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Deep Learning for License Plate Recognition

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Abstract: An innovative Automatic Vehicle License Plate Recognition (AVLPR) system that effectively identifies vehicles using deep learning algorithms. Accurate and real-time license plate identification has grown in importance with the rise in demand for improved security and traffic management. The convolutional neural network (CNN) architecture used in the AVLPR system enables the model to automatically learn and extract discriminative characteristics from photos of license plates. To ensure the system's robustness and adaptability, the dataset utilized for training and validation includes a wide range of license plate designs, fonts, and lighting situations. We incorporate data augmentation approaches to accommodate differences in license plate orientation, scale, and perspective throughout the training process to improve recognition accuracy. Additionally, we use transfer learning to enhance the system's generalization abilities by refining the pre-trained model on a sizable dataset.A trustworthy and effective solution for vehicle identification duties is provided by the Deep Learning-Based Automatic Vehicle License Plate Recognition System. Deep learning approaches are used to guarantee precise and instantaneous recognition, making it suitable for many uses such as law enforcement, parking management, and intelligent transportation systems.

Keywords: Deep Learning, Vehicle licence plate recognition, Convolution neural Network, Image Processing, Character recognition.

I. INTRODUCTION

In many nations, number plates are used to identify automobiles. The number plate identification system uses image processing methods to recognize automobiles based on their number plates. This technology is used for efficient traffic management and security functions like restricting entry to certain locations and locating wanted vehicles. The issue of number plate recognition is still difficult despite years of research. The number plate can appear anywhere in the image and can be of different sizes [1]. The system analyses an image to find neighbouring regions that contain the number plate. The number plate of a car can be automatically identified at a predetermined entry point and saved in the database. However, because there is no set size ratio for Indian plates, it is more difficult to identify them than foreign number plates. The work of recognition is made more difficult-by-difficult lighting circumstances, which affect image acquisition. The NPR system uses a photo-detection technique that involves taking a picture of the vehicle, removing the region of interest, and extracting and segmenting characters [2].

Due to their enormous potential to enhance vehicle identification and enhance numerous applications, such as traffic management, law enforcement, toll collection, parking management, and surveillance, automatic vehicle license plate recognition (AVLPR) systems have attracted a lot of attention in recent years. These systems make use of deep learning algorithms to automatically find and identify license plates in pictures or video streams taken by cameras placed in various places. For many facets of today's transportation and security infrastructure, the capability to precisely and quickly identify vehicle license plates is essential. Traditional techniques for reading license plates frequently depended on manually created features and rule-based algorithms, which had a limited ability to adapt to different settings and license plate designs. However, the field of computer vision and pattern recognition has been completely transformed by deep learning techniques, particularly Convolutional Neural Networks (CNNs), which have significantly improved AVLPR systems. Deep learning models are particularly suited for challenging recognition tasks like character recognition and license plate detection because they naturally acquire hierarchical representations from input.

The creation and application of a cutting-edge Deep Learning- Based Automatic Vehicle License Plate Recognition System is thoroughly examined in this paper. The main goal of this system is to improve character recognition and license plate detection accuracy, allowing for seamless integration. After processing the input photos, the CNN model produces bounding boxes that contain the identified license plate information. We are able to extract the regions of interest for additional processing using this bounding box information. In order to separate individual characters within the detected license plate region, we must first tackle the difficulty of character segmentation. The crucial step of character segmentation makes sure that each character may be processed separately for recognition. We provide a novel method that makes use of the geometrical characteristics and spatial

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relationships of characters to accomplish precise segmentation.

An important development in computer vision and transportation technology is the creation of a Deep Learning- Based Automatic Vehicle License Plate Recognition System. The system's capacity to precisely identify and recognize license plates in real-time opens up a wide range of opportunities for increasing security measures, enhancing transportation efficiency, and streamlining other urban management applications. The remainder of this study paper delves into the technical specifics of each component and presents in-depth experimental findings to support the effectiveness and efficiency of the system.

