DESIGNING OF COMPUTER VISION BASED SAFETY GEAR DETECTION USING YOLO V8 AND JETSON NANO

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Abstract—**Enhancing worker safety on construction sites is pivotal, as lapses in wearing safety gear such as helmets, masks, and vests can lead to potential hazards. To address this issue, we introduce a novel solution leveraging the YOLO V8 device to detect helmet usage among workers. However, challenges arise due to security unawareness and discomfort, causing helmet removal. To mitigate this risk, we propose an advanced system employing the Jetson Nano board and . This system not only detects helmet adherence but also monitors the use of safety masks and vests. Unlike the existing YOLO V5-based approach, our proposed system adopts YOLO V8, ensuring heightened accuracy. The integration of a CSI Camera Module further enhances real-time monitoring capabilities. Through the synergy of Jetson Nano, YOLO V8 and CSI Camera Module, we pioneer an innovative solution to enforce safety compliance by preventing unauthorized entry without proper safety measures.**

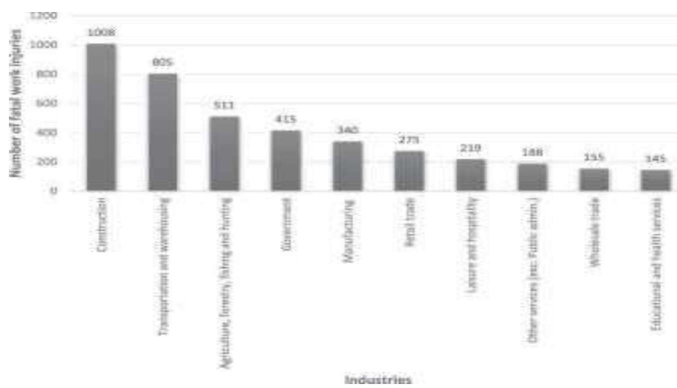
Index Terms— **NVIDIA Jetson Nano, Object detection, Deep Learning, YOLO V8, CSI Camera module.**

INTRODUCTION

THE primary objective of this project is to enhance workplace safety by automating the detection of safety gear such as helmets, vests, goggles, and gloves worn by workers in industrial settings. By employing YOLOv8, a state-of-the-art object detection model, the system will accurately identify safety gear with high precision and recall.[1]
Ensuring worker safety in industrial environments is paramount, and leveraging advanced technologies like computer vision can significantly enhance safety protocols. This project aims to develop a system capable of detecting whether workers are wearing appropriate safety gear using the YOLOv8 object detection algorithm. Additionally, the system will be integrated with the Jetson Nano, a low-cost, high-performance AI computing platform, for real-time inference.[2]

Upon completion, the project is expected to deliver a robust and scalable system capable of automatically detecting worker safety gear with high accuracy and efficiency. The integration with Jetson Nano will enable real-time monitoring of safety compliance, facilitating prompt intervention in case of violations and enhancing overall workplace safety standards.[3]
The implementation of this system can revolutionize workplace safety practices by reducing reliance on manual inspections and enhancing compliance monitoring. By leveraging cutting-edge technologies like YOLOv8 and Jetson Nano, organizations can mitigate risks, prevent accidents, and prioritize the well-being of their workforce.[4]

Fig1. Deaths due to lack of PPE kits in various sectors



The above bar graph depicts the fatal work injuries in different industrial sectors on an average at a yearly basis. The construction industry is one of the most hazardous industries with a significant rate of fatality and injury (Umer et al., 2018) as mentioned in the 2020 report of the US Bureau of labor statistics (Fig. 1).

