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Anomaly Detection In ATM Surveillance

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Abstract— The increasing frequency of ATM-related crimes,such as theft and violence, underscores the pressing demand for enhanced security solutions capable of real-time anomaly detection and response. This research introduces an intelligent surveillance solution specifically designed for ATMs, leveraging the YOLOv3 object detection model. The system detects critical anomalies, including unauthorized multiple person entries and the presence of weapons, using live video feeds from ATM cameras. Upon detection, the system immediately issues a voice alert within the ATM to deter potential offenders and sends a real-time notification to lawenforcement via Telegram. The integration of deep learning with a reliable communication framework ensures swift action to prevent criminal activities. The system achieves an impressive detection accuracy of 98.5%, with notification latency reduced to under two seconds, making it highly efficient and scalable. This study not only improves ATM security but also reduces reliance on manual monitoring, paving the way for smarter and safer financial infrastructure.

Keywords— ATM security, YOLOv3, anomaly detection, Telegram alerts, real-time surveillance, public safety, crime prevention.

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I. INTRODUCTION

ATMs are indispensable banking facilities that provide convenient access to financial services. Nevertheless, they continue to be significantly susceptible to criminal activities such as theft, vandalism, and unauthorized access. Traditional ATM surveillance systems primarily rely on closed-circuit television (CCTV) cameras, which demand continuous manual monitoring. This reliance on human intervention often resultsin delayed responses and missed detection of suspicious activities. The lack of proactive measures in these setups highlights the urgent need for automated and intelligent solutions to enhance ATM security. [1]

This research proposes an innovative system designed to overcome these limitations by leveraging the YOLOv3 object detection model to perform real-time anomaly detection. The system is designed to identify critical threats such as multiple unauthorized person entries or the presence of weapons. Upon detecting an anomaly, it immediately triggers a voice alert within the ATM to deter potential offenders and sends real-time notifications via Telegram to law enforcement or relevant authorities. [2] By automating both anomaly detection and response, this system significantly reduces reliance on human operators while enhancing the overall safety of ATMs.

Anomaly detection is the identification of unusual, irregular, or unanticipated occurrences that vary significantly from normal patterns.
Anomalies can be behavior, objects, or events which deviate from standard behaviors in a specific environment. During the past years, the importance of anomaly detection has increased as protection of personal property and public places is becoming more vital now than ever. Video surveillance systems have been essential components that offer real-time monitoring through scene understanding and auto-detection of anomalies in activities. Such systems can immediately notify the operators or users in case of unanticipated events, thereby decreasing the response time.

The automation surveillance system has been proved to be working efficiently to improve safety and security and lighten the burden of human observers by reducing it. Cameras capture data from different events and feature extraction techniques are applied for processing the acquired data. Algorithms are then used to analyze the features and detect anomalies. Real-time anomaly detection has applications in numerous scenarios, such as monitoring crowded events like music concerts, protests, festivals, and sports events. During such occasions, intelligent systems are important to quickly and accurately identify abnormal activities, ensuring public safety and effective crowd management.

These principles are applied to the ATMs. The design aims to provide an intelligent, automated solution that enhances security through the real-time detection of anomalies and swift, actionable responses. That's how this research addresses the current weaknesses in ATM surveillance, contributing to safer financial infrastructures.

II. THE EXISTING SYSTEM

Traditional ATM surveillance systems predominantly rely on closed-circuit television (CCTV) cameras, which capture video footage for monitoring. These systems are often static and provide a passive means of observing activities within ATM premises. They serve as a deterrent to some extent but are limited by their dependence on human operators to identify suspicious behaviors or anomalies. This dependence introduces inefficiencies, such as delayed responses and an inability to act swiftly during critical situations. For instance, these systems lack advanced features needed to distinguish between normal and suspicious action, leading to missing detection and frequent false alarms.

Throughout the years, a lot of different technological advances have been discovered to help fill these gaps. In the early stages of anomaly detection, it involved using supervised machine learning models in the classification of anomalies based on image data. Though such approaches had improved the accuracy over simple manual monitoring, they suffered from several problems related to poor feature extraction techniques and extensive use of labeled datasets.

