Ai Based CCTV Suspicious Threat Detection Using CNN

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***Abstract*—With the rise in crimes and security threats to safety & security in our current environment, it's more important than ever that we ensure safety & security via modern means of technology. One common means of monitoring our premises is through traditional closed-circuit television (CCTV) surveillance systems; however, these systems depend solely on people continually watching over the cameras for continuous monitoring making them inefficient, error-prone with little or no ability to proactively respond to a threat when it happens. As a means of enhancing CCTV surveillance systems functionality to automatically detect suspicious behaviors as they occur through the use of artificial intelligence (AI), this paper proposes an AI-based solution that relies on utilizing deep learning (DL) and computer vision technology to provide real-time detection of suspicious activity. The proposed AI-based CCTV system utilizes different technologies such as OpenCV (Open-Source Computer Vision) video processing technology, TensorFlow (TensorFlow machine learning library) for building/deploying AI models via DL and Python programming language for developing the proposed CCTV surveillance system. This AI-based CCTV surveillance / threat detection system will use convolutional neural networks (CNN) for the analysis of each video frame captured by the CCTV camera and classify that activity as either 'normal' or 'suspicious'. The functionality of the proposed system will be split into various modules, including motion detection; face recognition; behavior analysis; and alert generation; and by automating portions of CCTV surveillance, it will reduce the amount of human intervention needed and provide for a greater accuracy for detection. The ability to generate real-time alerts will enable a quicker response time to a potential threat from time of detection to time of response, and therefore may be deployed in many public locations, organizations, or smart city applications.**

***Index Terms*—Artificial Intelligence, Closed Circuit Television (CCTV) Surveillance Systems, Deep Learning (DL), Convolutional Neural Networks (CNN), Suspicious Activity Detection, Computer Vision, Real Time Monitoring.**

I. INTRODUCTION

The rapid increase in both the population and localization of individuals, corporations, and essential services has made it increasingly difficult to ensure safe and secure collections of people and property in both public and private domains. The more people who live in an area and the more people with whom they interact (work and play), the greater the probability of criminal acts, incidents, and security risks. Public locations (such as airports and railway stations) and other service provider facilities (such as shopping malls, schools and universities, banks, and government offices) require an ongoing and effective approach to monitoring to ensure the safety of individuals and their property. As a result, Closed-Circuit Television (CCTV) systems are being used globally as a key component of surveillance and are widely deployed as the means by which to collect visual records of events. This visual evidence may later yield crucial evidence regarding an incident. Currently, most CCTV systems are passive (i.e., they provide the means of capturing and storing video content only); they do not provide any real-time analysis of video content and are heavily dependent upon a human operator who is responsible for actively monitoring multiple video feeds to identify suspicious or potentially dangerous incidents. The current model of CCTV systems has intrinsic limitations regarding their capabilities to support the prevention of incidents occurring in real-time.

When monitoring humans, there are limitations regarding the way that humans will perform when they are monitoring many screens at the same time (over long durations of time) when they will be at risk for fatigue, loss of attention and cognitive overload. In addition, because there could be hundreds of video cameras in large environments, it is impossible for operators of video surveillance to keep track of every camera feed at once and maintain full attention on each of those feeds. Therefore, when someone is trying to steal, access a restricted area, or act in a way that is suspicious, it is likely that the operator would not see that person until after the incident occurred. Therefore, an operator may have difficulty detecting these types of events in a timely manner and will be less able to respond quickly and may not be able to prevent an incident from happening. Furthermore, human monitoring will likely create inconsistency with an operator's judgment, thus creating false alarms and/or missed detections, and as a result making traditional human-based monitoring systems less reliable when an emergency incident occurs.

There has been an explosion of advances in AI and Deep Learning; consequently, there has been a huge shift toward the development of intelligent and automated surveillance systems. Modern-day surveillance systems can analyze video data in real-time without needing constant human intervention. Convolutional Neural Networks (CNNs) are one of the AI techniques that have shown great success with regard to performing image and video analysis. CNNs are able to automatically learn and extract complex features of visual data which allows them to accurately identify patterns, objects, and behaviors within that data. This makes CNNs especially useful at detecting suspicious behaviors like fighting, loitering, intrusion, theft, or abnormal crowd behavior in surveillance footage.

