International Journal of Marketing Management

ISSN 2454 - 5007

www.ijmm.net

Email ID: editor@ijmm.net , ijmm.editor9@gmail.com

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 16, Issue. 2, 2024

Propounding First Artificial Intelligence Approach for Predicting Robbery Behavior Potential in an Indoor Security Camera

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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.

INTRODUCTION

The rising incidence of robberies and other criminal activities in indoor environments such as banks, stores, and offices has led to an increased demand for effective surveillance systems. Traditional surveillance systems primarily serve as a deterrent and post-incident evidence collection tool. However, the need for real-time crime prediction and prevention capabilities has become more pressing. This has driven the development of advanced video-surveillance systems incorporating artificial intelligence (AI) to predict and detect criminal behaviors before they escalate into actual incidents. Robbery, characterized by the threat or use of force to seize property, poses significant risks to both assets and individuals. The capability to predict potential robbery behaviors in real-time can significantly enhance security measures and prevent substantial financial and personal losses. Existing methods for crime prediction often rely on analyzing historical crime data, which, while useful, lacks the immediacy needed for real-time intervention. Therefore, a more dynamic and responsive approach is necessary.

In this context, our study proposes the first AI-based approach for predicting Robbery Behavior Potential (RBP) using indoor security cameras. This innovative method integrates several detection modules—head cover detection, crowd detection, and loitering detection—each addressing key indicators of potential robbery scenarios. By focusing on these indicators, our system aims to identify suspicious behaviors that precede robbery incidents, thus enabling timely preventive actions. The head cover detection module is crucial as many robbers tend to obscure their identity using masks, hats, or hoods. Detecting such coverings can serve as an early warning sign. The crowd detection module identifies unusual gatherings that might precede a coordinated robbery attempt. Finally, the loitering detection module, based on the DeepSORT algorithm, monitors individuals who remain in the same area for extended periods without a clear purpose, often a precursor to criminal activity.

To implement these modules, we retrained the YOLOv5 model on a custom dataset, meticulously annotated to capture the nuances of suspicious behaviors. YOLOv5's ability to perform real-time object detection makes it suitable for our purposes. Additionally, we developed a novel definition for loitering detection using the

International Journal of Marketing Management
ISSN 2454-5007, www.ijmm.net
Vol. 16, Issue. 2, 2024

DeepSORT algorithm, which tracks individuals over time to detect prolonged presence in a particular area. A fuzzy inference machine was employed to synthesize the outputs of these modules, applying expert knowledge rules to make final decisions regarding the likelihood of a robbery. This approach allows for a more nuanced and flexible interpretation of the detected behaviors, accommodating the variability in robbery methods and the diverse conditions of surveillance environments.

