IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

PERSONAL PROTECTIVE EQUIPMENT DETECTION IN CHEMICAL INDUSTRY

[1]Mohanraj S, [2]Dineshkumar S, [3]Kalaivani M, [4]Monish S
[1]Assistant Professor, [2 3 4]UG Scholars
[1 2 3 4]Department of Artificial Intelligence and Data Science,
[1 2 3 4]KGiSL Institute of Technology, Coimbatore, India

Abstract: The YOLOv8 algorithm is a deep learning-based object detection method that can recognize items inside an image with high accuracy. The system was trained on a huge collection of photos of employees wearing various PPE configurations, such as gloves, masks, goggles, and suits, allowing it to accurately recognize PPE usage. Real-time monitoring and alarms may be supplied to guarantee that safety standards are followed at all times by integrating the system with current security and safety monitoring systems. This technology integrates easily with current security and safety monitoring systems, enabling real-time monitoring and alarms to verify that safety standards are followed. The suggested method has the potential to considerably enhance chemical sector safety outcomes. The technology decreases the risk of accidents and injuries caused by PPE breaches by automating PPE detection. The system can also contribute to a safer working environment for employees by protecting them from dangerous chemicals and operations. Furthermore, by decreasing the requirement for manual monitoring and inspection by safety people, the system can increase operating efficiency and free up safety workers for other activities. Furthermore, by training the YOLOv8 algorithm on other datasets, this solution can be applied to multiple industries that need PPE compliance, such as healthcare and construction, allowing it to recognize particular forms of PPE, such as surgical masks and hard helmets.

***IndexTerms* - PPE Detection, YOLO v8, Deep learning, chemical industries.**

I. INTRODUCTION

Due to the inherent risks involved in handling chemicals, PPE detection is essential in the chemical sector. Workers are exposed to a variety of dangerous substances, therefore wearing protective equipment is important for minimizing accidents and diseases. It can be difficult to ensure safety requirements are followed, especially in big chemical factories with many of employees. Real-time PPE usage monitoring may be carried out automatically and effectively using object identification models like YOLOv8. The YOLO v8 model is a deep learning architecture that combines object identification and categorization using a single neural network. It is well-known for being quick and precise, which makes it perfect for real-time applications like PPE detection. This approach has been used in a variety of domains, including as object identification, facial recognition, and self-driving automobiles. It has been more well-liked recently in the industrial sector, especially for the PPE usage detection. Let's go over the various strategies for PPE detection, such as data augmentation methods, model training, and performance assessment. This survey's objectives are to present a summary of the most cutting-edge methods for PPE detection using YOLO v8 and to suggest topics for further investigation.

II. RELATED WORKS

2.1 Personal Protective Equipment Kit Detection using Yolo v5 and TensorFlow

The paper discusses the use of object detection in various sectors, especially in security and surveillance. Object detection is a technology that can be used to detect objects within an image or video. Performance metrics used to evaluate object detection models include mAP (Mean Average Precision), F1 Score, Precision and Recall. It explains how object detection can be used to detect people wearing masks in public places through the use of TensorFlow and Pytorch models. It focuses not only on the accuracy of the models but also on their deployability. A dataset from Kaggle is obtained and used performance metrics such as mAP, Loss Function, and Learning Rate to compare the TensorFlow Object Detection API and Yolo v5. The paper concluded that the Yolo v5 model is more effective at categorizing data, as evidenced by its lower classification loss compared to TensorFlow.

2.2 Computer Vision System Based for Personal Protective Equipment Detection, by Using Convolutional Neural Network

A system using computer vision technology, specifically a convolutional neural network, has been developed to monitor the completeness of personal protective equipment (PPE) worn by workers in an industrial environment. omputer vision technology is a field of study that focuses on enabling computers to interpret and understand the visual world. It has many applications such as image recognition, object detection, face recognition and more. Safety measures used on construction sites include PPE, safety nets, guardrails, safety harnesses and more. Mean Average Precision (mAP) is a metric used to evaluate object detection models. It is calculated as the average precision at different recall levels and is used to measure how well an object detection model identifies objects. A higher mAP score indicates better performance of the model. This system can detect workers who are not wearing PPE and provide a warning, contributing to decreasing work accidents and increasing worker safety. The system has been tested with 14,512 images and achieved an accuracy of 79.14% with a precision of 80%. The system can be implemented in workplaces with PPE requirements.

