Intelligent Multi-Group Marine Predator Algorithm With Deep Learning Assisted Anomaly Detection in Pedestrian Walkways

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ABSTRACT Anomaly Detection (AD) in Pedestrian Walkways (PWs) is critical to urban security and safety systems. It is widely used to detect abnormal or unusual behaviour, situations, or events in areas dedicated to pedestrian traffic, namely crosswalks, sidewalks, or pedestrian bridges. The main objective is to improve efficiency, safety, and security in the urban environment by identifying deviations and monitoring pedestrian activities from established norms. This kind of AD typically includes surveillance cameras, sensors, and advanced software algorithms. Using advanced machine learning (ML) and computer vision (CV) approaches, this technique continuously monitors the pedestrian area to detect potential threats and irregularities. Deep Learning Assisted AD in Pedestrian Walkways presents a novel and very efficient method to enhance security and safety in urban environments. Therefore, this study designs an Intelligent Multi-Group Marine Predator Algorithm with Deep Learning Assisted Anomaly Detection (MMPADL-AD) in Pedestrian Walkways. The MMPADL-AD system aims to ensure security in PWs via the AD process. The MMPADL-AD technique incorporates a NASNet feature extractor that proficiently extracts high-level features from surveillance data, allowing a deep understanding of pedestrian behaviors. Besides, the MMPADL-AD technique applies convolutional long short-term memory (ConvLSTM), inheriting the benefits of convolutional neural networks (CNN) and LSTM for the AD process. Finally, the MMPA has been used for the hyperparameter tuning mechanism, which optimizes the model's performance, ensuring accuracy and adaptability. Benchmark data accompanied an extensive set of experiments to ensure the higher effectiveness of the MMPADL-AD approach. The experimental results highlighted the supremacy of the MMPADL-AD approach over other DL methods.

INDEX TERMS Data science, artificial intelligence, intelligent computing, anomaly detection, computer vision.

INTRODUCTION

Yearly, 270,000 pedestrians nearly miss their lives on the world's highways. Responding to pedestrian security is integral to the struggle to stop road traffic damage [1].

Pedestrian accidents, such as further road traffic smashes, will not be as familiar as expected because they are avoidable and predictable [2]. Present technologies, including surveillance cameras (CCTV), computer vision (CV), and others, are utilized to protect pedestrians and support security walking, which requires understanding the risk factors for pedestrian smashes. The main goal of this research is to ensure the
security and safety of PWS by utilizing computer vision models [3]. The surveillance camera in public areas managed the CV-centric technique to absorb the status of the CV study team. The seized visual information comprises enhanced facts that are more correct than the alternative data sources such as radar signals, mobile communication, GPS, and many others [4], [5].

Anomaly detection (AD) is challenging for several reasons; primarily, the description of an anomaly varies from context to context [6]. Next, various options for what creates an anomaly may be unlimited. Then, strange data facts with real-world information tend to lie carefully to what is well-defined as usual. Finally, if anomalies rarely appear, robustness features from the data should be extracted [7]. The above-discussed list will only capture some of the probable reasons that make the problem so hard, but researchers have considered these points in past years while developing novel solutions to the problem. Due to dimensionality swelling, several conventional anomaly recognition models could better demonstrate complex high-dimensional supplies [8]. With the fast growth of Deep Learning (DL), numerous specialists have designed new techniques to integrate them with anomaly recognition. The concept behind this is to accord with AD, which means in the training stage, the method absorbs the distribution features of average data [9]. Once the testing is over, the method recognizes all information that does not fit into the usual class as abnormal data [10].

This study designs an Intelligent Multi-Group Marine Predator Algorithm with Deep Learning Assisted Anomaly Detection (MPADL-AD) in Pedestrian Walkways. The MPADL-AD system incorporates a NASNet feature extractor that proficiently extracts high-level features from surveillance data, allowing a deep understanding of pedestrian behaviours. Besides, the MPADL-AD technique applies convolutional long short-term memory (ConvLSTM), inheriting the benefits of convolutional neural network (CNN) and LSTM for the AD procedure. Finally, the MPDA has been used for the parameter tuning mechanism, which optimizes the model's performance, assuring accuracy and adaptability. An extensive set of experiments were performed on benchmark data to ensure the higher efficiency of the MPADL-AD technique.

