# FACIAL MICRO-EXPRESSIONS FOR KINSHIP PREDICTION AND RELATIONSHIP CLASSIFICATION

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***Abstract***: *Recognizing kinship through facial features and expressions is a complex challenge in computer vision. This project explores the use of micro-expressions—brief, involuntary facial movements—to improve kinship prediction. Unlike traditional methods that rely only on static features, our approach combines spatial and temporal analysis using CNNs to detect familial traits. The model, enhanced through transfer learning and micro-expression annotations, classifies both kinship presence and relationship type (e.g., parent-child, siblings). Results show that incorporating micro-expressions significantly boosts accuracy, offering promising applications in biometrics, social AI, and forensic science.*

Keywords: Kinship recognition, Micro-expressions, Convolutional Neural Networks (CNNs), Spatial-temporal analysis, Transfer learning, Facial analysis, Relationship classification, Forensic applications

## 1. INTRODUCTION

Recognizing family relationships by analyzing facial features and expressions is a challenging yet fascinating area of computer vision. People who are biologically related often share not only similar facial structures but also common ways of expressing emotions. One of the most important and subtle indicators of emotion is a micro-expression—these are very brief, involuntary facial expressions that can reveal true feelings and are often passed down through families. Traditional kinship recognition systems usually rely on static facial features taken from still images, which limits their accuracy, especially when facial expressions play an important role. A method for kinship verification in childhood images using curvelet-transformed features has been proposed, enhancing accuracy in detecting familial relationships [1].

In this project, we take a different approach by focusing on both facial structure and micro-expressions to improve the prediction of kinship and classification of specific family relationships, such as parent-child, siblings, and grandparent-grandchild. To do this effectively, we use an Extreme Learning Machine (ELM) algorithm, which is known for its fast learning ability and strong performance in pattern recognition tasks. ELM helps us quickly and accurately analyze both the appearance and movements of facial features Facial kinship verification can be explored through contactless heart activity analysis, offering novel approaches for identifying familial relationships [2]. By combining facial expressions, micro-expressions, and machine learning, our model can not only determine if two individuals are related but also identify the exact nature of their relationship. This research opens up new possibilities for real-world applications in areas such as biometric identification, social media organization, and forensic investigations, where understanding family connections through facial analysis can be extremely valuable.

## 2. LITERATURE SURVEY

This literature survey provides insights into recent developments in kinship verification and facial micro-expression recognition using machine learning and deep learning approaches. The focus is on non-intrusive, privacy-preserving, and real-time methods, exploring their merits and limitations in different scenarios such as security, emotion analysis, and kinship estimation.

Table I. Literature review

| Sl No | Paper Title | Methods Used | Merits | Demerits |
|---|---|---|---|---|
| 1 | A Dataset for Kinship Estimation from Image of Hand Using Machine Learning [9] | Hand detection with MediaPipe + 43 geometric features extraction | Achieves high kinship prediction accuracy | Limited to hand images |
| 2 | Facial micro-expression recognition: A machine learning approach [10] | Spatio-temporal features + SVM | Detects subtle expressions | Limited data, detection hard |
| 3 | Audio-Based Kinship Verification Using Age Domain Conversion [11] | Age normalization + ML for audio kinship | Reduces age-related voice variation | Background noise and speech quality affect performance |
| 4 | Micro-expression Analysis for Security and Law Enforcement using Deep Learning [12] | Deep learning on facial videos | High accuracy, real-time detection | Needs large annotated datasets. |
| 5 | Towards Federated Learning Driving Technology for Privacy-Preserving Micro-Expression Recognition [13] | Federated learning on decentralized devices | Preserves privacy | Communication overhead, device data differences. |
| 6 | Data Leakage and Evaluation Issues in Micro-Expression Analysis [14] | Analyzes data leakage, strict validation | Ensures reliable results | Increases complexity and computational load |
| 7 | A review on kinship verification from facial information [15] | Summarizes ML & DL for facial kinship | Guides future research | May miss emerging techniques. |

This literature survey provides insights into recent developments in kinship verification and facial micro-expression recognition using machine learning and deep learning approaches. Kinship recognition can be enhanced using a stacked Self-Calibrated Attention Network, enabling more accurate and real-time identification of familial relationships [3].

