Performance Enhancement Method for Multiple License Plate Recognition in Challenging Environment

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Performance enhancement method for Multiple License Plate Recognition in challenging Environment

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Abstract

Multiple-license plate recognition is gaining popularity in the Intelligent Transport System (ITS) applications for security monitoring and surveillance. Advancements in acquisition devices have increased the availability of High definition (HD) images, which also can capture images of multiple vehicles. Since License Plate (LP) occupies a relatively small portion of an image, therefore, detection of LP in an image is considered a challenging task. Moreover, the overall performance deteriorates when the low-resolution factor combines with an unconstrained environment, such as night, dusk, and rainy, etc. As it is difficult to locate a small object with varying conditions in an entire image, this paper proposes a two-step approach for plate localization in challenging conditions. In the first step, the Faster-Region-based Convolutional Neural Network algorithm (Faster R-CNN) is used to detect all the vehicles in an image, which results in scaled information to locate plates. In the second step, morphological operations are employed to reduce non-plate regions. Meanwhile, geometric properties are used to localize plates in the HSI color space. This approach increases accuracy and reduces processing time. For character recognition, the Look-Up Table (LUT) classifier using adaptive boosting with Modified Census transform (MCT) as a feature extractor is used. Both proposed plate detection and character recognition methods have significantly outperformed conventional approaches in terms of precision and recall for multiple plate recognition.

Keywords:

Deep convolutional neural network, automatic number plate recognition, modified Census transform, image morphology

1. Introduction

With the ever-increasing traffic situations in modern cities, the demand for intelligent transportation systems (ITS) is also increasing rapidly. License plate recognition (LPR) is a crucial component of ITS, which is used to identify vehicles based on their number plates (Anagnostopoulos, 2014). LPR includes license plate localization to find the location of the plate in an image, followed by segmentation and recognition of alphanumeric characters of the localized plate. Most LPR methods are capable to recognize a single vehicle in an image.

In recent years, there is a considerable increase in problems of traffic congestion, security monitoring and over speeding in modern cities (Asif et al., 2016). That has increased the demand for identifying multiple vehicles in an image. A high-resolution camera can monitor multiple lanes containing several vehicles. However, recognizing multiple vehicles becomes challenging as some plates will have a smaller size or low resolution (based on distance from the camera), different background colors, distortions, and different contrast, etc. as shown in **Fig.1**. Moreover, HD images also increase computational cost(Shen-Zheng Wang & Hsi-Jian Lee, 2003).

A number of methods have been proposed for license plate recognition over the years, using template matching (Massoud et al., 2013), artificial neural networks (Ibrahim & Kirami, 2017), adaptive boosting (Md. Mostafa Kamal Sarke et al., n.d.), Support Vector Machines (SVM) (Ho et al., 2009), and so on. However, most of these methods performed well in constrained environments, i.e., uniform illumination and fixed plates size, etc. In the recent past, deep learning (DL) methods have been widely used as powerful tools for machine learning applications, i.e., object detection, face detection, and recognition, etc. Multiple Convolutional Neural Network (CNN) approaches have been used for plate recognition. Cascaded CNN (Radzi & Khalil-Hani, 2011) has a high computational cost and multi CNN(Gerber & Chung, 2016) does not perform well for varying parameters of size and angle, etc. Faster RCNN has high speed but performance deteriorates for small objects (low resolution) plates and non-uniform illumination. Therefore, it can be concluded that existing approaches do not perform well when exposed to unconstrained environments like varying illuminations conditions, colored background plates and variations in plate and font sizes. Therefore, this paper proposes MLPR system capable to handle all the aforementioned problems. Major contributions of this paper are as follows.

- The proposed technique improves the accuracy of plate detection in challenging environments having non-uniform illumination conditions and low resolution (based on distance from the camera). Our technique divides plate detection problem into vehicle detection and plate localization, which results in scaled information for plate localization and helps to remove background noise and clutters.

- The proposed plate recognition algorithm does not put a restriction for uniform light conditions, low resolution or angular plates, etc. Moreover, the character recognition part is robust to varying illumination, low resolution, different orientations, and multiple fonts, etc. And experimental results have shown that the character size of 6×9 is recognized effectively.

Fig. 1. Korean License plates

In this paper, Faster RCNN is used for vehicle detection followed by plate localization using morphological operations in HSI color space. Geometric properties of area and aspect ratio of connected pixels are used for character segmentation. Moreover, this paper uses texture-based feature extraction method MCT, which is robust to illumination changes and low resolution (Park & Sim, 2011), with lookup table classifier in boosting framework for character recognition.

2. Related Work

This section briefly introduces the recent advances in Plate recognition systems.

2.1 License plate detection

Most of the existing work on plate detection target a single vehicle in an image. Therefore, the demand for multiple plate detection has increased considerably owing to an increase in multilane structure in modern cities. Edge detection methods consider an area with a higher density of characters as an LP. Combining this property with geometric properties of plates has been widely used to extract LPs. Vertical edge detection is more robust compared with horizontal edge detection, which provides inaccurate results owing to errors due to the car bumper area(Shen-Zheng Wang & Hsi-Jian Lee, 2003). A fast and robust vertical edge detection method was proposed that increases the speed of detection by eliminating unwanted lines(Al-Ghaili et al., 2013). Yepez and Ko(Yepez & Ko, 2018) proposed a plate detection method based on only morphological operations. They developed an algorithm to select appropriate structuring element (SE) from a set of SEs by training these SEs on the whole dataset. This approach could not perform well for multiple license plate recognition, due to variation in the size of plates in an image.

In (Hsi-Jian Lee et al., 2004), the block processing method was proposed which detects the area of LP by finding the maximum edge magnitudes among the blocks. Connected component labeling (CCL)(Anagnostopoulos et al., 2008) was used in binary images to label groups of connected pixels and use attributes such as the height/width ratio, and area to localize the plate. In(Cho et al., 2011) a character-based approach was used to localize an LP by calculating the distance between the characters on LP. Rizwan, et al (Asif et al., 2016) proposed a method for detecting Chinese plates by taking advantage of the chromatic component of the YDbDr space model. And eliminates non-plate regions by using an average of energy map and edge information of the plate.

