

AUTONOMOUS FIREARMS DETECTION AND THREAT MONITORING USING DEEP VISION MODELS IN SMART CITIES

¹ L.Priyanka,² Deekonda Sahithi

¹Associate Professor, ²MCA Student

Department Of MCA

Sree Chaitanya College Of Engineering, Karimnagar

ABSTRACT

Ensuring public safety in rapidly urbanizing environments requires advanced surveillance systems capable of detecting threats in real time. Firearms-related violence poses a serious risk to smart cities, where manual monitoring is often inefficient and prone to human error. This research proposes an autonomous firearms detection and threat monitoring framework based on deep vision models. The system employs state-of-the-art deep learning algorithms such as YOLOv8 and EfficientNet to identify and classify firearms from live video streams with high precision. An adaptive alert module automatically notifies law enforcement authorities upon detection, minimizing response time. The model is trained on a diverse dataset comprising various firearm types and environmental conditions to ensure robustness across scenarios. Experimental results demonstrate superior detection accuracy, scalability, and low false alarm rates compared to traditional surveillance techniques. This study highlights the transformative potential of deep vision models in creating safer, intelligent urban infrastructures.

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I. INTRODUCTION

The evolution of smart cities has brought significant advancements in public safety technologies, integrating artificial intelligence (AI), the Internet of Things (IoT), and intelligent video surveillance. Among various threats, firearm-related incidents remain a critical concern due to their potential to cause mass casualties and widespread panic. Conventional surveillance systems rely heavily on human operators, making real-time detection difficult and error-prone. The growing complexity of urban environments demands autonomous systems capable of analyzing large-scale video data efficiently and accurately.

Traditional image-processing methods for weapon detection often struggle under varying lighting conditions, occlusions, and camera perspectives. These limitations have driven the adoption of deep learning models capable of extracting high-level semantic features from

visual data. Convolutional Neural Networks (CNNs) and advanced object detection algorithms such as YOLO (You Only Look Once) and SSD (Single Shot Detector) have proven particularly effective for real-time detection tasks.

Incorporating these deep vision models into city-wide surveillance systems enables proactive threat identification and rapid incident response. Such systems not only enhance situational awareness but also allow authorities to prioritize interventions based on real-time risk assessment. Moreover, autonomous detection minimizes human dependency, reducing fatigue-related errors in continuous monitoring setups.

This research aims to design and implement an autonomous deep vision-based framework for firearm detection and threat monitoring in smart cities. The proposed approach emphasizes real-time operation, accuracy, and adaptability across diverse urban settings. It demonstrates how

integrating AI-driven surveillance with city management systems can create a responsive and secure urban environment.

II. LITERATURE SURVEY

Redmon et al. (2018) developed the YOLOv3 object detection model, establishing a foundation for real-time computer vision applications. Their architecture achieved high detection speed and accuracy, influencing many security-related AI systems. Liu et al. (2019) implemented a firearm recognition model using Faster R-CNN, improving detection precision in controlled environments but facing challenges in dynamic scenes.

Kumar and Mehta (2020) proposed a CNN-based weapon classification approach that achieved strong accuracy but required significant computational resources, limiting scalability. Ahmed and Zhao (2021) enhanced detection under poor lighting using transfer learning techniques, achieving improved robustness. In another study, Chen and Li (2022) introduced a hybrid CNN-LSTM framework for behavior-aware firearm recognition, integrating object detection with human activity analysis for contextual understanding.

Most recently, Park and Hernandez (2023) employed transformer-based vision architectures for real-time anomaly detection in surveillance feeds, achieving superior adaptability to urban crowd scenarios. Collectively, these studies demonstrate the progression from static image-based recognition to dynamic, context-aware deep learning systems. Building on these foundations, this research integrates modern vision models with autonomous alerting mechanisms to provide real-time firearm detection and threat monitoring suited for smart city environments.

