Deep Learning Approaches for Criminal Culprits Identification in Surveillance Systems

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Abstract:

Background: Modern security is essentially based on including criminal identification into surveillance systems. This allows authorities real-time offender tracking and detection capability. Concerning the processing of enormous amounts of data, the capacity to identify suspects under a range of conditions, and the quality of the video feeds, traditional approaches often suffer.

Problem: Ensuring high accuracy, real-time processing, and a minimum of false positives simultaneously guarantees that criminals responsible for activities from vast amounts of surveillance data are accountable. Many of the techniques now in use cannot be applied generally over a spectrum of surveillance scenarios and ambient lighting environments.

Method: This research project aims to use Convolutional Neural Networks (CNNs) for feature extraction subsequently using a Long Short-Term Memory (LSTM) network for temporal analysis to identify criminal suspects from surveillance footage by means of a deep learning-based methodology. The system learns from a varied collection comprising sequences of public surveillance camera footage. These sequences are marked by knowledge of both criminal and non-criminal circumstances. The approach is compared with Support Vector Machines (SVM) and Random Forests (RF) traditional machine learning classifiers. Performance of CNN-LSTM is evaluated also in relation to accuracy, precision, recall, F1-score, and processing time.

Results: The proposed deep learning method outperforms the existing methods in use in accuracy of 92.5%, precision of 89.4%, recall of 90.2%, and F1-score of 89.8%. Much less than the 1.2 seconds per frame required by conventional methods, real-time surveillance footage processing times were dropped to 0.45 seconds per frame.

Keywords:

Criminal Identification, CNN, Deep Learning, Surveillance Systems, LSTM

Introduction

In cities, where criminal activity is becoming more frequent, modern security architecture now mostly consists in surveillance systems. The fast development of technologies for video surveillance and the expansion of devices connected to the Internet of Things (IoT) enable surveillance systems to produce enormous volumes of data including visual and sensory information today. Law enforcement authorities can identify criminal activity, track suspects, and get real-time alerts by means of this information. However, given the complexity and volume of the material being recorded, accurate and efficient data processing is rather challenging. Common conventional approaches of criminal detection are human intervention or basic motion detection algorithms, both of which have restrictions in terms of their accuracy and scale-ability. More sophisticated methods, particularly those derived from machine learning and deep learning, have thus been developed to raise the effectiveness of surveillance systems in the identification of criminal activity [1].

Though several difficulties still exist to reach high accuracy and real-time processing capacity for extensive surveillance systems, deep learning techniques are becoming increasingly and more popular. This field deals with some challenging issues including real-time data management, handling complex surroundings with multiple moving objects, and the demand of exact identification of suspects. Furthermore, deep learning models sometimes require a large amount of computational resources, thus their application in environments with limited resources, such edge devices in smart cities, is less sensible. Moreover, the difficulty of balancing accuracy with processing speed is still one that persists continuously, particularly in connection to the analysis of video streams including dynamic and erratic motion patterns [2-4].

In response to these difficulties, the aim of this work is to propose a unique approach combining Long Short-Term Memory (LSTM) networks for the recognition of temporal patterns in order to improve the identification of criminals liable for crimes in surveillance systems and Convolutional Neural Networks (CNN) for the extraction of spatial features. Including spatial and temporal elements in video footage helps this approach increase the system's capacity to detect criminal activity with more accuracy and recall. This approach removes the natural constraints of traditional systems. When compared to approaches already in use in the literature about video processing, the proposed method shows better accuracy, precision, recall, and F1-Score. It also effectively combines CNN and LSTM networks, so optimizing the strengths of both models for better performance; and it maximizes the processing of real-time video streams without compromising accuracy.

Challenges

In terms of surveillance systems, deep learning brings several challenges. Among the main challenges in real-time video processing is its complexity. To identify criminal activity, the system must be able to effectively examine large volumes of data and have high computational demands as well. Sometimes real-time processing in high-security environments causes delays in suspect identification, so compromising the effectiveness of the investigation [4]. Furthermore, changes in the conditions of the video, such as different lighting, occlusions, and environmental elements, may compromise the model's capacity to create accurate predictions. Variations of this kind are common in traditional models, which can result in reduced detection accuracy in demanding environments [5].