2.3 Substation Safety Awareness Intelligent Model: Fast Personal Protective Equipment Detection using GNN Approach

A model has been developed to detect whether personal protective equipment (PPE) is being worn correctly for electrical hazards. The model uses a graph neural network technique and eight types of PPE have been considered, including medical masks. Only 50 images were collected for each PPE type, but the model was trained with diverse samples from multiple environments resulting in a robust and efficient model with a probability of similarity ranging from 79% to 100%. Suggestions on preserving personal privacy and PPE labels have been provided to address existing issues with computer-vision based PPE detection models.

2.4 Real-time Personal Protective Equipment (PPE) Detection Using YOLOv4 and TensorFlow

The system is developed using YOLOv4 computer vision model which performs well in real time object detection. YOLOv4 stands for You Only Look Once version 4 and is a state-of-the-art object detection model that can detect objects in real time with high accuracy. The detector is developed using a combined dataset consisting of collected images and captured images and can detect four classes of objects: face mask, face shield, gloves and person. The object detector has a mAP of 79% which stands for mean average precision and is a metric used to evaluate object detection models. Image augmentation is done on all the training set images which means that the images are modified in various ways to increase the size of the dataset and improve the performance of the model. The detector weight is converted to TensorFlow format to check live detection performance and features like live object count and record keeping are added.

2.5 A Deep Learning Model for Detecting PPE to Minimize Risk at Construction Sites

A deep learning model is developed for detection of PPE ignorance and the presence of unauthorized persons which will help security officers to take the right action to reduce the risk at the construction site. The model uses face recognition technology to alert security officers when workers or anyone entering the construction site without PPE. Mean Average Precision (mAP) is a metric used to evaluate object detection models. It is calculated as the average precision at different recall levels and is used to measure how well an object detection model identifies objects. A higher mAP score indicates better performance of the model. Deep learning is a subset of machine learning that uses artificial neural networks to simulate human decision-making. Safety measures used on construction sites include PPE, safety nets, guardrails, safety harnesses etc,

2.6 A Smart System for Personal Protective Equipment Detection in Industrial Environments Based on Deep Learning at the Edge

This is a system for real-time PPE detection based on video streaming analysis and Deep Neural Network (DNN). The system uses edge computing model in which the application for image analysis and classification is deployed on an embedded system installed in proximity of the camera and directly connected to it. The system does not require continuous image transmission towards a cloud system, thus ensuring bandwidth efficiency, reliability, and workers' privacy. A prototype of the proposed system is developed exploiting a low-cost commercial embedded system, i.e. a Raspberry PI, equipped with an Intel Neural Compute Stick 2. The system is tested with five different pre-trained convolutional neural networks (CNNs), fine-tuned to detect different PPEs, namely helmets, vests, and gloves. In their experimental evaluation, they first compared the five CNNs in terms of classification performance and inference latency. Then, they deployed each CNN on the real system and evaluated the system's throughput regarding the number of video frames analyzed each second.

III. SIGNIFICANCE OF METHODS

The significance of the methods discussed in the papers mentioned above lies in their application of deep learning and computer vision techniques to detect and monitor the usage of Personal Protective Equipment (PPE) in various industrial and public settings. These methods leverage state-of-the-art models such as YOLOv5, YOLOv4, and Convolutional Neural Networks (CNNs) to accurately and efficiently detect PPE items such as masks, face shields, gloves, helmets, vests, etc., in real-time or through image analysis.One key aspect of these methods is their potential to improve safety measures in various environments, such as construction sites, industrial settings, and public places, where the usage of PPE is crucial to prevent accidents and protect workers or individuals from potential hazards. By automatically detecting PPE compliance or non-compliance, these methods can provide timely warnings or alerts to workers or security officers, allowing them to take appropriate actions to minimize risks.

Another significant aspect of these methods is their focus on deployability and efficiency. Many of these methods utilize edge computing, where the deep learning models are deployed on embedded systems such as Raspberry Pi or Intel Neural Compute Stick 2, installed in proximity to the cameras. This allows for real-time analysis and classification of video streams without the need for continuous image transmission to cloud systems, ensuring bandwidth efficiency, reliability, and workers' privacy. Overall, the methods discussed in these papers have significant implications for enhancing safety measures in various environments and improving the effectiveness of PPE compliance monitoring. They demonstrate the potential of deep learning and computer vision techniques in addressing real-world challenges related to PPE usage and contribute to the development of intelligent systems for PPE detection and risk reduction in industrial and public settings.

