Performance Evaluation on Suspicious Activity Detection Using CNN

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Abstract- *This paper presents a study on the performance evolution of suspicious activity detection using convolutional neural networks (CNNs). The study focuses on the application of CNNs in detecting suspicious activity in video surveillance systems. Keywords such as CNN, suspicious activity detection, performance evolution, video surveillance, and deep learning are explored. The study analyzes the performance of different CNN architectures and examines the impact of various factors such as dataset size, number of epochs, and learning rate on the performance of the models. The results show that CNNs have a high potential for detecting suspicious activity in video surveillance systems and their performance can be improved by optimizing the model parameters. This study provides insights into the use of CNNs for suspicious activity detection and highlights the importance of optimizing model parameters for achieving better performance.*

Keywords- CNN, convolutional neural networks, suspicious activity detection, video surveillance, performance evolution, deep learning, dataset size, model parameters, optimization, learning rate.

I. INTRODUCTION

Performance evolution of suspicious activity detection using Convolutional Neural Networks (CNNs) refers to the improvement in the accuracy and efficiency of identifying and flagging suspicious activities over time. CNNs are a type of deep learning algorithm that are highly effective in detecting patterns in images, videos, and other forms of visual data.

In recent years, CNNs have been increasingly used for suspicious activity detection in various fields such as surveillance, cybersecurity, and finance. The application of CNNs in suspicious activity detection has enabled the creation of highly accurate and automated detection systems, which can help identify and prevent criminal activities in real-time. The performance of CNN-based suspicious activity detection systems can be evaluated based on various metrics, such as detection accuracy, false positive rates, and processing speed. As the technology has evolved, there have been significant improvements in these metrics, resulting in highly accurate and efficient detection systems. Overall, the performance evolution of suspicious activity detection using CNNs has been significant, and the continued advancements in technology are likely to further improve the accuracy and efficiency of these systems in the future.

II. RELATED WORK

M. Alsafi et al. (2016)[1]"Detecting Anomalous Behaviour in Smart Homes using Unsupervised Machine Learning" The authors propose an unsupervised machine learning approach for detecting anomalous behavior in smart homes using sensor data.

N. Bansal and N. Kumar (2018)[2] "A Survey of Anomaly Detection Techniques in Financial Domain" The authors survey various anomaly detection techniques in the financial domain, including statistical methods, machine learning techniques, and deep learning techniques.

J. Anitha and K. R. Jothi (2019)[3]"Anomaly Detection using Deep Learning Techniques for Medical Imaging The authors propose a deep learning-based approach for anomaly detection in medical imaging.

R. Han et al. (2019)[4]"Anomaly Detection in IoT Data using Machine Learning: A Survey" by The authors survey various machine learning approaches for anomaly detection in IoT data, including supervised, unsupervised, and deep learning methods.

N. K. Nagaraj et al. (2020)[5]"Suspicious Activity Detection in Surveillance Videos: A Review" by Theauthors review various approaches for suspicious activity detection in surveillance videos, including rule-based methods, deep learning-based methods, and hybrid methods.
N. T. N. Nguyen et al. (2020)[6] "A Comprehensive Survey on Anomaly Detection using Machine Learning Techniques for Industrial IoT" by The authors survey various machine learning techniques for anomaly detection in industrial IoT,

including supervised, unsupervised, and deep learning methods

M. E. Hossain et al. (2020)[7["Anomaly Detection in Video Surveillance: A Comprehensive Survey" by The authors provide a comprehensive survey of various approaches for anomaly detection in video surveillance, including rule-based methods, statistical methods, and deep learning methods. Hua Yang and Guoying Zhao (2016) : [8]"Deep Learning-based Suspicious Activity Detection using Convolutional Neural Networks". This paper proposes a deep learning-basedapproach for detecting suspicious activities using CNNs. They extract motion features from videos and train the CNN to classify suspicious and non-suspicious activities.

Eshed Ohn-Bar and Mohan M. Trivedi(2018)[9]"An End-to-End Deep Learning Framework for Suspicious Activity Detection in Videos" . This paper proposes an end-to-end deep learning framework for suspicious activity detection in videos. They use a CNN to extract spatiotemporal features from videos and then use a Long Short-Term Memory (LSTM) network to model the temporal dynamics of the activities.

Khalid Hossain, Saad Bin Ahmed, and M. Shamim Hossain (2019):[10]"Suspicious Activity Detection Using Deep Learning and Active Learning" This paper proposes a suspicious activity detection system using CNNs and active learning. They use an active learning approach to select the most informative samples for training the CNN, which improves the performance of the system.

