International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
DOI: https://doi.org/10.17762/ijritcc.v11i9.8112
***Article Received:** 07 July 2023 **Revised:** 26 August 2023 **Accepted:** 18 September 2023*

Deep Learning Based Automatic Vehicle License Plate Recognition System for Enhanced Vehicle Identification

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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 [3]. 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 [1] [4]. 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 relationships of characters to accomplish precise segmentation [5].

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 [6, 7]. 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.The 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.

III. 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

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from license plates. To reduce recognition errors and boost accuracy, the model's parameters 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[9].

Figure 1: Sample Images input dataset from the mentioned dataset

IV. PROPOSED METHEDOLOGY

The image is made simpler with this procedure without losing any of its key details.In this study, we introduce a novel method for improving, using a broad database, the recognition rate of deep learning models used for reading automobile license plates [12]. The suggested strategy enhances the overall performance of the license plate identification system by using Dataset photos, as shown in Figure 1. In order to process the input image, we first utilize a popular deep learning model, such as CNN (Convolutional Neural Network) or Lightweight CNN. This model enables us to identify the license plate's vicinity, which we refer to as the region of interest [9]. Utilizing CNN, a high-resolution license plate image is retrieved from this discovered ROI (Region of Interest) image.

1. 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 [14].

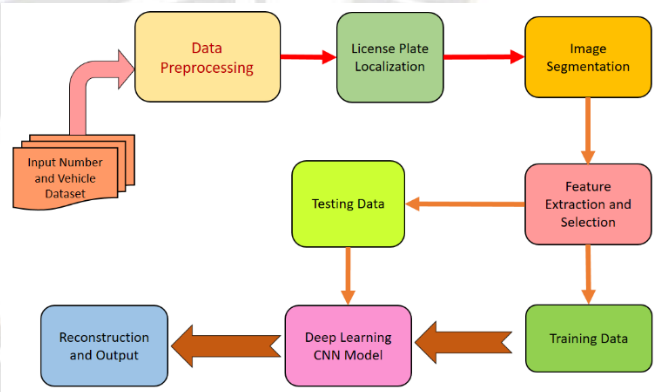

Figure 2: Proposed system of number plate recognition using Deep Learning

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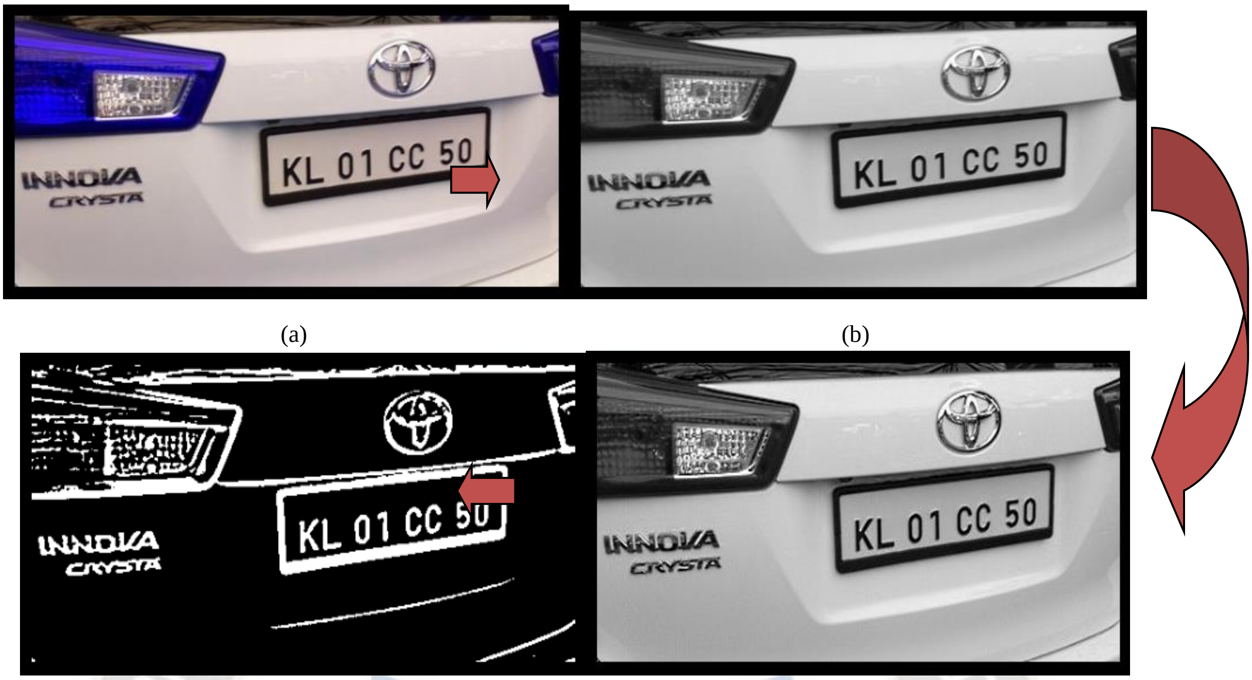

