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Comparison of SVM and CNN for License Plate Detection

M.V.B.T. Santhi,

Associate Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram,Guntur,India

Email: santhi_ist@kluniversity.in

Abstract:

Number Plate Detection, employing image processing, addresses the prevalent issues of traffic rule violations and vehicle thefts. A 2019 survey by The Hindu highlighted the substantial number of stolen vehicles (44,158) and violations (1,85,210) in 2018. Its objective is to develop an efficient model for automatically identifying license plates from captured images, applicable in entrance zones for security control and restricted areas like government offices and military zones. The system involves capturing images, detecting number plate areas, and utilizing Optical Character Recognition (OCR) to extract owner information. Recognizing the global challenge of number plate detection, the study compares Support Vector Machine (SVM) and Convolutional Neural Network (CNN) algorithms, using a Kaggle dataset. OpenCV is employed for image pre-processing, reducing processing time. Results indicate SVM outperforms CNN, achieving 89.02% accuracy compared to CNN's 77.83%, emphasizing its potential in enhancing security measures and addressing the increasing need for effective number plate detection systems worldwide.

Keywords: Detection, time, Support Vector Machine, Convolutional Neural Network,

1. Introduction

The developed number plate detection framework points at the recognition of the alloy plate that is located on a bike or a car followed by obtaining text content available in the image. A licensed numerical plate which is otherwise called a number plate, it is a sheet of metal with a number containing on it which is provided by the Government and is very useful when we need to obtain data of a vehicle. They are mainly located at both the foremost side and rear side of any vehicle and also helps towards recognizing the number.

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Locating and identifying a part or some text is extremely energizing exertion in the field of image processing. The framework contains 2key phases. Initial phase is to recognize the situation of the plate from a vehicle's image and followed by disassembly of all the text i.e, numbers is and letters from the numberiplate. The task of distinguishing is interesting due to effects caused by some disturbances like light etc.., Misconceptions in the predicted output will be incremented if the colour of the plate is related to the background. Noise on such images often leads to lowiaccuracy. And also there are some imperfections which may cause a deficiency in most applications due to the difficulty of the mother earth's conditions like rainfall, snowfall, mist along with others and also because of the unlikeness of the numberiplate attributes.

In the previous decade, the development in data innovation was massive. Therefore, its utilization to take care of significant everyday issues has also increased. Because of straightforwardness of distinguishing and finding the answers for different issues, it might be said that there is essentially no area which doesn't use information technology in a few or the other way. Information systems assume an enormous part in transportation sector. Artificial insight is required for a wide assortment of purposes traffic management, parking management, vehicle security, toll collection and lane enforcement.

The huge coordination of data innovations, under various parts of the cutting edge world, has led to the treatment of vehicles as theoretical assets in information systems. Since a self-ruling data framework has no significance with no information, there is a need to change vehicle data among the real world and the data framework. This can be accomplished by human agents or by special intelligent equipment that will permit recognizable proof of vehicles by their registration plates in genuine conditions.

As the usage of vehicles is increasing day by day, the need to serve the above purposes and effectively manage them has also increased. The root of all the aforementioned objectives lies in the detection of number plate. Therefore, finding the best system for the detection of number plates is the need of the hour. Our work focuses on finding the best algorithm for detecting the number plates from images or video frames containing cars. So, we compare the working Support Vector Machines and Convolutional Neural Networks and determine which suits the best for detecting number plates on vehicles.

2. Literature Survey

In [1] the authors used Relaxation Convolutional Neural Network and Alternately trained used

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Relaxation Convolutional Neural Network and trained them to recognize handwritten characters. In the R-CNN used, the neurons within a feature map do not share share the same convolutional kernel due to which the neural network has with more expressive power. This inturn increases the number of parameters. So, to regularize the neural network, ATR-CNN is used.

