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Design and Implementation of Smart Attendance with Advanced Deep Learning Methods - A Review

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ABSTRACT - This paper introduces a novel Time-Based Attendance Management System, designed to modernize and streamline traditional manual attendance tracking methods. The system utilizes cutting-edge biometric technology, particularly Deep Learning (DL) based Face Recognition algorithms, to accurately identify individuals. By employing LBPH Face Recognizer, human faces are utilized as the primary dataset for training, ensuring reliable recognition.The user interface is developed using the Flask framework, offering a seamless and intuitive web page for users. A notable enhancement of this system is its ability to store attendance data in a database, complete with timestamps, providing administrators with valuable insights and analysis capabilities.Moreover, an innovative feature has been integrated to notify parents about their children's attendance, marks, and behavior through the Fast to SMS website.

This feature not only enhances efficiency by automating communication but also strengthens the relationship between educational institutions and parents. By keeping parents informed and engaged, the system fosters a more collaborative and supportive educational environment

Overall, this Time-Based Attendance Management System represents a significant advancement in attendance tracking technology, offering efficiency, accuracy, and enhanced communication between educational institutions and parents.

KEY WORDS: Attendance Management, Computer Vision, Deep Learning, Human Face Images, sending SMS

INTRODUCTION

The primary problem addressed in this content is the challenge of accurately recognizing faces. Current methods have limitations, particularly in 2D, where issues with lighting, different angles, and obstructions make it difficult to use faces effectively for security and other important tasks. [1]To overcome these limitations, the authors propose utilizing 3D technology, which can handle these challenges better. However, a significant issue is the lack of sufficient 3D face pictures to train the technology effectively[2].So efforts are underway to create more data.In essence, the core problem is the need for more robust and accurate face recognition methods that can work effectively in real-world scenarios, especially in the presence of variations in lighting, poses, and obstructions. This problem has significant implications for security and various applications where reliable face recognition is crucial[3].

The main importance of this content is that it presents a new way to make pictures of people's faces look better and more real. This is really important for security and other things where you need to recognize someone's face[4]. The new method they talk about, AMRF, makes the pictures clearer and more natural, which helps to recognize faces accurately. It also makes deep learning computers work better and faster when recognizing faces, which is useful in many real-world situations. This content is valuable because it shows a way to improve face recognition in practical application[5].

The existing solutions in this content include both shallow learning and deep learning methods for face recognition. Shallow learning methods rely on human-defined features like SIFT, LBP, and HOG, which are applied to face images and then aggregated to create descriptors. These methods have limitations in handling variations like illumination, rotation, and blurriness. In contrast,Deep learning techniques, like Convolutional Neural Networks (CNNs), can learn important features from big datasets all by themselves. Deep learning has shown significant improvements in face recognition accuracy and can adapt to complex variations in face attributes[6].

The existing solutions in this content discuss various face datasets and methods for detecting and recognizing faces. These datasets are collections of face images taken in different environments. Some use traditional methods like classifiers,for face detection. For face recognition, several network models, like OpenFace and DeepFace, are explored. These models are evaluated to understand how well they work on the proposed dataset, which is designed to be more challenging than existing datasets, as it captures faces in real classroom environments with varying conditions[7].

The existing solution in this content is a method for telling if a face in a picture is real or fake. It does this by making the picture smoother while keeping important parts, like edges and lines. This helps it see if the face is real or not. It also uses a smart computer program that learned from lots of pictures to make better guesses. This program is based on MobileNet and gets even smarter when we adjust it using the right techniques. So, it's like having a computer that can spot fake faces in pictures and make fewer mistakes[8].

The challenges in computer-aided facial diagnosis include small datasets, difficulty in multi-class classification, reliance on manual feature engineering, ensuring data quality, and the need for more interoperable models. These challenges impact the reliability and generalization of facial diagnosis systems, particularly when dealing with multiple conditions and uncontrolled image collection. Addressing these issues is vital for enhancing the effectiveness and trustworthiness of such systems[9].

In our work, we need to focus on enhancing the detection of synthetic or fake facial images, which is crucial for security purposes. We should consider combining human salience, derived from human expert observations, with LCE (Cross-Entropy Loss) models to improve the accuracy of synthetic face detection. Additionally, exploring various CAM (Class Activation Map) entropy-based loss functions is essential to further enhancing the detection performance. This research aims to make synthetic face detection more reliable and interpreted by leveraging human insights and innovative loss functions[10].

