A Hybrid Technique for Real Time License Plate Localization with the aid of FFBPNN-APSO

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***Abstract*—Vehicle License Plate Recognition (VLPR) is an imperative constituent in Intelligent Transportation Systems (ITS), which encircles three foremost phases essentially License Plate Localization (LPL), Character Segmentation (CS), Character Recognition (CR). In this paper, we have intended to introduce a novel License Plate Localization algorithm subjected to Artificial Neural Networks (ANN). This proposed scheme involves distinct phases of pre-processing, image de-noising and enhancement, feature extraction, Neural Network training and License Plate detection. Followed by the mining of assorted statistical features, geometrical features, edge features and texture features from the vehicular image, they are given as the input to Feed Forward Back Propagation Neural Network (FFBPNN) in order to localize the License Plate. During the training process, the parameters of the FFBPNN will be optimized using the eminent Adaptive Particle Swarm Optimization (APSO) algorithm in order to improve the Neural Network convergence performance. The License Plate Localization of our proposed technique is analyzed with simple Feed Forward Back propagation Neural Network (FFBPNN) in terms of accuracy, sensitivity and specificity. The experimental outcomes demonstrate that the proposed procedure proficiently accomplishes an extremely high localization rate with elevated specificity (91.3%).**

Keyword-Vehicle License Plate Recognition, License Plate Localization, Artificial Neural Networks, Forward Back Propagation Neural Network and Adaptive Particle Swarm Optimization.

I. Introduction

For the period of the past few years, Intelligent Transportation Systems (ITS) [30] have a spacious blow in human being’s life since their purview is to get better transportation portability, safety and productivity over the exploitation of highly developed technologies. ITSs are composed of sixteen types of technology supported systems, which are categorized into Intelligent Infrastructure Systems (IFS) and Intelligent Vehicle Systems (IVS). Vehicle License Plate Recognition systems (VLPR) [7] [28] turns to be the ultimate auspicious forms of employing mainframe visualization techniques headed for Intelligent Transportation Systems (ITS) [24], which are applied to recognize automobiles unambiguously, has attained enormous attention nowadays. Seeing that the trucks in the passages are ever-increasing in number day by day, VLPR becomes an intentional research area to a great extent in various countries. The prerequisite of the automatic VLPR systems [17] is quite diverse for separate countries, because of the different types of License Plates being used there.

VLPR systems are extremely suitable in lots of real time applications [6] such as security and administration, public and private entryways, boundary security, destruction control, wagon thefts, vehicle parking management systems, automated traffic surveillance and tracking systems, encountering traffic infringements, Electronic Toll Collection (ETC) systems etc.

A dedicated VLPR [27] system incorporates three major separable successive modules: License Plate Localization (LPL), Character Segmentation (CS) and Character Recognition (CR) [9]. Each stage might have the need of further Digital Image Processing (DIP) approaches. The general structure of a VLPR system is shown in Fig. 1.

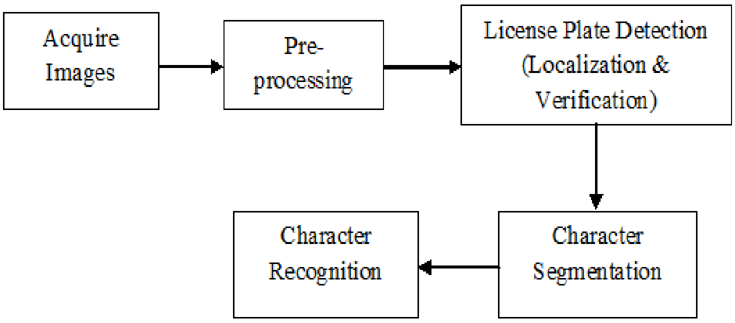

Fig. 1. General Structure of a VLPR system.

A. License Plate Localization (LPL)

It is the process of determining the position of the License Plate in the acquired and pre-processed motor vehicle input images, and to mine the License Plate region out of the surrounding background of the image in spite of the orientation and the dimension. It is the most demanding phase in VLPR system; as exceptionally elevated accurateness, real time character segmentation and exact decision making be able to be accomplished merely, if the License Plates are appropriately localized. On the whole VLPR systems to be precise, it has to locate the License Plates properly in dissimilar circumstances, whereas it should be rapid enough to meet up all the requirements of the ITS. For the reason that a huge percentage of the computational complexity is in LPL stage, the core time delay of the whole development is formed in this stage, which influences the entire calculating time delay of the VLPR systems. LPL involves two sub phases: Candidate Detection (CD) and Candidate Verification (CV).

