License Plate Recognition System for improving accuracy rate using Blob Detection Algorithm compared with Pixel Based Algorithm

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ABSTRACT

Aim: Machine Learning technique employed for license plate recognition system with improved recognition rate using Pixel Based Algorithm (PBA) classification in comparison with Novel Blob Detection Algorithm (BDA). **Materials and methods:** The sample size of license plate recognition system with improved recognition rate was sample 2000 (Group 1=1500 and Group 2 =1500). Comparative analysis of license plate recognition systems with improved recognition rate is performed by Novel Blob Detection Algorithm whereas number of samples (N=30) and Pixel Based Algorithm where number of samples (N=30) techniques. **Results:** The accuracy rate of Novel Blob Detection Algorithm is 95.98% whereas results of Pixel Based Algorithm accuracy rate are 92.42%. The Specificity rate is 94.81% for Novel Novel Blob Detection Algorithm whereas the results of Pixel Based Algorithm Specificity rate are 91.09%.The Sensitivity rate is 95.55% for Novel Blob Detection Algorithm whereas results of Pixel Based Algorithm Sensitivity is 92.63%. There is a significant difference in Accuracy rate (P=0.064). **Conclusion**: Novel Blob Detection Algorithm Classifier predicts the better classification in finding the accuracy, specificity, sensitivity for analysis of license plate recognition system with improved recognition rate when compared to Pixel Based Algorithm.

Keywords: License Plate Recognition, Novel Blob Detection Algorithm, Pixel Based Algorithm, Machine Learning, Image Processing, Accuracy Rate, Classification.

INTRODUCTION

Vehicle identification is a task that requires a lot of monitoring and control systems. People can identify cars by using license plates that contain alphabets and numbers. A variety of character combinations on license plates can be used for many purposes. For example, arresting the suspect's car, imposing a parking violation and confirmation of entry is possible. However, it is a broad task to identify all license plates for passing or parked vehicles. There was a need for license plate recognition (LPR), as well as the development of digital cameras and visual detection algorithms that make LPR automation possible [1]. It is clear that the default LPR system must have a few errors in image processing and classification. The system is concerned with law enforcement, criminal justice, and law enforcement that does not tolerate offenses. Some LPR programs for image processing and classification [2], [3] have obtained satisfactory information in restricted cases, and recent research seeks to increase the accuracy of the recognition [4], [5]. It is used in extremely different applications such as, access control, stopping the executives, ringing, client charging, conveyance following, traffic the board, policing and security administrations[6].

In recent years, there have been several machine learning algorithms developed for character segmentation on license plates. IEEE Explore published 73 research papers, and Google Scholar found 68 articles. Character images discovered from vehicle body parts should be sectioned from non-character pictures to be utilized as expected data for a potential LP after beginning location. This errand, notwithstanding, is testing a result of the variety of plate arrangements and complex open air conditions. Subsequently, most strategies work as it were in certain limited conditions. For instance, the further developed Otsu technique picks the limit esteem consequently. Since this technique mirrors the dispersion of absolute info, it encounters inadequacies when the force or shade of the information picture is changed locally. With the goal for binarization to stay powerful in halfway light changes, the Bradley [7] and Wolf [8] calculations have been presented. Nonetheless, neighborhood means by moving normal, which these techniques use, is defenseless against unexpected changes. Bernsen [9] proposed a strategy for taking care of lopsided light, especially for shadow evacuation; the further developed Bernsen calculation [6]is a technique for ascertaining two edge esteems to be more compelling with commotion. A person division utilizing superpixels was presented by Zhou [10]. Be that as it may, this strategy needs to prepare text highlights and can't recognize the characters of LP from those of standard characters. The human can perceive the characters effectively even if the blobs are divided, however the framework can be confused. He et al. has likewise detailed that Niblack's showed preferable execution over Sauvola's technique [11]. The movable boundaries in the binarization techniques are tuned for the investigations.Previously our team has a rich experience in working on various research projects across multiple disciplines[12]–[22]

The existing technique for License plate recognition in vehicles is used as a Pixel based method. The primary issue of the current procedure is accurate and real-time character segmentation based on machine learning under the situations when license plate boundaries are connected to inside characters, characters are connected to each other, and characters are broken [23] The main aim of this paper is to compare the two machine learning methods Pixel based algorithm, and Blob detection methods to better understand the effectiveness of license plate detection. The accuracy rate of the proposed license plate detection method can significantly improve by eliminating the unwanted edges using some morphological steps.