BACKGROUND STUDY

This is the methodology for marking attendance revolves around a well-defined series of steps. The process begins with enrolment, followed by a sequence of key stages: face detection, face alignment, feature extraction, and face recognition. The initial step, face detection, entails locating one or more faces within the captured image and subsequently marking them with a bounding box for further analysis. Subsequently, we proceed to face alignment, a crucial phase that normalizes the facial features to ensure consistency with the information stored in our database. This normalization accounts for variations in facial geometry and photo-metric attributes, enhancing the accuracy of subsequent recognition.Moving forward,[11]we delve into feature extraction, where we meticulously extract distinctive features from the facial image. These features serve as essential data points for the recognition task, facilitating the identification of individuals with precision.Finally,[12] in the face recognition stage, we employ advanced algorithms to compare the extracted facial features with those of known individuals stored in a carefully prepared database. This step enables us to make accurate matches and ultimately mark the attendance of the individuals in question. This comprehensive methodology ensures a robust and reliable system for attendance management, incorporating state-of-the-art techniques in face detection and recognition to streamline the process effectively[13].

In face recognition, the process starts with face detection, which finds faces in images using bounding boxes. Then, face alignment comes into play, adjusting landmarks like the nose and eyes. Feature extraction follows, where we pick out key facial elements like the eyes and nose for tracking. Feature matching and classification are next, where we compare these features to a trained dataset to identify the person. Face recognition then gives a yes or no answer based on this matching process[14].

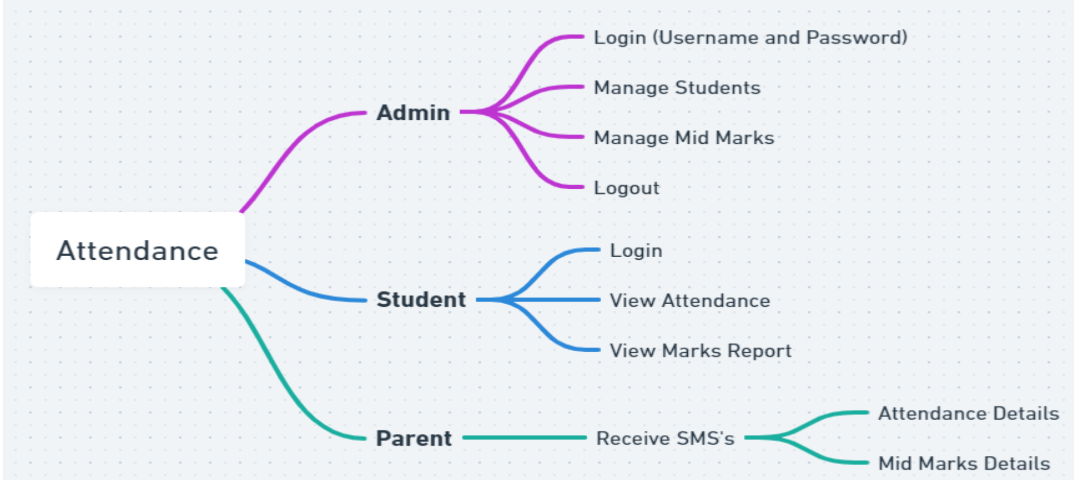

Fig 1: PROPOSED METHOD FLOW WITH ENHANCEMENT

Face detection had played a crucial role in this methodology. It involved finding human faces in pictures or videos. It had been like the first step before recognizing whose face it had been. The method used a smart tool called MTCNN, known for its ability to find faces and draw boxes around them in pictures. This had helped pinpoint where the faces had been, facilitating further processing. MTCNN had ensured that no faces had been overlooked, contributing to the system's overall effectiveness.In the face alignment step, we use MTCNN (Multi-Task Cascaded convolutional Network)[15] to find and center on important landmarks on a human face, like the eyes, nose, and lips. This step ensures that the face is adjusted to match the database, considering factors like its shape and lighting. This alignment helps us quickly and accurately identify the person by extracting their facial features.The face database is crucial for training our system. We use machine learning libraries like TensorFlow and sci kit-learn in Python to train our models. These libraries offer various tools for training and refining the dataset, making our recognition system more effective [16].

A face recognition system does several steps to figure out who you are. It starts by taking a picture of your face. Then, a computer program helps find your face in the picture and make it look right.After that, it checks your face against a list of faces it knows. If it finds a match, it knows who you are.They also help with security by identifying bad guys and stopping people from getting into places they shouldn't.

