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License Plate Recognition with Feature Salience and Neural Network

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Abstract*: *Character recognition algorithm is considered as a core component of License Plate Recognition (LPR) systems. Numerous methods for License Plate (LP) recognition have been developed in recent years. However, most of them are not advanced enough to recognize in complex background and still demand improvement. This paper introduces a novel system for LPR by analyzing vehicle images. Accurate segmentation of license plate and character extraction from the plate is accomplished. In the plate segmentation module, Hough transform is put forwarded to identify plate edges using line segments. Radon transform adjusts the skew between LP and the viewer, thereby improve the recognition result. Four features are extracted from the LP image, and best features are selected using feature-salience theory. Histogram projection is performed horizontally and vertically to isolate individual characters in the LP. Finally, Back Propagation Neural Network (BPNN) is used to identify the characters present in the LP. From experimental results, it is evident that the proposed system can recognize LP more efficiently and establish a good background for future advancements in LPR.

Index Terms*: *Hough Transform, Feature Salience, Histogram Projection, Back Propagation Neural Network, License Plate Recognition.

I. INTRODUCTION

License Plate Recognition (LPR) is a widely used surveillance technique that read LP registration numbers and identifies vehicle automatically. These systems compare the LP numbers with the database which is already available. Because of its huge application potential, LPR became a point of interest among researchers. LPR can be used by law enforcement agencies to locate missing vehicles and track a person. There are four important stages in LPR system: i) car image acquisition by using capturing device; ii) identification of LP area from the captured image; iii) extraction of features from the LP area; iv) Recognition of numbers and characters. The recovered identity of the vehicle can be used in real time or stored in the database for future use. Real time applications [1] of LPR are traffic pattern analysis, toll collection, parking management, vehicle access control etc. Ayodeji *et al* [2] developed a robust, country invariant LP detection system using GrabCut method. This algorithm was tested on 500 vehicles, and the accuracy obtained is high. The computational speed is also reduced by using this method. This algorithm can detect LP of any size and orientation. Al-Hmouz *et al* [3] introduced a novel approach for LP localization by statistically analyzing Discrete Fourier Transform (DFT). Five different statics were used to represent the LP signal in the frequency domain. Color based histogram is combined with DFT to achieve accuracy of 97.27%. Rizwan Asif *et al* [4] proposed Heuristic Energy Map-based approach to detect the edges and uniform histogram to segment LP. This framework is tested on 855 LP images from different countries and obtained recognition accuracy of 90.4%. The average real-time response time of the system is 0.25 seconds in complex backgrounds. Azam *et al* [5] introduced a novel method to recognize LP under poor environmental condition. This method involves contrast enhancement and statistical approach. Radon transform is used for the correction of skew. This system was tested on 850 images, and the recognition accuracy is 94%. Li *et al* [6] introduced deep neural network (DNN) to find a solution for LP recognition problem. They implemented a multiclass convolutional neural network (CNN), with high recall compared to other classifiers. Major improvement in this approach is that it doesn't require segmentation. The recognition accuracy achieved by this method is 94.85%.

Safaei *et al* [7] introduced a novel localization method using 3-D Bayesian saliency estimation. The object recognition algorithm is also based on Bayesian model. The execution time of this algorithm is 60ms, which is very low compared to other methods. The accuracy of this search free algorithm is 70%, which is less compared to other methods. Saini *et al* [8] presented a framework for the localization of LP, using multi-wavelet transform. The effectiveness of the system is improved by using skew correction and image enhancement techniques. This algorithm was tested on a single line and double line LP. The performance has been tested on LP of different countries, and the accuracy obtained was 88.36%. Wang *et al* [9] proposed a license plate recognition method using gradient information and cascading. Image preprocessing and LP detection were performed before LP confirmation. AdaBoost classifier is used for the detection of LP. Heuristic judgement and voting method are used for the verification of license plates. Wang *et al* [10] introduced SIFT features to solve the LP recognition problem. This method provided promising results in complex background, tilting, scaling and illumination variation.

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The accuracy of LP recognition obtained is 96%, and the execution time is 268ms. Some contamination, blurring, and low-resolution images cannot be processed accurately, due to unstable SIFT feature points. Yu *et al* [11] proposed a recognition method based on empirical mode decomposition (EMD) and wavelet transform. EMD analysis helps to locate the required wave peaks and locate LP. Experiments reveal that the accuracy of this method is 97.91%. This system can only detect the license plate and segment it.

