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A DEEP LEARNING BASED EFFICENT FIREARMS MONITORING TECHNIQUE FOR BUILDING SECURE SMART CITIES

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ABSTRACT

Crime prediction in video-surveillance systems is required to prevent incident and protect assets. In this sense, our article proposes first artificial intelligence approach for Robbery Behavior Potential (RBP) prediction and detection in an indoor camera. Our method is based on three detection modules including head cover, crowd and loitering detection modules for timely actions and preventing robbery. The two first modules are implemented by retraining YOLOV5 model with our gathered dataset which is annotated manually. In addition, we innovate a novel definition for loitering detection module which is based on DeepSORT algorithm. A fuzzy inference machine renders an expert knowledge as rules and then makes final decision about predicted robbery potential. This is laborious due to: different manner of robber, different angle of surveillance camera and low resolution of video images.We accomplished our experiment on real world video surveillance images and reaching the F1-score of 0.537. Hence, to make an experimental comparison with the other related works, we define threshold value for RBP to evaluate video images as a robbery detection problem. Under this assumption, the experimental results show that the proposed method performs significantly better in detecting the robbery as compared to the robbery detection methods by distinctly report with F1-score of 0.607. We strongly believe that the application of the proposed method could cause reduction of robbery detriment in a control center of surveillance cameras by predicting and preventing incident of robbery. On the other hand, situational awareness of human operator enhances and more cameras can be managed.

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I. INTRODUCTION

The project "A Deep Learning-Based Efficient Firearms Monitoring Technique for Building Secure Smart Cities" addresses a critical need in urban security infrastructure. In recent years, the concept of smart cities has gained prominence, leveraging advanced technologies to enhance efficiency, sustainability, and safety. However, ensuring public safety remains a significant challenge, particularly concerning the detection and prevention of firearms-related incidents. Traditional surveillance systems often struggle to detect firearms accurately in complex urban environments, leading to potential security vulnerabilities. In response to this challenge, this project proposes a novel approach that utilizes deep learning techniques to develop an efficient firearms monitoring system for smart cities. By leveraging convolutional neural networks (CNNs) and object detection algorithms, the project aims to accurately identify firearms in real-time video streams captured by surveillance cameras. The implementation of this advanced monitoring technique has the potential to enhance the security infrastructure of smart cities, enabling proactive intervention and rapid response to firearms-related incidents. Ultimately, the project seeks to contribute to the creation of safer and more resilient urban environments by leveraging the power of deep learning technology in firearms detection and monitoring.

II.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 onVGG16. The main goal is to sound an alert if the model spots guns five times in a rowin 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.

III.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

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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

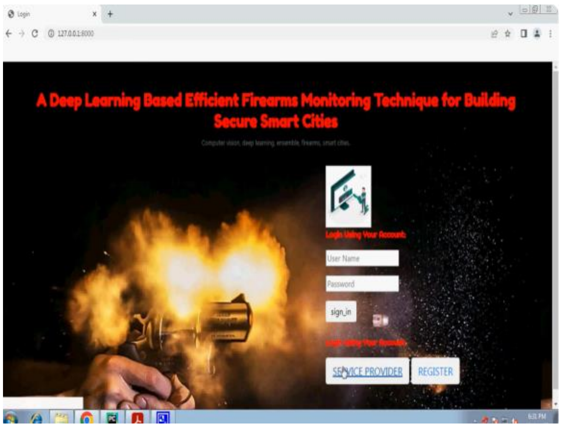
⋆ introducing a deep learning-based framework to improve the performance of object detection through ensemble

⋆ Thus, securing smart cities using intelligent surveillance.

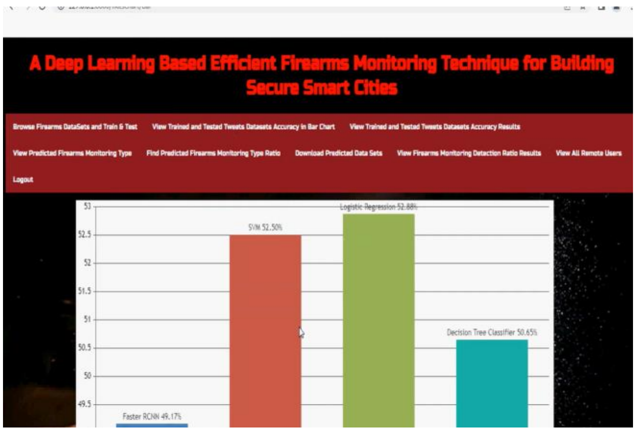
IV.MODULES

➢ **Service Provider**

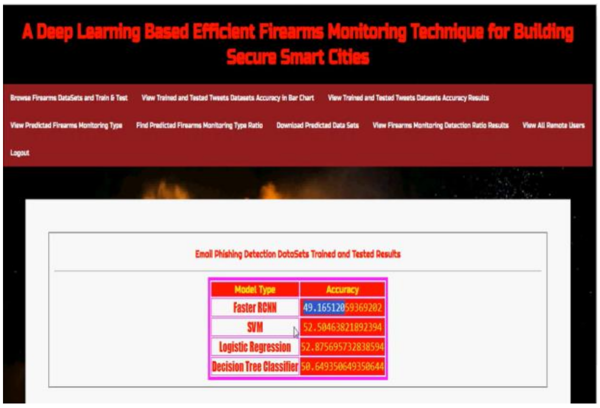
In this module, the Service Provider has to login by using valid user name and password.



