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# Enhanced Efficiency and Productivity through AAMS

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## ABSTRACT

The Traditional attendance management systems, which rely on human operations or RFID-based solutions, frequently struggle with scalability, accuracy, and efficiency. This thesis proposes an Automated Attendance Management System (AAMS) that employs a customized YOLOv9-C model for real-time facial recognition via deep learning. The model's performance is significantly improved by adding Squeeze-and-Excitation (SE) blocks and the Complete Intersection over Union (CIoU) loss function. On a custom dataset, the baseline YOLOv9-C model had 86.2% precision and 84.9% recall, with a mean Average Precision (mAP) of 89.9% at IoU threshold of 0.5. However, the revised YOLOv9-C(M) model demonstrated significant gains, including a mAP of 93.8%, as well as improved precision (94.1%) and recall (96.6%).These improvements can be due to the introduction of SE blocks, which promote feature recalibration, and the CIoU loss function, which maximizes bounding box localization and increases detection accuracy even in tough conditions such as occlusion or dimly lit areas. The improved YOLOv9-C model consistently outperforms the existing YOLO models (YOLOv5, YOLOv7, and YOLOv8s), according to a comparison study. The mAP for YOLOv5 was 80.2%, YOLOv7 was 89.1%, and YOLOv8s was 91.4%. In contrast, the upgraded YOLOv9-C model outperformed the others, with greater robustness, precision, and recall. The system employs a one kind of custom dataset to evaluate the model's performance in some scenarios and settings, as well as to ensure trustworthy workforce detection in diverse contexts. By automating the attendance process, this technology reduces errors, saves administrative time, and promotes institutional efficiency.

**Keywords:** AAMS, Deep Learning, YOLO, Custom Dataset, Workforce Detection, Attention Module and Data Augmentation.

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## INTRODUCTION

### Research Background

Attendance management is critical to a company's performance because it influences payroll accuracy, operational efficiency, and compliance with labor requirements. Traditional techniques for tracking attendance include punch cards, electronic spreadsheets, handwritten recordkeeping, and physical cards. These approaches have limitations, such as fraud, human error, and time-consuming administrative procedures (Sharma et al., 2020). Automated attendance management systems (AAMS) have overcome these challenges by combining mobile applications, RFID technologies, and biometric technology (Suryavanshi et al., 2021; Zafar et al., 2022; Kim & Lee, 2021). For modern businesses, YOLO architecture is essential as it overcomes issues associated with traditional approaches while providing significant improvements. YOLO ensures precise and consistent attendance records by utilizing real-time object recognition technology, including facial recognition, which reduces errors and increases productivity (Redmon et al., 2016; Zhang et al., 2023). This automation allows HR specialists and administrative personnel to focus on value-added activities, such as strategy planning and employee development (Gupta et al., 2019). YOLO's facial recognition technology provides real-time employee attendance information, allowing for efficient tracking of staff arrival and leave hours at the office (Redmon & Farhadi, 2018). This data improves scheduling and labor management, allowing for more timely adjustments to workforce numbers and increasing operational flexibility (Singh & Kumar, 2022). Businesses can improve resource allocation and handle issues more quickly by implementing real-time reporting solutions that provide important insights into attendance trends (Wang et al., 2022).

### Significance of the Study

Traditional tracking systems struggle with attendance fraud, while YOLO's facial recognition technology improves security by regularly checking employee identities. This additional safeguard not only protects the organization's financial interests but also provides a fair and equitable environment for determining attendance (Dai & Wu, 2021). Even while an AAMS may require significant upfront expenses, the long-term advantages frequently outweigh the drawbacks. Automating attendance monitoring can help businesses save money and enhance operations by lowering administrative costs, reducing errors, and eliminating attendance fraud (Gupta et al., 2019; Suryavanshi et al., 2021). YOLO-based Automated Attendance Management Systems (AAMS) are ideal for a variety of contexts due to their adaptability to changing organizational sizes and conditions. Businesses may lead technological innovation by investing in cutting-edge AAMS solutions like YOLO, which address current difficulties while forecasting future demands in human resource management (Zhang et al., 2023).

Nonetheless, many AAMS continue to have significant issues with accuracy and reliability, limiting their effectiveness and trustworthiness. Biometric systems, such as fingerprint and iris scanners, can have high error rates due to various factors, including age, physical characteristics, and environmental conditions (Patel & Joshi, 2020). Buddy punching can reduce the accuracy of attendance records, and radio-frequency identification (RFID) systems are also subject to errors (Sharma et al., 2020). Even when using automated systems, data entry errors can occur, affecting performance evaluations, payroll processing, and employee trust in general. Lighting conditions can also impact accuracy; dim or shadowed environments make it more challenging to identify and record worker attendance accurately (Wang et al., 2022). Routine calibration and maintenance are necessary to maintain AAMS accuracy, which may decrease performance and increase the likelihood of attendance monitoring errors (Dai & Wu, 2021). Poor maintenance or infrequent calibration may result in poor performance and an increased risk of errors in attendance tracking. Another challenge is administrative complexity, as many current systems require extensive setup and administration, ongoing maintenance, and training for managers,

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employees, and HR personnel. This can be a significant administrative load (Patel & Joshi, 2020). Implementing an AAMS involves added administrative costs, such as IT employee salaries, training expenses, and system maintenance and support resources (Kim & Lee, 2021). This research addresses these challenges by developing a sophisticated system that can determine whether or not a workforce is working, increasing efficiency and accuracy while reducing negative detection.

## Purpose of the Study

The purpose of this project is to create an Automated Attendance Management System (AAMS) that uses cutting-edge technologies like YOLO (You Only Look Once) for real-time object identification and facial recognition, as well as Single Board Computers (SBC) for efficient processing. The goals are to reduce administrative costs, eliminate fraud, and improve attendance management's security, dependability, accuracy, and real-time capabilities (Zafar et al., 2022). The first step in the project is to identify faults in the existing AAMS, such as security risks, onerous administration, and human error. The YOLO algorithm and Single Board Computer (SBC), which are critical components of the proposed system, will be the subject of further research in the coming phase. During the system design and architecture phase, the AAMS setup and the interaction of cameras, SBCs, and databases to process and store attendance data are determined. Security measures will be used to maintain data privacy compliance and protect biometric data from unauthorized access. YOLO, which can recognize employee faces in real time, is then used to integrate and deploy the AAMS on an SBC platform. Cameras will be installed at access points to collect attendance data. The data will be saved in a SQL database that is linked to the company's payroll and human resources systems. To ensure the system's dependability and functionality, testing and validation will be carried out. Following deployment, the AAMS generates real-time attendance data, which may be used to get insights into workplace management using data. HR departments can use this data to identify trends and take proactive steps to improve productivity, which will aid in staff planning decisions.