The rest of this paper is organized as follows. Section II presents the proposed License Plate Recognition in detail. The experimental results with output images and performance analysis are illustrated in Section III. Finally, section IV concludes this paper.

II. METHODOLOGY

The proposed LPR method consists of four distinct stages: i) License plate segmentation; ii) Pre-processing; iii) Isolation of characters; iv) Feature extraction and selection; iv) Recognition of characters. Most of these stages are developed by introducing novel approaches to make the LPR system unique. Fig. 1 shows the consecutive stages in the proposed LPR method. Segmentation [15] of license plate from the background is performed using Hough transform, by identifying lines in the image. Then thresholding is performed to convert the LP image into a binary image. Median filter and template matching technique are used to eliminate noise from the image. Skew correction is then performed using radon transform, to provide perfect alignment of the LP. Two steps in Optical Character Recognition (OCR) are character isolation and character recognition.

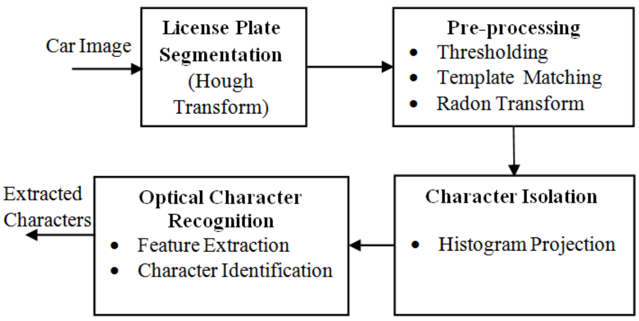

Fig 1. Stages in Proposed LPR System

A. License Plate Segmentation

Here, a technique to separate the license plate area from the captured image is presented. Compared to other features (such as length, width, and area) of a vehicle plate, shape features, texture features, and color features are more salient. Therefore, this paper mainly analyzes these three features and computes their salience. The contour of LP is in rectangular shape, for which the ratio between length and width is fixed. Hough transform (HT) is used to find vertical and horizontal lines in the image [12]. In this system, horizontal and vertical lines of the vehicle plates will produce two light dots at about $\theta = 0^o$ and $\theta = 90^o$ in Hough space. Fig.2 provides the representation of Hough transform. Length of the horizontal lines is about three times longer than the length of vertical lines. We define K=3 as the length-to-width ratio of LP and the probability density function of shape feature is obtained.

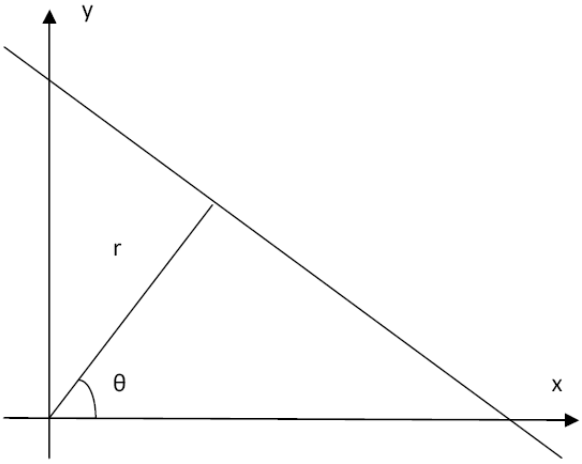

Fig. 2 Hough Transform

Basic concept behind Hough transform is the fact that, a line $y = mx + b$ can be delineated as a point (b, m) in the Hough space. For easy computing, it is better to use r and θ to represent lines using Hough transform. Using these parameters, the line equation can be written as,

$$y = \left(\frac{-\cos\theta}{\sin\theta}\right)x + \left(\frac{r}{\sin\theta}\right) \tag{1}$$

Eqn. (1) can be rearranged as,

$$r = x\cos\theta + y\sin\theta \tag{2}$$

A pair (r,θ) can be associate with each line in the image, which is unique if $\theta \in [0,\pi]$ and $r \in R$, or if $\theta \in [0,2\pi]$ and $r \geq 0$. This (r,θ) plane is known as *Hough Space* since the straight lines are in two dimensions. Fig 3 illustrates the representation of a straight line in Hough space.

