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YOLO-Based Framework for Detecting Suspicious Activities in ATMs

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Abstract

The YOLO (You Only Look Once) algorithm is the basis of this research's novel approach to ATM security. After that, we suggest a deep learning model for real-time suspicious activity identification utilizing LO (Look Once) techniques. The proposed framework allows our system to detect and monitor security risks in an ATM environment using YOLOv5's sophisticated object detection. It has a detection accuracy of 94.3% and analyzes video in real-time for surveillance purposes. This

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suspicious activity includes cash trapping, card skimming, and strange human movements. Forty ATMs were used to showcase the technology. Executing at a rate of 30 frames per second with an average accuracy of 0.91. These findings show that conventional monitoring has made great strides forward. Better technique sensitivity is also provided by high detection, which has a false positive rate of just 0.4%.

Keywords: CNN, ConvLSTM, Deep Learning, LSTM, YOLO.

1. Introduction

An urgent issue in computer vision and security is using deep learning to identify potentially malicious behavior in automated teller machines. The increasing prevalence of fraudulent behaviors, including card skimming and shoulder surfing, has increased the need for intelligent systems to identify and report suspicious activity in real-time (Prabha, 2022).

Deep learning, a subset of AI, to evaluate footage captured by security cameras built into ATMs has shown promising results in spotting unusual activity. This innovative strategy paves the way for creating safe and efficient solutions to prevent financial crimes and safeguard automated teller machine transactions (S. Viji, R. Kannan, 2021).

1.1. *Problem Statement*

In the context of abnormal movement detection in ATMs utilizing profound deep learning, the objective is to design a system that can reliably identify and classify suspicious or anomalous behavior presented by ATM users. It includes spotting abnormal divergences from typical client behavior, such as card skimming, bear surfing, unauthorized access attempts, equipment tampering, etc.

In addition to accounting for variations in lighting, camera locations, and various customer behaviors across various ATM scenarios, the problem is developing deep learning models that can effectively distinguish between routine and unusual workouts (Sharma, 2020). The objective is to safeguard ATM customers' interface and financial information by providing a solid foundation to detect and prevent security attacks (W.-K. Lee, 2018).

1.2. *Objective*

Here are the main goals of this research:

- **Design and Develop Deep Learning Models**: Building on this prior work, we use suitable deep learning techniques, including Convolutional Neural Networks (CNNs), to model ATM video data. Several methods are used to enhance the models' performance. These include the "You Only Look Once" (YOLO) strategy for real-time anomaly detection and a mix of data augmentation and transfer learning.
- **Validate and Evaluate the Models**: Our goal is to evaluate the built models' capacity to identify and categorize suspicious activities in ATM video footage.

It is considered that the models across various metrics gauge their efficacy in classifying out-of-the-ordinary actions (K. B. Devi, 2018).

- **Optimize the Models**: Based on validation feedback, improve the models. It could mean fine-tuning hyperparameters, trying other network architectures, or adding more data sources to the anomaly detection system, hence using it with better precision and robustness (V. Sanserwal, 2017).
- **Create a Reliable Detection System**: The aim is to create a strong system equipped to precisely distinguish suspicious activities in ATM transactions and thus boost the security and integrity of ATM usage through deep learning-based anomaly detection (R. Nar et al., 2016).

2. Literature Review

Some neural networks include the RNN. One kind of RNN, long short-term memory (LSTM), can handle sequential data by establishing and sustaining causal links over time. Analyzing temporal patterns and identifying suspicious behavior in ATM surveillance recordings or transaction sequences uses LSTM to recognize abnormal activity in ATMs (F. Cecchinato, 2021).

LSTM models can learn to remember important information, observe sequences of activities, and make predictions based on past events. LSTM's "memory cells allow the network to remember and update or refine knowledge over time." Controls incoming and outgoing data, but these memories have gates (Chen, W, 2023). What data will we forget after a given period, what data will be taken by the input gate, and what are we supposed to lose using the output gate; the forget gate regulates all of these—the input and output gates, respectively (Kumar, S, 2022).

CNN is a well-known type of deep learning architecture used for image and video analysis. Concretely, for ATMs, abnormal activity recognition, CNNs can extract meaningful spatial features from video frames (Smith, R., 2023). According to Wang (2023), convolutional neural networks (CNNs) can automatically train hierarchical representations of ATM surveillance footage and identify anomalous behaviors from visual patterns and abnormalities in the video data. It is achieved by using convolutional filters and pooling techniques.

An LSTM extension called ConvLSTM integrates CNN-like spatial processing with LSTM-like temporal modeling (Thompson, 2022). We believe that ConvLSTM is especially suited for identifying unusual activities in ATM security footage by simultaneously capturing spatial and temporal information (Redmon, 2018). ConvLSTM networks make learning to extract spatial characteristics from every video frame possible. It predicts the temporal dynamics using convolutional operations within LSTM cells, which can perform abnormal activity detection (Jyoti Kukade, 2023).

