Diyala Journal of Engineering Sciences

Journal homepage: https://djes.info/index.php/djes

ISSN: 1999-8716 (Print); 2616-6909 (Online)

Family Membership Detection from Palm-Skin Texture Using Transfer Learning: A New Kinship Approach

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ARTICLE INFO

Article history:
Received November 20, 2024
Revised August 02, 2025
Accepted August 06, 2025
Available online September 01, 2025

Keywords:
Skin Texture
Deep Transfer Learning
EfficientNetB0
VGG16
Kinship Detection

ABSTRACT

The detection of a person's membership in a family is crucial in many cases, and the need for it becomes urgent during and after wars and natural disasters. While DNA testing and facial images are common methods for kinship detection, they have limitations in certain scenarios. This paper presents an innovative approach to intrafamily kinship classification using palm skin texture images, a modality not previously explored for this purpose. Unlike conventional palm biometric verification aimed at individual identification, this research investigates inherited skin texture patterns to establish familial relationships. A hand palm dataset was created from the MKH (Mosul Kinship Hand) images dataset. It contains 332 segmented and annotated skin images from 84 individuals across 15 families, with multiple samples per person. Two deep convolutional neural network pre-trained models (VGG16 and EfficientNetB0) were used independently for feature extraction via transfer learning. Based on these features, neural network classifiers were designed to detect the membership of an individual to one of the given families. The results were evaluated using the appropriate metrics and gave a test accuracy of 96% by using EfficientNetB0 and 79% from VGG16. The findings of this study suggest that hand palm images may offer a promising and practical preliminary approach to kinship detection. The dataset utilized in this study is accessible upon request from the author to support reproducibility and encourage further research.

1. Introduction

It is essential to find families of dead bodies, unconscious individuals, old people with dementia, and children during and after earthquakes, tsunamis, wars, and other types of disasters. Finding the blood or genetic relative to a person or the family membership [1] are two types of kinship detection or verification. Kinship detection is crucial in family reunions, searching for missing people, and criminal investigations. The common method for kinship detection is via DNA testing, which is accurate and dependable but requires qualified labs and is expensive. It is based on comparing the DNA map with the saved maps or with the DNA map of a certain person suspected to be a relative [2]. For some reasons, like the degradation of biological samples and the difficulty in finding biological samples from kin, genetic kinship verification is unapplicable in some catastrophes [3]. Anyway, DNA test results are very reliable and officially considered. Kinship detection using computer vision is another approach and can be used in the same application fields [4]. Most studies have primarily focused on facial imagery. This

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DOI: 10.24237/djes.2025.18310

research, however, is driven by the need to identify family members in scenarios where facial data is either unavailable or unreliable, such as in disaster-stricken regions. Facial images are used in most cases to find the relationship between two people. It is less reliable until now and mostly used to detect whether two facial images are related or not. It is less expensive, doesn't rely on special tools or test labs, very fast, and can be applied using an ordinary processing unit via suitable software, and has attracted many researchers in the last few years [5]. Another field of application is criminal investigations, which needs the integration of many resources to solve criminal puzzles in the modern era [6].

Kinship detection from facial features is based on the fact that genetic heritages from parents cause visual similarities within the family. [7]. The same fact applies to other parts of the human body. [8 – 11], but it may be hard or impossible to detect visually. In the era of digital imagery, there is a need for detecting kinship in many applications of everyday life, from social usage to law enforcement. [12], and the revolution in deep learning for visual kinship recognition is just beginning [1].

Deep Transfer Learning (DTL) was employed in this work for feature extraction from images of the hand palm skin from a dataset generated for this purpose. VGG16 and EfficientNetB0 models were adopted for this purpose. VGG16 is a deep convolutional neural network (CNN) developed by the Visual Geometry Group at the University of Oxford. The architecture consists of 13 convolutional layers and 3 fully connected layers. It utilizes compact 3x3 filters, each combined with ReLU activation functions and max-pooling layers for image down-sampling [13]. The number of filters starts at 64 in the initial layers and increases to 512 in the final layers. VGG16 offers significant improvements over previous architectures due to its depth, enabling it to capture more complex features [14], though it is computationally intensive and slow to train. EfficientNetB0, developed by Google in 2019, is a compact and straightforward model from the EfficientNet series. It uses a compound scaling method to optimize network depth, width, and resolution, improving accuracy without significantly increasing computational demands. With fewer parameters than older architectures like VGG16 or ResNet, it achieves equal or superior accuracy [15]. It's ideal balance of accuracy and efficiency makes EfficientNetB0 widely used in transfer learning and various computer vision tasks [16, 17]. Both models are widely utilized for transfer learning[14, 18], acting as powerful feature extractors for image-related tasks due to their pre-trained weights on ImageNet, a dataset containing over 1.2 million labeled images across 1,000 distinct classes.

The biological mechanism of heredity was the basis and the motivation behind this research. This paper explores a novel approach to using skin texture images for detecting kinship or family membership. The adopted methods and tools are clarified, along with the demonstration and discussion of the test results showing the validity of the proposed idea.