Feature extraction and classification techniques have also been used. In (Md. Mostafa Kamal Sarke et al., n.d.), authors combined AdaBoost with Haar-like features in a cascaded manner for

license plate detection (LPD) and genetic algorithms (Sang Kyoon Kim et al., 1996) have been used to classify and identify plates based on color information by using geometric attributes CCL for localization. In(Khan et al., 2018) proposed an entropy-based feature selection method, followed by SVM for classification for plate detection. The proposed method performed segmentation by identification of the luminance channel and then used Otsu thresholding for binary segmentation of that channel. This method was only able to produce reasonable results on a small number of images.

Deep learning architectures have also been used for LPD. CNN has been used in a cascaded form, where the first CNN classifier searches for any text on the image and 2nd classifier is used to reject false positives, i.e., any other text from the text on LP (Li & Shen, 2016). H. Xiang (Xiang et al., 2017) proposed CNN based network that extracts low and high features at several stages to distinguish details of plate and background followed by three-loss layer architecture for accurate plate detection. To enhance efficiency, Rafique et al. [26] used the advanced structure of Faster R-CNN [27], which directly detects the plates in an end-to-end manner. A modified YOLO (Xie et al., 2018) was used for license plate localization, which had the capability of detecting license plates that had different variations like rotation, skewness and different orientations, this method had high computational complexity.

Faster –RCNN with VGG 16 as a feature extraction method, without utilizing the fully connected layers, was used for LPL (Li et al., 2019). This Deep learning method performed combined training of LPL and optical character recognition within a forward pass.

2.2 Character Segmentation

Character segmentation is a key step used to isolate characters for recognition. Most popular methods used geometric properties of area and aspect ratio (Kim et al., 2000), horizontal and vertical projection methods of characters were used to segment the plates (Otsu, 1979), and also multiple features were combined to segment the characters of LP (Nomura et al., 2005). A Convolutional Neural Network (CNN) based two-stage process is proposed(Zhang et al., 2018) to segment and recognize characters (0–9, A–Z). Tarigan et al.(Tarigan et al., 2017) proposed an LP segmentation technique consisting of horizontal character segmentation, connected component labeling, verification, and scaling.

2.3 Character recognition

Similarly, many methods and classification techniques have been proposed for recognition. The template matching method (Massoud et al., 2013) calculates the correlation between character and templates and the maximum correlation valued template is considered as a character. However, it has shown poor performance in variable character size, noise, and rotation, etc. Multilayer neural network is trained to recognize characters(Ibrahim & Kirami, 2017). The multistage classifier was used to recognize characters with lower case, upper case, digits, and two-line plates. This technique's performance deteriorates with varying illumination and small size of characters (Wen et al., 2011).

In (Shivakumara et al., 2018), CNN and Bi-Directional Long Short Memory (BLSTM) are combined for plate recognition. CNN was used as feature extraction due to its high discrimination ability and BLSTM is capable of extracting context information from past information followed

by Dense Cluster Voting (DCV) for classification. Bulan et al (Bulan et al., 2017) proposed a segmentation and annotation free method for plate recognition. They proposed a two-stage classifier, which first used a winnows classifier for candidate region extraction followed by CNN for plate classification. For optical character recognition, a segmentation free approach using hidden Markov models (HMMs) was proposed. In (Du et al., 2013), a research group developed a robust ALPR technique in unconstraint environments. In (Yang et al., 2018), researchers presented a novel architecture for Chinese LPR by cascading CNN and Extremal Learning Machines (ELMs). CNN is applied for feature extraction and the ELM is used as a classifier, which yields encouraging results with short training time. In (Radzi & Khalil-Hani, 2011), a cascaded Recurrent Neural Network (RNN) method integrated with a Short-Term Memory (STM) is proposed to recognize the sequential features. These features are extracted from the whole license plate via CNN.

3. Methods

This section describes the architecture of the proposed system. Fig. 2 shows the overall architecture of the method.

