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Intelligent System for Vehicles License Plate Recognition Using a Hybrid Model of GAN, CNN and ELM

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***Abstract* – The scientific community has given license plate recognition systems a lot of consideration. The current methods for vehicle identification need to be improved due to the swift increase in vehicle numbers. In order to lessen reliance on labor, a fully automated system is needed. With the growth of Intelligent Transportation Systems, demand for license plate recognition has increased significantly. License Plate Recognition (LPR) is susceptible to environmental factors such as a complex image background, angle view, and shift in illumination, it is still difficult to correctly recognize the digit letters on license plates. When reading license plates automatically, license plate recognition uses character recognition and image processing to identify the vehicles. The license plate detection and identification subsystems are typically combined into the vehicle license recognition system in order to locate the vehicle and identify the license plate. The Extreme Learning Machine (ELM) is used for categorization, identification, and training. This research suggests a GAN-CNN-ELM-based technique for detecting vehicle license plates. This method produces an accuracy of about 98.94% which outperforms the GAN-ELM, GAN-SVM, and GAN-CNN models.**

Keywords— Support Vector Machine (SVM), Convolutional Neural Network (CNN), License Plate Recognition (LPR), Extreme Learning Machine (ELM), Generative Adverserial Networks (GAN).

I. INTRODUCTION

In recent years, vehicle number plate recognition has become an increasingly vital technology. This technology helps to recognize license plates for vehicles in a quick and effective manner, without the need for significant amounts of human resources. Their heightened significance can be attributed to a number of different factors. Each and every one of the ever-increasing vehicles that use the roads is required to have a unique number plate. Because of the tremendous advancements in digital image processing technology, it is now possible to detect and identify number plates at a much faster rate. It is feasible that the full process will be finished in a time period of less than ms. The capacity to identify vehicles is helpful to a diverse range of different operators in a number of settings. It is feasible for agencies of government to apply it to detect automobiles that have been involved in illicit activity, check whether they have paid the annual fees or not and identify persons who violate traffic rules. In addition to the monitoring of vehicles, the identification of license plates is an essential component in a wide variety of systems, such as those used for the management of parking lots, the processing of toll payments, and other similar applications. And other systems where authorization is required. Automating the procedure frees up a significant amount of time for the security agents. In recent decades, there have been a number of notable advancements made in computer vision technologies that have been applied to real-world problems. In the past, the identification of vehicle number plates was accomplished by the use of pattern-matching procedures, which involved determining the height, contour area, width, and so on of the plate. Currently, a number of different deep learning models that have been trained over enormous amounts of data are routinely employed in Number Plate Recognition.

A crucial computer vision task is License plate recognition (LPR). In smart cities, it has numerous useful uses, such as electronic payment, on-road law enforcement, and monitoring. License plate extraction, Picture acquisition, character recognition and license plate segmentation are the four steps that make up a standard LPR system. The entire task is essentially solved once the image acquisition phase is under control.

The Vehicle Number Plate Detection System, for vehicles, is composed of the following three primary modules: image preprocessing, Character segmentation and character recognition. After the image has been loaded and converted to grayscale or binary, the denoising process can begin. The character segmentation and detection of the number plate area discover the many characters that are printed on the plates. Character recognition involves the retrieval of characters.

The length of parking time can be determined with the help of the LPR system. When a car passes through a gate, its license plate is read by a reader and then stored in a database. When a car subsequently exits the parking lot by an exit gate, the license plate is recognized and compared to the original one once more that was saved in the database. The price of parking is determined by taking into account the time difference.

Even though LPR has been incorporated into toll systems, and smart parking, it still has a number of issues with the supervision system. Despite advancements in commercial LPR systems, they mainly record frontal views of vehicles and numerous applications, such as smart toll management systems, IoT security systems, and smart parking systems utilize number plates (NP). The field of machine learning has made significant strides over the past 20 years.

Scalability is one of the main benefits offered by these models. CNNs are constructed using a hierarchical design in order to have the ability to learn deeper information provided by the image dataset. Convolutional neural networks do, however, have several shortcomings. There is a flatten layer and several fully connected layers in a CNN which is appended to the end of the networks for classification and recognition. Both forward transmission and backward propagation require some time, but it is beneficial to obtain an exact result. Therefore, we suggest employing Using an Extreme Learning Machine (ELM) will increase speed and maintain accuracy rather than using certain fully connected layers. There are two methods extracting a license plate from the vehicle: Rectangles in the image are looked for and their edges are detected. Some photos are either lost or not recognized during edge detection. Therefore, this data loss may result in a smaller training and testing dataset. The GAN is used to generate images from real-time photos in order to increase the dataset in the form of images. In this research, we evaluate the shortcomings of the techniques described and suggest a hybrid system that combines the best features of each system. So In this work, the hybrid training strategy was used to train the model of Generative Adversial network (GAN), Convolutional Neural Networks (CNN) and ELM to improve the accuracy.

