Strömberg Wavelet Transform Feature Extracted based Deep Belief Learning Classification for Pedestrian Detection

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ABSTRACT

Video surveillance system is a network of cameras, monitor/display unit and recorder. Surveillance task plays an essential part for finding the abnormal scenarios. Pedestrian detection is a key component for intelligent transport system and driver assistance system. But, the existing algorithms were inadequate for small-scale pedestrian detection. In order to address these problems, Strömberg Wavelet Transform Feature Extracted based Deep Belief Learning Classification (SWTFE-DBLC) Technique is introduced. Initially, the number of images is collected from the input database at the input layer. Consequently, preprocessing of input image is carried out in SWTFE-DBLC Technique to remove the noisy pixels from input image in hidden layer 1. After that, the features from the input images are extracted through transformation method in hidden layer 2. Then, the feature mapping is performed through determining the part score in the hidden layer 3. Lastly, the activation function is used in the output layer for performing efficient crime detection. By this way, SWTFE-DBLC Technique performs efficient pedestrian detection with higher accuracy and lesser time consumption. Results illustrates that the proposed SWTFE-DBLC Technique significantly improves true positive rate with minimal false positive rate and crime detection time with respect to image size and number of images.

Keywords: Video surveillance system, pedestrian detection, preprocessing, transformation, deep belief learning classification

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1. INTRODUCTION

Video Surveillance serves the observation of specific area within building, warehouse, school and additional locations to determine the crime, incidents and protect facility. A new end-to-end pedestrian detection method termed super-resolution detection (SRD) network was introduced in [1] to address the low-quality issues. But, the detection time was not reduced by using end-to-end pedestrian detection method. A dynamic selection scheme was designed in [2] for multispectral pedestrian detection. However, the accuracy level was not improved by designed scheme.

A novel trajeectory classification framework was introduced in [3] for identifying the pedestrians in real-world environments. The designed framework carried out background motion between two successive frames to balance the camera motion. However, the false positive ratio was not reduced. An automated deep learning based anomaly detection technique in pedestrian walkways (DLADT-PW) was designed in [4] for susceptible road user safety. DLADT-PW model was employed to identify anomalies in pedestrian walkways. But, the complexity was not minimized by DLADT-PW.

A pedestrian detection system depending on deep learning was introduced in [5] through adapting convolutional network to task. Though the computational time was reduced, the cost was not minimized. An auto-annotation framework was designed in [6] to identify the pedestrian instances. But, the false positive ratio was not improved by designed auto-annotation framework.

A new segmentation and context network (SCN) structure was designed in [7] to join the segmentation and context information for increasing pedestrian detection accuracy. The SCN model has good trade-off between accuracy and complexity. A new pedestrian detection acceleration algorithm called Non-Pedestrian Area Estimation (NPAE) algorithm was introduced in [8] to determine and to eliminate the non-pedestrian areas of image. RetinaNet was selected as the reference pedestrian detector. But, the true positive ratio was not improved by NPAE algorithm.

An IF-RCNN pedestrian detection method was designed in [9] to address the issues of pedestrian tunnels. However, the time complexity was not reduced by IF-RCNN pedestrian detection method. A new stationary wavelet dilated residual super-resolution (SWDR-SR) network was designed in [10] to improve the SR image edge information for pedestrian detection. But, the computational cost was not reduced by SWDR-SR network.

The drawbacks experienced by existing researchers are high computational cost, lesser true positive ratio, higher space complexity, higher detection time consumption, higher false positive ratio and so on. In order to address these problems, Strömberg Wavelet Transform Feature Extracted based Deep Belief Learning Classification (SWTFE-DBLC) Technique is introduced.

The main contribution of the article is given as:

The key objective of SWTFE-DBLC Technique is to perform efficient crime detection with minimal time consumption. In designed SWTFE-DBLC Technique, the number of images is gathered from the input database. Then, preprocessing of input image is carried out to remove the noisy pixels from input image. After that, the features from the input images are extracted through transformation method. Then, the feature mapping is performed through determining the part score. Lastly, the activation function is used in the output layer for performing efficient crime detection,

The rest of this paper is arranged into different sections as follows: Related work is discussed in section 2. The proposed SWTFE-DBLC Technique is described in Section 3. Section 4 presents experimental settings with the image database. The qualitative and quantitative analysis of the experimental results is discussed in section 5. Section 6 provides the details of the conclusion.