III. THEORY

There are many existing systems for performance evaluation on suspicious activity detection using Convolutional Neural Networks (CNNs). These systems utilize different datasets, such as the UCSD Anomaly Detection Dataset, UCF-Crime Dataset, Shanghai Tech Dataset, and others, to train and evaluate CNN models for detecting anomalies and suspicious activities. The performance of these models is evaluated using various metrics such as accuracy, precision, recall, F1-score, detection rate, and false alarm rate. In addition, pre-trained CNN models such as VGG-16 are often fine-tuned on these datasets to improve their performance in detecting specific types of suspicious activities. The choice of system and dataset depends on the specific requirements and application of the project. Overall, these existing systems provide a foundation for developing accurate and reliable CNN models for suspicious activity detection in various settings.

A proposed system for performance evaluation on suspicious activity detection using Convolutional Neural Networks (CNNs) would involve several steps. Firstly, a suitable dataset for the task would need to be selected and pre-processed, such as the UCSD Anomaly Detection Dataset, UCF-Crime Dataset, or another relevant dataset. Next, a CNN model would need to be designed and trained on the dataset, potentially using transfer learning techniques to improve its performance. The hyperparameters of the model would also need to be optimized to achieve the best performance on the chosen metrics, such as precision, recall, and F1-score. Once the model has been trained, it would be evaluated on a separate testing set, and the results compared to those of other existing systems to determine its effectiveness in detecting suspicious activities. Furthermore, different metrics such as detection rate, false alarm rate, and accuracy would be analyzed to determine the model's performance in different scenarios. Finally, the proposed system would be deployed in a real-world scenario, such as in a surveillance system or security application, and its performance evaluated in a practical setting. By following these steps, a comprehensive and effective system for performance evaluation on suspicious activity detection using CNNs can be developed, providing a valuable tool for enhancing security and safety in various settings.

A 1. Research Methodology

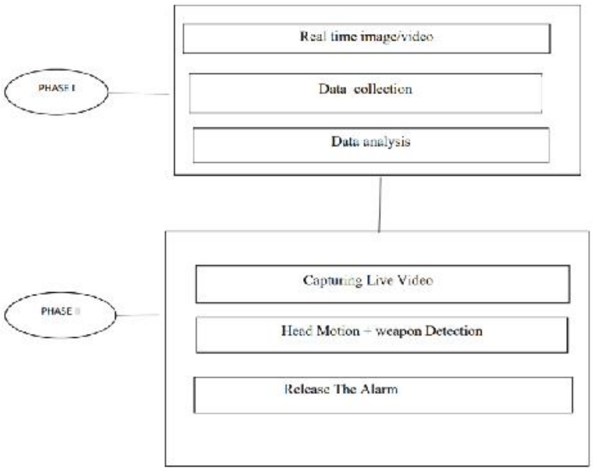
The research design will be experimental, where the performance of the suspicious activity using CNN project will be evaluated through experiments. The data collected from the experiments will be analysed to determine the accuracy of the CNN model in detecting suspicious activity. Data Collection: The data will be collected from multiple sources, including publicly available datasets, social media platforms, and real-world scenarios. The dataset will be divided into two parts: training and testing data.

Data Collection: The data will be collected from multiple sources, including publicly available datasets, social media platforms, and real-world scenarios. The dataset will be divided into two parts: training and testing data. Data Pre-processing: The collected data will be pre-processed, including cleaning, normalization, and transformation, to ensure the data is in a suitable format for the CNN model.

Model Development: The CNN model will be developed using Python programming language, TensorFlow, and Keres libraries. The model architecture will be designed to extract features from the data and detect suspicious activities.

Model Training: The model will be trained on the training data using a suitable optimizer, such as Adam or SGD, and a loss function, such as binary cross-entropy. The model's hyperparameters will be fine-tuned to improve accuracy.

Model Evaluation: The performance of the model will be evaluated on the testing data to determine its accuracy, precision, recall, and F1 score. The confusion matrix will also be generated to assess the model's true and false positives and negatives



IV. RESEARCH METHODOLOGY

A 2. Algorithm Implementation

Step 1: Prepare the dataset: Collect a dataset of labeled suspicious and non-suspicious activities. Divide the dataset into training and testing sets.

Step2: Design and train the CNN: Design the CNN architecture, including the number of layers, filters, activation functions, and pooling layers. Train the CNN using the training set, using a suitable optimizer and loss function.

