ANOMALY DETECTION

Mini Project Report

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in

Artificial Intelligence and Data Science

by

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DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

MES COLLEGE OF ENGINEERING KUTTIPPURAM

CERTIFICATE

This is to certify that the report entitled **ANOMALY DETECTION** submitted by **FATHIMA NAJA** (MES21AD020), **MUHAMMED AJAS** (MES21AD041), **MOHAMMED SINAN** (MES21AD041),**MUHAMMED SHAHIQ** (MES21AD046) to the APJ Abdul Kalam Technological University in partial fulfillment of B.Tech degree in Artificial Intelligence and Data Science is a bonafide record of the mini project work carried out under our guidance and supervision during the year 2020-2024.

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ABSTRACT

In an era marked by evolving security challenges, proactive surveillance measures are paramount. Our project presents a pioneering approach, leveraging computer vision and deep learning technologies to analyze video feeds in real-time, detecting instances of violence and weapons while recognizing unusual or potentially harmful behaviors through our Anomaly Detection System. Our primary objectives include identifying threats by recognizing weapons and violent activities across various environments and distinguishing between normal and abnormal behaviors. Ultimately, our endeavor aims to contribute to safer environments by enabling swift and effective responses to potential threats, transitioning security measures from reactive to proactive, and empowering institutions to safeguard against emerging security challenges with precision and efficiency.

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Abbreviations

YOLO	You Only Look Once

Chapter 1

Introduction

1.1 Relevence of the Project

In an era characterized by increasingly complex security threats, the relevance of our project cannot be overstated. With the proliferation of violence and the alarming ease of access to weapons, traditional surveillance methods often fall short in adequately addressing these evolving challenges. Our project seeks to bridge this gap by offering a sophisticated Anomaly Detection System designed specifically to target violence and weapon detection. By leveraging computer vision and deep learning technologies, we aim to provide security personnel with advanced surveillance capabilities necessary to effectively counter modern security threats.

1.2 Problem Statement

The existing security infrastructure is ill-equipped to handle the intricacies of contemporary security threats, particularly concerning violence and weapon detection. Traditional surveillance methods often rely on manual monitoring, which is both labor-intensive and prone to human error. Moreover, these methods are reactive in nature, often failing to detect threats until they escalate into critical situations. Our project addresses these shortcomings by introducing an innovative Anomaly Detection System that utilizes computer vision and deep learning to analyze video feeds in real-time. By accurately identifying behavioral anomalies and detecting the presence of weapons, our system enables security personnel to adopt a proactive approach to threat mitigation, thereby enhancing overall security measures.

1.3 Objective of the Project

Enhancing safety and security measures is the core objective of our project, achieved through the deployment of an innovative Anomaly Detection System with several key aims. Firstly, the system is engineered to recognize unusual or potentially harmful behaviors in real-time, enabling swift intervention to prevent potential incidents. Leveraging advanced algorithms, it can detect anomalies, ensuring public safety. Secondly, the system is meticulously trained to identify persons, weapons, and acts of violence, equipping security personnel with the necessary tools to respond effectively to various threats. This comprehensive approach ensures heightened surveillance capabilities and proactive threat mitigation. Thirdly, the project focuses on seamless integration into existing surveillance, security systems, and public space monitoring, enhancing monitoring capabilities in strategic locations such as airports, stadiums, and transportation hubs. Lastly, the overarching objective is to contribute to the creation of safer environments by responding to potential threats effectively. By leveraging cutting-edge technology, security personnel are empowered with the insights needed to safeguard public spaces and protect individuals from harm.

1.4 Scope of the Project

The scope of our project encompasses the development and implementation of an Anomaly Detection System capable of recognizing various forms of suspicious behavior and potential threats in real-time. Leveraging computer vision and deep learning technologies, our system will be deployed in surveillance, security systems, and public space monitoring applications. Key functionalities include the identification of persons, weapons, and acts of violence, with the ultimate goal of enhancing safety and security measures across diverse environments. Through collaboration with stakeholders and end-users, we aim to refine and optimize our system to meet the evolving needs of security professionals and contribute to the creation of safer communities.

