

DEEP CONTACTLESS 3D-MIDDLE FINGER KNUCKLE RECOGNITIONNigar M. Shafiq Surameery^a^a Information Technology Department, College of Computer and Information Technology, University of Garmian, Kurdistan Region-Iraq (nigar.mahmoud@garmian.edu.krd)*Received: Sept., 2021 / Accepted: Dec., 2021 / Published: Dec., 2021*<https://doi.org/10.25271/sjuoz.2021.9.4.854>**ABSTRACT:**

Automation security is one of the main concerns of modern times. A reliable and safe identity verification system is in great demand. A biometric verification system can represent a reliable method of identifying an individual. The knuckle pattern is considered to be one of the emerging hand biometrics because it has the potential to identify individuals. This presented work explores the potential for biometric identification utilizing the 3D middle finger knuckle. The study provides a new, simple, trained from scratch, but effective deep convolutional neural network model designed for 3D figure knuckle print recognition. The given model, to the best of the author's knowledge, is the first of its kind to use deep learning algorithms for 3D knuckle patterns on the middle finger for biometrics. An extensive experiment was carried out using (HKPolyU) the 3D knuckle image database of Hong Kong Polytechnic University. The suggested CNN model's performance has been evaluated using two session data obtained from different camera lenses. The model is designed to be implemented in a real-time system. It may be used in small-scale settings such as workplaces, homes, or personal devices like laptops and tablets, where training is simple. The experimental results were very encouraging and showed the potential for biometric applications utilizing the 3D middle finger knuckle pattern. The paper also performs a comparison of the identification performance of the system with different CNN models to choose the best result for the 3D knuckle recognition task. The results confirmed that even though various challenges compared with other studies in the same field, the proposed method provides relatively well solution with an accuracy of 71%.

KEYWORDS: CNN, Deep Learning, Finger Knuckle Recognition, Biometrics, Personal Authentication.**1. INTRODUCTION**

Automated personal identification and authentication systems have an essential concern for both academic research and industries because of their wide range of uses, which include anything from low enforcement security to e-commerce (Neware et al., 2014).

In the past 10 years, biometrics has attracted a lot of attention because of its many applications in various fields. Identification of identity data by physiological characteristics like a signature, face, iris, voice, fingerprint, finger-knuckle print, palm print, and hand geometry are extensively utilized in important security applications such as physical or logical access control systems, that present a novel difficulty in dealing with vast volumes of biometric data for quick and accurate identifying of individuals. This approach is also used in forensics applications where the person will be identified by utilizing morphological features, rotational and transformational variant pictures (Jain et al., 2004). Each of these traditional biometric identifiers has its advantages and disadvantages. The benefits of automated biometric authentication are significant, as they improve the dependability and security of e-business transactions. These benefits often exceed the privacy issues that accompany their use or implementation (K. Cheng & Kumar, 2012). These systems have some disadvantages as well. For example, the palm print recognition system cannot be easily embedded in existing security applications due to its large physical size. In addition, the pattern of blood vessels hidden under the skin is very obvious in individuals, even in identical twins, and is stable

for a long time. But this cannot be used mainly because it is a very expensive system compared to other biometric systems (Neware et al., 2014).

Hand traits biometric systems, for example, Fingerprints and finger knuckle prints, have recently become an active research frontier because of their varied characteristics for instance (i) it's simple to capture with low-cost equipment, (ii) hand traits contain extremely distinctive characteristics that allow personal identification, (iii) because they were collected in a contactless way and provided excellent quality in terms of both accuracy and speed, hand characteristics had a high user acceptance rate (Usha & Ezhilarasan, 2018).

The knuckle pattern is thought to be particularly important in defining individuality among these hand characteristics. It can be more easily imaged from a distance because the curved patterns and main creases can be simply seen with the naked eye.

Knuckle curves and creases are associated with the most identifiable information in knuckle patterns. Nevertheless, knuckle curves and creases are tough to extract for 2D pictures. This is due to lighting changes by uneven reflections from adjacent 3D knuckle surfaces, for example, which may significantly impact the intensity data. Therefore, using 3D knuckle information can more reliably characterize the knuckle pattern because the 3D information is not expected to change with changes in lighting (K. H. M. Cheng & Kumar, 2020).

