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A Dataset for Kinship Estimation from Image of Hand Using Machine Learning

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Abstract
Kinship (Familial relationships) detection is crucial in many fields and has applications in biometric security, adoption, forensic investigations, and more. It is also essential during wars and natural disasters like earthquakes since it may aid in reunion, missing person searches, establishing emergency contacts, and providing psychological support. The most common method of determining kinship is DNA analysis which is highly accurate. Another approach, which is noninvasive, uses facial photos with computer vision and machine learning algorithms for kinship estimation. Each part of the Human -body has its own embedded information that can be extracted and adopted for identification, verification, or classification of that person. Kinship recognition is based on finding traits that are shared by every family. We investigate the use of hand geometry for kinship detection, which is a new approach. Because of the available hand image Datasets do not contain kinship ground truth; therefore, we created our own dataset. This paper describes the tools, methodology, and details of the collected MKH, which stands for the Mosul Kinship Hand, images dataset. The images of MKH dataset were collected using a mobile phone camera with a suitable setup and consisted of 648 images for 81 individuals from 14 families (8 hand situations per person). This paper also presents the use of this dataset in kinship prediction using machine learning. Google MdiaPipe was used for hand detection, segmentation, and geometrical key points finding. Handcraft feature extraction was used to extract 43 distinctive geometrical features from each image. A neural network classifier was designed and trained to predict kinship, yielding about 93% prediction accuracy. The results of this novel approach demonstrated that the hand possesses biometric characteristics that may be used to establish kinship, and that the suggested method is a promising way as a kinship indicator.

Keywords
Hand geometrical features, Hand image dataset, Kinship prediction, MediaPipe, Neural Network.

I. Introduction

Kinship Verification is the process of achieving whether two people are related by blood. Because of its usefulness, it is a new and difficult subject that is receiving more and more attention [1]. Familial relationship prediction based on image processing and machine learning (ML) techniques is limited to facial images only. The hand images contain several biometric traits that were used to classify persons based on gender, age, or group affiliation. It can also be used for person identification and verification. A biometric technology is characterized as mean of verification, recognition, and their utilize in various spheres of life. Behavioral and Physiological are two divisions of biometric characteristics, as presented in Fig. 1 [2]. The choice of biometric trait in biometric system design is a critical issue. In theory, any behavioral, anatomical, or physiological characteristic of an individual can be used as a biometric feature . In the literature, geometric hand features make up the bulk of the hand features approved in most biometric systems [3]. Typical traits include finger length, finger breadth, palm width, and finger aspect ratio [4], finger

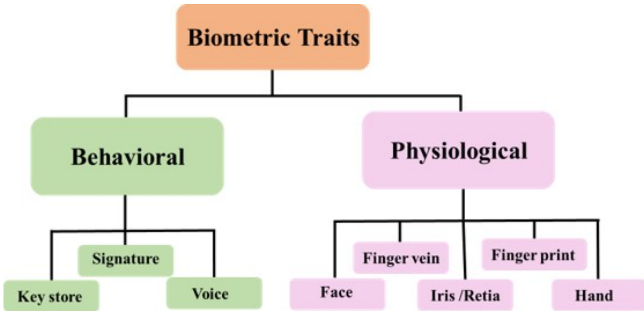


Fig. 1. Classification of Biometric traits

thickness, area of the fingertips, circle radii on the fingers and palms, and angles between fingers [3]. Images of the hand in general, or their geometry are not used in kinship recognition methods, but face images, and DNA analysis are common methods. DNA acquisition of sample has disadvantages such as long processing time, privacy issues, storage space, and lack of real-time matching [5].