MATERIALS AND METHODS

This work was carried out in Saveetha School of Engineering, SIMATS, Tamil Nadu, and India. It involves two sample groups requiring 300 samples per group and a total 450 sample sizes to be carried out for the license plate recognition system. Sample size was calculated by using previous study results. The output is obtained by using Python software for the license plate recognition system. A sample dataset of both proposed and existing methods are exported to Microsoft Excel document for verification using statistical. Analysis software (SPSS IBM tool) as an input. The test setup for the proposed system to implement with the following system. To train these datasets, required a monitor with resolution of 1024×768 pixels (7th gen, i5, 4 GB RAM, 500 GB HDD), and Python software with required library functions and tool functions. The calculation is performed utilizing G-power 0.8 with alpha and beta qualities are 0.05, 0.2 with a confidence interval at 95% [24].

A. Sample Preparation Group 1 [Existing Method- Pixel based algorithm]

The pixel based segmentation algorithm is to recognize the specific area of the license plate region in the advanced picture; the outcome should be a sub-picture that contains just the permit number plate. The median is determined by first arranging all the pixel esteems from the encompassing neighborhood into mathematical requests and afterward supplanting the pixel being considered with the center pixel value. If the neighborhood contains a significant number of pixels, the normal of the two center pixel esteems is utilized. Calculating the median value of a pixel area as can be seen; the focal pixel worth of 160 is fairly unrepresentative of the encompassing pixels and is supplanted with the middle worth: 125. A 4×4 square area is utilized here bigger areas will create more extreme smoothing. A picture cover secludes portions of a picture for handling. In the event that a capacity has a picture veil boundary, the capacity cycle or examination relies upon both the source picture and the image mask. An image mask is a 8-bit paired picture that is a similar size as or more modest than the examination picture. Pixels in the picture veil decide if comparing pixels in the assessment picture are handled. On the off chance that a pixel in the picture cover has a nonzero esteem, the comparing pixel in the examination picture is prepared. On the off chance that a pixel in the picture cover has a worth of 0, the comparing pixel in the examination picture isn't prepared. Pixels in the source image are prepared if related pixels in the image veil have values other than nothing. A cover influences the yield of the capacity that transforms the pixel esteems in a picture. The region wherein capacity applies a picture cover to the bouncing square shape of the locale need to measure is restricted. This procedure saves memory by restricting the picture cover to just the piece of the picture containing critical data.

B. Sample Preparation Group 2 [Proposed Method- Blob detection method]

In order to overcome the drawbacks and to provide an efficient and accurate rate of license plate recognition a license plate recognition system using blob detection method. Blob analysis is a cycle of allocating a name to each pixel in a picture, to such an extent that pixels with a similar name share certain visual attributes such as utilizing shading, shape, surface, and so on. In our strategy, they use Blob analysis to remove tag locales utilizing the shading appropriation from a picture grouping. A Look-Up-Table (LUT) with three shading segments (red, green, and blue) is made dependent on the shading circulation of a tag. This three-shading LUT is pre-worked by utilizing tag shading tests. In the wake of extricating the movement objects from a succession of edges, the framework figures “blobs identifying candidates” for license plates. Albeit the three-shading LUT may erroneously recognize up-and-comer areas, which are like license plate color, as license plates, they can confirm them through better division and check the rectangularity of the tags. Along these lines, the tags in a video grouping are recognized. The permit shading recognizable proof calculation extricates hand and face areas utilizing the shading circulation from the picture succession. They set up a three-shading LUT which is utilized for setting the shading dissemination. Following are the measures utilized in the blob detection algorithm.

Rule 1. In the event that the upper limit of one mass is more modest than the large UPBound, or on the other hand if its upper limit is greater than the generally LOWBound, the applicant blob is a non-character one.

