# A Novel Method for Recognizing Traffic Signs using Color and Texture Properties using the ELM Algorithm

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***Abstract*—Road accidents cause a lot of financial and human losses every year. One of the causes of these accidents is human error, and the driver ignores traffic signs. Therefore, accurate detection of these signs will help to increase the safety of drivers and pedestrians and reduce accidents. In recent years, much research has been done to increase the accuracy of panel recognition, most of which are problems that affect the diagnosis, such as adverse weather conditions, light reflection, and complex backgrounds. In the present study, considering the diversity of traffic signs' geometric shapes, the sign detection part has been done using a torsional neural network. Then, in the feature extraction section, we used LBP and HOG techniques, and at the end, the section was identified and classified using the ELM algorithm. The results obtained on 12569 images, 75% of which were used for training and 25% for experimentation, show that the accuracy of this research has improved by 95% compared to the essential work by 93%.**

***Keywords—Traffic sign recognition; torsional neural network; HOG Feature; LBP Feature; ELM Algorithm***

## I. Introduction

One of the most critical issues in car vision and pattern recognition, which has attracted the attention of many researchers today, is detecting traffic signs through images. Ignoring traffic signs is a disservice; many people die in accidents or disabilities yearly. With the advancement of technology and the competition of car factories, much research and work has been done on smart cars. Traffic signs increase traffic safety on roads and streets by giving drivers warnings. Therefore, automatic identification of traffic signs is one of the important components of a driver assistance system. The next generation of vehicles can also be considered an important component of automatic reduction vehicles. This system must have high speed and accuracy and perform real-time detection of symptoms in natural scenes.

Automatic detection of traffic signs is one of the problems of intelligent transportation systems today, which facilitates the recognition and interpretation of signs for users. It helps drivers identify traffic signs and pedestrians by warning them [1, 2].

In recent years, a great deal of research has been done to identify signs by intelligent vehicles. Factors such as bad weather, unfavorable weather conditions, light reflection and misdiagnosis of signs, placement of traffic signs and driving in the shade, placement of signs between leaves of trees, and very complex backgrounds such as the location of buildings, trees, and animals that complicate the background and the background is similar to the panel for detecting problematic symptoms. Because it takes a long time to separate the images from each other and correctly identify the traffic signs, the traffic sign recognition system must be prompt.

The challenge of recognizing traffic signs is their accuracy and short detection time. Much works have been done to detect traffic signs [1, 2], and due to the noise in the image, camera slip, and image quality, all of them have been aimed at accurately detecting traffic signs. In the research reviewed [1, 2], a traffic sign recognition system consists of three main identification steps: image reception, pre-processing, and detection of the area of traffic signs in the image. Early detection of traffic signs and their accuracy can help reduce accidents and human mortality [23], so if traffic signs can be detected intelligently by vehicles, it can be a great help in reducing road accidents.

The motivation of this study is that with the idea of recognizing traffic signs from standard data images. Since traffic sign detection is still a challenging task because of adverse weather conditions, light reflection, and complex backgrounds, it is required to establish a method to provide high accuracy in diagnosis by finding different features in traffic sign images.

The main purpose is to increase the accuracy of existing methods and to detect traffic signs according to the characteristics of color and texture. On the other hand, the use of ELM classification has been used to identify the shape of the symptoms better as well as to extract and pay attention to features such as color, shape, and texture [3].

The major contributions of this study are as, a) proposing a novel feature representation algorithm using color and texture features for finding different features to represent the traffic sign images, b) presenting a method for classifying traffic signs using color and PHOG features the SVM algorithm, c) developing a sign traffic detection method to deal with adverse weather conditions, light reflection, and complex backgrounds.

The rest of this paper is consisted of as, Section II presents the related works. The proposed method is described in Section III. Experimental results and performance analysis are discussed in Section IV. Finally, this paper concludes in Section V.

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## II. Related Works

Zhang et al., [29] proposed a cascaded R-CNN to extract the multiscale features in pyramids in order to address undetection and erroneous detection. With the exception of the first layer, each layer of the cascaded network fuses the output bounding box of the preceding layer for joint training. This technique aids in the identification of traffic signs. In order to highlight the features of traffic signs and increase the accuracy of traffic sign detection, a multiscale attention approach is presented to extract the weighted multiscale features using dot-product and softmax. Finally, to reduce the influence from a complicated environment and comparable fake traffic signs, we increase the amount of challenging negative examples for dataset balance and data augmentation in the training.

