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Kinship Detection Based on Hand Geometry Using ResNet50 Model for Feature Extraction

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ABSTRACT

Kinship (family relationships) detection is important in many domains; it can be used in forensic investigations, adoption, biometric security, and more. It is particularly necessary in times of conflict and natural disasters, such as earthquakes, as it can help with reunions, and searches for missing persons. The most popular and very accurate means of establishing kinship is DNA analysis. Another method which is non-invasive is kinship estimate using facial images and computer vision accompanied with machine learning algorithms. Every component of the human body contains embeddedinformation that may be taken out and used for that person's identification, verification, or classification. Finding characteristics that every family has in common is the foundation of kinship detection. This paper examines a novel approach of kinship detection using the hand geometry. Deep transfer learning using the ResNet50 model was used to extract geometrical features from hand images. A neural network classifier was designed and trained to predict kinship and assembled as a top layer for the ResNet model. The test accuracy of this novel methodology was 92.8% *yielding to the hand has geometrical features that can be used to detect kinship, and that the proposed method is a possible potential way to identify kinship. We built our own hand image dataset that contains kinship ground truth metadata since there were no such datasets before. We called it "Mosul Kinship Hand (MKH) dataset", which includes 648 photos of 81 people from 14 households (8 different hand images per person), and it was used in this research.*

Keywords:

hand geometrical features, kinship detection, transfer learning, ResNet50.

1. INTRODUCTION

With machine learning, we can now reliably predict the features and extract important facts from large databases, which has completely changed the way we approach complex problems. The possibility of using machine learning algorithms to determine a person's family membership based on visual signals from images has been made possible by this research. The human body's biometric features are classified into two categories: physiological and behavioral. Physiological characteristics include features like hand geometry, iris pattern, finger vein, and fingerprint; behavioral characteristics include human attitudes like handwriting, signatures, voice prints, and keyboard typing.

Multiple biometric features seen in hand images are used to categorize people according to their gender, age, or membership in a group. There are five different types of biometric modalities for the hand: hand shape [1], hand geometry [2], fingers geometry [3], palm feature [4], and hand skeleton [5]. Since any behavioral, anatomical, or physiological characteristic of an individual can be used as a biometric feature, selecting a biometric trait is crucial when designing a biometric system.

Most biometric systems consist mostly of geometric hand features [6]. When compared to other methods, hand geometry has several benefits, such as medium cost and low-cost algorithm, public popularity, and user-friendliness [2]. Nevertheless, no hand image collection based on kinship ground truth is available. Carefully selected and adjusted factors, such as image capturing setup, person selection and saving, and image coding, are necessary to produce a hand image dataset. Datasets, which can be acquired from scanners [7], digital cameras [8], mobile cameras [9], or USB cameras [8], are essential to hand biometrics research. The majority of hand biometric systems use 2D photos and are either created specifically for these kinds of images or to make them publicly available [10]. A summary of some of the literature on the use and purposes of hand image datasets is provided in Table 1. Contact-based and contact-free-based hand geometry systems are the two types of such systems. While contact-free systems let users place their hands within the gadget, contact-based systems use pegs to control hand placement. Numerous researches have shown that hand geometry could be successfully used for a variety of tasks, such as gender, age, and person recognition [11], [12], [13], [8]. "Identimat" was the first successful device to use hand geometry in the 1970s [12].

Hand geometry-based biometric systems identify or classify users based on features extracted from hand images. Features can be extracted manually using handcrafted approaches [14], or automatically using deep learning methods [15], [16]. Compared to previous methods, deep learning algorithms are more interpretable and problem-solving focused, demand high-end processors, and work better with enormous datasets.

Recently, there has been usage and research in the field of kinship detection by computer vision [17]. The majority of this field's research employs facial image analysis to establish the relationship between two people. Fang et al. attempted the first kinship verification using human features by automatically classifying pairs of 150 pairs of parent-child facial images as "related" or "unrelated." Using KNN as a classifier, the classification accuracy was 70.67% [18]. From that point on, research in this area was conducted using just facial images.