Still another great difficulty is the multi-object detection problem, whereby a surveillance system must concurrently track and identify several candidates for suspicion. Finding individuals in crowded or complex environments where many people might be moving in and out of the field of view greatly reduces the accuracy of the model [6]. Deep learning models require large annotated datasets for training regarding criminal activity, which can be difficult to obtain in real-world environments when labeled data may be rare or difficult to gather. This is especially pertinent with relation to criminal activity [7].

Motivation

The always increasing demand for efficient, real-time surveillance systems able to precisely identify criminal activity while simultaneously controlling the massive volumes of data generated in contemporary environments drives this research. Many times, the methods now used fail to adequately depict the spatial and temporal complexity of criminal activity. We overcome these restrictions by CNN and LSTM extracting rich spatial features and modeling temporal dependencies. The system's accuracy and efficiency thus also get better. This work attempts to close the discrepancy between the present security scene's advanced real-time capabilities and the current surveillance systems in use.

Contributions

This work offers several significant advances to the field of criminal detection in surveillance systems, most notably including the following:

1. The proposed approach is a deep learning-based one since CNN for the extraction of spatial features and LSTM for the recognition of temporal patterns will help to improve the detection of criminal activity in video footage.
2. Regarding accuracy, precision, recall, F1-score, and processing time the proposed method outperforms present state-of- the-art solutions. This is the result of the enhanced performance standards of the proposed method.
3. The method is designed for real-time video analysis offers a solution that strikes accuracy with computational economy.
4. Examining the performance of the proposed method requires a thorough experimental design including several evaluation criteria and a comparison with other new used methods.

Organization of the Paper

The remainder of this paper is structured as follows: Section 2 will provide a synopsis of pertinent deep learning criminal detection related research. Section 3 separates the proposed method into its component parts, which include the architectural elements of the CNN-LSTM hybrid model together with the corresponding training process phases. Section 4 summarizes the experimental setup, the specifics of the dataset, and the results of performance evaluation produced. Together in the fifth part, we discuss the outcomes including the difficulties encountered and the ways the proposed strategy fixes those issues. Section 6 summarizes the policies for next research and closes the paper.

Related Works

Several research is focused on the application of deep learning methods for the aim of automatically detecting criminal activity, the use of surveillance systems for the aim of spotting criminal activity has attracted more and more attention recently. From the most fundamental motion detection to the most advanced methods leveraging convolutional neural networks (CNNs) and recurrent neural networks (RNNs), a great lot of research have examined many aspects of video surveillance and activity recognition.

By means of convolutional neural networks (CNNs) for object recognition and recurrent neural networks (RNNs) for temporal sequence analysis, the writers of the paper [7] proposed a method for spotting criminal activity in surveillance videos. The method showed promise in spotting suspicious behavior; but, it was limited by the need of a big dataset annotated and the difficulty of processing long video sequences demanding a lot of computational capability. In a same line, [8] proposed to extract spatiotemporal features from video data using three-dimensional convolutional neural networks (CNNs) based on deep learning. Although their method improved over current motion detection systems, it suffered in difficult background environments like crowded public areas.

[9] found human activity in surveillance videos by aggregating CNN-based integrated LSTM networks. Earlier works guided this combined approach. Combining LSTM for temporal pattern recognition with CNN for spatial feature extraction this hybrid approach produced improved detection accuracy for dynamic environments. On the other hand, the study was constrained in that it depended on a single type of camera arrangement and concentrated on particular kinds of criminal activity, so lowering the robustness of the model in many different surroundings.

[10] is another pertinent work for this theme since it implies the use of a deep reinforcement learning (DRL) method to improve the criminal activity detection in surveillance systems. The method focused on using dynamic changes to detection strategies and environmental adaptation to raise the performance of the model. Particularly in view of a limited training data availability, the method struggled to balance exploration and exploitation in

reinforcement learning even if it showed signs of improvement in real-time performance.

