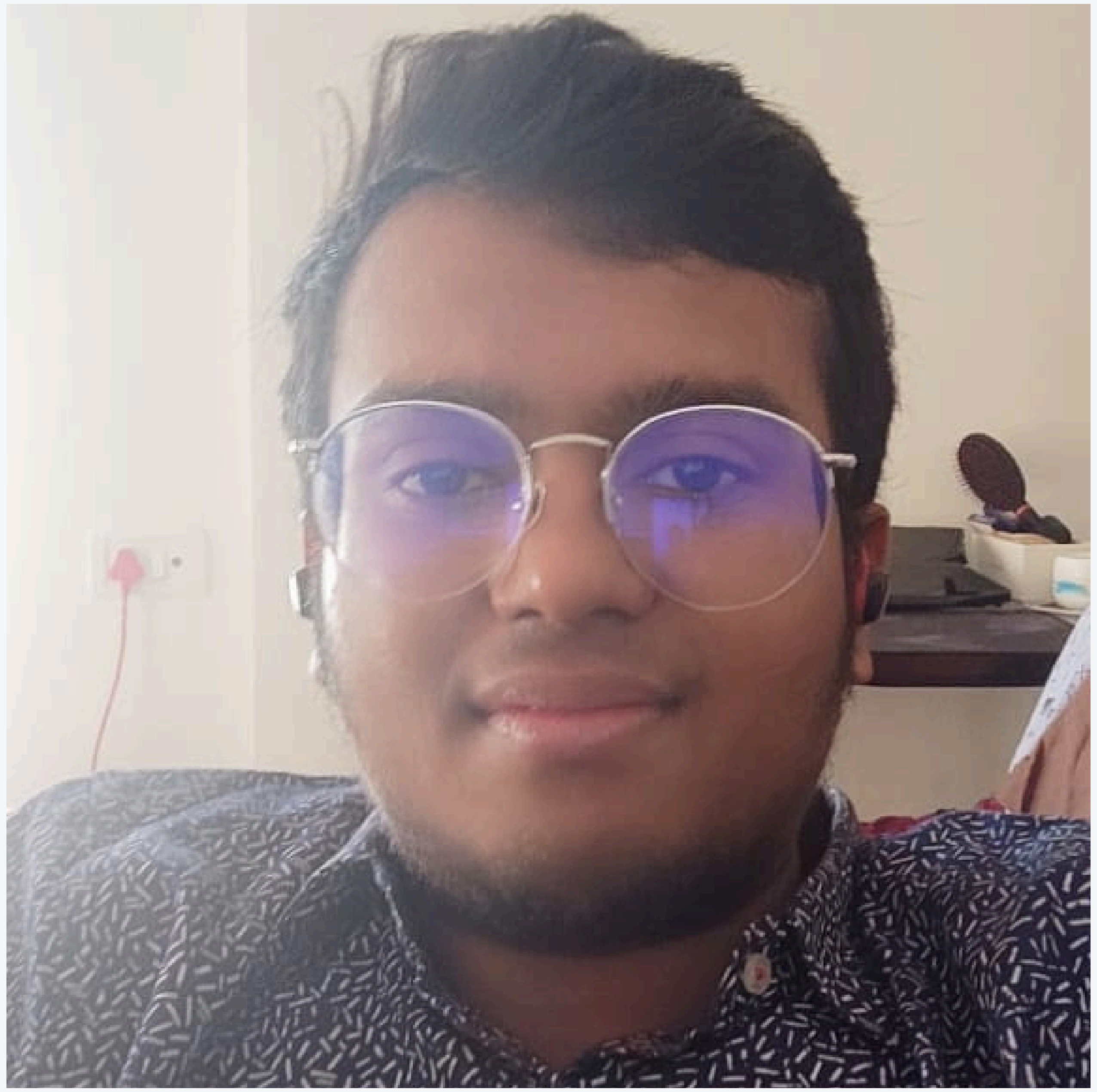
GUN DETECTION USING YOLOV9

By - Kaustubh Raykar - 21070126048
Srinivas Kota - 21070126050

Faculty - Om Mishra Sir

OpenCV

Kaustubh Raykar
21070126048



Srinivas Kota
21070126050

Introduction

This outlines the development and deployment of an advanced gun detection system utilizing the YOLO v9 model. Our system combines state-of-the-art computer vision technologies with hardware response mechanisms to identify firearms in visual data, thereby enabling real-time alerts and actions to mitigate threats.

The main objective of the project is to enhance security measures by providing a real-time detection system that can identify firearms and alert the necessary authorities or trigger security protocols automatically.