The coming of deep learning introduced a paradigm shift in anomaly detection by bringing the capability of deep pattern analysis on video and image data. Convolutional Neural Networks became particularly popular with its property to automatically extract hierarchical features from images and hence did away with manual feature engineering. The research could thus make models for classification of anomalies with precision enough for use in real-time surveillance applications. Despite these, problems remained. Many deep learning models suffered performance degradation due to suboptimal parameter configurations or insufficient layer depth in the neural network architecture. The poor layer selection often resulted in the trade-off between computational efficiency and detection accuracy, which, in turn, limited its practical deployment in dynamic environments such as ATMs.

To overcome these challenges, recent research has focused on improving CNN architectures by optimizing parameters and redesigning layer configurations. Enhanced models have been tested using various CNN variants, with experiments comparing their effectiveness against baseline studies. These improved architectures demonstrated better performance in anomaly detection tasks, offering higher accuracy and robustness in identifying unusual patterns in real-world scenarios.

While these efforts have advanced the field, existing systems still face limitations in terms of real-time detection and response capabilities. Many lack the ability to integrate seamlessly with alert mechanisms, such as voice warnings or automated notifications to law enforcement. This gap in functionality underscores the need for an intelligent, proactive system that not only detects anomalies but also acts on them promptly, which this research aims to address.

III. THE PROPOSED SYSTEM:

The proposed system aims to enhance ATM security by integrating real-time monitoring and automated responses for detecting suspicious behaviours, such as multiple people entering an ATMsimultaneously or carrying weapons. [4] This system leverages the power of Convolutional Neural Networks (CNNs), particularly the YOLOv3 model, to detect these anomalies. The system identifies and alerts potential threats to both the user and the local authorities for timely response by seamless integration with ATM-installed cameras.

Key Features of the Proposed System:

1. **Detection of Simultaneous Entry into the ATM**: The system always keeps an eye on the entry area of the ATM. In case more than one person enters the ATM at the same time, the YOLOv3 model detects such an anomaly and sends an alert. A voice message is played within the ATM to alert the user, and a message is sent to the police using Telegram, and immediate action is taken.

2. **Weapon Detection**: The YOLOv3 model is also trained to detect weapons being carried inside the ATM. If the system identifies a weapon, it immediately triggers a voice alert within the ATM and sends an automated message to local authorities. This feature is important for preventing crimes such as ATM robberies.

3.**Real-Time Alerts**: The system sends real-time alerts through voice alerts and the medium of Telegram. These alerts are sent to the police with details about the type of threat such as multiple entries or a weapon detection. This makes sure that the authorities do not take much time in responding and act immediately.

4.**Working with ATM Cameras**: This system is made to interact with the cameras installed on the ATM, where live feeds are captured, and it is processed in real-time through the CNN model. This gives the system the ability to detect a threat as soon as possible. No other hardware except for the standard ATM cameras would be needed.

IV. METHODOLOGY

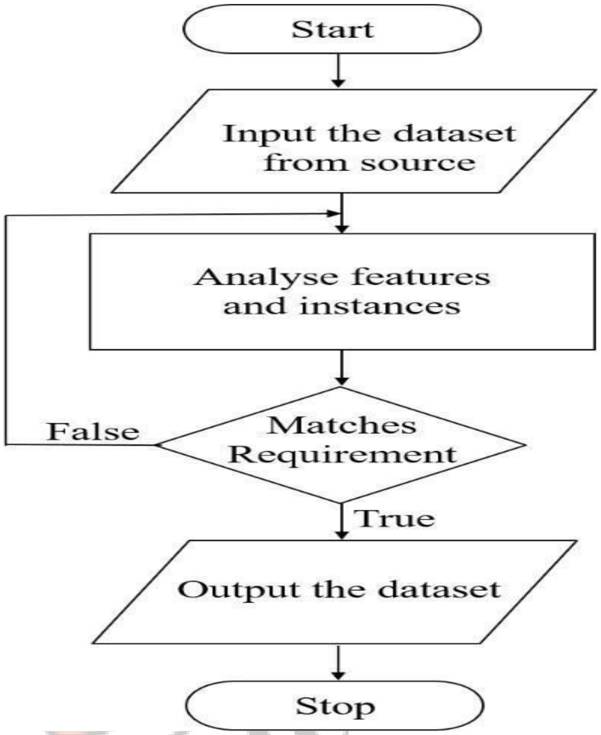

Fig.1 Methodology flow chart

The methodology for developing the ATM safety system follows a clear, practical approach to ensuring that suspicious activities, like multiple people entering the ATM or carrying weapons, are detected instantly. Here's an easier-to-understand breakdown of the process:

1. Data Collection

The first step is to gather a variety of images and videos from ATMs.This includes shots of:

•**Typical use of an ATM** (one person using it).