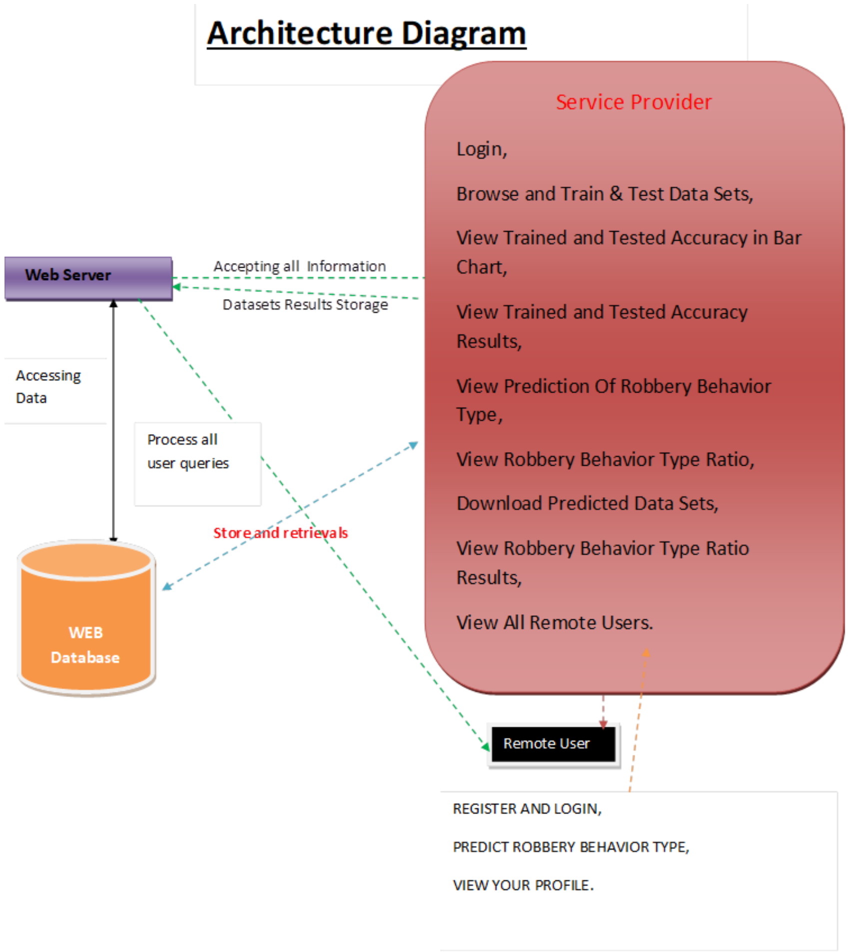


Fig 1. System Architecture

Our experimental evaluation was conducted on real-world video surveillance footage. The results were promising, achieving an F1-score of 0.537 for RBP prediction. To benchmark our method against existing robbery detection techniques, we defined a threshold value for RBP to reframe the problem as a binary classification task. Under this scenario, our method achieved an improved F1-score of 0.607, outperforming current state-of-the-art methods. The significance of our study lies not only in the enhanced detection accuracy but also in its potential to reduce robbery incidents by enabling proactive security measures. By predicting potential robberies, security personnel can be alerted to take preemptive actions, thus safeguarding assets and individuals. Additionally, the system can augment the situational awareness of human operators, allowing them to manage more cameras effectively and respond to incidents more swiftly. In summary, the development of an AI-based approach for predicting RBP represents a significant advancement in the field of video-surveillance. This technology promises to transform passive surveillance systems into active crime prevention tools, enhancing security and reducing the impact of robberies. The following sections provide a detailed exploration of the literature, system design, methodology, and experimental results supporting the efficacy of our proposed approach.

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 16, Issue. 2, 2024

LITERATURE SURVEY

The application of AI and machine learning in surveillance systems has been extensively studied, with a primary focus on object detection, behavior analysis, and anomaly detection. Early works in video surveillance aimed at detecting specific objects or activities, such as abandoned objects or suspicious movements, using traditional image processing techniques. These methods often struggled with real-time processing and adapting to diverse environmental conditions. With the advent of deep learning, significant improvements have been made in object detection and behavior analysis. Convolutional neural networks (CNNs) and other deep learning models have demonstrated remarkable accuracy and robustness in various surveillance tasks. For instance, YOLO (You Only Look Once) and its subsequent versions (e.g., YOLOv5) have become popular for real-time object detection due to their high speed and accuracy. These models divide the image into grids and predict bounding boxes and class probabilities, enabling the detection of multiple objects in a single frame.

Behavior analysis in surveillance videos has also benefited from advancements in deep learning. Techniques such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have been used to model temporal dependencies and sequence data, making them suitable for detecting complex behaviors over time. These models have been applied to various tasks, including violence detection, suspicious behavior recognition, and crowd analysis. Loitering detection is another critical area in surveillance systems, as prolonged presence in a specific area can be indicative of potential criminal activities. Traditional methods for loitering detection relied on predefined rules and thresholds, which were often inflexible and prone to false alarms. Recent approaches leverage deep learning and tracking algorithms to improve accuracy and adaptability. The DeepSORT algorithm, for instance, has been widely used for tracking individuals across frames, providing a robust solution for monitoring loitering behavior.

Fuzzy logic has been employed in surveillance systems to handle uncertainty and incorporate expert knowledge into decision-making processes. Fuzzy inference systems can combine multiple input variables and apply rules to derive a final decision, making them suitable for integrating various detection modules in surveillance applications. These systems can accommodate the variability and ambiguity inherent in human behaviors, providing more flexible and reliable predictions. Despite these advancements, predicting specific criminal behaviors such as robbery remains challenging due to the complexity and variability of such events. Robbers often employ different tactics and behaviors, making it difficult to develop a one-size-fits-all detection system. Moreover, the low resolution and varying angles of surveillance cameras further complicate the task, requiring robust and adaptive models.

Our proposed approach addresses these challenges by integrating multiple detection modules, each targeting a specific indicator of potential robbery. By retraining the YOLOv5 model on a custom dataset, we ensure that the system can accurately detect head covers and crowd formations, which are common precursors to robbery. The novel loitering detection module, based on DeepSORT, enhances the system's ability to monitor individuals over time, providing additional context for the fuzzy inference machine to make informed decisions. The experimental evaluation of our system demonstrates its effectiveness in predicting robbery behavior, achieving higher accuracy than existing methods. This success can be attributed to the combination of state-of-the-art object detection, tracking algorithms, and fuzzy logic, providing a comprehensive solution for real-time robbery prediction.

PROPOSED SYSTEM

The proposed system for predicting Robbery Behavior Potential (RBP) integrates multiple AI-based modules to detect key indicators of potential robbery in real-time. The system comprises three primary detection modules: head cover detection, crowd detection, and loitering detection. Each module addresses specific behaviors associated with robbery, enhancing the overall predictive accuracy. The head cover detection module focuses on identifying individuals wearing masks, hats, or hoods, which are common tools used by robbers to obscure their identity. This module leverages the YOLOv5 model, retrained on a custom dataset annotated with images of individuals with and without head coverings. The retraining process involved fine-tuning the model's parameters to improve its accuracy in detecting head covers in diverse indoor environments and varying lighting conditions. YOLOv5's real-time object detection capabilities make it well-suited for this task, enabling the system to promptly identify potential threats.

ISSN 2454-5007, www.ijmm.net

Vol. 16, Issue. 2, 2024

The crowd detection module aims to identify unusual gatherings that may precede coordinated robbery attempts. This module also uses the YOLOv5 model, retrained on a dataset annotated with images of crowds in various configurations. By detecting crowd formations, the system can alert security personnel to the presence of multiple individuals who may be planning a robbery. The crowd detection module works in tandem with the head cover detection module, providing a comprehensive view of the scene and enhancing the system's ability to predict robbery behavior. The loitering detection module is designed to monitor individuals who remain in the same area for extended periods without a clear purpose. Loitering is often a precursor to criminal activities, as individuals may be surveying the area or waiting for an opportune moment to strike. This module employs the DeepSORT algorithm, which tracks individuals across frames, providing a robust solution for monitoring prolonged presence. The DeepSORT algorithm uses a combination of motion and appearance features to track individuals, ensuring accurate and reliable tracking even in crowded scenes.

