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Pix2Pix GAN Image Synthesis To Detect Electric Vehicle License Plate

Kalpana.A
Member (Senior Research Staff)
Central Research Laboratory
Bharat Electronics Limited
Bengaluru, India
kalpanaa@bel.co.in

Anju John
Member (Research Staff)
Central Research Laboratory
Bharat Electronics Limited
Bengaluru, India
anjujohn@bel.co.in

Abstract: **The area of image processing is more intensive in development and research activities for decades. The role of image processing is huge in modeling, analytics, communication, computation, information security, information forensics and smart city application. Images are ubiquitous in day to day life and images or videos play dominant role in monitoring applications. But when it comes to development of specific application, collection of data is a very challenging task. Nowadays deep learning plays a significant role for generation of data. Robust technologies like Generative Adversarial Network (GAN) and Cycle GAN play a crucial role for generating realistic images with super resolution. GAN and its associated methods used for image synthesis improve the accuracy of deep learning models. In this paper, we analyze challenges of license plate recognition in realistic situation and experiments demonstrate that GAN can generate realistic images to improve the accuracy of license plate recognition.**

Index Terms**: Generative Adversarial Network, Image synthesis, Generator, License Plate Recognition, Deep Learning**

I. Introduction

In Smart City Intelligent traffic management system, Automatic Number Plate Recognition (ANPR) or Automatic License Plate Recognition (ALPR) plays important role. ANPR can be widely used in traffic monitoring, parking lot management and highway toll gate management systems. Nowadays plenty of deep learning approaches are available and they perform well to detect the license plates under constrained conditions. However, the real scene data is still challenging due to unconstrained environment effects. The algorithms work well with ideal situations when system is trained with enough field data. The performance of those approaches drop significantly in conditions like environment distortion, blurring, and extremely bright and dark conditions.

Moreover, there are major challenges like recognizing the license plate at large distance, vehicles with high speed and non standard license plates. Along with these another challenge we are facing is color of the license plates. Our trained custom dataset have the combination of private, commercial and rental vehicles license plates with background color of white, yellow and black. The trained deep learning model uses custom Indian vehicles dataset which is having more number of private, commercial and rental vehicles license plate images. These trained models have low accuracy for recognizing license plate of electric vehicles, which have white characters on green background.

The collection of real data from field is time consuming task. In current situation, on road electric vehicles count are less and the collected data from field is not sufficient for deep learning model training. It is a primary concern in current scenario as an enormous amount of data is important for high recognition accuracy.

II. Need of Data generation

Large amount of labeled data ensures the excellent performance in supervised deep learning networks. Recently, the impact of climate change, and incidents of increasing temperature, more droughts, floods, extreme weather conditions and rising sea level are causing serious problems for people all around the world. The vehicular pollution arising from increasing stock of vehicles, mainly with Internal Combustion Engines (ICE) has contributed significantly to deteriorating the air quality in Indian cities. The increase in the number of ICE vehicles in stock has led to India becoming the third-highest oil-consuming and greenhouse gas (GHG) emitting country worldwide. To address these issues, the central ministry announced a target to transition from new sales of ICE (Petrol & Diesel) vehicles to 100% plug-in electric vehicles (EV) by 2030. A major transition is happening among people as they move towards electric vehicles. To easily differentiate the electric vehicles from others, their license plates have been patterned with green background with white characters. Here the challenge is to detect the electric vehicle license plate with our custom dataset as we don't have sufficient electric vehicle license plates data.

In this paper, we explain the robust method for license plate recognition using Generative Adversarial Networks (GAN). The Generative Adversarial Network (GAN) is a method to train deep neural networks to generate models. Using GAN, we can generate realistic images, perform style transfer and create super resolution images [1] [2]. GAN alleviates the exhausting annotation work for human. Using this method, we can generate a massive amount of data in a required format and it can support to make our model work in different conditions.

III. Automatic Number Plate Recognition

Number Plate Recognition method involves capturing the number plate images from the intended scene, using an ANPR camera. Images are captured from live streaming video and further processed by a series of image processing based recognition algorithms to attain an alpha-numeric conversion of the captured images into a text entry. After obtaining an image of the scene, the deep learning based image enhancement methods are used to make a quality image. The ANPR system is depending on the robustness of the deep learning license plate detection and OCR algorithms. The general processes on ANPR system are image acquisition, number plate extraction, character segmentation and character recognition [9].

IV. Generative Adversarial Networks (GAN):

In leveraging proposed method GAN generates the electric vehicle license plates for two wheelers and four wheelers with various character fonts. While adding the generated data with real data, the trained deep learning improves the license plate prediction accuracy [4].

GAN generates synthetic license plate images for ANPR application. The generated images will be in various formats like font styles with hologram sticker. There are multiple ways to generate the images using GAN methods.

Pix2Pix method: Pix2Pix is a generic image translation algorithm which can convert the images from one domain to another. This method requires dataset which includes pair of related-images.