Upon conducting a literature review, we concluded that no previous work has employed hand images for kinship detection, also known as family-based person classification. There were also no datasets available for this purpose. The research questions were; Is it possible to detect kinship using a hand image? What and Which features are functional? how may this be accomplished, and in what ways?

If an appropriate image dataset with its ground truth labeling is not provided, this research cannot be accomplished. Therefore We have built our own hand image dataset with kinship metadata named "Mosul Kinship Hand" (MKH) dataset. The developed dataset's usability was validated through the use of machine learning techniques and hand geometry features.

2. THE PROPOSED METHODOLOGY

This paper investigates the use of hand images for kinship detection using supervised classifiers and transfer learning for feature extraction. The suggested task was to design and implement a system for classifying people according to their kinship based on images of their hands. This idea is considered novel. We collected

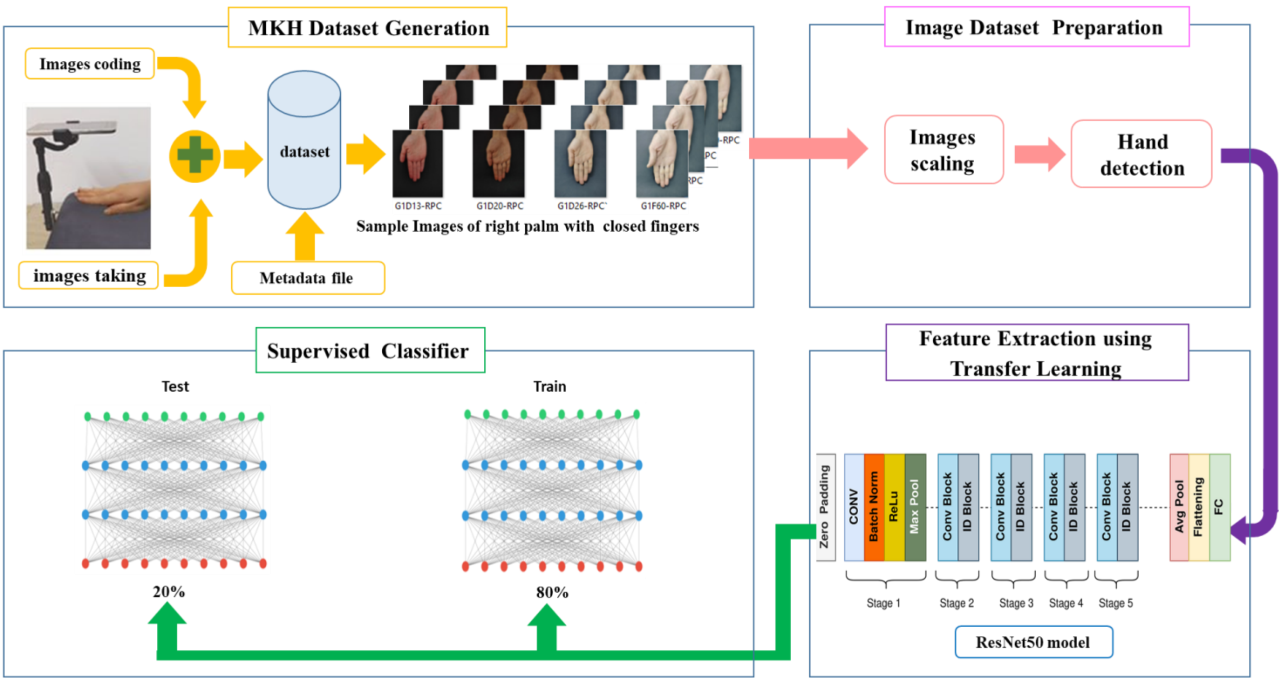

Fig. 1 Framework of the Proposed Work.

our own dataset because kinship relationships are not available in the public datasets. Gender classification divides the input images into two classes exclusively; person identification and verification to find a distinctive trait for each individual. Unlike the other two, the suggested research aims to determine an individual's participation in groups. The proposed framework is depicted in Figure 1.