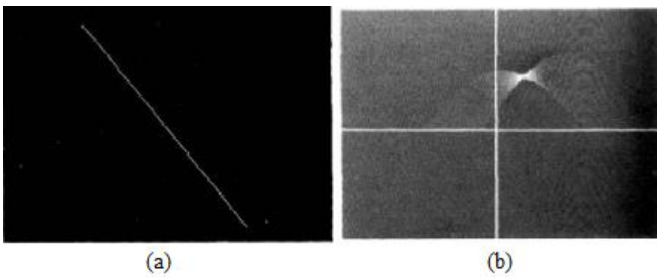

Fig. 3 (a) Straight Line (b) Hough Transform of Straight Line

.Preprocessing

The segmented number plate image must be converted to binary image for separating individual characters from the background. Threshold based segmentation is the common method used for this purpose. Thresholding is mathematically represented in Eqn. (3).

$$f(i,j) = \begin{cases} 1, & f(i,j) \geq t \\ 0, & f(i,j) < t \end{cases} \tag{3}$$

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Obviously, the key problem of getting binary image is how to choose the threshold (*t*). Maximum Entropy Criterion (MEC) is an unsupervised method to find a solution for threshold selection. Consider an image $f(x, y)$, having N x N pixels and m gray levels. $G_m = \{0,1, \ldots, m\text{-}1\}$ are the gray level values. $f_i \in$ Gm is the frequency of occurrence of gray levels. The probability of level i is given by;

$$P_i = \frac{f_i}{M \times N}, i \in G_m \tag{4}$$

MEC maximizes the aggregate of information acquired from the object and background. Recall that information measured in terms of entropy. The total information provided by A and B is given by:

$$TE = E_A(S) + E_B(S) \tag{5}$$

$$TE = in\{P(s)[1 - p(s)]\} - \frac{H(S)}{1 - P(S)} \tag{6}$$

MEC assumes the value of threshold so that the following measure in Eqn. (7) is minimized.

$$t = TE(S) = \max_{S \in G_m} TE(S) \tag{7}$$

LP images are affected by various types of noises during acquisition. The common types of noises are broken in pixels, holes and white spots. Meanwhile, the information present in the image will decrease due to the binary conversion. This will lead to noise. The presence of noise will adversely affect the extraction of presentable features. So it is mandatory that noise must be removed before further processing. A template matrix is used for removing noise from the given image. The structure of template matrices is shown in Fig. 4.

0	0	0
0	1	0
X	X	X

(a)

X	1	X
1	0	1
X	X	X

(b)

0	0	0
0	1	0
0	X	0

(c)

Fig. 4 Template Matrices for (a) Blur Removal (b) Filling Holes (c) White Spot Removal

The template matrix shown in Fig. 4(a) is used for blur removal. If a binary image region is matched with this template, then the center pixel is changed from 1 to 0. The template matrix shown in Fig. 4 (b) is used to fill small holes in the image. If a binary image region is matched with this template, then the center pixel is changed from 0 to 1. The template matrix illustrated in Fig. 4 (c) is used to remove white spots. If a region in the binary image is matched with this template, then the center pixel changes from 1 to 0.

Radon transform [13] is used to detect the skew angle in the segmented LP. Consider $f(x)=f(x,y)$ be continuous function in the range, $\mathbf{R}^2$. The Radon transform R_f is a continuous function defined in a space L represented by straight lines. The Radon transformation for a continuous function is given by,

$$R_f(L) = \int_L f(x)d(x) \tag{8}$$

Any straight line L corresponding to arc length z can be written as,

$$[x(z), y(z)] = \begin{bmatrix} (z\sin\alpha + s\cos\alpha), \\ (-z\cos\alpha + s\sin\alpha) \end{bmatrix} \tag{9}$$

where, *'s'* is the distance between straight line L and the origin. α is the angle made by the normal vector of along the x-axis. The coordinates (α,s) is considered as the coordinates in space that represent all lines in . Then Radon transform can be expressed in these coordinates using Eqn. (11).

$$R_f(\alpha, s) = \int_{-\infty}^{\infty} f(x(z), y(z))dz \tag{10}$$

$$R_f(\alpha, s) = \int_{-\infty}^{\infty} f\begin{pmatrix} (z\sin\alpha + s\cos\alpha), \\ (-z\cos\alpha + s\sin\alpha) \end{pmatrix} dz \tag{11}$$