IV. METHODOLOGY

4.1 YOLO V8 Model

YOLOv8 (You Only Look Once version 8) is an object recognition method that detects things within pictures or video frames using deep learning techniques. The method is part of the YOLO family of object identification algorithms and is widely regarded as one of the most accurate and efficient available today. YOLOv8 expands on prior versions of the YOLO algorithm and includes significant enhancements. One of the most significant advancements is the employment of a deeper neural network design that detects things more accurately. Furthermore, YOLOv8 employs a novel feature pyramid network (FPN) that allows the algorithm to recognize objects at various sizes and resolutions, enhancing object recognition accuracy.

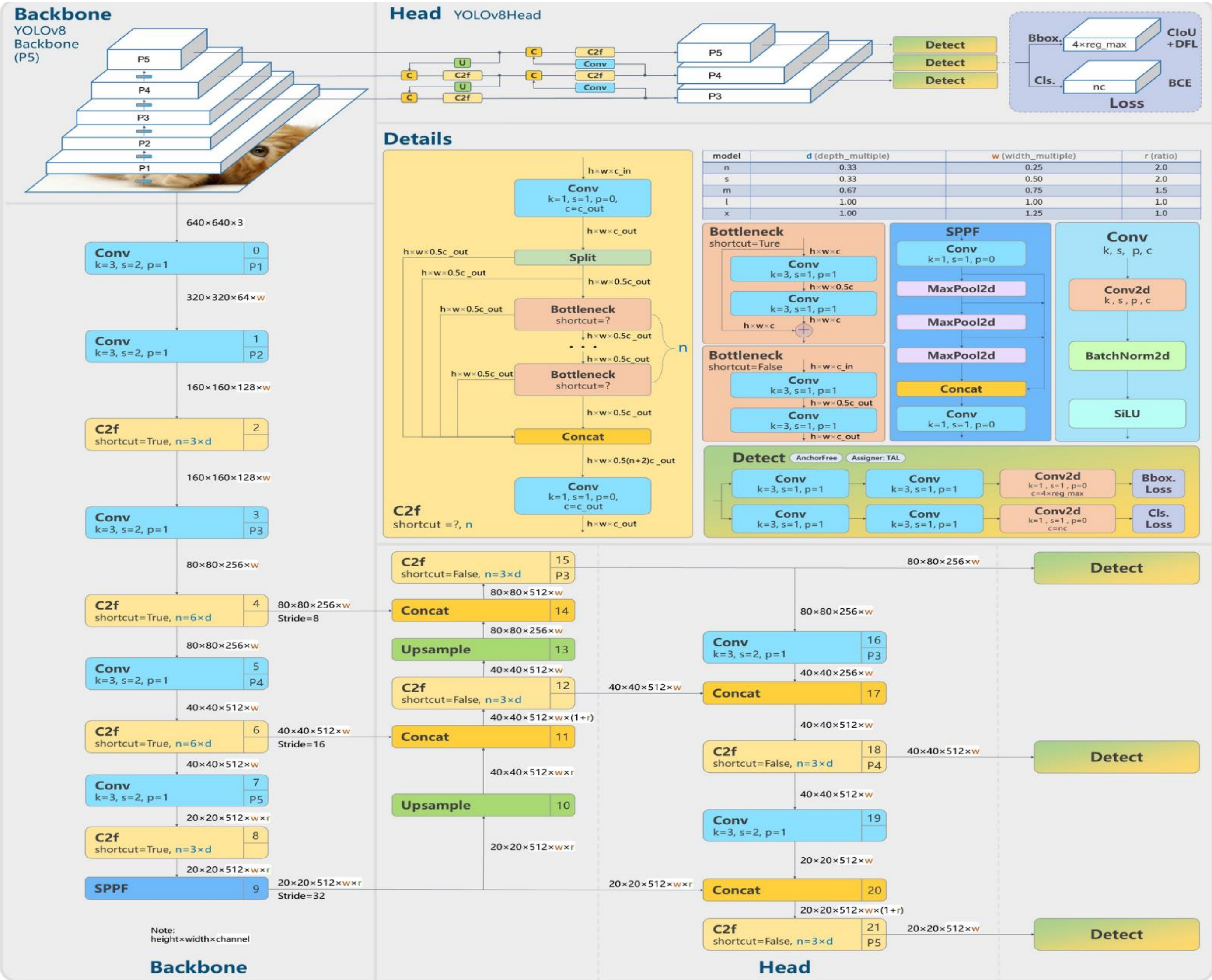

Fig 1.Architecture of YOLOV8

4.2 YOLO V8 working procedure

To utilize YOLOv8 for PPE detection, first collect a collection of photos of employees wearing various PPE configurations like as gloves, masks, goggles, and suits. The system is subsequently trained on this dataset to reliably recognize PPE usage. Once trained, the algorithm may be linked into current chemical industry security and safety monitoring systems, giving real-time monitoring and alarms to guarantee that safety rules are followed. The YOLOv8 algorithm analyses video feeds from security cameras and other sources during operation to recognize employees and their PPE usage. The algorithm can determine whether employees are wearing the requisite PPE, and it can warn safety officials to take appropriate action if PPE breaches are discovered.

- Collect a dataset of images of workers in various PPE configurations, including gloves, masks, goggles, and suits.
- Annotate the images to identify the location and type of PPE worn by workers. This step is crucial to train the algorithm accurately.
- Train the YOLOv8 algorithm on the annotated dataset using a deep learning framework such as TensorFlow or PyTorch. This step involves adjusting the algorithm's parameters to optimize performance.
- Test the algorithm on a separate set of images to evaluate its accuracy and adjust the parameters if necessary.
- Integrate the trained algorithm into the security and safety monitoring system in the chemical industry. This step may require additional hardware and software integration to enable real-time monitoring.
- Set up the algorithm to analyze video feeds from security cameras and other sources to detect workers and their PPE usage.
- Configure the system to alert safety personnel in cases where PPE violations are detected, enabling them to take appropriate action.
- Regularly evaluate the performance of the system and update the algorithm and hardware as necessary to ensure optimal performance.

