KINSHIP VERIFICATION AND RECOGNITION BY MICRO EXPRESSION USING MACHINE LEARNING

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Abstract: *Kinship Verification and Recognition (KVR) is a challenging subject in computer vision and pattern recognition that seeks to ascertain the level of relatedness between people based on their visual traits. Extreme Learning Machines (ELM) have become a potential method for kinship verification in recent years because of its quick and effective learning capabilities. This paper suggests a face image-based ELM-based method for kinship verification. In particular, it extracts facial features from input images using a deep Convolutional Neural Network (CNN) and feeds them into an ELM classifier to verify kinship. Experimental results show that the suggested ELM-based strategy works well, achieving good performance compared to conventional techniques. Potential uses for the suggested method include forensic investigations, genealogical research, and family reunion identification,1among1other1fields.*

Keywords: Kinship Verification, Face Recognition, Extreme Learning Machine (ELM), Convolutional Neural Network (CNN), Deep Learning, Facial Feature Extraction, Pattern Recognition, Computer Vision, Forensic Applications, Genealogical Research.

1. INTRODUCTION

Kinship verification and recognition refers to the ability of the machine to determine the degree of genetic and blood relationships between human faces. One of the most important ways to identify one another is through facial recognition. An interesting topic for research is automatic KVR. It has a significant impact on practical uses including forensics, historical and genealogical research, and the search for missing family members. Handcrafted features are those that the data scientist has manually designed. Learned features are those that come from a machine learning system automatically. The scattering transform, which yields non-linear invariant texture features, was used to compute it. Sharp proximity maps and superior detection results are obtained when handcrafted features are combined with raw data, as opposed to raw intensities using a similar type of CNN architecture [1].

The lack of a standardized method for merging divergent features and the fact that the assessment dataset being utilized has a significant impact on the identification of relevant features. Both the accuracy and comparison speeds of the current methods were incredibly slow. The rate of accuracy is between 50% and 60%. Photos with comparable visuals were deemed to be related to kinship. In the proposed method, the execution speed of the process is improved. The micro-expression parameter is used to find the similarities rather than relying solely on visual similarities [2]. The suggested technique improves accuracy by 10%. It facilitates real-time decision-making, lessens human bias, and enhances fraud detection. This scalable technology effectively supports humanitarian activities while saving time [3].

This paper provides an overview of kinship kinds and KVR applications. It provides a review of recent research, beginning with handcrafted methods and progressing through shallow metric learning and deep learning feature-based approaches. Additionally, the most popular datasets for kinship are examined that paves the path for further research in this area. The limits of KVR are also covered, including issues with age changes, noise, occlusion, and inadequate illumination [4]. Finally, issues with gender and age variation are also discussed.

2. LITERATURE SURVEY

This literature survey examines a range of studies that explore the use of machine learning and facial recognition technologies to identify kinship relationships. It starts with the theoretical background of Extreme Learning Machines, which offer a simpler way to train neural networks. Research on visual cognition is then highlighted in the poll, demonstrating how grouping things can improve our capacity to identify relationships. Numerous studies emphasize the importance of micro-expressions, or fleeting facial alterations that convey emotions, in kinship detection. The accuracy of these identifications is increased via a number of methods, such as spatio-temporal analysis, transfer learning, and Convolutional Neural Networks. The report also covers techniques that aid in automating the process of confirming family ties, such as metric learning and support vector machines [5]. Overall this review showcases the innovative approaches being used to understand human connections through facial expressions and emotional signals.