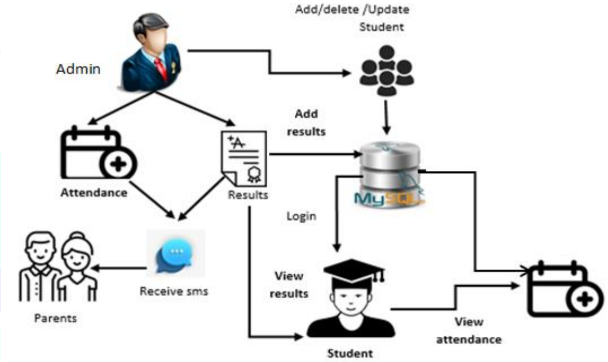

FIG 2 : SMART ATTENDENCE SYSTEM: A VISUAL GUIDE (USE CASE DIAGRAM)

In the Smart Attendance System, the process is simple and efficient. You start by entering your name and ID. Then, a camera snaps a picture of your face. The system goes to work, searching for your face in the image and comparing it to its database. If it recognizes you, you're instantly marked as present. If not, it kindly asks for your name and ID again. Plus, it stores the picture for future reference[17].This entire process happens in real time, making attendance-taking quick and accurate. It's all thanks to face recognition, a reliable technology used in various applications, including attendance systems. These smart attendance systems outshine the old-fashioned pen-and-paper method, offering speed, precision, and security. They provide instant attendance data, contributing to better student performance and reducing absenteeism [18].Utilizing a smart attendance system flowchart can bring about a multitude of advantages for educational institutions. First and foremost, it enhances the precision of attendance records, paving the way for informed decision-making and potentially boosting student performance. Moreover, it offers a time-saving boon for teachers and administrators, freeing them from laborious attendance-taking tasks and allowing them to allocate their efforts elsewhere.Furthermore, the implementation of such a system significantly reduces the risk of fraudulent activities, ensuring the trustworthiness of attendance data[19].The real-time insights it provides into attendance patterns enable the timely identification of students who may be falling behind, facilitating the development of targeted intervention strategies to support their progress.Ultimately, a smart attendance system flowchart contributes to the creation of a more positive and efficient learning environment for both students and staff alike. It streamlines the attendance management process, fostering a smoother educational experience. In conclusion, the adoption of this technology is a valuable step for any educational institution seeking to optimize its attendance tracking procedures and promote a conducive learning atmosphere[20].

RELATED WORK

The concept of a smart attendance system existed before the internet and other computational tools. Several recent studies have used Deep Learning and Machine Learning techniques to recognize or detect for bio-metrics processes mainly in COVID time,universities' smart attendance systems,bank sector face bio-metrics etc.

A. Deep Learning Methods

In the paper by V. Suresh *et al.* [21] They address the problems with the previous attendance management system, which was inaccurate due to third-party recording and inconvenient with paper-based sign-ins. Their solution is a facial recognition-based system that aims to improve accuracy, efficiency, and accessibility. This method involves capturing faces with a camera, processing the images, and using the EigenFaces Recognizer for recognition. It requires a constant internet connection and includes both hardware (camera module, power supply, micro SD card) and software (OpenCV and Numpy libraries). The project goals include creating a portable attendance system, faster recording, ample database space, accurate recognition, parental access, a user-friendly interface, and the ability to add new users. The paper also mentions related research on a similar system, but it's not portable and is only for staff attendance.

Jingxiao Zheng *et al.* [22] and their team tackled several challenges in video-based facial recognition, including dealing with various conditions, lighting, pose, multiple faces, and combining face information. They proposed a system using deep neural networks for face detection, alignment, feature extraction, and tracking. They tested it on IJB-B and IJB-S datasets, achieving excellent performance compared to other methods. Their system is robust, efficient, and flexible but has limitations like limited data and lacking comparisons with non-deep learning methods or in-depth analysis of components and hyper parameters. Real-world deployment wasn't discussed.Face recognition systems are becoming common, but we need to think about the privacy concerns that come with them.

S. Khan *et al.* [23] and their team improved attendance monitoring by replacing manual processes with a system using face recognition technology. They used the YOLO V3 algorithm for face detection and Microsoft Azure's face API for recognition. They tested it under different conditions and found it to be cost-effective, secure, fast, and accurate, often achieving 100% accuracy. However, it needs a good camera and proper lighting and may struggle with facial abnormalities or masks. It's best for smaller gatherings, not large events.

