AI-based Attendance Software Using FaceNet

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Abstract :

This report presents the design and implementation of an AI-based attendance system using the FaceNet facial recognition technology. The system automates recording attendance in educational settings by verifying student identities via a mobile application supported by a React Native interface and a Python Fast API backend. It highlights the integration of sophisticated machine learning algorithms to efficiently process and verify student attendance, reducing manual errors and saving instructional time.

Index Terms: Artificial Intelligence, Face Recognition, Educational Technology, FaceNet, Attendance System.

1 Introduction

Advancements in Artificial Intelligence (AI) have opened new avenues in various sectors, including education. Manual attendance recording in educational institutions is prone to inaccuracies and is a time-consuming process. Our AI-based system leverages Google's FaceNet technology to automate attendance, ensuring high accuracy and efficiency.

1.1 Contribution

This paper contributes to the field of educational technology by presenting a novel application of FaceNet, a leading facial recognition technology, in the context of automated attendance systems. The main contributions of this work include:

- Developing an integration of FaceNet with mobile and web technologies to create a real-time, automated attendance tracking system.
- Demonstrating the effectiveness of facial recognition technology in dynamic and diverse educational environments.
- Providing empirical evidence of the system's performance, showcasing high accuracy in face detection and recognition under varied conditions.
- Offering insights into the scalability and practical implementation challenges of deploying AI-based systems in real-world educational settings.

1.2 Paper Organization

The rest of this paper is organized as follows:

- Section 2, Background, provides an overview of facial recognition technology, particularly focusing on the FaceNet model and its applications in various fields.
- Section 3, Methods, details the methodology employed in developing the attendance system, including system architecture, model integration, and data processing.
- Section 4, Results, presents the findings from the deployment of the system, highlighting its detection and recognition accuracies.
- Section 5, Discussion, discusses the implications of the findings, limitations of the current system, and potential areas for further research.
- Section 6, Conclusion, summarizes the overall study and its contributions to the field of automated systems in education.

2 Background

FaceNet's deep learning framework has proven effective in various applications, particularly in identity verification through facial recognition. This technology's adaptation into an attendance management system proposes a streamlined approach for academic institutions.

2.1 Literature Review

The use of facial recognition technology in educational settings has gained substantial attention in recent years. Several studies have underscored its potential to significantly streamline administrative processes and enhance security protocols. Zhou et al. (2020) highlighted the efficiency of facial recognition systems in monitoring student attendance and behavior, which not only improves record accuracy but also student accountability.

Among facial recognition technologies, Google's FaceNet has emerged as a particularly influential model due to its robust performance in various applications. Schroff et al. (2015) introduced FaceNet as a deep learning algorithm capable of achieving high accuracy in both face detection and identity verification across challenging scenarios. The model's ability to generate a compact 128-dimension embedding of a face provides a precise and scalable approach to facial recognition, which is essential for processing large datasets typically found in educational environments.

Further research by Wang and Deng (2018) compared different facial recognition technologies and found that FaceNet consistently outperforms other models in terms of speed and accuracy, making it suitable for real-time applications like attendance systems. Moreover, its application in diverse settings has been tested, where it demonstrated a high tolerance for variations in lighting, facial expressions, and poses, which are common challenges in classrooms.

The integration of FaceNet into educational tools represents a convergence of machine learning and practical applications, offering insights into the future direction of educational technologies. However, the literature also indicates a need for ongoing evaluation of privacy concerns and ethical implications, as the widespread use of biometric data in schools poses unique challenges that must be managed with careful consideration of policy and regulation.

This review underscores the promising capabilities of FaceNet and other similar technologies, setting the stage for their potential to revolutionize traditional educational processes through automation and improved accuracy.

3 Methods

This section delves into the intricate methodology employed in developing and deploying the AI-based attendance system, integrating cutting-edge technologies in mobile app development, backend services, AI model training, and inference.

3.1 Mobile Application Development

3.1.1 Platform and Tools The mobile application is developed using React Native, a popular framework for building native applications using JavaScript. This choice allows for a single codebase to support both Android and iOS platforms, ensuring uniform functionality and reducing development time and costs. React Native's component-based architecture enables modular and manageable code, enhancing the maintainability of the application.