Table I .Literature review

Sl No	Paper Title	Methods Used	Merits	Demerits
1	Extreme Learning Machines : Theory and Applications [6]	Feedforward neural networks	Easy to implement	Efficiency is low
2	Representing multiple objects as an ensemble enhances visual cognition [7]	Selective attention to process only the most relevant information	Linear correlations between Visual cognition difficulty and gaze behaviors	Difficult to group visually similar objects
3	Image Retrieval Based On Color and Texture Features of the Image Sub-blocks [8]	Image is partitioned , color is extracted by HSV color space	Euclidean distance is used in retrieving the similar images	Accuracy in retrieving similar objects is low
4	Deep kinship verification via appearance shape joint prediction and adaptation based approach [9]	Deep learning pipeline based on shape and appearance	Two-phased training scheme and utilized large-scale face recognition data	-
5	Kinship Measurement on Salient Facial Features [10]	Local matching, bayes similarity scores	Perform reasonably well	Several challenges are there
6	A Convolutional Neural Network for compound micro-expression [11]	Convolutional Neural Networks (CNNs)	High accuracy	Limited generalizability
7	Facial Micro-Expression Based Kinship Recognition via Transfer Learning [12]	Transfer learning pre trained deep learning models (VGS-Face), Micro - expression classification	Improved model performance transfer learning reduces the need for extensive training datasets	Performance declines with unseen or highly varied data
8	Kinship Recognition Using Micro-Expressions and spatio-Temporal Analysis [13]	Spatio-Temporal feature extraction, Long short-Term Memory Networks	Efficient at capturing temporal dynamics in micro expression	Requires high-quality video inputs for optimal performance

Table I represents the techniques used, merits and demerits of the existing systems.

The majority of studies on identifying familial ties from minute facial expressions make use of advanced methods like deep learning and machine learning. Transfer learning with models like VGG-Face helps improve performance without requiring a lot of data, and CNNs are well-liked for identifying details in facial features [14]. While simpler approaches like SVMs are less effective and only function with smaller datasets, combining techniques like LSTM networks aids in tracking micro-expressions in video. Some more recent techniques, like Siamese Networks and deep metric learning, are excellent for comparing faces to determine a person's kinship [15]. Audio based Kinship verification is also proposed recently. [16] Overall, these approaches make kinship recognition more accurate but face challenges with computing power, data quality, and real-world use.

In the proposed system, a model is created for predicting family relationships by analyzing micro-expressions with the help of advanced Machine Learning techniques. Convolutional Neural Networks (CNNs) are used to extract and map detailed facial features that reveal genetic connections. Long Short-Term Memory (LSTM) networks are incorporated to handle the fleeting nature of micro-expressions, which will help us capture both the subtle changes in facial muscles over time and the detailed spatial features. Apply transfer learning to adapt pre-trained models to our kinship data, which will speed up training and boost performance. Our approach will include facial landmark detection and feature extraction to maintain accuracy despite variations in lighting, pose, and expression. Additionally, the system will be designed for real-time kinship predictions,making it useful for applications like family reunions, security, and forensic analysis [17].

3. PROPOSED SYSTEM

The proposed approach uses advanced machine learning algorithms to analyze face micro-expressions in order to identify kinship. An effective Extreme Learning Machine (ELM) is used to classify multiple face traits and complex expressions that are extracted by a deep Convolutional Neural Network (CNN). This combination provides quick processing while ensuring a high degree of kinship relationship accuracy. When evaluated on standard datasets, the system performs well in comparison to alternative approaches. The applications of the proposed work include ancestry research, forensic analysis, and family reunion.

Proposed system is divided into three sections:

(i) Architecture Design

(ii) Explanation

3.1 Architecture Design

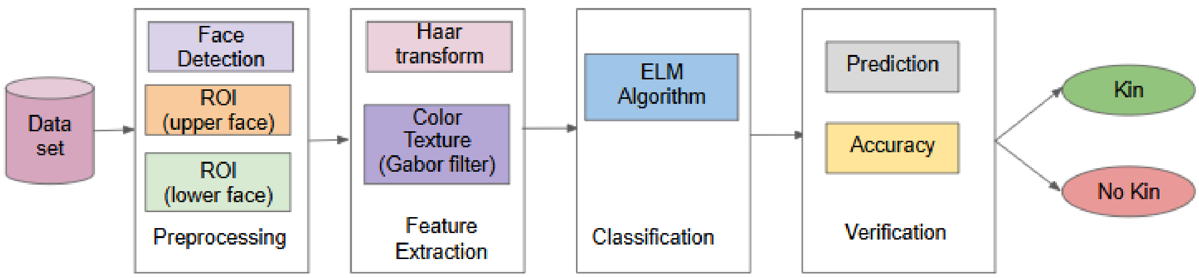

Fig.1 Block Diagram of the proposed system

The system goes through several steps to determine whether or not the two photos are related, including preprocessing, feature extraction, classification, and kinship verification. Additionally, we can determine the degree of kinship tie or recognition between the two facial photos. The automatic KVR systems can be applied to a wide range of tasks, including forensics, historical and genealogical research, identifying family members from an image collection, and locating missing parents or children. Fig.1 shows the block diagram of the proposed system

