Classification of License Plate Images from Real-Time Vehicles Using Generative Adversarial Network

Rajesh Sharma R[1], Sekar R[2], T. Kar[3], S. Chandra Sekaran[4], U. Sakthi[5] and T. Ch. Anil Kumar[6]

[1]*Department of CSE, SoEEC, Adama Science and Technology University, Shewa, Ethiopia.*

[2]*Department of Electronics and Communication, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur (DT), Andhra Pradesh, India.*

[3]*School of Electronics Engineering, KIIT Deemed to be University,Bhubaneswar, Odisha, India.*

[4]*Department of CSE, P.S.V College of Engineering & Technology, Krishnagiri, Tamil Nadu, India.*

[5]*Department of CSE, St. Joseph's Institute of Technology, Chennai, Tamil Nadu, India.*

[6]*Department of Mechanical Engineering, Vignan's Foundation for Science Technology and Research, Vadlamudi, Guntur, Andhra Pradesh, India.*

Corresponding author email: sharmaphd10@gmail.com

ABSTRACT

License Plate Recognition (LPR) is an advent research in Intelligent Transportation System (ITS) since it poses serious challenges in relation with image recognition. The robustness of ALPR gets reduced in real-world complex due to low quality images occurs from poor illumination, weather condition, complex background, perspective distortions and night light. In this paper, a deep neural network is used for classification and recognition of number plates in real-time moving vehicle under complex scenarios that mitigates the challenges associated. We develop a classification model using a deep learning algorithm namely Generative Adversarial Network(GAN) for the detection of number plates. The GAN network structure is optimized with 20-classes of CNN for the detection of number plates with higher accuracy. Such GAN forms an efficient network that performs classification with reduced errors. The simulation is conducted using python simulator to obtain the classification rates of the model. The extensive simulation shows that the GAN model obtains improved robustness against the real-time vehicle detection and improved scalability in terms of high classification accuracy.

KEY WORDS: NUMBER PLATES,DEEP LEARNING, ARTIFICIAL INTELLIGENCE, REAL-TIME CLASSIFICATION.

INTRODUCTION

Automatic License Plate Recognition (ALPR) has emerged as a significant frontier area of study in light of recent advances in intelligent transportation system (ITS). The majority of today's traffic systems, such as traffic flow control and parking lot entry authentication, use an ALPR method to perform license plate recognition (LPR). In future intelligent cities, ALPR is a major topic in the area of computer vision. The camera network installed at road intersections in intelligent cities would identify vehicles passing through the city in real time (Tran, T.H., et al 2019). ALPR consists of three phases in general: car identification, license plate detection (LPD), and ALPR (Wu, C., et al 2018, Xu, D. and Wu, Y., 2020).

Vehicle identification is the first stage in ALPR. The machine first catches the car in the scene in a real-life natural environment. A strong object detection algorithm is frequently needed (Chen, J., et al 2019, Bian, W., et al 2021 and Pan, Y., et al 2021). If the vehicle is not identified in the first stage, it would have a direct impact on the following steps. The license plate (LP) from the vehicles is

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detected in the next process. The detection system edge detection (Saravanan, V. and Raj, V.M., 2016) is widely used in LPD (Saravanan, V. and Raj, V.M., 2016, Yuvaraj, N.,et al 2021, Wang, J., et al 2019 and Sumathi, A. and Saravanan, V., 2015). Finally, the identified license plate number is recognized.

Despite advances in technology, most ALPR devices still display LPs from the front. Since these systems are based on complex constraints, often result in generalisation and cannot be used extensively. LPs in natural scenes, can look blurred due to the lens orientation, but people can still see them with the naked eye. Also, today the usage of wireless (Junos, M.H., et al 2021), low resource computing (Jia, W., et al 2020) devices are quite common in the usage (Dewi, C., et al 2021) that should be kept in the mind while creating the intelligence system.

In this paper, a deep neural network is used for classification and recognition of number plates in real-time moving vehicle under complex scenarios. A convolutional neural network (CNN) for the detection of number plates is optimized with 20-classes of CNN for the detection of number plates with higher accuracy. Such Dense CNN or GAN forms an efficient network that performs classification with reduced errors.