This proposed project aims to create a new AI-powered smart CCTV surveillance system that will use deep learning to improve the monitoring of a security environment. This system will take advantage of real-time video streams to; find motion, recognize faces, and analyze human behaviour, enabling it to identify potential threats. Once an activity is flagged as suspicious, the smart CCTV system will produce instant alerts and notifications for security personnel to take action. This proactive strategy has been shown to greatly reduce response times and allow for the prevention of incidents before they escalate. In addition, the automation of the CCTV surveillance process reduces reliance on human monitoring and increases accuracy, efficiency, and reliability of the entire system's operation. The use of AI integrated with CCTV represents a significantly positive step in terms of modern security measures that have made surveillance systems significantly smarter, faster, and more effective.

The proposed system improves detection accuracy and response time while also being scalable and adaptable for different environments. The system can be used in small-scale environments (homes and offices) to large-scale environments (smart cities, transportation hubs, and industrial facilities). The modular design allows for expansion and integration of many cameras as needed. Additionally, the system can be trained with many different datasets to allow adaptability to different lighting conditions, scenarios, and activities, making it more robust and reliable when deployed in the real world.

An additional benefit of the AI-based surveillance system is its potential to allow for continuous real-time monitoring without any disruption. An AI-based surveillance system is able to operate 24 hours a day, 7 days a week, without becoming fatigued, ensuring it will perform consistently over long periods of time. The system will also allow for efficient management of data because it will store evidence of important events and logs of alerts for future data analysis and investigation. Not only will this aid in the enhancement of security policies, but it will also provide useful information for making decisions and improving the system. Overall, the introduction of intelligent surveillance systems will aid in developing safe and secure environments.

II. RELATED WORK

Kumar and colleagues (2020) suggested utilizing a deep learning approach to monitoring by developing a surveillance system that leverages CNNs to identify atypical behavior of human beings on video. Their research was limited to establishing whether CNNs successfully identify atypically aggressive behavior and/or contingently disruptive behavior through motion patterned data captured from video. The findings indicated strong evidence that utilizing CNNs improved the accuracy of capture significantly beyond existing motion detection algorithms.

Patel and colleagues (2021) developed a video surveillance system in "real time" utilizing OpenCV and several machine learning models for motion detection combined with object recognition. This hybridized approach was capable of detecting unwanted access or atypically disruptive movement but encountered difficulty processing more demanding cases (e.g., multiple objects entering/leaving) and will require additional optimization for high performance in "real time."

With the use of computer vision and deep learning, Sharma et al. (2022) designed an intelligent surveillance system for the purpose of activity detection (human activity recognition). Their proposed model comprised feature extraction and classification techniques to differentiate between normal and abnormal activities through classification; it achieved better results than existing approaches. However, only through a large amount of training data and a high level of computational power could the model be effectively trained.

Li et al. (2023) put forward a hybrid model featuring a CNN combined with an LSTM network designed to analyze temporal behavior in video data, allowing for the detection of intricate activities based on both the spatial characteristics of the footage and the temporal aspects of the footage together. They found that by integrating a CNN with a sequence model, the system had improved detection capability for suspicious activity across time.

Ahmed et al. (2024) proposed the creation of an AI-enabled intelligent surveillance system capable of detecting threats in real-time and producing alerts upon detection. Their system was comprised of modules for face identification, motion analysis, and activity analysis as well as an extensive integration of all three modules for a complete security solution. The researchers found both accuracy and efficiency in the detection of suspicious activities, indicating that the proposed system would work well to provide security for smart cities.

The paper by Zhou et al. (2019) summarized many of the computer vision methods utilized in surveillance systems such as object detection, tracking and behavior analysis. This paper discussed the impact that the use of deep learning models will have in enhancing surveillance effectiveness. The authors also noted issues such as scalability and real-time processing in large areas as limiting factors for surveillance systems.