V. RESULTS AND DISCUSSION

5.1 Results

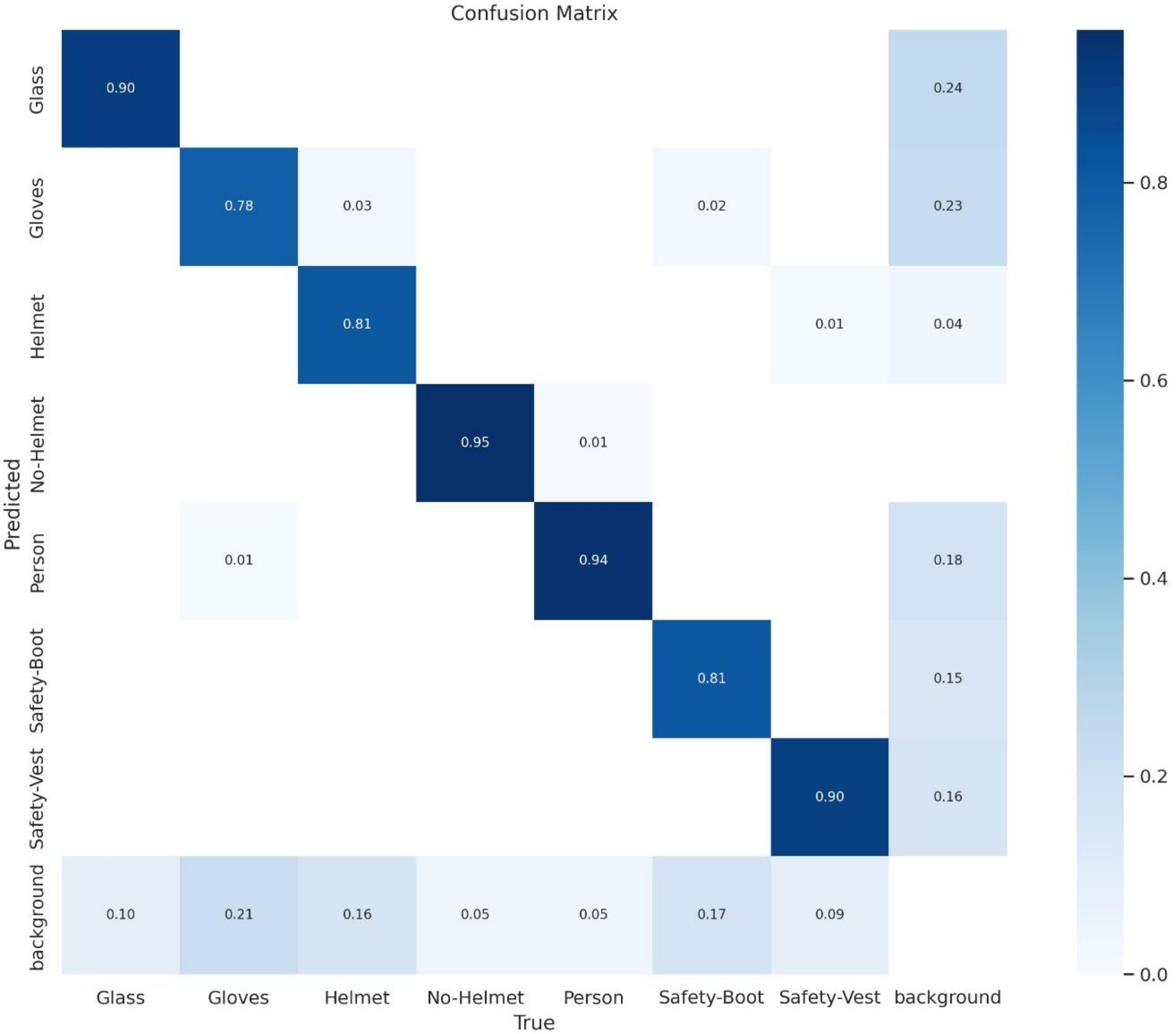

Fig 2. Confusion matrix

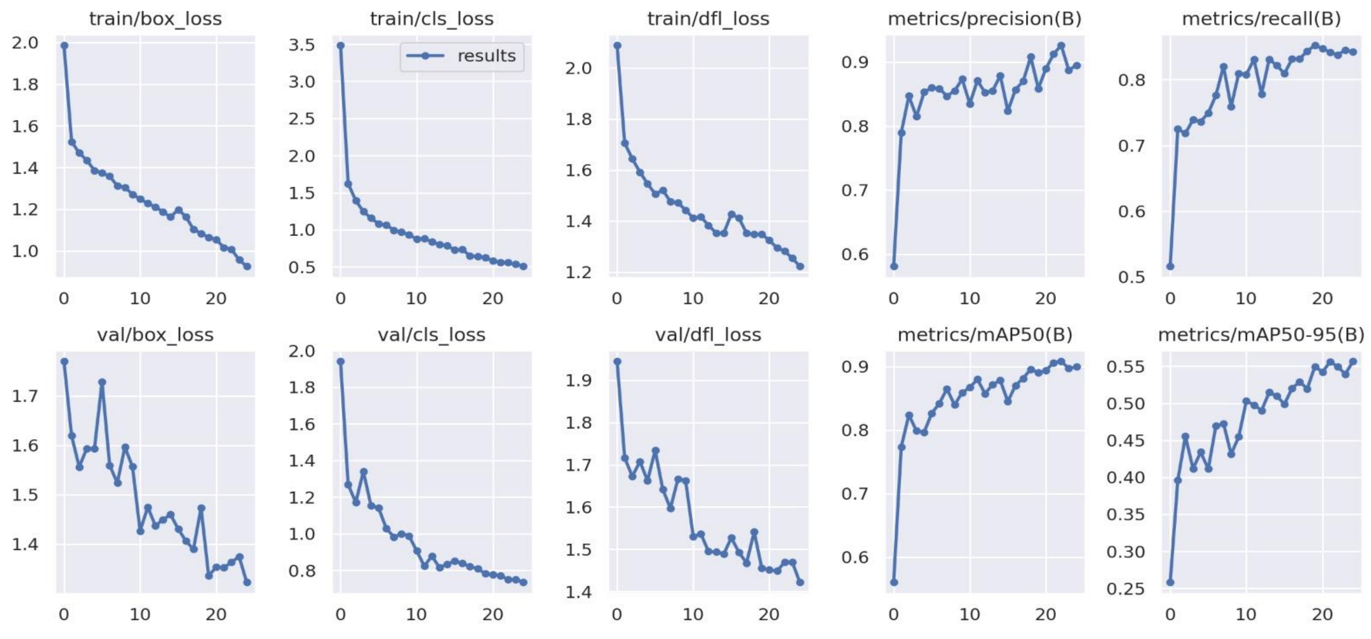

Fig 3. Evaluation metrics

Fig 4. Prediction of PPE on test images using trained model

5.2 Discussion and Challenges.

- Accuracy vs. Real-time Performance: Achieving high accuracy while maintaining real-time performance can be challenging, as it requires striking a balance between model complexity and inference speed.
- Edge Computing Support: Deploying object detection models on edge devices, such as cameras or drones, can be challenging due to limited computational resources and bandwidth.
- Model Interpretability and Explainability: Understanding and interpreting the decisions made by object detection models, including YOLOv8, can be challenging, especially in safety-critical applications where explanations and justifications are important for regulatory compliance.
- Model Deployment and Integration: Integrating YOLOv8 into existing industrial systems or workflows may pose challenges, including model deployment, maintenance, and version control, as well as compatibility with existing hardware and software infrastructure.

VI. ACKNOWLEDGMENT