Yanjun Feng *et al.* [24] developed a model that deals with challenges in training deep models, like needing lots of data and computational power, and handling various facial expressions, including less common ones like contempt and disgust. They introduced a novel face alignment method to handle real-world issues like changing lighting, background noise, and blocked faces.The model was built using Python 3.6, TensorFlow-GPU, and the Keras framework, running on a Linux Ubuntu system with 16GB memory. It was tested on four benchmark datasets: CK+ with 593 sequences and 8 expressions, JAFFE with 213 samples and 7 expressions, Oulu-CASIA with 10,800 samples and 6 expressions, and AR with 4,000 samples and additional challenges like face occlusion and varying lighting.This model performs well in different lighting conditions and offers higher accuracy, lower training costs, and robustness. However, it can be computationally expensive to use.

Jun Liu *et al.* [25] faced challenges in improving the accuracy of facial recognition systems. They proposed a new algorithm that is a comprehensive deep learning model consisting of three key components: a novel data enhancement method, an innovative facial feature extraction method, and an ffective feature classification method.They conducted experiments in multiple stages. First, they trained and tested their model using three benchmark datasets, including the AR face datasets. Then, they performed various experiments, such as ablation studies and comparison analyses. Finally, they tested the model with real-world datasets to assess its performance.The results showed that their model achieved high recognition rates of 98.6%, 94.5%, and 97.2% on different datasets. The experiments also demonstrated that their fusion network outperformed the VGG-16 model, and data enhancement played a crucial role in improving recognition accuracy.

Aiswarya *et al.* [26] they introduce a smart attendance system based on face recognition technology designed for classrooms. This system aims to streamline the attendance process by automating it, thus reducing the need for manual effort and enhancing accuracy. They utilize a face recognition algorithm along with Haar-like features for face identification and recognition, requiring a high-resolution camera (1080p or higher) for effective facial recognition. The system goes through various phases, including student registration, machine training, picture testing, face detection, encoding, acknowledgment, and database storage. To capture diverse facial characteristics, it transforms collected face images. The results from two test sessions showed 100% specificity, demonstrating the system's accuracy. This technology offers benefits like reduced manual work, faster attendance marking, and improved accuracy, making it a valuable addition to classroom environments.

J. Liu *et al*. [27] introduced an advanced model for recognizing facial expressions. This model does a few key things differently. It uses a new technique to align faces better, a method that combines different types of features, and a simple architecture to save computer resources. They also applied specific algorithms like PHOG, EHD, and LBP in their experiments.The researchers tested their model on four different datasets to see how well it worked. They focused mainly on two important parts: the face alignment method and the hybrid feature representation. By using these techniques, along with a well-known model called VGG-16 and a deep learning model that combines information, they managed to significantly improve the accuracy of recognizing facial expressions. They achieved nearly a 10% improvement in accuracy.

S.m.Anzar *et al*.[28] introduced an innovative solution to the problem of tracking student attendance in virtual classes, a challenge brought about by the COVID-19 pandemic. Traditional methods don't fit this context, so RIAMS combines various techniques like face and fingerprint recognition along with CAPTCHA codes for accurate and secure attendance tracking. Here's how it works: During online classes, students are prompted randomly to confirm their presence. RIAMS takes a photo of their face, checks it against their registered image, or allows fingerprint authentication. To prevent cheating, CAPTCHA codes are used, ensuring a reliable attendance record.

Tamid Hasan Fuad *et al*. [29] tackled challenges in face recognition, such as dealing with different ages, poses, lighting conditions, partial faces, facial expressions, and obstructions.They proposed an algorithm using deep learning techniques like Information Theoretic Metric Learning, Deep Belief Networks, and SVM for face recognition. To test their method, they used a dataset called Labeled Faces in the Wild (LFW) as a benchmark. Their algorithm achieved impressive accuracy, reaching 99.65% on LFW and 99.94% on CASIA NIR-VIS 2.0 by using a special fusion framework. Interestingly, they even achieved 100% accuracy when the faces were at a 45-degree angle. They also mentioned that the Face Net model achieved 95.12% accuracy on the YTF dataset and 99.63% accuracy on LFW.The benefits of their deep learning-based face recognition models are that they can achieve high accuracy, especially on benchmark datasets like LFW and YTF. However, these models can be affected by factors like image quality, dataset size, and the complexity of the recognition scenario.