Rule 2. In the event that the stature to width proportion of a blob is greater than ThHigh (for example 0.8) or more modest than ThLow (for example 0.3), the competitor blob is thought to be a non-character one.

Rule 3. In the event that the space of mass is greater than one 7th of the entire picture size, it needs further division.

Rule 4. On the off chance that any two neighbor sections acquired of which the widths are 2/3 more modest than the person normal width on a similar tag, they are connected (consolidated) into one fragment.

Rule 5. On the off chance that any section acquired in the past advances having width 1/3 greater than the person's normal width, it is isolated into two portions.

The blob recorded as a potential person block should coordinate with every one of the conditions to be recorded as a person block and held. Otherwise, the blob is viewed as a non-character block and subsequently is eliminated. After all blocks on the given license plate are checked, the process completes.

C. Statistical Analysis

For statistical implementation, the software tool used here is IBM SPSS V26.0. The independent sample t test was performed to find the mean, standard deviation and the standard error mean statistical significance between the groups, and then comparison of the two groups with the SPSS software will give the accurate values for the two different algorithms which will be utilized with the graph to calculate the significant value with maximum accuracy value (95.98%), mean value (95.98%) and standard deviation value (0.7821). Dependent variables are accuracy and independent variables are image size.

RESULTS

Table 1 Portrays the Evaluation Metrics such as Accuracy Rate, Specificity and Sensitivity of Novel Blob Detection Algorithm and Pixel Based Algorithm Classifier in which the Novel Blob Detection Algorithm shows higher values in all aspects of parameters.

Table I. Evaluation Metrics (Accuracy Rate, Specificity, and Sensitivity) of Pixel Based Algorithm (PBA) and Blob Detection Algorithm (BDA)

GROUP STATISTICS			
METHOD	**ACCURACY**	**SPECIFICITY**	**SENSITIVITY**
Pixel Based Algorithm (PBA)	92.42%	91.09%	92.63%
Blob Detection Algorithm (BDA)	95.98%	94.81%	95.55%

Table 2 shows the statistical calculation such as mean, standard deviation and standard error mean for Novel Blob Detection Algorithm and Pixel Based Algorithm. Accuracy rate parameter used in the t-test. The mean accuracy rate of Novel Blob Detection Algorithm is 95.98% and Pixel Based Algorithm is 92.42%. The Standard Deviation of Blob Detection Algorithm is 0.7821 and Pixel Based Algorithm is 1.2341. The Standard Error mean of Blob Detection Algorithm is 0.7817 and Pixel Based Algorithm is 0.9835.

Table II. The statistical calculation such as mean, standard deviation and standard error mean for Blob Detection Algorithm (BDA) and Pixel Based Algorithm (PBA). Accuracy rate parameter used in the t-test. The mean accuracy rate of Blob Detection Algorithm (BDA) is 95.98% and Pixel Based Algorithm (PBA) is 92.42%. The Standard Deviation of Blob Detection Algorithm (BDA) is 0.7821 and Pixel Based Algorithm (PBA) is 1.2341. The Standard Error mean of Blob Detection Algorithm (BDA) is 0.7817 and Pixel Based Algorithm (PBA) is 0.9835.

Group		**N**	**Mean**	**Standard Deviation**	**Standard Error Mean**
Accuracy Rate	Pixel Based Algorithm (PBA)	10	92.42	1.2341	0.9835
	Blob Detection Algorithm (BDA)	10	95.98	0.7821	0.7817

Table 3 displays the statistical calculations for independent samples tested between Blob Detection Algorithm and Pixel Based Algorithm. The significance for accuracy rate is 0.064. Independent samples T-test is applied for comparison of Blob Detection Algorithm and Pixel Based Algorithm with the confidence interval as 95% and level of significance as 0.8455. This independent sample test consists of significance as 0.001, significance (2-tailed), mean difference, standard error difference, and lower and upper interval difference.

Table III. The statistical calculations for independent samples test between Blob Detection Algorithm (BDA) and Pixel Based Algorithm (PBA). The sig. for accuracy rate is 0.064. Independent samples T-test is applied for comparison of Blob Detection Algorithm (BDA) and Pixel Based Algorithm (PBA) with the confidence interval as 95% and level of significance as 0.8455. This independent sample test consists of significance as 0.001, significance (2-tailed), mean difference, standard error difference, and lower and upper interval difference.

