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Research Article

Facial Kinship Verification in Forensic Investigation Using Deep Neural Networks

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Abstract:

The human face contains a wealth of information that is influenced by genetics. Family members often share common facial characteristics due to their shared genetic makeup. By comparing the facial features of individuals, forensic investigators can examine the degree of similarity and infer their kinship. Kinship verification provides a powerful tool in forensic investigations, contributing to the resolution of missing person cases, social media analysis, genealogy research, and historical study. The research problem is verifying if two people have a kinship by analyzing two face images together, extracting the relationship features between them, and then determining if they have Kin or not. A Kinship Verification model is proposed using a three-Dimensional Convolutional Neural Network. This work consists of the following stages: the preprocessing stage and the kinship verification stage, and each stage includes multiple steps that perform different functions. In the preprocessing stage, the input images are prepared to be suitable for deep neural network model by extract ROI, scaling, and normalizing them. The kinship verification stage is implemented to provide the kinship decision in two steps: the feature extraction step and then classification step to decide on those images: kin or not. Extensive experiments revealed promising results compared with many state-of-the-art approaches. The accuracy of the proposed system reached 92.25% in the KinFaceW-I dataset and 95.25%in the KinFaeW-II dataset.

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Facial image analysis is now a core research area of image processing, computer vision, and pattern recognition. This is because the human face contains huge social data including gender, age, and emotional state, in addition to identifying characteristics that may be used to ascertain an individual's identity.

Computer-based kinship detection and verification is one of the study topics dependents on face image analysis. Kinship verification is a process of determining the biological relatedness between individuals. These relationships may be: Father-Son (F-S), Father-Daughter (F-D), Mother-Son (M-S), and Mother-Daughter (M-D), etc. A parent's genes are passed on to their offspring, and as genes overlap, children inherit various characteristics from their parents, including likeness in look [1]. The Facial Kinship Verification model identify automatically whether two individuals are related [2].

While Deoxyribonucleic Acid (DNA) tests are a valuable tool for kinship verification, they do have certain limitations such as unavailable or inaccessible reference samples and ethical and privacy considerations. These limitations make DNA tests unfeasible solutions in some life scenarios related to forensic applications and video.

In addition, DNA needs many days to process, therefore it cannot be used in situations requiring real-time processing or with difficult users. Owing to the increasing expansion of multimedia, facial kinship verification has a substantial impact on several fields [3]

The difficulties of efficiently recognizing face characteristics including the size, shape, and colour of facial components cause low accuracy rates [4]. The most challenging and important phase in the verification process, as well as the system's core, is feature extraction because the salient features made accessible for recognition have a powerful effect on the precision of kinship verification and recognition tasks [5].

Fundamentally, there are two types of challenges to acknowledging kinship that can impact the precision of verifying facial kinship: directly challenging (associated with the kinship itself), which includes variations in gender, age, and feature likeness among relatives, and indirectly challenging (related to the database's environment), which can include lighting, noise, occlusion, facial expressions, position variation, clutter, and lower picture quality [6].

Deep neural networks are capable of learning complex representations and patterns from raw data, enabling more accurate predictions, which outperform various shallow techniques, and obtained quality on important visual recognition functions.

The facial kinship verification method is made up of a number of stages, each of which has a number of steps that serve various purposes, as illustrated in Fig 1. The preprocessing stage (which covers all aspects of image preprocessing), the kinship verification stage (which covers feature extraction, feature selection, and other activities that might result in salient features, and classification task).

