SUSPICIOUS HUMAN ACTIVITY RECOGNITION FROM SURVEILLANCE VIDEOS USING DEEP LEARNING

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ABSTRACT
Suspicious Human activity recognition (SHAR) is a significant area that helps improve surveillance and security systems by recognizing and reducing possible risks in different situations. The proposed research work focuses on the issue of correctly recognizing possible suspicious human behavior by using an innovative approach that harnesses the strength of sophisticated deep learning methods. Despite the abundance of research work on the topic of SHAR, the current methods need modifications with low levels of precision and efficiency. The proposed research work aims to address these issues by offering a complete methodology for recognizing and detecting suspicious human activities. By carefully collecting and processing data, as well as training models, we aim to address the issue of inaccurate and inefficient activity recognition in surveillance systems. By using Convolutional Neural Networks (CNNs) and deep learning models, such as the proposed time-distributed CNN model and Conv3D model, we attain greatly improved accuracy rates of 90.14% and 88.23%, respectively, which are superior to the existing research methods. Moreover, the efficacy of our method is verified by successfully conducting prediction experiments on unseen test data and YouTube videos. Through the means of the evaluation process of the trained models on the unseen test data, we identify the accuracy and ability to apply the learned knowledge to new situations. Moreover, the algorithms are used to predict the suspicious human behavior in a YouTube video, demonstrating the applicability of the algorithms in real-life surveillance situations. The results of this research work have important implications for improving surveillance and security systems to better identify and counter potential threats in various settings. Our method enhances the accuracy and effectiveness of SHAR, leading to the development of more reliable surveillance systems, ultimately improving public safety and security.

Keywords: *Suspicious Human Activity Recognition, Deep Learning, Surveillance Videos, Convolutional Neural Networks (CNN), Conv3D, Video Surveillance, Activity Detection.*

I. INTRODUCTION
The increased use of modern application packages is seen in different fields, such as banks, airports, and even in public places. Hence, it is important to implement effective security measures in different fields. The use of various surveillance techniques using CCTV cameras is common for monitoring different places. However, it is seen that the video data generated using these techniques is to be monitored regularly.

The recent advancements in machine learning, artificial intelligence, and deep learning techniques have enabled researchers to implement effective techniques for monitoring video data. Deep learning techniques, such as Convolutional Neural Networks (CNNs), have been found to be effective in extracting useful spatial features from video data. Apart from using CNNs for video data representation, various techniques such as Recurrent Neural Networks (RNNs), LSTM networks, have been used for effectively detecting activities in video data by considering temporal features in video data. Also, techniques such as Long-term Temporal Convolutions (LTC) have been introduced for effective video representation.

Though there are many advancements achieved in activity recognition by using deep learning methods, still there are certain limitations associated with it. Most of the surveillance systems have certain limitations, such as reduced precision, inefficient detection, and reduced activity recognition. Some systems are also not able to recognize the temporal relationships between different video sequences, which leads to classification errors. There is a need to improve the performance of activity recognition and include a wide range of suspicious activities.

In order to overcome the limitations of the above approaches, the current research proposes a deep learning-based technique for the recognition of suspicious human activities in video streams of a surveillance system. The proposed system recognizes the six major suspicious human activities like "Running," "Punching," "Falling," "Snatching," "Kicking," and "Shooting."

The effectiveness of the proposed technique has been proved by conducting prediction experiments on video streams. The proposed technique uses deep learning models to improve the efficiency of the surveillance system. The results of the current research contribute to the development of efficient and reliable automated systems for improving the security systems.