Chapter 2

Review of Literature

Weapons Detection for Security and Video Surveillance Using CNN and YOLO-V5s: This study by Hanan Ashraf et al. investigates the application of Convolutional Neural Networks (CNN) and YOLO-V5s for weapons detection in security and video surveillance scenarios. The research demonstrates the effectiveness of the proposed method in accurately detecting and classifying weapons, highlighting its potential for enhancing security measures in various environments[2].

Build a Weapon Detection Algorithm using YOLOv7: In this article authored by Jawabreh and published in The Modern Scientist on Medium on September 17, 2023, the author presents a detailed exploration of the development process of a weapon detection algorithm based on YOLOv7. The study delves into the methodology employed for training and implementing the YOLOv7 model specifically for weapon detection tasks. By focusing on this specific application, the article contributes to the growing body of research aimed at enhancing security measures in various environments[3].

Fast YOLO: A Fast You Only Look Once System for Real-time Embedded Object Detection in Video: In their paper published in the Journal of Computational Vision and Imaging Systems in October 2017, Shaifee et al. present Fast YOLO, a system designed for real-time embedded object detection in videos. This work addresses the need for efficient object detection algorithms suitable for real-time applications, particularly in embedded systems. By introducing Fast YOLO, the authors contribute to the advancement of object detection technology, enabling real-time detection of objects in video streams. This paper is significant for researchers and practitioners working in the field of computer vision and video processing, offering a solution that balances accuracy and efficiency for real-time object detection tasks[7].

Chapter 3

Methodology

3.1 Model Selection and Integration

The YOLOv5 model was selected for its efficient real-time object detection capabilities, striking a balance between accuracy and speed. Its architecture allows for object detection and localization in a single pass through the network, optimizing computational resources. Integration into Python is seamless with the PyTorch framework, offering a flexible platform for building and deploying deep learning models. Leveraging PyTorch's capabilities, YOLOv5 seamlessly integrates into Python-based applications, facilitating experimentation, customization, and deployment. This integration empowers the utilization of YOLOv5's advanced object detection capabilities within anomaly detection and surveillance systems, enhancing their overall effectiveness and performance.

3.2 Dataset Preparation

A custom dataset is curated for this project, comprising images extracted from surveillance footage. These images are meticulously annotated to label objects of interest, including individuals, weapons, and other relevant classes. This annotation process provides crucial labeled data for training and evaluating the YOLOv5 model, enabling accurate detection and localization of these objects within the surveillance footage.