B. Character Segmentation (CS)

It is the process of isolating License Plate characters by cutting the License Plate image in to small individual character’s images.

C. Character Recognition (CR)

It is the process of identifying or recognizing each and every character within the detached License Plate image which transforms character’s images into final distinguished characters amongst them.

There are so many existing techniques and algorithms of VLPR systems [1] – [30], for the exposure and extraction of License Plates. Existing techniques tackle numerous threats such as massive deviations in texture, size, figure, color, spatial orientations and convolution of the sight etc. of License Plate zones, capture of the motor vehicle images in mixed ecological and enlightening circumstances, images accommodating multiple License Plates in different positions and dimensions and a few images having background the same as patterns alike the License Plates etc. Shortcomings of the current VLPR systems influence its performance and give rise to the motivations to the proposed system. The majority of the existing systems work sound simply under some particularized contexts [19]. Because of the elevated wrong VLPR rate in compound background and computational intricacy in the existing systems, the License Plate Location algorithms are becoming more complicated and possibly will cause the high error and miss rate in VLPR systems. Aspiring at struggles mentioned above, there is a necessity of License Plate Recognition techniques with high quality and excellence.

In this paper an instant and real-time motor vehicle License Plate Localization system based on Artificial Neural Networks (ANN) is presented. Neural networks have been fruitfully used as classifiers in abundant applications. They can be also utilized to extort features automatically because of their excellent adoption susceptibilities. Nevertheless, for the Neural Network algorithm, the optimization process is especially time-consuming, and it frequently falls into local minimum. In order to solve this dilemma, we construct a new Neural Network, which is the FFBPNN network whose parameters are optimized by Adaptive Particle Swarm Optimization (APSO) Genetic algorithm (GA), which can effectively improve the network performances and License Plate Localization rate.

The remaining portion of our paper is prearranged as follows. Section II depicts the proposed system. Section III constitutes and demonstrates a review of experiments and results. Concluding observations are exhibited in Section IV.

II. THE PROPOSED SYSTEM

In this paper, we have deliberated to recommend a novel hybrid technique for real time License Plate Localization with the assist of Feed Forward Back Propagation Neural Network (FFBPNN) and Adaptive Particle Swarm Optimization (APSO) algorithms, which will prevail over the aforementioned predicaments that are present in the existing methods. In order to have a consistent localization of License Plates in real dynamic environment, quite a lot of stages and selections are mandatory. We typically exploit alike choices which have improved time complexity, to have the techniques in various phases significant for the real time systems. Here, in our paper we had constructed such a VLPR system and the related block diagrams of the whole stages of the algorithms used for this particular proposed system are displayed in Fig. 2 and Fig. 3, which covers the two subsequent phases:

- Training Phase
- Testing Phase

The succeeding discussion presents the algorithm of the proposed License Plate Localization technique.

A. Training Phase Algorithm for License Plate Localization

The flowchart for the training phase of the proposed License Plate Localization system is shown Fig. 2.