II. LITERATURE SURVEY

There have been several study studies published during the last few decades, It have been devoted to the topic of license plate recognition methods, the majority of which relied on the processing of grayscale method images, character extraction, and pattern recognition. Previous researchers have conducted extensive research in the field of image processing to detect the vehicle license detection using the grey scale method, localization, segmentation, and recognition[1].[2] Described an image processing method based on a modular system. They used Caffe net, one of several Deep Learning architectures, to recognize the images. [3] Proposed a method for detecting and recognizing vehicle license plates using segmentation and feature extraction. [4] The images of the number plate were deblurred using a proposed algorithm, and for recognition procedure the neural networks feed-forward method was used. The smearing and dilation technique for automatic vehicle identification was developed by [5]. A professional ANPR system was proposed by [6] for Brazilian NPs, deep neural networks are used. During the course of the research, a paper was devoted to analyzing both of the YOLO (You only look once) CNN networks. Frontal View or Number was the first integrated component. Network Plate Detection (NPD) that identifies vehicles Secondly, there were frontal views and a license plate. A network for segmentation (LPS) and character recognition (CR) that finds text in a cropped LP and differentiates it from other elements. A solid hierarchical NPRS has been presented by [7]. They found that YOLOv2 model and SVM integration can accurately record license plates. An effective real-time ANPR expert system employing the CNN YOLO. API was proposed by [8]. They used an open-source dataset for ANPR that includes 4500 annotated pictures and more than 30,000 NP characters from 150 different cars. The filters that were found by a large neural network after it had been trained for months on a large dataset consisting of thousands of images can be applied to a neural network that is significantly smaller according to [9]. We implemented deep neural network in ANPR as a result of their research article. A feature extraction technique developed by [10] is used to locate the NP in the image. It has become common practice to do vehicle detection before LPD, it narrows the search window and the number of false positives. Support Vector Machines (SVM) and Histogram of Oriented Gradients (HOG), feature descriptors described in [11][12][13], are used to construct this strategy. [14] Used an artificial neural network (ANN) to recognize and accurately extract Korean license plates. [14] study and [15] study were comparable. The Support Vector Machine (SVM) algorithm was used by [16]. To identify the license plate. [17] Concentrated on the employment of cameras as a crucial component to get a better image. The recognition of 20 Arabic and Latin characters was explained by Cowell et al. various methods for extracting information from colorful 22 backdrop licenses were highlighted by [18]. This particular CNN model for license plate recognition (LPR) also has a high degree of accuracy when used to character recognition. In order to effectively recognize Iranian license plates with Persian (Farsi) characters, [19] used both SVM and OCR (Optical Character Recognition). For the extraction of the plate region, Histogram equalization, followed by dilation and erosion, was suggested by [20]. SVM classifiers were employed for character recognition. A technique based on edge detection with the Hough Transform was put out by [21]. A technique was developed by [6] employing erosion, smearing, and dilation. Using enhanced prewitt operation, [22] and [23] identified a license plate. A strategy based on movable windows and template matching mechanism was suggested by Khalil [11]. [24] Make the ELM proposal in 2004. It is simply a feed forward neural network with one or more layers of hidden nodes; However, unlike other conventional layers, hidden nodes' parameters are assigned at random and do not require updating. Only the output weights of hidden nodes are learned in the first phase, thereby learning a linear model with parameters that could have closed-form solutions. According to [25] ELM performs better than other algorithms with higher accuracy, such as SVM. [26] Tests ELM on breast cancer classification problem and regression problem, and discover that ELM takes less time and has higher accuracy and also put out a technique for identifying traffic signs in that procedure, classifiers are trained using ELM while Histogram of Oriented Gradient variant (HOGv) features are extracted. The results demonstrate that the method may be applied with high computing efficiency and excellent recognition accuracy to unseen data. Convolutional neural networks

(CNN) and Support vector machines (SVM) techniques have both been used to build image classifiers, although both have certain drawbacks. In this paper we have introduced a hybrid system of GAN-CNN-ELM. This paper demonstrates that the suggested hybrid system outperforms GAN-ELM, GAN-SVM, and GAN-CNN models.

