Safety Helmet Detection Using Python

PRESENTED BY

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UNDER THE GUIDANCE OF DR. BANDANA BARMAN

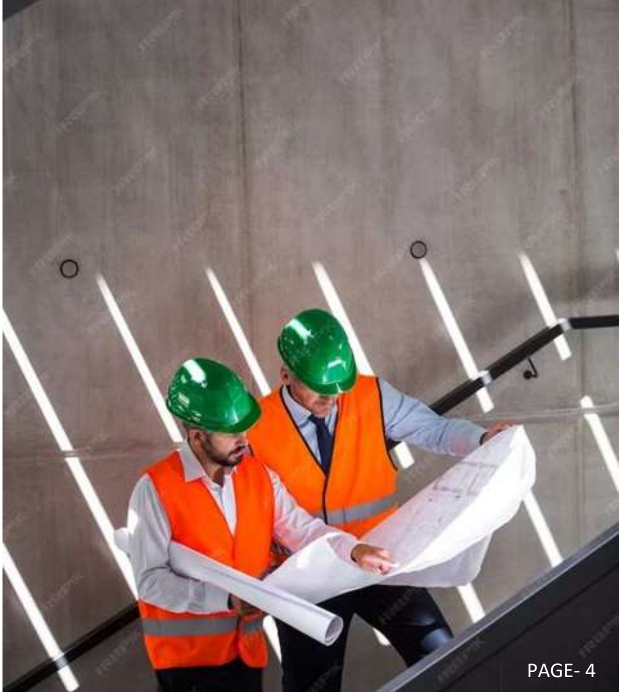
Aim Of The Project

The primary aim of the project is to enhance construction site safety through the implementation of a robust Safety Helmet Detection system using Python (YOLOv5). The overarching goal is to leverage computer vision technology to automate the monitoring of safety helmet usage among construction site personnel.

CONTENT

INTRODUCTION

The construction industry, inherently fraught with hazards, necessitates stringent safety measures. Among these, the use of safety helmets stands as a foundational practice to safeguard workers from head injuries. This project delves into the realm of automated safety helmet detection on construction sites, utilizing a synergy of Python programming, YOLOv5, and the Thonny Python IDE. Python, a dynamic and versatile language, is employed both for coding purposes (Python 3.10) and for model training (Python 3.9). The Thonny Python IDE, chosen for its simplicity and suitability for educational contexts, provides an accessible environment for coding, ensuring that the project remains pedagogically valuable. YOLOv5, renowned for its real-time object detection capabilities, becomes the fulcrum of our safety helmet detection system.



Previous Researches On Safety Helmet Detection

1) Safety Helmet Detection Based on YOLOv5 by Fangbo Zhou, Huailin Zhao, Zhen (2021) ,this research work proposes a safety helmet detection method based on YOLOv5 and annotates the 6045 collected data sets to establish a digital safety helmet monitoring system and shows the effectiveness of helmet detection based YOLov5.
2) Safety Helmet Wearing Detection Based on Jetson Nano and Improved YOLOv5 by Zaihui Deng,Chong Yao,and Qiyu Yin(2023), This study introduces an improved safety helmet-wearing detection model named YOLOv5-SN, aiming to address the shortcomings of the existing YOLOv5 models, including a large number of model parameters, slow reasoning speed, and redundant network structure.

While the mentioned research papers contribute significantly to the field of safety helmet detection using YOLOv5, it's common for studies to encounter gaps, difficulties, or areas that warrant further exploration. Here are some potential gaps or challenges that might be found in these research papers:

1. Handling Highly Occluded Helmets : Occlusions, where safety helmets are partially or fully hidden, pose a considerable challenge in real-world scenarios.

2. Generalization Across Diverse Construction Environments : Construction sites vary widely in terms of lighting conditions, backgrounds, and types of helmets used. Ensuring the model's generalization across diverse environments is crucial.

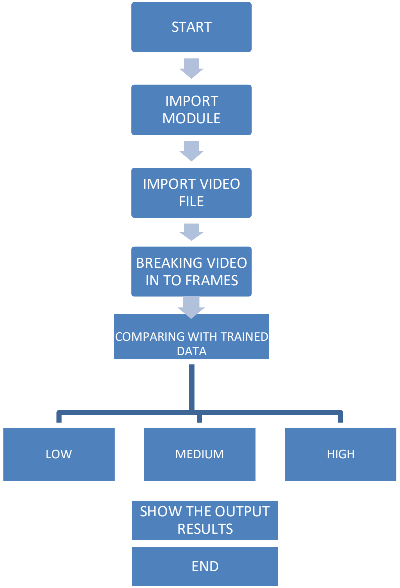
3. Ethical and Privacy Concerns : safety helmet detection systems become more prevalent, there is a growing need to address ethical considerations and privacy implications

4. Explainability and Transparency : The interpretability and transparency of YOLOv5-based safety helmet detection systems may not be well-explored in some studies.