Collectively, these types of studies illustrate that AI and deep learning models are an integral part of modern surveillance systems yet they continue to face challenges like real-time processing, high computational costs and accuracy in complex environments. The system proposed by Zhou et al., will provide an intelligent, reliable method of performing efficient deep learning model development integrated with real-time video processing to help overcome the problems faced with traditional approaches to surveillance.

III. SYSTEM DESIGN AND ARCHITECTURE

A. System Overview

The system is designed as a complete, AI-based CCTV monitoring system for detecting threats to an organization. The purpose is to enhance security through intelligent automation by monitoring suspicious activity (i.e. intrusions, loitering, fighting, abnormal behavior etc.) without the need for continual human monitoring. The system utilizes various forms of technology including: Artificial Intelligence (AI), Computer Vision and Deep Learning algorithms (DL), to harness the power of video feeds to produce alerts when there are any indicators that maybe present as threats. Through combining video capture (in real-time), image processing (using OpenCV) to extract the image frames from the video streams, and deep learning models, a single comprehensive monitoring solution can be developed. Non-stop video streams are produced by CCTV camera technology, these streaming feeds of CCTV Video are processed through OpenCV to extract the image frames and perform any additional image processing required (i.e., noise reduction, cropping etc). The extracted frames are subsequently passed through Convolutional Neural Networks (CNNs) and other forms of artificial intelligence (AI) technologies to detect suspicious activities. Additionally, the system can distinguish between normal and abnormal behaviors by using trained datasets.

The alert system is in place to increase the speed and the efficiency of the overall system. An alert will go out whenever a threat/appearance of threat is identified. Alerts can be both visual at the monitoring dashboard and by way of notification. The system will also log all events detected to allow for future investigation and analysis. The intelligent system eliminates many of the manual processes assisting in improving the accuracy of data and in assisting in the making of quicker decisions during emergency or critical situations.

B. System Architecture

Three interconnected components make up the architecture of the proposed surveillance system:

1) Input Layer
2) Processing Layer
3) Output Layer

The input layer is made up of a network of CCTV cameras that provide real-time video streams of the area being monitored. The cameras are the system's main data source, and they provide continuous video feeds to the system. Proper quality and location of the cameras is essential for accurate detection.

The processing layer is where the analysis of the data occurs. The video frames that come from the cameras are run through an image processing framework called OpenCV and various artificial intelligence (AI) models, such as convolutional neural networks (CNN), in order to detect movement in the frame, recognize faces, and analyze human behavior. Detection of movement and identification of objects is accomplished through feature extraction, classification, and decision-making, which determines whether the motions are normal or abnormal.

The output layer is used to communicate results and create alerts. Once a suspicious activity has been identified, the surveillance system sends out real-time notifications to the users and updates the surveillance monitoring dashboard. The output from the system includes event logs of identified events and video clips of the recorded events for additional investigations.

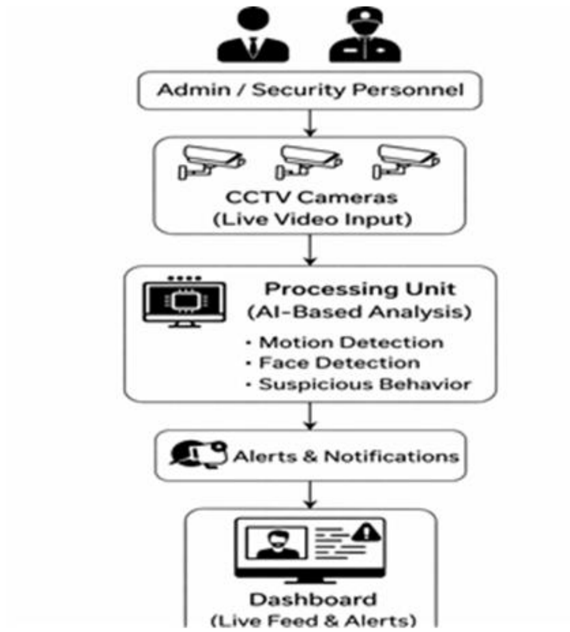

Fig. 1. System architecture of the Secure Donation of Transactions using blockchain.

