Integrating Transfer Learning with Neutrosophic Weighted Extreme Learning Machine for Violence Detection in Smart Cities

Nigora Khaytboeva[1,*], Sergey Bakhvalov[2], Veronika Denisovich[3], Rafina Zakieva[4]

[1]Department of Management and Marketing, Urgench State University, Urgench, 220100, Uzbekistan
[2]Department of Economics and Management of Elabuga Institute, Kazan Federal University, Kazan, 420008, Russia
[3]Institute of Digital Technologies and Law, Kazan Innovative University named after V. G. Timiryasov, Kazan, 420111, Russia
[4]Department of Industrial Electronics and Lighting Engineering, Kazan State Power Engineering University, Kazan, 420066, Russia
Emails: khaytboeva.n@mail.ru, bakhvalov.s.yu@yandex.ru, veronika.denisovich@inbox.ru, zakievarr@inbox.ru

Abstract

Neutrosophic logic extends conventional and fuzzy logic (FL) by integrating the concepts of indeterminacy, truth, and falsity, enabling for a further extensive management of uncertainty. In classical binary logic, a statement can be either true or false. FL extends this by adding degree of truth, where a statement is partially true or false. The smart city technology shown to be an effective solution to the problems regarding improved urbanization. The practical applications of a smart city technology to video surveillance relies on the ability of processing and gathering large quantities of live urban data. Violence detection is considered as a major challenge in smart city monitoring. The required computational power is substantial due to the large volume of video data gathered from the extensive camera network. As a result, the algorithm based on handcrafted features utilizing video and image processing fails to provide a promising solution. Deep Learning (DL) and Deep Neural Networks (DNNs) models are more reliable to handle these data. In this study, we introduce a Transfer Learning with Neutrosophic Weighted Extreme Learning Machine for Violence Detection (TL-NWELMVD) technique in smart cities. The TL-NWELMVD technique aims to recognize the presence of the violence in the smart city environment. In the TL-NWELMVD technique, the features can be extracted using SE-RegNet model. To enhance the performance of the TL-NWELMVD technique, a hyperparameter optimizer using monarch butterfly optimization (MBO) is involved. Finally, the NWELM classifier is applied for the identification of violence in the smart city environment. To investigate the accomplishment of the TL-NWELMVD technique, a widespread investigational outcome is involved. The simulation results portrayed that the TL-NWELMVD technique gains better performance compared to other models.

Keywords: Violence Detection; Transfer Learning; Monarch Butterfly Optimization; Membership Function; Neutrosophic Set; Fuzzy Logic

1. Introduction

The idea regarding the neutrosophic set (NS) from philosophic places to look to simplification of the concepts in FS and IFS [1]. An NS comes to be categorized with an indeterminacy membership function (MF) (IMF), truth MF (TMF), and falsity MF (FMF), and then every membership points to an actual standardized or else non-standardized sub-set in the non-standardized unit's intervals] −0, 1+[. In different IFSs, there are no limits to MF in an NS, and then the point of tentativeness involves the NS [2]. However, NSs are tough to apply for real-world difficulties whereas the values of the indeterminacy, falsity, and truth of MFs rest in] −0, 1+[. Accordingly, the theory extends to numerous NSs whose truth, falsity, and indeterminacy MFs accept a single value from the enclosed intervals of 1 and 0 [3]. The Smart City developing project is an initial creative investigation and growing

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024

area. Smart cities' actions and methodology have the goal of constructing and investigating information and achieving the latest bits of knowledge on the complexes and dynamics of cities [4]. Smart city surveillance techniques cover a wide variety of presentations comprising, urban traffic surveillance systems, violence detections, disaster management, and building structural damage detections [5]. Violence detections denote a main problem of smart-city surveillance methods. The cost-efficient result utilized a wireless sensor network-based framework. Nevertheless, likely solutions suggest nodes with small computing powers and partial communicating ranges. Several methods are used to conquer the issues [6].

The Detection and Recognition methods applied in standard detection systems are generally based on deep learning and machine learning algorithms [7]. The last study explains particularly that these involved small images, difficult violence detection scenes, the lack of real-time processing, and constant continuous monitoring, which were difficulties and restrictions. Despite that, one can able to identify violent activities in public spots using deep owed of training-based computer views [8]. Surveillance cameras are used for positioning in public places and private communities. The potential violent identifying techniques help to government or administration to consider quick and formal methods for detecting the severity method to prevent the destruction done to public properties and human lives, as everybody needs secured areas, streets, and working surroundings [9]. Machine learning (ML) is lower than Deep learning (DL) methods meanwhile it does not require any features engineering [10]. In that respect, a particular drawback is arrived are high computational costs and large trained databases.

This study introduce a Transfer Learning with Neutrosophic Weighted Extreme Learning Machine for Violence Detection (TL-NWELMVD) technique in smart cities. The TL-NWELMVD technique aims to recognize the presence of the violence in the smart city environment. In the TL-NWELMVD technique, the features can be extracted using SE-RegNet model. To enhance the performance of the TL-NWELMVD technique, a hyperparameter optimizer using monarch butterfly optimization (MBO) is involved. Finally, the NWELM classifier is applied for the identification of violence in the smart city environment. The simulation results portrayed that the TL-NWELMVD technique gains better performance compared to other models.