In summary, by combining cutting-edge technologies such as YOLO and SBC, the proposed AAMS seeks to improve accuracy and dependability while lowering administrative expenses, eliminating fraud, and increasing labor management effectiveness. The Automated Attendance Administration System (AAMS) reduces human error while increasing accuracy by automating data administration and attendance monitoring activities. It eliminates the need for human intervention by automating check-ins and outs using YOLO's real-time item detection and facial recognition technologies. Furthermore, this system ensures that attendance data is acquired and processed promptly, avoiding data input delays and inaccuracies that can occur during manual reconciliation. YOLO's machine learning capabilities enable it to maintain high reliability over time by learning from new data on a regular basis. The system's capacity to adapt to changing persons and new settings contributes to sustained accuracy and dependability.

The AAMS reduces administrative complexity by using the YOLO algorithm and Single Board Computers (SBCs). By automating and optimizing procedures, reducing the need for manual intervention, and improving system interaction, the new AAMS reduces administrative load and frees HR professionals to focus on more strategic projects. One of the primary advantages of an AAMS is its ability to automatically store data, which ensures that papers are easily accessible and well-organized. This streamlines data management while improving policy enforcement and decision-making. The Automated Attendance Management System (AAMS) may adapt to changing attendance management requirements without requiring significant administrative changes. It eliminates inconsistencies and ensures accurate reporting by implementing consistent data management and attendance tracking systems. By integrating with other payroll and HR systems, the solution removes the possibility of incorrect data.

The AAMS employs the YOLO algorithm and Single Board Computers (SBC) to enhance real-time data capabilities and provide precise and timely information. This connection reduces the chance of data conflicts by ensuring that payroll and related systems are using the most recent attendance data. To facilitate more efficient scheduling and workforce planning, the system provides administrators and HR personnel with a single dashboard from which they can examine real-time attendance data. Real-time monitoring enables you to identify attendance-related issues early on, such as unlawful access or frequent absences, and respond quickly to keep things running smoothly. To improve security and provide a comprehensive picture of employee mobility and access, the AAMS can be integrated with current access control systems. Administrators can use the AAMS's real-time analytics capabilities to create dynamic reports and visualizations of attendance data, providing critical information for strategic decision-making. This real-time service provides proactive control over workforce-related issues and attendance, increasing operational efficiency.

The proposed AAMS aims to improve security and fraud prevention in attendance management systems by integrating Single Board Computers (SBCs) and the YOLO algorithm. YOLO's facial recognition technology provides high-precision individual identification while reducing the possibility of unwanted entry and ensuring accurate attendance records. It also has anti-spoofing features, which detect fraudulent attempts to deceive the system. YOLO's algorithms prevent buddy punching by adjusting to shifting angles, illumination, and facial expressions, allowing only registered users to clock in and out. Any attempt to trick the system is detected by the system's real-time monitoring feature, which prevents unauthorized entries and guarantees that attendance records are accurate. All attendance data is safeguarded using encryption techniques to ensure its integrity and privacy. To restrict access to administrative activities and attendance data, the system employs strict access control measures. By integrating the AAMS with existing physical security systems, it is possible to ensure that access to restricted areas is controlled based on attendance records. The AAMS provides real-time alerts for security risks and keeps complete audit trails for all attendance-related procedures. It is intended to comply with data protection regulations such as the CCPA or GDPR, thereby safeguarding employee privacy and managing personal information legally. Only authorized personnel have access to the personal data gathered by facial recognition technology, protecting employee privacy and preventing sensitive information from being exploited.

## Related Work

Modern firms use Automated Attendance Management Systems (AAMS) to boost employee happiness, streamline operations, and increase efficiency. These systems track employee attendance precisely and efficiently using biometrics, RFID, and mobile applications (Wang et al., 2020). By optimizing the workflow, AAMS enhances workforce management and decreases manual tracking time. Establishing clear goals and penalties enhances employee satisfaction (Smith & Brown, 2022). However, early installation costs, employee resentment, privacy issues, and ethical and legal repercussions all present obstacles (Johnson et al., 2023). AAMS should be planned and implemented in such a way that all employees are treated fairly and equally (Jones, 2020).

Object recognition in computer vision has developed substantially over time, from classical techniques to the current deep learning era. Traditional techniques such as pattern matching, edge identification, and Histograms of Oriented Gradients (HOG) have been challenged by their sensitivity to scale, orientation, and opacity (Khan et al., 2018; Roberts, 2019). Machine learning techniques such as Support Vector Machines (SVMs) and decision trees have increased in prominence as tools for recognizing patterns and features in data (Chen & Lee, 2020). Feature learning has enhanced classical object detection, helping systems to adapt and interpret complicated visual patterns. Traditional approaches remain important in situations where interpretability, processing efficiency, and the availability of restricted data are essential factors (Park & Kim, 2021). As deep learning grew more popular, multi-layer neural networks—which can learn hierarchical data representations on their own—were developed and immediately embraced (Smith, 2021). Deep learning has applications in a wide number of areas, including banking, healthcare, and driverless cars (Brown et al., 2022). However, there are still questions about interpretability, ethical implications, and the need for larger labeled datasets (Lee, 2023).

Human Activity Recognition (HAR) is an important domain that independently detects human actions using sensor data and visual input. It has applications in sports analytics, smart homes, security monitoring, and healthcare (Singh & Patel, 2021). Advances in sensor- and vision-based technology have increased the precision and adaptability of HAR systems. Real-time processing, hardware acceleration, multi-modal human activity identification, and generalization are some of the challenges (Jones et al., 2022). Future research will focus on the development of resilient, adaptable, and generalizable systems, as well as the improvement of model generalization and the incorporation of human activity recognition using augmented and virtual reality technologies (Kim & Wang, 2021).