In[2] the authors used a combination of Optical Character Recognition Network and a faster version of RCNN architecture to recognize buttons in an elevator in handling the inter-floor navigation problem of service robots. Their architecture outperformed the traditional recognition pipelines

In [3],the authors proposed a algorithm to detect and identify text2in images or video frames which have a complex background and compression effects. Candidate text line is extracted first followed by the use of SVM to identify the text from the candidate. It has been tested on large datasets from different sources and this came out to be better than conventional methods methods in both identification quality and computation time.

In [4] the authors proposed a feature distance stack autoencoder (FD-SAE) to analyse the faults in rolling bearings of mechanical equipments. Differences were found between normal and faulty characteristics of original rolling bearing data. So, a SVM was used to classify the normal and faulty data followed by FD-SAE for fault classification. It had a simple structure and less computational complexity, the feature extraction efficiency increased and the training time got reduced

In [5] the author used both CNN and SVM methods to identify targets in infrared images which is an important task in defence operation. SVM was used to measure the linear separability of the classes and the baseline performance for the classes was obtained. Then a CNN model is applied to the dataset. It was found that CNN model increases the overall performance around 7.7% than SVM on prepared infrared image datasets.

3.Design and Implementation

3.1 Support Vector Machine

Support Vector Machine (SVM) stands out as a popular Supervised Learning algorithm, extensively applied to both Classification and Regression challenges in Machine Learning. Its primary application, however, lies in solving Classification problems. The SVM algorithm's objective is to establish an optimal decision boundary, known as a hyperplane, capable of effectively partitioning n-dimensional space into distinct classes. This facilitates the accurate categorization of new data points in the future. SVM identifies critical points, referred to as

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support vectors, which play a pivotal role in determining the hyperplane. The algorithm's nomenclature, Support Vector Machine, stems from its reliance on these key support vectors to construct the best decision boundary.

SVM can be of two types:

Linear SVM: When a dataset can be divided into two classes using only one straight line, it is said to be linearly separable data, and the classifier used to classify it is known as a linear SVM classifier. This is the situation in which linear SVM is employed.

Non-linear SVM: When a dataset cannot be classified using a straight line, it is referred to as non-linear data, and the classifier employed is known as a nonlinear SVM classifier. For non-linearly separated data Non-Linear SVM is used.

3.2 Convolutional Neural Networks(CNN)

Convolutional neural networks, or CNNs, are the most widely used neural network model for problems involving image recognition and classification. CNN was first developed in the 1990s by computer scientist Yann LeCun, who drew inspiration from how humans perceive and recognize objects with their eyes.

