JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

DETECTING PERSONAL PROTECTIVE EQUIPMENT USING YOLO

Shreyas Likhar[1], Vivek Tripathi[2], Ketki Kshirsagar[3]

[1,2] Students, Department of Electronics & Telecommunication, Vishwakarma Institute of Information Technology[3] Associate Professor, Department of Electronics & Telecommunication, Vishwakarma Institute of Information Technology

Abstract— **The primary objective of this paper is to develop a robust ML model capable of accurately identifying whether workers are wearing appropriate Persona Protective Equipment, including helmets, goggles, vests,gloves, and boots. The proposed system utilizes computer vision algorithms trained on a dataset of annotated images to recognize and classify different types of PPE. Additionally, the model incorporates real-time video processing to enable continuous monitoring of PPE compliance in dynamic work environments. Key components of the project include data collection, preprocessing,model training, and evaluation. Annotated imagesof workers wearing various PPE configurations are collected to construct a comprehensive datasetfor training and testing purposes. Image preprocessing techniques are applied to enhance the quality and consistency of the data. Several ML algorithms, including you only look once (YOLO), are trained on the dataset to learn the visual features associated with different PPE items**

I. INTRODUCTION

In this paper, we explore workplace safety is a fundamental concern across industries whereemployees are exposed to various hazards. Personal Protective Equipment (PPE) serves as a critical line of defense against these risks, yet monitoringcompliance with PPE protocols poses significant challenges. Manual inspection methods are often time-consuming, subject to human error, and may notprovide real-time feedback necessary for proactive risk mitigation. In response to these challenges, advancements in Machine Learning (ML) andcomputer vision offer promising solutions for automating safety analysis processes. [1]

This project focuses on leveraging ML techniques, specifically the You Only Look Once (YOLO) algorithm, to enhance safety analysis through theautomated detection of PPE in industrial settings. By integrating YOLO-based object detectionwithin a comprehensive ML framework, the aim isto develop a system capable of accurately identifying and localizing various PPE items wornby workers. The significance of this project lies inits potential to revolutionize safety management practices by providing efficient, real-time monitoring of PPE compliance. By automating thedetection process, organizations can not only improve the accuracy and reliability of safety inspections but also enable timely interventions toprevent accidents and injuries.

The performance of the developed model is evaluated using metrics such as accuracy, precision, recall, and F1-score. Extensive testing isconducted in simulated and real-world environments to assess the model's robustness andgeneralization capabilities. Furthermore, thesystem's efficiency in detecting PPE compliance is compared against manual inspection methods toquantify its effectiveness in improving workplace safety practices. This project outlines the pressingneed for automated safety analysis solutions, introduces the concept of PPE detection usingYOLO-based Machine Learning, and sets the stage for the subsequent sections where the methodology, implementation, and evaluation of the proposed system will be discussed in detail. Through this endeavor, the project aims tocontribute to the advancement of workplace safetypractices and foster a culture of proactive risk management in industrial environments. [3]

II. LITERATURE SURVEY

literature sources provide foundational knowledge, insights, and methodologies relevant to the project onSafety Analysis with the detection of PPE using Machine Learning using YOLO. They offer valuableinsights into object detection algorithms, techniques,and data sets that can inform the design, implementation, and evaluation of the PPE detection system.

"Real-Time Human Detection using YOLO" by Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi (2016): YOLO (You Only Look Once),a real-time object detection algorithm that can detectobjects in images with a single forward pass of a neural network. It provides insights into the architecture and performance of YOLO, which serves as the foundation for implementing PPE detection in the project. [1]

"YOLOv3: An Incremental Improvement" by Joseph Redmon, Ali Farhadi (2018): YOLOv3, an improved version of the YOLO object detection algorithm. It introduces enhancements to the architecture, including feature pyramid networksand improved bounding box prediction, leading to better detection accuracy and performance. Understanding these improvements is crucial foroptimizing PPE detection in the project. [2]

"Feature Pyramid Networks for Object Detection" by Tsung-Yi Lin, Piotr Dollár, Ross Girshick, Kaiming He, Bharath Hariharan, Serge Belongie(2017): Feature Pyramid Networks (FPN), a framework for building object detection systemswith high accuracy and efficiency. FPN improves the detection of objects at different scales by combining features from multiple levels of aconvolutional neural network. Integrating FPNtechniques may enhance the performance of PPE detection in the project. [3]

"Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields" by Zhe Cao, Tomas Simon, Shih-En Wei, Yaser Sheikh (2017):
an approach for real-time techniques can beneficialfor refining PPE detection, as it involves detecting the presence and configuration of human bodies, which are typically associated with wearing PPE. [4]

"Fast R-CNN" by Ross Girshick (2015): This paper introduces Fast R-CNN, a method for objectdetection that improves upon previous approachesby sharing convolutional features across proposals.While not directly related to YOLO, understandingthe principles of Fast R-CNN can provide insightsinto alternative object detection techniques andtheir potential applications. [5]

"ImageNet: A Large-Scale Hierarchical Image Database" by Jia Deng, Wei Dong, Richard Socher,Li-Jia Li, Kai Li, Li Fei- Fei (2009):
This paper introduces ImageNet, a large-scale dataset widely used for training and evaluatingobject recognition algorithms. ImageNet serves as a valuable resource for training the PPE detection model, providing diverse images of objects and scenes relevant to industrial environments. [6]

"ImageNet Large Scale Visual Recognition Challenge" by Olga Russakovsky, Jia Deng, Hao Su,Jonathan Krause, Sanjeev Satheesh, Sean Ma,
... & Fei-Fei Li (2015): This paper presents theImageNet Large Scale Visual RecognitionChallenge (ILSVRC), an annual competition aimed at advancing the state-of-the-art in image classification and object detection. [7]

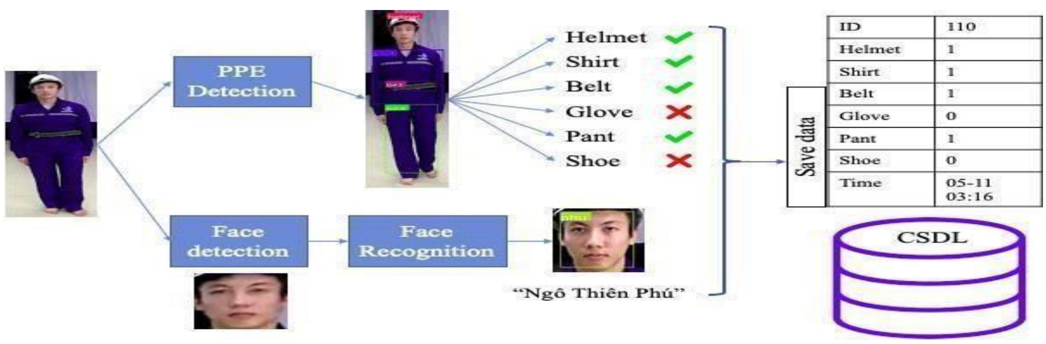

Figure 1 – Data Storage

`III. SYSTEM ARCHITECTURE

The methodology for the safety analysis project focusing on the detection of Personal Protective Equipment (PPE) using Machine Learning (ML) involves several keys (figure – 2) steps. Firstly, a diverse dataset of images or videos capturing workers in various industrial settings wearing different combinations of PPE is collected.