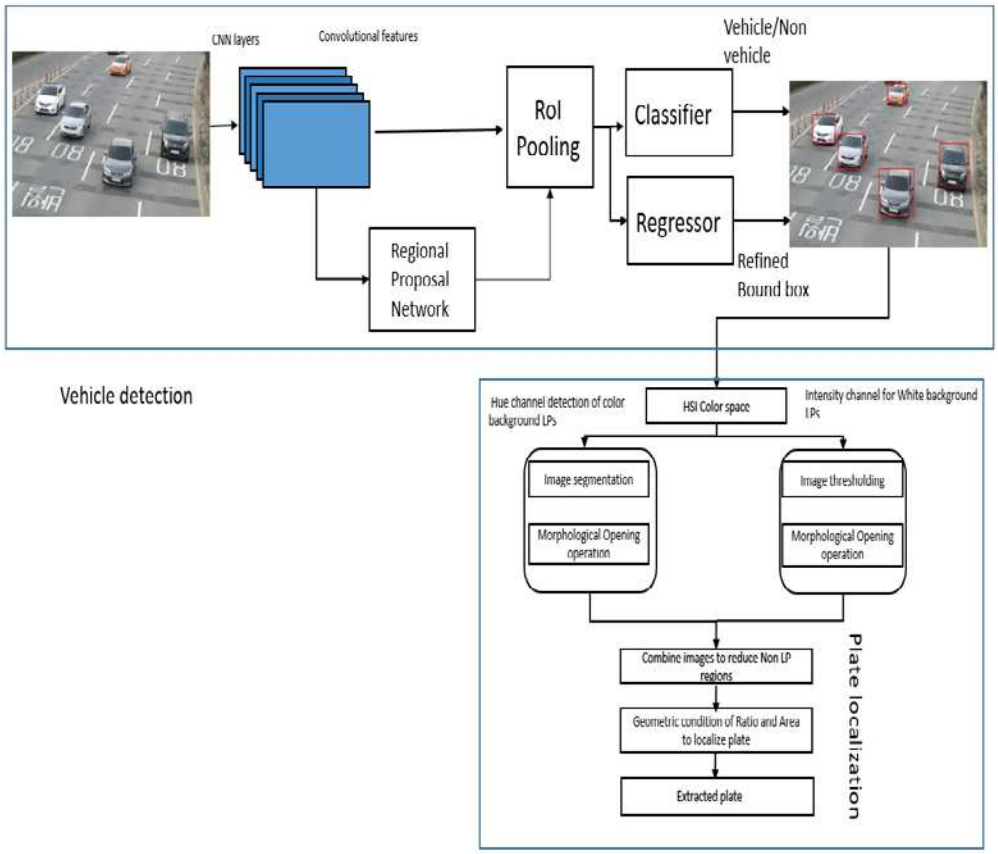


Fig. 2 Flowchart of proposed LPD's method

3.1 Vehicle Detection

Object detection is becoming a complex problem with an increase in applications such as multiple object tracking, and self-driving cars, etc. Many handcrafted (i.e. HoG and Haar) features and deep learning (R-CNN (Girshick et al., 2014), Faster-RCNN (Ren et al., 2017), YOLO (Redmon et al., 2016), etc.) methods were proposed. However, some have slow processing speed and others have a low accuracy rate. Faster-RCNN has shown the best detection rates among deep learning object detectors with real-time processing capabilities. However, Faster-RCNN performance deteriorates for small object detection (LPs in our case). Therefore, this paper uses Faster R-CNN for vehicle detection, which helps in providing relevant and scaled information in an image. Moreover, faster RCNN shows excellent results for vehicle detection as vehicle size is large as compared to the plate's size in multiple license plate detection cases.

Faster-RCNN is divided into two parts: Region Proposal Network (RPN) that generates a proposal for vehicles region, followed by fast R-CNN for vehicle/non-vehicle classification and to efficiently refine the proposal and detect the vehicles. To generate feature maps of the input image, we employ a pre-trained VGG-16 (K. Simonyan & d A. Zisserman, n.d.) model consisting of 13 convolutional, 5 max-pooling and FC layers. The feature maps are fed to RPN which scans each map by sliding window and generates proposals with bound boxes for vehicle region. For multiple vehicle detection scenarios, the network has to detect vehicles of multiple scales and aspect ratio as the distance between vehicle and camera vary. In order to deal with variable scales, anchors in RPN are introduced, which uses three scales $(128 \times 128, 256 \times 256 \text{ and } 512 \times 512)$ and 3 aspect ratios $(1{:}1, 1{:}2, 2{:}1)$, which results in 9 anchors at each location. As the size of each region proposal is different from each other, it is difficult to make efficient architecture for different sizes.

Region of interest (RoI) pooling simplifies the problem and extracts fixed-size feature representation. The features from RoI pooling are flattened into vectors. Eventually, these vectors are fed into two fully connected layers, the one for vehicle/non-vehicle classification based on each RoI SoftMax probability, and the other for predicting the rectangular coordinates for each region. In this method, faster RCNN architecture is trained using stochastic gradient descent with momentum (SGDM) that minimizes the error and quickly updates the weights. SGD uses only one sample data set from the training data to update weights while the gradient descent method (GD) must consider all training datasets to update the weights/parameters. The initial learning rate of 0.001 was used for training VGG 16 parameters and 0.0001 for the remaining parameters for 50k iterations. One image was randomly sampled per batch for training. Each image was resized to 600 and 1400 for shorter and longer sides respectively. **Fig. 3** shows the results of vehicles detected in an image using faster-RCNN.

Fig. 3 Test Image with vehicle detection

3.2 License Plate Localization

After successful vehicle detection, the next step is to locate the LP by using morphological operation in the HSI color space. This color space is known to be closely related to the color visualization of human beings (Gonzalez & Woods, 2006). The Vehicle area is converted to HSI color space, which separates the color information from the intensity (Gonzalez & Woods, 2006). The current approach uses hue information to determine the colored background plates by defining specific criteria, as ours is to find yellow-green and orange plates. Based on our experiment, the following criteria proved sufficient for our requirement.

If Hue is between ($H > 40°$ & $H < 60°$)

Background Color is orange

Else if ($H>80°$ & $H<120°$)

Background Color is green

and if ($H > 60°$ & $H < 80°$)

Background Color is yellow

White background plates and monochrome images are located using intensity information of HSI color space. **Fig. 4(a)** shows the binary image results intensity channel and **Fig. 4(b)** shows the segmentation result of the Hue channel.

Fig. 4 (a) Plate with white background (b) Plates with a colored background

After segmentation and binarization, the candidate's area contains regions of connected pixels. These connected components are labeled using the '4-connectivity labeling' method so that each pixel in the connected region has the same label. Edge detection methods have matrix multiplications that increase computational cost. Therefore, morphological operations have been used instead of edge detection to reduce computational complexity. After binarization, most of the large connected groups of background are eliminated. However, there is still undesirable information in an image, that can affect the accuracy of plate detection as can be seen from **Fig.4**. To minimize these areas and to enhance the pixel area of the plate, a morphological operations-based filtering approach consisting of open and close operation is designed. Morphological Open and close operations are shown in equation (1) and (2), respectively.

$$A \circ SE = (A \ominus SE) \oplus SE \qquad (1)$$

$$A \cdot SE = (A \oplus SE) \ominus SE \qquad (2)$$

In multiple plate detection, the size of LPs depends upon the distance of a car from the camera.

Fig. 5 (a) License plate with white background (b) colored background after morphological Operations

Thus, having more than one SE for one task can increase the computational load. After testing and verifying on a number of test images, an optimum SE was selected. **Fig. 5(a)** and **(b)** show the effect of morphological operations on both the binary images. Since most of the non-LP regions are removed. Finally, we apply two geometric conditions of area and aspect ratio to locate the license plate. In multiple license plate detection, plate size will vary depending on their distance from the camera. Therefore, having a multiple area and aspect ratio values is not an optimum solution. The experiment on a large number of test images was performed to find optimum values. Therefore, area values between 1500-4000 pixels and an aspect ratio of 0.2 -0.6 are used in the proposed method for plate localization. A similar process is carried on the remaining detected vehicles. **Fig. 6** shows the overall result of detecting multiple license plates by the proposed methods.

Fig. 6 Detection results of the Proposed method

3.3 Character Segmentation

The recognition of localized LP now proceeds to the segmentation step. This is a crucial step as recognition totally depends on how well the characters are separated from one another. In this study, pixel connectivity in binary images is used for segmenting characters (Wu et al., 2007).

First, the LP regions are converted to binary values by using Otsu's threshold method (Otsu, 1979). Next, a morphological thinning is performed to reduce the joining between the LP boundaries and text and in between characters that can negatively impact the process. The connected components are labeled based on pixel connectivity. The labeled pixels are considered and pixels having the same area and aspect ratio are detected as characters. **Fig. 7** shows segmented characters of some number plates with varying light conditions, different backgrounds, and multiple sizes, etc.