Software And Simulation Tools

The selection of tools and technologies is pivotal in determining the project's success. Python, with its 3.9 and 3.10 versions, serves a dual purpose. Python 3.10 becomes the coding backbone, providing an environment conducive to scripting and development. Python 3.9 takes center stage for model training, where the nuances of machine learning and deep learning algorithms are harnessed. Thonny Python IDE emerges as the coding environment of choice due to its simplicity, particularly beneficial in educational settings. Its lightweight nature and ease of use make it an ideal platform for coding tasks related to the safety helmet detection project. YOLOv5, characterized by its You Only Look Once architecture, exemplifies efficiency in real-time object detection, making it the cornerstone of our system.

Flowchart


START
IMPORT MODULE
IMPORT VIDEO FILE
BREAKING VIDEO IN TO FRAMES
COMPARING WITH TRAINED DATA
LOW
MEDIUM
HIGH
SHOW THE OUTPUT RESULTS
END

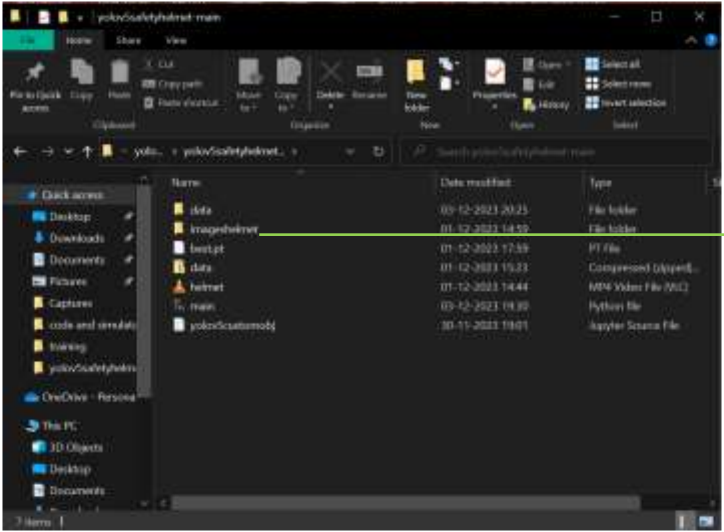
ALGORITHM

Our Approach for Safety Helmet Detection

1) step 1: Install Thonny Python IDE, yolov5 ,open CV module, NumPy module
2) step 2: Download the Images and move our main file.
3) step 3: Created the project video and train all images. we create the 'Rectangle' box to measure the size of our helmets.
4) step 4: Then create a new folder for storing our data and move all pictures here and make a zip file of it and upload in the g-drive.
5) step 5: Opens google collab for collaboration our code with our image file.
6) step 6: Download our custom model and store in the main folder.
7) step 7: Open Thonny Python IDE & give the code for the model, add the path, capture the video file.
8) step 8: Now our basic code is ready , we call the custom model and framing our models.
9) step 9: Finally detecting Safety Helmets in the Images and the project is done.

