UNIFORM AND ATTENDANCE TRACKING

A PROJECT REPORT

Submitted by

ARSHAD MUHAMMED HASHIM, CMA20CS016

ABHIJITH CA, LCMA20CS060

RICHIN P VARGHESE,CMA20CS047

MARY VARGHESE, LCMA20CS063

to

The APJ Abdul Kalam Technological University

in partial fulfillment of the requirements of the award of the Degree

of

Bachelor of Technology

in

Computer Science and Engineering

Carmel College Of Engineering & Technology

Punnapra, Alappuzha, Kerala – 688004

MAY 2024

DECLARATION

We undersigned at this moment declare that the project report **"UNIFORM AND ATTENDANCE TRACKING"**, submitted for the partial fulfillment of the requirements for the award of the degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by us. This submission represents our idea in our own words, and where ideas or words of others have been included, we have adequately and accurately cited and referenced the source. We also declare that we have adhered to academic honesty and integrity ethics and have not mispresented or fabricated any data, idea, fact, or source in our submission. We understand that any violation of the above will cause disciplinary action by the institute and/or the university and can also evoke penal action from the sources that have thus not been properly cited from whom proper permission has not been obtained. This report has not been previously formed as the basis for awarding any degree, diploma, or similar title of any other University.

Place: Alappuzha

Date:

Name of Students:

Arshad Muhammed Hashim

Abhijith CA

Richin P Varghese

Mary Varghese

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CARMEL COLLEGE OF ENGINEERING & TECHNOLOGY

PUNNAPRA, ALAPPUZHA, KERALA – 688004

CERTIFICATE

This is to Certify that the project report entitled "**UNIFORM AND ATTENDANCE TRACKING**" submitted by **Arshad Muahmmed Hashim, Abhijith CA , Richin P Varghese , Mary Varghese** to the APJ Abdul Kalam Technological University in partial fulfillment of the Computer Science and Engineering is a bonafide record of the project work carried out by them under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

Prof. Aparna A S(Guide)	Prof. Anoop R S
Assistant Professor	Head of Department, CSE
Department of CSE	

Signature

Date:

CONTENTS

ACKNOWLEDGEMENT

First and foremost, I thank god Almighty for giving me the opportunity, strength and wisdom to complete the Project successfully.

I wish to express my sincere gratitude to **Fr. Thomas Choolaparampil CMI, Chairman CCET, Fr. Justin Alukkal CMI, Director CCET,** and to our beloved **Principal Dr. Paul K Mathew**, for their constant support and encouragement in preparation of this project report and for making available library and technical facilities needed to prepare this report.

My sincere thanks to **Prof. Anoop R S**, Head of the Department of CSE for his valuable suggestions and guidance throughout the period of this report.

We would also like to express our boundless thanks and gratitude from the bottom of our heart to our guide **Mrs. Aparna A S, Assistant Professor** and Head of the Department**,Prof. Anoop R S**, Department of CSE, forhis valuable guidance and support.

I am very thankful to all my teachers and all the staff members of Computer Science and Engineering for their proper guidance and affection shown to me.

I express my sincere thanks to my classmates, family members and whole and sundry who had helped me during the course of for their wholehearted support.

Arshad Muhammed Hashim

Abhijith CA

Richin P Varghese

Mary Varghese

ABSTRACT

UNIFORM AND ATTENDENCE TRACKING

ABSTRACT

Uniform detection and attendance tracking using deep learning is a cutting-edge approach that leverages AI to automate the process of monitoring students' adherence to dress code policies in educational institutions. Advanced algorithms like CNNs, object detection, and image segmentation are used to identify students' attire and determine compliance with established dress code regulations. This technology can also integrate with existing attendance systems, enabling real-time attendance tracking and providing educators and administrators with valuable insights into student behavior.

The primary benefit of uniform detection and attendance tracking using deep learning is its exceptional accuracy and efficiency. Unlike traditional methods, this technology can rapidly process vast amounts of data and generate precise results in real-time, eliminating the risk of human error and freeing up staff members' time. Additionally, the use of deep learning algorithms ensures that the technology can adapt and learn from experience, continually improving its performance over time.

This technology promotes a safe and supportive learning environment by reinforcing dress code policies, minimizing distractions, and promoting a sense of unity and respect among students. It also allows educators to quickly identify and address any attendance irregularities, ensuring that students receive the support they need to succeed academically.

KEYWORDS: uniform detection, deep learning, object detection, image segmentation, Real-Time processing

LIST OF FIGURES

CHAPTER 1
INTRODUCTION

1.1 GENERAL BACKGROUND

In the era of technological advancements, deep learning has emerged as a powerful tool revolutionizing various aspects of our lives. One such domain where deep learning has made significant strides is in the field of attendance tracking and uniform detection. Traditional methods of attendance tracking, such as manual roll calls and paper-based systems, are often time-consuming, prone to errors, and lack efficiency. Deep learning-based attendance systems offer a more accurate, reliable, and automated approach to attendance management.

Deep learning algorithms, particularly convolutional neural networks (CNNs), have demonstrated remarkable capabilities in image and video analysis. These algorithms can effectively extract features from images and videos, enabling them to identify and track individuals in real-time. By employing deep learning techniques, attendance systems can accurately detect and recognize faces, even in challenging conditions such as varying lighting and occlusions.

The implementation of deep learning-based attendance systems typically involves two main stages: face detection and face recognition. Face detection involves identifying the presence of faces in an image or video frame. This task is crucial for narrowing down the search space for face recognition. Once faces are detected, face recognition algorithms extract unique facial features and compare them against a database of enrolled individuals. This process enables the system to accurately identify individuals and mark their attendance.

Apart from attendance tracking, deep learning can also be employed for uniform detection. Uniform detection involves identifying and verifying whether individuals are adhering to the prescribed dress code. Deep learning algorithms can be trained to recognize specific uniform components, such as shirts, pants, and accessories. This allows the system to automatically detect and flag individuals who are not in compliance with the uniform policy.

The integration of deep learning into attendance tracking and uniform detection systems offers several advantages over traditional methods deep learning has emerged as a transformative technology in the realm of attendance tracking and uniform detection. Deep learning-based systems offer a more accurate, reliable, and automated approach to attendance management, enhancing efficiency and streamlining processes in various settings, including educational institutions, workplaces, and access control systems.

1.2 OBJECTIVES

The objective of tracking uniform and attendance marking in a college is to maintain discipline, promote equality, and ensure regular participation of students in academic activities. Uniforms in still a sense of discipline and professionalism, preparing students for future professional environments. They also promote equality by minimizing visible socio-economic differences. Uniforms enhance campus security by making it easier to identify students. Regular attendance marking is crucial for tracking academic progress, identifying punctuality issues, ensuring active participation in classes, and complying with mandatory attendance policies. It also encourages students to take responsibility for their education. The ultimate goal of these practices is to create a conducive learning environment and facilitate student success.

1.3 SCOPE

The scope of tracking uniform and attendance marking in a college encompasses various facets of academic and campus life. It enables academic monitoring, ensuring students' active participation in their courses, and enforces the institution's policies on dress code and attendance. Uniforms enhance security measures by facilitating easier identification of students. Regular attendance tracking can help identify students facing difficulties, enabling timely support and intervention. The practice provides valuable data for administrative and academic decisions, such as curriculum planning and resource allocation. It also ensures regulatory compliance as many regions require institutions to maintain attendance records. Furthermore, adherence to uniform and attendance policies prepares students for professional life where punctuality and dress codes are often important. Overall, the scope is broad, impacting not just academic performance but also the overall functioning and effectiveness of the institution, making it an integral part of the educational system.

CHAPTER 2

LITERATURE REVIEW

2.1 Segmentation and selective feature extraction for human detection to the direction of action recognition

Human detection and action recognition are fundamental tasks in computer vision, with significant applications in surveillance, robotics, and human-computer interaction. The paper by Konwar et al. (2021) proposes a novel approach to human detection and tracking, specifically in the context of action recognition. Their method employs a combination of median filtering for noise reduction, graph cut for image segmentation, mathematical morphology for segmentation refinement, HOG (Histogram of Oriented Gradients) feature extraction, SVM (Support Vector Machine) classification, and particle filtering for human tracking. This comprehensive approach enables robust human detection and tracking under various conditions, including variations in lighting, colour, shape, size, clothing, and occlusion. Experimental results demonstrate the effectiveness of the proposed method, achieving an automatic multiple human detection rate of 97.61% and a total multiple human detection and tracking accuracy of 92% for an automatic visual surveillance system (AVSS). These results highlight the potential of the proposed method in real-time applications, particularly in surveillance, robotics, and human-computer interaction. Future research directions include investigating different feature extraction techniques, developing more efficient algorithms for real-time processing, and exploring deep learning-based approaches for human detection and action recognition tasks. Overall, the work by Konwar et al. (2021) provides a valuable contribution to the field of human detection and action recognition, offering a robust and accurate framework For human detection and particularly in the content of action recognition

2.2 Implementation of Simplified Normalized Cut Graph Partitioning Algorithm on FPGA for Image Segmentation

In their 2014 paper, Saha et al. propose a simplified normalized cut graph partitioning algorithm for image segmentation and implement it on an FPGA. They argue that the conventional normalized cut algorithm is computationally expensive and therefore not suitable for real-time applications. To address this issue, they propose a simplified algorithm that reduces the computational cost and makes it suitable for real-time applications. They also implement the simplified algorithm on an FPGA and demonstrate its effectiveness on a test case of malarial parasite detection. The study's main contribution is the development of a simplified normalized cut graph partitioning algorithm that is suitable for real-time applications. This is a significant contribution, as real-time image segmentation is important for many applications, such as medical imaging and video surveillance. The study also demonstrates the effectiveness of the simplified algorithm on a test case of malarial parasite detection. This suggests that the algorithm may be useful for other real-time image segmentation applications. In addition to the proposed simplified algorithm, the study also provides a review of related work. The authors discuss the advantages and disadvantages of the conventional normalized cut algorithm and other existing approaches. They also provide a detailed explanation of the proposed simplified algorithm and its implementation on an FPGA. The study is well-cited in the literature and has been used as a reference by many other researchers working in the field of real-time image segmentation. The proposed simplified algorithm is considered a promising approach for real-time image segmentation and may have many potential applications in real-world scenarios. The proposed simplified algorithm is based on the normalized cut algorithm, which is a graph-based image segmentation technique. The normalized cut algorithm partitions an image into two segments by minimizing the normalized cut, which is the ratio of the cut value to the sum of the weights of the edges in the cut. The normalized cut value is a measure of the strength of the connections between the two segments. The conventional normalized cut algorithm is computationally expensive . This makes it unsuitable for real-time applications. The proposed simplified algorithm reduces the computational cost by using a local search algorithm to find an approximate solution to the generalized eigenvalue problem. The proposed simplified algorithm was implemented on an FPGA and its effectiveness was demonstrated on a test case of malarial parasite detection. The results showed that the proposed algorithm was able to segment the malarial parasites in the image with high accuracy and in real time. The study by Saha et al. is a significant contribution to the field of real-time image segmentation.