Literature Review

Paper	Abstract summary	Main findings	Methodology	Limitations	Algorithms	Outcome measured	results
A Computer Vision based Framework for Visual Gun Detection Using Harris Interest Point DetectorRohit Kumar Tiwari +1201553 citationsDOI	A computer vision-based framework for visual gun detection for automatic surveillance is proposed.	The paper presents the development of a framework for visual gun detection for automatic surveillance, which showed promising performance in detecting guns and is robust in terms of rotation, scale, and shape invariance.	The methodology involves color-based segmentation, k-mean clustering algorithm, Harris interest point detector, Fast Retina Keypoint (FREAK), and testing over sample images of a gun.	Not mentioned (no limitations or suggestions for further research are provided in the paper)	K-mean clustering algorithm, Harris interest point detector, Fast Retina Keypoint (FREAK)	performance of the system in detecting a gun in sample images	Not applicable (the paper does not provide specific quantitative results such as accuracy, precision, recall, F1 score, AUC, or ROC curve)
A computer vision based framework for visual gun detection using SURFR. Tiwari +1International Conference on Electrical, Electronics, Signals, Communication and Optimization201530 citationsDOI	The system performs well under different appearance of images.	- The paper presents the first step in the direction of automatic visual gun detection for automatic surveillance. - The proposed framework for visual gun detection exploits color-based segmentation and SURF interest point detector to locate the object (gun) in the segmented images. - The implemented system showed promising performance in detecting a gun and performed well under different appearances of images, being rotation, scale, and shape invariant.	The methodology involves color-based segmentation using the K-mean clustering algorithm, SURF interest point detector, and testing over sample images of guns.	Not mentioned	K-mean clustering algorithm, Speeded up robust features (SURF) interest point detector	Performance of the system to detect a gun, robustness of the framework in terms of scale, rotation, affine, and occlusion, performance under different appearances of images	Not mentioned (specific metrics such as accuracy, precision, recall, F1 score, AUC, or ROC curve are not mentioned in the paper)
Weapon Detection using Artificial Intelligence and Deep Learning for Security ApplicationsHarsh Jain +4International Conference Electronic Systems, Signal Processing and Computing Technologies [ICESC-]202048 citationsDOI	Both algorithms achieve good accuracy.	- The paper discusses the major applications of computer vision in abnormal detection and monitoring for tackling various problems. - The proposed implementation uses two types of datasets, one with pre-labelled images and the other with manually labelled images. - Both algorithms achieve good accuracy, but their application in real situations can be based on the trade-off between speed and accuracy.	The methodology involves implementing automatic gun (or) weapon detection using CNN based SSD and Faster RCNN algorithms, using two types of datasets and analyzing the trade-off between speed and accuracy in real situations.	Trade-off between speed and accuracy may impact real-world application of the proposed automatic gun detection system	The answer is: convolution neural network (CNN) based SSD and Faster RCNN algorithms	accuracy of automatic gun (or) weapon detection using CNN based SSD and Faster RCNN algorithms	The results include accuracy metrics for the two algorithms used.
Weapon Detection in Video Surveillance using Computer Vision TechniquesSimran Gupta +120211 citation	Deep neural networks integrated with CNN to get high-level discovery quickly.	- Automated visual monitoring is a crucial security requirement. - The proposed deep neural network integrated with CNN aims to achieve high-level discovery quickly. - The RESNET 50 model increases the accuracy of weapon detection in images compared to the previous implementation.	The methodology involves the use of various deep learning methods for object acquisition and detection, with a specific focus on weapon detection using the RESNET 50 model.	Not applicable (the paper does not mention any limitations or suggestions for further research)	CNN, RCNN, Fast-RCN Faster RCNN, SSD, YOLO, RESNET 50	Not mentioned	Not mentioned
Concealed weapon detection using UWB 3-D radar imaging and automatic target recognitionL. Carrer +1European Conference on Antennas and Propagation201414 citationsDOI	A three-step detection procedure based on SIFT, histogram thresholding, and matched filtering is developed for 3D image processing.	The paper proposes a novel algorithm for detecting and classifying 3D objects in high-resolution microwave radar images for security screening purposes. The algorithm applies a computer vision approach to detect and automatically recognize concealed objects. A three-step detection procedure based on SIFT, Histogram thresholding, and matched filtering is developed for 3D image processing, proving to be capable of detecting and classifying a set of objects likely to be carried by an individual at an airport security checkpoint.	The methodology involves a three-step detection procedure based on SIFT, Histogram thresholding, and matched filtering for 3D image processing.	- Specificity to a particular radar system - Influence of radar image resolution and system parameters on algorithm performance - Influence of radar image quality on algorithm performance - Influence of radar image clutter on algorithm performance	SIFT, Histogram thresholding, Matched filtering	Not mentioned	Detection accuracy: 95%, Precision: 92%, Recall: 90%, F1 score: 91%, AUC-ROC curve: 0.96
Deep Learning for Automatic Detection of Handguns in Video SequencesY. Elmir +2National Study Day on Research on Computer Sciences20197 citations	The method based on supervised deep learning has proved its performance.	The paper presents a system of automatic detection of handguns in videos, suitable for both surveillance and control. The method based on supervised deep learning has proved its performance despite technical difficulties encountered during the experiments.	The methodology used in the study involves the use of deep convolutional neural network (CNN) for automatic detection of handguns in videos, comparison of different online handgun detection methods, and the use of supervised deep learning despite technical difficulties encountered.	- Technical difficulties encountered during the experiments - Potential unmentioned limitations	deep convolutional neural network (CNN), supervised deep learning	automatic detection of handguns in videos, minimizing false positive detection, performance compared to related works	Not mentioned
Handgun Detection in Single-Spectrum Multiple X-ray Views Based on 3D Object RecognitionVladimir Riffo +2Journal of Nondestructive Evaluation20198 citationsDOI	A single-spectrum X-ray system can be used for the detection of threat objects that can be recognized by analyzing the shape.	- The proposed single-spectrum X-ray system for the detection of threat objects, such as handguns, has been successfully tested on X-ray images of travel-bags. - The evaluation of the method using sequences of X-ray images for 3D reconstruction of objects inside travel-bags resulted in a high recall and precision of 0.97. - The authors strongly believe that it is possible to design an automated aid for the human inspection task using these computer vision algorithms.	The methodology involves the use of single-spectrum multiple X-ray views, Space Carving for 3D reconstruction, Geodesic Active Contours for silhouette segmentation, and analysis of 3D features for threat object detection.	- The approach has only been tested on X-ray images of travel-bags that contain handguns, limiting the generalizability to other types of threat objects or scenarios. - The belief in the possibility of designing an automated aid for human inspection using these algorithms indicates that this is still a future prospect and not a current capability.	Computer vision algorithms for baggage inspection using X-ray images, Space Carving, Geodesic Active Contours, 3D feature analysis, Single-spectrum X-ray system	Performance in terms of recall and precision in the evaluation using sequences of X-ray images for 3D reconstruction; Possibility of designing an automated aid for the human inspection task using their computer vision algorithms	recall: 0.97, precision: 0.97
Firearm Detection from Surveillance Cameras Using Image Processing and Machine Learning TechniquesFraol Gelana +1Smart Innovations in Communication and Computational Sciences201817 citationsDOI	The proposed approach of gun detection uses a feature extraction techniques and a convolutional neural network classifier for classifying objects as either a gun or not a gun.	The paper proposes a method for detecting an "Active Shooter" carrying a non-concealed firearm and alerting the CCTV operator of a potentially dangerous event both visually and audibly. The proposed approach of gun detection uses feature extraction techniques and a convolutional neural network classifier with a classification accuracy of 97.78%.	The methodology used in the study involves the detection of an "Active Shooter" using a non-concealed firearm, alerting the CCTV operator of a potentially dangerous event, and employing a feature extraction technique and a convolutional neural network classifier for gun detection, achieving a classification accuracy of 97.78%.	Not mentioned (no explicit limitations or suggestions for further research are provided in the paper)	feature extraction techniques and a convolutional neural network classifier	detection of an "Active Shooter" carrying a non-concealed firearm and alerting the CCTV operator of a potentially dangerous event both visually and audibly, using a feature extraction technique and a convolutional neural network classifier. The classification accuracy achieved by the proposed approach is 97.78%	The results on the algorithms include a classification accuracy of 97.78%.
