Crime Anomaly Detection in Smart Cities

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Abstract

In the context of smart cities, ensuring safety and security is paramount, and the increasing deployment of surveillance cameras presents both an opportunity and a challenge. This paper introduces an automated Crime Anomaly Detection System (CADS) that harnesses the capabilities of Deep Learning (DL) and computer vision to address this challenge. CADS follows a systematic workflow, starting with the collection of video data from smart city surveillance cameras. It then employs a series of preprocessing steps, including video-to-frame conversion, noise reduction using the Sobel Filter, and contrast enhancement via contrast stretching. Segmentation is achieved through optimized Region-based Convolutional Neural Networks (R-CNN), which identify Regions of Interest (ROIs) within frames. These ROIs serve as the focal points for feature extraction, which encompasses a diverse set of techniques such as Histogram of Oriented Gradients (HOG), Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), Zernike Moments, and Binary Robust Invariant Scalable Key points (BRISK). Then the DL model with Siamese-based Convolutional Networks (SCN) is also used for extracting the features from the segmented images. These two types of features are concatenated and given to feature selection. To refine the extracted features, CADS introduces a hybrid feature selection approach that combines White Shark Optimizer (WSO) and Squirrel Search Algorithm (SSA), called Hybrid Squirrel updated White Shark Optimizer (HSWSO). The selected features are given to an Optimized Recurrent Neural Network (ORNNs) to accurately identify and classify criminal activities, including abnormal behavior, theft, and violence.

Introduction

Video surveillance has drawn a lot of attention in our daily lives due to the steadily growing demand for protection for people and their possessions. The administration and monitoring of public zones may be done more safely and securely due to video surveillance systems. Observation recordings can particularly pick up a variety of real-world anomalies [1,2]. The authorities can be informed of such unusual events so they can respond immediately when they are discovered. As a result, an important problem that has been researched in a number of application sectors is the automated identification of abnormalities. In terms of crime detection, this paper presents an overview of numerous techniques used to identify actual abnormalities in video surveillance [3,4,5]. Anomalies, often known as outliers, are data points that do not fit the definition of normal behaviour. The term “anomaly detection” refers to the identification of anomalous activity or events that deviate from normal

behaviour. The importance of finding anomalies comes from the fact that data anomalies may be translated into information that can be applied to or used in a variety of application fields [6,7,8]. Considering that complex systems have several moving parts that constantly redefine what constitutes “standard” performance, a new proactive strategy is needed to identify abnormal behaviour.

In order to increase public safety, surveillance cameras are often employed more and more in public spaces, such as roads, stores, shopping malls, and sidewalks. However, the capacity of law enforcement agencies for monitoring has not kept up [9,10,11]. As a result, the usage of surveillance cameras and an inefficient camera-to-human monitor ratio provide a glaring flaw. So the simplest approach to anomaly identification is to choose a zone representing typical behaviour and label as an anomaly in the data any discovery that does not correlate to this region [12,13]. The automatic identification and correct detection of anything unfamiliar as anomalous is a challenging issue that has been approached in a number of ways throughout the years. Video surveillance is particularly important for identifying unusual occurrences like robberies, accidents, or other illegal activities [14,15].

The majority of the methods now in use for video surveillance anomaly detection take into account a variety of problem formulation elements, including the presence of the data, access to the labelled data, the nature of the abnormalities to be discovered, etc. Furthermore, due to the increasing dimensionality of data, traditional kinds of data-driven algorithms only produce less-than-ideal outcomes. Therefore, it is urgently necessary to create clever computer vision algorithms for automatically spotting abnormalities in surveillance footage in order to reduce labour and time waste. Nevertheless, the aim of any effective anomaly detection system is to be able to promptly alert users to an event that deviates from normal patterns. The foremost contribution of the paper is as follows,

The remaining paper is organized as follows: Section 2 covers the literature review, Section 3 explains the detailed proposed methodology, the results obtained for the proposed methodology are compared with the existing techniques in Section 4, and finally Section 5 concludes the paper with a detailed conclusion.

Literature review

In this section, some of the recent existing papers related to crime anomaly detection are discussed with their drawbacks.

In 2022, Watanabe et al. [16] suggested a real-world video anomaly detection via the extraction of key features from videos. The paper provides a quick and reliable approach for detecting video anomalies. The suggested approach analyses the whole movie and automatically extracts and learns the aspects that were crucial for classifying anything as normal or abnormal. With a straightforward self-attention method, salient characteristics may be extracted. A typical video merely captures the

usual condition in all of its frames. However, the aberrant video consists of a mix of frames in both normal and abnormal states.

In 2023, Kamoona et al. [17] used the deep temporal encoding-decoding to detect multiple instance-based video anomalies. Instead of a collection of separate instances, the paper treats video instances (clips) as sequential visual data. Then make use of a deep temporal encoding-decoding network, which was intended to record the spatiotemporal development of video instances across time. This also suggests a brand-new loss function that increases the average gap between predictions for regular and abnormal case types. In real surveillance applications, a low false alarm rate provided by the new loss function is essential.

In 2023, Ali [18] introduced a video anomaly detection in real-time for intelligent surveillance. In order to create a completely automated surveillance system, the study uses background subtraction (BS), a convolutional autoencoder, and object identification. The foreground items were then supplied to the convolutional autoencoders, which separate aberrant events from regular ones and instantly recognize warning indicators of violence. In order to reduce human involvement in video stream processing, object detection was then applied to the full scene, and the region of interest was marked using a bounding box. When a possible anomaly is detected, the network raises an alarm to warn of the discovery of possibly suspicious behaviours.

In 2023, Qasim and Verdu [19] utilized the deep convolutional and recurrent models, a method for detecting video anomalies. A deep convolutional neural network (CNN) and a simple recurrent unit (SRU) are combined in that study to create an automated system that can detect abnormalities in videos. In contrast to the SRU, which gathers temporal characteristics, the ResNet architecture extracts high-level feature representations from the video frames that were input. The video anomaly detection system was more accurate due to the SRU's expressive recurrence and ability for highly parallelized implementation.

In 2021, Pustokhina et al. [20] recommended an automatic deep learning-based anomaly detection for the protection of vulnerable road users in pedestrian crossings. That study develops the automated deep learning-based anomaly detection system (DLADT-PW) for the protection of vulnerable road users. The DLADT-PW model aims to identify and categorize the different anomalies that exist in the pedestrian pathways, such as autos, skateboarders, jeeps, etc. Preprocessing is the first stage in the DLADT-PW model, and it was used to reduce noise and improve picture quality. Additionally, the detection method uses the Mask-RCNN with DenseNet model of the Mask Region Convolutional Neural Network.

In 2020, Zahid et al. [21] introduced an ensemble framework for detecting anomalies in security videos. The bagging framework IBaggedFCNet that is provided in that study uses the strength of ensembles for reliable classification to find anomalies in videos. Our method, which examines the cutting-edge Inception-v3 image classification network, eliminates the need for video segmentation before feature extraction because it can lead to unreliable segmentation findings and a large memory

footprint. That has used a bagging ensemble (IBaggedFCNet) to empirically demonstrate the resilience of binary classifiers.

In 2021, Sarker et al. [22] have suggested an anomaly detection in unsupervised scenes of video surveillance. It is suggested in this study to use a weakly supervised learning system to detect anomalies in video surveillance settings. Utilizing a temporal convolutional 3D neural network (T-C3D), spatiotemporal characteristics were retrieved from each surveillance video. Afterward, a unique ranking loss function widens the gap between the classification scores of anomalous and regular films, lowering the incidence of false negatives. The concept has been assessed and compared to cutting-edge methodologies, yielding competitive performance without fine-tuning, which also verifies its generalization capabilities.

