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Kinship Verification Based on Intelligent Techniques: Survey

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Abstract— *Kinship verification is the process of using observable characteristics, including facial features or other biometric data, to ascertain whether two people are familial related. Current approaches to kinship verification encounter multiple challenges, despite their significance in fields such as biometric security, family reunification, and forensic investigations. The most accurate way to confirm kinship is by DNA analysis, which is expensive, time-consuming, and invasive; in contrast, the traditional methods using manual comparison and facial recognition are more prone to human mistake. Visual verification of kinship among family members can be difficult to reliably rely on due to genetic variability, aging, and environmental influences. Automated methods that can reliably and efficiently confirm kinship using non-invasive methods are required, especially in situations where immediate identification is essential, like in the investigation of missing persons cases and disaster response. This study explores the use of different verification kinship techniques, ranging from various machine learning techniques reaching to up-to-date deep learning techniques. Finally, this study will discuss the datasets, preprocessing, methodology, advantages, disadvantages, and performance measures of selected state-of-the-art studies of kinship verification, and present the best technique used in kinship verification with the most related dataset.*

Index Terms— *Kinship verification, Deep learning, Machine learning.*

I. INTRODUCTION

The kinship term refers to the relationships between people based on family ties, which can be biological, cultural, or legal. It encompasses the bonds formed via blood (genetic relationships) among siblings, parents, and children, as well as extended family members like cousins. It also encompasses relationships formed by marriage (affinal relationships), such as those between spouses, in-laws, and step-siblings. Verification is a crucial process for systems to ensure quality and reliability across several domains using various methods, performance benchmarking, and standards [1]-[3].

Kinship verification is the process of determining the existence and nature of familial relationships between individuals. It plays an important role in various domains, including forensic investigations (such as finding missing persons and criminal investigations), improved security systems, genetic and medical research, family reunification, and immigration and citizenship [1]- [7]. *Fig. 1* shows general kinship verification process [1].

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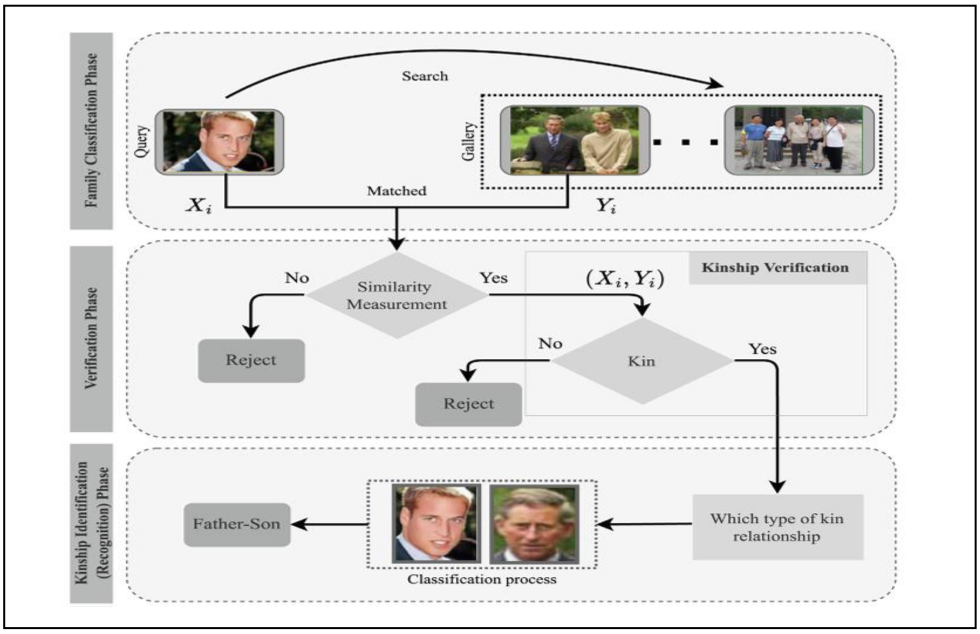

FIG. 1. FLOWCHART OF GENERAL KINSHIP VERIFICATION PROCESS [1].

Traditional approaches to kinship verification, such as DNA analysis, are highly accurate but often invasive, costly, and time-consuming. Recent developments in computer vision and machine learning have created new opportunities for non-invasive kinship verification techniques. The most researched of these has been facial recognition. Facial images contain a wealth of information that can be used to deduce family relationships. However, the challenge lies in precisely capturing and interpreting the subtle similarities and differences in facial features that indicate kinship, especially when age, gender, and environmental factors are taken into account. In recent advancements the integration of learning methods has significantly enhanced the effectiveness of kinship verification systems. These systems, renowned for their feature extraction capabilities have proven successful in analyzing visual data [1]-[7]. This study delves into kinship verification systems by utilizing learning techniques and datasets aiming to offer a practical method, for comprehending and confirming kinship relationships.

