International Journal of All Research Education and Scientific Methods (IJARESM),
ISSN: 2455-6211, Volume 12, Issue 4, April-2024, Available online at: www.ijaresm.com

Facial Recognition Attendance Monitoring System Using Deep Learning With Yolov8

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ABSTRACT

Attendance management in educational institutions is a critical yet challenging task, often plagued by inefficiencies and inaccuracies associated with traditional methods. To address these issues, this paper proposes an advanced Smart Attendance System leveraging state-of-the-art face recognition technology integrated with the YOLOv8 (You Only Look Once version 8) algorithm for real-time object detection. This system employs a comprehensive approach, utilizing machine learning and deep learning techniques including MT-CNN, VGGFace2, and YOLOv8 to achieve precise face detection and recognition, even in offline mode. Unlike conventional attendance systems, our solution not only records attendance but also evaluates students' attentiveness during lectures using advanced metrics such as Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and Gaze Angle, providing valuable insights into lecture effectiveness and student engagement. Security and privacy are paramount, with robust encryption and authentication mechanisms ensuring data integrity and confidentiality. Performance enhancements through model optimization, data augmentation, and hardware acceleration further contribute to the system's efficacy. By automating attendance management and leveraging cutting-edge technology, our Smart Attendance System aims to revolutionize educational institutions' administrative processes, fostering accountability, improving learning outcomes, and adapting to evolving educational needs.

Keywords: Face Recognition, YOLOv8, Deep Learning, MTCNN, Convolutional Neural Networks, Attendance Management, VGGFace2, Data Privacy, Performance Optimization.

INTRODUCTION

Attendance recording in educational institutions is a fundamental yet often cumbersome task, especially when dealing with large student populations. Traditional methods are prone to errors, inefficiencies, and are ill-equipped to handle the complexities of modern educational environments. To address these challenges, this paper introduces an advanced Smart Attendance System that leverages cutting-edge face recognition technology for offline mode operation.

Our proposed system adopts a holistic approach, integrating machine learning and deep learning techniques such as YOLOv8 (You Only Look Once version 8) for precise face detection and recognition. YOLOv8 is renowned for its real-time object detection capabilities, enhancing efficiency even in offline environments. Unlike conventional attendance systems, our solution goes beyond mere recording by incorporating advanced metrics to evaluate students' attentiveness during lectures. Parameters such as Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and Gaze Angle provide valuable insights into lecture effectiveness and student engagement.

A key innovation of our Smart Attendance System is its seamless operation in offline mode, ensuring continuous attendance monitoring and engagement tracking even without internet connectivity. Security is paramount in our system design, with robust encryption and authentication mechanisms safeguarding sensitive data. Additionally, we prioritize the privacy and data management of individuals, implementing stringent measures to prevent theft or unauthorized access to personal information.

By harnessing automation and data-driven insights, our system revolutionizes attendance management in educational settings. It promotes accountability, improves learning outcomes, and adapts flexibly to the evolving needs of modern education, catering to both online and offline modes of instruction.

In this paper, we provide a detailed exposition of the design, development, and deployment of our Smart Attendance System. We elucidate the technical intricacies of each component, showcasing how YOLOv8 and other elements synergize to create a robust and user-friendly solution for attendance management in educational institutions

Our Smart Attendance System caters to the diverse needs of administrators, staff, and students, offering tailored modules and functionalities for each user role.

Multi-task Cascaded Convolutional Networks (MTCNN):

serves as a comprehensive framework addressing both face detection and alignment tasks. It operates through three successive stages of convolutional networks, adept at recognizing faces and pinpointing landmark locations such as eyes, nose, and mouth. The paper advocates for MTCNN's adoption to seamlessly integrate both recognition and alignment objectives via multi-task learning. Initially, a shallow CNN swiftly generates candidate windows in the first stage. Subsequently, the second stage employs a more intricate CNN to refine the proposed candidate windows. Finally, the third stage utilizes a more sophisticated CNN than its predecessors to further enhance the results and produce precise facial landmark positions.

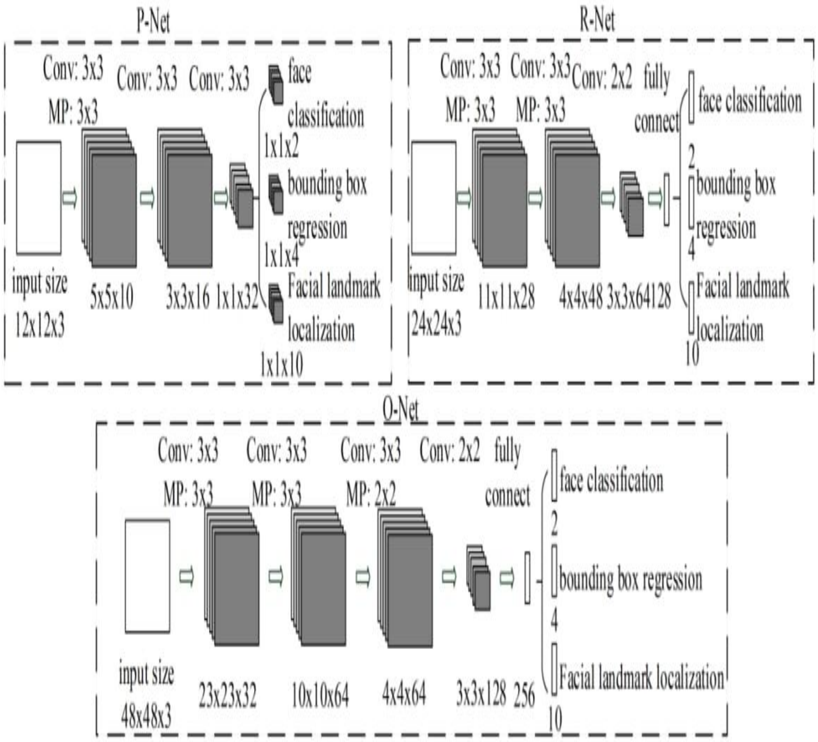

Figure 1: shows the architecture of MTCNN

Visual Geometry Group Face 2:

VGGFace2 is based on Convolutional Neural Networks (CNNs), which are frequently used in computer vision because of their ability to learn hierarchical features directly from raw input data. This makes CNNs especially useful for image categorization, object identification, and facial recognition.