In 2023, Islam et al., [23] have suggested an anomaly detection system for smart city surveillance with IoT support. That research effort proposes an effective and reliable approach for identifying abnormalities in surveillance huge video data using Artificial Intelligence of Things (AIoT). The research study suggests a hybrid approach that combines 2D-CNN with ESN for smart surveillance, a crucial application of the AIoT. The input videos are fed into the CNN as a feature extractor, which then refines the features before being sent through the autoencoder, which was then fed into the ESN for sequence learning and anomalous event detection. To ensure the proposed model's capabilities and applicability throughout AIoT contexts in a smart city, it was lightweight and deployed over edge devices.

In 2021, Ullah et al., [24] described a powerful deep features-based intelligent anomaly detection system that can function in surveillance networks with lowered time complexity. The suggested framework first extracts spatiotemporal characteristics from a set of frames by sending each one to a CNN model that has already been trained. The traits that may be derived from the series of frames were useful for identifying unusual events. The multilayer Bi-LSTM model is then used to classify the retrieved deep features, which can reliably categorize ongoing anomalous/normal occurrences in complex surveillance scenes of smart cities.

In 2022, Ul Amin et al., [25] have suggested EADN, a minimally complicated deep learning-based model that may be used in a surveillance system for anomaly detection. Using a shot boundary detection method, the video is split into prominent shots at the model's input. Next, a CNN with time-distributed 2D layers is given the selected frame sequence in order to extract prominent spatiotemporal properties. The collected characteristics were enhanced with useful data that makes it easier to detect anomalous events. Finally, for the purpose of anomaly identification, LSTM cells were used to learn spatiotemporal information from a series of frames per sample of each abnormal occurrence.

2.1. Problem statement

The need for reliable and effective techniques to identify abnormalities in video data is increasing in a world that is continuously changing, and that depends more and more on video surveillance and monitoring systems. The difficulty is in differentiating between typical and aberrant occurrences or behaviours in video feeds, which can vary from security breaches and accidents to peculiar actions in crowded places, and all of which have significant ramifications for the safety and security of the general public. Existing methods for detecting video anomalies have a number of drawbacks, including high false alarm rates, issues with managing a variety of video material, and a requirement for time-consuming human parameter adjustment. In addition, conventional approaches frequently find it difficult to adjust to altering environmental factors and developing hazard scenarios.

In order to overcome these difficulties, the cited studies provide novel strategies that make use of DL techniques like CNNs, RNNs, ensemble methods, and other cutting-edge methodologies to automatically and precisely identify abnormalities in video data. The ultimate goal of these techniques is to increase the overall reliability of anomaly detection and the performance of surveillance and security systems by extracting spatiotemporal information, learning temporal patterns, and doing all three simultaneously. The goal of these research efforts is to create effective, real-time anomaly detection systems that are capable of reliably recognizing anomalous occurrences or behaviours in video streams while minimizing false alarms. These systems have the ability to improve the security and safety of a variety of contexts, including smart cities, transport networks, and surveillance applications, by supplying early warning and prompt response to unanticipated events.

Overall, the issue raised in these publications is the need for highly effective and reliable algorithms for detecting anomalous occurrences or behaviours in video data for improved surveillance, security, and safety applications. By doing so, they hope to create solutions for anomaly identification that are more precise and effective than those offered by conventional methods.

Proposed methodology

The most crucial component of security systems with a wide variety of applications in daily life is video surveillance systems. It is particularly important for remote facility monitoring in both public and private spaces. Video surveillance in this sense means keeping an eye out for instances of incorrect human behaviour, sometimes known as real-world anomalies. However, the conventional method of integrating humans in real-world anomaly detection takes a long time and entails a number of overheads. As a result, an important field of research is automated anomaly identification in video surveillance utilizing intelligent algorithms. This work provides a thorough analysis of automated anomaly identification in video surveillance using pre-processing, segmentation, feature extraction, classification, and prediction techniques with an emphasis on crime detection in particular.

The overall block diagram of the proposed model is shown in Figure 1.

The anomaly detection begins with the conversion of video data into individual frames, employing video-to-frame conversion techniques. Subsequently, the frames undergo denoising using the Sobel Filter method to enhance their quality, followed by contrast enhancement through contrast stretching. The system identifies ROIs within the frames, a critical step achieved by OR-CNN. Diverse feature extraction techniques are employed, encompassing handcrafted features like HOG, SIFT, and SURF. Texture and shape features are harnessed through Zernike Moments, while local features are described using BRISK. The visual-based features are extracted using the SCN. These two features are concatenated and given to the HSWSO for selecting the optimal features. Then the Optimized RNN model is introduced for anomaly detection, encompassing a wide range of activities, including abnormal behavior, theft, and violence.

Pre-processing

Preprocessing is the method used to get rid of the shadow and noise areas in the video frames. The first phase in video processing is called preprocessing, and it involves utilizing filtering algorithms to separate the noise or the shadow region.

3.1.1. Video-to-Frame Conversion

The IoT devices are utilized to gather the surveillance videos initially. The frame conversion procedure then occurs. Here, frames from a video may be retrieved and turned into images. The input video must be transformed into frames in the following steps after being captured. By breaking up various human behaviours into smaller frames, framing is performed. The number of movements present in the video is simply determined.

3.1.2. Denoise the frames using the Sobel Filter

The Sobel operator, a gradient-based edge detection method, is utilized for removing the noise content present in the input image. The gradient of the picture intensity function is approximated using a discrete differentiation operator. The traditional Sobel operator uses two kernels, one for each picture. represents the gradient estimate in the direction, while represents the gradient estimation in the y-direction. The following equation may be used to compute the absolute gradient magnitude:

However, this equation is frequently approximated to:

The gradient’s directions may be found as:

Because it can detect edges in pictures with redundant information like noise, the Sobel operator is a popular gradient-based operator for edge detection. The reason is that each picture is differently

divided into two rows and columns here, increasing the edge components on both sides and giving the edges a highly brilliant and thick appearance.

3.1.3. Contrast stretching

The critical and fundamental step of contrast stretching must be included in all image-processing-based methods that improve a picture's visual quality. Numerous techniques are available in this sector to improve the object quality of the image. Contrast stretching is a method for enhancing contrast in images that involves extending the image's intensity values to span the desired range from 0 to 1. It eliminates any potential uncertainty in distinct regions of the dataset's picture. The distance between the top and lower brightness values in this function rises nonlinearly when the picture contrast is increased. Every grey level brightness of a pixel is given a weight in the range of (0,1). Eq. (4) displays the weight function:

Where is a spatial coordinate, is the slope of the weight function, and m is the greatest brightness value in the input picture, where is the grey level brightness of the image.

Segmentation using RCNN

The pre-processed image is given to the RCNN for segmentation. The anomaly regions are segmented in this stage. Since the CNN-based object detection methods employ a similar sliding window mechanism to discover objects, they need a lot of computational power. RCNN adopted a selective search strategy in order to improve CNN's performance by providing fewer region recommendations. To overcome spatial linkages, recognize the objects at different aspect ratios, and detect objects at different pyramid levels while maintaining the fine details for melanoma detection, the regions must be down-sampled. To effectively recreate these oscillations and precisely follow the shape and location of the damaged parts, RCNN image pyramids collect deep feature descriptions. By continuous smoothing and down-sampling, the visual pyramid represents the picture, and the subscript indicates different layers of the image pyramid. One might consider the entire smoothing and down-sampling procedure, which is shown in Eq. (5) as:

The selective search stage of the RCNN precisely represents the anomalous attributes by capturing the texture, colour, and intensity of patches over many layers. Each layer represents a probable abnormality at the local level. Three hyperparameters of the RCNN architecture are the quantity, number, and layout of output features.

Feature Extraction

The features present in the segmented regions are extracted using the Handcrafted Features like Histogram of Oriented Gradients (HOG), SIFT (Scale-Invariant Feature Transform), SURF (Speeded-Up Robust Features), Texture and Shape Features like Zernike Moments, and Local Feature Descriptors

like BRISK (Binary Robust Invariant Scalable Keypoints). Then the SCN model is also used for extracting the visual features, and these two types of features are combined and given to the feature selection stage.

