



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

# IJRSET

International Journal of Innovative Research in  
**SCIENCE | ENGINEERING | TECHNOLOGY**



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 12, Issue 5, May 2023

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

Impact Factor: 8.423

 9940 572 462

 6381 907 438

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# Anomaly Detection using video surveillance

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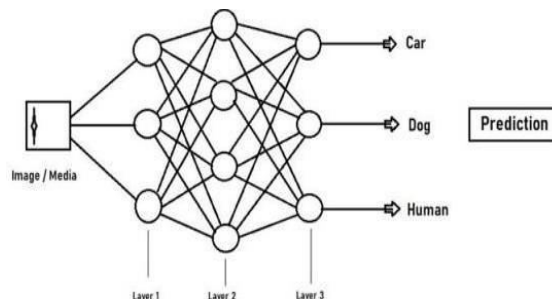
**ABSTRACT:** In contrast to full-frame learning, this Project offers a method for learning aberrant behaviour in video by locating an attention zone using spatiotemporal information. In our suggested method, a deep convolution network is created to differentiate normal and anomalous events by utilising C3D (Convolution 3-dimensional) to fully utilise spatiotemporal relations. To validate its effectiveness, our system is trained and tested against a large-scale UCFCrime anomaly dataset. This dataset contains 1900 lengthy and uncut real-world surveillance movies, which are divided into 950 anomaly events and 950 normal events. During the training and testing phases, approximately 13 million frames are learned. As demonstrated in the experiments section, the suggested visual attention model can achieve 99.25 accuracy.

**KEYWORDS:** distinction; keyframe extraction; intelligent surveillance networks; detection of crime.

## I. INTRODUCTION

While keeping an eye on public violence is crucial for safety and security, surveillance systems are now frequently used in public spaces and infrastructure. A key use of video surveillance is the detection of unusual events, such as accidents, robberies, or illegal activity. However, the majority of current monitoring systems also require human operators and manual inspection, which is prone to interruptions and fatigue. Consequently, the demand for clever computer vision algorithms for automated video anomaly / violence detection is rising.

A **Convolutional Neural Network** (ConvNet/CNN) is a Deep Learning method that can take in an input image, give various elements and objects in the image importance (learnable weights and biases), and be able to distinguish between them. Anomaly detection (aka outlier analysis) is a step in data mining that identifies data points, events, and/or observations that deviate from a dataset's normal behavior. Anomalous data can indicate critical incidents, such as a technical glitch, or potential opportunities, for instance a change in consumer behaviour



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### Contribution of research :

An important issue that has been studied across a variety of fields and application domains is anomaly detection.



While some anomaly detection methods are more general in nature, others have been developed specifically for certain application domains. An organised and thorough summary of the research on anomaly detection is attempted in this survey. We have divided existing techniques into many groups based on the fundamental strategy each technique has taken. We have established important presumptions for each category that the approaches rely on to distinguish between typical and abnormal behaviour. These presumptions can be used as guides to determine whether a particular technique is effective in a given area when applied to it. We give a basic anomaly detection technique for each category and then demonstrate how the various existing strategies within that category are variations of the basic technique.

This template makes it simpler and shorter to understand the methods that fall under each category. We also list the benefits and drawbacks of the techniques in each category for each category.

## II. LITERATURE SURVEY

One of the main causes of fatalities in the twenty-first century is the growth in crime [1]. One option for quickly identifying unforeseen criminal actions is a smart video surveillance system. Massive numbers of surveillance cameras have recently been installed in various locations across the world for public safety. The constraints of manual monitoring make it difficult for law enforcement agencies to identify or avoid abnormal actions. To identify odd behaviour, it takes a clever computer vision system that can distinguish between normal and abnormal events without human intervention. An automated system like this is helpful for monitoring and reduces the amount of labour needed to maintain manual observation for 24 hours.