II. LITERATURE REVIEW

In 2019, R. F. Rachmadi et al. [8] recommendation was made to employ fusion CNN (convolutional neural network) classifiers, for image-based kinship verification. The study evaluated two configurations; the fusion CNN (EFNet) that utilizes two face images as input and the late fusion CNN (LFNet) that involves two CNN networks along, with two fully connected layers. The FIW (Family in the Wild) dataset is used to test how well these classifiers work. The experiments involve using both softmax and angular softmax (A Softmax) loss functions. Evaluations are conducted through a 5-fold-cross validation, on the FIW dataset. The performing single model is LFNet with A Softmax achieving an accuracy of 62.66%. Combining multiple fusion CNN classifiers boosts performance to the accuracy of 64.22%. However, the complexity of fusion architectures the method poses challenges, in training and evaluating models. To enhance kinship verification accuracy future research outlined in this paper will delve into architectures refine transfer learning methods and emphasize face segmentation techniques that target facial areas.

In 2019 A. Chergui et al. [9] proposed a kinship verification approach using multiple descriptors and multi-block (MB) face representation. This method uses a set of descriptors (local binary pattern (LBP), local phase quantization (LPQ), and binarized statistical image features (BSIF)) with TTest for

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feature selection and SVM for classification. The approach is tested on 5 datasets: Cornell KinFace, UB KinFace, Family 101, KinFaceW-I, KinFaceW-II. These datasets contain family members. In future work, they will use more descriptors and face representation methods, deep features and improve computational efficiency to boost kinship verification system. In this paper, using different labels makes approach more robust to face variations. T-Test for feature selection reduces computation and overfitting. On the other hand, the combination of several descriptors and multi-block representation, results in increased computational cost when extracting features and representation them. The accuracy of the approach largely relies on correct preprocessing of face, which can greatly impact performance if handled poorly, and does not quite exhaust the potential of deep learning techniques.

In 2019, A. Chergui et al. [10] used deep learning algorithms especially ResNet architecture for feature extraction of the facial images for kinship verification requires the following preprocessing: alignment, cropping and resizing, normalization on those faces. Deep features can be extracted using ResNet models scales such as ResNet-18, Res-Net-50, and ResNes-10. Selecting significant features, and then to classify kinship relations SVR machine learning classifier was used. The experiments used five databases: Cornell KinFace, UB KinFace, Family 101, KinfaceW-I and KinFaceW-II. The combination of all three ResNet models produced the most successful result. For the purpose of advancing family relationship confirmation, further research in this paper will involve studying other deep learning models, for instance AlexNet and ImageNet, through fine-tuning. Additionally, there is need to incorporate other features like age and gender in order to improve accuracy. However, higher accuracy is achieved by combining various ResNet models. This method provides a balanced approach to deep learning models using traditional machine learning techniques. On the other hand, the use of multiple deep learning models results in increased computational complexity. Consequently, the adaptability of the method on novel datasets may be limited because it depends on pre-trained models without additional transfer learning or fine-tunning it.

In 2020, M. Wang et al. [11] came up with deep kinship matching and recognition (DKMR) framework to solve a difficult problem of recognizing relatives in family photographs where there are several people. Instead of concentrating on pairwise kinship matching, present approaches try to recognize exact kinship relationships in nuclear family photographs. The framework includes three key components: DKM-TRL, DKR-GA, and R-CRF. DKM-TRL is the first model named as deep kinship matching model, since the Siamese CNN is trained on image triples to predict whether a relation between two individuals is of kin or not. The second model, DKR-GA is called deep kinship recognition model and it utilizes gender as well as relative age features when classifying the relationship type among family members like parent-child, siblings. The previous two models' outputs are used by the reasoning conditional random field (R-CRF) model to reason about what family tree is optimal.The datasets used are the Group-Face dataset, TSKinFace dataset, and FIW (Families in the Wild) dataset. This paper suggested extending their work to recognize kinship in images of extended families and adding other cues such as spatial information and body cues that recognize exact kinship relationships within nuclear family photos. The framework consists of three main modules: DKM-TRL, DKR-GA, and R-CRF. The first model is the is the deep kinship matching model (DKM-TRL), in which the Siamese CNN is trained to predict between kin and non-kin relationships by learning from triples of images. The second model, the deep kinship recognition model (DKR-GA), is trained using gender and relative age attributes to predict exact kinship categories (e.g., parent-child, siblings). The third model, reasoning conditional random field (R-CRF), infers the optimal family tree that uses the outputs from the previous two models, along with common kinship knowledge, to construct a family tree. The datasets used are the Group-Face, TSKinFace, and FIW. This paper suggested extending their work to recognize kinship in images of extended families and adding other cues such as spatial information and body cues. However, it incorporates relative age and gender to enhance the model's ability to distinguish between different kinship categories. The R-CRF module effectively constructs family trees that add a layer of reasoning