2. RELATED WORKS

Pedestrian detection was essential one for intelligent transportation system with better safety and mobility. Part-Aware Multi-Scale Fully Convolutional Network (PAMS-FCN) was introduced in [11] to address the occlusion issues in pedestrian detection. A Region-of-Interest (RoI) pooling module was employed to mine the body parts with diverse response through voting. A discrete cosine transformation (DCT) technique was introduced in [12] to improve the intensity of images. But, the PSNR was not improved by DCT technique.

Pose-Embedding Network was designed in [13] to embed the human pose information with visual description for pedestrian detection. Region Proposal Network generated candidate proposals with confidence scores. But, the pedestrian detection time was not minimized by Pose-Embedding Network. A deep small-scale sense network (SSN) was introduced in [14] for small-scale pedestrian detection. However, the computational cost was not minimized.

A boosted multi-task model was introduced in [15] to consider their variances. The designed model used multi-task learning algorithm to link the pedestrians in different occlusion levels. A pedestrian appearance model was introduced in [16] for pedestrian detection in real-world images. But, the false positive rate was not reduced by pedestrian appearance model.

A new feature learning method termed Feature Calibration Network (FC-Net) was introduced in [17] to detect the pedestrians under different occlusions. In FC-Net, the pedestrians were selective and decisive for detection. An attribute-aware pedestrian detector was introduced in [18] with feature detection. However, the complexity was not reduced by attribute-aware pedestrian detector.

A multi-scale network was employed in [19] to predict the pedestrians with appropriate feature maps. A new multi-view-pose part ensemble (MVPPE) detector was introduced in [20] to handle the pedestrian variability, view and partial occlusion. The feature combination method increased the description capabilities of pedestrian features.

3. METHODOLOGY

Surveillance performs behavior monitoring with many activities for information gathering. Many researchers carried out their research on video surveillance methods. But, the true positive rate was not improved and time consumption was not minimized by existing methods. In order to address the existing issues, a new method called Strömberg Wavelet Transform Feature Extracted based Deep Belief Learning Classification (SWTFE-DBLC) Technique is introduced. The main aim of SWTFE-DBLC Technique is to perform pedestrian identification for crime detection. The architectural diagram of SWTFE-DBLC Technique is illustrated in figure 1.

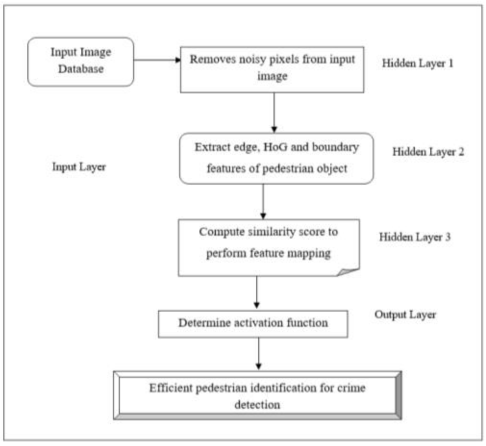

Figure 1 Architecture Diagram of SWTFE-DBLC Technique for Pedestrian Detection

Figure 1 describes the architecture diagram of SWTFE-DBLC Technique for Pedestrian Detection. Initially, the number of images is collected from the input database at the input layer. Consequently, preprocessing of input image is carried out to remove the noisy pixels from input image in hidden layer 1. After that, the features from the input images are extracted through transformation method in hidden layer 2. Then, the feature mapping is performed through determining the part score in the hidden layer 3. Lastly, the activation function is used in the output layer for performing efficient crime detection.

3.1 Strömberg Wavelet Transform Feature Extracted based Deep Belief Learning Classification (SWTFE-DBLC) Technique

Deep learning is an artificial intelligence with human brain functioning behavior in creating patterns and processing input for decision making. Deep learning studies from the large unlabeled image to interpret and process. Deep learning is same as the nervous system structure. Every neuron connects with one another and sends the information. Each layer accepts the information and transmits to the next one. Deep learning in SWTFE-DBLC Technique comprises five layers, namely one input, three hidden and one output for efficient crime detection. Initially in SWTFE-DBLC Technique, the number of input image is collected at an input layer. Then, the collected images are transmitted to the hidden layer 1. The first process in SWTFE-DBLC Technique is preprocessing for eliminating the noise artifacts in input image. Wiener filtering is carried out in SWTFE-DBLC Technique to enhance image quality, to eliminate the noise, to preserve edge within image and to attain the smoothen image. Let us consider, the number of input images is denoted as '$I_1, I_2, \ldots\ldots, I_n$'. The image is denoised to remove the noisy pixels from input images through Wiener filtering technique. The filtering technique eliminates the noise and performs filtering as well as noise smoothing. Consequently, Wiener filter eliminates the blurring and noise in input image. The wiener filtering is a linear assessment of original image and expressed as,

$$W(a,b) = \frac{H^*(a,b)S_{xx}(a,b)}{|H(a,b)|^2 S_{xx}(a,b) + S_{\eta\eta}(a,b)} \quad (1)$$