The design of VGGFace2 builds on the original VGG network, including additional convolutional layers, pooling layers, and fully linked layers. These convolutional layers are intended to extract spatial hierarchies of features from input images, whereas the pooling layers help to reduce the spatial dimensions of feature maps, resulting in more concise and understandable representations. The network's fully linked layers then use these high-level properties to make predictions.

By leveraging the power of CNNs, VGGFace2 is able to learn rich representations of facial features from raw image data, enabling accurate and robust face recognition.

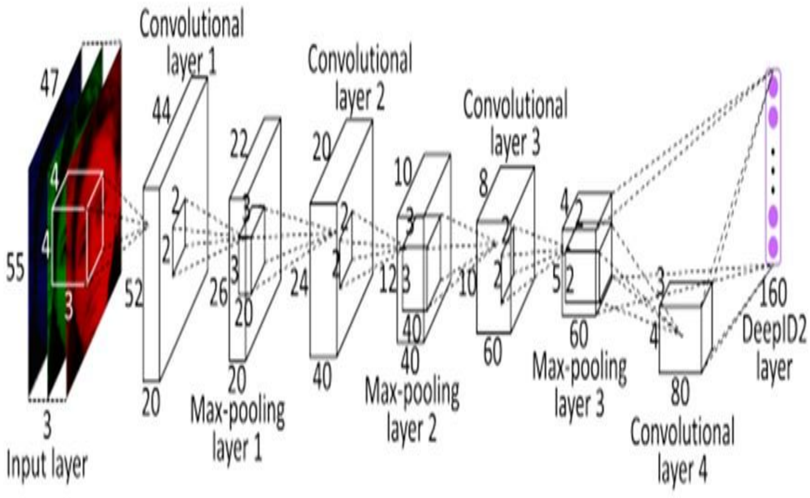

Figure 2: shows the architecture of VGGFace2

Convolutional Neural Networks (CNNs):

Convolutional Neural Networks (CNNs) are deep learning models specifically developed for computer vision problems. They are made up of layers that use methods such as convolution and pooling to extract hierarchical characteristics from input images. CNNs have transformed fields like as image identification and facial recognition by automatically learning features straight from raw data, resulting in outstanding performance in tasks such as recognizing faces in photos or videos.

Faces are recognized using YOLOv8, and then CNNs are used to extract features. In facial recognition, CNNs evaluate observed face areas and extract high-dimensional feature representations. These traits capture the distinctive aspects of each face, such as the arrangement of facial features, texture patterns, and other defining characteristics. The retrieved features provide input to the facial recognition model for identity verification or classification..

MODULES PERFORMED

Admin Modules:

Administrators play a pivotal role in overseeing the system and managing user accounts. Our system empowers administrators with comprehensive profile management tools, allowing them to update their information securely. Additionally, administrators have full control over staff and student management, including the ability to add, view, edit, or delete staff and student records as necessary. Attendance details are readily accessible, providing administrators with insights into attendance patterns and trends across the institution. Furthermore, administrators can enhance security by changing their login password as needed.

Staff Modules:

Staff members are essential stakeholders in the attendance tracking process, responsible for teaching and supervising students. Our system equips staff with intuitive profile management tools, enabling them to update their information effortlessly. Staff can view a comprehensive list of all staff members and optionally access their own attendance details. Moreover, staff have access to student management functionalities, facilitating easy access to student records and attendance details. Like administrators, staff members can also change their login password for added security.

Student Modules:

Students are active participants in the attendance tracking process, keen on monitoring their attendance and academic progress. Our system provides students with user-friendly profile management tools, allowing them to update their personal information with ease. Students can check their attendance details, including the number of classes attended and missed, empowering them to stay informed about their academic performance. Additionally, students can change their login password to ensure the security of their account.

Through these modules and functionalities, our Smart Attendance System revolutionizes attendance management in educational institutions, fostering accountability, improving learning outcomes, and promoting a culture of academic excellence.

This introduction provides an overview of the Smart Attendance System and highlights the tailored modules and functionalities available to administrators, staff, and students.