Huge attempts have been devoted to overcoming the safety and health challenges on the construction sites (Ahn et al., 2019). Occupational Safety and Health Administration (OSHA) regulations have been developed by Personal Protective Equipment (PPE) as one of these attempts. According to OSHA 3151-12R, "*Personal protective equipment, commonly referred to as "PPE", is worn to minimize exposure to a variety of hazards. Examples of PPE include gloves, foot, and eye protection, protective hearing devices (earplugs, muffs) hard hats, respirators, and full body suits*" (OSHA, 2004). These measures can help in tackling specific hazards. Table 1 lists the personal protective equipment for protecting

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different body organs against potential hazards (Yang et al., 2020)

This paper presents a comprehensive investigation into the application of deep learning techniques, specifically focusing on a YOLOV8 based model for the early detection of PPE kit detection in different industrial sectors like construction, transportation etc. using images which consists of both images with PPE and without PPE kit , the study aims to develop an efficient and accurate predictive model capable of detecting the PPE kit with high sensitivity and specificity.[5]

Through this research endeavor, we strive to contribute to the ongoing efforts in enhancing the workers safety by providing PPE detection with innovative tools for early detection and intervention, ultimately aiding in the mitigation of fatal injuries related complications and saving lives.

METHODOLOGY

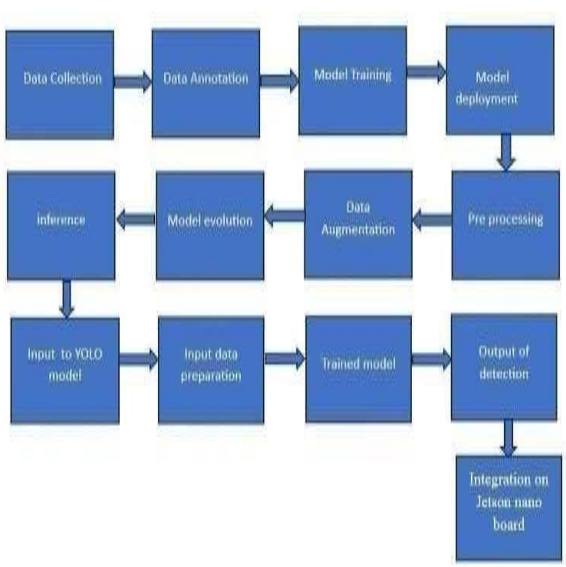

Fig2. Block diagram of safety vest detection using yolo v8

A) DATASET COLLECTION

Gurucharan et al. collected a dataset of safety helmet and vest images from the Kaggle website.
This dataset contained a total of 17,240 images. Within this dataset, there were divided into images which only consists of only helmet, only vest, both helmet and vest and neither of them. To ensure the model robustness and prevent overfitting, the dataset was split into training and testing sets, with 80% of the data used for training and 20% for testing. This method investigates the optimization of detection models for deployment on the jetson nano, addressing memory and computational constraints with maintaining acceptable accuracy levels. Additionally, the use of deep learning algorithm such as YOLO V8, in conjuction with NVIDIA is explored for real time applications. The integration of CSI camera module is to provide high speed detection. The YOLO V8 model ensures heightened accuracy and efficient.