Kinship recognition is a very important manner, especially after disasters, for criminal evidence, for missing children, and family relative verification [6] . In some cases, a person's face may be smashed or injured, therefore, its image cannot be used for kinship recognition. Here in this study, we are attempting to employ hand images for kinship recognition (especially the detection of the relatedness of an individual to a certain family) to offer additional assistance tools or to be fused with kinship recognition based on facial images. The first barrier in this way was the absence of hand-image's dataset based on kinship ground truth. To produce an image dataset, there were many parameters that should be selected properly and fine-tuned to get useful data like, image capturing setup, persons' information selection and saving, and image coding. This is called "image acquisition stage ", that is a crucial step in any biometric framework [7], after the image is captured, pre-processing is carried out to only get hand area information. Feature extraction is the next stage, and it is a distinctive form of reduction of dimensionality in image processing, can be performed using handcrafted methods or deep learning methods. This structure of hand consists of the length of the fingers, the width of the palm, the thickness of the palm, and the width of the fingers at various points. Even though these indicators do not greatly differ throughout the population, they can nevertheless be used to various situations [7]. The resultant feature vector from this stage will be used as an input to an artificial neural network for class prediction. As compared to other approaches, hand geometry offers numerous benefits, including a low computational methodology, a short template size, and a user-friendly design [8].

II. Literature Review

Databases are the basis for hand biometrics research. There are several hand image datasets created by researchers, which can be obtained from a scanner [9], a digital camera [10], or a USB camera [11]. Most hand biometric systems work with 2D images [?]. The objectives of datasets establishment were, special purpose (ID, gender recognition, etc.) or to make datasets available in the public domain to help researchers. Contact-based and contact-free-based hand geometry systems are the two categories. Pegs control the user's hand placement in contact-based, also known as peg-based. The freedom of putting the hand within the device in contact-free, also known as peg-free, might be viewed as a significant gain in practice. In a recent work-study, based on the contact-free-based hand geometry biometrics approach presented in [11], a large dataset of human hand images using USB Document Camera, (11K Hands), which contains dorsal and palmar sides of human hand images with a size 1600*1200. Another dataset was presented in [10], denoted as U-HD 1, It contains the right and left hand frontal and dorsal images of 57 persons (males and females), using a Samsung digital camera. The researchers in [12] used a scanner to collect 180 images of palms with a size of 2528*1800 pixels. Table I summarizes some literatures that deals with the use of hand images dataset and their purpose. Numerous earlier efforts have demonstrated success in a variety of applications using the databases indicated above and others, including identification, hand recognition, age determination, and gender determination. [10, 13–15]. The earliest successful device using the hand geometry technique was "Identimat," which was implemented during the 1970s [14]. With the increasing demand for reliable and automatic solutions, biometric recognition is becoming ever more widely deployed in many commercial, government, and forensic applications. In 2015, a work for verification purposes was presented [16]; Using the IIT Delhi Touchless Palmprint Database, the system achieved an accuracy of 95.5%. Hussein et al., achieved the same accuracy for identification and verification purposes; they worked on a hand image dataset of 35 persons and classified images using an artificial neural network [13]. In Gender Recognition Challenges, Mahmoud Afifi, tested a set of state-of-the-art techniques on the "11k Hands" dataset for gender classification, and the results showed that dorsal hand images possess distinctive features that could help with gender recognition and biometric identification problems [11]. Another work showed 90% accuracy in human gender recognition using the U-HD 1 hand image dataset [10]. A technique for predicting human age using hand photographs was reported in 2020; the results included a categorization into 17 age groups ranging from 18 to 75; the model employed was trained using the "11K Hands" dataset; and the approach demonstrated a 96.5%

accuracy rate [15]. Hand geometry systems are based solely on their shape, not on their fingerprints, so the reader can even read dirty and low-resolution hand images [5]. Hand geometry-based biometric systems use the numerous features retrieved from hand photographs to carry out tasks like identification or classification. Feature extraction can be performed using manual; handcrafted methods [17] [18] [19] or automated; deep learning methods [20] [21]. By learning from experience, ML enables computers to be programmed without explicit experience [22]. A recent development in machine learning is deep learning [23].Deep learning algorithms are better suited for large datasets, require high-end machines, feature engineering, a longer execution time, and are more interpretable and problem-solving-oriented than traditional methods [24]. The length, breadth, and aspect ratio of the fingers are common geometrical properties, as well as the width of the palm [4].