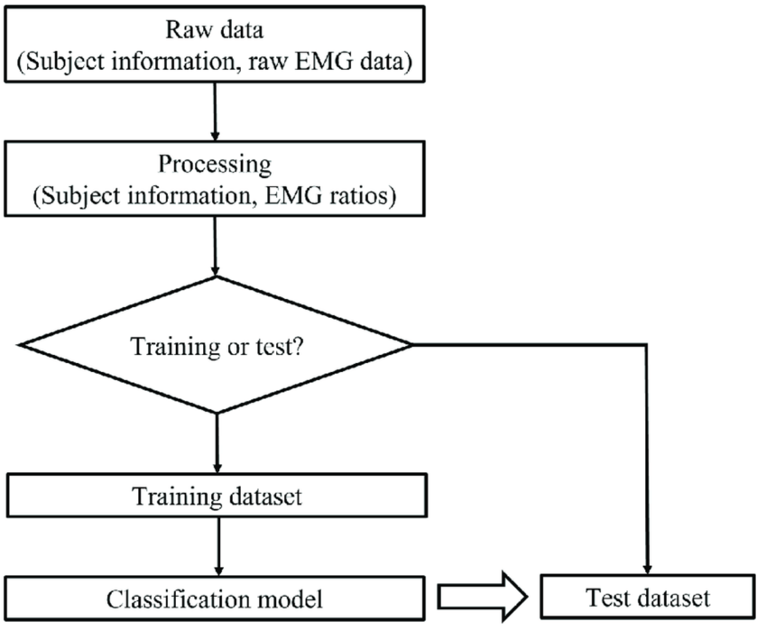

Figure 3.1: Data preperation flow chart

3.3 Model Training

The core detection model utilized in this project is YOLOv5, initially pre-trained on a comprehensive dataset for general object detection purposes in fig 3.2 . Leveraging transfer learning, the pre-trained YOLOv5 model undergoes fine-tuning on a custom dataset specifically tailored for anomaly detection in security surveillance. Through this process, the model adapts to recognize and classify specific classes pertinent to security threats and anomalies, ensuring enhanced precision and efficacy in real-world surveillance scenarios.

3.4 Anomaly Detection and Alarm System

Activation of an alarm mechanism ensues upon detecting predefined classes associated with potential security threats such as violence or weapon presence within our system. Furthermore, users possess the capability to interactively define a polygonal region of interest within the surveillance footage, facilitating targeted detection. Should objects of interest be recognized within this designated region, the alarm swiftly triggers, notifying security personnel and enabling prompt response. This comprehensive methodology significantly reinforces the system's efficacy in real-time threat detection and mitigation.