This study presents the following key contributions:

- **Introduction of Palm Skin Texture:** Proposes palm skin texture as an innovative and supplementary biometric modality for verifying kinship relationships.
- **Development of a Dedicated Dataset:** Establishes a new dataset comprising palm skin images from 15 families (84 individuals, 332 images), to facilitate research in kinship detection.
- **Comparative Analysis of Deep Learning Models:** Evaluates two deep transfer learning models, VGG16 and EfficientNetB0, for extracting features from palm skin images, incorporating the impact of data augmentation and fine-tuning techniques.
- **Validation of Feasibility:** Demonstrates the practicality and potential of leveraging deep learning methods with palm skin texture for effective kinship detection.

This paper is structured in sequence as literature review, dataset generation, methodology, results and discussion, and conclusions.

2. Literature Review

Since a new idea is presented here and there were no previous works on the same research line, the following literature review will demonstrate the related research lines and methods focusing on computer vision and machine learning techniques.

2.1. Face Kinship

Facial kinship verification (FKV) employs computer vision methodologies to ascertain familial relationships through the analysis of facial images. It has attracted researchers in the last few years and is still facing challenges [19]. FKV is based on facial feature extraction, either via handcrafted or deep convolutional neural network (DCNN) methods [20]. However, it still needs more investigation, considering the specialty of each family and the differences in the relative images [21]. Human FKV was compared with computerized methods [22], showing superior performance for machines with still images and for humans with video streams [23]. A method was proposed to reduce the aging effect on FKV using two feature sets: identity-set and age-set [24]. An improved algorithm for kinship detection utilized age transformation, where artificial intelligence adjusted facial images to resemble nearby ages, achieving an accuracy of 76.38% [5]. RR. Fang et al. used cropped regions from facial images to identify a person's family [25]. In another investigation, a comparison method focused on identical facial segments from parents and children was used instead of analyzing their entire facial images [26]. FKV was enhanced through a fusion of several types of texture descriptors along with facial features [27] or by combining two types of features [28].

Another approach studied the kinship detection of a child based on features from both parents, instead of one of them[29] . Other research lines focused on identifying identical twins [30], finding kinship type [31], and using video for FKV rather than photos [32]. The prediction of a child's facial appearance from facial images of his parents was presented as a new method [33]. Two types of features were utilized to classify photos of groups of people as family or non-family using CNN: geometrical and textural features of the faces [34].

Improvements of 5.2% to 10.1% over prior work were achieved using a DCNN employing a specific facial key points method [35]. 3DCNN was utilized for FKV by leveraging salient features [36]. Resnet50 model was adopted by A. Othmani et al. to extract pattern features from facial images of two persons and find kinship using a deep neural network classifier with 11 classes, achieving an accuracy of 60% [7]. C. Bisogni and F. Narducci conducted experiments on Siamese Neural Networks (SNN) to detect kinship and its type, but the results were unpromising for kinship type detection [37]. Several other methods for kinship detection and classification exist. Notably, X. Wu, E. Granger, and colleagues were the first to combine audio feature fusion with facial image features for kinship verification, employing metric learning with SNN [38]. E. Liagre and colleagues studied the kinship of individuals buried in the Middenbeemster cemetery by analyzing the structure of foot bones, discovering that these anatomical features indicated close genetic relationships among them [39]. A study on the inheritance of lip-print patterns from parents was conducted using samples from the Deutero-Malay population. The findings indicate that a child's lip pattern tends to resemble the mother's more closely than the father's [40]. Research by G. O'Brien and K. Murphy revealed that siblings' fingerprints are largely similar, differing only in certain unique characteristics that serve as personal identifiers. They also discovered that the primary features of fingerprints are genetically inherited across multiple generations within families [41]. The genetic inheritance of fingerprints from parents was also investigated using Deep Transfer Learning (DTL) techniques [4]. Also, kinship detection from hand geometry features through DTL was studied and verified with an accuracy of 93% [11].

2.2. Skin Texture

Human skin, the body's largest organ, has garnered considerable research attention across various scientific fields, including computer vision. The skin's texture was analyzed for various purposes, including health assessment and disease detection or classification, using different feature extraction techniques [42]. Palmar skin exhibits characteristics that make it well-suited for personal verification and identification purposes, as it is less susceptible to alteration by environmental conditions and routine activities.

2.3. The Research Gap

Facial image analysis has proven valuable for kinship verification. However, its application in forensic investigations and disaster victim identification is limited by challenges such as physical disfigurement and privacy concerns. While hand geometry and lip prints have emerged as potential tools for kinship verification, their development remains nascent. To bridge these gaps, palm skin texture is introduced as an innovative and supplementary biometric modality, offering enhanced kinship detection capabilities, especially in complex scenarios.

