Journal of
Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7766198

PERFORMANCE ANALYSIS OF LICENSE PLATE RECOGNITION USING MACHINE LEARNING

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Abstract
Automatic number plate recognition plays a vital role in an intelligent transportation system. The intelligent transportation system enforced the government's traffic control law. The enforcement of automatic number plate recognition reduces the traffic load and accident recovery on the roadside. Several emerging machine learning algorithms increase the accuracy of number plate recognition, but realistic problems still exist. The performance of accuracy depends on several factors, like feature extraction, character segmentation, and training of characters for recognition. In this paper, we study several algorithms of advanced machine learning, such as support vector machines, deep neural networks, convolutional neural networks, and recurrent neural networks. The support vector machine overcomes the limitation of overfitting problems in classification algorithms. The other three algorithms, DNN, CNN, and RNN, are categories of deep learning algorithms that boost the performance of classification of number plate characters. The classified characters increase the automatic number plate recognition. The deep neural network is a multiple hidden layer-based network that improves the rate of recognition. the counter-race between CNN and RNN algorithms in concern for accuracy in recognition. For the validation of algorithms, three standard datasets were employed, such as the FZU cars dataset, the Stanford cars dataset, and the HUMAin2019 dataset. For the testing, we created five sets of car image groups, numbered 100 to 500. The performance of algorithms is estimated as accuracy, precision, and recall. The analysis of the results suggests that CNN's algorithms are better than other existing algorithms for number plate recognition.

Keywords: - NPR, Deep Learning, Machine Learning, image processing, DNN

Introduction

Automatic number plate recognition plays a vital role in the intelligent transportation system (ITS). Automatic number plate recognition depends on two factors, information processing and image processing. The information processing of number plate recognition handles the numerical and alphabets of number plates [1,2,3,4]. The image processing handles the processing of the captured image of the vehicle number plate. The processing of captured image of number plate employed several processes such as filtration, feature extraction, segmentation and vectorization of number plate data. The accurate rate of number plate recognition has gained a lot of attention mainly because of its several practical applications such as traffic law enforcement, collecting toll payments, and managing exit and entrance in vehicle parks and many other applications. Despite several studies of automatic number plate recognition, it handles problems of recognition and accuracy using conventional and machine learning algorithms [5,6]. The processing of the number plate recognition system has two tasks, one is to locate the number plate and the other is to identify the number plate characters. The characters recognition employed several algorithms of segmentation and classification to detect characters of number plates. Traditional characters recognition algorithms frequently employ character segmentation [7], which implements segmentation using prior knowledge such as fixed character spacing, connected component analysis, and project-based methods. The segmentation-free algorithm, such as sequence labelling, can effectively avoid the character segmentation error affecting the recognition accuracy, though handcraft features are frequently unable to be used to accurately segment. Before detecting a licence plate, some studies denoise the image and boost the resolution for noisy scenes. Some studies have suggested using tilt correction algorithms to correct licence plates or segmented characters in scenes with skewed shooting angles in order to increase recognition rates [8,9]. The critical processing of characters segmentation and employed algorithms decline the accuracy of recognition. Despite several algorithms of segmentation, some optimization and machine learning algorithms are employed for enhancement of recognition rate [10.11]. The other approach of number plate recognition is feature-based number plate recognition. The feature-based number plate recognition employed transform-based methods like discrete wavelet transform (DWT) and discrete cosine transform (DCT). The DWT-based number plate recognition algorithms extract the lower content of features and employed neural network and machine learning algorithms for recognition of number plates. Convolutional Neural Networks (CNNs) are used for feature extraction and character reading, while Connectionist Temporal Classification, number classifiers, etc. are used for licence plate recognition thanks to the advantages of deep neural networks [12,13,14]. These techniques work well with standard licence plates. An additional rectification step is needed before recognition when the licence plate images are crooked or bent. In this paper we study number plate recognition using advance machine learning algorithms such as support vector machine, deep neural network, convolution neural network (CNN) and recurrent neural network (RNN). The employed algorithms tested on a reputed number plate dataset and measured some standard parameters and analysed the performance of advance machine learning algorithms. The main objective of this paper is to analyse the recognition accuracy of algorithms and validate the results of experiments. The rest of the paper explores as in section II related work in the area of number plate recognition, in section III methodology of number plate recognition, in sections IV describes the experimental analysis, in section V concludes the work.

II. Related work

The related work arranges in the ways of limitation and employed methods for recognition of number plates. The variation of accuracy of number plate recognition declines the performance of intelligent transport systems. The recent work mentioned in table-1

Table-1 related work of automatic number plate recognition

Reference No. & Year	**Applied Methods**	**Experimental Result**	**Limitations**
[1]. 2020	Adaptive framework	With the combination of several modules at different levels, their suggested network's cumulative recognition performance improves from 86.25 percent to 96 percent, according to their findings.	Model training error is high.
[2]. 2020	Deep learning algorithms YOLO RCNN OSTU	The most powerful recognition algorithm currently available is the enhanced technique based on YOLO discussed by, which can reach a recognition accuracy of 94.3 percent for numerous scenarios in several nations while processing each image in only 13.62 milliseconds.	Compare and visualize existing license public plate datasets depend on the number of images, resolution, and environmental complexity, and generate a prediction to other license plate recognition research directions.
[3]. 2020	Statistical modeling framework CWSMM WSMM SMM	In a single cycle, the CWSMM technique yields 1.51%. The green phase length for the WSMM technique is 4.69. In the red phase length, the SMM technique gets 6.28 percent.	The network-level LPR dataset used only has six days of data, limiting the quantity of data that can be discussed to train the DLG model. It will be interesting to test the with larger LPR datasets and see if performance improves with varied training data sizes.