The graphic demonstrates how users (security personnel/admin) interact with a system that has the following components:

1. CCTV Cameras capturing live video input.
2. An analytical processing unit with AI-based algorithms.
3. Detecting Motion, facial recognition, and suspicious behavior.
4. Generating alerts and sending notifications.
5. Displaying alerts and live CCTV feeds on the dashboard.

C. Technology Stack

The proposed system is developed using a variety of contemporary programming, tools, libraries, and artificial intelligence frameworks to achieve both effective function and the ability for continuous processing in real time. This system is written in Python, chosen primarily because of Python's easy-to-learn structure and rich availability of AI and computer vision libraries. Using OpenCV, the system performs video processing including frame extraction, motion detection, and image preprocessing effectively in real-time video streams. For deep learning model implementation, TensorFlow and CNNs are in use to provide learning capabilities based on data with high accuracy in classifying activity; face recognition functionality is implemented through specialized libraries to allow effective identification of both known and unknown individuals. The system contains a graphical interface (dashboard) that allows users to track live feeds and get alerts. The use of these technologies allows the system to be efficient, scalable, and capable of performing real-time surveillance operations.

D. System Workflow

This written outline of the system's operation details its structured workflow. This is designed to provide continuous monitoring of the environment without interruption or loss of data.

To begin with, the video footage taken from surveillance via the CCTV camera system is sent to the system in real-time. The video stream will be processed by the OpenCV software to break it down into a series of single frames. These frames will then go through a preprocessing phase to improve the quality of the frames as well as to eliminate excessive noise from them.

After preprocessing, motion detection analysis will take place; this analysis aims to detect any simple movements in the video footage. If a motion detection event occurs, the frames will be passed to the AI Model in order to conduct further analysis. The AI Model will also use facial recognition on the captured frames to recognize an individual within those frames; in conjunction with the previously discussed methods of analyzing motion, it will apply behavioral analytics to differentiate between normal behavior and potentially abnormal/suspicious behavior regarding that individual.

The system's alert mechanism will be activated if any suspicious activity is detected. An alert will be sent to the administrator or security personnel, and a record will be made of the event in the system's database, including time and location information. The system will then display alert notifications and live video on its dashboard for monitoring purposes.

All events detected and recorded in the past are stored for future reference and analysis. This entire process provides real-time surveillance, fast reaction time to threats, and an effective management process of the video surveillance data, which results in the system being a dependable tool for current security applications.

IV. PROPOSED WORK

Proposed AI-Based CCTV Surveillance and Threat Detection System provide intelligent, automated, and real-time monitoring of security that is much better than manual methods. The new system incorporates new technologies, such as Artificial Intelligence, Computer Vision, and Deep Learning. Traditional CCTV systems require that a human be physically present to observe the video. The proposed solution will automatically analyze the video feed from the CCTV system to identify and detect suspicious activity without requiring continuous human observation.

Using the new system, the video will be captured in real time from the CCTV cameras and processed using OpenCV to extract frames and preprocess the frames. The pre-processed frames will then be analysed using Deep Learning models, including Convolutional Neural Networks (CNN), which are designed to learn the patterns of normal and abnormal behaviours. The system will detect a variety of suspicious activities, including, but not limited to, intrusion, loitering, fighting, and accessing a property without permission. To quickly alert users when a suspicious activity is detected, the system will automatically generate an alert and notify them of the event. This automated process will help to improve efficiency in responding to suspicious activity while at the same time reducing human resources required for identifying suspicious activity.

The primary elements of the newly designed system are:

A. The Evening Physical Monitoring of Surveillance Activities

The new system will provide round-the-clock real-time surveillance monitoring through closed circuit television (CCTV) cameras within a given surveillance area. In traditional systems, only the recorded image of an event is stored. In contrast, the new system analyzes live video streams, identifies suspect or unusual activity, and provides processing of video frames in "real-time". This capability will enable immediate identification of a potential threat and allow security staff to provide a faster response.