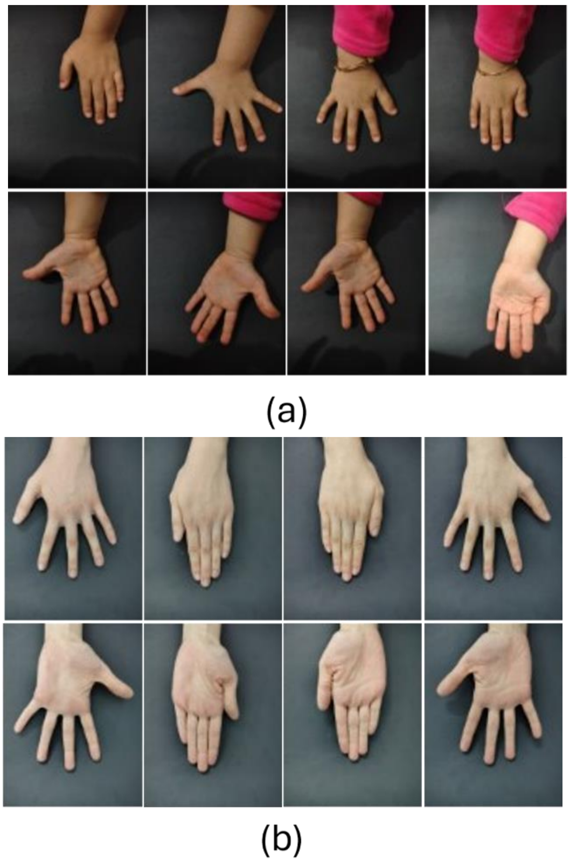

Figure 1. Samples for two individuals of the MKH dataset, showing 8 images per person, with each person represented by 8 images. Images of girls from two different families; a 7-year-old (a) and a 13-year-old (b).

3. Dataset Generation

This section demonstrates the generation of the skin image dataset from the source dataset.

3.1. Source Dataset

A skin image dataset was generated in this study, utilizing the MKH (Mosul Kinship Hand) image dataset [11] as a foundation. The MKH dataset comprised hand images collected from 84 individuals across 15 families. For each participant, eight images were acquired, consisting of two palm and two dorsal views for each hand, with both open and closed finger configurations. The age range of the participants spanned from 3 to 70 years, with a demographic distribution of 44 females and 40 males. Figure 1 illustrates representative samples from the MKH dataset.

3.2. Skin image dataset generation

The generation of our dataset was demonstrated here. Only hand palm images from the MKH dataset were adopted in this work. Four palm-hand images for each of the 84 individuals were preprocessed to get the palm skin images. Image preprocessing consisted of image cropping and

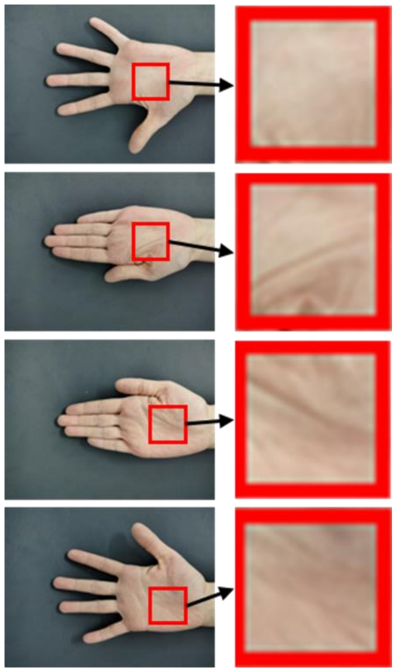

Figure 2. ROI cropping from the MKH dataset to generate the palm skin image dataset.

Table 1. Summary of the generated dataset.

	Family	# of individuals per family	# of images per family	# of train images	# of test images	Individuals	Age-Range (years)
1	FA	6	24	19	5	F-M-1S-3D	13-60
2	FB	5	20	16	4	F-M-3D	3-36
3	FC	6	24	19	5	F-M-3S-1D	10-52
4	FD	6	24	19	5	F-M-2S-2D	9-59
5	FE	6	24	19	5	F-M-4S	26-62
6	FF	7	28	23	5	F-M-4S-1D	20-56
7	FG	4	16	13	3	F-M-1S-1D	37-70
8	FH	7	28	22	6	F-M-2S-3D	9-60
9	FI	4	16	13	3	M-3D	28-60
10	FJ	3	12	9	3	1S-2D	29-38
11	FK	5	20	16	4	F-M-2S-1D	17-55
12	FL	7	28	22	6	F-M-2S-3D	5-42
13	FM	6	24	19	5	F-M-2S-2D	17-53
14	FN	5	20	16	4	M-1S-3D	14-60
15	FO	6	24	19	5	F-M-2S-2D	7-50
Sum	**15**	**83**	**332**	**264**	**68**	**12F-14M-27S-30D**	**3-70**

FA: Family A & so on. F-M-1S-2D: Father-Mother-one Son-two Daughters & so on.

resizing. The palm region of images (ROI) was cropped to an area of 762×762 pixels from each hand image, or resized after cropping if the required area size cannot be achieved, as shown in Figure 2. Four images were taken for each person, except family number 15 had 16 images instead of 20 due to the lake in the MKH dataset. In total, 332 images were generated, labelled, and saved across families, as detailed in Table 1. Figure 3 shows samples from the generated dataset. This dataset was used for training and testing the proposed classifier.