3.1.2 Functionality The application's core functionality includes interfacing with the device's gallery for image selection and integrating a custom date picker for selecting the attendance date. The user interface is designed to be intuitive, allowing users to easily navigate through the gallery, select an image, and choose the corresponding date using a calendar widget. These elements are critical for ensuring the correct data is captured for processing attendance.

3.1.3 Data Submission Once the user selects an image and a date, the application packages this information into a JSON object. The image is converted into a base64 encoded string to ensure compatibility with JSON formats and to facilitate easy transmission over HTTP. The date is formatted as an ISO string. This packaged JSON object is then sent to the backend through a RESTful API call using the HTTP POST method, ensuring secure and efficient data transmission.

3.2 Backend Services

3.2.1 Technology Stack The backend is constructed using Python, leveraging the Fast API framework, which is renowned for its high performance and ease of use. Fast API supports asynchronous request handling, making it well-suited for applications requiring high concurrency and swift response times, such as real-time attendance processing. The choice of Python also allows for seamless integration with various data processing and machine learning libraries essential for handling the AI components of the system.

3.2.2 API Endpoints

- **Image and Date Reception Endpoint:** A dedicated POST endpoint is established to handle incoming data from the mobile application. This endpoint is responsible for parsing the JSON payload to extract the encoded image and the attendance date. The image undergoes decoding from its base64 format back into a binary image format suitable for processing.

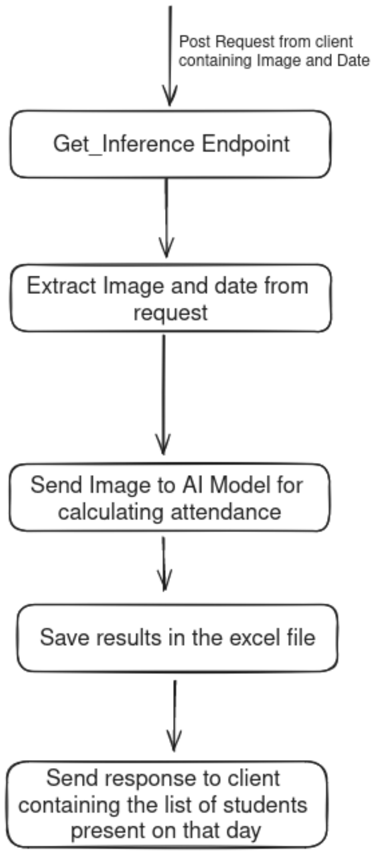

Figure 1. Endpoint which is going to accept the image from the client and feed it into the model for inference

- **Image Processing and Attendance Computation:** Once the image is decoded, it is temporarily stored in a secure location on the server for processing. The backend utilizes the pre-loaded AI model to process the image, detect faces, and compute attendance. This involves extracting facial features, comparing them against pre-stored data, and identifying the present students.
- **Response Handling:** After processing, the backend compiles a list of identified students along with their attendance status and sends this information back to the mobile application in the form of a JSON response. This ensures that users receive immediate feedback on the attendance processing results.

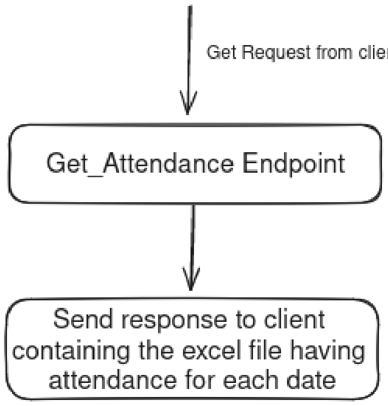

Figure 2. Endpoint which is going to give the excel file record of the attendance for each date

3.3 AI Model Training

The training of the AI model is a critical stage in the deployment of the AI-based attendance system. It ensures that the model can accurately recognize and verify the identities of students based on their facial features.

3.3.1 Model Selection The cornerstone of our facial recognition system is the FaceNet model, which is accessed through the Keras library as a pre-trained model. FaceNet is renowned for its superior accuracy in facial recognition tasks across diverse datasets and environments, making it an ideal choice for educational settings where varied lighting and angles can pose a challenge. The model works by converting high-dimensional facial data into compact, 128-dimensional embeddings that uniquely identify each individual.