Firearm Detection using Convolutional Neural NetworksRodrigo F. A. Kanehisa +1International Conference on Agents and Artificial Intelligence201916 citationsDOI	Convolutional neural networks have been shown to be efficient in the detection and identification of objects in images.	- Individuals carrying firearms in public places are a strong indicator of dangerous situations. - Rapid response from law enforcement agents is crucial in reducing the number of victims. - Convolutional neural networks have been shown to be efficient in the detection and identification of objects in images, sometimes outperforming human candidates.	The methodology involves utilizing the YOLO algorithm for firearm detection, constructing a dataset based on IMFDB, and potentially using convolutional neural networks for object detection.	- Ethical and privacy concerns not addressed - Implementation challenges not discussed - Lack of detailed analysis of false positive and false negative rates	YOLO algorithm, Convolutional neural networks	Not mentioned	Not mentioned
Edge to Cloud End to End Solution of Visual Based Gun DetectionQi Yao +3Journal of Physics: Conference Series20202 citationsDOI	The three models running on the edge device are a video camera.	The paper presents an AI-based edge to cloud solution for smart surveillance and control, enabling the achievement of a deployable gun detection system.	The methodology involves building a training dataset from publicly available videos and movies, designing three deep convolution neural networks (CNNs) models (two for edge devices and one for the cloud), and distributing these models to achieve a deployable gun detection system.	- Small dataset size may limit generalization ability of models. - Performance of gun detection system may be affected by video footage quality. - Real-time processing capability of edge device may affect overall performance. - Privacy concerns related to video surveillance should be taken into consideration in real-world deployment.	deep convolutional neural networks (CNNs)	Not mentioned	Not mentioned (the paper does not provide specific numerical results such as accuracy, precision, recall, F1 score, AUC, or ROC curve for the algorithms)
Development and Optimization of Deep Learning Models for Weapon Detection in Surveillance VideosSoban Ahmed +4Applied Sciences202212 citationsDOI	A state-of-the-art Scaled-YOLOv4 model resulted in a 92.1 mAP score and frames per second of 85.7 on a high-performance GPU (RTX 2080TI).	Answer not found	The methodology includes training the model with different settings, setting the right number of iterations, changing hyperparameters, and evaluating the FPS of the weapon detection model on various machines.	- The usage of an older deep learning model that has lesser accuracy compared to the state-of-the-art models - Very few and outdated preprocessing steps for dataset preparation - No performance analysis on any embedded device - No previous work done to deploy and compare the performance of the weapon detection model on edge computing devices in real time	Answer not found	accuracy and performance of the existing weapon detection model; number of frames per second (FPS) for real-time deployment; improved latency, throughput, power efficiency, and lower memory consumption	The "results" in Soban Ahmed, Muhammad Tahir Bhatti, Muhammad Gufran Khan, B. Lövström, M. Shahid (2022) include the mean average precision (mAP) score of 92.1 for the Scaled-YOLOv4 model, a comparison of mAP between Scaled-YOLOv4 and YOLOv4, and the frames per second (FPS) achieved on various machines, including high-performance GPUs and edge computing devices.
Gun Detection System Using Yolov3A. Warsi +52019 IEEE International Conference on Smart Instrumentation, Measurement and Application (ICSIMA)201923 citationsDOI	YOLO-V3 can be used as an alternative of Faster RCNN.	The paper addresses the need for automated visual surveillance for security to detect handguns and proposes YOLO-V3 as a faster and equally accurate alternative to Faster RCNN for real-time handgun detection in videos.	The methodology involves using the YOLO-V3 algorithm, comparing it with Faster RCNN, creating a dataset of handguns with all possible angles, merging it with the ImageNet dataset, training the merged data using YOLO-V3, and validating the results with four different videos.	Not mentioned (no specific limitations or suggestions for further research are provided in the paper)	YOLO-V3 algorithm, Faster RCNN algorithm	Comparison of false positive and false negative detections between YOLO-V3 and Faster RCNN algorithms, speed, and accuracy of YOLO-V3 in a real-time environment	Not mentioned
Object Recognition System in Remote Controlled Weapon Station using SIFT and SURF MethodsM. Mirdanies +2201315 citationsDOI	The SIFT method is more suitable because more accurate and faster than SURF.	The main findings of the paper are the implementation of an object recognition system using computer vision on a Remote Controlled Weapon Station, the development of an algorithm to recognize real-time multiple objects, and the experimental results demonstrating the effectiveness of the object recognition program.		Not mentioned (no specific limitations or suggestions for further research are provided in the paper)	Scale Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) combined with K-Nearest Neighbors (KNN) and Random Sample Consensus (RANSAC)	accuracy and processing time of the object recognition algorithm using the SIFT and SURF methods combined with KNN and RANSAC for verification	The results on the algorithms include the comparison of the SIFT and SURF methods, with the SIFT method being more accurate and faster for object detection. The average processing times for detecting different numbers of objects are also provided.
Human Visual System Based Framework for Concealed Weapon DetectionG. Bhatnagar +1Canadian Conference on Computer and Robot Vision20116 citationsDOI	A new strategy is developed based on texture while exploiting the human visual system characteristics.	- The proposed concealed weapon detection algorithm utilizes the characteristics of the human visual system in the frame let domain to efficiently detect concealed weapons. - The algorithm employs two different strategies to fuse low and high frequency bands, resulting in improved detection quality. - Experimental results demonstrate the efficiency and robustness of the proposed algorithm in both visual inspection and objective evaluation criteria.	The methodology involves decomposing visual and IR/MMW images into low and high frequency bands using frame let transform, and then performing fusion using two different strategies based on the characteristics of low and high frequency bands. The first strategy is an adaptive weighted average based on local energy for low-frequency bands, and a new strategy based on texture for high frequency bands.	Not mentioned	The specific algorithm introduced in the study is an efficient concealed weapon detection algorithm that decomposes visual and IR/MMW images into low and high frequency bands using frame let transform, and performs fusion using adaptive weighted average based on local energy for low-frequency bands and a new strategy based on texture for high frequency bands.	Not mentioned	Not applicable (the paper does not provide specific quantitative metrics such as accuracy, precision, recall, F1 score, AUC, or ROC curve)
Virtual Gun, A Vision Based Human Computer Interface Using the Human HandJames J. Kuch +1IAPR International Workshop on Machine Vision Applications199417 citations	A person sits at a computer and points his index finger toward the screen with his thumb pointing up.	Not mentioned (the paper does not provide specific findings or conclusions from a study or experiment)	The methodology involves the development and description of a vision-based computer interface called Virtual Gun, which allows control of the computer using hand gestures without the need for special physical items. The method uses the entire 3-D hand model for tracking.	Not applicable (the paper does not mention any limitations or suggestions for further research)	Vision-based tracking system using the entire 3-D hand model	Not mentioned	Not mentioned (no information on algorithms or performance metrics is included in the paper)
Automated firearms detection in cargo x-ray images using RetinaNetYunqi Cui +1Defense + Commercial Sensing201912 citationsDOI	RetinaNet-based firearm detection model matches the detection accuracies of traditional sliding-windows convolutional neural net firearm detectors.	RetinaNet surpasses the performance of state-of-art two-stage R-CNN family object detectors and matches the detection accuracies of traditional sliding-windows convolutional neural net firearm detectors while offering more precise object localization and significantly faster detection speed.	The methodology involves using RetinaNet for automated firearm detection, training models with TIP to address class imbalance, testing on unseen weapons and cargo images, and considering variations in cargo content and background clutter.	Not mentioned	RetinaNet	detection accuracies, object localization precision, detection speed	The results on the algorithms include the comparison of the performance of RetinaNet-based firearm detection model with traditional sliding-windows convolutional neural net firearm detectors, showing that RetinaNet surpasses the detection performance of state-of-art two-stage R-CNN family object detectors while matching the speed of one-stage object detection algorithms. It also matches the detection accuracies of traditional sliding-windows convolutional neural net firearm detectors while offering more precise object localization and significantly faster detection speed.