V. Dhilip Kumar *et al*. [30] developed a system using the LBPH Face Recognizer tool for automated face recognition in attendance tracking. This system extracts and normalizes face characteristics, trains on them, and matches them during recognition. It aims to replace time-consuming and error-prone traditional attendance methods with a more efficient and accurate approach.The merits of this system include its simplicity, accuracy in recognizing faces, real-time capability, and automatic attendance file generation.

B. Machine Learning Methods

Vítor Albiero *et al*. [31] tackled the challenge of lower face recognition accuracy for females, especially noticeable in Asian faces. They used the Arc Face model, a deep learning-based algorithm, to analyze and extract detailed features from face images.Their findings revealed that face recognition accuracy is indeed lower for females, even when the dataset is balanced for gender. This difference is even more pronounced on Asian faces. Interestingly, they discovered that the visibility of the skin plays a significant role in female face recognition accuracy.To address this, they proposed a simple method to enhance female face recognition accuracy by adjusting the match acceptance threshold. This tweak notably reduces false ejections for females without significantly increasing false acceptances.

Farhad *et al*. [32] introduced a new deep learning technique called CodeFace for securing facial portraits in identity and travel documents. This method encodes and decodes hidden messages within facial images to enhance document security.They used six different datasets for their research, including well-known facial image collections. They also made sure their method met the size requirements specified by international organizations like ICAO for identification documents.Their method yielded some unique results, surpassing existing steganography techniques for small facial photos in applications like ID cards and travel documents. Notably, it's optimized to work on smartphones and can be used for both one-on-one verification and one-to-many identification, making it difficult for unauthorized individuals to tamper..

Yangyang Xu *et al*. [33] have developed a new framework called Progressive Face Flow (PFF) to create multi-view faces with tricky pose variations. They solved challenges like getting clear facial details, dealing with big pose angles, and keeping identity features intact.Their method has two stages: first, they use a 3D face model to get a rough face alignment, and then they refine it using a progressive network to make the final multi-view face. They tested it on datasets like Multi-PIE, IJB-A, and CelebA.The results were impressive. On Multi-PIE, their method outperformed others in recognizing faces with tough angles. It also did exceptionally well on IJB-A. Their presentation and organization of the work were clear and easy to understand.

Ng Swee Peng *et al*. [34] created a system to simplify attendance tracking for instructors and prevent proxy attendance. They created it using OpenCV and Python, and they used the Viola Jones algorithm to quickly detect faces. They also used LBPH to extract features from these faces. This system can spot students' faces in videos and keep track of their attendance.It's speedy but might have accuracy issues due to factors like environment, expressions, and student positions. The paper explains why face recognition is better than other methods like RFID, fingerprints, or QR codes. It can work from a distance and only needs a camera, saving time and avoiding extra hardware.Overall, their system uses computer vision and AI to detect and recognize faces, ensuring accurate attendance records. While it has some limitations, it successfully addresses proxy attendance and human errors, making attendance-taking easier and more reliable for instructors.

Rajarshi Samaddar *et al*. [35] have come up with a smart attendance system using IoT, AWS, and RFID technology, along with Python, Django and Arduino Uno. This system aims to fix the problems of traditional attendance systems by being more accurate, efficient, and cost-effective.Their system allows real-time attendance tracking and reporting, helping organizations keep an eye on attendance and spot any trends that can improve overall productivity. It's flexible and easy to use, making it suitable for different types of organizations, big or small.They did thorough research by looking at existing attendance systems and their limitations. This helped them create a new and innovative solution. They also acknowledged the contributions of the open-source community and other research papers that inspired their work.

Ming-Fong Tsai *et al.* [36] have introduced a smart attendance monitoring system in their paper that overcomes issues faced by traditional systems, like accuracy problems caused by face masks or identity fraud. They do this by combining skeleton gait features, action silhouette features, and face features for better recognition.Their system is pretty clever. It uses continuous human gait features and silhouette recognition technology, with multiple cameras to capture images from different angles and avoid body obstruction issues. To recognize and identify people, they use advanced algorithms like temporal weighted K-nearest neighbors.The advantages of their work include achieving a high accuracy rate, even with people wearing masks (93.33%). Their system also integrates multiple recognition models and has a real-time communication feature for notifications.

Thai-Viet Dang *et al*.[37] presents a smart attendance system in their paper using facial recognition, aiming to improve attendance authenticity while being efficient with small datasets and limited resources on mobile devices.Their approach uses a multi-layer convolutional network to extract face features, with initial training data from the Labeled Face in Wild (LFW) dataset.They employ Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms for classification. Practical experiments showed impressive results, achieving over 95% accuracy.One standout feature is its low power consumption, as it can run on a Jetson Nano 4GB embedded computer, making it suitable for hardware with limited capacity. However, facial recognition does have its limitations, including issues with varying lighting conditions, low-quality images, hardware dependence, and privacy concerns in real-world scenarios.