II. RELATED WORK

Although Human activity recognition has been a topic of intense research in current literature, this section will discuss the recent developments in this field. The most recent research work in Human activity recognition is primarily focused on the fields of machine learning and deep learning algorithms. In the field of machine learning, a comparative study was performed to focus on Human activity recognition using 2d-skeletal facts. They utilized the Open Pose library to obtain visual and motion information based on 2d landmarks of human skeletal joints. The researcher evaluated five supervised machine learning algorithms, namely support Vector machine (SVM), Naive Bayes (NB), Linear Discriminant (LD), k-nearest neighbours (KNNs), and feed-forward backpropagation neural networks. The primary objective was to identify four awesome activity commands: sitting, standing, walking, and falling, with the k-nearest neighbours (KNNs) performing the best. In another research work, an online continuous Human action recognition (CHAR) system was developed for skeletal data captured using Kinect depth sensors. Their approach utilized a variable-length maximum Entropy Markov model (MEMM) for continuous hobby reputation without the requirement for prior detection of activity start and end points. Moreover, a single approach utilized bone information from a depth camera, relying on machine learning for correct recognition of human actions. Unlike other approaches, where each activity is recognized through a unique set of cluster differences not used by activity instances, a single approach using skeletons was introduced to analyze the spatial-temporal features of human activity sequences. Their approach utilized the use of Minkowski and cosine distances to compute the dissimilarity of joint information extracted from Microsoft Kinect. The approach was trained and validated using publicly available datasets such as MSR each day activity 3D and Microsoft MSR 3D motion. The approach utilized the extremely Randomized Tree approach to show promising results in the improvement of monitoring systems for the elderly. Notably, this was achieved through the use of the low-cost depth sensor and open-source libraries. Emphasized the effectiveness of CNNs in handling challenges posed by image identification. Their study involved the classification of a broad range of videos, where a dataset of 1 million videos was categorized into 487 different groups. Exploring a broad range of approaches to integrate local spatio-temporal information into CNNs, they developed a multi-resolution approach to hasten the training process. By retraining the higher layers of the model with the UCF-one hundred and one action recognition dataset, the team observed huge improvements in the generalization abilities of the model, resulting in an astonishing accuracy boost from the baseline model's 43.9% to 63.3%. Analyzed the recent developments in the application of CNNs for the detection of human activities in videos. Their focus then turned to methods that remembered both the visual and the actions of the subjects. The study investigated the application of CNN towers to leverage the strengths of spatio-temporal knowledge, highlighting the strength of integrating spatial and temporal networks at a convolution layer without compromising performance. With the inclusion of a modern CNN model for the fusion of video capability over both space and Time, the authors demonstrated excellent generalization performance on standard evaluation datasets. Suggested a recognition method with a CNN to enhance the accuracy of indoor human activity recognition with geographical location information. Their state-of-the-art system, comprising

convolutional layers, fully connected layers, and max pooling layers, achieved quality results with proper identification of six actions with a recognition rate of 86.7%, proving the feasibility of their method. Explored the use of deep learning and transfer learning techniques for fall detection by examining data mined from security cameras. Based on the CNN AlexNet model, the classifier is designed specifically for fall detection. The objective was to enhance its efficiency by incorporating novel heuristics that consider the temporal relationship of frames and the average duration of fall activities delved into the use of the You Look Only Once (YOLO) network as the basic CNN model for real-time affected person surveillance with the objective of fall detection. By retraining the model for 32 epochs with classified affected person behavior snapshots, the researchers achieved an outstanding accuracy of 96.8% in action recognition, highlighting the ability of their approach. In their research, introduced an innovative anomaly detection method using a pre-trained CNN model for function extraction from video frames observed through processing with BD-LSTM. Their method showed promising results on the UCF-Crime dataset, establishing the efficacy for correct anomaly detection in surveillance systems. Our proposed work aims to identify six suspicious actions (Running, Punching, Falling, Snatching, Kicking, and Shooting) that have not been explored in the present literature yet An automatic video detection system is required because of the difficulties involved in observing the images from the cameras installed in public locations. Although the existing research work has achieved immense success in the field of intelligent surveillance, the task of achieving perfect detection and accuracy rates is challenging.