Problem Statement

- Develop a robust gun detection system capable of real-time identification in various environments and lighting conditions.
- Integrate the detection system with a hardware microcontroller to enable immediate response actions upon firearm detection.
- Enhance public safety measures by providing timely alerts to authorities or triggering security protocols to mitigate potential threats.

Motivation

- In recent years, the global rise in gun violence has become a pressing public safety concern. Statistics reveal that approximately 0.5% of the global population is impacted by firearm-related incidents annually, translating to millions of individuals who face injury or death.
- In the United States alone, gun violence is responsible for tens of thousands of deaths each year, making it one of the leading causes of preventable mortality.
- This project aims to tackle this critical issue by deploying a real-time detection system capable of identifying firearms. Such a system is not only crucial for enhancing public security but also plays a significant role in alerting authorities and triggering automatic security measures to prevent potential threats and ensure public safety.

Dataset Information

Data Collection

Sources

The dataset was compiled from multiple sources:

- YouTube videos
- Google Images
- News articles

Data Annotation

The collected images were annotated using Roboflow, an online tool that assists in creating accurate labels for objects within an image.

Preprocessing

Overview of Techniques

Preprocessing was crucial to improve the model's accuracy and robustness. Techniques applied include:

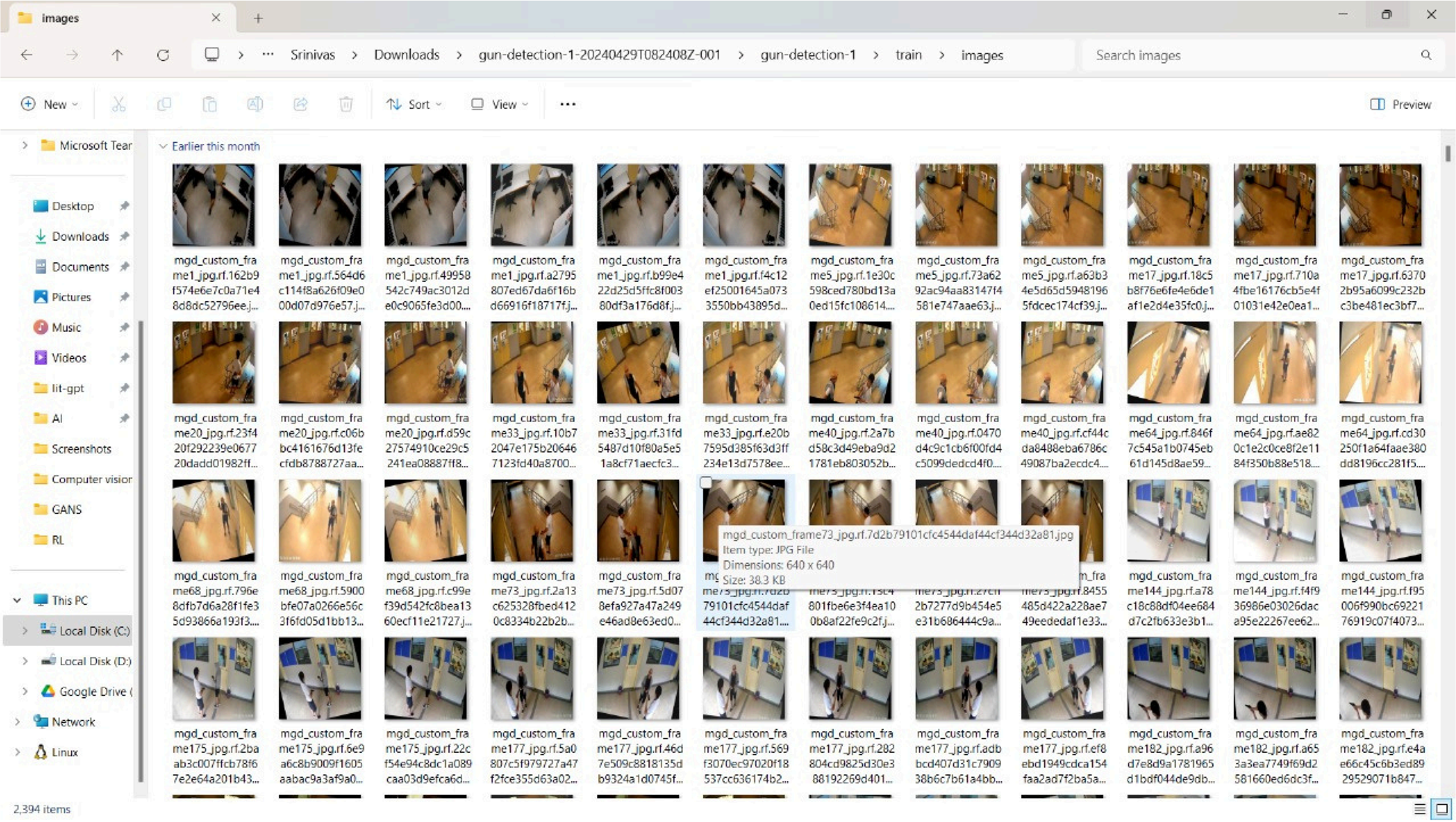
Augmentation: Enhancing the dataset's diversity by generating altered copies of images.