Fig. 7 Character Segmentation

3.4 Character Recognition

In Multiple plate detection scenarios, the size of plates will vary depending on the distance from the camera. Therefore, the characters isolated during the segmentation step will also have variable sizes. Therefore, techniques such as template matching do not perform well due to their requirement of fixed size. The resolution of characters plays a crucial role in the identification of characters. Moreover, conventional approaches don't perform well on challenging environments, and various illumination conditions, i.e. rainy time, dusk time, cloudy and underground parking images, etc.

For character recognition, AdaBoost with modified census transform (MCT) (Park & Sim, 2011) as a feature extractor is used with a lookup table classifier (LUT). LUT is efficient in multi Gaussian samples classification, whose sensitivity to a fixed number of bins is suitable for the character recognition process. **Table 1** shows the algorithm for character recognition. Texture-based analysis plays a vital role in vision-based applications, focusing mainly on how to derive texture features by taking advantage of neighborhood properties. Local binary pattern (LBP) computes a local representation of texture by comparison of center pixel to its neighboring pixels in a defined mask. However, LBP features have shown poor results when the center pixel value is changed due to varying illumination conditions. Therefore, in our proposed method, MCT features are used and provided excellent results for texture description in the character recognition process in changing light conditions. **Fig. 8** shows a calculation of the MCT feature with a 3×3 window from segmented character. MCT features first compute the mean intensity value of the 3×3 window around that specific pixel. For each pixel in the window, MCT assigns “1” if the current pixel value is higher than mean value and it assigns “0” otherwise. This binary value is converted to decimal to obtain the feature value. This integer value represents an independent local pattern. Therefore, a 3×3 kernel can have a total of 511 feature values.

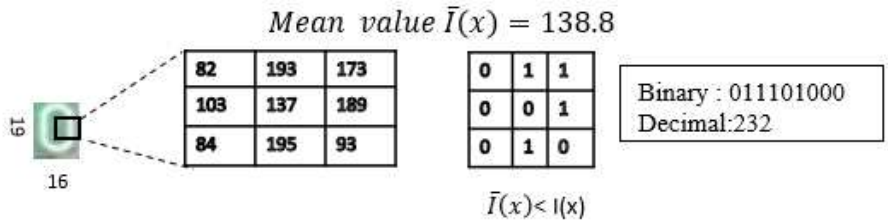


Fig. 8 MCT Feature Extraction

Next, the LUT classifier is used for the classification of MCT features at every pixel location of the character to produce 511 bin feature indices. 511 bin histogram is created Γ(x) for all samples in the training set. LUT assigns +1 if positive samples are greater and -1 otherwise, as shown in (3).

$$h(x,k) = \left\{ \begin{matrix} +1 \ \ if \ L^{pos}(x,k) \ > \ L^{neg}(x,k) \\ -1 \ otherwise \end{matrix} \right\} \tag{3}$$

Pattern value

Pixels location

	0	1	2	...	509	510	decision
1	-1	-1	1	...	1	-1	1
2	1	-1	-1	...	-1	1	-1
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
303	-1	1	-1	...	-1	-1	1
304	-1	1	-1	...	1	-1	-1

Fig. 9 LUT classifier

Fig. 9 shows an example of the LUT classifier, where rows represent the pattern value and columns represent the weak classifier candidates. AdaBoost is an iterative method that sequentially selects a weak classifier pixel location with minimum weighted error in every iteration of learning. Finally, a strong classifier is constructed from the sum of all weak pixel classifiers as shown in (4).

$$H(\Gamma) = \sum_{t=1}^{T} \alpha_t h_t\big(x, \Gamma(x)\big) \tag{4}$$

As character recognition is a multiclass problem, we use one against all classification techniques to construct k=50 classifiers for 50 classes. Each classifier is trained by taking positive examples from one class and negative examples from the remaining classes. The output of the multi-class classifier is activated for class having maximum output among all binary classifiers. For outputs of multiple binary classifiers, a multi-classifier generates a vector output S as shown in (5).

$$t = arg \max_{i=1\ldots k} (H(\Gamma)_i)$$
$$S_i = \begin{cases} +1 & if\ i = t, i = 1 \ldots k \\ -1 & OtherWise \end{cases} \tag{5}$$

Table 1 Character Recognition with AdaBoost Algorithm

- $\Gamma(x) = \otimes_{q \epsilon N'(x)} C(\bar{I}(x), I(x))$ MCT feature at pixel x, ($N'(x)$ neighboring pixels, $\bar{I}(x)$ average of neighboring pixels and C checks if $(\bar{I}(x) < I(x))$ and returns 1 if true and other wise 0.
- Boosting Round: $i = 1, \ldots, T$
- Choose a weak classifier $h_t(\mathrm{x}, \Gamma(x))$ at pixel x. which is chosen using $x = argmin_p\ \varepsilon_t(x)$. Where $\varepsilon_t(x) = \sum_{i|h_t(x,\Gamma(x) \neq C_i} D_t(i)$, C_i represents class if sample i (positive or negative) $D_t(i)$ is weight of sample i at each iteration of t like $D_t(i) \sum_i D_t(i) = 1$
- Weight computation from error

  $\alpha_t = {}^1/_2 \ln\left(\frac{1-\varepsilon_t(p)}{\varepsilon_t(p)}\right)$Update the weights

  $$D_{t+1}(i) = \frac{D_t(i) e^{-\alpha_t C_i h_t(x, \Gamma_i(x))}}{\sum_i D_t(i)}$$

- Local index LUT are generated

  $$L^{pos}(x, k) = \sum_{i \epsilon S_{pos}} D_t(i) I(\Gamma(x) = k)$$

- Final strong classifier is combination of weak classifiers

  $$H(\Gamma) = \sum_{t=1}^{T} \alpha_t h_t(x, \Gamma(x))$$

4. RESULTS/ DISCUSSION

In this section, the experimental results describe the effectiveness of the proposed method. A total of 4179 (resolution 1920 x 1080) images were taken, using 2000 for testing and 2179 for training purposes, in varying illumination conditions and environments, i.e. (night, day, dusk, cloudy weather, rainy weather, and parking).