3.3.2 Face Detection and Embedding Generation

Image Acquisition and Preprocessing For the purpose of training, a substantial dataset consisting of various classroom images is curated. These images are typically captured in real classroom settings to mimic the actual application environment as closely as possible. Each image is meticulously processed through several stages:

1. **Face Detection:** Each classroom image is subjected to face detection using the Haar Cascade classifier, an effective object detection method proposed by Paul Viola and Michael Jones. This classifier is particularly suited for real-time processing due to its ability to rapidly detect faces using a series of haar-like features.
2. **Preprocessing:** Detected faces are extracted and then preprocessed to align with the input requirements of the FaceNet model. This preprocessing involves resizing each face to 160x160 pixels, converting the image color from BGR (Blue, Green, Red) to RGB (Red, Green, Blue) since OpenCV captures images in BGR format by default, and normalizing the pixel values to aid in the model's performance.

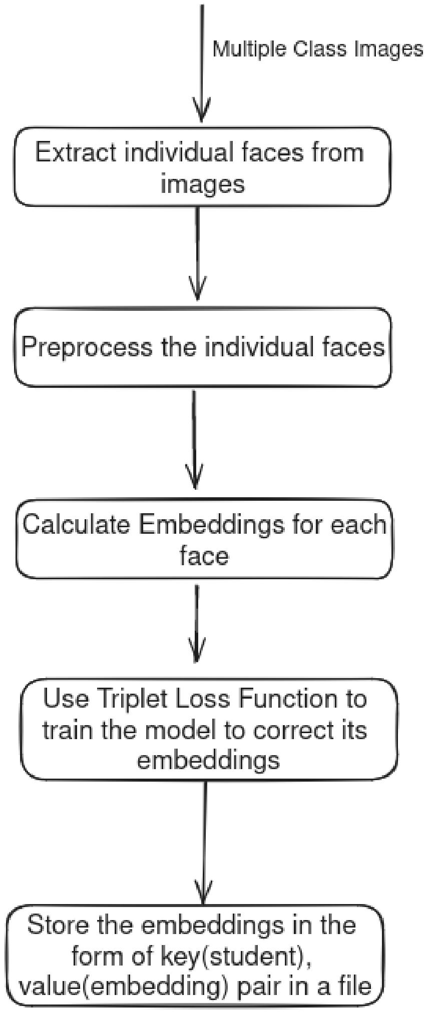

Figure 3. Architecture of the model working on both Haar Cascade for face extraction and FaceNet for embeddings generation

3. **Embedding Generation:** For each preprocessed face, the FaceNet model generates a facial embedding. This embedding is a high-dimensional vector that encodes unique facial features into a compact form. These embeddings are critical as they represent each student's facial signature, which will be used for matching during the attendance verification process.

Validation and Storage The processed faces, along with their corresponding embeddings, are stored locally for manual review. This step is crucial as it allows system administrators to visually inspect and verify the accuracy of face detection and to ensure that the embeddings are correctly associated with the respective student identities.

3.3.3 Embedding Storage Once validated, the embeddings are systematically stored in an '.npz' file—a compressed file format provided by NumPy, which allows for efficient storage of array-like data. These embeddings are structured as a dictionary where the key represents the student's name or identifier, and the value is the corresponding embedding vector. This format is highly efficient for

Figure 4. FaceNet model architecture

Figure 5. Triplet loss Function used to minimize the distance between alike embeddings and maximize the distance between different embeddings

subsequent retrieval and comparison operations during the system's inference phase.

3.4 *AI Model Inference*

3.4.1 Loading Embeddings Upon system initialization, the backend service loads the pre-computed embeddings from the '.npz' file into memory. This pre-loading is crucial as it significantly reduces the latency associated with loading data on-the-fly and allows the system to quickly respond to API requests by having all necessary data ready for immediate processing.