Avramović et al., [30] presented a traffic sign detection approach based on "You Only Look Once" (YOLO) architectures as baseline detectors for improving the speed and accuracy of traffic sign identification and recognition in high-definition photographs. To meet the real-time performance requirement, a number of preprocessing techniques were suggested. To evaluate the method, tests on a big dataset of traffic signs demonstrate the ability of the method to recognize high-definition images in real time with high recognition accuracy.

Cao et al., [31 proposed an algorithm for traffic sign detection and dealing with the poor real-time performance of deep learning-based traffic sign recognition techniques. In this method, spatial threshold segmentation is firstly performed using the HSV color space, and traffic signs are successfully identified using shape features. Second, utilizing the Gabor kernel as the initial convolutional kernel, adding the batch normalization processing after the pooling layer, and choosing the Adam method. As their results show, the model is much improved over the original LeNet-5 convolutional neural network model. The German Traffic Sign Recognition Benchmark serves as the foundation for the classification and recognition experiments on traffic signs.

## III. Proposed Method

Initially, after downloading images from the GTSRB database [5-8], a torsional neural network is used to detect traffic signs. Extraction of shape properties by HOG technique which is a shape descriptor, based on histogram and statistical information of image spectra as well as its inclination and angles, and finally by extracting texture properties along with shape properties by LBP technique which can increase the sensitivity of HOG, extract light reflections and improve cluttered and complex backgrounds. The features are categorized using the ELM algorithm by forming a feature matrix to detect the panel type and normalizing this matrix, which is also the input matrix to the category. Finally, the accuracy is checked [9-14]. Fig. 1 shows the steps of the proposed method as a flowchart.

### A. Torsional Neural Network

Twisted neural networks are very similar to artificial neural networks. These networks consist of neurons with learnable (adjustable) weights and biases [15]. Each neuron receives several inputs and then calculates the product of the weights multiplied by the inputs and finally presents a result using a nonlinear conversion (activation) function [16-22]. The entire network also provides a derivative score function, with raw input image pixels on one side and points for each category on the other. These types of networks still have a fully operational cost function (SVM, Softmax) in the last layer, and all the points about conventional neural networks are also valid here. Given the above, the difference between a torsional neural network and an artificial neural network is that torsional neural network architectures explicitly assume that their inputs are images, assuming certain features can be embedded within the architecture. With this action, the forward function can be implemented more optimally, and also, by doing so, the amount of network parameters is significantly reduced [24-26].

Neural networks receive an input (in the form of a vector) and then pass it through several hidden layers. Finally, an output resulting from hidden processing layers appears in the network output layer. Each hidden layer is made up of some neurons that are connected to all the neurons in the previous layer. The neurons in each layer act independently and have no connection. The last layer plays the role of representing the score of each class [27, 28].

### B. Characteristics of Texture and LBP Technique

The texture is the measurement of changes in the brightness of surfaces, which determines the quantity level for properties such as smoothness and order. An essential feature of the texture is that it is less sensitive to changes in light intensity than the color feature. Compared to color, texture requires a preprocessing step to produce texture descriptors. There are different texture descriptors. Gray Level Cooccurrence Matrix is a two-dimensional histogram that expresses simultaneous events expressing image intensity values in a given direction and distance.

The local binary pattern (LBP) operator was first proposed by Ojala et al. [26]. Experiments have shown that the LBP operator has a high ability to represent tissue. The LBP algorithm is a local feature extraction algorithm. The LBP algorithm is one of the most potent feature extraction algorithms in machine vision science, and many developments based on this algorithm have been proposed.