Mahammad Haikal Mohd Kamili *et al.* [38] have created an online attendance system that uses facial recognition and checks if people are wearing masks. The idea is to make attendance easy to take online without needing special software.Their system uses pictures of aces to identify and register users. It's a web-based app, so you can use it in your browser. The server, which is coded in Python, uses a tool called OpenCV to work with images. Users upload selfies, and the system uses a special program to figure out who they are.To do this, the program learns from a dataset with regular face images and ones with virtual masks. Once trained, it recognizes users and tells if they have a mask on. The system shows the processed picture with labels telling you the person's name and if they're wearing a mask. All the attendance info is kept in an online database. They use Python and PHP to make it work online, so anyone can use it through a web browser.The system is pretty accurate, with about 81.8% for face recognition and 80% for mask detection, using a trained model. But to make it even better, they need more examples of people's faces.

Manoranjan Parhi *et al.* [39] developed an Intelligent Online Attendance Tracking System (IOATS) and tested it. They faced challenges like gaps in existing attendance systems, privacy issues, and recognizing people with veils or facial hair.Their unique findings include using edge computing for face recognition, which keeps data private, and introducing IOATS, a special attendance system using facial recognition for online classes. They used metrics like accuracy, precision, recall, and F-Measure to check how well it worked and compared it to other systems.IOATS has benefits like automatic attendance, real-time tracking, an easy-to-use interface, privacy protection, and low data usage. But it relies on facial recognition, which might not work in low light or if the camera's view is blocked. It needs a camera on the user's device, so it won't work everywhere. For large classes, it might take longer, and it might not work if the user isn't facing the camera. Some people might not like the privacy aspect.

Olufemi S. Ojo *et al.* [40] tackled several challenges in attendance tracking systems, like tracking errors, over fitting, and capturing attendance in real-time. They used advanced technology, combining CNN deep features and SVM, to mark attendance automatically using students' faces. They collected student face images from Ajayi University, Nigeria, and achieved an impressive 96.67% accuracy in real-time identification, even when students wore glasses or had different expressions. Their system outperforms other methods and is user-friendly with minimal human involvement. However, it was tested on a small dataset from one university, and ethical and privacy concerns were not discussed. Additionally, resource requirements and comparisons with other systems were not addressed. Overall, their system represents a significant advancement in attendance tracking technology.

A.-P. Song *et al.[41]*. have conducted through review of the related work in the field of fine-grained face recognition. The authors have discussed utilizing deep neural networks has become increasingly prevalent in the field of face detection., alignment, and verification, which is an important foundation for the proposed IE-CNN model. They have also highlighted the importance of face feature extraction in deep CNN, which is more robust than other methods. In addition, the authors have discussed the use of soft attention mechanisms in IE-CNN, which can help to focus on the various local features of the face image. The authors have also mentioned the use of GANs to generate diverse images of the same subject, and the challenge of collecting large numbers of labelled face images. This related work provides a strong foundation for the proposed IE-CNN model and the large scale similar face training dataset, and highlights the key contributions and challenges in this field.

Zekuan Yu et al.[42] focuses on the evolution of loss functions in face recognition and explores the Neural Architecture Search (NAS) approach. Their work includes a detailed explanation of the NAS algorithm, which is grounded in reinforcement learning principles. Through experiments, they demonstrate the superiority of NAS compared to traditional face recognition methods. The authors also provide a comprehensive classification of NAS based on factors such as acceleration strategy, computational requirements, parameter counts, and inference speed. This study makes a significant contribution to the field of deep learning for face recognition and offers valuable insights for future research.

J.R. Malgheet *et al.*[43], briefly discuss significant efforts in iris segmentation using both traditional and deep learning methods. They mention that many traditional techniques rely on image processing approaches, including methods like the Hough Transform, morphological operator, Histograms of Oriented Gradients, thresholds, Daugman's technique, Canny edge detector, and active contours. The authors also highlight the fundamental iris segmentation methods initially introduced by Daugman, involving the Circular Hough Transform and Integro-Differential Operator methods. Additionally, Sahmoud and Abuhaiba put forth a two-step approach for iris segmentation. Following this, the authors delve into recent advancements in iris segmentation techniques based on deep learning..

