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Kinship Recognition based on Deep Scattering Wavelet Convolutional Neural Network on Wild Facial Image

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ABSTRACT:
Kinship verification is a process that two or more people has a family relation such as father and son or other family relation. Numerous studies have been presented to investigate the relationship between people. Kingship verification can be done based on image of face. Most of the methods presented on face images work well on face data sets recorded under controlled conditions. However, due to the complex nature of environments, rapidly and accurately examining human kinship in real-world unrestricted or wild-type scenarios is still a challenging research. In this paper, in order to overcome the aforementioned challenges, an efficient and new method is presented. In the proposed method, a method is used to launch the operation to create a map. The created feature map is stable against deformation, transition, scaling, direction and Dilation in wild images. Group-Face and TSKinFace databases are used for simulation. In order to evaluate the evaluation of the proposed method, average recall of 94.1, precision 94.6, accuracy 94.7, specificity 93.8, and finally F_Measure 95.0 were used. The superiority of the proposed method in all comparisons shows the effectiveness of the proposed method in diagnosing kinship.

KEYWORDS: Kinship, Deep learning, Dispersion Wavelet, Convolution Neural Network.

1. INTRODUCTION

Biological and psychological research has shown that people who are closely related usually have similar faces [1]. Biologists have proven that the genetics of the child and the parents, or even the children with each other, is such that it has a positive effect on the structure of the face and creates similarity and overlap of similar characteristics. The results of the research have shown that similar genes create a similar structure in the face of individuals [2]. Recognition of kinship or in other words, recognition of inheritance from the face is used in areas such as family courts, human trafficking, cyberspace exploration, and determining child ownership [3-5]. In diagnosing a kinship relationship, the goal is to identify the type of family relationship between two people based on facial images [6]. In most studies, studies are performed on two pairs of images. Each person has a role to play in recognizing a relationship. Maps in a typical family include father F, mother M, daughter D, son S, sister Si, and brother B. Based on the main maps, father-son F-S, father-daughter F-D, mother-son M-S, mother-daughter M-D, sister-brother Si_B, brother-brother B-B, sister-sister Si-Si can be defined [7].

In order to distinguish kinship from face images, two categories can be presented [8]. These methods are

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traditional methods in identifying algorithms and methods based on deep learning. In other words, this division can be expressed as methods based on conventional machine learning and methods based on deep learning [9]. In the traditional machine learning method, pattern recognition processes are used. In this method, after pre-processing the image, various properties including textural, spectral, geometric, and statistical properties are extracted from the desired image [10-13]. These features are further reduced in another step by methods based on principal component analysis, PCA [14-16], and independent component analysis ICA. In these methods, feature selection methods can be used to select the most effective features [17-20].

In traditional methods of recognizing kinship, extracting effective features from images is an essential step. The extracted properties are used to create a one-to-one mapping between the desired images [21]. Extracting unique features is very important in creating accurate one-to-one mapping [22]. In addition to the importance of these features, feature extraction in facial images to identify kinship can be divided into two categories [23-26].

Gaussian as HOG, and Gabor have also been introduced in this field [14]. Feature extraction can be done manually by the user [18]. It can also be extracted automatically. In this case, the accuracy of detection and identification depends very much on the algorithm designed by the user to extract the feature [27]. Features extracted from the image can be extracted locally or globally [28]. Although the appearance-based can provide good and unique global features to identify, the big challenge in this category of features is the instability of changes in the face. These features change with the slightest change in the face, including facial expressions, frowns and smiles, changes in brightness, and coverage of the face. Even changing the scale of the face causes changes in the extracted feature vector [29]. Also, the efficiency of recognition and recognition by these features with challenges such as non-uniqueness, duplication, and being affected, changes in the face of which features [30]. Another challenge is the difficulty of extracting local features. In other words, a suitable algorithm must be designed to extract these features [31]. In both of these methods, global as well as local features, types of features are not learned for identification [32]. Both of these methods can be classified as static methods. In order to overcome the challenges of extracting the most effective features, deep learning methods have been proposed [33].