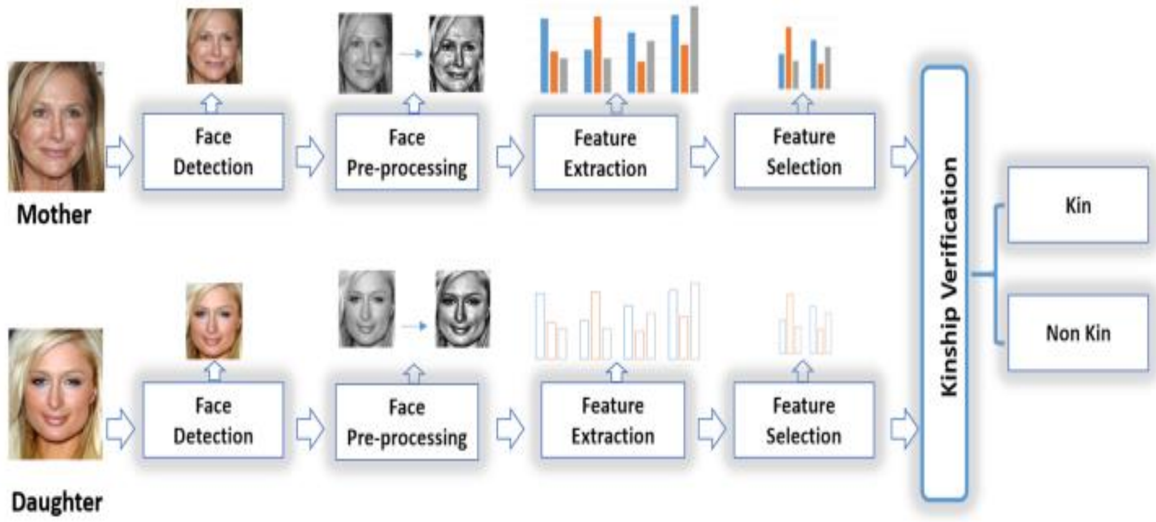

Figure- 1 A General Facial Kinship Verification Framework

1. Related Work

Facial kinship verification is an active area of research, with many studies focusing on the most effective techniques for extracting distinguishing characteristics used in existing kinship verification methods.

Xiaoting Wu et al.[7] introduced a Similarity Metric-based Convolutional Neural Network (SMCNN) technique on KinFaceW-I and KinFaceW-II datasets for kinship verification. The SMCNN structure utilizes two identical convolutional neural networks with eight layers each. The L1 norm between two CNN outputs was calculated, and a decision was made using a learned threshold. The superior results are obtained with KinFaceW-II due to the cropped image sharing a comparable environment, such as chrominance and brightness. The verification accuracies are 72.7% and 79.25% for KinFaceW-I and KinFaceW-II datasets respectively.

Chergui et al. [8] uses (ResNet) for the feature extraction stage, in addition to our suggested pair feature extraction function and Rank Features (T-test) to reduce the number of features through feature selection, and then uses the Support Vector Machine for kinship verification decision. On the Cornell Kin Face, UBKin, Familly101, KinFace-I, and KinFace-II datasets, the kinship verification accuracy is 87.16%, 83.68%, 82.07%, 79.76%, and 76.89%, respectively.

Chergui et al. [9] provided a method for extracting features that are based on combining several descriptors (Local Binary Patterns (LBP), Local Phase Quantization (LPQ), and Binarized Statistical Image Feature (BSIF)). The Multi-Block (MB) representation approach was used, and the effect of alternative feature representations for verifying kinship was examined to minimize the number of features selected using the TTest function. A Support Vector Machine (SVM) was used for kinship classification. This technique achieves kinship verification accuracy of 84.74% On Cornell KinFace, 82.74% on UBKin, 81.69% on KinFace-I, 80.12% on KinFace-II, and 78.16% on Familly 101.

Yan & Wang [10] use an attention network for facial Kinship Verification. The attention network is designed to extract information about the local parts and guide learning by adding a mask to five facial feature portions of each face to assist the network in focusing on extracting more discriminative information in these areas. The attention network performs well on KinFaceW-I and KinFaceW-II. They outperformed basic CNN with 82.6% and 92.0% accuracy.

Zhang et al. [11] Deep learning techniques have been presented for their promising performance. Using shape and appearance complementary information. Both are necessary when determining kinship from face photos. To train this model with limited kinship data, the researchers used an adaptation-based two-phase training approach using large-scale face recognition data, with the verification accuracy (78.3%) on the KinFaceW-I dataset.

Goyal & Meenpal [12] used variable feature descriptors (Local Binary Pattern (LBP) and Histogram of Gradient (HOG)) to identify salient features. Then, a Support Vector Machine (SVM) classifier is used to obtain an understanding of the retrieved face characteristics. The results showed that the (LBP –SVM) technique outperformed (HOG-SVM). On the KinFaceW-I dataset, the LBP-SVM approach's mean accuracy was 75.57 %. On the KinFaceW-I dataset, the HOG-SVM technique had an average accuracy of 73.35 %.

Mukherjee & Meenpal [13] provided a method relies on a compound local binary pattern (CLBP) and local feature-based discriminate analysis (LFDA). Long feature vectors were generated using these two techniques. The only methodology that accelerated the process and selected the best features was the entire feature vector-based LFDA feature selection method. A KNN classifier was used. They used the KinFace W-I and KinFace W-II datasets; the accuracy was 82.82 and 89.36.

