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AN EFFICIENT ALGORITHM FOR REAL TIME LICENSE PLATE LOCALIZATION

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ABSTRACT

The target of this paper is to build up a well-organized algorithm hinged on Automatic Vehicle Registration Plate Recognition system. It is the mining of License Plate data from vehicle pictures or videos, which accommodates three parts such as License Plate Localization, Character Segmentation and Character Recognition. In this paper, we have projected an efficient License Plate Localization algorithm subjected to Adaptive Neuro Fuzzy Inference System. This proposal involves a mixture phases of pre-processing such as Gray Scale conversion, Sobel edge map detection and morphological image binarization. Followed by the Maximally Stable External Region text region detection, geometrical and texture features are drawn out to be granted as input to ANFIS for the training purpose for localizing the License Plates. The proposed method is deliberated to achieve localization of any category of License Plates covering at all categories of environmental surroundings. In this efficient method of License Plate Localization, the empirical results express reasonably forceful localization rate as 93.61%. The proposed system provides a rapid sprouting technology and a fundamental constituent for the Intelligent Transport Systems.

Keywords: automatic vehicle registration plate recognition, license plate localization, adaptive neuro fuzzy inference system, maximally stable external region, intelligent transport systems.

INTRODUCTION

Intelligent Transportation System (ITS) [1][2][3][4][5] turns to be an extremely essential for the advancement of transportation communications of day today life, which owe a spacious blow as the outlook to look up a flexible and secure transportation in order to augment the efficiency, over the usage of highly developed technologies. Automatic Vehicle Registration Plate Recognition (AVRPR) system [6][7][8][9][10] is a chief application of ITS's [11] which is an image processing method to make out automobiles by means of their particular License Plates. AVRPR is a demanding field of research owing to its priority to an extensive series of real world commercialised applications such as traffic jamming and supervising for traffic rule imposition; electronic payment systems for involuntary toll collection and parking charges; arterial and freeway administration for traffic surveillance; public safety systems for the right of entry control to constrained regions, boundary passage snooping, anti-terrorism, tracking of hijacked wagons etc; with slightest human being interference.

Normally, an Automatic Vehicle Registration Plate Recognition (AVLPR) system [12][13][14][15][16] is made up of five modules [17][18], which are represented as in Figure-1.

1. Image Acquisition
2. Image Enhancement
3. License Plate Localization (LPL)
4. Character Segmentation (CS)
5. Characters Recognition (CR)

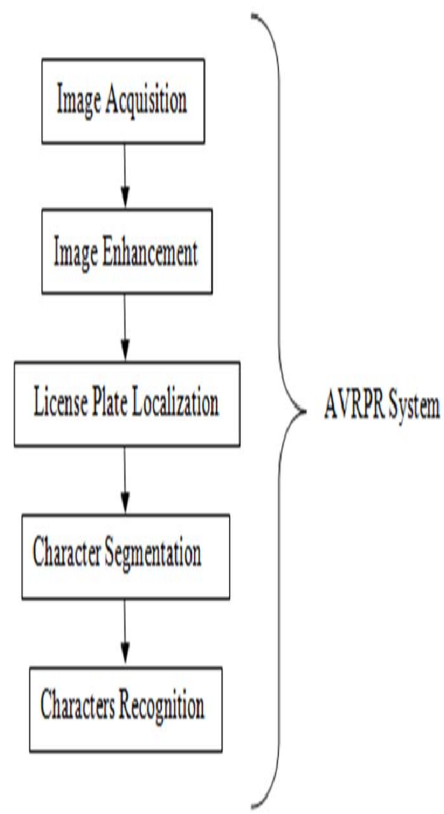

Figure-1. Flowchart of the AVRPR system.

Subsequent to the Image Acquisition, Image Enhancement is functioned for suppressing the noises and illumination problems and to perk up the quality of the motor images. Later the License Plate Localization step endues the categorization of the true License Plate and the false License Plate regions, which is well thought-out as the ultimate one, which points to an immense accurateness and a real time segmentation and identification of License Plates. The Characters Segmentation phase disconnects characters from remains in a License Plates so that only the clear-cut outlines of every character picture parts is reserved for identification. After all, the Character Recognition phase transforms automobile pictures depending on the predefined recognition systems.

