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Deep Convolutional Neural Networks for Kinship Prediction: An Effective Method

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Abstract:-

Objective: In this paper, we worked on kinship verification, has many applications, such as, finding missing children, identify family and non-family member etc. our aim is to kinship prediction using similarity computation to identify kin and non-kin based on image dataset.

Method: To measure the accuracy of the proposed method on primary 96-family dataset includes 410 images and 77,887 different pairs. The data was split into 80% for training and 20% for testing. We proposed Siamese Deep Convolutional Neural Network model with deep algorithm.

Findings: We find that our suggested model performs better, with an average similarity score of 72.73%.

Novelty: The outcomes from our primary kinship datasets indicated that the proposed techniques outperformed both state-of-the-art kinship verification methods and human capabilities in our kinship verification task. The experimental results demonstrated the superior efficacy of our approach in comparison to existing methods and human performance.

Keywords: Convolutional Neural Network, Deep learning, Siamese Neural Network, Image-based kinship verification.

1. Introduction

In recent times, the field of image processing has seen significant advancements, leading to the emergence of kinship verification. A relatively new facet of biometrics, kinship recognition, has gained attention [1]. The utilization of human facial images for identifying relationships poses a challenging research problem in both biometrics and computer vision [2]. The analysis of human facial images has attracted considerable interest from the image processing and computer vision community over an extended period, encompassing areas such as face recognition, gender detection, face detection, landmark identification, and the perception of facial attributes like age [3]. Relationship verification involves determining whether two individuals are biologically related by assessing their similarity [4]. Kinship analysis encompasses verification, classification, and recognition. In relationship verification, the objective is to ascertain whether two human faces share a blood relation (i.e., kin or non-kin). Family classification aims to identify the family to which a subject belongs, using faces from all family members, both for training and testing, with one member excluded. Kinship recognition, also known as kinship detection, involves distinguishing between genetically close individuals, such as kin, and non-kin. In the realm of computer vision, a well-established method is employed to address this type of problem, which utilizes two human face images to precisely determine the kin relationship. These methods predict specific classes, such as father-daughter (FD), mother-daughter (MD), father-son (FS), mother-son (MS), brother-brother (BB), brother-sister (BS), sister-sister (SS), among others [5]. In real-world scenarios, kinship verification finds diverse applications, including forensic analysis for locating missing children, social work assessments, and the construction of a family tree based on a photo album. The study of kinship verification reveals various scenarios, such as the apparent similarity between two individuals with no blood relation and cases where individuals share a blood connection but exhibit distinct features.

Additionally, the impact of varying image conditions within society underscores the significance of kinship verification in addressing these challenges.

Numerous research endeavours have explored the realm of facial kinship verification. In [6], the authors introduced deep Siamese Neural Networks for recognizing facial expressions in diverse settings, evaluating their algorithm using AffectNet, FER2013, and Compound Facial Expressions of Emotion (CFEE) datasets. Meanwhile, [7] employed NRML metric learning and an SVM classifier to generate a discriminative feature vector for kinship verification on the KinFaceW-I and KinFaceW-II databases, measuring accuracy. Exploring image-based kinship verification, [8] investigated the fusion of CNN classifiers, including EFNet and LFNet, and designed a fusion CNN classifier with ResNet-50, ResNet-101, and DenseNet, assessing performance on the FIW dataset. In [9], the author proposed a family-aware CNN classifier for visual kinship verification, achieving favorable results on the FIW dataset using deep face models such as ResFace-101, SphereFace, and VGGFace. Feature extraction and classification for decision-making (kin or non-kin) were addressed in [10], where the author proposed ALEXNET, SVM, and KNN models alongside new deep neural network models like GoogleNet, ResNet-50, and Inceptionv3, with AlexNet yielding the best results on the KinFaceW-I and KinFaceW-II database.

An approach involving face preprocessing, feature extraction, and selection for kinship verification across five databases (Cornell, UB KinFace, Family 101, KinFace W-I, and KinFace W-II) was proposed in [11]. The authors achieved high accuracy using deep feature models, including VGGNet, AlexNet, ResNet, and ImageNet. [12] introduced a kinship face generator network in three stages, focusing on robust facial feature extraction, an adversarial scheme, and a cycle-domain transformation approach, demonstrating promising results on the FIW dataset. Finally, [13] applied a deep fusion Siamese neural network to the RFIW2021 dataset, obtaining effective results using ResNet50 and SENet50 deep learning architectures.