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beyond simple classification. On the other hand, the framework is designed for nuclear families and may not perform well with extended families, which limits its applicability. The constant weights of the VGG-Face model may make it more difficult to fine-tune the network as a whole for certain kinship recognition tasks.

In 2021, R. F. Rachmadi et al. [12] conceived a technique to authenticate kinship on the basis of a two-fold VGG-Face convolutional neural network (CNN) classifier for images. Two classifiers are investigated: one with a single fully-connected layer and another with two fully-connected layers after the convolutional networks. The method uses a multi-task learning strategy to improve speed while utilizing the powerful feature extraction capabilities of the VGG-Face architecture to identify kinship relationships. The families in the wild dataset is used to evaluate the system. On a single classifier, the suggested dual VGG-Face CNN classifier obtains an average accuracy of 64.71%. When using an ensemble of classifiers, the accuracy slightly improves to 65.49%. This paper plans to extend the classifier by adding face parsing or segmentation techniques to focus on specific face regions. They also consider using data augmentation for verification of second-generation kinship. However, the reduction of fully-connected layers significantly decreases the number of parameters, making the model more efficient and faster to train. The use of a multi-task loss function helps in learning more robust features. The ensemble of classifiers provides a slight improvement in accuracy. On the other hand, the method shows lower accuracy in second-generation kinship, like grandparent-grandchild relationships. Dependence on pre-trained VGG-Face models may limit the flexibility and adaptability of the approach to new or unseen data variations.

In 2021, L. Skowronski et al. [13] evaluated how well different supervised machine learning (ML) methods work for classifying plant populations that differ in their genetic kinship. It compared these recent ML approaches with Fisher and Anderson's traditional discriminant analysis techniques. Tested machine learning algorithms for classification, including naive bayes, k-nearest neighbors (kNN), decision tree (DT), support vector machine (SVM), random forest, and multi-layer perceptron neural networks (MLP/ANN). Additionally, the classical methods Fisher discriminant and Anderson discriminant methods. This paper, conclude that machine learning methods generally outperformed classical discriminant methods across all similarity conditions. kNN, random forest, naive bayes, and SVM maintained high accuracy even when populations had up to 96.88% similarity. Some ML algorithms (e.g., kNN and random forest) required less computational power compared to ANN, making them suitable for large-scale applications. DT and MLP/ANN lost accuracy under high similarity conditions, with significant classification errors. The majority of misclassifications were between populations with highly similar genetic backgrounds, indicating the challenge of distinguishing closely related populations.

In 2021, S. Passmore et al. [14] investigated the coherence of traditional kinship typologies using modern statistical methods and an extensive new database called Kinbank. The Kinbank database has a large global sample of 1,107 languages and 988 kin types. It reveals that kinship systems are less internally coherent and more diverse than previously thought. Canonical typologies show restricted predictive value across generations. This paper, which introduces the concept of kinship space, offers a new way to visualize and understand the diversity and structure of kinship systems. The multidimensional nature of kinship data can make it challenging to draw clear inferences about the relative importance and evolution of kinship types.

In 2022, J.H. d. Vries et al. [15] suggested focusing on the effect of compromising DNA quantity and quality on the effectiveness of SNP microarray analysis for kinship classification in the context of investigative genetic genealogy (IGG). The work offers concrete data on how DNA degradation impacts kinship categorization and genotyping accuracy, with an emphasis on the Illumina Global Screening Array (GSA). Kinship classification success was evaluated for siblings, first cousins, and second cousins at varying levels of DNA degradation. In DNA quantity, for siblings and first cousins, the

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kinship categorization success rate was still high at 250 pg, and 1 ng for second cousins. For the DNA quality, depending on the kinship degree, genotyping accuracy and kinship classification success declined with increased fragmentation, reaching zero at an average DNA fragment size of 150 base pairs. The main issue with compromised DNA is false-negative results, which could lead to missing potential matches in IGG applications.

