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GAN-based synthetic data augmentation for increased CNN performance in Vehicle Number Plate Recognition

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***Abstract* - In today's modern era, parking remains a big problem for a lot of people. This problem consumes a person individual's time by finding the right spot for parking. In the current research, the concept of an automatic parking system using the vehicle license plate or the number plate recognition is discussed. It will improve the process with much less hassle by removing human interaction. It will also lead to advancement in the security of vehicles evading the requirement of a slip or a magnetic card which is used to goes in and out for registering vehicles in a parking place. The researcher uses image processing algorithms to make an entry in the database of the parking automatically. AVNPR (Automatic Vehicle Number Plate Recognition) is used for the identification of the number of plates. Due to noise issues, deep algorithms like CNN (convolutional neural networks), RNN (recurrent neural networks) do not correctly recognize the miss-identification of the numbers in the vehicle plate. This problem is rectified by the authors by using the GAN (Generative adversarial networks) algorithm. GAN helps to create high-resolution images from a single low-resolution image. After applying the GAN, the classification of the vehicle plate is done through CNN. During experimentation, the proposed approach achieves 99.39% recognition accuracy for a vehicle number plate. Hence, the proposed system is suitable for identifying the numbers in the vehicle number plate automatically. Moreover proposed system compared with existing models, it has been found that it has achieved higher accuracy than the other models.**

Keywords—Convolutional Neural Network; Data Augmentation; Image processing; Stochastic gradient descent; Cross-Entropy

I. INTRODUCTION

AVNPR is one of the most used techniques in the past few decades. It is a technology that can recognize every vehicle number plate correctly to an extent. It involves low-level image processing techniques and high-level artificial intelligence methods. AVNPR can help to identify missing vehicles [1] from the parking lot or help the owners to manage a proper database of cars entering and leaving the lot. It is a system that consists of software and hardware. They use images [2] either taken by a camera or greyscale or an infrared sensor. The camera takes the image of the number plate and sends it further to the processing unit where the raw data is processed and extracted into characters and converts the pixels into numerically readable characters. This technology [3] is finding its application in the traffic law implementation by recognizing the number plate [4] and access the record simultaneously giving detailed information about the owner. It is also useful in recognizing stolen cars and border monitoring. Before the character recognition [5], the number of plates must be separated from the background images. This is the step that causes an effect on the accuracy and processing speed significantly. Some of the difficulties that are faced during the recognition section are the bad quality of image, or the image distortion, or the camera angles. To extract a number plate from a vehicle, there are two methods used:

- Edge Detection
- Checking for the rectangles in the image

During edge detection, some images are either lost or not identified. Hence this loss of data can decrease the training and testing dataset. For increasing the dataset in the form of images, the GAN [6] is used for generating images from real-time images. Firstly, it has to ensure that the object i.e. the number plate is in the field of view. Secondly, it has more chances of recognizing [7] some alphabets wrongly and pick up the alphabets or the numbers [8] that are not even written. So, to solve the latter problem, the concept of CNN on AVNPR. This system is different as it has fully convolutional layers [9]. The AVNPR process diagram is shown in fig 1.