Figure 3: Preprocessing of Input images stepwise (a) Original Input Image (b) Grayscale Image (c) Maximize Contrast Image (d) Adaptive Thresholding Image

These pre-processing procedures serve to set up the image for the later phases of character recognition and license plate detection. The system can successfully extract the license plate region and enable accurate character identification by converting the image to grayscale, enhancing contrast, and performing adaptive thresholding. This results in an increased recognition rate for the license plate recognition system [15].

2. License Plate Localization:

For precisely detecting and retrieving license plate information from pictures or video streams, License Plate Localization is a crucial part of the complete License Plate Recognition system. The system's total performance in duties like traffic monitoring, toll collection, parking management, and law enforcement is directly impacted by the localization accuracy. Deep learning-based object detection models and other cutting-edge methods have greatly increased the resilience and accuracy of license plate localization in practical settings [18].

Figure 4: Counter Findings

Potential license [19] plate regions are found by looking for contours in the binary image; this serves as the first step in further identification and localization of the license plate. Due to its ease of use and efficiency in separating objects from the background, contour-based license plate localization is a widely used technique in computer vision and image processing applications.

3. License Plate Segmentation:

The localized license plate region is subsequently separated into individual characters or components for recognition and analysis in the License Plate Segmentation stage of License Plate Recognition (LPR) systems. The characters on the license plate are separated during this phase in order to get them ready for character recognition later on.Selecting Boxes by Character Size: The potential character regions are filtered based on their size and aspect ratio [22].

In order to correct perspective distortion, the license plate area is first binarized. In the image segmentation equation (1), T is the threshold value, and f and g are the input and output images, respectively. If the pixel value (x,y) of the input picture f is less than the threshold value T during processing, the corresponding pixel value is set to 0, or 0. In contrast, the matching pixel value becomes 1 if it is greater than or equal to the threshold value. As a result, a divided binary image that separates regions according to their intensity in relation to the threshold value is produced.

$$g(x,\ y) = \{\text{if } f(x,y)\ \geq T,\ 1 \text{if } f(x,y) < T,\ 0$$

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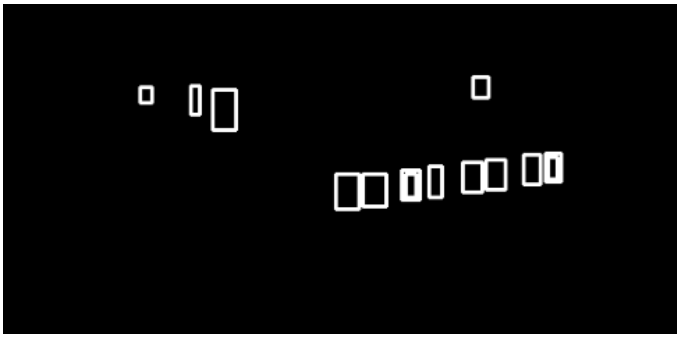

Figure 5: Selecting Boxes by Characters

Selecting Boxes by Arrangement of Contours: Further filtering is applied based on the arrangement of contours in the license plate.

$$I \oplus H \equiv \{(p+q) \mid \text{for every } p \in I,\ q \in H\}$$

$$I \ominus H \equiv \{p \in \mathbb{Z}2 \mid (p+q) \in I, \text{ for every } q \in H\}$$

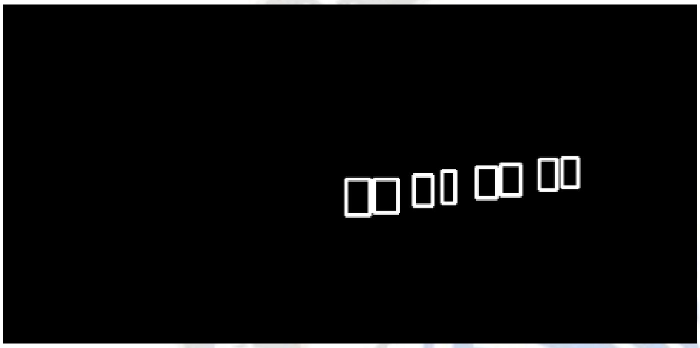

Figure 6. Final Selected Boxes

Imposing Boxes on Original Image: The selected character boxes are overlaid on the original car image to visualize the progress.