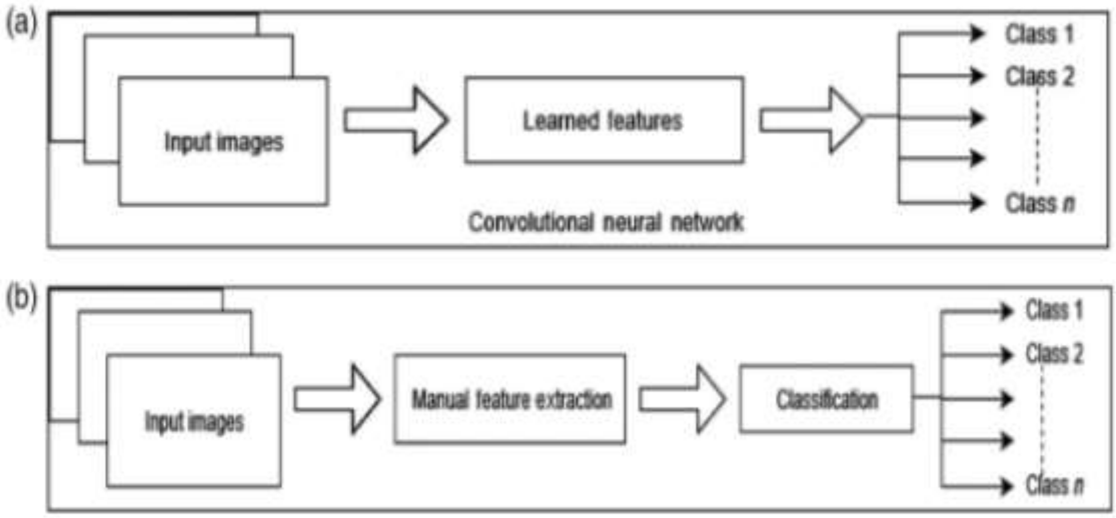

Figure 1 ConvolutionaliNeuraliNetworks for Image Classification

When it comes to classifying picture data, Convolutional Networks (ConvNets) are the most effective models. Their multilayer structures are influenced by biological research. Invariant

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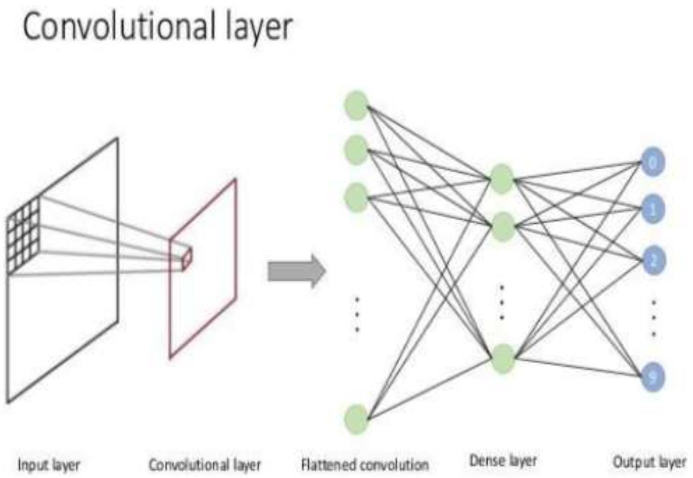
characteristics are automatically and hierarchically trained using these models.Prior to learning how to recognize and integrate these elements to understand more complex patterns, they initially seek for and identify low level features.These various feature levels/stages originate from various network layers. Additionally, every layer has a set quantity of neurons and is displayed in three dimensions: depth, breadth, and height.

Convolutional neural networks can be seen as having two distinct sections, which helps to explain their structure. Images are shown as a matrix of pixels in input. It is two dimensions in grayscale. A third dimension with a depth of three is used to depict the color of the input image, representing the primary colors (Red, Green, Blue).'



CNN Used in Image Recognition:

Convolution-Based Neural Systems CNNs are employed for picture identification and classification due to their great accuracy. It employs a hierarchical approach that builds a network and culminates in a fully-connected layer that processes accurate outputs by connecting all of the neurons in the network.

CNN, or artificial neural networks, are widely employed for image processing. While CNN is frequently utilized for image analysis, it can also be applied to other data analysis and classification issues.It also possesses some kind of specialty, which allows it to identify the elements and recognize patterns in it.

Image Features in CNN

Convolutional Layers have filters which detect the patterns. Different patterns in an image are:

1. Multiple edges
2. Shapes

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3. Textures

4. Objects etc.…

There are different number of detectors can be used as filters such as:

1. Edge Detector

2. Corner Detector

3. Shape Detector

A convolutional neural network comprises three different types of layers, each of which can be tuned and does a particular function with the input data.

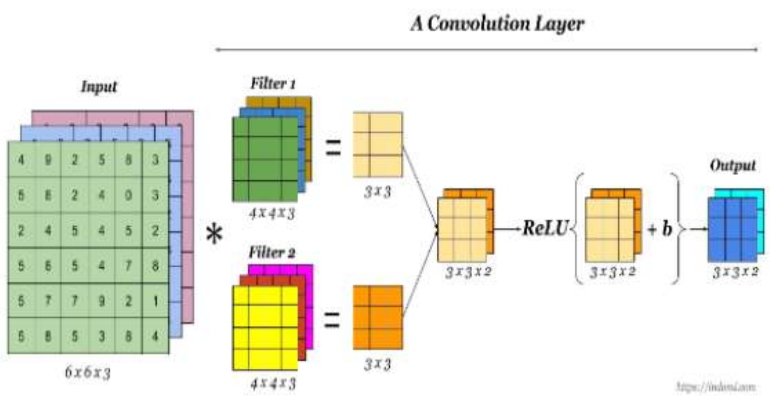
1.Convolutional layer

2.Pooling layer

3.Fully connected layer.