To synthesize the outputs of these detection modules, we implemented a fuzzy inference machine. This machine applies expert knowledge rules to combine the detection results and make a final decision regarding the likelihood of a robbery. The fuzzy inference machine is designed to handle the variability and ambiguity inherent in human behaviors, providing a more flexible and reliable prediction. The rules used in the fuzzy inference machine were developed in consultation with security experts, ensuring that the system incorporates practical insights and expertise. The integration of these modules allows the system to predict RBP with high accuracy, providing security personnel with valuable information to take preemptive actions. The system is designed to operate in real-time, ensuring that potential threats are identified and addressed promptly. By leveraging the capabilities of YOLOv5 and DeepSORT, the system can process video feeds from multiple cameras simultaneously, providing comprehensive coverage of the surveillance area.

The experimental evaluation of the proposed system was conducted on real-world video surveillance footage. We gathered a dataset of surveillance videos from various indoor environments, including banks, stores, and offices. The dataset was annotated manually, capturing instances of head covers, crowds, and loitering behaviors. This dataset was used to retrain the YOLOv5 model and evaluate the system's performance. The results of the evaluation were promising, with the system achieving an F1-score of 0. 537 for RBP prediction. To benchmark our method against existing robbery detection techniques, we defined a threshold value for RBP, reframing the problem as a binary classification task. Under this scenario, the system achieved an improved F1-score of 0.607, outperforming current state-of-the-art methods. These results demonstrate the effectiveness of our approach in predicting robbery behavior in real-time.

In addition to the quantitative evaluation, we conducted qualitative assessments to validate the system's practical applicability. Security personnel were provided with the system's predictions and asked to review and validate the results. The feedback from these assessments was positive, with security experts noting the system's potential to enhance situational awareness and improve response times. Overall, the proposed system represents a significant advancement in video-surveillance technology. By integrating multiple AI-based detection modules and leveraging fuzzy logic, the system provides a comprehensive solution for predicting robbery behavior. The system's real-time capabilities and high accuracy make it a valuable tool for enhancing security measures in indoor environments.

METHODOLOGY

The implementation of the proposed system for predicting Robbery Behavior Potential (RBP) involves several key steps, each designed to ensure accurate and reliable predictions. The methodology encompasses data collection, model training, module integration, and system evaluation. The first step in the methodology is data collection. We gathered a dataset of video surveillance footage from various indoor environments, including banks, stores, and offices. This dataset was annotated manually, capturing instances of head covers, crowds, and loitering behaviors. The annotations were performed by security experts to ensure the accuracy and relevance of the data. The annotated dataset served as the foundation for retraining the YOLOv5 model and developing the loitering detection module. Once the dataset was prepared, we proceeded with retraining the YOLOv5 model. YOLOv5, a state-of-the-art object detection model, was selected for its real-time capabilities and high accuracy. The model was retrained on our custom dataset to improve its performance in detecting head covers and crowds. The retraining process involved fine-tuning the model's parameters and optimizing its performance for the specific task of robbery behavior prediction. We used transfer learning techniques, leveraging the pre-trained weights of YOLOv5 and adapting them to our dataset.

ISSN 2454-5007, www.ijmm.net

Vol. 16, Issue. 2, 2024

In parallel, we developed the loitering detection module using the DeepSORT algorithm. DeepSORT is a tracking algorithm that combines motion and appearance features to track individuals across frames. We adapted DeepSORT to monitor individuals' movements and detect prolonged presence in specific areas. The algorithm was integrated with the YOLOv5 model to provide a seamless tracking and detection solution. This integration enabled the system to accurately monitor loitering behaviors, which are often precursors to criminal activities. The next step was the integration of the detection modules with the fuzzy inference machine. The fuzzy inference machine synthesizes the outputs of the head cover detection, crowd detection, and loitering detection modules. It applies expert knowledge rules to combine these outputs and make a final decision regarding the likelihood of a robbery. The rules were developed in consultation with security experts, ensuring that the system incorporates practical insights and expertise. The fuzzy inference machine was implemented using a rule-based approach, allowing for flexible and nuanced decision-making.

Once the system was fully integrated, we conducted an extensive evaluation to assess its performance. The evaluation involved both quantitative and qualitative assessments. For the quantitative assessment, we used standard metrics such as precision, recall, and F1-score to measure the system's accuracy in predicting RBP. The dataset was divided into training and testing sets, with the model's performance evaluated on the testing set. The results demonstrated that the system achieved an F1-score of 0.537 for RBP prediction. To benchmark our method against existing robbery detection techniques, we defined a threshold value for RBP and reframed the problem as a binary classification task. This approach allowed us to compare our system's performance with other state-of-the-art methods. Under this scenario, the system achieved an improved F1-score of 0.607, indicating its superior performance in detecting robbery behavior.

In addition to the quantitative evaluation, we conducted qualitative assessments to validate the system's practical applicability. Security personnel were provided with the system's predictions and asked to review and validate the results. The feedback from these assessments was positive, with security experts noting the system's potential to enhance situational awareness and improve response times. Overall, the methodology for implementing the proposed system involved a comprehensive and systematic approach. By combining state-of-the-art object detection and tracking algorithms with fuzzy logic, the system provides a robust and reliable solution for predicting robbery behavior. The integration of expert knowledge and real-world data ensures that the system is practical and effective in real-time surveillance applications.