Kinship detection using computer vision is a new topic, and it has been used and studied for the last several years [25]. Most research in this field checks if two people are from the same family or not through facial images. The first attempt at kinship verification using human traits was made by Fang et al. by automatically classifying pairs of 150 pairs of parents and children's face images as "related" or "unrelated", The classification accuracy was 70.67% using KNN as a classifier [26]. From that point forward, endeavours continued in this field, which were all in light of facial images. From this literature review, we concluded that there were no previous works that have used the image of hands for kinship detection (Family-based person classification). In addition to that, there were no available datasets for this purpose. So, the research questions were, Can the image of hands be used for kinship detection? How? What are the useful features? and what are the appropriate methods to achieve this goal? This cannot be achieved without providing a suitable image dataset attached by its ground truth labelling. Hand geometry features and machine learning techniques were adopted to validate the usage of the created dataset.

III. Methodology

This paper proposes a new method to determine kinship relations based on hand biometric features using handcraft features extraction and supervised classifier. The proposed work was to design and implement a persons' kinship classification system based on the images of their hands. This proposal has not been addressed before. None of the available datasets have ground truth relating to kinship relations, so we had collected our own dataset. No previous work specified the most beneficial region or features of the hand to be used for that purpose therefore, many experiments have been done to find out that. In this research we also studied and investigated the most useful way for classification. In addition to that, a suitable image acquisition setup, the type of imaging device or devices and the pose of the hand had been investigated. Person identification and verification is the way to find a unique feature for each person, while gender classification is to separate the input images into two classes only. The proposed research differs from both, it needs to find the membership of a person to one of many groups or clusters. Framework of ANN proposed model shown in Fig. 2.

A. Dataset Creation

The dataset collection and metadata file were prepared during the image acquisition stage. Lighting, distance, direction for image capturing were selected practically from many experiences. Finally, following setup was used:

- A mobile phone application was prepared to be used for data collection and saving.
- Image capture setup was sat up for image capturing which consisted of mobile phone, holder, basement.
- The parameters of setup are empirically selected for practical image photography.
- The parameters of setup are empirically selected for practical image photography.
- Images are saved in jpg format.

For each individual 8 different images were captured (left hand-dorsal, left hand-palm, left hand-dorsal with open fingers, left hand-palm with open fingers) and the same for the right hand. Fig. 3 shows example of the generated dataset. Several experiments have been done, many images for many families have been collected and some of them were rejected for different reasons like (lighting problems, image noise, clipped images, bad resolution, and others).The useful images were saved and marked using a systematic code which contains relation of person to a family, age, hand side (right/ left , dorsal/palm), as characterized in Fig. 4. Dataset was collected by the researcher and his colleagues by applying the same procedure. Each image was accompanied using an Excel file with ground truth and information about each family (No. of person, No. of male, No. of female, age range, and the relation to other families). The generated dataset consists of 648 hand images of 81 subjects, they were (39 male and 42 female) belong to 14 families. The subjects have varying ages between 3 - 70 years old. Fig. 5 presents the number of families, the total number of people in each family, and the gender breakdown for each family. The major challenges are associated with non-uniform illumination and changes involved in hand positioning during the acquisition process.

B. MediaPipe

Google created the open-source MediaPipe framework. The initial release took place in 2019 [30] is a computer vision

TABLE I.
COMPARISON BETWEEN SOME OF THE REVIEWED HAND IMAGE DATASETS

	Refrences				
	[10]	[11]	[27]	[28]	[29]
Name	U-HD	11k hand	IITD Version1	PolyU Version2	NA
No. of image	15-17/person	11076	2300	7752	1200
No. of people	57	190	230	193	NA
Age	18-50	18-75	12-57	10-55	NA
Right- left	both	both	both	both	both
Image size(pixel)	1536 * 2048	1600 * 1200	800 * 600	NA	1290 * 270
Hand side	Dorsal - Palme	Dorsal - Palme	Palme	Palme	Palme
Capturing device	Digital camera	USB camera	Camera	Camera	Laptop camera
Purpose	Gender	Gender and ID	ID	General	Hand posture