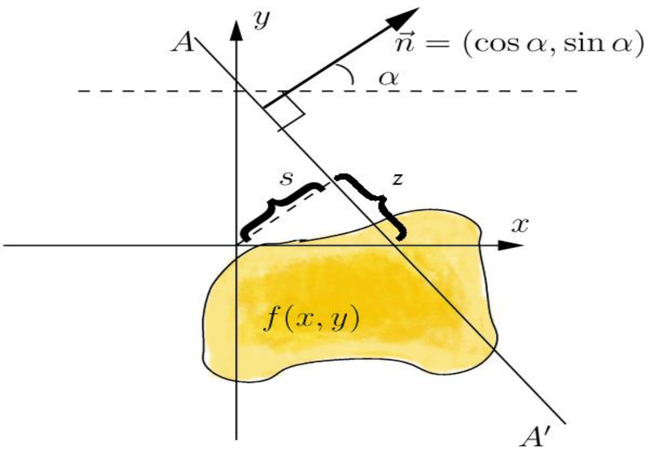

Fig. 5 Radon Transformation

Radon transform is the aggregate of Radon transform of each pixel in the image. Radon function calculates the projections of an image along particular directions as illustrated in Fig. (5). Radon transformation is primarily performed to identify the largest line present in the image and is represented as the highly visible line in the segmented LP. This line segment is used for the estimation of skew angle. Finally, the segmented image is turned in the reverse direction by the estimated angle and it is extracted through a bounding box method [13].

B. Character Isolation

The segmented LP has to be divided into seven separate images for the identification of characters. The isolation algorithm is built on accumulations of lateral histogram in vertical and horizontal directions. Horizontal projection is initially performed.

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A sudden increase in the row sum indicates the bottom or top of a character. With prior information about the LP structure, only required numbers of rows are searched. Therefore, the beginning of the widest peak in the vertical projection is considered as the top of a character. The end portion of the peak is considered as the bottom of a character. Vertical segmentation of the LP is performed to find spaces between the characters. Spaces are identified by inspecting the maximum value of column sums of intensity values. This approach searches for the transformation from valleys to peaks by counting the number of pixels with intensity value '0' in each column. During this process, deletion, merging and splitting are performed so as to check whether the components satisfies the structural conditions. If the conditions are satisfied, character recognition procedure is initiated. The histogram projection process is illustrated in Fig.6.

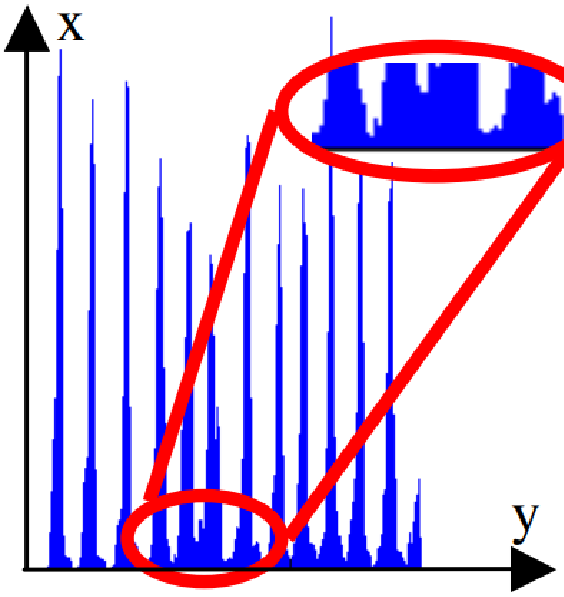

Fig. 6 Histogram Projection

C. Optical Character Recognition

Inorder to train the neural network [14] we need to extract multiple features and calculate their saliency. To compute zoning density, the character images are divided into $m\times n$ $(m = 4, n = 4)$ zones. From each zone, the number of black pixels is computed. The feature thus obtained will have 16 components to represent input character image. Next feature is the vertical projection v{(i)|i = 1, 2, . . ., 16}, where, v(i) is the count of black intensity in the i^{th} column. Another feature is the contour feature which can be calculated as follows. In the k^{th} row, the character image is scanned from the left contour to right contour. Wherever a pixel becomes black, the width $L(P_k)$ is computed between the pixel and its left boundary. Similarly the width $R(P_k)$ between a pixel and its right boundary is also calculated. Finally, line segment feature is extracted from the input character image. The total number of line segments present in each row and column are counted. According to the feature salience theory, we should apply first feature 1 to identify characters before other features. After that we should adopt rest of the features in sequence. Therefore, the proposed method will fuse together these four features for character recognition. Inorder to assign digit signature to its corresponding ASCII representation, a back propagation neural networks (BPNN) is designed. This network consist of one input layer, one hidden layer and one output layer with Log-Sigmoid transfer functions, as shown in Fig. 7.