We would like to thank Dr. Kalpana S, Head of the Department, Department of Artificial Intelligence and Data Science for her firm support during the entire course of this project work and who modelled us both technically and morally for achieving greater success in this project work.

We express our sincere thanks to our guide, Mr. Mohanraj S, Assistant Professor, Department of Artificial Intelligence and Data Science, for his constant encouragement and support throughout the course, especially for the useful suggestions given during the course of the project period and being instrumental in the completion of the project with complete guidance.

We also thank all the faculty members of our department for their help in making this project a successful one. Finally, we take this opportunity to extend our deep appreciation to our Family and Friends, for all they meant to us during the crucial times of the completion of this project.

A huge thanks towards the team members: Dineshkumar S, Kalaivani M, Monish S.

VII. REFERENCES

[1] Meng Zhao; Masoud Barati (2023) - Substation Safety Awareness Intelligent Model: Fast Personal Protective Equipment Detection using GNN Approach https://ieeexplore.ieee.org/document/10008075

[2] Gionatan Gallo; Francesco Di Rienzo; Federico Garzelli; Pietro Ducange; Carlo Vallati (2022) - A Smart System for Personal Protective Equipment Detection in Industrial Environments Based on Deep Learning at the Edge https://ieeexplore.ieee.org/document/9925236