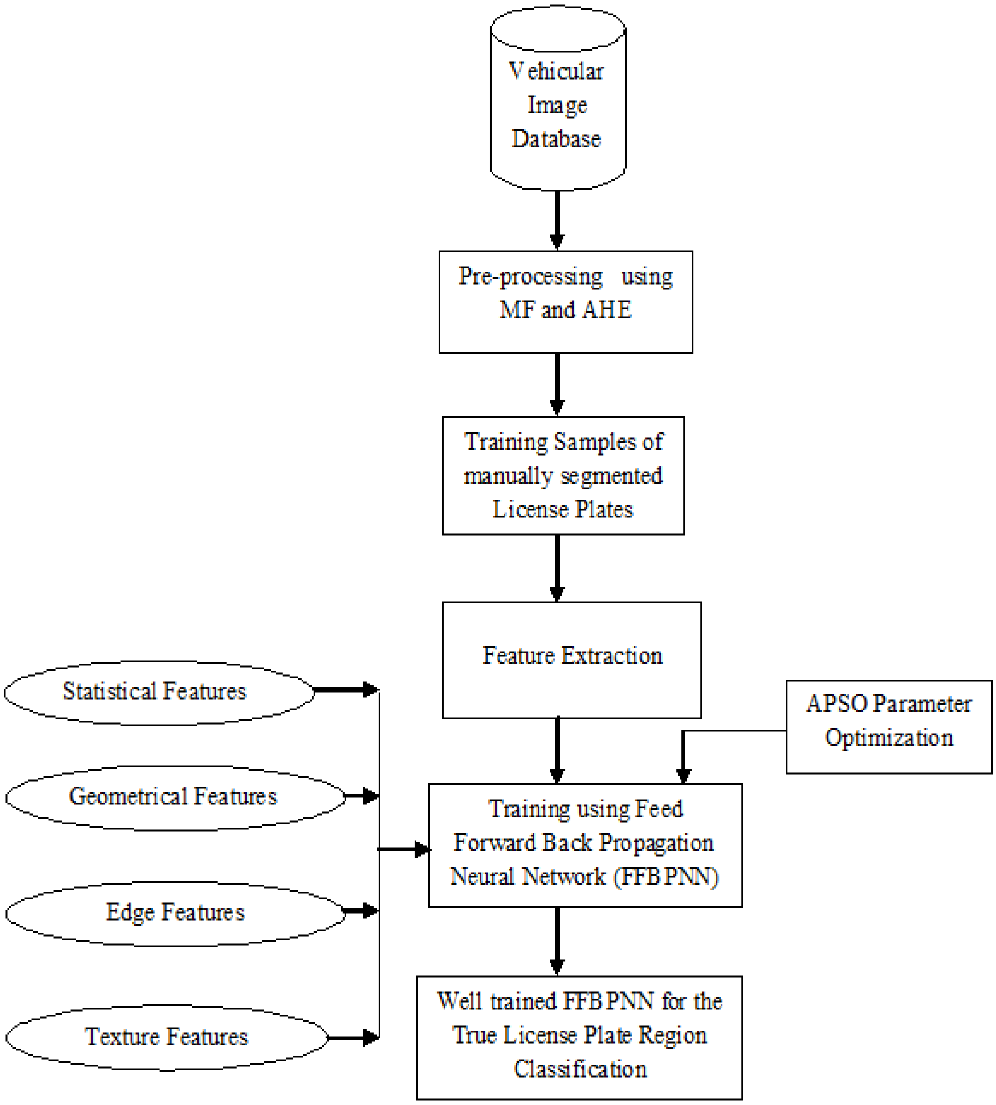

Fig. 2. The flowchart for the training phase of the proposed algorithm

1) Vehicular Image Database

A database of 76 Indian vehicle images having License Plates has been collected by means of digital cameras, from various places especially parking places, public and private roads, streets, passages etc. in terms of dissimilar illumination and weather conditions, orientations and slopes, dimensions and resolutions, altering backgrounds, a few taken distant from the motor vehicle and some close to the vehicle, some desirable images used for training purposes etc. and few are collected from World Wide Web (WWW). The vehicular image database is gathered concerning the aforesaid properties, ever since this particular VLPR system should work in real time, to include the majority of obtainable scenarios in the training process and testing our proposed system in opposition to them.

2) *Pre-processing*

For more appropriate visual sensitivity and further computations, the choice of parameters on the camera awfully provides the pre-processing [25] [20] quality of the motor vehicle images. Pre-processing stage is obligatory to make it possible to obtain high performance in the localization of License Plates, in this proposed VLPR algorithm. Numerous Neural Network approaches have been employed to these pre-processing techniques in order to generate improved quality and to amplify the convergence rapidity of the image. The pre-processing techniques for the proposed system use three central sub processes:

- *Gray Scale Conversion(GSC)*

In the pre-processing mode, initially the acquired image is transformed into Gray Scale image from RGB multicolor image [21]. Since the classification of objects within an image is an extremely complicated task, Gray Scaling is concerned to make the background of the vehicle image clearer [18]. The RGB color space is converted into Gray space by means of the typical formula:

$$\mathrm{G}(\mathrm{x},\mathrm{y}) = 0.2989 * \mathrm{Red} + 0.5870 * \mathrm{Green} + 0.1140 * \mathrm{Blue} \tag{1}$$

where, G(x,y) is the Gray Scale image.

During this Gray Scale Conversion, a number of key parameters such as thin edges, color variations etc. may perhaps get squandered. The subsequent processes of Median Filtering (MF) and Adaptive Histogram Equalization (AHE) will help to prevent such fatalities.

- *Median Filtering(MF)*

It is unavoidable that original vehicle images have noises. So the Gray Scale images are yet again pre-processed using Median Filter to lessen or eliminate the existence of unnecessary data and noise. The foremost benefit of carrying out Median Filtering [26] is that it intensifies the high frequency more and it conserves edge pixels too; whereas detracting or extracting noise pixels. So Median Filtering turns to be so advantageous for us to distinguish the edges within the images and is a good choice for our proposed system too, since edge pixels of the vehicle images co-operate an extremely vital role here, which ultimately improves the License Plate recognition rate. In this filtering scheme, it scans the image pixels row by row from top to bottom and replaces the gray value of each pixel by the median of gray values of its neighboring pixels.