III. PROPOSED SYSTEM

The number of vehicles on the road has increased exponentially, which is one of the primary causes of traffic congestion and violations. LPR (License Plate Recognition) has been developed to reduce violations while also automating traffic management. In India, various LPR techniques are used, but their effectiveness is very low. The proposed system aims to optimize and improve LPR efficiency. Stanford car dataset from Kaggle is used for training. The dataset contains 16,185 images from 196 different classes. It is divided into two parts: training and testing. The training data consists of 8144 images, and the testing data consists of 8041 images. Then two folders called train and validation need to be created.

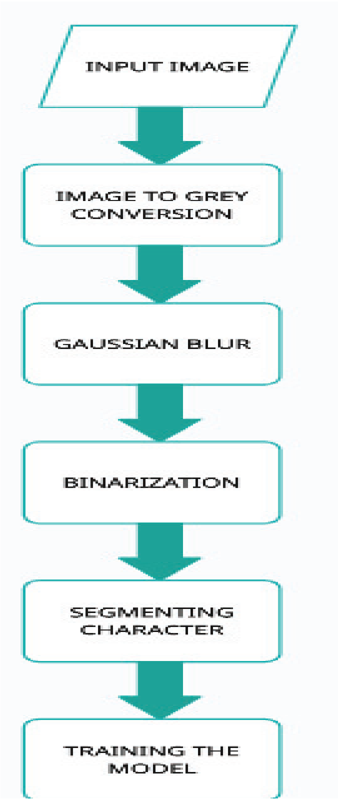

Fig. 1. Flowchart of Lisence Plate recognition

Figure 1 depicts the proposed method's flowchart. The image is given in the input. Then it will transform the colored image to a greyscale image, where the image only has one 8-bit channel with values which ranges from 0-255, where 0 represents black and 255 represents white, as opposed to the original image's three channels (BGR). Then again it transforms the grayscale image into a binary image, in which each pixel now has a value of 0 or 1, where 1 represents white and 0 represents black. Applying a threshold with a value between 0 and 255 in this case results in the resulting binary picture assigning a value of 1 to all pixels in the gray scaled image with a value higher than 220. Additionally, any pixels with values lower than 220 will be assigned a value of 0 in the new binary image. It uses an adaptive thresholding to remove insignificant parts from the image because the images were shot under various settings, lighting conditions, and environments. The threshold value of the neighborhood area, whose size is 20, and the weighted sum of neighborhood values, the weights of which are calculated using a Gaussian window is 10, are the two values that our algorithm calculates. Then segmentation of alphanumeric characters on a vehicle's license plate are extracted. This will look for and locate a curve connecting all continuous points of the same hue or intensity after deleting and eliminating unnecessary parts from the image. It employed the hierarchy technique to build a complete list of hierarchy in order to discover all contours, but we do not require every boundary points. This paper uses the straightforward contour approximation method because we only need 4 points for this and because our LP is rectangular. Then segmentation of alphanumeric characters on a vehicle's license plate are extracted. Finally training the model by using GAN-CNN-ELM model.

A. *GAN-CNN-ELM MODEL:*

The main approach has three steps: Image preprocessing, CNN feature extraction, ELM classification.

1) *Image Preprocessing*

Image preprocessing involves segmentation, clipping, data improvement techniques include generative adversarial networks, graphic transformations, and augmentation.

a) *Image Enhancement*

Image enhancement is used for minimizing the effect of irrelevant data, encouraging the model to extract more picture features, and recognizing license plates from a variety of features.

b) *Data Enhancement*

To reduce noise interference and to standardize the dataset Data Enhancement is done. To improve the data, it requires visual transformation using three different techniques: horizontal flipping, rotation, and translation.

c) *Generative Adverserial Network:*

The unavailable samples are removed after the graph transformation, which further reduces the amount of training data that is accessible [27]. By creating models to collect a significant amount of data, the current data are trained to address the issue of insufficient training data. This increases the network's capacity for generalization and strengthens its stability**.**

GANs are made up of a generator network and a discriminator network. The generator does its best to learn how real data are distributed. The discriminator gets the ability to determine regardless of whether the input data are actual data or generated data, both types of data compete with one another in games and training to eventually reach the equilibrium state.

2) *CNN FEATURE EXTRACTION*

In CNN feature extraction the convolution layer calculates convolution, while the pooling layer samples descending. These two layers extract the key image features. This method extracts features using ResNet50.