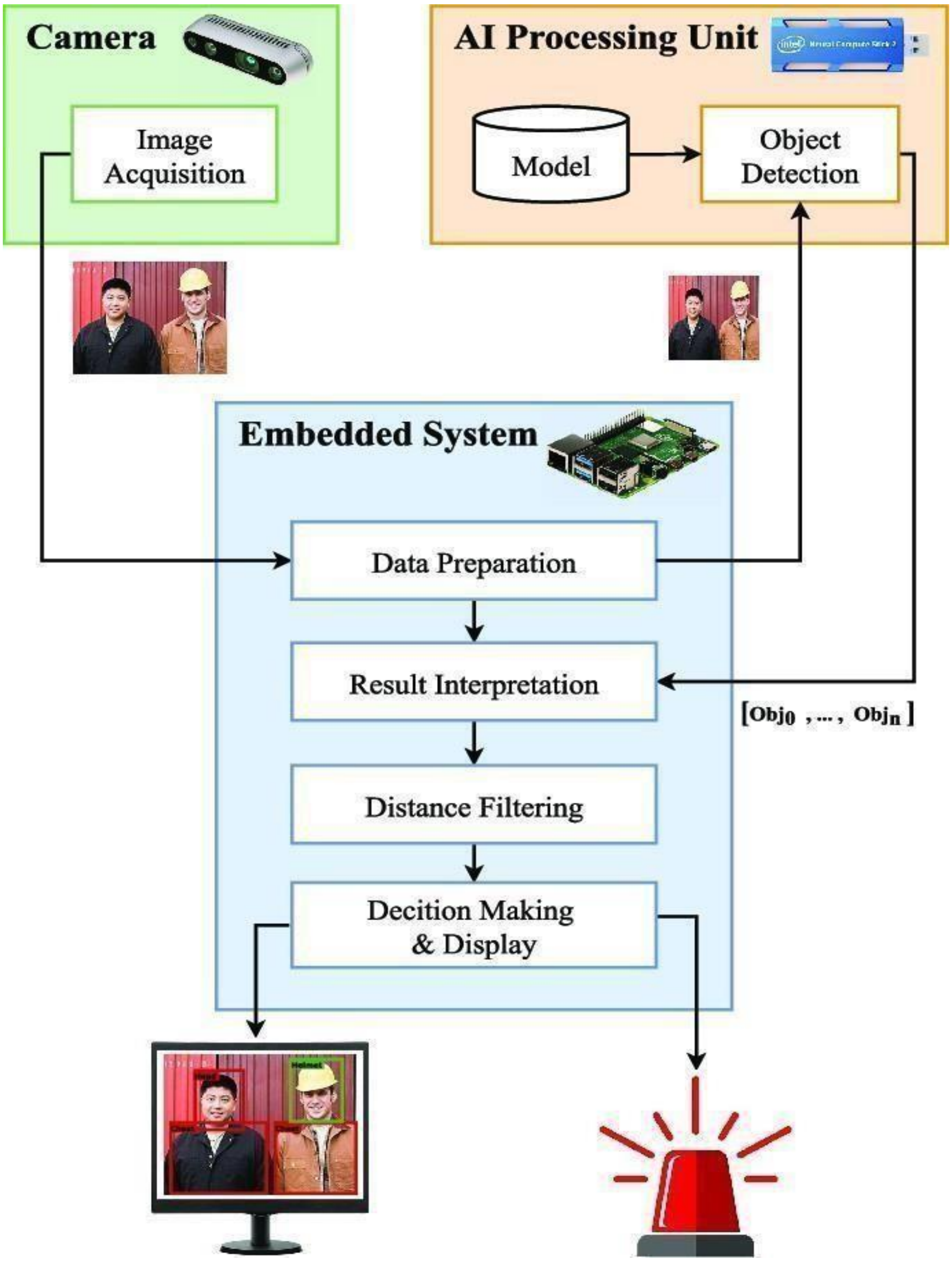

Figure 3 – Block Diagram

Figure 2 - Block Diagram

This dataset is meticulously annotated, with eachPPE item labeled using bounding boxes to facilitate model training. Subsequently, the collected data undergoes preprocessing to enhance its quality and prepare it for training. This preprocessing may include resizing images, augmenting the dataset for increased diversity, and splitting it into training, validation, and testing sets (figure – 2). With thedataset prepared, a suitable ML model architecture isselected for PPE detection, considering factors such as real-time requirements and efficiency. The chosenmodel, often based on object detection frameworks like YOLO (You Only Look Once), is then trained on the annotated dataset using transfer learning techniques, fine-tuning model parameters to optimize performance. [9]

Following training, the model's performance is evaluated using metrics such as mean Average Precision (MAP), precision, recall, and F1-score on the validation set. Iterative refinement of the model architecture and training process may occur based on evaluation results. Once trained, the model is optimized for deployment, considering factors such as model size and computational complexity. Real- time inference capabilities aredeveloped to enable the model to process streaming video data from industrial cameras, detecting PPE items with confidence scores. Integration with existing safety monitoring infrastructure or standalone deployment is carried out, followed by extensive testing in real-world industrial settings to validate system performance. Maintenance plans are established to ensure themodel remains up-to-date and effective indetecting PPE compliance, with regular updatesand monitoring for any drift in accuracy orperformance. Through this methodology, the project aims to develop a robust ML-based PPE detection system, contributing to enhanced safety analysis and compliance monitoring in industrial environments. [7]

IV. HARDWARE

- Camera

Cameras or sensors are required for capturing images or video streams of workers wearing PPE in real-world environments. Depending on the deployment scenario, (figure – 2) the number andtype of cameras or sensors may vary [3]

- STORAGE

Adequate storage space is necessary for storing datasets, trained models, and related files. Solid-State Drives (SSDs) or high-capacity Hard DiskDrives (HDDs) are recommended to ensure fast dataaccess. (figure – 1) [5]

- Memory

Sufficient RAM is essential for handling large datasets during model training and inference. The amount of required RAM depends on the dataset size, model complexity, and batch size used duringtraining. [5]