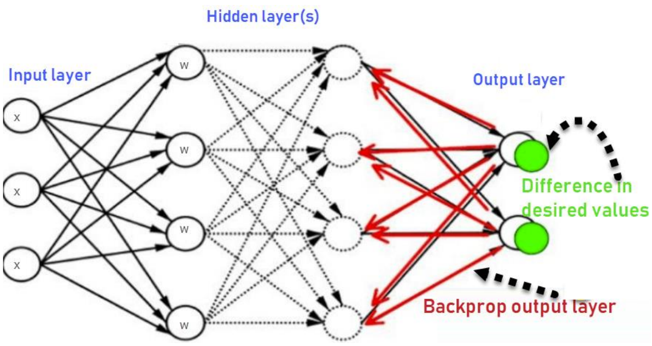

Fig. 7. Back Propagation Neural Network

The BPNN receives feature values in sequence and passed through the first log-sigmoid hidden layer containing 15 neurons. The log-sigmoid function is illustrated in Fig. 8. Finally it enters the output log-sigmoid layer containing 13 neurons to provide a vector. The output vector represents the sequence of letters (A-Z) and numbers (0-9).

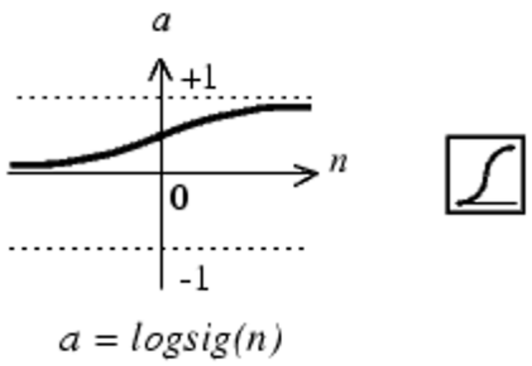

Fig. 8 Log-Sigmoid Function

It can be concluded that each value is used to represent the probability of classification of input signature to a specific letter or number. The final result is provided through a competitive transfer function which returns the index with the optimum value. The network is initially trained using Gradient descent technique using adaptive learning by providing a single set of letters and signatures.

III. RESULTS AND DISCUSSION

The experiments were performed on a workstation with Intel i3 processor having 2.4 GHz speed and 4 GB RAM. The complete work is implemented using MATLAB 2017b software. 200 Input images were used for the experiment purpose. 100 images were used for training the BPNN and 100 images were used for testing. Inorder to maintain uniformity in database, all image are resized to 512x512. The input vehicle images are shown in Fig. 9.

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Fig. 9 Input Image from the dataset

The input image is then segmented using Hough transform to obtain the LP region. The segmented LP image thus obtained is used for further processing. The output image showing License Plate region is shown in Fig. 10.

Fig. 10 Segmented License Plate

Then the segmented LP image is divided into individual characters and numbers. That is using histogram projection technique the image is divided to obtain the individual character output. The histogram projection is carried out, in the vertical direction and horizontal direction. The vertical histogram projection is shown in Fig. 11 and horizontal histogram projection is shown in Fig. 12. The output of character isolation process is given in Fig. 13.

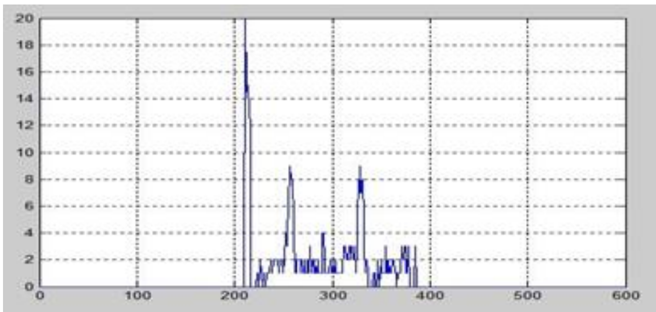

Figure 11 Vertical Histogram Projection

BPNN is trained to classify the alphabets and numbers into individual categories. The vector feature maps of complete alphabet and number dataset are obtained in feature extraction process. Based on feature salience theory, features are provided one by one based on the saliency and defined as a target vector.