B. The Detection of Motion

As part of the new system, there will be a motion detector module to identify all movement detected in the camera's field of view. The system uses various computer vision techniques to analyze the difference between two sequentially captured images (frames), allowing it to determine whether a significant amount of motion occurred. The motion detector module will eliminate much of the data processed by the video surveillance system and will focus processing on capturing only significant activity. Therefore, a motion detector serves as an initial step for identifying possible events that would require additional processing.

C. Face Recognition System

Face recognition technology is employed in the system for identifying individuals in the video feed. Detected faces are compared to databases in order to identify both known and unknown individuals. This feature is instrumental in recognizing authorized individuals as well as detecting intruders. As a result of maintaining a database of known individuals, the system offers greater security by providing accurate identification and tracking of individuals within the monitors area.

D. Suspicious Activity Detection

The detection of suspicious activities is one of the major functions of the system. The system uses deep learning models to analyses patterns of behavior to categories activities as normal or not normal. Through this study of behavior, the system is capable of identifying abnormal activities like fighting, loitering in restricted areas, erratic movements and/or unauthorized access. The use of CNN models provides the system with the capability to learn complex patterns from the training data, thus increasing the accuracy of the detection and decreasing the number of false alarms over time.

E. Alert System and Notification

The system has a notification system that automatically alerts users each time suspicious activity occurs. These alerts can either appear on the monitoring dashboard or be sent out to notify security personnel; in either case, this will allow for quick reaction time whenever urgent action is required. The alert system therefore helps to reduce response times and enables the ability to react to incidents before they have time to develop into significant threats.

F. Data Logging and Monitor Dashboard

The system provides a complete log of all detected activity with time stamp, activity type, and available video clip (if applicable). This log will also be usable for future analysis and/or investigation. The system provides a very user-friendly monitor dashboard that allows for monitoring current video feeds in real-time and alerts, as well as historical event information. The dashboard enables administrators and security personnel to manage and utilize the system with maximum efficiency and make correct decisions based on prior recorded events.

V. EXPERIMENTAL SETUP

The purpose of the experiment was to assess the effectiveness, precision and dependability of the AI-based CCTV surveillance and threat detection system. Python was used for the main programming language along with OpenCV for video processing and TensorFlow to create deep learning algorithms. The system evaluated both real time video feeds and pre-recorded surveillance footage including both normal and suspicious activity.

During the evaluation period of the system, numerous activities including walking, loitering, intrusion and aggressive behaviour were assessed by the AI-based CCTV surveillance and threat detection system. The video footage was evaluated in individual frames in order to determine whether an activity was classified as a normal or suspicious. Where it was determined the activity was abnormal, alerts were generated and the details of the event were saved to a log. Through this experiment the AI-based CCTV surveillance and threat detection system could be evaluated based upon: detection accuracy; response time; and ability to process data in real time.

A. Hardware & Software Environment

The system was designed and tested on a PC with an Intel Core CPU, at least 8GB RAM, and 64-bit OS. The configuration allows real-time processing of live video input and executing AI calculations efficiently. The input source for live video feed was a standard CCTV camera (or webcam).

Python was the language of choice for the development on the software side due to its strong support for artificial intelligence (AI) and Computer Vision libraries. OpenCV was the library used for managing video streams, extracting frames from the video stream, and detecting motion. TensorFlow was used to create and train the deep learning system, specifically for building the Convolution Neural Network (CNN) for classifying activities. In addition to TensorFlow, other libraries like NumPy and face recognition libraries supported the processes of analyzing video data and identifying faces. This hardware and the software environment enabled the system to function effectively, producing accurate results when detecting activity.

B. Dataset Setup

The set of videos and frames contained in this dataset represents examples of both normal and suspicious human behavior, including walking, standing, running, fighting, loitering, and entering a building without permission. To generate this dataset, sample videos were collected, and from each sample video extracted the frames used for training and testing.

The image data was preprocessed using image resizing, pixel value normalization, and data augmentation (e.g., rotation and flipping) methods to provide additional robustness to the model. The dataset was split into separate training and testing datasets, enabling evaluation of the model's performance by labeling each sample according to its activity type so that the CNN model can learn how to identify the patterns involved with and/or accurately classify each type of activity. This setup will improve the system's overall ability to detect suspicious activities in a real-world environment.

