Al-Rafidain Journal of Computer Sciences and Mathematics (RJCSM)

www.csmj.uomosul.edu.iq

Machine Learning Techniques for Kinship Verification: A Review

Olivia Khalil Oraha[1] and Yusra Faisal Mohammad[2]

[1,2] College of Computer Science and Mathematics, University of Mosul, Mosul, Iraq
Email: olivia.23csp60@student.uomosul.edu.iq[1] and yusrafaisalcs@uomosul.edu.iq[2]

Article information

Article history:
Received 02 February ,2025
Revised 25 April ,2025
Accepted 04 May ,2025
Published 26 June ,2025

Keywords:
Kinship verification,
Machine learning,
Deep learning,
Transfer learning Datasets,
Features extraction.

Correspondence:
Olivia Khalil Oraha
Email:
olivia.23csp60@student.uomosu.edu.iq

Abstract

Kinship verification is an automatic determining process of people relationships, if two or more individuals are in kin relation or not. Since the verifying of a kinship is the most challenging problem for many applications, where become beneficial in many fields such as investigation cases of missing people through war and natural disasters, biometric security and more. The DNA test is the most common surgical method to detect the kin relations between individuals of families but it does not work with some applications scenarios that need to real time results due to the DNA takes hours or days to give a result. Thus, with the progress of years the kinship verification entered the computer vision world to determining the relationships using machine learning (ML) algorithms such as deep learning, transfer learning techniques and others. Each part of the human body may have a significant embedded information (features) that extracted and analyzed for verification or recognition and classification for that individual. This paper presents a comprehensive review of the kinship verification methods used, datasets, features extraction and what the accuracy achieved.

DOI: 10.33899/csmj.2025.157153.1171,

1. Introduction

The kinship refers to the features or characteristics shared between the family members [1] and the kinship verification can be defined as an automatic process which determining if two or more individuals represented by their facial photos or videos are in kinship relation (belong to the same family) or not [2][3][4][5] therefore, the multimedia technology is an important field to prove and improve our experiences [6].
Verifying the kinship received a lot of attention over years in the field of computer vision and other of researches' fields such as inheritance [7] and social media [8][9][10], where it helps to reunion the family, finding the missing people and criminal investigations [2] therefore, it became an active research topic in computer vision using machine learning techniques where the first research was in 2010 presented by fang and others to recognize if two individuals are in kin relation or not using their facial images[11].
The facial photos became the most biometric modalities used in kinship verification domain [4] thus, the researchers begun establish or create databases containing of faces images for many families obtained or captured from the internet such as in [29] and [31][45].
Other researchers started to combine the human's face photo with corresponding voice to verifying the kinship where they create the datasets containing videos of families such as in [48]. This paper will describe a brief review of certain kinship verification researches, datasets and the techniques used in it.

2. Machine Learning (ML)

Machine learning can be defined as a branch of artificial intelligence which has revolutionized many fields in the last few decades [12]. Give the computers devices ability to learn without programming, it teaches the machines about how should the data handled efficiency, recently, ML techniques were explored to handle many Problems [13]. The purpose of ML is learning from data. Machine learning depend on various algorithms to solve the problems of data and the algorithm type rely on the type of problem needed to solve and the kind of model. The commonly used ML techniques are supervised learning and unsupervised learning [14], in the kinship verification domain the supervised learning is used.

2.1. Supervised Learning

A Kind of machine learning that uses labeled datasets for training, the supervised learning algorithms needs external assistance thus, are given labeled data to learn the relationship between the input and output data. The input dataset is divided for training and testing where the output data need to be classified. The algorithms learn certain patterns from the set of data during training to be applied on the test data for classifications or prediction. **Figure 1** below shows the workflow of the supervised machine learning [14].

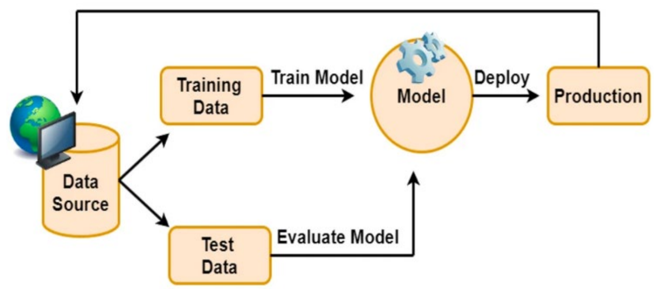

Figure 1. Supervised learning workflow

2.2. Unsupervised Learning

The kind of ML, unlike the supervised learning the unsupervised learning does not need to external assistance thus, cannot know what is the exactly correct result. These methods should discover the categories, patterns, characteristics or classifications by itself in the input dataset and code it in the result [15].