2.1 The MKH Dataset

Data collection and storage were done via a mobile application that was created for this purpose. The setup parameters for the best image capturing technique were selected empirically. JPG format was used to store the images. Eight distinct hand images (hand dorsum, hand palm, hand dorsum with open fingers, and hand palm with open fingers for both hands), were captured for every individual. An example of the Mosul Kinship Hand (MKH) generated dataset is shown in Figure 2. Many images for multiple families were collected; however, some of them were rejected due to problems like lighting, noise in the images, image clipping, low quality, and other causes. The useful images were saved and marked using a systematic code that includes details about an individual's age, hand side, palm, dorsal, open, closed , and the relation to their family. The final dataset consists of 648 hand images of 81 individuals aged 3 to 70, and it is made available for public research upon the request of the author.

2.2 Features Extraction

Table 1 Summary of some of the reviewed hand image datasets.

	[19]	[23]	[8]	[1]
Name	11k hand	IITD Version1	U-HD	NA
N. of image	11076	2300	15/person	1200
N. of people	190	230	57	NA
Age	18-75	12-57	18-50	NA
Right- left	both	both	both	both
Image size(pixel)	1600 x 1200	800 x 600	1236x2048	1290 x 270
Hand side	Dorsal - palm	palm	Dorsal-palm	palm
Capture device	USB camera	camera	Digital camera	Laptop camera
Purpose	Gender recognition & ID	ID	Human gender classificatio n	hand posture recognition

Dimensionality reduction, another name for feature extraction, is important because it makes models simpler, improves human interpretation, lowers computing costs, and guards against overfitting and duplication [21].

Our dataset's features were extracted using the pre-trained ResNet model, and then we designed and trained a back propagation feedforward ANN to make use of these features in the task of classifying hand images. Using a pre-trained ML model, known as transfer learning, has the main advantage of utilizing CNN's capacity to extract general features from a sizable dataset, which can be useful even in cases where the dataset is small. These models can be applied to both fine-tuning and

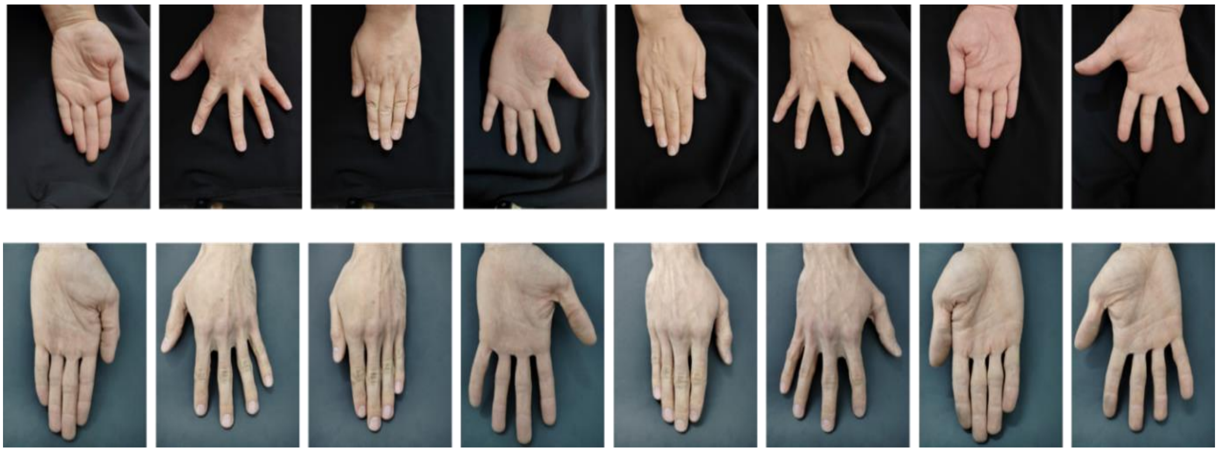

Fig. 2 Eight hand images are represented visually for a Person in the first row and for another Person in the second row.

Feature extraction techniques can help a machine learning-based model or system understand the data better, make predictions more accurately, and save costs on computing or training time [20].

feature extraction. About 1.2 million photographs were used to train the ResNet50 model, and an additional 50,000 images for validation and 100,000 images for testing, so it is a deeply trained model on feature extraction, and it can be used to extract features from other types of images that were not used in training.