- The MPADL-AD model effectively extracts high-level features from surveillance data, allowing for deep comprehension of pedestrian behaviours and improving the technique's capacity for interpreting convolutional scenarios.
- Incorporates the merits of CNN and LSTM models for anomaly recognition processes, allowing the method to comprehend spatial and temporal reliabilities in pedestrian movement patterns effectively.
- Implement the MPDA technique for hyperparameter optimization, and the model's performance is fine-tuned to ensure heightened accuracy and adaptability, consequently boosting its effectiveness in real-world settings.

II. LITERATURE REVIEW

In [11], an effective technique is proposed to detect abnormal things automatically and focus anomalous things amongst multi-pedestrian crowds through DL and conditional random field (CRF). In the first stage, the pre-processing is executed on removed frames, and then super-pixels are created by utilizing an enhanced divide transform. Then, the objects are separated by employing a CRF. The areas of interest are restricted by applying conditional possibility, and the sequential connection is executed to track the areas with pedestrian groups and pedestrians with other items. Al Sulaitie [12] developed a novel Golden Jackal Optimization with DL-based AD in PWs (GJO-DL-ADPW) for road traffic security. This study demoralized the Xception model for the real extraction feature procedure. The GIO approach is often used in this research to determine the optimal hyperparameter. At last, the Bi-LSTM network is employed for anomaly recognition reasons.

Pustokhina et al. [13] devised an automated DL-based AD technique in PW (DLADT-PW) for exposed road consumer security. In the first stage, the DLADT-PW method contains pre-processing, which is then used to extract the noise and increase image quality. The Mask-RCNN with the DenseNet model was also mainly applied for the recognition procedure. Ullah et al. [14] developed a new and effective Gaussian kernel-based integration method (GKIM) for irregular object recognition and localization in pedestrian movements. The GKIM combines spatial-temporal features for effectual and robust motion images to capture characteristic and significant information regarding anomalous things. Next, the author proposed a block-based recognition structure by testing a recurrent CRF by employing the features of GKIM.

Sophia and Chitra [15] propose a Panoptic FPN-based AD and Tracking (PFPN-ADT) technique for PWs. The main aim is to distinguish and organize dissimilar variances in pedestrian footpaths, such as skaters, vehicles, etc. The method includes a panoptic segmentation technique and a FPN, which are utilized for item detection. For object detection, a Compact Bat Algorithm (CBA) with SAE was used for the detection of familiar items. Alsolai et al. [16] project a new SCA with DL-based AD in PW (SCADL-ADPW) system. The developed SCADL-ADPW model recognizes the occurrence of variances in the PW on RSls. To achieve this, the SCADL-ADPW model employs the VGG16 method for the feature vector group. The SCA technique was also mainly intended for the optimum parameter tuning procedure. The LSTM method can be exploited for AD.

García Aguilera et al. [17] developed advanced technology using pre-trained super-resolution (SR) and CNN techniques. This method is divided into two portions. Offline, the pre-tested CNN method estimated a massive dataset of city series to identify and start the common sites of interest parts. Zeng et al. [18] designed a Hierarchical spatiotemporal graph CNN (HSTGCNN) model. Chopra et al. [19] introduce an effectual watermarking model employing a map-based security key via exclusive-OR operation. In [20], an unsupervised
DL and nearest neighbour classification model is presented, which comprises deblurring with DeblurGAN-v2, semantic segmentation with a hybrid CNN-VIT model, multiscale feature aggregation with an attentional feature fusion module, and K-nearest neighbour classification using pre-trained features.

III. THE PROPOSED MODEL

This article has established an automated AD using the MMPADL-AD method for security in PWs. The MMPADL-AD technique analyses the surveillance videos to ensure security in PWs via the AD process. The MMPADL-AD technique incorporates a NASNet feature extractor, ConvLSTM classifier, and MMPA-based hyperparameter optimizer. Fig. 1 depicts the entire procedure of the MMPADL-AD methodology.