Handcrafted Features

1. HOG

Segmenting and organizing the image into blocks of cells is the first stage in the HOG calculation. Calculating the gradient magnitude and gradient orientation for each pixel inside the block is done using Eq. (6) and Eq. (7), which are presented as,

Where and are the 1D-filtered horizontal and vertical gradients, respectively. A feature vector is used to describe the distribution of the unsigned gradient orientation for each block cell, weighted according to its magnitude. The descriptor for each block is produced by normalizing these feature vectors and concatenating them; this is symbolized by the letters, where is the number of blocks in the picture and n is the number of feature vectors. These blocks serve as the picture sample's focal points. In order to create the keypoint matrix from which to extract the descriptor for each block independently, where is the number of items in the blocks descriptor, and m is the number of elements in the training set of pictures. Eq. (8) can be used to find c's value.

where CPB represents the number of cells in a block, and bins is the number of orientations.

SIFT

The one-dimensional SIFT approach is a novel use of the two-dimensional SIFT technology. The method is widely applied to extract traits from images in order to perform image recognition. Since they are distinguishable from the surrounding images and are unaffected by brightness or rotation, the characteristics of a picture that successfully passes SIFT's screening procedure are considered vital when it comes to image identification. Therefore, in the context of image processing, the spectral spots picked by SIFT are referred to as crucial regions. These spectral points were designated as typical spectral points in the current investigation because they extract the main visual characteristic of the spectrum. It should be emphasized that chemical information from the spectrum was not taken into account while selecting these sites. Building a Gaussian pyramid, deducting from it to produce a Difference of Gaussian (DOG) pyramid, and then searching for unique spots of varied sizes are the basic steps of the SIFT technique. The essential SIFT stages are as follows:

Construct a pyramid with Gaussian-shaped sides. The base picture (spectrum) is first altered using a Gaussian transform and other scale-changing factors. The augmentation of the spectrum and

Gaussian convolution kernel completes the Gaussian filtering of a spectrum at different transformation scales, shown in Eq. (9) as,

Where is the sample space's coordinate? The spectrum is constructed using various x sample intervals and sampling scales. Different sample intervals result in various picture extraction scales. The definition of the Gaussian convolution kernel function is as follows in Eq. (10):

Where is the Gaussian normal distribution's variance? The scale at which the spectrum is smoothed depends on the value of. The Gaussian scale transforming factor is another name for. As a consequence, groups of images (spectra) are produced using the converted spectra at different sampling rates, and each group has a multi-layer spectrum after Gaussian filtration. The Gaussian pyramid is a shape formed by several scale spaces designated by the letters. Different layers in a single group are produced by Gaussian transformation factors r, which are multiples of the starting Gaussian transforming factor. Initial, which is recorded as, refers to the first layer in the first group. Images in the same group have identical sizes. The Gaussian pyramid's structure is therefore determined by O and S (the number of levels in each group) as well as the initial Gaussian scale adjustment factor.

SURF

The use of the SURF descriptor to extract anomaly features is made possible by its reliability, speed, and enhanced robustness. In this scenario, simple 2D box filters are used to determine the interest locations. It uses a scale-invariant blob detector based on the hypothesized determinant of the Hessian matrix ||. Next, using the approximations for a blob detector, Eq. (11) calculates the Hessian matrix, represented as, and using a relative weight known as, the Hessian matrix is balanced in this scenario. The Gaussian function difference is used to determine the local maxima of each blob descriptor. In order to obtain a stable point, the first selected square matrix is subjected to non-maximum 3×3×3 suppression. With the help of these techniques, the crucial characteristics are extracted and added to the dual classification.

Texture and Shape Features

Zernike Moments

The image function is projected onto the orthogonal polynomial to produce the Zernike moment. The definition of the -order and -degree Zernike moments for a single-channel digital picture is given in Eq. (12):

Where is an even integer that meets the condition that, and is the normalization factor, or the number of pixels that the picture is transferred to in the unit circle. indicates conjugation. Additionally, the

unit circle possesses orthogonality for the orthogonal polynomial, which is defined in Eq. (13) as:

When is an orthogonal radial polynomial, and it has the following form:

The calculation origin of the picture boundary points is shifted to the image's centroid and normalized simultaneously in order to guarantee the algorithm's scale and translation invariance.

Eq. (12) to Eq. (16) can be combined to determine the Zernike moments of any order of single-channel digital pictures. In general, low-order moments may be used to describe an object's fundamental characteristics, whereas high-order moments can be used to describe the object's specific details.

Local Feature Descriptors using BRISK

BRISK is a method for scale-space Key point identification and binary description. The picture pyramid's octave layers are where key points are found. Using quadratic function fitting, the position and scale of each key point are transformed into a continuous domain representation. The BRISK descriptor is generated as a binary string in two steps after the BRISK characteristics have been discovered. The first step aids in the creation of a rotation-invariant description by estimating the key points' orientation. Strong brightness comparisons are used in the second step to provide a description that accurately and effectively describes the characteristics of the local location. A sample pattern that looks like concentric circles and designates places is used by the BRISK description. To avoid aliasing effects, the pattern's intensity of each pi-point is smoothed with a Gaussian. The sample points are collected into pairs and sorted into two classes: short pairs if the distance between them is less than or equal to, and long pairs if the distance exceeds. While the short pairings are utilized to construct the descriptor following rotation correction, the large pairs are used to estimate rotation. The computation of the local gradients of the BRISK descriptor is given by:

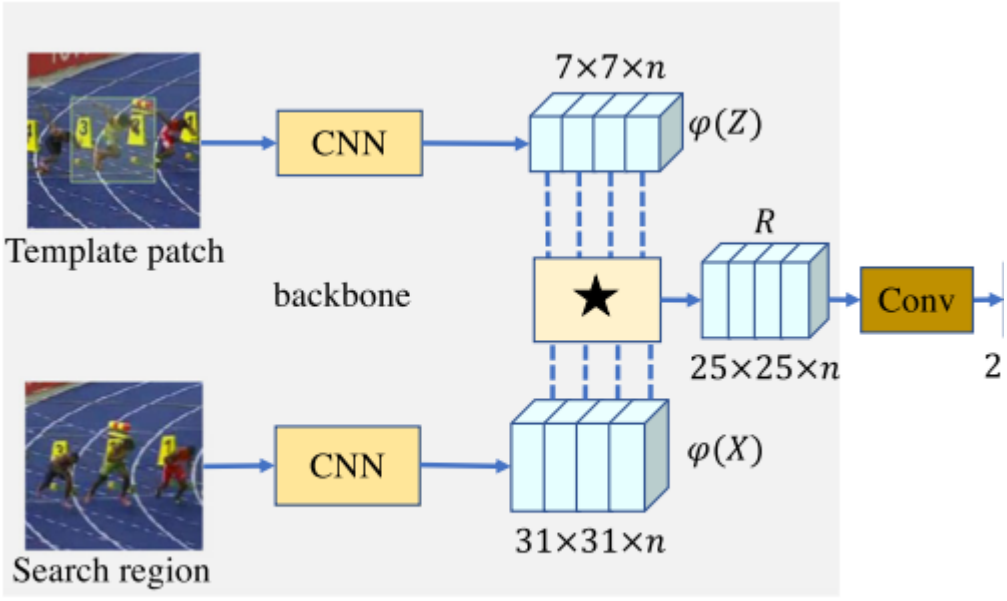
The smoothed intensity at scale is represented by, while denotes the local gradient between the sample pair. The average gradient in the directions is used to estimate the rotation angle. To get a descriptor that is rotation-invariant, the short pairs are rotated by an angle. In order to construct the descriptor, BRISK takes the collection of short pairs (), rotates the pairings by the orientation to obtain $-\theta$ to get (), and then compares the smoothed intensity such that each bit b corresponds to:

An encoded binary string known as the binary descriptor can be used to characterize each important point.