2.3 Convolutional Neural Networks for Aerial Multi-Label Pedestrian Detection

Aerial multi-label pedestrian detection presents a challenging yet promising field with significant applications in surveillance, traffic monitoring, and crowd management. This task involves identifying and classifying pedestrians in aerial images while simultaneously assigning multiple labels based on their activities or characteristics.

To effectively address the challenges of low resolution and background clutter, Soleimani and Nasrabadi propose a novel two-step framework using convolutional neural networks (CNNs). In the first step, a Single Shot Multibox Detector (SSD) efficiently generates object proposals from small regions of aerial images. These proposals serve as potential pedestrian candidates, significantly reducing the computational burden on the subsequent classification stage.

The second step employs a CNN specifically designed for multi-label classification. It utilizes dense connections and a SoftMax activation function to produce a probability distribution over the predefined labels for each pedestrian. This approach enables the CNN to assign multiple labels to each pedestrian, providing a richer and more nuanced understanding of their activities.

The proposed framework achieved state-of-the-art results on two aerial pedestrian datasets, PASCAL VOC 2012 and KITTI, outperforming traditional methods and other CNN-based methods, particularly in classifying multiple labels for pedestrians.

The ability to extract multiple labels from aerial imagery holds immense value in various applications. Traffic monitoring systems can gain insights into pedestrian behaviour, enabling better traffic management and reducing congestion. Surveillance systems can identify and track individuals, enhancing security and public safety. Crowd management systems can assess and predict crowd behaviour, aiding in emergency response and event planning.

As CNN technology continues to evolve, we can expect further advancements in aerial multi-label pedestrian detection, enabling even more sophisticated and accurate analyses of pedestrian activity and behaviour.

2.4 Mask R-CNN: A Breakthrough in Instance Segmentation

Instance segmentation, the task of simultaneously detecting and segmenting individual objects within an image, has emerged as a crucial technique in computer vision. In 2017, a groundbreaking paper titled "Mask R-CNN" by Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick introduced a novel deep learning architecture that revolutionized instance segmentation. Mask R-CNN surpassed previous methods in both accuracy and efficiency, establishing itself as a cornerstone of modern object detection and segmentation frameworks.

At the heart of Mask R-CNN lies its extension of Faster R-CNN, a two-stage object detection algorithm. Faster R-CNN first generates a set of potential object locations, known as regions of interest (ROIs), and then classifies and refines the bounding boxes for each ROI. Mask R-CNN builds upon this framework by introducing a parallel branch specifically dedicated to predicting segmentation masks for each ROI. This additional branch, coupled with a binary mask loss function, enables Mask R-CNN to not only identify objects but also precisely delineate their outlines within the image.

To further enhance the performance of Mask R-CNN, the authors implemented a data augmentation pipeline that effectively expands the training dataset. This pipeline incorporates techniques such as random image flipping, scaling, and cropping, which introduce variations in the training data and prevent the model from overfitting to specific patterns.

The effectiveness of Mask R-CNN was demonstrated through its remarkable performance on several benchmark datasets, including the COCO Object Detection Challenge. Mask R-CNN achieved state-of-the-art results in all three tracks of the challenge: instance segmentation, bounding-box object detection, and person key point detection. Notably, Mask R-CNN outperformed all existing single-model entries, including the winners of the COCO 2016 challenge.

The contributions of Mask R-CNN extend beyond its exceptional performance. The paper's conceptual simplicity, flexibility, and generalizability have paved the way for numerous advancements in the field of instance segmentation. The introduction of the segmentation branch has become a standard component in modern object detection architectures, and Mask R-CNN has served as the foundation for various extensions, including Panoptic Segmentation and Cascade Mask R-CNN. Beyond instance segmentation, Mask R-CNN has found applications in a wider range of computer vision tasks, including image understanding, object tracking, and autonomous driving. Its ability to precisely identify and segment objects has proven invaluable in these domains, enabling more accurate scene interpretation and autonomous decision-making.

In conclusion, Mask R-CNN stands as a seminal contribution to the field of computer vision. Its innovative architecture, coupled with its remarkable performance and generalizability, has propelled instance segmentation to new heights and paved the way for countless advancements in object detection and segmentation. Mask R-CNN remains a cornerstone of modern computer vision frameworks, enabling a wide range of applications and driving the development of increasingly sophisticated and versatile object recognition systems.

2.5 Instance Segmentation of Newspaper Elements Using Mask R-CNN

The digitization of newspapers has gained significant traction worldwide, resulting in vast archives of digitized newspapers. These archives hold immense historical and informational value, serving as a rich source of knowledge about past events, cultural trends, and societal developments. To effectively extract knowledge from these archives, it is crucial to logically deconstruct newspaper pages into their constituent elements, such as articles, advertisements, and headers. This deconstruction process enables efficient information retrieval, content analysis, and knowledge discovery from the vast trove of digitized newspaper data.

However, the task of deconstructing newspaper pages into their constituent elements is not without its challenges. Newspaper pages typically exhibit complex layouts, diverse styles, and varying shapes of elements, making it difficult to automate the deconstruction process using traditional image processing techniques. Additionally, the linguistic diversity of newspapers poses further challenges, as the language-dependent nature of traditional methods limits their applicability to newspapers from different linguistic backgrounds.

To address these challenges, Almutairi and Almashan (2019) proposed a deep learning-based approach for the instance segmentation of newspaper elements using Mask R-CNN. Mask R-CNN is a powerful object detection and instance segmentation framework that has demonstrated state-of-the-art performance in various applications. The authors employed Mask R-CNN to create a language-agnostic model capable of segmenting newspaper pages into their main elements based solely on visual features.

To evaluate the effectiveness of their proposed approach, Almutairi and Almashan (2019) conducted experiments on a dataset of 200 digitized newspaper pages from various sources. The dataset was annotated with bounding boxes and instance masks for each element: articles, advertisements, and headers. The model was trained using a combination of pre-trained weights and fine-tuning on the newspaper dataset.

The experimental results demonstrated the effectiveness of the proposed approach. The model achieved an average precision (AP) of 0.82 for instance segmentation, indicating its ability to accurately identify and segment newspaper elements. Additionally, the model exhibited robustness to variations in layout, style, and language, making it applicable to a wide range of newspapers.

The study by Almutairi and Almashan (2019) presents a promising approach for instance segmentation of newspaper elements using Mask R-CNN. The proposed method demonstrates high accuracy and robustness, making it a valuable tool for large-scale newspaper digitization and knowledge extraction initiatives. The language-agnostic nature of the model further expands its applicability to newspapers from diverse linguistic backgrounds.

2.6 AUTOAUGMENT: Learning augmentation strategies from data

Auto Augment represents a groundbreaking approach in the field of data augmentation, introducing automated techniques for learning augmentation policies directly from the training data. The method, proposed by researchers at Google Brain, leverages reinforcement learning to discover optimal augmentation policies, relieving practitioners from the burden of manual policy design. The core idea of Auto Augment involves the use of a controller neural network that learns to generate augmentation policies by sampling from a discrete search space. The controller is trained using a reward signal based on the performance of a target neural network on the validation set. Through a series of iterations, the controller refines its policy, adapting augmentation strategies to the specific characteristics of the dataset. The literature on Auto Augment explores its application primarily in computer vision tasks, such as image classification. The method has demonstrated remarkable success in improving the generalization of deep neural networks, surpassing human-designed augmentation policies. Auto Augment's ability to adapt to diverse datasets showcases its potential for addressing the challenges posed by domain-specific variations. Researchers have extended Auto Augment to different modalities and tasks, including object detection and segmentation. The literature discusses the transferability of learned policies across related tasks, highlighting the versatility of Auto Augment in enhancing model performance in various scenarios. Despite its success, the literature also acknowledges challenges associated with computational costs and the need for large-scale datasets for effective policy learning. Additionally, ongoing research explores the integration of Auto Augment with other augmentation techniques, such as traditional transformations and generative models, to further boost the diversity and quality of augmented data. In conclusion, the literature on Auto Augment underscores its role as a pioneering technique in automating the process of data augmentation, showcasing its effectiveness in improving the generalization of deep learning models across diverse applications. As research continues, Auto Augment is expected to contribute significantly to the advancement of augmentation strategies in machine learning

2.7 Data Augmentation In Classification And Segmentation A Survey And New Strategies

The survey on data augmentation in classification and segmentation provides an in-depth exploration of strategies aimed at enhancing the performance of models in these specific tasks. The survey covers a wide range of techniques, methodologies, and recent advancements in the domain, shedding light on both established practices and emerging trends. Classification Augmentation Strategies: The survey delves into data augmentation techniques tailored specifically for image classification tasks. Traditional transformations, such as rotation, flipping, and scaling, are discussed alongside more advanced strategies like colour jittering, cutout, and mix-up. The impact of these techniques on improving model accuracy, robustness, and generalization is thoroughly examined. Segmentation Augmentation Techniques: Researchers have developed segmentation-specific augmentation strategies, considering the spatial nature of the task. This includes techniques like elastic deformations, random cropping, and affine transformations that preserve the spatial relationships within images. The survey explores how these strategies contribute to better segmentation results and address challenges like class imbalance. Combined Augmentation Approaches: The survey discusses the effectiveness of combining both classification and segmentation augmentation strategies. This holistic approach aims to optimize the overall model performance by addressing the unique requirements of each task simultaneously. Generative Models for Image Synthesis: The survey covers the integration of generative models, such as GANs, for generating synthetic images that serve as additional training data. The use of generative models in both classification and segmentation tasks is examined, showcasing their potential in expanding training datasets. Domain-Specific Augmentation Strategies: Researchers have developed task-specific augmentation techniques for domains such as medical imaging or remote sensing. The survey investigates how these domain-specific strategies cater to the unique characteristics and challenges of particular application areas. Auto Augment and Reinforcement Learning Policies: The survey explores the application of automated techniques like Auto Augment, where augmentation policies are learned through reinforcement learning. This includes the adaptation of learned policies for both classification and segmentation tasks, emphasizing their versatility.