CycleGAN method: In cycleGAN, mapping happens between two data distributions from source to target domain. This method translates the set of image from one domain to another.

SimGAN method: Simulated+ Unsupervised (S+U) model improves the realism of a simulator's output using unlabeled real data**,** while preserving the annotation information from the simulator [3].

For electric vehicle license plate generation, we are using Pix2Pix conditional GAN. This approach is a combination of generator, discriminator, and text recognition.

V. License Plate generation using Pix2Pix method

Existing CNN or OpenCV based image-to-image translation methods do not generate realistic images. Pix2Pix is a GAN model and is mainly used for image-to-image translation and it learns mapping from input image to output image. The trained network on simple GAN generates a variety of images. The trained simple GAN model works well for larger dataset [5]. In our proposed method, we are using conditional GAN as we need to generate specific kind of data or images.

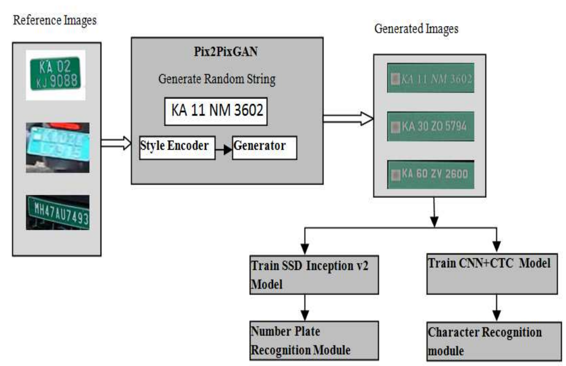

Fig 1: The architecture of proposed model

In Pix2Pix cGAN module target image is generated based on a given input image. To create the initial set of images, the arbitrary number is generated by following Indian vehicle license plate rules. Generated random number is placed on empty pixel image along with hologram symbol if it is required. The raw image was generated using OpenCV image processing technique and these images are given as an input to the Pix2Pix cGAN generator model to generate a translated version of the image[6] [8][21].

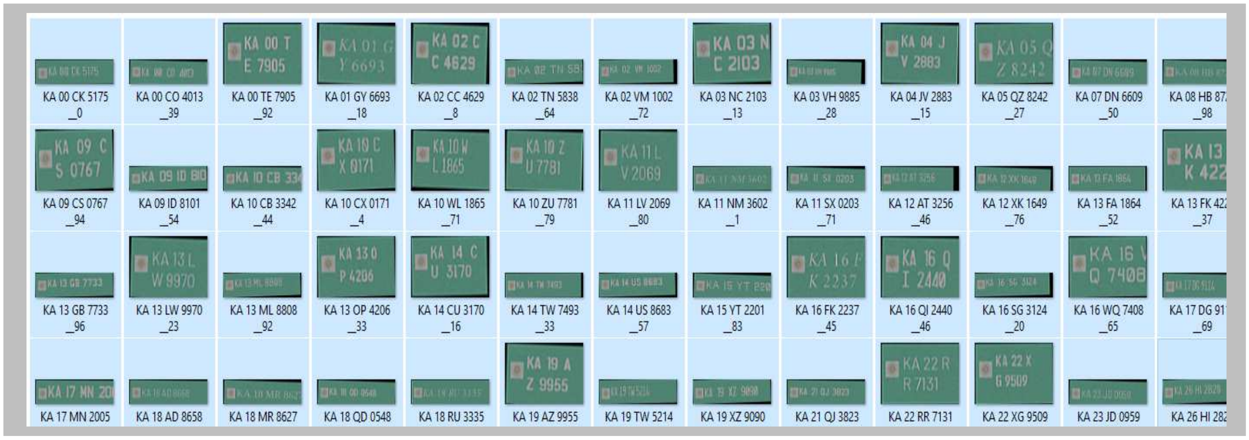

Fig 2: Result of generated sample dataset

The Pix2Pix cGAN generator model creates new reasonable synthetic images. After creating the synthetic images, shades are passed to the generated images to look as realistic. Finally, random jitter is applied to make the images look more realistic (see figure 1).

The pix2pix cGAN model uses u-Net network for image-to-image translation [10]. In discriminator step, PatchGAN is used to improve the details of the resultant image [7]. In discriminator step, the model takes N*N patch image and predict the patch of image is real or not. The conditional GANs learn a mapping from given image x and random noise vector z to the output y,

$$G: \{x, y\} \rightarrow y$$

The produced output using pix2pix_cGAN Generator cannot be distinguished from real images by an adversarial trained discriminator [12][15][17][18][19]. Pix2pix_cGAN architectural network is built using Tensorflow and Keras deep learning frameworks [11][13][14][16][20]. The Pix2Pix_cGAN generates two types of input images. The generated single line license plate images are approximately 140x60 pixels and the two line license plates image are approximately 100x50 pixels (see figure 2).