[4]. 2020	Image binarization, FANS OTSU	FANS increase the recognition rate up to 1.32 times better than Otsu. And also increase the detection rate up to 1.19 times better than Otsu.	The disadvantage of the Otsu approach is that it is sensitive to brightness and noise, which is inconvenient because most machine photos are taken in an open area.
[5]. 2020	OKM-CNN ELM CNN	On the applied dataset, the OKM-CNN model had the highest overall accuracy of 0.981.	To distinguish multilingual LPs, the OKM-CNN model's performance can be improved. Furthermore, the incorporation of a bio-inspired optimization algorithm-based parameter tuning procedure can improve the experimental results of the OKM-CNN model.
[6]. 2021	Neural architecture RP Net Yolo	RP Net can reach 91 % accuracy for license plate identification.	A standard contribution to the ALPR environment reason of, to their knowledge, no earlier efforts for license plate recognition entirely on edge devices with accuracy comparable to solutions designed to run on server-grade hardware have been made. However, there are certain limitations to the generalizability of these findings, and the discussed technique can be expanded for

			upcoming prospective study topics.
[7]. 2020	YOLO RNN Cycle GAN	Their technique, in particular, yields 0.8 percent accuracy 0.6 percent on LE, and 0.9 percent on RPincrements on AC.	For license plate recognition, theydiscussed an LSTM-based sequence decoder that cannot be trained in parallel over time steps. A transformer-like decoder could be investigated in the future to speed up training.
[8]. 2021	Bi-Directional Recurrent Neural Network (BRNNS). Connected Component Analysis (CCA).	With real-time processing speed and an AP0:5 score of 86 percent, and work outcomes (82.7 percent detection rate and 60.8 percent OCR F1 score) (27.2 frames per second).	They want to test their system in a variety of real-world settings to see how it performs on a daily basis. They also wish to use preprocessing processes on the plates that have been recognized and create their own Bangla license plate OCR system. When compared to, this can enhance recognition performance. What the Vision API has to offer right now.
[9]. 2020	CNN in LPR systems	Shows the adversarial cases created using their method have better concealment and attack success rates. These adversarial samples are nearly invisible to human sight, but they can mislead hyper LPR	To overcome the problem of local optimization throughout the optimization process the production of adversarial examples in their topic can be described as an

		with a 93 percent attack success rate.	optimization problem in which the goal is to identify the best spot position. This attack is modelled as a new optimization problem that aims to determine the best attack point rather than pixel perturbation values, as in earlier work. This difficult optimization problem is solved using a genetic algorithm.
[10]. 2020	AVLPR framework	The suggested approach achieves 98.5, 92.6, and 96.4 percent accuracy in identifying, segmenting, and recognizing the plate number using 300 car photos with varied pixels.	Research will look at LP identification from fast, darker and blurry vehicle photos, and recognition from many LPS in a single image. Furthermore, font similarity difficulties in identifying LP characters will be considered using DL structure.
[11]. 2020	STGGAT GRU GAT RNN	RMSE 6.375 MAE 4.657 MAPE (%) 38.97 %	Multiple factors, such as traffic accidents and weather, have an impact on traffic volumes. Only historical traffic volumes and spatial dependencies are used in the prediction model in this study. Furthermore, accurate traffic volume estimates at urban crossings are difficult

			due to the high-frequency variations at the short scale.
[12]. 2020	ALPR system FCN-based ROI-based method	Plate Recognizer is the name of the ALPR system used in the comparison. It achieves an overall character recognition rate of 94.3337 percent, which is significantly lower than ours (RCNN 99.453 percent and ROI 99.953 percent).	Integration of these modules and application of their strategy to other places with similar problems to Macau would be fascinating.
[13]. 2020	License plate recognition (RLLPR).	With 7000 training photos, the suggested technique obtains a character recognition rate of up to 96 percent for 4000 test images. The outcome demonstrates that using a multi-task process to classify characters is a good idea. In addition, instead of employing multi-task classifiers, a recurrent network such as LSTM can be used.	Before completing the recognition stage, plate boxes must be preprocessed and enhanced. Uneven lightening owing to poor lighting, degradation in the acquired image, skewed plate box, and complex background when merged with plate characters are some of the issues that might occur in a license plate photograph.
[14]. 2020	Automatic License Plate Recognition (AVLPR). ANN HOG SVM SAE	HOG+ANN 99.70 HOG+SVM 98.90 HOG+SAE 94.30 HOG+KNN 97.60	Authors will improve their process by using more complicated photos with several automobiles to recognize license plates. In addition, the size of the training database will be increased in order to

	KNN		reduce misclassification of comparable classes.
[15]. 2019	optical character recognition (OCR)	The suggested technique has an accuracy of 83 percent, while the filters Gaussian Blur and Filter 2D have accuracy of 80 percent and 72 percent, respectively.	It was possible to establish that character identification is sensitive to ambient lighting, and additional experiments with different types of filters, as well as new deep learning approaches, will be used in outcomes of their works to increase accuracy.
[16]. 2020	ALPR YOLOv3	EER 32.46 LPD 18.36 AOLP subset RP's accuracy drops to 93.29 percent without artificial data, whereas their technique achieves 99.51 percent accuracy without artificial data. Furthermore, as indicated by the low accuracy of 83.63 percent,	The character segmentation and character recognition procedures are combined in the LP recognition issue, which is posed as an object recognition problem. Using their suggested international LP layout identification algorithm, their system can detect license plates from multiple nations. To the best of their knowledge, LPs from most nations can be divided into two categories: single line and double line.
[17]. 2020	SVM ANN.	The usage of the Tesseract Engine for text recognition	There are various reasons why the discussed method does

	YOLO-based CNN	improves the performance of ALPR systems by up to 99.2%. The Python programming language was used to complete this work. Researcher also get 87% accuracy for the SVM and 90.2% for ANN.	not involve picture segmentation. As previously stated, the extracted LPs may have issues such as size, tilt, non-uniform brightness, and other disturbances.
[18]. 2020	ALPR license plate recognition system. CNN	The claimed detection success rates for license plates, Character segmentation and recognition rates are 97.16 percent, 98.34 percent, and 97.16 percent, respectively. The overall success rate is given in percentages. 93.54 percent, to be exact.	The characters on the license plate are recognized by the license plate recognition network. To prevent character segmentation, they used Bidirectional RNNs to treat this as a sequence labelling problem.
[19]. 2020	VTM LSTM GRU CNN	RMSE 9.84 MAE 7.34	For citywide traffic status estimate and prediction, combining the speed and occupancy received from mobile sensors (GPS devices) with fixed traffic detectors will be an intriguing topic.
[20]. 2020	Neural Networks Framework BPNN	For localization, distinction, and segmentation, the percentage accuracy is 100 percent, 100 percent, and 100	As the outcome the license plate serves as a means of identifying the vehicle's location and owner. The license plate is a metal