After login successful he can do some operations such as Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart,



View Trained and Tested Accuracy Results,



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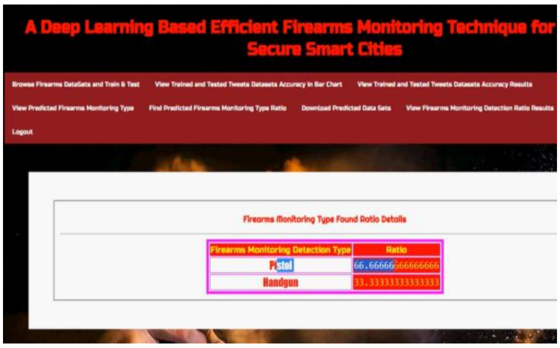
View Predicted Type, View Type Ratio, Download Predicted Data Sets, View Type Ratio Results,



View All Remote Users.

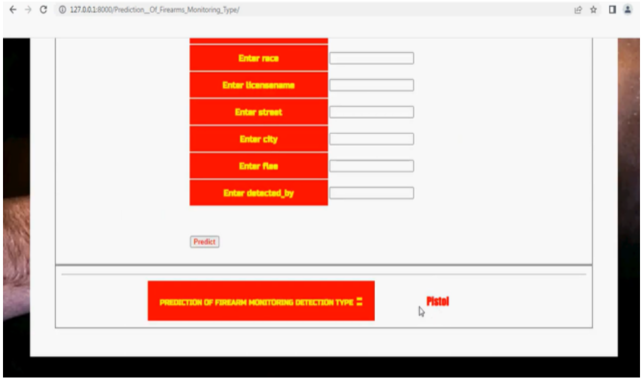
➢ **View and Authorize Users**

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.

➢ **Remote User**

In this module, . 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, after login we have to Predict Type,



VIEW YOUR PROFILE.

V.CONCLUSION

This research work proposes an approach for RBP prediction in video surveillance images. There are several challenges of CCTV videos like the various ways for robbery incidence, variety in camera angle mounted in different places and low resolution of video images acquired by CCTVs. Tackling these obstacles ensues timely actions and prevents robbery fully or partially observable from surveillance videos. This work is conducted because based on our extensive literature review, despite significance of preventing robbery occurrence, no RBP prediction has been done before. We extract some common scenarios of robbery occurrence with the help of an expert comments and by watching several robbery videos from CCTVs. We investigate these scenarios to deduce more common features between them and implement a practical approach for RBP prediction. Our study proposes a deep-learning based approach with the help of fuzzy inference machine to calculate potential of robbery. This approach provides a retrained YOLOV5 algorithm by gathering proper dataset of human with or without head cover. This deep-learning based algorithm is used to efficiently implement crowd and head cover detection modules. This paper also executes loitering module by our defined methodology which calculates the Euclidean traveled distance of individuals using Deep SORT method. A fuzzy inference machine is delineated to infer robbery potential of videos for every 10 frames and average them for every snippet based on three module results. The proposed method is applied to the Robbery folder of UCF-Crime dataset and F1-score of proposed system is 0.537. This result shows that our proposed methodology can correctly predict robbery potential for more than half of the videos.

Accordingly, we change the problem of predicting to robbery detection one. Thus, we can compare it with prior literature which have worked on the anomaly-detection specially the robbery detection and their dataset is UCF-Crime. F1-score of detection method is 0.607 and it is utmost among other methods. The result proves that our proposed scenario-based system works correctly with high ability in detecting and also predicting robbery behavior. Our proposed approach can be used by any places which have surveillance cameras and want to prevent robbery crime. They do not need to employ a person to watch the real time videos of theses cameras precisely and infer the robbery potential. However, this person should watch the videos uninterruptedly to not make a mistake. Additionally, any one can make our methodology privately by changing the thresholds value due to particular culture.

We can increase F1-score by improving loitering detection accuracy. As future work, we intend to achieve an improved tracking algorithm for low-resolution video images by improving Deep SORT method. Human of low-resolution videos cannot be detected precisely to track. This is because the detector of Deep SORT algorithm is FRR CNN. Therefore, we will change detection framework of Deep SORT algorithm to retrained YOLOV5 by low-resolution human images. The proposed YOLOV5 will have only one object class, low resolution images.

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