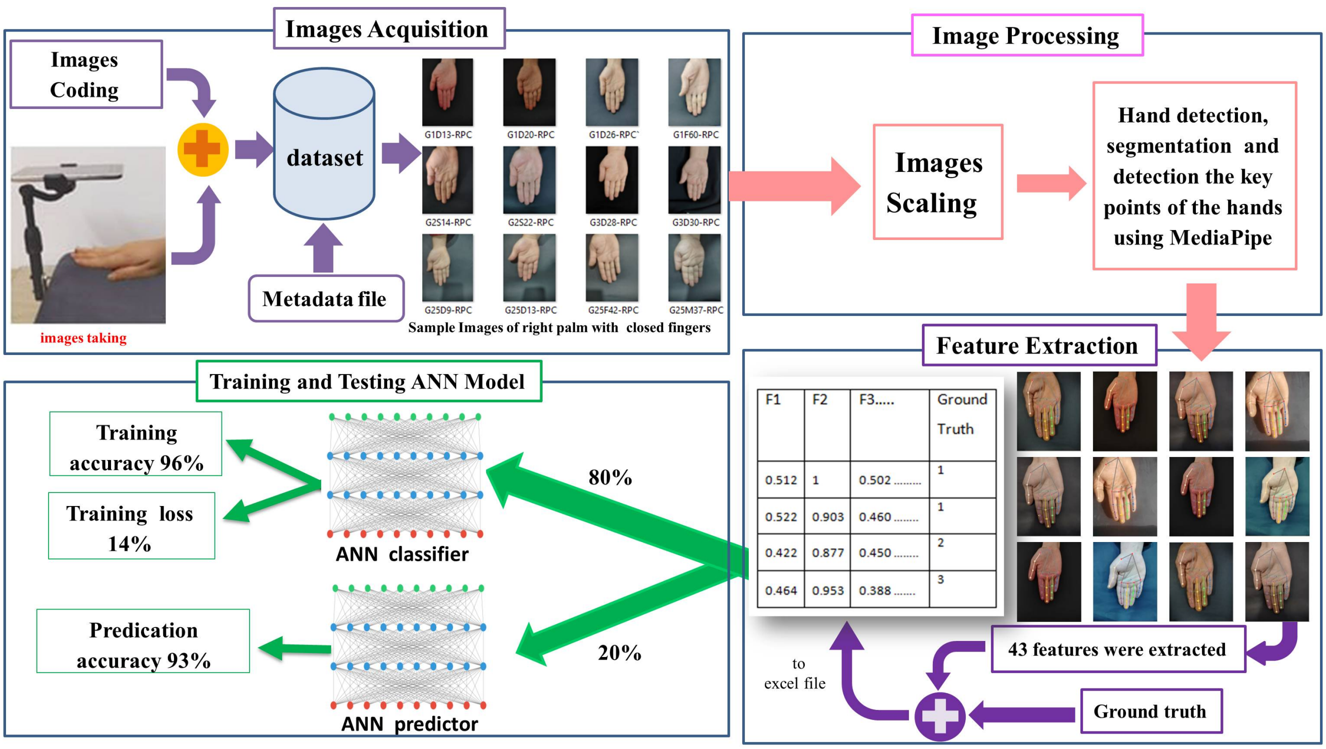


Fig. 2. Framework of the Proposed Work

system that employs deep neural networks and machine learning techniques to properly identify and track the essential hand parts in real-time, including the fingertips, palm, and wrist. A few applications provided by MediaPipe include hair segmentation, face detection, multi hand tracking, object detection, and monitoring. It refers to 21 joints or knuckle coordinates [31] as in Fig. 6 [18]. After the image is captured, pre-processing is carried out to only get hand area information. In our study, we utilized the MediaPipe method to recognize and segment the hand region after resizing the photos to 450*600 pixels. The aforementioned method was utilized to detect hands and identify significant hand key points that would serve as a guide for the feature extraction procedure.