II. REVIEW OF LITERATURE

The front license plate photos are used largely in the training of the traditional public license plate recognition model. When trying to read license plates in CCTV photos of vehicles, this method has difficulties. Due to variables like tilting license plates or inadequate resolution under general environmental conditions, the identification rate drastically reduces in such circumstances. Retraining the model and building a new database are conventional solutions to this problem, which are both expensive and time-consuming. The authors of [1] implemented an ANPR (Automated Number Plate Recognition System) with an 80% accuracy rate. The ANPR system excelled at both vehicle identification and traffic control.

The authors of [2] established an effective method for extracting license plates, which was useful for finding abandoned automobiles, identifying moving vehicles, and improving parking arrangement systems. The technique used stationary vehicles and took pictures at a fixed angle perpendicular to the horizon. Character identification on the license plates was accomplished via recognition of alphanumeric characters. Character division, optical character recognition (OCR), and format matching were three significant technological improvements that the authors of [3] suggested as part of a quick method for car-license detection (CLPD).

The inventors of [4] created an Automatic Number Plate Recognition (ANPR) system intended to recognize automobile license plates. When the vehicle arrived at the specified location, the system took a picture of it and then used a segmentation procedure to extract the pictures. After being used for character identification, optical character recognition became a commonly used security system solution.

The authors of [5] created a practical method for increasing ITS (intelligent transportation systems) and traffic management. They contrasted two strategies for obtaining license plate numbers with those already in use. Using a region-based method, the retrieved license plate parts were further broken down into individual characters. The recognition methodology coupled a template matching strategy with a configurable iterative thresholding mechanism.

The writers' thesis, which was delivered in [6], was on how to identify stolen vehicles. They used connected component analysis and straightforward yet efficient morphological techniques for localizing the license plates. With an amazing precision of 90% for four-wheeler number plates, the system was tested on 20 samples. cThe authors of [8] introduced a system that uses ANPR technology to help traffic officers identify vehicles that violate traffic laws. The number plate text is extracted from the photos taken by cameras and stored by the ANPR system. A bright flash can be added to cameras to boost image illumination, and infrared lighting is employed to ensure day and night photo capture.

An efficient method based on morphological operations and the edge detection (Sobel) technique was presented by the authors in [9]. This method was designed to use a bounding box technique to isolate and segment each letter and number that makes up the license plate. A template matching methodology was used to identify the license plate information after segmenting the numerals and characters.

DATASET

The dataset used for Car License Plate Detection is essential for training and assessing the effectiveness of the system for detecting license plates. Such datasets typically include a sizable number of photographs of automobiles with clearly visible license plates and matching annotations indicating the precise location and bounding box coordinates of the license plates within the photographs. There are total 433 images in this dataset [8].A key component of developing a reliable license plate recognition system is the ALPR (Automatic License Plate Recognition) Character Train. A deep learning model, such as a Convolutional Neural Network (CNN) or Recurrent Neural Network (RNN), is trained in this method using a huge dataset of identified license plate characters. The model gains the ability to reliably identify and categorize individual characters from license plates. To reduce recognition errors and boost accuracy, the model's parameters

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are optimized during training. The license plate recognition system performs better overall because to a well-trained ALPR character recognition model, which makes it easier for it to recognize and understand license plate characters in actual situations

III. PROPOSED METHODOLOGY

This section provides a concise description of the methods employed in the experiments. The first part gives an overview of the two neural network architectures that serve as the base for the probabilistic deep learning methods. The second part explains the three probabilistic deep learning methods deep ensemble, Batch Ensemble, and MC-dropout. A. Backbone Neural Network Architectures for License Plate Recognition We evaluate the efficacy of the probabilistic deep learning methods with two neural network architectures as a backbone. The first backbone is a license plate recognition CNN. The second backbone employs license plate recognition and super-resolution in the multi-task learning framework SR2. W adapt the following implementation details for both backbones: all neural network architectures use ReLU as an activation function. Additionally, batch normalization is performed after each trainable layer. As a result, the following order is used in all architectures presented in the paper: trainable layer - batch normalization - ReLU.