In AVRPR system, License Plate Localization is the opening and elemental phase, which will have an effect on the upcoming outcomes of Character Recognition. For this reason, we investigate to stumble on a first-rate scheme for the License Plate Localization. An assortment of approaches has been built-up in recent times for the competent finding of License Plate locality from the motor images, which will be insufficient to meet up all the desires of recent systems. Generally the License Plates come out in altered categories of text styles and fonts, either in one or multiple rows, changed sizes, spacing and count of characters and inclination. These fluctuations cause difficulties in localizing or recognizing the License Plates. These problems will turn into heavy troublesome for the period of night-time because of the reduced and non uniform illumination lighting situations, intensities of the compound surroundings etc. In this paper we put forward a novel and efficient method for the License Plate Localization which makes use of the MSER region detection [19] and ANFIS [20] classification for the extracted geometrical and texture features, which give a very nice localization rate of License Plates. So, the proposed approach will more effective than existing methods under the aforesaid uncontrolled conditions.

In the next, the association of the paper is indicated as follows. The Section 2 gives the complete overview and description of the proposed AVRPR algorithm. Section 3 presents the sample set formation and experimental results; in the end, Section 4 pursues conclusions and future scope and Section 5 gives references.

PROPOSED AVRPR METHOD FOR LICENSE PLATE LOCALIZATION (LPL)

The first development phase in an Automatic Vehicle Registration Plate Recognition (AVRPR) System is the revealing of the License Plates, in which the inputs are the pictures of motor vehicles and the result is a picture segment accommodating the License Plates and a combination of activities are performed for obtaining them.

A detailed architecture of the proposed License Plate Localization system is shown in Figure-2. The highlighting steps involved in the proposed License Plate Localization system are:

i. Read Input Image
ii. Gray Scale Conversion
iii. Sobel Edge Map Detection
iv. Maximally Stable External Region (MSER) License Plate Text Regions Detection
v. Morphological Image Binarization
vi. Geometrical and Texture Features Extraction
vii. Adaptive Neuro Fuzzy Inference System (ANFIS) Classification: Training and Testing
viii. ROI Detection and License Plate Extraction

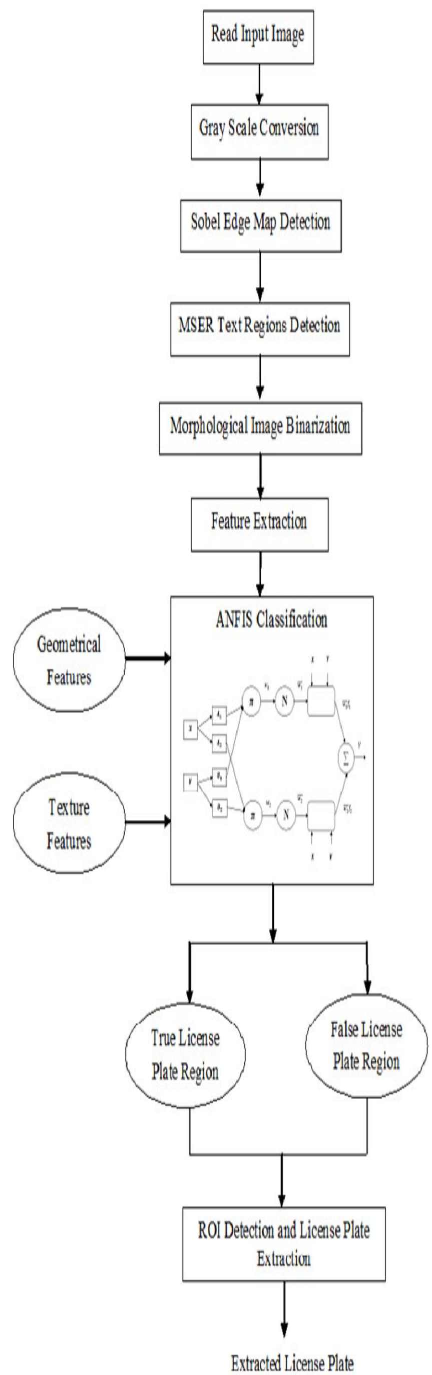

Figure-2. Proposed architecture for the license plate localization (LPL).

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The subsequent discussion presents a detailed overview of the proposed algorithm for the License Plate Localization (LPL).

Read input image

Image attainment is especially a chief step in the Automatic Vehicle Registration Plate Recognition (AVRPR) System. The database involves 70 photographs with License Plates of motor vehicles, which is collected with the help of a camera and the camera parameters, such as the category, resolution, brightness, shutter quickness and direction, have to be careful.