In deep learning methods, led by the CNN convolution neural network method [34], local and global information is extracted from images in the convolution process [35]. Local information including lips, eyes, eyebrow position, forehead length, and jaw angle is extracted in multiple cannulation layer processes for detection [36, 37]. Then, with the help of a fully connected neural network, the type of relationship or the presence or absence of a relationship is identified. Recognition of similarities between two faces is possible both from the information of the local members of the face and through the information of the face in general. Convulsive neural networks are able to produce different features of local facial organs to identify the type of kinship [38].

The success of deep-learning methods in detecting kinship has been in images in which no masking or facelift has occurred. But in the real world, faces are often transformed [39]. In the analysis of kinship, the similarity between the images is calculated, and based on the obtained score, the type of kinship and even its presence or absence is determined [40]. Thus, adapting images to facial expressions such as frowns and smiles, facial expressions such as glasses or virtues in men, light changes in recorded images, and even cosmetic surgery and the use of cosmetics can be a daunting task for automated kinship detection algorithms [41]. Changes can also be understood with changes due to aging or facial changes. Facial aging is a biological process that leads to gradual changes in facial geometry and texture. Changes caused by the expressed cases can appear in general or in part on the face. The resulting changes make it difficult to model such non-uniform transformations for face-based kinship recognition algorithms [42]. The use of face images in recognizing kinship relationships has been considered by researchers. However, attention to facial challenges such as facial expressions such as frowns and smiles, light on the face, cover or wild facial expressions have received less attention in these studies. In studies that do not consider multiple facial expressions, because there is no face change factor, it is possible to have a kinship relationship with higher efficiency. However, in wild facial images, conventional methods cannot be used because they have to be adapted to changes in the face and in different situations. In wild facial images, the pixels of the facial image change locally and even globally, making it very difficult to identify the relationship.

The main purpose of this study is the intelligent use of in-depth learning in the design of an efficient and reliable unit in the detection of kinship in wild facial images. In addition to detecting kinship, the proposed method will take into account challenges such as noise in the image, image rotation, light changes, and emotional states in the image of the face. The innovations of this research can be listed as follows:

- Considering the various challenges of the face in recognizing the kinship relationship and overcoming it
- Designing a new convolutional neural network in order to detect kinship in facial images

This paper is organized as follows. In the second part, the research background will be presented. In the third part, the proposed research method will be presented. In the fourth part, the evaluation of the proposed method will be done in full. In the fifth section, the conclusion of the article is presented.

2. TECHNICAL WORK PREPARATION

In 2012, Xia et al. introduced the first diagnosis of kinship related to kinship and its diagnosis in three categories [23]. In 2014, Guo et al. presented a graph-based model for determining the type of kinship relationship in detail [43]. In 2015, Zhang et al. proposed a simple canonization neural network in the detection of kinship. The proposed convulsive neural network uses the main images and the whole face for training [44]. In 2016, Kohli et al. Proposed hierarchical learning to identify the type of relationship. The hierarchical method presented in this study has used a kind of human learning to identify the relationship [9]. In 2017, Lu et al. proposed a DDML discriminative deep metric learning for teaching a deep neural network. In the proposed method, hierarchical nonlinear transformations are applied to different images. These hierarchical transformations accelerate metric learning [1]. In 2018, Robinson et al. diagnosed kinship relationships using convolutional neural networks in a researcher-made database [6]. In 2018, Tidjani et al. used deep learning features to determine and identify the type of relationship. The proposed method uses four steps: using the DCTNet Discrete cosine transform network, creating a binary histogram of the output of the convolution layers, creating an ordered normalization to remove the DCT Net binary matrix, and using a multilayer neural network to differentiate or resemble the sample. The accuracy of the proposed method is reported to be 75% on average [45]. In 2020, Wang et al. proposed a deep identification and adaptation method to identify the type of relationship between members of a family [46]. In 2020, Goyal et al. proposed an EKV eccentricity-based kinship verification [2]. In 2021, Yan et al. used a defined communication network to identify the type of kinship relationship using local facial information [27]. In 2021, Li et al. introduced a machine learning-based approach based on spatial pyramid learning-based called SPLE [28]. In 2021, Layadi et al. extracted the features of fine-grained structures from an unsupervised learning method [47].

