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SUSPICIOUS ACTIVITY DETECTION USING CNN

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ABSTRACT

Suspicious Activity Detection using Convolutional Neural Networks (CNNs) is an innovative approach aimed at enhancing security and surveillance systems by automatically identifying and flagging suspicious behaviors in real-time. This paper presents a deep learning-based model leveraging the power of CNNs to detect suspicious activities from video feeds, thereby providing a robust solution for modern security challenges. The proposed system employs CNNs to analyze visual data and identify patterns associated with suspicious activities, such as unauthorized access, loitering, or aggressive behavior. By training the model on a diverse dataset containing various normal and suspicious activities, the system learns to distinguish between routine and potentially dangerous behaviors accurately. Key contributions of this work include the development of an efficient CNN architecture optimized for real-time processing and high accuracy in detection. The model is evaluated using extensive video datasets from public surveillance systems, demonstrating its effectiveness in various real-world scenarios. Additionally, the system incorporates advanced preprocessing techniques to handle different lighting conditions, camera angles, and environmental noise, ensuring reliable performance across various settings.

1. INTRODUCTION

In today's world, ensuring public safety and security is of paramount importance, with surveillance systems playing a

crucial role in monitoring and mitigating potential threats. Traditional surveillance systems, however, largely rely on human operators to manually observe and identify suspicious

activities, which can be both labor-intensive and prone to human error. As the volume of surveillance footage

increases, the need for automated systems that can efficiently and accurately detect suspicious activities becomes more pressing. Convolutional Neural Networks (CNNs), a class of deep learning models renowned for their effectiveness in image and video analysis, offer a promising solution to this challenge. By leveraging the capabilities of CNNs, it is possible to develop systems that automatically analyze video feeds, identify suspicious behaviors, and alert security personnel in real-time. This not only enhances the efficiency of surveillance operations but also significantly improves the accuracy and speed of threat detection. This paper explores the use of CNNs for suspicious activity detection, focusing on developing a robust model capable of analyzing visual data from surveillance cameras. The proposed system is designed to detect a range of suspicious activities, such as unauthorized access, loitering, and aggressive behavior, by learning to recognize patterns associated with these behaviors. Training the model on a comprehensive dataset that includes

both normal and suspicious activities enables it to distinguish effectively between routine behaviors and potential threats.

III. EXISTING SYSTEM

Existing systems for suspicious activity detection in surveillance environments typically rely on a combination of manual observation and traditional computer vision techniques. Human operators monitor video feeds from numerous cameras to identify potential threats, which can be highly labor-intensive and prone to fatigue and oversight. Additionally, these systems often employ basic motion detection and object tracking algorithms to flag unusual movements or behaviors. However, traditional computer vision techniques face several limitations. They usually depend on predefined rules and heuristics, making them less adaptable to new or unexpected types of suspicious activities. These systems also struggle with variations in lighting conditions, camera angles, and background clutter, which can result in high false positive and false negative rates. The reliance on manual tuning and rule-based approaches limits their scalability and effectiveness, particularly in complex

and dynamic environments. Furthermore, many existing systems lack the ability to learn and improve over time, as they do not leverage advanced machine learning techniques. This leads to inconsistent performance and an inability to handle the diverse and evolving nature of suspicious activities. As a result, there is a pressing need for more sophisticated and automated solutions that can overcome these limitations and provide more reliable and efficient surveillance capabilities.

Draw backs :

1. Complexity and Resource Intensiveness: CNN-based systems can be computationally expensive and require significant resources, limiting their deployment on edge devices or in environments with limited computing power.
2. Training Data Limitations: CNNs require large amounts of labeled training data to learn effectively. Obtaining and annotating such datasets for diverse suspicious activities can be challenging and time-consuming.

