Kinship identification using age transformation and Siamese network

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Kinship identification is used for kinship verification by using facial images. Presently kinship identification is done by using traditional convolutional neural networks along with a transfer learning-based approach. While the transfer learning approach is useful in many fields, however, it lacks for identification of humans' kinship accurately due to the fact that transfer learning models are trained on a different type of data that is significantly different as compared to human face image data additionally, to identify kinship big data is also required. An improved technique by using big data on Siamese and age transformation algorithm for kinship identification is presented in this paper. The results are satisfactory as 76.38% accuracy achieved that can be improved by improving the LAT algorithm for the kinship identification using facial images.

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Abstract

Kinship identification is used for kinship verification by using facial images. Presently kinship identification is done by using traditional convolutional neural networks along with a transfer learning-based approach. While the transfer learning approach is useful in many fields, however, it lacks for identification of humans' kinship accurately due to the fact that transfer learning models are trained on a different type of data that is significantly different as compared to human face image data additionally, to identify kinship big data is also required. An improved technique by using big data on Siamese and age transformation algorithm for kinship identification is presented in this paper. The results are satisfactory as 76.38% accuracy achieved that can be improved by improving the LAT algorithm for the kinship identification using facial images.

Introduction

The volume of Big Data generated by the business, social media, public industry, non-profit sectors, and scientific research have increased tremendously [1]. This data contains a lot of useful information in textual, pictorial, audio, and video format. Meanwhile, extracting useful information from pictorial data is a challenging task due to its complexity, volume, and veracity. This pictorial data contains many useful and worthwhile information that could be used for various purposes [2, 3].

In the last few years, researchers are interested to extract kinship information from pictorial data having human faces which can be used for different purposes. As the face image data not only provides different unique features of humans but also contains a wealth of information that can be used for various purposes [4]. The purpose to extract genetic relationships between human images is to verify human kinship, which is useful information for medical sciences, psychologists, security agencies, family album organization. Furthermore, it can be utilized in image annotation, searching of missing children, human trafficking, and can be used to solve problems of immigration and border patrol [4, 5, 14].

Face Recognition and verification is an active area of research from the last two decades. It has been studied enthusiastically to make computers capable as more and more intelligent like applications developed for HCI (Human-Computer Interface), security, robotics, entertainment, games, etc. [6]. In parallel after face recognition, now age and gender detection techniques are also proposed. Levi and Hassner proposed a classification technique for age and gender using convolutional neural networks [7]. Similarly, Dehghan A. et al. proposed the genetic identification technique in which they used gated autoencoders and tried to determine the resemblance of parent and child [8]. They find the resemblance by using father, mother and children facial features similar to found in anthropological studies however, it only works if there is much resemblance of offspring with parents and therefore, causes poor performance in case children having little or no resemblance with their parents. On the other hand, Hu J proposed another technique of kinship verification for videos using video face dataset KFVW, which were prepared in wild conditions to handle kinship verification for the video-based study. This technique handles some pose identification however, the experimental data indicate that the matric-based learning is not an effective technique for kinship identification [9].

Amongst these challenges, researchers are adopting the pre-trained network Convolutional Neural Network as a transfer learning with CNN layered architecture and training algorithm to get better results for kinship identification & verification. However, the shortcoming of such models is that they lack in kinship identification as transfer learning models are trained on a significantly different type of data as compared to human face images. Moving onwards, to solve the problems of limited datasets. Joseph P. R. et al introduced a database named Recognizing Family In the Wild

(RFIW). It is the first large-scale image database especially for kinship recognition and exploits the challenges of kinship recognition [10].

Meanwhile, methodologies proposed so far have several challenges such as limited pair of images for parents and children. A classifier trained using transfer learning and limited scale dataset fails while recognizing real-world images. This study, in this regard, is aimed towards proposing and providing an effective technique for performing kinship identification through image data.

This research work, instead of comparing direct images of parents and children suggests an approach of age transformation and converts images of parents and children into same age of 16-20-year age and then compares them to get better accuracy of similarity. In this model, we have used a pre-processing stage of age transformation before going to image comparison for kinship identification and verification. Our model first uses an age transformation algorithm to transform facial images by increasing or decreasing the age of face images and making them at the same stage of age. After making images at the same stage of age, it makes images to close similar and will make it easy to compare images and finding similarities between them to exploit kinship identification between them. Furthermore, the robustness of our technique is validated through extensive experiments analysis on a huge dataset.

The contributions of this paper include 1) proposing improved pre-processing of dataset images through employing the use of the Life Span Age Transformation (LAT) algorithm for transforming the images onto the same scale of age, 2) using Siamese network for performing the feature extraction from the transformed images, 3) introduced technique is validated by using the state-of-the-art benchmarked dataset namely RFIW (Recognizing Family in the Wild), 4) finally, extensive experiments conducted on the dataset using the proposed technique identify the improved effectiveness. Moreover, the comparative analysis indicates that the proposed technique outperformed the existing methods.