2. Literature Works

Dalal et al. [11] proposed YOLO method with TL for intellectual surveillance in IoT-based home surroundings. Quantization models are used to enhance YOLO method. Utilizing YOLO with quantization, the technique was elevated for usage on mobile platforms and edge device that have restricted calculating skills. Therefore, with restricted technique, the object recognition models was utilized in numerous real uses. In [12], dual DL techniques of dissimilar features are projected to identify speech data having violent behaviour beside data, which contains non-violent behaviour patterns. The initial method is depend upon conventional deep neural networks (CDNN), while another method utilizes light-weight DNNs. Khan et al. [13] proposed an AI-based structure named Violence Detection Network (VD-Net), permitted by Intelligent IOT (IIoT). The method uses lightweight special task temporal convolution network (ST-TCN) and numerous layers of bottleneck to concentrate on significant feature in the input series. The learned features distributed from the classifier to distinguish among nonviolent and violent actions. Moreover, if violence is identified, then the method is expected to generate an attentive, which is then conveyed to related departments.

Shoaib et al. [14] concentrated on violence recognition in huge video datasets, suggesting dual keyframe-based methods called AreaDiffKey and DeepkeyFrm. KFCRNet and EvoKeyNet are the developed identification techniques, which influence extraction of feature from optimum keyframe. EvoKeyNet utilizes an evolutionary mode for selecting optimum feature aspects, whereas KFCRNet used a combination of BiLSTM, LSTM, and GRU techniques with a scheme of voting. Elakiya et al. [15] This paper projected a violence recognition structure based on CNN with LSTM feature extraction procedure and perfected the image frame hyperparameters from removed feature utilizing Random forest (RF) classifier upgraded with the weight score over Weight least square (WLS) model. The combination of LSTM and CNN structure was used to decrease the difficulty of the extraction learning procedure. The dynamic weighing scheme has been projected with WLS model. Many same parameters as hyperparameter were modified over a RF classifier. Jaafar and Lachiri [16] presented a model depends on the 4 multi-modal fusion with DL models. The projected method utilizes DNN method. The primary multi-modal fusion model is depend upon an intermediate level, which covers the forecasts of video, audio, and the 5 meta-features by executing many DNN. The second fusion model utilizes the integration of the dissimilar features with meta-

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024

feature as classes. The further dual fusion approaches are element-wise processes, which uses element-wise product and concatenation utilizes the element-wise addition.