Image pre-processing

In order to handle every sort of illumination inconveniences, first-class pre-processing or enhancing techniques should be considered. This phase should be helpful to get rid of the sway of illumination and to build the License Plate significant. The pre-processing procedures practiced in our proposed system are Gray Scale Conversion, Sobel Edge Map Detection and Morphological Image Binarization.

Gray scale conversion

Initially, the RGB motor picture is changed into Gray Scale image, in order to boost the implementation speediness and formulates it to the subsequent stages of the AVRPR system. Towards the extortion of additional data pertinent to the particular vehicle, a weighted sum of the R, G and B factors are [21][22][23][24][25] organized, with 8 bits/pixel and support 256 dissimilar intensities as:

$$GS = 0.5870 * R + 0.2989 * G + 0.1140 * B \quad (1)$$

where, GS is the Gray Scale image.

Sobel edge map detection

Edge detection is a widespread progression for pinpointing pixel strength transformations or the consequential discontinuities within them. The prosperity and power of edges are the effectual features that are extensively approved for the exposure of text regions and shows potential performance. In order to keep away from the chance of false License Plate region detection, it is essential to attain the noise-free and unbroken edges, which accentuate lofty spatial frequency regions. Experimentally, in our proposed system, the most excellent outcomes are achieved through the application of Sobel filters.

Morphological image binarization

This function is developed to detach the background details from the remaining parts of the motor picture; which turns to be very helpful for the triumph of the subsequent phases in AVRPR system. A binary picture is resulted here which requires a small amount of time to mine any relevant data from it and enhances the quality also. Dilation and erosion are the morphological operations used in our proposed binarization method and these imperative processes are obligatory in License Plate detection in order to abolish noises and preserve only things to signify the targeted result; which also joins wrecked letters with in the License Plates and eliminates the parts that are narrower than the License Plate characters.

Maximally stable external region (MSER) license plate region detection

A Maximally Stable External Region (MSER) method is proposed in our paper, which can be applied as a technique for the detection of blobs within the images; which is resourceful in terms of solidity, dimension, perspective, magnitude, blur and brightness changes while comparing with traditional region detection methods. MSER algorithm constantly produced satisfactory grade for every analysis, ensuring its reliability and dominances over the ordinary characteristics such as stoutness, discrimination and repetition velocity, which turns to be very supportive in finding the text regions and for the accomplishment of characters.

Feature extraction

Feature Extraction is the fraction of mining the appropriate features that are helpful for the exposure of License Plates. The License Plates subsist wherever within the vehicle image and so if they can be renowned by such features; only those pixels are to be processed which satisfy the required features projecting the characters comprising within it. Assortment of precise features is vital to acquire the most excellent outcomes in AVRPR systems and the execution time also affects the real time identification of License Plates.

Even though the MSER algorithm figures out for the most part of the text regions, some stable non-text regions are also encountered here within the images. So a rule-based approach will be helpful to take away those non-text areas. This paper implements a simple ANFIS approach for discerning among the text and non-text regions, based on geometric and other texture properties. Characteristically, a permutation of these two approaches delivers healthier outcomes and advances the effectiveness also.

Here, the geometrical properties extracted include Aspect Ratio, Eccentricity, Euler Number, Extent, Solidity features.

Aspect Ratio *(Ar)*

In general, for a peculiar state or country, License Plate magnitudes are preset which is helpful for the establishment of the License Plate region. The rectangularity of the License Plate margin is another major aspect for doing so and here the Aspect Ratio is the ratio of width to height, and so it turns to be a good geometrical feature, seeing as a width of the License Plate is greater than height.

Eccentricity *(E)*

It gives the proportion of the distance connecting the ellipse foci and its main axis extent, ranging the values

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between 0 and 1. An ellipse which shows the Eccentricity as 0 gives a circle and as 1 gives a line segment.

Euler Number *(E_n)*

Various regions acquired from the MSER region detection algorithm, are discriminated by Euler Number, which results the difference between the number of objects and holes within the images, which also produces the value as zero or negative for the alphanumeric regions, whereas positive value for the remaining regions.

Extent *(E_x)*

Extent gives the fraction of pixels within the required region to that of within the whole bounding box and is formulated as its area divided by the area of the bounding box.

Solidity *(S)*

Solidity gives the area portion of the region when balancing to its convex hull.