2.3. Deep Learning (DL)

Deep learning is a field of machine learning, also referred to as deep neural network [16] where depend essentially on the definition of the artificial neural network (ANN) [17]. DL focuses on building and training the ANNs to learn the characteristics and categories classification [18][19]. A deep learning presented to eliminate the handcrafted features [20] therefor, the DL model can extract and learned features automatically [21][22][23]. DL algorithms are the most common methods used to learn the kinship [57] due they make a great performance in extracting features and improving speed [24].

2.4. Transfer Learning (TL)

Transfer learning is the enhancement the performance of learning in a novel task via transfer the knowledge from another related task that has been already trained. That is, applying the learned knowledge from previous experimental when the new related task is encountered. The TL become a common topic in machine learning field [25][26].

3. Dataset

Verifying the kinship based on various biometrical characteristics appearing in people photos or videos, as shown in **Figure 2**. Different datasets are introduced summarized in **Table 1**.

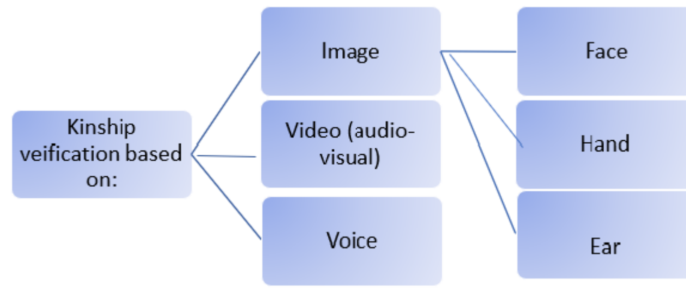

Figure 2. Biometrical categories of kinship verification

3.1. Kinship based- images Datasets

- Cornellkin dataset [11][27] the first kinship widely dataset presented at 2010, consists of familial face photos involve four relations (father-son, father-daughter, mother-son, mother daughter).
- UB KinFace [44] is the first dataset that consists of the familial face images include young, old parents and child images where the theory is that the young parents' photo is serve as a bridge between children and old parents.
- KinFaceW-I and KinFaceW-II (2014) are subset from the KinFaceW dataset [28][29]. The KinfaceW-I/II include four relations but they differ from each other in the collecting way where in the KinFace-I, the kin pairs are collected from various or different photos while in the KinFaceW-I dataset, the kin pairs are collected from the same image.
- FIW (families in the wild) dataset (2016) [30][31][45] the large-scale and comprehensive dataset contains over 1000 photos of families' individuals. Involve facial images from different period and include 11 relations: same generation, first and second generations.
- MKH (mosul kinship hand) dataset (2023) [54] consists of 648 hand images from 81 individuals of 14 families captured using mobile phone camera. Involve various kin relations.
- KinEar [56] dataset (2024) consists of 1477 ear images of individuals from 19 families, each family member having 15-31 ear images. Include various kin relations (parent-child, sibling-sibling).

3.2. Kinship based-video Datasets

- KIVI (kinship video) (2018) [46] the multimodal kinship database contains both face and voice modalities for each individual. Consist of 500 videos. Obtained from YouTube.

- TALKIN (talking kinship) 2019 [48] multimodal kinship dataset consists of facial videos with individuals talking modalities takin from YouTube.
- FIW-MM (fiw with multimedia) kinship dataset (2021) [52] the extended of FIW dataset consist of 200 families' videos obtained from YouTube which contain of three data types per individual in per video: visual, vocal and visual-audio.