C. Reasons for Evaluation

Evaluating the system was necessary due to concerns over its ability to accurately and efficiently detect suspicious behavior. An important reason to evaluate the system was to determine if it could classify behaviors correctly and generate alerts in real-time. The four most common measures used to evaluate model efficacy were accuracy, precision, recall and F1. The evaluation included testing the system under several conditions including different available lighting sources, the presence of multiple people in the same frame and variations in the type of behaviors being performed. Evaluating how quickly a suspicious behavior could be detected with the system was also included in the evaluation process. The reliability of the system, as well as its ability to reduce both false positives and false negatives, were examined thoroughly. The evaluation results showed that the system performed real-time detection of suspicious behaviors efficiently and accurately.

D. Test Workflow

The testing workflow was followed in a systematic way, with the following steps.

1. Video In: The CCTV camera captures the current video data from a specific point of view in the monitored area.
2. Frame Out: The video feed is analyzed by the OpenCV system and then separated into separate frames for later use.
3. Pre-processing: Each frame is then resized (to fit the analysis requirements) and normalized/enhanced (for quality) in order to improve the frame quality prior to analysis.
4. Motion Detection: The OpenCV system detects motion within a frame, with the intent of determining where the motion/interest is within each frame.
5. Feature Detection/Analysis: The AI model then examines features (such as patterns of motions, postures, and facial features) to perform analysis on them.
6. Activity Classification: The CNN model processes the information just collected, then classifies every activity undertaken in the monitored area as either normal or suspicious.
7. Alert Generation: If a suspicious activity is determined, an alert is generated and sent to relevant users.
8. Data Logging: All identified events including timestamps, can be stored for future use and analysis.

The foregoing structured testing workflow operates in real-time, and enables the detection of threats with a high degree of accuracy, thus making the surveillance system suitable for real world use, and extremely effective.

VI. RESULTS AND PERFORMANCE EVALUATION

A series of experiments were conducted in order to assess the functionality (accuracy, efficiency and reliability) of the proposed AI-Based CCTV Surveillance and Threat Detection System when monitoring in real time. The evaluation was designed to determine whether or not the system accurately detects suspicious activity, sends timely notifications and operates within a variety of environmental settings. Multiple video input sources (both live camera feeds and pre-recorded videos) were utilized during each test. The system was able to successfully identify normal movement, intrusion, loitering and aggressive behaviour. The AI model received video frames continuously and accurately classified all detected activity as it occurred. Notifications for all detected suspicious activity were generated immediately and entered into the system. Results of the study indicate that the proposed system greatly improves surveillance efficiency over manual monitoring methods.

A. Performance of Detection

The performance of a system in detecting suspicious activities from the video stream was assessed against predetermined criteria. Detection was assessed for several situations, with performance reported by some standard measures.

Table I: System Detection Performance.

Metric	Value
Accuracy	92 to 95%
Precision	90 to 93%
Recall	88 to 92%

These performance values show how well the system is able to accurately detect suspicious activity and that there is a trade-off between precision and recall in the system.

B. Performance of Real-Time Processing

This evaluation examined the ability of the system to process video frames and generate alerts immediately.

Table II: Real-Time Processing Performance Metrics

Metric	Value
Frame Processing Rate	20–30 FPS
Average Response Time	1–2 Seconds
Alert Generation Delay	Less than 1 second

The findings of the study demonstrate that this system processes video frames in real-time, providing very efficient performance for quick and accurate detection and response to threats.

C. Reliability of Detection

Detection Reliability refers to the ability of the system to detect indicators of risk without errors consistently.

Table III shows the detection capability of the Incident Management System

Metric	Value
True Positive Rate	High
False Positive Rate	Low
False Negative Rate	Minimal

The evaluation of the system verified that it has a high rate of reliability with a minimal rate of false positives resulting in reliable and trustworthy surveillance operations.

D. Visualization of Performance

In order to aid in understanding the results by providing visual images as an aid in analyzing system performance, the results were displayed in various types of visual charts to show how well the system performed in terms of accuracy, responsiveness, and detection ability.