Anomaly detection methods based on sparse coding have so far demonstrated promising outcomes in the literature [2–5]. These methods are taken for granted as being commonplace for identifying anomalies. These methods are trained to create a vocabulary of typical events from the first few frames of a movie. Despite being computationally efficient, this method performs poorly when it comes to accurately identifying abnormal events. Anomaly detection methods based on weakly supervised multi-instance learning (MIL) are also investigated in [3,5,6]. In these methods, the videos are divided into a predetermined number of segments during the training phase. These sections create a collection of examples for both positive and negative samples.

Sparse coding methods are not ideal for surveillance contexts since they are dynamic. For instance, changing the vocabulary from typical to anomalous events results in a significant amount of false-positive and false-negative results. Additionally, it is extremely challenging to spot anomalous events in noisy, low-resolution videos. Machines must rely on visual features while people can use their intuition to distinguish between common and unusual events. The existing approaches typically have a large percentage of false alarms, which lowers performance. Furthermore, these methods have a limited performance when used in real-world scenarios despite performing well on small datasets. We developed a straightforward and effective lightweight methodology to detect anomalies in surveillance films in this study to allay these worries.

Two major categories are used to discuss the literature on anomaly detection techniques: Deep feature-based methods and conventional handmade feature-based methods for identifying abnormal events.

Anomaly detection used to be very reliant on low-level, manually created feature-based approaches. These techniques mainly consist of three stages: (1) feature extraction, which involves extracting low-level patterns from the training set; (2) feature learning, which is distinguished by the distribution of encoding regularity or normal events; and (3) outlier detection, which involves identifying separated clusters or outliers as anomalous events. For instance, Zhang et al. [7] used spatiotemporal features to characterise frequent occurrences using the Markov random field. Similar to this, Mehran et al.'s [8] social interaction model estimated cooperative forces and used optical flow to identify normal and deviant behaviour. Additionally, Nor et al.'s [9] explainable anomaly detection framework was suggested as a tool for prognostic and health management PHM. Their framework is built on a preset Bayesian deep learning model.

the likelihood and prior distributions. To develop the local and global explanations for the PHM tasks, it offers additive explanations. Similar to this, Ullah et al. [10] develop an attention-based LSTM for sports video action identification. Convolution block attention was employed to enhance the spatial properties. Similar to this, the refined



feature maps are classified into various sports actions using a fully connected neural network with a softmax. Selicato et al. [11] focused on finding anomalies in the gene data when compared to visual data. They provide an ensemble-based method, for instance, combining principal component analysis (PCA) and hierarchical clustering to identify normal and aberrant gene expression matrices. An ensemble of deep models was suggested by Riaz et al. [12] for spotting anomalies in complicated scenes. A human position estimation model that recognises the human joints is incorporated in the initial stage. The second phase involves treating the discovered joints as features and providing them to a densely connected complete CNN for anomaly detection.

More recently, Zhao et al. [13] reported an unsupervised method for detecting abnormalities in films utilising online query signals and sparse reconstruction skills learnt from a learned vocabulary of all events. This method used a time-varying sparse coding style. It has remained difficult to acquire the capacity to spot anomalies in a timely manner, which . Deep feature-based models have surpassed conventional approaches in a number of nonlinear, high-dimensional data fields, including, among others, activity recognition and video summarization. A system created by Liu et al. [14] used a CNN to encode video frames and a ConvLSTM to identify abnormal events. In a surveillance setting, their encoder uses motion variation to encode anomalies. An RNN and a convolution autoencoder were suggested by Hasan et al. [15]. For the purpose of detecting video anomalies, Luo et al. [14] developed a convolutional LSTM model with an autoencoder. They also extended on their work by employing an autoencoder-stacked RNN to find abnormalities. has drawn the attention of various academics. Sparse Combination Learning (SCL), for instance, was used by Lu et al. [4] who examined their method on both local and cloud servers.