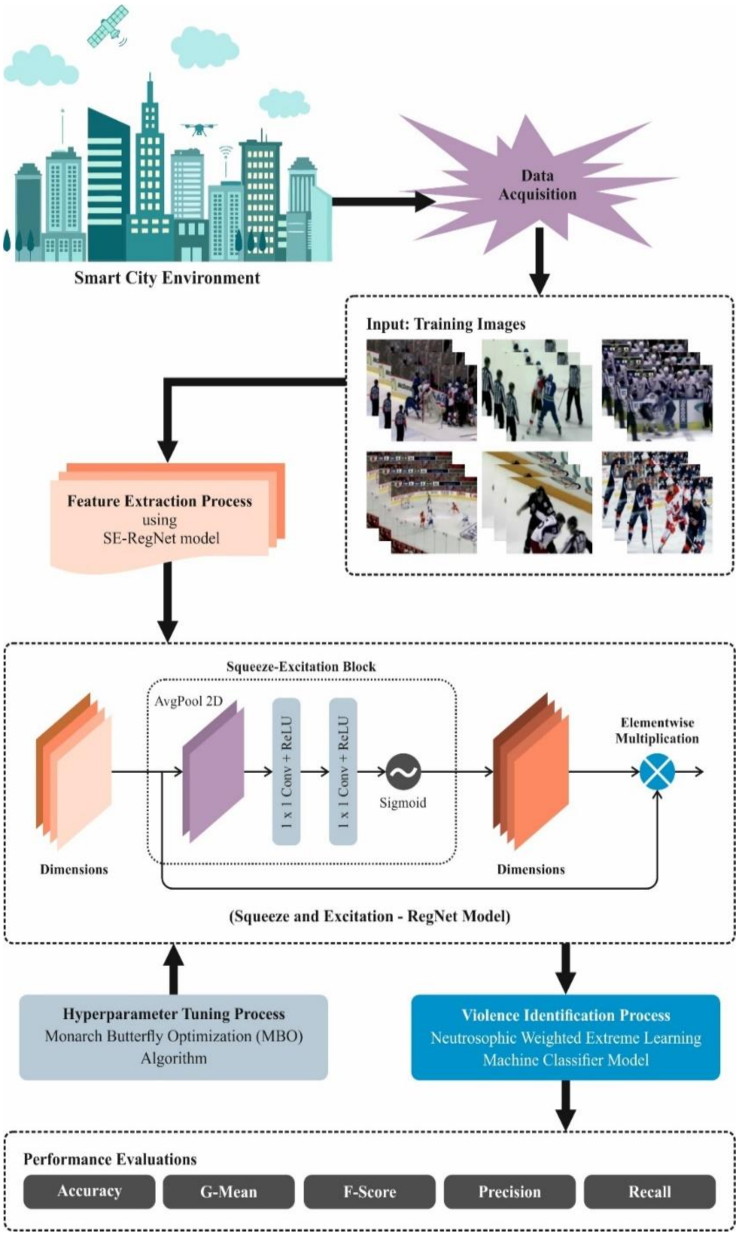


Figure 1. Workflow of TL-NWELMVD methodology

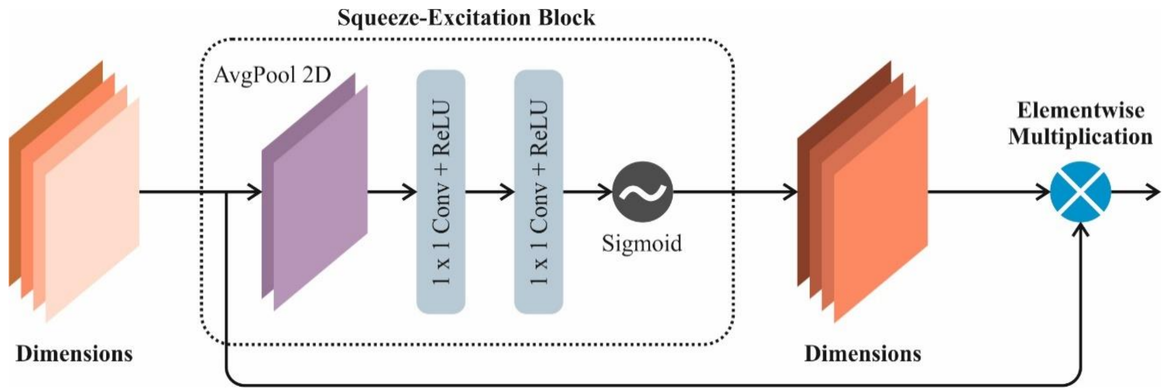
3. Materials and Methods

In this study, we have developed a novel TL-NWELMVD methodology in smart cities. The TL-NWELMVD technique aims to recognize the presence of the violence in the smart city environment. To accomplish that, the TL-NWELMVD technique has feature extractor, MBO based parameter tuning, and NWELM based detection process are demonstrated in Fig. 1.

A. Feature Extraction Process

Primarily, the TL-NWELMVD technique undergoes the features can be extracted using SE-RegNet approach. The SE-RegNet method represents a cutting-edge architectural integration, integration the strengths of SE blocks with

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024



effectual RegNet structure [17]. SE blocks that adjustably recalibrate each channel feature responses, enhance the network's ability to represent information by systematically capturing the relationships between channels, reaching significant performance improvements with minimal extra computational requirements. The choice of SE-RegNet is determined by the condition for model proficient at processing, accomplished of accentuating pertinent features and reducing unrelated ones. The combination of SE blocks into RegNet structure purposes to use spatial and each channel attention mechanisms, so enhancing feature extractor and learning efficiency placing SE-RegNet as a better election for this challenging area. Fig. 2 depicts the architecture of SE-RegNet.

Figure 2. SE-RegNet Architecture

Central to its design is the integration of SE blocks that present a dynamic channel-wise attention mechanism for improving the feature learning method. These blocks deploy global average pooling to reduce spatial data as a succinct channel descriptor that is after developed by a sequence of FC layers, ensuing in an each channel modulation of the mapping features depends on the learned significance of all the channels.

B. Hyper parameter Tuning

To enhance the performance of the TL-NWELMVD approach, a hyper parameter optimizer using MBO is involved. Every butterfly in an algorithm of monarch butterfly is $X = x^1, x^2, \dots, x^D$, and the locations are intended by fitness function (FF) $F(X)$ [18]. The population of monarch butterfly is spread on dual lands such as landl and land2. For an arbitrary monarch butterfly, its probability on land1 and land2 is p, and l-p. The overall population was separated into dual sets. During this research work, the p rate is 5/12. The population on land1 was migrant, while on land2 has been adaptive to the atmosphere.

The population on land1 is migrant, and the population of entities is p. The mathematical calculation is given below:

$$x_{new}^{d} = \begin{cases} x_{r1}^{d}, rand * peri \leq p \\ x_{r2}^{d}, rand * peri > p \end{cases} \tag{1}$$

Whereas, x_{new}^{d} denotes the dth dimension of a novel individual, $r1$ and $r2$ refers the random individual in land1 and land2, respectively. $rand$ denotes the uniform randomly generated integer among 0 and 1, $peri$ refers to a constant, and the p rate is 5/12. That is, $D/2$ dissimilar sizes of individuals are nominated from the dual sets to produce a novel individual.

The novel individual fits to the set of land1. Once the individual is higher than the equivalent parent class, it substitutes the parent class, or else it can be wild. Furthermore, the formulation displays that this is a process that could not be divided from the local optimal, and no novel location is made. If the population converges, the novel individual could not alter much, which is parallel to the crossover process of the genetic model.

Different the population of land1, the land2 population is intended as below to adjust to the atmosphere:

$$x_{i,new}^{d} = \begin{cases} x_{best}^{d}, rand\ 1 \leq p \\ \chi_{r3}^{d}, randl > p \& rand2\ \geq BAR \\ \chi_{r3}^{d} + \frac{S_{\max}}{t^2} \cdot Levy\left(x_i^d\right), rand1 > p \& rand2\ > BAR \end{cases} \tag{2}$$

where x_{best}^{d} refers to the dth dimensional of an optimum individual; $r3$ signifies to the randomly generated individual from land2; S_{mox} denotes the highest stride length, which commonly takes the value of 1; t denotes the

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024

present iterations count; $Levy$ is the arbitrary levy fight; $rand1$ and $rand2$ are uniform randomly generated numbers among 0 and 1; and BAR refers to the constant value of 5/12.