Table 2 compares the results in terms of recall and precision ratio of detection method with existing methods when applied to images with multiple license plates. Fig. 3 shows the results for challenging illuminating and weather conditions throughout the day.

Table 2 Comparison with Existing Methods

Method	Precision ratio	Recall ratio
Edge [31]	80.17%	84.89%
AdaBoost + Haar [13]	85.45%	89.95%
CNN [17]	87.05%	91.45%
Multi -CNN	89.19%	93.31%
Faster RCNN	92.87%	94.97%
Proposed	94.57%	96.72%

The proposed method outperforms conventional methods in terms of both precision and recall. There were 5543 vehicles in 2000 images used for the testing process. The proposed method detected 5361 LPs correctly with accuracy (recall rate) of 96.72%. Recall and precision are defined as follows

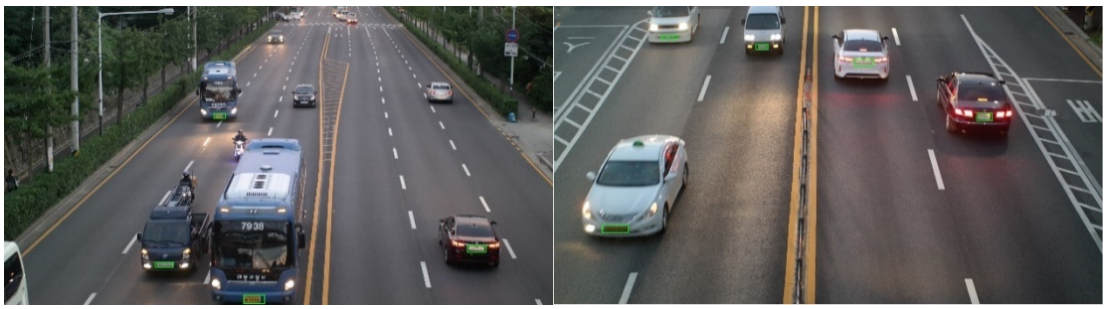
$$\text{Recall} = \frac{No\ of\ correctly\ detected\ LPs}{Total\ no\ of\ vehicles}$$

$$\text{Precision} = \frac{No\ of\ correctly\ detected\ LPs}{Total\ detected\ \ (including\ False\ positives)}$$

Fig. 10 shows the results for challenging illuminating and weather conditions throughout the day.

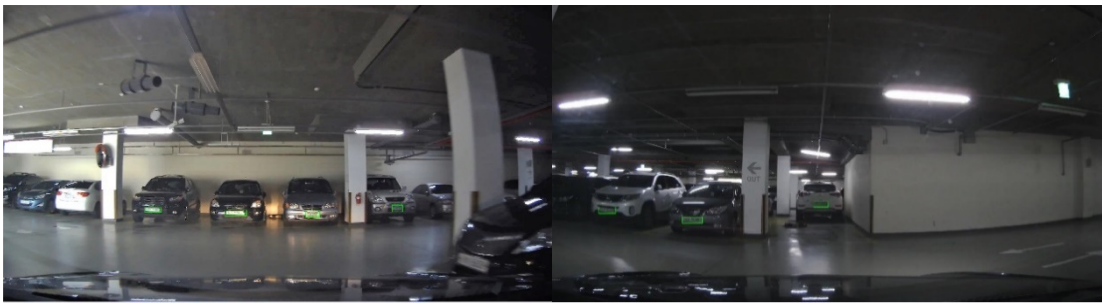
(a)

(b)



(c)

(d)



(e)

(f)

Fig. 10 Results of images takes (a) sunny day (b) night time (c) dusk (d) cloudy (e) Underground parking (f) Rainy

The recall ratio of the proposed method is 13% higher than of edge detection method since the edge method was unable to detect color background number plates. Precision is higher when compared with the AdaBoost method, as the AdaBoost method also detects headlights and text as a license plate. Li, et al [17] trained a 37 class CNN system for character detection in images followed by a CNN classifier as a false positive eliminator. This method also produced more false positives in real-world scenarios where images had text other than LP. The proposed method results in an average of 3-10% better than conventional methods in multiple license plate scenarios.

Character recognition performance is evaluated in **Table 3**. The proposed recognition method was tested on all the plates successfully detected. We compared the performance of the presented method with popular methods. First, a scale-invariant feature transform is used for feature extraction and a support vector machine is used for classification. The second method is a 3-layer multilayer neural network for character recognition. The third method is a traditional convolutional neural network having two convolution layers, 2 fully connected layers followed by SVM for classification.

SIFT and SVM based method was unable to classify characters due to partial occlusion in

rainy images, the effect of vehicle headlights in basement images, and exposure to strong sunlight. ANN has worst results as broken characters and two font characters on plates were unrecognizable by this method. As CNN can automatically learn features, it has performed better than both existing methods. However, its performance degraded for low resolution (based on the distance of camera) characters. The proposed method outperformed these methods in terms of accuracy in the challenging condition i.e. varying illumination images as per the results shown in table 3.

Table 3 Character recognition

Method	Precision ratio	Recall ratio
SIFT-SVM	84.13%	87.97%
ANN	87.36%	91.32%
CNN	90.05%	94.67%
Proposed	94.57%	98.02%

Fig. 11 shows the comparison of character recognition performance of conventional approaches with the proposed method for low-resolution character and demonstrates the superiority of the proposed scheme when compared with the benchmarks.

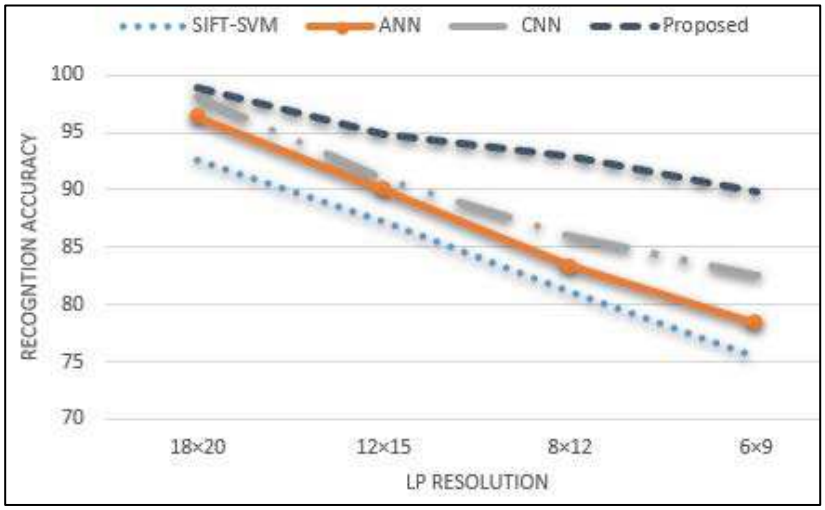


Fig. 11 Accuracy vs Resolution

Table 4 lists the overall (detection + recognition) performance results obtained under different lighting conditions and weather conditions. Our dataset consists of images taken during-night time, daytime, dusk, and cloudy weather. Images taken during cloudy and sunny days produce a