- Processing Unit (CPU/GPU)

High-performance CPU or GPU is recommendedfor training and inference tasks, (figure – 2) especially if working with large datasets or complex ML models. GPUs are particularly beneficial for accelerating neural network. [1]

V. SOFTWARE

- Operating System:

A compatible operating system such as Linux (e.g., Ubuntu, CentOS) or Windows is needed for running ML frameworks, libraries, and related software tools.Linux is often preferred for its stability and performance in ML development environments. [6]

- Development Environment:

Integrated Development Environments (IDEs) such as Jupyter Notebook, PyCharm, or Visual Studio Code are commonly used for ML model development,experimentation, and code debugging.[10]

- ML Frameworks:

ML frameworks like TensorFlow, PyTorch, or Keras are essential for building, training, and deploying ML models. Choose the framework based on project requirements (figure – 6), familiarity, and communitysupport. [6]

- Object Detection Libraries:

Libraries such as OpenCV, TensorFlow Object Detection API, or Detectron2 provide pre- implemented algorithms (figure – 3) and tools for object detection tasks, including PPE detection. [4]

- Annotation Tools:

Annotation tools like LabelImg, VGG Image Annotator (VIA), or LabelBox are required for annotating images or video frames with bounding boxes around PPE items during dataset preparation.

- Deployment Tools:

Tools for deploying ML models in productionenvironments, such as TensorFlow Serving, ONNX Runtime, or Docker, (figure – 2) may be needed to deploy the PPE detection system on edge devices or cloud platforms. [4]

- Documentation and Version Control:

Utilize documentation tools (e.g., Sphinx) and version control systems (e.g., Git) to maintain project documentation and track changes to code, datasets, and model configurations. [1]

- Communication and Collaboration Tools:

Collaboration platforms (e.g., GitHub, GitLab) and communication tools (e.g., Slack, Microsoft Teams)facilitate collaboration among team members and streamline project management tasks [1]

VI. Working

- Data Collection:

Gather a diverse dataset of images or videos (figure – 1) showcasing workers wearing various PPEconfigurations in industrial settings. [7]

- Data Annotation:

Annotate each image or video frame by marking bounding boxes around PPE items, includinghelmets, goggles, vests, gloves, and boots [7]

.

- Data Preprocessing:

Resize images, augment datasets, and normalizepixel values to prepare the data for training. [7]

- Model Training:

Utilize the YOLO algorithm to train the ML modelon the annotated dataset, (figure – 4) enabling it to recognize and localize PPE items. [5]

- Model Evaluation:

Assess the trained model's performance using metrics like accuracy, precision, recall, and F1- score to ensure effective PPE detection. [5]

- Real-time Inference:

Deploy the trained model for real-time inference onstreaming video data, allowing it to detect and localize PPE items in industrial environments. [2]

- Visualization and Alerting:

Visualize detected PPE items in real-time on video feeds and trigger alerts for non-compliance with safety protocols. [1]

- Deployment and Integration:

Integrate the ML-based PPE detection system into existing safety monitoring infrastructure or standalone applications. [7]

- Testing and Validation:

Conduct extensive testing to validate the system's performance under various conditions and ensure reliability in real-world scenarios. [4]

- Maintenance and Updates:

Regularly update the model and system to adapt to changing workplace conditions and PPE requirements, ensuring ongoing effectiveness and accuracy. [10]