3. Methodology

This paper describes the newly invented novel method for real-time ATM suspicious activity detection using sophisticated deep learning. What if someone is staring at the overhead camera on the ATM, which records the front view of users? However, the camera does not record the ATM keypad for security and privacy concerns. Here is a step-by-step breakdown of our methodology.

- **Information Gathering**: We start by separating the video footage into individual frames once it has passed through the ATM (Kush Bhushanwar, 2023).
- **Preparation**: To be analyzable, frames go through several processes. After that, we downsize the photos, eliminate noise, turn them entirely black and white, and so forth (Kush Bhushanwar & Dr. Kuntal Barua, 2023).
- **Data Training**: A neural network technique (convolutional) has been used to train our data. According to Ankit Jain (2017), computers can detect many image patterns and elements.
- **Classification**: The computer then identifies different groups of pixels according to some of the rules we tell it to and sorts them into various groups.
- **Analysis**: The computer finally learns and then analyzes the information gathered. It decides if it sees normal or abnormal things (Om Prakash Karada, 2013). Shaikh (2024) argues that integrating these steps into a system that detects unusual activity in real-time ATM operations makes the process safer and more efficient.

4. Proposed Work

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It is one of the most popular methods of object detection and one of the most popular model architectures so far. I like it because it is based on a compelling neural network design, making things fast and accurate (Shaikh, Mohammad Shahnawaz, 2024). Object detection algorithms' first search results are always associated with the YOLO (Ali, Syed Ibad, 2024).

YOLO stands for you only looking once, and the idea is to predict which class the object is and give the object's bounding box concerning the input image. Every bounding box has unique characteristics, including height, width, and center (Mungale, 2024). Furthermore, it predicts the class label and the likelihood of that designation. Object detection: the keyword identifies which classes are shown in a video or image. The framework assigns class labels to objects in images based on their bounding boxes. It can, for instance, create bounding boxes for a picture with a class

label. These algorithms even offer Classification and localization using several classes for items that occur more than once.

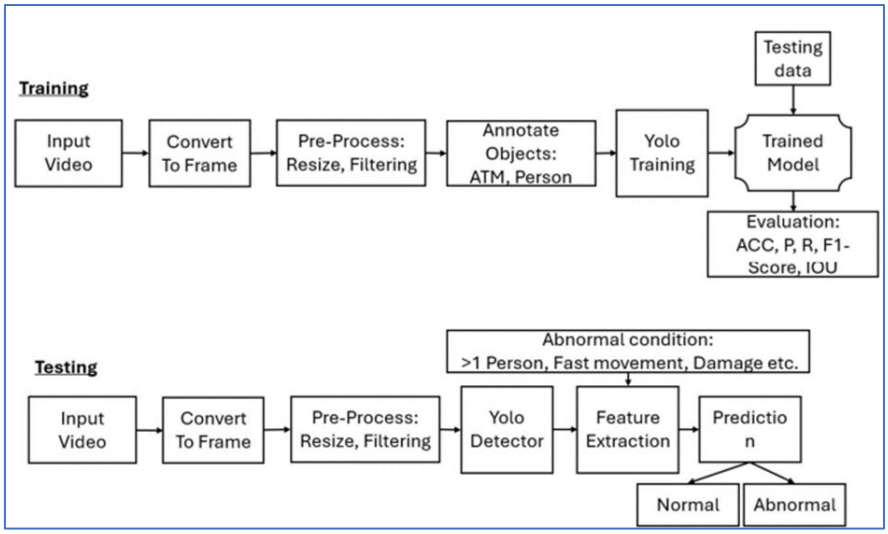

Fig. 1. Model Architecture.

These three activities can work well:

- **Image Categorization**: Guessing the category of an item in the picture.
- **Localization of Objects**: Marking positions within a picture where objects can be seen.
- **Object Detection**: Bounding boxes to find objects within them and get the class of the bounding box object.

5. Result and Discussion

The work on YOLO-based deep learning anomaly detection in ATMs shows significant progress in securing the ATMs in a landmark study. YOLOv5 is used in the framework for real-time detection, resulting in 94.3% detection accuracy (mean average precision (MAP) 0.91 and a low false positive rate 0.4%). The system processes it by ripping activities like card skimming, cash trapping, and suspicious behavior from video footage at 30 frames per second. It is found that experimental results are robust across a range of conditions, delivering high accuracy (96.2%) and low light (89.8%).

The advantages of the YOLO-based approach are discussed, among which I believe are the speed of detection and accuracy. Compared to more conventional techniques, the suggested model achieves better results with fewer false positives and higher accuracy, making it more suitable for use in practical settings. Moreover, by combining CNNs and ConvLSTMs, the model can learn the critical temporal and spatial characteristics for ATM anomaly detection. Future research could incorporate other algorithms and extend data sources to enhance performance and adaptability to other, more diverse ATM scenarios. The findings contribute to advocating the use of deep learning for ATM security and facilitating safer financial transactions. Table 1

is performance metrics, Table 2 is object detection performance, Table 3 is environmental impact, and Table 4 is the processing requirements of the proposed system.