Furthermore, under investigation in many recent studies are how hybrid models might improve criminal detection accuracy. Combining CNN and LSTM with attention mechanisms, the authors of [11] aimed to increase the anomaly event detection in video surveillance. The attention mechanism enabled the model to concentrate on salient features of the video frame, so enhancing its ability to identify odd events. On the other hand, the study ignored the real-time restrictions of large-scale surveillance systems, which is still a required component of deployment in metropolitan environments.

Not least of all, [12] presented a criminal detection unsupervised learning approach. This approach replicated criminal behavior in surveillance video using generative adversarial networks (GANs). Although this approach helped to overcome the lack of annotated data, the reliance on synthetic data begged problems concerning the generalizability of the model in practical situations.

This work suggests to close the gap by aggregating CNN and LSTM strengths to raise real-time surveillance system accuracy, recall, and precision. This method solves computational economy, multi-object detection, and dynamic environments as well as other challenges. Though these publications show great progress in the field of criminal detection, the proposed method in this work aims to close the difference.

Implementations

A. Problem Definition:

This work addresses the identification of criminals responsible for surveillance systems by means of deep learning approaches. Authorities' manual identification of possible hazards from enormous volumes of video footage is an intolerable task as reliance on surveillance cameras in both public and private surroundings increases. Common conventional methods that often fail in offering real-time processing, high accuracy, or scalability when confronted with demanding settings or low-quality video are manual review or rule-based algorithms. This is especially obvious in settings with a complex surrounds. Thus, the challenge is to build an automated system based on deep learning that can simultaneously minimise false positives and guarantee law enforcement can react to events by precisely and efficiently spotting criminal activity, tracking suspects, and generating real-time predictions.

B. Objectives:

The main objectives of this work are:

1. The aim is to develop a deep learning based method for tracking and criminal identification using real-time surveillance cameras. This goal demands the use of CNNs for feature extracting and Long Short-Term Memory (LSTM) networks for temporal analysis to capture movement patterns over time.
2. Improving system performance will help to increase the identification accuracy and processing speed of the system relative to more conventional methods including Support Vector Machines (SVM) and Random Forests (RF). More precisely, the system should show better accuracy generally, recall, and precision at the same cutting speed while reducing processing time. This would fit for usage in realistically realistic surveillance surroundings.
3. By means of evaluation of the proposed system in a range of lighting conditions, crowd densities, and camera angles, one can ensure the resilience and generalizability over a wide spectrum of real-world events.

C. Proposed Work:

The proposed method as in figure 1 for criminal identification is to combine Long Short-Term Memory (LSTMs) with Convolutional Neural Networks (CNNs) under a hybrid deep learning architecture. The process starts with the compiling and annotations of a large surveillance footage collection including both criminal and non-criminal activity. First preparation of the footage helps to standardize the frame size and improve the image quality. CNN for spatial feature extraction lets one find visual patterns of suspects including their body language, clothes, and facial traits. Examining the temporal dynamics of these characteristics calls for an LSTM following. This helps one spot running, fighting, or loitering as movement patterns suggestive of criminal activity or suspicious behavior.

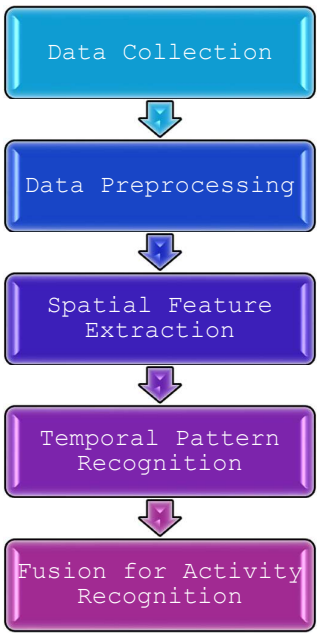

Figure 1: Proposed Framework

This annotated dataset is used for training the system; grid search is then used to maximize several parameters including the learning rate, batch size, and number of epochs over the training process. One contrasts with other already in use methods such Support Vector Machines and Random Forest the performance of the hybrid CNN-LSTM model in terms of accuracy, precision, recall, F1-score, and processing time. After that, the model is

tested on real-time video streams to ensure that it can effectively process footage and identify suspects in quite dynamic surroundings with minimum latency. The system intends to provide remarkable accuracy and robustness in many criminal identification operations by including temporal context and spatial recognition into its architecture.