3. MATERIAL AND METHODS

It is difficult to identify the type of relationship in facial images through a person's controlled postures when shooting or in an uncontrolled or wild state. Due to the complex environmental conditions, the uncontrollable conditions as well as the light in the environment, the angle of the face, the use of covers such as glasses and hats, and even the use of cosmetics have caused the accuracy of kinship identification in research and uncontrolled situations to be very low. Conventional methods of recognizing the type of kinship focus on the entire facial structure. In other words, the whole face is given to the algorithm without any changes. Based on this image, the algorithm detects the presence or absence as well as the type of relationship. Fig. 1 shows some images in different situations. In these images, the lower part of the face may be covered with a mask or scarf. Even the upper parts, such as the eyes, should be covered with glasses or a hat. In addition to obstruction in images, other conditions in the image may also cause obstruction. Facial expressions such as frown, smile, and light on the face also make the recognition algorithm challenging. Less research has addressed this issue. In this article, in addition to recognizing the desired relationship, obstruction states in the image as well as facial expressions will be considered.

Fig. 1. Sample of images with different moods and coverage on the face.

Deep neural networks have been widely used in image analysis and processing. Convolution neural networks are a type of deep networks that have been very successful in various applications and have been able to show their superiority. In this section of the paper, a new method in the diagnosis of kinship ligament based on deep learning in convolutional neural networks is presented. This section discusses it in detail. To determine the relationship of kinship in the proposed method, three basic steps have been considered: Pre-processing step, deep network training, and kinship identification step. In each of these steps, processes have been performed that have improved the accuracy as well as increased the accuracy criteria. Fig. 2 shows the block diagram of the method proposed in the training step. The proposed method is fully described below.

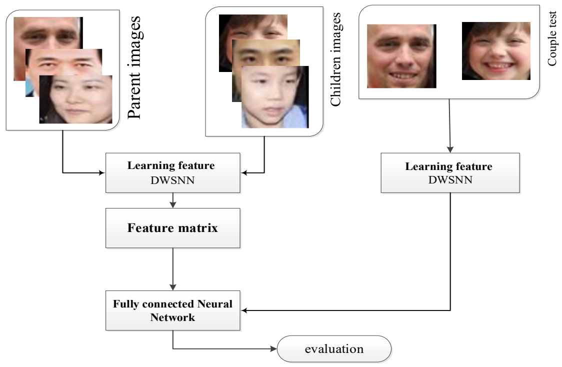

Fig. 2. Block diagram of the proposed method in detecting kinship.

In the feature learning stage, the features of the images of the faces of the parents as well as the children are extracted using the scatter wavelet in different scales and directions, the image subbands. The settings and parameters applied to the scatter wavelet descriptors to learn the features of face images include the following.

1. In the first step, the wavelets are produced by cascade filters. The input of this step is the size of the converted signals, the filter parameters, and the scattering and wavelet parameters, and the output of this step is a cellular array of the wavelet transform that is needed to scatter the conversion.
2. In the second step, the scatter conversion is calculated using the cell array of the previous step and the input image of the face, but this conversion does not have the correct format to enter the classifier. Therefore, in the third step, a format conversion on this scatter conversion is done and is prepared in the form of a matrix for convolution. Fig. 3 shows the output images of each step of the scatter wavelet transform on a scale

Fig. 3. Output of each stage of scattering wavelet transform in one scale and eight directions.

In a typical convolution neural network, the convolution process is used in the pool layers. In pool layers, different kernels are used for Canvolve operation in the image, which creates different feature maps, although this process reduces the number of variables, local connection learning, and immutability. But in wild images, the face will not be very efficient. In order to improve the feature maps and apply them to subsequent processes in this research, instead of using a simple convolution process, Wavelet Scattering will be used.

The scatter wavelet-based method is one of the methods for creating feature maps that has good temporal and computational complexity. In this conversion, a set of wavelet filters, including the Gabor wavelet, are used in different directions and angles, to extract the most distinctive features and in different faces. Therefore, in order to produce a stable feature map against deformation, transfer, scale, direction, and dilation in wild images, a scattering wavelet can be used instead of convolution. In the convolution neural network section, 12 convolution stages and the ReLu activator function, six integration steps, and three prototyping steps are used. In this part, the image enters the convolutional neural network and its output is identification. Fig. 4 shows a designed example of convolutional neural network stages. The output of the convolution process will be classified using a fully connected network. This fully connected neural network is a multilayer perceptron neural network (MLP) [49].