In 2022, B. v. Leeuwena et al. [16] explored the significance of specific facial features with particular attention to facial hair traits and age-related features in automated kinship recognition, building on earlier human-based kinship recognition studies. Using pre-trained metrics from the StyleGAN2 model, and used FTW (Families in The Wild) dataset. The study aims to understand which facial features are most important for automated kinship recognition, contributing to the explainability of AI models in this domain. Although the study shows promising results, it also identifies several challenges, including the requirement for clear facial images and the limitations of current transfer learning methods. Future work should focus on expanding the feature set and exploring more kinship recognition-compatible models.

In 2023, A. Othmani et al. [17] proposed a deep learning-based kinship verification techniques applied to facial photos to address the problem of imbalanced data. Kinship verification is a technique that uses facial patterns to visually determine whether two people are related. This method has great promise for applications such as child-missing identification and social media analysis. Deep features are extracted from every face image using ResNet50. The performance is evaluated on the FTW dataset, which achieved high accuracy that outperformed the existing approaches. This paper handles the issue of imbalanced data by using one-hot encoding and data augmentation.

In 2023, F. Ramazankhani et al. [18] suggested a kinship verification system that merges feature fusion, SVM classification together with (neighborhood repulsed metric learning) NRML metric learning for learning distance function that can represent similarity and dissimilarity between facial image pairs. The system analyzes facial images to determine kinship relations by considering facial image texture as well as color features (including RGB, HSV, and grayscale). However, feature extraction can be implemented at the block level, which improves the verification accuracy. It also investigates a Siamese convolutional neural network for kinship detection. The KinFaceW-I and KinFaceW-II databases were utilized by the performance to evaluate if there were increased accuracies in verifying relationships. This may lead to an increase of system complexity and probably the need for more computing power because the process involves combining features and extracting blocks at block level. In the future to improve kinship verification systems can handle exploring deep learning in order to make them better.

In 2024, N. Nader et al. [19] suggested an approach of kinship validation that combines characteristics from various viewpoints and emphasizes color and texture properties represented in different color spaces. The approach proposed weaves various feature extraction approaches, some of which are explored in kinship verification for the first instance. The system design of six-step is concerning low accuracy and illumination variations alterations. Transform RGB pictures into HSV as well as LAB color spaces to counteract the problem of non-uniform lighting. Make use of different techniques for extracting attributes, such as local binary pattern (LBP), scale-invariant feature transform (SIFT), color correlogram (CC), dense color histogram (DCH), and heterogeneous auto-similarities of characteristics (HASC). Calculate the absolute difference between the corresponding features of parent and child images. Then used the Gentle AdaBoost for classification. The proposed approach, evaluated on the KinFaceW-I and KinFaceW-II datasets, achieved an accuracy of 79.54% and 90.65%, respectively. This paper introduces feature extraction methods (HASC, CC, and DCH) and a classifier (Gentle AdaBoost) not previously used in kinship verification. With larger datasets, deep learning techniques may scale more successfully than the method's dependence on hand-crafted features and

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traditional machine learning. The authors plan for further improvement through the integration of deep learning techniques and larger datasets.

In 2024, S. Aktürk et al. [20] suggested using pedigree and ancient genome simulations to assess the four kinship estimate tools: lcMLkin, NgsRelate, KIN, and READ. Simulating genetic data based on known pedigrees to generate reference kinship levels. The aim is to assess these tools' performance using low-coverage palaeogenomes, which are often employed in ancient DNA research. Can be correctly classified even with one thousand SNPs; it obtained F1 scores of 85% using READ and 96% with NgsRelate and lcMLkin. while, READ and KIN had lower accuracy rates (69% and 79%, respectively), but NgsRelate and lcMLkin obtained great accuracy (F1 > 90%) with 5K SNPs. The results could not accurately reflect the intricacies of actual ancient DNA samples because they were based on simulations. Because every tool has different limitations, it is necessary to employ several tools simultaneously to get reliable estimations. This study highlights the need for continued development of more powerful methods to improve the accuracy and reliability of kinship estimation in the context of ancient DNA research.