Figure 7. Box Imposing on Original Image

Rotate Plate Images: The license plate images are rotated based on the detected orientation.

Figure 8: Image Rotating on Original Image

Thresholding Again to Find Characters: Thresholding is performed on the rotated plate images to enhance the visibility of characters.

Figure 9: Image Thresholding

Taking Negative Again: The negative of the threshold images is obtained to improve character segmentation.

Figure 10: Negative Image

Find Contours Again in the Cropped License Plate: Contours are detected again in the cropped license plate images to isolate individual characters.Segment Characters: The characters are segmented from the license plate images for further processing.

$$E = \sum k = 1N\big(yi - (axi + b)\big)2$$

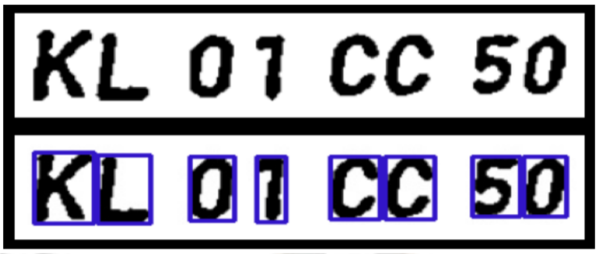

Figure 11: Separating the Characters in the Plate

Figure 12. Separating the Characters in the Plate

The accuracy and efficiency of character identification strongly depend on the correct segmentation of individual characters, making license plate segmentation a crucial step in the whole license plate recognition process. In particular, in difficult real-world circumstances with different font styles, noise, and occlusions, advanced techniques like deep learning-based segmentation models have demonstrated promising results in attaining accurate and robust license plate segmentation.

4. Feature Extraction and Selection:

Following character detection and isolation in license plate segmentation, the following further procedures are carried out to get the characters ready for character recognition:

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Denoising: To remove any noise or artifacts that may have been added during image processing or segmentation, denoising techniques may be applied to the pre-processed character pictures. Denoising improves the character images' clarity and quality, which makes them better suited for feature extraction and recognition.

Feature Extraction: From the segmented and denoised character pictures, pertinent characteristics are recovered. Character recognition algorithms use these qualities, which stand for each character's unique traits, as input. The extraction of shape-based features (such as contour shape), texture-based features (such as histograms of directed gradients), and local descriptors (such as Scale-Invariant Feature Transform - SIFT) are all frequently used feature extraction approaches.

5. Classification Model:

5.1 Convolution Neural Network:

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.

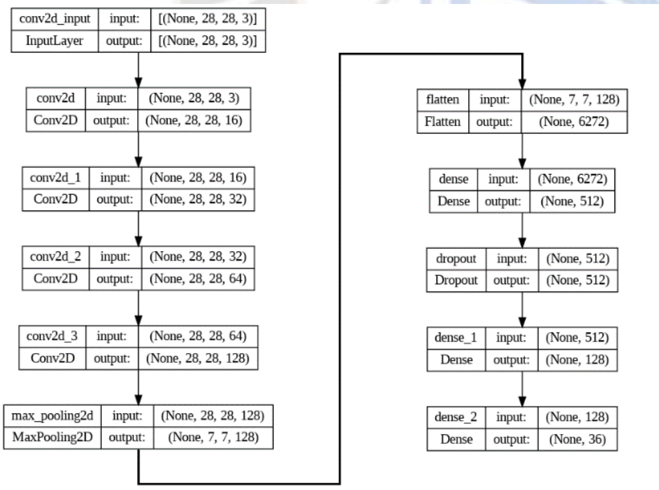

Figure 13: Architecture flowchart of CNN model

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 = 'relu')

two GRU layers (activation = 'relu')

model compilation

loss function: 'categorical_crossentropy'

optimizer = 'adagrad'

training CNN technique with training instances

employing techniques to test instances

return *Confusion Matrix* $Cm * m$

5.2 Lightweight Parallel CNN Model:

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

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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.