Visual Feature Extraction Using SCN

A specific type of neural network architecture called a siamese network is made for similarity-based tasks like image comparison or verification. The word "Siamese" refers to the concurrent processing of two input samples by two twin subnetworks that are identical to one another. When given similar

inputs, these networks learn to produce similar embeddings, and when given different inputs, distinct embeddings. SCN can be used in the context of visual feature extraction to collect visual representations that highlight similarities or contrasts between pictures or regions of interest. The process of extracting significant and pertinent information from visual data, such as pictures or video frames, is typically involved in this. For purposes of further analysis or activities, such as object recognition, classification, or anomaly detection, visual feature extraction seeks to represent the data in a way that maintains key properties.



Siamese Subnetwork

This paper creates a Siamese subnetwork for visual feature extraction in this case by using the Siamese architecture with convolutional neural networks. The subnetwork is divided into two branches: the target branch, which accepts the tracking template patch as input, and the search branch, which accepts the search region. The CNN architecture used by the two branches produces two feature maps numbered and, as its output. By using the Huber loss, a response map may be produced in order to incorporate the information of these two branches. It anticipates that the response map will be able to maintain a wealth of information association since it will need to decode it in the upcoming bounding box prediction subnetwork in order to learn the target's location and scale. Although noted that separate feature channels often absorb diverse semantic information, the Huber loss layer can only provide a single-channel compressed response map, which lacks relevant features and crucial information for further decoding. It also creates several semantic similarity maps using a depth-wise Huber loss:

The channel-wise correlation procedure is shown by where. The resultant response map, which has the same number of channels, is rich in data for regression and classification. Given that CNN features are retrieved using many layers, each layer encodes characteristics of various aspects at varying depths. For localization, low-level features like edge, corner, colour, and form that better reflect visual

qualities are essential, but high-level features are better at representing semantic properties that are vital for discriminating. These integrate the features obtained from the final three residual backbone blocks, which are designated as, and respectively, in order to improve inference for recognition and discrimination. In particular, we carry out a channel-wise concatenation:

It has 256 channels. Consequently, has channels. To create a multi-channel response map, a Depth-wise Huber loss is applied between the searching map and the template map. The response map is then shrunk to 256 channels using a kernel convolution. The following computation may be speed up, and the number of parameters can be greatly decreased by the dimension reduction. The final dimension-reduced response map is used as the RNN's input for the prediction of bounding boxes.

Huber loss function

A loss function used in robust regression is called the Huber loss. Compared to least squares, it is less susceptible to data outliers than mean squared error. They deliver more consistent and dependable outcomes. The formula combines the mean absolute error for big mistakes with the mean squared error for minor errors. The Eq. (21) defines the Huber loss function.

Where delta is a parameter that regulates the transition between the two regimes, "linear" and "quadratic" sections of the loss function, and error is the difference between the predicted value and the real value. The visual features are concatenated with the other features and given to the feature selection stage.

Feature Selection using HSWSO algorithm

In feature selection, the concatenated features are given as the input, and the optimal features are chosen using the HSWSO algorithm. HSWSO is the combination of the White Shark Optimizer (WSO) and the Squirrel Search Algorithm (SSA). The movement towards the optimal shark can be improved by using the updated position of SSA optimization. This may avoid the optimization from falling into local optima.

Initialization of HSWSO

The following 2D matrix illustrates a population of n WSO in a search domain space, with each shark's location signifying a potential solution to the anomaly detection issues.

Where indicates the number of option variables for a particular assignment, and represents the position of all sharks in the search region. Based on the lower () and upper () boundaries of the search space in the dimension, it may be determined as follows:

Where is a random number within a range [0, 1]. The initial fitness values are calculated for the initial

solutions given in Eq. (22) and then an updating process is placed in case the new position is better than the previous one.

4.3. Speed of Movement towards Prey

The great white shark glides towards its prey in undulating motions at a pace, and when it detects the position of its prey by its wave hesitation. Eq. (24), which shows how a white shark locates prey, uses a delay in the waves caused by the prey's movement.

Where is the updated velocity at iteration, is the current velocity at iteration, is the global best solution at iteration, the position of the shark at iteration is denoted as, and are the two random values which range between 0 and one. Then it depicts the swarm's knowledge of the most popular place during iteration. The great white sharks' optimal position is determined by a number called, which may be described as follows.

Where = arbitrary numbers produced at random with a distribution in the range [0, 1].

Where and stand for the initial and secondary velocities for the motion of the white shark, and k = current, K = maximum iterations. Following a careful study, it was determined that they had values of 0.5 and 1.5, respectively.

The acceleration factor was found to be 4.125 after significant investigation, and is denoted by the symbol τ.

4.4. Movement in the Direction of the Optimal Prey

The location update technique described in Eq. (29) was employed in this context to illustrate how white sharks behave as they approach prey.

The binary vectors a and b are defined in Eq. (30) and Eq. (31), respectively.

Where the outcome of a bitwise operation is represented by. Eq. (33) and Eq. (34) respectively explain the frequency of a white shark's wavy motion and the number of times the shark strikes its prey.

Where the parameter denotes the great white shark's movement force, the control exploration and exploitation locations are determined by the constants and.

4.5. Squirrel-based Optimal Shark Movement

Sharks can maintain their position in front of the target's closest, most beneficial competitor. Eq. (35) illustrates the expression for this phenomenon. The position updating strategy of the Squirrel is

utilized to improve the optimal shark movement.

Where represents the position of the upgraded shark, returns 1 or -1 to change the search route, and, and represent random numbers. Eq. (36) states that target and shark lengths are in the range [0, 1]. According to Eq. (37) and suggested to indicate the strength of white sharks, is a parameter.

Where the location factor controls the amount of exploitation and exploration.

Where is the gliding angle, which can be computed using Eq. (39), and is the constant value of 8, is the constant value of 18,

Eqs. (40) and Eq. (41) may be used to compute the drag force and the lift force.

Where is the air density, is the body's surface area, is its frictional drag coefficient, is the squirrel's gliding speed, and is a chance value.

Anomaly detection using ORNN

The HSWSO algorithm is used for optimizing the basic RNN model, and then the Optimized RNN (ORNN) model is utilized for performing the anomaly detection. Unsupervised and supervised learning are combined in the conventionally used ORNN. The sequence data used to create this model might be as deep as it is lengthy. Each layer in the RNN model is connected by a feedback loop that has the ability to remember data from earlier inputs. Because of this, the model could become more reliable. This model's input layer has an index of at time, whereas the hidden layer has an index of at the same time. The layer is hidden at times. The output layer at time, designated as, has index. The weight matrix U links the hidden layer with indices to the input. The weight matrix connects layers with the indices that were previously hidden. With input units and an index of the weight matrix, the hidden layer, and the output layer. hidden units are present, and output units are present. The following formulas set the parameters for an RNN's computations. To calculate in the first step, the input at this stage and the previously hidden state are utilized:

Where is a tanh or ReLU-type nonlinear function. It is necessary to compute in order to determine the first hidden state, which is typically initialized to all zeros. In the second stage, using the formula, the output at step t is calculated as:

For recurrent networks, the following formulas are used:

To create a composite representation of the data, these findings are connected along a predefined axis in a process known as concatenation. The final prediction made by the model, which is typically a binary classification, is the model's output.

Result and discussion

In this section, the efficiency of the proposed anomaly detection model is compared with the existing anomaly detection techniques in terms of the performance metrics. The anomaly detection dataset [26] is used for implementing this proposed work, and the MATLAB platform is utilized for implementation.

4.1. Performance metrics

The performance metrics and their calculation formulas are given in this section.

Sensitivity

Simply dividing the total positives by the percentage of genuine positive forecasts yields the sensitivity value.

Specificity

Specificity is determined by dividing the number of accurately anticipated negative outcomes by the total number of negatives.

Accuracy

The proportion of correctly identified information to all of the data in the record is known as the accuracy. The precision is described as,

Precision

By employing the entire sample used in the classification process, precision is the representation of the total number of genuine samples that are appropriately taken into consideration during the classification process.