Color-Based Segmentation (CBS) is a computer vision technique that divides photos or video frames based on color properties. Its uses include industrial quality control, object detection, and biological imaging (Chen, 2020). The cluster of a Cluster-Based Subset (CBS) is defined using the k-means technique (Wu & Li, 2022). In one study, blades and weapons were recognized and classified using Human-Centered Design (HCD) and Cognitive Behavioral Science (CBS) approaches; however, the model's accuracy was limited due to training on a less significant dataset (Zhang & Lee, 2021).

Artificial intelligence is mostly based on neural networks, which mirror the networked arrangement of the human brain. They use activation functions to introduce nonlinearity and weighted connections to process data (Kim, 2020). The strength of neural networks is their continuous training process, which is versatile thanks to backpropagation techniques. For specialized tasks, many neural network types are used, such as feedforward neural networks (FNN), convolutional neural networks (CNN), recurrent neural networks (RNN), and long short-term memory (LSTM) networks (Lee, 2022; Roberts et al., 2020). Deep learning, with its hidden layers, has raised the bar in natural language processing and photo identification. Neural networks are changing a variety of sectors by balancing computer efficiency and human-inspired design (Smith et al., 2023).

Convolutional Neural Networks (CNNs) change image processing and pattern recognition by applying filters to input data via convolutional layers. CNN designs are built up of convolutional, pooling, and fully connected layers (Khan et al., 2022). These layers use filters to detect spatial patterns and apply high-level variables for regression or classification. CNN training involves backpropagation to optimize weights, whereas transfer learning increases performance on specific tasks. CNNs have achieved unprecedented levels of accuracy in object detection, segmentation, and image classification, changing image-related jobs (Johnson, 2021). They are applied in a range of applications, including art production, medical imaging, driverless cars, and natural language processing (Smith & Patel, 2020). Despite this, CNNs continue to suffer from overfitting and poor interpretability (Wang & Brown, 2023). This study tries to overcome these difficulties by looking into creative designs and training methodologies. Attention mechanisms let CNNs capture contextual information more effectively (Kim & Wu, 2022). CNNs have an unparalleled ability to extract specific features from visual input, marking a paradigm change in image processing. Their flexibility extends beyond aesthetics, making them helpful in a variety of fields (Lee, 2022).

## Methodology

The Automated Attendance Management System (AAMS) presents an innovative alternative to traditional attendance management systems. It lowers fraud and human error by accurately and consistently tracking employee attendance via Single Board Computers (SBCs) and the YOLO algorithm. This technology boosts company productivity and efficiency by improving procedures and lowering HR duties. The AAMS's real-time monitoring features offer timely updates on employee attendance as well as a smooth connection to payroll and workforce management systems. Its customizable design allows it to be customized for a number of organizational scenarios, including small and large organizations. Sensitive data is safeguarded by sophisticated security safeguards, decreasing privacy worries.

The AAMS leverages the YOLO technique, which is well-known for its real-time object identification and facial recognition capabilities, to overcome constraints in conventional systems. This accelerates decision-making, enhances the accuracy and dependability of attendance records, and removes the need for human interaction. By the using facial recognition to validate a person's identification, the system prioritizes security and fraud protection by forbidding buddy punching and guaranteeing that only authorized personnel may clock in and out. To protect key attendance data, the system's architecture employs secure storage techniques and encrypted data transmission. The AAMS decreases administrative workload, allowing HR staff to focus on higher-value duties. Because of its modular design, the system can be changed to accommodate a wide range of scenarios, making it an adaptable option for enterprises of all sizes. The AAMS revolutionizes attendance tracking by giving major advantages in labor management, data quality, and productivity.

Object detection is a crucial component of computer vision, allowing systems to identify and locate objects in images or videos. The You Only Look Once (YOLO) algorithm is a cutting-edge solution for real-time object detection that divides the input image into a grid of pixels. The neural network can assess the entire image in a single forward cycle, with each cell predicting bounding boxes, confidence ratings, and class probabilities. Because of its unique single-shot design, which enables for real-time image processing, YOLO is suited for low-latency applications such as autonomous vehicles and video surveillance systems. Its precise, grid-based technique allows it to provide entire projections and record global backdrop, making it valuable in scenarios that demand contextual information and object interactions. However, the grid layout of YOLO, which adds to limited spatial resolution, may make it difficult to determine exact contextual relationships between things. It may also show vulnerability to item overlaps, particularly in congested regions, which could result in erroneous bounding box estimates. A varied and well-annotated dataset is key to YOLO's efficacy. Despite its drawbacks, the YOLO architecture changed object identification by finding a balance between accuracy and speed. It is an interesting choice for many applications because to its global context awareness and real-time efficiency. However, in order for implementation to work, the benefits and negatives must be properly considered.

### Data

An Automated Attendance Management System (AAMS) is trained for object detection with a proprietary dataset named Working & Not Working. The dataset includes 1680 images of people in various stages of employment to enable the model differentiate between working and not-working settings. By optimizing for real-time object detection, the YOLOv9-C model minimizes mistakes in discriminating between working and not working states while boosting speed and accuracy. The dataset's properties include a controlled environment, complete annotations for each instance, homogeneity in background features, and consistent ambient and backdrop settings. These characteristics improve the accuracy of productivity analysis and attendance tracking by providing a solid foundation for training and testing the YOLOv9-C model. Data preparation is crucial for assuring the dataset's quality and usability. The data processing pipeline contains the following steps: data collection, normalization, annotation, quality control, and splitting. Photographs of people in "working" and "not working" scenarios are collected under carefully controlled conditions that assure matching lighting, posture, and attitude. While annotation alignment is crucial to the model's learning process, normalization guarantees that pixel intensity values remain constant across the collection. Quality control increases the general robustness of the collection by removing aberrant photos and erroneous annotations. During the training phase, 25% of the data is used for testing and hyperparameter modifications, with the remaining 75% being used for training. Annotations are supplied to ensure smooth interaction with the YOLOv9-C model design, and all photographs are translated to a standard format. Data augmentation techniques like as flipping, rotation, and scaling are used to extend the diversity of datasets.