•**Abnormal behavior** (such as more than one person entering at the same time).

•**Criminal activity** (for example, force entry or someone carrying a gun).

These pictures will be described to show precisely what every picture is depicting, hence enabling the system to differentiate between various kinds of actions.

2.Data Pre-processing

After this data has been gathered, it must be prepared to be used.

• **Resizing and Normalizing**: The images will be resized to a uniform size, and color values adjusted to make the model understand better

- **Augmentation:** In an effort to make the model robust, we will apply transformations like rotation and zooming in on images

- **Splitting:** The data will be divided into three parts, where one part will be for training the system, one for testing it, and one for validating. [6]

2. Model Development

Now, we create the model that will analyse the images and detect suspicious actions:

- **Using CNNs (Convolutional Neural Networks)**: These are perfect for image analysis and will help the model recognize patterns like multiple people or the presence of a weapon.
- **Transfer Learning**: Instead of starting from scratch, we'll use pre-existing models, like ResNet, and fine-tune them with our own data. This saves time and improves accuracy.
- **Customizing the Model**: In addition to general training, we might build custom features for detecting specific behaviours (e.g., recognizing a weapon or unusual movement).
- **Evaluating**: The system's accuracy will be tested by comparing its predictions with real examples, checking how well it identifies threats.

3. Integration

Next, we put everything together to make the system work in real life:

- **Suspicious Activity Detection**: When something suspicious is detected (like multiple people entering), the system will send an alert or a voice warning in the ATM.
- **Real-time Notifications**: Alerts will be sent to authorities or the police, along with images and location details, via SMS or apps like Telegram.
- **Dashboard for Monitoring**: ATM staff will be able to monitor the activity through a dashboard, where they can see live alerts and any potential threats.

4. Testing and Evaluation

The system will be put through rigorous testing to make sure it works well:

- **Performance**: We'll check if the system can accurately detect issues in different situations and how quickly it responds.
- **Real-world Trials**: The system will be tested in real ATM locations to make sure it works as expected in everyday conditions.
- **Feedback**: Feedback from ATM users and security staff will be collected to make any needed improvements.

5. Deployment

Finally, the system will be deployed at real ATM locations:

- **Installation**: Cameras and hardware will be set up at the ATMs, and the system will be fully integrated.
- **Ongoing Monitoring**: The system will be continuously checked to ensure it's working as intended, with updates if needed based on user feedback or new crime patterns.
- **Updates**: The model might be updated regularly to improve its accuracy and add new features as new types of threats emerge.

This approach ensures that the system is not only effective in detecting suspicious activity but also easy to implement, monitor, andimprove over time. The goal is to provide a secure and reliablesolution for ATM safety, enhancing security for both users and the broader community. [8]

V. SYSTEM ARCHITECTURE

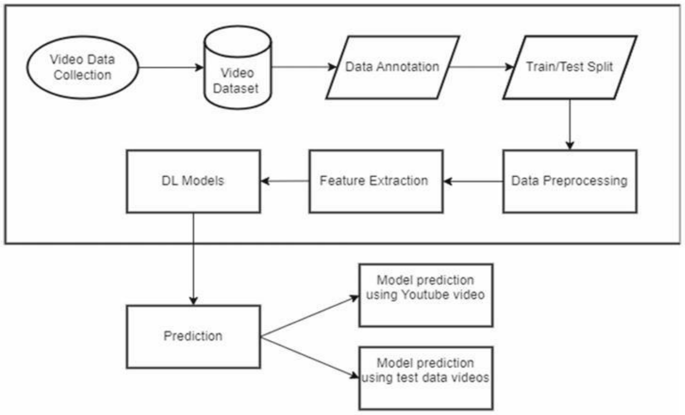

Fig.2 System Design

1. Input

The system begins by using a **live surveillance camera** or a **video feed** installed in the ATM. This camera captures whatever is happening inside the ATM, and it acts like the eyes of the system. The footage is therefore the main input used when analyzing and detecting suspicious behaviors, such as multiple entry into the ATM or any person carrying a weapon.