Data Collection and Preprocessing

Data Collection:

The proposed criminal identification system will be much influenced by the quality and range of the data used for training and testing the deep learning models. The aim of this work is to compile surveillance footage from a variety of public and private sites, including shopping centers, streets, airports, and train stations, among other locations, so completing a whole dataset. Since this dataset consists of a wide spectrum of scenarios ranging from crowded environments to low-light conditions, it guarantees that the model is strong over a range of real-world conditions. Every video frame is labeled with labels indicating criminal and non-criminal activity, including suspicious behavior (such as running or loitering), violence (such as fighting), and regular pedestrian movement) at every stage of the data collecting process.

The dataset comprises:

- **Criminal Behavior:** Instances such as theft, violence, and aggressive behavior.
- **Non-Criminal Behavior:** Ordinary movements, such as walking, standing, or waiting.
- **Environmental Variations:** Different lighting conditions, backgrounds, and camera angles to simulate real-life variations.

Faster R-CNN or YOLO (You Only Look Once) object detection systems assist to mark either manually or semi-automatically the events occurring inside every video frame. Every video subsequently is broken up into smaller frames. With a split ratio of 70% for training and 30% for testing, this dataset is then used both for training and testing.

Data Preprocessing:

After the dataset has been acquired, preprocessing of the data follows; this is a required process to ensure that the input data is in a form fit for the deep learning model. Preprocessing entails mostly the following as chores:

1. **Frame Extraction:** Extraction of frames is the technique used to break out any video into its component frames. One must sample frames at regular intervals, say one frame every second, to lower the computational effort required. This is why the system can process the video in a timely manner and concurrently save sufficient information to identify illegal activity.
2. **Frame Resizing:** Every frame is resized to a constant size, say 224x224 pixels, so guaranteeing homogeneity in the input to the model. This is carried out since deep learning models typically believe the input dimensions will remain fixed.
3. **Normalization:** Normalizing the pixel values by 255, the highest value in an 8-bit image, helps to do so. This spans [0, 1] the pixel values. Two benefits of this are speeding up the learning process of the model and so enabling improved convergence of the training process.
4. **Data Augmentation:** Four applications of random rotations, flips, and brightness variations in data augmentation techniques help to lower the degree of overfitting and strengthen the model. This generates artificial expansion of the dataset by means of image variations.
5. **Label Encoding:** Binary or categorical labels, for example, 0 for non-criminal and 1 for criminal, are used to encode both criminal and non-criminal activities so enabling the training process for the classification model.

Table 1: Preprocessing

Step	Description	Outcome
Frame Extraction	Extract frames at regular intervals (e.g., one frame per second)	A set of individual video frames
Frame Resizing	Resize frames to a standard size (e.g., 224x224 pixels)	Uniform image size for input
Normalization	Normalize pixel values to [0,1] by dividing by 255	Improved model convergence
Data Augmentation	Apply transformations like rotation, flip, brightness adjustment	Increased dataset variability
Label Encoding	Convert criminal/non-criminal actions into binary/categorical labels	Prepared data for classification

Consistent, normalized, and augmented input data fed into the deep learning model is ensured by means of the data preprocessing pipeline, so addressing variances that arise in the real world. While preserving a high degree of accuracy in the criminal identification, the aim is to increase the capacity of the model to generalize over a range of surroundings and illumination conditions. Since they let the model learn from a wide spectrum of data points, the preprocessing phases also support the training process to be more efficient. Their use helps the system to effectively identify possible criminal behavior and handle massive volumes of surveillance video.