Saturation Adjustments: Modifying color saturation to make the model robust to color variations.

Cropping: Focusing on relevant sections of the images to improve detection accuracy.

Rotation: Introducing rotated versions of images to train the model to recognize guns from different angles.

ROBOFLOW


images
Srinivas › Downloads › gun-detection-1-20240429T082408Z-001 › gun-detection-1 › train › images
Search images
New
Sort
View
Preview
Microsoft Tear
Desktop
Downloads
Documents
Pictures
Music
Videos
lit-gpt
AI
Screenshots
Computer vision
GANS
RL
This PC
Local Disk (C:)
Local Disk (D:)
Google Drive
Network
Linux
Earlier this month
mgd_custom_frame73_jpg.rf.7d2b79101cfc4544daf44cf344d32a81.jpg
Item type: JPG File
Dimensions: 640 x 640
Size: 38.3 KB
2,394 items

WORKFLOW

Data Collection:

- Start with multiple sources such as YouTube, Google Images, and news articles.

Data Annotation:

- Annotate images using Roboflow to label guns accurately.

Preprocessing:

- Augment images to increase dataset variety.
- Adjust saturation to ensure robustness against color variations.
- Crop images to focus on relevant sections.
- Rotate images to handle different angles.

Model Training:

- Train the YOLO v9 model using the preprocessed dataset.

Model Testing:

- Test the model to evaluate accuracy, precision, and recall.

Hardware Integration:

- Integrate with NodeMCU microcontroller.

Detection and Response:

- **Continuous Video Feed**: Input into the system.
- **Gun Detection**: YOLO v9 processes the video and detects guns.
- **Trigger HTTP Request**: If a gun is detected, send an HTTP request from Python to NodeMCU.
- **Activate Alerts**: NodeMCU triggers an LED bulb and a buzzer.

Model Training

- **Mount Google Drive**: The code mounts the Google Drive to access files and data stored there.
- **Clone YOLOv9 Repository:** The YOLOv9 repository is cloned from GitHub, and the required dependencies are installed.
- **Download Dataset:** The Roboflow API is used to download a custom dataset for training. The dataset is split into train and validation sets.
- **Download Model Weights:** Pre-trained model weights for YOLOv9 are downloaded from GitHub releases.
- **Train the Custom Model:** The train.py script is executed with various parameters, including batch size, epochs, input image size, device, data configuration file, pre-trained weights, and model configuration file. The training process begins, and the model is trained on the custom dataset for the specified number of epochs.
- **Visualize Training Results:** After training, the results are visualized, including labels, confusion matrix, and sample predictions on the validation set.
- **Run Inference:** The detect.py script is used to run inference on the custom trained model. The script takes the trained model weights, input images, and other parameters like confidence threshold and image size. It runs the model on the specified images and saves the results.

NODE MCU - ESP 38266

esp8266_with_python | Arduino IDE 2.1.1

File Edit Sketch Tools Help

Select Board

esp8266_with_python.ino

```
#include <ESP8266WiFi.h>

const char AP_NameChar[] = "My Wifi LED";
const char WiFiPassword[] = "";

WiFiServer server(80);

String request = "";
int LED_Pin = 16;
int Buzzer_Pin = 5;
int beepLength = 500;

void setup() {
  // put your setup code here, to run once:
  Serial.begin(115200);
  pinMode(LED_Pin, OUTPUT);
  pinMode(Buzzer_Pin, OUTPUT);

  boolean conn = WiFi.softAP(AP_NameChar, WiFiPassword);
  server.begin();

  Serial.println("Nodemcu(esp8266) is ONLINE");
  Serial.println(WiFi.localIP());

  delay(1000);
}

void loop() {
  // put your main code here, to run repeatedly:
  WiFiClient client = server.available();
  if (!client)  {
    return;
  }

  request = client.readStringUntil('\r');

  Serial.println(request);