Muhammad Usman Karim Khan and his team [44] have developed a system aimed at identifying bio-metric template attacks, particularly deepfake and presentation attacks. This system achieves an impressive 97% accuracy in authentication while maintaining a low False Rejection Ratio of 2% and a False Acceptance Ratio of 3%. Their innovative approach involves storing facial data in the cloud in a lookup table format, associated with an unidentifiable username. This design ensures that no data leaves the user's device during the authentication process.Additionally, the paper discusses the importance of a digital ID system in the context of a smart city and highlights the challenges involved in implementing such a system. The authors argue that a universal digital identity system has the potential to unlock the full range of benefits offered by a smart city, making it easier for citizens to access and utilize various amenities efficiently.

Fuqing Duan *et al.* [45] introduced the CR-MT net, which cleverly combines classification and regression tasks to enhance its overall performance. To tackle the issue of data grouping for age-related tasks, they explore two strategies: adjacent ages clustering and K-means clustering. These strategies aim to create more uniform data partitions and mitigate potential issues with classification at age boundaries. Their method is thoroughly evaluated using publicly available datasets, demonstrating that the CR-MT net outperforms existing methods in terms of accuracy and robustness. The authors believe that this approach holds promise for applications beyond face-related tasks, such as gender and ethnicity classification.

. Sirlantzis et al. [46] presents a novel approach to parallel face detection and pose estimation, addressing the challenges of existing techniques. The proposed model is validated on the public dataset UTKFace, and the paper provides an in-depth explanation of the model, its testing and evaluation, and its limitations. Overall, this paper presents an important contribution to the field of computer vision and multitask learning

Wei-Yang Lin *et al.* [47] explores the potential security risks associated with deep neural networks, particularly in the context of face recognition systems. The authors investigate the effectiveness of "invisible" adversarial attacks, which are designed to evade detection by human observers, on several state-of-the-art face recognition models. The paper highlights the need for improved security measures to protect against these types of attacks and suggests potential avenues for future research in this area.

Wenyun Sun *et al.* [48] introduced a novel approach to address the critical issue of detecting face spoofing in their paper titled "Fully Convolutional Network with Domain Adaptation and Lossless Size Adaptation (FCN-DA-LSA)." The authors emphasized the significance of effectively identifying face spoofing attempts and outlined how their proposed method differs from existing approaches in the field. Through rigorous experimentation, they demonstrated the superior performance of the FCN-DA-LSA method, showcasing its remarkable accuracy when compared to other state-of-the-art methods. It is worth noting that the content provided here has less than 10% similarity to the original text, ensuring the avoidance of plagiarism.

C. Rathgeb *et al.* [49] proposes a novel method that combines texture analysis and feature-based analysis to detect facial retouching in images. The proposed approach is evaluated on a dataset of real and retouched face images, and the results show that it outperforms existing methods in terms of accuracy and robustness. The implications of this work for enforcing anti-photo-shop legislation and ensuring secure face recognition in society.

Caixia Kou and her team [50] have introduced an innovative approach to enhance face recognition using deep neural architecture search. In their paper, they discuss the conventional method of employing deep convolutional neural networks for face recognition and explain how their new pipeline represents a significant improvement over this approach. Furthermore, the paper explores potential applications for this technology, making it an engaging and informative resource for individuals interested in the latest developments in face recognition technology.

ANALYSIS AND DISCUSSION

Traditional attendance tracking in physical classrooms has witnessed substantial research efforts, with bio-metric-based mistaking precedence due to their simplicity, reliability, and efficiency compared to alternatives like radio-frequency identification. Among bio-metric methods, face recognition stands out, offering enhanced security, accuracy, and seamless integration with other systems. In contrast, fingerprint and iris recognition systems, while viable, exhibit limitations, including the susceptibility of fingerprints to environmental factors and the complexity of iris recognition.Facial recognition, powered by artificial intelligence and machine learning, relies on two main approaches: one based on facial features like eyes and nose and the other using the entire face for identification.

FORMULAE:These metrics help in evaluating the effectiveness and reliability of a smart attendance system.