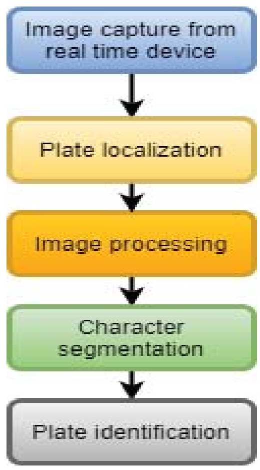

Fig. 1. Block diagram of AVNPR process

II. RELATED WORK

During the past years, various techniques were proposed [1] to identify the number written on plates of a vehicle. In the 1990s, recognition for number plates has been started [2]. In this era, boundary lines extraction techniques were used as an approach for the number plate's recognition, the popular algorithm like gradient filter was used to get the boundary lines. After that, lines were [3] detected and a set of two parallel lines was considered to be the area of license plate recognition. Also, some authors [4] proposed vertical band clipping in which the whole image was clipped into three or more vertical bands, and later it was analyzed and further processed to detect the license plates. Some authors suggested [5] to directly process the image by converting them to grayscale and then perform image filtering and image binarization. At the end, Optical Character Recognition (OCR) has been used for images characters recognition and then the outcomes are matched with alphanumeric database that have been used during training process of artificial neural network (ANN) algorithm approach. The authors [7] proposed a novel approach known as a secondary positioning algorithm which will first recognize the HIS color after that template is matching with the individual relation coefficient. The authors [8] use CNN for fine-grained image classification for a vehicle number plate. They capture the images through YOLOV3 architecture. During prediction, CNN [10] has achieved high accuracy as compared to other deep learning approaches during angle and noise variations. Some researchers [11] recognize the vehicle number plate through RNN. The projection analysis and component are analyzed through segmentation for images and RNN recognizes the characters automatically. The authors [12] predict the vehicle plate number through CNN but some images are noisy or having low intensity therefore CNN decreases the prediction accuracy. For achieving more accuracy than CNN in noisy images, D-PNR is used for noisy and hazy images. Many of the authors [13] recognize license plate recognition through CNN and synthetic images. An LPR algorithm based on extreme regions and Boltzmann's restricted machines was also proposed [14]. The first excessive discovery [15], [8] of license plates is done using edge detection and image filtering. Character circuits are then extracted using external circuits which are also used to filter the plate region. The characters were finally seen using Boltzmann's [16], discriminatory equipment trained in bullet samples drawn from real images augmented by rotation and sound. However, local plate making only [17] works with plates of a certain size and size of the feature and has not shown strong evidence in the changes of perspectives. Few researchers [18], [19], [20], [21] have tried to figure out the best data practice that has been used for in-depth learning in the activities of inequality and light flow limitations. They found that while sample variability and camera information helps, image authenticity is enhanced, the results are also supported by our test results in the visual state of the license plate recognition.

III. PROPOSED METHODOLOGY

A number plate is the most significant feature to identify different vehicles. AVNPR system detects characters on a number plate. When the vehicle passes through the camera, the number plate number is read and instantly matched with the vehicles of interest (VOI) database. The developed AVNPR [22] system mainly focuses on checking characters on a plate not only in English but also in other languages such as Hindi. Calibri and Times New Roman are the most commonly used fonts for recognition. So, to achieve better results from an AVNPR their efficiency must be improved. CNN has revolutionized the process of image recognition. This helps in figuring out the analysis of images. The AVNPR camera takes a picture of the license plate and sends it the images to GAN. The GAN will generate the images so that synthetic images are generated. CNN is applied to the generated images. The CNN processes the image through the deep learning techniques it is trained for and gives an output image. The methodology is described in fig 2.

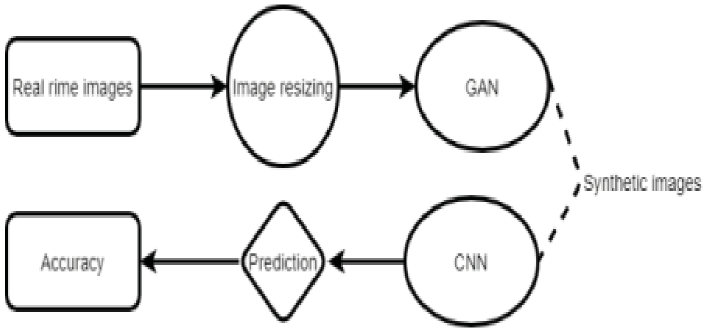

Fig. 2. Proposed methodology

For different applications like data and image synthesis, image recognition, image super-resolution, and classification, GAN is used extensively nowadays. The proposed framework has GAN generator and discriminator functions. The hybrid model is trained together whereas the generator generates images that are similar to real images whereas discriminator tries to differentiate between real and fake images. This type of feature is really important when training samples are limited. This hybrid model helps in improving the classification accuracy as well as helps in minimizing the problem of overfitting that will be raised by CNN.

A. *Image processing techniques*

Image processing techniques are used to apply some operations on images such that important features are extracted from the images. It is associated with signal processing where input and output both have images but in output, features of the images are also connected. These output images will become an input for GAN. In the current research, the image resizing technique is used. The images are resized with a size of 250*250 pixels.