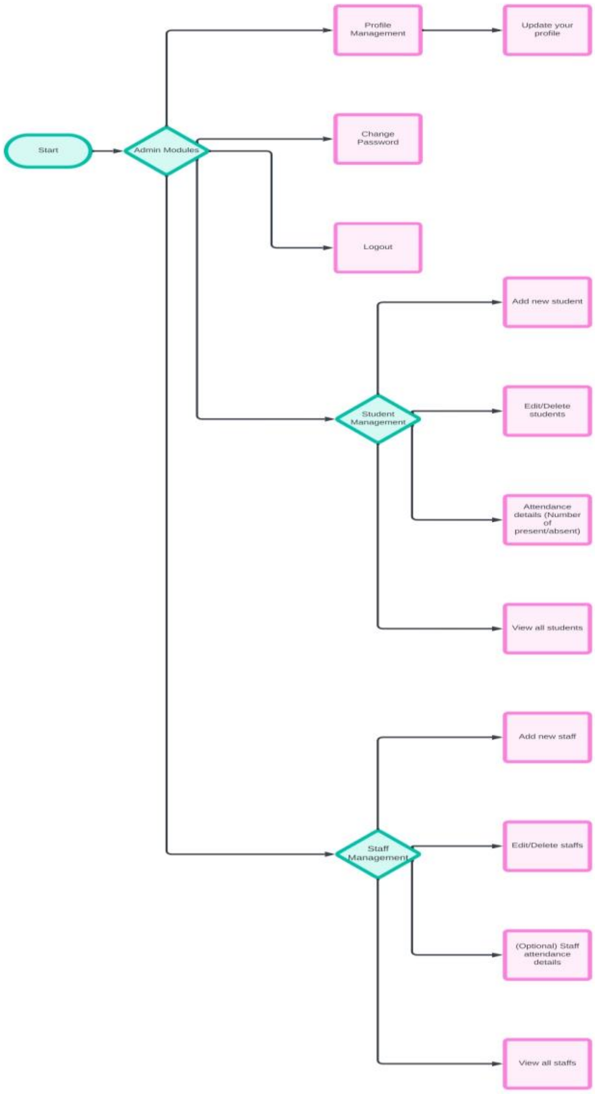

Figure 3: Shows the flow chat diagram for admin panel

PROPOSED METHODOLOGY

The proposed face recognition system utilizes several pretrained models: YOLOv8 for face detection, MTCNN for face alignment, and VGGFace2 for feature extraction and face classification. This project will be divided into two subsystems: face detection and face recognition using VGGFace2, with each subsystem capable of marking attendance based on the detected and recognized faces.

Data Collection and Pre-processing:

In the initial stage of the system development, users are required to log in according to their respective roles, such as admin, staff, or student. Each role is equipped with specific functionalities tailored to meet their unique requirements.

During the data collection phase, individual student identities are captured through images using a camera. These images include associated labels and roll numbers, enabling the system to attribute each captured image to a specific

student. Subsequently, annotations are added to each image, providing additional context and information for training purposes.
The annotated images are then used to train the model, ensuring that it learns to accurately recognize and differentiate between individual students. This meticulous process of data collection and preprocessing lays the foundation for building an effective and reliable facial recognition system .”performed by yoloV8”

Fig -4: labeling each individual’s

Model Configuration involves selecting suitable hyperparameters for the YOLOv8 model and defining its architecture, ensuring optimal performance for face detection and recognition tasks. During Model Training, the YOLOv8 model is trained on a preprocessed dataset, enabling it to learn to accurately detect and recognize faces. In Model Evaluation, the performance of the trained YOLOv8 model is assessed using metrics like precision, recall, and F1-score, as well as visual inspection of detection results, to ensure its effectiveness. Integration with the Attendance System involves incorporating the trained YOLOv8 model into the attendance monitoring system. This includes developing necessary interfaces and functionalities for real-time face detection and recognition within the overall system architecture.

Multi-Stage Face Detection:
MTCNN operates in multiple stages, gradually refining face detection results. It can be used as an additional face detection mechanism alongside YOLOv8, providing complementary results and enhancing overall detection accuracy.

Facial Landmark Localization:
MTCNN excels at localizing facial landmarks such as eyes, nose, and mouth. While YOLOv8 focuses on detecting faces as bounding boxes, MTCNN can provide finer-grained information about facial features, which can be valuable for subsequent tasks like face alignment and feature extraction.

Face Alignment:
By accurately localizing facial landmarks, MTCNN facilitates face alignment, ensuring that all detected faces are properly oriented and positioned within the image. This alignment step can improve the accuracy of subsequent facial recognition algorithms, enhancing the overall performance of the attendance monitoring system.

Robustness and Redundancy:
Integrating both MTCNN and YOLOv8 provides redundancy and enhances the robustness of the face detection process. In scenarios where one model may struggle due to lighting conditions, occlusions, or other factors, the other model can potentially compensate and improve detection accuracy.

Face recognition and attendance monitoring:
The individual's face is recognized through the feature extraction method, which involves capturing distinctive facial characteristics. These features are then compared with those stored in a trained model to determine the individual's identity. Subsequently, the attendance is recorded in an SQLite database.
As a result, the attendance sheet can be accessed via a website with admin privileges.