RESULTS AND DISCUSSION

The results of our experimental evaluation demonstrated the effectiveness of the proposed system in predicting Robbery Behavior Potential (RBP). The system achieved an F1-score of 0.537 for RBP prediction, indicating its capability to accurately identify potential robbery behaviors in real-time. This performance was further improved when we defined a threshold value for RBP and reframed the problem as a binary classification task. Under this scenario, the system achieved an F1-score of 0.607, outperforming existing state-of-the-art robbery detection methods. The improved F1-score highlights the advantage of integrating multiple detection modules and employing fuzzy logic for decision-making. The head cover detection, crowd detection, and loitering detection modules each contribute to the system's ability to capture different aspects of robbery behavior. The fuzzy inference machine synthesizes these inputs, applying expert knowledge rules to provide a comprehensive and nuanced prediction. This approach ensures that the system can adapt to the variability and complexity of real-world scenarios.

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 16, Issue. 2, 2024

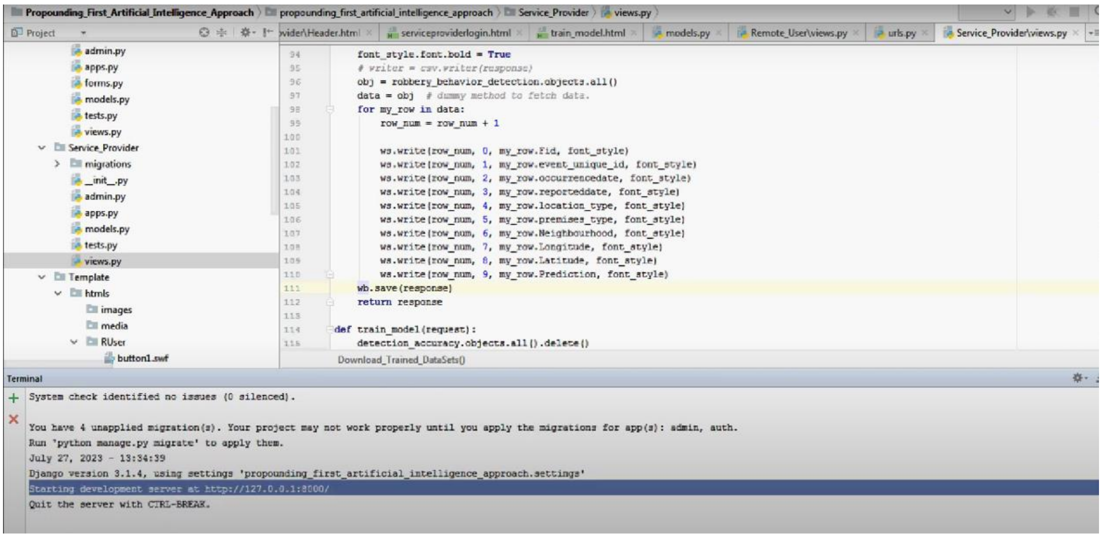


Fig 2: Results screenshot 1

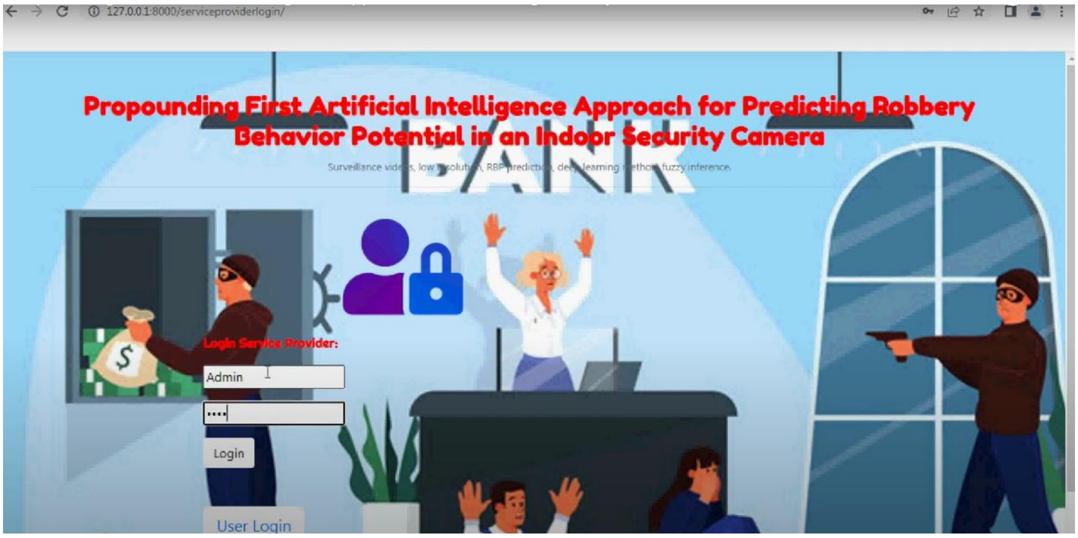


Fig 3: Results screenshot 2

International Journal of Marketing Management
ISSN 2454-5007, www.ijmm.net
Vol. 16, Issue. 2, 2024