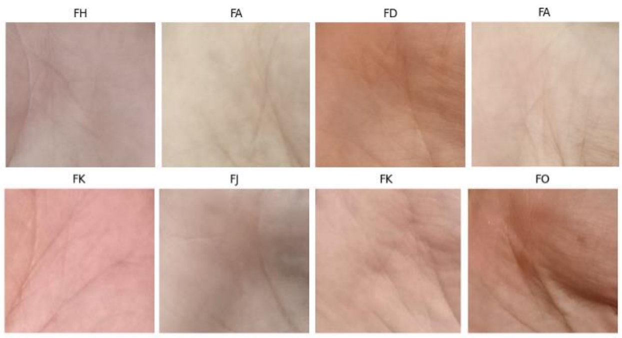

Figure 3. Samples of the generated dataset for hand palm skin images.

4. Methodology

The method we proposed for kinship verification is based on identifying common traits in the skin of the hand palm that are inherited from parents to children. These traits can be unique to each family. In our approach, we used the generated dataset in the subsequent steps, as shown in Figure 4. The first step is data splitting, where the dataset's images are divided into 80% for training and 20% for testing, then saved in separate files. The second step involved feature extraction using deep transfer learning (DTL) techniques, testing two pre-trained models, VGG16 and EfficientNetB0, across separate experiments. The third step deals with designing the classifier. The classification layers of each model were replaced with an appropriate neural network classifier, customized and connected to the feature extractor's output. The classifier was designed to assign each person to one of the 15 families in the dataset. The fourth step involves training, where the parameters of the feature extractors (VGG16 or EfficientNetB0) remain unchanged, and only the classifiers' parameters are updated during the training epochs. After training, the models are tested using the dataset's test portion. We proposed two main approaches: one using

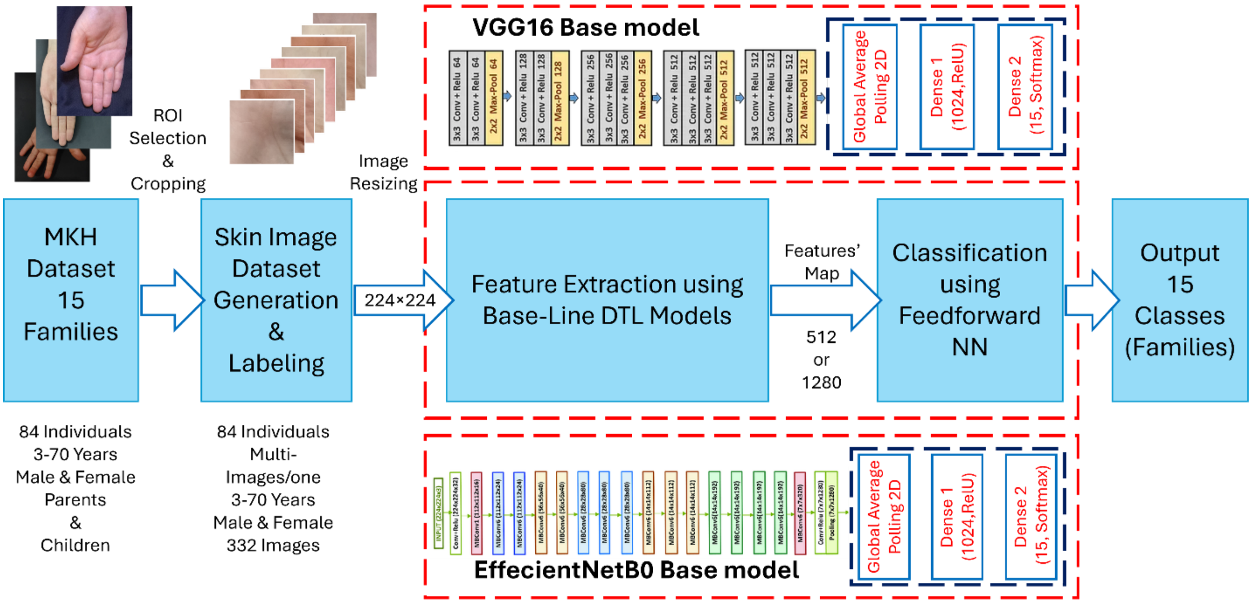

Figure 4. The block diagram of the proposed system.

VGG16 and the other using EfficientNetB0. For each approach, two experiments were conducted—one using the dataset images directly and the other employing data augmentation—resulting in four distinct experiments. Implementation was carried out in Python using Google Colab, a cloud-based platform. The results were evaluated using standard metrics and compared with each other and the state-of-the-art. The workflow diagram is shown in Figure 5.

4.1. Data splitting

The dataset was split into two groups for machine learning (ML) preparation. The test group contains 20% of the data, organized into a main folder with 15 subfolders representing different families. Similarly, the train group, located in another main folder with 15 subfolders, contains the remaining 80% of the data. The test images were carefully selected to ensure diversity in age, gender, and image quality for reliable results. In total, the training data comprises 264 images, while the test data consists of 68 images.