Table 1. Kinship datasets

Reference	Dataset	Year	Data type	Source
[11][27]	Cornellkin	2010	Facial images	Internet
[44]	UB KinFace	2011	Facial images	Internet
[28][29]	KinfaceW-I/II	2014	Facial images	Internet
[30][31][45]	FIW	2016	Facial images	Internet
[54]	MKH	2023	Hand images	Offline, mobile's camera
[56]	KinEar	2024	Ear images	Offline, various devices
[46]	KIVI	2018	Video	YouTube
[48]	TALKIN	2019	Video	YouTube
[52]	FIW-MM	2021	Video	YouTube

4. Feature Representations and methods

The extracted features from certain input dataset (images, video) are important to verifying the Kinship. There are various kinship verification methods that used to extract features based on feature representations [5][32]:

1. Saliency features: involve comparing the similarity of salient part in facial such as eyes, nose and mouth to find the kinship [33]. DAISY descriptor [34] is used to extract saliency features and compute the similarity.
2. Handcrafted features: the previous features are effect of the geological information such as expressions and shape variations and will impact on the verification accuracy [5]. Therefore, the researchers [35] develop methods to extract handcraft features and the local binary pattern (LBP) [36] is widely used for extract handcraft features.
3. Metric learning: measure the proper distance between the input pairs based on the feature extraction method [37]. The commonly distance metric used in kinship verification is Euclidean distance [38] and other method.
4. Deep learning: the embedding information (features) are effectively extracted and learned using method-based deep learning such as convolution neural network (CNN) [39].

5. Classification

Classification is a common task of making decision [40]. That is, mapping an object to a pre-defined category or set depending on some information of this object [41]. The purpose of classification methods is to map or group data into the required structure based on shared features. Classification process depend on learning algorithm which create a classification model. large set of information are used for training and other data with unknown classification for testing after these two processes the classification is applied [42]. In the kinship domain, the classification is to determine if individuals are belonging to the family or not based on their trained features, often the classification in kinship is kin (1) or non-kin (0). Fang et al [43] was the first that demonstrate this where the family classification is a classification problem of several categories and each category is represent family. Depending on image or video, needed to determine the family which individual belonged.

6. Literature Review

the main objective of this study is to demonstrate the various techniques and algorithms to verify the kinship relationships of families:

Xia S, Shao M, Fu Y., presented in 2011 their work which aimed to verify the kinship through reduce the huge distance in distribution between old parent and children thus they used an intermediate distribution (young parent facial images) close to both to reduce the gap between them by using the proposed Transfer Subspace Learning method. For this reason, they create a new dataset called UB KinFace which consists of old parent, young parent and children's facial photos of 180 individuals collected from internet, the Gabor features are extracted. The proposed method achieved 56.11% accuracy showed that the TSL is a valid method to kinship verification field. [44].

Robinson J, Shao M, Wu Y, Fu Y., presented their study in 2016 to solve the limitations and challenges that encountered the previous kinship recognition images dataset by collecting the largest scale and most comprehensive kinship verification images dataset called Families in the Wild (FIW) which consist images of 1000 unconstrained families from web and 11 relations to verify involved. To extract features, the authors applied the Scale In variant Feature Transformation (SIFT) and Local Binary Patterns (LBP) to extract the handcraft features and then they present the VGG-Face CNN which is a pre-trained model to extract other types of features, they found that the exact tuning of a pre-trained CNN with triple loss function for kinship verification and SoftMax classifier for family recognition enhance the accuracy. [45].

Kohli N, Yadav D, Vatsa M, Singh R, Noore A., introduce their study in 2018 which aimed to enhance the accuracy in the verifying kinship based on videos by proposing a new

Supervised Mixed Norm Autoencoder (SMANE) that is a deep learning framework. A novel unconstrained dataset is established called kinship video (KIVI) which is the largest database consist of internet-quality videos of 503 person from 211 family. The proposed three stages SMANE algorithm extract the spatial and temporal information from the KIVI videos frames then encodes the kinship spatiotemporal signals for kinship verification, the proposed method achieves 83.18% accuracy. [46].

Tidjani A, Taleb-Ahmed A, Samai D, Eddine A., introduce their research in 2018 which addressed the using of a deep discrete cosine transform network (DCTNET) to extract the most important features from facial images via 2D-DCT filters to verify the kinship relations. The extracted features are binarized and divided to non-overlapping histograms then normalized them, the last step is that the different pairs are distinguished. The method is applied on UBKinFace, KinFaceW-I and KinFaceW-II datasets where the KinFaceW achieved 89.25% accuracy, the high accuracy demonstrates the significant of deep features in kinship verification. [47].