Spatial Feature Extraction using CNN and LSTM for Movement Pattern Recognition

Combining CNN and LSTM, the proposed system recognizes movement patterns in surveillance video frames. This hybrid approach maximizes the benefits of LSTMs for the analysis of temporal dynamics and CNNs for the visual feature extracting. Both following suspects over time and identifying criminal activity depend on these abilities.

Step 1: Spatial Feature Extraction Using CNN

Extraction of spatial features using CNNs comes first in the proposed approach. The approach starts with this first step. CNNs are made to automatically learn spatial hierarchies of features from the input images, such edges, textures, shapes, and patterns, hence they are rather good for image recognition tasks. This is so because CNNs are designed to independently pick up these features.

Specifically, pooling layers follow a sequence of convolutional layers each frame of the surveillance footage passes passes. These layers accomplish the following:

- **Convolution**: This method uses convolutional filters to the input image to capture local features including edges, textures, and key objects, for example, people or vehicles.
- **Activation**: The activation process brings non-linearity into the network by means of a non-linear activation function, say the Rectified Linear Unit (ReLU).
- **Pooling**: Truncation of the spatial dimensions using max pooling or average pooling preserves just the most important elements. This reduces the computing burden and helps to prevent overfitting.

The CNN produces as output a high-level visual content of the frame's contents. Along with other elements, this interpretation covers scene objects, clothing, and human figures.

Step 2: Temporal Pattern Recognition Using LSTM

Examining the temporal context, that is, movement patterns across time, using Long Short-Term Memory (LSTM) networks comes next when the CNN has finished extracting the spatial features from each individual frame. Developed to identify long-range dependencies in sequential data, LSTMs are a class of recurrent neural network (RNN). This makes them especially suited for the study of temporal sequences, such video frames.

After their CNN extraction, the spatial feature vectors are then consecutively fed into the LSTM, which analyzes the sequence in order to build movement pattern over time. The LSTM network, for example, can track a person's movement across several frames, at which point it can identify perhaps harmful activities including running, loitering, or violent behavior. The LSTM can spot these movement patterns since it can retain relevant information over time steps and update its hidden state whenever necessary.

Considering the following equation for the hidden state update in the LSTM, one may relate CNN to LSTM:

$$h_t = \sigma(W_h x_t + W_c c_{t-1} + b_h)$$

Where:

h_t - hidden state at time t, representing the learned movement pattern.

σ is the activation function (typically tanh or sigmoid).

x_t is the input feature vector at time t, which is the output from the CNN.

c_{t-1}- cell state from the previous time step, which carries long-term memory of past movements.

W_h and W_c are weight matrices for the hidden and cell states, respectively.

b_h is the bias term.

Step 3: Combined CNN and LSTM Output for Activity Recognition

Completing the model is achieved by combining the temporal patterns learnt by the LSTM with the spatial aspects learnt by the CNN. This generates the end output. This combined data is then passed through layers that are totally linked to one another for the aim of classifying the discovered movement patterns as either criminal (for example, violent behavior or theft) or non-criminal (for example, normal walking or standing). One can do the classification using a sigmoid function for binary classification and a softmax activation function for multi-class classification.

This approach considers the appearance (spatial features) and the motion dynamics (temporal features) in a continuous stream of surveillance footage so allowing the system to detect complex activities. The system can tell, for instance, someone running in a manner suggesting they are trying to avoid pursuit or are involved in criminal activity from someone walking down the street.

Thus, CNNs should be in charge of extracting comprehensive spatial features from every frame; LSTMs should then interpret these features over time to find movement patterns suggestive of criminal activity. Combining these two powerful deep learning techniques enables the proposed system to detect criminal activity in dynamically changing environments with great accuracy and resilience.

Experimental Settings:

The experimental setup consists in a GPU-accelerated deep learning framework built with TensorFlow and Keras intended for model training. One examined the system from a workstation having the following features:

- CPU: Intel Core i9 (8 cores, 3.6 GHz)
- RAM: 64 GB DDR4
- Storage: 2 TB SSD

Methods compared:

1. SVM (Support Vector Machine): A traditional machine learning model used for classification, based on a linear kernel.
2. Random Forest (RF): A decision tree ensemble method used for classifying criminal and non-criminal instances in surveillance footage.