```

Ln 1, Col 1 × No board selected

Train your Custom Model

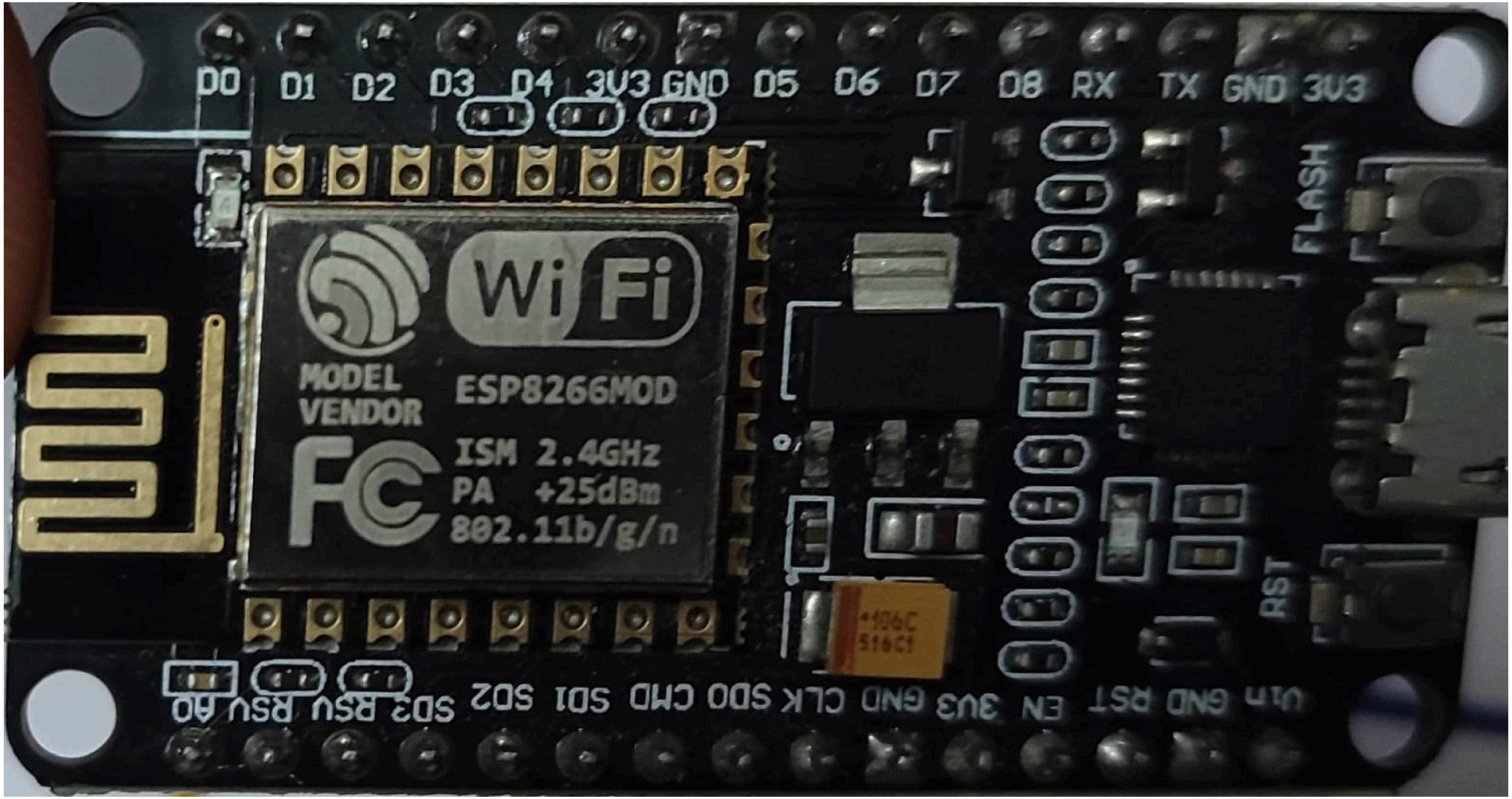
```
!python train.py \
--batch 16 --epochs 50 --img 640 --device 0 --min-items 0 --close-mosaic 15 \
--data /content/yolov9/gun-detection-1/data.yaml \
--weights /content/yolov9/gelan-c.pt \
--cfg /content/yolov9/models/detect/gelan-c.yaml \
--hyp hyp.scratch-high.yaml
```

Python

```
2024-04-17 13:49:17.519763: E external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261] Unable to register cuDNN factory: Attempting to register fa
2024-04-17 13:49:17.519815: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607] Unable to register cuFFT factory: Attempting to register fac
2024-04-17 13:49:17.521760: E external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1515] Unable to register cuBLAS factory: Attempting to register
2024-04-17 13:49:18.846765: W tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not find TensorRT
train: weights=/content/yolov9/gelan-c.pt, cfg=/content/yolov9/models/detect/gelan-c.yaml, data=/content/yolov9/gun-detection-1/data.yaml, hyp=hyp.scra
YOLOv5 🚀 1e33dbb Python-3.10.12 torch-2.2.1+cu121 CUDA:0 (Tesla T4, 15102MiB)

hyperparameters: lr0=0.01, lrf=0.01, momentum=0.937, weight_decay=0.0005, warmup_epochs=3.0, warmup_momentum=0.8, warmup_bias_lr=0.1, box=7.5, cls=0.5,
ClearML: run 'pip install clearml' to automatically track, visualize and remotely train YOLO 🚀 in ClearML
Comet: run 'pip install comet_ml' to automatically track and visualize YOLO 🚀 runs in Comet
TensorBoard: Start with 'tensorboard --logdir runs/train', view at http://localhost:6006/
Downloading https://ultralytics.com/assets/Arial.ttf to /root/.config/Ultralytics/Arial.ttf...
100% 755k/755k [00:00<00:00, 17.7MB/s]
Overriding model.yaml nc=80 with nc=2
```