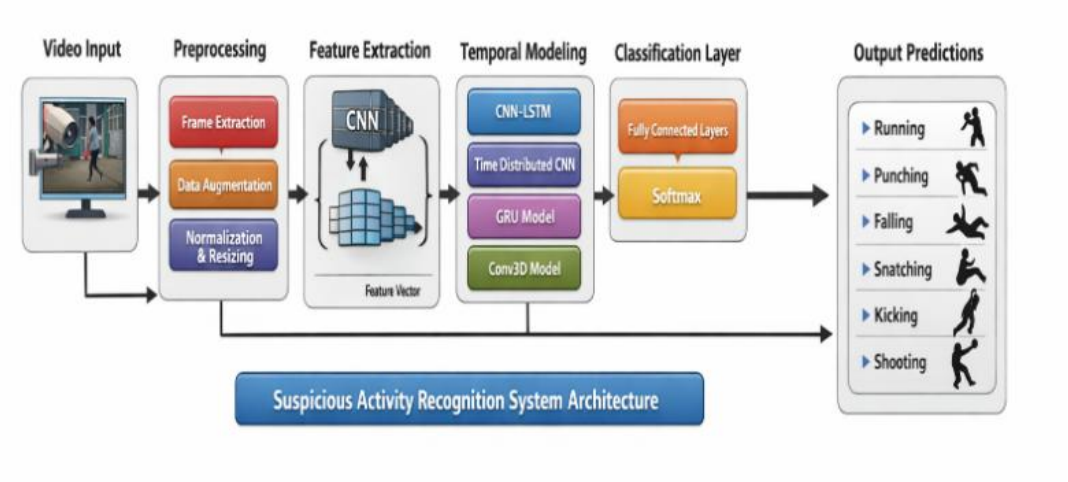
Table 1: Literature Review

Ref.	Title	Problem Statement	Solution	Framework / Technique	Limitations
[1]	Predictive Crime Analytics Using Random Forest (2025)	Crime prediction models often fail to integrate with real-time emergency response systems.	Developed a predictive crime analytics model to estimate crime probability using historical datasets.	Random Forest classifier and predictive analytics	Analytical model only; lacks real-time emergency alert integration.
[2]	AI-Based Smart Surveillance for Crime Detection (2025)	Traditional surveillance systems struggle to detect suspicious behavior automatically.	Implemented AI-based monitoring systems capable of detecting abnormal human activities in public areas.	Deep Learning, CNN-based video analytics	Requires large computational resources and surveillance infrastructure.
[3]	Deep Learning-Based Surveillance Anomaly Detection (2024)	Surveillance systems often fail to detect unusual activities automatically in real-time environments.	Proposed deep learning models capable of identifying suspicious behavior in surveillance footage.	Convolutional Neural Networks (CNN)	Dependent on CCTV infrastructure and large datasets.
[4]	GPS-Enabled Emergency Alert Applications (2024)	Emergency response systems experience delays due to	Developed mobile applications that automatically send location-based alerts during emergencies.	GPS tracking and mobile alert systems	Lacks predictive intelligence and behavioral learning.

		inefficient communication mechanisms.			
[5]	Intelligent Women Safety Monitoring System Using Machine Learning (2024)	Women safety applications lack automated risk detection mechanisms.	Proposed ML-based monitoring systems capable of identifying abnormal movement patterns.	Machine Learning classification and anomaly detection	Requires continuous sensor data and internet connectivity.
[6]	IoT-Based Smart Women Safety Device Using Machine Learning (2023)	Women safety systems often depend on manual panic alerts.	Developed wearable IoT devices integrated with ML algorithms to send emergency alerts with location tracking.	IoT sensors, GPS modules, machine learning classification	Still dependent on manual trigger mechanisms.
[7]	Crime Hotspot Prediction Using Clustering Techniques (2023)	Identifying high-risk crime areas using historical crime data remains difficult.	Used clustering techniques to analyze crime data and identify dangerous zones.	K-Means clustering and crime analytics	Does not provide real-time monitoring or emergency alerts.
[8]	Smart Safety Systems for Women Using IoT and Machine Learning (2023)	Women safety technologies lack integration between sensors and intelligent analytics.	Proposed IoT-enabled wearable safety systems integrated with ML for threat detection.	IoT sensors and machine learning models	Limited predictive capability and scalability.
[9]	Mobile Applications for Women's Safety: Design and Impact (2020)	Most women safety apps rely on manual panic buttons and reactive responses.	Evaluated mobile applications using GPS tracking and emergency communication systems.	GPS tracking and mobile safety apps	Reactive system without predictive risk detection.
[10]	Machine Learning for Public Safety: A Survey (2020)	Public safety systems struggle to analyze large volumes of surveillance data efficiently.	Provided a survey of ML methods used in crime prediction and anomaly detection.	Machine Learning classification and anomaly detection	Conceptual study; lacks implementation framework.