3.4.2 Face Matching and Attendance Verification

Operational Flow When a new image arrives via the backend API from the mobile application, the following sequence of operations is executed:

1. **Face Detection:** The received image is first processed using the Haar Cascade classifier to detect all present faces. This stage is critical as it prepares the raw input for subsequent matching and verification.
2. **Embedding Computation:** For each detected face, the system computes the embedding using the same FaceNet model used during training. This ensures consistency in how the features are extracted and represented.
3. **Comparison and Matching:** Each newly computed embedding is then compared against the pre-stored embeddings from the training phase. The comparison is typically done by calculating the Euclidean distance between embeddings. If the distance between a new embedding and any stored embedding falls below a predefined threshold, a match is found, indicating that the student corresponding to the stored embedding is present.
4. **Output Generation:** The system compiles a list of all students whose embeddings match those detected in the image, marking them as present. This list is then formatted into a JSON response and sent back to the mobile application.

System Output The final output of the inference process is a meticulously compiled list of students who have been verified as present. This list is not only sent back to the mobile application for user confirmation but is also used to update attendance records in the system's database,

3.5 *Attendance Recording and Reporting*

3.5.1 Attendance Marking Using the list of detected students and the date provided, the backend marks attendance in an Excel sheet. This sheet keeps a record of attendance across multiple dates.

3.5.2 Response Generation The backend then sends a response back to the mobile application, which includes the list of students detected as present. Additionally, there is functionality to download the attendance record as an Excel file directly from the application.

3.5.3 User Interface The mobile application displays the attendance results on the user interface and offers an option to download the comprehensive attendance report.

This detailed methodology ensures that the system is robust, user-friendly, and effective in automating the process of recording attendance using advanced facial recognition technology.

4 Results

4.1 *Accuracy of the Model*

The accuracy graph displays two key metrics: the total number of predictions made by the model (70) and the number correctly predicted (63). This results in an accuracy rate of approximately 90%, which indicates a high level of model performance in correctly identifying the target class out of the total cases examined. Such a high accuracy rate is indicative of the model's robustness and its effectiveness in handling the dataset used for training and validation.

4.2 *F1 Score Analysis*

The F1 Score is a crucial metric in evaluating the model's accuracy, especially in scenarios where class imbalances influence the precision and recall differently. The model achieved a precision of 1.0, indicating no false positives were recorded. The recall value at 0.9 suggests that 90% of actual positives were correctly identified by the model. The high precision and recall reflect the model's efficacy in not only identifying positive instances but also in minimizing false alarms, culminating in an F1 Score that provides a balanced view of both precision and recall.

4.3 *Recall Count*

This graph highlights the recall aspect of the model, showcasing that out of 55 actual positive cases, 48 were correctly identified as positive (true positives). This metric is particularly important in contexts where failing to identify a positive case (false negative) could have more severe implications than incorrectly identifying a negative case as positive (false positive). The recall ratio here demonstrates the model's capability to effectively capture the majority of positive cases.

4.4 *Overall Metrics Comparison*

The overall metrics comparison provides a comprehensive view of the model's performance across various parameters. The model exhibits high scores across all metrics with an accuracy of 0.9, precision of 1.0, recall of 0.85, and an F1 Score of 0.9. These metrics collectively indicate a well-tuned model that balances its precision and recall effectively, op-

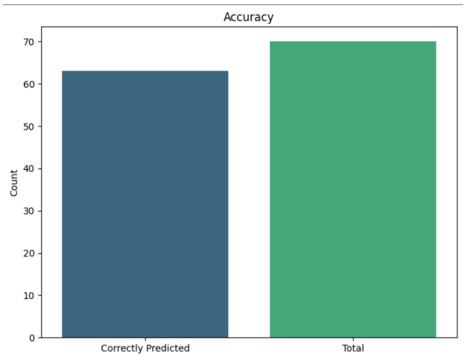

Figure 6. Bar graph showing the number of correctly predicted cases against the total cases.

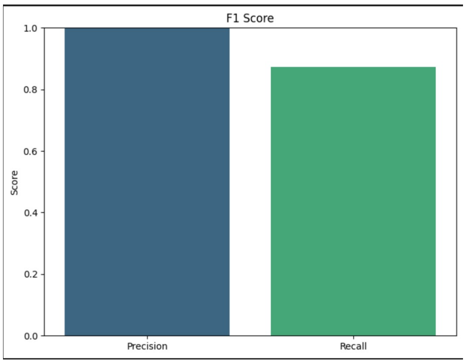

Figure 7. Bar graph showing the precision and recall values used to calculate the F1 Score.