Evaluation Metrics and Benchmarks: The survey discusses the metrics commonly used to evaluate the effectiveness of augmentation strategies in classification and segmentation. Benchmark datasets and challenges specific to these tasks are explored to provide a comprehensive understanding of performance measurement. Challenges and Future Directions: The survey addresses challenges associated with applying data augmentation in classification and segmentation, such as potential introduction of biases and computational costs. Additionally, it outlines potential avenues for future research, including the exploration of novel augmentation techniques and strategies for emerging tasks. The survey provides a thorough examination of data augmentation strategies in the context of classification and segmentation. By covering a spectrum of techniques and addressing task-specific considerations, it serves as a valuable resource for researchers and practitioners seeking to optimize model performance in these crucial areas of computer vision.

2.8 A Survey On Image Data Augmentation For Deep Learning

Deep convolutional neural networks have performed remarkably well on many Computer Vision tasks. However, these networks are heavily reliant on big data to avoid overfitting. Overfitting refers to the phenomenon when a network learns a function with very high variance such as to perfectly model the training data. Unfortunately, many application domains do not have access to big data, such as medical image analysis. This survey focuses on Data Augmentation, a data-space solution to the problem of limited data. Data Augmentation encompasses a suite of techniques that enhance the size and quality of training datasets such that better Deep Learning models can be built using them. The image augmentation algorithms discussed in this survey include geometric transformations, colour space augmentations, kernel filters, mixing images, random erasing, feature space augmentation, adversarial training, generative adversarial networks, neural style transfer, and meta-learning. The application of augmentation methods based on GANs are heavily covered in this survey. In addition to augmentation techniques, this paper will briefly discuss other characteristics of Data Augmentation such as test-time augmentation, resolution impact, final dataset size, and curriculum learning. This survey will present existing methods for Data Augmentation, promising developments, and meta-level decisions for implementing Data Augmentation. Readers will understand how Data Augmentation can improve the performance of their models and expand limited datasets to take advantage of the capabilities of big data.

CHAPTER 3

EXISTING SYSTEM

3.1 GENERAL BACKGROUND

Traditional methods for uniform detection rely on hand-crafted rules and heuristics to identify students who are not dressed in accordance with school policies. These methods typically involve visually inspecting images captured by surveillance cameras and manually annotating students as either compliant or non-compliant. However, this approach has several limitations and drawbacks.

Firstly, manual annotation is time-consuming and labour-intensive, requiring a team of human operators to review hours of footage and label each student individually. This process is not only expensive but also prone to errors, as fatigue and boredom can lead to inconsistent annotations.

Secondly, traditional methods struggle to handle variations in lighting, pose, and appearance. For instance, if a student's face is partially obscured or their uniform is worn differently than usual, the manual annotation process may incorrectly classify them as non-compliant. Similarly, changes in lighting conditions or shadows can make it difficult to accurately assess whether a student is wearing the correct uniform.

Thirdly, traditional methods cannot easily accommodate new students or updates to school policies. When new students join the school or uniform regulations change, the manual annotation process must start from scratch, requiring significant resources and time to retrain the annotation team.

Lastly, manual annotation does not provide real-time feedback to students, teachers, or administrators. Any issues with uniform compliance are typically identified after the fact, leading to delays in addressing problems and potential consequences for both students and staff.

In summary, traditional methods for uniform detection suffer from numerous challenges, including high labour costs, limited accuracy, difficulties handling variability, and slow response times. Our proposed system addresses these shortcomings by leveraging advances in deep learning algorithms, enabling faster, more accurate, and more efficient uniform detection.

3.2 DISADVATAGES OF EXISTING SYSTEM

- **Time-consuming and labour-intensive:** Manual annotation requires a team of human operators to review hours of footage and label each student individually, which is not only expensive but also prone to errors due to fatigue and boredom.
- **Limited accuracy:** Traditional methods struggle to handle variations in lighting, pose, and appearance. For instance, if a student's face is partially obscured or their uniform is worn differently than usual, the manual annotation process may incorrectly classify them as non-compliant.
- **Difficulties handling variability:** Changes in lighting conditions or shadows can make it difficult to accurately assess whether a student is wearing the correct uniform.
- **Slow response times:** Manual annotation does not provide real-time feedback to students, teachers, or administrators. Any issues with uniform compliance are typically identified after the fact, leading to delays in addressing problems and potential consequences for both students and staff.
- **Inflexibility:** Traditional methods cannot easily accommodate new students or updates to school policies. When new students join the school or uniform regulations change, the manual annotation process must start from scratch, requiring significant resources and time to retrain the annotation team.

CHAPTER 4

PROPSED SYSTEM

4.1 GENERAL BACKGROUND

The proposed system is a comprehensive solution designed to address the limitations of traditional methods for uniform detection and attendance tracking. It leverages state-of-the-art technologies in computer vision, machine learning, web development, and cloud services to provide a more accurate, efficient, and automated process.

The system begins with image segmentation, where it uses bounding boxes to segment the images. This is a common technique in computer vision used to locate objects of interest in an image. By drawing bounding boxes around these objects, the system can focus on specific areas for further processing, reducing computational load and improving efficiency.

For feature extraction, the system uses YOLOv5, a state-of-the-art object detection model. YOLO, which stands for “You Only Look Once,” is known for its speed and accuracy. Unlike other object detection models that require multiple passes through the image, YOLO performs detection in a single pass, making it faster and more efficient. The “v5” indicates that this is the fifth version of the model, which has been improved and optimized over time.

The system also includes a face detection module implemented in Python. Face detection is a crucial component of the system as it enables the identification of individuals for attendance tracking. The Python module likely uses machine learning algorithms to detect faces in the segmented images.

All the information, including the extracted features and attendance records, are stored and retrieved from a PostgreSQL database. PostgreSQL is a powerful, open-source object-relational database system known for its robustness, scalability, and performance. It provides advanced features such as multi-version concurrency control and point-in-time recovery, making it an excellent choice for this system.

The entire process is managed through a website using FastAPI as the backend. FastAPI is a modern, fast web framework for building APIs with Python based on standard Python type hints. It’s easy to use and offers automatic interactive API documentation, making it a great choice for managing the system’s operations.

The system also uses AWS cloud services for encoding images for face comparison. AWS, or Amazon Web Services, is a secure cloud services platform that offers computing power, database storage, content delivery, and other functionalities. By leveraging AWS, the system can efficiently handle large volumes of images and perform complex computations for face comparison.

In summary, the proposed system integrates various cutting-edge technologies to provide a comprehensive solution for uniform detection and attendance tracking. It addresses the limitations of traditional methods, such as high labour costs, limited accuracy, difficulties handling variability, slow response times, and inflexibility, offering a more accurate, efficient, and automated solution. By leveraging advances in deep learning, database management, web development, and cloud services, the system is poised to revolutionize uniform detection and attendance tracking in various sectors.

4.1.1 OPENCV

OpenCV is a powerful tool that can be used to develop a system for uniform and attendance tracking. The first step would be to collect video data. This can be done using OpenCV's VideoCapture function, which allows real-time video capture from a camera connected to your computer. The captured frames can then be processed in real-time or stored for later analysis.

For uniform tracking, image processing techniques such as colour detection can be used. For instance, if the uniform has a specific colour, OpenCV functions like in Range can be used to detect this colour in the video frames.

For attendance tracking, face recognition techniques can be applied. OpenCV provides pre-trained models like Haar cascades and the LBPH Face Recognizer for this purpose. Faces detected in the video can be compared with a database of known faces to identify the person and mark their attendance.

4.1.2 FACE DETECTION

OpenCV offers a face recognition module that can be used for face detection. This module primarily uses machine learning algorithms and comes with pre-trained models for this purpose. One of the most commonly used models is the Haar cascades, which is effective in detecting faces in an image or real-time video. The process involves converting the image or video frame to grayscale and then using the detect Multiscale function to identify the faces. Each detected face is returned as a rectangle with coordinates (x, y, w, h), where (x, y) are the coordinates of the top left corner, and w and h are the width and height of the rectangle, respectively. This face detection module forms the basis for further processes like face recognition, where each detected face can be compared against a database of known faces for identification. It's a powerful tool but requires careful calibration to work effectively in different lighting conditions and orientations. It's also important to consider privacy and ethical implications when using such technology.

4.1.3 UNIFORM DETECTION

Detecting uniforms using YOLOv5 involves a series of steps. You start by collecting and annotating your dataset, which should contain images of the uniforms you want to detect. After annotation, you set up the YOLOv5 environment, define your model configuration and data configuration YAML files, and then train the YOLOv5 model on your dataset. Once the model is trained, you can test it on new images to see how well it can detect uniforms. Finally, you evaluate the model's performance using metrics like precision, recall, and mean Average Precision (mAP) to understand how well your model is performing and if you need to further fine-tune it. This is a high-level overview of the process, and each step involves more detailed procedures that you might need to follow based on your specific use case and environment. Always refer to the official YOLOv5 documentation for the most accurate and detailed instructions.

4.1.4 POSTGRESQL

PostgreSQL is a robust, open-source object-relational database system that can be used to manage a wide range of data, including student and advisor information, student images, and attendance records. You can create tables for students and advisors, each with relevant fields. For instance, the student table might include fields like student_id, name, major, advisor_id, student_image, and attendance. The advisor table could have fields like advisor_id, name, and department. The student_image field can be of BYTEA or BLOB data type to store the binary data of images, and the attendance field can be a boolean or date type depending on your requirements. Relationships can be established between these tables, such as linking each student to their respective advisor using the advisor_id. PostgreSQL's advanced features like transactions, views, and stored procedures can further enhance the management and analysis of your data. Remember to follow best practices for database design and security, especially when handling sensitive data like images.