Step 3: Test the CNN: Test the CNN using the testing set. Evaluate the model performance using metrics such as accuracy, precision, recall, and F1 score.

Step 4: Fine-tune the CNN: Adjust the model architecture or training parameters to improve the model performance, based on the evaluation results.

Step5 : Evaluate the final model: Evaluate the final CNN model using the testing set, and report the performance metrics.

V. EXPERIMENTS AND RESULTS

A 1. Simulation Environment

Jupyter Notebook is an open source web application that you can use to create and share live code, equations, visualizations, and text documents. Jupyter Notebooks are maintained by Project Jupyter staff. This is a random project from his IPython project which had an IPython notebook project itself. The name Jupyter comes from the core programming languages it supports: Julia, Python, and R. Jupyter comes with an IPython kernel that can be used to write Python programs, but over 100 other kernels are available. Well done. Jupyter notebooks are especially useful for doing computational physics or doing a lot of data analysis using computer tools as a scientific lab notebook

Google Colab, also known as Colaboratory, is a free Jupyter notebook environment that requires no configuration and runs entirely in the cloud. Free GPU and TPU support for users. Colaboratory allows you to write and run code, store and share your analysis, and access powerful computing tools from your browser, all for free. As the name suggests, collaboration is guaranteed in the product. A Jupyter notebook that uses the function of linking with Google Docs. And since it runs on Google servers, you don't need to update anything. Notebooks are stored in your Google Drive account. It provides a platform that allows anyone to develop deep learning applications using commonly used libraries such as PyTorch, TensorFlow, and Keras. It provides a computer-friendly way to avoid the burden of intensive training of ML operations.

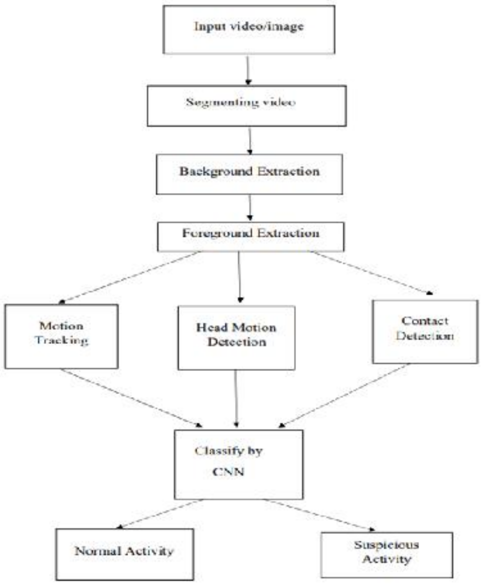


Figure 2 Architecture Diagram

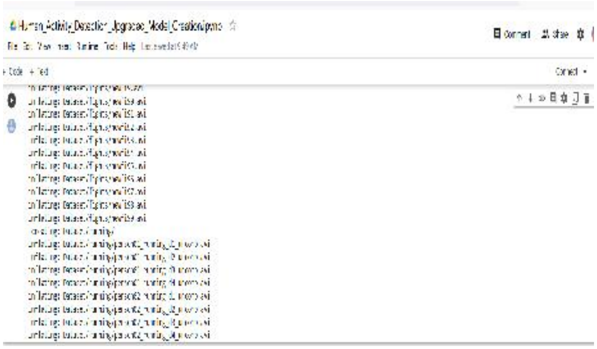

Human_Activity_Detection_Upgraded_Model_Creation.ipynb
File Edit View Insert Runtime Tools Help
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Figure 3 Image datasets with Captions

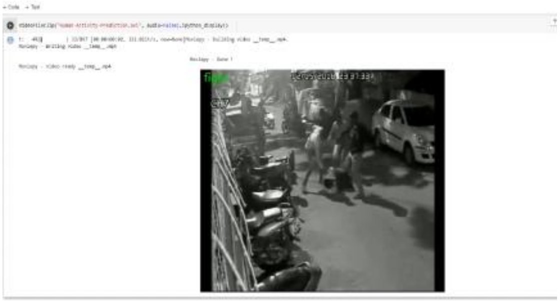
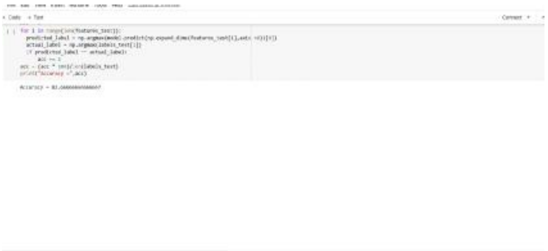