Group		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval (Lower)	95% Confidence Interval (Upper)
Accuracy Rate	Equal variances assumed	7.237	0.064	16.732	18	.000	11.332	0.9832	11.7854	13.8201
	Equal variances not assumed			8.124	12.671	.000	11.782	0.8901	10.3344	12.8946

Figure 1 Shows the Accuracy Rate of Blob Detection Algorithm and Pixel Based Algorithm Classifiers. Blob Detection Algorithm has higher values in terms of accuracy rate compared with Pixel Based Algorithm. Variable results with an accuracy rate of 95.98% for Blob Detection Algorithm whereas results of Pixel Based Algorithm accuracy rate are 92.42%.

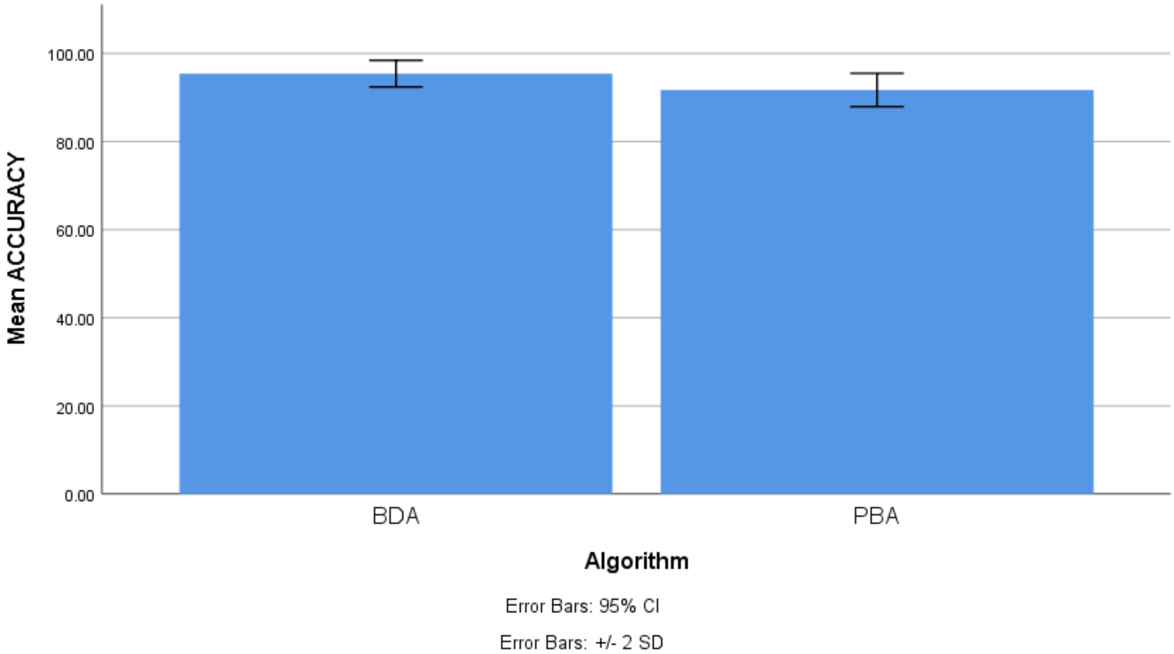

Fig. 1. Group Statistics (Accuracy Rate %) of different Blob Detection Algorithm (BDA) and Pixel Based Algorithm (PBA) whereas results of Pixel Based Algorithm (PBA) accuracy rate are 92.42% with error bar +/-2 SD.

Figure 2 Shows the Sensitivity of Blob Detection Algorithm and Pixel Based Algorithm Classifiers. It represents the Blob Detection Algorithm having lower values in terms of Sensitivity comparison with Pixel Based Algorithm. Variable results with a Sensitivity rate of 95.55% for Blob Detection Algorithm whereas results of Pixel Based Algorithm Sensitivity rate are 92.63%.