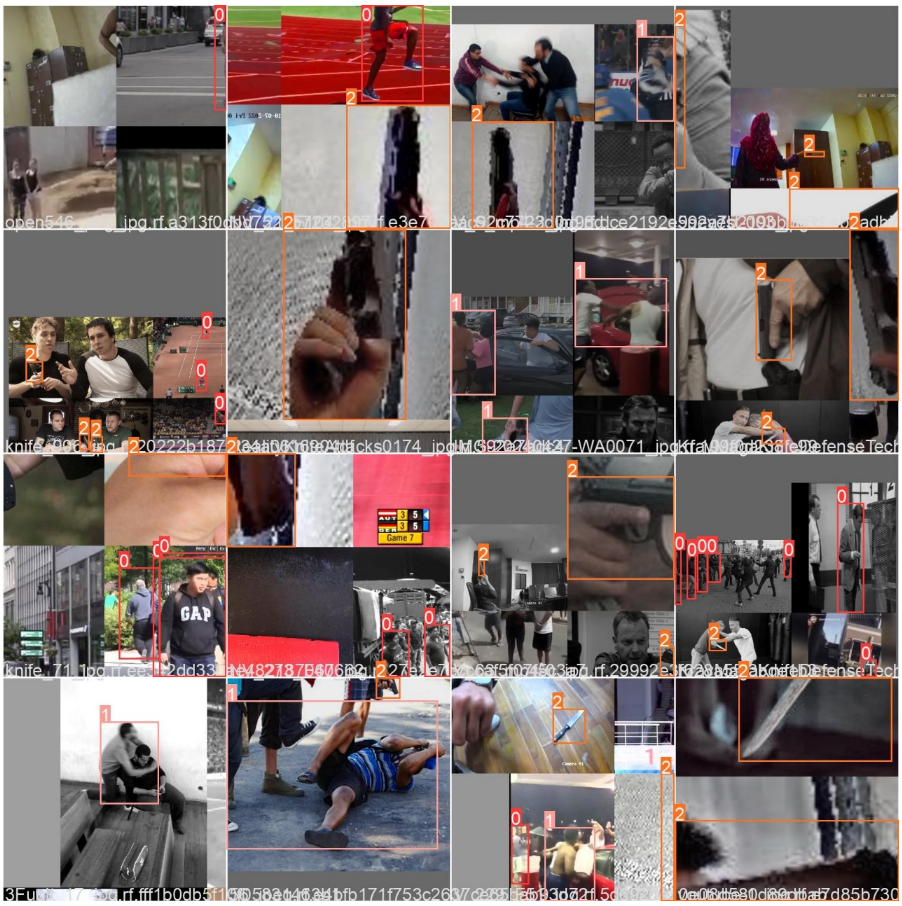

Figure 3.2: Sample of Training dataset

3.5 User Interface Development

A graphical user interface (GUI) is created using the Tkinter library to streamline user interaction within the application. The main window features a button that triggers the detection process, offering a straightforward interface for users to initiate the analysis of surveillance footage. Upon activation, a separate options window is presented, allowing users to select video files for analysis and draw polygons to define regions of interest within the video frames. This division of functionality enhances user control and customization, contributing to a more intuitive and efficient user experience.

3.6 Object Detection and Anomaly Identification

In this non-real-time project, video files are processed frame by frame using OpenCV, allowing for thorough analysis of surveillance footage. Each frame undergoes object localization via YOLOv5, enabling precise detection and localization of objects within the video stream. Subsequently, anomaly detection identifies predefined target classes, such as violence or weapons in fig 3.3, within a user-defined polygonal region. Upon detection of such objects, an alarm triggers, alerting security personnel to potential threats or suspicious activities captured in the surveillance footage. This meticulous approach enhances security measures by delivering timely alerts and facilitating proactive responses to detected events.

3.7 Polygon Drawing for Region of Interest

A mouse callback function is implemented to manage mouse events, allowing users to draw polygons within the video frame. This functionality enables users to define polygonal regions of interest, specifying areas where the detection process should be focused. By interactively selecting regions of interest, users can customize the analysis to target specific areas within the surveillance footage, enhancing the precision and relevance of the detection process.