From (1), '$S_{xx}(a,b)$' and '$S_{\eta\eta}(a,b)$' represents the power spectra of original image and additive noise. '$H(a,b)$' symbolizes the blurring filter. '$W(a,b)$' denotes the Weiner filter. Wiener filter includes inverse filtering and noise smoothing. It performs the deconvolution process and eliminates the noise with compression process through high pass and low pass filter. Then, the pre-processed image is sent to the hidden layer 2. In that layer, the feature extraction process is performed using Strömberg wavelet transform. Strömberg wavelet transform in SWTFE-DBLC Technique is a smooth orthonormal wavelet transform to provide sufficient information for original image synthesis with minimum time consumption. Strömberg wavelet transform is used to decompose the preprocessed images into diverse sub-blocks in horizontal and vertical direction for crime detection.

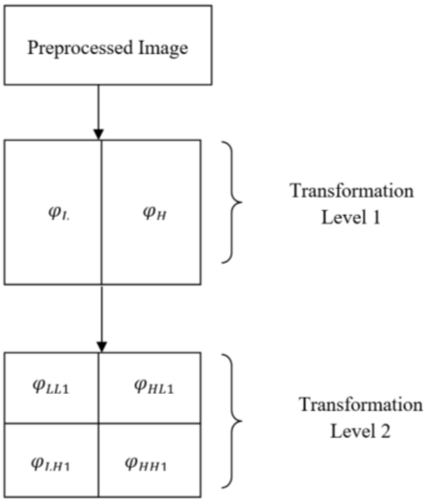

Figure 2 Preprocessed Image Decomposition

Figure 2 explains the image decomposition through wavelet transform. The wavelet transformation of image decomposition is achieved as,

$$SW(t) = 2^{i/2}\,\delta^p\,(2^i t - m) \quad (2)$$

From (2), '$SW(t)$' represent the Strömberg wavelet transform at time period 't'. 'i' and 'm' symbolizes an integer. 'δ^p' symbolize the Strömberg wavelet of order 'p'. After transformation process, HOG feature is computed for every gradient part.HOG feature of image represents the local object appearance and shape. The boundary features are extracted and center of image is represented by$(0,0)$. The distance from center of point to the edge is determined to find the outline of image. The distance from the center to the edge is determined as,

$$Distance = \sqrt{(m_2 - m_1)^2 - (n_2 - n_1)^2} \quad (3)$$

From (3), 'D' denotes the distance. The point (m_1, n_1) is the center i.e. $(0,0)$. The point (m_2, n_2) represents the edge. By this way, every point on perfect shape of the boundary is extracted in the hidden layer 2. After performing the feature extraction, the mapping process is carried out in SWTFE-DBLC Technique at the second hidden layer. The feature extraction process is carried out through tanimoto similarity coefficient for increasing the accuracy level and minimizing time consumption.

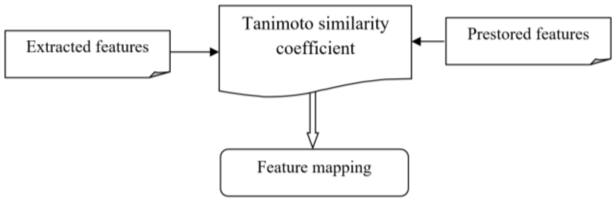

Figure 3 Flow process of Tanimoto Similarity Feature Mapping

Figure 3 illustrates the flow process of tanimoto similarity feature mapping in SWTFE-DBLC Technique to obtain the crime detection. Tanimoto similarity coefficient is used for mapping the extracted feature with the prestored feature (i.e., testing features). Tanimoto similarity coefficient between the two features is determined as,

$$TS_c = \frac{|fea_{test} \cap fea_{train}|}{|fea_{test}| + |fea_{train}| - |fea_{test} \cap fea_{train}|} \quad (4)$$