For extracting the texture properties from the background, we make use of DWT (Discrete Wavelet Transform) features and some of the Gray-Level Co-Occurrence Matrix (GLCM) properties such as homogeneity

Discrete Wavelet Transform *(D_{wt})*

It leads to the withdrawal of the essential contrast features such as low resolution Approximation of original image (A), Horizontal (H), Vertical (V) and Diagonal (D) bands which direct to seek out for the needed License Plates. The foremost benefit is that it can localize numerous License Plates within a single picture in dissimilar orientations, under the uncontrolled environments.

Homogeneity *(H)*

It measures the proximity of the allocation of pixels within the GLCM to the GLCM diagonal.

Adaptive neuro fuzzy inference system (ANFIS) classification

The AVRPR system requires a classification scheme that takes the extracted features as the inputs and concludes whether it encounters either the true or the false License Plate region. Here our aim is to select a classifier which exploits superior outcomes and so in our proposed system, we utilize an Adaptive Neuro Fuzzy Inference System (ANFIS) as classifier.

An Artificial Neural Network (ANN) [26][27][28][29][30][31] is data computing hypothesis, constructed by means of numerous integrated neurons in order to give solutions for our complex problems. Their noteworthy capability to draw out sense from convoluted rough data; can be useful to haul out the patterns which may be moreover intricate to be perceived by erstwhile practices. Soft computing is a realistic substitute for the solutions for the multifarious estimation inconveniences, which can effortlessly coalesces the intellectual system such as Neural Networks and the real world system dynamics such as fuzzy logic; whereas Neural Networks supply the arithmetical authority of the brain and the fuzzy logic provides the verbal control with the linguistic management for the transformation of the input status to the required result.

Adaptive Neuro Fuzzy Inference System (ANFIS) integrates the Artificial Neural Network (ANN) and Fuzzy Inference System (FIS) [32] and utilizes a Back Propagation (BP) algorithm for diminishing the error rate; it may be helpful in such a way that even though the objectives are not provided, it can accomplish the best possible outcome swiftly. Here, the inputs are given to the input layer by performing the input membership functions and the output is viewed in the output layer by performing output member functions. The ANFIS structure of our proposed system is given in the following section.

ANFIS training

The features are extracted from the MSER region detected images and are given to ANFIS classifier. Fuzzy classifier is a fuzzy set which produces either zero or one values depending on the harmonization of the mined features. Here ANFIS classifier categorizes the regions as the true License Pate region and the false License Pate region, depending on the values of the output (0 or 1). In our proposed work, we have extracted the seven features which are helpful for training of the ANFIS.

Commonly, ANFIS architecture encompasses five layer nodes; in which the first and fourth layers hold adaptive nodes while the second, third and fifth layers own fixed nodes and the number of neurons in each layer will be same as the number of fuzzy rules. The proposed architecture has seven inputs to the ANFIS system and has only one output. The Rule basis for the proposed ANFIS system is given by:

then

$$Y = p_i A_r + q_i E + r_i E_n + s_i E_x + t_i S + u_i D_{wt} + v_i H + w_i$$

then

$$Y = p_i A_r + q_i E + r_i E_n + s_i E_x + t_i S + u_i D_{wt} + v_i H + w_i \tag{2}$$

where,

p_i, q_i, r_i, s_i, t_i, u_i, v_i, w_i are the design parameters that resolute from the training process and Y is the output within the fuzzy region provided by the fuzzy rule.

In this FIS, the result of apiece rule is a linear permutation of the input variables followed by the summation of a constant value. The absolute result is the weighted average of every rule's outcome. The corresponding equivalent proposed ANFIS structure is presented in Figure-3.

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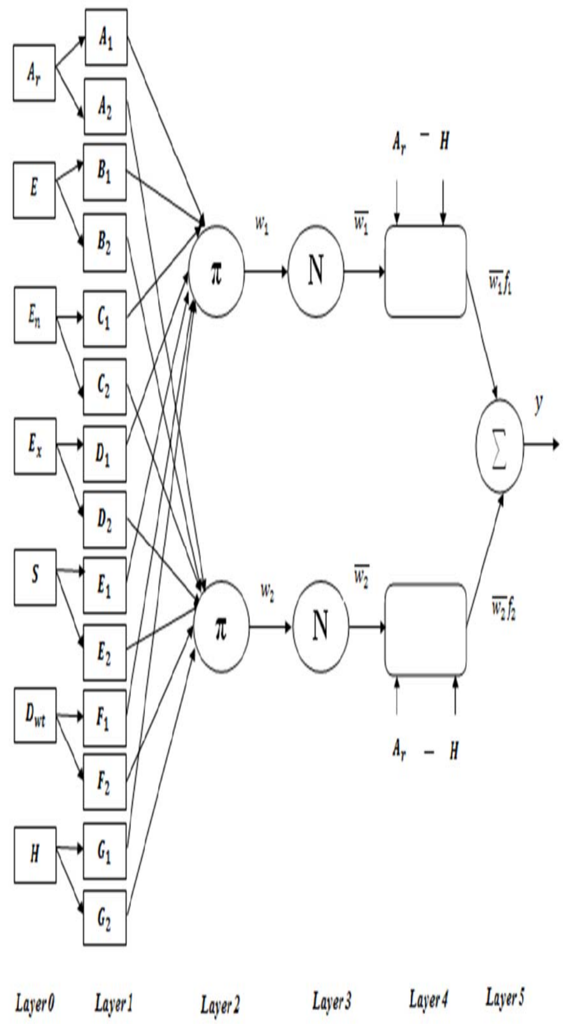

