemble methods, including Voting Ensemble, Weighted Average Ensemble, Stacking Ensemble, and Average Ensemble. The FRR, FAR, and EER values are reported for each model. The FRR represents the rate at which genuine samples are incorrectly rejected, while the FAR indicates the rate at which impostor samples are incorrectly accepted. The EER is the point at which the FRR and FAR are equal, representing the overall performance balance of the model.

By examining the values in the table, it can be observed that the Average Ensemble achieves the lowest FRR of 0.1115, indicating a low rate of rejecting genuine samples. Additionally, the Average Ensemble also achieves the lowest EER of 0.0560, signifying the best overall balance between FRR and FAR. The table provides a comprehensive overview of the performance of individual models and ensemble methods, highlighting their effectiveness in terms of FRR, FAR, and EER. This information can assist in selecting the most suitable model or ensemble method for middle finger knuckle identification tasks.

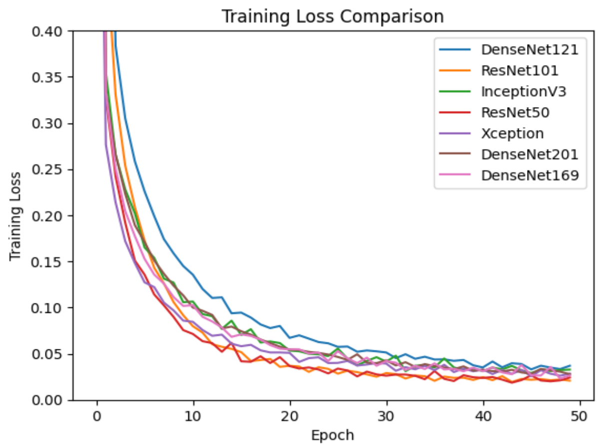

Fig. 2: Training Loss.

In this Figure 2 Training loss graph, each model is represented by a different colored line. The vertical axis represents the value of the training loss function, while the horizontal axis represents the number of training epochs. We can see that some models, such as the yellow (ResNet101) and red (ResNet50) lines, converge quickly and reach low final loss values, while others, such as the green (InceptionV3) and blue (DenseNet121) lines, take longer to converge and have higher final loss values. By comparing the performance of these seven models using the training loss graph, we can gain insights into each model's relative strengths and weaknesses.

The training accuracy graph in Figure 3 illustrates the performance of multiple deep learning models, with each model represented by a unique colored line. The vertical axis represents the model's accuracy on the training data, while the horizontal axis represents the number of training epochs. We can see a lot of variation in the performance of the different models. Some models, such as the red (ResNet50) and purple (XceptionNet) lines, achieve high accuracy early in training and maintain it throughout. Others, such as the yellow (ResNet101) and blue (DenseNet121)

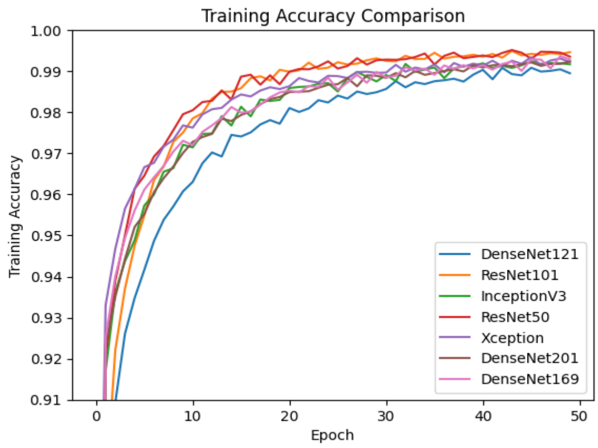

Fig. 3: Training Accuracy.

lines, take longer to reach high accuracy and have more fluctuations over time. The model represented by the yellow line is highly stable, with consistent accuracy throughout the training process.

V. Conclusions and Future Works

Biometric-based personal identification is a commonly employed approach to automatically recognize an individual's identity. The unique textural pattern formed by the bending of the finger knuckle is highly distinguishable. This paper introduced a novel approach to personal identification by utilizing a 3D photometric image of the middle finger's knuckle. We employed ensemble learning techniques to develop an authentication system that enhances the overall identification performance. This method obtains exceptional accuracy levels, surpassing other state-of-the-art models while maintaining an impressively low false acceptance rate. It would be helpful for real-time and modest environments such as workplaces, classrooms, or individual gadgets like cell phones and laptops. In future research, the exploration of image enrichment technologies can be pursued to identify potential avenues for enhancing the obtained results.

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