Chergui et al. [14] developed a strategy based on examining two images to determine kinship. The deep features are extracted using the VGG-face model after the face preprocessing stage. Then, using Fisher Score (FS), feature pairs are represented and normalized to determine the salient features. SVM classifier is used to make the final decision in kinship. On Cornell KinFace, UBKinFace, KinFaceW-I, KinFaceW-II, and Familly 101, the accuracy was 92.89%, 90.59%, 86.65%, 81.11%, and 84.82%.

2. Proposed Model

This work proposes a Three-Dimensional Convolutional Neural Network (3D CNN) model with a new architecture for facial kinship verification. The proposed model employs two face images of two humans as inputs and learns their shared features in order to predict if these are kin or not, this model is non-intrusive, cost-effective, and can be readily implemented. The main stages of the proposed model can be illustrated in Fig.2.

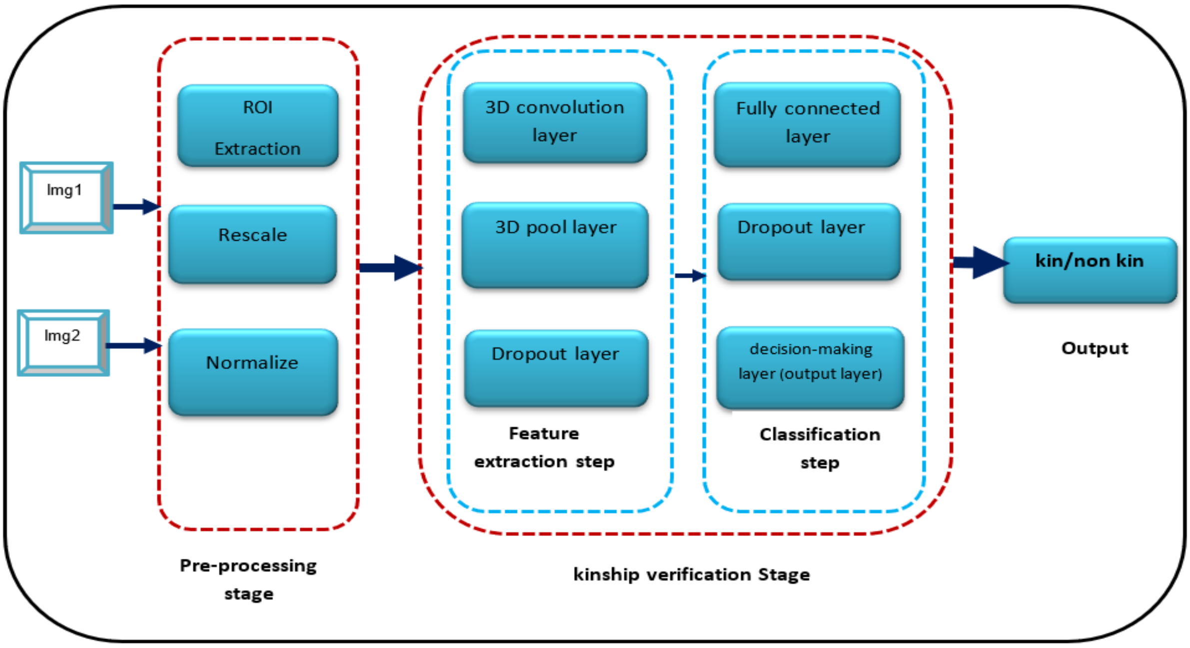

Figure 2. Block Diagram of the Proposed System

The proposed model uses two benchmark datasets: the KinFaceW-I dataset and KinFaceW-II dataset, the KinFaceW-I dataset, KinFaceW-II dataset created by Lu et al.,[15], and these data are arranged in four kinship relations: Father-Son (F-S), Father-Daughter (F-D), Mother-Son (M-S), and Mother-Daughter (M-D) as illisturate in table 1.

Datasets	F_S	F_D	M_D	M_S	Total	Image_size	Source_image
KFW-I	156	134	126	116	1066	64×64	many images
KFW-II	250	250	250	250	2000	64×64	one image

Table 1. The description of the two utilized kinship datasets, KFW-I and KFW-II.

The proposed model is implemented in two modes : training and testing modes. Each data set is separated into two sub-datasets: 85% of the training and 15% of the testing datasets and then the training dataset also is split into 85% for real training and 15% for validation data.

2.1 Pre-Processing Stage

The first stage of the system is preparing the input images in order to provide generalization by extracting ROI, scaling, and normalizing steps. The Region Of Interest (ROI) extraction step is responsible for cropping a part of the limits of the object under study from the image based on facial features. Multi-Task cascaded Convolutional Neural Networks (MTCNN) are used in this step to detect accurate faces and then extracted them.