From (4), 'TS_c' represent the tanimoto similarity coefficient. 'fea_{test}' indicates the testing features. 'fea_{train}' symbolizes the training features. The tanimoto similarity coefficient (TS_c) provides the mapping values between '0 and '+1'. If the similarity value provides '+1' indicates two features are correctly matched and '0' indicates the two features are not matched. The hidden layer 3 results are transmitted to the output layer. In that layer, logistic activation function is determined for crime detection. It is given as,

$$LAF = \frac{1}{1+e^{-TS_c}} \quad (5)$$

From (5), 'LAF' symbolizes the logistic activation function. By this way, the final results are obtained at an output layer with higher accuracy for crime detection. The algorithmic process of the SWTFE-DBLC Technique is described as given below,

Algorithm 1: Strömberg Wavelet Transform Feature Extracted based Deep Belief Learning Classification
Input: Database, images $I_1, I_2, I_3, I_4 \ldots\ldots I_n$ **Output:** Increase accuracy and reduce time consumption

Begin

Step 1: Collect the number of images in input layer

Step 2: For each input image

Step 3: Apply wiener filter to remove the noise artifacts in an input

Step 4: Obtain pre-processed image

Step 5: End for

Step 6: For each preprocessed image

Step 7: Apply transformation '$SW(t)$'

Step 8: Decompose image into sub-blocks

Step 9: Extract the vein features

Step 10: End for

Step 11: Perform feature mapping

Step 12: Measure similarity between extracted feature and pre-defined features

Step 13: If (TS_c = +1) **then**

Step 14: Two Features are correctly mapped

Step 15: else

Step 16: Two Features are not mapped

Step 17: Perform crime detection when features mapped through logistic activation function

Step 18: End if

Step 19: Return (crime detection results)

End

Algorithm 1 explains the algorithmic steps of Strömberg Wavelet Transform Feature Extracted based Deep Belief Learning Classification. Weiner filtering is used to preprocess the image to improve the quality and attain the noise free image. After that, the feature extraction is carried out to extract the HoG, boundary and edge from the image. Then, the feature mapping is carried out between training features and testing features for performing crime detection. This in turn helps to improve the accuracy and time consumption during feature extraction.

4. EXPERIMENTAL EXPLANATION

The proposed SWTFE-DBLC Technique and the existing end-to-end pedestrian detection method [1] and existing dynamic selection scheme [2] is implemented with help of MATLAB for crime detection. Many Images are gathered from UMN classification dataset. The input image is preprocessed to eliminate the noisy artifacts and attain the better quality. The HoG, edges and boundary features are extracted from pre-processed images. At last, classification is carried out with help of the extracted features for performing the crime detection.

5. RESULTS AND DISCUSSION

The proposed SWTFE-DBLC Technique and the existing end-to-end pedestrian detection method [1] and existing dynamic selection scheme [2] are evaluated through true positive rate, false positive rate and pedestrian detection time.

5.1 Pedestrian Detection Time (PDT)

Pedestrian detection time is defined as the amount of time taken for detecting the pedestrian. It is the product of number of images and time consumed for detecting pedestrian from one image. It is formulated as,

$$PDT = n * pedestrian\ detection\ from\ one\ image \quad (6)$$

From (6), pedestrian detection time is formulated. 'n' symbolizes the number of images. It is measured in terms of milliseconds (ms).

Table 1 Tabulation of Pedestrian Detection Time

Number of Images	Pedestrian Detection Time (ms)		
	End-to-End Pedestrian Detection Method	Dynamic Selection Scheme	SWTFE-DBLC Technique
10	32	25	19
20	36	27	22
30	39	30	25
40	42	32	28

50	45	37	31
60	48	40	35
70	51	44	38
80	54	47	40
90	57	49	43
100	60	52	46

Table 1 describes the experimental results of pedestrian detection time for different image varies from 10 to 100. The attained results of pedestrian detection time using SWTFE-DBLC Technique are compared to the two conventional methods namely the end-to-end pedestrian detection method [1] and dynamic selection scheme [2]. The proposed SWTFE-DBLC Technique consumes lesser pedestrian detection time than existing methods. Let us consider that number of images is 20 for conducting experiments. By using SWTFE-DBLC Technique, the pedestrian detection time consumed is 22ms whereas the pedestrian detection time of the conventional methods [1] and [2] are 36ms and 27ms correspondingly. The various pedestrian detection time results are achieved for every technique. The graphical representation of pedestrian detection time is demonstrated in figure 4.