As shown in Eq. (1), the local properties of LBP are usually symmetrical circles in a neighborhood, comparing images with its neighbors.

$$\mathrm{LBP}(P,R) = \sum_{i=0}^{P-1} u(g_i - g_c)2^i \quad (1)$$

In Eq. (1), $p$ is the number of neighborhoods, $R$ is the neighborhood radius, $gi$ is the brightness of the $i$-$th$ pixel ($i = 0, \ldots, P-1$), $gc$ is the brightness of the central pixel, and $u(x)$ is a step function that has the relation (Eq. 2) is defined.

$$U(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

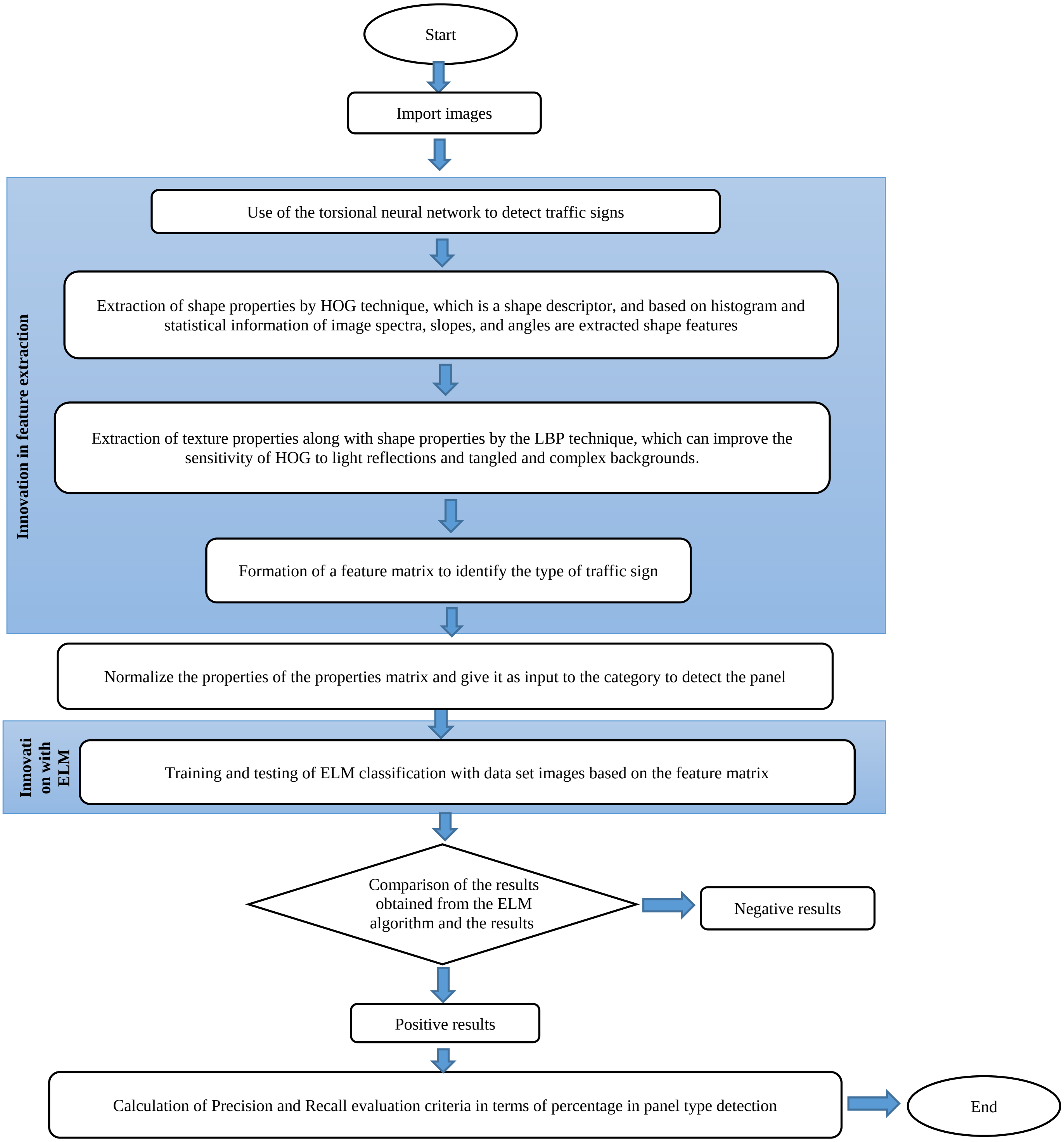


Fig. 1. Flowchart steps of the proposed method.