		percent, respectively. The first approach has a recognition rate of 94.5 percent, while the second method has a rate of 91 percent.	rectangle that has the information (number, county, and province) and hangs at the front and back of the vehicle.
[21]. 2021	neural network (CNN) convolution.	For the image data block, the approach has a high accuracy rate of 94 percent and a no return rate of 88 percent. CNN is also the most optimal use for the suggested enhancement, according to experimental data.	Copyright infringement detection, sophisticated traffic light frameworks, and brand-related insight calculation on the go. These are usually descriptions and point-based findings. The cycle juice is based on the original data. Many networks have realized that the vehicle logo categorization is packed into a fully integrated layer that makes full use of the original data.
[22]. 2020	CNN. OCR LP detection	Recognition accuracy of up to 95% was achieved in tests, with a response time of 66 MS/LP. When employed under demanding situations, RILP showed to be resilient and trustworthy, producing satisfactory results in a fair amount of time.	The modular structure of RILP should be upgraded in terms of the type of connections in order to attain a greater rate of FPS and better throughput. Currently, each stage of recognition takes up some disc space and relies on slow IO, but sending data between stages via OS pipes or other similar ways would be much faster.

			RILP's network architecture is novel, but it still has to be evaluated and fine-tuned to increase performance.
[23]. 2021	ALPR CNN BPNN	The recognition accuracy of LPR is 96.04 percent. R-CNN In a real-time scenario, 92 percent of vehicles are detected, and 83 percent of license plates are detected. Algorithm discussed by OCR 80% Accuracy 80 percent Gaussian Blur Accuracy Filter 2D Accuracy of 72 percent	During the recognition and detection operations, the bulk of neural networks are utilized. It's usually dependable, although it almost always adds to the run time. Combining identification and recognition into a single neural network helps solve this problem. In some cases, certain strategies are effective.
[24]. 2020	CNN *Capsule Network (CN)* ANPR	It is praiseworthy that their system can accurately recognize the license plate string with a 98 percent accuracy even with all conceivable changes in the data, and it can also be supplemented with an Internet of Vehicles for intelligent traffic control.	Due to illumination, contrast, and hence intensity change, pictures might become fuzzy, distorted, and unappealing. Due to illumination, contrast, and hence intensity change, pictures might become fuzzy, distorted, and unappealing.
[25]. 2020	LPR	Plate recognition, character segmentation, and character recognition all had accuracy rates of 91.58 percent, 93.11 percent,	This will make it difficult to discover the license plate region because the system may identify the erroneous white pixels

		and 80.25 percent, respectively.	region due to the complicated background.
[26].2020	NPR CNN CCA YOLO SVM	With a variety of distances between vehicles and camera, it was able to detect number plates with a 92.78 percent success rate. Character segmentation achieved a success rate of 97.94 percent, while character recognition achieved a success rate of 96.91 percent.	Vertical projection has also been utilized to discern the actual number plate from regions that same as the number plate.
[27]. 2020	CRNN CNN RNN STN CTC	The accuracy of network identification without STN was 86.54%, while the accuracy of adding STN was 94.53 %.	Character identification based on deep learning treats character identification as a sequence marking problem, and models the input image and the sequence of character labels to achieve the goal of character end-to-end identification.
[28].2020	SSD CNN	The accuracy of plate detection is 81.2%. The accuracy of symbol detection is 95.2%. Symbol identification has a 99.32% accuracy rate.	In more complicated cases, it is anticipated to increase detection, segmentation, and license plate identification accuracy without sacrificing processing speed.
[29]. 2021	ANPR OCR	In comparison to models utilized by prior researchers, their technique obtains 99.39	Poor file resolution, mainly due to the plate being too far away, but also occasionally due

		percent better accuracy during vehicle number plate identification.	to the use of a low-quality black-and-white camera. Images that are smeared, especially if they are moving. Overexposure and shadow reflection result in poor lighting and low contrast. During number plate reading, the camera's angle of view changes due to vehicle lane changes.
[30]. 2020	LPR EQ-LPR-E EQ-LPR, EQ-LPR-S EQ-LPR-P	EQ-LPR-E 94.35 % EQ-LPR-S 96.07 % EQ-LPR-P 94.03%	An efficient quality-aware license plate identification system is built by incorporating Siamese networks for plate stream detection and quality awareness in traffic videos.

III. Methodology

The advancement of machine learning algorithms enhances the accuracy and recognition of number plates. Machine learning algorithms like support vector machines, deep neural networks, convolution neural networks, and recurrent neural networks the major issue in the recognition of number plates is the mapping of features to characters and the training of data. The complex structure of characters and mapping of features pose a problem of data overfitting and training error. Despite these issues, advances in machine learning algorithms reduce the problems of number plate recognition.

A. Support Vector Machine (SVM)

Support vector machine is a powerful and widely used tools for data classification and function evaluation. The processing of data sampling in support vector machine employed linear separation and non-linear separation. The working of support vector machine like binary classification algorithm[25]. The non-linear support vector machine mapping the feature data with respect to one plane to another plan. The separation of data plan is non-linear and decision factor correlate with margin function of support vector. The hyperplane of equation is derived as

$$WD.xi + b \geq 1 \; if \; yi = 1$$

(1)

$$WD.xi + b \leq -1 \; if \; yi = -1$$

Here W is weight vector, x is input vector yi label o class and b is bias.

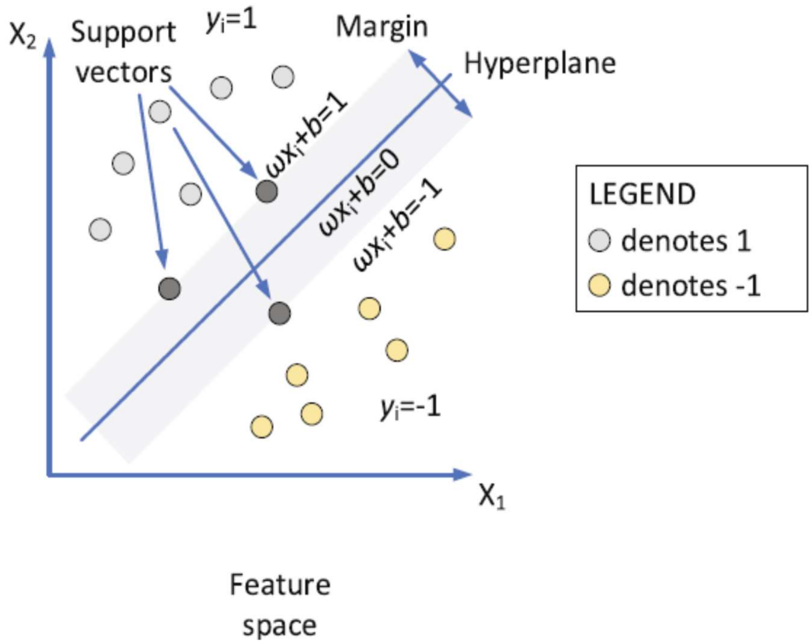

Figure 1 process block diagram of support vector machine.