The outline of the paper is given below: section 2 provides the related works. Section 3 discusses the proposed GAN model. Section 4 evaluates the entire work with possible network performance metrics. Section 5 concludes the work with possible directions for future scope.

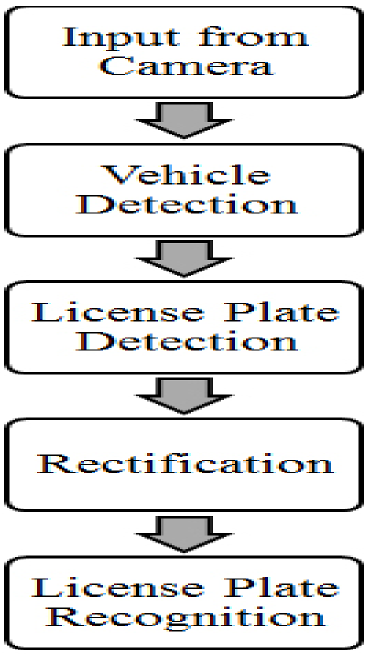
Related work: In order to increase the efficiency of text identification and recognition methods, (Raghunandan, et al. 2019) suggested a new mathematical model based on the Riesz fractional operator for improving details of license plate images. By enhancing the edge intensity in each input signal, the proposed model performs Riesz fractional derivative convolution.Wang et al. 2020 suggested a multi-task CNN for license plate identification and recognition with improved precision and lower computing costs, as well as a detailed data collection of Chinese license plates. To identify license plates, we first trained a Multi-task CNN. Then, to further enhance recognition accuracy, we added an end-to-end system for recognizing license plate detail. Henry et al. 2021 proposed a deep ALPR scheme that could be used for international limited partnerships.

LP detection, coherent character identification, and global LP architecture detection are the three key stages in the proposed solution. The bounding boxes of the projected characters are returned by the character recognition network, but no detail about the LP sequence is provided. A wrong LP number is one that has the wrong series. He and Hao (2021) suggested a rigorous system for detecting and correcting multiple license plates with extreme distortion or skewing in a single image, then feeding them into a license plate recognition module to get the final result. Unlike other methods for detecting and recognisinglicense plates, our approach uses affine transformation to correct the blurred license plate image during identification. It can not only prevent intermediate errors from accumulating, but it can also increase recognition accuracy.

This paper proposes a comprehensive license plate recognition model developed by Zou, Y., et al. [30], which consists of license plate feature extraction, character localization, and character feature extraction. The model will completely remove character features from license plates and activate regional features of characters. Then, using Bi-LSTM and the background location information for license plates, identify each license plate character. Finally, after Bi-LSTM placement, 1D-Attention is used to improve valuable character features while reducing unnecessary character features, resulting in successful acquisition of license plate character features.For the identification and identification of mixed type LPs, Huang, Q., et al. 2019 suggested ALPRNet, a single neural network. Two completely convolutional one-stage target detectors are used in ALPRNet to simultaneously detect and identify LPs and characters, and assembly module that outputs license plate characters.

Proposed Method: The ALRP consists of series of steps that involves the detection of vehicle, detection of license plate and then the recognition of license plate.

