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FACIAL VERIFICATION OF FAMILIAL RELATIONSHIPS USING DEEP LEARNING AND SIAMESE NEURAL NETWORKS

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ABSTRACT

Facial kinship verification is all about figuring out if two people are related by blood by looking at their faces. This task is different from traditional face recognition because it looks for small similarities that may exist between different people in a family. This work develops a deep learning-based method that uses a Siamese neural network to compare pairs of facial images and find out how similar they are in a learned feature space. The system processes input images through the same network branches and uses a distance metric to figure out how related they are, as well as a classification system based on a threshold. An uncertainty region is added to handle cases that are on the edge of being true or false. This makes the system more reliable.The system also uses explainable AI methods to give visual and numerical information about the prediction, such as heatmaps and region-wise analysis of facial features like the eyes, nose, and mouth. The model is tested on datasets like KinFaceW and Families in the Wild. It works well on structured data, but it shows problems when used in the real world. The findings suggest that integrating similarity learning with interpretability can yield a more transparent and effective approach for kinship verification.

Keywords: *Deep Learning, Explainable AI, Grad-CAM, Face Similarity, Siamese Neural Network, and Facial Kinship Verification.*

1. INTRODUCTION

Recent improvements in machine learning have made it possible for systems to do complicated visual analysis tasks that were hard to automate before. One of these tasks is facial kinship verification, which tries to find out if two people are related by looking at how similar their facial features are. Face recognition aims to identify the same person across various images, whereas kinship verification focuses on comparing different individuals to identify inherited traits.

This problem is hard by nature because the similarities between related people are often small and can change depending on things like age differences, lighting, facial expressions, and image quality. In certain instances, unrelated individuals may exhibit visual similarities, whereas related individuals may lack pronounced visual resemblance. These differences make it hard to trust simple visual or rule-based methods.

The previous techniques relied on handcrafted features like facial shape and texture patterns. However, they were not very effective in understanding the relationship between various features. With the arrival of deep learning, the algorithms are now capable of extracting relevant features automatically. The Siamese neural network model is employed in this study to determine the similarity between two facial images instead of classifying them.

Besides making predictions, the model is developed with the intention of offering some understanding on how the decision-making process takes place. This can be attributed to the inclusion of explainable artificial intelligence tools that assist in determining which facial features play significant roles in the prediction process. The system also offers various measures, including distances and similarity measures among others.

2. LITERATURE SURVEY AND BACKGROUND

Facial kinship verification has gone through several phases of development, starting with classical image

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processing solutions to deep learning approaches to today. The first studies utilized handcrafted features such as LBP, HOG, and face structure geometries. Such techniques could not be considered efficient because they did not account for the variability of faces in real images.

After the advent of machine learning techniques, the approach towards solving facial analysis tasks switched to classifiers based on algorithms like SVMs and k-NNs. Although these approaches showed better performance results, they were heavily reliant on handcrafted features, limiting their generalizability.

The arrival of deep learning boosted the results achieved previously. CNN architectures provided the opportunity for automatic feature generation. They allowed learning high-level abstractions from image data. Siamese neural networks become suitable for facial verification tasks because they are designed specifically for learning similarity between images rather than classification.

The availability of datasets with family structure, such as KinFaceW and Families in the Wild, helped progress in kinship verification considerably. Recent developments include studies on applying techniques of explainable AI in order to provide explanations for predictions made by models. In other words, users are able to see which parts of an image are significant for prediction. Combining both similarity learning and feature extraction can provide even better results. This is what the current project aims to achieve.

3. PROPOSED METHODOLOGY

The suggested method consists of a number of stages which are systematically organized to confirm familial relation between two faces. This involves several stages like pre-processing, extraction of features, computing similarity, classification, and interpreting results. Each of these stages is designed to ensure consistent processing of inputs and extraction of relevant facial features. The main objective of the method is to learn similarity relations between people, while remaining resistant to any changes.

3.1 Data Preprocessing

Preprocessing of input images is done in order to standardize them. This consists of resizing the images, scaling the image pixels, and using facial recognition techniques. Data augmentation methods like flipping the image horizontally and changing its brightness are used.

3.2 Siamese Neural Network Architecture

The primary element of the system is a Siamese Neural Network which comprises two convolutional branches that are similar to each other and share weights. Both branches process one image each and produce facial feature embeddings.