In 2024, S. I. Fathi and M.H. Aziz [21] suggested approach for kinship recognition using hand geometry. To extract geometric information from hand images, the method uses deep transfer learning with the ResNet50 model, followed by a neural network classifier built as the top layer on the ResNet50 model to estimate kinship. The model achieved classification accuracy 92.8%. The study also presents a newly created dataset, the Mosul Kinship Hand (MKH) dataset, which includes 648 hand images of 81 people from 14 households. However, the creation of the MKH dataset provides a valuable resource for further research in this area. On the other hand, the high training accuracy suggests potential overfitting, which could be addressed with more data and additional regularization techniques. Future work should concentrate on expanding the dataset, improving classification accuracy, and testing its efficacy for a variety of populations.

In 2024, T. Navghare et al. [22] proposed a method to predict kinship relationships (father-daughter, father-son, mother-daughter, and mother-son) based on image similarity computations using facial images. It has significant applications in finding biometric security, missing persons, and family reunification. A Siamese architecture combining ResNet and VGGNet models. The accuracy of the suggested model is 72.73%. The creation of the primary dataset (96 families) addresses the lack of publicly available datasets for kinship verification, providing a valuable resource for future research. Potential future research could include enlarging the dataset, enhancing the interpretability of the model, and utilizing the approach in real-world scenarios.

In 2024, X. Zhu et al. [23] proposed a similarity mining framework that uses Siamese network of deep learning techniques with implicit pattern learning to determine whether two people are biologically related from face photos. The method relies on finding relationship cues and small patterns in faces that look like family. They tested on Cornell KinFace and FIW (Families in the Wild) datasets. On FIW dataset, the accuracy was 93% which is better than baseline methods. Besides using handcrafted features, implicit pattern learning improves kinship verification. The model can be used in practical scenarios (e.g. border control and genealogy research). But deploying in real-world is complicated by the model complexity and possible bias in the datasets.

In 2024, E. O. Belabbaci [24] suggested a hybrid technique for kinship verification that combines 2D Stationary Wavelet Transform (2DSWT)-CNN features with Multiscale Retinex (MSR) preprocessing. Robust kinship verification by enhancing face feature extraction for multi-scale spatial dependencies and illumination problems is the goal. MSR is used to level illumination and enhance contrast to improve facial images. 2DSWT is used to get fine-grained information about face likeness. The CNN ensures that kinship related spatial patterns are learned efficiently. Feature vectors of matched images are compared using a distance-based classifier. They used FIW and Cornell KinFace datasets for evaluation. On FIW dataset, the accuracy was 92%. The model works well in various illumination

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conditions due to MSR preprocessing. Although the model achieves good accuracy, it becomes more difficult to interpret the learned features because of the combination of MSR and 2DSWT.

In 2024, S. A Najafabadi [25] suggested approach to real-world face photos, used a Deep Scattering Wavelet Convolutional Neural Network (DSW-CNN) for kinship recognition. The method captures multi-scale spatial information and improves kinship verification by combining wavelet transforms with deep learning. Wavelet Scattering Transform used as a pre-processing level on face photos, it extracts multi-level invariant features that reduce the sensitivity to noise, changes in illumination and minor changes in facial features, while the CNN provides strong learning and classification ability. FIW, KinFaceW-I, and KinFaceW-II Datasets were used for evaluation. The accuracy achieved 89% on KinFaceW-II and 91% on FIW. Robustness to Noise and Lighting Variations is improved by the scattering wavelet treatment. But adding the scattering wavelet level increases computational complexity and requires more training resources.

III. DISCUSSION

This section will present a discussion about all the faces of the introduced studies to detect the most important parameters related to advanced kinship verification. Table I, Table II, and Table III, respectively, demonstrate the comparison of the different kinship verification studies, focusing on the datasets, preprocessing, methodology, advantages, disadvantages, and performance accuracy that are used for kinship verification methods.