Methodology:

Siamese Deep Convolutional Neural Network

A specialized architecture called the Siamese deep convolutional neural network is intended for a number of applications, such as kinship verification, face verification, and image similarity comparison. Learning a similarity metric that can quantify the degree of similarity or dissimilarity between two input images is the fundamental concept behind the Siamese network. Two key characteristics of Siamese structures for identical ANNs are symmetry and merging. Using the same set of weight coefficients acquired during the pre-training phase and permitting the parallel translation of preliminary descriptions of objects under comparison into a feature space makes comparison easier [14]. A Siamese deep convolutional neural network's workflow includes steps like gathering datasets, arranging the data pairs, and preprocessing them. To improve the robustness of the model, the input image in the processing dataset is resized to 64 by 64, cropped into various regions (left-top, left-bottom, right-top, and right-bottom), and any necessary data augmentation techniques are applied. Using this Network Architecture, ResNet, VGG, or specially created Sub-networks may function as networks. The contrastive loss, which serves as the loss function, penalizes the model when the expected similarity between similar and dissimilar items is excessively high or low. Utilizing the contrastive loss function and the prepared dataset, train the Siamese network. The network gains the ability to generate similarity scores for input pairs and extract discriminative features. To track the model's development during training and make any required modifications, assess the model's performance on a different validation set.Test the model on a hold-out test set after training to see if it can predict the Siamese neural network's similarity score structure depicted in Figure 1 and see how well it generalizes to new data.

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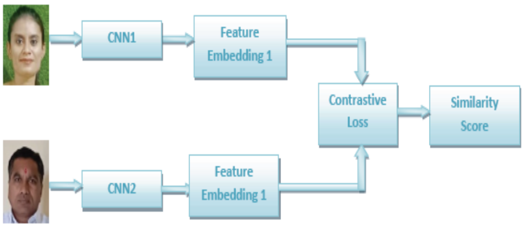


Fig.1 Siamese deep convolutional neural network.

For a variety of applications, the Siamese deep convolutional neural network provides an efficient method of learning similarity metrics. The workflow of this study using a Siamese deep convolutional neural network is shown in Fig 2. By adhering to this methodology, we can adapt and deploy it for the specific use case, achieving accurate similarity comparisons between pairs of data samples.

Data Set:

95 father images are included in the primary dataset of 96 families that we have gathered and are shown in Figs. 3 and 4. 96 pictures of mothers pictures of the sun and 127 daughters. The input image in the processing dataset is cropped into four different regions (left-top, left-bottom, right-top, and right-bottom) and resized to 64 by 64.

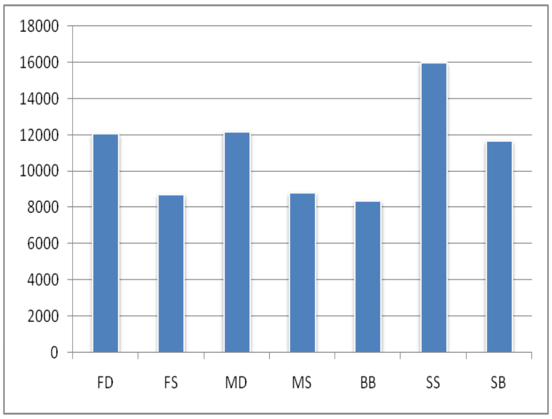


Fig. 3 Pairwise distribution on images

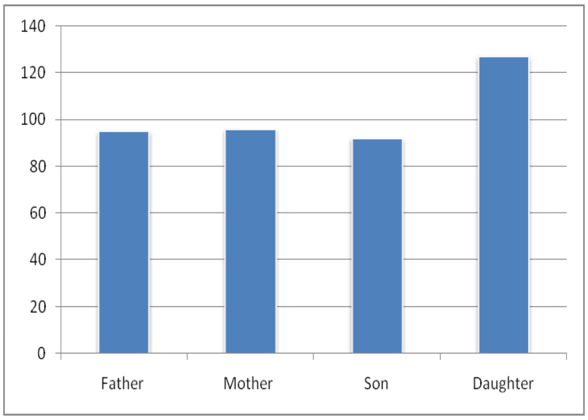


Fig.4 No. of individual images

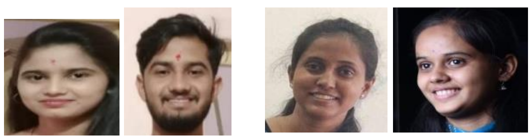
Tensorflow, sklearn.utils, sklearn.model, selection, pathlib, cv2, random, numpy, OS, matplotlib.pyplot, and tensorflow.keras are some of the Python packages and libraries we used in this work. and the layers, losses, optimizers, metrics, model, resnet, train_test_split, and shuffle libraries are contained in this package. In addition, we have divided seven different kinds of relationship pairs into two groups. Father-son (F-S), mother-son (M-S), father-daughter (F-D), and mother-daughter (M-D) are the four types of relations that make up the first group. As seen in Fig. 5, the second group consists of brother-sister (B-B), sister-sister (S-S), and brother-brother (B-B) relationships that span two generations.

Parent-Child

F-D M - D

F - S M - S

Siblings



S - B S – S

B - B

Result and Discussion

This section examines our findings and draws comparisons with those of other methods. The verification outcomes of various kinship verification algorithms on various datasets are displayed in Table 1. Our approach performs noticeably better than the most advanced approach. When compared to the previous best one different dataset using different methods, Human B, the previous best method for kinship verification, increases the average similarity score by 1.83% and achieves 0.85% for the FD subset, 0.65% for the FS subset, 1.06% for the MS subset, and a slight decrease for the MD subset.