A. FEATURE EXTRACTOR: NASNET MODEL

At this stage, the NASNet approach extracts the features from the surveillance video frames. There is considerable progress in DL and computer vision [21]. It is well-known for its capability to optimize and discover NN architecture automatically for feature extraction, enabling it to capture complicated representations and patterns in visual information effectively. NASNet works based on a neural architecture search (NAS) model that automates designing NNs, saving engineers and researchers considerable effort and time. At the core of NASNet’s power is its capability to select and search for optimum NN cell architecture. This process includes exploring different combinations of skip-connection, convolutional, and pooling operations to create NN cells. NASNet detects architecture that achieves better outcomes on a given task through evolutionary or reinforcement learning algorithms. Once these optimum cells are detected, they are stacked to construct robust DNNs personalized for feature extraction. The feature extractor could effectively capture abstract and hierarchical features from the images or other visual information. NASNet has shown remarkable performance on different CV tasks, including object detection and image classification, which outperform manually designed architecture. This makes NASNet an invaluable mechanism for a DL practitioner, as it streamlines the procedure of network design and allows the extraction of discriminative and meaningful features from images, benefiting applications such as AD, image recognition, etc.

B. DETECTION MODULE: CONVLSTM

The ConvLSTM model is applied for classification, which inherits the benefits of CNN and LSTM. LSTM network is a kind of RNN commonly known for addressing drawbacks of long-term memory and processing the data sequence of typical RNN [22]. LSTM lengthens the RNN model using a separate memory unit and gate module controlling the network’s data flow. The gate mechanism includes input, forget, and output gates. This gate controls the data flow throughout the network to enable which data will persist from the memory cell. LSTM network can preserve essential data and remove irrelevant data. Then, to differentiate independent memory cells from hidden state $h_t$ in LSTM, it is signified as $c_t$. The forget gate $f_t$ attains input $s_t$ and $h_{t-1}$ to decide that
data should be maintained in $c_{t-1}$. The activation function, $0_r$, and $f_h$ gates are sigmoid layers where all the values are projected within $[0,1]$, whereas $c_{t-1}$ provides the data retention to define the scale. The abovementioned processes are defined formally by using the following expression:

$$
\tilde{i}_t = \sigma (W_{xi}x_t + W_{hi}h_{t-1} + W_{xc}c_{t-1} + b_i) 
$$

(1)

$$
\tilde{f}_t = \sigma (W_{xf}x_t + W_{hf}h_{t-1} + W_{xc}c_{t-1} + b_f) 
$$

(2)

$$
\tilde{o}_t = \sigma (W_{xo}x_t + W_{ho}h_{t-1} + W_{xc}c_t + b_o) 
$$

(3)

$$
c_t = f_t c_{t-1} + i_t \theta (W_{xc}x_t + W_{hc}h_{t-1} + b_c) 
$$

(4)

$$
h_t = o_t \theta (c_t) 
$$

(5)

$W_{xi}$, $W_{hi}$, $W_{xf}$, $W_{hf}$, $W_{xo}$, $W_{ho}$, $W_{xc}$, $W_{hc}$, and $W_{hc}$ are the weight matrices for the gates and cell state memory. The bias of gates is denoted as $b_i$, $b_o$, $b_f$, and $b_c$ while representing an entry-wise multiplication process, $c_t$ is a cell state, and $h_{t-1}$ is a prior hidden state. Likewise $\theta$, it shows a hyperbolic tangent function, and $\sigma$ represents the logistic sigmoid function. Eqs. (6) & (7) shows the activation functions:

$$
\sigma (x) = \frac{1}{1 + e^{-x}} 
$$

(6)

$$
\theta (x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} 
$$

(7)

Learning via the FC layer of LSTM has proved effective in handling temporal relations, but a redundancy from spatial information has made it increasingly difficult. The whole connection LSTM has added an extension having convolution assembly in input-to-state transition and state-to-state transition to address these challenges. By forecasting mechanisms and forming encoding, stacking multiple layers of ConvLSTM has made the network incapable of spatiotemporal forecasting and precipitation new casting. Like the classical full connection LSTM, ConvLSTM is essential for dealing with more complicated sequences. This layer acts as an encoder that encodes the input-refined series with a defined size later transmitted to LSTM. ConvLSTM employs convolution operations for hidden-hidden and input-hidden connections.