III. METHODOLOGY

A. System Architecture



The system architecture for the proposed system has been designed in a manner that can automatically detect and classify suspicious human activities in videos using deep learning techniques. The system architecture is divided into different stages.

The different stages of the system architecture include:

1. Video Input Module
The videos are collected from different sources.

2. Preprocessing Module
The videos are then pre-processed for better model robustness.

3. Feature Extraction Module
The pre-processed videos are then fed into a pre-trained Convolution Neural Network (CNN) model for extracting spatial features from each video.

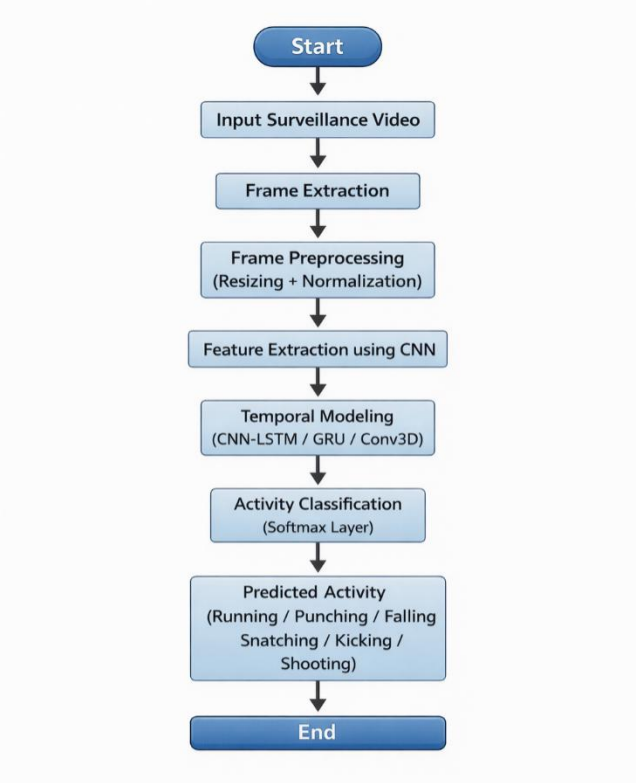
4. Temporal Modeling Module
Temporal modeling is included in the system for classifying different activities in videos using deep learning techniques such as CNN-LSTM, Time Distributed CNN, GRU, and Conv3D.

5. Classification Layer
The features are then passed through a fully connected layer followed by a Softmax layer for classifying the activities.

6. Output Module
The system classifies one of the following activities as a suspicious activity:

- Running
- Punching
- Falling
- Snatching
- Kicking

B. System Flowchart



The proposed suspicious human activity recognition system consists of a set of operations to recognize suspicious human activity in the video feed.

1) Input Surveillance Video

The first operation of the suspicious human activity recognition system is to take the video feed from the video source, which may be provided by different sources.

2) Frame Extraction

The video provided by the video source is split into different frames, which can be achieved by using video processing techniques. The video is split into a specified number of frames to maintain uniformity.