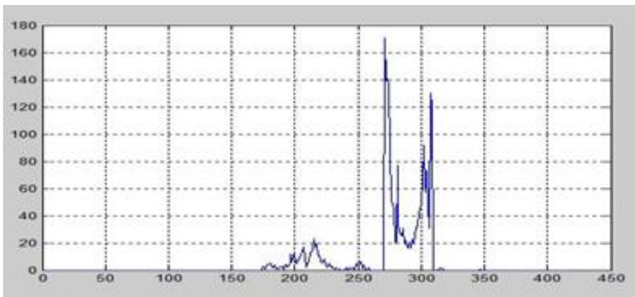

Fig. 12 Horizontal Histogram Projection

Fig. 13 Isolated Characters

The target vector includes 36 targets corresponding to alphabet and numbers dataset. The BPNN is trained for varying number of hidden layers and different number of samples for validation and testing. The number of hidden layers of BPNN is varied for each session by increasing 5 at a time. Number of the images used for training is also varied randomly. The accuracy of the neural network in all phases for all types of combinations hidden layers is recorded. The output is obtained as a text file and it is illustrated in Fig. 14.

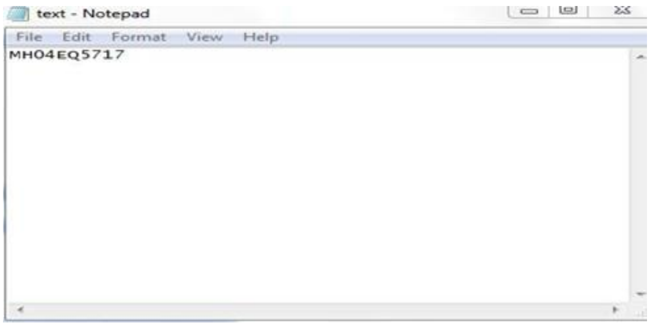

Fig. 14 Output of License Plate Recognition System**.**

The number of hidden layers in the BPNN is altered to obtain the optimum network for classification. The number of hidden layers is increased by 5 and the accuracy of LP recognition is calculated. When the number of hidden layers is increased, the accuracy of recognition also increased. The maximum accuracy was obtained for 20 hidden layers (98.4%).The lowest accuracy was obtained for 5 hidden layers (97.2%).

Table 1 Performance of Proposed Classifier

Hidden Layers	Accuracy (%)		
	Training	**Validation**	**Testing**
5	93.2	90.3	97.2
10	96.6	94.8	97.6
15	96.3	94.3	98.2
20	97.3	98.4	98.4

Table 1 displays the change accuracy provided by BPNN for different hidden layers. The average recognition accuracy obtained for the proposed system is 97.85%. The time required for recognition is 0.252 seconds. Bayesian method recognized LP in 0.060 seconds, but the accuracy was low. The performance comparison is given in Table 2 and it is graphically represented in Fig. 15.

Table 2 Performance Comparison

Method	Accuracy	Time (Sec)
Heuristic Energy Map [3]	90.4	0.250
Bayesian [6]	70	0.060
Multi-Wavelet [7]	88.36	0.326

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SIFT-ANN [9]	96	0.268
FS-BPNN (Proposed)	97.85	0.252

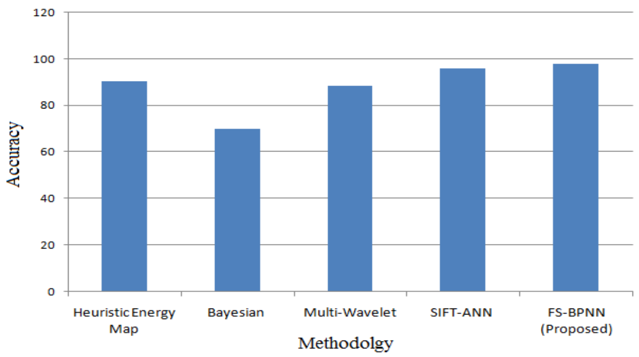

Fig. 15 Performance Comparison

IV. CONCLUSION

In this paper we developed a novel algorithm by combining feature salience and BPNN, specially designed to recognize car LP. The algorithms were defined on a training set of 100 images, and the following test phase was performed on 100 images. The obtained results are satisfactory enough and make the system able to work efficiently in practice. We got an overall efficiency of 97.85% for the system as the system has been tested with nearly 100 vehicle number plates. The average time required for recognizing license plate is 0.252 sec. There is a scope in the future where the system can be able to work where the number plate, the color and the font of the plate is identical with varied font sizes. There are also some situations where the systems fail to get the accuracy in the issues like stains, smudges, variety font styles, blurred regions and the sizes. The future works can be extended to minimize all these error.

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