Recall

Recall rate is a measure of how many genuine samples overall are considered when categorizing data using all samples from the same categories from the training data.

F- Score

The definition of the F-score is the harmonic mean of recall rate and accuracy.

Negative Prediction Value (NPV)

The NPV is defined as the ratio of TN and the sum of TN and FN.

Matthews correlation coefficient (MCC)

The two-by-two binary variable association measure, sometimes referred to as MCC, is shown in the equation below,

False Positive Ratio (FPR)

The FPR is computed by dividing the total number of adverse events by the total number of adverse events that were incorrectly classified as positive.

False Negative Ratio (FNR)

It is often known as the “miss rate,” is the probability that a true positive may go unnoticed by the test.

4.2. Overall comparison of the proposed anomaly detection model

In this section, the result obtained for the proposed anomaly detection model is compared with the existing techniques like CNN, RNN, Bi-directional Long Short-Term Memory (Bi-LSTM), Gradient Recurrent Unit (GRU), and Long Short-Term Memory (LSTM). The performance metrics for the proposed and existing techniques are compared in Table 1.

Table 1: Overall comparison of the proposed and existing techniques

Techniques	Sensitivity	Specificity	Accuracy	Precision	Recall	F-Measure	NPV	FPR	FNR	MCC	Youden Index
Proposed	0.902149	0.992473	0.986021	0.902149	0.902149	0.902149	0.992473	0.007527	0.097851	0.894622	0.894622
CNN	0.85435	0.988796	0.979193	0.85435	0.85435	0.85435	0.988796	0.011204	0.14565	0.843146	0.843146
RNN	0.819438	0.986111	0.974205	0.819438	0.819438	0.819438	0.986111	0.013889	0.180562	0.805548	0.805548

Bi-LSTM	0.834621	0.987279	0.976374	0.834621	0.834621	0.834621	0.987279	0.012721	0.165379	0.821899	0.821899
GRU	0.624178	0.971091	0.946311	0.624178	0.624178	0.624178	0.971091	0.028909	0.375822	0.595269	0.595269
LSTM	0.69793	0.976764	0.956847	0.69793	0.69793	0.69793	0.976764	0.023236	0.30207	0.674694	0.674694

The table presents the performance metrics of various machine learning models, including Proposed, CNN, RNN, Bi-LSTM, GRU, and LSTM, in a binary classification task. Each metric assesses a different aspect of the models' performance. Sensitivity (or recall) measures the model's ability to correctly identify positive instances, with the Proposed model achieving a score of 0.902149. Specificity gauges the models' aptitude for correctly identifying negative instances, with the Proposed model scoring 0.992473. Accuracy reflects overall correctness, where the Proposed model achieves 98.60%. Precision quantifies the accuracy of positive predictions, with the Proposed model scoring 90.21%. Negative Predictive Value measures the accuracy of negative predictions, with a score of 99.25% for the proposed model. The False Positive Rate is low at 0.007527, and the False Negative Rate stands at 0.097851. The Matthews Correlation Coefficient is high at 0.894622, indicating strong model performance, and the Youden Index aligns with this value. Overall, the proposed model demonstrates robust performance across these metrics, making it a promising choice for the binary classification task.

Sensitivity measures the proportion of true positive predictions among all actual positive instances. In the proposed technique, sensitivity is 0.902149, indicating that 90.21% of actual positive instances were correctly classified as positive. Specificity measures the proportion of true negative predictions among all actual negative instances. In the proposed technique, specificity is 0.992473, indicating that 99.25% of actual negative instances were correctly classified as negative. The sensitivity and specificity are shown in Figure 3.

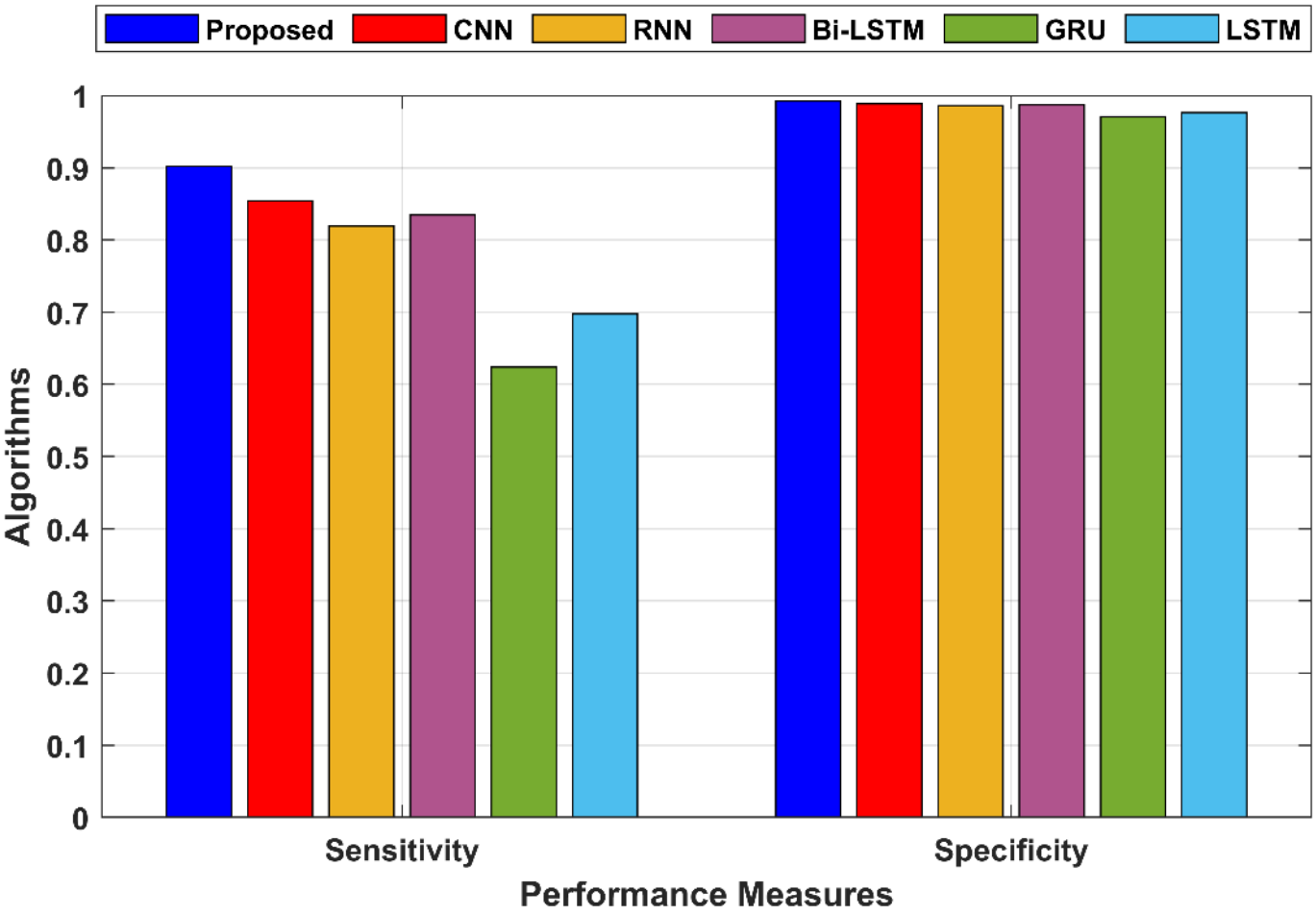


Figure 3: Comparison of the sensitivity and specificity

Accuracy measures the overall correctness of the predictions, considering both true positives and true negatives. In the proposed technique, accuracy is 0.986021, meaning that 98.60% of all instances were correctly classified. Precision measures the proportion of true positive predictions among all predicted positive instances. In the proposed technique, precision is 0.902149, indicating that 90.21% of the positive predictions were true positives. The Youden Index is a measure of the model's effectiveness in distinguishing between the two classes. In the proposed technique, the Youden Index is 0.894622, indicating a good ability to discriminate between positive and negative instances. Figure 4 compares the accuracy, precision, and Youden Index for the proposed and the existing techniques.

