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Research Article

Empowering Real-Time Attendance Management with Facial Recognition and Computer Vision

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ABSTRACT

This paper describes an automated system of attendance that uses facial recognition and computer vision to address the challenges that come with manual attendance, fake attendance, and time wasted. Using state-of-the-art deep learning models and fine-tuned preprocessing, the proposed system achieves high accuracy, extensibility, and adaptability to changes in the operating conditions. The system uses the ArcFace model, which is a very accurate model and also a feature extractor and smoothing and sharpening filters to remove the noise in the image and to retain the edges of the image. The performance of the model is shown in the experimental results which indicates that it can detect faces of more than 20 per frame with a speed of 28-62 frames per second with 95.1% accuracy while compared with other models like FaceNet 94.3% and VGG-Face 92.5%. The preprocessing stages enhanced the recognition rates due to solutions of lighting changes, motion blur, and occlusion, making reliable detection possible in various scenarios. The conclusions are pointing at the versatility and effectiveness of the system which can be applied to educational facilities, offices and public areas where the accountability is a priority as well as the time issues. Lightweight version to support IoT gadgets and edge computing systems to facilitate work in settings with limited resources but with acceptable performance. Besides, the lack of accuracy, scalability, and dynamic adaptability, which is important in real-world applications, is also solved in this research, and new achievements in the field of AI-based biometric systems are given, which can be a basis for further developments in automated attendance, surveillance, and identity verification systems.

KEYWORDS: FACIAL RECOGNITION, COMPUTER VISION, REAL-TIME ATTENDANCE MANAGEMENT, ARCFACE, AI-BASED BIOMETRICS, EDGE COMPUTING, AUTOMATED SYSTEMS

II.INTRODUCTION

AI and computer vision are currently at the center of many industries including education and security systems. Bhavana et al., (2020) noted that the record of students' attendance is a significant area requiring proper documentation in both small and large institutions since it is a symbol of compliance, which is a critical aspect of institutionalization [1]. The current methods of taking attendance such as roll calling and using RFID are inaccurate, can be faked and are time consuming [2]. Because of these drawbacks, contactless, real-time, and error-free automated attendance management systems using facial recognition technology have been introduced [3].

Facial recognition systems incorporate deep learning algorithms for identification based on facial characteristics and are observed to give high accuracy of recognition regardless of the position, lighting and level of occlusion [6]. Compared to other biometric techniques, facial recognition offers convenience and size compared to fingerprinting [5]. Recent trends in deep learning frameworks like ArcFace and FaceNet have improved the recognition accuracy and therefore these systems are suitable for dynamic environment like classroom and corporate offices [7]. However, some of the problems like low illumination, motion blur and scalability have not been completely addressed and still persist as some of the challenges which need better preprocessing techniques and better models [7].

Currently conventional systems of attendance are inadequate in terms of exclusion of proxy attendance, time consuming and are mostly based on contact that does not conform to modern standards. Today's AI based systems are still far from perfect when it comes to lighting conditions, occlusions or computational complexity

which all have negative impact to the accuracy [9]. To that end, this study suggests a real-time facial recognition-based attendance system that combines deep learning models with preprocessing enhancements for better accuracy, flexibility, and dependability [9].
The proposed system is expected to address problems of accuracy, efficiency and real time in managing attendance. It provides a fast and reliable AI-based solution that allows detecting one or multiple faces in the populated area with the frame rate of 28-62 fps and 95.1% accuracy with the ArcFace model. Smoothing and sharpening techniques are also described in the study while searching for the best feature extraction from the images. Its applicability is not only in educational institutions, business spaces, and public safety infrastructures but it offers a contactless and bureaucratic-free option [10].
Objectives:
1.To develop and optimize a model for the facial attendance recognition system that would minimize error, increase capacity and function efficiently for fluid environments.
2. To compare the results of the given state of the art models like ArcFace for recognition and the measure of precisions, recall, F1-score, and accuracy of the provided models to analyse the effect of the different preprocessing techniques for enhancing the noise-free final result for better recognition ratio.