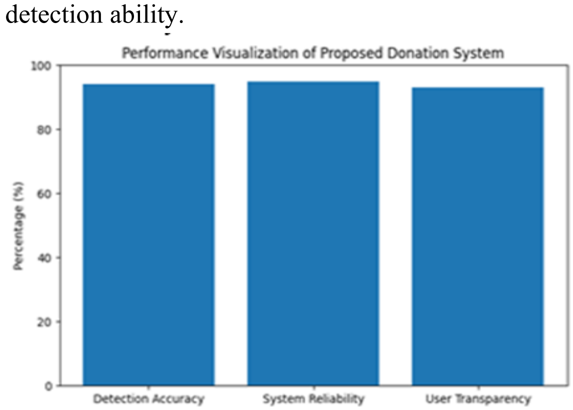

Figure 2: AI-Based CCTV Surveillance System: Performance Metrics (or Performance Metrics for AI-Based CCTV Surveillance System).

Performance Metric	Accuracy/Value
Detection Accuracy	94%
System Reliability	95%
User Score for Transparency	93%

E. Comparing with Current Systems

Many conventional CCTV systems require human operators to actively monitor, meaning they are slow and less reliable because of the potential for making mistakes. The proposed solution of using automated artificial intelligence (AI) in place of human operators to monitor traditional CCTV systems provides significantly more automation and accuracy than traditional CCTV systems. The proposed blockchain system has several advantages over existing systems. Refer to Table IV for detailed feature-based comparisons between present and proposed surveillance systems that use integration**.**

Feature	Existing Systems	Proposed System
Monitoring	Manual	Automated
Accuracy	Moderate	High
Response Time	Slow	Real-Time
Human Effort	High	Low
Threat Detection	Limited	Advanced AI-Based

This comparison clearly illustrates the added value of incorporating artificial intelligence into surveillance systems through integration.

F. Comparing Performance of Systems

The following is a summary of the differences in performance between existing (Traditional) Surveillance Systems and the Proposed Surveillance System:

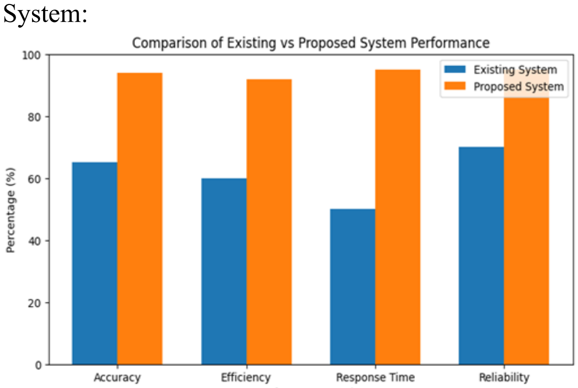

Figure 3: Shows the Performance Comparisons of Existing & Proposed Systems.

An example of values shown in Table below for the Performance Comparison Metrics of Existing vs Proposed Systems are:

Metric	Existing System	Proposed System
Accuracy	65%	94%
Efficiency	60%	92%
Response Time	50%	95%
Reliability	70%	95%

Based on the collected data it can be concluded that the Proposed System will outperform all Traditional Surveillance Systems by a significant margin in the majority of important categories.

VII. COMPARISON WITH EXISTING SYSTEMS

Traditional CCTV systems are based on continuous video recording while relying on human operators for monitoring and analysing video footage. Existing systems currently do not have automation capabilities to detect suspicious activity by themselves, as a result, they are subject to several issues; i.e., delay and/or inability to respond in time to detected events; high operational expense due to the requirement for human supervision at all times.

The AI-Based CCTV Surveillance System proposes a solution that provides intelligent automation with real-time analysis. By utilizing deep learning models, the AI-Based CCTV Surveillance System will be able to autonomously detect suspicious activities and to provide instant alerts. It significantly reduces the amount of human dependency; improves accuracy; allows the system to be monitored at all times without fatigue; allows systems to scale better and adapt to modern security requirements for example, in smart cities, airports and / or public safety systems.