The MBO method derives a fitness function to attain an improved classification accomplishment. It determines a positive numeral to depict the improved accomplishment of the candidate outcomes. In addition, the minimization of the classification error rate is considered as the fitness function, as depicted in Eq. (3).

$$fitness(x_i) = ClassifierErrorRate(x_i)$$

$$= \frac{No.of\ misclassified\ samples}{Total\ number\ of\ samples} * 100 \quad (3)$$

C. Violence Detection using NWELM Classifier

Finally, the NWELM classifier is applied for the identification of violence in the smart city environment. Neutrosophy is a general method of intuitionistic FL philosophy [19]. Where, there is no limitation for indeterminacy, falsity, truth, so they contain a unit real range values for every element NS, and they are independent. Occasionally, intuitionistic fuzzy logic is not sufficient for resolving few real issues, which is engineering issues. Therefore, neutrosophic elements are more significant for demonstrating these issues in a mathematically. Much research work was led in numerous regions of computer science and mathematics as Smarandache prepared the description of philosophical.

Description 3. Assume E as a universe of discourse and $A \subseteq$E.$A = \{(x, T(x), I(x), F(x)): x \in E\}$ as a NS or SVNS, whereas $I_A, T_A, F_A: A \to]^{-}0, 1^{+}[$ denotes the functions of the IMF, TMF, and FMF, correspondingly. Where, $-0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3^{+}$.

Description 4. For SVNS A in E, the three-way $\langle T_A, I_A, F_A \rangle$ was named as SVNN.

Description 5. Assume $n = \langle T_n, I_n, F_n \rangle$ as a SVNN, where the score function n is assumed below:

$$s_n = \frac{1+T_n-2I_n-F_n}{2} \quad (4)$$

Whereas, $s_n \in [-1,1]$.

Description 6. Assume $n = \langle T_n, I_n, F_n \rangle$ as a SVNN, where the accuracy function n is assumed below:

$$h_n = \frac{2+T_n-I_n-F_n}{3} \quad (5)$$

While $h_n \in [0,1]$.

Description 7. Assume n_1 and n_2 as a dual SVNN. Next, the position of dual SVNN is distinct as below:

(I) When $s_{n_1} > s_{n_2}$, then $n_1 > n_2$,

(II) When $s_{n_1} = s_{n_2}$ and $h_{n_1} \geq h_{n_2}$, then $n_1 \geq n_2$.

Assume a training dataset as $[x_i, t_i], i = 1, \ldots, N$ belongs to dual classes, whereas $x_i \in R^n$ and t_i denotes the classes [20]. In dual classification, t_i is both -1 and $+1$. Next, a $N \times N$ diagonal matrix W_{ii} was measured, where everyone is linked with a sample of training x_i. The weight process normally allocates greater W_{ii} to x_i, which derives from the smaller class.

An optimizer issue is used to enlarge the distance of marginal and to minimalize the weighted cumulative error as:

$$Minimize: \ ||H\beta - T||^2 \ and \ ||\beta||. \quad (6)$$

Additionally:

$$Minimize: L_{ELM} = \frac{1}{2}||\beta||^2 + CW\frac{1}{2}\sum_{i=1}^{N} ||\ \xi_i||^2, \quad (7)$$

$$Subjected\ to: h(x_j)\beta = t_i^T - \xi_i^T, i = 1,2, \ldots, N, \quad (8)$$

Whereas, $T = [t_1, \ldots, t_N]$, ξ_i denotes the vector of error and $h(x_i)$ represents the feature map vector from the hidden layer (HL) with esteem to x_i, and β. By utilizing the Karush−Kuhn−Tucker and Lagrage multiplier theorem, the binary optimizer issue could be resolved. Therefore, HLs weight vector of output β could be resultant

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024

from Eq. (8) about left or right pseudo-inverses. The right pseudo-inverse has been suggested since it includes inverse of a $N \times N$ matrix. Or else, left pseudo-inverse is highly appropriate because it is simpler to calculate matrix reverse of size LxL whereas L is lesser than N:

$$If\ N\ is\ small:\ \beta = H^T(\frac{I}{C} + WHH^T)^{-1}WT, \quad (9)$$

$$If\ N\ is\ large: \beta = H^T(\frac{I}{C} + H^TWT)^{-1}H^TWT. \quad (10)$$

In WELM, the authors implemented dual dissimilar weighting schemes. At first, the minority and majority class's weights have been formulated below:

$$W_{minority} = \frac{1}{\#(t_i^+)}\ and\ W_{majority} = \frac{1}{\#(t_i^-)}, \quad (11)$$

In 2nd , the related weights are formulated as:

$$W_{minority} = \frac{0.618}{\#(t_i^+)}\ and\ W_{majority} = \frac{1}{\#(t_i^-)}. \quad (12)$$

WELM allocates the similar value of weights to every models from the minority class and other similar value of weight to every models in the majority class. While this process functions well in few imbalanced datasets, allocating the similar value of weight to every models in a class that contain outlier samples and noise. In order to deal with outlier samples and noise in an imbalanced dataset, dissimilar values of weight are required for every sample in all class. So, we offer a new technique for determining the impact of every samples in its class. NCM clustering could define a noise, samples, and indeterminacy memberships that employed in order to calculate a value of weight for that model.