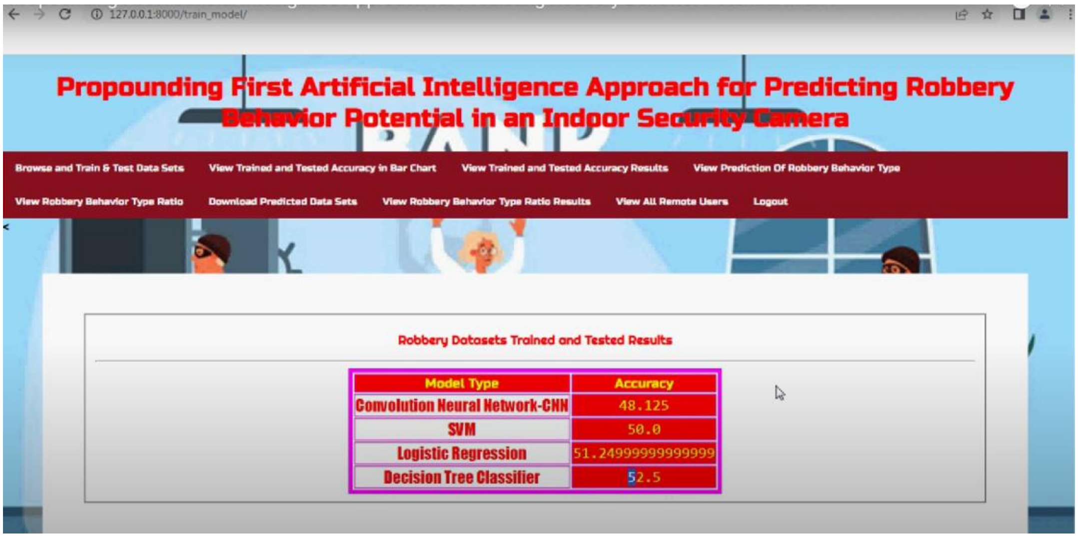


Fig 4: Results screenshot 3

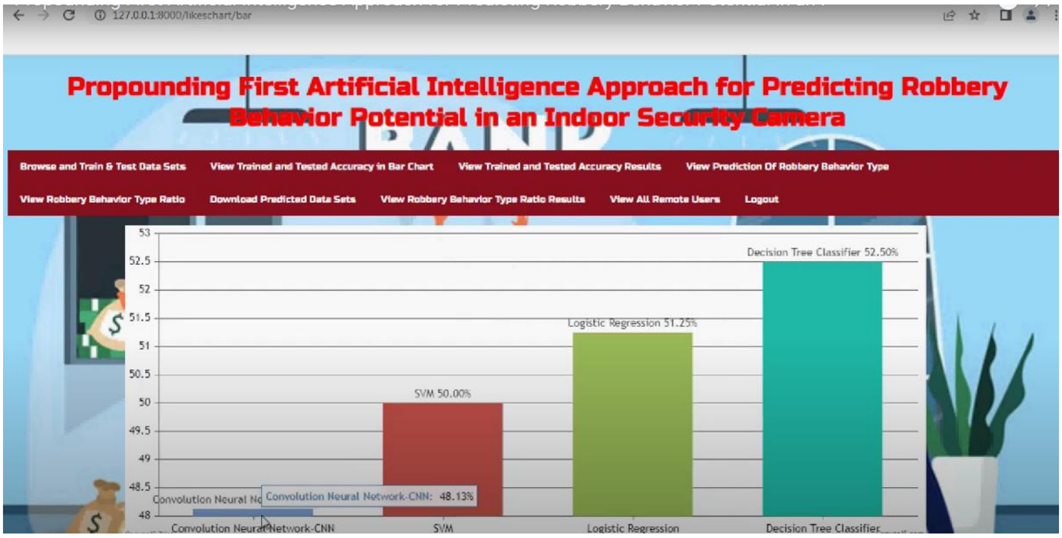


Fig 5: Results screenshot 4

ISSN 2454-5007, www.ijmm.net