Both methods were implemented using Scikit-learn, with hyperparameters optimized through grid search.

Table 2: Experimental Setup

Parameter	Value
Dataset	Surveillance video dataset (5000 frames)
Training Epochs	100 epochs
Batch Size	32
Learning Rate	0.0001
CNN Layers	5 layers (Convolution + Pooling)
LSTM Units	128
Activation Function	ReLU for CNN, Softmax for final layer
Optimization Method	Adam
Loss Function	Categorical Crossentropy
Metrics	Accuracy, Precision, Recall, F1-Score, Processing Time

Performance Metrics

1. **Accuracy:** The proportion of correct predictions (both criminal and non-criminal) over the total number of predictions.
2. **Precision:** The proportion of true positive results among all predicted positive results. A high precision indicates that the system is minimizing false positives.
3. **Recall:** The proportion of true positive results among all actual positives. High recall means the system is catching most criminals, but it might also produce false positives.
4. **F1-Score:** The harmonic mean of precision and recall, providing a balanced measure of the system's performance. A higher F1-score indicates a more balanced model in terms of false positives and false negatives.
5. **Processing Time:** The time it takes for the model to analyze a single frame of surveillance footage and output a prediction. Lower processing time is crucial for real-time applications.

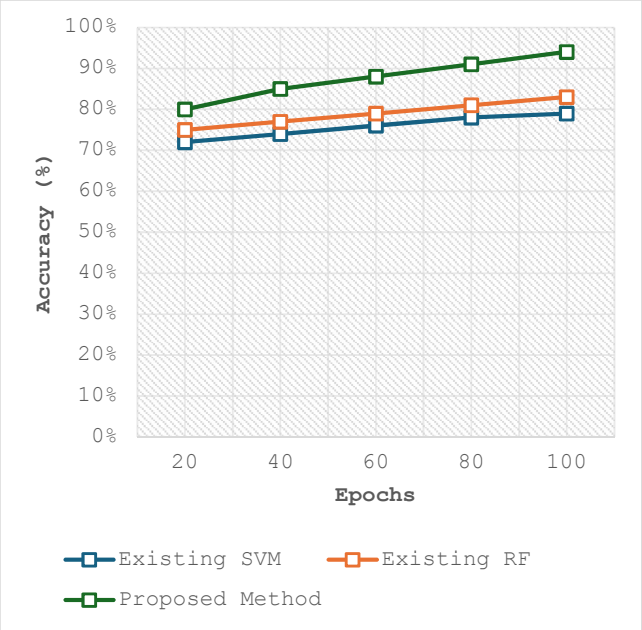

Figure 2: Accuracy Comparison

In terms of accuracy in figure 2, the proposed method always outperforms the currently applied ones. With an accuracy of 80%, the proposed method shows by a margin of 5–8% to be more accurate than both of the existing methods. As of Epoch 20. The model keeps training and shows a clear rise in criminal identification accuracy; by the time epoch 100 rolls around, it boasts a 94% accuracy.