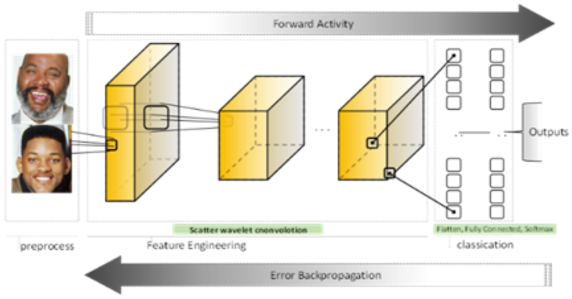

Fig. 4. Convolutional neural network used in scattering wavelet-based feature learning.

4. RESULTS AND DISCUSSION

In this paper, a new and effective method for detecting kinship based on deep method is presented. In the proposed version, after applying the scattering wavelet in the convolution phase in 12 layers, a rich vector of facial features is created, this rich vector is used to detect the relationship of kinship in a gifted education network. In this part of the research, the proposed method on Group-Face datasets, TSkinFace, will be evaluated. Several evaluation criteria will be used to evaluate the proposed method.

4.1. Research Database

Four datasets have been used to match and identify kinship in this paper. In these databases, a central family includes common father-son relationships F-S, father-daughter F-D, mother-son M-S, mother-daughter M-D, sister-brother Si_B, brother-brother B-B, sister-sister Si-Si. These databases are group-face datasets [43] and TSKin-Face datasets [50].


Fig. 5. Sample images in the TSKinFace database.

The Group-Face database contains 106 family photos. From these images, 98 group images with 322 pairs of faces were selected for the experiment. The TSKinFace dataset includes only three types of Nuclear family, including father-son F-S, father-daughter F-D, mother-son M-S, mother-daughter M-D, sister-brother Si_B, brother-brother B-B, sister-sister Si-Si Is. Fig. 5 shows an example of the images in this database.

$$\text{Recall}=\frac{TP}{TP+FN} \quad (1)$$

$$\text{Precision}=\frac{TP}{TP+FP} \quad (2)$$

$$\text{ACC}=\frac{TN+TP}{TN+FN+FP+TN} \quad (3)$$

$$\text{Specificity}=\frac{TN}{TN+FP} \quad (4)$$

$$\text{F\_Measure}=\frac{2*TN}{2*TP+FP+FN} \quad (5)$$

4.٢. Evaluation Criteria

To evaluate the proposed method, the criteria of call rate, accuracy, precision, sensitivity, specificity, and criterion F are considered. The following equations show the calculation of these criteria. In the above relationships, Recall is the call rate, Precision is accuracy, ACC is Accuracy, Sensitivity is specificity, and finally, F_Measure is the criterion f [51]. TP is true positive, TN is true negative, FP is false positive and FN is false negative.

To determine the kinship relationship using the proposed convolutional neural network, the best parameters for the algorithms were identified by performing several experiments. The parameters set in this network to detect the type of relationship are as follows.

convolution layers: 12
Filters: 3 × 3
dense layer with weights: 256, 128 ,2
Softmax: 2
batch size: 128
Learning rate: 0.0001
Scatter wavelet scale; 2
scatterwavelet directions: 8
Scatter wavelet depth: 2

Recall, accuracy, precision, sensitivity, specificity, and finally the criterion f are used. It is also designed with a 12-layer convolutional neural network and specifications similar to the parameters used. Table 1 shows these evaluations. As can be seen from the results of Table 1, the proposed method performed better than a convolutional neural network in the desired criteria. The reason for this superiority is to create a feature-rich vector of Word images. In other words, with scattering wavelets, images are obtained that contain multiple properties of directions, scales, and depths. These images are transformed into a suitable feature vector in a conversion process and then identified by a fully connected neural network. On average, the results obtained in relational detection had numbers higher than 95. This number represents the superiority of the proposed method. Also, based on the results obtained in the proposed DWSNN method, this method is better at identifying homosexual, sister-sister, brother-brother, father-son, and mother-daughter family relationships than heterosexual brother-sister, father-daughter, and mother-son relationships. The reason for this difference in the structure of people's faces is acceptable intuitively because the resemblance of homosexuals is much closer to each other than heterosexuals. This result is acceptable since the deep neural network operates on the structure of the human mind.