Fig. 2 illustrates the architecture of ConvLSTM. The ConvLSTM layer with convolution operation is used to replace matrix multiplication operation in RNN, and this layer can be used to know which data should be forgotten or retained from the prior cell state. Likewise, ConvLSTM decides which data needs to be stored in the existing cells. The ConvLSTM model can be defined in Eqs (12) to (16). After ConvLSTM, other LSTM layers are plugged in to learn the feature maps and provide the last prediction. This hybrid connection makes it more effective and efficient concerning image classification:

$$
i_t = \sigma (W_{xi}x_t + W_{hi}h_{t-1} + W_{xc}c_{t-1} + h_t) 
$$

(8)

$$
f_t = \sigma (W_{xf}x_t + W_{hf}h_{t-1} + W_{xc}c_{t-1} + b_f) 
$$

(9)

$$
o_t = \sigma (W_{xo}x_t + W_{ho}h_{t-1} + W_{xc}c_t + b_o) 
$$

(10)

$$
c_t = f_t c_{t-1} + i_t \theta (W_{xc}x_t + W_{hc}h_{t-1} + b_c) 
$$

(11)

$$
h_t = o_t \theta (c_t) 
$$

(12)

C. HYPERPARAMETER TUNING: MMPA

Lastly, the MMPA adjusts the hyperparameter value of the ConvLSTM model. MPA is a new optimization algorithm that draws inspiration from predator and prey behaviors while searching for food [23]. MPA is simple and easy to implement. It has good performance in optimization problems. However, it prematurely converges due to an imbalance in its exploitation and exploration abilities. The study proposes an MMPA to optimize the MPA performance. The multi-group process splits the original population into various groups. This group creates an Elite matrix and top predator using communication information and multiple strategies.

The multi-group mechanism splits the population into various groups, which produces the top predator using different strategies. The proposed MMPA might achieve collaborative work throughout groups and optimize the use of each performance through a multi-group process and producing approach.

Accordingly, the top predator is critical to the optimizer technique. The top predator is used to construct an Elite matrix as part of the optimizer algorithm to discover food. This will recommend four producing approaches to create the top predator and Elite matrix to enhance the performance of MMA further.

1) GENERATION METHOD I

The optimum outcomes of a group of people. During the optimization procedure, if the parameters related to the outcomes are autonomous, it is easy to generate the best solutions by interchanging knowledge inside the identical group. Where $\alpha = 0.5$ iteration ($0 = 1, 2, 3, \ldots$), the optimum outcomes $y_{best,h}(a)$ of the similar group generates an Elite matrix in strategy I.

$$
y_{best,h}(a) = Best \{y_{1,h}(a), y_{2,h}(a), \ldots, y_{a,h}(a)\} \ldots (13)
$$

In Eq. (13), $y_{1,h}(a), y_{2,h}(a), \ldots, y_{a,h}(a)$ represent the $i^{th}$ group’s $a$ solutions.
2) GENERATION METHOD 2
The average of a similar group’s solution. The control of method 2 is identical to method 1. In strategy 2, when \(itr = aS\) iteration \((i = 1, 2, 3 \ldots)\), then average performance \(y_{\text{avg},i}(u)\) is generated by averaging \(l\) suitable method of the identical group for the diversity of the population. The \(y_{\text{avg},i}(u)\) is used to make the Elite matrix,

\[
y_{\text{avg},i}(u) = \frac{y_{1,i}(u), y_{2,i}(u), \ldots, y_{l,i}(u)}{l}.
\]

In Eq. (14), \(y_{1,i}(u), y_{2,i}(u), \ldots, y_{l,i}(u)\) is the \(l\) appropriate solution of \(i^\text{th}\) groups.

3) GENERATION METHOD 3
The whole group’s optimum technique. During the optimization process, if the parameter related to the solution is weakly connected, it leads to the best solutions by interchanging data among each group. Where \(itr = aS\) iteration \((i = 1, 2, 3 \ldots)\) is applied in method 3, the optimum option \(y_{\text{max}}(u)\) of complete groups is utilized to generate the Elite matrix.

\[
y_{\text{max}}(u) = \text{Best} \{y_1(u), y_2(u), \ldots, y_0(u)\}.
\]

\(y_1(u), y_2(u), \ldots, y_0(u)\) is the \(O\) solution in the entire group.

4) GENERATION METHOD 4
The average of whole groups’ performances. The impact of method 4 is similar to that of method 3. In strategy 4, when \(itr = aS\) iteration \((i = 1, 2, 3 \ldots)\), the average solution \(y_{\text{avg}}(u)\) is calculated by summing the optimum solution of all the groups for population diversity. \(p_{\text{max,y}}(u)\) is used to make the Elite matrix.

\[
y_{\text{avg}}(u) = \frac{y_{\text{max},1}(u), y_{\text{max},2}(u), y_{\text{max},3}(u), \ldots, y_{\text{max},H}(u)}{H}.
\]

In Eq. (16), the letter \(H\) refers to the total number of groups. \(y_{\text{max},1}(u), y_{\text{max},2}(u), y_{\text{max},3}(u), \ldots, y_{\text{max},H}(u)\) is the best outcome of all the groups.