The minimization formulation of support vector

$$Minimize \; \frac{1}{2}||w||2 + C\sum_{i=1}^{n} \varepsilon i \,, i = 1,2, \dots \dots, n$$

$$subject \; to \; y_i(w^T D.x1 + b) \geq 1 - \varepsilon 1$$

$$\varepsilon_i \geq 0 \; i = 1,2, \dots \dots, n \dots \dots \dots \dots \dots \dots \dots \dots . (2)$$

Here C is constant, n is number of observation and $\varepsilon 1$ is slack variable.

The rule of decision function is

$$f(x) = \sum_{i=1}^{n} yi\alpha iK(xi, xj) + b \dots \dots \dots \dots \dots \dots . (3)$$

B. Deep Neural Network (DNN)

Deep neural networks have a complex network model and adhere to the same structure as standard artificial neural networks. It aids in the development of models and the clear definition of complex hierarchies. It processes the data from the input layer, which is the first of "n" hidden layers, and after each epoch, the error rate of the input data is gradually reduced by adjusting the weights of each node, back propagating the network and continuing until better results are achieved. In the input layer, any number of inputs can be designated as input nodes. In order to intensify the learning process, DNN typically has more nodes than the input layer. There are an unlimited number of distinct output nodes that can be defined in the output layer. The number of nodes in the input and output layers, bias, learning rate, initial weights for adjustment, number of hidden layers, number of nodes in each hidden layer, and stop condition for stopping the execution of the epochs are said to be the parameters used in DNN. The processing of deep neural network follows this step[28,29,30].

1. Define a neural network with an input layer having n input nodes.
2. Initialize the number of hidden layers needed to train the data.
3. Define the learning rate and bias value for every node. The weight will be randomly selected in initial forward propagation.
4. Define the activation function

Rectified linear unit $(ReLU: f(x)) = max(0, x)$

5. Define the number of epochs to back propagate the value from the output node.
6. Train the network for given set of training data.
7. After the network is trained, pass the test data to the trained network to find the classification rate of the model.
8. Train the network until the number of epochs is completed (or)

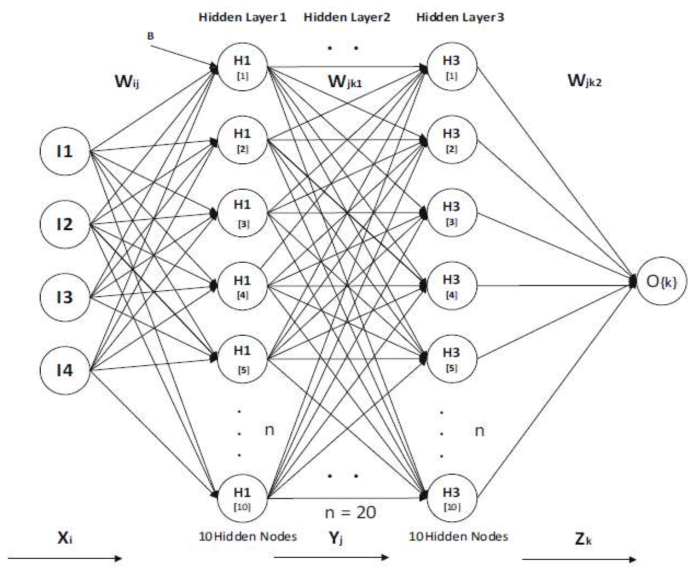

Figure 2 representation of deep neural network

C. Convolution Neural Network (CNN)[22]

The CNN is set of input layer, convolutional layer, pooling layer, fully connected layer and output layer. The varying capacity o layers robust the CNN classifier for the classification and detection of data. consider that the input features of CNN are map of layer x is Mx(M0=F). now the convolutional process can be expressed as

$$Mx = f\left(M_{x-1} \bigotimes Wx + bi\right) \dots\dots\dots\dots\dots\dots\dots\dots (4)$$

Here Wx is the convolutional kernel weight vector of the x layer, the symbol ⊗ represents convolutional approach, bi is the offset vector of x layer. F(x) is the activation function. By providing various window values, the convolutional layer extracts various feature information from the data matrix Mi1 and various feature information from the data using various convolution kernels. By sharing the same weight and offset throughout the convolution operation, the same convolution kernel adheres to the notion of "parameter sharing," significantly reducing the number of parameters used by the complete neural network. Following the convolutional layer, the pooling layer typically samples the feature map using various sampling algorithms. The pooling layer may be written as follows if Mx is the input and Mx+1 is the output of the pooling layer.

$$M_{x+1} subsampling(Mx) \ldots\ldots\ldots\ldots\ldots\ldots.(5)$$

The window region's mean or maximum value is typically chosen by the sampling criterion. The pooling layer primarily minimizes the feature's size, which lessens the impact of redundant features on the model.

D. Recurrent Neural Network (RNN)

A recurrent neural network (RNN) is able to process a sequence of arbitrary length by recursively applying a transition function to its internal hidden state vector ht of the input sequence. The activation of the hidden state ht at time-step t is computed as a function f of the current input symbol xt and the previous hidden state ht−1

$$h_t = \begin{cases} 0 & t = 0 \\ f(h_{t-1}, x_t) & otherwise \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots (6)$$

The state-to-state transition function, or f, is frequently used as the product of an element-wise nonlinearity and an affine transformation of both xt and ht. Traditionally, one RNN is used to map the input sequence to a fixed-sized vector for sequence modelling. The vector is then fed to a SoftMax layer for classification or other purposes. Unfortunately, a drawback of RNNs with this type of transition function is that during training, the gradient vector's components may grow or decay exponentially over lengthy sequences. It is challenging for the RNN model to learn long-distance correlations in a sequence because of the issue with exploding or vanishing gradients.