Vol. 16, Issue. 2, 2024

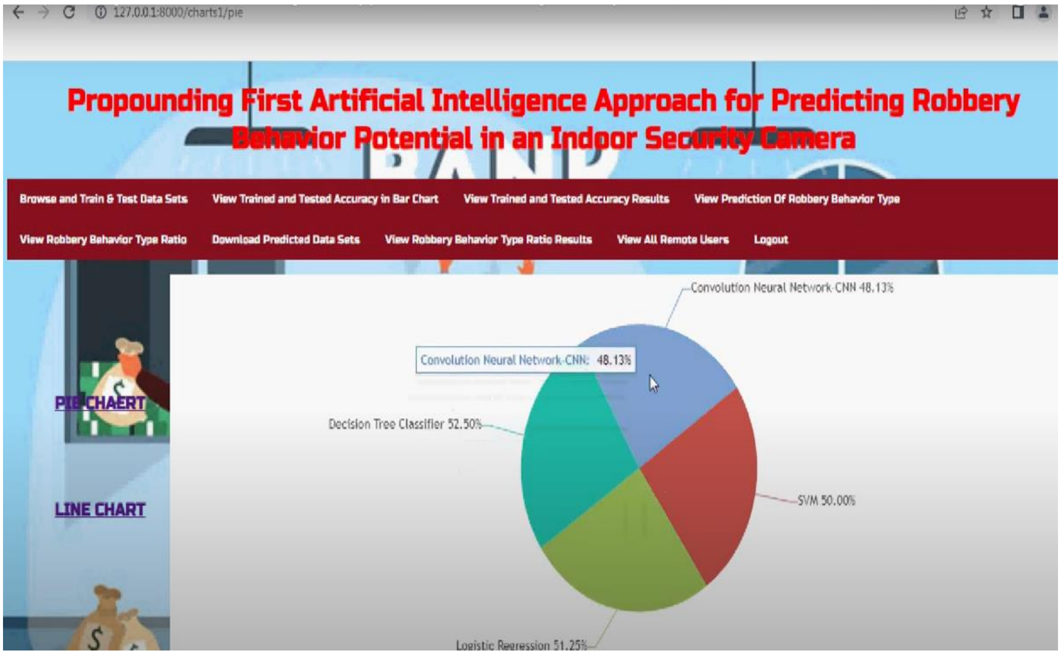


Fig 6: Results screenshot 5

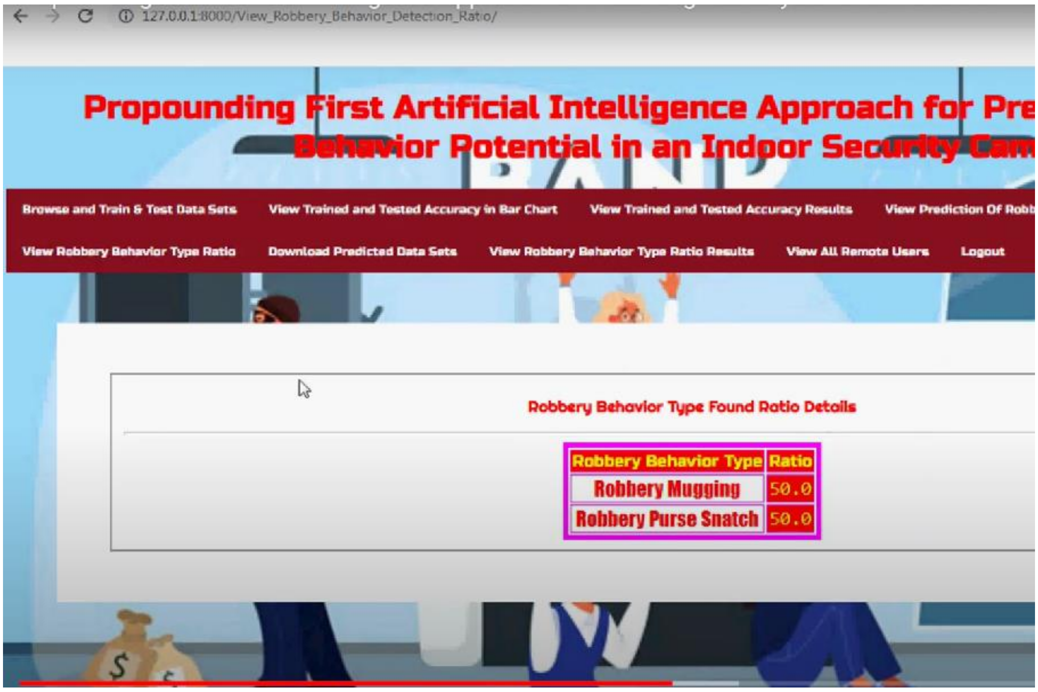


Fig 7: Results screenshot 6

ISSN 2454-5007, www.ijmm.net