3.3 Similarity Computation

Comparisons of the features generated by both branches are performed via a distance measure like the Euclidean distance. The lesser the value of the distance, the more similar the images; otherwise, they are dissimilar.

3.4 Threshold-Based Decision Mechanism

A threshold is utilized to determine whether two images belong to the same category or not. Moreover, there exists an uncertainty zone that addresses those instances when the model has low confidence.

3.5 Explainable AI Integration

Interpretation of results can be improved using Grad-CAM to produce heatmaps showing regions of the face that are significant to the model decision. Analysis at the feature level by analyzing facial regions including eyes, nose, and mouth is included.

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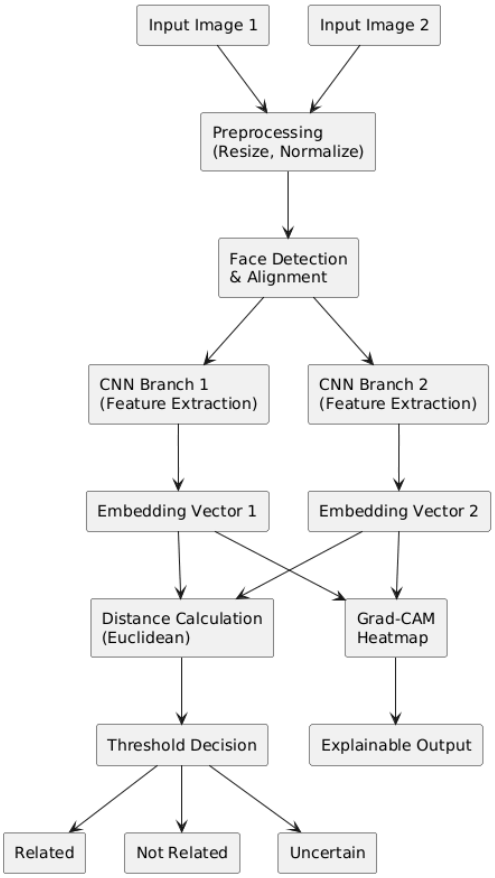

Figure 1: Block Diagram of Proposed System

4. EXPERIMENTAL SETUP

4.1 Target Platform and System Configurations

The suggested system for facial kinship verification was developed based on commonly used open source libraries for deep learning algorithms. The network was built using TensorFlow and Keras as the underlying framework in Python 3.x environment. Processing of images was done using OpenCV and Pillow libraries, while other helper libraries included NumPy and Matplotlib.

The training and testing of the system were done on a computer with Intel i7 processor and 16 GB RAM. The training process was done using CPU due to limitations of the hardware resources. Inference stage was optimized for maximum performance and efficiency. All development was done in Visual Studio Code using a virtual environment.

4.2 Dataset Configuration Protocols

The algorithm was trained and tested on public kinship-related data collections, including KinFaceW and Families in the Wild (FIW). The KinFaceW dataset is composed of organized image pairs of parents and children, whereas the FIW dataset includes diverse family image pairs in more naturalistic settings.

For the training process, some family instances were selected, and the pairs were created dynamically. The positive pairs (those depicting related persons) and negative pairs (non-related persons) were balanced to avoid any bias in the learning process. Image processing included resizing the image into 224 × 224, normalizing pixel intensities, and detecting faces.

Augmentation methods like flipping the image horizontally, varying image brightness, and applying a small zoom in were used to generalize well.

4.3 Model Training Configuration

Siamese Neural Network was trained by employing contrastive loss for understanding similarities in pairs of images. For training, Adam optimizer was applied with a learning rate set at 0.001. Training was conducted on mini-batches with 32 samples per batch. A threshold was calculated based on the validation dataset, which allowed sorting pairs of images into groups of related and non-related pairs.

The model generates embeddings of both inputs, and Euclidean distance served as a similarity metric.

4.4 Standard Evaluation Metrics Parameterization

Performance of the system was tested using several measures to make sure that it is being analyzed thoroughly. As mentioned earlier, the problem requires a binary classifier (related/not related). Thus, the following performance metrics were considered:

Accuracy - measures the correct prediction rate

Precision - measures the rate of correct positive prediction

Recall - measures the detection rate of the algorithm regarding relatedness of images

F1-Score - harmonic mean of precision and recall

Distance-based threshold testing - classification technique

These performance measures guarantee a holistic analysis of the system, given the problems encountered in such tasks.