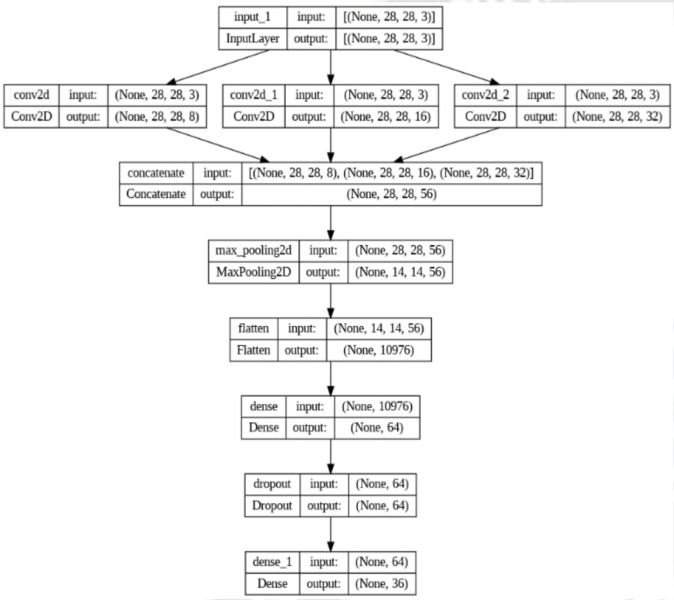

Figure 14: Flowchart of Lightweight Parallel CNN Model

6. Evaluation Metrics:

Following is a summary of the four performance evaluation measures that were utilised to evaluate the proposed illness prediction model:

- The number of accurate predictions where the model correctly identifies a patient as having a chronic disease is known as true positives (TP).
- The number of accurate predictions where the model properly identifies people without any diseases is known as true negatives (TN).
- False Positives (FP): The quantity of inaccurate predictions in which the model misdiagnoses a healthy person as having a condition.
- False Negatives (FN): The proportion of inaccurate predictions in which the model incorrectly classifies a patient as healthy when, in reality, they are suffering from a chronic illness.

The model's precision, recall, and overall performance in predicting the presence or absence of chronic diseases are all valuable insights revealed by these metrics.

a) Precision:

A performance evaluation statistic known as the precision or positive predictive value (PPV) calculates the proportion of accurate forecasts to all correct values, including both true and incorrect ones. It is denoted mathematically as follows:

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

In other words, precision describes how accurate or precise the model is at foreseeing favorable events. With a high precision, the model is less likely to misclassify negative cases as positive, or have a high rate of false positives.

Recall shows how well a model can locate and identify positive examples. With a high recall, the model is less likely to categories positive cases as negative, indicating that it has a low rate of false negatives.

b) Recall:

The number of true positives, or TP, in this equation denotes the accuracy of patients with chronic conditions' forecasts. False positives (FP) are the number of instances where a healthy person was mistakenly identified as having an illness. The accuracy or positive predictive value is calculated by dividing the number of true positives by the total of true positives and false positives.As a performance evaluation statistic, recall—also referred to as sensitivity or true positive rate (TPR)—measures the proportion of correctly anticipated values to the total of correctly positive and incorrectly negative predicted values. It is denoted mathematically as follows:

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

The number of true positives, or TP, in this equation denotes the accuracy of patients with chronic conditions' forecasts. False negatives, or FN, are the number of instances where a patient was incorrectly classified as healthy. The recall or true positive rate is calculated by dividing the total number of true positives by the sum of true positives and false negatives.

c) F1 Score:

The precision and recall parameters are combined through a weighted average in the performance evaluation statistic known as the F-measure (F). When the distribution of classes is unequal or the values of false positives and false negatives varies greatly, it is especially helpful. When recall and precision are equally important, the F1-Score, a particular variation of the

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F-measure, is frequently employed. It is denoted mathematically as follows:

$$F1 \text{ score } = \frac{2 \times \text{Recall} \times \text{Precision}}{(\text{Recall} + \text{Precision})}$$

Precision in this equation stands for accuracy, also known as positive predictive value, Recall for recall, also known as true positive rate, and is a weighting factor that establishes the respective weights of accuracy and recall. We get the F1-Score when is set to 1.