B. *Generative adversarial network*

Through image resizing technique, the images are resized. But, during resizing the images, some input images are destroyed hence it will decrease the dataset size for both training and testing purposes. The GAN is used for data augmentation. The GAN is used for generating images data from real-time images. In GAN, data generator and discriminator are used. The data discriminator is an enemy of the generator. The generator will generate images from real-time images by adding some noises. After adding noises, images are generated. Then, the discriminator will match the generated images with real-time images. If the generated images are not matched with the generated images then the discriminator will reject those images otherwise it will generate synthetic images. After resizing of images, the GAN is used for increasing dataset size so that the maximum accuracy during prediction is achieved.

GAN works very well on unlabeled data and this algorithm after training learns the internal representation of data. It means learning the intricate and muddled distribution of data and can generate new examples that probably can be drawn from the original data. The data that is generated by this algorithm is exactly similar to real data. The discriminator is known as a classifier and used for classification.

C. Convolutional neural network

CNN is used in image processing [6] for either classification or prediction. The GAN images are applied to the convolution layer. The convolution layer applies the filter on those images so that image is converted into matrix form. The matrix is converted into nonlinearity form through an activation function. Generally, for nonlinearity, the RELU activation function is used for CNN. Due to increasing feature parameters, the prediction accuracy decreases. The pooling layer is applied for decreasing feature parameters. But after decreasing the feature parameters, overfitting and under-fitting problems can occur for training and testing datasets. For solving these problems, the dropout layer is used. The dropout sets the hidden neuron to zero. The FCN layer maps the features from connected layers. From the step convolution layer to the pooling layer is described under the feature extraction technique and from dropout to FCN is described as a classification or prediction technique. The working of CNN with layers is described in fig 3.

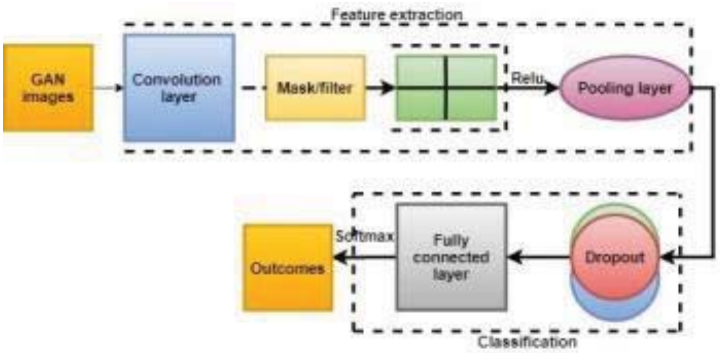

Fig. 3. Overview of CNN

$$T = X * F \quad (1)$$

where X is an input image and Y is a filter

$$T = ((n\text{-}f+1),(n\text{-}f+1)) \quad (2)$$

where n is an dimension of an image and f is an dimension of filter

$$T = w^z . X + b \quad (3)$$

where w is a weight and b is called bias.

D. Accuracy estimation

For prediction, performance parameter accuracy is used for estimation. The accuracy is defined as a correct prediction out of the total number of predictions

IV. EXPERIMENTS

For the prediction of a vehicle number plate, the performance of CNN is calculated in terms of accuracy. During the resizing of images some images are destroyed, the GAN will generate images so that maximum prediction of vehicle number plate can be achieved. In particular, no standard dataset is available for vehicle plate recognition. In the previous section, CNN working is explained for vehicle plate number recognition.

A. Dataset

We increase the Pascal VOC 2007 [23] data by adding some publically available datasets. Some images are captured with the help of a camera and some are added for both training and testing. The details are mentioned in table 1.

Table 1: Images collection with category

Dataset	**Images**
Pascal VOC 2007	250
Publically availability dataset	300
Images captured with the help of a camera	100

B. Image pre-processing

After the collection of data, image pre-processing techniques are applied. The image resizing image processing technique is applied to that dataset. The images are resized according to 416*416 values. During image resizing, some images are having smaller size values so we will reject those images for experimentation. Firstly, images are resized and normalized as the current research targets to inspect the performance of CNN alongside the input size. The features that have been considered are edge detection, the minimum number of characters are six, square or oval-shaped number plates, texture, and color.

C. Image generation

During image pre-processing of images, some images are destroyed. Hence the images dataset size is reduced. For increasing the images dataset, the GAN is used. The STARGAN is used for implementation. During the training of GAN, it takes a sample noise set with real-time images. The discriminator part is used to train the data and a sample noise subset having m size is created. After creating a noisy subset, the generator part is used for training the above-mentioned data. The images which are generated with help of GAN are shown in fig 4 and fig 5.