VII. Results

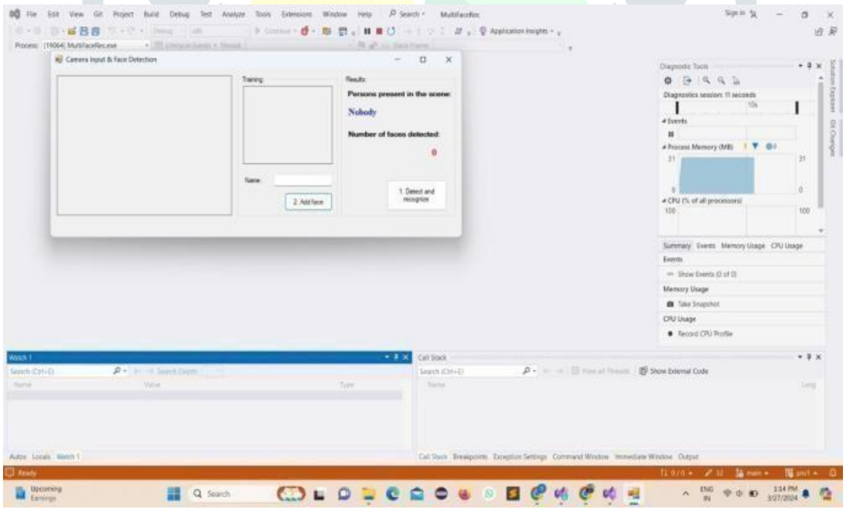

Figure 3 – Backend

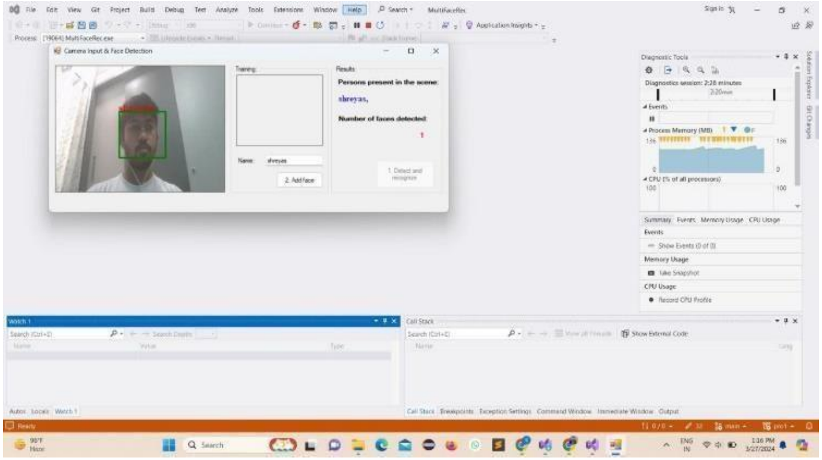

Figure 4 – Model Training

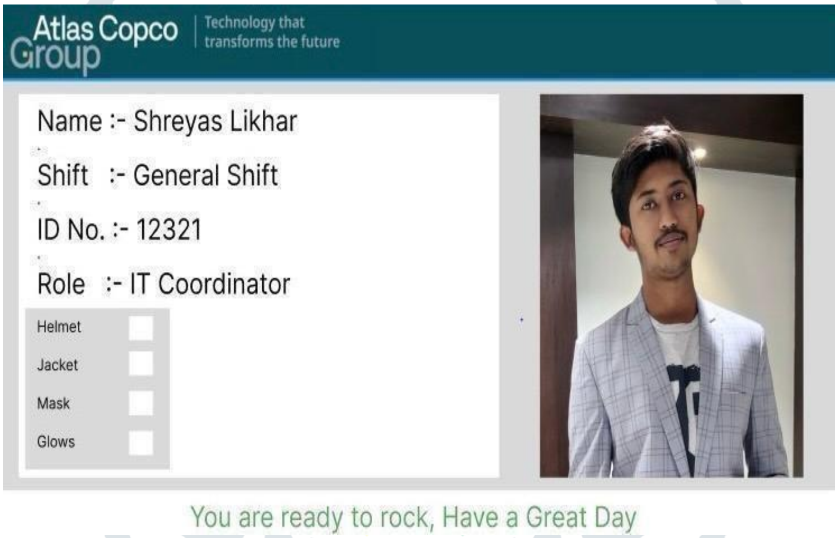

Figure 5 – Frontend

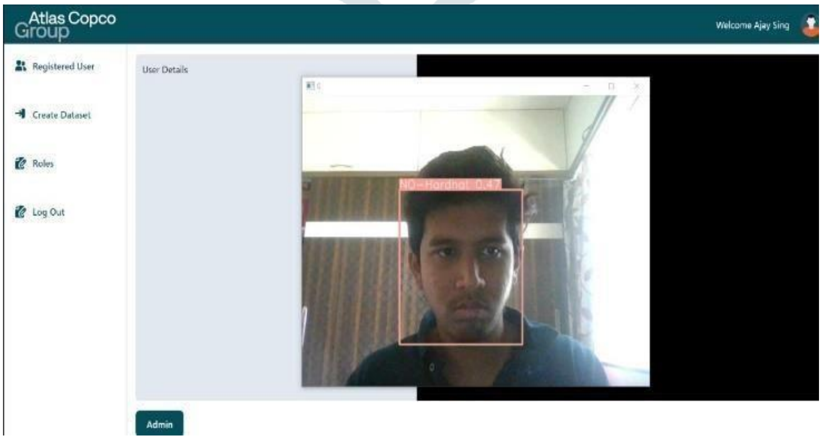

Figure 6 – Model Testing

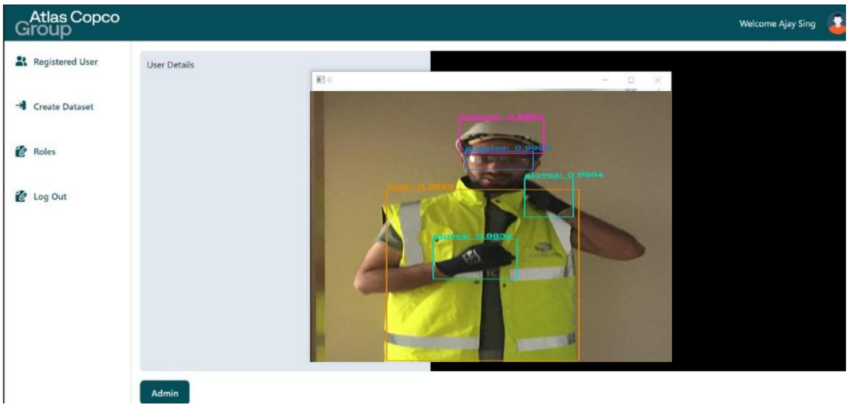

Figure – 7 Real Time Application

VIII. FUTURE SCOPE

In future endeavors, the scope of work for the project on safety analysis, specifically targeting the detection of Personal Protective Equipment (PPE) using Machine Learning (ML), offers promising avenues for advancement. Furtherexploration could involve extending thecapabilities of the PPE detection system toencompass a broader spectrum of PPE items beyond the standard ones such as helmets, vests, goggles, gloves, and boots. This expansion may include specialized PPE tailored to specific industries or environments, thereby enhancing the system's applicability across. [8]

diverse work settings. Additionally, futurework could delve into fine grained classification distinguishing between various types and variations of PPE items to provide more detailed insights into compliance levels. Semantic segmentation

x. Conclusion

The project focusing on safety analysis throughthe detection of Personal Protective Equipment(PPE) using the YOLO (You Only Look Once)algorithm, several key findings emerge such asthe performance evaluation of the ML-based PPE detection system reveals promising results,(figure – 6) with high accuracy, precision, recall, and F1- score achieved across various PPE categories.

techniques could be explored to precisely outlinethe boundaries of PPE items within images or video frames, offering a finer level of analysis. Integrating anomaly detection algorithms would enable the system to identify irregular or non- standard PPE usage patterns, facilitating early intervention in safety violation