TABLE I. COMPARISON OF VARIOUS KINSHIP VERIFICATION METHODS ON THE DATASETS, PREPROCESSING, AND METHODOLOGY

Reference	Dataset	Preprocessing	Methodology
[8]	FIW Dataset	_____	Used fusion CNN with two configurations are: early fusion and late fusion. Using both softmax and A-Softmax loss functions.
[9]	-Cornell KinFace -UB KinFace -Family 101 -KinFaceW-I -KinFaceW-II.	-Features extraction using LBP, LPQ, and BSIF. - Divides the image into multiple blocks. - Features selection using TTest. - Using SVM classifier.	Used multiple descriptors and multi-block (MB) face representation techniques.
[10]	-Cornell KinFace -UB KinFace -Family 101 -KinFaceW-I -KinFaceW-II.	- Face Preprocessing includes face alignment, cropping, resizing, and normalization. - Feature Selection using T-test. - Using SVM classifier.	Used ResNet deep models (ResNet-18, ResNet-50, and ResNet-101) makes it suitable for extracting rich features from images.
[11]	- Group-Face - TSKinFace - FIW	- Face detection and alignment according to coordinates of eye location and crop them into 6 4 × 6 4. - Augmentation training data by cutting and mirroring facial pairs.	Proposed DKMR consists of three modules: DKM-TRL, DKR-GA, and R-CRF. Which recognize kinship in images of extended families and adding other cues such as spatial information and body cues.
[12]	FIW Dataset	_______	Using a dual VGG-Face classifier: one with a single fully-connected layer and another with two fully-connected layers. and conjunction multitask learning to improve results.

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[13]	Simulation genotypic data of plant populations.	———	It compared recent ML approaches with Fisher and Anderson's traditional discriminant analysis techniques for classifying kinship.
[14]	Creation Kinbank database has a sample of 1,107 languages and 988 kin types.	Comprised data collection and standardization	Used recent statistical techniques and creation new database named Kinbank to examine the coherence of conventional kinship typologies.
[15]	264 DNA samples	-Preparation DNA Sample. -Artificial fragmentation of DNA samples to produce different levels of degradation.	Concentrating on how compromising DNA quantity and quality affects SNP microarray analysis's ability to classify kinship.
[16]	FIW Dataset	-Clear facial images. -Face Detection and alignment. -Shuffling and splitting dataset involve an 80/20 ratio.	Using pre-trained StyleGAN2 model to understand which facial features are most important for automated kinship recognition with particular attention to facial hair traits and age-related features.
[17]	FIW Dataset	————	Using the ResNet50 model for kinship verification applied to facial photos to address the problem of imbalanced data.
[18]	-KinFaceW-I -KinFaceW-II	-Extracted RGB, HSV, and grayscale from facial images. -Divided images into blocks.	Using feature fusion, block-level and Siamese convolutional neural network to determine kinship relations.
[19]	-KinFaceW-I -KinFaceW-II	-Images enhancement. -Convert RGB image to HSV and LAB color spaces.	Apply fusing features from different perspectives for kinship verification. It attempts to solve issues, including low accuracy and illumination variations.
[20]	Pedigree and ancient genome simulations	-Data simulation. -Formatting data to preparation for tools.	Using pedigree and ancient genome simulations to assess the four kinship estimate tools.
[21]	Construct MKH dataset	- Creation MKH dataset. - Images scaling and hand detection.	Using hand geometry for kinship verification, the method applies deep transfer learning with the ResNet50 model, then estimates kinship using a neural network.
[22]	Creation dataset of 96 families	- Creation dataset. -Image resizing to 64x64 pixels. -Image Cropping. - Data augmentation.	Using ResNet and VGGNet models to predict kinship relationships based on the similarity of facial images.
[23]	-FIW Dataset -Cornell KinFace	Used face detection, alignment, image augmentation and dataset balancing.	Using Siamese network of deep learning techniques with implicit pattern learning to determine whether two people are biologically related from face photos.
[24]	-FIW Dataset -Cornell KinFace	Used multiscale retinex , wavelet transformation and data augmentation.	Using hybrid technique for kinship verification that combines 2D Stationary Wavelet Transform (2DSWT)-CNN features with Multiscale Retinex (MSR) preprocessing.
[25]	-FIW Dataset -KinFaceW-I -KinFaceW-II	Used scattering wavelet transform, face detection and image augmentation.	Using a Deep Scattering Wavelet Convolutional Neural Network (DSW-CNN) for kinship recognition.

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TABLE II. COMPARISON OF VARIOUS KINSHIP VERIFICATION METHODS ON ADVANTAGES AND DISADVANTAGES