Wu S, Granger E, Feng X, Kinnunen T, Hadid A., presented in 2019 their research which addressed determining whether two individuals share a family relationship based on both facial and vocal data. They establish a new dataset called TALKIN consists of several videos contain facial and vocal information, collected from internet under unconstrained environment, four relations are obtained. They used for extract features the VGG and LSTM for face and Resnet-50 for voice Then the authors proposed the deep Siamese network to fuse the facial and vocal data (multimodal fusion). The proposed method achieved 74.1% accuracy which is improved the kinship. [48].

Chergui A, Ouchtati S, Mavromatis S, Bekhouche S, Lashab M, Sequeira J., presented their research in 2020 aimed to verify if two people have kin relation or not using their facial images automatically. They proposed VGG-face CNN to extract deep features from images and normalized them also they used the fisher score for features selection and SVM classifier to make the kin or non-kin decision on five datasets are: Cornell, UB KineFace, Family 101, KineFaceW-I and KineFaceW-II and take four relations where the first two datasets archive 92.89% and 90.59% respectively. [49].

Goyal A, Meenpal T., represented in 2021 the spatial frequency features extraction by performing the dual-tree complex wavelet transform (DT-CWT) and aimed to verify that the facial image pair (parent and child) have a kin relation or not. They proposed a global-based DT-CWT (G-DTCWT) that applied on full facial photos and extract the global features, local patch-based DT-CWT (LP-DTCWT) applied on the facial patch images, combine the global and local features and the selective patch- based DT-CWT (SP-DTCWT) that select the more representative patch. The authors used FIW, KinFaceW-I ans KinFaceW-II databases where the experimental results of accuracy demonstrate that the SP-DTCWT achieve 95.85% on KinFaceW-I, 95.30% on KinFaceW-II and 80.49% on FIW datasets. [50].

Robinson J, Khan Z, Yin Y, Shao M., proposedin 2021 their research, which goal is to boost the kinship detection system power using multimodal dataset. They extend the families in the wild (FIW) dataset which consisted of large scale of visual kinship recognition images via adding the multimedia (MM) data and called it families in the wild multimedia (FIW-MM) dataset that consist of 200 families' videos obtained from YouTube which contain of three data types per individual in per video: visual, vocal and visual-audio. The features extracted separately for visual and audio, where for visual and frames of video they use the deep learning Arcface CNN, and the ResNet34 for audio then use the template adaptation (TA) which is the transfer learning form with the Support Vector Machines (SVMs) template to fuse the extracted features. [51].

Dong G, Pun C, Zhang Z., proposed in 2021 a new cooperative weighting framework to extract feature based on the familial facial images called cross generation feature interaction learning (CFIL) for build a powerful kinship verification system. The authors used four datasets KinFaceW-I, KinFaceW-II, FIW, UB KinFace databases that consist of the face photos of families. The proposed method (CFIL) extracts local and non-local features from parents and children image pairs and used one unified learning structure to combine the feature extraction and similarity function into. The KinFaceW-I and kinFaceW-II datasets achieved 97.2% that is a high accuracy result. [52].

Wu X, Zhang X, Feng X, López M, Liu L., proposed kinship verification based on human faces and voices in 2022. The research aim is to improve accuracy of kinship verification by propose a method that fuse or combine both facial and vocal features. They establish a dataset called TALKIN-Family contains visual and corresponding vocal kinship of individuals captured from 246 familial videos talking under various environments and scenarios with mentioned to individuals age, gender where their ages ranging from 5 to 81 years old. The features extracted separately using InsightFace with ResNet-34 architecture for face and ResNet-50 pretrained on Voxceleb2 for voice then these modalities are fused using the proposed deep learning method-based fusion called unified adaptive adversarial multimodal learning (UAAML) which consists of the adversarial learning to align the visual-vocal extracted features and attention learning to emphasize the importance of each vocal and visual features during fusion, jointly with contrastive loss to distinguish between kin and non-kinship. [53].

Ghosh P, Shomaji S, Woodard D, Forte D., in 2023 proposed a deep learning extractor of kinship features framework called KinFaceNet that extract features from one input facial photo without the related kin image. KinFaceNet framework uses the pre-trained ResNet-34 face recognition model that transfer learned to verify the kinship domain with triplet loss. the 512-dimensional features are extracted from the facial image then mapped to compressed Euclidian distance where the kin images are much closer than non-kin images. The FIW and KinFaceW datasets are used where the KinFaceW-II achieve 88% accuracy using the proposed KinFaceNet. [54].