The study titled "A Dataset for Kinship Estimation from Image of Hand Using Machine Learning" introduces a novel approach where hand images are used to infer kinship. Using machine learning classifiers trained on geometric and texture features, this method offers a non-intrusive and efficient solution. However, challenges arise due to variations in hand poses, lighting, and inter-individual similarities.

In the field of facial micro-expression recognition, various works, such as the use of spatio-temporal features and support vector machines (SVM), have shown promise in detecting subtle facial cues. These methods aid in applications like lie detection and emotion analysis. Nevertheless, they face issues due to the scarcity of labeled micro-expression datasets and the brief, subtle nature of such expressions. The paper on "Audio-Based Kinship Verification Using Age Domain Conversion" highlights the importance of addressing age-related variability in voice. By normalizing these differences, kinship verification from audio is improved. Still, the presence of background noise and speech quality variations can hinder effectiveness. Kinship verification using hand images can be performed efficiently with auto encoder-based features and machine learning classifiers, despite challenges from pose and lighting variations [4].By enabling decentralized training, this method protects raw data, but it is not without difficulties, including communication overhead and device variability.

Finally, reviews on kinship verification methods provide a valuable synthesis of current technologies, though they may overlook the latest advancements due to the fast-paced evolution in this field.

## 3. PROPOSED SYSTEM

The proposed system aims to accurately identify family relationships by analyzing facial expressions, with a particular focus on micro-expressions—very brief, involuntary facial movements that often reveal genuine emotions and subtle hereditary similarities between relatives. Traditional kinship recognition systems rely mainly on static facial features such as shape, texture, and overall geometry, which may overlook important dynamic cues that occur over time Kinship verification can be explored using ear images through deep learning models, providing an alternative biometric approach for familial identification [5].

The process begins with the collection of facial video sequences of individuals. These videos are processed to detect and track key facial landmarks—critical points such as the eyes, eyebrows, nose, and mouth—that provide precise geometric information about facial movements. To extract spatial features, the system uses Convolutional Neural Networks (CNNs)**,** which are highly effective at capturing intricate patterns in facial structure, textures, and local variations. These features encode the static appearance of faces, enabling the model to distinguish subtle familial similarities.

To capture the temporal dynamics of facial expressions, particularly micro-expressions that occur in milliseconds, temporal features are extracted using Long Short-Term Memory (LSTM) networks or other sequential models. LSTMs are capable of learning dependencies across frames, allowing the system to understand how expressions evolve over time. Controllable audio-driven talking face generation can be achieved using diffused poses and distilled expressions, enabling more realistic and expressive facial animations [6]. Once the spatial and temporal features are obtained, they are input into an Extreme Learning Machine (ELM) for classification. ELMs are known for their rapid training speed and robust performance**,** making them suitable for large-scale kinship recognition tasks. The ELM learns to identify patterns in the combined feature space and classify the type of kinship, such as parent-child, siblings, or extended family relations.