The authors developed the NCM clustering models depend upon the NS theorem. In NCM, a novel cost function has been proposed to overwhelm the fault of FCM technique on outlier data and noise points. In NCM model, dual novel kinds of elimination were proposed for outlier and noise eliminations. The objective function was expressed below:

$$J_{NCM}(T, I, F, C) = \sum_{i=1}^{N}\sum_{j=1}^{C}(\overline{w}_1 T_{ij})^m \|x_i - c_j\|^2$$

$$+ \sum_{i=1}^{N}(\overline{w} I_i)^m \|x_i - \overline{c}_{imax}\|^2 + \delta^2 \sum_{i=1}^{N}(\overline{w} F_i)^m, \quad (13)$$

Whereas, m denotes a constant. For every point i, $\overline{c}_{imax}$ refers to the mean of dual centers. T_{ij}, I_i and F_i represents the membership values, which belongs to the determinate groups, boundary areas and noisy dataset. $\theta < T_{ij}, I_i, F_i <$ 1:

$$\sum_{j=1}^{c} T_{ij} + I_i + F_i = 1. \quad (14)$$

Therefore, the MFs have been computed below:

$$T_{ij} = \frac{\overline{w}_2 \overline{w}_3 (x_i - c_j)^{-\left(\frac{2}{m-1}\right)}}{\Sigma_{j=1}^{C}(x_i - c_j)^{-(\frac{2}{m-1})} + (x_i - \overline{c}_{imax})^{-(\frac{2}{m-1})} + \delta^{-(\frac{2}{m-1})}}, \quad (15)$$

$$I_i = \frac{\overline{w}_1 \overline{w}_3 (x_i - c_{imax})^{-\left(\frac{2}{m-1}\right)}}{\Sigma_{j=1}^{C}(x_i - c_j)^{-(\frac{2}{m-1})} + (x_i - \overline{c}_{imax})^{-(\frac{2}{m-1})} + \delta^{-(\frac{2}{m-1})}}, \quad (16)$$

$$F_i = \frac{\overline{w}_1 \overline{w}_2 (\delta)^{-\left(\frac{2}{m-1}\right)}}{\Sigma_{j=1}^{C}(x_i - c_j)^{-(\frac{2}{m-1})} + (x_i - \overline{c}_{imax})^{-(\frac{2}{m-1})} + \delta^{-(\frac{2}{m-1})}}, \quad (17)$$

$$C_j = \frac{\Sigma_{i=1}^{N}(\overline{w}_1 T_{ij})^m x_i}{\Sigma_{i=1}^{N}(\overline{w}_1 T_{ij})^m}, \quad (18)$$

Here, c_j denotes the center of jth group; $\overline{w}_1$, $\overline{w}_2$, and $\overline{w}_3$ refers to the factors of weight and δ denotes the regularization factor. Each input sample in every majority and minority classes were linked with a T_{ij}, I_i, F_i.

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024

Once the clustering technique was used in NCM, the every sample of majority and minority classes weights are attained below:

$$W_{ii}^{minority} = \frac{C_r}{T_{ij}+I_i-F_i} \; and \; W_{ii}^{majority} = \frac{1}{T_{ij}+I_i-F_i}, \tag{19}$$

$$C_r = \frac{\#(t_i^-)}{\#(t_i^+)}, \tag{20}$$

Here, C_r denotes the ratio of numerous samples from the majority class to many instances in the minority class.

The method of NWELM is made of 4 steps. The first step requires using the NCM model depend upon the pre-calculated center of cluster, as per to the class labels. Therefore, T, I and F membership values are defined for the subsequent step. The weights are computed from the defined T, I and F membership rates in the second stage.

In Stage 3, the parameters of ELM were adjusted, so samples and weights were served into the ELM for calculating the H matrix. The HL weighted vector β has been computed as per H, W and classes. Lastly, the conclusion of the class labels of the test dataset was achieved in the last stage of the algorithm.

The NWELM algorithm procedure is mentioned below:

Input: Considered training dataset.

Output: Predicted classes.

Step1: Set the cluster center as per the considered dataset and run procedure of NCM to get T, I and F values for every data points.

Step2: Calculate $W_{ii}^{minority}$ and $W_{ii}^{majority}$ as per the Eqs. (19) and (20).

Step3: Alter the parameters of ELM and run NWELM. Calculate the matrix of H and get β as per the Eqs. (9) or (10).

Step4: Compute the class labels of test dataset depend upon β.

4. Performance Validation

The performances validation of the TL-NWELMVD technique is tested using hockey fights dataset, which contains 1000 instances with two classes are represented in Table 1.