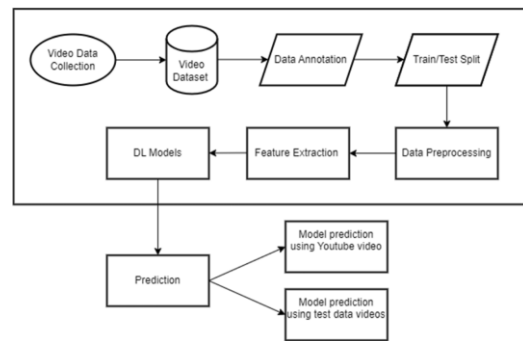
IV.PROPOSED SYSTEM

The proposed system for suspicious activity detection leverages Convolutional Neural Networks (CNNs) to provide a more efficient and accurate alternative to traditional surveillance methods. Unlike existing systems that rely on manual observation and basic computer vision techniques, the proposed system automates the detection process by utilizing deep learning models capable of analyzing video feeds in real-time. This system is designed to identify a wide range of suspicious activities, such as unauthorized access, loitering, and aggressive behavior, by learning from a comprehensive dataset containing examples of both normal and suspicious behaviors. The CNNs extract and analyze features from video frames, enabling the system to recognize complex patterns and make accurate detections. Key advantages of the proposed system include its ability to handle diverse and challenging environments, such as varying lighting conditions and camera angles, through advanced preprocessing techniques. This ensures consistent performance and reduces the incidence of false positives and negatives. Additionally, the system is scalable and can be easily updated with new data, allowing it to adapt to evolving security threats.

Advantages

The proposed system for suspicious activity detection using CNNs offers several advantages over existing systems:

1. **Improved Accuracy:** CNNs are well-suited for learning complex patterns in visual data, leading to higher accuracy in detecting suspicious activities compared to traditional methods.
2. **Efficient Use of Resources:** The proposed system optimizes the use of resources by leveraging the parallel processing capabilities of CNNs, making it suitable for deployment on edge devices and in resource-constrained environments.
3. **Generalization to New Activities:** By training on a diverse dataset, the proposed system can generalize well to new or unseen activities, reducing the need for frequent retraining or fine-tuning.



System architecture

V.METHODOLOGY

The methodology for the Suspicious Activity Detection Using Convolutional Neural Networks (CNNs) project involves several critical steps to ensure effective detection and classification of suspicious activities in video surveillance footage.

- **Data Description and Collection:** The project begins with collecting a diverse dataset from public sources such as the UCF Crime or VIRAT dataset. These datasets contain videos annotated with various types of activities, including both normal and suspicious behaviors. The dataset encompasses different environments, lighting conditions, and types of suspicious activities to enhance the model's robustness and generalization capabilities. A key consideration is addressing the potential imbalance in the dataset,

where certain types of suspicious activities might be underrepresented compared to others.

- **Data Preprocessing:** Data preprocessing involves several steps to prepare the video data for effective model training. First, videos are converted into frames at consistent intervals (e.g., every second) using tools like OpenCV. This frame extraction process is crucial for breaking down video sequences into manageable image data. To tackle issues related to data imbalance, techniques such as data augmentation are employed. Augmentation methods, including rotation, flipping, and brightness adjustments, are applied to increase the variability of the training data and help the model generalize better. Additionally, missing or incomplete labels are addressed through imputation strategies to maintain dataset quality.
- **Feature Extraction and Normalization:** After preprocessing, key features are extracted from each frame, focusing on motion patterns, object interactions, and temporal sequences. These features are essential for identifying and

distinguishing suspicious activities from normal behaviors. To ensure that these features are on a consistent scale and to improve model training, feature normalization is performed. This involves transforming feature values to have a mean of 0 and a standard deviation of 1, thereby preventing features with larger scales from disproportionately influencing the model.