4.2 SYSTEM ARCHITECTURE

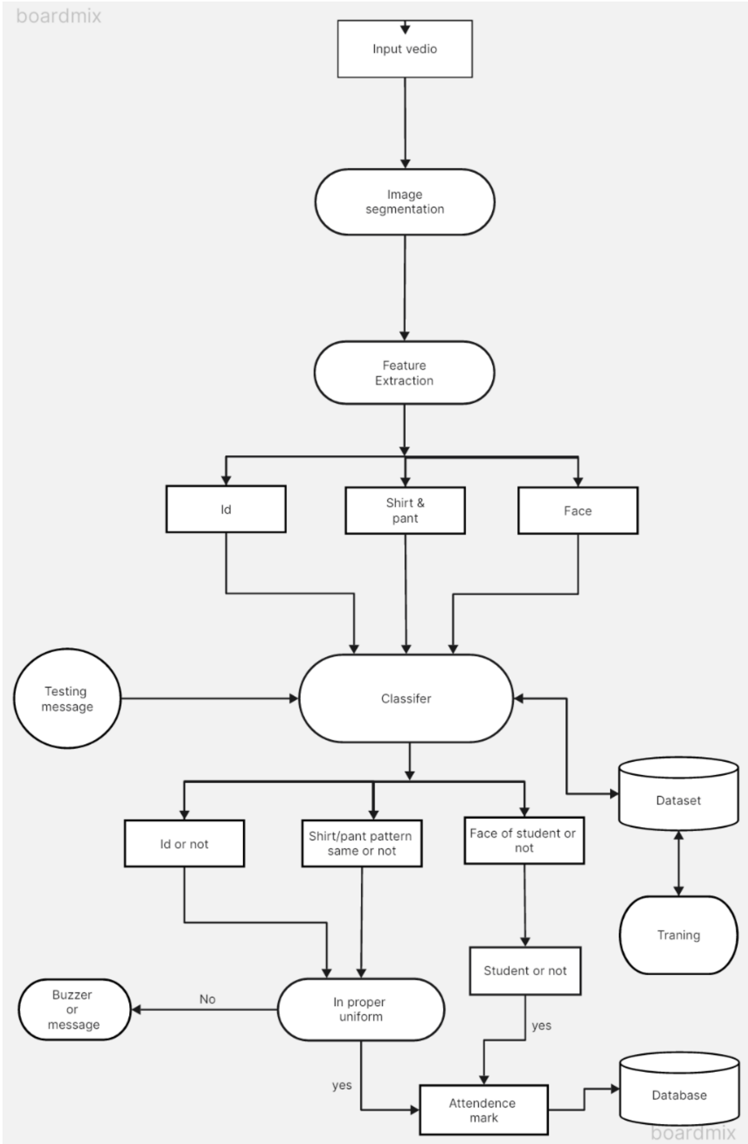


FIG 4.1 System architecture

1. **Input Video:** The process begins with an input video, likely footage from a surveillance camera in a school environment.
2. **Image Segmentation:** The video frames are processed for image segmentation, where bounding boxes are drawn around potential areas of interest. This could be individual students in the frame.
3. **Feature Extraction & Sort:** The segmented images are then passed through a feature extraction process. This uses YOLOv5, a state-of-the-art object detection model, to identify and sort the features of interest.

4. **Face Detection & ID Check:** The system then branches into two paths. One path uses a Python module for face detection to identify whether the face belongs to a student or staff member. The other path checks for a matching ID from the features extracted.
5. **Attendance Update & Alert System:** If a match is found, the system checks the attendance status and updates it accordingly. If no match is found, an alert is triggered.
6. **Database Interaction:** All the information is stored and retrieved from a PostgreSQL database. This includes attendance records and feature data.
7. **Web Interface & Cloud Services:** The entire process is managed through a website using FastAPI as the backend. AWS cloud services are used for encoding images for face comparison.

This system architecture integrates various technologies such as machine learning ,database management ,web development , and cloud services for efficient processing and storage of data related to attendance tracking through facial recognition. It aims to overcome the limitations of traditional methods and provide a more accurate, efficient, and automated solution for uniform and attendance tracking.

4.3 ADVANTAGES OF PROPOSED SYSTEM

1. **Unparalleled Precision, Speed, and Efficiency:** The system leverages the latest advancements in computer vision and machine learning to accurately identify and classify different types of uniforms in images with high precision and speed.
2. **Robust Preprocessing and Feature Extraction**: The system uses Median Filters for preprocessing to eliminate noise and enhance the overall quality of the images. It also uses Histogram of Gradient (HOG) feature extraction to capture the unique characteristics of each uniform, such as colour, texture, and pattern.
3. **Advanced Object Detection:** The system employs both RCNN and YOLO series models for object detection, which identify the locations and boundaries of the uniforms in the images.
4. **Data Augmentation:** The system applies data augmentation techniques to the datasets during training, generating additional training data by rotating, scaling, flipping, and cropping the existing images. This increases the robustness of the model by simulating various scenarios.

5. **Precise Image Segmentation:** The system uses the Mask R-CNN model for image segmentation, which precisely identifies and separates the uniform regions from the rest of the image.
6. **Automated Attendance Marking:** The system locates and extracts faces from the uniform images using Mask R-CNN and marks attendance based on the detected faces. Notifications are subsequently sent to teachers or relevant authorities, ensuring that the attendance tracking process is automated, streamlined, and accurate.
7. **Adaptability:** The system is capable of learning and adapting to various environmental factors, such as diverse lighting conditions, poses, and occlusions, resulting in superior performance and accuracy.
8. **Robustness and Error Resistance:** The integration of multiple models and techniques ensures that the system is highly robust and resistant to errors, enhancing its effectiveness in real-world scenarios.
9. **Versatility:** The system offers a powerful and versatile solution for various industries, including education, healthcare, law enforcement, and beyond.
10. **Scalability:** The system’s cutting-edge architecture enables it to deliver unmatched accuracy, efficiency, and scalability, poised to revolutionize the way we detect and classify uniforms in images, streamlining processes, improving accuracy, and enhancing productivity across various sectors.

4.4 SYSTEM DESIGN

4.4.1 SYSTEM WORKFLOW

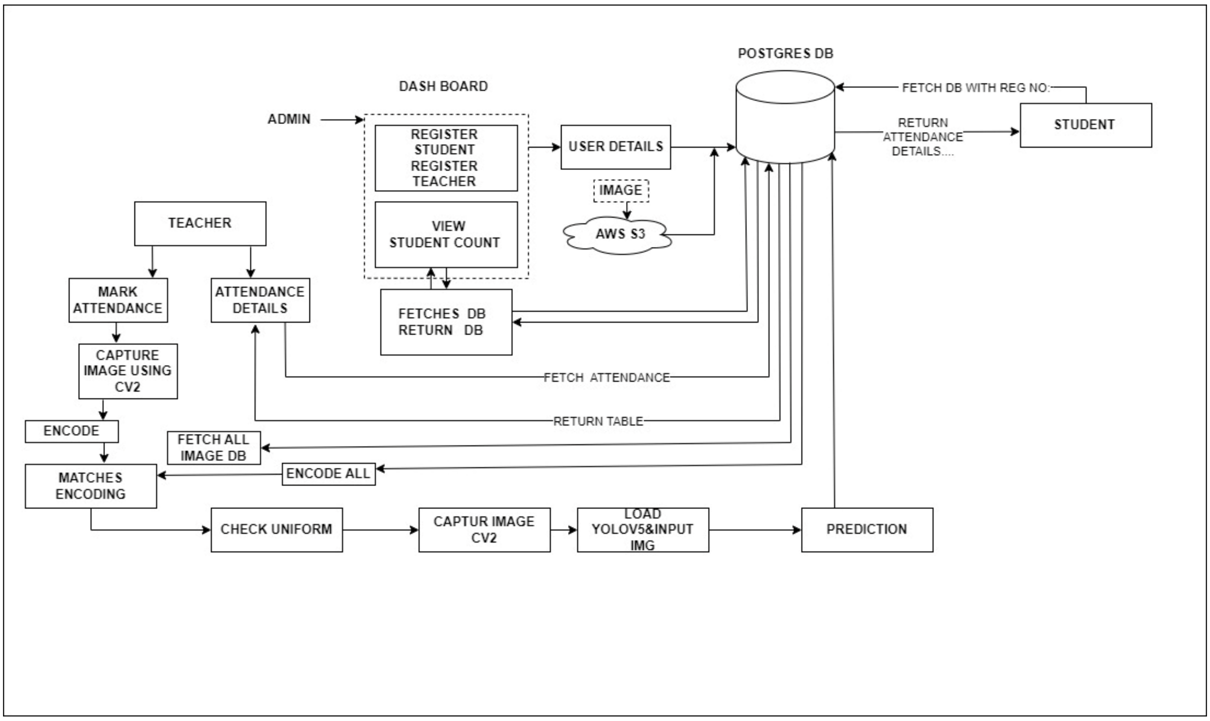


FIG 4.2 Workflow Diagram

- **Admin :** These are the primary users of the system. They have the authority to register new students and teachers into the system. This registration process involves entering relevant details such as name, class, section, and other necessary information. The system is designed to be user-friendly, allowing admins and teachers to easily navigate through the interface and perform necessary actions.
- **Teacher:** Teachers are registered by the admin. They have the ability to mark attendance for the students. The attendance is marked by capturing images using OpenCV, checking uniforms using YOLOv5, and encoding matches for face recognition.
- **Student:** Students are registered by the admin. Their attendance is marked by the teachers using the system. The system captures their images, checks their uniforms, and uses face recognition to confirm their identity.
- **Dashboard:** This is the central hub of the system where users can view and manage information. It provides a visual representation of the data, making it easier for users to understand and interpret. The dashboard might display various metrics such as total

number of students, attendance percentage, number of students in uniform, etc. It provides a quick overview of the current status and allows users to drill down for more detailed information.

- **User Details:** This component of the system is where the details of the students and teachers are stored. It includes information such as name, age, class, section, and other relevant details. This data is crucial for the system to identify individuals and track their attendance. It also allows the system to maintain a record of each individual's attendance history.
- **Postgres DB:** This is the backbone of the system where all the user details, attendance records, and other data are stored. PostgreSQL is a powerful, open-source object-relational database system known for its robustness, scalability, and performance. It provides advanced features such as multi-version concurrency control and point-in-time recovery, making it an excellent choice for this system. The use of a database ensures that the data is organized, secure, and easily accessible.
- **Encode Face Details:** This suggests that the system uses facial recognition technology. The faces are encoded for future matching. This encoding process involves converting the facial features into a unique numerical representation that can be compared with other encoded faces. This is a crucial step in the attendance tracking process as it allows the system to identify individuals based on their facial features.
- **Matching Encodes:** This is the process where the system matches the current face encodes with the previously stored encodes to recognize the person. This matching process is what enables the system to identify individuals and mark their attendance. It is a complex process that involves comparing the numerical representation of the current face with the stored encodes to find a match.
- **AWS S3:** This indicates that the system uses AWS S3 for storing images. AWS S3 is a scalable object storage service offered by Amazon Web Services. It is designed to store and retrieve any amount of data from anywhere on the web. By leveraging AWS S3, the system can efficiently handle large volumes of images and perform complex computations for face comparison.