Reference	Advantages	Disadvantages
[8]	- Performance Improvement. - Innovative Loss Functions.	- Ensemble approach add complexity to the process. - Low accuracy. - Transfer learning dependency.
[9]	-Enhanced accuracy. -Feature Reduction. -Robustness.	- Computational complexity. - Dependence on preprocessing. - Limited work of deep learning.
[10]	-Improved accuracy by using multiple ResNet models. -Comprehensive methodology that used deep learning with machine learning techniques.	- Computational complexity. -Reliance on pre-trained models.
[11]	- It incorporates gender and relative age, enhancing the model's ability to distinguish between different kinship categories. - Achieves better accuracy.	- Dependence on preprocessing. - VGG-Face model’s weights are fixed may make it more difficult to fine-tune the network.
[12]	- Reduction of fully-connected layers decreases the number of parameters, making the model more efficient and faster to train. -Using of a multi-task loss function helps in learning more robust features. -The ensemble of classifiers provides enhancement in accuracy.	-lower accuracy in second-generation kinship. - Dependence on pre-trained VGG-Face models may limit the flexibility and adaptability of new or unseen data variations.
[13]	- ML shows higher accuracy -Some ML methods (e.g., kNN and Random Forest) required less computational power compared to ANN, making them suitable for large-scale applications.	-DT and MLP/ANN lost accuracy under high similarity conditions. -The misclassifications with highly similar genetics indicate the challenge of distinguishing closely related populations.
[14]	-The Kinbank database offers a large and diverse samples. -Provides a new way to visualize and understand the diversity and structure of kinship systems.	-The multidimensional nature of kinship data can make it challenging to draw clear inferences about the relative significance and evolution of kinship types.
[15]	Proves that the GSA platform can successfully classify kinship, even with significantly lower DNA quantities.	-Decreased accuracy with DNA degradation. -The possibility of false-negative results, which could lead to missing possible matches in IGG applications, is the main issue with compromised DNA.
[16]	Uisng StyleGAN2 provides a sophisticated method for feature extraction	-Requirement a large set for clear facial images that limit applicability in the real-world. -The limitations of current transfer learning methods.
[17]	Handle the issue of imbalanced data by using one-hot encoding and data augmentation.	-The research doesn't provide comprehensive information on the preprocessing steps. - Computational complexity.
[18]	The using both of feature fusion and NRML metric learning Improved accuracy.	feature fusion and block-level extraction increasing computational requirements.
[19]	- Offering a comprehensive feature set. -Solve illumination issue by convert to HSV and LAB color spaces. - Achieved high accuracy.	The method’s reliance on handcrafted features and classical machine learning may not scale as effectively as deep learning approaches with larger datasets.

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[20]	Assesses several tools and presents a detailed analysis of their advantages and disadvantages.	The results could not accurately reflect the intricacies of actual ancient DNA samples because they were based on simulations.
[21]	-Research investigates hand geometry, an unconventional biometric property. -The creation MKH dataset is a helpful resource in this field.	- The small size of the dataset affects the generalization of the results. -The high training accuracy suggests potential overfitting.
[22]	The creation dataset is valuable resource in this field.	- The limited size of the dataset. - Model complexity.
[23]	The using implicit pattern learning improves kinship verification.	The deploying in real-world is complicated by the model complexity and possible bias in the datasets.
[24]	The model works well in various illumination conditions due to MSR preprocessing.	it becomes more difficult to interpret the learned features because of the combination of MSR and 2DSWT.
[25]	Robustness to noise and lighting variations is improved by the scattering wavelet treatment.	The adding the scattering wavelet level increases computational complexity and requires more training resources.

TABLE III. COMPARISON OF VARIOUS KINSHIP VERIFICATION METHODS FOCUSING ON THE PERFORMANCE ACCURACY

Reference	Performance
[8]	64.22% accuracy.
[9]	The accuracy achieved on Cornell KinFace, UBKin, KinFace-I, KinFace-II, and Familly 101 was 84.74%, 82.74%, 81.69%, 80.12%, and 78.16%, respectively.
[10]	Cornell KinFace, Familly 101, UBKin, KinFace-I, and KinFace-II yielded accuracy rates of 87.16%, 83.68%, 82.07%, 79.76%, and 76.89%, respectively.
[11]	The accuracy achieved on Group-Face, TSKinFace, and FIW was 75.58%, 82.94%, and 75.36% , respectively.
[12]	The dual VGG-Face classifier obtains an average accuracy of 64.71%. While an ensemble of classifiers, the accuracy slightly improves to 65.49%.
[13]	Machine learning methods generally outperformed classical discriminant methods across all similarity conditions. kNN, Random Forest, Naive Bayes, and SVM maintained high accuracy even when populations had up to 96.88% similarity.
[14]	Canonical typologies show limited predictive value across generations.
[15]	Kinship categorization success rates remain high for siblings and first cousins at 250 pg, but decrease with fragmentation, reaching zero at an average fragment size of 150 base pairs.
[16]	-10-fold cross-validation was used to evaluate accuracy. -The study found that automatic kinship recognition performs decreases when the top or bottom half of the face is removed.
[17]	This paper achieved high accuracy that outperformed the existing approaches.
[18]	Results indicate that 73% and 82% accuracies are found for deep features derived through the Siamese neural networks in the datasets of KinFaceW-I and KinFaceW-II, respectively.