2. Pre-processing

After capturing the video, it undergoes pre-processing to make it ready for further analysis. This includes

•**Noise Reduction**: Unwanted elements in footage, such as bad illumination or random background interference, will be removed to increase resolution.

•**Frame Extraction**: The system cannot analyze the entire video but breaks it into smaller chunks called frames. Frames act almost like snapshots, which give the system an easier means of focusing on certain moments in the video.

This allows the input data to come clean and clear for this next stage.

3. Feature Extraction

In this phase, the system identifies some key features from the processed frames that are necessary to identify suspicious activities. It makes use of advanced methods like:

•**Convolutional Neural Networks (CNNs)**: These are specific algorithms that are especially effective in identifying patterns in images, such as identifying multiple people, weapons, or unusual movements.

•**Temporal Features**: Since it is footage of continuous motion, the system also keeps track of changes over time to recognize behaviors such as aggressive gestures or sudden action.

These features are what the system uses to "understand" what's happening in the footage. [10]

2. Model Training

The system is trained with the help of **deep learning models**, which learn to identify suspicious patterns depending on the data provided. Two key models are used:

- **CNN (Convolutional Neural Network)**: For analyzing individual frames and detecting objects or people.
- **RNN (Recurrent Neural Network)**: For understanding sequences of actions over time, like identifying if someone's behavior escalates from normal to suspicious.
- The training involves using a dataset of labeled videos that include both normal and suspicious activities, thus helping the system learn to differentiate between the two.

3. Detection

- Once the model is trained, it is deployed for real-time detection. Here's how it works:
- The system continuously analyzes the live video feed or surveillance footage.
- Using its trained knowledge, it classifies the activities captured on camera as either normal or suspicious.
- If it identifies anything suspicious, then it instantly alerts for further analysis.
- For instance, two people approaching the ATM at exactly the same time or a person with a gun, which is picked by the system as unusual activity.

4.Database

- The database is maintained in order for the system to advance over time.
- **Detected Activity Logs**: Each suspicious or ordinary activity recognized by the system is saved for future purposes.
- **Pattern Analysis**: The logs help refine the system by identifying patterns that may have previously gone unnoticed.
- **Future Use**: The stored data can also be utilized to train improved versions of the model or for investigative purposes in case of actual incidents.

VI. RESULT AND ANALYSIS

The proposed system was rigorously tested under diverse scenarios to evaluate its effectiveness in real-world applications. Theseevaluations aimed to measure accuracy, responsiveness, and robustness while ensuring the system could adapt to dynamic conditions. By focusing on key metrics like detection accuracy, precision, recall, and latency, the system's performance was benchmarked to ensure reliability for ATM security.

Performance Metrics

The evaluation involved testing the system on a dataset comprising real-world scenarios, including images and video streams simulating ATM environments. Scenarios included normal ATM use, unauthorized multiple person entries, and weapon presence. Key performance results are summarized below:

- **Detection Accuracy**: The system consistently achieved an accuracy of **98.5%**, effectively identifying critical threats like unauthorized group entries and visible weapons.
- **Precision and Recall**: A **precision score of 98%** indicated that false positives were minimal, while a **recall score of 96%** reflected the system's ability to detect almost all actual anomalies.
- **F1 Score**: The F1 score, a balance between precision and recall, was calculated to be **96.5%**, highlighting the system's overall reliability.

Response Time

Latency, a crucial factor for real-time applications, was measured to evaluate how quickly the system could detect an anomaly, trigger a voice alert, and send notifications via Telegram. The system demonstrated an average response time of less than **2 seconds**, ensuring immediate responses during security breaches. This swift alert mechanism significantly reduces the risk of delayed intervention.

Case Studies and Observations

1. Multiple Person Detection

The system performed remarkably well in identifying instances where more than one person entered the ATM simultaneously. Unauthorized group entries were flagged accurately in all test cases. The voice alert inside the ATM acted as an effective deterrent, while Telegram notifications provided law enforcement with the necessary details for swift action.