4.4.2 Use Case Diagram

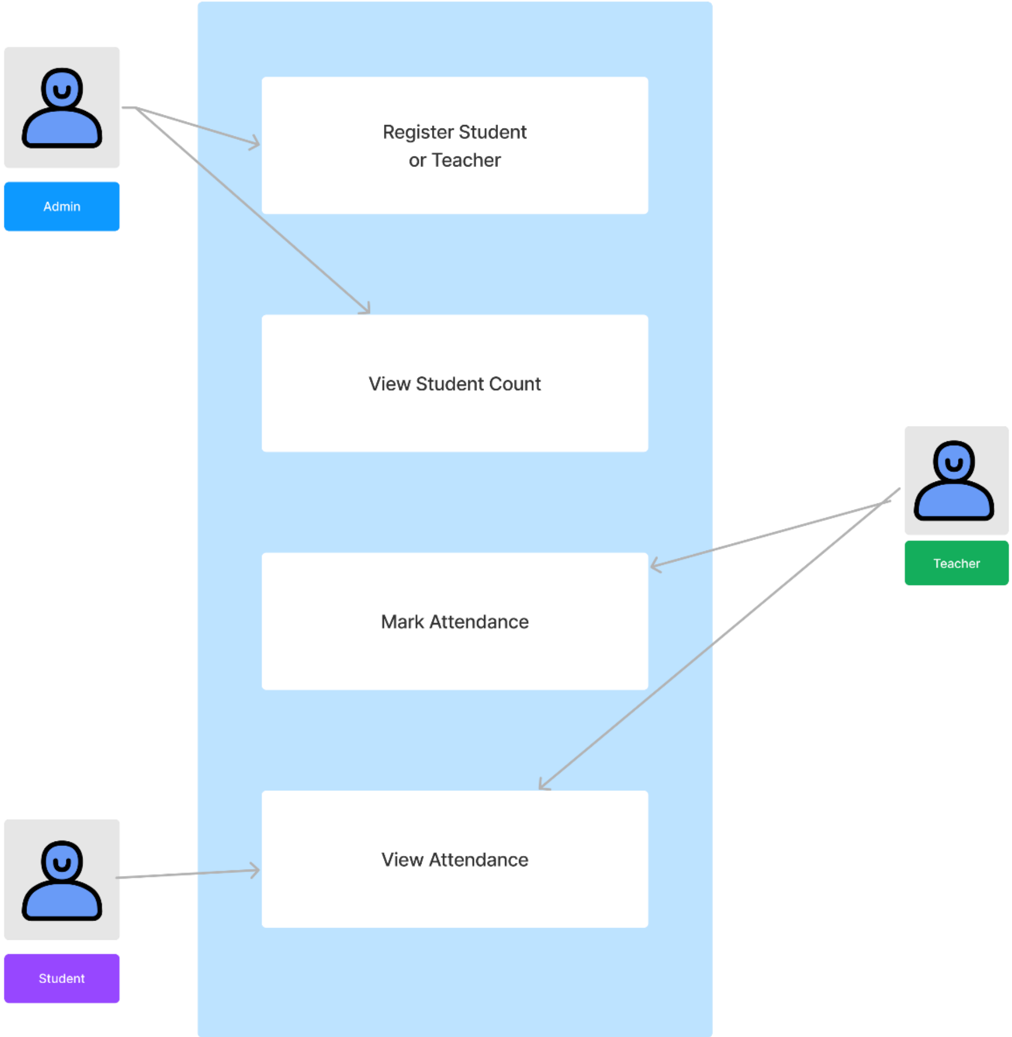


FIG 4.3 Workflow Diagram

The use case diagram represents an educational system with three key actors: Admin, Teacher, and Student. Each actor has specific interactions with the system, defined by their roles and responsibilities.

The Admin is a crucial actor with the authority to register new students or teachers into the system. This registration process is vital as it adds new users to the system, enabling them to access various functionalities based on their roles. The Admin also has the ability to view the total count of students. This function provides a quick overview of the number of students in the system, which can be useful for administrative and planning purposes.

The Teacher is another important actor. Their primary role involves marking attendance for students. This function is essential for tracking student participation and ensuring accountability. Teachers also have the ability to view attendance records. This access allows them to monitor student attendance patterns, identify issues, and take necessary actions.

The Student is the final actor. Their interaction with the system is primarily through the 'View Attendance' use case. This function allows students to check their attendance records, promoting transparency and enabling them to keep track of their attendance status.

The use cases represent the specific functionalities available to the actors. 'Register Student or Teacher' and 'View Attendance' are exclusive for both Admin and attendance tracking. 'Mark Attendance' is exclusive to the Teacher, aligning with their role in student management. 'View Student Count' is specific to the Admin, aligning with their administrative role.

In conclusion, the use case diagram provides a clear picture of the system's functionalities and the interactions of different actors with these functions. It serves as a valuable tool in system design and development, ensuring that all necessary functionalities are covered and appropriately assigned to each user role. By outlining the system's operations, it aids in understanding the system's workflow, facilitating efficient system utilization and management. This diagram is particularly relevant in an educational context, where efficient management of student data and streamlined administrative processes are crucial. It highlights the potential of such a system in enhancing educational administration, paving the way for more effective and efficient educational processes.

4.4.3 SEQUENCE DIAGRAM

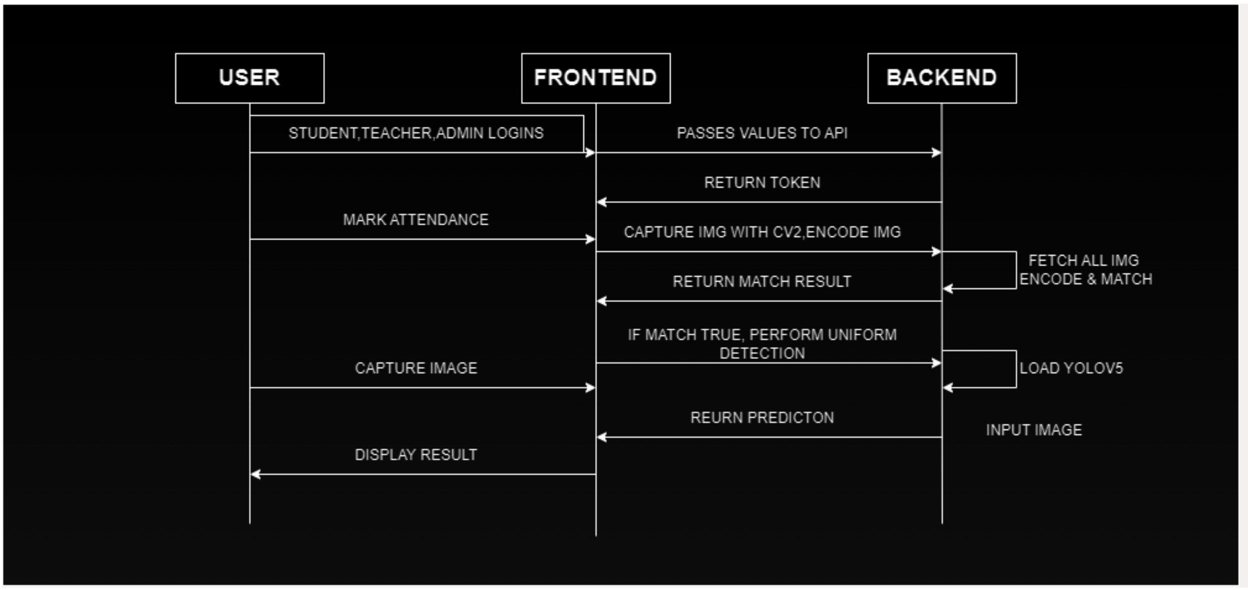


Fig 4.4 Sequence Diagram

This diagram represents the interaction between a user, a frontend, and a backend in a system. Here's a step-by-step breakdown:

1. User Interaction: The user, who can be a student, teacher, or admin, logs into the system. They can mark attendance and capture an image.
2. Frontend Processing: Once the user performs these actions, the frontend takes over. It passes the values to the API and captures the image using the cv2.encode function in OpenCV. If a match is found (presumably, this refers to a face recognition match), it performs an upload action.
3. Backend Processing: The backend receives the data from the frontend. If a match detection is true, it performs an upload action. The backend also has its own set of actions. It fetches all the encoded images and matches them. It loads the YOLOv5 models and inputs the images for processing.

This sequence diagram is a visual representation of how different parts of your software system interact with each other during specific operations related to user authentication and image processing tasks. It outlines how data flows through various components from user input to final output display. This can be very helpful in understanding the flow of data and control in your system.

CHAPTER 5

SYSTEM REQUIREMENTS

5.1 HARDWARE REQUIREMENTS

A computer having 64-Bit windows OS, 4 GB RAM (min), Processing speed of 2.9 GHz wasused for performing all training and testing. The experimentation times are computed with a GPU hardware configuration

5.2 SOFTWARE REQUIREMENTS

Python 3.x: The latest iteration of the language, Python 3.0, is incompatible with previous 2.xreleases. The language is mostly the same, but many details have changed, particularly in the way built-in objects like dictionaries and string function, and many deprecated features have finally been eliminated.