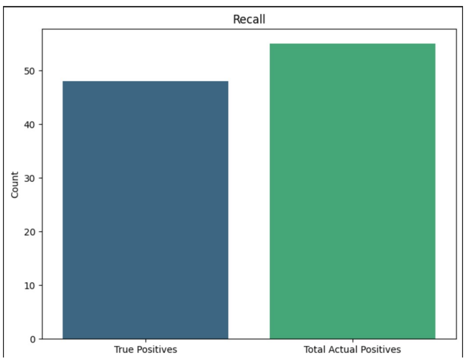

Figure 8. Bar graph showing the number of true positives against the total actual positives.

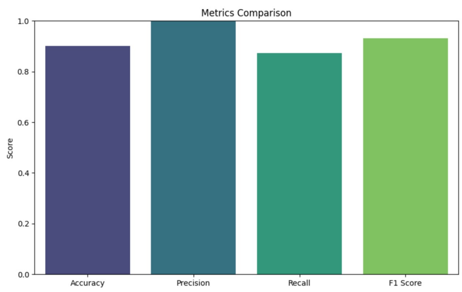

Figure 9. Comparison of key performance metrics: Accuracy, Precision, Recall, and F1 Score.

timizing the F1 Score, and thereby ensuring minimal misclassification in both positive and negative predictions.

These results collectively demonstrate the robustness and reliability of the facial recognition model in accurately classifying and predicting the defined classes, making it highly suitable for practical deployment in scenarios requiring high precision and reliability.

5 Discussion

The AI-based attendance system, as evidenced by the results, marks a substantial improvement over traditional manual methods of attendance tracking. The implementation of FaceNet technology allows for highly accurate facial recognition, significantly reducing the time and potential human errors associated with manual attendance logging. However, several challenges remain that could impact the system's efficiency and accuracy.

5.1 Challenges in Dynamic Facial Expression Handling

One of the primary challenges lies in the system's ability to accurately recognize faces across a range of dynamic expressions. Facial expressions can significantly alter the appearance of facial features, which, in some cases, might lead to misidentification or non-recognition issues. Although FaceNet is robust in handling a variety of facial expressions, the variations in extreme expressions under real-world classroom settings can occasionally exceed the training parameters of the pre-trained model.

5.2 Occlusions and Environmental Variability

Another challenge is managing occlusions, where objects or attire such as eyeglasses, hats, or scarves partially obscure the face. Additionally, variations in lighting conditions, such as those caused by changes in weather or classroom lighting, can affect the performance of the facial recognition system. These factors can reduce the clarity of facial features necessary for accurate recognition.

5.3 Future Enhancements

To address these issues, future work will focus on several areas:

- **Enhanced Training Set:** Expanding the diversity of the training dataset to include more varied expressions and occlusion scenarios can help improve the model's robustness.
- **Algorithmic Improvements:** Investigating advanced machine learning algorithms that can better generalize across the non-ideal conditions could enhance recognition accuracy.
- **Real-Time Feedback Mechanisms:** Implementing mechanisms that allow for real-time feedback could help in immediately rectifying any misidentified or missed attendance entries.

6 Conclusion

The deployment of the AI-based attendance system utilizing FaceNet technology represents a significant advancement in the automation and digitization of attendance management within educational institutions. This system not only enhances the accuracy and reliability of attendance records but also introduces a level of efficiency that frees up valuable instructional time for educators.

6.1 Impact on Educational Technology

The successful integration of this system demonstrates the potential of artificial intelligence in transforming everyday educational administrative tasks. By automating attendance, schools can ensure more accurate data collection, reduce fraudulent practices, and better monitor student attendance patterns, which are essential for educational planning and assessment.

6.2 Broader Implications

Moreover, the implications of such technology extend beyond mere attendance tracking. They pave the way for broader applications in educational settings, such as student engagement analysis and event management, where similar technologies can be adapted for broader surveillance and monitoring tasks, ensuring a comprehensive understanding of the educational environment.

In conclusion, while challenges remain, the strides made by implementing an AI-based system such as this underscore the transformative potential of AI in education. Continuous improvements and adaptations to this technology will likely see it becoming a staple in educational institutions worldwide.

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