### III. PROPOSED SYSTEM DESIGN

Anomaly conduct is difficult to characterise precisely because it is highly subjective and varies greatly from person to person. Furthermore, it is unclear how to assign 1/0 labels to anomalies. Furthermore, due to a lack of sufficient examples of anomaly, anomaly detection is typically treated as a low likelihood pattern detection problem rather than a classification problem. We pose anomaly identification as a regression problem in our suggested approach. The anomalous video portions should have greater anomaly scores than the typical video segments. The most straightforward solution would be to apply a ranking loss that rewards high scores for aberrant video portions over typical segments.

We suggest using deep learning to identify real-world anomalies in surveillance footage. It may not be best to discover anomalies by using only normal data because of how intricate these realistic anomalies are. We try to take use of both typical and unusual videos. By employing a deep MIL framework with weakly labelled data, we create a general model of anomaly identification to eliminate labor-intensive temporal annotations of anomalous segments in training films. A new large-scale anomaly dataset with a range of real-world anomalies is presented in order to validate the suggested methodology. The experimental results on this dataset demonstrate that our suggested anomaly detection methodology outperforms baselinemethods by a large margin. Additionally, we show how useful our dataset is for the task of recognising anomalous activity.

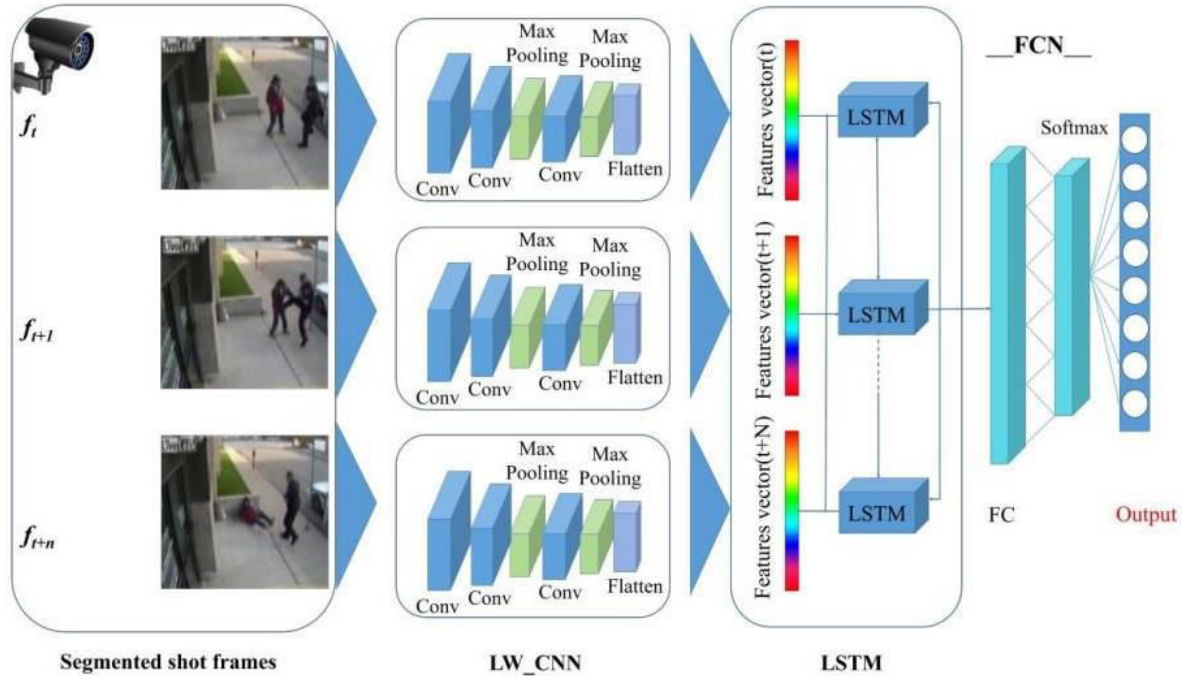


Figure 2 : proposed system architecture

#### IV. RESULTS AND DISCUSSION

Since we collected event labels for the anomalous videos during data collection but did not use them for the anomaly detection method discussed above, our dataset can be used as a benchmark for the recognition of anomalous activity. We take 50 movies from each event for activity recognition and divide them into training and testing groups in a 70-30 ratio. Based on a 10-fold cross validation, we present two baseline results for activity recognition on our dataset.