3.1 Architecture Design

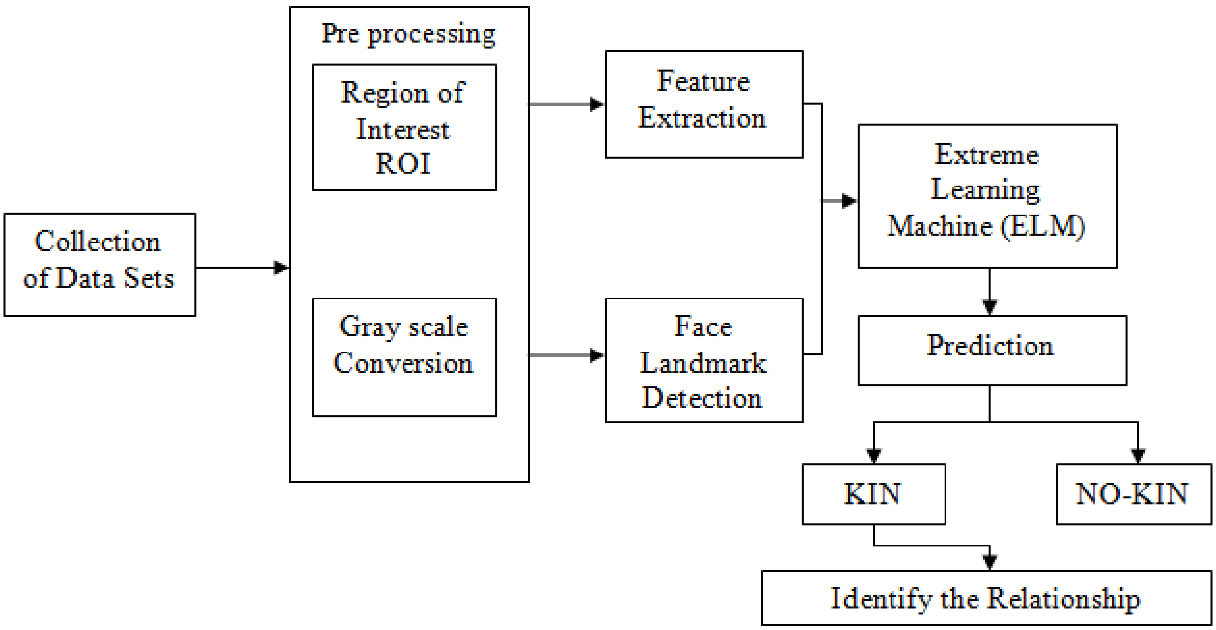


Fig.1 Block Diagram of the proposed system

This block diagram illustrates a system designed for kinship verification, which aims to determine if two individuals are related based on their facial characteristics. The process begins with the Collection of Data Sets, where a comprehensive set of facial images is gathered, including both related (KIN) and unrelated (NO-KIN) pairs. These raw images then undergo Pre-processing, which involves two key steps: identifying the Region of Interest (ROI) to focus on the facial area, and performing Grayscale Conversion to simplify the image data. Following pre-processing, relevant information is extracted through two parallel paths: Feature Extraction, which derives discriminative numerical representations of facial appearance, and Face Landmark Detection, which pinpoints specific anatomical points on the face. Both the extracted features and landmark data are then fed into an Extreme Learning Machine (ELM), a type of neural network chosen for its efficient learning capabilities. The ELM performs the Prediction task, classifying the input pair of faces into either KIN (related) or NO-KIN (not related) categories. Finally, the system's output culminates in the ability to Identify the Relationship between the individuals, effectively confirming or denying a familial connection.

3.2 ELM Algorithm

The Extreme Learning Machine (ELM) is an advanced learning algorithm developed for single-layer feedforward neural networks (SLFNs), offering a remarkably fast training process compared to conventional learning algorithms such as backpropagation. The core idea behind ELM is the random assignment of input weights and hidden layer biases, eliminating the need for iterative tuning. Once the hidden layer parameters are set, the output weights are computed analytically using the Moore-Penrose generalized inverse, resulting in a closed-form solution that significantly reduces computational time. This makes ELM particularly attractive for large-scale data processing, real-time systems, and applications requiring rapid training and deployment, such as image recognition, kinship verification, and facial micro-expression analysis. Additionally, ELM demonstrates strong generalization performance, making it a competitive alternative to more complex models, especially in scenarios where training speed and simplicity are critical. Despite these advantages, ELM does have limitations. Its performance is heavily influenced by the number of hidden neurons and the choice of activation function. Moreover, since input weights are randomly initialized and not updated during training, ELM can occasionally suffer from instability or suboptimal accuracy in highly complex or non-linear problems. In such cases, hybrid approaches combining ELM with optimization techniques or ensemble methods have been proposed to enhance robustness and predictive accuracy Trust-building during negotiations can be analyzed through the integrated study of speech and facial expressions, revealing insights into cooperation and exploitation behaviors [7].