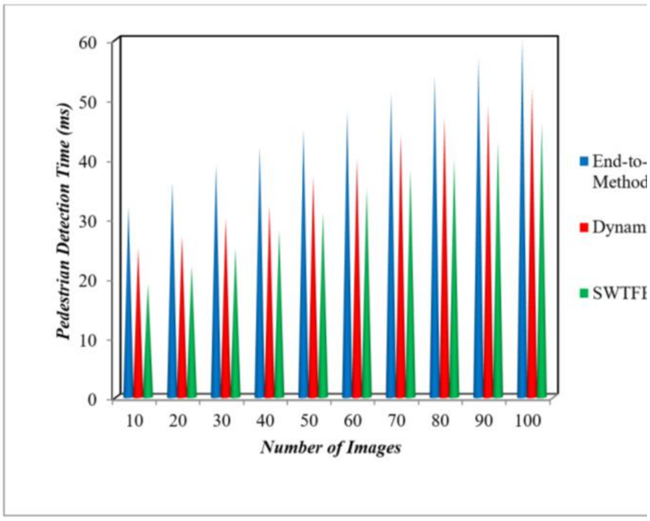

Figure 4 Measurement of Pedestrian Detection Time

Figure 4 shows the pedestrian detection time results. The number of images is considered in the horizontal axis as well as pedestrian detection time is attained at vertical axis. The green color cone represents the pedestrian detection time of SWTFE-DBLC Technique whereas blue color and red color cone represents the pedestrian detection time of end-to-end pedestrian detection method [1] and dynamic selection scheme [2]. The pedestrian detection time consumption of proposed SWTFE-DBLC Technique is lesser than existing methods. This is due to the application of deep belief learning classifier in SWTFE-DBLC Technique. Weiner filtering preprocesses the image and attains noise free image. After that, the feature extraction extracted the HoG, boundary and edge from the image. Then, the feature mapping is carried out between training features and testing features for performing pedestrian detection with minimal time consumption. Finally, proposed SWTFE-DBLC Technique reduces pedestrian detection time consumption by 31% compared to end-to-end pedestrian detection method [1] and 15% compared to dynamic selection scheme [2] correspondingly.

5.2 True Positive Rate

True positive rate (TPR) is defined as number of images that are correctly detected pedestrian. TPR is defined as the ratio of number of pedestrians that are correctly identified from images to the total number of images. It is measured in terms of percentage (%). True positive rate is formulated as,

$$TPR = \frac{Number\ of\ pedestrains\ that\ are\ correctly\ deteced\ from\ images}{n} * 100 \quad (7)$$

From (7), true positive ratio is calculated. 'n' symbolizes the number of images.

Table 2 Tabulation of True Positive Rate

Number of Images	True Positive Rate (%)		
	End-to-End Pedestrian Detection Method	Dynamic Selection Scheme	SWTFE-DBLC Technique
10	60	70	80
20	63	72	82
30	65	73	85
40	67	75	87

50	70	77	89
60	72	79	90
70	75	81	92
80	78	83	93
90	80	85	95
100	83	88	97

Table 2 describes the experimental results of true positive rate for different image varies from 10 to 100. The attained results of true positive rate using SWTFE-DBLC Technique are compared to the two conventional methods namely, end-to-end pedestrian detection method [1] and dynamic selection scheme [2]. The proposed SWTFE-DBLC Technique attains higher true positive rate than existing methods. Let us consider that number of images is 50 for conducting experiments. By using SWTFE-DBLC Technique, the true positive rate attained is 89% whereas the true positive rate of the conventional methods [1] and [2] are 70% and 77% correspondingly. The various true positive rate results are attained for every technique. The graphical representation of true positive rate is demonstrated in figure 5.