1) License Plate Recognition CNN:

The license plate recognition CNN consists of convolutional layers, max pooling layers, and fully-connected layers. All convolutional layers have a receptive field of 3 × 3. The max pooling layers have a pool size of 2 × 2. In contrast to [3], our proposed license plate recognition CNN contains additional batch normalization layers to stabilize training. The architecture is structured as follows. After the input, there are three sequences of two convolutional layers followed by a max pooling layer with 64 filter kernels, 128 filter kernels, and 256 filter kernels, respectively. Then, there are two blocks, each with a convolutional layer with 512 filter kernels followed by max pooling. Then, the features maps are flattened followed by two fully-connected layers with 1024 and 2048 nodes. Finally, the CNN has seven fully-connected output layers with 37 nodes each. Here, softmax replaces the ReLU activation, and batch normalization is omitted.

2) SR2 : SR2 consists of shared layers followed by a split into two branches, one for super-resolution and the other for license plate recognition. We use FSRCNN

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for super resolution and the baseline CNN for the license plate recognition. FSRCNN was selected because its first layer is similar to that of the license plate recognition CNN (LPR CNN). Therefore, the shared layers in the SR2 framework do not differ from the original layers of the individual CNNs. FSRCNN consists of five steps. First, features are extracted using a convolutional layer with 56 filter kernels and a receptive field of 5×5. Then, the feature maps are shrunk using 12 filter kernels with a receptive field of 1×1. Afterward, four convolutional layers with 12 filter kernels each and a receptive field of 3×3 perform a mapping. Next, one convolutional layer with 56 filter kernels and a receptive field of 1 × 1 expands the features maps. The last step is a convolutional layer with 192 filter kernels and a receptive field of 9 × 9 followed by a pixel shuffling.

3) Uncertainty Quantification Methods

This paper compares three different probabilistic deep learning methods in the context of license plate recognition. These methods are Monte Carlo dropout, deep ensembles, and Batch Ensemble. Dropout is a common technique to regularize neural networks. The work by Lorch et al., for example, uses dropout in their CNN. Thus, models trained with dropout can benefit from our findings without the need for re-training. Existing methods that do not utilize dropout during training might consider using their pipeline to train multiple models to get a deep ensemble. As deep ensembles require high computational power and memory, we additionally explore the efficacy of Batch Ensemble on the task of license plate recognition. The remainder of this Section presents details on the configuration of these three approaches.

4) Data Pre-processing:

This is a crucial phase in which we take each and every image, use OpenCV to turn it into an array, and then scale it to 224 by 224, the standard suitable size for the pre-trained transfer learning model. An image processing technique as shown in figure 3 that is frequently used to portray a picture using only shades of gray is the conversion of the image to grayscale.

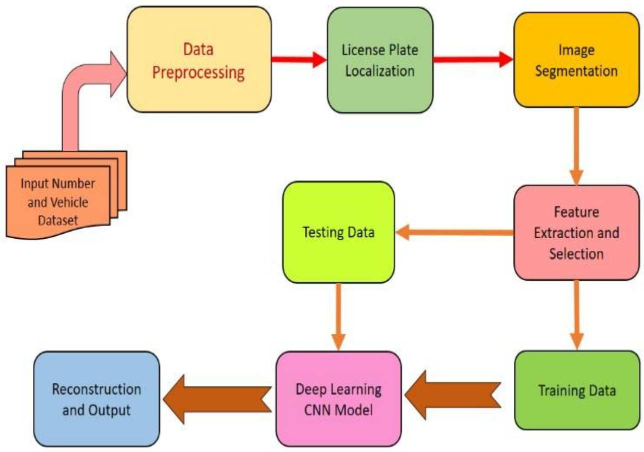

Fig .1 Proposed system of number plate recognition using Deep Learning

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A deep learning [21]system called ConvNet, also referred to as the Convolutional Neural Network (CNN), uses input data and applies biases and weights to various components. The input is then divided into its numerous components, as seen in Algorithm 1. When compared to other algorithms, CNN's ability to minimize the amount of pre-processing required for data preparation is one of its key advantages. This is because CNN has the capability to automatically learn and enhance filters