3) Frame Preprocessing

After the extraction of the video frames, the preprocessing of the video frames occurs by resizing the video frames that were extracted in the previous operation and normalizing the video frames for the stable training of the model. The resizing operation is performed to maintain uniformity among the video frames.

Feature Extraction using CNN

Convolutional Neural Networks have been used to extract significant spatial features from each and every video frame. The features include different visual activities such as human posture, motion, and interaction with objects.

Temporal Modelling

As different activities carried out by humans require temporal modeling, different approaches such as CNN-LSTM, GRU, and Conv3D have been used to carry out the analysis on the video frames and track the motion activities.

Activity Classification

Then, the extracted features are given as input to fully connected layers and a Softmax classifier to determine the possible class of activity carried out.

Predicted Activity Output

The proposed system has the ability to predict different suspicious activities from different classes such as Running, Punching, Falling, Snatching, Kicking, and Shooting.

The proposed workflow has the ability to carry out the automation of suspicious activity detection, thus improving the surveillance systems of modern times.

C. Performance Evaluation

Model performance was evaluated using the following metrics:

Accuracy –

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision –

$$Precision = \frac{TP}{TP + FP}$$

Recall –

$$Recall = \frac{TP}{TP + FN}$$

F1 Score –

$$F1 = \frac{2(Precision \times Recall)}{Precision + Recall}$$

Sample Calculation

Assume:

- TP = 90
- TN = 80
- FP = 10
- FN = 20

$$Accuracy = \frac{90 + 80}{90 + 80 + 10 + 20}$$

$$Accuracy = \frac{170}{200} = 0.85$$

D. Experimental Setup

Software environment:

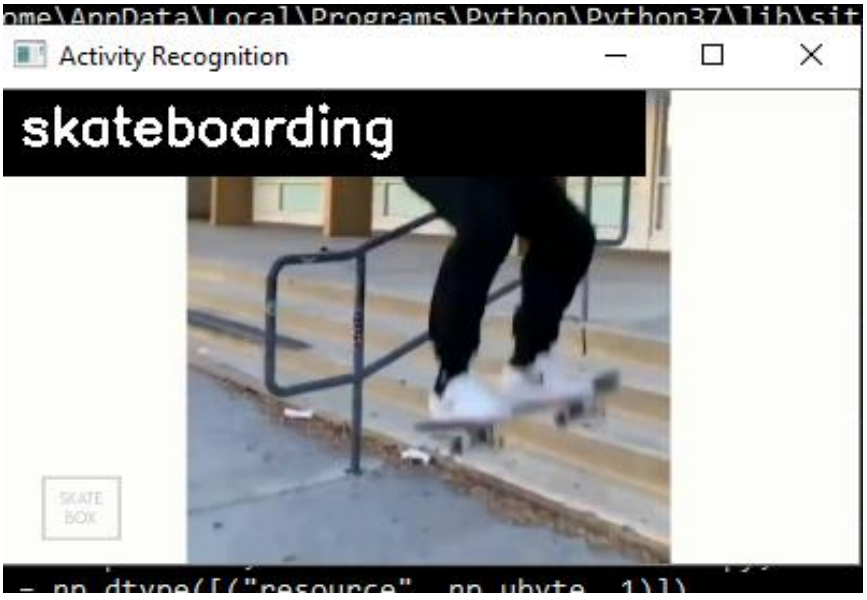
- Python 3.8
- TensorFlow 2.x
- Keras API
- OpenCV
- Scikit-learn
- Matplotlib

Hardware configuration:

- Intel Core i9 processor

- GPU-enabled environment
- 4GB+ RAM
- Windows 11 (64-bit)