Convolution Layer: A series of filters with parameters that must be learned make up a convolutional layer. In comparison to the input, the filters' weight and height are lower.The input volume is convolved with each filter in order to produce or compute a neural activation map.

To categorize the images and their components, place the Dense layers above the Convolution layer. Nonetheless, the 2D array serves as the thick layer's input data. Additionally, a 4D array is the result of the convolution layer's processing.



RELU: Rectified Linear Unit (ReLU) is the activation function which is responsible for transforming the summed weighted input from the node into the activation of the node or output for that input .The most successful non-linearity for the CNN’s is the Rectified Non-Linear unit (ReLU), which fights the vanishing gradient problem occurring in sigmoids. ReLU is easier to compute and generates/produces sparsity .

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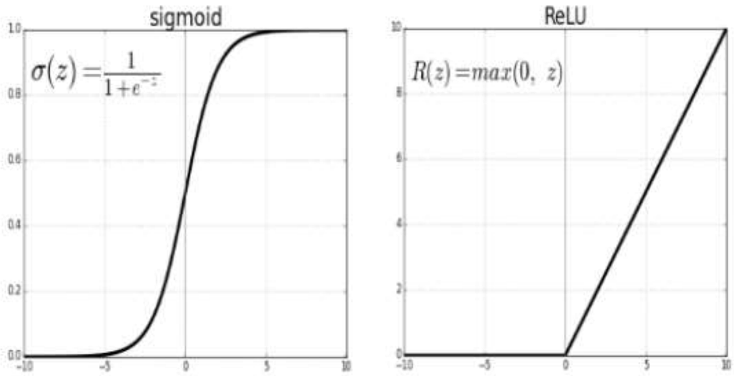
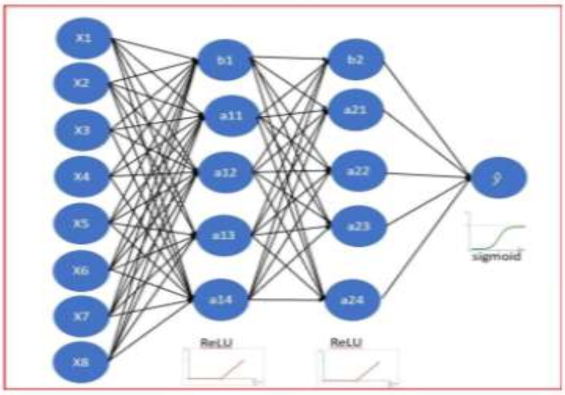
SIGMOID: This Sigmoid function (squashing function) has two useful properties that: It can be used to model a conditional probability distribution and its derivative has a simple form.





4.Results

Figure 2 Input Image

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Figure 3 Image after performing the lightening operation

Figure 4 Image after performing thresholding operation

Figure 5 The contour detected with number plate

Figure 6 Final output of the algorithms

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Algorithm	Correct predictions	False Predictions	Accuracy
SVM	2076	256	89.02
CNN	1875	517	77.83

Table 1 Accuracy of the algorithms with a dataset size of 2332

5.Conclusion

It was discovered that SVM is superior to CNN in terms of number plate detection. It turned out to have an accuracy of 89.02%. By developing an SVM-based system and employing a larger dataset than the one used for this analysis, this work can be improved in the future. Better results will result from this, and the police and transportation departments will be able to operate more effectively and efficiently.

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