CHAPTER 6

RESULT AND DISCUSSION

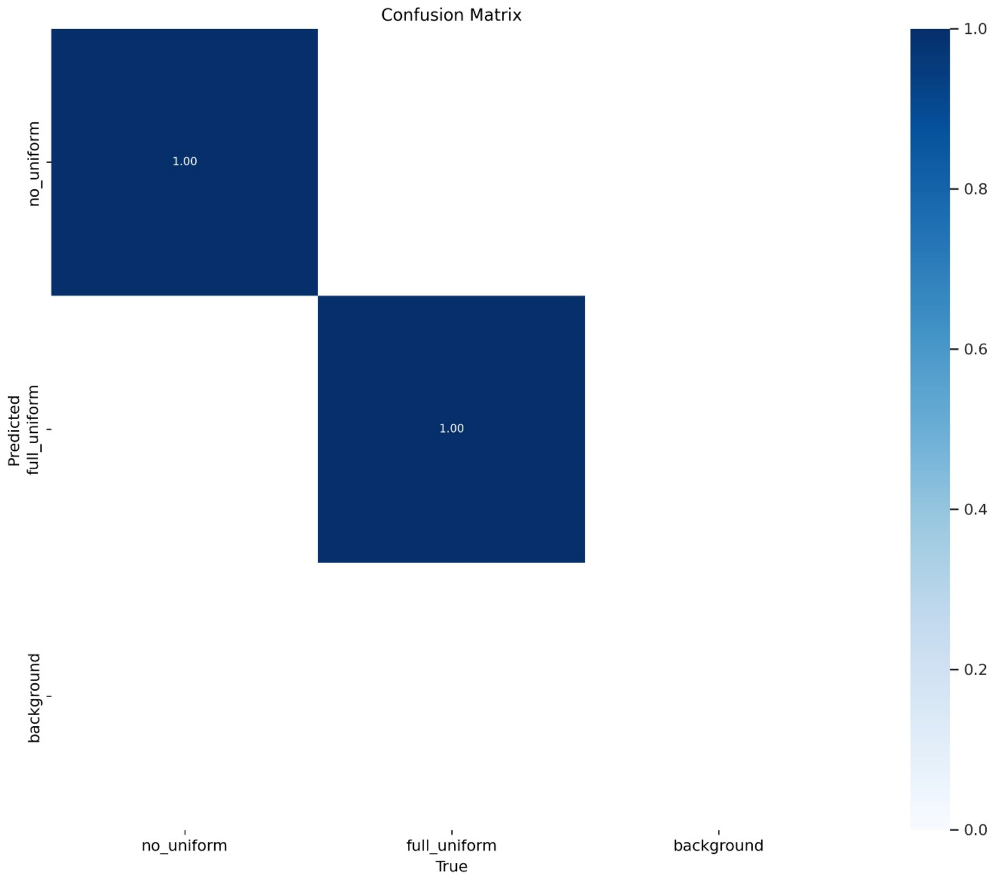


Fig 6.1 Confusion Matrix

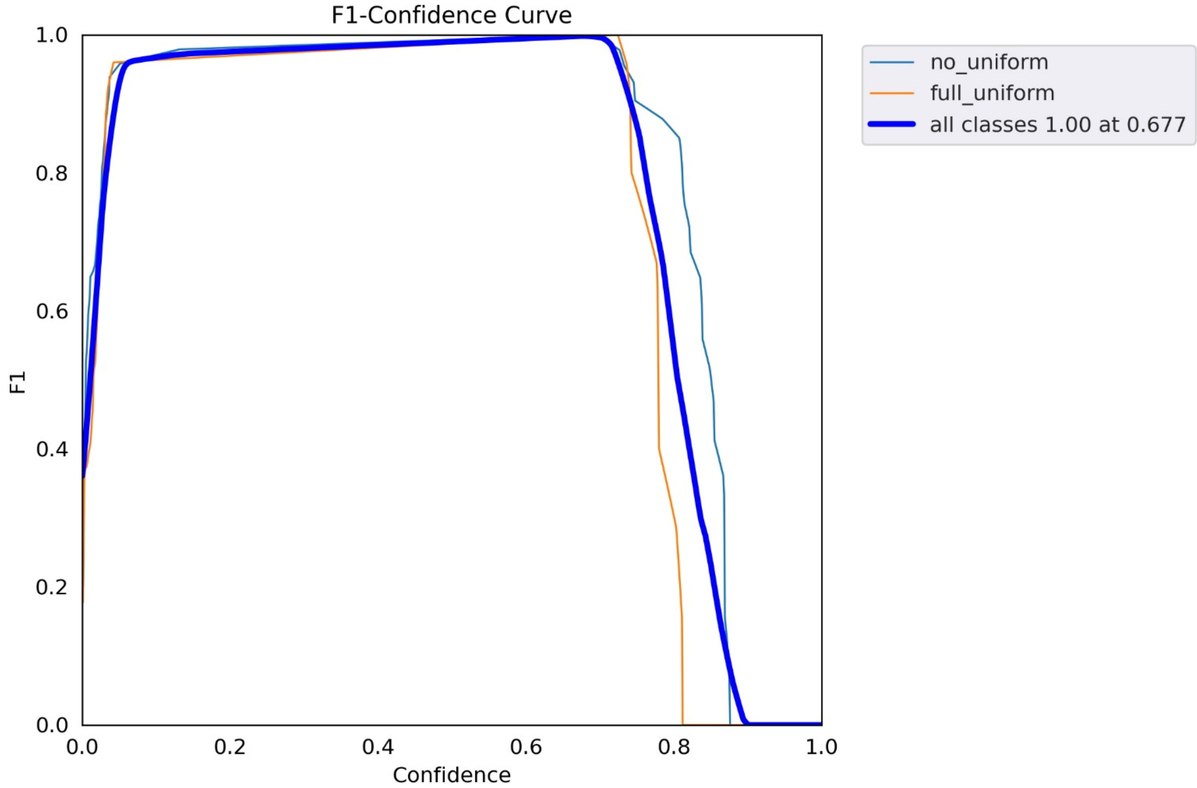


Fig 6.2 Confidence Matrix

Fig 6.3 Result(uniform detection)

Fig 6.4 Result (non uniform detection)

confusion matrix, which is a table used to describe the performance of a classification model. This matrix is particularly useful for understanding the performance of your model in terms of its ability to correctly classify images into 'no_uniform', 'full_uniform', and 'background' classes.

From the image, it seems that your model has achieved perfect classification for the 'no_uniform' and 'full_uniform' classes, as indicated by the value of 1.00 in the matrix. This suggests that your model has been able to correctly identify all instances of these two classes without any false positives or negatives.

In terms of discussion, this result is quite impressive as it indicates a high level of accuracy in your model's predictions. However, it's important to consider other performance metrics as well, such as precision, recall, and F1 score, to get a more comprehensive understanding of your model's performance. Additionally, you might want to test your model on a diverse set of images to ensure that it generalizes well to unseen data.

The 'background' class seems to have lower values, indicating that there might be some misclassifications happening there. You might want to investigate this further, perhaps by looking at the specific instances where the model is making errors and trying to understand why these errors are occurring.

Overall, your model seems to be performing well on the 'no_uniform' and 'full_uniform' classes, but there may be room for improvement in the 'background' class. This could potentially be addressed through techniques such as additional training data, data augmentation, or tuning of the model parameters.

CHAPTER 7

FUTURE SCOPE

The future scope of this project is extensive and holds immense potential. The current system, which uses YOLOv5 for uniform detection and OpenCV for face recognition, coupled with PostgreSQL for data storage, serves as a robust foundation for numerous enhancements and expansions.

The real-time tracking and analysis capabilities of the system can be significantly improved. Immediate feedback on uniform compliance and attendance could be provided, making the system more dynamic and responsive. The uniform detection feature, currently powered by YOLOv5, could be expanded to identify other aspects of student attire. This could include school badges, specific accessories, or even adherence to dress codes on special occasions. Such enhancements would ensure comprehensive compliance with school policies.

The face recognition module, currently using OpenCV, could be improved with the integration of deep learning algorithms. These algorithms could provide more accurate and efficient recognition capabilities. They could handle varying lighting conditions, different angles, and changes in appearance, such as hairstyles or glasses, making the system more robust and reliable.

The integration with PostgreSQL allows for efficient storage and retrieval of student and advisor details. However, the potential of this integration goes far beyond mere storage. It opens avenues for advanced data analytics, which could help identify trends and patterns in attendance. This could provide valuable insights for the management, helping them understand attendance behaviour and take necessary actions.

The webpage interface of the system could be optimized for mobile devices. This would allow parents and advisors to monitor attendance and uniform compliance on the go, making the system more accessible and user-friendly. Notifications could be integrated into the system, alerting parents or advisors of any non-compliance immediately.

Furthermore, the system could be integrated with other institutional systems such as grading or disciplinary systems. This would provide a comprehensive overview of student performance and behaviour. It could help identify correlations between attendance, uniform compliance, and academic performance, providing a holistic view of the student’s school life.

The potential for expansion and enhancement is immense, making this project a valuable tool for educational institutions. As technology advances, the system could incorporate more features, such as automatic generation of reports, integration with school calendars, or even predictive analytics for attendance. This project, therefore, holds the promise of transforming how educational institutions manage attendance and uniform compliance, leveraging technology for efficient and effective management. The future scope is vast, and with the right enhancements, this project could set a new standard for educational management systems.

CHAPTER 8

CONCLUSION

In conclusion, the proposed system represents a significant advancement in the field of uniform detection and attendance tracking. It is a testament to the power of integrating multiple technologies to solve complex problems. By leveraging state-of-the-art techniques in image segmentation, feature extraction, face detection, and database management, the system offers a comprehensive solution that addresses the limitations of traditional methods.

The use of bounding boxes for image segmentation allows the system to focus on specific areas of interest, reducing computational load and improving efficiency. The application of YOLOv5 for feature extraction enables the system to identify and classify uniforms with high precision and speed. The inclusion of a Python module for face detection ensures accurate identification of individuals for attendance tracking. All these processes are tied together with a PostgreSQL database that provides robust and scalable data management.

The system's backend is managed through a website using FastAPI, a modern, high-performance web framework for building APIs with Python. This allows for easy management of the system's operations and provides a user-friendly interface for users. The use of AWS cloud services for encoding images for face comparison further enhances the system's capabilities, allowing it to handle large volumes of images and perform complex computations efficiently.

The proposed system not only improves the accuracy and efficiency of uniform detection and attendance tracking but also offers scalability and adaptability. It can easily accommodate new students or updates to school policies, making it a versatile solution for various industries, including education, healthcare, law enforcement, and beyond.

Moreover, the system's ability to provide real-time feedback and alerts ensures timely and effective communication with teachers and relevant authorities. This feature is particularly beneficial in a school environment, where timely attendance tracking and uniform compliance are crucial.