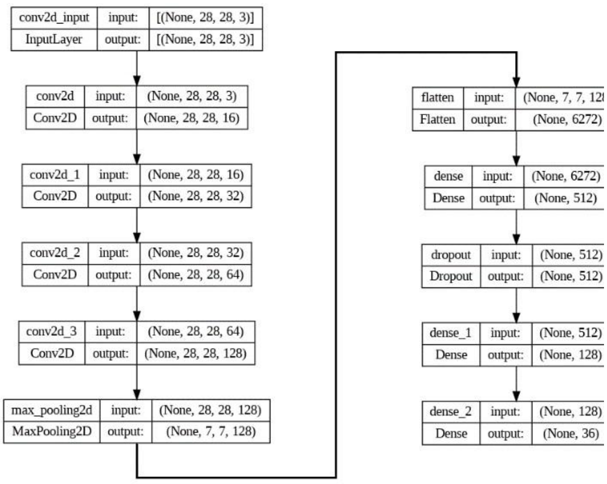

Fig.2 Architecture flowchart of CNN model

CNN Model Algorithm:

Feature Optimization and CNN

Input:

Data instances

Output:

Confusion Matrix

$(Accuracy, precision, recall, FPR, TPR)$

Dataset Optimization

Remove the redundant instances

Feature Selection

Using Pearson's Correlation equation, compute the correlation of the attribute set Set Cf

if $corr\_value > 0.8$

add attribute to Cf

else

increment in an attribute set C

return Cf

Classification

Create training and testing sets from the dataset.

Training set: 80%

Testing set: 20%

add model

three Convolution layers $(activation = \text{'}relu\text{'})$

two GRU layers $(activation = \text{'}relu\text{'})$

model compilation

loss function: '*categorical_crossentropy*'

$optimizer = \text{'}adagrad\text{'}$

training CNN technique with training instances

employing techniques to test instances

return *Confusion Matrix* $Cm * m$

5) Lightweight Parallel CNN Model:

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Parallel CNN Model for Lightweight License Plate Recognition. High recognition accuracy is one goal of the suggested model, which also strives to be computationally effective and appropriate for real-time applications.

The following significant characteristics make up the Lightweight Parallel CNN Model:

- Multiple parallel CNN branches make up the model's parallel architecture, and each branch is in charge of extracting a particular feature from the input image. The model may simultaneously collect a variety of data from several license plate regions because to this parallel architecture.
- Lightweight Design: Compared to conventional deep CNN architectures, the model is designed to have fewer parameters and calculations. This increases its computational speed and memory efficiency, making it perfect for contexts with limited resources.
- Depth-wise Depth-wise separable convolutions, which divide the usual convolutional operation into depth-wise and point-wise convolutions, are used in the model. With the expressiveness of the model preserved, this significantly lowers computing complexity.
- Multi-scale Feature Fusion: The model's parallel branches record features at many scales, enabling it to manage differences in license plate sizes and fonts with ease. The elements that were collected from the parallel branches are then combined to create an accurate depiction of the license plate.
- Using a sizable dataset of tagged photos of license plates, the model is trained. To reduce recognition errors and increase accuracy during training, common optimization techniques like stochastic gradient descent or Adam are used.

IV. RESULT AND DISCUSSION

The tests were carried out on a Windows 10 computer with 8GB of RAM and an Intel i5 processor running at 2.4 GHz. The Python OpenCV library was used to construct the image processing tools. The system was evaluated using both photos and videos, taking into account a variety of difficult conditions, including plates with erratic lighting, plates with styled lettering, plates in close-up, plates from a distance, and plates that were angularly skewed. Images with various environmental settings, including scenes with various

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lighting and plate conditions, were chosen to assure thorough testing. In order to determine the system's robustness and accuracy in real-world circumstances, the system's performance on these various test cases was evaluated during the testing phase. The system's capacity to handle varied situations and generate reliable results was thoroughly tested through testing under a variety of difficult conditions.