Fig3. Sample Images in dataset collection

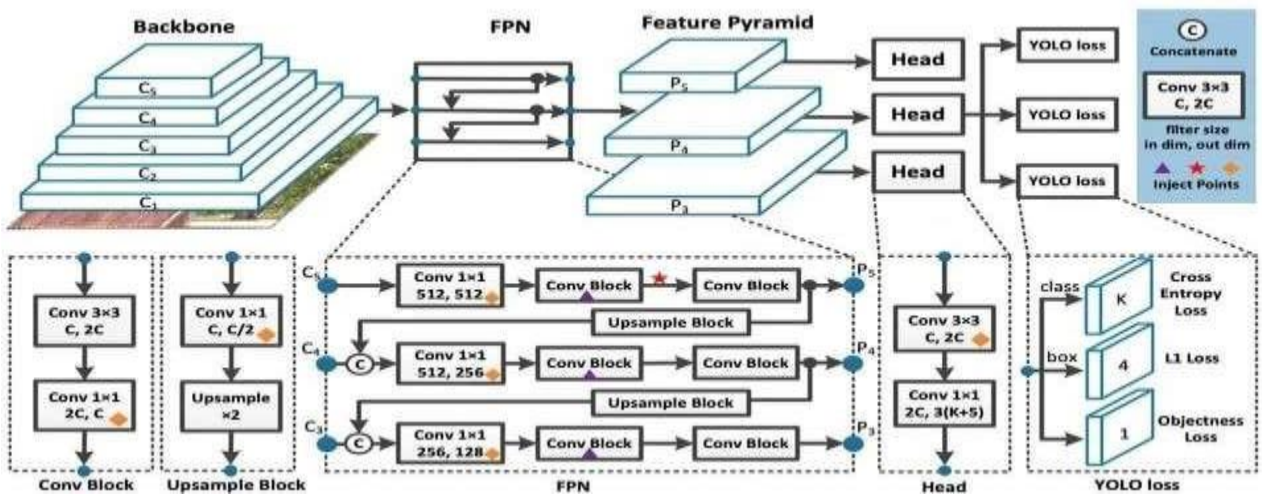

Fig4. YOLO V8 ARCHITECTURE

B) TRAINING THE MODEL

The core principle of YOLOv8 is efficiency without compromising accuracy. At its heart, YOLOv8 leverages the power of deep learning, particularly convolutional neural networks (CNNs), to process entire images in a single pass. This stands in stark contrast to traditional object detection methods that involve scanning images multiple times at different scales, which can be computationally intensive. With YOLOv8, a single forward pass through a CNN suffices, making it exceptionally fast and efficient. This efficiency is a game-changer, particularly in real-time applications such as autonomous vehicles, surveillance systems etc.

Our training model takes an image as input and divides it into a grid, typically with a size of 13x13 or 26x26, depending on the specific type. Each grid cell is responsible for predicting objects within its spatial domain. The network extracts high-level features from the input image using a deep convolutional neural network (CNN). YOLO v8 predicts the bounding box for objects by regressing the coordinates of the top-. left corner, width and height of the box. Additionally, it calculates a confidence score that indicates the probability of the predicted Object in the bounding box. Along with bounding box predictions, YOLO v8 also predicts class probabilities for each grid cell. This means that the model can not only detect objects but also identify their relative categories. Once the predictions are made, a confidence threshold is applied to filter out low-confidence detections. Non-maximum suppression is then used to remove duplicate or overlapping bounding boxes, ensuring that only the most accurate search continues.

C) IMPLEMENTATION ON JETSON NANO

For implementing object detection on jetson nano, we had a created a environment where a specific version of python is installed. After that we had installed the dependencies like ultralytics and Pytorch and all the necessary software which is required to train the model. Now download the pre-trained model which is used in the process(training the model) and collect the dataset as mentioned in the dataset collection. Fine-tune the pre-trained YOLOv8 model on the safety gear dataset . This step involves adjusting the model's parameters to improve its performance on the specific task of safety gear detection. Since the Jetson Nano has limited computational resources, optimize the trained model for inference on the Nano's GPU. This may involve quantization, pruning, or other techniques to reduce the model's size and computational complexity.

RESULTS AND DISCUSSIONS

This application serves as a convenient tool for users in different industrial domains so that by using camera module in jetson nano it will detect whether the person is wearing the PPE kit or not. By applying deep neural networks on classes can give us more accurate detection. This predictive capability is crucial for the users with the timely information about the status of workers wearing PPE or not. Our application supports both the images and as well as the videos. This process eliminates the manual checking in the industrial areas and improves the necessity of the PPE kit and decreases the check in time of the workers so that they can enter the work areas as early as possible.

A) ACCURACY

The accuracy of the training the model is very important in detection techniques. It defines the model's performance in object detection. In order to get high accuracy we already divided the dataset into two categories train and validation so that the training model cannot undergo overfitting and as well as it improves the accuracy of the model. To achieve high accuracy we trained the model with large datasets and undergo the training in several iterations. While implementing on jetson nano we just trained very few images due to its memory insufficiency nature and other complexities.