Figure 1: High Level Methodology of Proposed Study

The remaining paper is organized as follows. In section II, we have listed the related work. Section III outlines the proposed methodology in detail. In Section IV we present the achieved experiments results and discuss them in detail. Finally, we conclude our research in Section V and list the possible future directions.

Related Work

In the computer vision community, researchers are interested in kinship verification (family or not family) by applying different face recognition and machine learning techniques. Fang et al. introduced the problem and used simple features for kinship identification like color of eyes and skin, distances between facial parts for kinship verification [11]. Subsequently. Xia et al. claimed the similarity between parents and their children is quite large and proposed an approach of kinship learning by removing gap between two facial images of a parent, one image of young age and one image old age along with children's images [12]. Lu et al. used a metric learning approach for kinship verification and found effective features, which provided the most discriminative results [13]. Levi G and Hassner T proposed a methodology of classification using age and gender by applying convolutional neural networks and got better results [7]. Dehghan A. et al. proposed the genetic identification technique by determining resemblance between parent and offspring via gated auto encoders. They used deep learning techniques to learn the most discriminative features between parent and children to find out resemblance between them. That approach deals with resemblance by using father and mother facial shape and extracted a similar face with combination of father and mother facial features [8]. Yan H, Hu J. revealed that Euclidian similarity metric is not powerful way to measure the similarity of facial images especially when they captured in wild conditions. They clarify that similarity metric can handle the problem in better way to deal face variations as compared to Euclidian similarity. They used mid-level feature vector with discriminative metric learning and proposed prototype-based discriminative feature learning approach for kinship verification [13, 14]. Yan H, Hu J. proposed a methodology of video-based kinship verification by using data set of video faces called Kinship Face Videos in the Wild (KFVW). Dataset built by capturing facial images from videos for kinship verification. This methodology analyzes the human faces in video by getting training set from video poses and then apply distance metric learning approaches to get positive semi definite matrix (PSD) for face recognition and kinship identification [9]. Joseph P.R. et al Introduced the first large-scale image database for kinship recognition called Families In the Wild (FIW) and exploits the challenges in kinship recognition. The FIW database consists of thousands of images of faces for kinship recognition [10]. Yong L. et al presented a framework in which knowledge of face recognition from large scale data-driven transferred and then it fine-tuned metric space to get discrimination of kin related people. They also proposed an augmented strategy to balance the images of family members and also used triplet and ResNet to extract face encoding for kinship identification [15]. In early techniques, kinship verification uses handcrafted descriptors from facial images to perform classification for learning. Fang et al. used facial features like colors of eye and skin and distance of eye-to-nose for kinship verification [11]. Zhou et al. proposed an approach based on spatial pyramid features for kinship verification. This approach used Gabor based gradient orientation features of facial images [16]. Liu et al. applied transferrable approach of fisher vectors derived from each facial images to extract similarity for kinship verification [17]. Kohli et al. proposed an approach to achieve kinship similarity using self-similarity descriptor. They introduced that kinship verification is a two-factor classification problem. They revealed that low-level features couldn't be used as well underlying source of visual resemblance between people having kinship relation [18]. In Shallow metric based approaches, metric learning methods used to learn discriminative features for kinship verification. These approaches learn a Mahalanobis distance using handcrafted features identification and try to get better score of similarity between kinship-related pair with non-kinship-related pairs [5]. In Deep learning based approach Kaiming He [19], Kohli et al [20] motivated kinship identification and verification after getting impressive success by applying deep learning approaches for classification of different facial images. Many techniques have adopted deep metric learning to get discriminant features for kinship verification. Dehghan et al. introduced an approach of fusing the features using gated auto-encoders. They extracted optimal features by reflecting parent-offspring resemblance [8]. Zhang et al. (2015) adopted an approach of kinship verification using convolution neural network (CNN) to train the algorithm with concentrated image pairs [21]. Kaming He et al introduced deep residual learning approach for image recognition. Their approach used residual training with neural networks, and multiple layers as learning residual functions [19]. Duan Q, Zahng L., Zuo W proposed deep kinship verification technique named Coarse to Fine Transfer(CFT) using Convolutional Neural Network (CNN) from face recognition to kinship recognition and used Deep Transfer Learning [22]. Wang S et al proposed the Kinship Verification on Families in the Wild with Marginalized Designing Metric Learning (DML). That technique used largest kinship verification using Auto-encoder and Discriminative Low-rank Metric Learning (DLML) algorithm for feature discrimination [23]. Yana H and Hu J proposed a kinship verification technique, which works on videos. This technique is using distance metric learning on dataset of Kinship Face Videos in the Wild (KFVW) for kinship verification [24]. Lu J. et al developed a discriminative deep multimetric learning (DDMML) methodology in which they used multiple neural networks jointly to maximize the association of different features of each sample and it reduces the distance of positive pair and increases the distance of negative pair [25]. Yong Li et. al introduced kinship verification technique using KinNet: Fine-to-Coarse Deep Metric Learning and Pre-training the network and minimizing a soft triplet loss. They used four CNN networks to boost the performance [15]. Liu W. et. al introduced SphereFace a deep hyper sphere embedding for face recognition. They addressed angular SoftMax loss and angular margins problem. Their technique uses 64-layer CNN neural network for training and used discriminative constraints on a hypersphere to get the better face recognition (FR) problem under open-set protocol [26]. Savas and Akin introduced an approach of synthesizing child faces with pre-trained model by analyzing facial images of parents [27]. Habin Y. & Chaohui S worked on Multi-scale Deep Relational Reasoning for Facial Kinship Verification and used two convolutional neural networks, which share network parameters and extracted different scales of features for kinship identification [28]. After using convolutional neural network researchers moved to find kinship using Generative Adversarial Network (GAN), introduced by Iain Good fellow [29]. Fady S. at el proposed GANKIN: generating Kin faces using disentangled GAN and approach of image synthesis from parents to children, they also used pertained FaceNet and GAN network [30]. Tuan H et al. proposed an approach Recognizing Families through Images with pertained encoders, they used pre-trained networks FceNet, Siamese and FGG network to get encoding of face image and finding kinship between facial images [31]. Similar keeping in view the efficiency factor of GAN based approaches, we also used GAN based age transformation algorithm and Siamese network to build and train our model.