- *Adaptive Histogram Equalization(AHE)*

After the elimination of the noises, Histogram equalization is exploited to scrutinize the precise white level background pixel intensity of the License Plate image and is a well accepted procedure to enhance the appearance of a deprived contrast of the image. Accordingly, following the pre-processing, the shadowiness, blurriness, contrast, heterogeneous illumination, resolution etc. of the pre-processed vehicular images will be enhanced by means of Adaptive Histogram Equalization technique. It diverges from the normal Histogram Equalization procedures in such a way that it figures out quite a lot of histograms, each corresponding to a distinctive segments of the image and by making use of them to redistribute the lightness values of the image, which considerably influence the localization phase.

3) *Training Samples of manually segmented License Plates*

Subsequently, the image License Plate location or portion will be segmented manually from the pre-processed and enhanced images. Hereafter these pre-processed and enhanced images became set for Feature Extraction phase, which directly feeds to Neural Networks inputs as training and testing parameters.

4) *Feature Extraction*

Feature extraction is one of the primary steps in the VLPR system, which measures the significant features to be used in the License Plate detection process that inimitably depict the License Plate image. In view of the fact that fine, effective and correct features can make the detection practice uncomplicated and trim down the error rate; how to choose them to progress the accurateness and to attain excellent outcomes in the detection process of License Plate, is especially important. Various authors have explored several fundamental features of the extracted regions; at this point, a comparable but extra proficient technique is promoted for interrogating such features over our vehicular image database After segmenting training samples of License Plates manually, the statistical features, geometrical features, edge features and texture features of the particular portion of License Plates will be computed from the manually segmented License Plate area and those features will be given to the Feed Forward Back Propagation Neural Network (FFBPNN) to accomplish the training process. We concentrate on four basic features to select an appropriate License Plate candidate region from the input image.

- *Statistical Features***:** Mean, Variance and Histogram.

$$\text{Mean } (\mu) = \frac{1}{x*y}\sum_{i=0}^{x}\sum_{j=0}^{y} p(i,j) \tag{2}$$

where,

x – Number of rows within the image

y – Number of columns within the image

p (i, j) – pixel value at location (i, j)

$$\text{Variance } (\sigma 2) = \frac{1}{x*y}\sum_{i=0}^{x}\sum_{j=0}^{y} p(i,j) - \mu(i,j) \tag{3}$$

$$\text{Histogram } (\text{H}) = \sum_{x=H-10}^{H=10} h(x) \tag{4}$$

- *Geometrical Features*: Area, Aspect Ratio and Region Intensity.

Area (A) = Actual number of pixels in the region

$$\text{Aspect Ratio } (\text{AR}) = \frac{w}{h} \tag{5}$$

w=width of the image

h=height of the image

Region Intensity (RI) = Specifies the value of the pixel with particular intensity in the region.

- *Edge Features*: Edge density (ED = Density of vertical edges at the License Plate area is considerably higher than its neighbourhood).

$$\text{Edge Density } (\text{ED}) = \frac{\text{sum(i=1,w) sum(j=1,h) e(i,j)}}{N} \tag{6}$$

where,

e=edge map image magnitude of vertical edge at (i,j)

N=w x h

- *Texture Features*: Contrast, Correlation, Energy and Homogeneity.

$$\text{Contrast } (\text{C}) = \sum_{i=0}^{x}\sum_{j=0}^{y} |i-j|\ p(i,j) \tag{7}$$

$$\text{Correlation } (\text{Cr}) = \sum_{i=0}^{x}\sum_{j=0}^{y} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma i\ \sigma j} \tag{8}$$

$$\text{Energy } (\text{E}) = \sum_{i,j} p(i,j) \tag{9}$$

$$\text{Homogeneity } (\text{Hy}) = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{10}$$

In order to accomplish improved detection rate and a potential result in License Plate Localization, we have suggested a combination of features.Thus there are eleven features extracted from the License Plate image. These features are used for the classification process using Feed Forward Back Propagation Neural Network (FFBPNN). Thus the output from the extraction process will be used in the next stage which is the training process.

5) *Well trained Feed Forward Back Propagation Neural Network (FFBPNN) for the True License Plate Region Classification.*

Artificial Neural Network (ANN) is a multidisciplinary analysis of Computer Science and Biology, which is an influential means for resolving multifaceted engineering dilemmas and has been broadly employed in various applications. A Neural Network is a collection of neurons which are stimulated by the image pixels. FFBPNN algorithm is a supervised classification technique, which maps non-linear procedures, which allots an image to a particular class depending on its features. The primary structural design of the FFBPNN owns three layers Input layer, Hidden layer and Output layer respectively; which are shown in Fig.3.