Data augmentation, or suitably altering the dataset, is a key strategy for strengthening machine learning models. It is used to alleviate class imbalance issues, increase the diversity of training examples, and improve the model's generalization skills when working with a dataset that includes both working and not-working situations. The goal is to verify that the model can reliably discriminate between these two states in a range of real-world events. Brightness modulation, noise addition, and random rotations are examples of data augmentation techniques that replicate environmental changes and improve the model's flexibility to varied working circumstances. The addition of more diverse samples to the collection, such as scaling, zooming, and horizontal flipping, boosts generalization for state detection. To prevent the model from memorizing specific cases, randomization is utilized in the training procedure to combat overfitting owing to individual occurrence modification. The model's capacity to function consistently in practice is increased by simulating real-world circumstances via transformations such as rotation, translation, and perspective alterations. Pattern recognition is performed by recognizing minor deviations between normal and aberrant behavior, allowing the model to generalize across a wide range of operational situations. By providing more instances from the underrepresented class, preference and class imbalance are reduced, and the model is exposed to both groups equally.

(a) (b) (c) (d)

**Figure 1 (a) Original Picture; (b) Augmented Picture (Rotation 90, Zoom in, Left Flipped); and (c) Augmented Picture (Rotation 90, Zoom in) (d) Augmented Picture (left rotation 90, zoom in)**

The "RandAugment" technique is meant to diversify and increase the complexity of the indoor workforce detection dataset. This approach employs class-weighted sampling, jittering, random scaling, random translating, rotating, flipping, brightness/contrast adjustments, and random cropping. When these methods are merged, they provide a larger and more diversified dataset including 3420 pictures, allowing the model to accurately assess if a scenario is performing in a number of scenarios.

## Model Development

The newest model in the YOLOv9-C (You Only Look Once) family of object detection models has transformed real-time object recognition by distinguishing a large number of items in images using a single neural network. By incorporating cutting-edge approaches into design, training tactics, and optimization procedures, the model improves on previous incarnations, including YOLOv5 and YOLOv7. Its architecture combines the concepts of EfficientNet and Cross-Stage Partial Networks (CSPNet), which reduce processing costs while increasing learning capacity. The YOLOv9-C neck architecture incorporates a Path Aggregation Network (PANet) and a Feature Pyramid Network (FPN), which combine data from many backbone tiers to improve the model's ability to detect minute features and complex patterns. It retains the dense prediction technique of its predecessors, which employs bounding box regression and class probability predictions of various sizes. The transformer-inspired self-attention methodologies used by YOLOv9-C improve detection performance when recognizing objects that are partially covered or closely related. By emphasizing multi-stage characteristics, the Hybrid Task Cascade (HTC) design improves detection and provides more precise object boundary detection. YOLOv9-C achieves high speed while maintaining accuracy by combining optimization approaches such as anchor-free prediction with effective networks such as EfficientNet. Adding characteristics to transformer-based self-attention algorithms like PANet and FPN improves detection accuracy, particularly for small and difficult-to-find objects. Because YOLOv9-C is designed to work with a variety of hardware configurations, it may be expanded and modified to support a wide range of applications. Its disadvantages include increased processing complexity, difficult training and fine-tuning, the possibility of overfitting on small datasets, and high CPU power usage. Despite these challenges, YOLOv9-C advances the limits of real-time detection efficiency and accuracy while also setting a new standard for object identification models.

Machine learning and deep learning algorithms apply loss functions to examine the differences between the actual ground truth and the projected output. Reducing the loss function during training tries to increase the model's performance and accuracy. Common loss functions include mean squared error, cross-entropy loss, and specialized loss functions for specific purposes such as object detection and natural language processing. Limitations of IoU loss functions include the inability to examine object localization accuracy, the fact that they are non-differentiable, and the difficulty of applying them directly to backpropagation training. Additionally, they provide little gradient information, making it difficult to fully train models. Small adjustments to the threshold can have a large affect on the computed IoU and loss since IoU does not consider object localization precision.

The Complete Intersection over Union (CIoU) loss function is a significant breakthrough in neural network-based object recognition, providing a more thorough assessment technique for bounding box predictions. YOLOv9-C can be used to construct a CIoU loss function for infrared object detection by altering the codebase's loss function and adapting the training process to workforce images on an improved custom dataset. The CIoU loss comprises of processes such as identifying the overlap between the ground truth and expected bounding boxes, measuring aspect ratios, punishing the difference in distance between the centers of the ground truth and intended bounding boxes, and adding the IoU and penalty terms. In computer vision, the Complete Intersection over Union (CIoU) loss function is an important tool for object detection, which is necessary in applications such as self-driving automobiles and surveillance systems. It examines disparities between predicted and ground truth bounding boxes by taking into account geometric features and spatial overlap. The main shortcomings

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of CIoU are its susceptibility to changes in bounding box aspect ratios and its inability to manage bounding box localization difficulties. CIoU is made up of three primary terms: IoU, aspect ratio, and distance. Despite these disadvantages, CIoU is better at managing objects of varied shapes since it can accept changes in aspect ratios. Furthermore, it boosts localization accuracy by delivering more precise bounding box center point estimates.