In addition, 2D imaging biometric systems are more vulnerable to spoofing attacks. One person impersonates another person by showing printed images, which poses a severe challenge to

maintaining the integrity of the biometric system. Printed photos cannot display 3D information; therefore, 3D knuckle imaging systems may simply detect such spoofing attacks. Finally, rendering replicas of 3D knuckle patterns is very hard because they need subjects to purposefully show their fingers in complicated imaging situations, which are distinct from those needed for secretly obtained 2D knuckle pictures. In short, there are reasonable arguments that adding 3D knuckle patterns to biometrics can resolve some of the limitations of using other hand features (K. H. M. Cheng & Kumar, 2020).

The current restriction of such 3D knuckle recognition is the limited ability of the traditional methods. However, recently, Convolutional Neural Networks (CNN) have achieved good performance in image classification. (Zhihui Xie¹, Zhenhua Guo¹, 2018) The applications of this method have been studied in several specific biometric recognition problems, such as fingerprint recognition (Lin & Kumar, 2018), iris recognition (Zhao & Kumar, 2017) and face recognition (Parkhi et al., 2015). It is highly motivated to apply CNN to advance the recent 3D middle finger knuckle recognition framework.

Therefore, the development of an automated biometric system based on 3D middle finger knuckle patterns using CNN is investigated in this study, which can be used for different potential technologies areas such as e-business and forensics.

This paper's structure is as follows: First, section 2 discusses the previous related studies. The suggested model is explained in Section 3, while section 4 illustrates the experimental setup Section 5 summarizes and provides the findings from the evaluation of the proposed model's effectiveness. Finally, in Section 6, conclusions are made, and significant recommendations for future study are addressed.

2. RELATED WORK

The popularity and widespread scope of biometric recognition systems have attracted several researchers in this area in the recent decade. Because 3D finger knuckle identification is a relatively new subject with just a few earlier researches, this work was backed up by literature from 2D finger knuckle identification.

The authors in (Zhang & Li, 2011), proposed a novel biometric system for feature extraction depending on finger knuckle texture analysis. They presented a novel feature recognition approach based on the Riesz transforms and encoded it using a 6-bit coding system. In addition, in 2011 (Zhang et al., 2011), the authors offered a different finger knuckle print identification method for extracting both local and global characteristics of finger knuckle print pictures. Hegde et al., in (Hegde et al., 2013) applied a personal identification utilizing finger knuckle prints in real-time. Their study used three distinct methods to extract the finger knuckle features: Gabor Wavelet transform, radon transform, and correlation-based identical. Aoyama et al. (Aoyama et al., 2014) introduced a new biometric approach based on local block similarity for finger knuckle print recognition. In this algorithm, 2D discrete Fourier transforms have been used to achieve phase data, which is needed as feature data, from finger knuckle print images. The authors in (Kumar & Xu, 2016) utilized a publicly available database, compared experimental findings on a variety of major and minor knuckle patterns. Outperforming findings are obtained, and it is acceptable to use this method as a standard for measuring performance from 2D knuckle pictures.

Several studies have been conducted to investigate the patterns by utilizing 3D ear (Ganapathi et al., 2018) (Cadavid & Abdel-Mottaleb, 2008), 3D face (Chang et al., 2005) (Jahanbin et al., 2011), and 3D fingerprints (Liu et al., 2017) (Kumar & Kwong, 2013); as a result, reliable and more accurate biometric techniques have been developed. Meanwhile, other studies have focused emphasis on 3D finger knuckle identification.

Authors in (K. H. M. Cheng & Kumar, 2020) examined the 3D data of finger knuckle patterns, and a novel feature descriptor framework was created to identify unique 3D features for much more accurate identification of 3D finger knuckle patterns. Their research on the use of 3D finger knuckle patterns in identity verification has shown promising results, as it may provide a theoretical upper limit on the performance that can be expected from these patterns.