VI. Data Augmentation for Character Recognition

In ANPR system, once the license plate is detected, character recognition is done using a segmentation free approach named CTC-CNN. CTC (Connectionist Temporal Classification) decoding ensures accurate license plate recognition even with two neighbouring characters appearing connected in the captured image. It also eliminates need for extensive preprocessing and segmentation of individual characters before recognition. Providing license plate training data in different styles, fonts and character sizes are critical for good performance of CTC decoding.

Data augmentation significantly improves the accuracy of CTC-CNN based character recognition. GAN based license plate synthesis enables the model to be trained with more number of realistic license plates for different state codes, fonts and colors.

VII. Experiments

The ANPR application is experimented with two datasets. First data set is called real_10k and it has around 10k data with more number of commercial and private license plate images. The second dataset is called gan_lp11k dataset and it is having around 11k data with addition of electric vehicles license plate images. Both datasets were trained using SSD Inception v2 model separately. For fair comparison, same video was tested with both trained models.

VIII. Implementation Results

Fig 3 and Fig 4 shows the application which was tested on field with two different datasets. The ANPR application is developed using python and C++ and deployed on field. Live video input is captured using RTSP protocol and the developed application has the capability to run on edge devices and desktop CPU or GPU devices. Two inference processes are running in parallel to detect the license plate and recognize the characters from the detected license plate. Fig 3 shows the result of real_10k dataset and it clearly shows that trained model using real_10k is not able to predict electric vehicle license plate. Fig 4 shows the result of gan_lp11k dataset and it clearly indicates that electric vehicle license plate is predicted by gan_lp11k dataset. Table 1 shows the comparison chart between two datasets and their accuracy of license plate detection. The prediction accuracy is improved while using gan_lp11k dataset.

Table 1: Result with read_10k dataset

Sl. No	Dataset	real_10k	gan_lp11k
1.	**Number Plate (NP) Detection** [SSD Inception V2]		
	Accuracy (%)	95	97

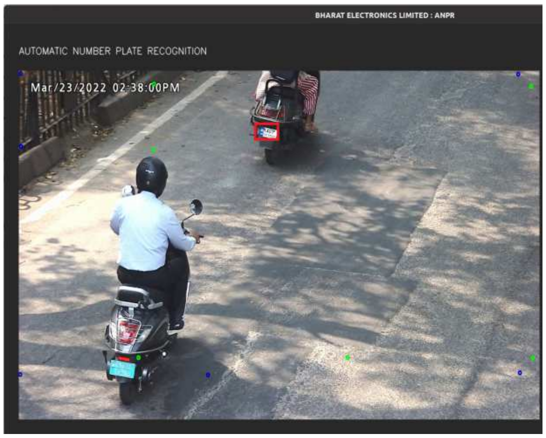

Fig 3: Result with read_10k dataset

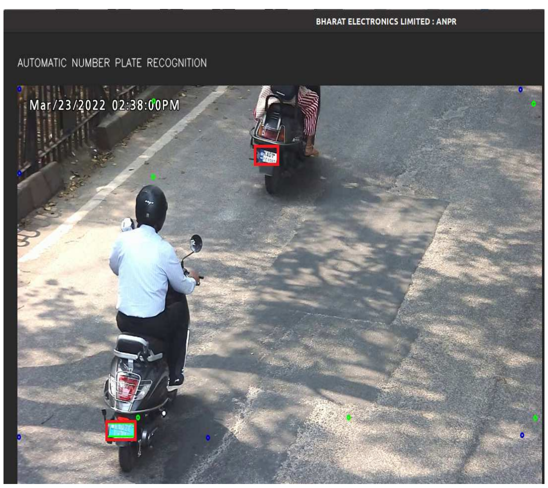

Fig 4: Result with gan_lp11k dataset

The field data captured for license plate recognition was highly skewed with a high proportion of vehicles registered in Karnataka (State Code: KA). Most of the data was captured in Bangalore and hence license plates from some states were not available in the dataset. Also, the proportion of military vehicles was limited in the real field data. However, the ANPR system should perform well for vehicles registered all over India, as well as for commercial and defense vehicles.

In order to ensure high accuracy of ANPR system, synthetic plates were generated with different state codes. Several plates were synthesized with syntax of defense vehicles. GAN was used to make these synthetic plates appear realistic. This experiment provided better character recognition accuracy, compared to the model trained without synthetic plates.

IX. CONCLUSION

In this paper, we have explained a robust model to detect the license plates in unconstrained conditions. The proposed model solves the issues of shortage of electric vehicle license plate dataset using conditional GAN. The generated images using conditional GAN improved the performance of the detection and character recognition module. Using conditional GAN, users can specify a certain condition and generate the particular images for the specified label. In future, we can generate realistic images based on requirements to solve the data insufficiency issues using this proposed method. Using this method, we can train the deep learning model to detect the license plate for other countries as well.

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