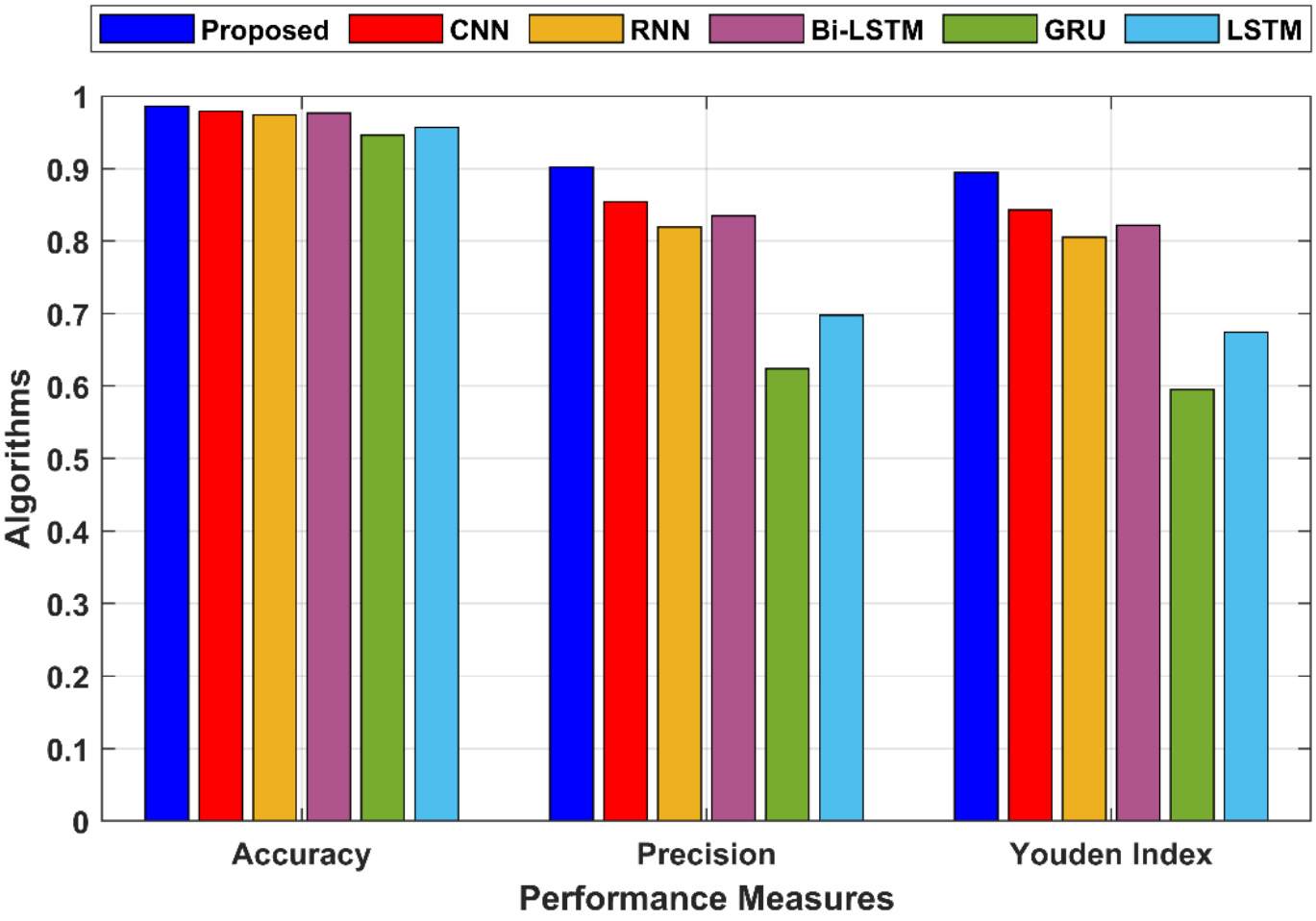


Figure 4: Comparison of the accuracy, precision, and Youden Index

The F-Measure is the harmonic mean of precision and recall and provides a balanced measure of a model's performance. In the proposed technique, the F-Measure is 0.902149, indicating a balanced performance. MCC is a correlation coefficient between the observed and predicted binary classifications. In the proposed technique, MCC is 0.894622, indicating a strong positive correlation. The MCC and the F-Measure values are compared in Figure 5.

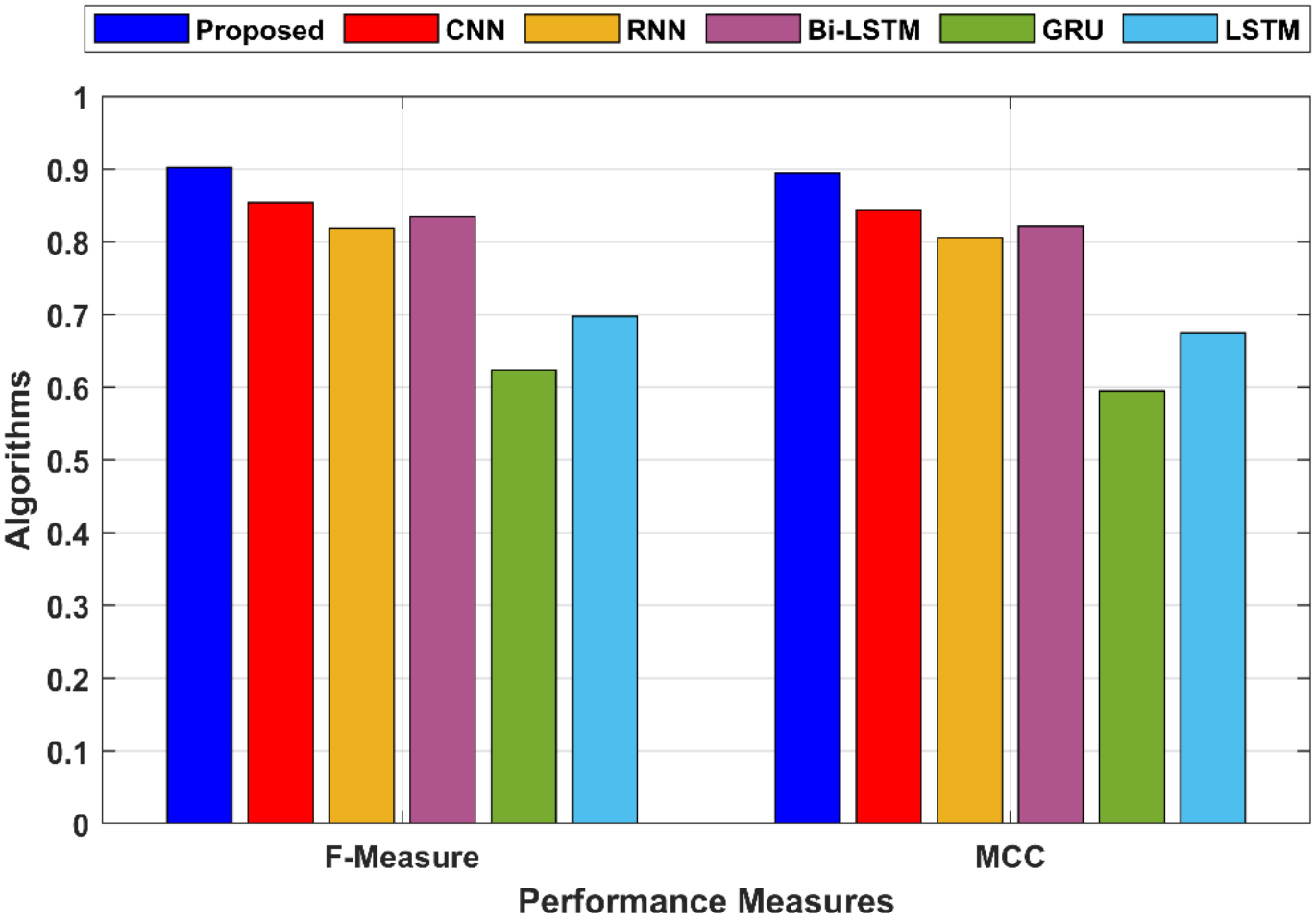


Figure 5: Comparison of the MCC and F-Measure

Recall has already been explained in point 1. It measures the proportion of true positive predictions among all actual positive instances. In the proposed technique, recall is also 0.902149. NPV measures the proportion of true negative predictions among all predicted negative instances. In the proposed technique, NPV is 0.992473, indicating that 99.25% of the negative predictions were true negatives. Figure 6 compares the proposed and existing models' recall and NPV values.