2.3 ANN Classifier

The ANN structure is essential for problem-solving. If the number of input and output is fixed, the ANN model's performance is determined by the number of hidden layers and the number of neurons in each hidden layer.

The suggested architecture of an Artificial Neural Network (ANN) is intended to be used for a classification problem, specifically utilizing the features that have been taken from a ResNet50 model which provides 1000 features. As shown in Figure 3, there are 1000 nodes in the input layer, and each one accepts a unique feature from the feature set obtained by ResNet50. Then, the 512-node initial hidden layer is added to identify complex patterns in the data. Next, a dropout layer with a 0.5 rate deactivates half of the nodes randomly during training to reduce overfitting. The 256-node second hidden layer improves the learnt representations even further. For regularization, an additional dropout layer with a 0.5 rate is added. The output layer, consisting of 14 nodes, displays the network's goal for classification in 14 different categories.

The overall architecture places a strong emphasis on the use of dropout layers to improve model generalization—a critical function when working with potentially sparse training data.

2.4 Trianing and Testing

using the backpropagation and an optimization method known as (Adam), The proposed neural network was trained and tested using our own established and labeled dataset of 14 families. The data was split manually to 80% for training and 20% for testing. The classifier was trained and tested using 81 right palm hand images with closed fingers (RPC) (67 images for training, 14 for testing), where disparity was adopted for the selection of the test set as shown in Figure 4.

The ANN classifier was trained on the training set of the MKH dataset. The ResNet50 model was frozen while training. Then the test set was used to evaluate the classification performance of the proposed method.