Suppose eight neighborhoods are used to extract LBP patterns. In this case, 56 uniformly significant patterns and two patterns for the state where the brightness of the neighborhoods is all more or less than the central pixel, and a pattern for the other states is considered. In total, image pixels are tagged with 59 patterns. The normalized histogram of the repetition of these patterns constitutes the LBP features. The minimum amount of binary pattern produced is used to make the patterns more resistant to rotation; therefore, the LBP pattern is resistant to the period in the form of Error! Reference source not found is defined.

$$LBP^{riu2}(P,R) = \begin{cases} \sum_{i=0}^{P-1} u(g_i - g_c) & \text{if } U(LBP(P,R)) \leq 2 \\ P+1 & \text{otherwise} \end{cases} \quad (3)$$

In this case, the number of significant patterns will be seven. As a result, image pixels are tagged with 10 patterns. This paper uses period-resistant LBP patterns. In recognizing traffic signs, searching for a way that is easy to identify and has good accuracy is of great importance. In this paper, the torsional neural network method is used for detection, and then using LBP and HOG; the features were extracted after normalization of the feature matrix as input to the ELM algorithm for classification.

## IV. Analysis and Interpretation of Evaluation Results

This research was implemented with MATLAB software version 8.3 and on a system with Intel Core i7 specifications with 2.2GH processing power and 6GB of main memory. The database used in this article is the GTSRB database [5-8]. Considering that the essential work [1] has been implemented on 1000 images from this database while implementing on 1000 images to compare with the essential work on 12569 images in the GTSRB database [5-8], the proposed method has been implemented.

### *A. Evaluation Data Set*

The data used in this study compared with the essential work of 1000 images, of which 800 are noise-free images and 200 are noise-free images to implement the proposed method on all images. The database contains 12569 images downloaded from the GTSRB [5-8], among which 60 are related to speed limit data of 20 km / h, and 720 are related to traffic signs. The speed limit is 30 km / h, 750 pieces of data are related to traffic signs, the speed limit is 50 km / h, 450 pieces of data are related to traffic signs, the speed limit is 60 km / h, and 660 pieces are data. Traffic signs are a speed limit of 70 km / h, 600 pieces of data are related to traffic signs' speed limit of 80 km / h, and 120 data are related to traffic signs with a speed limit of 80 km / h, 480. The number of data related to traffic signs is 100 km / h, 450 of the data related to traffic signs. The speed limit is 120 km / h, 480 pieces of data are related to traffic signs, overtaking is prohibited, 660 images are related to prohibited truck overtaking, 420 pieces of data are related to a two-way intersection, 690 Images of the main street, 720 images of a right of way, 240 pieces of data related to traffic stop signs, 210 pictures of no entry signs, 120 pieces of data related to traffic signs of no-entry trucks, 360 pieces of data related to no-entry traffic signs, 390 pieces of data related to traffic signs, 60 pieces of data related to traffic signs to the left, 120 pieces of data related to traffic signs to the right, 90 images of left turn on the road, 120 pieces of data Bump traffic signs, 150 data slippery road traffic signs, 90 road images approaching from the right, 480 data from workers' traffic signs working, 180 warning images to traffic lights. As we approach the traffic, 60 pieces of data related to traffic signs at the crossing Cloud pedestrian, 180 warning pictures of children playing, 90 warning pictures of cyclists, 150 pieces of data related to frozen road data, 240 pieces of data related to traffic signs for animal crossings, 60 stop signs, 209 number of data related to right-turn traffic signs, 120 data related to left-turn traffic signs, 390 data related to traffic signs for forwarding movement, 120 pieces of data related to two-way intersection traffic signs, 70 news images of entering the street from the right, 690 news images of the one-way road from the right, 90 images of the one-way road from the left, 120 pieces of data related to traffic signs, 60 pieces of data related to traffic signs allowed overtaking, 60 images No truck overtaking is prohibited.