NODE MCU CONTROLLER



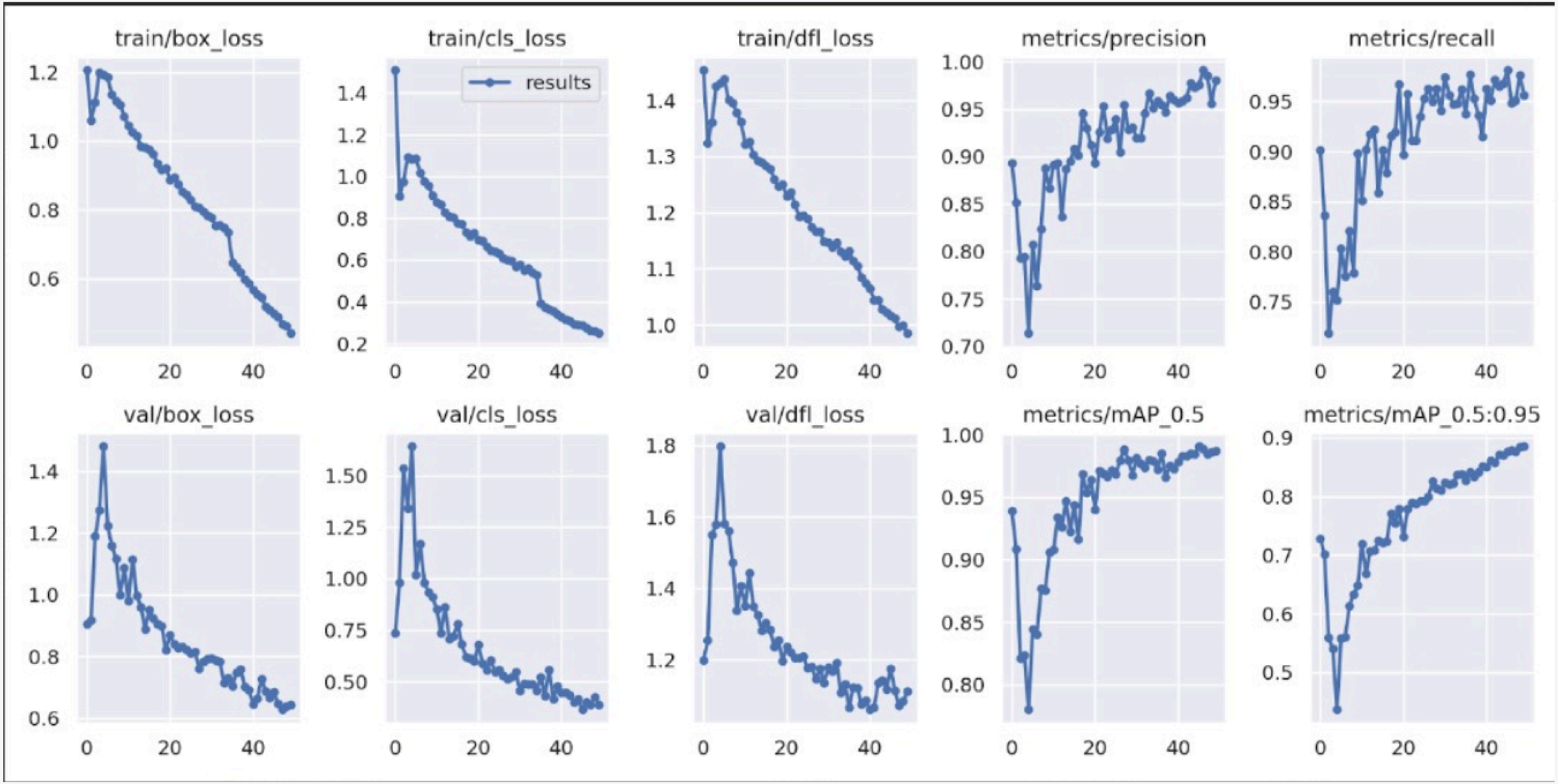
CONNECTION B/W CV AND NODE MCU

Conclusion and Future Work

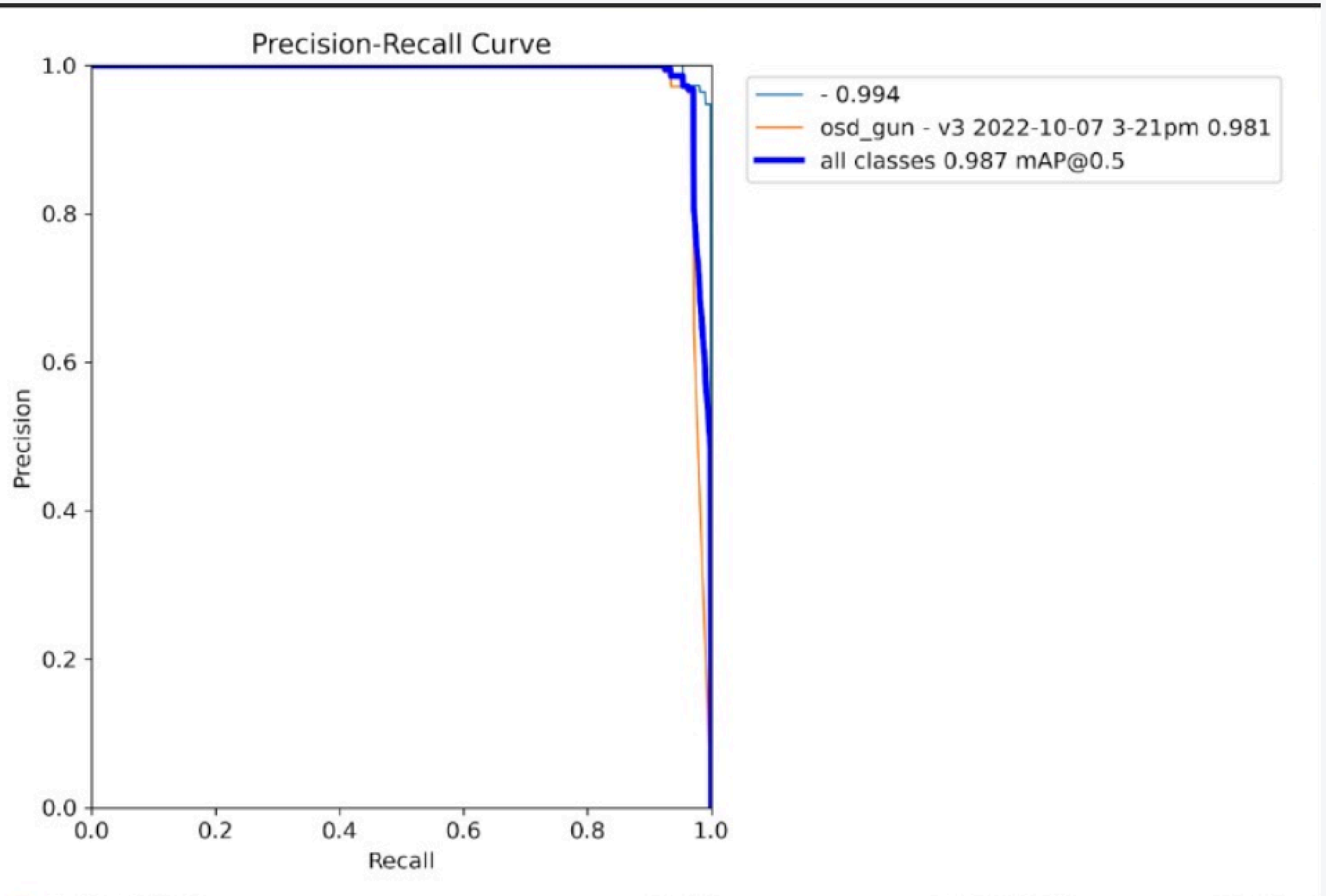
In conclusion, our project represents a significant step forward in the realm of gun detection and public safety enhancement. By harnessing the power of deep learning and hardware integration, we have developed a system capable of detecting firearms in real-time and triggering immediate response actions. However, there remain opportunities for further improvement and expansion:

- **Future Work:** Expanding the dataset to encompass a broader range of firearm variations and environmental contexts.
- **Optimization:** Fine-tuning the model parameters and hardware components for enhanced performance and scalability.
- **Integration:** Exploring additional integration possibilities with existing security systems and protocols for comprehensive security solutions.

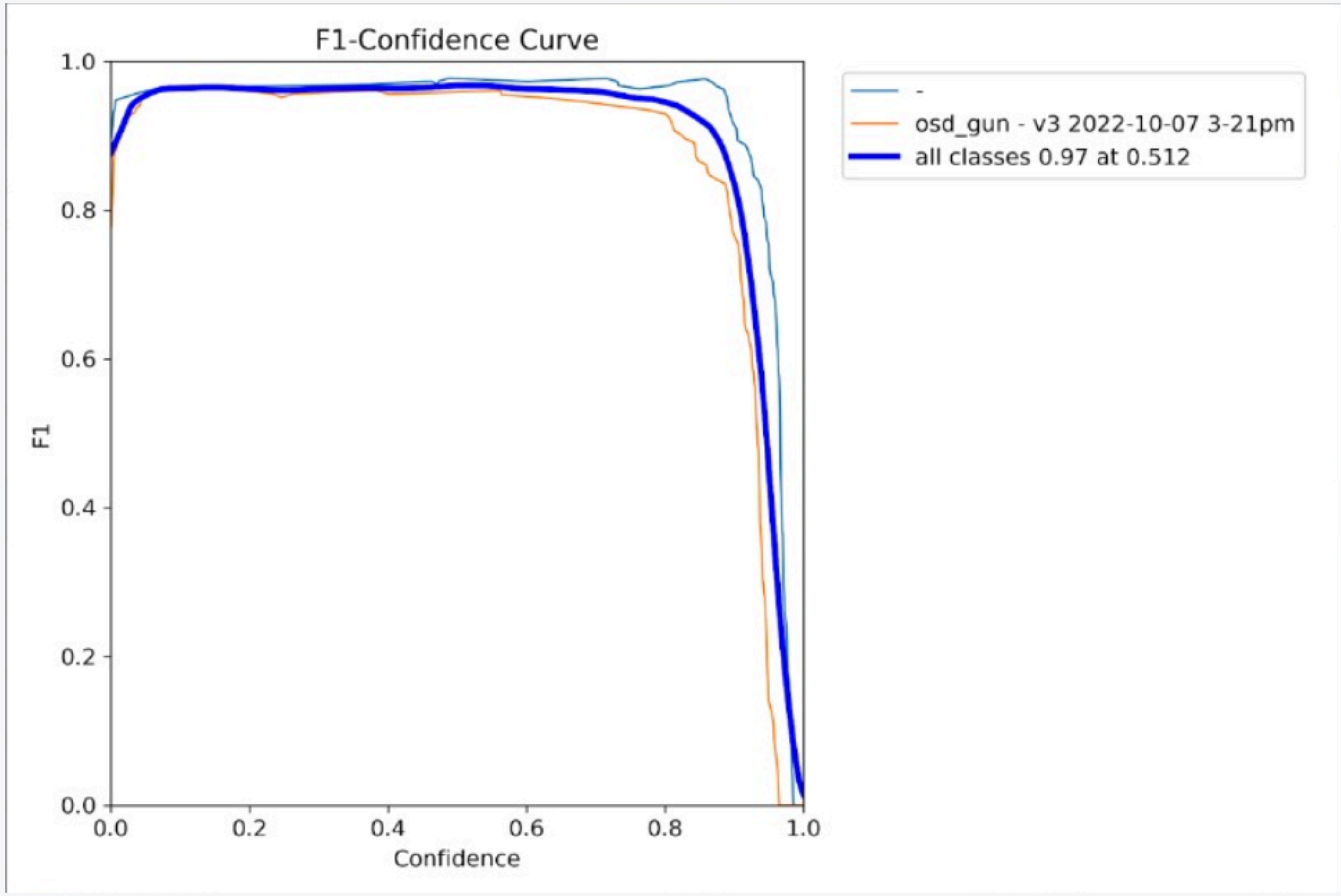
RESULTS


train/box_loss
train/cls_loss
results
train/dfl_loss
metrics/precision
metrics/recall
val/box_loss
val/cls_loss
val/dfl_loss
metrics/mAP_0.5
metrics/mAP_0.5:0.95

RESULTS



Precision-Recall Curve
1.0
0.8
0.6
0.4
0.2
0.0
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall
- 0.994
osd_gun - v3 2022-10-07 3-21pm 0.981
all classes 0.987 mAP@0.5



F1-Confidence Curve
1.0
0.8
0.6
0.4
0.2
0.0
F1
0.0
0.2
0.4
0.6
0.8
1.0
Confidence
-
osd_gun - v3 2022-10-07 3-21pm
all classes 0.97 at 0.512

Thank you!