For graphical evaluation, the average of the obtained results is shown in Fig. 6. As can be seen from the graphic results, the proposed method has a significant advantage in the criteria under discussion.

Table 1. Results obtained in the evaluation criteria discussed in the Group-Face database.

Metric	method	F-S	F-D	M-S	M-D	Si-B	B-B	Si-Si	MEAN
Recall	CNN	83.2	81.4	80.7	84.1	79.9	81.7	82.3	81.9
	DWSNN	**96.3**	**94.1**	**95.2**	**96.7**	**94.3**	**95.2**	**96.9**	**95.5**
Precision	CNN	81.4	79.3	82.1	83.2	80.5	81.1	82.9	81.5
	DWSNN	**96.0**	**95.9**	**93.5**	**94.1**	**96.5**	**95.5**	**96.0**	**95.2**
Accuracy	CNN	82.4	82.3	81.1	82.7	83.4	84.0	82.1	82.5
	DWSNN	**96.7**	**95.3**	**94.8**	**95.0**	**93.7**	**96.2**	**97.1**	**94.5**
Specificity	CNN	82.1	81.1	83.5	81.2	81.3	82.4	85.1	82.3
	DWSNN	**95.7**	**94.2**	**93.8**	**95.9**	**94.1**	**93.8**	**94.0**	**94.5**
F_Measure	CNN	84.6	82.5	83.0	81.9	82.3	84.7	83.2	83.1
	DWSNN	**95.8**	**95.7**	**94.7**	**94.8**	**93.1**	**95.2**	**93.8**	**94.7**

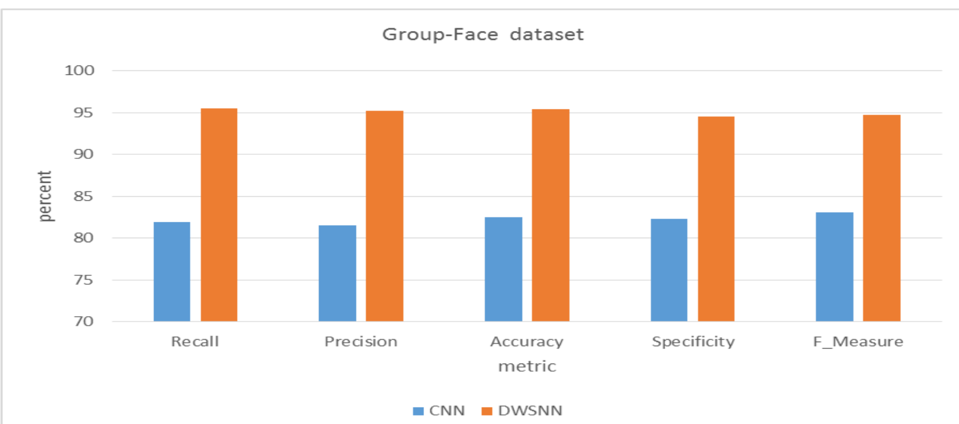

Fig. 6. Graphic comparison of CNN method and DWSNN proposed method in evaluation criteria in Group-Face database.

4.٣. TSKinFace Datasets

As with the evaluation for the Group-Face dataset, similar evaluations were performed for TSKinFace. Table 2 shows the results of this evaluation. As expected, the DWSNN proposed method performed better than the CNN method in all the criteria discussed in the article. This advantage is due to the characteristic images obtained from the scattering wave scale, the number of scattering wave directions, and the scattering wave depth used in the convolution process. As with the Group-Face database, this method is better at identifying the same sexuality as sister-sister, brother-brother, father-son, and mother-daughter family relationships than heterosexual brother-sister, father-daughter, and mother-son relationships. The reason for this difference can be traced to the structure of people's faces. This difference is acceptable because the resemblance of homosexuals is much closer to each other than heterosexuals. This result is acceptable since the deep neural network operates on the structure of the human mind.

A graphical comparison of the results is shown in Fig. 7. As the results show, the proposed method has a significant advantage over CNN.

Table 2. Results in the evaluation criteria discussed in the TSKinFace database.