C. Features Extraction

In our proposed work and based on the 21 key points that were obtained from the MediaPipe algorithm, we extracted 43 features from the image of right palm with closed fingers (RPC) for each individual in our dataset. As shown in Fig. 7 and Table II, the extracted features were 9(1 to 9) features

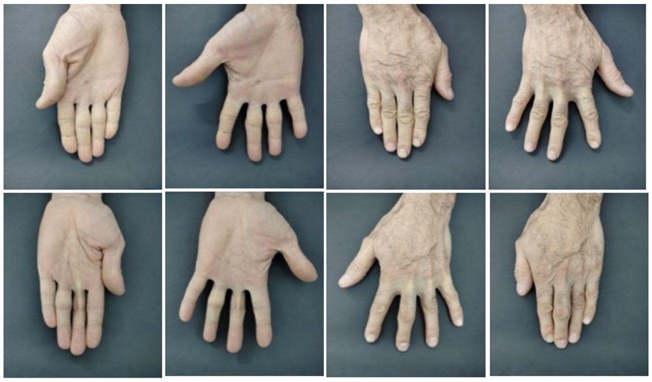


Fig. 3. Examples of the proposed dataset, eight hand images from the same person

Fig. 4. Image renaming method

based on slops. Slop calculation formula equation 1 [32], 21 (10 to 30) features based on angles that calculated as (2) [33], and 13 (31 to 43) features based on rational fingers' length. The resultant feature vector having the size (number of images multiplied by number of features/image) will be used.

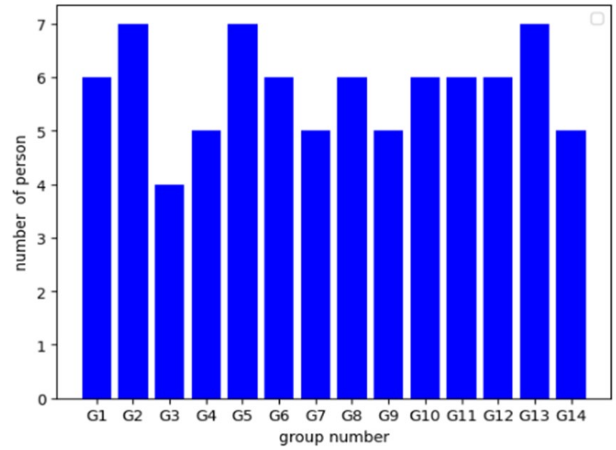
$$\text{slope} = \frac{y_2 - y_1}{x_2 - x_1} \tag{1}$$

$$\cos\theta = \frac{\mathbf{u}\cdot\mathbf{v}}{\|\mathbf{u}\|\|\mathbf{v}\|} \tag{2}$$

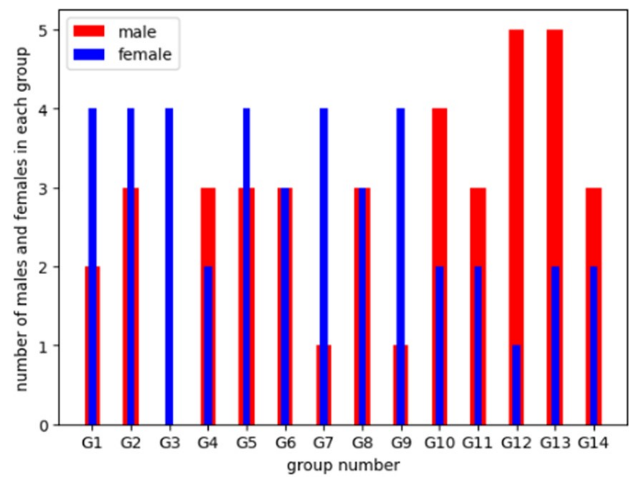
u and v are vectors.