IV. RESULT ANALYSIS



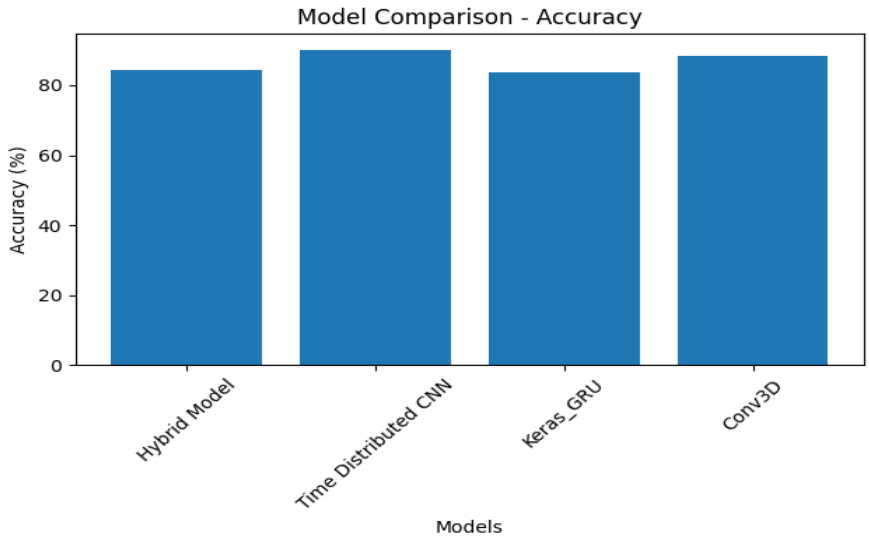
This section presents the experimental outcome obtained from the evaluation of four deep learning models: Hybrid CNN-LSTM, Time Distributed CNN, Keras_GRU, and Conv3D. The evaluation was carried out on the basis of Accuracy, Precision, Recall, and F1-Score. The dataset used for the experiment included 564 training videos and 142 testing videos.

A. Accuracy Comparison

Figure 1 shows the accuracy of classification for each of the models.

The Time Distributed CNN model had the highest accuracy of 90.14%, followed by the Conv3D model with 88.23%. The Hybrid model had an accuracy of 84.51%, while the Keras_GRU model had an accuracy of 83.80%.

The accuracy shown in Figure 1 represents the relative accuracy of each model for classification.

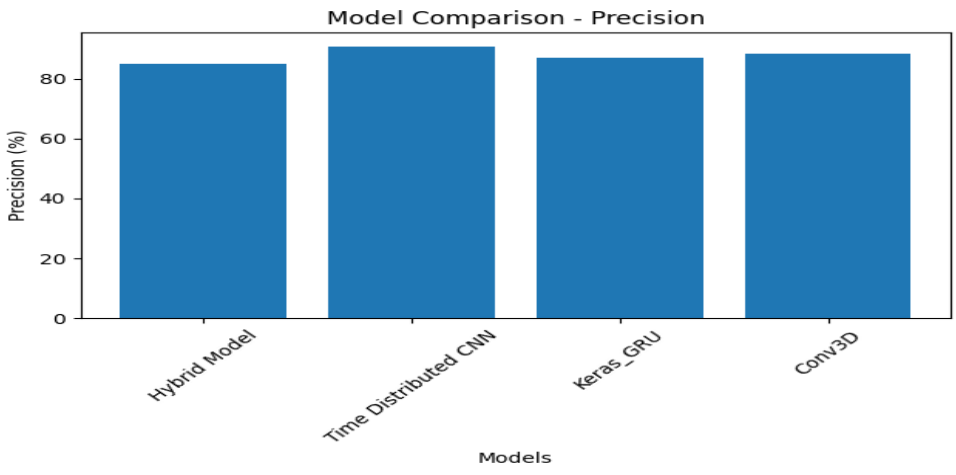


B. Precision Analysis

Figure 2 illustrates the precision values for all models.

The Time Distributed CNN model had the highest precision value of 90.78%, which indicates the highest percentage of correctly predicted positive samples among all positive predictions. The Conv3D model had a precision value of 88.20%, while the Keras_GRU and Hybrid models had precision values of 87.10% and 84.89%, respectively.