3.2 Explanation

3.2.1 Data Set : Cornell KinFace

The first step is to collect a large dataset of facial images containing individuals representing different kinship relationships (e.g., parent-child pairs, sibling pairs). The dataset is then split into training, validation, and testing sets, ensuring a balanced representation of related and unrelated pairs. This process creates a robust dataset tailored for training machine learning models to detect kinship accurately [18]. The distribution of kinship pairs is as follows: 13% mother-son (M-S), 25% mother-daughter (M-D), 22% father-daughter (F-D), and 40% father-son (F-S).Individuals' faces are arranged in familial pairings in the Cornell KinFace dataset. As a result, there were 150 pairings (300 photos) with different ages, genders, races, and occupations. Seven of the 150 family pairs are removed due to privacy concerns. There are 779 family pairings in all, and each pair includes a pair of pictures of parents and children or siblings. People from a variety of age groups, genders, and nationalities are included in the dataset [19]. Expression is used as a parameter in this Kinship verification approach. The ROI reveals the facial similarities. In this instance, the extraction and classification technique is used to identify the lower portion of the facial expression. The Kin Face dataset is used to create the images. Father-son (FS), mother-son (MS), mother-daughter (MD), and father-daughter (FD) data were used in the trials in the KinFace dataset. The four relations have 156, 134, 116, and 127 pairs of kinship photos in the KinFace collection [20]. There are 250 pairs of kinship photos in each connection for the KinFace dataset.

3.2.2 Preprocessing

All of the data that is currently available will be separated into two categories: training data and testing data. The identified ROI, which is separated into two primary sections, is used for the training process and the current tests. These are the lower face (the region surrounding the mouth) and the upper face. Reduce the size of the facial image on KinFace to 48 x 48 (grayscale) for ROI. The distribution pattern of color feature values on the lower face on the x (mouth height) and y (mouth width) axes, which have been normalized to one dimensional feature size for sample emotions, can be examined in the results of the lower face transformation image above.

3.2.3 Feature Extraction

After the face regions have been identified, use the Haar cascade to extract pertinent features from them. Variations in facial features, such as corners, edges, and lines, are captured by Haar-like features and can be useful for estimating kinship [21]. Color texture information can be extracted from facial photos using a variety of texture feature extraction techniques. By convolving the image with a bank of Gabor filters at various sizes and orientations, color texture features can be extracted. Color variation-related texture information is captured in the answers.

The distribution of colors in an image can be represented by computing color histograms. It is possible to extract textural information pertaining to color variations by taking into account the spatial features. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two examples of deep learning models that can employ the color texture data as input once they have been retrieved [22]. Color texture data and other multi-modal inputs can be used to train the model in an unsupervised way to develop meaningful representations of kinship ties [23].

3.2.4 Classification: ELM Algorithm

The Extreme Learning Machine (ELM) method is a machine learning technique that is intended to learn quickly and effectively, particularly for problems involving regression and classification. The hidden layer's input weights and biases are fixed and initialized at random in this single-layer feedforward neural network (SLFN). ELM does not require backpropagation or other iterative training algorithms, in contrast to typical neural networks. The time and computer resources required for training are greatly decreased because it uses a straightforward closed-form solution to compute the output weights directly. Even though ELM is straightforward, it has demonstrated universal approximation capabilities, which means that if it has enough hidden neurons, it can simulate complex functions.