The fitness choice is a primary factor in the MMPA technique. The encoded results have been exploited to assess the goodness of the performance candidates. The accuracy values are the primary condition used to design an FF.

\[
\text{Fitness} = \max (P)
\]

\[
P = \frac{TP}{TP + FP}
\]

Meanwhile, \(TP\) and \(FP\) are true positive and false positive values.

**IV. RESULTS AND DISCUSSION**
The anomaly detection outcome of the MMPADL-AD system is tested on three datasets: UCSDPed1, UCSDPed2, and Avenue datasets, as represented in Table 1.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>No. of Videos</th>
<th>Training Set</th>
<th>Testing Set</th>
<th>Average Frames</th>
<th>Dataset Length</th>
</tr>
</thead>
<tbody>
<tr>
<td>UCSDPed1 (Bikens, small cars, walking across walkways)</td>
<td>70</td>
<td>36</td>
<td>201</td>
<td>5 min</td>
<td></td>
</tr>
<tr>
<td>UCSDPed2 (Bikens, small cars, walking across walkways)</td>
<td>28</td>
<td>16</td>
<td>165</td>
<td>5 min</td>
<td></td>
</tr>
<tr>
<td>Avenue (Run, throw, new object)</td>
<td>37</td>
<td>16</td>
<td>839</td>
<td>5 min</td>
<td></td>
</tr>
</tbody>
</table>

**FIGURE 3.** Accu. curve of MMPADL-AD algorithm on UCSDPed1 dataset.

Fig. 3. These curves deliver an appreciated understanding of the technique’s learning growth and its capability to generalize. However, as the number of epochs rises, an observable development in TR and TS \(\text{accuracy}\) curves becomes apparent. This improvement designates the model’s ability to improve and identify designs in both datasets.

**FIGURE 4.** Loss curve of MMPADL-AD technique loss values under the TR procedure on the UCSDPed1 dataset. The decreasing trend in TR loss with epochs specifies that the
method repeatedly refines its weights to decrease prediction errors on both databases. This loss curve replicates how well the technique fits the TR data. Notably, the TR and TS loss constantly drop, validating the method’s effective learning of designs obtainable in both TR and TS data. In addition, it displays the model’s version in decreasing differences among predictive and novel TR labels.

Table 2 and Fig. 5 represent the TPR outcomes of the MMPADL-AD method on the UCSDPed1 dataset [24]. The outcomes signify that the SF and MPFCA algorithms are depicted as the lowest outcome. At the same time, the EADN and AMDN models have managed to report moderate performance. Meanwhile, the ADP-W-FLIH0 model has tried to accomplish considerable outcomes. However, the MMPADL-AD technique reaches maximum TPR performance over varying FPR rates.

**TABLE 2:** TPR outcome of MMPADL-AD algorithms with other systems on UCSDPed1 database.

<table>
<thead>
<tr>
<th>TPR</th>
<th>MMPCA</th>
<th>SF</th>
<th>AMDN</th>
<th>EADN</th>
<th>ADP-W</th>
<th>FLIH0</th>
<th>MMPADL-AD</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>1</td>
<td>0.311</td>
<td>0.322</td>
<td>0.346</td>
<td>0.368</td>
<td>0.389</td>
<td>0.396</td>
<td>0.401</td>
</tr>
<tr>
<td>2</td>
<td>0.519</td>
<td>0.525</td>
<td>0.531</td>
<td>0.538</td>
<td>0.546</td>
<td>0.551</td>
<td>0.555</td>
</tr>
<tr>
<td>3</td>
<td>0.611</td>
<td>0.617</td>
<td>0.624</td>
<td>0.631</td>
<td>0.637</td>
<td>0.641</td>
<td>0.646</td>
</tr>
<tr>
<td>4</td>
<td>0.677</td>
<td>0.682</td>
<td>0.688</td>
<td>0.693</td>
<td>0.698</td>
<td>0.703</td>
<td>0.707</td>
</tr>
<tr>
<td>5</td>
<td>0.718</td>
<td>0.723</td>
<td>0.728</td>
<td>0.733</td>
<td>0.738</td>
<td>0.743</td>
<td>0.747</td>
</tr>
<tr>
<td>6</td>
<td>0.751</td>
<td>0.756</td>
<td>0.762</td>
<td>0.767</td>
<td>0.772</td>
<td>0.777</td>
<td>0.781</td>
</tr>
<tr>
<td>7</td>
<td>0.783</td>
<td>0.788</td>
<td>0.793</td>
<td>0.798</td>
<td>0.803</td>
<td>0.808</td>
<td>0.812</td>
</tr>
<tr>
<td>8</td>
<td>0.806</td>
<td>0.811</td>
<td>0.816</td>
<td>0.821</td>
<td>0.826</td>
<td>0.831</td>
<td>0.835</td>
</tr>
</tbody>
</table>