better result due to consistent light conditions, except for cases when LPs are affected by the reflection of sunlight from surroundings. Images of a car parked in the basement also produced good results with exception to a reflection of other cars' headlights. Worst results were produced during dusk time owing to the quickly varying illumination during this time of day.

Table 4 Performance comparison for varying conditions

Weather	# of images	Total Vehicles	Detection rate	Character recognition
Sunny	450	1193	97.98%	98.97%
Night	295	839	97.73%	98.31%
Dusk	397	1120	94.12%	96.43%
Cloudy	438	1175	97.87%	98.45%
Parking	205	589	96.43%	98.01%
Rainy	215	627	95.53%	97.91%
Total	2000	5543	96.72%	98.02%

Moreover, dimming sunlight, street lights, and cars' headlights have a negative impact on the overall performance of the method, especially when vehicles are at a far distance from the camera. Results of images taken in rainy conditions are also encouraging. However, some characters were not recognized owing to images getting blurred due to water pouring down the windscreens of the cars containing the camera.

The proposed method performed better than the state of art methods due to the following reasons:

- All CNN-based methods used several down-sampling stages, in which most of the information on the plate was removed before the detection stage. Hence, CNN methods were not able to achieve better accuracy. However, in the proposed method, a two-step approach was used instead of several down sampling approaches. In this two-step approach, the vehicle is first detected and then its license plate region is detected. This resulted in an improvement in the accuracy of plate detection in comparison with CNN.
- The existing Faster R-CNN methods used nine anchor boxes of three scales and three aspect ratios to detect various objects. However, in the current method for vehicle detection with optimized Faster R-CNN, four different anchor boxes of two scales (256 × 256 and 512 × 512) and two aspect ratios (1:1 and 1:2) were used. This resulted in improving the learning optimization speed and also significantly reduced the false positives. These two factors helped to improve the overall precision of the system.

- The same color of LP with different values of color components in the day and night hours makes a difficult condition to handle particularly in extreme cases. However, the proposed algorithm resulted in the efficient handling of this difficulty. In this application, the HSI color model has been applied, in which any component of the color can be altered separately without disturbing others. This feature of the proposed model is very effective in dealing with adverse conditions such as extreme light conditions, where can be dealt with only altering intensity component. This characteristic of the current model resulted in achieving high precision even in challenging conditions.

The proposed license plate recognition algorithm has become more efficient by integrating boosting based methodology with LDA.

- The developed algorithm for license plate recognition used the LDA, which considers the within-class and between-classes variance of license plates to extract the features. This particular approach led to the usage of fewer parameters as compared to using the character segmentation approach. Also, this integrated approach of boosting based methodology with LDA to extract features resulted in detailed plate information. The experiment results have also shown that recognition performance has been boosted significantly by using this approach.
- This study revealed that accurate identification of the license plates in an uncontrolled environment is still a challenging task. Although the proposed approach resulted in effective recognition of the task during different times of the day. However, it is still very difficult to recognize license plates in highly complicated backgrounds, such as occlusion, broken plates, and plates with mud.
- The proposed algorithm encompasses no heuristic processes, for instance, the plate colors or character space, rather it recognizes the labels all at once from the whole license plate image. Moreover, the proposed algorithm avoids intermediate steps, such as character separation. This algorithm can be trained and tested with only the image and labels required for training. Due to the aforementioned characteristics, the developed algorithm yields high license plate recognition accuracy.

5. Conclusion

In this paper, a multiple license plate recognition method, for high--resolution images, was presented, which works in challenging illumination conditions in real-time scenarios. The proposed technique divided plate detection into two steps. In the first step, faster-RCNN was used to detect all the vehicles in an image resulting in scaled information to locate plates. And morphological operations were used to reduce non-plate regions and geometric properties were used to localize plate HSI Color space. Then, character recognition is executed by a LUT classifier using adaptive boosting with MCT as a feature extractor. Experimental results showed that the

detection rate of the proposed method is much higher than existing methods, with an overall detection rate of 96.72% and a recognition rate of 98.02% in multiple LPs and varying illumination scenarios. The proposed algorithm might be suitable for real-time ITS applications.

Abbreviations

ITS: Intelligent Transport Systems, RCNN: Region-based Convolutional neural Network, Adaboost: Adaptive Boosting, MCT: Modified Census Transform, LUT: lookup Table, LDA: Linear Discriminant Analysis,

Availability of data and material

Some data can be shared on request

Competing interests

The authors declare that they have no conflict of interest.

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Authors' contributions

All authors have equivalent contributions.