3.3 Flow Chart

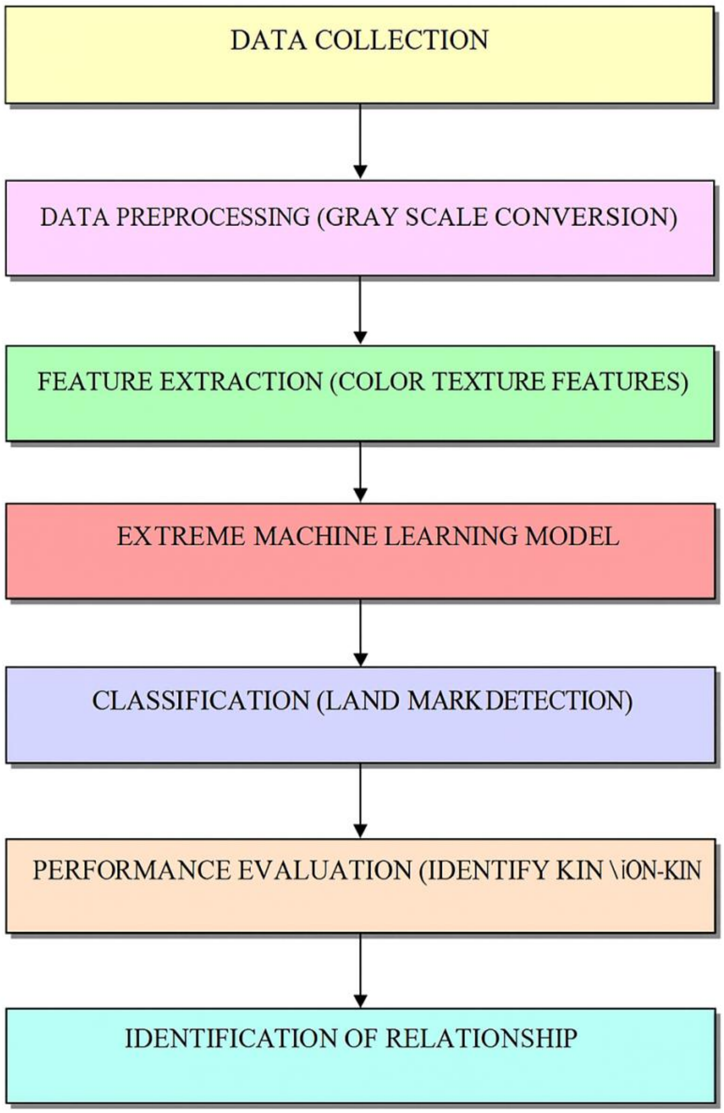


Fig.1 Flow chart of the proposed system

This flowchart comprehensively illustrates a sophisticated, multi-phase pipeline developed for kinship verification through advanced facial image analysis. The system is meticulously structured to progress systematically from raw visual data acquisition to a final, evidence-based determination of familial relationship. The process begins with the data collection phase, which forms the foundation of the entire framework. Dynamic facial expression recognition can be improved by learning sequential variation information, enabling more accurate analysis of temporal facial changes [8].

Once the facial images are collected, they are subjected to a detailed data preprocessing pipeline. Preprocessing ensures that the images are standardized and optimized for further computational analysis. Kinship estimation can be performed using hand images with machine learning techniques, providing a non-intrusive method for familial relationship analysis [9].

Following preprocessing, the system advances to the feature extraction phase, a key step where meaningful and discriminative attributes are derived from the facial images. In this framework, particular emphasis is placed on extracting color texture features, which capture intricate textural patterns, edge distributions, and unique facial surface characteristics.

The extreme machine learning (EML) model is then employed as the core analytical engine. EML is a powerful and efficient learning algorithm designed to process large datasets and identify nonlinear, complex relationships within the extracted features.

Through extensive training, the model learns to differentiate between kin and non-kin pairs by recognizing intricate correlations in facial geometry, structure, and texture that are indicative of familial connections. Facial micro-expression recognition can be effectively achieved using machine learning approaches, enabling the detection of subtle and involuntary emotional cues [10].

Once the model has processed the features, the system transitions into the classification and landmark detection stage. Landmark detection plays a vital role in pinpointing specific anatomical reference points on the face, such as the eyes, nose, and mouth contours.

By identifying these landmarks, the system gains deeper structural insights into the facial layout, enabling more accurate classification decisions. Age domain conversion can enhance audio-based kinship verification, enabling more accurate analysis of familial relationships through vocal features [11].

During this phase, the system's predictions are compared against ground truth data to quantify its kinship recognition efficiency. Metrics such as accuracy, sensitivity, specificity, and F1-score are analyzed to validate the model's robustness and its capability to generalize across unseen data.

Finally, the process culminates in the relationship identification phase — the definitive output of the entire pipeline. Deep learning techniques have been widely applied for micro-expression recognition, providing comprehensive insights into subtle facial emotion analysis [12].