Although in last few years, some encouraging results are obtained from proposed methodologies for kinship identification and verification but still, automatic kinship verification is being performed poorly in the real-world applications used in daily life. Due to non-availability of large-scale datasets, results are not too accurate to handle the kinship identification problems. As existing datasets like Family101, UB KinFace, Cornell KinFace, KinFaceW-I, and KinFaceW-II are providing few examples but they fail to achieve true distributions of genetic or kinship relationships. They have limited pair of images for parents and children, Classifier trained on limited scale dataset fails while recognizing real world image.

To handle these issues, we proposed an approach to find the kinship relationship between parents and children. Our methodology uses Age Transformation and convert images of parents and children to the age of 15-20 because images of this age have maximum facial features, which can be a good source for the discrimination of features between facial images. After the process of age transformation and converting facial images to young age for both parent and children, these faces get close to each other in facial look and expression and then it makes it easy to find the similarity between them. With these images, there is much probability to get faces of parents and images close with each other and ultimately it will make easy for face encoder to generate close face encoding. In result, we get low distance value while finding cosine similarity. Diagram 3 is showing effect of age transformation

Proposed Work

This section outlines the proposed methodology for performing the kinship identification. In the proposed methodology, we present a model of deep relational network that uses a per-processing stage of age transformation of two facial images before comparing them to exploit kinship relationship from facial images. In this scheme, it first transforms facial images by increasing or decreasing age factor and making two images into same stage of age and then compares them to find and verify kinship. After transforming facial images, we propose the use of Siamese network with two convolutional neural networks by sharing parameters between them. Afterwards, it extracts different scales of features to find similarity between images by using triplet loss. Additionally, we also aim to conduct experiments on widely used facial kinship dataset namely RFIW. In this methodology, the proposed model uses age transformation and convert facial images at same stage of age between 16 and 20 years. However, we consider this age, because in this age period persons face looks strong and can provide clear facial features and we can get better encoding of facial images. Furthermore, after getting encoding of transformed faces, we apply triplet loss on three faces of parents and images and extract kinship relationship between parents and images. In addition, we have employed the use of parents' images as anchor and negative part of triplet while children's images as positive part of triplet. We fixed father and mother position of being positive or negative to each other while training in Siamese network. Likewise, we used age transformation algorithm of that provided close pair of facial images of parents and children for processing to exploit kinship identification between them. This age transformation algorithm will provide images for processing to consider for kinship identification. More graphical representation and the working flow of our proposed methodology is depicted in *Figure 2*.

Figure 2: Effect of Age Transformation

Model Training

The proposed model uses age transformation and feature encoding of face images with triplet loss to extract facial similarity to identify kinship. In first stage, it converts facial images to the images of persons having approximate age of 16-20 years. After doing conversion of two input images with age between 16-20 year, these converted images are processed with Siamese network to extract feature encoding for further processing.

Figure 3: Working of Proposed Methodology

To extract feature, it uses ResNet 50 with two fully connected layers and one output Dense Layer. It extracts feature vector of 128x128 for all input facial images and uses triplet loss to discriminate features for kinship identification. It maximizes the distance of anchor image with negative image and minimize the distance with positive image. Size of input images 224x224x3 and feature vector returned by Siamese network is 28. During the training process hard sample selection for positive or negative pairs are not equally important. the pairs with higher loss might have more impact on the model training. Training set can be defined as: Let X^a, X^p and X^n are finite set of images for Father, Children and Mother having 'm' number of images for each set. $X^a = \{x^a_1, x^a_2, \ldots x^a_m\}$ is set of anchor images for father images, $X^p = \{x^p_1, x^p_2, \ldots x^p_m\}$ is set of positive images taken from children's images, $X^n = \{x^n_1, x^n_2, \ldots xn_m\}$ is set of negative images taken from set of mother images. Then input sample taken from these three sets will be power set of three sets to make a set of triplets. let $X = \{(x^a_1, x^p_1, x^n_1), (x^a_2, x^p_3, x^n_4) \ldots (x^a_n, x^p_n, x^n_n)\}$ is a power set of images having three members as triplet of anchor as x^a, positive as x^p and negative image as x^n respectively. Where sequence of triplet members anchor, positive and negative members with images of father, child, and mother respectively. After getting feature extracted from pre-trained Siamese network we get a set of features $F(X) = \{[f(x^a_1), f(x^p_1), f(x^n_1)], \{[f(x^a_2), f(x^p_2), f(x^n_2)] \ldots \{[f(x^a_n), f(x^p_n), f(x^n_n)]\}$.