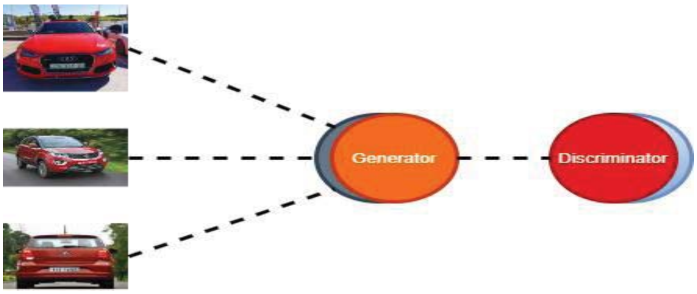

Fig. 4. Apply GAN on different images dataset

D. Recognition

The vehicle plate number is recognized through CNN. The detailed description of CNN was also described in section 3.3. After generated images through GAN, these are used for training and testing on CNN. The filter that has been used in the CNN Convolution layer is of any size (16, 32, 64, 128). Then, Max pooling (2*2) has been applied to an array of pixels generated by the filter. The input size of an image is 416*416*3 and the output of the image is 416*416*16. During Max pooling, the activation function 'Relu' is used. The optimizer 'Adam' is used along with 100 epochs. The description of CNN in each layer is shown in fig 6.

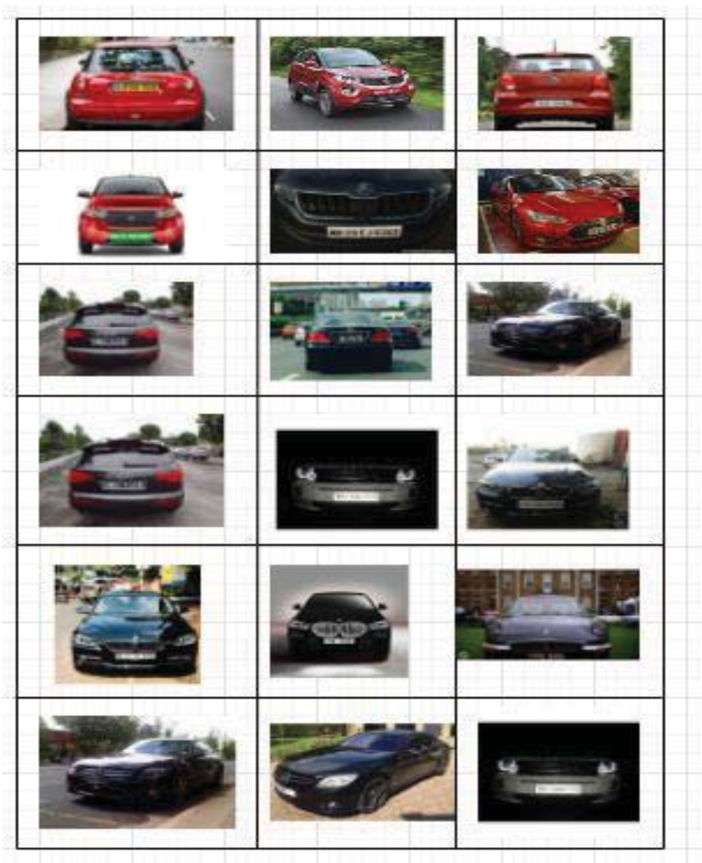

Fig. 5. Generated images through GAN

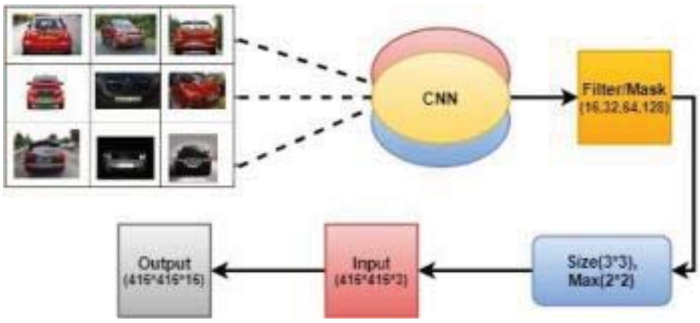

Fig. 6. CNN workflow

The CNN is implemented using python language with the usage of tensor flow for deep learning calculations. The generated images are used for training and testing purposes. In CNN, the filter is applied to each image. The filter is depending on the processor. Therefore, the filter converts the image into a matrix form. After generating a matrix through the filter, the pooling function is applied. For pooling, the max-pooling function is used. Then input for the next layer is depending upon the size of the matrix generated through the max-pooling function. Then, the Softmax activation function is applied for feature maps. The 80% dataset is used for training purposes and 20% is used for testing purposes. The recognition of vehicle number plates through CNN is shown in fig 7.