### *B. Analyze and Evaluate the Results*

First, the images are detected using a torsional neural network described in detail. As described in the previous sections, the torsional neural network is an improved version of the artificial neural network. There is a difference in the structure and operation of this type of network. Unlike an artificial neural network, the input matrix is the intensity of image brightness in a torsional neural network. The features are extracted by mapping and reducing the dimension of this matrix, and classification and detection operations are performed. If the feature extraction operation is performed separately in the artificial neural network, the classification operation will be performed after the feature extraction and normalization of the features. In fact, in torsional neural networks, the spatial dependence of the data is essential for network training and feature extraction from the input matrix. Therefore, this type of network can be used in problems where neighborhood information and spatial dependence make sense. Fig. 2 shows how this detection occurs. After the segmentation of images and detection of traffic signs by the torsional neural network, features are extracted from the detected areas to determine the shape of the traffic sign. Properties are extracted using the texture method and LBP technique, and also the HOG method is used to extract the properties and form the properties matrix. In this paper, we compare the primary article method [1], which uses the PHOG method and different color channels for extraction and SVM algorithm for classification [4], and the proposed method, which uses LBP and HOG for feature extraction and ELM for classification. The baseline work used 1000 images for evaluation, using 800 images with noise or negative images and 200 non-noise images or positive images. Table I shows the comparison of the two methods.

In Table I, as can be seen, four different shapes are presented with different proposed methods and different categories, and the results show that the proposed method has very acceptable accuracy.

The following matrix, called the perturbation matrix, has five rows and five columns of the number of data tested, and their results are shown. In this matrix, the horizontal axis of the actual output or the class label is given, and the vertical axis of the output estimated by the category is shown.

TABLE I. COMPARISON OF THE PROPOSED IDEA AND THE BASIC WORK

| Row | Shape type | Color channel method and PHOG with SVM classification [1] | LBP and HOG methods along with ELM algorithm |
|---|---|---|---|
| 1 | circular | 93.52% | 100% |
| 2 | Triangle | 96.45% | 95.8% |
| 3 | Inverted triangle | 94.50% | 100% |
| 4 | Diamond | 95.16% | 100% |
| 5 | Average | 95.02% | 98.95% |


Fig. 2. Sample GTSRB database images.

An example of the output of a traffic sign detection algorithm is shown in Fig. 3.