IV. Experimental analysis

To test and verify machine learning algorithms for number plate recognition using MATLAB software package version 2014R. MATLAB software provides functions and script files for image processing and machine learning algorithms. For the validation and analysis of algorithms, we use three standard datasets: the FZU cars dataset, the Stanford cars dataset, and the HumAIn2019 dataset[5,6,7]. All three datasets are divided into sample sizes of 100, 200, 300, 400, and 500 car images. The performance of algorithms is estimated as accuracy, precision, and recall. The formula of parameters is

$$\text{Accuracy} = \frac{TP + TN}{TP+FP+FN+TN}$$

$$\text{Recall} = \frac{TP}{TP+}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

Table1 Comparative result of analysis of algorithms SVM, DNN, CNN, and RNN measure accuracy using FZU car datasets.

image	SVM	DNN	CNN	RNN
100	91.56	92.78	92.87	93.58
200	92.82	93.45	94.82	94.88
300	90.52	91.76	93.85	94.24
400	92.86	93.87	94.54	95.57

500	91.54	92.57	93.78	94.84

Table2 Comparative result of analysis of algorithms SVM, DNN, CNN, and RNN measure precision using FZU car datasets.

image	SVM	DNN	CNN	RNN
100	92.86	93.78	93.87	94.56
200	91.64	92.86	93.73	94.65
300	93.52	94.57	95.15	95.45
400	92.58	92.89	93.59	94.82
500	91.86	92.54	93.66	94.79

Table3 Comparative result of analysis of algorithms SVM, DNN, CNN, and RNN measure recall using FZU car datasets.

image	SVM	DNN	CNN	RNN
100	92.81	93.62	94.78	95.44
200	91.67	92.55	93.84	94.76
300	93.65	93.89	94.77	95.25
400	92.36	93.64	94.58	94.68
500	91.68	92.57	93.48	94.74

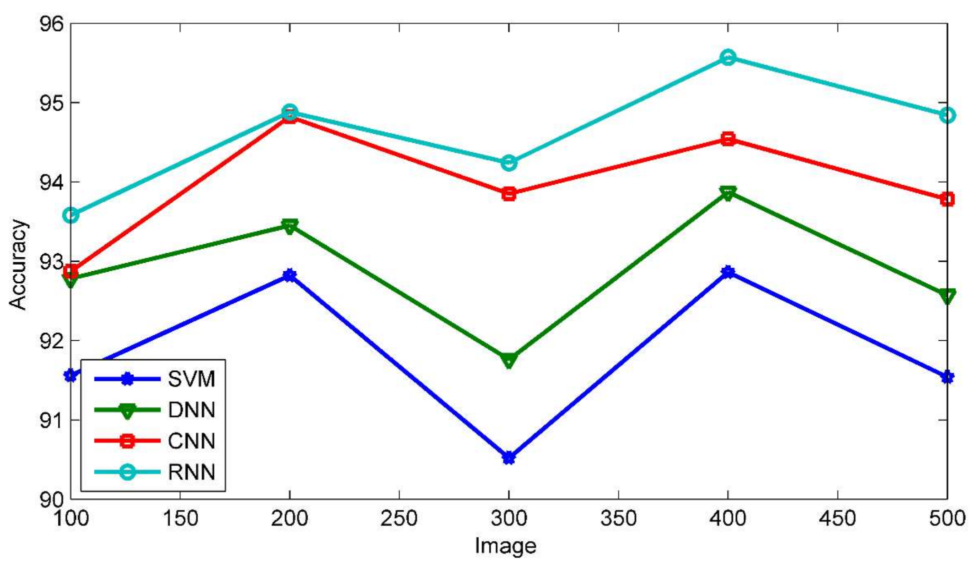

Figure: 3 Comparative performance of result analysis of SVM, DNN, CNN, and RNN, using method of Accuracy and image.

We observed that minimum value of RNN is 93.58 is the same DNN value of CNN and SVM is less than RNN in which most of the work value is of SVM and the most value of RNN is 94.84 and SVM value is less than 90.52 is the same as 92.86 id the value of type DNN which works 91.76 and the value of CNN is also 92.78 is the same as the highest CNN value of 94.82

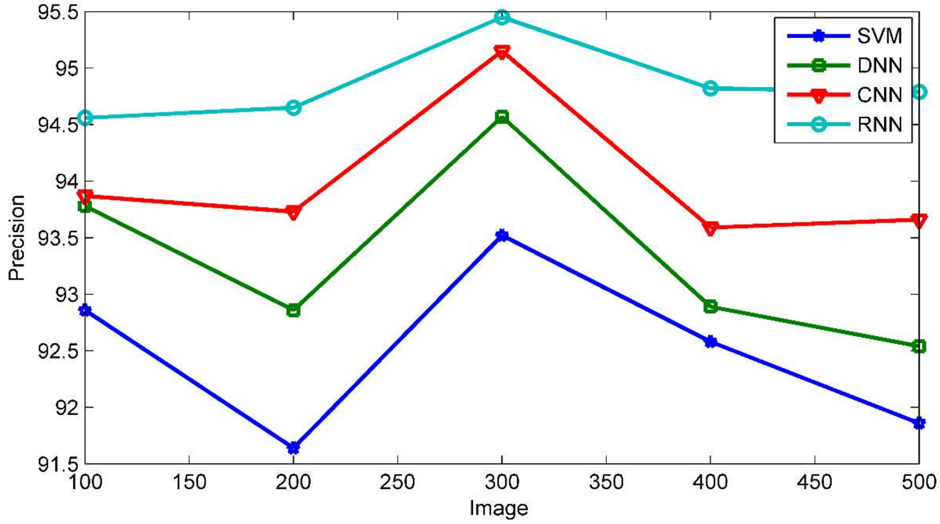

Figure:4 Comparative performance of result analysis of SVM, DNN, CNN, and RNN, using method of precision and image.