The results indicate the capacity of the models to minimize the number of false positive predictions in the suspicious activity classes.

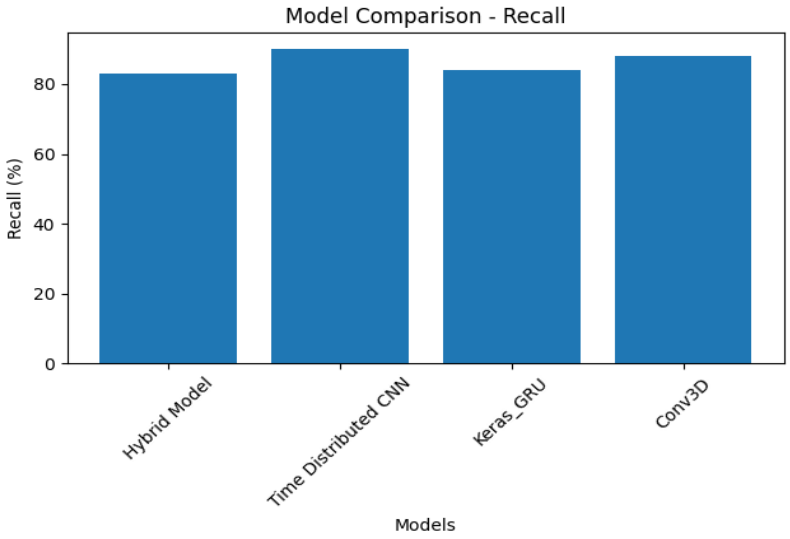


C. Recall Evaluation

The recall results of the architectures tested are shown in Figure 3 below.

The Time Distributed CNN model achieved a recall of 90.14%, which is the highest percentage of true positive instances of suspicious activities correctly identified as such. The Conv3D achieved a recall of 88.20%, Keras_GRU achieved a recall of 84.10%, and the Hybrid model achieved a recall of 83.10%.

The recall metrics show the differences in the ability of the models to correctly identify true instances of suspicious activities.

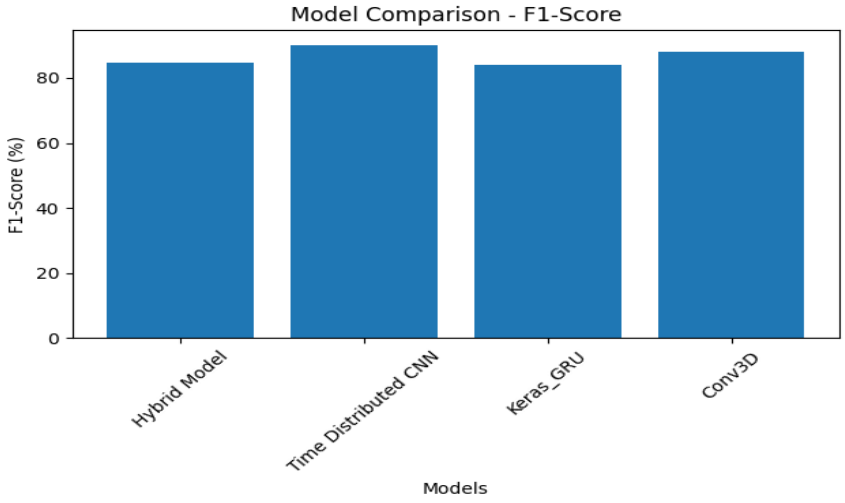


D. F1-Score Comparison

The F1-Score for each model is depicted in Figure 4, which is a combination of precision and recall.

The Time Distributed CNN model had an F1-Score of 90.14%, followed by Conv3D with an F1-Score of 88.20%. The Hybrid model and Keras_GRU model had an F1-Score of 84.72% and 84.10%, respectively.

The F1-Score values indicate the trade-off between precision and recall in classification.