MMPADL-AD technique accomplish an enhanced AUC\textsubscript{score} of 99.57%. On the other hand, the ADP-W-FLIH0, EADN, binary SVM, MIL-C3D, TSN-Optical Flow, Spatiotemporal, and TSN-RGB approaches obtain decreased AUC\textsubscript{score} values of 99.36%, 98.36%, 96.73%, 94.99%, 92.86%, 91.57%, and 90.49%, respectively.

For computing the effectiveness of the MMPADL-AD approach on the UCSDPed2 dataset, we have produced accu\textsubscript{y} curves for the TR and TS sets, as illustrated in Fig. 7. These curves provide valuable perceptions into the model’s learning development and its capacity to simplify. Since it increases the epoch numbers, a perceptible development in TR and TS accu\textsubscript{y} curves becomes evident. This growth shows the model’s ability to improve and distinguish patterns from TR and TS datasets.

Fig. 8 also summarises the MMPADL-AD methodology loss values during the TR procedure on the UCSDPed2 dataset. The decreasing trend in TR loss over epochs shows that the approach frequently improves weights to diminish prediction errors on both databases. This loss curve
TABLE 3. TPR outcome of MMPADL-AD algorithm with other methodologies under UCSDPed2 database.

<table>
<thead>
<tr>
<th>TPR</th>
<th>MPCC A</th>
<th>SF</th>
<th>AMD N</th>
<th>EAD N</th>
<th>ADPW - FLHIO</th>
<th>MMPADL - AD</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.0000</td>
<td>0</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
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<tr>
<td>5</td>
<td>0.0718</td>
<td>0.123</td>
<td>0.3000</td>
<td>0.245</td>
<td>0.5654</td>
<td>0.7292</td>
</tr>
<tr>
<td>10</td>
<td>0.2474</td>
<td>0.266</td>
<td>0.4764</td>
<td>0.532</td>
<td>0.6423</td>
<td>0.7963</td>
</tr>
<tr>
<td>15</td>
<td>0.3615</td>
<td>0.414</td>
<td>0.5441</td>
<td>0.999</td>
<td>0.7870</td>
<td>0.9470</td>
</tr>
<tr>
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<td>0.490</td>
<td>0.6751</td>
<td>0.744</td>
<td>0.8617</td>
<td>0.9586</td>
</tr>
<tr>
<td>25</td>
<td>0.5580</td>
<td>0.645</td>
<td>0.6895</td>
<td>0.779</td>
<td>0.9035</td>
<td>0.9796</td>
</tr>
<tr>
<td>30</td>
<td>0.6882</td>
<td>0.729</td>
<td>0.8621</td>
<td>0.924</td>
<td>0.9367</td>
<td>0.9995</td>
</tr>
<tr>
<td>35</td>
<td>0.7149</td>
<td>0.926</td>
<td>0.9199</td>
<td>0.945</td>
<td>0.9587</td>
<td>0.9989</td>
</tr>
<tr>
<td>40</td>
<td>0.7711</td>
<td>0.873</td>
<td>0.9303</td>
<td>0.951</td>
<td>0.9853</td>
<td>1.0000</td>
</tr>
<tr>
<td>45</td>
<td>0.7947</td>
<td>0.925</td>
<td>0.9386</td>
<td>0.957</td>
<td>0.9767</td>
<td>1.0000</td>
</tr>
<tr>
<td>50</td>
<td>0.8283</td>
<td>0.940</td>
<td>0.9563</td>
<td>0.964</td>
<td>0.9815</td>
<td>1.0000</td>
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The TPR outcomes for the MMPADL-AD model are shown in Table 3. The TPR is the True Positive Rate, which measures the proportion of actual positive cases that are correctly identified. The table compares the performance of MMPADL-AD with other methodologies such as MPCC A, SF, AMD N, EAD N, ADPW - FLHIO, and MMPADL - AD.