In the same year, the author in (K. H. M. Cheng, 2020) used the surface key points extracted from the 3D knuckle surface to develop a more effective matching method to solve 3D knuckle recognition problems. The results of their comparative experiments with the most advanced methods on the publicly available 3D knuckle database show that their method can provide more than 23 times faster with performance improvement on the accuracy. Although their work focuses on 3D knuckle recognition, the performance of the method on other publicly available databases with similar 3D biometric patterns (including 3D palmprints and 3D fingerprints) has been shown to verify the performance of the proposed model. Moreover, the authors in (K. H. M. Cheng & Ajay, 2021) introduced a new curvature-based feature generated from the 3D finger knuckle surfaces descriptor and a method based on the statistical distribution of the encoded feature space to calculate the similarity function. Their proposed feature representation uses insights into 3D geometry to accurately encode curvature information. When calculating the similarity between a pair of templates, they calculate the similarity function according to the probability mass distribution of the coded feature space. They utilize an insight in 3D geometry that, for a pair of neighbouring surface normal vectors, the distance between their heads is shorter than the distance between their tails if the surface was concave. Therefore, they could distinguish whether a local shape was convex or concave along a specified direction and encode the curvature information as binary templates of preferable sizes for further comparisons. Their approach can be extended to templates with different sizes, and more importantly, was significantly better than the state-of-the-art methods, which was proven in the publicly available 3D knuckle database. In addition, they presented the generalizability of their method by evaluating it on other publicly available biometric datasets of similar patterns, such as 3D palmprint and finger vein.

However, the authors in (K. H. M. Cheng & Kumar, 2021) highlighted the difficulties related to the construction of biometrics, such as the lack of training data and significant intra-class or train-test sample variability seen in real-world applications, and presented a novel deep neural network-based method for contactless 3D finger knuckle recognition. Also, to create a much more powerful deep feature representation, their technique concurrently encodes and integrates deep information from various scales. This was the first time a neural network method to 3D finger knuckle identification was developed.

Accordingly, a complete investigation of 3D knuckle patterns identification utilizing convolutional neural networks is satisfactory, and this work has focused on that.

3. PROPOSED MODEL

Convolutional Neural Network (CNN) is one of the widely used deep learning algorithms in image classification applications. It consists of three different types of layers, called convolutional layers, pooling layers, and fully connected layers. In the CNN algorithm, input images are received and passed through the CNN layer to extract its features. Then, the classification result is produced. The convolutional layer uses the kernel or filters to extract features from the image, as these kernels or filters detect

information by moving over each input image. In the first layer of CNN, in the picture, there are just a few basic patterns and colours are recognized, but patterns and colours that are more complicated are detected when going through the sequential layers. The filter uses the convolution process to locate features, and finally, as a result, a feature map is created. CNN's complexity decreases as the picture travels through the pooling layer. The characteristics are combined in the fully connected layers, and the SoftMax classifier is used to give the classification result(Guo et al., 2016).

However, 3D fingers knuckle identification using neural network techniques also comes with some challenges. For example, a large amount of training data is required by many existing neural network models, obtaining this large amount of data can be impractical for each human subject because, in real forensic or biometric scene scenarios, the availability of samples might be very limited with only one or even a few samples been available. Moreover, the development of a neural network based approach in this new 3D finger knuckle recognition problem requires experimental cycles for customizing network architecture and fine-tuning hyperparameters.

Therefore, this research, proposed a new simple CNN model that requires appropriate time and efficiency for the learning phase, especially we use ordinary personal computers with a normal CPU-based system.

The proposed CNN model receives an input image size of (224 × 224 × 3) and a total number of 26 subjects. There are five convolutional layers, three pooling layers, and three fully connected layers in this model. Figure 1 depicts the proposed model network architecture. As shown in Figure 1, the filter size has been increased from 64 in the first convolutional layer to 512 convolutions in the last convolutional layer to reduce invalid features that may be formed by noises in the previous layer or the input images. Additionally, small and medium changes between images can be detected with the help of convolution windows of different sizes. Moreover, each convolutional layer followed by a Rectified linear unit (ReLU) activation function, which has strong biological and mathematical underpinning. It represents a non-linear activation function that transforms the result of the convolution layer to a non-linear output by replacing all negative values with zero and is described as (Agarap, 2018)

$$Y = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} \quad (2)$$

where the output of the convolution layers is Y.