Its ability to generalize effectively to unknown data is a result of this feature. Due to its scalability, strong generalization ability, and quick training speed, ELM is well-suited for real-time applications and big datasets. Because the approach may provide great performance at minimal computational costs, it has been effectively used in a variety of fields, including data mining, bioinformatics, and image recognition. An expedient and effective substitute for conventional neural networks is offered by ELM. It is a useful tool for many machine learning applications because of its ease of use and efficiency. You can take advantage of ELM's ability to tackle challenging issues if you comprehend its fundamental ideas and benefits.

One feedforward neural network type that provides a quick and effective learning process is the Extreme Learning Machine (ELM). ELM employs a single-layer feedforward network with randomly generated hidden layer parameters, in contrast to conventional neural networks that depend on iterative optimization strategies like backpropagation. By randomly initializing the hidden layer's weights and biases, it considerably speeds up training compared to more conventional techniques like backpropagation.

3.2.5 Verification

This step is responsible for identifying and determining whether the two input facial images are kin or non-kin once absolute features have been extracted from them. The classifier is trained using a dataset of tagged kin facial images to achieve this categorization. Evaluating the possibility or likelihood that two people have a certain kinship relationship such as parent-child, brother, or grandparent-grandchild is the aim of kinship verification [24]. Usually, to complete this procedure, the biometric characteristics of the people in question are compared, and any patterns or similarities between them are examined. Facial photographs are frequently employed as the main biometric indication in facial-based kinship verification. Relevant facial traits or representations, such as deep learning embeddings, texture descriptors, or facial landmarks, are extracted from the photos [25] [26]. The similarities or differences between pairs of people are then measured using these characteristics.

4. SIMULATION RESULTS AND DISCUSSION

The proposed system is simulated using Python 3.10.6. Python is a high-level programming language known for its simplicity, readability, and versatility. It is used for artificial intelligence, data analysis, web development etc

Case : 1 Kin Faces:

In the first case, two images (Fig.2 and Fig.3) are taken that come under “kin faces”.

We know that the image appears to be a visual representation of facial detection using bounding boxes. The meaning for the various boxes with different colors is described as follows: The main face detection box showing the area where the face is identified is represented by a blue box. Green box highlights the detected eyes and the red box represents the region of the nose. The detected mouth region is represented by a sky blue box.

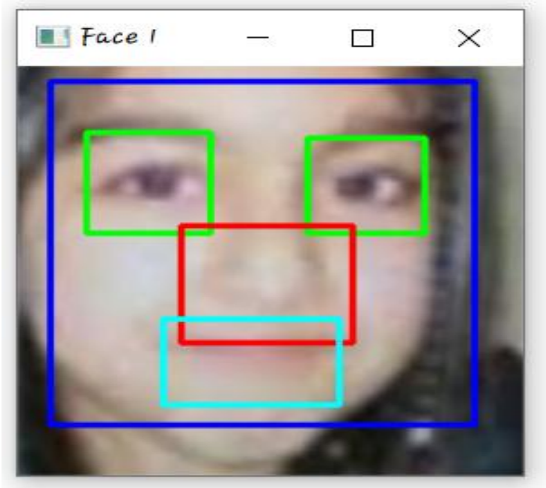

Fig 2. Face 1: Kin identification

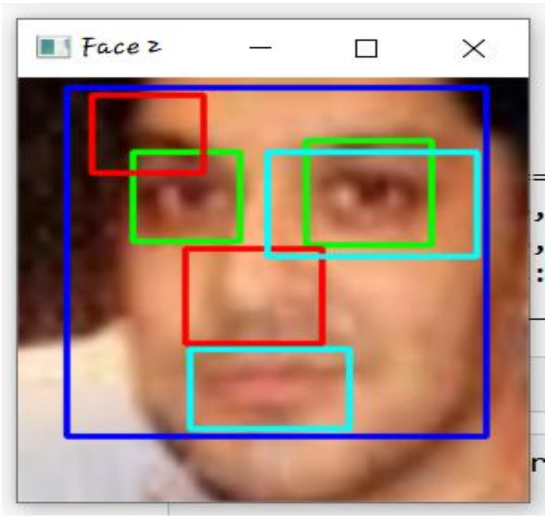

Fig 3. Face 2: Kin identification

Case 2 : No-Kin Faces:

In the second case, two images (Fig.4 and Fig.5) are taken that come under “No-kin faces”.