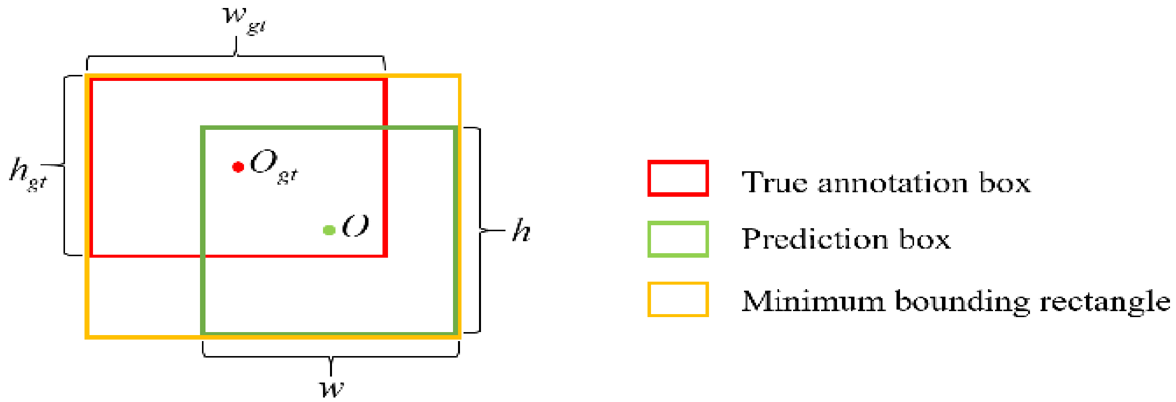


**Figure 2 Schematic diagram of CIoU**

CIoU is used to train neural networks for object recognition, such as single-shot multibox detectors (SSD) or region-based convolutional neural networks (R-CNN). It develops models that excel in object identification and border delineation by achieving a balance between bounding box localization and classification accuracy. The CIoU loss function is a helpful tool for creating object recognition in neural networks, highlighting its importance in enhancing object identification precision.

The squeeze-and-excitement (SE) block is a modular module that improves a neural network's mimetic ability by explicitly simulating interdependencies across feature map channels. It improves CNN performance by modifying channel-wise feature responses and is simple to integrate into existing convolutional layers. By pooling global spatial data, Squeeze decreases the dimensionality of feature maps to one per channel. To mimic inter-channel dependency, the excitation operation comprises two fully connected (FC) layers with a central nonlinearity.

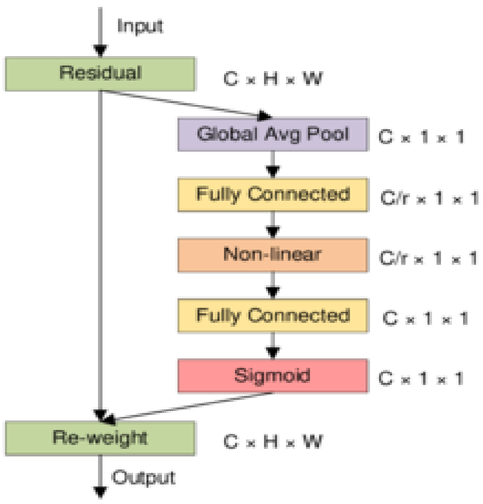


**Figure 3 SE block Attention Module**

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Volume-05 | Issue-03 | September-2024

To improve feature representation and performance on tasks such as object identification and picture classification, the recalibration stage reweights the original input feature map with channel-wise weights obtained during the excitation phase. SE blocks improve CNN accuracy and performance on tasks such as segmentation, object detection, and classification. They provide a practical way for improving performance without significantly increasing the model's size or inference time because they add relatively little computational overhead to the network's complexity. SE blocks can be easily included into the majority of CNN designs, such as ResNet, DenseNet, and Inception, without altering the network's core design. When geographical context is critical, it can be difficult because the SE block only considers channel interactions and ignores spatial data.

## Method of Calculating Efficiency

The Automated Attendance Management System (AAMS) is one technology that uses efficiency calculations to increase productivity and promote personal growth. It allows for more accurate performance evaluation and targeted help by taking into account the unique needs of different academic levels. Every day, the efficiency coefficient—which measures the change in productivity from the previous day—is calculated. YOLOv9-C is used in the AAMS approach, which combines feature extraction, real-time face detection, and data augmentation to improve accuracy and efficiency. An efficiency coefficient is used to assess the system's effectiveness, highlighting the benefits of automation over manual alternatives. The Automated Attendance Management System (AAMS) relies heavily on efficiency computation since it increases job productivity and promotes worker or student growth. It is critical to develop an algorithm that takes into account the fact that workloads vary significantly depending on academic level—PhD students generally have higher demands than master's students, whilst bachelor's students typically have lower workloads. By tailoring the efficiency calculations to the unique needs of each educational level, the AAMS can measure performance more precisely, provide more targeted assistance, and foster an environment that encourages output and personal development. Here is the calculation we approached:

$$EC = \frac{O_n \times A_n}{T_n} \tag{1}$$

Where:
EC= Efficiency Coefficient,
$O_n$= Actual output or tasks completed for the day.
$A_n$= Accuracy of the tasks or quality (percentage of tasks done correctly)
$T_n$= Actual working time (hours/day).

Comparison of Efficiency: Once the efficiency coefficient is calculated for each day, the change in productivity compared to the previous day is determined by:

$$DE = \frac{EC_n - EC_{n-1}}{EC_{n-1}} \times 100 \tag{2}$$

Here, this formula tells whether the efficiency has increased or decreased relative to the previous day.

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## RESULTS

In this phase, first of all we compare the result of base YOLOv9-C and our modified one which is called YOLOv9-C(M). For this comparison we need to look at the bellow table than we will discuss the results between them.

**Table 1 Result Analysis of YOLOv9-C and YOLOv9-C(M)**

| Trained Model | Precision(%) | Recall(%) | mAP@0.5(%) | mAP@0.5:0.95(%) |
|---|---|---|---|---|
| YOLOv9-C | 86.2 | 84.9 | 89.9 | 76.2 |
| YOLOv9-C(M) | 94.1 | 96.6 | 93.8 | 91.8 |

### Comparison of mean Average Precision(mAP)

The YOLOv9-C basic model is compared to the modified YOLOv9-C model, which incorporates Squeeze-and-Excitation (SE) blocks and the Complete Intersection over Union (CIoU) loss function. This comparison began with the YOLOv9-C base model and achieved an 89.9% mean Average Precision (mAP) on the custom dataset. This result shows that the base model can handle object detection tasks properly in its default configuration. Although this mAP value is satisfactory, it is still subject to improvement, particularly when working with complex datasets requiring more exact object classification and localization.

The modified YOLOv9-C model, using the CIoU loss function and SE blocks, achieved a considerably higher mAP of 93.8%. This significant 3.9% increase relative to the baseline model demonstrates the extent to which these changes improved the model's effectiveness. Using SE blocks improves feature recalibration in the neural network, which facilitates this enhancement. SE blocks allow the model to focus on critical components of the input image by selectively emphasizing important features while suppressing less important ones. Improved detection accuracy, especially for small or difficult-to-identify items. Moreover, the CIoU loss function improves the bounding box regression procedure. CIoU, an improved variation of the IoU (Intersection over Union) measure, takes into account the aspect ratio, distance, and overlap between the predicted and ground truth boxes. This improves overall detection quality by reducing misalignment and allowing for more accurate localization of objects in images.