This sequence of set is used for extracting similarity of children with father and mother to get kinship relation of Father-Son (F-S), Father-Daughter (F-D), Mother-Son (M-S) and Mother-Daughter. For sibling relationship, we change some sequence of power set, we take one sibling image as anchor, one as positive and one image as negative, if third image of sibling does not exist then for negative position we take any random image from the set of mother or father. So, for negative position random set of images: $Xr = P\ \{Xa \mid Xn\}$. Then set of triplets for sibling relationship Brother-Brother (B-B), Sister-Sister (S-S) and Brother-Sister (B-S) is as follows: $X^{s} = \{(x^{p}_{1}, x^{p}_{2}, x^{r}_{1}), (x^{p}_{2}, x^{p}_{3}, x^{r}_{2}) \dots (x^{p}_{n}, x^{p}_{m}, x^{r}_{n})\}$

Loss Function

Loss function for the triplet loss on the extracted feature, For three cases

1. While comparing father images with child images, if D_f is distance of child image with father image and D_m is distance of child image with mother image then we define the loss function as:

$$D_{f} = ||f(P) - f(A)||^{2},\ D_{m} = ||f(P) - f(N)||^{2}$$

and some margin 'm' as hyper parameter, whereas A, P, N are anchor, positive and negative images, and f(A), f(P) and f(N) are features of father, child, and mother images respectively. If father image is closer to child image then we increase the distance of child image with mother image and decrease the distance of child image with father image, so loss function to get similarity between father and child will be: $£_{f}\ (A, P, N) = max\ (D_{f} - D_{m} + m, 0)\ if\ D_{f} < D_{m}$

2. While checking similarity of children with mother then we revert the loss function. To find the similarity of child image with mother image, we increase the distance of child image with father image and decrease the distance of child image with mother image then loss function will be:

$$£_{m}\ (A, P, N) = max\ (D_{m} - D_{f} + m, 0)\ if\ D_{f} > D_{m}$$

3. While comparing sibling images, we use distances measures of two sibling images S1, S2. We find the distance between siblings and random image as : $Ds_{1} = ||f(S1) - f(S2)||^{2}, D_{s2} = ||f(S1) - f(N_{r})||^{2}$ where *f(S1), f(S2) and f(Nr)* features of siblings and a random image respectively, After calculating distance and using margin 'm' as hyper parameter, we can define the loss function as:

$$£s\ (A,P,N) = Max\ (D_{s1} - Ds_{2} + m, 0).$$

Where D_{s1} is distance of one sibling with other sibling, similarly Ds_{2} is distance of sibling with random image to find triplet loss and minimize distance between first with second sibling

Network Structure

To select information from different scales of features for input to the relational network, we use the pre-trained Siamese network and get a feature map $R^{512\times3x3}$ and then we split this feature maps into 3x3 blocks with 256 features. In this way, each feature can represent a face area of each image. Therefore, we can get rich information from face images for processing of kinship. Each feature of size $R^{256\times1}$ will provide information of the faces in triplet of face images respectively. After that relational network first analyzes these selected features with multiple multi-layer perceptron that share parameters. Each perceptron consists of some fully connected layers and relu activation

Figure 4: Working of Age Transformation Method

functions.

This multi-layer perceptron will extract the relation of features and output feature of size $R^{128\times1}$. Then we compare these features of size $R^{128\times1}$ at element level to represent distance between features of faces. Lastly, we use another multi-layer perceptron to find similarity of faces for kinship identification from the relation of different face images. It also consists of some fully connected layers and relu activation functions. A detailed structure of these multi-layer perceptrons is in diagram 4. To optimize the network our cross-entropy loss function will be used with below specifications:

$$L = \sum N_i \left[-y_i \log(\hat{y}_i - (1 - y_i) \log(1 - \hat{y}_i)\right]$$

where L denotes the loss, N represents the number of samples, y_i is the ground truth of ith sample, and $\hat{y}_i$ is the prediction of ith sample.

The CNN structure model uses the deep relational network; it consists of multiple convolutional layers, maximum pooling layers, batch normalization layers and relu activation functions. Input CNN network is a pair of face images $\in R^{3x64x64}$. Three scale of features, which are generated by network, these are used for calculation and analysis of kinship from facial images, these three scales of features consist of sizes $R^{128x9x9}$, $R^{128x4x4}$ and $R^{128x2x2}$.