Table 1. Similarity score of the proposed model compared with several state of the art datasets

Method	FD	FS	MD	MS	Avg.	Dataset
DCML (Top-1) [15]	47.5	41.6	49.4	48.8	46.83	CACD
MDLN [16]	63.1	66.4	63.2	60.8	63.4	TSKinFace
WGEML [17]	66.2	68.22	63.22	68.32	66.54	FIW
ResNet+SDMLoss [18]	69.02	68.60	72.28	69.59	68.37	FIW
SphereFace [19]	69.25	71.03	70.36	70.76	70.35	FIW
Proposed Model (SDCNNA)	**70.1**	**71.68**	**73.08**	**76.06**	**72.73**	**Our Data Set**

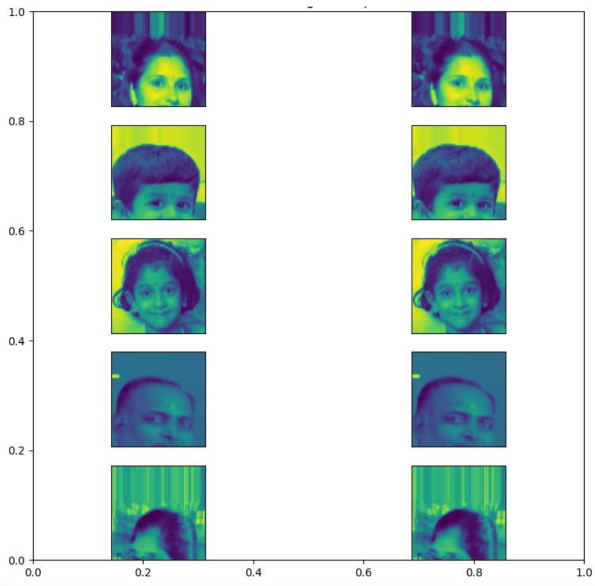


Fig.6 Sample positive Images

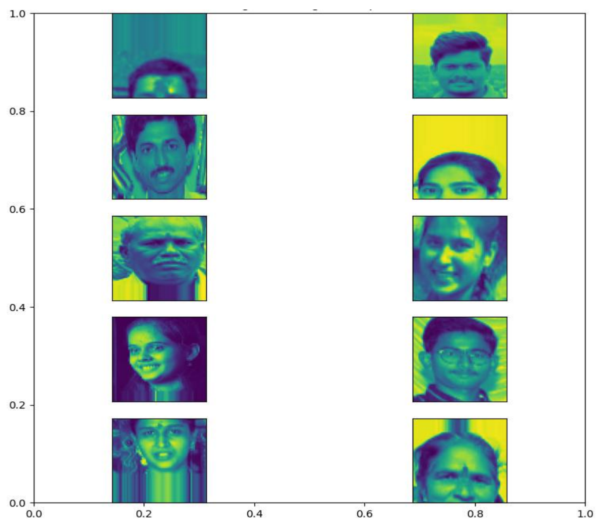


Fig.7 Sample negative images

Figure 2 shows facial images from our primary collected datasets along with a few sample positive and negative pairs. Figure 8 shows the proposed train model with accuracy, validation accuracy, loss, and validation accuracy.

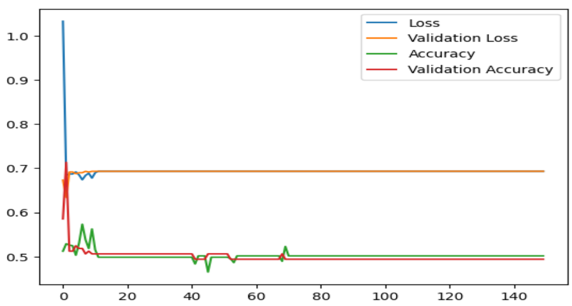


Fig.8 FD train model (up to160 epoch)

Conclusion:

In order to solve the kinship verification problem, we presented a Siamese deep CNN model in this work that combined ResNet and VGGNet and used the Adam optimizer. This model double-replicates the CNN model to predict a similarity score. Two persons' faces are fed into each instance. The network's training goal is to use similarity scores to extract similarities between image pairs and identify relationships. Four categories of relationships are distinguished by it: mother-daughter, mother-son, father-daughter, and father-son. Our suggested model, when tested against SPP, Sphere-Face, Multi Abstract Fusion, and other models, achieves an average similarity score of 72.73% on the main dataset, according to experiments. These findings may encourage more research into kinship verification from facial images for practical applications, and it would be advantageous to address this difficulty in subsequent studies. Furthermore, we plan to emphasize the integration of deep learning techniques with the findings from this research more in future research endeavours.

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