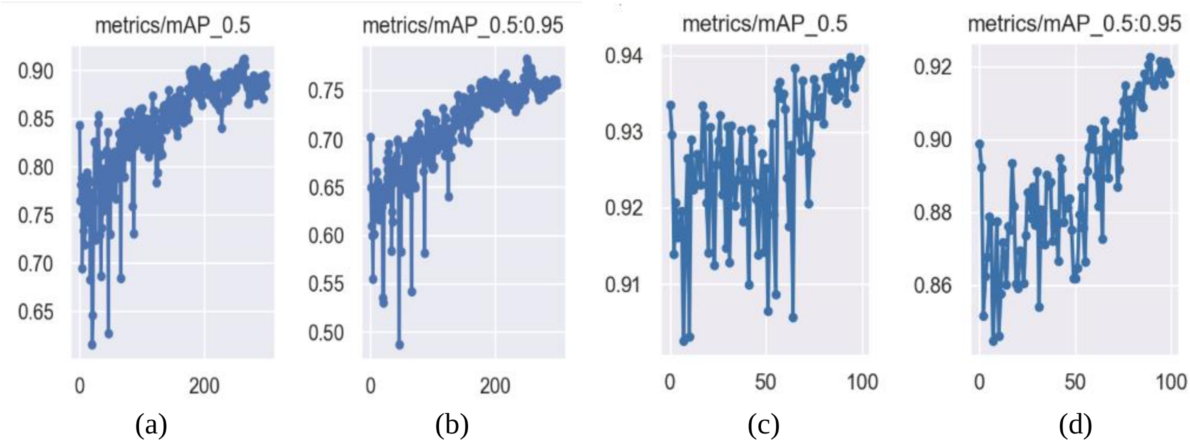


**Figure 4 (a), (c) is the mAP@0.5 of Base YOLOv9-C and YOLOv9-C(M) respectively, (b), (d) is the mAP@0.5:0.95 of Base YOLOv9-C and YOLOv9-C(M) respectively**

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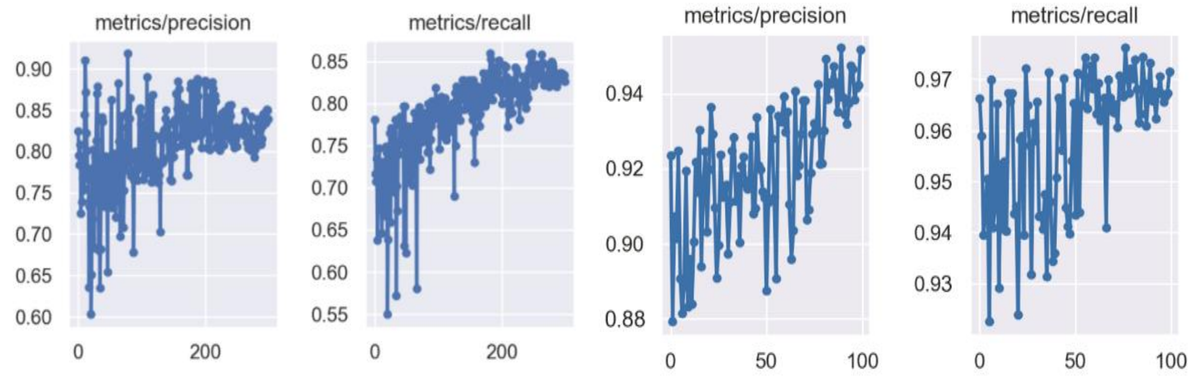
Volume-05 | Issue-03 | September-2024

In summary, the addition of SE blocks and the CIoU loss function significantly improves the performance of the modified YOLOv9-C model over the standard model. The enhanced bounding box accuracy using CIoU and improved feature recalibration with SE blocks allow the redesigned model to achieve superior performance, as evidenced by the 93.8% mAP value. As a result, it is a more reliable option for object detection tasks, especially when using custom datasets with high accuracy and precision requirements.

### Comparison of Precision and Recall(PR)

The precision and recall metrics reveals that altering the YOLOv9-C model resulted in significant performance gains in addition to an increase in mAP.




(a) (b) (c) (d)

**Figure 5 (a), (c) as precision of YOLOv9-C and YOLOv9-C(M) respectively (c), (d) are recall.**

With a precision of 86.2% and a recall of 84.9%, the YOLOv9-C basic model appears to have struck a good balance between accurately identifying items and detecting the majority of relevant objects. These metrics also show the underlying model's shortcomings in terms of identifying all relevant items and reducing false positives, which can result in missing instances in some cases. In comparison, the modified YOLOv9-C model outperformed the conventional model with an accuracy of 94.1% and a recall of 96.6%, indicating advantages of 7.9% in precision and 11.7% in recall, respectively. This massive increase in precision demonstrates the model's enhanced ability to reliably classify objects, significantly lowering the number of false positives. The improved model significantly reduces missed detections and false negatives, demonstrating that it is substantially more successful at recognizing nearly all objects in the dataset. This is evidenced by the significant improvement in recollection. This comparison shows that the YOLOv9-C model has been upgraded to improve not only precision and recall alone, but also the overall balance of these critical criteria. As a result, the new model provides a far more reliable tool for object detection. While more recall ensures that no important objects are overlooked, increasing precision reduces the number of misclassifications, hence improving the system overall. These changes are critical to ensuring that the AAMS tracks attendance accurately and consistently without errors, hence improving the system's dependability and efficiency.