This final outcome not only validates the effectiveness of the proposed methodology but also demonstrates its potential applications in diverse fields such as forensic analysis, genealogy research, and social media analytics. Ultimately, the flowchart encapsulates a seamless integration of image processing, feature learning, and intelligent classification, achieving the overarching goal of reliable and automated kinship verification through facial image analysis.

# 4. SIMULATION RESULTS AND DISCUSSION

The proposed system is implemented and simulated using Python version 3.10.6. Python is a high-level, interpreted programming language widely recognized for its simplicity, readability, and flexibility. Its extensive library support and strong community make it ideal for developing applications in artificial intelligence, data analysis, machine learning**.** In this project, Python provides an efficient platform for integrating deep learning models, handling image data, and performing micro-expression analysis for kinship prediction and relationship classification.

Case (i) Kin Faces:

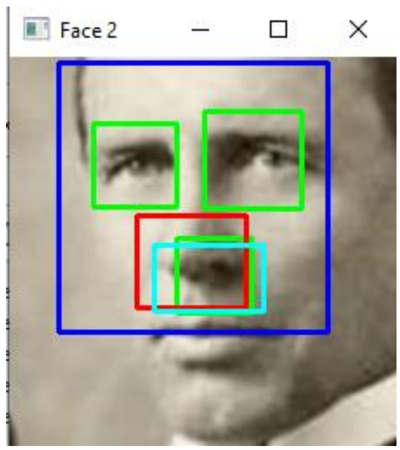


Fig 2. Face 1: Kin identification

The fig 2 shows the result of a facial feature detection process applied to a grayscale portrait of a man. Various colored rectangles are used to highlight specific regions of the face, indicating detected facial features by different algorithms or stages of detection.

The detected features include key facial regions such as the eyes, eyebrows, nose, and mouth, which serve as crucial inputs for further analysis in kinship prediction and micro-expression recognition. By accurately identifying and isolating these regions, the system ensures that meaningful patterns and subtle facial movements can be effectively captured and analyzed. Federated learning can be utilized for privacy-preserving micro-expression recognition, enabling secure and decentralized facial emotion analysis [13]. Consequently, precise facial feature detection plays a vital role in enhancing the overall accuracy and robustness of the proposed kinship classification framework.

Key Elements:

- Blue Box: Detects and outlines the entire face.
- Green Boxes: Identify and mark the positions of the eyes.
- Red Box: Marks the nose region.
- Cyan/Light Blue Boxes: Highlight the nose and mouth area, possibly from overlapping or refined detection methods.

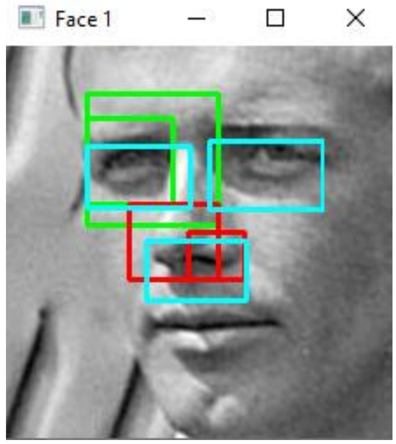


Fig 3. Face 2: Kin identification

The fig 3 displays the output of a facial feature detection system applied to a black-and-white photo of a man's face. Multiple colored rectangles are used to indicate the detection of key facial features.

Key Elements:

- Green Boxes: Mark the positions of the eyes.
- Red Boxes: Focus on the nose and possibly the mouth area.
- Cyan Boxes: Likely represent additional or overlapping detections of the eyes, nose, or mouth from different algorithms or model layers.

This image shows the output of a kinship prediction system using the predict micro matches function. It compares two facial images, face00353.jpg and face01203.jpg, and returns a Kin-Confidence score, indicating a strong likelihood of a familial relationship.