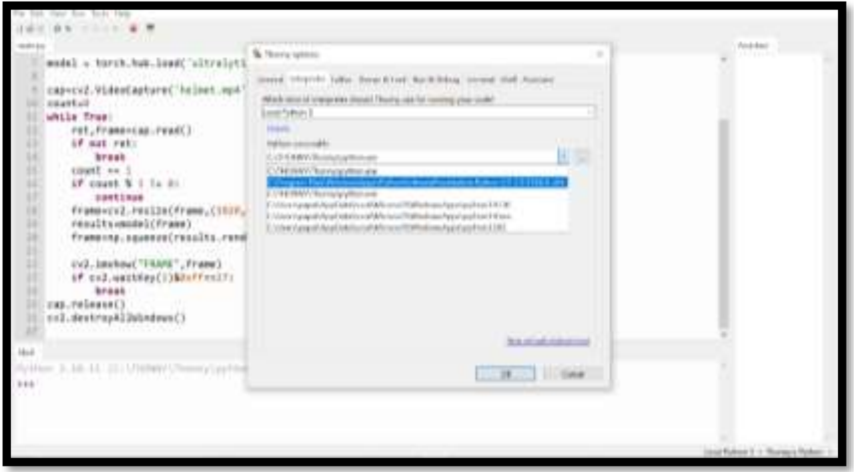
RESULTS

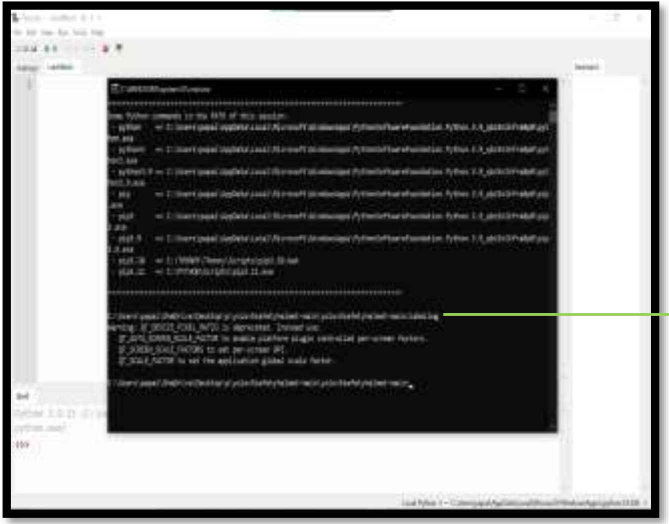
Main File Location



DOWNLOAD IMAGES

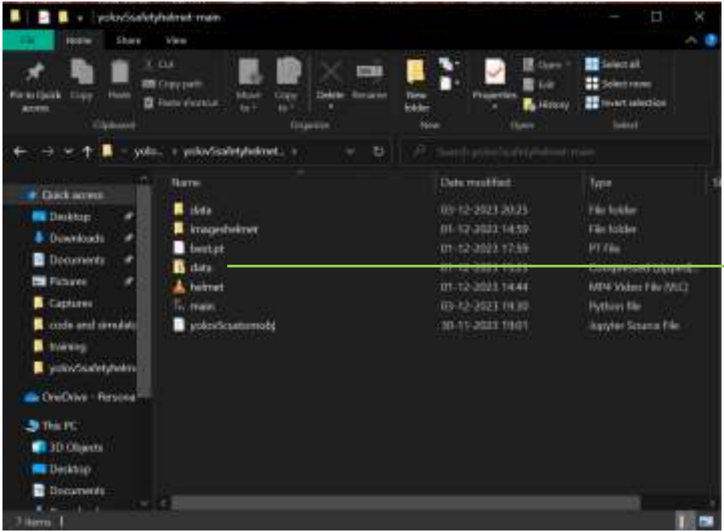
SELECTING PYTHON VERSION 3.9 WHICH WILL
HELP FOR TRAINING THE DATA USED.





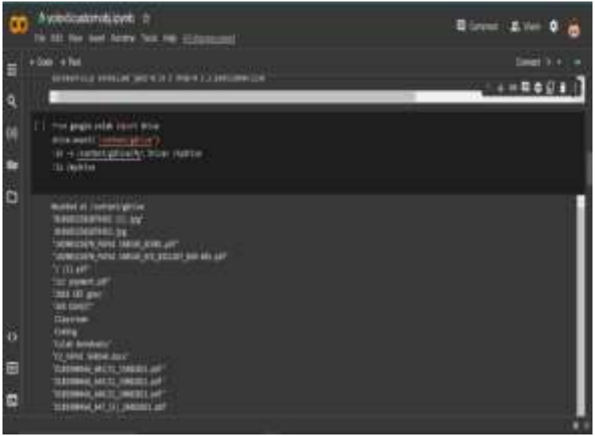
LABELIMG COMMAND

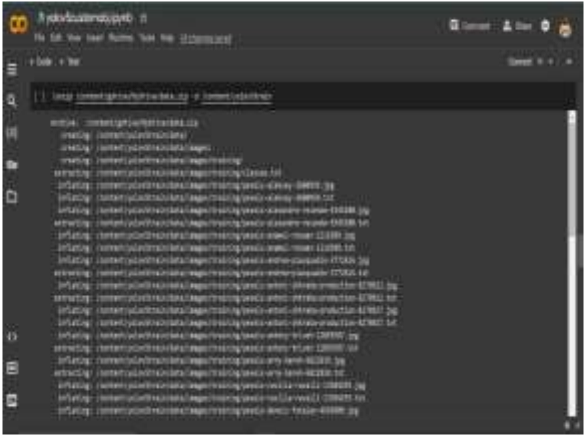
TRAINING AND LABELLING THE IMAGES. HERE CREATING 'RECTANGLE' BOX ON HELMETS.