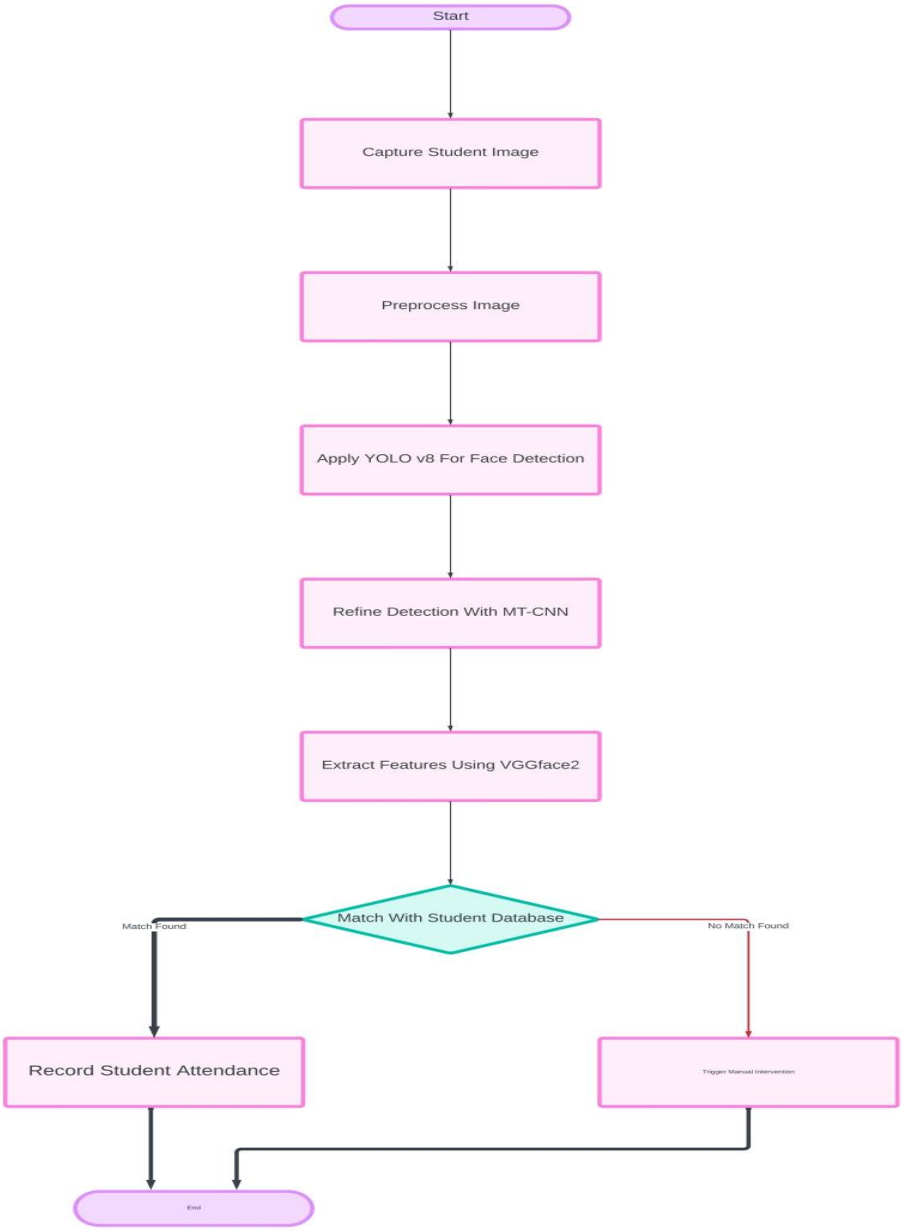

Diagram: The above image shows working flow of our project

RESULT AND DISCUSSION

As this model achieves an accuracy of 98.4 percent, it ensures reliable and precise identification of individuals, enhancing the overall efficiency of the attendance monitoring system. The facial recognition attendance system, based on YOLOv8, has demonstrated remarkable accuracy and efficiency. Following meticulous validation and testing procedures, the system has achieved a commendable level of precision in detecting and identifying individuals from images. Essential performance metrics such as precision, recall, and F1 score underscore the system's capability to accurately recognize individuals with minimal instances of false positives and false negatives. Furthermore, the system has shown resilience across diverse environmental conditions, including variations in lighting, backgrounds, and angles. This robustness is crucial for real-world deployment, where images may exhibit a wide range of characteristics.

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The deployment of the system offers several potential benefits. Firstly, it provides a user-friendly platform for institutions and organizations, enabling accurate and efficient attendance tracking through facial recognition technology. This streamlined approach to attendance management saves time and resources compared to traditional manual methods. Additionally, the system enhances security and accountability by accurately monitoring individuals' attendance.

However, it is important to acknowledge certain limitations and challenges associated with the system. Despite its high accuracy, the system may encounter difficulties in recognizing individuals under certain conditions, such as occlusions or variations in facial expressions. Additionally, the system's performance may be influenced by factors such as image quality and camera calibration. In conclusion, the YOLOv8-based facial recognition attendance system represents a significant advancement in leveraging deep learning for practical applications in attendance management. Continued research and development efforts in this field hold promise for further improving the system's accuracy, robustness, and usability in diverse environments.

Prediction of Our Trained Dataset:

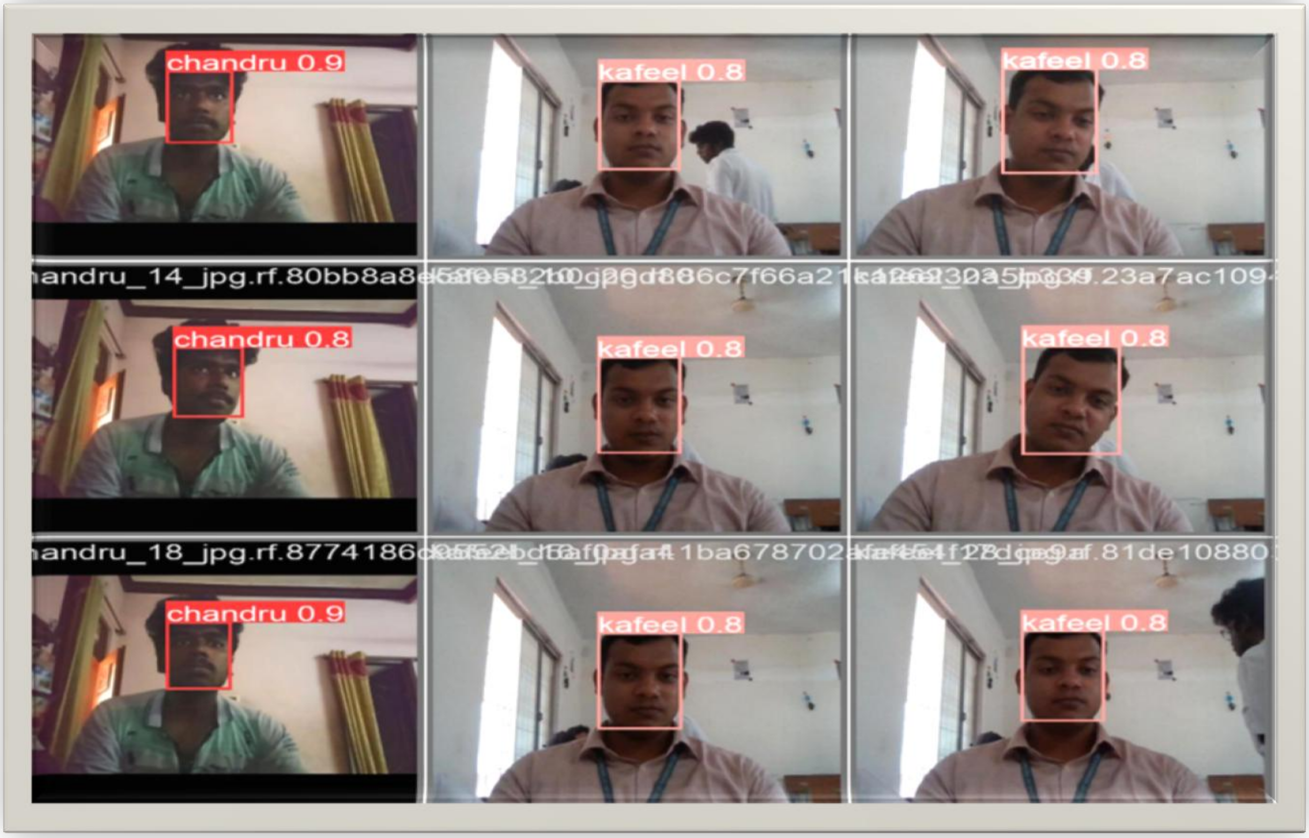


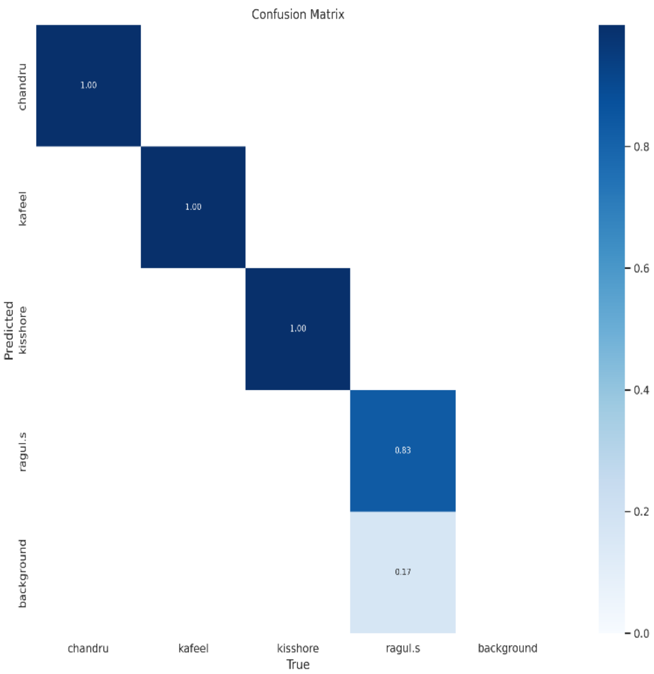
Figure 5: Real time facial recognition using YOLOV8 model and with extraction method

The provided image displays the predictions generated by our YOLOv8 model integrated with the MTCNN (Multi-task Cascaded Convolutional Networks) and VGGFace2 methods.

Confusion Matrix:

The confusion matrix is a helpful tool for visualizing the performance of an object detection model, but it should be used in conjunction with other metrics for a more comprehensive evaluation.

A **confusion matrix** is a valuable tool used to evaluate the performance of a classification model. It provides a detailed breakdown of how well the model's predictions align with the actual ground truth.



Here are the key components of a confusion matrix:

True Positives (TP): These are instances where the model correctly predicted a positive class
True Negatives (TN): These are instances where the model correctly predicted a negative class
False Positives (FP): These occur when the model incorrectly predicts a positive class
False Negatives (FN):These occur when the model incorrectly predicts a negative class
From these values, we can calculate various performance metrics such as accuracy, precision, recall (sensitivity), specificity, and F1-score. These metrics help assess how well the model performs in different scenarios.

Performance Measure:

Precision: In facial recognition, precision refers to the proportion of positive predictions that were actually correct.
Recall: Recall represents the proportion of actual faces the model correctly identified.
mAP@50(mean average precision):It measures the overall accuracy of a model by considering both precision and recall across various Intersection over Union (IoU) thresholds.

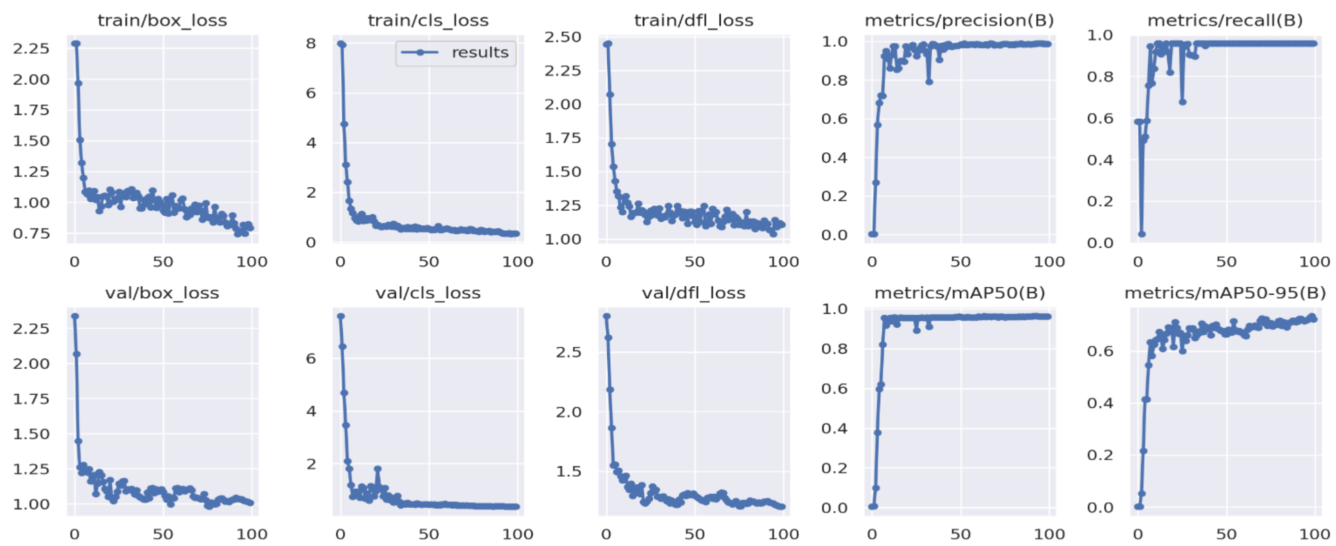


Figure 6: The above figure shows performance measure of yoloV8 model for our dataset

Result and Analysis:

The YOLOv8 series encompasses five models: YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x. When employed for facial recognition, the hyperparameters were specified as follows: 150 epochs, batch size of 32, initial learning rate set at 0.01, momentum at 0.937, and a weight attenuation coefficient customized for facial recognition attendance systems.