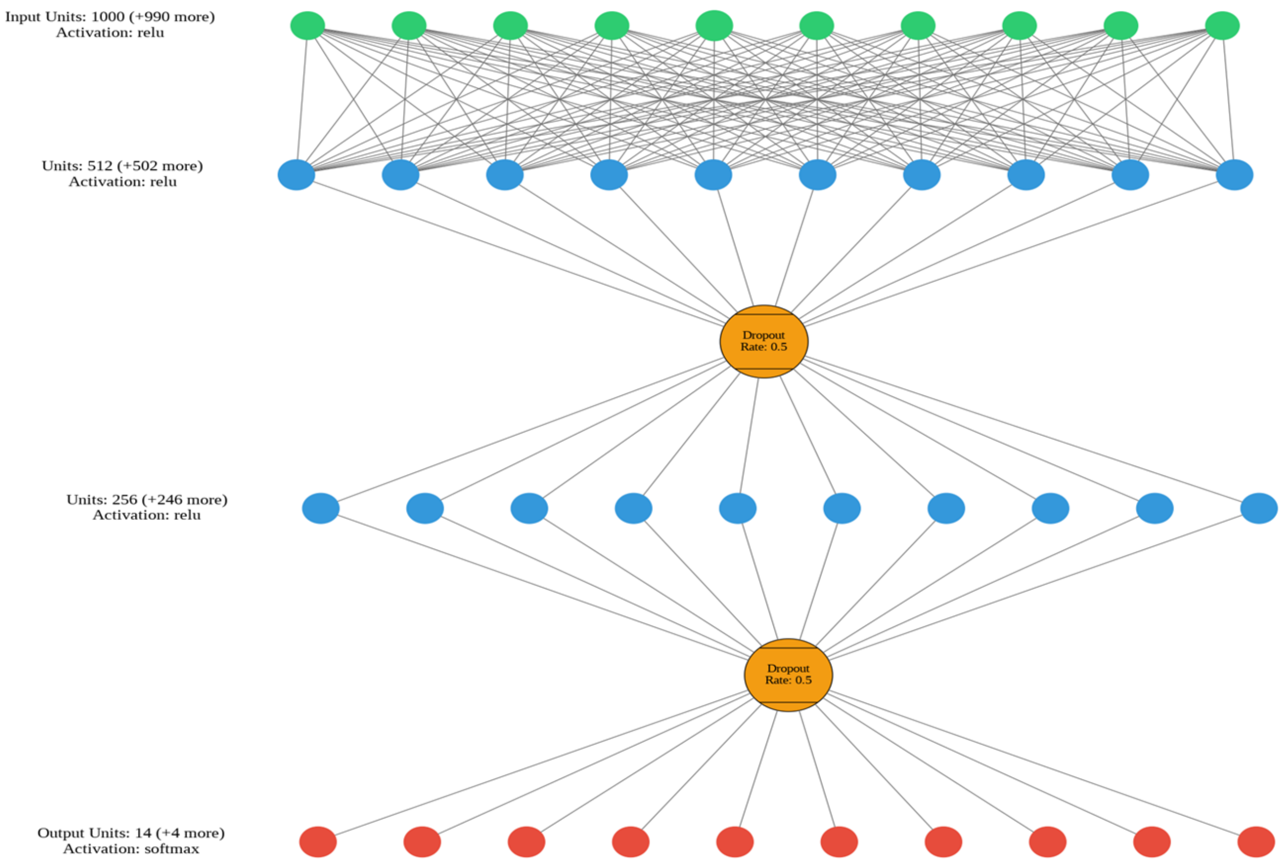

Fig. 3 The Architecture of the proposed ANN classifier.

Fig. 4 The Test Images that Isolated from RPC Sub-Dataset.

3. RESULTS AND DISCUSSIONS

The accuracy was calculated for the evaluation of both training and testing results according to equation (1).

A confusion matrix breaks down the model's predictions in detail. It displays the true positives, false positives, and false negatives. The training accuracy and loss curves, in addition to the confusion matrix for testing predictions are shown in Figure 5 and listed in Table 2. With just 67 training images and 14 test images, the model was trained on a rather small dataset but gave acceptable results due to the use of deep transfer learning techniques. The training accuracy was 96.77%, demonstrating its capacity to efficiently learn and generalize patterns from the given data, despite the small size of the training set.

The prediction accuracy was 92.8% throughout testing, which indicates that it is capable of accurately classifying people based on family relations using hand images.

Table 2 Summary of the Results.

Number of training images	67 images
Number of testing images	14 images
Train accuracy	0.9677
Prediction accuracy	0.928
Training time	21s
Prediction time	0.1s

The model's computational efficiency is demonstrated by its low training duration of 21 seconds. The model can classify data quickly, as evidenced by the prediction time, which is remarkably short at 0.1 second.

$$accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} * 100\% \quad (1)$$

4. CONCLUSION

Throughout this research,a methodical approach was used to investigate the suitability of hand geometry for kinship detection. To act as the study's main source of information, a specialized database was created by the authors and called the MKH dataset. A metadata file with image descriptions, information, and labeling was created and attached to the MKH image dataset. Transfer learning using the pre-trained ResNet50 CNN model was used for deep feature extraction. ANN was designed to be used as an upper layer on ResNet50 model for classification. The ResNet50 model was selected empirically and found to be suitable for hand geometrical feature extraction.

The results of this novel approach demonstrated that the hand has geometrical characteristics that may be used to classify persons to their famelies, and that the suggested method is a promising way as a kinship indicator.

Our work aim was to show that kinship detection by human hands is possible, rather than achieving high classification network accuracy. By finding useful features, employing data augmentation methods, training the ANN model with features taken from several hand aspects, and utilizing deep learning methods, we hope to improve the results through future works.