Figure-3. Architecture of the proposed ANFIS system.

The individual layers of the proposed ANFIS structure are described below:

Layer 0: Input layer

It has seven nodes, which are the number of inputs to the proposed system. Here, *Ar, E,* E_n, E_x, *S,* D_{wt} and *H* are the input nodes.

Layer 1: Fuzzification layer

This layer has adaptive nodes having its membership value to a linguistic expression as a Gaussian Function with the mean values symbolized by $\mu_{Ai}(Ar)$, $\mu_{Bi}(E)$, $\mu_{Ci}(E_n)$, $\mu_{Di}(E_x)$, $\mu_{Ei}(S)$, $\mu_{Fi}(D_{wt},)$ and $\mu_{Gi}(H)$ respectively. In general,

$$\mu(x_i) = \frac{1}{1 + [(\frac{x_i - c_i}{a_i})^2]^{b_i}} \tag{3}$$

[

where, i=1,2; $\mu(x_i)$ is the Membership Function for the given input value x_i and a_i, b_i and c_i are the premise parameters of the respective functions.

Layer 2: Inference or rule layer

The second layer has fixed nodes labelled π, where its output is resulted by the product of the inputs to perform as the firing power of a rule.

$$w_i = \mu A_i(A_r).\mu B_i(E).\mu C_i(E_n).\mu D_i(E_x).\mu E_i(S).\mu F_i(D_{wt}).\mu G_i(H) \tag{4}$$

where, i=1,2.

Layer 3: Implication or normalization layer

The third layer also has fixed nodes labelled *N*; the i[th] node computes the ratio of the i[th] rule's firing strength to the rules' firing strengths sum as:

$$\overline{wi} = \frac{w_i}{w_1 + w_2} \tag{5}$$

where, i=1,2 and the outputs are known as normalized firing strengths.

Layer 4: Aggregation layer

The fourth layer consists of adaptive nodes, having a node function

$$\overline{wi}fi = \overline{wi}(p_0 + p_1x_1 + p_2x_2) \tag{6}$$

where, i=1,2; $\overline{w_i}$ is a normalized firing strength produced by layer 3; $\{p_0, p_1, p_2\}$ is the parameter set of the node known as the consequent parameters.

Layer 5: Defuzzification layer

The fifth layer contains a single fixed node, labelled ∑, which calculates the result as the summation of the net outputs of the nodes in the layer 4,which is calculated as,

$$Y = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

The ANFIS exploits a hybrid learning algorithm for the training purpose and here the Back Propagation algorithm is applied in our proposed system for the parameters in layer 1 and layer 4.

ANFIS testing

The performance of the proposed AVRPR system is estimated by giving additional number of vehicular pictures to the ANFIS classifier. For localizing the License Plates, each picture is scrutinized at all potential positions and is given to the feature extraction stage and the results are passed to the ANFIS classifier.

ROI detection and license plate extraction

The ROI extraction is the accomplishment of the take away of only the required fraction of the picture which encloses the obligatory features or description in order to detect the License Plate character region within it. Accordingly the License Plate extraction phase is used to eradicate the pixels which do not fit in to the true License Plate region.