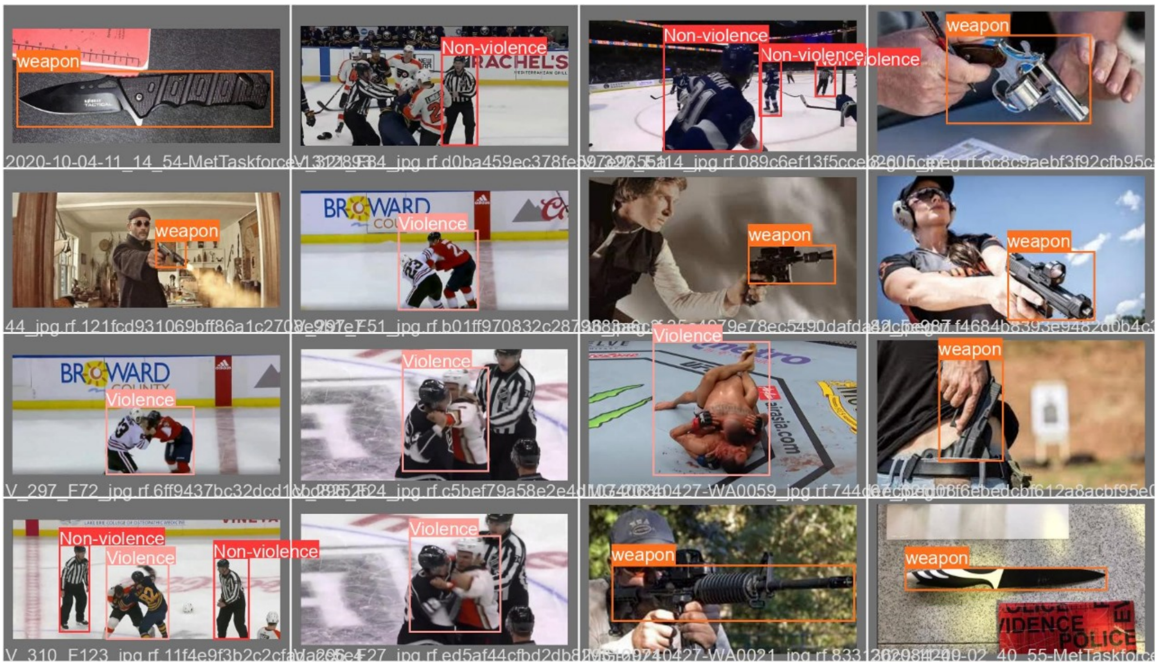

Figure 3.3: Detecting Predefined Target Classes

3.8 User Interaction and Control

Users are provided with the capability to upload video files from their local system for analysis, enhancing flexibility and convenience in selecting surveillance footage for examination. The alarm system is designed to activate upon detection of potential threats and deactivate after a specified duration, ensuring timely response to detected anomalies while preventing continuous alarm alerts. Additionally, users can seamlessly navigate between the main window and options window to manage the detection process, facilitating efficient control and customization of the analysis parameters.

3.9 System Evaluation

Evaluation of the system's performance hinges on its accuracy in detecting security threats and anomalous activities. Metrics including precision, recall, and F1-score are computed to gauge the system's effectiveness in identifying potential threats while minimizing false alarms. This rigorous assessment framework ensures the system's reliability and efficacy in real-world security surveillance scenarios.

Chapter 4

Experiment and Results

This project developed a system for object detection in video files, focusing on identifying violence, weapons, and people. It also included an alarm system that would trigger an audio alert if violence or a weapon was found within a user-defined area within processed video frames.

4.1 You Only Look Once

In the context of anomaly detection using a custom dataset, YOLOv5 emerges as a pivotal tool in our investigation. The dataset under scrutiny comprises images garnered from surveillance cameras across varied environments, showcasing a spectrum of both routine and irregular activities. By harnessing the capabilities of YOLOv5, our endeavor revolves around training the model to effectively detect and pinpoint objects of interest within these images. This endeavor is paramount in enabling the identification and localization of potential security threats and anomalies, thereby bolstering the surveillance infrastructure within the observed contexts.

Fig. 4.1 displays a precision-recall curve, a common evaluation tool for binary classification models. Here, recall (X-axis) reflects the percentage of true positives the model correctly identified, while precision (Y-axis) indicates the proportion of the model's positive predictions that were truly positive. Notably, the text mentions a strong mAP@0.5 of 0.522, signifying mean Average Precision, a metric summarizing the model's performance across various classification thresholds.