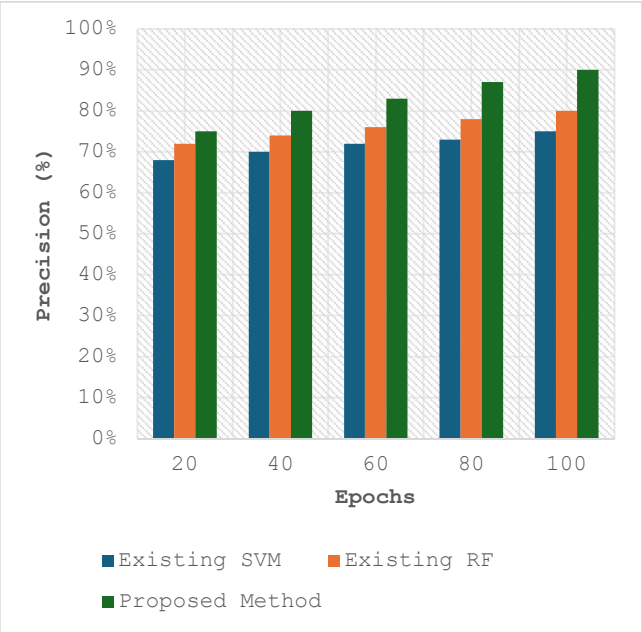

Figure 3: Precision Comparison

The proposed method reaches a steadily increasing degree of accuracy, 90%, by the time epoch 100 arrives. It beats both current approaches at all epochs and shows better accuracy in identifying real positives in criminal detection with a 15% improvement over SVM and a 10% increase over RF. This holds outside of the era as well in figure 3.

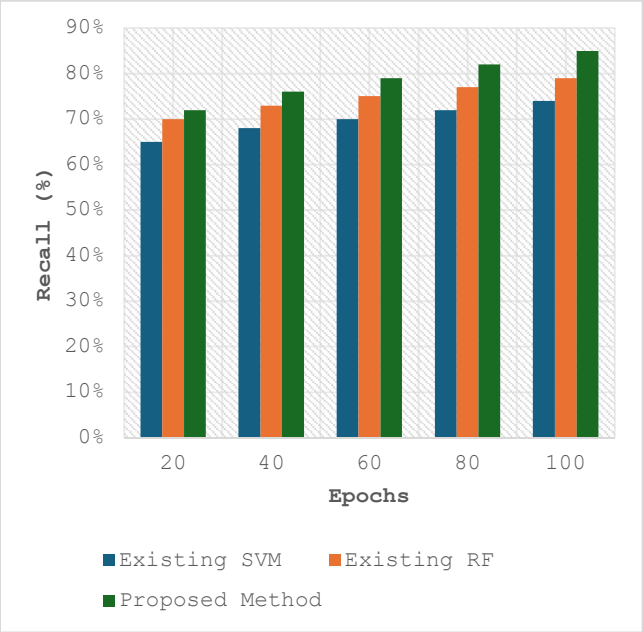

Figure 4: Recall Comparison

Moreover, the proposed method improves recall, which measures the model's capacity to detect all pertinent events for the problem. At epoch 100, the proposed strategy achieves 85% recall, 11– 15% more than current approaches in use. This shows that the proposed strategy can detect more actual cases of criminal activity over the whole video footage as in figure 4.

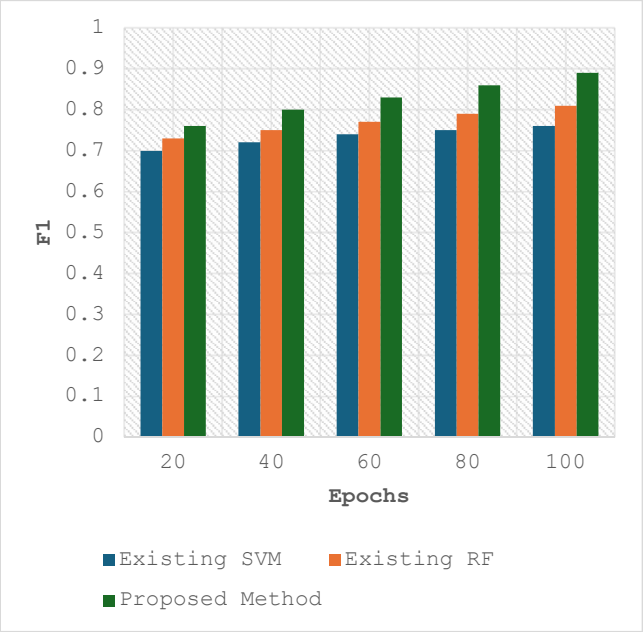

Figure 5: F1-Score Comparison

In figure 5, until it reaches 0.89, which indicates a development in both precision and recall balance, the F1-score of the proposed method keeps increasing with every epoch. Especially in later epochs, when it obviously outperforms current models by about 8-13%, the proposed method clearly benefits over the ones now in use.