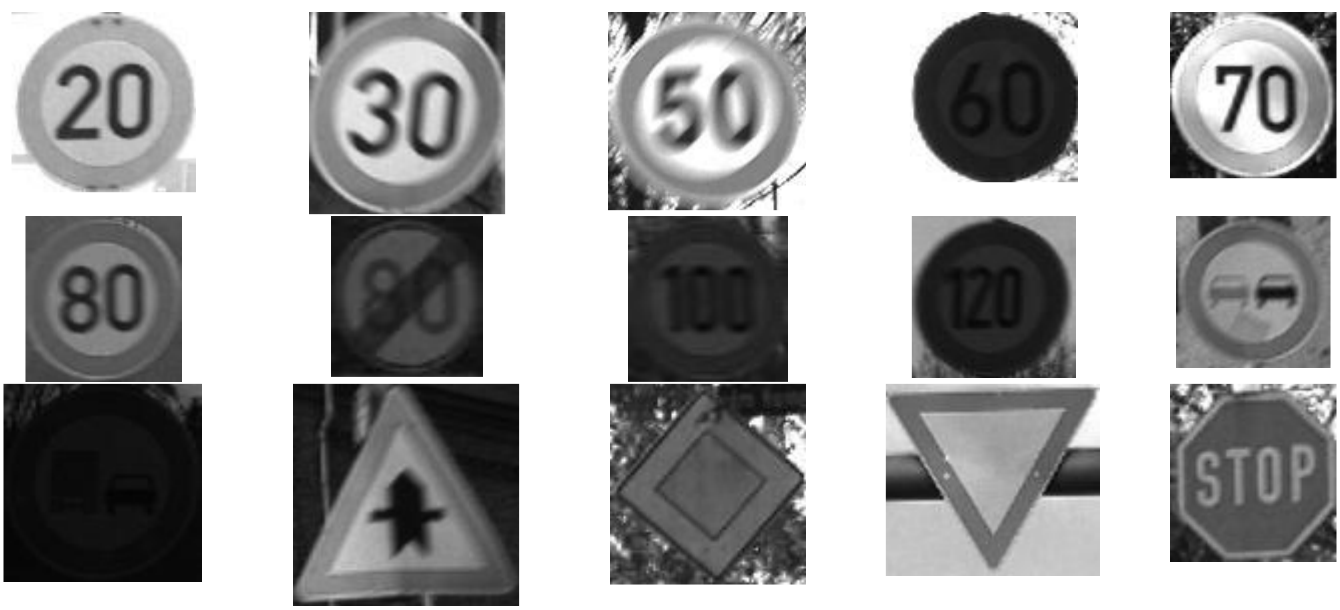

Fig. 3. Traffic signs detected by the proposed method.

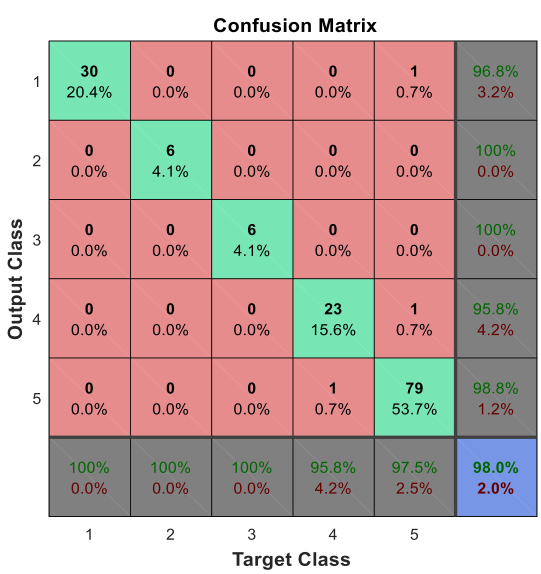


Fig. 4. The proposed method perturbation matrix is based on the basic paper data.

As shown in Fig. 4, in the first 30 categories of data related to circular traffic signs, the category correctly places the data in its group, and the classification accuracy for this group is 100%. In the second group, which is related to rhombus-shaped traffic signs, category six has correctly categorized the data related to this category. The classification accuracy is 100% for this group. In the third group, which is related to triangular traffic signs, and vice versa, six data are categorized correctly, and the classification accuracy for this group is 100%. In the fourth group, related to simple triangular traffic signs, out of 24 data, one case was incorrectly classified in group five and the rest correctly. The classification accuracy for this group is 95.8% out of which 81% data is related to the background model. One case is incorrect in category four. One data is incorrectly categorized in category one, the rest of the data is categorized correctly, and the classification accuracy for this group is 97.5%. The absolute accuracy in this category is 98%. Also, in the following Fig. 5, the ROC diagram of the proposed method is shown on the data set introduced in [5].

Given that in the primary working method [1], the data used is selected. In order to prove the suitability of the proposed methods of extracting the proposed feature and algorithm, extracting all the images related to the GTSRB site, which contains 12569 images, has been used for implementation. A base of 1000 images has been used. After image detection by the torsional neural network, the properties are extracted by LBP and HOG. After normalizing the images and forming the feature matrix, the obtained matrix is given as input to the ELM classifier for classification and then output in 43 classes. In this study, 75% of the images were used for training, and 25% were used for experiments. Table II shows the execution times of the different parts of the proposed algorithm.

As shown in Table II, in addition to the appropriate accuracy and high generalizability of the Maximum Learning Machine category, the speed of immediate implementation of this category has been measured, which has not been considered in the essential work. Another criterion used to evaluate the algorithm's performance is the classification accuracy, which in the proposed method for classifying data into 43 accuracy classes is 95.31%.

For this evaluation, the k-fold approach was used, where the value of k was considered equal to 10. At each stage, 90% of the data is set aside for training and 10% for testing. This process is repeated 10 times to consider all the data for testing and training the system which will be averaged on the accuracy obtained. The ROC diagram for this category is shown in Fig. 6. In this diagram, the larger the area under the curve, the higher the classification accuracy. The pivotal components of this chart are the Misdiagnosis Rate (FPR) and the True Diagnosis Rate (TPR).