D. ANN Classifier

A neural network (NN) is one of the most used machine learning algorithms [34]. The fundamental components of a typical neural network are lots of small, interconnected processing units, or "neurons," each of which generates a series of real-valued activations for the intended outcome. An ANN is composed of a network of artificial neurons, also known as network nodes [35]. The ANN structure is critical in solving problems, in the case that the number of input and output is fixed, the performance of the ANN model depends on the number of hidden layers and the neurons in each hidden layer. The characteristics retrieved from each hand picture



(a)



(b)

Fig. 5. Statistics of the created dataset.(a) Number of individuals per family. (b) Male-female count per family.

were mapped to a distinct label, and the output was fed to fully connected layers using ReLU activation function. We created an ANN model with two hidden layers of 10 neurons each. The final layer has a 14-node output and a softmax activation function. Fig. 8 and Fig. 9 show visual mode and table mode of network's structure. The network has 444 trainable parameters and 0 non-trainable parameters.

IV. Results and Discussion

Our own established dataset contains the hand images of 81 people. The images were acquired using a mobile camera. There were no pegs to direct the fingers, rings and other hand ornaments could be worn without being restricted. The classification task was achieved by building the appropriate neural

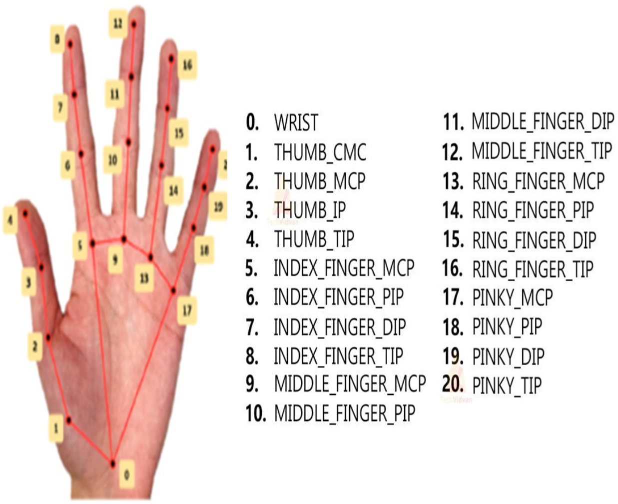
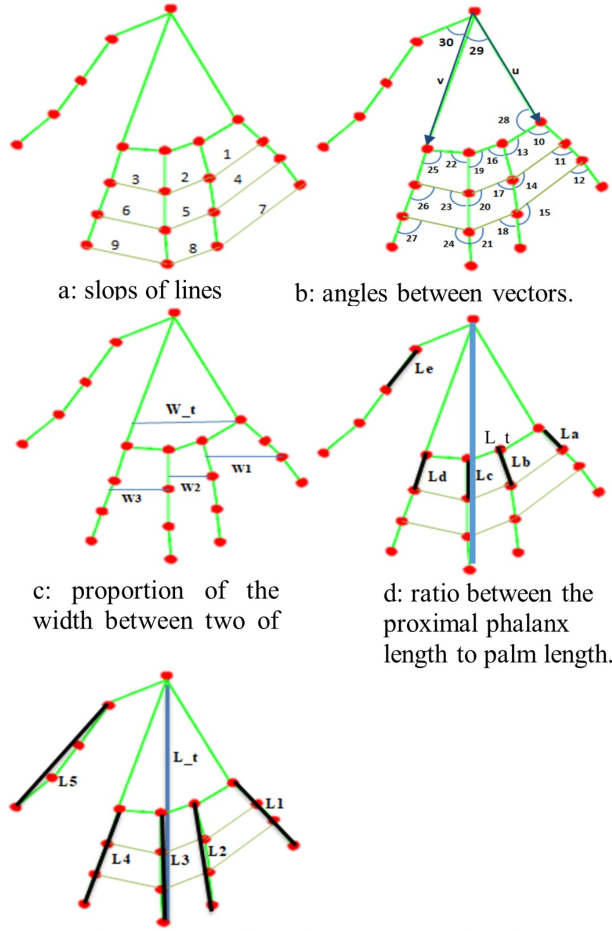


Fig. 6. Positions of the 21 hand key points [18]

TABLE II.
PROPERTIES OF HAND GEOMETRY FEATURES

Property	Description	Number
Line slop	slop of lines between two knuckle	9
Angles of knuckle	first calculate the vector between any two knuckles then find the angles between each two vectors.	21
Width	proportion of palm width to horizontal distance between two knuckle	3
proximal phalanx length	proportion of palm length to proximal phalanx length from each finger	5
Finger length	proportion of palm length to length of each finger	5



a: slops of lines

b: angles between vectors.

c: proportion of the width between two of

d: ratio between the proximal phalanx length to palm length.

e: ratio between the finger length to palm length.