The reason for choosing the ReLU activation function is that, it is more efficient than other functions as all the neurons are not activated at the same time, rather a certain number of neurons are activated at a time. This implies that a neuron will be deactivated when the output of linear transformation is zero. In some cases, the value of the gradient is zero, due to which the weights and biases are not updated during the backpropagation step in neural network training. (Sharma et al., 2020)

In addition, a cross channel normalization layer has been used after the first and the second ReLU layers, which is helping to reduce detonating gradient and empowering a higher rate and faster merging for learning.

In the pooling layers, average pooling and maximum pooling are the most commonly used strategies. A detailed theoretical analysis of their performance was carried out by Bro et al. (Boureau et al., 2010). Schiller et al. (Scherer et al., 2010) further compared the two pooling operations and found that maximum pooling can lead to faster convergence, select excellent invariant features and improve generalization ability. (Guo et al., 2016) Thus, maximum pooling is applied after the first, second, and last convolutional layers with filters of size 3

× 3 and strides 2 × 2 to decrease the size of the feature map. Meanwhile, a feature map of 5 × 5 × 1024 pixels is obtained after the last pooling layer, which is then forwarded to the first fully connected layer as a single vector. In the fully connected layers, the first two layers contains 4096 nodes. They are followed by ReLU layer and dropout layer with 50% reduction of the neurons number, which helps the model to learn from neurons in different subsets and increases the required iterations to converge while reducing the time of training for each epoch. However, the third fully connected layer has 26 nodes, representing the 26 subjects in the CNN proposed model. Each Finally, the SoftMax function is used for classification purposes. the SoftMax function is a set of multiple sigmoid functions that are used in binary classification. It can be used for multiclass classification problems. In all conceivable classes, the probabilities of every class are computed, and the class with the greatest probability is selected as the target class. The yielded value is between 0 and 1.

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}} \quad \text{for } j = 1, \dots, K. \quad (3)$$

Since we are building a model to classify multiple classes, the SoftMax function is the best choice. This is because the output layer of the network will have the same number of neurons as the number of classes in the target. (Sharma et al., 2020) (Zeng et al., 2015)

The proposed model is trained to utilize both continuous forwards, backward passes on the presented training set.

Regarding the classification task of the proposed Model, specific metrics were recorded as follows: (a) where the model correctly predicts the right classes (True Positives, TP), (b) the model incorrectly predicts the wrong classes (False Negatives, FN), (c) the model correctly predicts the wrong classes (True Negatives, TN), and (d), the model incorrectly predicts the right class (False Positives, FP). Based on those metrics the accuracy, sensitivity, recall, precession and F1-Score of the model have been computed. The following equations explain the aforementioned metrics. (Nada Alay & Heyam H. Al-Baity, 2020)