Metric	method	F-S	F-D	M-S	M-D	Si-B	B-B	Si-Si	MEAN
Recall	CNN	84.0	80.9	80.1	82.3	80.1	83.1	84.4	81.1
	DWSNN	**95.9**	**93.5**	**92.8**	**97.0**	**92.9**	**95.1**	**95.1**	**94.6**
Precision	CNN	82.2	80.7	81.5	84.7	81.0	82.7	83.8	83.8
	DWSNN	**94.1**	**93.7**	**94.0**	**95.8**	**93.7**	**96.3**	**95.7**	**94.7**
Accuracy	CNN	83.7	81.1	82.7	84.6	82.9	84.1	83.8	83.2
	DWSNN	**95.8**	**93.9**	**91.8**	**95.1**	**94.7**	**95.9**	**96.0**	**94.7**
Specificity	CNN	83.0	80.8	82.3	83.4	82.7	84.0	86.0	83.1
	DWSNN	**94.4**	**93.1**	**94.8**	**96.0**	**93.7**	**96.1**	**95.2**	**94.7**
F_Measure	CNN	83.2	91.7	82.5	82.7	80.2	83.9	85.2	82.7
	DWSNN	**94.9**	**94.5**	**93.1**	**95.0**	**93.7**	**95.8**	**95.1**	**94.5**

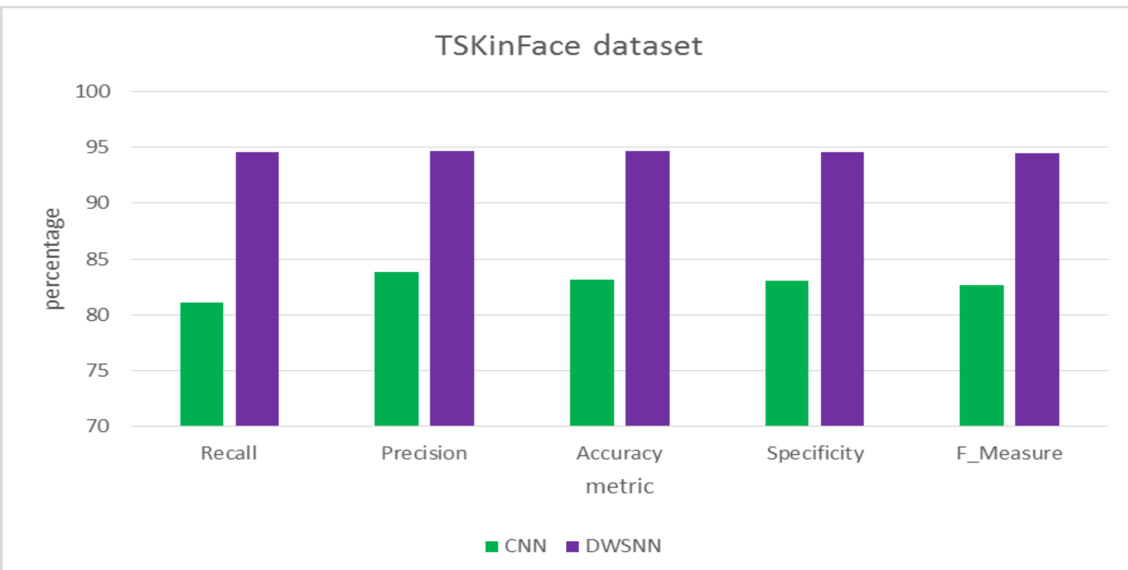

Fig. 7. Graphic comparison of the CNN method and the proposed DWSNN method in the evaluation criteria in the TSKinFace database.

Comparing the proposed method in the relationship of kinship, in the two datasets TSKinFace and Group-Face, in Tables 1 and 2, the superiority of the results in the Group-Face database can be seen. It should be noted that this superiority is not seen only in the criterion of sensitivity. With superiority in other criteria, comprehensive superiority in this database will be acceptable. Although this advantage does not make much difference, it can be attributed to the quality of the images and the number of images in the databases in question. Fig. 8 shows this comparison.