V. 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 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 15, 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 16.

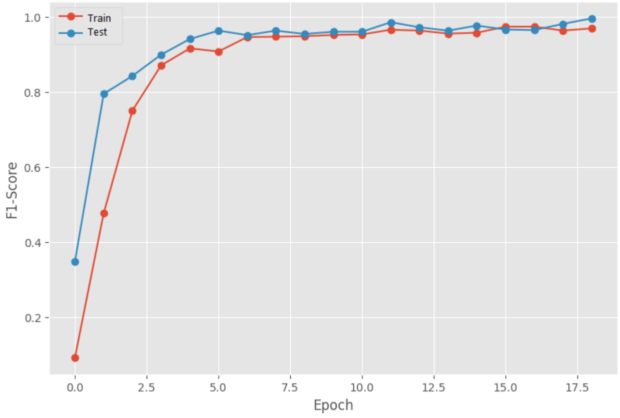

Figure 15:CNN F1-Score Comparison Graph

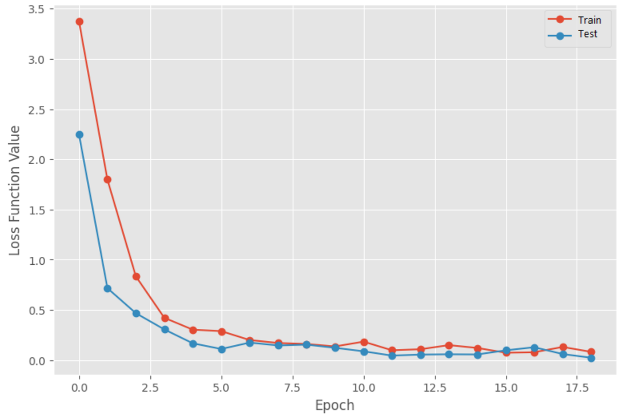

Figure 16: CNNLoss Comparison Graph

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 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

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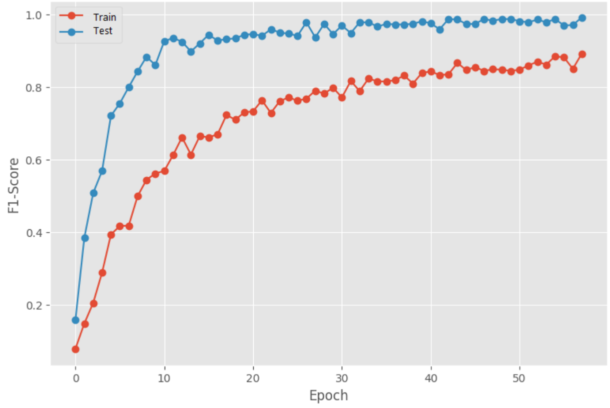