Table 1: Specification on dataset

Hockey Fights Dataset	
Class	No. of Instances
Violence	500
Non-Violence	500
Overall Instances	1000

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024

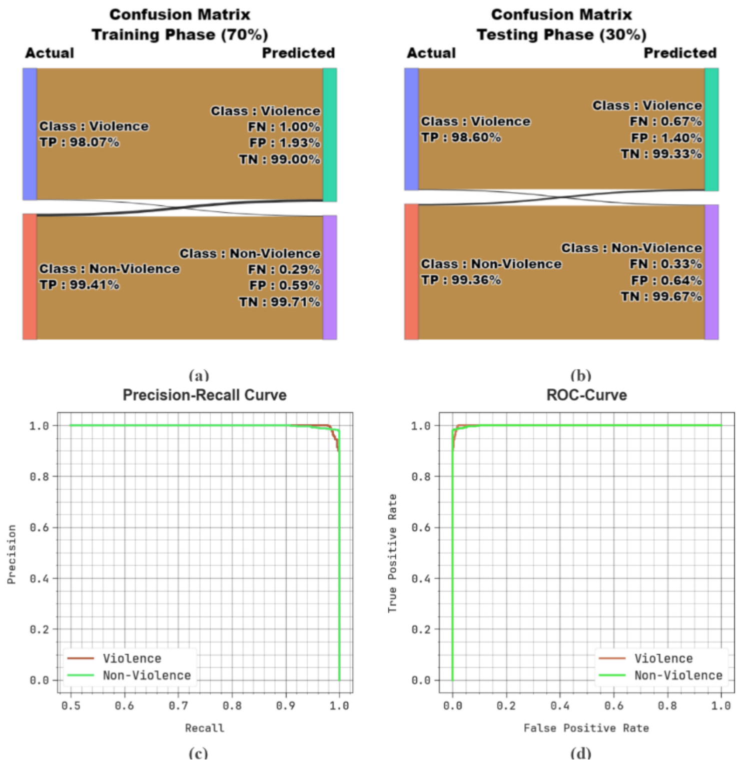


Fig. 3. Classifier outcome of (a-b) 70% and 30% confusion matrices and (c-d) PR and ROC curves

Fig. 3 shows the classifier outcomes of the TL-NWELMVD approach. Figs. 3a-3b depicts the confusion matrices shown by the TL-NWELMVD approach on 70%TRP and 30%TSP. The figure signified that the TL-NWELMVD method has accurately recognized and classified the overall two classes. Simultaneously, Fig. 3c depicts the PR evaluation of the TL-NWELMVD approach. The figure illustrated that the TL-NWELMVD method attained optimum PR performance under two classes. Lastly, Fig. 3d depicts the ROC analysis of the TL-NWELMVD technique. The figure showed that the TL-NWELMVD technique exhibited superior output with optimum ROC values under two classes.

In Table 2, brief detection values of the TL-NWELMVD approach are represented for 70%TRP and 30%TSP. The outcomes depicted that the TL-NWELMVD model precisely detected two classes.

The average violence detection outcomes of the TL-NWELMVD method on 70%TRP is shown in Fig. 4. The values depict that the TL-NWELMVD method can efficiently detect the instances. It is also seen that the TL-NWELMVD method attains an average $accu_y$, $prec_n$, $reca_l$, F_{score}, and G_{mean} of 98.70%, 98.74%, 98.70%, 98.71%, and 98.72%, subsequently.

Table 2: Violence detection outcome of TL-NWELMVD technique on 70%TRP and 30%TSP

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	G_{Mean}
TRP (70%)					
Violence	99.44	98.07	99.44	98.75	98.75
Non-Violence	97.95	99.41	97.95	98.67	98.68
Average	98.70	98.74	98.70	98.71	98.72
TSP (30%)					
Violence	99.30	98.60	99.30	98.95	98.95
Non-Violence	98.73	99.36	98.73	99.05	99.05
Average	99.01	98.98	99.01	99.00	99.00

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024

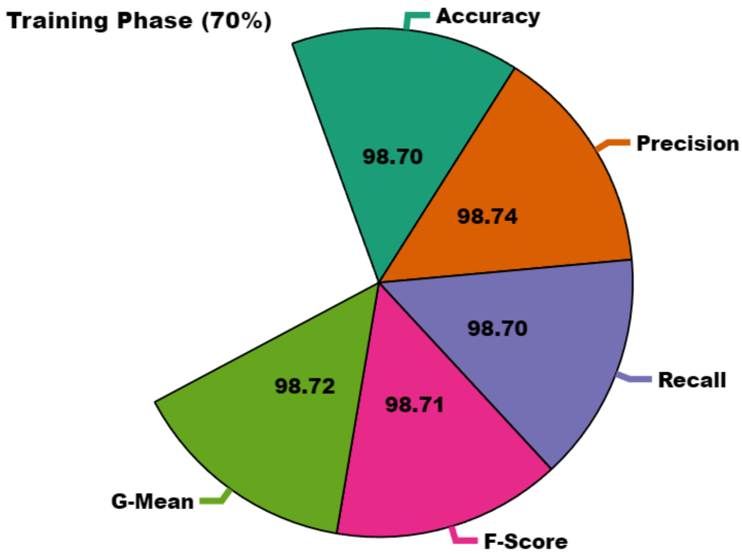


Figure 4. Average outcome of TL-NWELMVD method on 70%TRP

The average violence recognition outcomes of the TL-NWELMVD approach on 30%TSP is illustrated in Fig. 5. The outcomes show that the TL-NWELMVD approach can efficiently detect the instances. It is also seen that the TL-NWELMVD model attains an average $accu_y$, $prec_n$, $reca_l$, F_{score}, and G_{mean} of 99.01%, 98.98%, 99.01%, 99.00%, and 99.00%, appropriately.