The first layer of network is a multi-layer perceptron having multiple fully connected layers, batch normalization, dropout layers and relu activation functions. The input feature size of first layer is $R^{256\times1}$ and output feature size is $R^{64\times1}$. Second multi-layer perceptron consists of multiple fully connected layers and the relu activation function. The input feature size is $R^{64\times1}$ and the output feature size is $R^{2\times1}$. We extract two feature maps for a given pair of face images and these parent and child images are shared by convolutional neural network. After sharing images, corresponding local regions of these two feature maps are concatenated and sent to the relational network.

Our model explicitly establishes relations between three feature maps rather than the making relation within one another.

Results and Discussion

The CNN-based deep relational network is utilized for extracting the features from the facial images of the dataset. *Table 1*. outlines the details of the included parameters for the CNN-based deep relational network. It represents that, unlike the previously existing models, our model explicitly establishes relations between three feature maps rather than the making relation within one another. Additionally, it depicts that our model takes 10 images of each member and find the triplet loss on 128 features maps of each 10 images for one member, in total used 30 features map for one comparison to find the similarity between them. The proposed model delivers the optimal performance by utilizing this methodology.

In this section of the study, we have listed the experiments and achieved results by employing the use of the proposed technique of utilizing a deep relational network along with the LAT age transformation algorithm [32]. We have used the large dataset of Recognizing family in the wild (RFIW) for the training and validation of our proposed technique. In the first phase, we convert images of datasets RFIW to different life stages for age transformation. After the age transformation of facial images, we convert images at the same stage of ages by adjusting the age factor. In the first stage, we transform facial images by increasing or decreasing the age factor and making two images into the same stage of age. In the second phase, we train our algorithm by comparing two images and evaluating metrics and parameter settings to extract kinship relation accuracy.

Table 1: Parameters of Deep Relational Network

Age Transformation

For Age Transformation, we have employed the use of Lifespan Age Transformation Synthesis algorithm, proposed by Roy Or-El et al. [32]. Using this algorithm, we prepare our data set images for comparison that converts images at different stages of life, and afterward, we pick the images of age between 15-20 and use them for feature extraction. *Table 2*. outlines the training and validation accuracies observed on different relationships, by utilizing the proposed model.

Table 2: Achieved Model Performance for different Relationships

Similarly, *Table 3*. represents the observed results on the baseline dataset. While comparing accuracy with a model trained on dataset RFIW, the results from *Table 3.* indicate that our proposed model has delivered better performance as compared to the existing state-of-the-art models, by improving the overall accuracy.

Table 3: Comparison of Results on Baseline Dataset

Meanwhile, the previously existing models have failed to deliver improved performance for up to 73.21% accuracy. The proposed model has outperformed existing state-of-the-art models by delivering an accuracy of 76.38%. Furthermore, we plan to improve the model and accuracy in the future, by improving the underlying relational network and applying it to transformed images with the same stage of age.

Conclusion

Kinship identification is used for kinship verification by using facial images. Meanwhile, the previous studies have explored this area by employing the transfer learning-based solutions. This study, however, presents a different approach to perform kinship verification.

In this study, we have introduced a technique that uses pre-trained LAT model along with Siamese network for performing kinship identification. Additionally, we have employed the use of age transformation approach for finding similarities of parents with children. The extensive experimental results were used to validate the performance of our proposed model. Furthermore, the comparative analysis with previously carried out studies reflect that our model outperformed the existing state of the art models using similar approach, thereby, delivering an overall accuracy of 76.38%. In future, we aim to improve the model performance by improving the underlaying relational network and applying it on transformed images with same stage of age.