Fig. 7. (a – e) Geometric representation of feature set

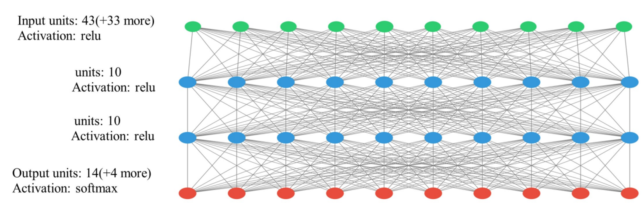


Fig. 8. Summary of the proposed ANN architecture

network model. A supervised artificial neural network that was described in Section D was trained and tested using 79 right palmar images from our own established dataset belonging to 14 families. All data were randomly split into two groups: training data and testing data, where training data make up 80% of the dataset and testing data make up 20%(63 images for training, 16 for testing). 43 features were extracted from each image (3397 features in total) and fed into the ANN for training and testing purposes. Evaluating the results of a classification task using a neural network involves a variety of metrics and strategies to determine how well the model is performing. Accuracy is a common metric that calculates the proportion of correctly classified inputs, as depicted in (3). The confusion matrix of the results is shown in Fig. 10 and Table III. Our goal in this work is not to attain high classification network accuracy, but to demonstrate the viability of kinship identification using human hands. We aspire, through our subsequent experiences, to improve result by identifying effective features, using data augmentation techniques, training the ANN model with features extracted from more than one aspect of the hand and using deep learning algorithms.

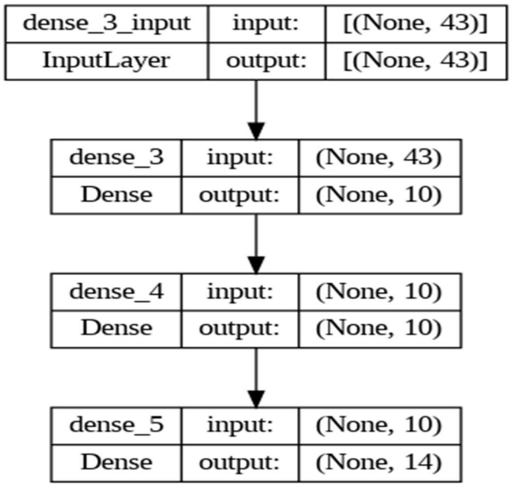


Fig. 9. The structure of the proposed ANN

In future, we plan to apply deep transfer learning for feature extraction as an alternative method to the handcrafted features extraction method that we had applied.

$$\text{Accuracy} = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ o\ Predictions} * 100\% \quad (3)$$

TABLE III.
SUMMARY OF PROPOSED MODEL RESULTS

Number of training images	63 images
Number of testing images	16 images
Train Accuracy	0.9677
Loss	0.1428
Prediction accuracy	0.9375
Training time	82s
Prediction time	1s

V. CONCLUSION

In this work, we created a database for studying the potential of employing hand biometric for kinship verification and have offered a set of helpful metadata of the proposed dataset, which is still being built and is expected to grow. Additionally, we used the ANN model for multiclassification problem to test the suggested dataset. The results of this novel approach demonstrated that the hand possesses biometric characteristics that may be used to establish kinship, and that the suggested method is a promising way as a kinship indicator. As a replacement for the manual feature extraction method, we used in the past, deep transfer learning is a method we intend to use in the future.