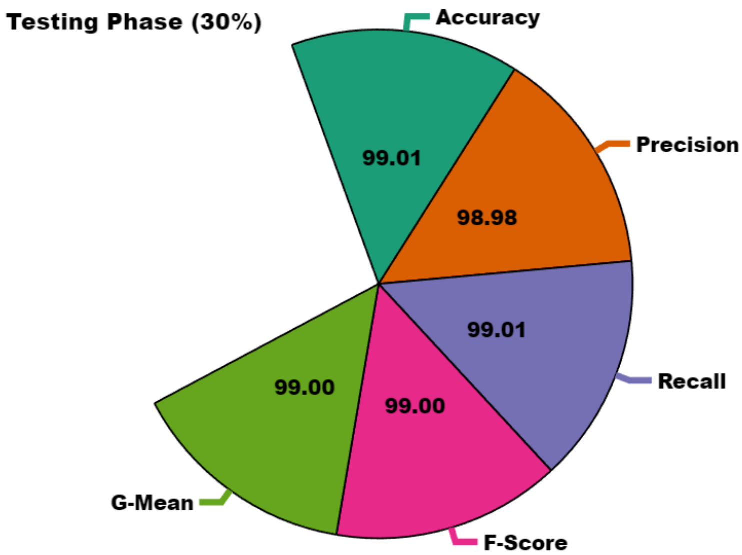


Figure 5. Average outcome of TL-NWELMVD method on 30%TSP

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024

Figure 6. $Accu_y$ curve of the TL-NWELMVD technique

In Fig. 6, the training and validation accuracy outcomes of the TL-NWELMVD technique is shown. The accuracy outcomes are evaluated in an interval of 0-25 epochs. The figure accentuated that the training and validation accuracy outcomes portrayed a growth, which demonstrated the capacity of the TL-NWELMVD technique with enhanced accomplishment over various iterations. Furthermore, the training accuracy and validation accuracy remains closer over the epochs, which shows less minimum overfitting and depicts improved accomplishment of the TL-NWELMVD approach, exhibiting consistent anticipation on unseen instances.

In Fig. 7, the training and validation loss graph of the TL-NWELMVD approach is shown. The loss outcomes are evaluated over an interval of 0-25 epochs. It is shown that the training and validation accuracy outcomes portrays a reducing tendency, which depicted the capacity of the TL-NWELMVD approach in balancing a trade-off between data fitting and generalization. The intermittent mitigation in loss values further confirms the enhanced accomplishment of the TL-NWELMVD approach and tune the anticipation outputs gradually.

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024

Figure 7. Loss curve of the TL-NWELMVD approach

To illustrate the superiority of the TL-NWELMVD method, an elaborated comparative study is shown in Table 3 and Fig. 8 [22]. The outcomes depict that the SVM, Inception-ResNet, and HOG3D-KELM techniques exhibited least values of $accu_y$. Simultaneously, the CNN-BiLSTM and MobileNet methods reached slightly enhanced$accu_y$. In the meantime, the Motion-IWLD and TSODL-VD methods illustrated closer outcome of $accu_y$. Nonetheless, the TL-NWELMVD method portrayed an enhanced accomplishment with an $accu_y$ of 99.01%.

Table 3: $Accu_y$ outcome of TL-NWELMVD technique with existing approaches

Techniques	Accuracy (%)
TL-NWELMVD	99.01
TSODL-VD	98.72
CNN-BiLSTM	95.32
Motion-IWLD	97.42
MobileNet Model	93.83
Inception-ResNet	91.32
SVM Model	92.71
HOG3D-KELM	93.54

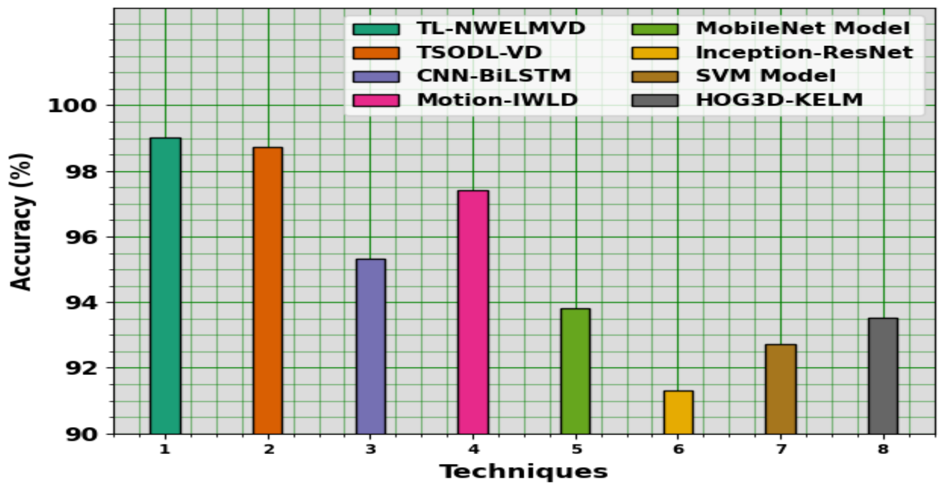


Figure 8. $Accu_y$ outcome of TL-NWELMVD approach with existing models

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024

5. Conclusion

In this study, a novel TL-NWELMVD approach is introduced in smart cities. The TL-NWELMVD approach aims to recognize the presence of the violence in the smart city environment. To accomplish that, the TL-NWELMVD technique has feature extractor, MBO based parameter tuning, and NWELM based detection process. Initially, the TL-NWELMVD technique undergoes the features can be extracted using SE-RegNet model. To enhance the performance of the TL-NWELMVD technique, a hyperparameter optimizer using MBO is involved. Finally, the NWELM classifier is applied for the identification of violence in the smart city environment. To investigate the performance of the TL-NWELMVD technique, a widespread investigational outcome is involved. The simulation results portrayed that the TL-NWELMVD technique gains better performance compared to other models.