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Figure 1

High Level Methodology of Proposed Study

Diagram showing working of methodology

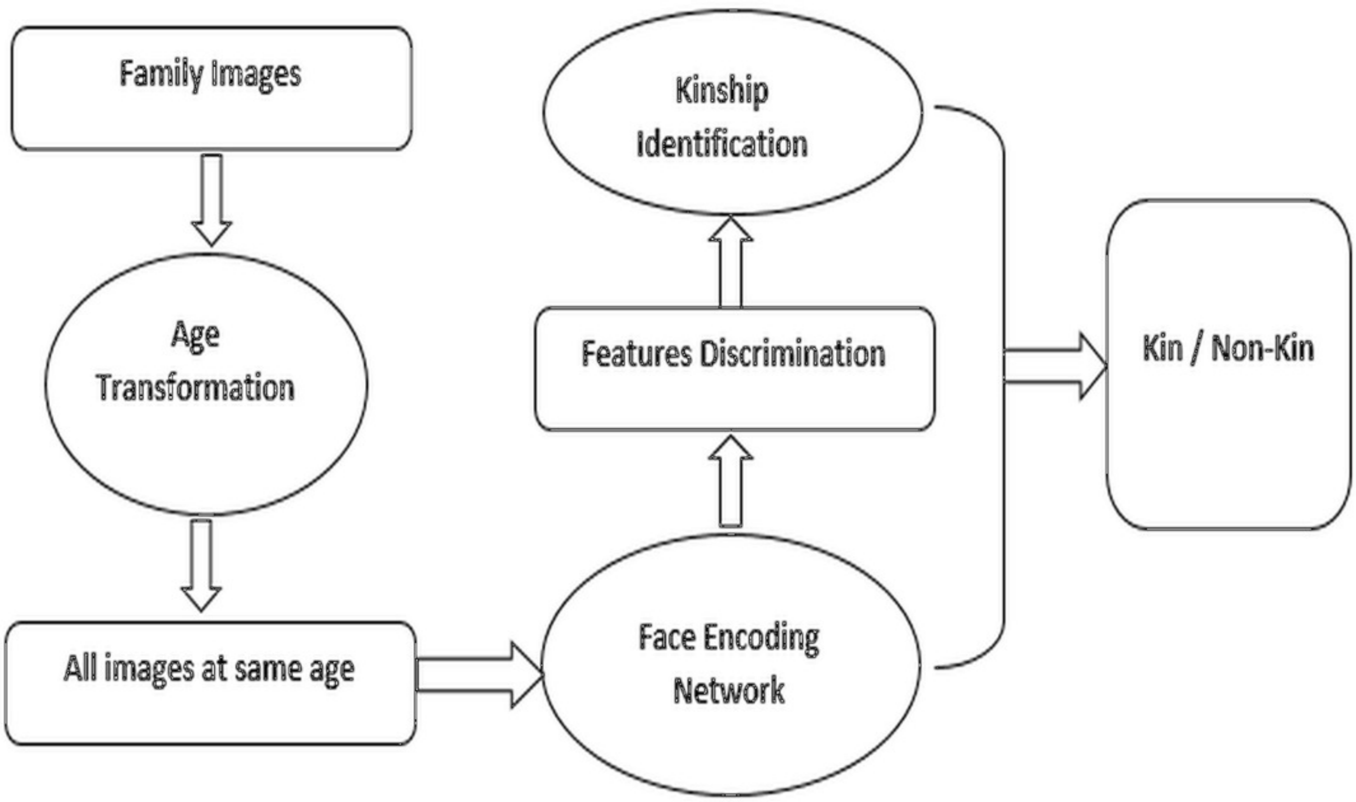

Figure 2

Effect of Age Transformation

Diagram to eloborate Effect of Age Transformation on Facial Images

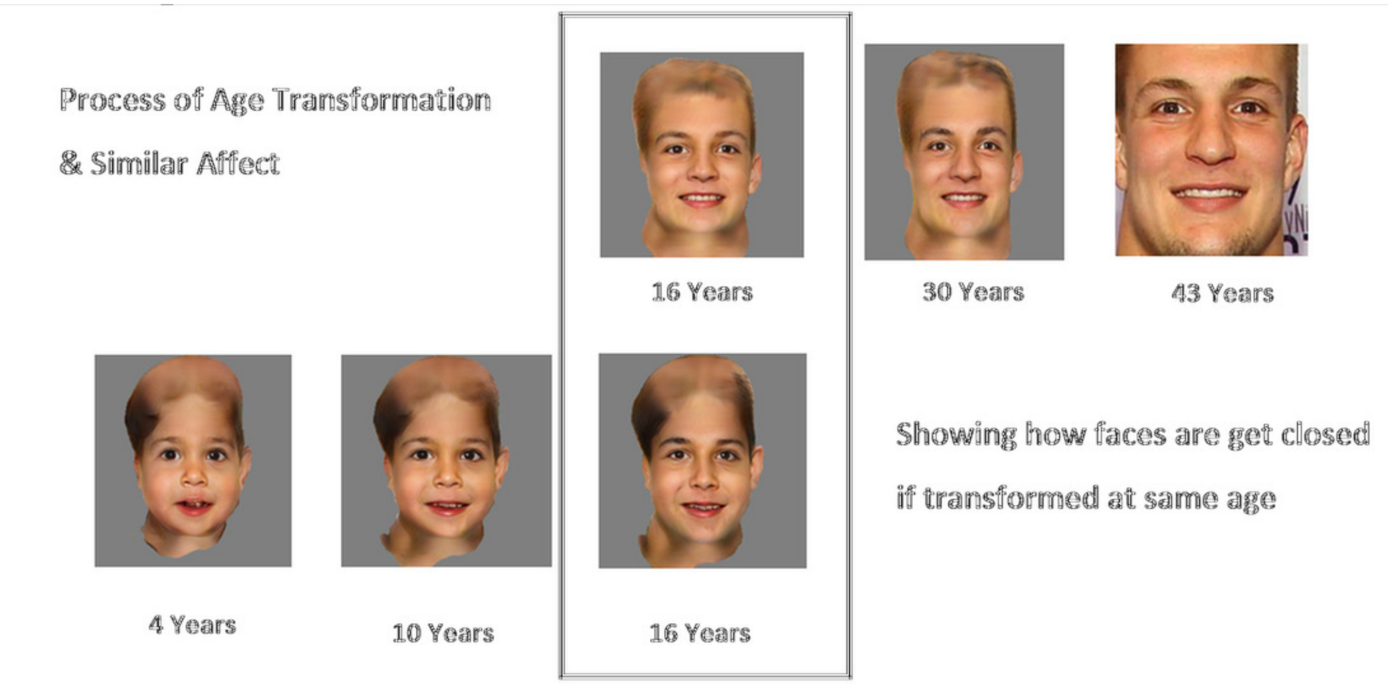

Figure 3

Working of Proposed Methodology