### Comparison of Loss Functions

Sidewise from the significant increases in precision, recall, and mean average precision (mAP), a key difference between the original and updated YOLOv9-C models is their diverging loss functions, which are critical in deciding the models' bounding box accuracy performance. The base YOLOv9-C model uses the conventional IoU (Intersection over Union) loss function to estimate the overlap between the predicted and ground truth bounding boxes. IoU loss has been widely used in object detection; nevertheless, there are certain limits. It ignores the aspect ratios and distance between the centers of the

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Volume-05 | Issue-03 | September-2024

two boxes, focusing solely on the area where they intersect. As a result, the loss may not accurately reflect how well the boxes are aligned, even when the predicted bounding box is close to the ground truth. This may result in less-than-optimal predictions, especially when the objects are small or require precise localization. The modified YOLOv9-C model uses the more advanced CIoU loss function, which provides a more complete bounding box regression technique. Aside from assessing overlap, CIoU also considers the aspect ratio, scale, and space between the centers of the anticipated and ground truth boxes.

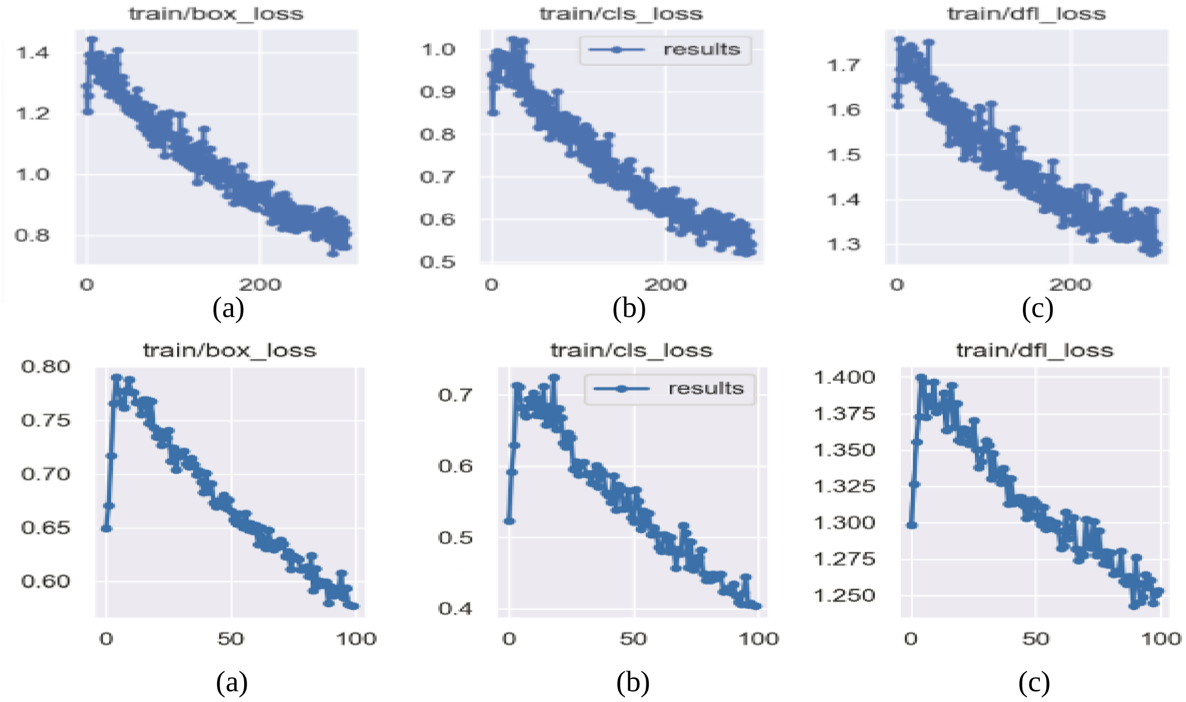


**Figure 6 (a), (d) are box loss as YOLOv9-C and YOLOv9-C(M), respectively (b), (d) are class loss and (c), (f) are dfl loss**.

As a result, CIoU can punish boxes that are not perfectly aligned as well as those with significant form differences, resulting in more accurate and precise predictions. When these extra elements are included, the CIoU loss function improves object detection accuracy significantly, especially in complex situations where objects have different sizes, shapes, and locations.

In practical, the improved model provides better bounding box predictions during training thanks to the addition of the CIoU loss function. Compared to the basic model, which uses the standard IoU, this results in faster and more efficient convergence, reducing overall loss. The model can handle complicated datasets more effectively because to CIoU, which ensures that predicted bounding boxes are not only close to the real objects but also properly aligned in terms of size and form. The increased localization accuracy is a direct result of the upgraded YOLOv9-C model's improved performance, as indicated by higher mAP, precision, and recall values.

## Robustness Test

In our foundational baseline experiment to improve efficiency and productivity in our Automated Attendance Management System (AAMS), we tested three of the most powerful object identification frameworks: YOLOv5s, YOLOv7, and YOLOv8s. These types are suited for our purpose since they each offer distinct advantages in terms of precision, speed, and adaptability to a variety of settings. The selection of these specific models was motivated by their shown performance in a variety of object recognition tasks, their ability to meet real-time processing requirements, and the architectural benefits they provide. This project aims to thoroughly examine how well these models identify and distinguish humans in a variety of indoor environments, establishing a benchmark for future enhancements to our system.

We begin by using YOLOv5, a model known for striking an excellent balance between speed and accuracy. Because of its effectiveness, it has been widely used in industrial applications. This makes it suitable for real-time attendance detection, where quick recognition is required. The training method is done with the augmented custom dataset to establish a baseline performance.

We then implemented YOLOv7, which has been shown to outperform its predecessors in terms of speed and detection accuracy. This model extracts features using complicated training methodologies and improved backbone networks. Its architectural elements are especially useful in complex indoor contexts where accurate detection is required. For YOLOv7, we use a similar training technique to assess the model's success in managing various situations.

Finally, we implemented YOLOv8s, one of the most recent version of the YOLO series, which is known for its cutting-edge features that improve detection speed. YOLOv8s is an excellent tool for detecting attendance in busy environments because to its streamlined architecture and multi-scale detection features, which improve performance in identifying objects of varied sizes. In the baseline experiment, which has done with YOLOv5s, YOLOv7s, and YOLOv8s, provides a benchmark for the performance of these object detection frameworks. The findings will not only help us choose the best model for real-time applications, but will also advance the field of automated systems and object detection research. Our goal is to develop an AAMS that significantly increases productivity and efficiency in attendance monitoring through continuous review and improvement.