Fathi S, Aziz M., in 2023 presented their research which is aimed to detect the kinship relations based on hand geometrical images features. The new dataset created by the authors called Mosul Kinship Hand (MKH) images captured from 14 families of 81 individuals consisted of 648 images where 8 of hand positions per person taken. The hand images are detected, segmented and found the geometrical points by the Google MdiaPipe which is an open-source framework, in addition the 43 geometrical features extracted from each hand image by Handcraft feature extraction. The extracted features are fed into a supervised Artificial Neural Network (ANN) classifier for training and testing, which is the most machine learning algorithms used and consists of neurons also known as network nodes. The result achieved was about 93% prediction accuracy demonstrate the effectiveness of hand geometry for kinship detection. [55].

Fathi S, Aziz M., presented in 2024 their research which is aim to verify the kinship based on hand's images using supervised classifier and deep transfer learning for features extraction. They used the MKH (Mosul Kinship Hand) photos dataset photos captured from 14 families consisted of 648 images where 8 of hand positions per person taken. The geometrical hand features are extracted by employed transfer learning using pre-trained ResNet50 model which provides 1000 features which are fed into an Artificial Neural Network (ANN) classifier. The ANN classifier was designed as an upper layer on ResNet50 and trained to classify the kinship relations based on geometrical features of hand images. The accuracy test achieves 92.8% demonstrated that the hand geometrical features can be used in kinship verification. [56].

Dvoršak G, Dwivedi A, Štruc V, Peer P, Emeršič Ž., presented in 2024 their research which is highlighting to detect kinship relations based on ear images using deep learning models in other words to verify if two input ear images belong to individuals are in kinship relation or not. They establish a novel dataset called KinEar, that contains ear images captured from 19 families consist of 15 to 31 ear images for each individual where 1477 images are the total number in the dataset. The authors employed the Siamese Network training architecture with 5 deep learning models as backbones which are: VGG16, ResNet-152, USTC-NELSLIP, AFF, CoTNet and for testing they use various performance indicators where the VGG16 model with an ROC-AUC achieve 69.2% score which demonstrate that the data from ear images can be useful for kinship verification. [57].

Khalaf R, Al-Shakarchy N., in 2024 proposed a system of kinship verification that improve if two persons or individuals are in kin relation or non via facial features of two input photos using a novel architecture of convolution neural network of three dimensional (3D CNN). They used three databases: FIW [7] [28], KinFaceW-I and KinFaceW-II [69] which consisted of facial images that scaled and normalized to be fed into 3D CNN for features extraction step, then the two images are classified to verify the kinship depending on the extracted features. accuracy that the proposed kinship verification system achieved using 3D CNN was positive results where 83.75% in KinFaceW-I, 91% in KinFaceW-II and 75.5% in FIW dataset. [58].

Navghare T, Muley A, Jadhav V., presented their work in 2024 which aimed to compute the similarity between the photos pairs to handle the kinship verification. they implemented Siamese CNN model employing ResNet and VGGNet, utilizing Adam optimizer on their own dataset (created by them) consists of 410 facial images of 96 family takin four relationships. the similarity result is predicted through using the CNN model twice where is achieved 72.73% average of similarity. [59].

Table 2. Summary of literature review

Author & ref.	Year	Dataset	Method	Accuracy %	Feature extraction method	Advantages	Limitations or challenges
Xia et al. [44]	2011	UB KinFace	Transfer subspace learning	56.11	Gabor features	Reducing the distance between the old parent and children via young parent facial photos	Limited samples for training
Robinson et al. [45]	2016	FIW	Fine-tunning CNN	71	VGG-Face, Pre-trained CNN	Creating the largest and most comprehensive facial images dataset	Unbalanced sample and variations in images quality
Kohli et al. [46]	2018	KIVI	SMNAE	83.18	Spatial and temporal, SMNAE	Enhancing the accuracy based on video	Uncontrolled dataset
Tidjani et al. [47]	2018	UB KinFace KinFaceW-I/II	DCTNET	89.25	DCTNET via 2D- DCT filters	High accuracy by using deep features extractor	Limited samples and variations in the quality of dataset
Wu et al. [48]	2019	TALKIN	Deep Siamese	74.1	VGG + LSTM for	Create a new videos dataset	Internet videos quality