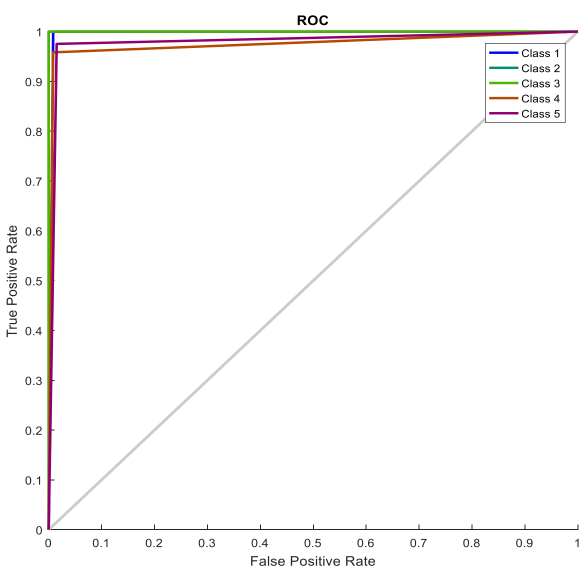


Fig. 5. ROC diagram of the proposed method on reference data [1].

TABLE II. EXECUTION SPEED IN SECONDS

| Total data testing time by ELM | Total data training time by ELM | HOG attribute for an image | Local LBP attribute for an image |
|---|---|---|---|
| 0.30 | 13.63 | 003/0 | 005/0 |

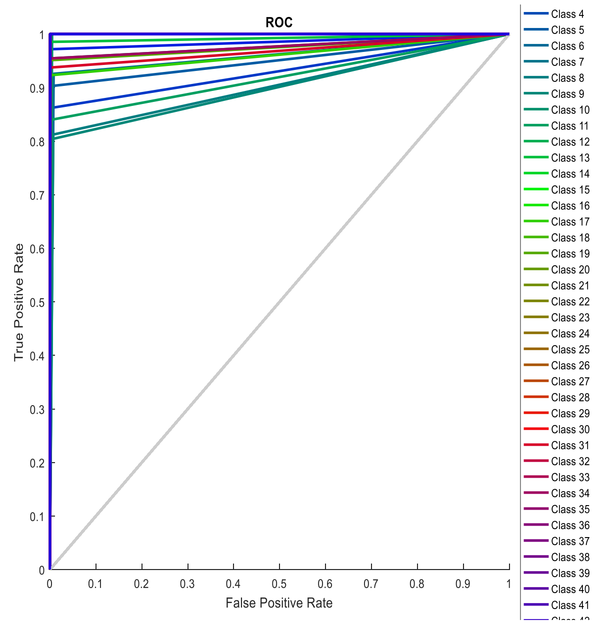


Fig. 6. ROC diagram of the proposed method.

## V. CONCLUSION

In this paper, a novel method for classifying traffic signs is presented. The primary work with 1000 images in four classes using color and PHOG features using the SVM algorithm has reached an average accuracy of 95.03%, while the proposed method uses detection. Torsional neural network and feature extraction using tissue feature with LBP technique and HOG feature with ELM classification in 1000 images reached 98.95%, considering that the baseline work did not use all the data related to GTSRB. In this method, extraction of texture properties along with shape properties by the LBP technique can improve the sensitivity of HOG to light reflections and tangled and complex backgrounds. Therefore, feature of the texture is that it is less sensitive to changes in light intensity than the color feature. To prove the superiority of the proposed method, the proposed method is implemented on all data of the GTSRB site, and the results obtained from 12569 images in 43 classes have achieved 95.3% accuracy. Lastly, this study intends to propose a novel feature representation algorithm using color and texture features for finding different features to represent the traffic sign images, presenting a method for classifying traffic signs using color and PHOG features the SVM algorithm, and developing a sign traffic detection method to deal with adverse weather conditions, light reflection, and complex backgrounds. The advantages of this method include the appropriateness of the selected features and the appropriate classification algorithm. However, the weakness is sensitivity in tough light condition and complicated background. For future study, the proposed method can be extended to deal with the tough variation in complex background and light conditions.

## VI. ACKNOWLEDGEMENT

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