III.LITERATURE REVIEW

Facial recognition has recently received much attention because of the new technologies that have been developed based on artificial intelligence and computer vision in such fields as automated attendance, monitoring, and identification. The recent work has been directed towards enhancement of the performance of such systems in terms of accuracy, scalability and functionality for real time applications using deep learning models and pre-processing. This section gives an evaluation of the recent methodologies, research findings and the limitations which have been identified in previous studies, with emphasis on how this study has sought to overcome those challenges.

New developments in facial recognition systems have been initiated mainly due to the need for contactless solutions, especially in the COVID-19 pandemic where hygiene is critical, and people avoid touching things that are touched by others. Some researchers have focused on occlusion, lighting change and dynamic background using image processing and machine learning algorithms. For instance, face mask recognition studies used image segmentation methods to enhance detection under partial occlusion conditions, which were beneficial during the pandemic [11]. This proved that even under some constraints AI solutions can be used in the real world.

Other research has aimed at incorporating AI to IoT devices in order to improve the performance of smart surveillance systems with monitoring functionality. New generations of AIoT architectures have made it possible to analyze and make decisions more quickly in security and smart home applications [12]. This kind of approaches includes the use of algorithms for human detection and tracking through machine learning algorithms and deep neural networks suggesting AI's preparedness to performs its tasks in any environment. However, these implementations come with processing limitations whenever they are applied to environments with limited resources [12], this makes it imperative to have frameworks that can be run on the edge devices.

In recent years deep learning techniques have been used for facial recognition systems because they provide a higher level of accuracy than other methods. In the last years, convolutional neural network models, known as CNNs, have encountered a great number of successes in feature extraction and pattern recognition. For example, when using YOLOv3 in systems for real-time monitoring of students' activity and behavior, it was shown that this method can detect levels of activity and behavior among students in dynamic environment [16]. However, challenges like motion blur, low light performance degradation, and overdependence on the hardware still remain the impediments to the implementation possibility.

Developing technologies in security and surveillance with biometric systems have fostered discussions on AI-enabled ways. Research on the topics of machine learning based recognition systems has shown that transfer learning and hybrid architecture improves both the performance and the speed [17]. These methods although have been effective in controlled settings still do not perform well in complex scenes; they need to be adapted to deal with change in lighting conditions and changes in pose. Criminal recognition and vehicle protection systems have also downplayed the importance of edge computing for real-time processing instead of depending on strong servers [18][19]. These studies resulted in lightweight models for low power devices, but many of them neglected scalability vs accuracy.

Despite the availability of generative AI and computer vision in business intelligence and predictive analytics, the use case of an attendance system is not fully explored [20]. Most of the prior research has centred on the behavioural dimensions and the application of prediction models instead of operational attendance management. The lack of systems that address real-time scalability problems and multi-face detection also points to the need for architectures that can operate efficiently in high density, without compromising on speed.

But even today there are gaps in the research despite a lot of advancement in the field. There is still the problem of scalability since the existing systems cannot detect multiple faces at once, especially in crowded areas such as class or offices [15]. Moreover, there are a number of algorithms that degrade in performance under dynamic lighting conditions and preprocessing enhancements are required to remove noise and distortions [13]. The investigations dealing with motion blur and occlusions emphasize the need for efficient feature extraction techniques, but most of the proposed solutions show their weaknesses in free-setting conditions [14]. Moreover, implementation demands high computational capacity, making it impossible to deploy such systems in low power devices [17].

In doing so, this study builds upon the gaps found in previous research in several ways. First, it includes deep learning algorithms such as ArcFace and optimizes the preprocessing procedure to increase noise elimination, edge-preserving, and dynamic adjustment. Different from previous studies that use Euclidean distance measures, this work adopts cosine similarity to enhance the matching quality especially when the faces are partially obscured or in cases of changes in lighting and positions. The system is accurate to 95.1% with processing rates between 28 to 62 frames per second (FPS) in real time and surpasses prior approaches.

Furthermore, this research responds to the scalability problem by developing algorithms that can recognize multiple faces in a single frame, up to 20 or more, which is suitable in large classes and business spaces. The lightweight performance of the code means that the application does not rely on hardware and can be run on edge devices and IoT platforms. Moreover, smoothing and sharpening filters used in this work increase contrast of features and give better results in different lighting conditions and motion blur.