E. Comparative Summary

Table1 summarizes the numerical performance results obtained from the testing dataset.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Hybrid Model	84.51	84.89	83.10	84.72
Time Distributed CNN	90.14	90.78	90.14	90.14
Keras_GRU	83.80	87.10	84.10	84.10
Conv3D	88.23	88.20	88.20	88.20

V. DISCUSSION

A. Evidence Supporting Performance Differences

The improved performance of the Time Distributed CNN model may be attributed to its ability to perform convolution on the sequence of frames while maintaining weight sharing. This approach allowed for the efficient extraction of spatial features before the temporal aggregation.

Although the Conv3D model directly captured spatio-temporal information through three-dimensional convolution, its performance was only slightly worse than that of the Time Distributed CNN model. This could be attributed to the increased complexity of the parameters or the sensitivity of the model to the small number of training samples.

The Hybrid CNN-LSTM and GRU models had stable but lower accuracy. This could be attributed to the fact that recurrent networks require more data for efficient learning of temporal information. With a moderately sized dataset, these models may not have utilized their learning capacity to the fullest extent.

C. Comparison with Existing Approaches

Compared to more conventional machine learning methods, such as SVM-based activity recognition or manually designed feature extraction algorithms, the deep learning models employed in this study have been able to achieve significantly higher levels of classification accuracy. The anomaly detection algorithms employed in previous studies have often been based on optical flow or skeleton images, which are extremely sensitive to environmental variations.

The accuracy levels achieved are in line with the latest advancements in deep convolutional models for video classification tasks. The results of this study further validate the growing evidence that transfer learning and temporal modeling can have a significant positive impact on activity recognition in surveillance videos.

Compared to other large-scale benchmark studies, which have been trained on millions of video samples, the present study has been carried out on a relatively smaller custom dataset. As such, while the accuracy levels achieved are certainly competitive, direct comparison with other large-scale public benchmarks is not recommended.

D. Strengths of the Proposed Approach

The following strengths were noticed:

1. Transfer learning helped in reducing the training time and improving the robustness of the features.

2. Automatic annotation helped in maintaining consistency in the annotations.

3. Equal distribution of classes helped in avoiding bias in the models.

4. Various architectures were compared in the same experimental setting.

5. Validation on unseen and real-world videos helped in ascertaining the applicability of the approach.

E. Limitations

Some of the methodological constraints that need to be pointed out are:

1. The dataset size, although balanced was not very large and may hamper generalization.

2. The videos were obtained from a few sources, which may not be very representative of the environment.

3. Evaluation of real-time performance assessment was not done in terms of inference time.

4. The six activities were predefined, which may not cover the entire spectrum of anomalies.

5. Validation across datasets was not done.

These constraints indicate that the findings should be interpreted within the experimental scope.

F. Future Research Directions

Future work may focus on:

- Increasing dataset diversity and size
- Incorporating transformer-based video architectures
- Implementing attention mechanisms
- Evaluating cross-dataset generalization
- Measuring computational efficiency for real-time deployment

Further experimentation with larger datasets would help determine whether the observed performance trends remain consistent under expanded training conditions.

VI. CONCLUSION

In this paper, we have proposed a deep learning approach for recognizing suspicious human activities in surveillance videos. We have created our own dataset consisting of six suspicious activities, namely running, punching, falling, snatching, kicking, and shooting. Different deep learning models such as Hybrid CNN + LSTM, Time Distributed CNN, Keras_GRU, and Conv3D have been developed. Among all the models, the Time Distributed CNN model has achieved the highest accuracy of 90.14%. The experiment results have demonstrated that the proposed approach is efficient and can be used in real-time surveillance systems for recognizing suspicious human activities.

VII. FUTURE WORK

Looking into the future, there are a number of ways in which the system could be improved. For instance, the size of the dataset could be increased, and more categories of suspicious activities could be included. In addition, the system could be improved by employing more advanced deep learning models. Future studies could be aimed at real-time processing and enhancing the accuracy of the system.

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