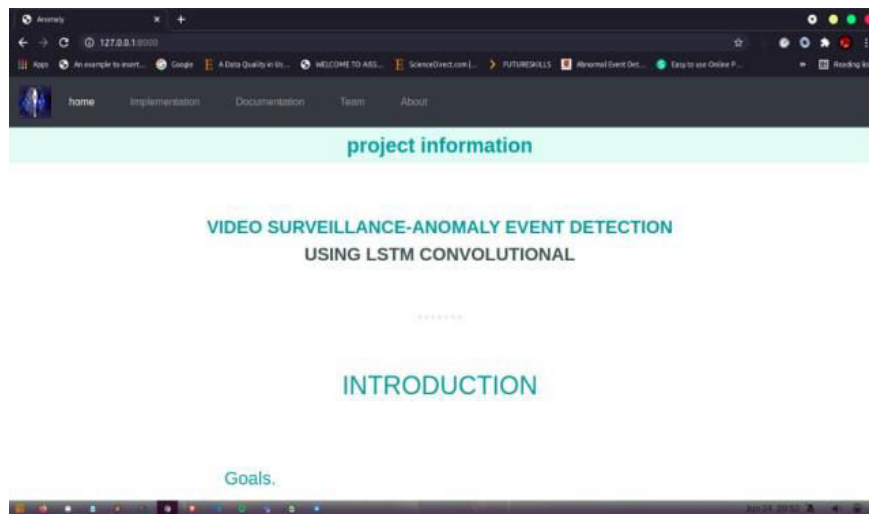


Fig.3.Home page of proposed system

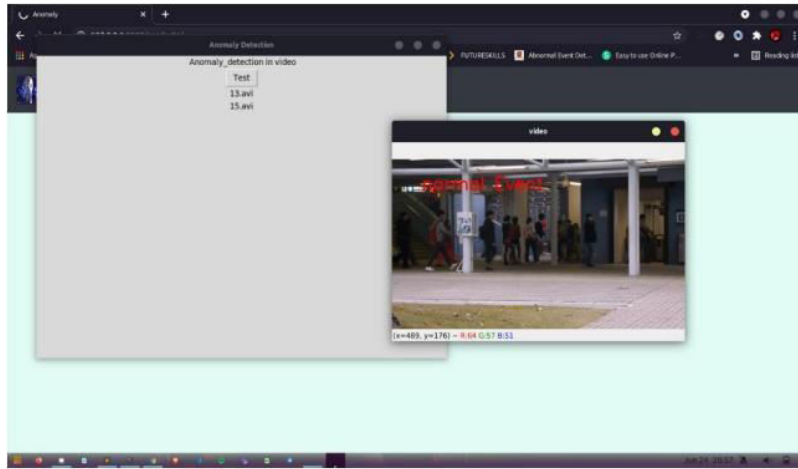


Figure 4 : Normal activity detection experiment-1

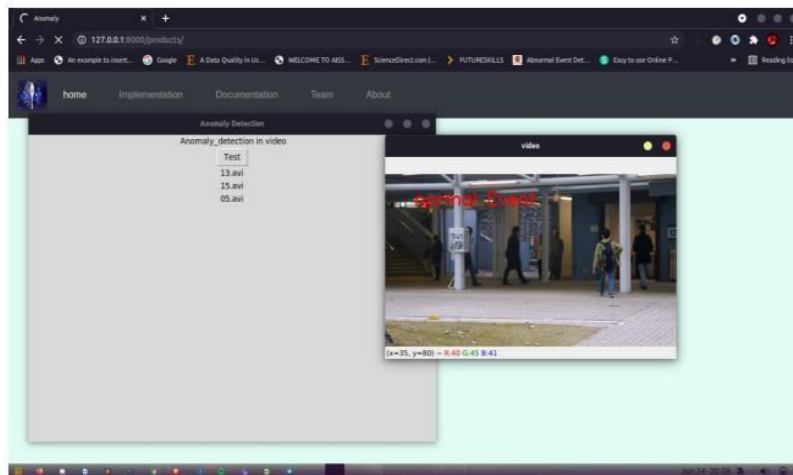


Figure 5 : Normal activity detection experiment-2

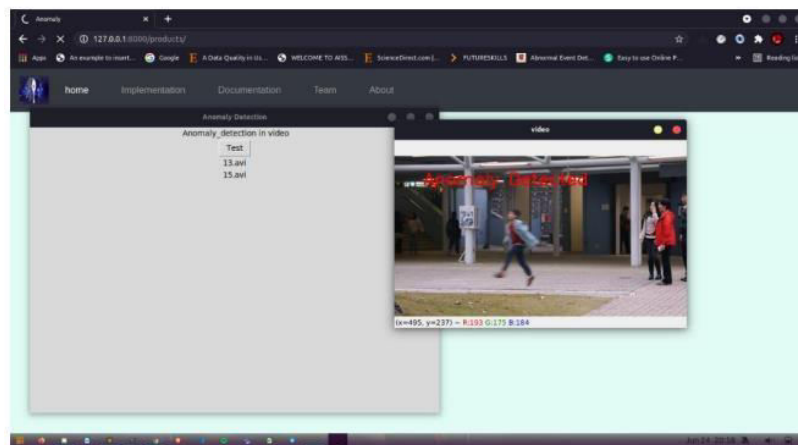


Figure 6 : Anomaly activity detection experiment-1

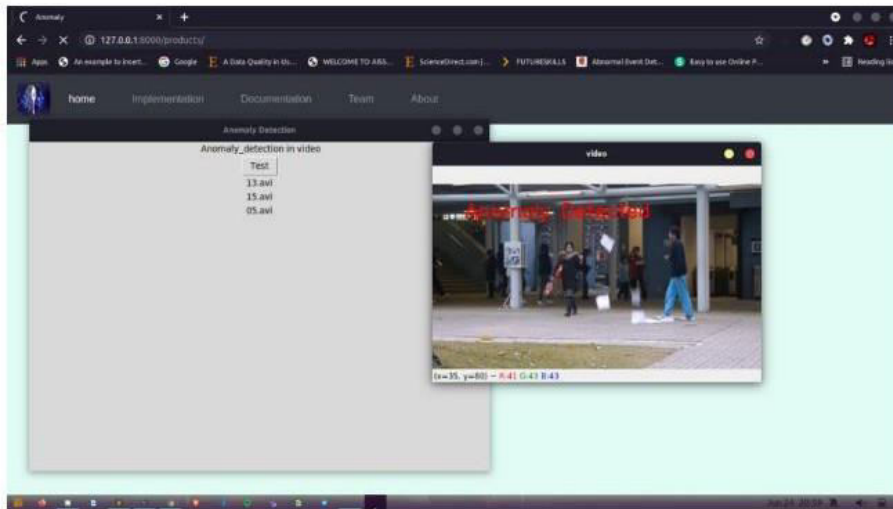


Figure 7: Anomaly activity detection experiment-2

On this dataset, the aforementioned investigations' system action recognition techniques perform poorly. This is due to the fact that the recordings are lengthy, uncut surveillance videos with significant intraclass variances. Consequently, our dataset is a distinctive and difficult dataset for detecting abnormal activity.

### V. CONCLUSION

On this dataset, the aforementioned investigations' system action recognition techniques perform poorly. This is due to the fact that the recordings are lengthy, uncut surveillance videos with significant intraclass variances. Consequently, our dataset is a distinctive and difficult dataset for detecting abnormal activity. We concentrate on developing an algorithm to identify abnormal events using deep learning, i.e. Convolutional Neural Network to automate the process of video surveillance analysis

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