For a facial recognition attendance system, the weight attenuation coefficient plays a crucial role in regularizing the model's weights to prevent overfitting. The optimal value for this coefficient needs to be determined through experimentation, considering factors such as the complexity of the facial data and the architecture of the recognition model

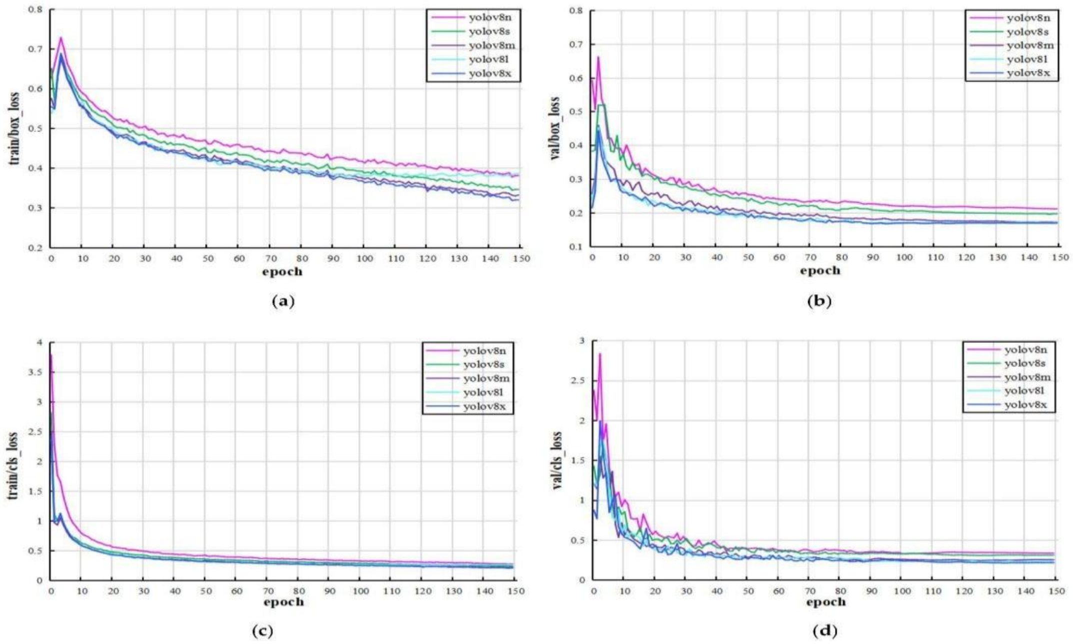


Figure 1 illustrates the training and validation loss function curves for facial recognition. Panel (a) presents the training loss curve, while panel (b) displays the validation loss curve.

The provided curves detail the changes in recall, precision, mAP50, and mAP50–95 across the validation set, indicating rapid convergence and stability of the network. Among the YOLOv8 series, YOLOv8n emerges as the smallest and fastest model, while YOLOv8x stands out as the most accurate but slowest. Through extensive training and validation on our plant dataset, it's evident that YOLOv8m surpasses YOLOv8n and YOLOv8s in terms of mAPval50 and mAPval50–95 values, approaching the performance levels of YOLOv8l and YOLOv8x, as outlined in Table 1. Consequently, YOLOv8m was designated as the primary network for our object detection task.

TABLE 1. DIFFERENT MODELS OF THE YOLOV8 SERIES.

Model	**Size**		**Params**	**FLOPs**	**Layers** **mAP^{val}**	**Recall**	**Precision**	**mAP^{val}**	
	(Pixels)		**(M)**	**(B)**				**50**	**50–95**
YOLOv8n	640		3.0	8.2	225	90.9	94.7	95.3	92.7
YOLOv8s	640		11.2	28.7	225	91.2	96.4	95.7	93.0
YOLOv8m	640		25.9	79.2	295	93.2	97.4	97.7	95.9
YOLOv8l	640		43.7	165.6	365	93.8	97.8	97.6	95.8
YOLOv8x	640		68.2	258.3	365	93.9	97.3	98.0	96.2