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[19]	The accuracy achieved on KinFaceW-I and KinFaceW-II datasets, was 79.54%, and 90.65%, respectively.
[20]	NgsRelate and lcMLkin achieved excellent accuracy (F1 > 90%) with 5K SNPs, but READ and KIN had lower accuracy rates (69% and 79%, respectively).
[21]	92.8% accuracy.
[22]	72.73% accuracy.
[23]	The accuracy achieved on the FIW dataset was 93%, that outperforming baseline methods.
[24]	On FIW dataset, the accuracy was 92%.
[25]	The accuracy achieved 89% on KinFaceW-II and 91% on FIW.

As indicated in the tables above, which illustrate various kinship verification techniques. They are all diverse in terms of datasets, preprocessing, methodology, advantages, disadvantages, and accuracy measurements. Most of the recent methods rely on using deep learning models with other machine learning techniques.

Most of the methods, such as those in [8], [12], [16], [17], [23], [24], and [25] assessed on the FIW which, abbreviations of family in the wild dataset, which is the largest dataset currently available for kinship verification. This includes 1,000 families with 11 distinct kinship relationships. Some approaches collect their data through simulations, such as those in [13], [15], and [20]. Others create their own datasets, such as in [14], [21], and [22]. Datasets like KinFaceW-I, KinFaceW-II and Family 101 are more structured but smaller, while others like Group-Face or custom-built datasets [21], and [22] are for hand geometry biometrics.

According to preprocessing, models that use face alignment, cropping and normalization [10], [16], [23], and [24] perform better because of standardized input images. Advanced methods like Multiscale Retinex preprocessing [24] and scattering wavelet transformations [25] are robust against illumination and noise but increase computational cost.

According to methodology indicated, some studies explore non-facial cues like body geometry or hand features [21]. While these are interesting new directions, they have limited datasets and overfitting risk. Models perform better on first-generation kinship (parent-child, siblings) but struggle with second-generation or distant relations [12]. Same challenge applies to ancient DNA-based kinship estimation [15], and [20]. Hybrid architectures combining traditional descriptors (LBP, LPQ) with CNNs [9], and [18], and state-of-the-art deep models like ResNet [10], and [22] improves accuracy but increases complexity. Advanced loss functions (A-Softmax, and NRML) and implicit pattern learning [23] improves kinship verification but complicates deployment. Advanced models using hybrid techniques (e.g., MSR and 2DSWT in [24]) performs well but reduces interpretability. Interpretable models using traditional machine learning techniques [9], [13], and [19] may struggle with large datasets and complex relationships.

The high accuracy achieved in [13] showed ML approaches had higher accuracy than traditional analysis techniques for classifying kinship. Whereas lower accuracy was achieved in [8] based on fusion CNN with two configurations, which had innovative loss functions but were dependent on transfer learning.

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IV. CONCLUSIONS

This survey offers an extensive review of representative kinship verification techniques and publicly available datasets. Representative approaches are compared based on their datasets, preprocessing, methodology, advantages, disadvantages, and performance measures.

Here's a summary of the conclusions drawn from current research and experiments: Accurately verifying kinship relationships with non-invasive techniques like facial image analysis is possible, as shown by the application of deep learning and other machine learning algorithms. In regards to kinship prediction, models like Siamese networks, ResNet, and VGGNet have demonstrated remarkable accuracy, frequently outperforming manual techniques. The development of specialized datasets, such as the MKH dataset, has been essential to the training and validation of these models.

In conclusion, the topic of kinship verification with deep learning and face recognition technology is an exciting field for real-world applications. Based on the examination of existing kinship verification, we think that further kinship datasets are still required for particular issues. Even if the accuracy and efficiency of existing models are rather good, more research and development is required to fully exploit the benefits of these sophisticated techniques and overcome any remaining challenges. To further improve accuracy, future research should concentrate on improving the model's robustness and investigating biometric features other than facial images.

Recommendation for future work, the field of kinship verification is moving forward with hybrid deep learning models, advanced preprocessing and multi-modal approaches. But there are still challenges in terms of dataset bias, computational cost and generalization to real-world. Future research should balance performance and efficiency with multi-modal biometric systems for robust kinship verification. These studies show the trade-offs between model complexity, performance and real-world usability. Solving these challenges will bring kinship verification to practical and scalable applications.

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