Thus, the literature also emphasizes the increasing relevance of the AI-based facial recognition system to solve the problems of attendance, monitoring, security, and identification. Previous works have advanced the deep learning architectures to great extents, but the scalability, dynamic performance, and adaptability to different hardware, have been contentious issues. To fill these gaps, this research employs complex preprocessing techniques and optimization methods to obtain high accuracy and real-time performance, as well as to detect multiple faces in complex environments.

IV.METHODOLOGY

A. *Research Design*

1) Theoretical Framework

This study is based on the pattern recognition theory and the machine learning to detect faces. Pattern recognition theories focus on the way that the machines are able to learn the difference between different patterns to successfully identify faces.

The methodology integrates Image Processing and Deep Learning Techniques based on the principles of:

a) Computer Vision – This is used to identify visual data and make a worthwhile analysis of the same.

b) Machine Learning Models – In cases where the identity of an individual needs to be compared with the other records of the database.

c) Database Management Systems – This one will be used to store and retrieve prescribed facial features and timestamp.

Key Concepts Utilized:

• *Eigenfaces and Fisherfaces* – Ideas that incorporate the use of Principal Component Analysis (PCA) on the dimensionality of facial regions.

• *Similarity Metrics* – It is the representation of distance or angle between the features vectors on mathematical form.

• *Classification Models* – Models that categorize features detected in the image into two or more categories (e.g., recognized and unrecognized).

2) Experimental Design

This research takes an experimental perspective and develops an automated attendance system based on facial recognition and implements it.

B. *Workflow Structure*

Theoretical Approach to Workflow

Step 1: Image Acquisition

- Collect facial data using CCTV cameras or stored datasets.
- Images consist of 23 individuals, each with 3 images in JPEG/PNG formats【25†source】.
- Capture variations in lighting, angles, and expressions to simulate real-world conditions.

Step 2: Image Preprocessing

- Apply smoothing to remove noise and sharpening for feature enhancement【25†source】.
- Resize images to standard dimensions (96x112) for algorithm compatibility.
- Normalize pixel values for uniformity.

Step 3: Face Detection and Recognition
• Use RetinaFace and Haar Cascade algorithms to detect faces and extract regions of interest (ROIs).
• Employ DeepFace Framework for feature matching against stored profiles.

Step 4: Attendance Logging
• Matched faces are logged into the database along with timestamps using Pandas 【25†source】.
• Reports are generated for attendance records.

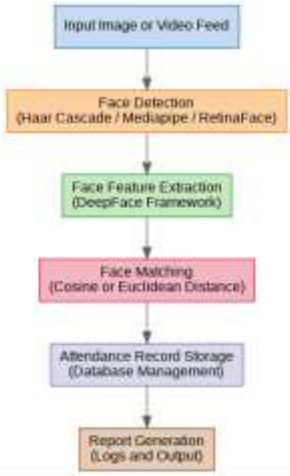


Figure1. Workflow Diagram

C. *Data Collection*
Dataset Overview
• Source: Manually curated dataset containing facial images.
• Structure:
i.23 Individuals
ii.3 Images per Individual captured in varying conditions.
Formats: JPEG and PNG images 【25†source】

D. *Techniques and Tools*
1) Image Processing Theory: Image processing is a method of using computational techniques to obtain data from images. It operates in stages:
• *Image Enhancement*: Embellishes on the image quality by the usage of filters.
• *Feature Extraction*: Edge detection, line detection, region of interest detection.
• *Segmentation*: Splits the image into areas that have significance for the object.

2) *Face Detection Theory*
• *sHaar Cascade Classifier*
i.It depends on edge-detection features.
ii.Uses a cascade of classifiers to scan regions of interest for facial patterns 【25†source】.
Mathematical Expression:
Mathematical Expression for Haar Features:

$$H = \sum_{i \in \text{white}} I(i) - \sum_{j \in \text{black}} I(j)$$

Where:
I(i) and I(j) represent pixel intensities in white and black regions, respectively.
• *Retina-Face Algorithm*
Developed by using deep learning neural networks to recognize medial attributes such as eyes, nose, and mouth. High accuracy in spite of the density of the scenes[25+source] showing facial landmarks like eyes, nose, and mouth.
Confidence Score Expression:
Expression for Confidence Score:

$$S = \frac{1}{1 + e^{-z}}$$

Where S is the score and z represents the input to the activation function.