B) OUTPUTS DETECTED AND OUTPUT GRAPHS

Fig5.OUTPUTS OBTAINED AFTER TRAINING

Fig6.OUTPUTS ATTAINED FOR BATCH-1

Fig7. OUTPUTS ATTAINED FOR BATCH-2

Fig8.OUTPUTS ATTAINED FOR BATCH-3

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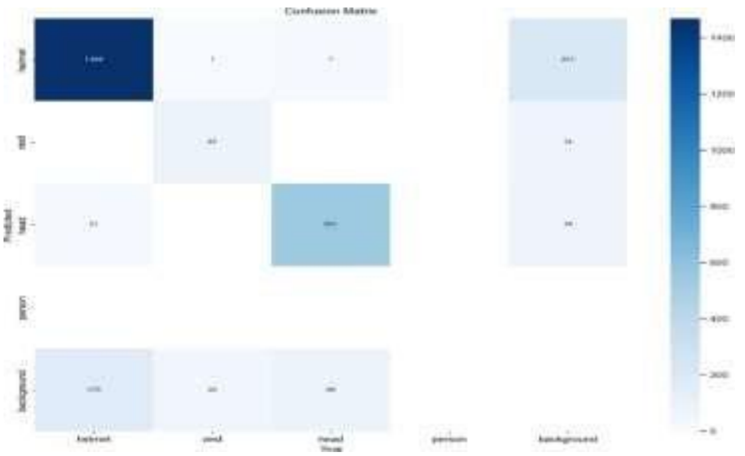