$$Accuracy = (TP+TN)/(TP+TN+FP+FN) \quad (4)$$

$$Sensitivity = TP/(TP+FN) \quad (5)$$

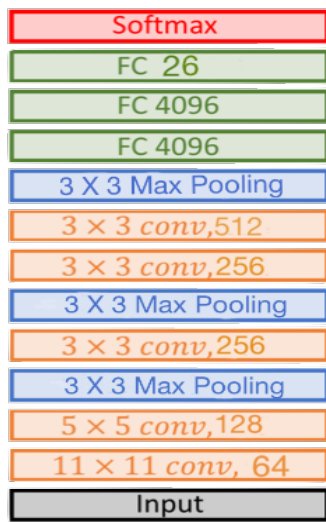
$$Precision = TP/(TP+FP) \quad (6)$$

$$Recall = TP/(TP+FN) \quad (7)$$

$$F1\text{-score} = 2*((Precision * Recall) / (Precision + Recall)). \quad (8)$$



(a) Proposed CNN Layers



(b) Proposed CNN Architecture

Figure. 1. The structure and the sequence of layers for the proposed network

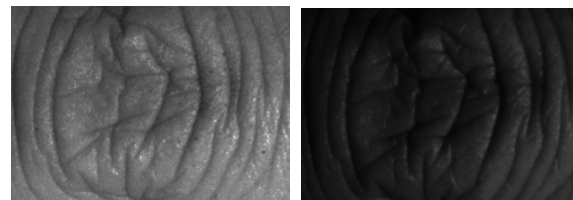
4. EXPERIMENTAL SETUP

In this study, the recently publicly available HKPolyU 3D finger knuckle image database (K. H. M. Cheng & Kumar, 2020) has been used for the performance evaluation of the proposed convolutional neural network. The 3D knuckle picture database from Hong Kong Polytechnic University is a two-stage database containing 2D and 3D knuckle images. This database has been acquired using a photometric stereo approach for the 3D imaging. The biometric imaging device consists of a camera, seven evenly distributed illuminations, a control circuit, and a computer. The database was obtained from 228 different subjects. Of the 228 subjects, 190 volunteered to provide data in session 2. Six forefinger pictures and six middle finger images are included in each session for each subject. However, there are 7 photometric stereo images for each 3D image. Therefore, forty-two 3D forefinger photometric stereo images and forty-two 3D middle finger photometric stereo images are available for each subject in each session.

This database of 3D finger knuckles includes challenging pictures that may reflect real-world situations in which the second session photographs were collected in different and various imaging situations or with a multiple imaging lens and lighting (K. H. M. Cheng & Kumar, 2021). See Figure. 1. Based on the concept used in (K. H. M. Cheng & Kumar, 2020), the authors observed that using the forefinger image can achieve better performance than using the middle finger image. However, we attempted to mitigate the impact of the issue with the middle finger by proposing a CNN model convenient to be used for testing middle fingers. Therefore, only the middle finger images of randomly selected 26 subjects have been used for the study. The selection of the subject was not correlated to any criteria's. However, Using more subjects is possible while taking longer for the training and testing process.

For each subject, there are forty-two 3D middle finger photometric stereo pictures available; therefore, 1092 images in session 1 have been used for training the proposed model, and the same number of images in session 2 has been used for the testing purpose. A total of 2184 images were tested and utilized to assess the suggested convolutional neural network's performance and quality.

The pictures in the dataset are divided into two different folders for testing and training, with samples for each subject in each folder. (See Figure. 2 for example).



Subject1_session1 Subject1_session2

Figure 2. 3D finger knuckle examples

5. EXPERIMENTAL RESULTS AND DISCUSSION

This part covers the outcomes obtained after running the proposed model. The experiment was conducted on a machine equipped with an Intel Core i7-2.8 GHz processor using MATLAB 2019b and Mac OS High Sierra.

To evaluate the performance of the proposed model, the accuracy and the testing time were calculated. The epochs and mini-batch size are changed during the training process to find the best model for 3D knuckle recognition. (See Table 1)

The reason behind using the mini-batch gradient descent, the batch of a fixed number of training examples, is to be able to update the parameters frequently as well as use vectorized implementation for faster computations.

Table 1. The results for different epochs and mini-batch size

Tests	Mini-Batch Size	Epochs	accuracy	Test time
Test 1	10	10	0.5321	19.225061
Test 2	15	10	0.7106	26.067008
Test 3	10	30	0.6923	24.173157
Test 4	15	30	0.619	23.611178
Test 5	16	30	0.6932	21.458587
Test 6	32	30	0.5549	19.232478

Based on the above results, the best model selected for the 3D knuckle recognition system is Test 2, the model with 10 epochs and a mini-batch size=15 has achieved a recognition rate= 71.06.

It can be seen from Figure 3 that the training validation accuracy obtained from Test 2 is equal to 96% in 1 hour and 32 seconds. The training time is relatively long because a computer with normal CPU capability is used, and the image dataset is rather large (224*224). Due to the small amount of data for each subject, the initial value given by the pre-training model is very low, less than 10%. Using small amounts of data for each person was to be closer to real forensic or biometric scenarios, where the availability of samples can be limited to one or a few samples for each subject.

The training loss value of the pre-training model is also shown in Figure 3. It is seen that the loss values decreased in the pre-trained model during the training stage.