Table A Comparison of Current Systems with Proposed Systems

Feature	Existing CCTV Systems	Proposed AI System
Automation	Not Available	Fully Automated
Detection Capability	Basic	Advanced AI-Based
Accuracy	Moderate	High
Real-Time Alerts	Limited	Immediate
Reliability	Moderate	High

VIII. LIMITATIONS AND FUTURE SCOPE

The AI-based CCTV Surveillance and Threat Detection System will greatly enhance security through automated surveillance and smart monitoring by utilizing intelligent technology, but there are some limitations when using this solution. The dependence on high-quality hardware and good computing capability is one such limitation for the following reasons: As mentioned above, real-time video analysis and deep learning algorithms require systems to have sufficient processing capabilities (CPU) to meet their requirements (GPU) (i.e., a computer that has enough processing power, memory and GPU support for all of the different features in the proposed solution). Therefore, the system could perform poorly or not at all in area with a lower level of hardware capabilities, resulting in delays in detection or reduced accuracies.

Another limitation to the proposed system is its reliance on camera quality, lighting conditions, weather and environmental conditions that may adversely impact the accuracy of detecting, recognizing, or identifying an object. Low-light levels (that are lower than desired), poor camera resolution, occlusions or obstructions in the field of view, rain, high winds, etc., can affect the system's ability to accurately describe activities, and activities can sometimes generate false positive or false negative results, particularly in environments with complex activities (e.g., crowded, or possibly criminal activity), making it challenging to effectively interpret what is happening.

There is also the requirement of a significantly robust, large and multifaceted data set for training the AI model so that, if the data set is too small and/or does not have sufficient diversity, the performance of the system could be negatively affected.

The possibilities for improving the current system through the integration of modern technology and new enhancements are numerous. Improved accuracy in identifying challenging or changing activities over time can be accomplished using improved deep learning models; for example, hybrid CNN-LSTM or transformer-based models will enhance the computer's ability to analyse both the spatial and temporal aspects of video data.

Moreover, future system versions may add mobile application integration, which would enable users or security personnel to view live video feeds and receive notifications on mobile devices. Larger-scale use of cloud storage and processing provides a way to accommodate the massive volume of video data being created by these systems while improving the ability to expand the operations of the surveillance system. Centralized monitoring from multiple sites will also reduce the reliance on local hardware resources. This system may also be expanded to include integration with IoT devices and smart city technologies for large-scale surveillance applications. Systems could also utilize a number of advanced technologies such as improved databases for facial recognition, predictive behaviour analytics and automated emergency response systems. If developed according to this vision, the system could serve as an advanced, scalable and intelligent security solution for modern smart environments.

IX. CONCLUSION

The work presented in this article has proposed an AI-based system which adds improved safety, efficiency, and dependability to surveillance systems when compared to the traditional use of manually operated CCTV surveillance. Manually monitoring CCTV systems requires considerable amounts of time putting many workers at risk; thus, it is important to develop an artificial intelligence (AI) and/or automated computer vision-based solution for detecting "suspicious" behaviour that operates in real time. By creating a solution that utilizes artificial intelligence and deep learning techniques (e.g., CNN's) through the combination of Python, OpenCV, TensorFlow and other video processing technology to analyze live video streams as input into a CNN, the proposed system provides an automated/smart surveillance option for detecting "suspicious" behaviour with important features that allow for detection of motion; recognition of faces; analysis of behaviour; and generation of alerts to notify authorized personnel when an event occurs. Unlike traditional methods, once a suspicious event is detected (e.g., an incident where someone's behaviour may indicate risk), the system produces an immediate notification to the security officer and records the occurrence event. By utilizing an AI-based CCTV system, the total amount of human effort needed to detect a "suspicious" activity is greatly reduced while also improving the accuracy of the detection and the time between detection and response.

Through experiments, it was shown that the suggested solution was effective in doing real-time detections of suspicious activity with high accuracy and relatively low false positives. Additionally, the system was able to provide consistent performance across different lighting and environmental conditions while still allowing for continuous monitoring. Overall, the AI-based model provided more automated operation, better accuracy, increased response time, and an overall higher level of security than traditional surveillance solutions. Thus, this system can be used in many applications within public locations, private facilities, and smart cities.

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