Funding: “This research received no external funding”

Conflicts of Interest: “The authors declare no conflict of interest.”

References

[1] Abobala, M., 2020. n-Cyclic Refined Neutrosophic Algebraic Systems Of Sub-Indeterminacies, An Application To Rings and Modules. International Journal of Neutrosophic Science, 12, pp.81-95.
[2] Abobala, M,. "Classical Homomorphisms Between Refined Neutrosophic Rings and Neutrosophic Rings", International Journal of Neutrosophic Science, Vol. 5, pp. 72-75, 2020.
[3] Alhamido, R., and Abobala, M., "AH-Substructures in Neutrosophic Modules", International Journal of Neutrosophic Science, Vol. 7, pp. 79-86 , 2020.
[4] Hatip, A., and Olgun, N., " On Refined Neutrosophic R-Module", International Journal of Neutrosophic Science, Vol. 7, pp.87-96, 2020.
[5] Ibrahim, M.A., Agboola, A.A.A, Badmus, B.S., and Akinleye, S.A., "On Refined Neutrosophic Vector Spaces I", International Journal of Neutrosophic Science, Vol. 7, pp. 97-109, 2020.
[6] Ye, L., Wang, L., Ferdinando, H., Seppänen, T. and Alasaarela, E., 2020. A video-based DT–SVM school violence detecting algorithm. Sensors, 20(7), p.2018.
[7] Baba, M., Gui, V., Cernazanu, C. and Pescaru, D., 2019. A sensor network approach for violence detection in smart cities using deep learning. Sensors, 19(7), p.1676.
[8] Pujol, F.A., Mora, H. and Pertegal, M.L., 2020. A soft computing approach to violence detection in social media for smart cities. Soft Computing, 24(15), pp.11007-11017.
[9] Ullah, F.U.M., Ullah, A., Muhammad, K., Haq, I.U. and Baik, S.W., 2019. Violence detection using spatiotemporal features with 3D convolutional neural network. Sensors, 19(11), p.2472.
[10] Jain, A. and Vishwakarma, D.K., 2020, August. Deep NeuralNet for violence detection using motion features from dynamic images. In 2020 third international conference on smart systems and inventive technology (ICSSIT) (pp. 826-831). IEEE.
[11] Dalal, S., Lilhore, U.K., Sharma, N., Arora, S., Simaiya, S., Ayadi, M., Almujally, N.A. and Ksibi, A., 2024. Improving smart home surveillance through YOLO model with transfer learning and quantization for enhanced accuracy and efficiency. PeerJ Computer Science, 10, p.e1939.
[12] Bakhshi, A., García-Gómez, J., Gil-Pita, R. and Chalup, S., 2023. Violence detection in real-life audio signals using lightweight deep neural networks. Procedia Computer Science, 222, pp.244-251.
[13] Khan, M., El Saddik, A., Gueaieb, W., De Masi, G. and Karray, F., 2024. VD-Net: An Edge Vision-Based Surveillance System for Violence Detection. IEEE Access, 12, pp.43796-43808.
[14] Shoaib, M., Ullah, A., Abbasi, I.A., Algarni, F. and Khan, A.S., 2023. Augmenting the Robustness and efficiency of violence detection systems for surveillance and non-surveillance scenarios. IEEE Access, 11, pp.123295-123313.
[15] Elakiya, V., Puviarasan, N. and Aruna, P., 2024. Detection of violence using mosaicking and DFE-WLSRF: Deep feature extraction with weighted least square with random forest. Multimedia Tools and Applications, 83(14), pp.40873-40908.
[16] Jaafar, N. and Lachiri, Z., 2023. Multimodal fusion methods with deep neural networks and meta-information for aggression detection in surveillance. Expert Systems with Applications, 211, p.118523.
[17] Debnath, S., 2021. Application of intuitionistic neutrosophic soft sets in decision making based on game theory. International Journal of Neutrosophic Science, 14(2), pp.83-97.
[18] Wang, Y., Ma, W., Song, L. and Cai, Z., 2024. HCSMBO: A hybrid cat swarm and monarch butterfly optimization algorithm for energy consumption optimization in industrial internet of things. Alexandria Engineering Journal, 102, pp.279-289.
[19] Taş, F., Topal, S. and Smarandache, F., 2018. Clustering neutrosophic data sets and neutrosophic valued metric spaces. Symmetry, 10(10), p.430.

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024

[20] Akbulut, Y., Şengür, A., Guo, Y. and Smarandache, F., 2017. A novel neutrosophic weighted extreme learning machine for imbalanced data set. Symmetry, 9(8), p.142.

[21] https://www.kaggle.com/datasets/yassershrief/hockey-fight-vidoes

[22] Aldehim, G., Asiri, M.M., Aljebreen, M., Mohamed, A., Assiri, M. and Ibrahim, S.S., 2023. Tuna swarm algorithm with deep learning enabled violence detection in smart video surveillance systems. IEEE Access.

DOI: https://doi.org/10.54216/IJNS.250136
Received: January 14, 2024 Revised: April 9, 2024 Accepted: July 5, 2024