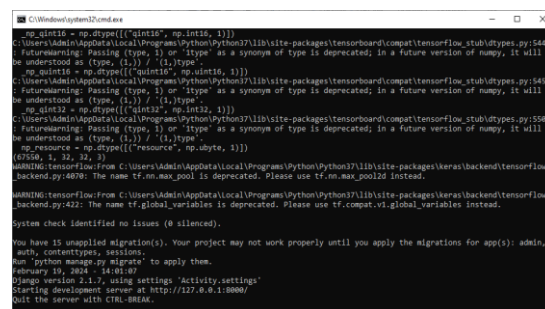
- **Model Development and Training:** The core of the methodology involves designing and training a CNN model tailored for activity detection. The CNN architecture is chosen for its ability to capture spatial hierarchies in images, while additional temporal processing layers (such as 3D convolutions or recurrent layers) may be incorporated to handle the sequential nature of video data. During training, the binary cross-entropy loss function is used to quantify the difference between the true labels and the predicted probabilities. This loss function is minimized using gradient descent, which iteratively updates the model parameters to improve accuracy.

➤ **Evaluation and Metrics:** To assess the model's performance, various evaluation metrics are employed. Accuracy is calculated to determine the proportion of correct predictions made by the model. Precision and recall are also computed to evaluate the model's ability to correctly identify suspicious activities, with precision focusing on the accuracy of positive predictions and recall on the model's ability to detect all relevant instances. The F1-score, which combines precision and recall, provides a balanced measure of the model's performance. These metrics help in understanding the strengths and limitations of the model and guide further refinement.

➤ **Deployment and Maintenance:** Following successful training and evaluation, the model is integrated into a real-time video surveillance system. This involves setting up a pipeline for processing live video feeds and applying the trained CNN model to detect and classify suspicious activities. The deployment phase includes monitoring the system's performance and ensuring its efficiency in real-world conditions.

Ongoing maintenance involves updating the model with new data and refining the system based on feedback and performance analysis to maintain its effectiveness over time.

To run project double click on run.bat file to start web server

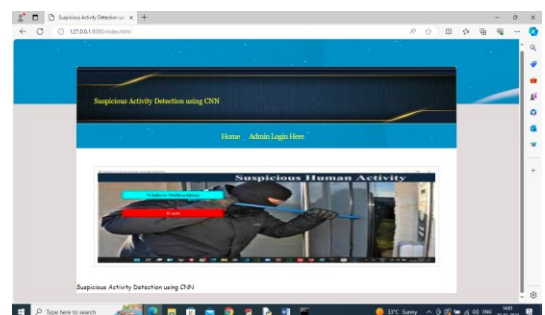


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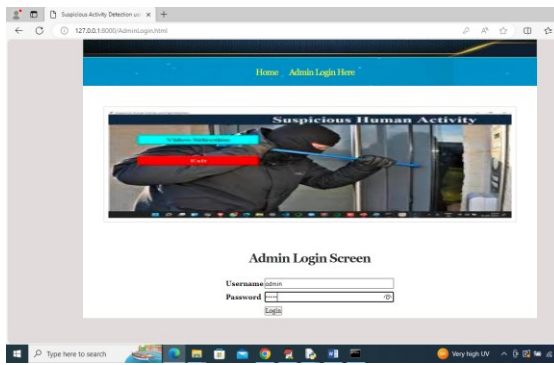
C:\Windows\system32\cmd.exe
> python run.py
np.uint16 = np.dtype([('uint16', np.int16, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:548:
FutureWarning: Passing (type, 1) or 'type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, 1) / {1} type
  np_uint16 = np.dtype([('uint16', np.uint16, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:549:
FutureWarning: Passing (type, 1) or 'type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, 1) / {1} type
  np_uint16 = np.dtype([('uint16', np.uint16, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:550:
FutureWarning: Passing (type, 1) or 'type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, 1) / {1} type
  np_resource = np.dtype([('resource', np.ubyte, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\keras\backend\tensorflow_backend.py:4870:
WARNING: tensorflow: from C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\keras\backend\tensorflow_backend.py:4870:
the name tf.nn.max_pool is deprecated. Please use tf.nn.max_pool2d instead.
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\keras\backend\tensorflow_backend.py:4927:
WARNING: tensorflow: from C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\keras\backend\tensorflow_backend.py:4927:
the name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.
System check identified no issues (0 silenced).
You have 15 unapplied migration(s). Your project may not work properly until you apply the migrations for app(s): admin,
auth, contenttypes, sessions.
Run 'python manage.py migrate' to apply them.
February 19, 2024 - 14:01:47
Django Version 4.1.7, using settings 'Activity.settings'
Starting development server at http://127.0.0.1:8000/
Quit the server with CTRL-C.