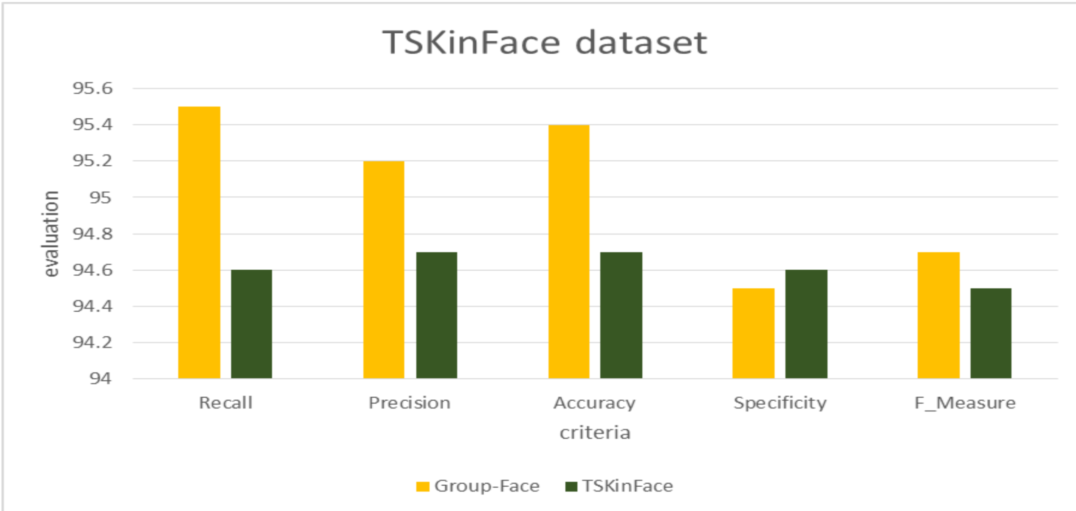

Fig. 8. Graphic comparison of the proposed DWSNN method in evaluation criteria in TSKinFace database.

4.٤. Comparison with Other Research

In order to further evaluate the proposed method and prove its superiority, the proposed method has been compared with other studies. Table 3 shows the comparison of the diagnosis of kinship with the research in question. The database used in all these studies is the TSKinFace database. As can be seen from the results of the table and the methods being compared, the superiority of the proposed DWSNN method over these methods is evident.

Table 3. Comparison of the proposed DWSNN method and other methods in the diagnostic precision criterion in TSKinFace database.

Method	Average Precision
Sparse Group Lasso [52]	70.7
NRML [8]	74.2
Gated autoencoder [53]	80.8
DDML [54]	81
ITML [55]	74
Large margin nearest neighbor (LMNN) [56]	72.9
RSBM-block-FS [50]	82.6
Deep kinship matching and recognition (DKMR) [46]	91.4
Proposed DWSNN	94.6

Since the proposed method is simulated on four databases, it is also examined to evaluate the results in other databases. Table 4 shows the results of the evaluation on the Group-Face database. The proposed deep learning method, due to the creation of many subbands of face images in the convolution network input and the creation of a rich vector of a variety of features, has been able to record far better results.

Table 4. Comparison of the proposed DWSNN method and other methods in the detection accuracy criterion in the Group-Face database.

Method	*Average Accuracy*
CNN + Softmax [57]	54.6
CNN + Softmax + Graph-based [58]Traditional methods or shallow structure [59] and hand crafted [60]0 in Scale Invariant *Feature* Transform as SIFT, Local binary patterns as BP, Histogram of	73.2
CNN-pred + Softmax + Graph-based[46]	75.4
CNN + DKR-GA + Graph-based [46]	77.2
CNN + DKR-GA + R-CRF [46]	78.5
Proposed DWSNN	94.7

5. CONCLUSION

In the research, the proposed method was simulated based on Group-Face and TSKinFace. Recall evaluation criteria were recall rate, precision accuracy, ACC accuracy, sensitivity, feature specificity and finally F_Measure was used for evaluation. These criteria were examined in cases of father-son F-S, father-daughter F-D, mother-son M-S, mother-daughter M-D, sister-brother Si-B, brother-brother B-B, sister-sister Si-Si. In the initial evaluation, the proposed method was compared with a 12-layer CNN convolutional neural network. The superiority of the proposed method was evident in all evaluations. It was also compared with other research related to the field of research. The superiority of the proposed method was evident in all evaluations.

Data Availability. Data underlying the results presented in this paper are available from the corresponding author upon reasonable request.

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Conflicts of interest. The authors declare no conflict of interest.

Ethics. The authors declare that the present research work has fulfilled all relevant ethical guidelines required by COPE.

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