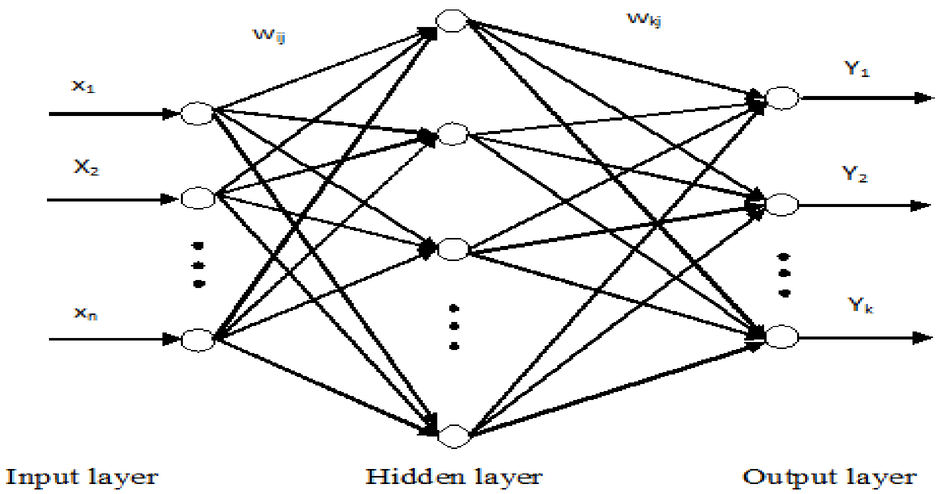

Fig. 3. The general structure of the FFBPNN

To put together the inputs lead to a precise output, the training process is performed. During the training process, the original weight is arbitrarily produced and customized iteratively. The weight is customized by means of the error between the consequent and the required outputs. The learning process of the Neural Network is done by modifying the weights and by fine-tuning these weights, it is able to make the consequent output nearer to the needed output. It is extremely relevant that the expansion of the size of the training database within the Neural Network will progress the effectiveness and exactness of the License Plate Localization rate.

The underlying concepts of the FFBPNN algorithm is be encapsulated as follows:

x_{ij} stands for the input from node i to unit j, and w_{ij} stands for the related weight.

δ_n stands for the error term allied with unit n.

- Initialize each weight w_i to any small arbitrary value
- As far as, the ending condition is met, do
  - For each training instances $<(x_1,\ldots x_n),t>$ do
    - Input the instance $(x_1,\ldots,x_n)$ to FFBPNN and compute the outputs y_k
    - For each output unit k
      - Compute error term, $\delta_k=y_k(1-y_k)(t_k-y_k)$
    - For each hidden unit h
      - Compute error term, $\delta_h=y_h(1-y_h)\ \Sigma_k\, w_{h,k}\, \delta_k$
    - For each weight $w_{,j}$ do
    - $w_{i,j}=w_{i,j}+\Delta w_{i,j}$ where, $\Delta w_{i,j}= \eta\ \delta_j\ x_{i,j}$

In order to get classify the true License Plate region and false License Plate region, Feed Forward Back Propagation Neural Network (FFBPNN) [22] is trained with the statistical features, geometrical features, edge features and texture features extracted from each and every manually segmented License Plate images from the database. The extracted features are given as the input to Neural Network for training and classification purpose. This particular FFBPNN consists of 11 input units, N hidden units and only one output unit Y, which will be the true License Plate region or false License Plate region. The structure of the proposed FFBPNN is given as below:

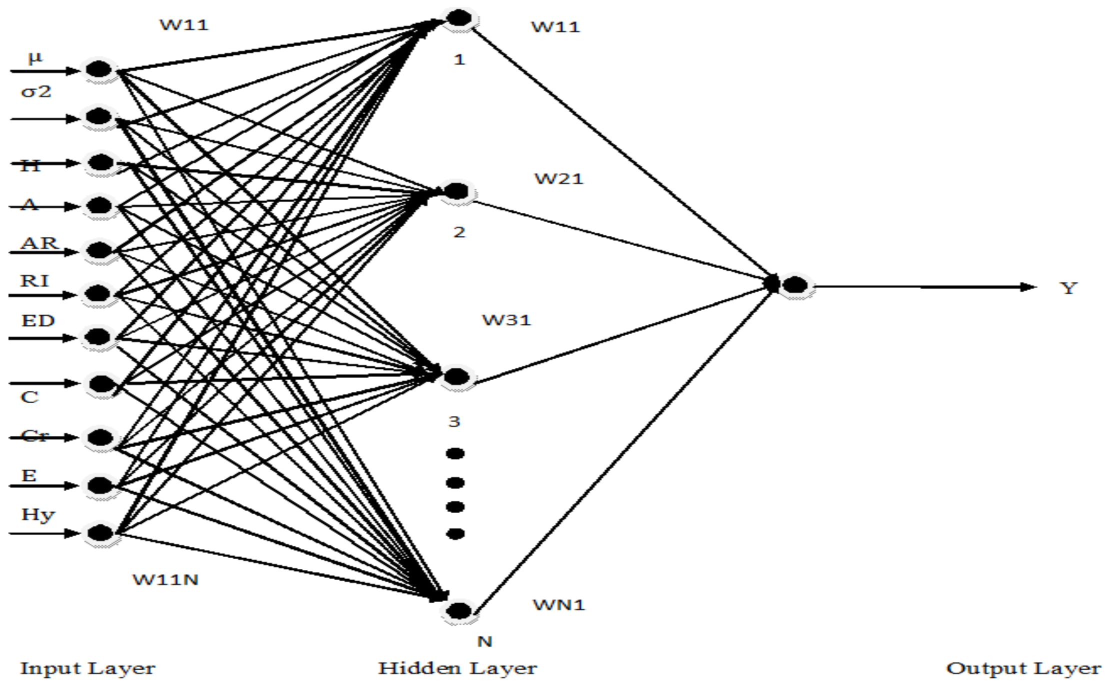

Fig. 4. Architecture of the proposed FFBPNN

6) APSO Parameter Optimization

During the training process, the parameters of FFBPNN will be optimized using the well known optimization algorithm known as Adaptive Particle Swarm Optimization algorithm (APSO), which exhibits stupendous performance while solving global optimization problems. APSO is commensurate with Particle Swarm Optimization algorithm (PSO) concerning algorithm consistency, solution precision and convergence swiftness, which is based on genetic theory and natural selection of parameters.

In our proposed system, APSO is helpful to triumph over the convergence speed flaws within the FFBPNN training process. Although FFBPNN has the capability of self organization, fault tolerance and self-adaption; its convergence is very sluggish and can simply thrust into local minimum. Therefore the learning process of FFBPNN by far turn out errors, if preliminary weights are not set suitably and it is complicated to find out the number of hidden layer nodes, since the assortment of the preliminary weights are arbitrary. But at the same time, Genetic Algorithms are globally convergent and independent of the preliminary values. So we construct a new network called FFBPNN-APSO by optimizing the parameters using APSO incorporating the benefits of global searching of APSO Genetic Algorithm and the instructive searching of FFBPNN. Here, the original interconnection of the weights and thresholds of FFBPNN are optimized with APSO so that the training and learning quickness are amplified, which establishes the accurateness, robustness and network convergence performance of the License Plate Localization problem.

B. Testing Phase Algorithm for License Plate Localization

The performance of the FFBPNN-APSO will be evaluated by giving more number of testing images. While the testing process, the given input image is pre-processed using Median Filter initially to remove the noise. Then, the contrast of the pre-processed image will be enhanced using AHE technique. After that, the features of the whole image will be calculated by dividing the whole image into number of blocks. Followed by the calculated statistical features, geometrical features, edge features and texture features will be given to the well trained FFBPNN-APSO to detect that the given input block has the license plate area or not. By combining all the blocks from the testing image the Region of Interest (ROI) or the true License Plate region will be localized, which can be cropped or segmented using some Morphological Opening and Closing operations, in order to remove the unwanted regions from the testing image to isolate the License Plate.