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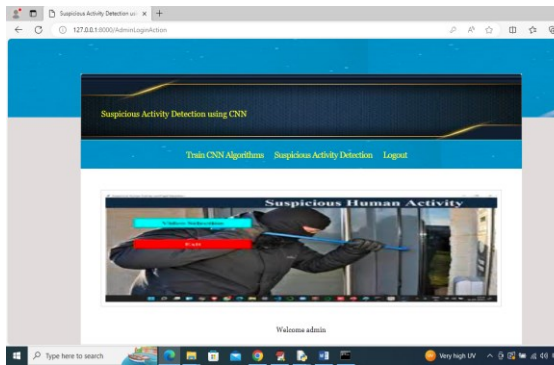
In above screen python web server started and now open browser and enter URL as <http://127.0.0.1:8000/index.html> and press enter key to get below page



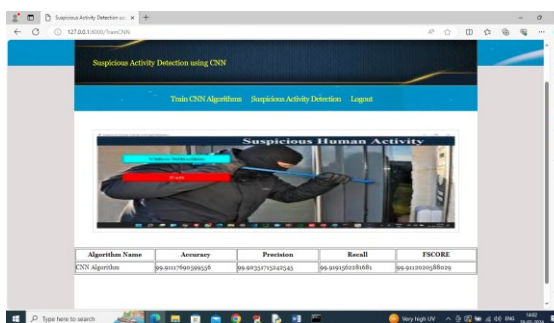
the screen click on 'Admin Login' link to get below login page



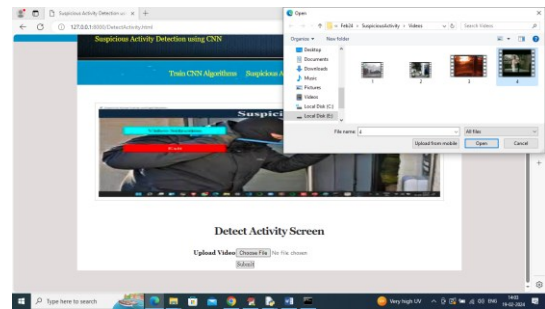
After that admin can login to system using username and password as 'admin' and after login will get below page



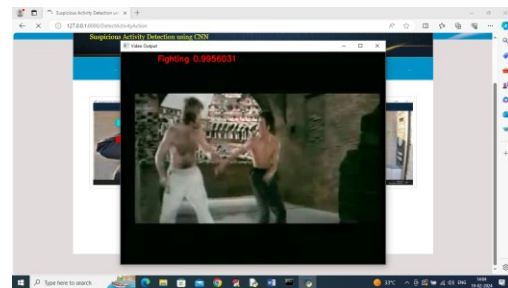
Then click on 'Train CNN Algorithm' to train model and get below page



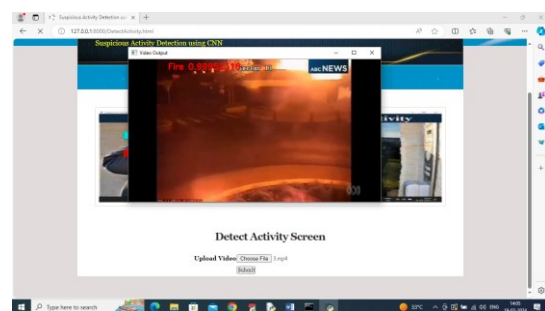
CNN training completed and it got 99% accuracy on test and now click on 'Suspicious Activity Detection' link to get below page



upload any video and then click on 'Open' and 'Submit' button to play video with detection