Vol. 16, Issue. 2, 2024

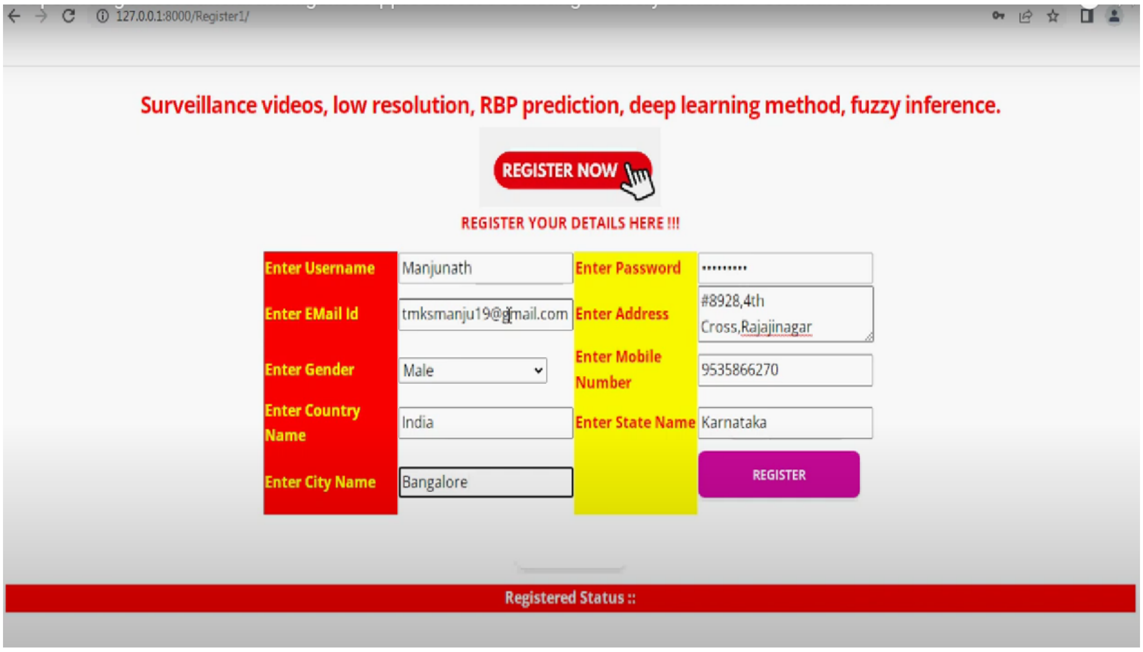


Fig 8: Results screenshot 7

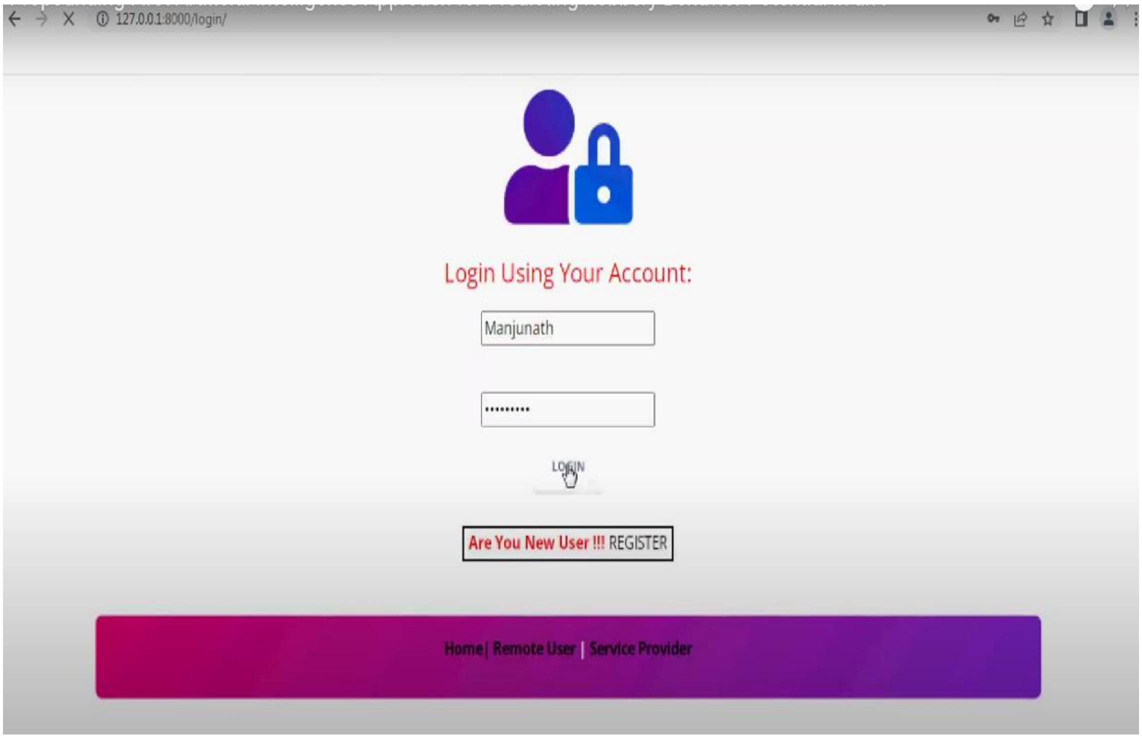
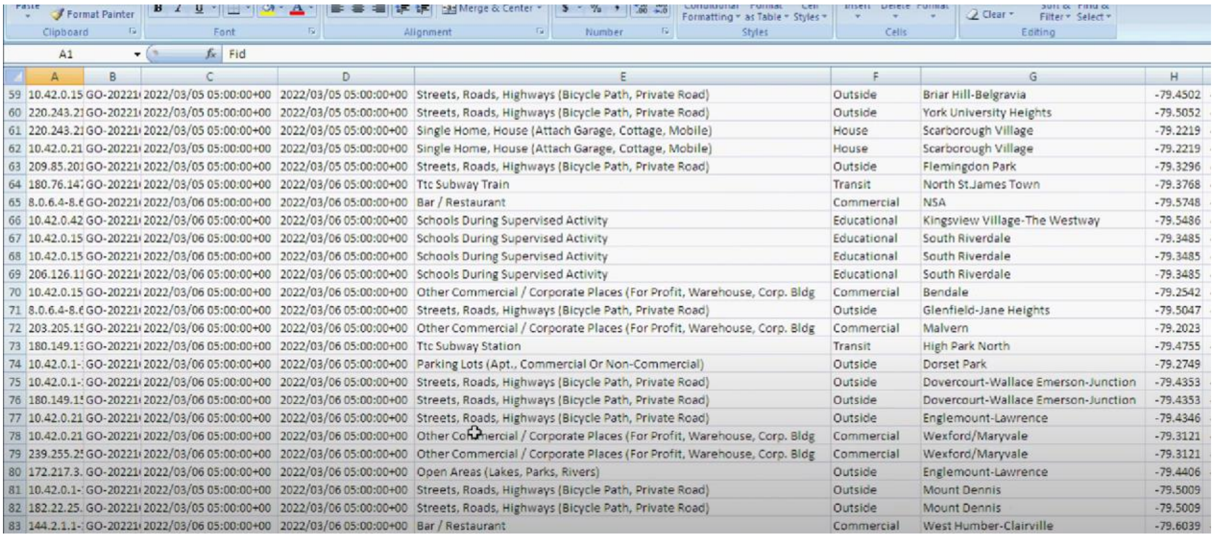