In essence, the proposed system is a powerful tool that harnesses the potential of deep learning, computer vision, web development, and cloud services to revolutionize uniform detection and attendance tracking. It stands as a shining example of how technology can be used to streamline processes, improve accuracy, and enhance productivity. As we move forward, systems like this will undoubtedly play a pivotal role in shaping the future of various sectors, driving efficiency, and fostering innovation.

In a world where technology is rapidly evolving, the proposed system serves as a reminder of the limitless possibilities that lie ahead. It is a testament to human ingenuity and the power of technology to transform our lives for the better. As we continue to explore and push the boundaries of what is possible, systems like this will undoubtedly lead the way, lighting the path towards a future where technology and human ingenuity work hand in hand to solve complex problems and create a better world.

REFERENCES

[1].L. Ren, J. Lu, J. Feng and J. Zhou, "Uniform and Variational Deep Learning for RGB-D Object Recognition and Person Re-Identification," in IEEE Transactions on Image Processing, vol. 28, no. 10, pp. 4970-4983, Oct. 2019, doi: 10.1109/TIP.2019.2915655.

[2].Praveen, Boddu. (2020). THE SMART DRESS-CODE MONITORING SYSTEM(SDCMS) FOR STUDENTS IN SCHOOLS.

[3].V.S., Pamulapati, Y.S. Rohan, V.S Kiran, S. Sandeep, and M.S. Rao, " Real-Time Face Tracking Using Matlab And Arduino". Electronics And Communication Engineering, Vasireddy Venkatadri Institute Of Technology, 2018

[4]. A. Soleimani, N. M. Nasrabadi, E. Griffith, J. Ralph, and S. Maskell, "Convolutional Neural Networks for Aerial Vehicle Detection and Recognition," NAECON 2018 - IEEE National Aerospace and Electronics Conference, Jul. 2018.

[5]. C. Wei and X. Yang, "Dress Code Surveillance at Power Grid Construction Site via Object Detection," *2021 3rd International Conference on Electrical Engineering and Control Technologies (CEECT)*, Macau, Macao, 2021, pp. 203-207, doi: 10.1109/CEECT53198.2021.9672656

[6]. A. Antoniou, A. Storkey, and H. Edwards, "Data augmentation generative adversarial networks," arXiv preprint arXiv:1711.04340, 2017.

[7]. D. E. Holler, M. Behrmann, and J. C. Snow, "Real-world size coding of solid objects, but not 2-D or 3-D images, in visual agnosia patients with bilateral ventral lesions," Cortex, vol. 119, pp. 555–568, Oct. 2019

[8]. M. Andriluka, L. Pishchulin, P. Gehler, and B. Schiele. 2D human pose estimation: New benchmark and state of the art analysis. In CVPR, 2014. 8

[9]. Justin J, Alexandre A, Li FF. Perceptual losses for real-time style transfer and super-resolution. ECCV. 2016;2016:694–711.

APPENDIX

SOURCE CODE

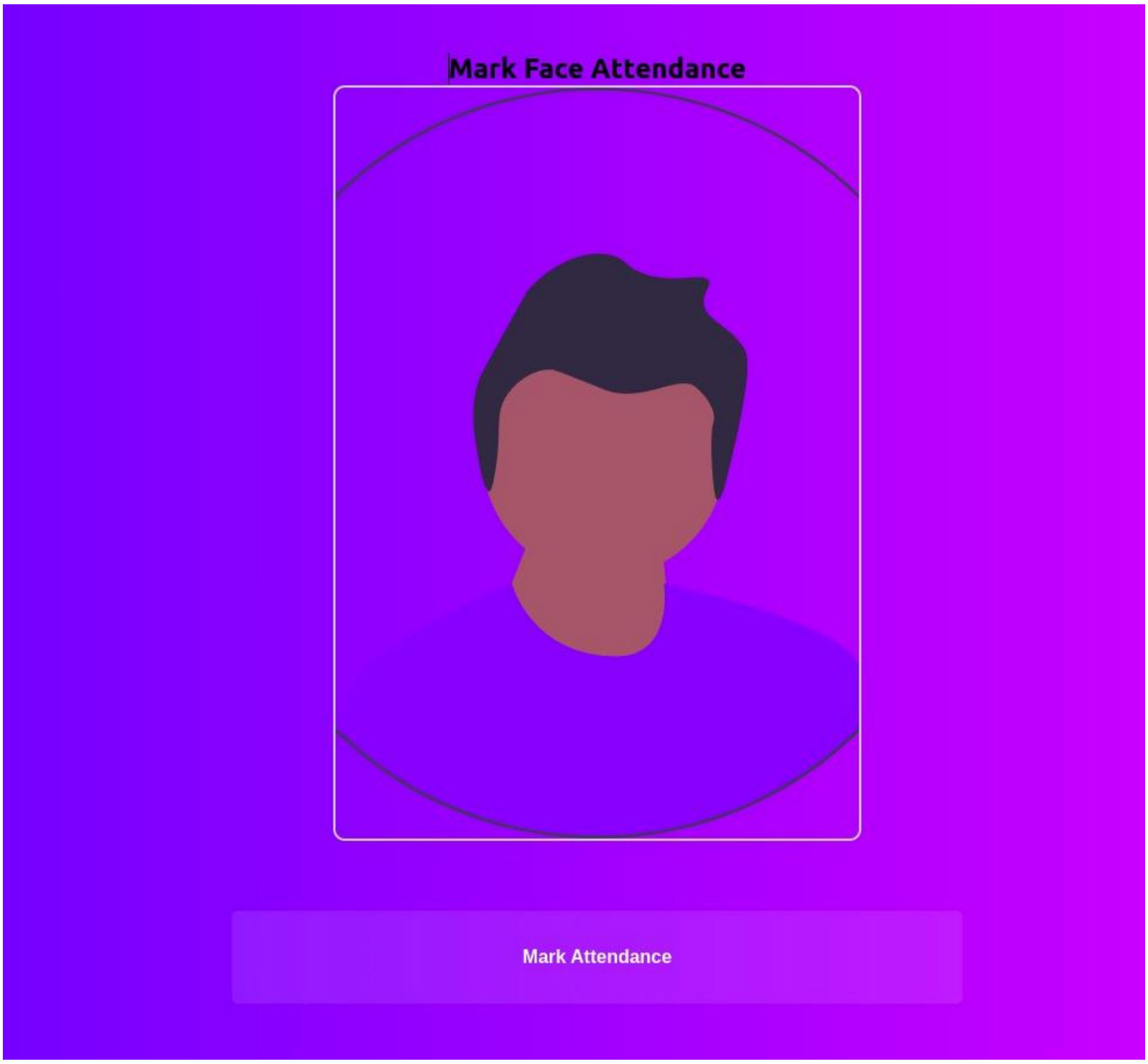
LOADING AND ENCODING FACE

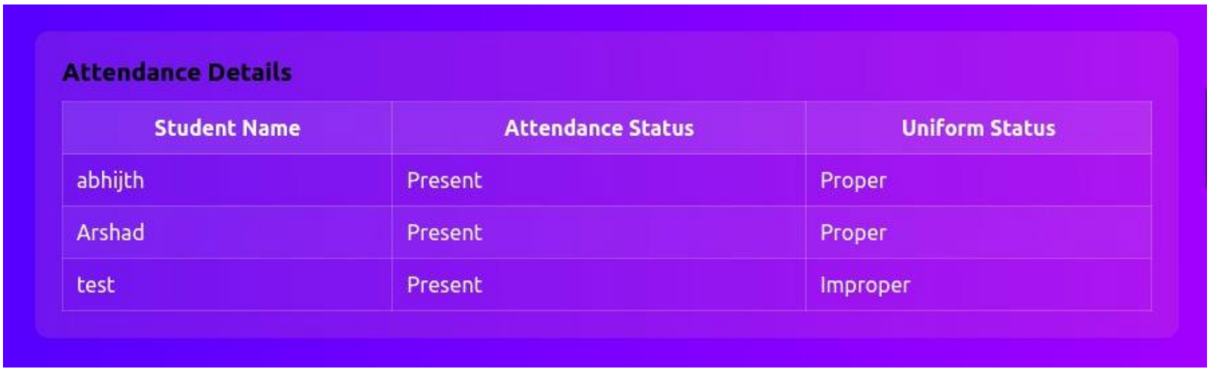
```python
current_dir = os.path.dirname(os.path.abspath(__file__))
yolov5_dir = "/home/nevin/Documents/yolov5" # Modify this path as per your setup
detect_py_path = os.path.join(yolov5_dir, "detect.py")

# Load face encodings from database
async def load_known_faces():
    async with database.transaction():
        query = "SELECT photo, name FROM student"
        results = await database.fetch_all(query)

    known_faces = []
    known_names = []
    for row in results:
        photo_path = os.path.join(current_dir, "images", row['photo'])
        known_faces.append(face_recognition.load_image_file(photo_path))
        known_names.append(row['name'])

    return known_faces, known_names

# Encode known faces
async def encode_known_faces():
    known_faces, known_names = await load_known_faces()
    known_encodings = []
    for img in known_faces:
        face_encoding = face_recognition.face_encodings(img)
        if len(face_encoding) > 0:
            known_encodings.append(face_encoding[0])
        else:
            print("No face found in one of the images.")
    return known_encodings, known_names

```

UNIFORM DETECTION MODEL LOADING

```python

# Path to the YOLOv5 project directory
YOLOV5_PROJECT_DIR = "/home/arshad/Documents/yolov5"
# Path to the detect.py script
DETECT_SCRIPT_PATH = os.path.join(YOLOV5_PROJECT_DIR, "detect.py")
# Path to the directory where detection results are temporarily saved
DETECT_RESULT_DIR = os.path.join(YOLOV5_PROJECT_DIR, "runs/detect")
# Path to store the final result
FINAL_RESULT_DIR = "/home/arshad/Documents/projects/test_backend/app/result"
# Absolute path to the weights file
WEIGHTS_FILE = "/home/arshad/Documents/yolov5/runs/train/exp8/weights/last.pt"

# Global variable to count the number of attempts
attempt_count = 0

@app.get("/detect-uniform")
async def detect_uniform(name: str = Query(..., description="The name of the student")):
    global attempt_count



    # Initialize webcam
    video_capture = cv2.VideoCapture(0)

    # Capture a single frame
    ret, frame = video_capture.read()

    # Capture photo
    image_path = "/home/arshad/Documents/yolov5/data/train_data/images/test/uniform_test.jpg"
    cv2.imwrite(image_path, frame)

    # Release the webcam
    video_capture.release()

    # Run uniform detection model
    command = [
        "/home/arshad/anaconda3/envs/yolov5custom/bin/python3",
        DETECT_SCRIPT_PATH,
        "--weights",
        WEIGHTS_FILE,
        "--source",
        image_path,
        "--project",
        FINAL_RESULT_DIR,
        "--name",
        "exp",
        "--exist-ok"
    ]
    subprocess.run(command)