1. CNN Model:

Two different approaches were tested in the evaluation of the License Plate Recognition system: the conventional CNN (Convolutional Neural Network) and the suggested Lightweight Parallel CNN. Separate datasets for training and testing were used for the evaluation.For, shown in figure 3, the CNN model, the system obtained an F1 score of 89.55% during the training phase, showing a strong balance between recall and precision. The overall accuracy was 88.01%, and the specificity, which calculates the genuine negative rate, was 84.01%. According on these criteria, the CNN model performed satisfactorily throughout training. The loss for CNN has shown in figure 4.

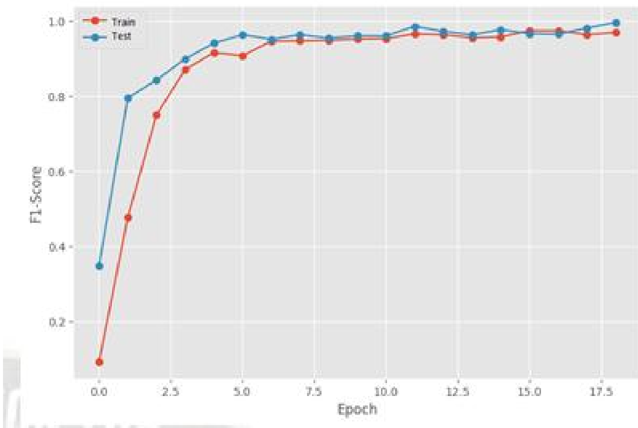

Fig.3 CNN F1-Score Comparison Graph

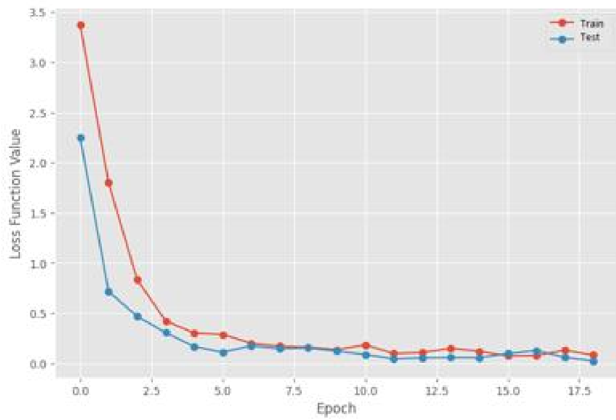

Fig.4 CNNLoss Comparison Graph

However, the Lightweight Parallel CNN greatly outperformed the conventional CNN. The Lightweight Parallel CNN achieved a remarkable F1 score of 96.88% during the training phase as shown in figure 17, demonstrating its superior capacity to recognize license plates reliably. The overall accuracy increased to 97.01%, and the specificity was also much higher at 95.01%.Using a different dataset, the review process was further expanded to include the testing stage. Both models kept

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up their impressive performance, demonstrating their capacity for generalization. The F1 score for the CNN model was an amazing 99.11%, and the specificity and accuracy were equally good at 98.11% and 99.31%. The loss comparison for training and testing for Lightweight parallel CNN has been shown in figure 18