XI. REFERENCES

[1] Building Machine Learning Powered Applications By Emmanuel Ameisen

[2] Cao, Z., Simon, T., Wei, S. E., & Sheikh, Y, "Realtime multi-person 2D pose estimation usingpart affinity fields", In Proceedings of the IEEE conference on computer vision and patternrecognition (2017).

[3] Cao, Z., Simon, T., Wei, S. E., & Sheikh, Y, "Realtime multi-person 2D pose estimation usingpart affinity fields", In Proceedings of the IEEE conference on computer vision and patternrecognition. (2017).

[4] Redmon, J., Divvala, S., Girshick, R., & Farhadi,"You only look once: Unified, real-time object detection", In Proceedings of the IEEEconference on computer vision and pattern recognition. (2016).

[5] Girshick, R. “Fast R-CNN”, InProceedings of the IEEEinternational conference on computer vision. (2015).

[6] OpenCV Tutorial: https://www.pyimagesearch.com/2018/11/12/yolo-object-detection-with-opencv/

[7] OpenCV's Documentation and Tutorials:https://docs.opencv.org/4.x/index.html

[8] Rokade, Rajeshree, Ketki Kshirsagar, and Jayashree Sonawane. "Assessment of Sign Using Facial Expression and Hand-gesture Recognition." (2020):121-133.

[9] Adhau, Janhavi, Vaibhav Adsare, Deep Jadhav, Ketki Kshirsagar, and Jayashree Tamkhade. "IoT- Based Face Recognition with SNN." In 2023 2nd International Conference on Futuristic Technologies(INCOFT), pp. 1-6. IEEE, 2023.

[10] Kshirsagar, Ketki Prashant, and Rajeshree Amitkumar Shinde. "Comparing techniques of segmenting hand region." In 2017 2nd InternationalConference on Communication and Electronics Systems (ICCES), pp. 721-724. IEEE, 2017.