Fig. 7. Recognized images through CNN

V. RESULTS AND DISCUSSION

After recognition of images through CNN, the recognition accuracy is measured. Some of the authors used particularly CNN for vehicle number plate prediction while other uses specifically deep learning techniques. Image processing techniques have also been used for fine-grained images before recognition. These fine-grained images are helpful for classification. The comparison is also mentioned in table 2 with other popular models. The accuracy is calculated as:

$$Accuracy = CP/NP \quad (4)$$

where,
CP is the number of correct predictions
NP is the total number of prediction

During experimentation, the combination of CNN and GAN achieves higher accuracy than previous models.

Table 2: Comparison of Models

Authors	**Referenced study**	**Model**	**The accuracy achieved (%)**
Wang et.al(2018)	[1]	Artificial neural network(ANN)	75
Liu et.al(2018)	[3]	CNN	93.74
Rafique et.al(2018)	[7]	Region based CNN	93.85
Izidio et.al(2019)	[2]	CNN	93.10
Bjorklund et.al(2019)	[5]	CNN	98.3
Pustokhina et.al(2020)	[10]	Convolutional recurrent neural networks	95.6
Omar et.al(2020)	[6]	CNN	97.15
Proposed method		GAN+CNN	99.39

Wang et.al achieves 75% recognition accuracy of vehicle plate through ANN. But, most authors used CNN for vehicle number plated recognition as shown in fig 8. However, deep learning techniques are very helpful for fine-grained image classification. The proposed method achieves 99.39% accuracy of vehicle number plate recognition. As noticed in table 2, none of the researchers has proposed a hybrid approach for vehicle number plate recognition.

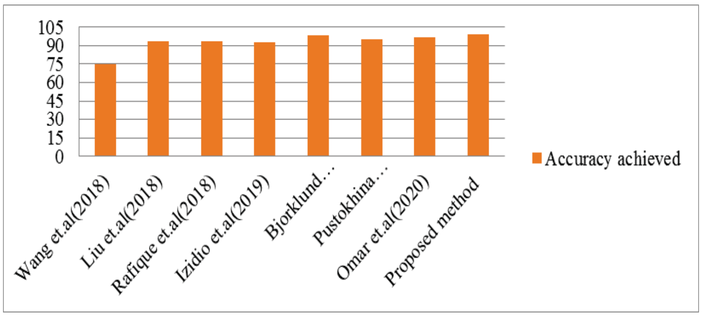

Fig. 8. Accuracy Metric

In the future, hybrid recognition methods like SVM + CNN, GAN + CNN +SVM can be used on the large dataset for improving the results. More features can be extracted to enhance accuracy. The direct and candid extension for the current research can be done on conditional GAN and semi-supervised settings. The architecture which has been proposed can be adapted for handling more complex networks.

VI. CONCLUSION

The current research targets to propose a novel approach that is an amalgamation of GAN and CNN for vehicle number plate recognition. Our approach uses the image resizing technique for image resizing. New images are captured through a camera device therefore these images are added in the previous dataset. But during image resizing, some images are destroyed due to low size values. Therefore, for increasing dataset images in the form of data augmentation, GAN is used. After generated images are applied for classification or recognition which is done with the help of CNN. From the literature, it can be said that this is the first time that such vehicle number plate recognition is done through a hybrid approach. The test result shows that the proposed method is more effective for both acquisition and detection purposes. During vehicle number plate recognition, our method achieves 99.39% more accuracy as compared to other models used by previous researchers. In the future, if the images dataset is increased then there are chances of improving the accuracy of vehicle number plate recognition. For improving the classification accuracy, we can implement the hybrid approach known as CNN-SVM for vehicle number plate recognition.

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