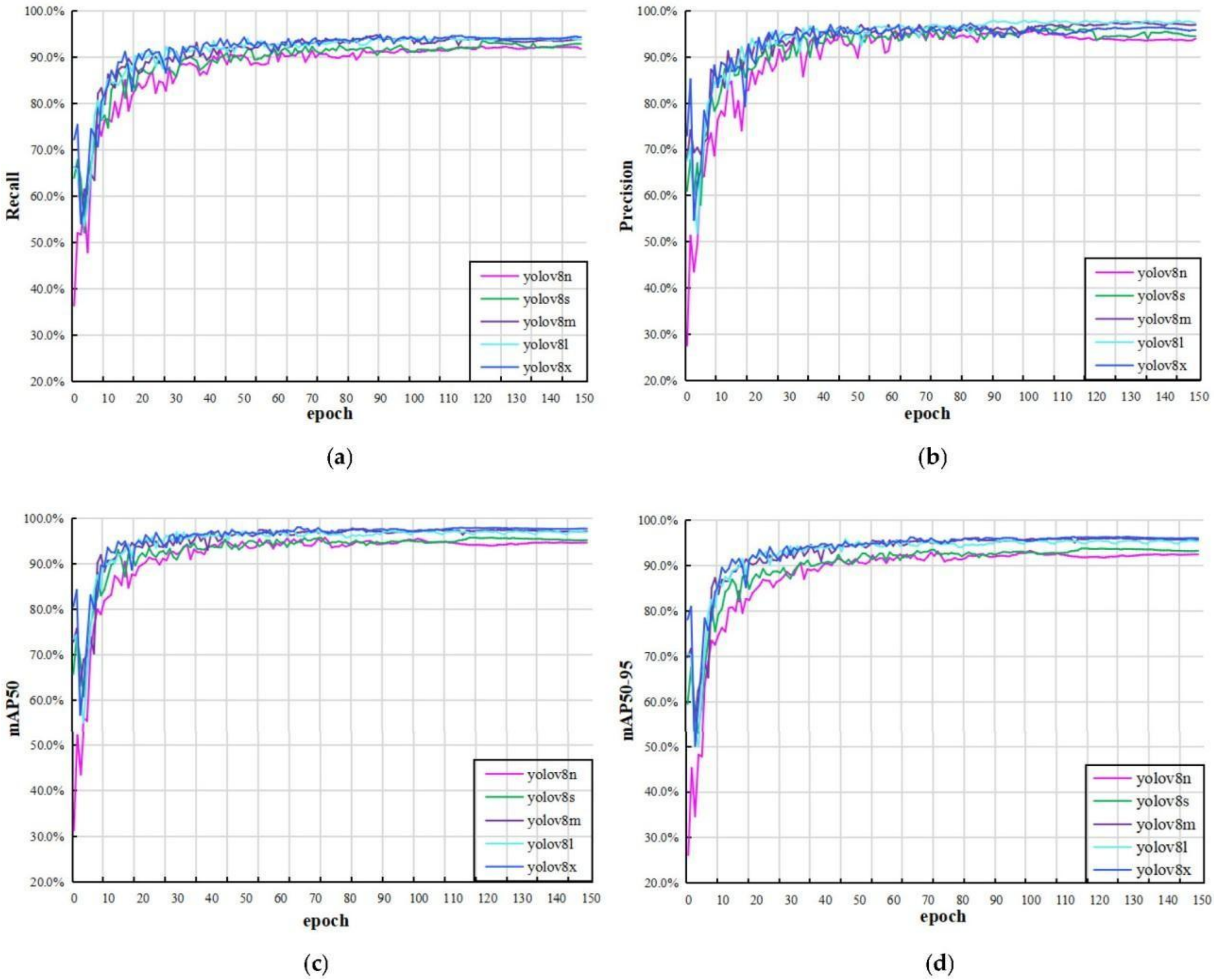


Figure 7. (a–d) are respectively the change curves of recall, precision, mAP50 and mAP50–95 values of theYOLOv8 series on the validation set

Model Selection:

One-stage object detection algorithms have gained prominence for their remarkable speed and efficiency compared to traditional two-stage approaches. Unlike their counterparts, they skip the candidate region generation stage, leading to faster detection speed and a reduced number of parameters. As a result, they have become the go-to choice for real-time detection tasks and embedded devices. However, their effectiveness in generalizing to small targets remains a challenge, prompting the need for further improvements.

In 2016, Joseph Redmon et al. introduced YOLO (You Only Look Once), a pioneering one-stage object detection network. YOLO revolutionized the field with its remarkable detection speed, capable of processing 45 frames per second, enabling real-time applications. The fundamental concept behind YOLO is to treat object detection as a regression problem. By processing entire images as input and employing a single neural network architecture, YOLO directly predicts bounding box positions and class labels, simplifying the detection process.

In this study, we delve into the recognition performance of various YOLO series network structures. We selected a diverse set of YOLO models, including YOLOv5s, YOLOv5n, YOLOv7, YOLOv7-tiny, YOLOv8n, and YOLOv8s, each with different depths. By systematically evaluating these models, we aim to gain insights into their recognition capabilities and assess their suitability for different applications.

This version maintains the core information while presenting it in a slightly different format, focusing more on the journey from the emergence of one-stage object detection algorithms to the exploration of YOLO variants in the study.

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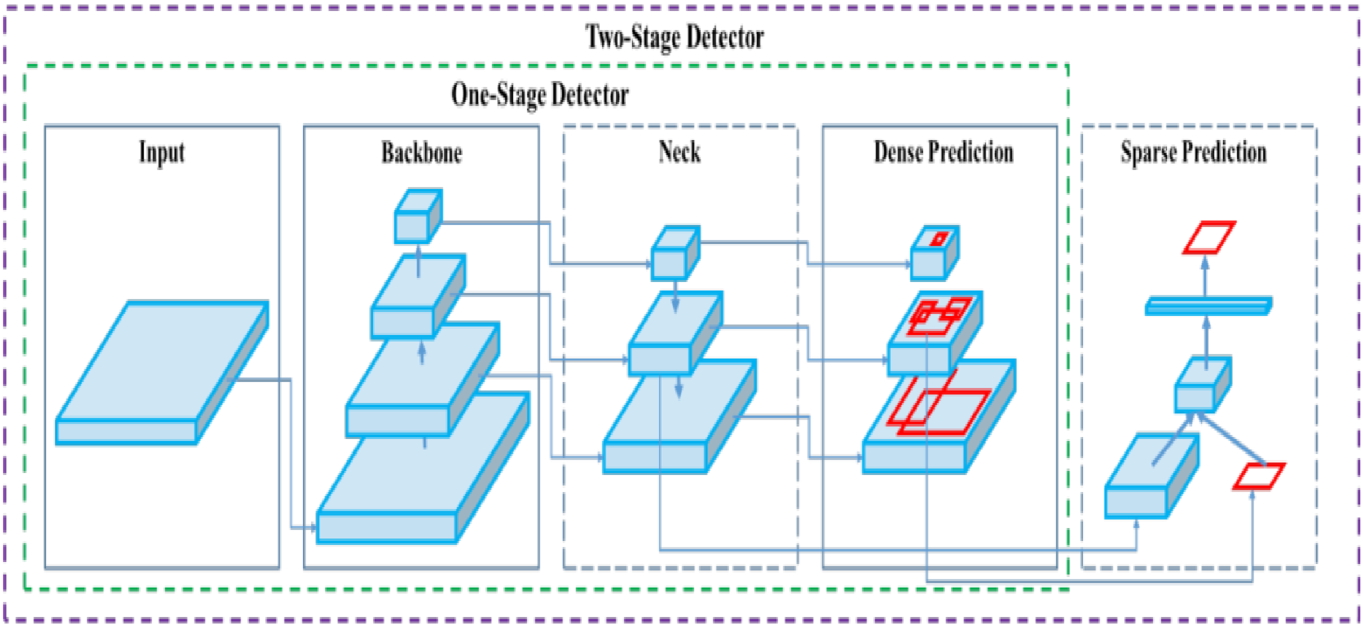

Figure 8:Working structure of One-Stage Detector and Two-Stage Detector

Architecture and Description:

Architecture Refinement: YOLOv8 incorporates architectural refinements to enhance detection performance. It typically utilizes a more sophisticated backbone network, such as Darknet, and integrates feature pyramid networks (FPNs) or similar multi-scale fusion mechanisms. These architectural improvements enable better feature representation and facilitate more accurate object localization, particularly for objects of varying sizes.