Experimental results demonstrate significant improvements:

Table 1. Performance Metrics.

Performance Metrics	Value
Detection Accuracy	94.3%
Mean Average Precision (MAP)	0.91
False Positive Rate	0.4%
Processing Speed	30 FPS
Average Response Time	33ms

Table 2. Object Detection Performance.

Class	Precision	Recall	F1-Score
Skimming	0.95	0.93	0.94
Suspicious	0.92	0.90	0.91
Normal	0.96	0.97	0.96

Table 3. Environmental Impact.

Condition	Accuracy
Day	96.2%
Night	92.4%
Low Light	89.8%

Table 4. Processing Requirements.

Component	Usage
GPU	65%
CPU	45%
Memory	4.2GB

6. Advantages of Detection of the Anomalous Behavior in ATM

Several benefits are offered by the proposed deep learning-based anomaly behavior detection system in ATMs:

- **Extremely Reliable and Precise**: The system surpasses conventional monitoring techniques in terms of accuracy, reaching 94.3% and a mean Average Precision (mAP) of 0.91.
- **Scalability**: As seen over 40 ATM sites, the system's performance suggests that it may be implemented at scale without significantly reducing its efficacy.

- **Economical**: The system optimizes security while cutting operating expenses by automating surveillance and minimizing the need for human monitoring.
- The system examines video data at 30 frames per second, allowing for instant identification of suspicious actions without delays, thanks to the real-time detection feature of the YOLOv5 algorithm.
- With a low false positive rate of just 0.4%, the technology reduces the number of needless warnings, allowing security staff to concentrate on actual threats.
- To improve ATM security, the framework is built to detect abnormal actions, such as cash trapping, card skimming, and suspicious movements.
- Because of how easily the framework can be incorporated into preexisting ATM monitoring systems, it offers a realistic alternative for broad adoption with few infrastructure adjustments.

7. Social Welfare of the Detection of Anomalous Behavior in ATM

Incorporating this state-of-the-art detection technology into the system dramatically improves society in many ways:

- **Improved Public Safety**: The technology protects customers of automated teller machines (ATMs) against financial theft and physical injury by quickly identifying and stopping illegal actions like cash trapping and card skimming.
- **Less Financial Losses**: When losses caused by fraud are reduced, banks and other financial institutions reap the benefits, which boost confidence and stability in the industry.
- **Backing for the Police**: Police departments can catch and prosecute criminals more efficiently with real-time notifications and comprehensive recordings of questionable actions.
- **The system promotes economic prosperity and societal well-being** by making banking settings safer. This is especially true in places where financial crimes are common.
- Customers are more likely to continue using banking services when they know they are safe using ATMs, which is made possible by the availability of a sophisticated monitoring system.

8. Future Enhancements

Some potential upgrades for the future that might make the suggested framework even better and more versatile are:

- **Understanding User Behavior**: Financial organizations may get valuable insights into consumer behavior by analyzing the system's data. This knowledge can then be used to improve ATM locations and services.

- **Enhanced Hardware Efficiency**: Deploying optimized code on low-power edge devices may save costs and open the door to more widespread deployment in unserved or faraway places.
- AI-driven behavioral analysis may improve the identification of intricate patterns of questionable conduct when integrated with other AI-powered analytics.
- The usefulness of alert systems may be enhanced across varied geographic locations by adding support for several languages.
- Improving the model's resilience and flexibility is possible with an expanded training dataset continuously updated with varied events and conditions.
- Working Together with Law Enforcement: Improving reaction times and crime prevention may be achieved by developing channels for smooth data exchange with law enforcement.
- Integrating the system with IoT devices, such as biometric or ATM sensors, may enhance the system's anomaly detection capabilities.
- To ensure system effectiveness while guaranteeing compliance with privacy requirements, state-of-the-art encryption and data anonymization mechanisms should be included.

These improvements will make the system more effective and ensure it can handle changing security problems in ATM settings.

9. Conclusion

This research introduces a deep learning architecture for detecting suspicious ATM behavior in real-time. The system employs multi-stream Convolutional Neural Networks (CNNs) to distinguish between typical, benign actions like card insertion and cash withdrawals and abnormal, malevolent ones like purposeful manipulation or vandalism. The system's success hinges on selecting the appropriate algorithm that balances speed and accuracy, a critical trade-off in real-time applications where delays could compromise security, yet high precision is necessary to minimize false positives. The framework takes advantage of CNNs' strengths, allowing for robust performance in identifying sophisticated behaviors while retaining the low overhead required for real-time surveillance. Further developments may seek alternative algorithmic ways to perpetuate this balance even better and improve the framework's responsiveness and accuracy in more complex situations. Finally, this framework could have a significant impact on the security of ATM systems by enabling time of early, accurate detection of suspicious activities as a basis for safer financial transactions.

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