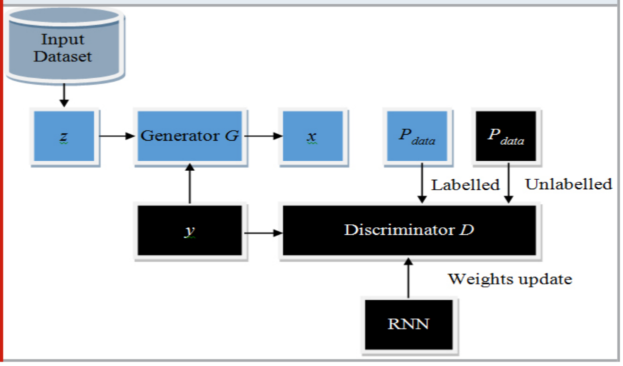
Figure 1: Proposed Architecture on ALPR



Vehicle Detection: The study used GAN algorithm for the license plate detection in vehicles, since the vehicle is one of the underlying artefacts in many traditional detection algorithms. We found the following problems when selecting an object detection algorithm: The algorithm, for one, necessitates a high level of accuracy. Second, the algorithm necessitates a fast measurement speed, so any missing identification vehicle would result in the total license plate detection being skipped. Finally, the measurement is inexpensive and broadly applicable. Many real-world implementations would be hampered by the massive model size and high processing costs. We choose GAN after consideration because it runs quickly and has excellent accuracy and measurement reliability.

License Plate Detection and Recognition: We proposed LPD using GAN that takes into account the firing angle. Figure 2 shows the configuration of an LPD network for distortion correction. The network will learn to identify LPs in natural scenes with varying degrees of distortion and correct the skewed LPs that resembles the front view.

Figure 2: GAN network structure



The two neural networks form the basis of GAN. To begin, the generator network generates plausible synthetic sampling x from real data pdata. The noise vector z from the pz distribution is transformed into newer samples x by the generator network. Second, the discriminator network retrieves samples from the actual data distributionspdata, then retrieves and classifies samples from GAN is trained to solve an optimization problem in which the discriminator is maximised while the multiplier is minimised.

$$\min_G \max_D f(D,G) = \mathop{E}_{x\sim P_{data}}\left[\log D(x)\right] + \mathop{E}_{x\sim P_z}\left[\log\left(1-D(G(z))\right)\right] \quad (1)$$

where
G - generator,
D - discriminator,
f(D,G) - objective function,

The sigmoid activation function in the second network is the final layer, which is given below:

D(x), D(G(z)) $\in$ [0,1].

The activation functions are then maximized while predicting goal values on real samples, with the error minimized. In order to predict the false samples, the generator, on the other hand, reduces the discriminator. As a result, the discriminator's output has a significant impact on the generator loss. The research employs the cross-entropy objective function, which aids in the updating of RNN weights through backward learning, or backpropagation, during the training period, as seen in Figure 2. The fitness function has been chosen to be stable with an enhanced likelihood estimator, which improves the accuracy of the GAN-RNN classifier when the probable weights are modified. To check the output of the GAN classifier, the analysis uses a loss function. Validating the model produces an error in the context of (Khan, M.A., et al 2019). The cross-entropy improves the feedback or real mark prediction likelihood. Maximizing the log-likelihood of the input data reduces the loss function. The following expression represents the cross-entropy loss function:

$$C_E = -\sum_i \left(b\log(w_i) + (1-b)\log(1-w_i)\right) \quad (2)$$

$$f = -\sum_{c=1}^{M} C_E(c,Y)\log C_E(c,Y) \quad (3)$$

where,

M- total classes,
log - natural logarithm function,
y- binary indicator
c- class label
O- observed data and
p- predicted observation.

The incurred loss from the training samples (N) is defined using a loss function.

$$\min_w f = -\sum_{i=1}^{M} f(b_i, Y_i) \quad (4)$$

where,
b - True label
Y - Predicted label.

RESULTS AND DISCUSSION

The performance of the GAN model is tested against various performance models that includes accuracy, sensitivity, specificity, F-measure and percentage error. The proposed method is evaluated on various images using CCPD datasets with 290k images and it is simulated in python. Accuracy is defined as total test images that are recognized accurately i.e. it is the ratio of total accurate predictions vs. total predictions.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

where:

TP - true positive
TN - true negative
FP - false positive

FN - false negative

F-measure is the weighted harmonic mean of precision and recall, which is given below.

$$F-measure = \frac{2TP}{2TP+FP+FN} \quad (6)$$

Sensitivity is the ability of model to identify correctly the true positive rate.

$$Sensitivity = \frac{TP}{TP+FN} \quad (7)$$

Specificity is the ability of model to identify correctly the true negative rate.