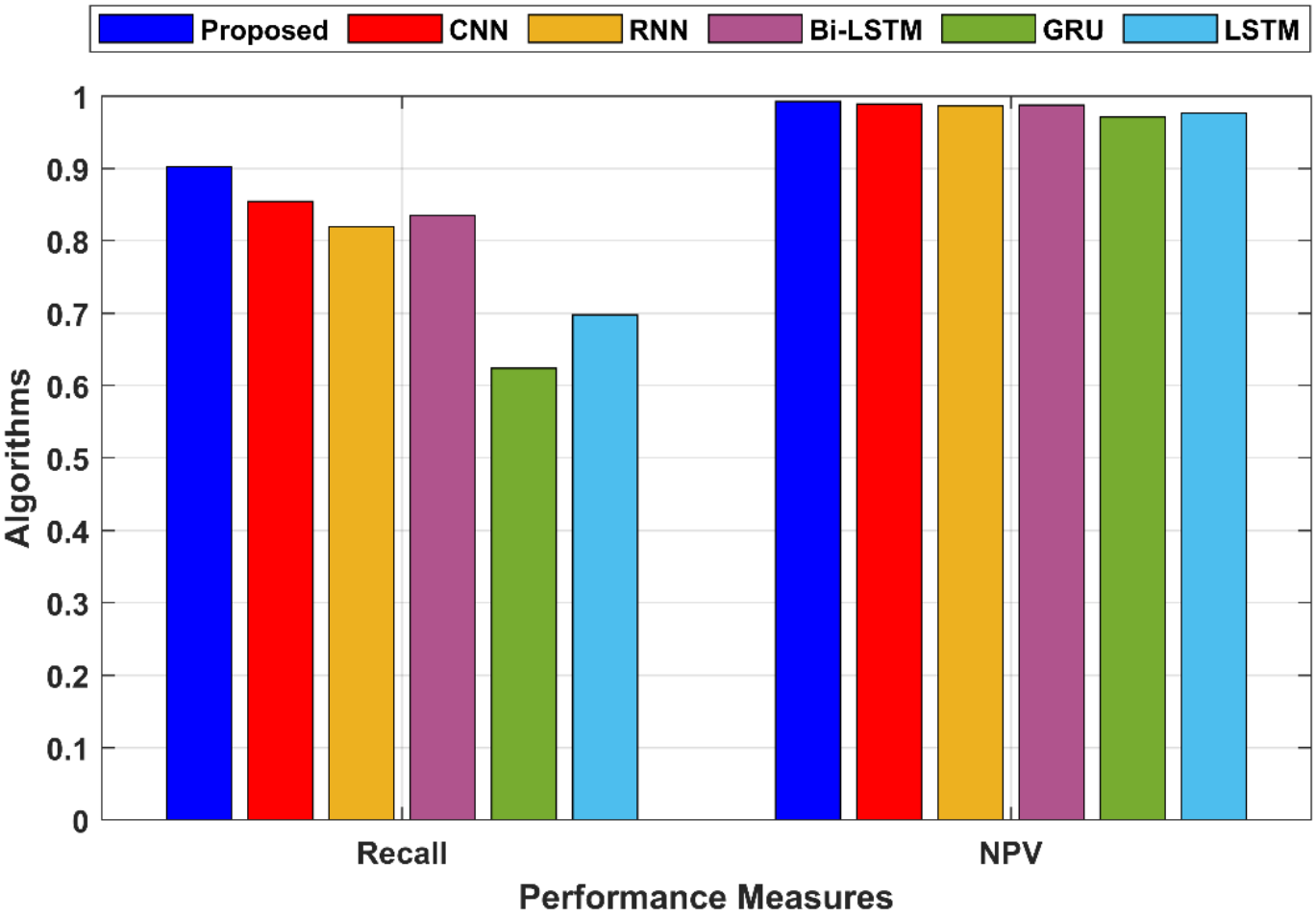


Figure 6: Comparison of the Recall and NPV

FPR measures the proportion of false positive predictions among all actual negative instances. In the proposed technique, FPR is 0.007527, indicating a low rate of false positives. FNR measures the proportion of false negative predictions among all actual positive instances. In the proposed technique, FNR is 0.097851, indicating a moderate rate of false negatives. The graphical comparison of FPR and FNR is shown in Figure 7.