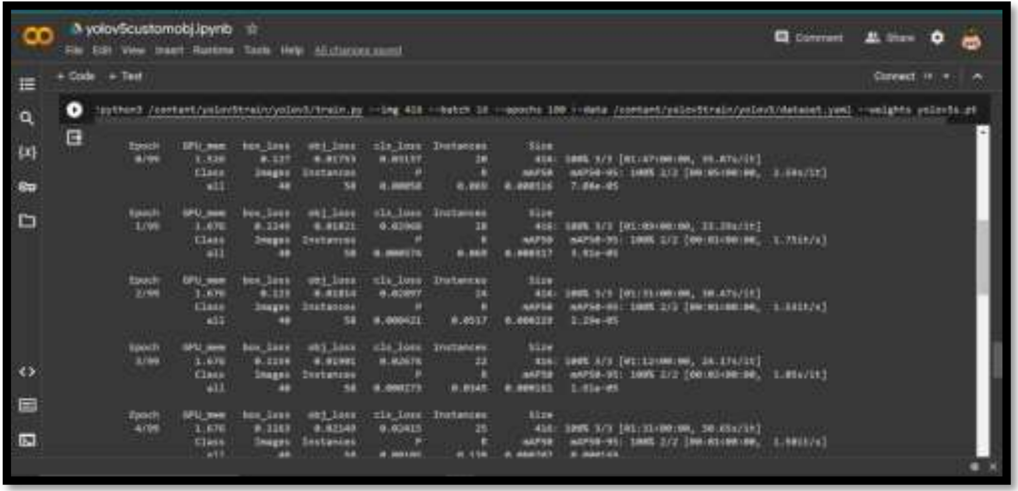
DATA ZIP FILE

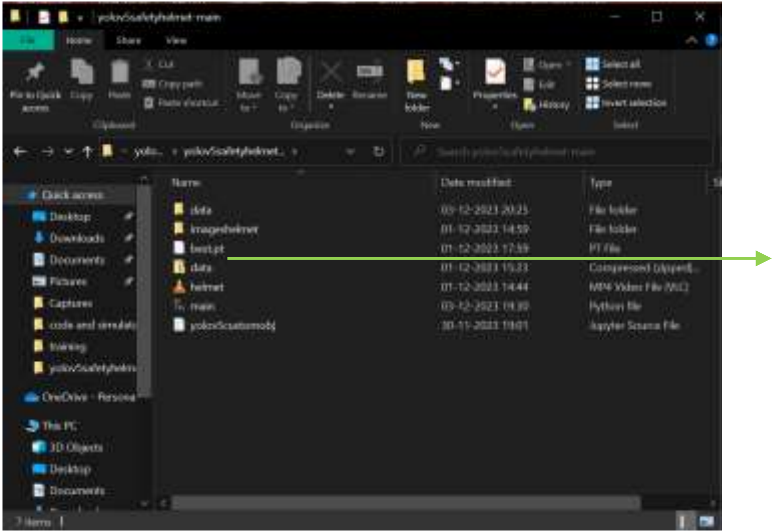
UNZIPING FILE IN GOOGLE COLLAB





HERE YOLOV5 MODEL GENERATE





CUSTOM MODEL FILE

WRITING OUR MAIN CODE USING PYTHON VERSION 3.10 IN THONNY IDE .

```python
import cv2
import torch
import numpy as np

path='C:/Users/papai/OneDrive/Desktop/p/yolov5safetyhelmet-main/yolov5safetyhelmet-main/best.pt'

model = torch.hub.load('ultralytics/yolov5', 'custom',path, force_reload=True)

cap=cv2.VideoCapture('helmet.mp4')
count=0
while True:
    ret,frame=cap.read()
    if not ret:
        break
    count += 1
    if count % 3 != 0:
        continue
    frame=cv2.resize(frame,(1020,600))
    results=model(frame)
    frame=np.squeeze(results.render())
```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count += 1
if count % 3 != 0:
continue
frame=cv2.resize(frame,(1020,600))
results=model(frame)
frame=np.squeeze(results.render())
cv2.imshow("FRAME",frame)
if cv2.waitKey(1)&0xFF==27:
break
cap.release()
cv2.destroyAllWindows()

Input Source

OUTPUT

OUTPUT IN THE FORM OF VIDEO

 

OUTPUT IN THE FORM OF IMAGE

Conclusion

In conclusion, this project has successfully realized the development and implementation of a safety helmet detection system, contributing to the broader goal of improving construction site safety. The automated monitoring system, empowered by YOLOv5 and Python, stands as a testament to the intersection of technology and safety. By leveraging these tools, we have created a reliable solution that has the potential to mitigate risks and enhance the well-being of construction site workers.

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Thanks!