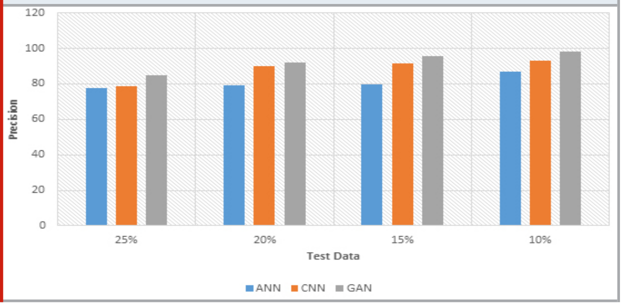
$$Specificity = \frac{TN}{TN+FP} \quad (8)$$

Mean Absolute Percentage Error (MAPE) to validate the losses incurred in the model from the pre-processed datasets.

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (9)$$

Figure 3: Accuracy

Figure 4: Precision



The figure 3 shows the results of accuracy, where the proposed method achieves higher rate of recognition than other methods. The figure 4 shows the results of precision, where the proposed method achieves higher rate of precision than other methods. The figure 5 shows the results of recall, where the proposed method achieves higher rate of recall than other methods. The figure 6 shows the results of f-measure, where the proposed method achieves higher rate of f-measure than other methods. The figure 7 shows the results of MAPE, where the proposed method achieves reduced rate of MAPE than other methods.

Figure 5: Recall

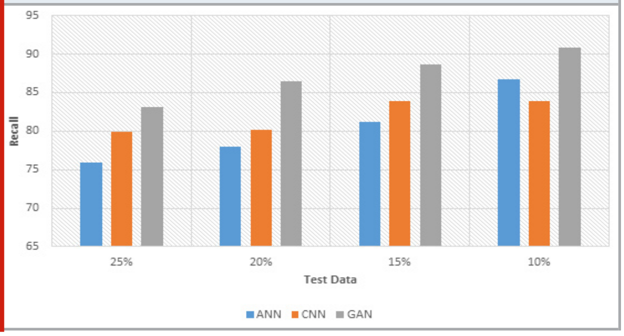


Figure 6: F-measure

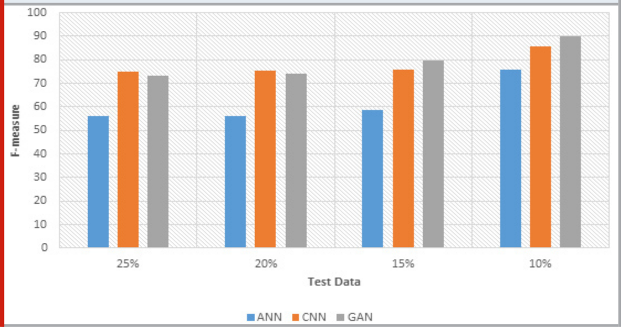
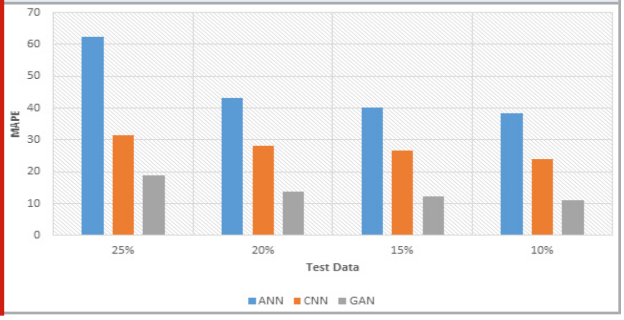


Figure 7: MAPE



CONCLUSION

In this paper, GAN model used in classification of ALPR in real-time scenarios overcome various challenges including: poor illumination, weather condition, complex background, perspective distortions and night light. The GAN model helps in extraction of regional features from the license plate and it extracts the character features. Such recognition helps in locating the license plate character via GAN model. The GAN model improves the character features through preprocessing and training and that eliminates the redundancy associated with useless feature extracted. The effective feature acquisition helps in easier classification of license plate than other methods. The extensive simulation conducted shows that the proposed GAN model obtains improved performance under complex scenarios with high robustness. The results shows that the proposed method achieves a recognition rate of 98.4% than other existing methods.

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