Fig. 7 and Fig. 8 illustrate the Accuracy and Loss curves for MMPADL-AD under the UCSDPed2 dataset. These curves indicate how well the model performs over time and across iterations.

Fig. 9 presents the TPR outcome for MMPADL-AD. The TPR curve shows the proportion of true positive classifications at each FPR (False Positive Rate) level. The performance of the model is evaluated by comparing it with other methodologies, as shown in the table.

Reproducible research ensures that the methodology and results can be validated independently. The accuracy plots in Fig. 7 and Fig. 8 provide insights into how well the model generalizes to different datasets. The TPR plot in Fig. 9 visually confirms the model's efficacy in distinguishing between positive and negative cases.

The outcome analysis in Table 3 highlights that the SF and MPCC A techniques have shown the least performance. Similarly, the EADN and AMDN methods have achieved moderate performance. Meanwhile, the ADPW-FLHIO technique has tried to achieve significant outcomes. However, the MMPADL-AD model reaches extreme TPR performance over varying FPR rates.

Fig. 10 explains a comparative $AUC_{score}$ outcome for the MMPADL-AD model. The achieved values of the MMPADL-AD method resulted in an improved $AUC_{score}$ of 99.36%. In addition, the ADPW-FLHIO, EADN, binary SVM, MIL-CID, TSN-Optical Flow, Spatiotemporal, and TSN-RGB approaches attain diminished $AUC_{score}$ values of 99.19%, 98.30%, 97.16%, 95.50%, 94.36%, 92.48%, and 90.44%, respectively.

To compute the efficiency of the MMPADL-AD approach on the Avenue dataset, we have created a list of curves for...
Fig. 12 also offers an overview of the MMPADL-AD technique loss values during the TR procedure on the Avenue dataset. The lesser development in TR loss with epochs designates that the methodology frequently refines its weights to decrease forecast errors on both databases. This loss curve imitates how well the method fits the TR data. Mainly, the TR and TS losses are regularly lesser, specifying that the model is productive patterns learning in both data. Additionally, it displays the model’s variation in minimizing differences between predictive and new TR labels.

Table 4 and Fig. 13 denote the TPR outcome of the MMPADL-AD approach on the Avenue database. The performance depicts that the SF and MPPCA techniques have shown the most minor performance. At the same time, the EADN and AMDN models have accomplished reported moderate results. Meanwhile, the ADPW-FLHIO approach

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Fig. 13. TPR outcome of MMPADL-AD algorithm on Avenue dataset.

Fig. 14 shows a comparative AUC score outcome of the MMPADL-AD model. The attained values of the MMPADL-AD model accomplish a greater AUC score of 99.05%. On the other hand, the ADPW-FLHBO, EADN, binary SVM, MIL-C3D, TSN-Optical Flow, Spatiotemporal, and TSN-RGB techniques acquire reduced AUC score values of 98.96%, 97.78%, 96.24%, 95.02%, 93.31%, 91.41%, and 89.47%, correspondingly.

These results show the practical ability of the MMPADL-AD methodology in anomaly detection.

V. CONCLUSION

This article has established an automated AD using the MMPADL-AD method for security in PWs. The MMPADL-AD technique analyses the surveillance videos to ensure security in PWs via the AD process. The MMPADL-AD technique incorporates a NASNet feature extractor, ConvLSTM classifier, and MMPA-based hyper-parameter optimizer. The NASNet feature extractor enables the derivation of high-level features from surveillance data, allowing a deep understanding of pedestrian behaviors. The ConvLSTM model is applied for classification, which inherits the benefits of CNN and LSTM. Lastly, the MMPA is used for the hyperparameter tuning mechanism, which optimizes the model’s performance, assuring accuracy and adaptability. Benchmark data accompanied an extensive set of experiments to ensure the higher efficiency of the MMPADL-AD method. The simulation values highlighted the supremacy of the MMPADL-AD method with other DL methodologies. The efficiency of the MMPADL-AD method may be restricted in highly crowded or dynamic pedestrian environments. Future studies may focus on improving the robustness of the model to several environmental conditions.

ACKNOWLEDGMENT

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REFERENCES