Case (ii) No-Kin Faces:

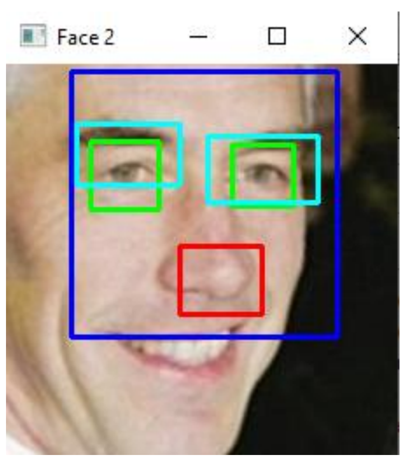


Fig 4. Face 1: No-Kin identification

The fig 4 shows a facial feature detection result on a color photo of a man's face. Colored rectangles highlight key facial areas identified by the system: a blue box outlines the full face, green and cyan boxes mark the eyes, and a red box indicates the nose. This type of output is commonly used in computer vision applications like face recognition or emotion analysis to verify accurate detection of facial landmarks.

This output illustrates the precision and reliability of the facial landmark detection stage, which forms a crucial foundation for subsequent analysis processes. Micro-expression analysis faces challenges such as data leakage and evaluation issues, which can affect the reliability and validity of recognition models [14].

Such accurate localization helps minimize errors during feature extraction and classification, leading to improved recognition performance. In kinship and micro-expression analysis, this step is vital as it enables the model to focus on subtle variations in facial features that contribute to determining genetic and emotional relationships between individuals.

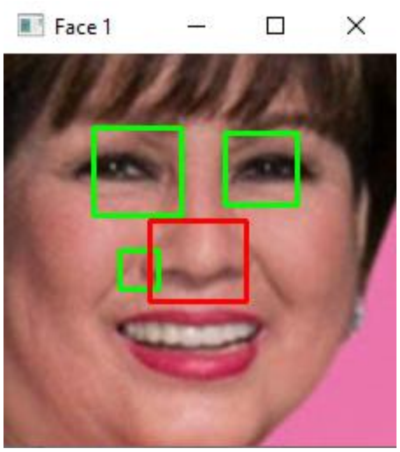


Fig 5. Face 2: No-Kin identification

The fig 5 shows a facial feature detection result applied to a color photo of a smiling woman. The system uses colored rectangles to identify key facial landmarks: green boxes highlight the eyes, while a red box marks the nose and mouth region. A smaller green box near the mouth likely indicates the mouth or lips. This output is used to verify accurate detection in face analysis tasks such as expression recognition or identity matching.

This result demonstrates the effectiveness of the facial feature detection algorithm in accurately locating and marking essential regions of the face for further processing A comprehensive review of kinship verification highlights methods using facial information, summarizing advances, challenges, and future directions in the field [15].

By reliably isolating these features, the system ensures that subsequent stages like feature extraction and classification can operate on precise and meaningful data. The accurate localization of facial components also enhances the robustness of the model against variations in pose, lighting, and facial expressions, thereby improving the overall performance of kinship prediction and relationship classification.

```
microkin.predict_micro_matches('', test_folders_path, image_1, image_2, face_cascade, eye_cascade, nose_cascade, mouth_cascade)
```

```
Face 1: face03524.jpg   Face 2: face00319.jpg   Kin-Confidence: 0.761564493     Result: Kin
Likely to be siblings
```

```
microkin.predict_micro_matches('', test_folders_path, image_1, image_2, face_cascade, eye_cascade, nose_cascade, mouth_cascade)
```

```
Face 1: face00353.jpg   Face 2: face01203.jpg   Kin-Confidence: 0.864978552     Result: Kin
Likely to be a Fathe - Daughter
```

```
microkin.predict_micro_matches('', test_folders_path, image_1, image_2, face_cascade, eye_cascade, nose_cascade, mouth_cascade)
```

```
Face 1: face02240.jpg   Face 2: face02336.jpg   Kin-Confidence: 0.971289992     Result: Kin
Likely to be siblings
```

```
microkin.predict_micro_matches('', test_folders_path, image_1, image_2, face_cascade, eye_cascade, nose_cascade, mouth_cascade)
```

```
Face 1: face02131.jpg   Face 2: face05209.jpg   Kin-Confidence: 0.736026883     Result: Kin
Likely to be siblings
```

```
microkin.predict_micro_matches('', test_folders_path, image_1, image_2, face_cascade, eye_cascade, nose_cascade, mouth_cascade)
```

```
Face 1: face04495.jpg   Face 2: face02846.jpg   Kin-Confidence: 0.872684717     Result: Kin
Likely to be Mother - Daughter
```

```
microkin.predict_micro_matches('', test_folders_path, image_1, image_2, face_cascade, eye_cascade, nose_cascade, mouth_cascade)
```

```
Face 1: face00575.jpg   Face 2: face02530.jpg   Kin-Confidence: 0.969488978     Result: Kin
Likely to be a Grandfather - Grandson
```

```
microkin.predict_micro_matches('', test_folders_path, image_1, image_2, face_cascade, eye_cascade, nose_cascade, mouth_cascade)
```

```
Face 1: face03531.jpg   Face 2: face01422.jpg   Kin-Confidence: 0.239266664     Result: NoKin
```