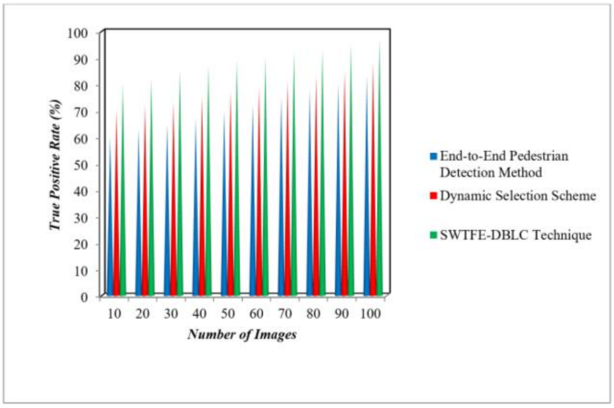

Figure 5 Measurement of True Positive Rate

Figure 5 shows true positive rate results. The number of images is considered in the horizontal axis as well as true positive rate is attained at the vertical axis. The green color cone represents the true positive rate of SWTFE-DBLC Technique whereas blue color and red color cone represents the true positive rate of end-to-end pedestrian detection method [1] and dynamic selection scheme [2]. The true positive rate of proposed SWTFE-DBLC Technique is higher than existing methods. This is because of applying deep belief learning classifier in SWTFE-DBLC Technique. In proposed technique, weiner filtering removes the noise from input image. After that, the feature like HoG, boundary and edge gets extracted from the image. This in turn performs pedestrian detection with higher true positive rate. Finally, proposed SWTFE-DBLC Technique increases the true positive rate by 25% compared to end-to-end pedestrian detection method [1] and 14% compared to dynamic selection scheme [2] correspondingly.

5.3 False Positive Rate

False Positive Rate (FPR) is defined as number of images that are incorrectly detected pedestrian. ER is defined as the ratio of number of pedestrians that are incorrectly identified from images to the total number of images. It is measured in terms of percentage (%). True positive rate is formulated as,

$$FPR = \frac{Number\ of\ pedestrains\ that\ are\ incorrectly\ deteced\ from\ images}{n} * 100 \quad (8)$$

From (8), false positive ratio is determined. 'n' symbolizes the number of images.

Table 3 Tabulation of False Positive Rate

Number of Images	False Positive Rate (%)		
	End-to-End Pedestrian Detection Method	Dynamic Selection Scheme	SWTFE-DBLC Technique
10	40	30	20
20	37	28	18
30	35	27	15
40	33	25	13
50	30	23	11
60	28	21	10
70	25	19	8
80	22	17	7
90	20	15	5
100	17	12	3

Table 3 explains the experimental results of false positive rate for different image varies from 10 to 100. The attained results of false positive rate using SWTFE-DBLC Technique are compared to the two conventional methods namely, end-to-end pedestrian detection method [1] and dynamic selection scheme [2]. The proposed SWTFE-DBLC Technique attains lesser false positive rate than existing methods. Let us consider that number of images is 80 for conducting experiments. By using SWTFE-DBLC Technique, the false positive rate attained is 7% whereas the false positive rate of the conventional methods [1] and [2] are 22% and 17% correspondingly. The various false positive rate results are attained for every technique. The graphical representation of false positive rate is illustrated in figure 6.

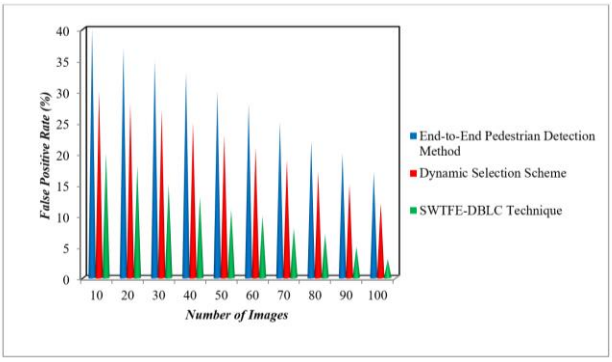

Figure 6 Measurement of False Positive Rate

Figure 6 shows false positive rate results. The number of images is considered in the horizontal axis as well as false positive rate is attained at vertical axis. The green color cone represents the false positive rate of SWTFE-DBLC Technique whereas blue color and red color cone represents the false positive rate of end-to-end pedestrian detection method [1] and dynamic selection scheme [2]. The false positive rate of proposed SWTFE-DBLC Technique is lesser than existing methods. This is because of deep belief learning classifier in SWTFE-DBLC Technique. Weiner filtering preprocesses the image to remove the noise. The feature extraction extracted HoG, boundary and edge from input image for performing pedestrian detection with minimal false positive rate. Finally, proposed SWTFE-DBLC Technique reduces false positive rate by 64% compared to end-to-end pedestrian detection method [1] and 52% compared to dynamic selection scheme [2] correspondingly.

6. CONCLUSION

A new technique termed SWTFE-DBLC Technique is introduced for performing efficient pedestrian detection. The number of images is collected from input database. The preprocessing of input image removes the noisy pixels from input image. The features from the input images are extracted through transformation method. Then, the feature mapping is performed through determining the part score. Finally, the activation function is used for performing efficient crime detection. By this way, SWTFE-DBLC Technique performs efficient pedestrian detection with higher accuracy and lesser time consumption. The experimental analysis is carried out with help of image dataset. The qualitative and quantitative results shows that the proposed SWTFE-DBLC Technique attained better performance when compared to traditional methods.

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