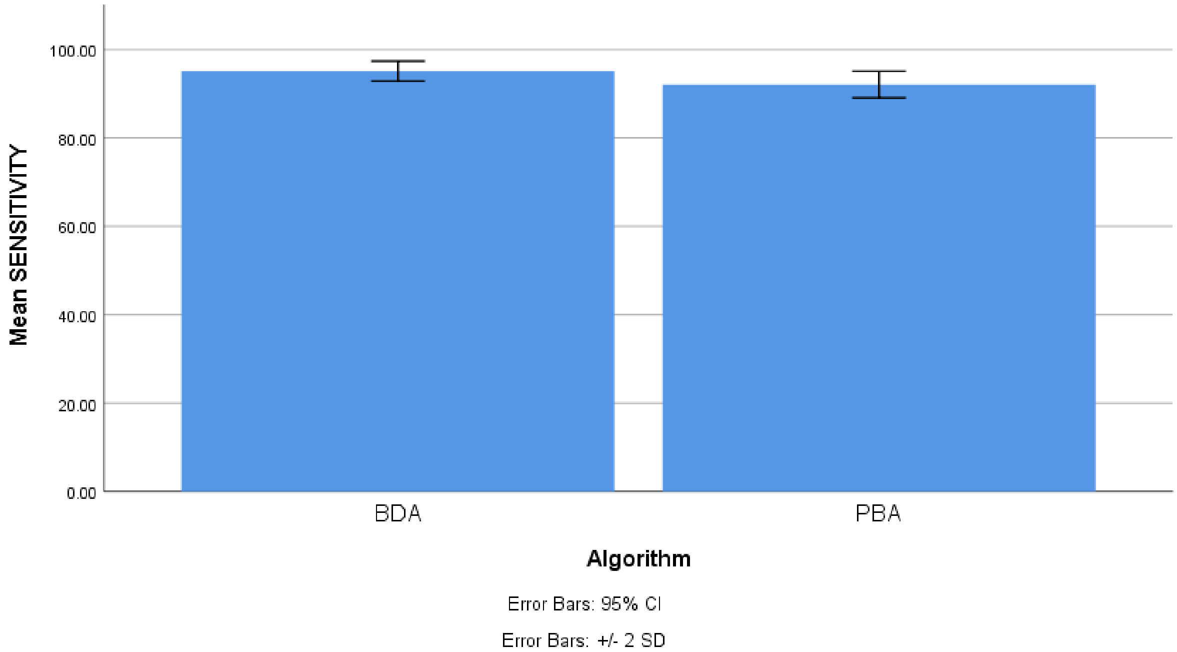

Fig. 2. Group Statistics (Sensitivity) of different Blob Detection Algorithm (BDA) and Pixel Based Algorithm (PBA) with error bar +/-2 SD..

Figure 3 Shows the Specificity of Blob Detection Algorithm and Pixel Based Algorithm Classifiers. It represents the Blob Detection Algorithm having higher values in terms of Specificity comparison with Pixel Based Algorithm.