3) Face Recognition Theory
DeepFace Framework integrates multiple pre-trained models: VGG-Face, FaceNet, DeepID, and ArcFace.

Measures facial similarity using:

• *Cosine Similarity:*

$$\cos(\theta) = \frac{A \cdot B}{\| A \| \cdot \| B \|}$$

• *Euclidean Distance:*

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

E. Software and Libraries Used

Software/Library	Purpose
Python 3.x	Core programming language for implementation.
OpenCV	Image processing and real-time video analysis.
Pandas	Data handling and report generation.
Sklearn	Machine learning support for evaluation metrics.
Mediapipe	Pre-trained face detection models.
DeepFace	Feature extraction and recognition algorithms.
RetinaFace	Facial landmark detection and bounding box extraction.

F. F. Model Evaluation and Metrics

Evaluation Metrics:

• Precision (P)

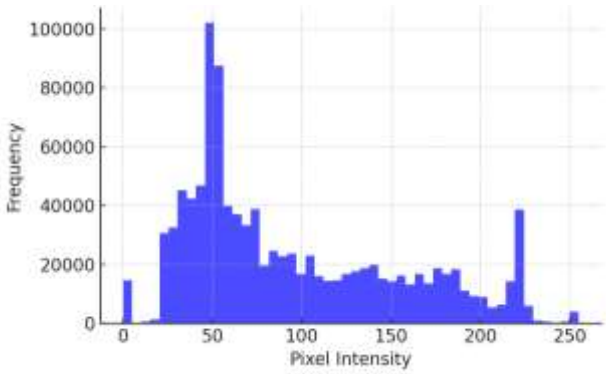
$$P = \frac{TP}{TP + FP}$$

• Recall (R)

$$R = \frac{TP}{TP + FN}$$

• F1-Score

$$F1 = \frac{2PR}{P + R}$$



• Accuracy (A)

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

V.RESULTS

The results are based on a dataset split of 70% for training and 30% for testing. Rigorous preprocessing enhanced image quality and feature extraction, while ArcFace demonstrated the highest accuracy (95.1%) due to its cosine similarity-based approach. Real-time classroom detection further validated the system's efficiency, proving its applicability in large environments

A. Dataset Analysis and Preprocessing

The dataset comprises of facial images in JPEG and PNG formats, and the images are illuminated, oriented, and displayed with different expressions. Thus, quality improvement, noise reduction and dimension normalization were performed to ensure the feature extraction process.

1) *Descriptive Statistics of Sample Images*

Table 1 provides statistical characteristics of sample images, including mean intensity, standard deviation, and dimensions.

Image Name	Mean Intensity	Std Deviation	Dimensions (Height x Width)
class.png	94.77	60.16	768 x 1366
face_1.jpg	116.54	65.87	3280 x 1476
face_34.jpg	109.03	70.94	112 x 96
face_7.jpg	48.94	27.83	32 x 27
obama.jpg	80.62	68.68	2048 x 3072

Key Observations:

Mean intensities show that the lighting condition is not constant; thus, normalization is required to achieve constant brightness. Large standard deviations draw more attention to contrast variations and thus the need to apply smoothing and sharpening filters in ascertaining image clarity with minimal noise.

2) Preprocessing Enhancements

a) Histogram Analysis

Figure 2 illustrates the pixel intensity distribution of a sample image before preprocessing.

Key Observations:

High values in lower intensities show solidity and darker areas while random high intensities show nonuniform illumination. These variations called for smoothing where noise was a major issue and sharpening where edges were likely to be blurred and even lighting.