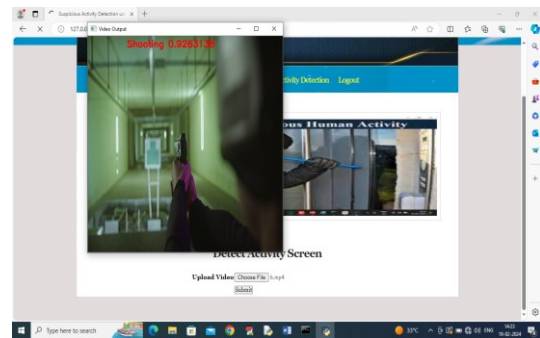
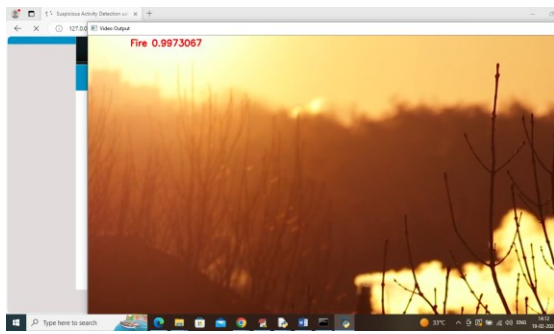


Here the video Fighting detected and similarly you can upload and test other videos

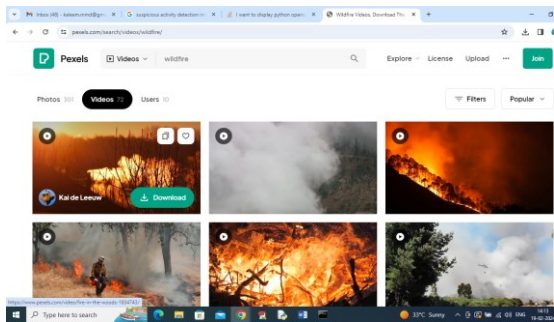


In screen Fire detected Burglary detected and similarly you can upload and test other videos and while video playing you can press 'q' to terminate playing and upload other videos.

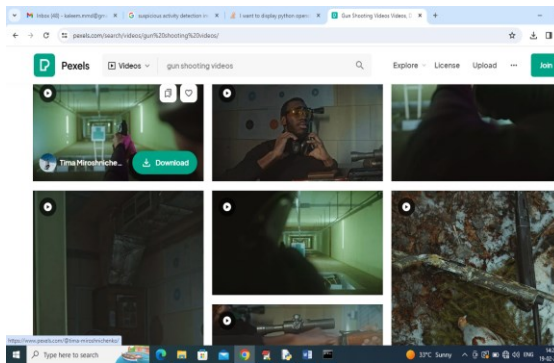
Below testing video we have downloaded from net



video shooting is detected



Fire video downloading and testing from above page and Shooting video downloading from below page



Above video detection output showing in below page

VI.CONCLUSION

In conclusion, the use of Convolutional Neural Networks (CNNs) for suspicious activity detection has shown promising results in various applications, including surveillance, security, and fraud detection. CNNs excel at learning spatial hierarchies of features, making them well-suited for analyzing visual data such as images and videos, which are common in surveillance systems. Key findings from this study indicate that CNNs can effectively extract and learn complex patterns from video data, enabling them to distinguish between normal and suspicious activities. The ability to automatically learn features from raw data reduces the need for manual feature engineering, making CNNs particularly advantageous for tasks where the nature of suspicious activities may vary. Furthermore, the study highlights the importance of dataset quality and size in training CNN models for suspicious activity detection.

A large, diverse dataset with annotated examples of both normal and suspicious activities is crucial for training robust and generalizable models. Challenges in deploying CNNs for suspicious activity detection include the need for substantial computational resources, especially for real-time applications, and the potential for model biases based on the training data. Addressing these challenges requires ongoing research in model optimization, dataset curation, and fairness in AI algorithms

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