[3] Nigel Dale Then Yung; W. K. Wong; Filbert H. Juwono; Zee Ang Sim (2022) - Safety Helmet Detection Using Deep Learning: Implementation and Comparative Study Using YOLOv5, YOLOv6, and YOLOv7 https://ieeexplore.ieee.org/document/10010490

[4] Adban Akib Protik; Amzad Hossain Rafi; Shahnewaz Siddique (2021) - Real-time Personal Protective Equipment (PPE) Detection Using YOLOv4 and TensorFlow. https://ieeexplore.ieee.org/document/9550808

[5] Ali Taha Ahmed Al Daghan; Vineeta; Snigdha Kesh; Asha S Manek (2021) - A Deep Learning Model for Detecting PPE to Minimize Risk at Construction Sites. https://ieeexplore.ieee.org/document/9622658

[6] Pallavi Udatewar; Abhishek Desai; Gauri Godghase; Arunkumar Nair; Pranali Kosamkar (2021) - Personal Protective Equipment Kit Detection using Yolo v5 and TensorFlow. https://ieeexplore.ieee.org/document/9645811

[7] Faishal Zhafran; Endah Suryawati Ningrum; Mohamad Nasyir Tamara; Eny Kusumawati (2020) - Computer Vision System Based for Personal Protective Equipment Detection, by Using Convolutional Neural Network. https://ieeexplore.ieee.org/document/8901664

[8] Diego Gonzalez Dondo; Javier Andres Redolfi; R. Gastón Araguás; Daiana Garcia (2021) - Application of Deep-Learning Methods to Real Time Face Mask Detection. https://ieeexplore.ieee.org/document/9451245