We observed that minimum value of RNN is 95.45 is the same DNN value of CNN and SVM is less than RNN in which most of the work value is of SVM and the most value of RNN is 94.56 and SVM value is less than 93.52 is the same as 91.64 id the value of type DNN which works 94.86 and the value of CNN is also 93.59 is the same as the highest CNN value of 95.15

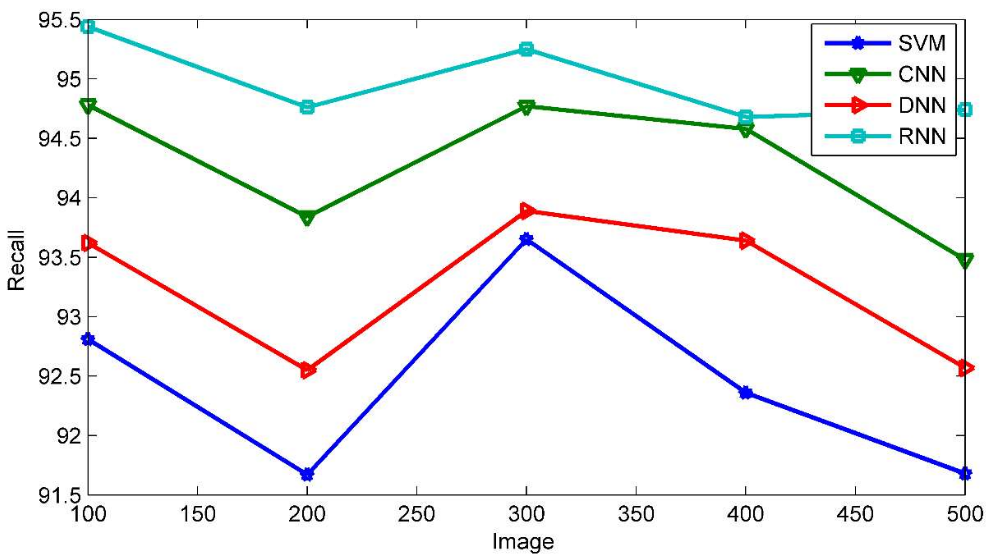

Figure:5 Comparative performance of result analysis of SVM, DNN, CNN, and RNN, using method of Recall and image.

We observed that minimum value of RNN is 95.44 is the same DNN value of CNN and SVM is less than RNN in which most of the work value is of SVM and the most value of RNN is 94.68 and SVM value is less than 93.65 is the same as 91.67 id the value of type DNN which works 93.64 and the value of CNN is also 94.77 is the same as the highest CNN value of 93.48

Table4: Comparative result of analysis of algorithms SVM, DNN, CNN, and RNN for accuracy using HumAln 2019dataset.

Image	SVM	DNN	CNN	RNN
100	91.63	92.52	93.41	94.71
200	92.89	93.54	94.56	95.23
300	91.67	92.74	93.84	94.47
400	93.15	93.89	94.87	95.18
500	92.45	93.49	94.25	95.26

Table5: Comparative result of analysis of algorithms SVM, DNN, CNN, and RNN for precision using HumAln 2019 dataset.

Image	SVM	DNN	CNN	RNN
100	92.61	93.57	94.48	95.69
200	91.88	92.51	93.67	94.95
300	92.68	93.78	94.34	95.39
400	92.18	93.21	94.46	95.14
500	93.46	93.59	94.25	95.29

Table:6 Comparative result of analysis of algorithms SVM, DNN, CNN, and RNN for Recall using HumAln 2019 dataset.

Image	SVM	DNN	CNN	RNN
100	91.65	92.87	93.84	94.39
200	92.82	93.55	94.27	95.35
300	91.38	92.27	93.44	94.87
400	93.22	93.29	94.83	94.96
500	92.41	92.58	93.33	94.78

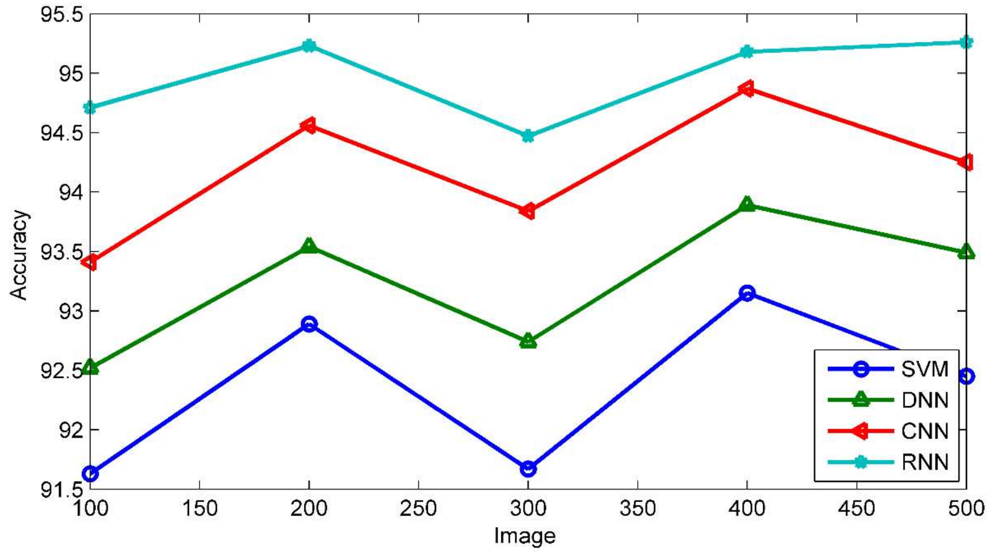

Figure:6 Comparative performance of result analysis of SVM, DNN, CNN, and RNN, using method of accuracy and image.

We observed that the highest value of SVM is 93.15 and the highest value of DNN is 93.89 and the highest value of CNN is 94.56 and the highest value of RNN which is of the form 95.26 which is higher and better than all other value.