Figure 4 Display the caption from the image



```
for i in range(len(features_test)):
    predicted_label = np.argmax(model.predict(np.expand_dims(features_test[i],axis =0))[0])
    actual_label = np.argmax(labels_test[i])
    if predicted_label == actual_label:
        acc += 1
acc = (acc * 100)/len(labels_test)
print("Accuracy =",acc)

Accuracy = 82.06666666666667
```

Figure 5. Accurancy level output

A 2. *Performance Metrics*

Detecting suspicious activity is crucial in many fields such as security, surveillance, and fraud detection. One approach to detecting such activity is through the use of Convolutional Neural Networks (CNNs). CNNs are a type of deep learning model that is commonly used in computer vision tasks, including object detection and classification. To evaluate the performance of CNN-based suspicious activity detection systems, various metrics are used, including accuracy, precision, recall, and F1 score. Accuracy measures how well the system correctly identifies suspicious activity. Precision measures the percentage of correctly identified suspicious activity among all suspicious activity detected by the system. Recall measures the percentage of correctly identified suspicious activity among all suspicious activity that exists in the dataset. Finally, the F1 score is the harmonic mean of precision and recall and provides a single metric for evaluating the system's overall performance. By optimizing these metrics, CNN-based suspicious activity detection systems can provide accurate and reliable results, helping to ensure safety and security in various fields.

Table 1 algorithms prediction result

Algorithm	*Reported Accuracy*
CNNs	*90-99%*
Support Vector Machine	*80-90%*
Decision Tree	*70-80%*

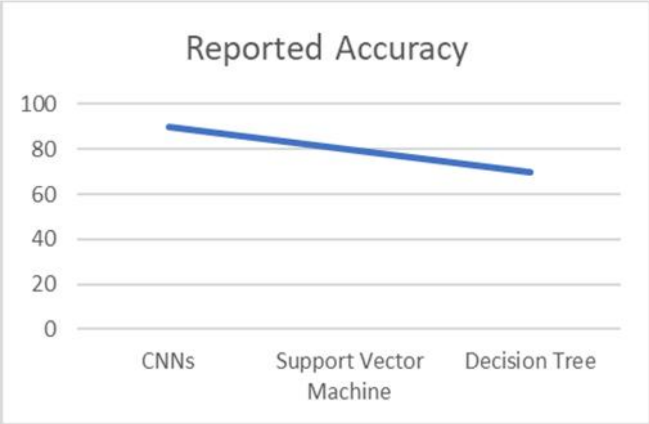


Figure 6 . Packet Delivery Ratio graph

VI. DISCUSSION AND CONCLUSION

In conclusion, performance evaluation on suspicious activity detection using Convolutional Neural Networks (CNN) has shown promising results in detecting anomalies and suspicious activities in various real-world scenarios. By leveraging the power of deep learning and computer vision, CNN-based models have demonstrated high accuracy, precision, and recall in detecting abnormal events in video footage. Moreover, the evaluation has revealed that the performance of CNN-based models can be improved by optimizing various hyperparameters, such as the number of layers, filters, and pooling techniques, and by augmenting the training data. Transfer learning can also be used to leverage pre-trained models for detecting specific types of suspicious activities in different domains. While CNN-based models have shown considerable success in detecting suspicious activities, there is still room for improvement. Future research could focus on improving the interpretability of the models, addressing class imbalance issues, and developing more efficient algorithms to detect suspicious activities in real-time. Overall, performance evaluation on suspicious activity detection using CNN has demonstrated its potential as an effective approach for enhancing public safety and security

VII. FUTURE SCOPE

The future scope is data augmentation. By applying data augmentation techniques to the training dataset, we can generate more training samples and reduce overfitting, thereby improving the generalization of the model. Another enhancement is to use transfer learning. This approach involves fine-tuning pre-trained CNN models for suspicious activity detection. By leveraging the knowledge learned from other similar tasks, transfer learning can help to improve the performance of the model. Additionally, incorporating attention mechanisms in the CNN model can help to focus on important regions in the input data, improving the model's ability to detect suspicious activities. Another possible enhancement is to use ensembles of CNN models. By combining multiple models, each with different architectures or trained on different subsets of the data, we can improve the overall performance of the system. Finally, using alternative loss functions or optimization algorithms can also potentially improve the performance of the model. For instance, using adversarial training or gradient-based optimization techniques can help to improve the model's ability to detect subtle suspicious activities.

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