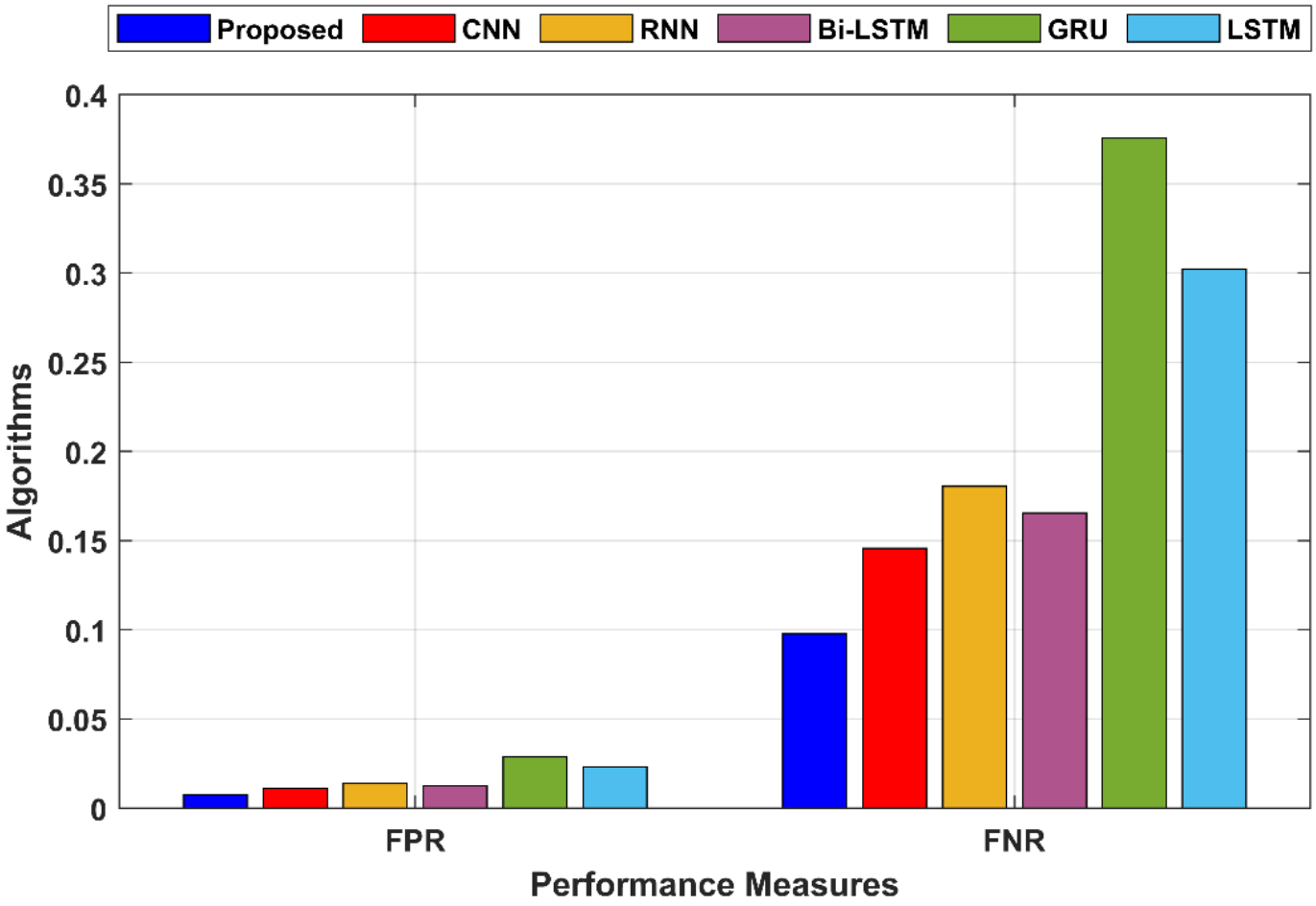


Figure 7: Graphical comparison of FNR and FPR

Conclusion

In conclusion, the introduction of the Automated Crime Anomaly Detection System (CADS) presents a significant advancement in the realm of smart cities, where safety and security are of paramount concern. With the proliferation of surveillance cameras, CADS seizes the opportunity to enhance public safety while also addressing the challenge of efficiently monitoring vast volumes of video data. CADS follows a systematic workflow, beginning with data collection from smart city surveillance cameras and proceeding through a series of preprocessing steps, segmentation, and feature extraction techniques, including cutting-edge deep learning models like Siamese Convolutional Networks. The culmination of these efforts is the accurate identification and classification of criminal activities, spanning abnormal behavior, theft, and violence.

The Hybrid Squirrel updated White Shark Optimizer (HSWSO), which ensures that only the most relevant features are retained for analysis. This refinement process not only improves the efficiency of the system but also enhances the precision of anomaly detection. In the dynamic landscape of smart cities, CADS serves as a beacon of technological progress, showcasing how advanced deep learning and computer vision technologies can be harnessed to create safer and more secure urban

environments. CADS offers a blueprint for the integration of cutting-edge technology into urban security infrastructure, paving the way for the continued development of smarter and safer cities.

Reference

1. Elia, R., Plastiras, G., Pettemeridou, E., Savva, A. and Theocharides, T., 2022. A real-world data collection framework for a fused dataset creation for joint human and remotely operated vehicle monitoring and anomalous command detection. CAAI Transactions on Intelligence Technology, 7(3), pp. 432-445.
2. Blanchard, A. and Sapsis, T., 2022. Informative path planning for anomaly detection in environment exploration and monitoring. Ocean Engineering, 243, p. 110242.
3. Patrikar, D.R. and Parate, M.R., 2022. Anomaly detection using edge computing in video surveillance system. International Journal of Multimedia Information Retrieval, 11(2), pp. 85-110.
4. Ullah, W., Ullah, A., Hussain, T., Khan, Z.A. and Baik, S.W., 2021. An efficient anomaly recognition framework using an attention residual LSTM in surveillance videos. Sensors, 21(8), p. 2811.
5. Tariq, S., Farooq, H., Jaleel, A. and Wasif, S.M., 2021. Anomaly detection with particle filtering for online video surveillance. IEEE Access, 9, pp. 19457-19468.
6. Thakare, K.V., Sharma, N., Dogra, D.P., Choi, H. and Kim, I.J., 2022. A multi-stream deep neural network with late fuzzy fusion for real-world anomaly detection. Expert Systems with Applications, 201, p. 117030.
7. Ingle, P.Y. and Kim, Y.G., 2022. Real-time abnormal object detection for video surveillance in smart cities. Sensors, 22(10), p. 3862.
8. Lin, W., Gao, J., Wang, Q. and Li, X., 2021. Learning to detect anomaly events in crowd scenes from synthetic data. Neurocomputing, 436, pp. 248-259.
9. Maqsood, R., Bajwa, U.I., Saleem, G., Raza, R.H. and Anwar, M.W., 2021. Anomaly recognition from surveillance videos using 3D convolution neural network. Multimedia Tools and Applications, 80(12), pp. 18693-18716.
10. Balasundaram, A. and Chellappan, C., 2020. An intelligent video analytics model for abnormal event detection in online surveillance video. Journal of Real-Time Image Processing, 17(4), pp. 915-930.
11. Wu, C., Shao, S., Tunc, C., Satam, P. and Hariri, S., 2021. An explainable and efficient deep learning framework for video anomaly detection. Cluster computing, pp. 1-23.
12. Mandala, J., Akhila, P. and Reddy, V.S., 2021. An Integrated Reinforcement DQNN Algorithm to Detect Crime Anomaly Objects in Smart Cities. International Journal of Advanced Computer Science and Applications, 12(12).
13. Zhu, S., Chen, C. and Sultani, W., 2020. Video anomaly detection for smart surveillance. In Computer Vision: A Reference Guide (pp. 1-8). Cham: Springer International Publishing.
14. Rehman, A., Saba, T., Khan, M.Z., Damaševičius, R. and Bahaj, S.A., 2022. Internet-of-things-based suspicious activity recognition using multimodalities of computer vision for smart city

security. Security and communication Networks, 2022.
15. Isafiade, O.E. and Bagula, A.B., 2020. Series mining for public safety advancement in emerging smart cities. Future Generation Computer Systems, 108, pp. 777-802.
16. Watanabe, Y., Okabe, M., Harada, Y. and Kashima, N., 2022. Real-World Video Anomaly Detection by Extracting Salient Features in Videos. IEEE Access, 10, pp. 125052-125060.
17. Kamoona, A.M., Gostar, A.K., Bab-Hadiashar, A. and Hoseinnezhad, R., 2023. Multiple instance-based video anomaly detection using deep temporal encoding–decoding. Expert Systems with Applications, 214, p. 119079.
18. Ali, M.M., 2023. Real-time video anomaly detection for smart surveillance. IET Image Processing, 17(5), pp. 1375-1388.
19. Qasim, M. and Verdu, E., 2023. Video anomaly detection system using deep convolutional and recurrent models. Results in Engineering, 18, p. 101026.
20. Pustokhina, I.V., Pustokhin, D.A., Vaiyapuri, T., Gupta, D., Kumar, S. and Shankar, K., 2021. An automated deep learning based anomaly detection in pedestrian walkways for vulnerable road users safety. Safety science, 142, p. 105356.
21. Zahid, Y., Tahir, M.A., Durrani, N.M. and Bouridane, A., 2020. Ibaggedfcnet: An ensemble framework for anomaly detection in surveillance videos. IEEE Access, 8, pp. 220620-220630.
22. Sarker, M.I., Losada-Gutiérrez, C., Marron-Romera, M., Fuentes-Jiménez, D. and Luengo-Sánchez, S., 2021. Semi-supervised anomaly detection in video-surveillance scenes in the wild. Sensors, 21(12), p. 3993.
23. Islam, M., Dukyil, A.S., Alyahya, S. and Habib, S., 2023. An IoT Enable Anomaly Detection System for Smart City Surveillance. Sensors, 23(4), p. 2358.
24. Ullah, W., Ullah, A., Haq, I.U., Muhammad, K., Sajjad, M. and Baik, S.W., 2021. CNN features with bi-directional LSTM for real-time anomaly detection in surveillance networks. Multimedia tools and applications, 80, pp. 16979-16995.
25. Ul Amin, S., Ullah, M., Sajjad, M., Cheikh, F.A., Hijji, M., Hijji, A. and Muhammad, K., 2022. EADN: An efficient deep learning model for anomaly detection in videos. Mathematics, 10(9), p. 1555.
26. Dataset is taken from https://www.dropbox.com/sh/75v5ehq4cdg5g5g/AABvnJSwZI7zXb8_myBA0CLHa?dl=0 dated on 04/10/2023.