3) *ELM CLASSIFICATION*

ResNet50 loaded the pre-trained model weight to preserve and extract features. The neural network's last layer is used for outputs. The feature vector $L \times I$ is retrieved from each photo using the ResNet50 model, where r is the row vector $and\ L\ is$ the number of feature

$$\overrightarrow{f_i} = [y_1, y_2, \cdots y_L] \quad (1)$$

Matching the one-time code labelled 3 × 1

$$\mathbf{I}_i = [\mathrm{I}_0, \mathrm{I}_1, \mathrm{I}_2] \quad (2)$$

The features of images are extracted into a $N \times L$ feature matrix to be used as the dataset for ELM classification, where N is the total number of pictures and L is the total number of characteristics.

$$\mathbf{F} = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_N \end{bmatrix} = \begin{bmatrix} Y_{11} & \cdots & Y_{1L} \\ \vdots & \ddots & \vdots \\ Y_{Nr} & \cdots & Y_{NL} \end{bmatrix} \quad (3)$$

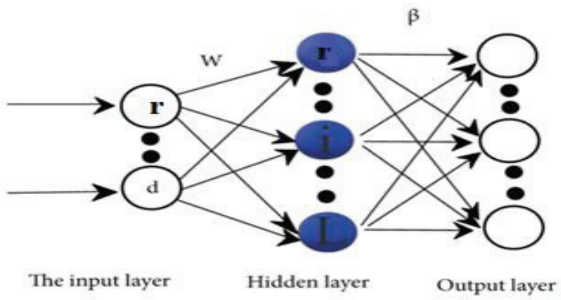

Fig. 2. Flowchart of ELM

The ELM network built is shown in Figure 2. In ELM network the implied nodes can be produced at random using a collection of continuous probability distributions rather than having to be changed using back propagation (BP). The two stages of the ELM are learning and feature mapping. In this algorithm, the image feature vector is used as input data in the input layer, and the following equation displays the ith node's output result.

$$f(y_i, w_i, b_i) = y_i \cdot w_i + b_i \quad (4)$$

This is the same as converting a P-dimensional to an L-dimensional vector.

$$h(x) = [p(y_0, w_0, b_0), \cdots, p(y_L, w_L, b_L)] \quad (5)$$

The sigmoid function is employed in this case, where w_i is the ith link between a hidden layer node and an input layer node, b_i is the bias, and g is the activation function.

$$p(y_i, w_i, b_i) = \frac{1}{1 + e^{-(y_i \cdot w_i + b_i)}} \quad (6)$$

As well as being the weight of the ith hidden layer node and the jth output layer node, In the output layer the number of nodes is expressed as M. Then, node j output (mapping) is shown.

$$f_j(y) = \sum_{i=1}^{L} \beta_i \cdot p(y, w, b) = h(y)\beta \quad (7)$$

The characteristic matrix of a particular training sample is denoted by the following $H(x) = [h_1(x), \cdots, h_m(x)]^T$ in the learning stage. This includes the m mappings produced during every stage of the mapping process. The objective function is displayed in the following:

$$\frac{1}{2} \parallel H\beta - T \parallel_2^2 \quad (8)$$

Where the least squares method is solved by using β.

$$\beta = \arg min \left(\frac{1}{2} \parallel H\beta - T \parallel_2^2 \right) = H * T \quad (9)$$

H* denotes a generalized expression for the inverse moment of H.

$L_1\ is\ the$ Error function now includes the regular term T. which helps to prevent over fitting and increase the ELM model's capacity for generalization.

$$\frac{1}{2} \parallel H\beta - T \parallel_2^2 + \alpha \parallel \beta \parallel \quad (10)$$

β's solution is as follows:

$$\beta = (H^T H + \alpha \cdot \mathbf{I})^{-1} H^T \quad (11)$$

I stands for the unit matrix.

To sum up, the ELM training process involves the following steps: By setting the hidden layer parameter, the output matrix ||H|| and weight matrix ||β|| of the hidden layer to the random continuous distribution$(w_i, b_i) i = 1, \cdots, L$, are calculated

After the mapping in the first step, given a set of samples Y, it first becomes H(Y), and the category of the samples is then given as

$$label(Y) = argmax(\, H(Y).\beta \,) \quad (12)$$

The greatest value in the array is returned by the argmax function's index; That is to say, the category number with the highest likelihood of the forecast is category number.