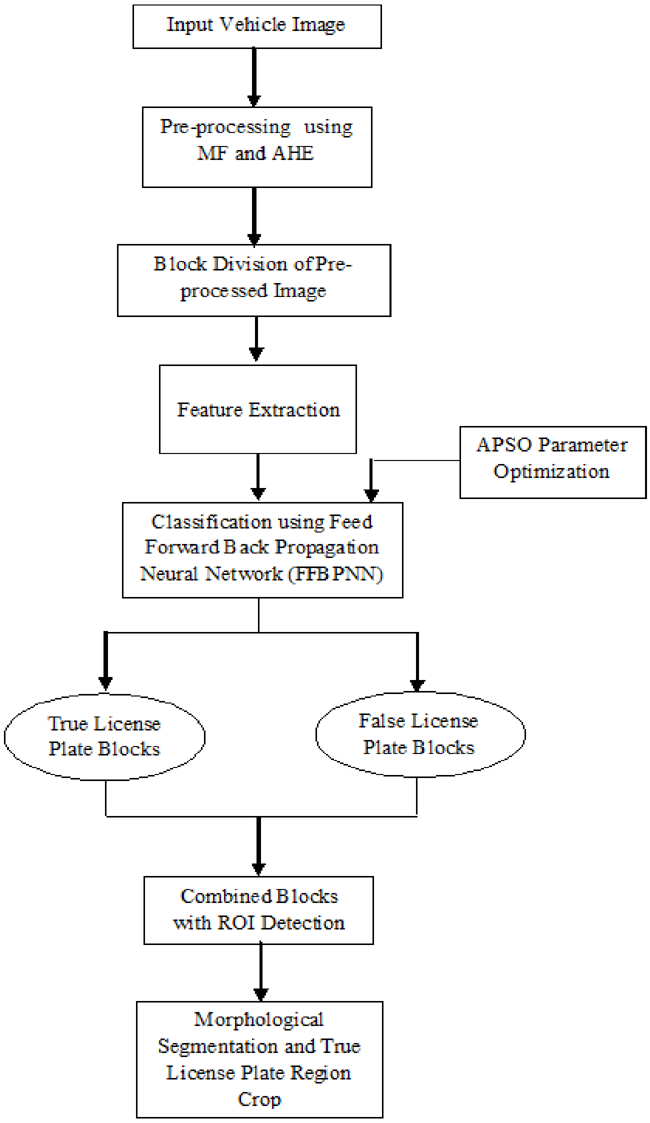

Fig. 5. The flowchart for the testing phase of the proposed algorithm

III. EXPERIMENTAL RESULTS AND DISCUSSION

The input vehicle image of the proposed system is presented in Fig. 6, while the output can be viewed as Fig. 13.

Fig. 6. RGB Input Image

Fig. 7. RGB to Gray Scale Image

Fig. 8. Median Filter

Fig. 9. Adaptive Histogram Equalization

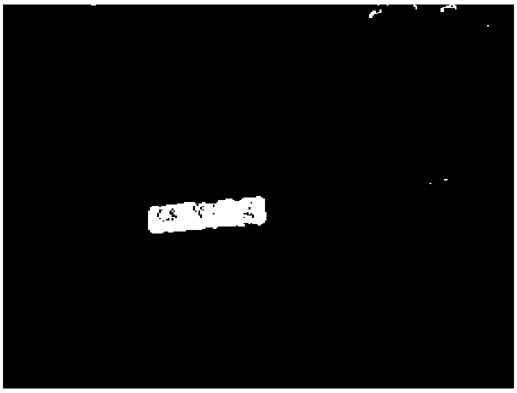

Fig. 10. Neural Network Classified with Region Grouping

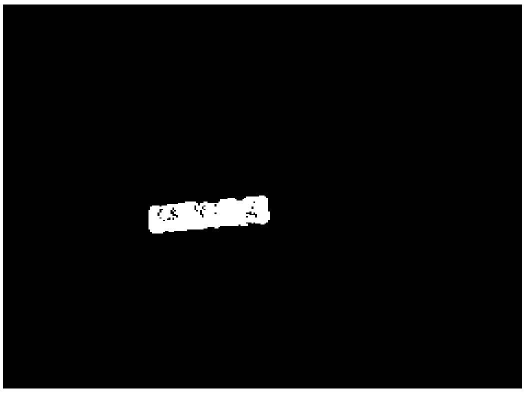

Fig. 11. Remove Unwanted Region using Morphology Operator

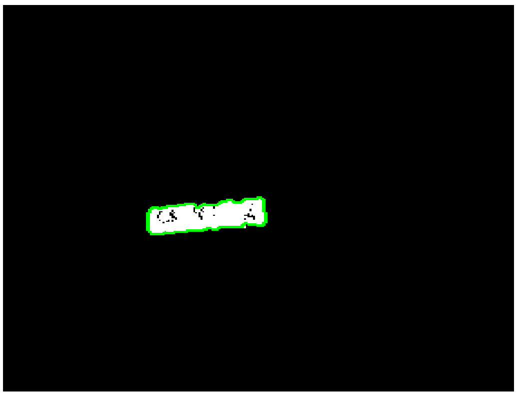

Fig. 12. Contour of Input Image

Fig. 13. License Plate Detection

The proposed system is estimated by providing additional quantity of images to the FFBPNN-APSO classification. Experimental results explains that the robustness and exactitude are perceptibly upgraded, which to a great extent enhance the License Plate Localization rate also. Here the localization of License Plates of VLPR system is done using FFBPNN-APSO classifier with eleven features in the vehicle images which knows how to make simpler the code, uncomplicated to apply and get better quality of License Plate Localization process; at the same time as acquiring fine performance and encourages expandability of VLPR structures through the localization of additional License Plates than that of the originally designated. Experimentations confirm so as to this particular procedure obtained incredibly lofty exactness of 86.13% for the localization of License Plates successfully and hurriedly, even if during apparent or drizzling day, darkness or sunshine, or underside the complex atmosphere. Implementation of our proposed VLPR architecture is performed in the functioning of MATLAB platform.