5. RESULTS & DISCUSSION

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The Facial Verification of Familial Relationship System was tested on different sets of images, where some were standard images while others were taken from the real world. The system works by analyzing two input images and providing output in the form of classification results together with additional measures like similarity value, distance, and threshold.

Figure 2: Overview of the Application

Figure 3: Image Input

In a case study, for instance, the output was 0.715 for similarity and 0.569 for distance with a threshold of 0.650. In this case, since the obtained distance is smaller than the threshold, the system outputs the classification of the pair as "Related." This means that the representations of the two faces are very similar in the features space, implying a possible family link between them.

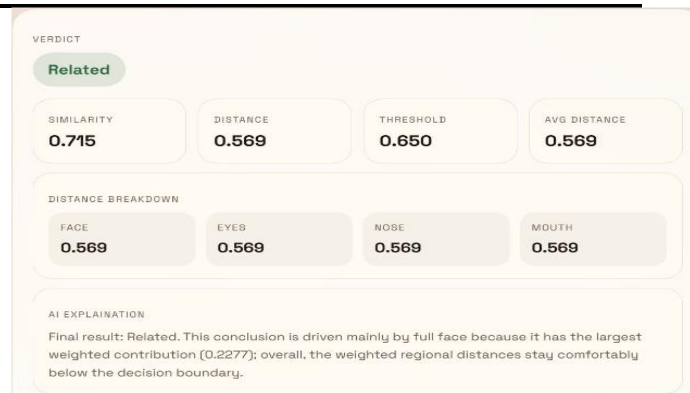

Figure 4: Verdict/Output

Moreover, the system gives the distance for different facial regions like face, eyes, nose, and mouth. Nevertheless, from the output of the system, the distance in each region was equal, which implies that the model used mostly the global appearance of the face rather than the individual regions to make predictions. This can suggest that the method of feature extraction is ineffective.

In addition to the numerical output, the system gives an AI explanation that gives reasons for making the particular prediction. From this, one can understand the role played by each region in predicting the outcome. From most of the explanations, one can observe that the full face plays the biggest role in making decisions.

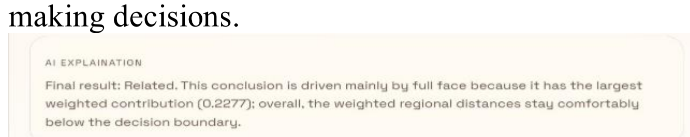

Figure 5: AI Explanation

On the whole, the model works reliably on images from the dataset and delivers explainable results by using quantitative measures and explanations. Nevertheless, differences between real-world images and restrictions on feature extraction reduce prediction accuracy and reliability.

6. CONCLUSION AND FUTURE WORK

Finally, the implemented approach is the demonstration of the application of deep learning technology for the purpose of verifying kinship among people using their faces. Specifically, instead of employing standard feature extraction methodologies, the developed model learns the patterns by processing facial images, which makes it possible to draw

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comparisons and determine whether two given subjects look similar.

An interesting aspect that should be highlighted is that the proposed approach makes attempts at providing explanations alongside prediction results. Thus, not only the classification itself is performed, but similarity values, distances, as well as visual interpretations are delivered, helping users get a better idea of the process of decision-making. It is worth noting that, despite the mentioned attempts, the dependency of the decision on global rather than region-based facial patterns is noticeable.

When conducting the evaluation, it became apparent that the system delivers consistent results in the case of structured testing data sets. However, inconsistencies in terms of accuracy appeared when processing unstructured real-life images. Lighting, posing, image quality, as well as a wide age gap between the analyzed persons affected the results significantly. Moreover, feature-level analysis is not fully independent, since the algorithm relies mostly on global facial attributes in order to make a decision.

In terms of potential improvements, it would be reasonable to develop a more powerful and accurate way of extracting features from facial images to increase the contribution of region-based patterns to the final decision-making process. Moreover, it would be beneficial to collect additional testing samples to enhance the generality and eliminate the existing biases. The adjustment of similarity thresholds and uncertainties is also considered.

Future work may include research into new deep learning architectures and improved landmark detection approaches in order to increase accuracy. What is more, the explanation functionality may be further developed in terms of visualization. Overall, there is a considerable potential for developing the presented system in a more accurate and reliable product.

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