IV. RESULT AND DISCUSSION

The number of nodes in the hidden layer and the input used to build the model are two parameters for the ELM that must be decided upon beforehand during training. The model's generalization effect, degree of fitting, and training effectiveness are all impacted by several parameters. The general rule is that there shouldn't be too many features and that there shouldn't be as many hidden nodes as there are input dimensions. In the analysis experiment, K-fold cross-validation is used to identify the ideal size of both the input layer and the hidden layer to enhance the capability of the model. to generalize by reducing overfitting. According to experimental findings, the most accurate cross-validation method is 4 Fold, hence it is finally utilized to train the model of GAN-CNN-ELM.

The number of chosen features serves as the training parameter, and the impact that the hidden layer has on accuracy is now being investigation. The following is the process that is used to select the number of hidden nodes:0, 200, 400, 600, 800, 1000, 1200, and 1400. Then, under 4-fold cross-validation, three distinct models of GAN-ELM, GAN-CNN, GAN-SVM, and GAN-CNN-ELM are trained. Figure 3 displays the training results.

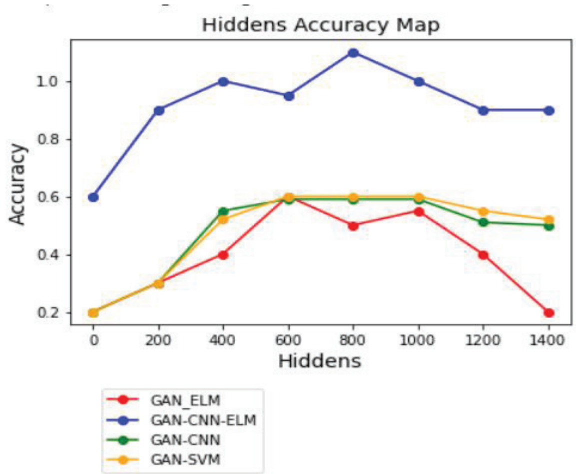

Fig. 3. Comparison of model accuracy under various hidden layers.

According to the experimental findings, the accuracy is significantly and quickly impacted when the nodes of hidden layer increases from 10 to 200 as shown in Figure 3. Between stages of 600 and 900 the accuracy tends to be consistent. The model began to over fit after the 800th node, and its capacity for generalization is poor. Therefore, there are about 800 optimum hidden nodes, which performed well in our experiment. The outcomes of the experiment also demonstrate the inefficiency of the single ELM classifier. A regularized ELM classifier is added to increase accuracy, and the GAN-CNN-ELM classifier model significantly increases accuracy.

TABLE I. COMPARISON OF MODEL CROSS-VALIDATION PER FOLD AND WITH AND WITHOUT CROSS-VALIDATION AND ACCURACY(%)

Models	Fold1	Fold2	Fold3	Fold4	With cross validation	Without cross validation
GAN-ELM	78.33	75.21	79.23	74.56	80.63	75.00
GAN-CNN	85.43	86.87	82.22	80.12	88.25	80.34
GAN-SVM	70.65	73.89	68.52	75.00	78.49	69.85
GAN-CNN-ELM	98.56	97.32	98.33	97.21	98.94	97.78

Having determined that 800 was the optimal number of hidden nodes, this study uses 4-fold cross-validation to evaluate the accuracy of each fold and the accuracy of the testing dataset both without and with model cross-validation. In Table 1, the experimental findings are displayed. The experimental results show that applying 4-fold cross-validation improves the model's accuracy performance in the final test set.

TABLE II. ACCURACY COMPARISON OF THE MODELS.

MODEL	ACCURACY (%)
GAN-ELM	80.6
GAN-CNN	88.3
GAN-SVM	78.5
GAN-CNN-ELM	98.9

Selected are four reasonably accurate models: GAN-ELM, GAN-CNN, GAN-SVM, and GAN-CNN-ELM which is shown in Table II. The findings of the aforementioned experimental comparison demonstrate that, the GAN-CNN-ELM algorithm model is much superior to that of the other three models.

V. CONCLUSION:

In this work, the input images were changed to grey conversion. Then grey has been transformed into binary and segmentation of alphanumeric characters were done. For training the model we have used GAN-CNN-ELM Vehicle Number detection system that enhances picture features and expands sample data via image enhancement and graphic transformation. To get a lot of data, we train the GAN. Multilayer features are extracted using ResNet50. ELM classifiers classify feature values to reduce training time. While on comparison models such as GAN-ELM, GAN-SVM, GAN-CNN and GAN-CNN-ELM in conjunction to classify license plate images. Our experiments shows that GAN+CNN+ELM model performs well on comparison of GAN-ELM, CNN-ELM, GAN-SVM. In future research into the KELM method will be conducted to further enhance the training speed of models, and multiscale convolution will be employed to optimize the system's generalization degree and the diversity of recognition.

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