			network		face, Resnet-50 for voice		
Chergui et al. [49]	2020	Cornell	CNN	92.89	VGG_face CNN	The effective performance of deep features extractor in kinship verification	The facial internet images variate in quality, lighting.
		UB KinFace		90.59			
		Family 101					
		KinFaceW-I/II					
Goyal and Meenpal [50]	2021	KinFaceW-I	DT-CWT	95.85	G-DTCWT, LP-DTCWT, SP-DTCWT	Effective method	Variations in quality and complexity in feature extraction
		KinFaceW-II		95.30			
		FIW		80.49			
Robinson et al. [51]	2021	FIW-MM	SVM	89.8	ArcFace CNN, Resnet-34	Improving the kinship verification accuracy using multimedia	Uncontrolled internet videos dataset
Dong et al. [52]	2021	UB KinFace	CFIL	97.2	Local and non-local features using CFIL	Building a robust kinship system, extract several relationships combined the features extraction with similarity metric	Variations in dataset include quality, lighting and etc.
		KinFaceW-I/II					
Wu et al. [53]	2022	TALKIN family	UAAML	97.63	InsightFace with ResNet-34 for face, ResNet-50 for voice	Improve the multimedia kinship system accuracy	UAAML has complex structure, it needs high computational source and the variations in dataset such as the age.
Ghosh et al. [54]	2023	KinFaceW-I	Deep transfer learning	88	Pre- trained ResNet-34 with triple loss	Reducing the total time of training also it can be use in another application and it is compatible with any pre-trained model.	Contrast in dataset include lighting and quality.
		KinFaceW-I/II					
		FIW					
Fathi and Aziz [55]	2023	MKH	ANN classifier	93	Geometrical hand features by MdiaPipe	The effectiveness of hand geometry for kinship verification	Limited dataset size, non-uniform lighting and positions of hand
Fathi and Aziz [56]	2024	MKH	ANN classifier, deep transfer learning	92.8	Deep features via resnet-50	Capability of detect kinship relationships without medicine	Limited dataset size, non-uniform lighting and positions of hand
Dvoršak et al. [57]	2024	KinEar	Siamese network	69.2	VGG16	The data from ear images can be useful for kinship verification	The lighting variations and angle of the images
Khalaf and Al-shakarchy [58]	2024	KinFaceW-I	3D CNN	83.75	Deep features via 3D CNN	The effective performance for kinship verification	Low resolution photos involved that effect on accuracy result
		KinfaceW-II		91			
		FIW		75.5			
Navghare et al. [59]	2024	Their own dataset	Siamese CNN	72.73	ResNet and VGGNet	The effective performance of a deep model in kinship prediction	Image conditions

7. Discussion and Future work

This review research highlights on the evolution and current modern trends of kinship verification using machine learning, deep learning and features extraction methods starting from hand-crafted features extraction from small face images dataset obtained from Internet, this field has progressed towards to more large datasets and advanced deep learning methods such as deep Siamese network and CNN. The kinship verification datasets are not restricted on the face images only, the researchers explored multiple modalities dataset such as videos that include facial vocal model also hand and ear images datasets are used for kinship verification. Even that still are limitations and challenges such as small, unbalancing and diverse datasets, variations in images lighting, resolution, quality and other factors that effect on the accuracy also the complexity in some features extraction method and computational sources. Based on the reviewed studies and some challenges and limitations, the following recommendations, collect a novel database contains of clear images in terms of high quality, lighting and other factors, also be balanced dataset, improve the fuse of diverse modalities using more efficient and robust techniques to improve model accuracy. Lastly establish a new kinship verification dataset consist of families voice recordings only to prove that the human voice has some features that can help to verify the kinship and this offering new direction in kinship verification field.

Conclusion

This review provides the different datasets: photos and videos, features representation and methods and previous studies in kinship verification. In addition, providing the main advantages and the limitations or challenges according on various factors that encountered the study and impact on the accuracy of kinship predictions such as the size of datasets, the varying in images conditions and etc. Using deep learning models to verify the kinship demonstrate the effective accuracy results thereby the kinship verification domain become more difficult task with technology progress and increasing interest with increase the data resources.

Acknowledgement

The authors would express they're thanks to college of Computer science and Mathematics, University of Mosul to support this review paper.

Conflict of interest

None.

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