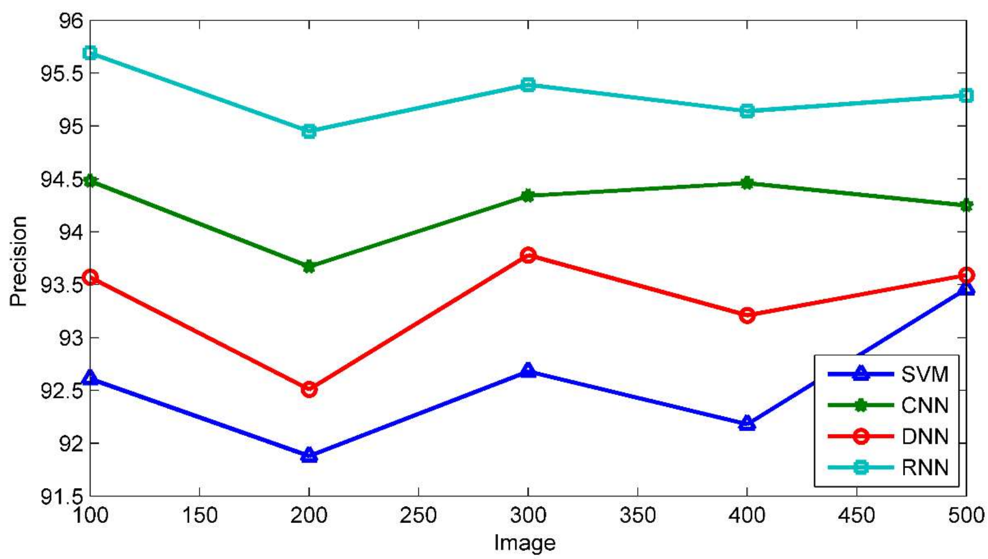

Figure:7 Comparative performance of result analysis of SVM, DNN, CNN, and RNN, using method of precision and image.

We observed that the highest value of SVM is 93.46 and the highest value of DNN is 93.78 and the highest value of CNN is 94.48 and the highest value of RNN which is of the form 95.69 which is higher and better than all other value.

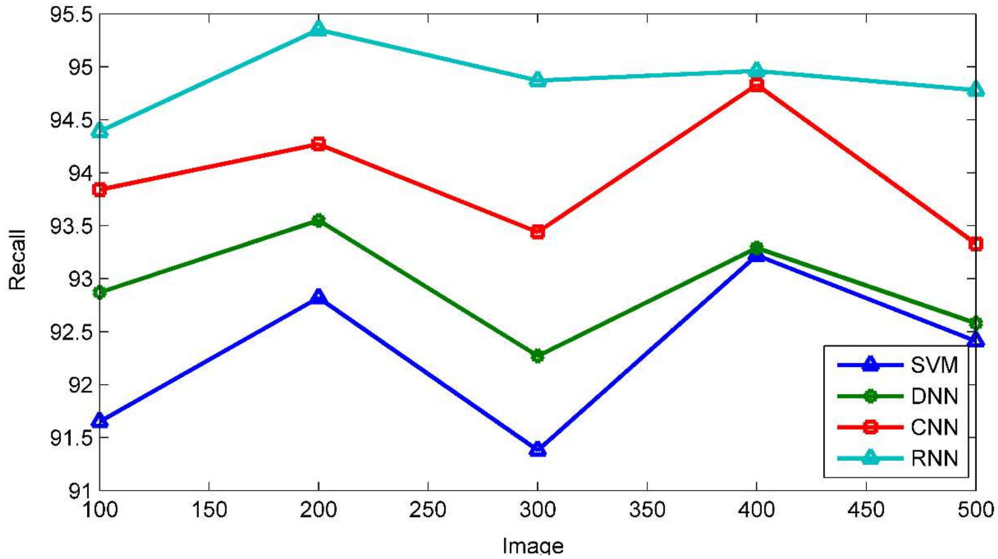

Figure: 8Comparative performance of result analysis of SVM, DNN, CNN, and RNN, using method of recall and image.

We observed that the highest value of SVM is 93.22 and the highest value of DNN is 93.55 and the highest value of CNN is 94.83 and the highest value of RNN which is of the form 95.35 which is higher and better than all other value.

Table:7 Comparative result of algorithms SVM, DNN, CNN, and RNN for Accuracy using Stanford cars dataset.

Image	SVM	DNN	CNN	RNN
100	92.67	93.81	94.89	95.37
200	91.82	92.58	93.26	94.38
300	92.11	93.17	94.42	95.21
400	93.19	94.39	94.78	95.14
500	91.46	92.59	92.69	93.89

Table:8 Comparative result of algorithms SVM, DNN, CNN, and RNN for precision using Stanford cars dataset.

Image	SVM	DNN	CNN	RNN
100	93.47	93.87	94.91	95.29
200	92.86	93.18	94.16	95.31
300	91.51	92.23	93.28	94.68
400	92.67	93.44	93.91	94.84

500	93.68	93.96	94.66	94.97

Table:9 Comparative result of analysis of algorithms SVM, DNN, CNN, and RNN for Recall using Stanford cars dataset.

Image	SVM	DNN	CNN	RNN
100	92.17	93.83	94.15	94.79
200	91.82	92.38	93.26	94.32
300	92.49	93.34	94.88	95.25
400	91.57	92.43	93.64	93.98
500	92.89	93.56	94.68	95.22

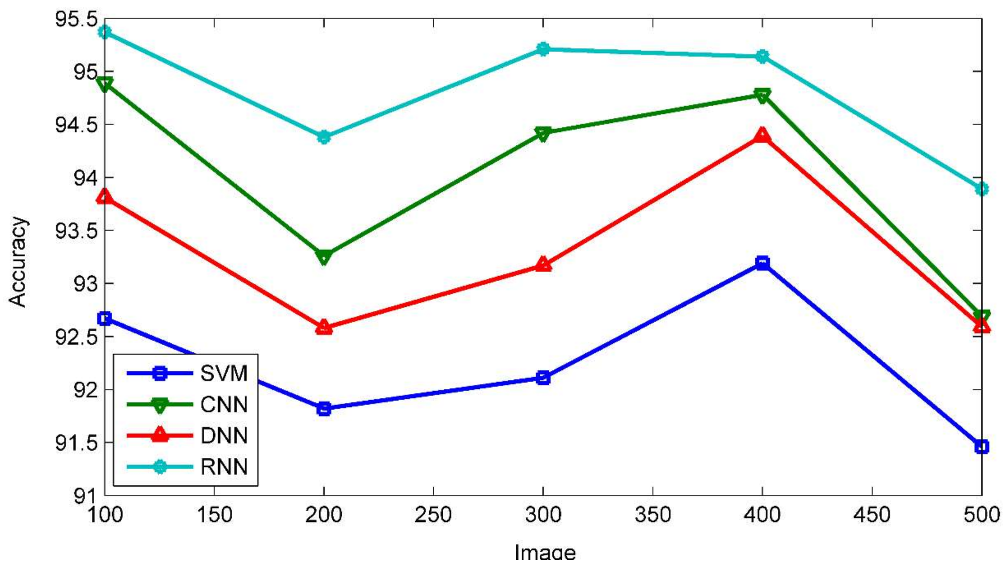

Figure: 9 Comparative performance of result analysis of SVM, DNN, CNN, and RNN, using method of accuracy and image.