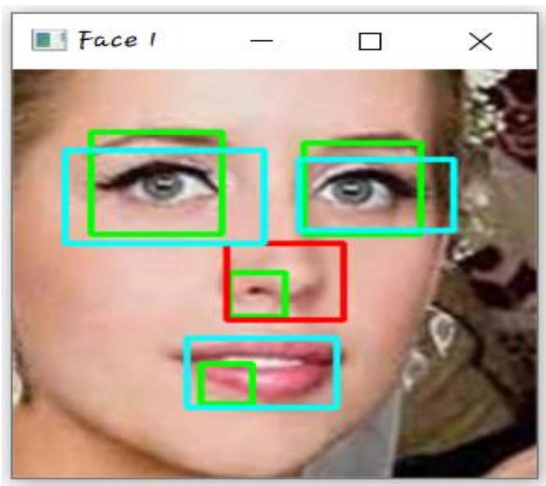

Fig 4. Face 1: No-Kin identification

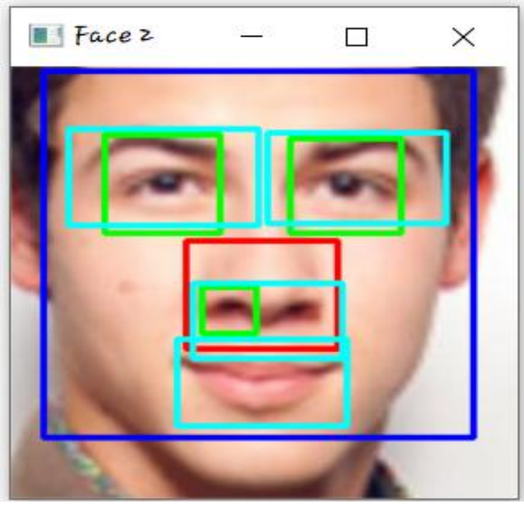

Fig 5. Face 2: No-Kin identification

Some of the processes involved in the Kinship Verification and Recognition includes: face detection, face recognition, face alignment, expression analysis and speech or lip reading. Face detection deals with detection of the facial region and face recognition is identifying the individuals by using unique facial features. Face alignment is the technique to prepare the faces for the most advanced methods of deep learning modes. The last process involves the mouth region for detecting the lip movements.

5. CONCLUSION AND FUTURE ENHANCEMENT

As we know, age has a profound effect on facial features. It is difficult to confirm the kin relationship because of this age variation, which maximizes the difference between the child's and old parent's faces because the old parent's facial features alter when compared to their early face. Changes brought on by aging, such as wrinkles, skin tone, and facial structure, might mask familial similarities and make kinship identification difficult. Another issue that affects the accuracy of kinship verification is gender. Gender has a significant impact on verification accuracy since father-daughter kinship accuracy is lower than mother-daughter kinship accuracy and father-son kinship accuracy is better than mother-son.

Age and gender significantly impact kinship recognition accuracy. Aging alters facial features, making it harder to detect familial similarity, while gender differences affect verification rates. Improving micro-expression recognition through advanced algorithms, and expanding the system to include kinship verification, can enhance accuracy and practical applications.

Increasing the accuracy of the algorithm for micro-expression recognition is one possible improvement. Better feature extraction methods, larger training data sets, or more advanced machine learning models could all help achieve this. Enabling the real-time recognition of micro-expressions in videos would be an additional improvement. This could be accomplished by deploying specialized hardware for faster processing, increasing processing speed, or modifying the algorithm to operate with live video streams.

Enabling kinship verification is an additional possible improvement to the program, which currently concentrates on kinship recognition. Instead of only figuring out the degree of kinship, this would entail figuring out whether two people are related. Future developments in kinship recognition utilizing micro-expressions might concentrate on creating lightweight, real-time models for quicker analysis in applications like surveillance and genealogical research, as well as using multi-modal data, such as voice and gestures, to increase accuracy.

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