Figure 17: Lightweight Parallel CNN F1-Score Comparison Graph

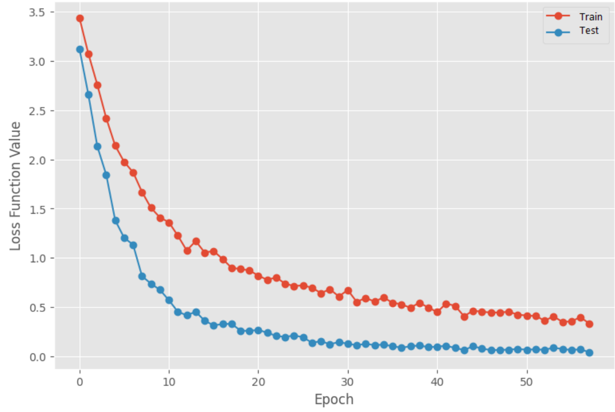

Figure 18:Lightweight Parallel CNN Loss Comparison Graph

Table 1: Comparison of Method with Evaluation parameters

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

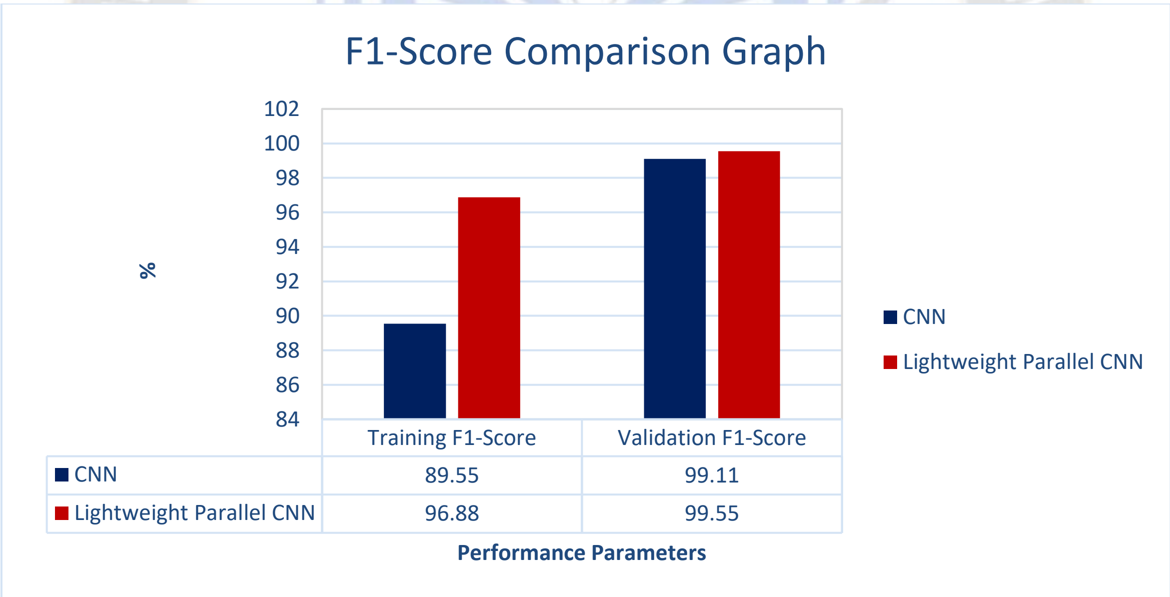

Figure 19: Training and Validation F1-Score Comparison Graph of CNN and Lightweight Parallel CNN

However, during testing, the Lightweight Parallel CNN once more demonstrated higher performance. The Lightweight Parallel CNN displayed outstanding accuracy and robustness in real-world scenarios, even in difficult circumstances including unevenly lighted plates, plates with styled typefaces, and tilted plates, with an F1 score of 99.55%, specificity of 99.15%, and accuracy of 99.85%. The evaluation findings show that the Lightweight Parallel CNN model performs much better than the conventional CNN in recognizing license plates. Its superiority in properly identifying and recognizing license plates in a variety of settings is demonstrated by its better F1 score, specificity, and accuracy. It turns out that the Lightweight Parallel CNN model is a more useful and efficient approach, making it appropriate for real-time applications and situations with limited resources.

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VI. CONCLUSION

The proposed model presented and assessed a Lightweight Parallel CNN Model for License Plate Recognition, contrasting it with the conventional CNN model in terms of performance. The objective of this research was to create a more effective and precise system that can manage difficult situations, such as plates with erratic illumination, plates with styled letters, and tilted plates. The experimental findings unequivocally show that the Lightweight Parallel CNN model is superior to the conventional CNN. The standard CNN only managed an F1 score of 89.55% during training, compared to the Lightweight Parallel CNN's outstanding F1 performance of 96.88%. Both during the testing and training stages, the Lightweight Parallel CNN beat the conventional CNN in terms of specificity and accuracy, demonstrating its resilience and generalization ability.The Lightweight Parallel CNN passed testing with an exceptional F1 score of 99.55%, demonstrating its capability to detect and recognize license plates reliably even in difficult real-world circumstances. The model's dependability and effectiveness were further confirmed by the unusually high specificity and accuracy, which were 99.15% and 99.85%, respectively.The Lightweight Parallel CNN model's parallel architecture, depth-wise separable convolutions, and multi-scale feature fusion are responsible for its success. Due to its efficient design, it can effectively gather and process a variety of data from photos of license plates, improving recognition precision and accelerating computation.

In future the Lightweight Parallel CNN model may be improved upon and optimized in the future through additional study. To assure the model's efficacy in various real-world circumstances, its performance can also be assessed on larger and more varied datasets. Real-time processing using the paradigm in embedded systems or edge devices may also be a useful direction for use in practical applications. The Lightweight Parallel CNN model has a tremendous deal of promise to transform License Plate Recognition technology and advance different parts of the infrastructure for law enforcement, security, and transportation.

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