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CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

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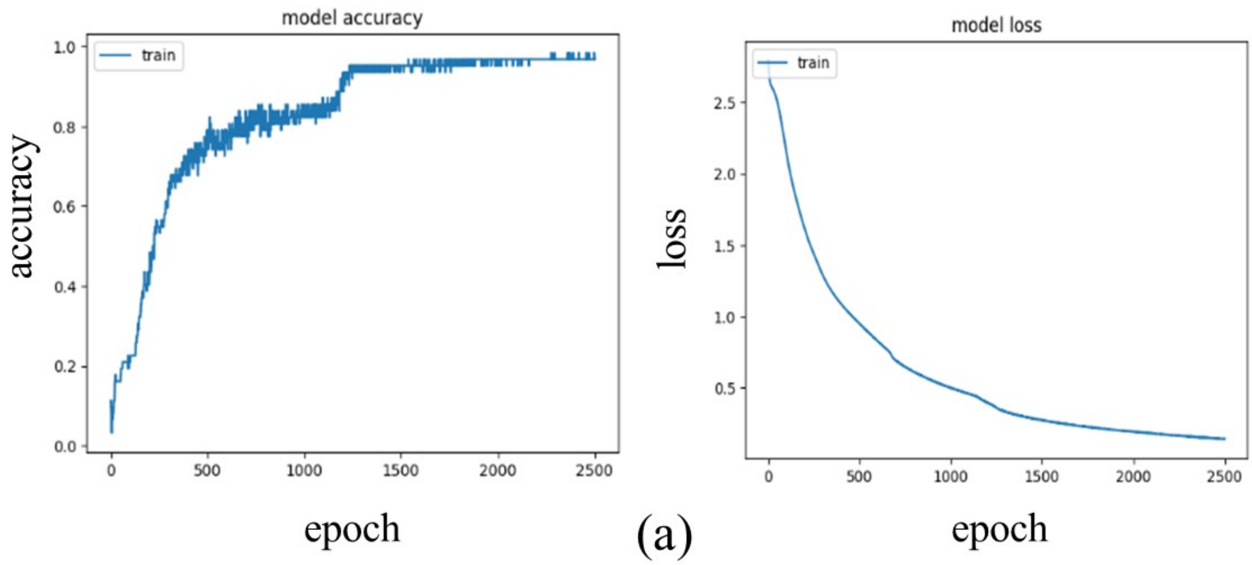
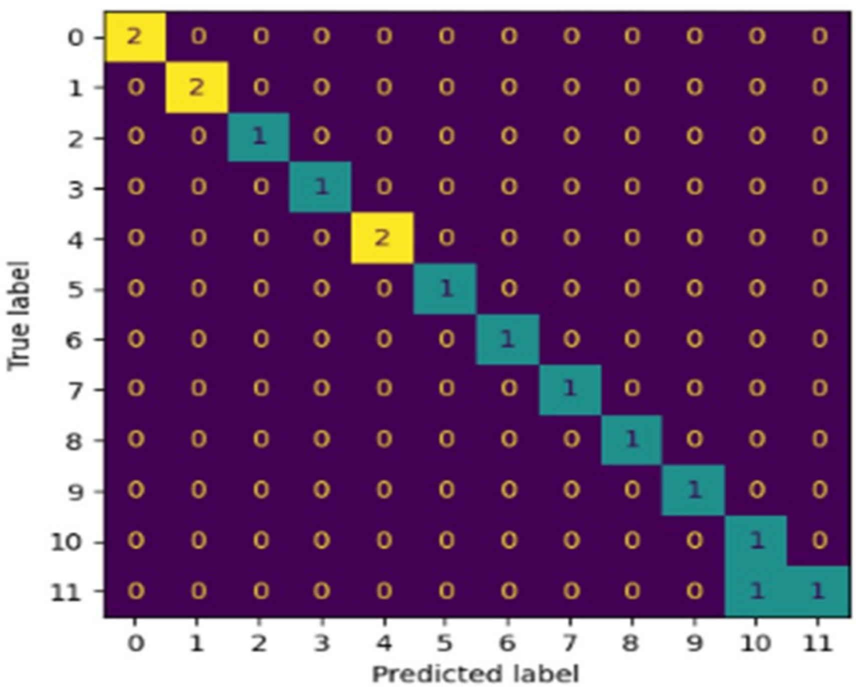


(a)



(b)

Fig. 10. (a) Accuracy and loss curve, (b) Confusion Matrix of the predicted

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