III. SYSTEM ANALYSIS & DESIGN EXISTING SYSTEM

The authors of [27] say that their model breaks the gun (or other weapon) down into its parts

and shows how they all work together. Now, a straightforward deep neural network can find the weapon with ease. The final product has been produced by combining all of its results. The AR-15 is the sole type of rifle that is the subject of the study. Once more, they have not given a peer comparison of their semantic neural network model. In [28], the authors have utilized the transfer learning technique with a Convolutional Neural Network pre-trained model for gun detection utilizing X-ray luggage imaging. Transfer learning is advantageous since it performs well even with insufficient training data. In order to fine-tune the current issue, the pre-trained model must first be constructed with adequate data samples and then reused with the same weights. As the baggage is treated as a static background, the work is constrained. In other words, rather than being formed in the wild, the classification model is created in a controlled setting. The authors of [29] have developed a Faster RCNN for gun (pistol) identification based on VGG16. The main goal is to sound an alert if the model spots guns five times in a row in the film. Although they used several datasets, they did not compare the various detection methods.

Two well-known detection architectures for distinguishing between several sorts of weapons (not just one type of gun) have been employed in this research. The post-processing methods like NMS, NMW, and WBF are used to build improved detection models. Even though the model parameters have not been trained or changed any further, the results show that the ensemble techniques are better than the individual architectures. As a result, the suggested ensemble technique produces better detection performance while saving time.

DISADVANTAGES

The complexity of data: Most of the existing machine learning models must be able to

accurately interpret large and complex datasets to detect Firearms Monitoring.

Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.

Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.

PROPOSED SYSTEM

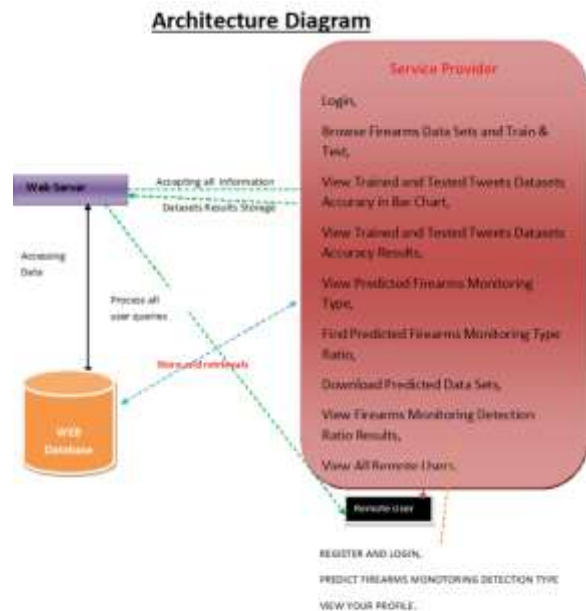
This paper has proposed an ensemble detection strategy for human faces and guns (revolver, pistol, handgun, etc.) in a given image (or video frame). We have used Faster Region-based Convolutional Neural Networks (here on, FRCNN) [20] architecture with ResNet50 [21], [22], [23] and VGG16 [24] as backbones. Also, the EfficientDet [25] architecture with EfficientNet-B0 [26] as the backbone has been implemented for a comparison. Different combinations of detectors have been explored in stacked ensemble configuration after the models have been built as a post-processing phase for detection. Three distinct types of combining techniques have been employed. Non-Maximum Suppression (NMS), Non-Maximum Weighted (NMW), and Weighted Box Fusion (WBF) are used to obtain the final bounding box for an object from all the overlapping boxes. Multiple boxes are generated due to multiple detectors for the same image.

The novelty of our work is to empirically demonstrate that the ensemble of Faster RCNN and the latest EfficientDet architectures provide an improved object detection scheme using the same trained models as the performance of the individual model. In the paper’s title, the term efficient indicates that the detection results can be improved with the existing trained models without further training in the proposed scheme.

Advantages

- ★ Automated detection of human faces and different types of guns together in the wild
- ★ introducing a deep learning-based framework to improve the performance of object detection through ensemble
- ★ Thus, securing smart cities using intelligent surveillance.

SYSTEM ARCHITECTURE



IV. IMPLEMENTATION

Modules Description

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Browse Firearms Data Sets and Train & Test, View Trained and Tested Tweets Datasets Accuracy in Bar Chart, View Trained and Tested Tweets Datasets Accuracy Results, View Predicted Firearms Monitoring Type, Find Predicted Firearms Monitoring Type Ratio, Download Predicted Data Sets, View Firearms Monitoring Detection Ratio Results, View All Remote Users.