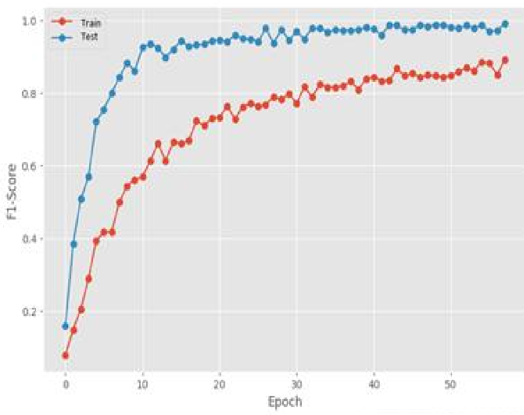

Fig.5 Lightweight Parallel CNN F1-Score Comparison Graph

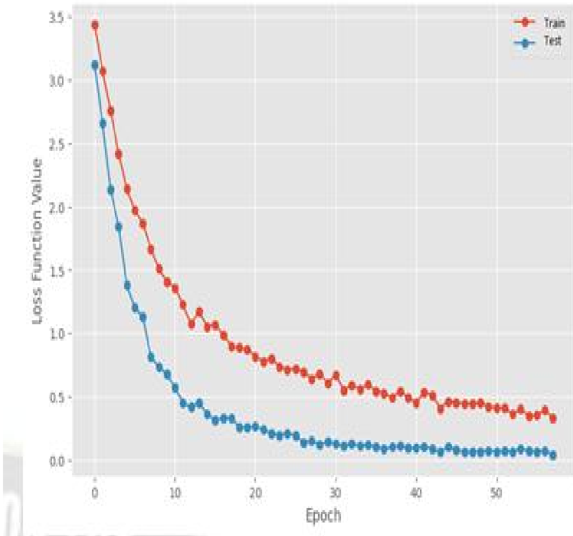

Fig.6 Lightweight Parallel CNN Loss Comparison Graph

Method	Training			Testing		
	F1 Score	Specificity (%)	Accuracy (%)	F1 Score	Specificity (%)	Accuracy (%)
CNN	89.55	84.01	88.01	99.11	98.11	99.31
Lightweight Parallel CNN	96.88	95.01	97.01	99.55	99.15	99.85

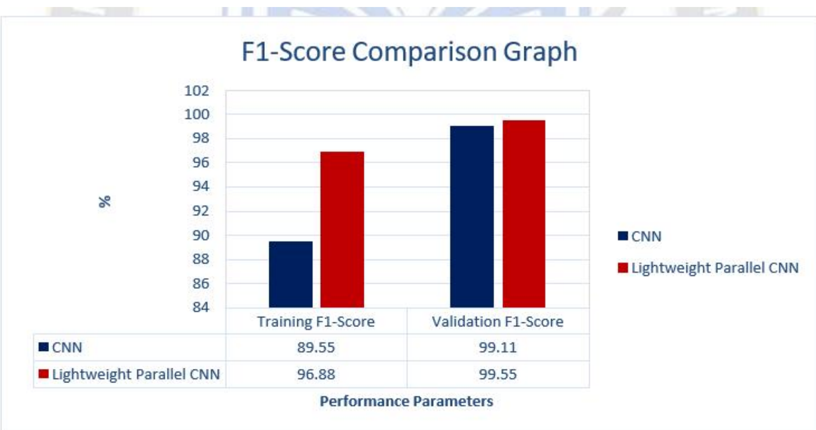

Fig.7 Training and Validation F1-Score Comparison Graph of CNN and Lightweight Parallel CNN

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V. CONCLUSION

This paper proposes to model uncertainty for the task of license plate recognition explicitly. To the best of our knowledge, this has not been explored yet but offers helpful features for license plate recognition. For example, we demonstrate that the quantification of the prediction uncertainty allows the detection of misclassifications. We identify automatic license plate recognition and forensic license plate recognition as applications that benefit from predictive uncertainty. We investigate three well-known probabilistic deep learning methods that quantify predictive uncertainty: Batch Ensemble, MC-dropout, and deep ensemble. Two neural network architectures are the backbones for these techniques. A state-of the-art license plate recognition CNN serves as a baseline backbone. To exploit the benefits of multi-task learning, we combine super-resolution and license plate recognition in the SR2 framework as a second backbone. License plate recognition in the wild is complex since images stem from various acquisition settings. One must always consider a lower quality of the test data than that of the training data. We propose probabilistic deep learning as a tool to detect when the data and thus the character recognition are less reliable. For this purpose, the models are trained on high-quality images and tested on noisy or blurred lower-quality images. Except for Batch Ensemble, all probabilistic deep learning methods provide reasonable uncertainty estimates even for severely degraded images. Even better results are obtained when license plate recognition is combined with super-resolution in the SR2 framework. The SR2 framework improves both character recognition accuracy and detection of false predictions. For the future, we see super-resolution as a tool to additionally verify the prediction of images with a reduced quality. Here, the predictive uncertainty obtained per pixel can help identify less reliable character predictions of the LPR CNN. The hyperparameter of MC-dropout allows setting a stronger focus on either character recognition performance or reliable detection of false predictions.

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