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Figures

Figure 1

Korean License plates

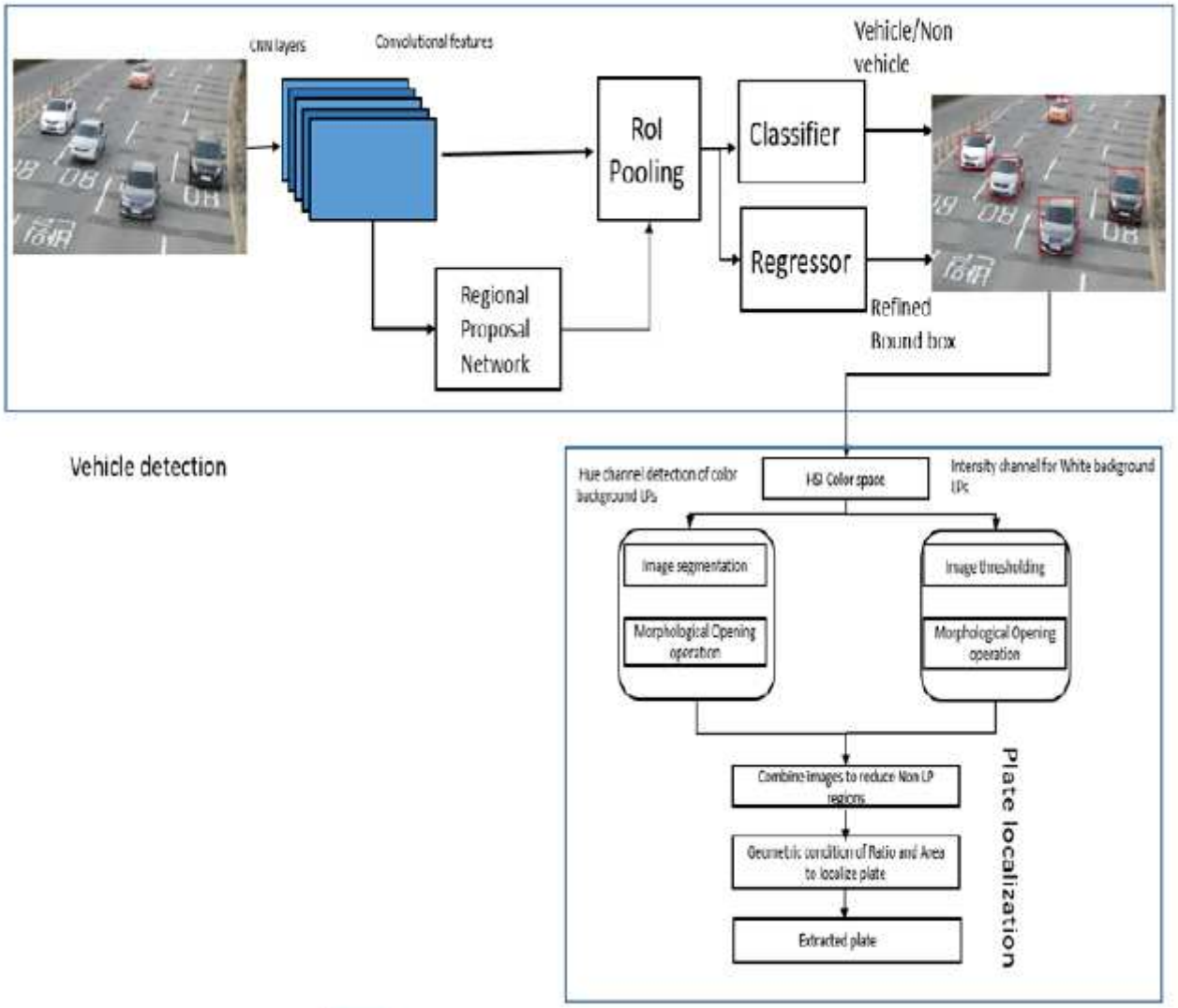


Figure 2

Flowchart of proposed LPD’s method

Figure 3

Test Image with vehicle detection

Figure 4

(a) Plate with white background (b) Plates with a colored background

Figure 5

(a) License plate with white background (b) colored background after morphological Operations

Figure 6

Detection results of the Proposed method

Figure 7

Character Segmentation

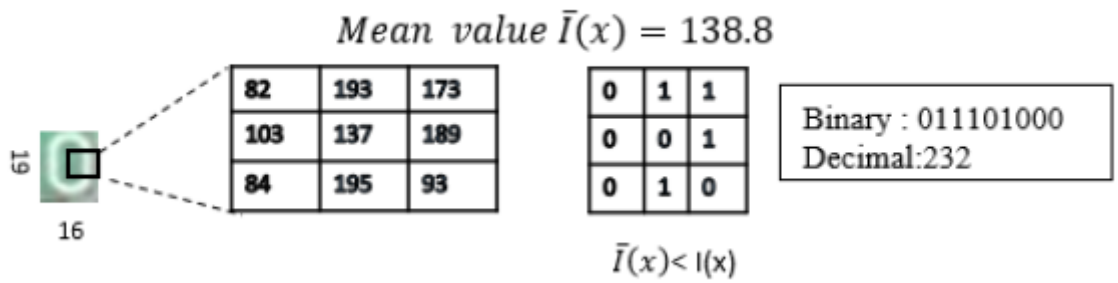
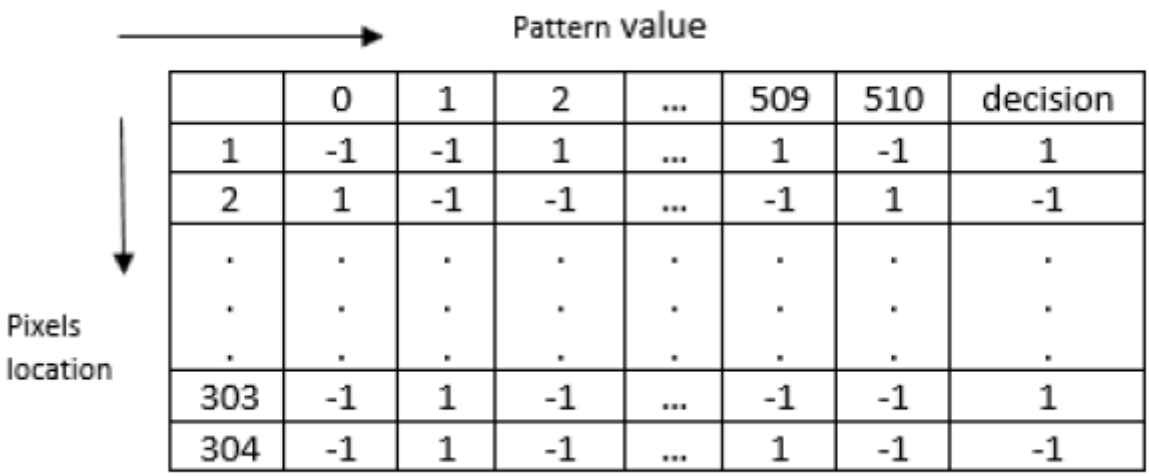


Figure 8

MCT Feature Extraction



	0	1	2	...	509	510	decision
1	-1	-1	1	...	1	-1	1
2	1	-1	-1	...	-1	1	-1
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
303	-1	1	-1	...	-1	-1	1
304	-1	1	-1	...	1	-1	-1