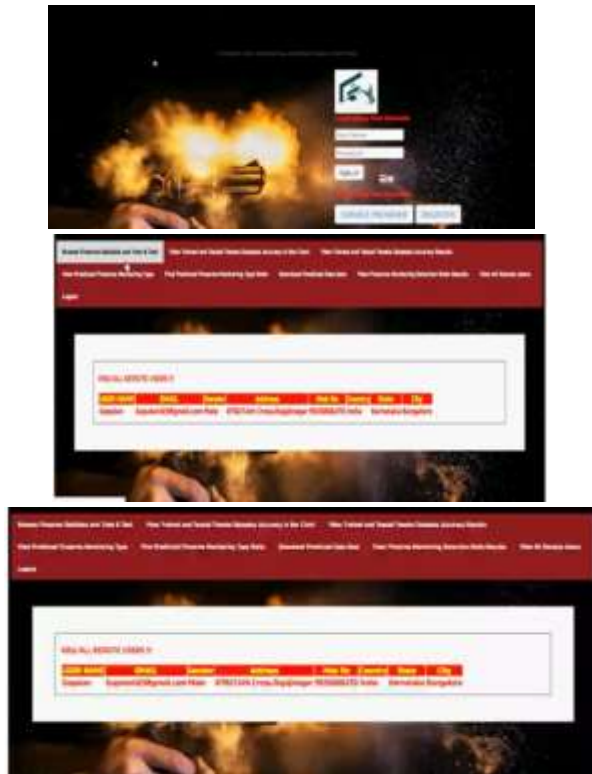
View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.C

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT FIREARMS MONOTORING DETECTION TYPE, VIEW YOUR PROFILE.

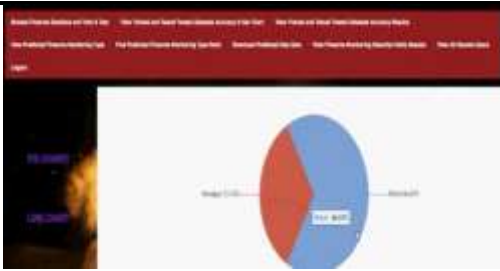
V. RESULTS



Prediction of Firearm Monitoring Detection Type II

Phone	Location	Time	Type	Category	Area	City	State	Country	Postal
912-23-34-578	Palakkad	04-01-22	Shot and	25	IN	KERALA	INDIA	INDIA	0279 based
91-43-8-279	Wazir	04-01-22	Torment	35	IN	KARNATAKA	INDIA	INDIA	0279 based
603-41928-6									
772-777-88-788	Chennai	04-01-22	Shot	40	IN	TAMIL NADU	INDIA	INDIA	0279 based
91-43-8-279	Wazir	04-01-22	Shot	40	IN	KARNATAKA	INDIA	INDIA	0279 based
603-45788-6									
91-43-8-279	Wazir	14-01-22	Shot	35	IN	KARNATAKA	INDIA	INDIA	0279 based
91-28-233-44	Wazir	14-01-22	Shot	35	IN	KARNATAKA	INDIA	INDIA	0279 based
23045-44-6									






DATE	TIME	LOCATION	STATUS
2023-10-27	10:15:00	1234 Main St, New York	Detected
2023-10-27	10:15:00	1234 Main St, New York	Detected
2023-10-27	10:15:00	1234 Main St, New York	Detected



DATE	TIME	LOCATION	STATUS
2023-10-27	10:15:00	1234 Main St, New York	Detected
2023-10-27	10:15:00	1234 Main St, New York	Detected
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DATE	TIME	LOCATION	STATUS
2023-10-27	10:15:00	1234 Main St, New York	Detected
2023-10-27	10:15:00	1234 Main St, New York	Detected
2023-10-27	10:15:00	1234 Main St, New York	Detected

VI. CONCLUSION

This study presents an autonomous deep learning framework for firearm detection and threat monitoring tailored for smart city surveillance systems. By leveraging advanced vision models such as YOLOv8 and EfficientNet, the proposed system achieves high accuracy and real-time responsiveness while

minimizing false positives. The integration of an automated alert mechanism ensures rapid communication with law enforcement, enhancing the efficiency of emergency response operations.

The framework demonstrates scalability across multiple camera feeds and adaptability to diverse environmental conditions, making it practical for large-scale urban deployments. Beyond firearm detection, the system provides a foundation for broader applications in intelligent threat analytics and proactive urban safety management. Future work will explore multimodal fusion incorporating audio cues and predictive analytics to further enhance situational awareness in next-generation smart cities.

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