4.2. Feature extraction

Human skin texture is a complex 3D structure that varies between different organs and can exhibit multiple textures within the same organ. Additionally, factors such as age, gender, health, and life circumstances contribute to significant differences in skin texture. This diversity complicates the task of identifying common features across families. One recent method for extracting subtle skin textural features that are not perceptible to the human eye involves the use of deep convolutional neural networks (DCNN) [40, 43]. CNN was used to detect and classify skin lesions, demonstrating superior performance compared to feature extraction methods [44]. The proposed work adopted the DTL technique for this purpose. DTL employs a CNN model pre-trained on extensive data and adapts it for feature extraction from a different data type, leveraging insights gained from the pretraining. This method effectively addresses the challenge of limited data size. Investigations and experimental works were conducted to find some suitable models for the skin image data and led to the selection of two models, that are the VGG16 and the EfficientNetB0 [16, 18, 45, 46] The DTL models were reconfigured by removing the fully connected or the prediction layers at the top, where the output of the last layers are the extracted features from the input image. The EfficientNetB0 model extracts 1024 features, while VGG16 produces 512 features. In contrast to traditional transfer learning, which involves fine-tuning select layers, this study initially froze pretrained weights to mitigate overfitting caused by the limited dataset size. Subsequent experiments exploring the effects of fine-tuning revealed significant performance enhancements for VGG16.

4.3. The classifier

The extracted features should be classified into one of the fifteen categories of this research. The classifier included a global average pooling layer followed by two fully connected layers, Dense-2 and Dense-3, which transform the 2D feature matrix into a vector of estimates. Dense-2 integrates features from the pre-trained model to generate decisions, while Dense-3 serves as the classification layer, determining the probable distribution across the 15 dataset families using SoftMax activation. The added dense-2 layer for the VGG16 model accepts 512 features, while that added to the EfficientNetB0 model comprises 1024 input features, and the dense-3 layers for both models have the same number of predictions. As a result, the deep CNN model that served as the feature extractor and the three compensated layers that served as the classifier made up the entire classifier architecture.

4.4. Training and Testing

During the training phase, the pre-learned feature extractor settings were retained to leverage prior knowledge. The classifier stage is the only stage that should be trained, and it can be trained faster due to its shallow depth. Two training methods were employed. The first method used the original training data without modifications, while the second incorporated data augmentation. Throughout training, data augmentation was dynamically applied, generating a new version of each image with random transformations every time it was fed into the model. The transformations included random rotations between +40 and -40 degrees, shifts in width and height up to 20%, shear

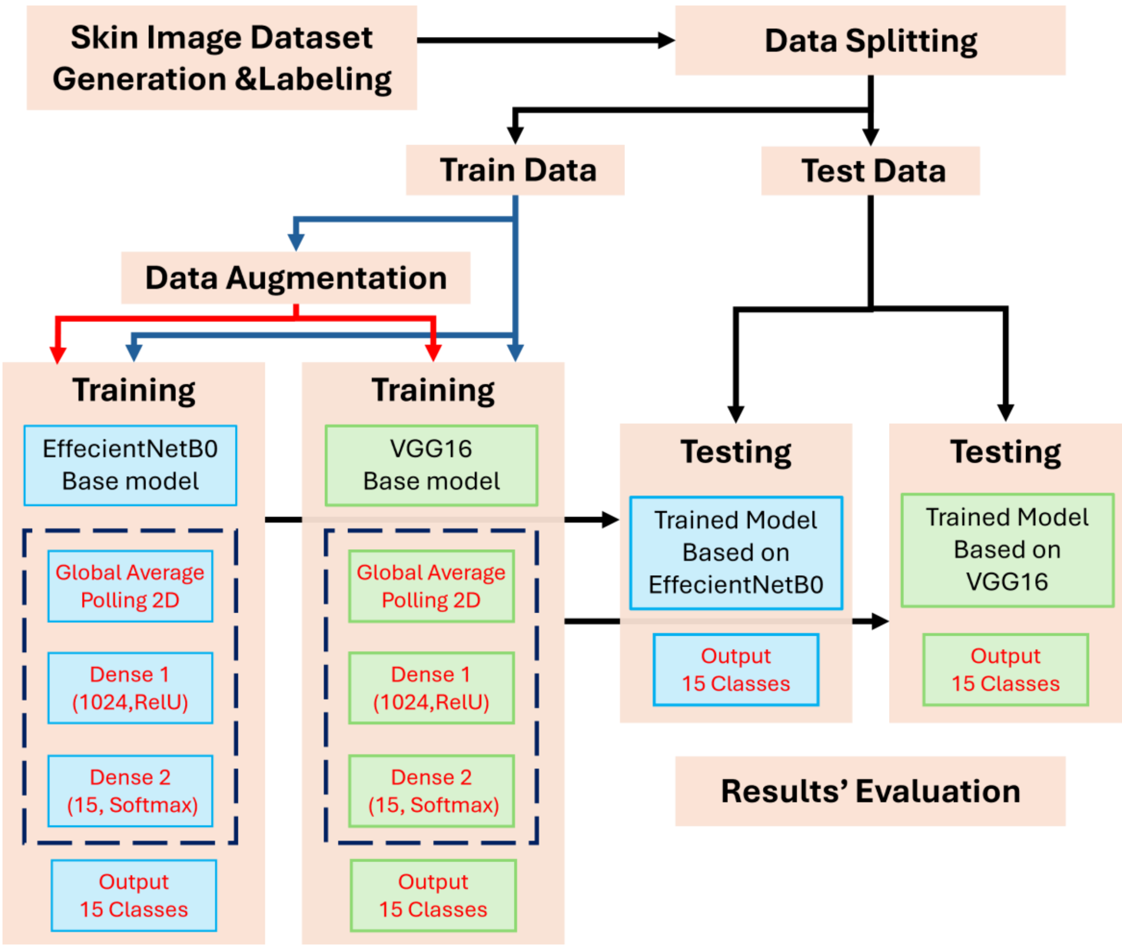

Figure 5. The workflow diagram of the proposed methodology.

transformations up to 20 degrees, and random zooming between 80% and 120%. For each epoch, the augmented images match the number of training images, totaling 264. Over 100 epochs, this results in 26,400 images. Augmentation was exclusively applied to the training images. The training batch size was set to 32, and the validation batch size to 16, to appropriately match the sizes of the training and validation datasets.