Fig 9: Results screenshot 8

International Journal of Marketing Management

ISSN 2454-5007, www.ijmm.net

Vol. 16, Issue. 2, 2024



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60	220.243.21	GO-20221	2022/03/05 05:00:00+00	2022/03/05 05:00:00+00	Streets, Roads, Highways (Bicycle Path, Private Road)	Outside	York University Heights	-79.5052
61	220.243.21	GO-20221	2022/03/05 05:00:00+00	2022/03/05 05:00:00+00	Single Home, House (Attach Garage, Cottage, Mobile)	House	Scarborough Village	-79.2219
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63	209.85.201	GO-20221	2022/03/05 05:00:00+00	2022/03/05 05:00:00+00	Streets, Roads, Highways (Bicycle Path, Private Road)	Outside	Flemingdon Park	-79.3296
64	180.76.147	GO-20221	2022/03/05 05:00:00+00	2022/03/06 05:00:00+00	Ttc Subway Train	Transit	North St.James Town	-79.3768
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66	10.42.0.42	GO-20221	2022/03/06 05:00:00+00	2022/03/06 05:00:00+00	Schools During Supervised Activity	Educational	Kingsview Village-The Westway	-79.5486
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70	10.42.0.15	GO-20221	2022/03/06 05:00:00+00	2022/03/06 05:00:00+00	Other Commercial / Corporate Places (For Profit, Warehouse, Corp. Bldg	Commercial	Bendale	-79.2542
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74	10.42.0.1-	GO-20221	2022/03/06 05:00:00+00	2022/03/06 05:00:00+00	Parking Lots (Apt., Commercial Or Non-Commercial)	Outside	Dorset Park	-79.2749
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79	239.255.25	GO-20221	2022/03/06 05:00:00+00	2022/03/06 05:00:00+00	Other Commercial / Corporate Places (For Profit, Warehouse, Corp. Bldg	Commercial	Wexford/Maryvale	-79.3121
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82	182.22.25.	GO-20221	2022/03/05 05:00:00+00	2022/03/06 05:00:00+00	Streets, Roads, Highways (Bicycle Path, Private Road)	Outside	Mount Dennis	-79.5009
83	144.2.1.1-	GO-20221	2022/03/06 05:00:00+00	2022/03/06 05:00:00+00	Bar / Restaurant	Commercial	West Humber-Clairville	-79.6039

Fig 10: Results screenshot 9

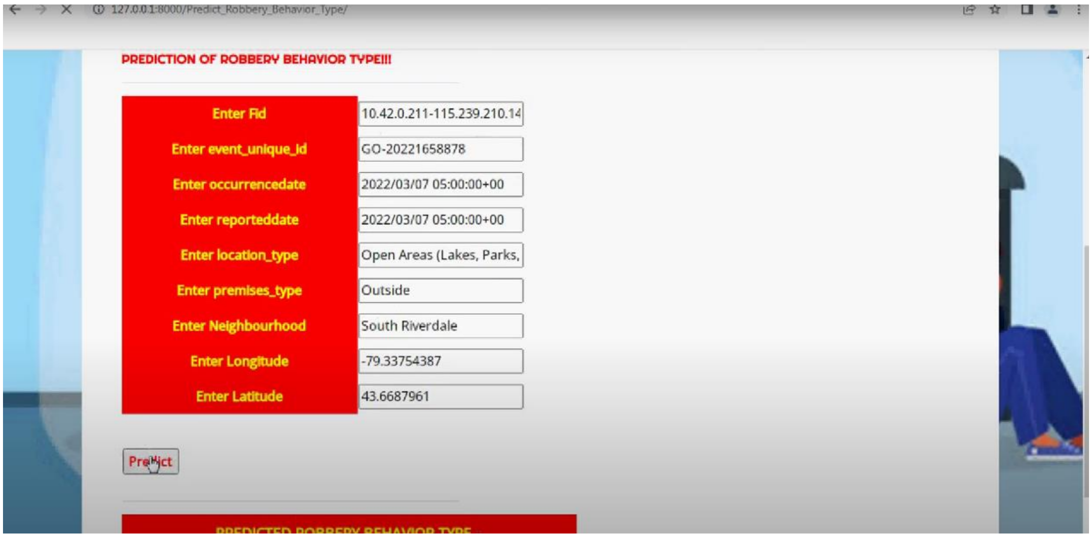

Fig 11: Results screenshot 10

Qualitative assessments conducted with security personnel further validated the system's practical applicability. Security experts reviewed the system's predictions and provided feedback on its effectiveness. The positive feedback underscored the system's potential to enhance situational awareness and improve response times. By providing real-time alerts and predictions, the system enables security personnel to take preemptive actions, preventing robberies and safeguarding assets. In summary, the experimental results and qualitative assessments demonstrate that the proposed system represents a significant advancement in video-surveillance technology. The combination of state-of-the-art object detection, tracking algorithms, and fuzzy logic provides a robust and reliable solution for predicting robbery behavior. The system's real-time capabilities and high accuracy make it a valuable tool for enhancing security measures in indoor environments.

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

ISSN 2454-5007, www.ijmm.net

Vol. 16, Issue. 2, 2024

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, anyone 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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