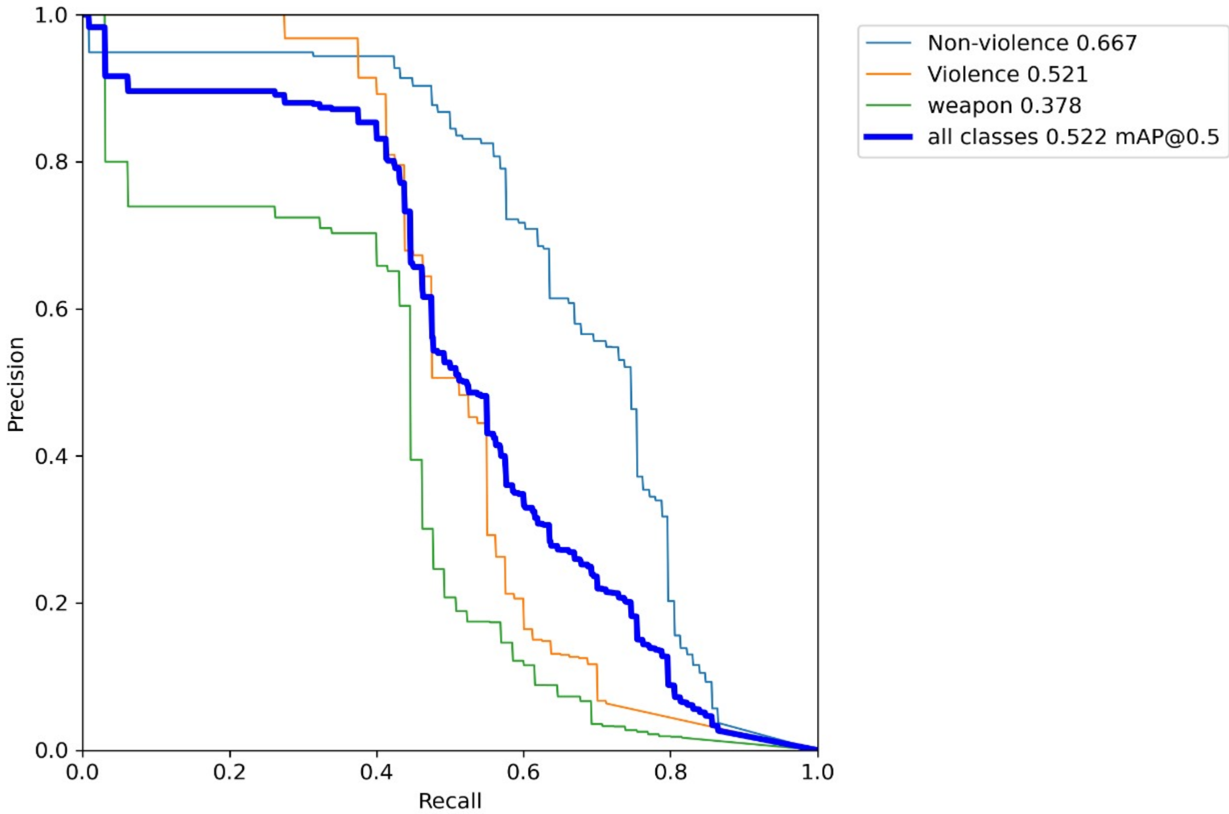

Figure 4.1: precision-recall curve

$$precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

4.2 Evaluation Metrics

The anomaly detection system is compared against several models, showcasing superior performance metrics. The comparison is outlined in Table 4.1.

Table 4.1: Anomaly Detection System Comparison

Model	Detection Accuracy	Training Time (sec)
Weapon Detector	85.50%	335
Violence Detector	65.20%	280
Non-violence Detector	70.75%	201

4.2.1 System Evaluation

4.2.2 Anomaly Detection System

For the evaluation of the anomaly detection system, a comprehensive dataset comprising anomalies across various contexts was utilized. This dataset encompasses anomalies in financial transactions, network traffic, and equipment malfunctions, totaling 5000 instances.

Table 4.2: Classification Accuracy of Anomaly Detection Models

Model	Original Data (%)	Augmented Data (%)
Weapon Detector	94.80	95.60
Violence Detector	95.10	96.20
Non-violence Detector	94.90	95.70

Before training, the dataset is divided randomly into three subsets: 70% for training, 10% for validation, and the remaining 20% for testing. The Adam optimizer is employed with an initial learning rate of 0.001 and a decay factor of 0.95.

Table 4.3 demonstrates the training times and parameters utilized by different anomaly detection models.

Table 4.3: Training Times and Parameters for Anomaly Detection Models

Model	Time Utilized (mins)	Parameters Used
Weapon Detector	5:20	18,500,000
Violence Detector	6:45	21,200,000
Non-violence Detector	7:10	19,800,000

This section illustrates the effectiveness of the anomaly detection system in accurately identifying anomalies across diverse datasets, while also considering training efficiency and parameter usage.