We also explored fine-tuning both VGG16 and EfficientNetB0 by leveraging their pre-trained weights as initial parameters. A subset of their upper layers was unfrozen and trained alongside the added classification layers, enabling the models to adapt their learned features to our palm skin texture dataset. To retain the pre-trained knowledge, a lower learning rate was applied to the fine-tuned layers. Similar to the fixed feature extraction approach, training was performed both with and without data augmentation, resulting in eight distinct experimental configurations

4.5. Metrics for evaluation

Accuracy, precision, recall, F1-score, training curves, and confusion matrices were used here to demonstrate and discuss the results. Accuracy is the ratio of correct predictions to all the predictions, as shown in the equation (1). Precision can be defined as the true positives to the total correct predictions, as depicted in the equation (2). Recall is calculated as the ratio of true positives to the total number of samples in the class, as shown in the equation (3). The F1-score metric measures the weighted average of recall and precision, as demonstrated in the equation (4). The training and validation curves sketch the accuracy and the loss for each case across training epochs. The confusion matrix presents a color-coded, chessboard-style square table that compares predicted classes to true classes for the test data. The diagonal cells starting from the top-left represent the true positive predictions for each class.

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - Score = 2\, .\, \frac{Precision \cdot Recall}{Precision + Recall} \tag{4}$$

Where: TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

5. Results and discussion

The results of the experiments utilizing the two adopted DTL models are demonstrated and discussed here.

5.1. VGG16 Experiments

The proposed classifier utilized the pre-trained VGG16 model to extract features from skin images and was trained on two versions of the dataset: one with augmentation and one without. Validation accuracy reached 85% without data augmentation and 79% with augmentation. Figure 6 illustrates the training and validation curves. Figure 7 depicts the confusion matrices for both scenarios. Given that this was the initial step in this line of research, the results appear to be satisfactory. However, the results indicated that the original VGG16 model architecture may not be well-suited for skin texture images. Further investigations are necessary to draw a definitive conclusion.

5.2. EfficientNetB0

After experimenting with the VGG16 model, the pre-trained EfficientNetB0 model was selected. It's newer, features an optimized architecture, operates faster, and is used for similar image types [16, 18]. Training on the same dataset resulted in a validation accuracy of 94% without data augmentation and 96% with data augmentation. Figure 8 and Figure 9 demonstrate the training-validation curves, and the confusion matrices, respectively, for the two cases.

EfficientNetB0 performed better than VGG16 because it uses a compound scaling method and is better at identifying small details in skin texture.

Fine-tuning VGG16 resulted in improved validation accuracy and F1-score, increasing from 85% to 90% in both metrics when combined with data augmentation. However, the performance remained below that of the EfficientNetB0 model, which achieved 96% accuracy and F1-score without fine-tuning.

In contrast, EfficientNetB0 showed no measurable gains from augmentation during fine-tuning, maintaining a steady validation accuracy of 74%. Furthermore, VGG16 exhibited greater sensitivity to regularization and data augmentation, while EfficientNetB0 maintained more consistent generalization capabilities.

VGG16 exhibits superior and more reliable generalization performance on this dataset, although it necessitates greater computational resources. In contrast, the pre-trained EfficientNetB0 offers an efficient approach to extracting skin texture features when employed without fine-tuning. Misclassifications between the FF/FI and FL/FM families, as observed in the confusion matrices, likely stemmed from inconsistent lighting conditions, a limited number of FI samples, and age-related variations combined with artefacts present in FL/FM images. The shared skin characteristics across these families highlight the necessity for a larger and more diverse dataset. To improve the proposed method's performance, consider expanding the dataset, ensuring data balance, and optimizing the model architecture, and exploring alternative models for DTL. Table 2 details the evaluation metrics obtained across the four scenarios, contrasting the results achieved with and without fine-tuning in each instance. All metrics were calculated using the macro average according to equation (5), which are non-weighted values.

$$\text{Macro Average Metric} = \frac{\sum_{i=1}^{N} \text{Metric(i)}}{N} \quad (5)$$