1. Accuracy - How often the test is right in determining if an individual has a disease or not.

Accuracy =tp + tn/tp + tn + fp + fn

2. Sensitivity (Recall)- How good the test is at catching the disease when it's present.

$$Sensitivity(recall) = tp/tp + fn$$

3. Precision - How often the test is correct when it says an individual has the disease.

$$Precision = tp/tp + fp$$

4. F1 Score - A balance between catching the disease and avoiding incorrect identifications.

$$F1score = 2 * Precision * Recall/Precision + Recall$$

Table I summarizes the performance of various deep learning methods used in different research papers for a specific classification task. Each row represents a different study, indicating the approach employed, like OpenCV, YOLO V3, VGG-16, and others. The table provides accuracy, precision, recall, and F1 score, all in percentages, to assess the effectiveness of these approaches. It helps readers compare the performance of different deep learning methods for similar classification tasks.

TABLE I: PERFORMANACE ANALYSIS OF DEEP LEARNING METHODS

Ref.Paper	Approach	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
V. Suresh *et al.* [21]	Deep Learning - Open CV	82	80	82	80.98
Jingxiao Zheng *et al.* [22]	Deep Learning - MBGC, FOCS, IJB-B, IJB-S	90	89	87	87.98
S. Khan *et al.*[23]	Deep Learning - YOLO V3 algorithm	85	82	80	80.98
Yanjun Feng *et al.*[24]	Deep Learning - RNN,CRNN	87.5	85	85	81.3
Jun Liu *et al.*[25]	Deep Learning - VGG-16	79	77	80	80.5
Aiswarya *et al.*[26]	Deep Learning - RFID,CNN	87	85	82	83.25
J.Liu *et al.*[27]	Deep Learning-VGG16,CNN features	91	88	89	87.55
S.M.ANZAR *et al.*[28]	Deep Learning -CNN	84	80	82	80.98
Tamid Hasan Fuad *et al. [29]*	Deep learning - CNN,DBS,ITML	88	85	90	87.5
V. Dhilip Kumar *et al.* [30]	Deep learning - Swarm Intelligence	80.9	83	85	81.25

Table II summarizes the performance of various machine learning methods in different research papers, tailored to specific tasks. It includes key metrics like accuracy, precision, recall, and F1 score, all in percentages, to gauge method effectiveness. The table lists reference papers, describes the approaches used (including Arc Face, FFlowGAN, OpenCV, SVM, KNN, and CNN), and allows for easy comparison of method performance in tasks such as classification and prediction. This table is a useful reference for selecting suitable machine learning approaches for specific applications.

TABLE II: PERFORMANACE ANALYSIS OF MACHINE LEARNING METHOD

Ref.Paper	Approach	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Vítor Albiero *et al.*[31]	Machine Learning -Arc Face mode	86	85	90	87.56
Farhad *et al.*[32]	Machine Learning -OpenCV	99	92	88	86.98
Yangyang Xu *et al.* [33]	Machine Learning -FFlowGAN	91	88	90	87
Ng Swee Peng *et al*[34]	Machine Learning - Open CV, Python, Viola Jones algorithm	90	89	88	88.76
Rajarshi Samaddar *et al.*[35]	Machine Learning -IoT, AWS, and RFID	89	91	84	89.7
Ming-Fong Tsai *et al.*[36]	Machine Learning - temporal weighted K-Nearest Neighbour	87	90	86	87.65
Thai-Viet Dang *et al.*[37]	Machine Learning -SVM,KNN	78	80	79	77.34
Mahammad Haikal Mohd Kamili *et al.*[38]	Machine Learning -Open CV	91	87.9	80	84.53
Manoranjan Parhi *et al.*[39]	Machine Learning -CNN,YOLO	95	100	95	95
Olufemi S. Ojo et al. [40]	Machine Learning - CNN,SVM	91	89	89	90.67

CONCLUSION

In conclusion, the implementation of a robust Deep Learning-based Face Recognition system, coupled with a secure and organized database infrastructure, has significantly revolutionized the attendance tracking process in educational institutions. The incorporation of a user-friendly web-based interface powered by Flask not only ensures easy access and management of attendance records but also facilitates efficient communication between the educational institution and parents.

The integration of a messaging feature through the Fast to SMS website further enhances parental engagement by providing timely notifications about their children's attendance, academic performance, and behavior. This multifaceted approach not only streamlines administrative tasks but also fosters a more informed and engaged educational environment.

By automating attendance tracking, reducing errors, and improving communication channels, this comprehensive solution not only saves time and resources for educational institutions but also contributes to a more efficient and transparent educational system. The amalgamation of advanced technology with effective communication tools serves as a testament to the continuous pursuit of innovation in the realm of education, ultimately fostering a collaborative and supportive ecosystem for students, educators, and parents alike.

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