## Result Analysis with predecessor YOLO Models

YOLOv8 has an accuracy of 89% and a recall of 91%, while the modified YOLOv9-C outperforms it on both criteria. Furthermore, the YOLOv9-C(M)'s mAP performs slightly better than YOLOv8's mAP, demonstrating improved performance across multiple IoU thresholds. This implies that, despite considerable localization restrictions, YOLOv9-C(M) has better performance retention. The YOLOv9-C(M) model has improved precision and recall metrics, increasing the likelihood of correctly identifying genuine positives while lowering false detections.

When YOLOv9-C (M) is compared to older models like YOLOv7 and YOLOv5, the advantages become more apparent. YOLOv9-C(M) significantly improves precision and memory compared to YOLOv7. The increase in mAP over YOLOv7 demonstrates the improvements made to the YOLOv9c architecture and approach. Compared to modified YOLOv9-C, YOLOv5s performs poorly in terms of recall and precision. These findings reflect the accomplishments of the YOLO series and emphasize the importance of ongoing development and optimization in object identification technology.

**Table 2 : Ablation experiment table For YOLOv5s, YOLOv7, YOLOv8s, YOLOv9-C, YOLOv9-C(M)**

| Model | Precision | Recall | mAP@0.5 | mAP@0.5:0.95 |
|---|---|---|---|---|
| YOLOv5s | 81.1 | 79.8 | 80.2 | 55.7 |
| YOLOv7 | 83.4 | 82.3 | 89.1 | 71.3 |
| YOLOv8s | 89.3 | 85.1 | 91.4 | 77.8 |
| YOLOv9-C | 86.2 | 84.9 | 89.9 | 76.2 |
| YOLOv9-C(M) | 94.1 | 96.6 | 93.8 | 91.8 |

The ablation study demonstrates how the YOLO series models have evolved and improved over time, with significant gains in detection accuracy and robustness observed with each repetition. In terms of precision, recall, and mAP, the YOLOv9-C(M) model outperforms the other models. Although both YOLOv8 and the original YOLOv9-C perform well, YOLOv9-C(M) performs significantly better because to the addition of the SE block attention module and the CIoU loss function. Overall, the YOLOv9-C(M) model exceeds its predecessors, establishing itself as a reliable option for difficult detecting tasks. This is especially true for applications that require cutting-edge detection capabilities, as it strikes a superior balance between detection accuracy and resilience. Developments in the neighborhood.

## Compute Efficiency

As we approached two equations for computing Efficiency Coefficient, now Our project's efficiency is calculated using a methodical procedure based on our university policies. A master's student must work in the laboratory for 40 hours per week, or 8 hours per day, to maintain an efficiency coefficient of one. Each week, you can evaluate overall performance by calculating daily efficiency and comparing weekly efficiency over a month.

**Table 3 Example of a student's one week data**

| Days | Completed Task(O) | Accuracy of task(A) | Working Hours(T) | Efficiency Coefficient (EC) |
|---|---|---|---|---|
| Monday | 25 | 0.90 | 8 | 2.8125 |
| Tuesday | 30 | 0.85 | 9 | 2.8333 |
| Wednesday | 20 | 0.95 | 7 | 2.7143 |
| Thursday | 28 | 0.80 | 8 | 2.8000 |
| Friday | 35 | 0.88 | 10 | 3.0800 |

Assume a master's student is obliged to work 40 hours per week, Monday through Friday. Every day, the student records the number of hours worked, the accuracy with which their duties are performed, and their overall efficiency. This technique allows for a full examination of a student's performance and work consistency throughout time. For calculating weekly efficiency. To compute the weekly efficiency coefficient, we take the average of the daily EC values:

$$EC(week) = \frac{EC_{(Monday)} + EC_{(Tuesday)} + EC_{(Wednesday)} + EC_{(Thrusday)} + EC_{(Friday)}}{5}$$

$$EC(week) = \frac{2.8125 + 2.8333 + 2.7143 + 2.8000 + 3.0800}{5} = 2.84802$$

This value of 2.84802 reflects the student's overall efficiency for one-week. If we need to compute the difference of Efficiency Coefficient of students based on week to week we need to calculate another week as well, after that we will get the difference of a student efficiency either increase or decrease. When compared week-to-week, it helps in identify efficiency, productivity changes, or areas where task management can be improved. The calculation focuses on evaluating the efficiency of a student in the lab by considering both the hours worked and the quality of tasks completed. This efficiency is calculated daily, aggregated weekly, and then compared over a month. It accounts for lab-specific regulations, which can vary depending on the level of study and the lab's requirements.

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Volume-05 | Issue-03 | September-2024

## CONCLUSION

To distinguish between working and not working scenarios in the workplace, this study developed an Automated Attendance Management System (AAMS) using deep learning models such as YOLOv5s, YOLOv7, and YOLOv8s. The AAMS improved detection efficiency and accuracy while reducing false positives and negatives in attendance data by employing techniques such as the SE block and CIoU loss function. Furthermore, it enabled real-time monitoring and rapid response to attendance discrepancies. By tailoring the concept to specific professional tasks or academic degrees, the AAMS demonstrated customizable solutions by providing businesses and students with tailored coaching. The system allows organizations to track production changes over time, potentially reducing costs and improving operational effectiveness.

Nonetheless, the AAMS contains inherent biases and limitations, such as poor performance in real-world circumstances and impediments. To ensure that the system works properly, staff workers must adhere to specific protocols. The AAMS reduces administrative tasks, improves attendance tracking accuracy, and promotes overall operational efficiency, all of which have significant real-world implications in the healthcare, business, and education sectors.

In addition to increasing engagement and student accountability, it may help companies make real-time, data-driven choices. The project fosters a culture of performance accountability and monitoring by stressing efficiency calculations to drive continuous improvement.

## CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

**Anisul Islam Jonayed:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing original draft. **Haifeng Sun:** Resources, Writing-review & editing, Supervision, Project administration. **Abdullah Al Nayeem Mahmud Lavu:** Conceptualization, Writing & review &editing. **MD Toufik Hossain:** Conceptualization, Writing- review & editing.

## DATA AVAILABILITY

The data can be obtained from the authors upon request.

## CONFLICT OF INTEREST

The author declare they have no known conflict of interest which could have influenced the work presented in this paper.

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Not Applicable.

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