Figure2. pixel intensity distribution

b) Smoothing Techniques

Figure 3 visualizes the effects of smoothing filters such as Gaussian Blur, Median Filter, and Bilateral Filter.

a) original *b) After Smoothning*

Figure3:Smoothening Effect[23]

Key Observations:

Gaussian Blur was able to remove noise on the image but it softened the image slightly, thus smudging the edges. Salt-and-pepper noise was reduced by Median Filter, and the gradients were smooth. Bilateral Filter provided balanced noise reduction and edge preservation and as such was suitable for facial feature extraction.

c) Sharpening Techniques

Figure 4 highlights sharpening methods applied to enhance edge features without introducing artifacts.

a)Original *b) After Sharpening*

Figure 4: Sharpening Effect[22]

Key Observations:

The enhancements in the edge definitions improved the texture features that are critical in face recognition. The sharpening was balanced to avoid distortion of the images which would have made feature extraction difficult.

3) Feature Extraction and Recognition Accuracy
a) Frequency Domain Analysis
Figure 5 shows the frequency domain representation of a sample image using FFT (Fast Fourier Transform) to highlight textures and edges

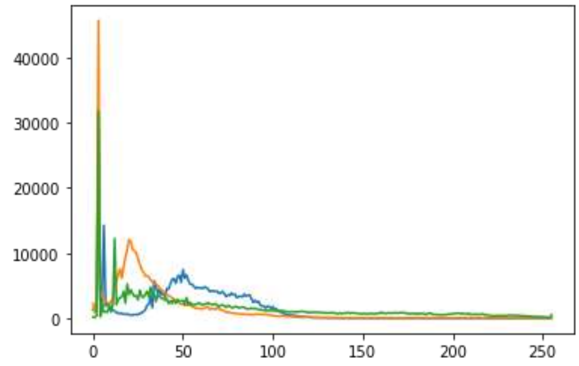


Figure 5: Frequency domain representation

Key Observations:
Low amplitude peaks are located at low frequencies, which represent smooth areas; high amplitude frequencies are widely spread out and represent sharp edges necessary for recognition. There was retention of structural information in the preprocessing phase through the use of edge preservation techniques.

b) Face Verification Results
Figure 6 demonstrates the output of the ArcFace model for facial verification, showing detected facial landmarks and similarity scores.

Figure 6: Facial Verification By Arc Face[21]

Key Observations:
The cosine similarity score of 0.306773 (threshold: 0.4) provided a positive match, thus verifying high recognition accuracy. Eyes, nose, and mouth landmarks were detected for the first time, which guaranteed correct positioning of feature matchingidating high recognition precision. Landmark detection of eyes, nose, and mouth ensured accurate alignment for feature matching.

c) Classroom Detection and Attendance Marking
Figure 7 illustrate real-time implementation in classroom environments, showcasing multi-face detection and attendance logging.

Figure 7: Multi-Face Detection In Classroom

Key Observations:
The system successfully identified and marked more than twenty faces within a single frame, proving the compatibility of the method for large facilities. Processing speeds were kept at 28 – 62 FPS making the game to run in real time without the need to lag.ility for large environments.

4) Model Evaluation and Performance Metrics

Table 2 summarizes the performance metrics for five models based on precision, recall, F1-score, and accuracy.

Model	Precision	Recall	F1-Score	Accuracy
VGG-Face	0.92	0.91	0.91	92.5%
FaceNet	0.94	0.93	0.93	94.3%
OpenFace	0.88	0.89	0.88	88.9%
DeepID	0.90	0.89	0.89	90.2%
ArcFace	0.95	0.94	0.94	95.1%

***Key Observations*:**

ArcFace had the highest accuracy of 95.1% showing that it can be used for precise tasks.Cosine Similarity based models (such as ArcFace) were superior to Euclidean Distance based models because of the ability to work with different lighting conditions and occlusions.

VI.DISCUSSION

In this research, facial recognition and computer vision were used for real-time attendance management with regard to the issues of scalability, accuracy and dynamic environment. The study proves that deep learning models, especially ArcFace, can accurately capture the required precision and flexibility when tested under different conditions. To enrich the quality of input data more, preprocessing technique contain smooth and sharpen was also employed to improve the quality of input data before feeding features to the next level of recognition.