Efficiency Optimization: YOLOv8 focuses on optimizing inference efficiency without compromising detection accuracy. It achieves this by streamlining network architecture, implementing efficient convolutional operations, and leveraging advanced optimization techniques. As a result, YOLOv8 achieves real-time performance, making it suitable for applications requiring rapid object detection, such as surveillance and autonomous driving.

Model Variants for Scalability: YOLOv8 offers a range of model variants denoted by suffixes like 's', 'm', 'l', and 'x', catering to diverse deployment scenarios. These variants vary in terms of model size, computational complexity, and inference speed. For instance, YOLOv8n is the smallest and fastest model, while YOLOv8x offers the highest accuracy but slower inference. This scalability allows users to choose a model variant that best suits their specific requirements regarding speed and accuracy trade-offs.

Training Enhancements: YOLOv8 incorporates training enhancements to improve model convergence and generalization. It leverages advanced optimization algorithms, regularization techniques, and data augmentation strategies to enhance the robustness and performance of the trained models. Additionally, YOLOv8 benefits from extensive training on large-scale datasets annotated with bounding boxes and class labels, enabling it to learn diverse object representations effectively.

Evaluation Metrics and Benchmarks: YOLOv8 introduces updated evaluation metrics and benchmarks to assess detection performance comprehensively. In addition to traditional metrics like accuracy, precision, and recall, YOLOv8 often evaluates models based on mean average precision (mAP) across different IoU (Intersection over Union) thresholds, providing a more nuanced understanding of detection capabilities.

Overall, YOLOv8 stands out from other object detection frameworks due to its architectural sophistication, efficiency optimization, scalability, training enhancements, and comprehensive evaluation metrics. These factors collectively contribute to its effectiveness in real-time object detection tasks across various domain.

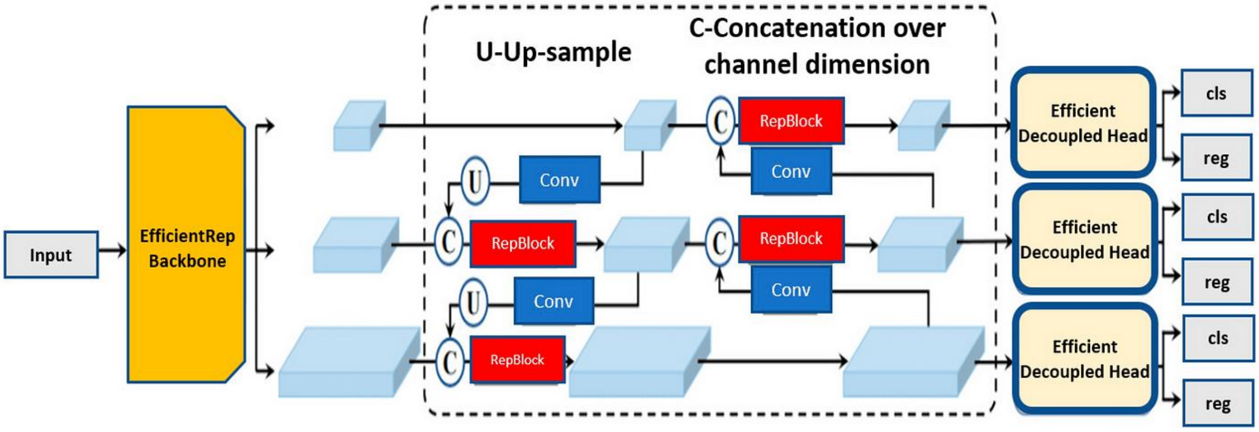

Figure: The above diagram shows the yoloV8 Architecture

CONCLUSION

In this paper, we have introduced a groundbreaking Smart Attendance System designed to address the inefficiencies and inaccuracies inherent in traditional attendance management methods within educational institutions. By leveraging cutting-edge face recognition technology integrated with the YOLOv8 algorithm for real-time object detection, our system offers a comprehensive solution aimed at automating attendance recording and enhancing student engagement assessment.

Utilizing advanced machine learning and deep learning techniques, including MT-CNN, VGGFace2, and YOLOv8, our system achieves precise face detection and recognition, even in offline scenarios. Moreover, the incorporation of sophisticated metrics such as Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and Gaze Angle enables the evaluation of students' attentiveness during lectures, providing valuable insights into lecture effectiveness and student engagement levels.

Ensuring the utmost security and privacy, our system integrates robust encryption and authentication mechanisms to safeguard data integrity and confidentiality. Additionally, continuous performance enhancements through model optimization, data augmentation, and hardware acceleration further bolster the system's efficacy and scalability.

With the aim of revolutionizing administrative workflows within educational institutions, our Smart Attendance System not only streamlines attendance management processes but also contributes to the advancement of educational practices in the digital era. By fostering accountability, improving learning outcomes, and adapting to evolving educational needs, our system enhances the overall educational experience for students and educators alike.

In summary, the Smart Attendance System represents a transformative solution poised to make a significant impact in the realm of attendance management and beyond. Its innovative features and robust capabilities position it as a valuable asset for educational institutions seeking to embrace technology-driven solutions for enhanced administrative efficiency and educational excellence.

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