The best model has been evaluated via the confusion matrix, where all the cases can be considered to evaluate the model. (See Figure 4)

It is clear from the results, that the proposed CNN method performs relatively well on the images used in this study. However, there is an obvious overfitting issue in the model where the training accuracy exceed 96% while the testing accuracy was just about 71%. One of the main reasons for network overfitting is the small size of the training dataset that have been used for each subject to be closer to real forensic or biometric scenarios. When the network tries to learn from a small data set, it tends to have greater control over the data set and ensure that all data points are fully satisfied. Thus, the network will try to remember every data point but failing to capture the overall trend of the data. Thus, the best performance has been obtained as a sensitivity of 71.06%, recall of 71.06%,

precession of 75.57%, and F1-Scor value of 70.41 % for the pre-trained model of Test2, in 26.067 seconds. See Table 2. The results were compared with some of the works that have been done recently in this area, including the works that have been mentioned in this research paper. The proposed model was compared with the recent solutions for both of the "Contactless Biometric recognition utilizing 3D Finger Knuckle Patterns." (K. H. M. Cheng & Kumar, 2020) and "Deep Feature Collaboration for Challenging 3D Finger Knuckle Identification (K. H. M. Cheng & Kumar, 2021) that are proposed in 2020 and 2021. These researches represent the earlier researches that are available to investigate the use of 3D finger knuckle patterns for biometric recognition. The proposed system provides relatively well results despite various challenges. As clear in Table 3, the main challenges of this study can be summarized as follows:

- 1- The authors in (K. H. M. Cheng & Kumar, 2020) and (K. H. M. Cheng & Kumar, 2021) notices that the fore-finger images attain a better performance compared to using the middle finger images. Therefore, they used fore-finger images in their studies. However, just middle-finger images were employed in this study to evaluate the suggested model's performance.
- 2- The lack of studies in this new biometric identifier has proven to be difficult to create such a deep neural network from scratch. Since (K. H. M. Cheng & Kumar, 2021) is the only previous study on the CNN-based approach for the 3D finger knuckle recognition problem.
- 3- This study, containing images that can be considered challenging with representing real-world scenarios where the second session of the images was obtained using different camera lenses, see Figure 2. Therefore, there are notable differences between the trained and the tested images that result in noticeable regression in the performance.

Lastly, it is important to note that the CNN model proposed in this work is very simple, yet effective to play a role in the use of 3D middle finger knuckle patterns for biometric recognition as it can work in environments that can be considered small like houses, offices or personal devices, where the training can be done easier.

Table 2.Values of performance metrics

Subjects	Sensitivity	Recall	Precession	F1-Score
P1	85.71	85.71	92.31	88.89
P10	88.10	88.10	66.07	75.51
P11	38.10	38.10	84.21	52.46
P12	92.86	92.86	95.12	93.98
P13	76.19	76.19	69.57	72.73
P14	78.57	78.57	68.75	73.33
P15	100.00	100.00	95.45	97.67
P16	59.52	59.52	86.21	70.42
P17	90.48	90.48	88.37	89.41
P18	61.90	61.90	52.00	56.52
P19	76.19	76.19	66.67	71.11
P2	69.05	69.05	90.63	78.38
P20	80.95	80.95	97.14	88.31
P21	76.19	76.19	35.16	48.12
P22	42.86	42.86	100.00	60.00
P23	54.76	54.76	52.27	53.49
P24	85.71	85.71	73.47	79.12
P25	95.24	95.24	52.63	67.80
P26	61.90	61.90	59.09	60.47
P3	21.43	21.43	60.00	31.58
P4	80.95	80.95	69.39	74.73
P5	33.33	33.33	93.33	49.12
P6	88.10	88.10	86.05	87.06
P7	73.81	73.81	100.00	84.93
P8	100.00	100.00	65.63	79.25
P9	35.71	35.71	65.22	46.15
Avg.	71.06	71.06	75.57	70.41

Table 3. Feature comparison with recent solutions

Challenges	Proposed Model "Deep 3D-Middle Finger Knuckle Recognition"	Biometric Identification "3D Finger Knuckle Patterns" (K. H. M. Cheng & Kumar, 2020)	Deep Feature Collaboration "3D Finger Knuckle Identification" (K. H. M. Cheng & Kumar, 2021)
Type finger images employed in this study	Middle-finger images were employed in this study	Fore-finger images were employed in their study	Fore-finger images were employed in their study
Lack of research efforts on this new biometric identifier	It represents the first study working on 3D middle-finger knuckle recognition using CNN	It represents the first study working on 3D fore-finger knuckle recognition	It represents the first study working on 3D finger knuckle recognition using CNN
Collecting the second session of images	The images belonging to the second session were acquired using different camera lenses	Not mentioned	The images belonging to the second session were obtained using different camera lenses

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