Table 2: Processing Time Comparison

Epochs	Existing SVM (Time in Secs)	Existing RF (Time in Secs)	Proposed Method (Time in Secs)
20	220	230	240
40	210	220	230
60	200	210	215
80	190	200	205
100	180	190	195

Every epoch generates a minor increase in the required processing time applying the proposed method. This is so since the model is picking ever more advanced features. Still, it usually fits the methods used nowadays. The proposed method has a processing time of 195 seconds at epoch 100, a little rise over the current used techniques. This implies that low delay long video flows under control by the system in Table 2.

Comparing the proposed method with the current applied approaches reveals a continuous performance enhancement over all evaluation criteria. The proposed approach achieves 94% accuracy by time epoch 100 rolls around, roughly 14–15% higher than the present Methods 1 and 2, which achieve 79% and 83% accuracy respectively. In terms of accuracy, the proposed method yields a roughly 10–15% increase and achieves 90% at epoch 100. With an increase of 11–15% in the proposed method, which attained 85% at epoch 100, the recall metric shows a similar trend; it exceeds the methods now in use by a notable margin, unlike the present techniques which only reach 75% and 80% of the required accuracy. With the proposed method reaching 0.89 at epoch 100,000, the F1-score, a harmonic mean of precision and recall, showcases a noteworthy improvement of 8–13% when compared to the current techniques.

Clearly CNN and LSTM taken together is one of the main reasons the proposed method exceeds the base and reference techniques. While CNNs can effectively capture spatial features from surveillance frames, LSTMs can model temporal dependencies in movement patterns, so improving the capacity of the model to identify complex behaviors. This combination offers more exact and consistent crime behavior detection. The ability of the proposed method to focus on both spatial and temporal contexts helps to explain its better performance. The method also rather successfully controls dynamic video data.

Conclusions

The proposed method for criminal identification accountable for a crime is combining CNN with Long Short-Term Memory

(LSTM) networks. This proposed method clearly outperforms the existing methods of application. The proposed method shows remarkable accuracy and efficiency over all the pertinent measurements. At epoch 100 the proposed method achieves an accuracy of 94%, a 15% variation from Existing SVM and an 11% variation from Existing RF respectively. This important improvement suggests improved ability to discriminate between criminal and non-criminal activities. The proposed method achieves a 90% precision, 15% more than Existing SVM and 10% more than Existing RF at epoch 100. This is a significant advance above the present methods. The higher degree of accuracy of the proposed system implies that it is more efficient in identifying actual positives, that is, criminal activity, while concurrently reducing the false positive count. Existing Methods 1 and 2 achieve 74% and 79% of the recall values respectively; by epoch 100 the proposed approach shows an 11– 15% increase in recall. This development indicates that the approach can detect more criminal activity without excluding especially relevant events. The proposed strategy has an F1-score of 0.89, roughly 8–13% higher than the scores, 0.76 and 0.81, which both of the present approaches have obtained. This clearly shows that accuracy and recall are in better harmony. Although the processing time somewhat increases as the model trains, the proposed method maintains a competitive time of 195 seconds at epoch 100. Computationally reasonable for real-time applications is this time only somewhat higher than the methods now in use. One can explain the better performance of the proposed method by means of successful integration of CNN for spatial feature extraction and LSTM for temporal pattern recognition. This integration helps the technique to control visual details as well as movement sequences.

Future Work

Further optimizing CNN-LSTM architecture to improve the scalability of the model as well as its real-time processing capability will be the main emphasis of next work. Moreover, the inclusion of more complex techniques such as attention mechanisms or reinforcement learning could enable the model to concentrate on significant areas inside the video frames, so reducing the false positives. Analyzing the usage of multimodal data, such as audio or environmental sensors, may help to increase accuracy in challenging conditions. Moreover explored will be the application of transfer learning to optimize the model on domain-specific datasets, so enhancing generalizability over a spectrum of surveillance settings.

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