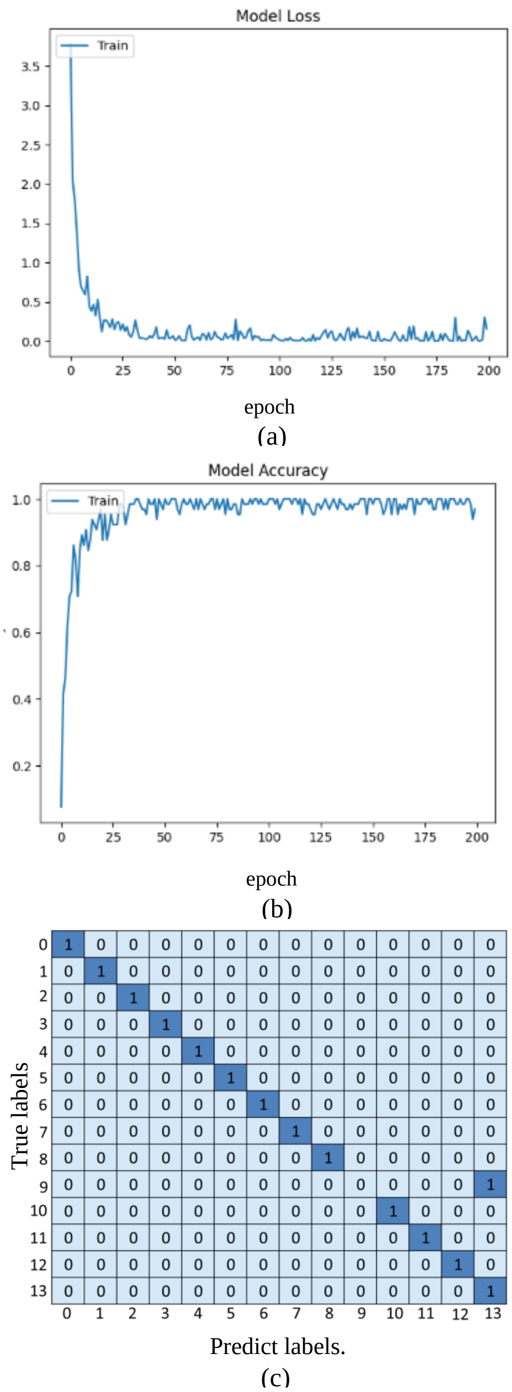

Fig. 5 (a) Trian Accuracy Curve, (b) Loss Curve, (c) Confusion Matrix of the Predicted Result.

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استخدام تعلم الآلة لتصنيف الأفراد استنادًا إلى صور اليد

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الملخص

إن اكتشاف علاقات القرابة (العلاقات العائلية) مهم في العديد من المجالات؛ ويمكن استخدامه في تحقيقات الطب الشرعي، والتبني، والأمن ، وغيرها . وهو ضروري بشكل خاص في أوقات النزاع والكوارث الطبيعية، مثل الزلازل، لأنه يمكن أن يساعد في البحث عن الأشخاص المفقودين. الوسيلة الأكثر شيوعًا والأكثر دقة لإثبات القرابة هي تحليل الحمض النووي. هناك طريقة بديلة غير جراحية وهي تقدير القرابة باستخدام صور الوجه وخوارزميات التعلم الآلي.

يحتوي كل جزء من جسم الإنسان على معلومات مدمجة يمكن إخراجها واستخدامها لتحديد هوية ذلك الشخص أو التحقق منه أو تصنيفه. إن العثور على الخصائص المشتركة بين كل عائلة هو أساس اكتشاف القرابة. نحن ندرس النهج الجديد لاكتشاف القرابة باستخدام هندسة اليد. لقد أنشأنا مجموعة البيانات الخاصة بنا لأن حقيقة القرابة كانت مفقودة من مجموعات بيانات الصور اليدوية المتوفرة. تم جمع مجموعة بيانات تمت تسميتها يد قرابة الموصل (MKH)، والتي تضمنت 648 صورة لـ 81 شخصًا من 14 أسرة (8 صورة يد لكل شخص)، باستخدام كاميرا هاتف ذكي تم إعدادها بشكل مناسب.

تصف هذه الورقة أيضًا التنبؤ بالقرابة في التعلم الآلي باستخدام مجموعة البيانات هذه. تم استخدام نموذج ResNet50 لاستخراج الميزات العميقة من مجموعة بيانات الصور اليدوية. تم تصميم وتدريب مصنف الشبكة العصبية للتنبؤ بالقرابة. وأظهرت نتائج هذه المنهجية الجديدة أن اليد لديها ميزات يمكن استخدامها للكشف عن القرابة، وأن الطريقة المقترحة هي وسيلة محتملة لتحديد القرابة.

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الكلمات الدالة:

ميزات اليد البيومترية، كشف القرابة، نقل التعلم، الشبكة العصبية.