We observed that the value of SVM is less 91.82 and similarly the value of DNN is also less which is 92.58 and the value of CNN is also something like this 93.26 talking about the value, it is more than the rest of value 95.37, which is as follows:

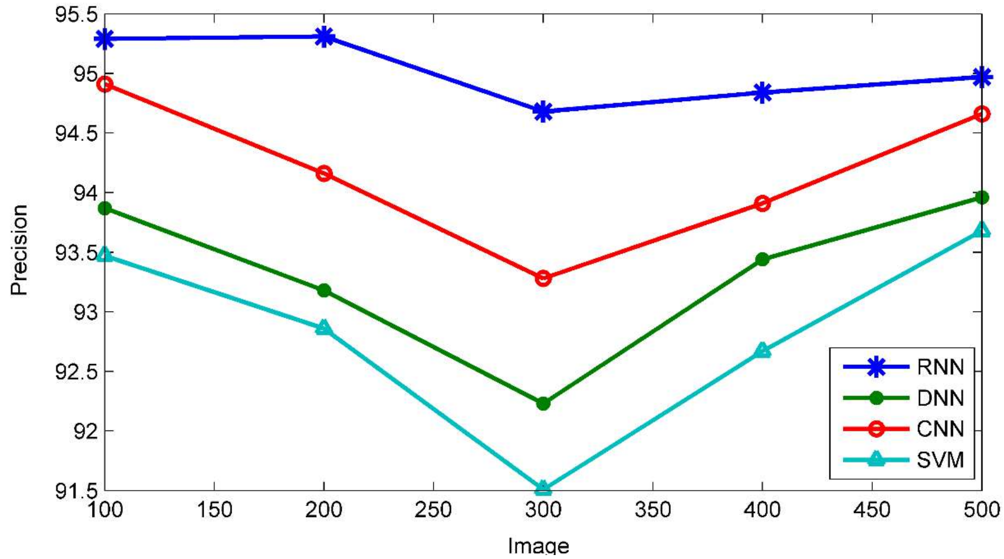

Figure:10 Comparative performance of result analysis of SVM, DNN, CNN, and RNN, using method of precision and image.

We observed that the value of SVM is less 91.51 and similarly the value of DNN is also less which is 92.23 and the value of CNN is also something like this 93.28 talking about the value, it is more than the rest of value 94.68, which is as follows:

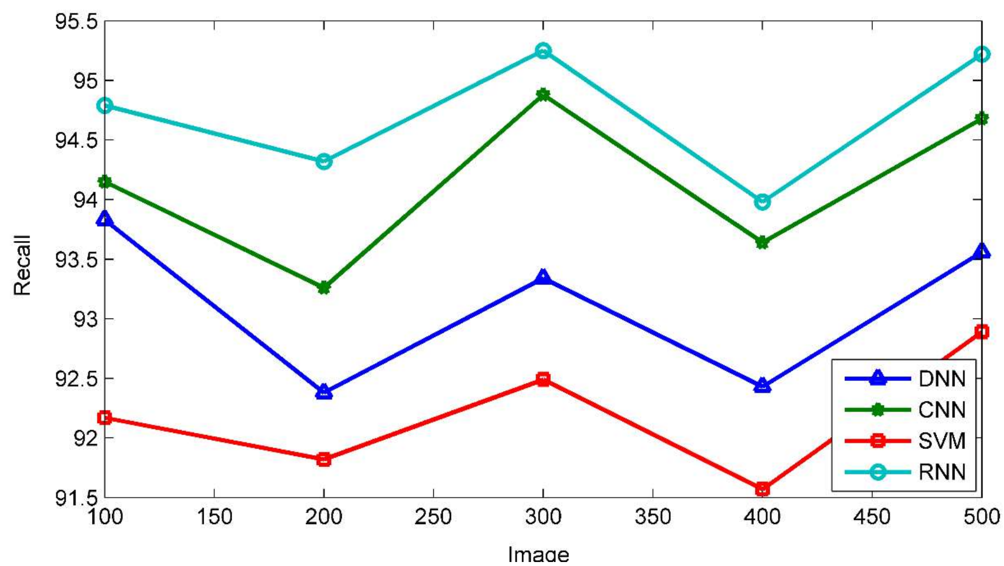

Figure:12 Comparative performance of result analysis of SVM, DNN, CNN, and RNN, using method of recall and image.

We observed that the value of SVM is less 91.57 and similarly the value of DNN is also less which is 92.38 and the value of CNN is also something like this 93.26 talking about the value, it is more than the rest of value 93.98, which is as follows:

V. Conclusion & Future Work

This paper explores the machine learning algorithms for licence plate recognition. The rate of recognition in automatic number plate recognition is an important factor. The rate of recognition depends on several factors, such as sampling of raw images of vehicles, segmentation of characters, and training of characters for recognition. There are several machine learning algorithms developed for number plate recognition. In this paper, we study four machine learning algorithms: support vector machines, deep neural networks, convolutional neural networks, and recurrent neural networks. The employed algorithms were tested on different datasets, like the FZU cars dataset, the Stanford cars dataset, and the HUMAin2019 dataset. The accuracy, precision, and recall performance are mentioned in table 1, table 2, table 3, table 4, table 5, table 6, table 7, table 8, and table 9. The analysis of tabular results from different datasets suggests that the CNN algorithm is better than the RNN algorithm. The others result also show that the DNN algorithm is better than support vector machines. The rate of classification accuracy of number plates depends on the processing of images. The segmentation of characters in real-time environments deflects the edges of images. Now some authors describe edge-based number plate recognition. In the future, focus on optimisation of feature processing for number plate recognition.

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