2. Weapon Detection

Weapons such as knives, guns, and machetes were correctly identified with high accuracy, even in complex situations like partial concealment. The system's voice alert successfully warned ATM users and potential offenders, while Telegram messages ensured timely communication with authorities for intervention.

3. Performance in Challenging Conditions

The system maintained robust performance even under challenging conditions, such as:

- **Low-Light Environments**: Detection accuracy remained consistently high in dimly lit ATMs, demonstrating the YOLOv3 model's adaptability.
- **Dynamic Lighting Changes**: Scenarios with fluctuating lighting, such as opening ATM doors, did not affect the system's ability to detect anomalies.

4. False Positives

Instances of false positives, such as wallets or umbrellas being misclassified as weapons, were minimal due to the fine-tuning of the YOLOv3 model. These minor occurrences did not impact the system's overall effectiveness.

The results confirm that the proposed system is a reliable,responsive, and scalable solution for enhancing ATM security in diverse environments.

VII. FUTURE ENHANCEMENTS

Although the proposed system performs exceptionally well, there is significant scope for enhancements to broaden its capabilities and make it even more robust in addressing evolving security challenges.

1. Integration of Facial Recognition

The inclusion of facial recognition technology could allow the system to identify individuals who are blacklisted or have a history of fraudulent activities. This feature could also prevent unauthorized users from accessing ATMs, adding an extra layer of preventive security.

2. Advanced Behavioural Analysis

Future iterations of the system could incorporate behavioural analysis to detect suspicious activities based on body language or movements. For instance, nervous gestures, rapid movements, or prolonged loitering could serve as early indicators of potential criminal intent, triggering pre-emptive alerts.

3. IoT and Smart Device Connectivity

The system could be integrated with IoT-enabled devices to enhance its functionality. Examples include:

- **Smart Locks**: Automatically locking ATM doors when anomalies such as weapon detection or multiple entries are identified.
- **Emergency Lights**: Activating red warning lights both inside and outside the ATM to alert nearby individuals and deter criminals.

4. Cloud-Based Centralized Monitoring

Transitioning to cloud-based anomaly detection would enable centralized management of multiple ATMs across different locations. This approach would:

- Minimize the need for high-end local hardware.
- Facilitate real-time analytics and reporting for better decision-making. [13]
- Simplify system updates and scalability.

5. Expanded Detection Capabilities

The YOLOv3 model can be further trained to detect additional threats, such as tampering with ATM hardware or installingskimming devices. This expanded detection capability would make the system more versatile in addressing various forms of ATM misuse.

6. Multilingual Voice Alerts

Adding support for multiple languages in the voice alert system would make it more effective in diverse regions. Clearcommunication in local languages ensures that warnings are understood by all users, improving safety.

7. Block Chain-Based Incident Logging

Incorporating block chain technology for logging detected anomalies can provide tamper-proof records of all incidents. This feature could serve as reliable evidence for investigations and ensure accountability for actions taken.

VIII. CONCLUSION

This research demonstrates the successful implementation of an intelligent anomaly detection system for ATM security, leveraging the YOLOv3 deep learning model. The system excels at identifying critical threats such as unauthorized group entries and weapons, ensuring real-time responses through voice alerts and Telegram notifications.

Unlike traditional surveillance systems that rely heavily on manual monitoring, the proposed solution automates both anomaly detection and response. It significantly enhances ATM security by reducing the time required for intervention and mitigating risks associated with delayed action. With high detection accuracy, minimal latency, and robust performance across varying conditions, the system is both practical and scalable for widespread deployment.[14]

While the current implementation addresses key security challenges, future enhancements—such as facial recognition, IoT integration, and behavioural analysis—can further extend its capabilities. By adapting to evolving threats and leveraging cutting-edge technologies, the system has the potential to become a comprehensive solution for ATM and public security.

In conclusion, this research lays the foundation for a safer financial infrastructure by integrating advanced technologies into ATM surveillance. The system not only deters criminal activities but also ensures a timely and effective response, making it a vital step toward modernizing security measures for the banking sector.

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