Image scaling (Resize) means the Uniformity of image dimensions by decreasing or increasing the sum of all the pixels contained in an image to be (64X64). It is a more important step to make sure that the results are valid for any input image size.

Image normalization is an essential preprocessing step. It is a process that changes the range of pixel intensity values so that each pixel value has a value range between 0 and 1 by dividing all pixel values by 255.

2.2 Kinship Verification Stage

A 3D CNN model is used in this stage to perform a facial kinship prediction process in order to produce the verification decision. This stage includes two major steps (feature extraction step and then classification step), both of them is constructed up of multiple layers that perform diverse functions depending on the goal of each layer. These layers are 3D convolutional, non-linear, pooling, dropout, and fully connected layers.

The 3D convolution layers employ 3D kernels (filters) on two face images to determine important features then produce feature maps. The number of filters represents the layer's depth and have size (32, 64, 128) respectively for the three convolution layers with kernel size (3, 3, and 3). The kernel coefficient values can be selected through the training process and were represented by the saved weights.

A "Rectified Linear Units (ReLUs)" function is used on all non-linear layers except the final non-linear layer which used the "sigmoid" function" on the output layer. The ReLUs allow the model to learn and represent more complex relationships between inputs and outputs by strengthening strong features and weakening weak ones.

The Pooling layers provide resilience against noise by decreasing the resolution of the features by passing a single neuron with maximum value in one layer from the clustered of several neurons in the previous layer using a max-pool function of clustered neurons.

Finally, the Dense layers (fully connected layers) flatten the output of previous layers and predict the class of a face sample. The decision-making layer (output layer) employs a sigmoid activation function.

Dropout layers are included in the proposed system to avoid overfitting and making generalizations on unseen data. During the training process, it chooses 50% of the neurons at random and sets their weights to zero. It is an easy way to reduce the model's sensitivity to noise while it is being trained while keeping the required level of complexity for the architecture of the proposed model.

3. Results and Discussion

The proposed model is implemented in two modes: the training mode and the testing mode. During the training mode, the model attempt to learn features on the training dataset and weights are updated based on loss, accuracy, and mean square error functions until the model converges on the lowest error and stable. Fig 3 illustrates the behavior of the proposed model in training and validating datasets in term of learning curve and Table 2 illustrates the values of the hyperparameters utilized, the hyperparameter's values are chosen depending on the trial and error way.

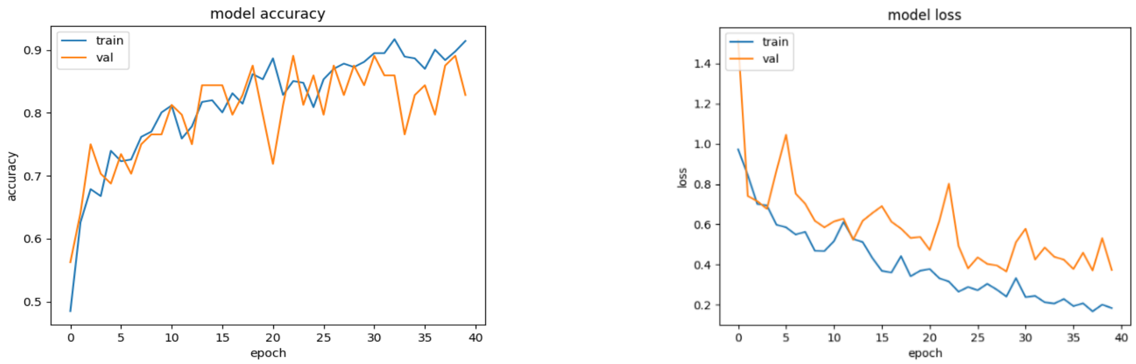

Figure.3. the Learning Curve of proposed model

Table 2. The hyperparameters values

Hyperparameters	Value
Learning rate	0:001
Batch size	32
Metrics	Accuracy
Loss function	Binary cross entropy
Optimizer	Adam
Kernel size	3*3*3

Based on the fact that deep neural network models are stochastic which causes have different overall skills and obtained different predictions each time the same model is fit on the same data. The proposed model is evaluated in two directions: variance and stability. The Variance direction evaluation estimates the architecture skill when the same model is trained on different data, by using 10-fold Cross-validation as shown in Table 3.