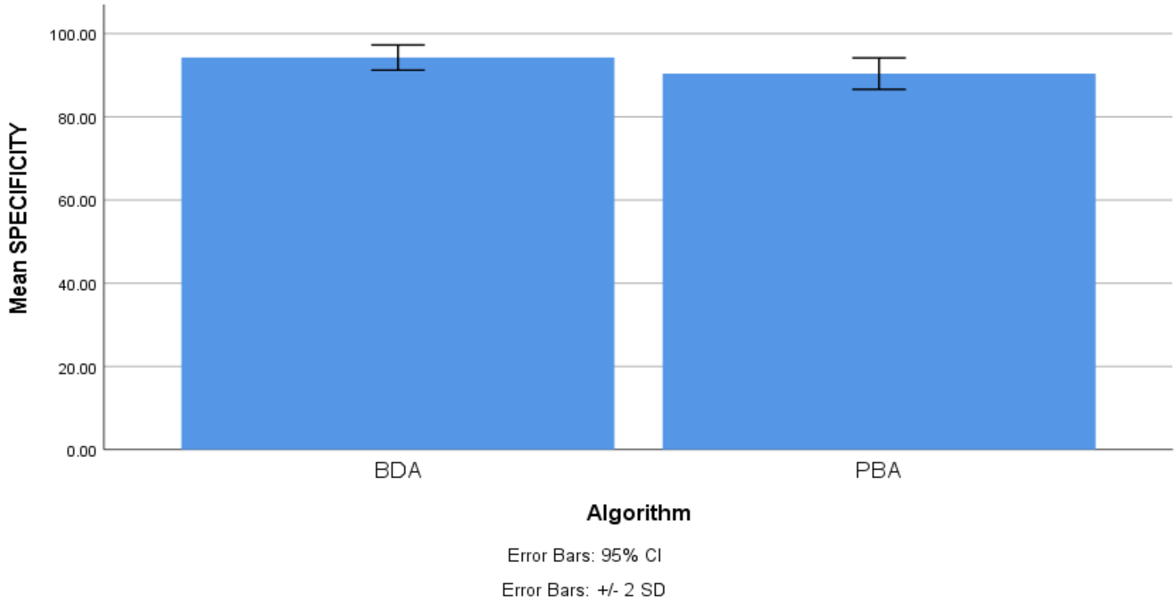

Fig. 3. Group Statistics (Specificity) of different Blob Detection Algorithm (BDA) and Pixel Based Algorithm (PBA) with the error bar values of +/-2 SD.Variable results with a Specificity rate of 94.81% for Blob Detection Algorithm whereas results of Pixel Based Algorithm Specificity rate are 91.09%.

DISCUSSION

The Accuracy Rate of Blob Detection Algorithm Method is 95.98% higher compared with Pixel Based Algorithm method that has an accuracy rate of 92.42%. To test the presentation of our proposed blob detection calculation, a sum of 450 vehicle pictures are utilized for the investigations. 300 vehicle pictures are taken as image processing that contain 285 apparent number plates [25]. The other 150 pictures are utilized as test pictures that contain 139 apparent number plates [26], [27].

Each one has its own procedures to reduce a number of blobs, compared pixel based and blob detection methods. Pixel based method uses compactness values and our Blob detection method uses CR scores [28]. Drops of accuracy are quite different between two methods. Pixel based method showed low accuracy of fewer than 90%. Selecting blobs of higher compactness values is good to avoid a falsely connected large blob, but it tends to select small fragmented blobs inside true character blobs [29]. The pixel based method one does not use compactness value but simply selects a largest blob among overlapping blobs. The rule of defining overlap state is adjusted to make the pixel based method have a similar number of blobs to the proposed blob detection method. The blob detection method has much higher accuracy, even after removing blobs. Our blob removing step with CR score drops just 0.2% in accuracy. Pixel based strategy begins for certain underlying limits and iteratively alters them by applying some contracting or development activities. It provides a less accuracy rate because of disregarding minute highlights during the time spent limiting the energy over the whole way of their forms. It is a tedious strategy. Blob identification calculation based methodology carves the person through the stroke availability and histogram projection. It detects the accuracy rate more efficiently.

The proposed work includes the most important Blob Detection Algorithm and Pixel Based Algorithm classifiers for predicting the analysis of license plate recognition systems. The proposed model exhibits Blob Detection Algorithm and Pixel Based Algorithm, in which the Blob Detection Algorithm classifier has the highest values. The limitation with this study is a diversified dataset with varying letter styles used in different number plate patterns used in different countries. The future work will be focused on testing the system for varying font styles as well as with the mulle plate localization and recognition.

CONCLUSION

The proposed model exhibits the Blob Detection Algorithm and Pixel Based Algorithm method, in which the Blob Detection Algorithm has the highest values. The Accuracy Rate of Blob Detection Algorithm Method is 95.98% higher compared with Pixel Based Algorithm method that has an accuracy rate of 92.42%.The Specificity and Sensitivity of Blob Detection Algorithm Method is efficient when compared with Pixel Based Algorithm that has lesser values in analysis of license plate recognition system.

DECLARATIONS

Conflicts of Interest

No conflict of interest in this manuscript

Author Contributions

The author PK was involved in data collection, data analysis & manuscript writing.The author JJT was involved in conceptualization, data validation, and critical review of manuscripts.

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