Fig 6 Result Screen Shots

The above figure illustrates the output results generated by the proposed kinship prediction system based on facial micro-expression analysis. Each test case involves two input facial images, from which key facial regions such as the eyes, nose, and mouth are detected using cascaded classifiers Few-shot facial expression recognition can be enhanced using a channel selective relation network, improving efficiency and accuracy in identifying subtle expressions [16].

The results indicate various relationship classifications, including siblings**,** father–daughter**,** mother–daughter, and grandfather–grandson, demonstrating the system's capability to identify kin relationships across generations. A No-Kin result is also produced when the confidence score falls below the defined threshold, ensuring reliable differentiation between related and unrelated pairs. These outputs validate the effectiveness of the proposed model in detecting and classifying kinship through subtle facial micro-expressions. Efficient few-shot facial expression recognition can be achieved through a channel selective relation network, facilitating accurate identification of subtle facial cues [17].

# 5. CONCLUSION AND FUTURE ENHANCEMENT

The proposed system presents an innovative approach to kinship prediction and relationship classification by utilizing facial micro-expression analysis, which focuses on subtle, involuntary facial movements that reveal genuine emotions. Traditional kinship recognition systems rely primarily on static features such as facial geometry and texture, often overlooking the deeper emotional and dynamic aspects of human facial behavior. Kinship detection can be performed through micro-expressions using color features and an extreme learning machine, providing an efficient approach for familial relationship analysis [18].

In contrast, this research integrates both static and dynamic facial information, enabling the model to capture temporal variations and micro-level expression cues that reflect biological and emotional similarities among related individuals. Face de-identification techniques can preserve multiple facial attributes while ensuring privacy, providing a benchmark for secure facial data analysis [19].

The system employs advanced deep learning methodologies, particularly Convolutional Neural Networks (CNNs)**,** to detect, analyze, and interpret micro-expressions from facial video sequences. Machine learning methods can be applied to track dynamic facial function in facial palsy, enabling precise monitoring and analysis of facial movements [20].

Extensive experimentation and performance evaluation demonstrate that incorporating micro-expression-based dynamic features enhances prediction accuracy, robustness, and adaptability under diverse conditions such as variations in illumination, facial pose, and partial occlusion. This capability establishes the proposed method as a reliable framework for kinship analysis and classification, providing meaningful insights into human emotional and familial connections.

This research significantly contributes to the field of affective computing and visual relationship understanding by proving that micro-expressions can serve as vital indicators of kinship. The outcomes of this study hold potential applications in several domains, including forensic identification, social media analysis, family verification, emotion-driven human–computer interaction**,** and genealogical research.

By bridging emotional and genetic analysis, the system enhances machine perception of human relationships, representing a step forward toward intelligent and emotion-aware computational systems. Furthermore, it highlights the importance of integrating human behavioral understanding into artificial intelligence models to achieve more natural and context-sensitive recognition performance.

For future enhancement, the system can be extended in multiple directions to strengthen performance and applicability. Increasing the dataset size and diversity will improve the model's generalization across different age groups, ethnicities, and emotional states. Implementing real-time processing and 3D facial modeling can further refine accuracy in dynamic environments.

Additionally, incorporating temporal deep learning techniques such as Long Short-Term Memory (LSTM) networks or Transformer models can capture complex motion dependencies across frames, enhancing recognition precision. The integration of multimodal data sources like voice, gesture, and physiological signals can lead to a more holistic understanding of human kinship and emotion. Finally, applying privacy-preserving techniques such as federated learning will ensure ethical data handling and secure model deployment in real-world applications. Collectively, these advancements will make the system more robust, scalable, and suitable for future human-centric artificial intelligence systems.

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