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RESULTS AND DISCUSSION

The proposed License Plate Localization algorithm for the Automatic Vehicle Registration Plate Recognition (AVRPR) system is experimented using MATLAB R2013a for localizing the License Plates and dissimilar samples of vehicle License Plate pictures are tested to substantiate the exactness of our proposed system. For the ANFIS training phase, we have used a dataset of 120 motor pictures and 70 pictures are tested and the proposed system discovers the localized License Plate with high effectiveness and with a localization rate of 93.61%. The investigational results achieved here demonstrate that the proposed system functions on form, yet when the vehicular pictures are captured on uncontrolled atmospheres. The input motor vehicle image of the proposed system is accessible in Figure-4, Figure-5 represents gray scale image, Figure-6 represents edge map image, Figure-7 depicts MSER Regions, Figure-8 presents morphological binarized image, Figure-9 gives feature extraction and ANFIS classification; while the output in the form of the image containing the localized License Plate is observed as in Figure-10.

Figure-4. Input image.

Figure-5. Gray scale image.

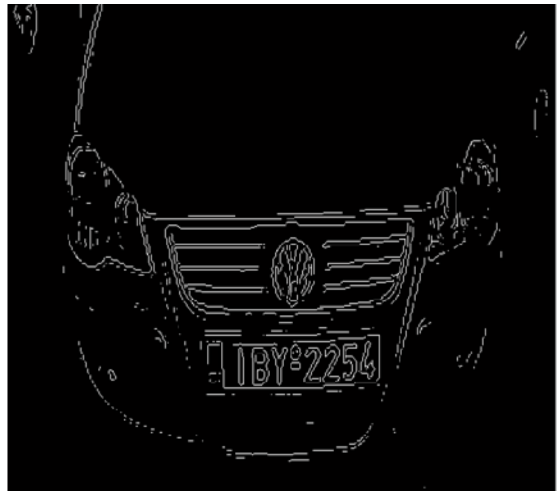

Figure-6. Edge map image.

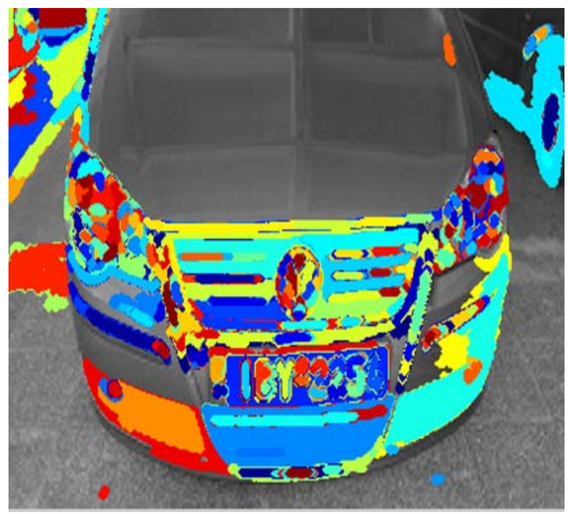

Figure-7. MSER regions.

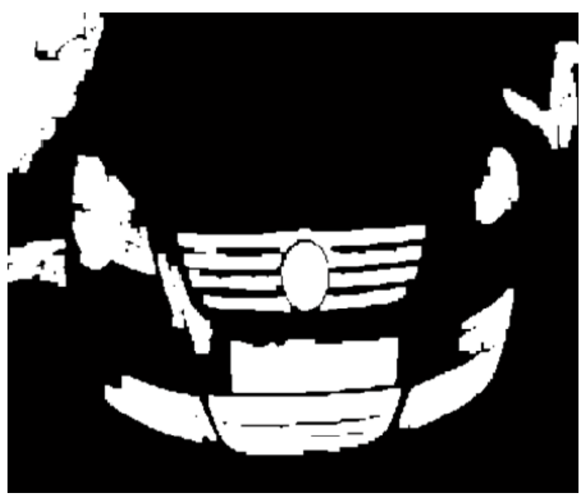

Figure-8. Morphological binarized image.

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Figure-9. Feature extraction and ANFIS classification.

Figure-10. Localized license plate.

CONCLUSIONS

The real time License Plate Localization (LPL) algorithm offered in our paper establishes ANFIS classification approach for the automated detection of the motor vehicle License plates true regions; is exceedingly functional even in handling with intricate uncontrolled situations, while building an efficient Automatic Vehicle Registration Plate Recognition (AVRPR) system. MSER algorithm for region detection, along with the geometrical and texture features plays a central responsibility for finding the candidate text regions and for availing characters within it. This proposed procedure is also constructive in exploiting multiple numbers of License Plates from the vehicular pictures; in view of the fact that it utilizes Discrete Wavelet Transform (DWT) features and within a rational computational time. The future plan of our proposed procedure is based on, to extend this system to the residual phases of the AVRPR systems, such as Character Segmentation (CS) and Character Recognition (CR).

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