Figure 9

LUT classifier

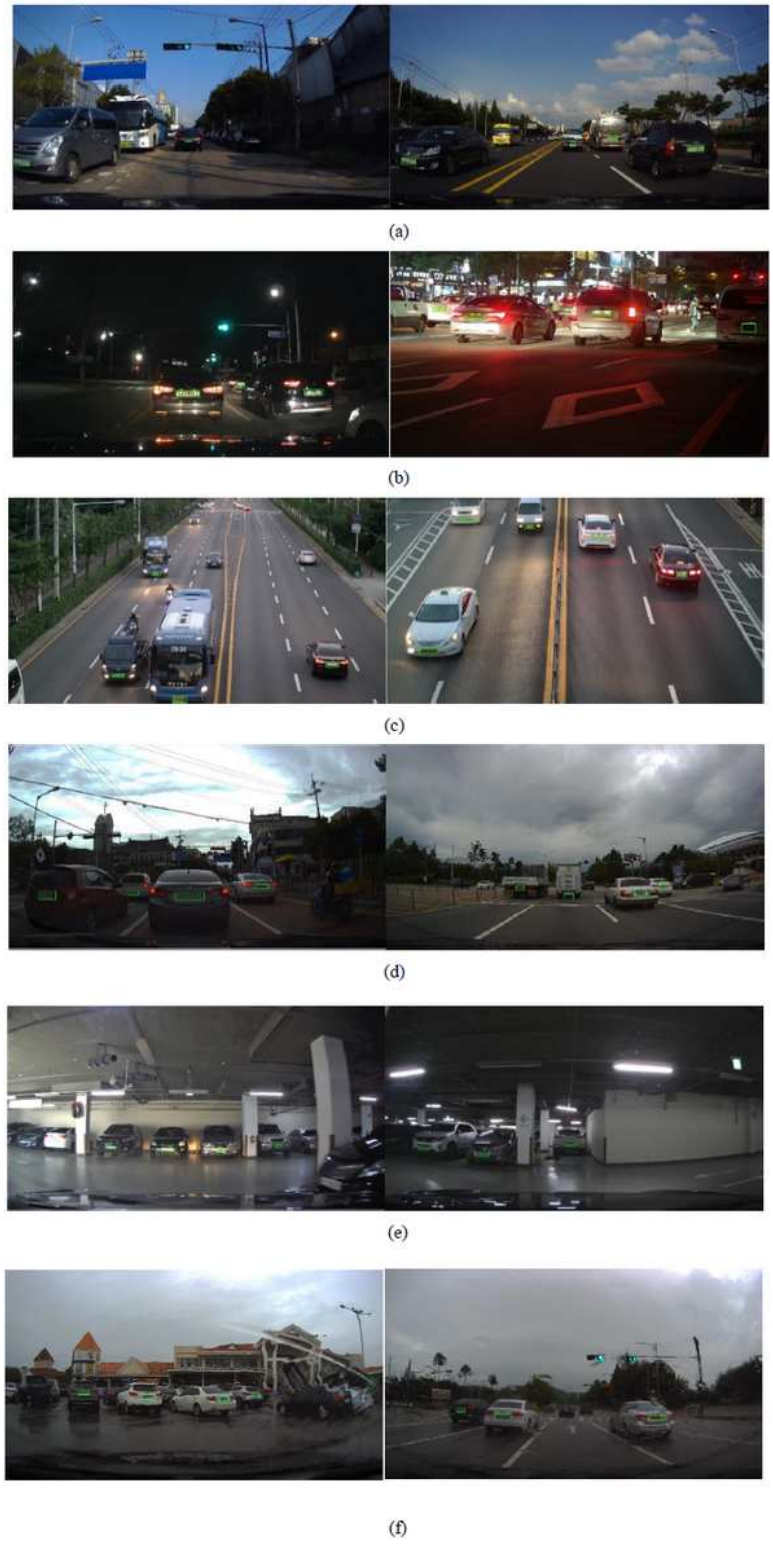


Figure 10

Results of images takes (a) sunny day (b) night time (c) dusk (d) cloudy (e) Underground parking (f) Rainy

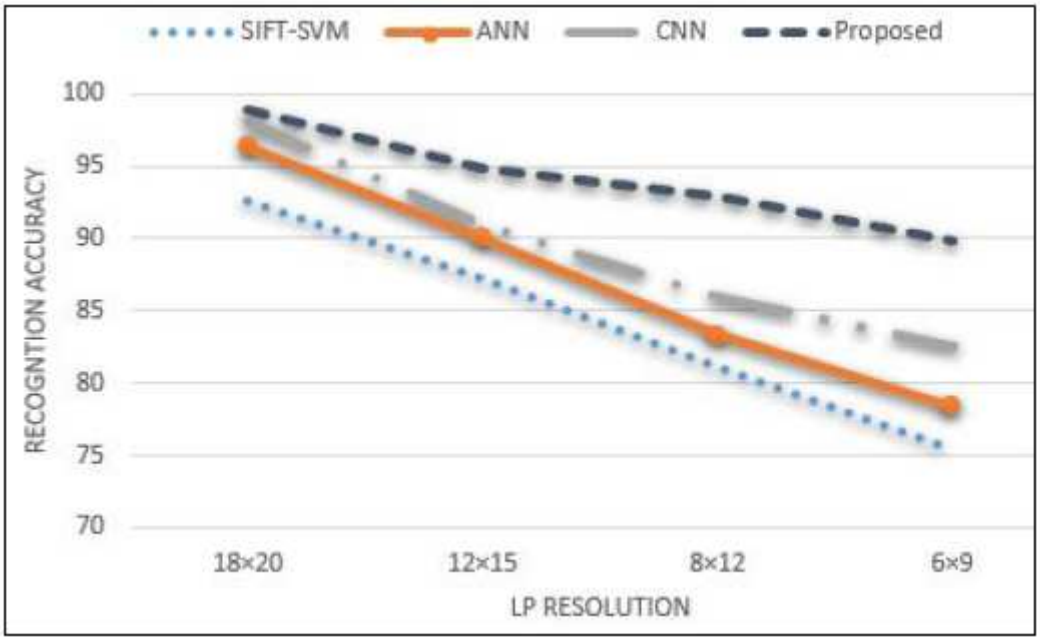


Figure 11

Accuracy vs Resolution