The recital of the proposed FFBPNN-APSO system is analogized with simple FFBPNN system; with regard to the ROC (Receiver Operating Characteristic) parameters especially; accuracy, sensitivity and specificity as exposed in TABLE I. Here, for calculating these measurements; True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) terms are utilized and a mixture of formulas depend on that are specified as follows:

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (11)$$

$$Sensitivity = \frac{(TP)}{(TP+FN)} \quad (12)$$

$$Specificity = \frac{(TN)}{(TN+FP)} \quad (13)$$

TABLE I. Performance of the FFBPNN-APSO System and Simple FFBPNN System

ROC parameters	Proposed FFBPNN-APSO System	Simple FFBPNN System
ACCURACY	86.13%	69.28%
SENSITIVITY	72.8%	61.7%
SPECIFICITY	91.3%	76.5 %

The accuracy of our proposed VLPR system is 86.13%. Superior performance of our technique is acknowledged by the accuracy because the accuracy of proposed FFBPNN-APSO is 16.85% upper while collated with simple FFBNN system. At the same time as, in view of sensitivity, the proposed system has 72.8% and is 11.1% upper than simple FFBPNN. Specificity of the proposed technique is as well extensively upper seeing as the proposed technique has 91.3% specificity which is 14.75% better than simple FFBPNN.

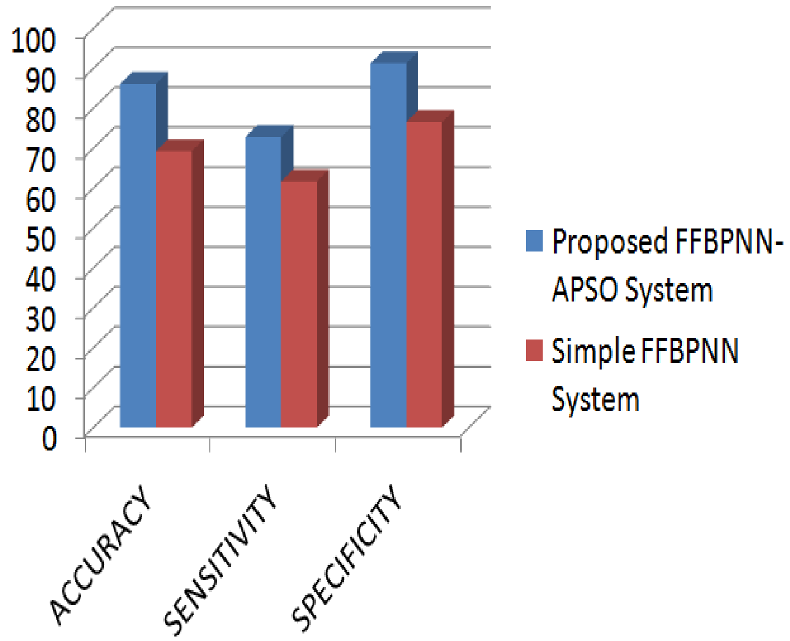

Fig. 14. Proposed FFBPNN-APSO based system and simple FFBPNN's performance in terms of Accuracy, Sensitivity and Specificity

In Fig 14, ROC parameters of the proposed FFBPNN-APSO based system are examined against simple FFBPNN. By surveying the chart, it is implicit that accuracy of proposed procedure is conspicuously superior to the simple FFBPNN. The sensitivity and specificity measures of the proposed FFBPNN-APSO based technique are also outstandingly elevated than the simple FFBPNN. These ingredients point out that our proposed system has privileged performance.

IV. CONCLUSION

Proposed system will be capable of practicing motor images in real time and healthier discrimination of License Plates with diverse sizes from composite back grounds; which turns to be a hybrid and high superiority License Plate Localization technique. APSO algorithm is handled to surmount the limitations of convergence swiftness in FFBPNN, so that the learning and training velocity is amplified and the unsurpassed network convergence performance is procured, which sustains the strength and precision of the License Plate Localization dilemma. Accordingly proposed FFBPNN-APSO based technique secured enhanced performance when compared to the simple FFBPNN. We endeavor our upcoming work as to expand our proposed FFBPNN-APSO system to the enduring phases of the License Plate Recognition systems, such as Character Segmentation and Character Recognition.

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