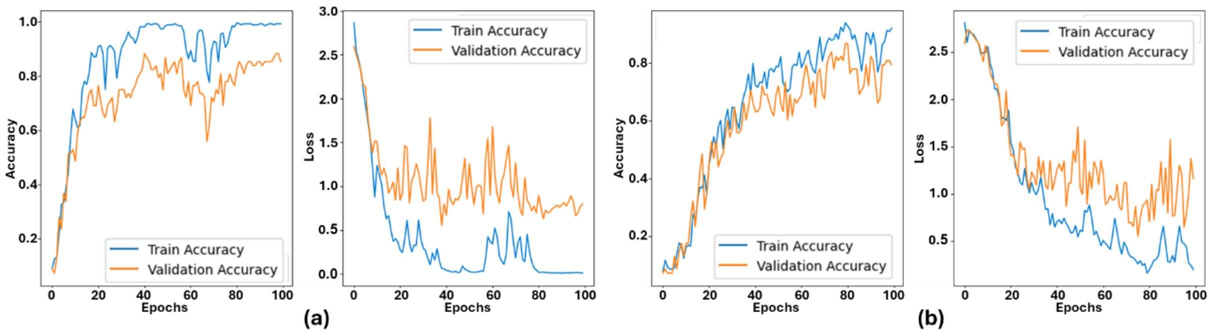

Figure 6. Training accuracy and loss curves using VGG16 with no data augmentation (a), and with data augmentation (b).

Figure 7. Confusion matrices for the validation phase using VGG16 with no data augmentation (a), and with data augmentation (b).

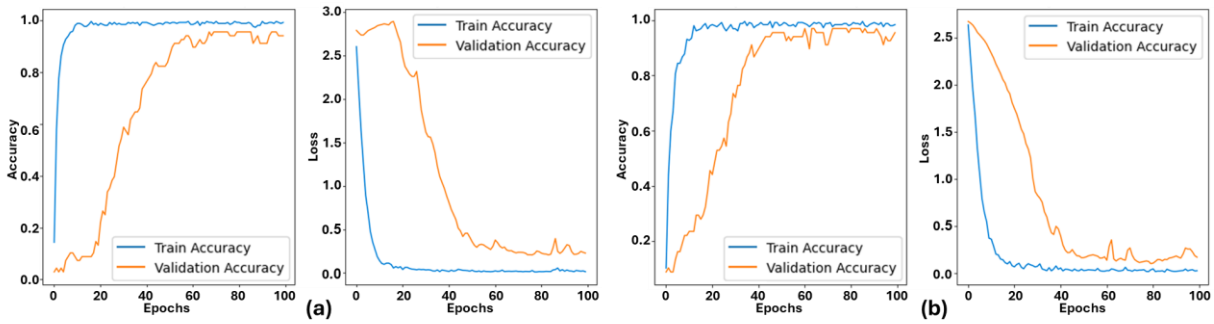

Figure 8. Training accuracy and loss curves using EfficientNetB0 with no data augmentation (a), and with data augmentation (b).

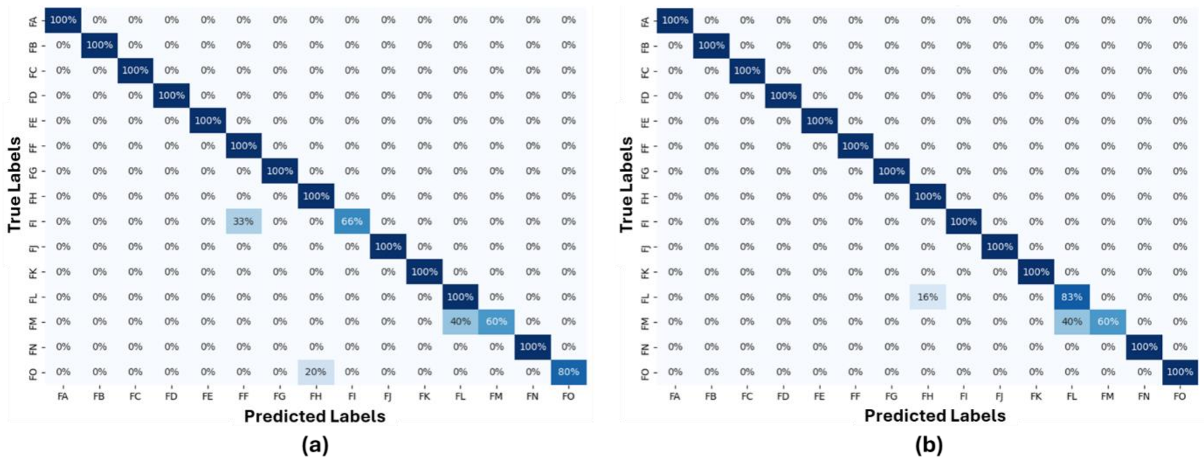

Figure 9. Confusion matrices for the validation phase using EfficientNetB0 with no data augmentation (a), and with data augmentation (b).

5.3. Some results for kinship verification using computer vision

In the absence of prior comparable studies, this research highlights the superior accuracy achieved using computer vision techniques. Comparative analyses of related prior studies are presented in Table 3 and Table 4. Table 3 provides a comparison with VKV using facial images, outlining the dataset, methodology, and peak accuracy attained. Table 4 broadens the comparison to encompass various modalities. The accuracy of the proposed approach is on par with current state-of-the-art methods. The FKV accuracy reached 92.4% for mother-daughter pairs [21], 76% for mother-daughter pairs, and 79% for non-relatives [37]. The average accuracy across classes was 94.59%. Kinship detection accuracy based on hand geometry was 93% [11], while lip print analysis yielded 58.06% accuracy for parents and biological offspring [9].