Table 3. The 10-fold cross-validation of proposed system

Dataset	Accuracy of each fold										model accuracy
	Kinship	1	2	3	4	5	6	7	8	9	10	
KinFaceW-I	F-S	70.85%	70.37%	74.07%	74.07%	88.88%	73.07%	92.30%	91.0%	90.0%	92.30%	81.70% (+/-14.68%)
KinFaceW-I	F-D	70.25%	74.07%	62.96%	66.66%	92.59%	88.88%	95.29%	92.59%	90.0%	100.0%	83.33% (+/-15.11%)
KinFaceW-I	M-S	70.23%	80.76%	61.53%	87.46%	83.99%	72.00%	100.0%	92.00%	83.99%	95.99%	82.80% (+/-11.60%)
KinFaceW-I	M-D	73.07%	73.07%	70.38%	91.15%	87.99%	80.00%	100.0%	92.00%	92.00%	92.00%	85.17% (+/-10.95%)
KinFaceW-II	F-S	76.74%	83.72%	81.39%	93.02%	88.37%	92.85%	97.61%	100.0%	100.0%	100.0%	91.37% (+/-8.05%)
KinFaceW-II	F-D	74.41%	72.09%	93.02%	83.72%	95.34%	100.0%	95.23%	100.0%	100.0%	100.0%	91.38% (+/-8.24%)
KinFaceW-II	M-S	74.41%	90.69%	88.37%	88.37%	93.02%	90.47%	100.0%	97.61%	95.23%	100.0%	91.82% (+/-7.14%)
KinFaceW-II	M-D	72.76%	73.74%	90.69%	93.02%	90.69%	95.23%	100.0%	100.0%	95.23%	100.0%	91.14% (+/-8.68%)

After the model is stable, the performance of the proposed model is evaluated on unseen data (test dataset) using (accuracy, recall, precision, and F1-Score) metrics as shown in tables 4 and 5 respectively.

Table 4. The evaluation measures values on KinFaceW-I

DATA(Kinship)	Accuracy	Recall	Precision	F1-score
F-S	87%	84.5%	87.5%	85.5%
F-D	97%	98%	97%	97.5%
M-S	91%	89%	92.5%	91.5%
M-D	94%	95%	95%	95%

Table 5. The evaluation measures values on KinFaceW-II

DATA(Kinship)	Accuracy	Recall	Precision	F1-score
F-S	98%	98.5%	99%	99%
F-D	94%	94.5%	95%	94.5%
M-S	95%	96%	96%	96%
M-D	94%	94.5%	94.5%	95%

The comparative of proposed model with other state-of-the-art methods presented in table 6 and 7 respectively.

Table 6. A comparison of the proposed approach with other state-of-the-art methods in KinFaceW-I

KinFaceW-I	Method	F-S	F-D	M-S	M-D	Accuracy
Goyal & Meenpal [12]	HOG,LBP+SVM	75.6 %	77.8%	73.3%	75.6%	75.57%
Zhang et al. [16]	AdvKin	75.70%	78.30	77.60%	83.10%	78.68%
Liu et al. [17]	AIAF + IFW	88.70 %	80.80	82.60%	88.20%	85.08%
Our proposed model	3D CNN	87%	97%	91%	94%	92.25%

Table 7. A comparison of the proposed approach with other state-of-the-art methods in KinFaceW-II

KinFaceW-II	Method	F-S	F-D	M-S	M-D	Accuracy
Xiaoting Wu et al.[[7]	SMCNN	75%	79%	78%	85%	79.25 %
Chergui et al [8]	ResNet	77.6%	76.5%	76.21%	77.13%	76.89%
Van and Hoang [18]	(LBP)+SVM	87%	82%	71%	87%	81.8%
Our proposed model	3D CNN	98%	94%	95%	94%	95.25%

5. Conclusions and future work

This paper presents a proposed facial Kinship verification model based on extracting the salient features that are related in two face images using 3DCNN. Employing a 3DCNN provides the best method to verify kinship. The two face images can be acquired, analyzed and build related maps between them together. The ReLU activation function used in convolution layers provided the ability to deal with Various illumination conditions by removing all the weak elements from the two images at the same time and keeping only those that carry a positive (high) value which leads to extracting salient related features in the sample and neglecting the undesired one. Reduction in the memory and the computation complexity requirements are presented by using the same coefficients across all images in a sample; as well as by analyzing two face images together. The detection of the face accurately is the most serious task in the efficiency of the proposed system, all analysis and examination works of the sample are based on it (face images). So, Face detection based on MTCNN can detect faces with uncontrolled conditions images such as non-uniform illumination, pose direction, face rotation, etc. whereas other methods such as Haarcascade cannot deal with these conditions.

In the future, the model that was proposed can be developed to determine the level or degree of kinship of the input images, and then the Map Reduce concept can be used to attempt to apply the model in real time.

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