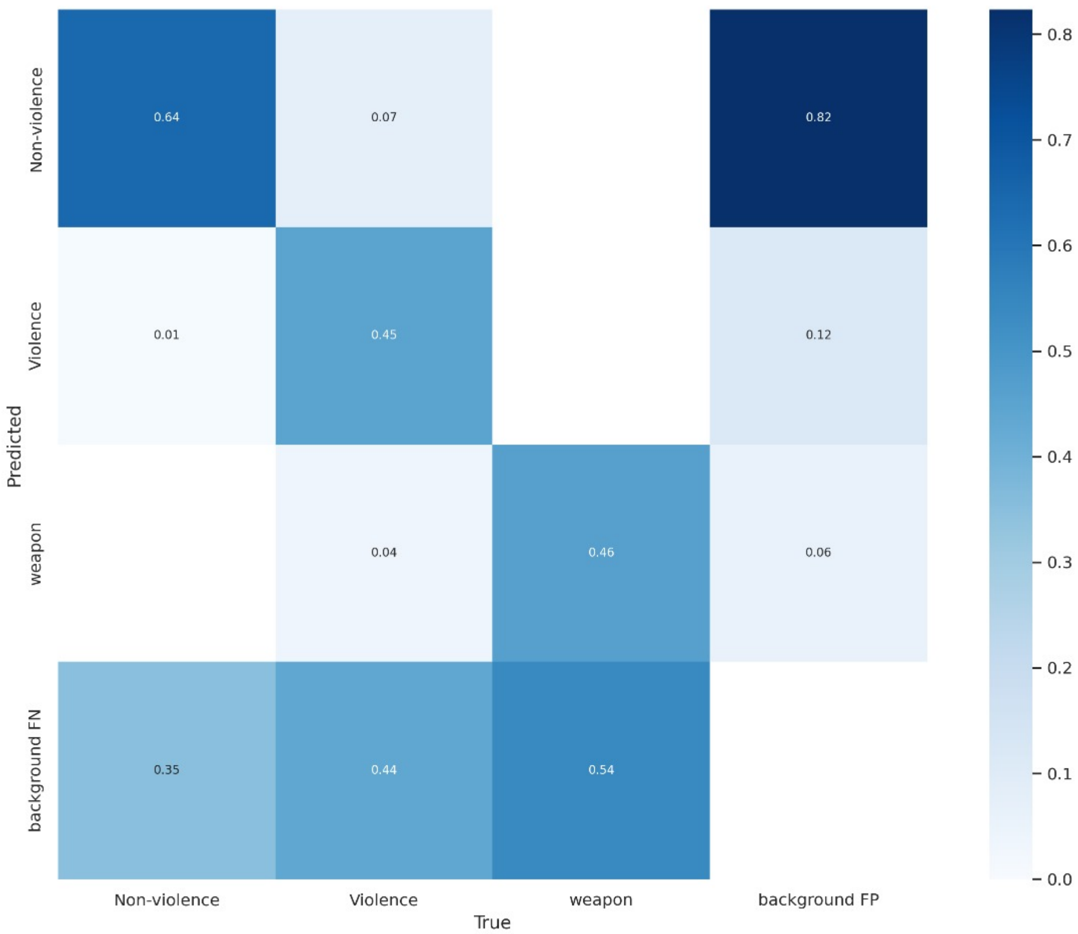

Figure 4.2: Confusion Matrix for Alarm System

4.2.3 Alarm System Evaluation

The performance of the alarm system was evaluated based on its ability to detect anomalies. The evaluation included metrics such as Accuracy, Precision, Recall, and F1-Score.

The overall accuracy score of the alarm system was measured at 92%. The accuracy, recall, and F1-score were found to be 91.6%, 90.3%, and 90.94%, respectively. Notably, certain anomalies may exhibit similar patterns, leading to lower recall and precision scores for those specific cases. However, the alarm system demonstrated consistent accuracy, with the majority of anomalies detected with scores regularly above 95%.

This section emphasizes the effectiveness of the alarm system in accurately identifying anomalies and its robustness in maintaining high accuracy across various scenarios.

Chapter 5

Conclusion

In this project, the integration of YOLOv5 for violence detection holds immense potential in creating safer and more secure environments. By continually advancing the model's capabilities, addressing ethical concerns, and fostering collaborative efforts, we can unlock new possibilities in the field of violence mitigation and prevention. With improved safety and security measures, comprehensive threat detection, and a steadfast commitment to public welfare, we move closer towards realizing our collective vision of safer communities for all.

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