This Diagram shows Working of Proposed Methodology, how methodology works to achieve kinship identification

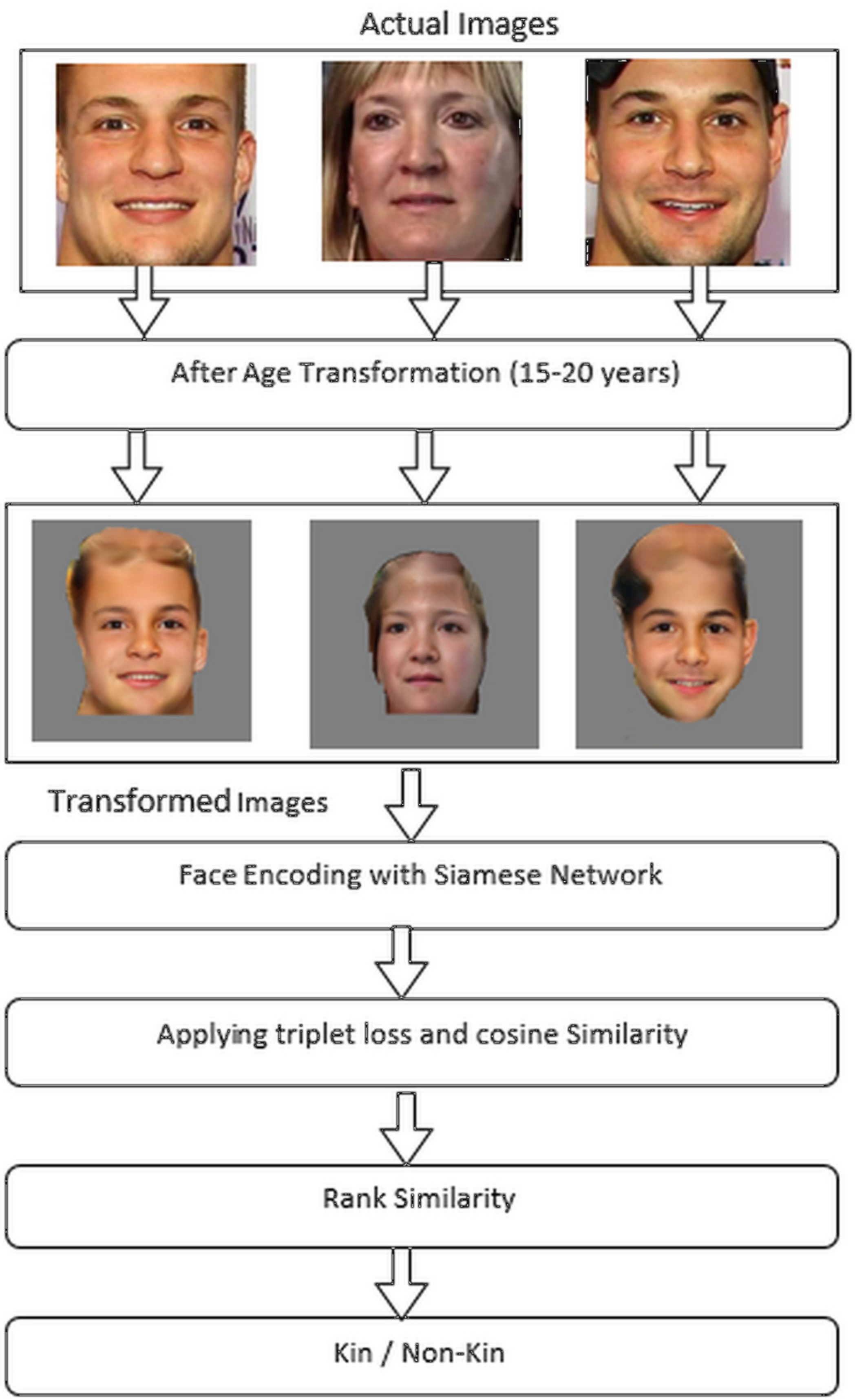
Actual Images
After Age Transformation (15-20 years)
Transformed Images
Face Encoding with Siamese Network
Applying triplet loss and cosine Similarity
Rank Similarity
Kin / Non-Kin

Figure 4

Working of Age Transformation Method

This Diagram shows Working of Age Transformation Method used for kinship identification