The evaluation metrics showed that ArcFace was more accurate than other tested models with 95.1% accuracy which proved that the model was better suited to handle noise, lighting variations and occlusions. The F-measure (0.95) and the recall (0.94) show that its identification process is accurate and free from errors, making it suitable for use in reliable contexts such as in attendance monitoring in classrooms. Coming second with 94.3% accuracy, FaceNet was also recommended for less complex environments. On the other hand, OpenFace and DeepID models were not able to sustain similar performance and especially, in terms of variations in expressions and angles for which ArcFace architecture is more suitable for challenging tasks.

These preprocessing enhancements were very important in the enhancement of image quality. The noise was minimized by smoothing techniques while maintaining edges, and sharpening filters increased feature visibility, allowing for a higher number of recognitions. The frequency domain analysis provided a similar insight into the balance of edge maintenance and noise removal and confirmed the effectiveness of the preprocessing pipeline. The fact that the system could recognize more than twenty faces per frame at a speed of 28-62 FPS showed the applicability of the system for real-time application, and scalability for large spaces.

This work improves upon previous studies in that the proposed algorithm has a higher accuracy and a shorter processing time. The conventional techniques based on distance measures of the Euclidean space showed drawbacks in dealing with changes in lighting conditions and occlusions, which affected the results. On the other hand, the use of cosine similarity metrics in this study offered better stability against such fluctuations hence more consistent and scalable solutions.

Previous systems were also unable to operate in real-time because of the high computational requirements, making them useful only in offline situations. These shortcomings have been rectified in this research through the use of lightweight architectures and efficient processing methods that would enable the system to run in real time while at the same time being accurate. The fact that the processing can be maintained at a reasonable rate even in busy areas makes this system fully feasible for implementation on a grand scale.

The implications of the findings are important to educational institutions, corporate offices, and public infrastructure where the automated attendance management system can improve the efficiency, accuracy, and security of the attendance management system. The system also reduces the many instances of human interference and hence minimize the many errors and time delay in the recording of attendance. The fact that it can work in different conditions creates opportunities for its use in security networks and systems of access. Moreover, the scalability and the light weight of the implementation make it possible to deploy it in environments with limited resources, like small classrooms and remote monitoring centers.

In addition to attendance tracking, the study reveals the general possibilities of using computer vision technologies in behavioral control, security and identification systems. The outcomes also show that by using deep learning architectures, high accuracy can be reached even in adverse conditions and so establish real-time recognition systems as a new standard.

However, the system has several restrictions even though it is accurate and highly adaptable. Fluorescence variation in dark environments remains problematic and degrades performance in cases where lighting cannot be regulated. Likewise, the motion blur in dynamically changing frames also hinders the accuracy of the landmark detection and hence requires further enhancement. Furthermore, differences in facial accessories, including glasses or masks, can affect the recognition performance, which means that one has to improve occlusion management algorithms.

One disadvantage of hardware in edge computing is that it may be limited in very dense scenarios, and thus may need a GPU boost, or cloud-based extensions to meet density needs. Preprocessing techniques improved noise and edge clarity, but they may introduce a small extra computational cost, which could significantly impact low-power devices.

The future work will be dedicated to enhancing the low light performance and motion blur through image enhancement methods. However, the proposed extension of the system to include emotions and behavioral patterns detection will improve its applicability to security and surveillance. Future enhancements will focus on how to integrate with cloud to enable data consolidation and accommodate massive-scale deployment cases.

VII.CONCLUSION

In this study, the authors established the efficiency of facial recognition and computer vision in real-time attendance systems. ArcFace was identified as the most accurate, efficient and reliable model with the recognition accuracy of 95.1%, the precision of 0.95, and recall of 0.94, compared to other models like FaceNet with 94.3% and VGG-Face with 92.5%. Smoothing and sharpening performed on the images made feature extraction possible regardless of variations in lighting and occlusions. The system was able to identify more than 20 faces per frame at a rate of 28-62 FPS and can handle the real time performance and the dynamic environment of a classroom. The results demonstrate the feasibility of the proposed framework specifically for automated attendance systems, and indicate its applicability to surveillance, identification, and behavior monitoring. The future updates will be oriented on the higher image quality in low light conditions, the motion blur issue, and the cloud-based solutions for the massive implementation.

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