5.4. Discussions

The study demonstrated the effectiveness of using skin texture for kinship detection. As illustrated in Table 3, most existing approaches rely on facial features for kinship classification. In contrast, our research takes a novel direction by utilising palm skin texture, an underexplored aspect in the realm of intrafamily classification. While DTL techniques proved useful for feature extraction, the EfficientNetB0 model showed superior compatibility with skin texture images compared to VGG16. Data augmentation enhanced performance, particularly with the EfficientNetB0 model, unlike VGG16. This difference could be attributed to the alterations in skin texture caused by some of the augmentation methods used, which may disrupt the palm skin feature extraction process in VGG16. Additionally, DTL techniques effectively addressed the issue of limited data size. Data augmentation's impact on model

Table 2. Results' summary of the proposed work scenarios.

Model	Augmentation	Fine Tuning	Accuracy	Precision	Recall	F1-Score
VGG16	No	No	85%	89%	85%	85%
		Yes	79%	82%	80%	80%
	Yes	No	79%	83%	80%	79%
		Yes	**90%**	**93%**	**90%**	**90%**
EfficientNetB0	No	No	**96%**	**97%**	**96%**	**96%**
		Yes	74%	76%	74%	72%
	Yes	No	94%	96%	94%	94%
		Yes	74%	76%	74%	72%

Table 3. Comparison with existing research employing facial analysis techniques.

Study	Modality	Dataset	Method	Accuracy
[5]	Face	Private	SNN with age transformation	76.4%
[7]	Face	Public	ResNet + DNN	60%
[12]	Face	Public	K-Means	94.59%
[21]	Face	Private	AdvKin (CNN)	95.2%
[37]	Face	Public	SNN	79.6%
Present Study	Palm Skin	MKH	EfficientNetB0 + NN	**96%**

Table 4. Comparison with prior work across modalities.

Study	Modality	Method	Accuracy
[9]	Lip Print	Statistical Analysis	58.06%
[11]	Hand Geometry	DTL	79.6%
[21]	Face	AdvKin (CNN)	95.2%
Present Study	Palm Skin	EfficientNetB0 + NN	**96%**

performance revealed intriguing, model-specific behaviour. For VGG16, used as a fixed feature extractor, data augmentation surprisingly resulted in a drop in validation accuracy, decreasing from 85% to 79%. This unexpected outcome likely stems from VGG16's sensitivity to geometric distortions introduced by augmentation techniques such as rotations, shifts, shearing, and zooming. While these transformations aim to enhance data variability, they may have unintentionally altered subtle skin texture patterns, disrupting VGG16's reliance on precise spatial hierarchies. Fine-tuning the VGG16 architecture, coupled with data augmentation, significantly reduced overfitting and enhanced accuracy by 11%, highlighting the effectiveness of fine-tuning in adapting VGG16 to palm texture features. Conversely, applying fine-tuning to the EfficientNetB0 architecture led to a sharp decline in accuracy (from 96% to 74%), indicating that its pretrained weights are already well-optimized for capturing texture features. The validation accuracies achieved were comparable to those of other computer vision-based kinship verification methods.

5.5. Limitations

This study has several limitations that warrant discussion and will guide future research directions.

- **Dataset limitation:** While transfer learning and data augmentation techniques were employed, the generalizability of this study is limited by the relatively small dataset size.
- **Cross-validation:** The absence of publicly available palm skin kinship datasets limits validation against real-world data or across different databases. Further investigation is required to ascertain the generalizability of the proposed method.
- **Architectural investigation:** This proof-of-concept study demonstrated the potential of using palm skin for kinship detection. However, it did not encompass hyperparameter optimization, layer-wise

analysis, or exploration of alternative deep learning architectures.

6. Conclusions

This paper presents a novel approach to kinship detection based on palm skin texture. As a pioneering effort in this area, it requires further validation. Deep transfer learning techniques were utilized to extract features from skin images. A dataset was generated from the MKH dataset for training and testing, leveraging the pretrained capabilities of VGG16 and EfficientNetB0 models. The evaluation involved eight scenarios, using two deep learning models with two data augmentation conditions and two fine-tuning instances. EfficientNetB0 demonstrated superior performance compared to VGG16, achieving a validation accuracy of 96% versus 90%. This foundational study presents encouraging initial results, laying the groundwork for future investigation. Further research directions include investigating additional skin areas, integrating data from multiple regions, and applying feature fusion techniques. The combination of handcrafted features with those extracted from deep convolutional neural networks (CNNs), as well as the evaluation of Siamese Neural Networks, may lead to improved VKV identification performance. Broader validation across diverse datasets and dataset expansion are crucial for ensuring generalizability. While this study focused on VGG16 and EfficientNetB0 architectures, future work may explore layer-wise analysis, hyperparameter optimization, deeper architectural insights, and the application of alternative deep transfer learning (DTL) models such as ResNet and DenseNet for feature extraction.

Conflict of interest

The author would like to declare that there were no conflicts of interest.

Acknowledgement

The author expresses gratitude to the University of Mosul, the College of Engineering, and the Computer Engineering Department for their invaluable support in completing this work.

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