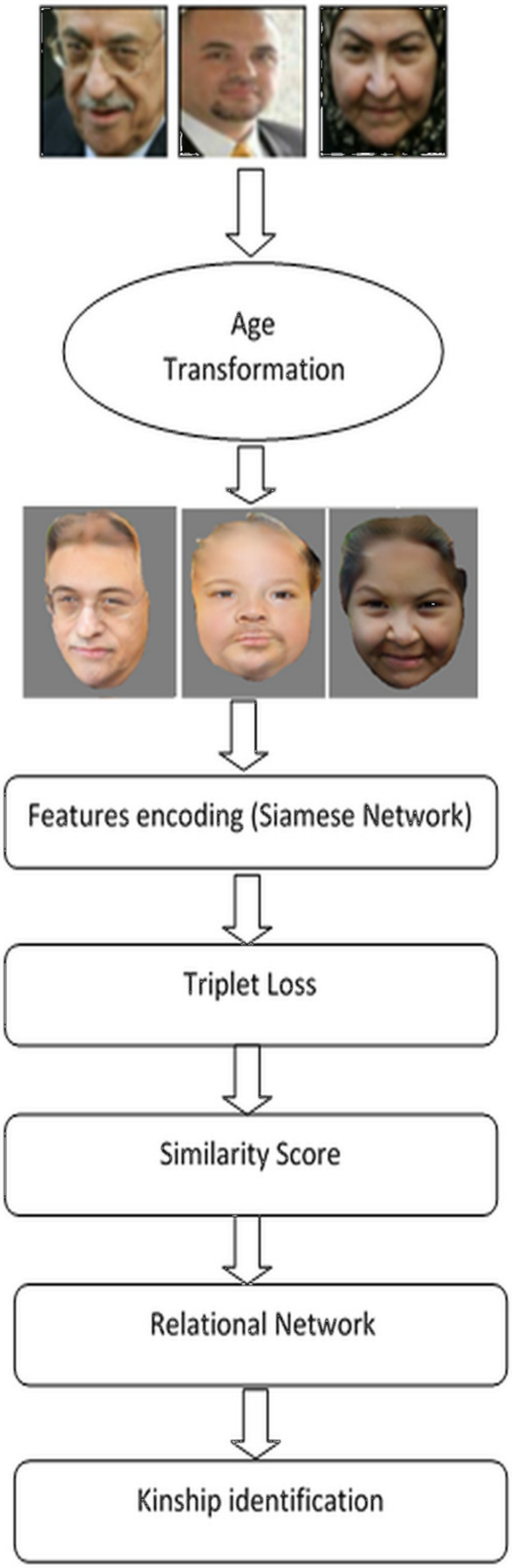
Age
Transformation
Features encoding (Siamese Network)
Triplet Loss
Similarity Score
Relational Network
Kinship identification

Table 1(on next page)

Parameters of Deep Relational Network

Table showing parameters of training network

Table 1: Parameters of Deep Relational Network

Setting	**Input Size**	**Output Size**	**Kernel**	**Stride**	**Padding**
SIAMESE NETWORK	3*256*256	512*1	3	1	**0**
DENSE-1+ BN + RELU	512*1	256*1	2	2	**0**
DENSE-2 + BN + RELU	256*1	256*1	2	1	**0**
DENSE-3	**256*1**	**128*1**	**2**	**2**	**0**
		Relational Network			
Conv-1+ BN + RELU	10x128x128x128		3	1	2
Conv-2+ BN + RELU	10x128x128x128		3	1	2
Conv-3+ BN + RELU	10x128x128x128		3	1	2
Dense (Flatten)+SIGMOID	1x128		**Kin / Not Kin**		

Table 2 (on next page)

Achieved Model Performance for different Relationships

Table Showing Model Performance for different Relationships

Table 1: Achieved Model Performance for different Relationships

Training Accuracy		**Validation Accuracy**		
Relation	**Accuracy (%)**	**Relation**	**Accuracy (%)**	**Mean (%)**
Father-Son	80.12	Father-Son	76.16	78.14
Father-Daughter	77.15	Father-Daughter	73.00	75.07
Mother-Son	75.75	Mother-Son	72.75	74.25
Mother-Daughter	79.17	Mother-Daughter	77.0	78.08
Overall Mean				**76.38**

Table 3(on next page)

Comparison of Results on Baseline Dataset

Table representing Comparison of Results on Baseline Dataset

Table 1: Comparison of Results on Baseline Dataset

Sr. No.	Methodology	Classifier	Accuracy
1	Joseph P. Robinson (2018). Visual Kinship Recognition of Families in the Wild	Cosine similarity SVM	69.18%
2	Ghatas, F. S., & Hemayed, E. E. (2020). GANKIN: generating Kin faces using disentangled GAN	GAN	71.16%
3	Tuan H et al. (2020). Recognizing Families through Images with Pretrained Encoder	Pre-trained CNN	73.21%
4	**Proposed Methodology**	**Pre-trained LATS + Siamese**	**76.38%**