```

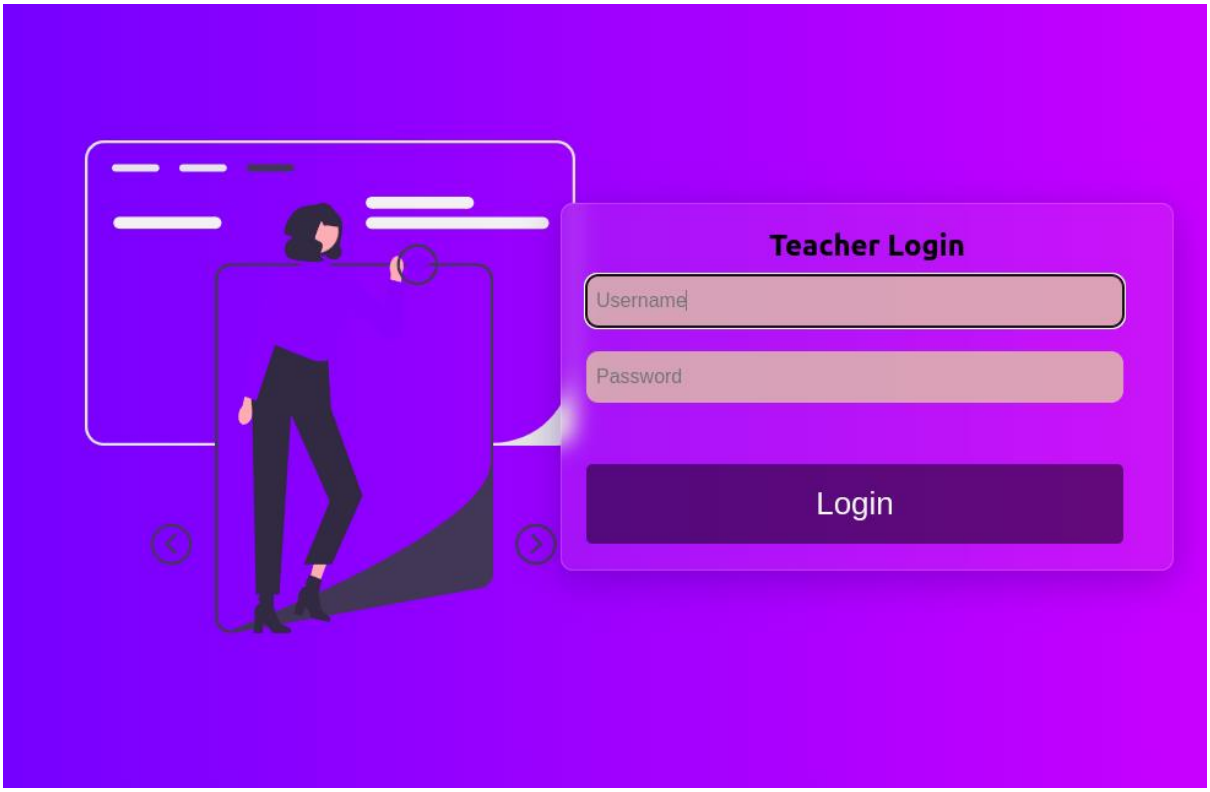
USER INTERFACE

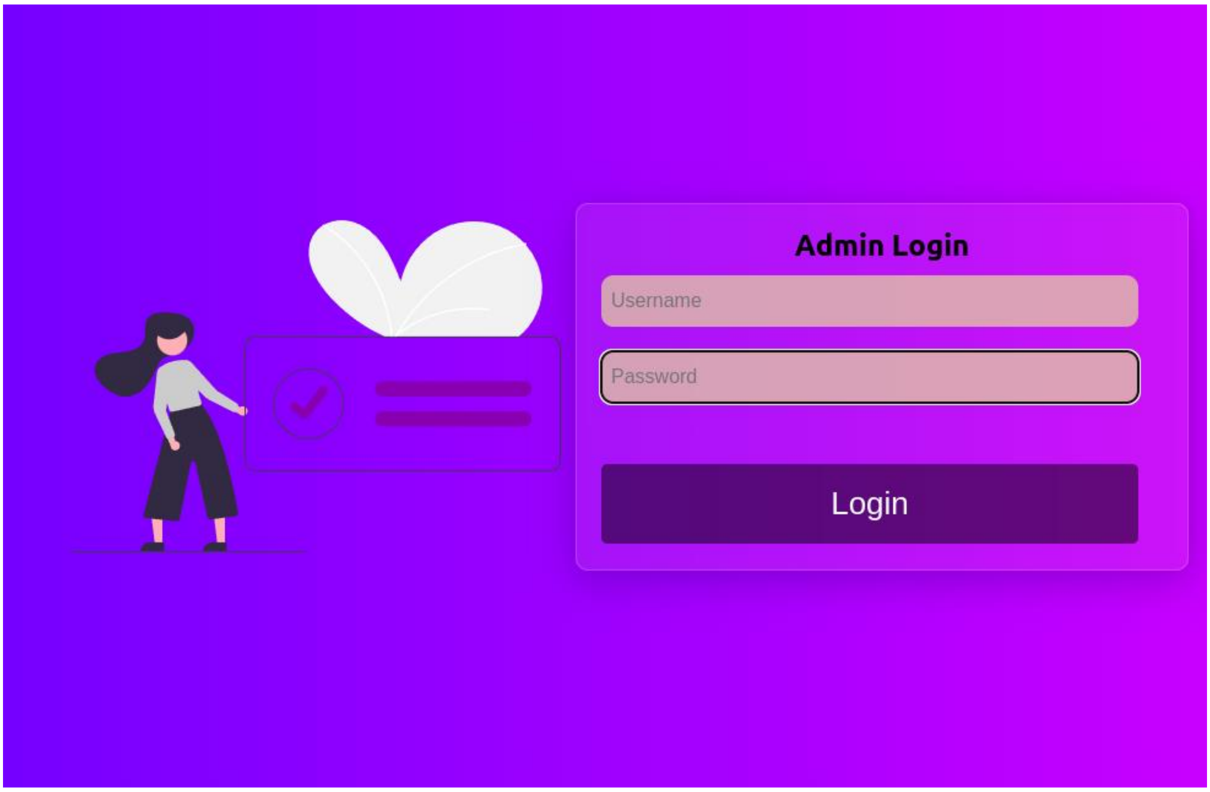


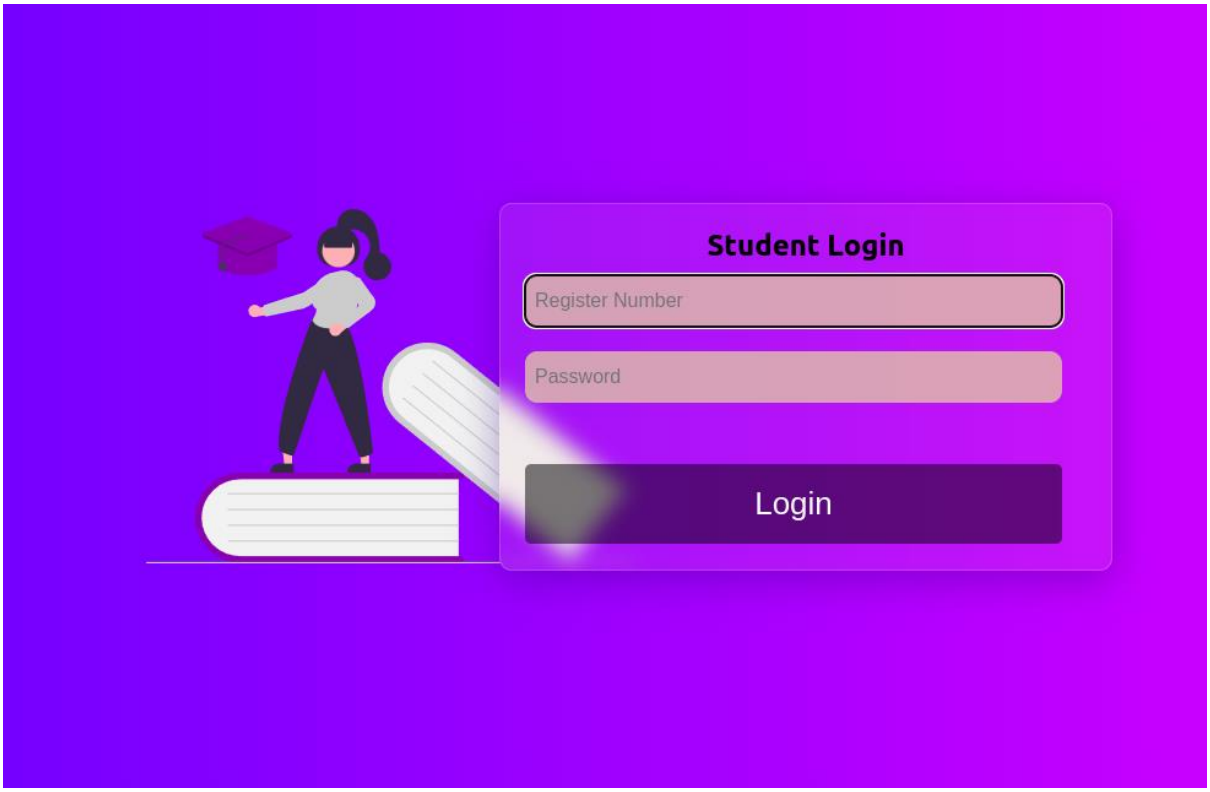


Attendance Details

Student Name	Attendance Status	Uniform Status
abhijth	Present	Proper
Arshad	Present	Proper
test	Present	Improper


Teacher Login
Username
Password
Login


Admin Login
Username
Password
Login


Student Login
Register Number
Password
Login