Fig9. Confusion matrix without Normalization

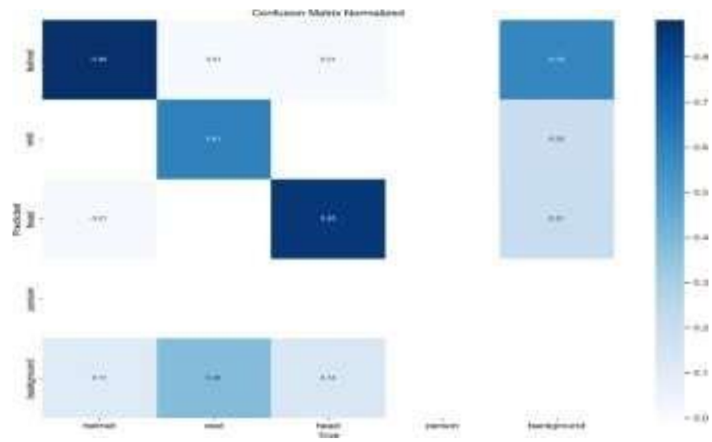

Fig10. Confusion matrix with Normalization

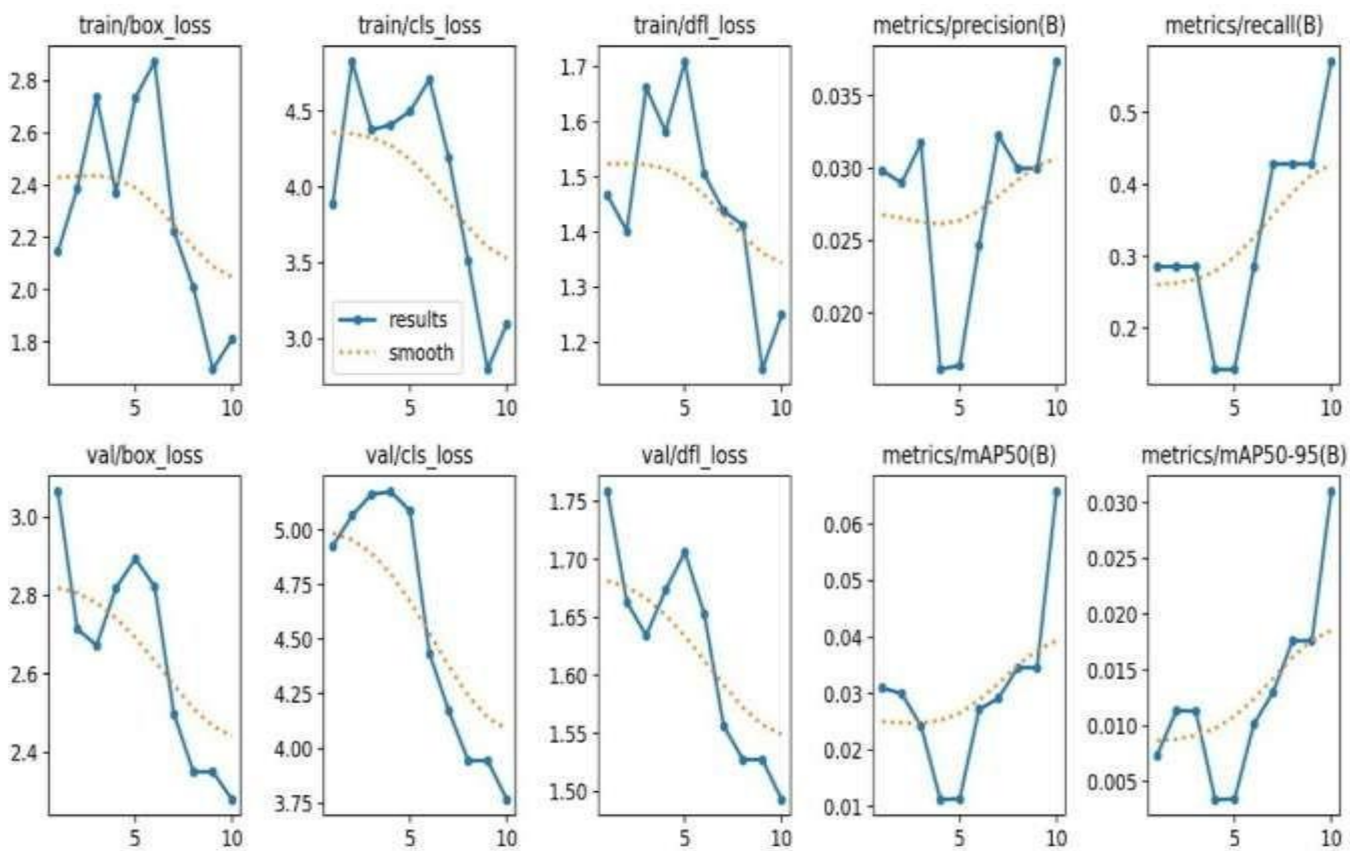

Fig11. Output graphs obtained for precision and Map

It represents the output graph for the object detection based on mAP and prediction. With this graph, we can simply say that our precision is inversely proportional to the bounding box loss. So that we can easily say it has achieved high mAp with respect to the less boundingbox loss.

Fig12. Output Detecting On Jetson Nano

Fig13.Real time results obtained on jetson nano board

CONCLUSION

The given project presunts the results on object detection using yolo v8 both on software and as well as software (Jetson nano). The map is the common evaluation matrix for all the object cetection algorithms that measures the accuracy of the predicted bounding boxes for objects in an image.

The first methodology listed is yolo v3, which achieved a mAP OF 85%, rician the second methodology which achieved a mAP of 92.7% with a slightly better performance. Yolo v4, the third methodology which achieved a mAP of 93.11%. Yolo v5, the fourth methodology achieved a mAP of 95%. Yolo v7, the fifth methodology achieved a mAP of 97%. Finally, yolo v8 outperformed all the other methodologies with a remarkable mAP of 99%.

Based on the project, it is evident that the yolo v8 methodology is the most accurate among the reference detection methods. However, it is important to consider that the performance of an object detection detection algorithm can be affected by various factors, such as the complexity of the image dataset, the training techniques and the hardware specifications used.

Overall, the results of the project demonstrate the progress made in object detection methodologies over the years, with yolo v8 achieving a very high levelof accuracy, which is impressive and opens up possibilities for applications in fields such as autonomous vehicles and security systems.

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