DEVELOPMENT AND DATA ANALYSIS OF A DEEP LEARNING-POWERED IoT SYSTEM FOR REAL TIME SMART NUMBER PLATE DETECTION IN FOGGY WEATHER CONDITIONS

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by

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CANDIDATE DECLARATION

I Piyush Anand hereby certify that the work which is being presented in the thesis entitled Development and Data Analysis of a Deep Learning-Powered IoT System for Real Time Smart Number Plate-Detection in Foggy Weather Conditions in partial fulfillment of the requirements for the award of the Degree of Master of Technology submitted in the Department of Software Engineering, Delhi Technological University in an authentic record of my work carried out during the period from August 2023 to May 2025 under the supervision of Dr. Sanjay Patidar.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

Piyush Anand

This is to certify that the student has incorporated all the corrections suggested by the examiner in the thesis and the statement made by the candidate is correct to the best of our knowledge.

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CERTIFICATE BY THE SUPERVISOR

I hereby certify that Piyush Anand (Roll no 2K23/DSC/10) has carried out their research work presented in this thesis entitled "Development and Data Analysis of a Deep Learning-Powered IoT System for Real Time Smart Number Plate-Detection in Foggy Weather Conditions" for the award of Master of Technology from the Department of Data Science, Delhi Technological University, Delhi under my supervision. The thesis embodies results of original work, and studies are carried out by the student himself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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Development and data analysis of deep learning powered IoT system for real time smart number plate detection under foggy condition

Piyush Anand

ABSTRACT

Number plate recognition of automobiles is a crucial aspect in smart transport systems supporting automatic vehicle tracking and identification. License plate recognition during foggy and hazy weather conditions, however, still poses a challenge due to visibility issues and fuzzy image features. The objective of this research is to suggest an in-real-time number plate recognition system by deep learning for identification under adverse weather conditions with datasets collected using IoT devices. The proposed approach is three-pronged: image dehazing via dark channel prior algorithm for enhancement as step one, license plate detection through a CNN-based object detection model, and recognition of characters using Optical Character Recognition (OCR) techniques with super-resolution enhancement. Although in this instance the IoT system is not being created, for simulation of real-world conditions, the research utilized IoT-source image databases. Experimental results show that high identification rates were achieved even in heavy haze and fog by the proposed approach, which attests to its effectiveness under adverse weather conditions and future implementation in smart surveillance systems. The technique is a low-cost, flexible method that can be trained and tuned for many real-time traffic and security tasks, particularly in areas most affected by poor weather. In addition, the method reduces reliance on human observation, maximizes operational effectiveness, and can be adapted to existing traffic infrastructure with minimal change. Its flexibility also makes it possible to be coupled with cloud-based solutions for continuous learning and remote monitoring to ensure maximum long-term system performance and responsiveness. Its modularity ensures that upgrading and enhancing is effortless, and the compatibility flexibility in a broad spectrum of image sources makes it highly versatile. Overall, this project promotes the creation of smart traffic management through a reliable license plate recognition solution for harsh environmental-conditions.
The accuracy of the model at 20 Epochs is 93% and with trained on 50 epochs it reached to 96%.

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LIST OF ABBREVIATIONS

ANPR	Automatic Number Plate Recognition
IoT	Internet Of Things
DCP	Dark Channel Prior
SRCNN	Super Resolution Convolution Neural Network
CNN	Convolution Neural Networks
RNN	Recurrent Neural Networks
GPU	Graphics Processing Unit
EDA	Exploratory Data Analysis
YOLO	You Only Look Once
ANN	Artificial Neural Networks
ReLU	Rectified Linear Unit

CHAPTER 1

INTRODUCTION

The operation of intelligent transportation systems (ITS) has transformed urban transport, public safety, and intelligent infrastructure management. Automatic Number Plate Recognition (ANPR) is perhaps the most critical technology that is spearheading the change, which is a solution that allows automatic detection and reading of vehicle number plates using image processing and computer vision methods. ANPR technology is being deployed in great volumes on a massive variety of applications ranging from traffic surveillance, tolling, and access control to law enforcement and car tracking. While there have been enormous advancements in computer vision elsewhere, real-time recognition of number plates under adverse conditions—primarily fog—is still challenging. Fog severely damages image quality by reducing contrast, scattering light, and hiding visual characteristics. These conditions hinder the operation of classical number plate readers based on maximum visibility and observable image features in a bid to recognize and detect alphanumeric characters.

To overcome these constraints, this thesis introduces a new solution based on state-of-the-art deep learning techniques and data research in such a way to provide fog-immune real-time number plate detection. Originality is derived from using Object Detection Convolutional Neural Networks (ODCNN)[4] for number detection, Super-Resolution CNN (SRCNN)[5] for image upsampling, and Dark Channel Prior (DCP)[7] for haze removal supported by an IoT-capable data acquisition system.In this research, the role of the Internet of Things (IoT)[8] is restricted to data acquisition, where smart cameras and sensors are deployed to capture real-world traffic scenes under foggy conditions. The captured data is then computed offline or from edge servers based on the proposed deep learning pipeline. It supports fog-removal, image enhancement, and object detection within a modularity context, this article attempts to accomplish an emphatic, real-time number plate recognition model capable of operating in low-visibility environments.

Deep learning provides an impactful solution for pattern recognition and object detection through neural networks. After the neural network is trained with a large amount of training data, it improves computer vision and can detect patterns more accurately. Some of various datasets available are CCPD Dataset (Chinese City Parking Dataset), Stanford Cars Dataset, Indian Vehicle Dataset, Brazilian Mercosur Dataset[4,7,12,13,15,17].

1.1 Background

The intelligent transport systems (ITS) have seen enormous development with the convergence of technologies such as computer vision, machine learning, and Internet of Things (IoT). Automatic Number Plate Recognition (ANPR) is the most crucial component of ITS that allows identification and tracking of vehicles based on their number plates. ANPR systems are used extensively in traffic system monitoring, automatic tolling collection, car tracking, parking control, and police enforcement applications. Conventional ANPR systems rely heavily on good image data, which is a major limitation in real-world scenarios where visibility conditions can be very poor due to weather phenomena such as fog, rain, or snow.

Fog, in particular, is a serious challenge to vision-based systems. It brings about severe visual degradation caused by scattering and attenuation of light and results in poor contrast, fuzzy edges, and reduced visibility. These effects reduce the performance of ANPR systems, particularly detection accuracy and character recognition. ANPR systems, if they are to operate under such conditions, need to be equipped with sophisticated image processing capability to improve visibility and recover essential image details.

Deep learning has become in the last few years a strong tool for visual recognition tasks such as object detection, image classification, and super-resolution. Convolutional Neural Networks (CNNs) have been highly successful in these tasks. ODCNNs such as YOLO[2,3,21], SSD[18], Faster R-CNN and Transfer Learning[6] like MobileV-Net are now the norm for number plate detection because they can carry out exact, real-time localization of image objects. However, the performance of such models is largely reliant on the quality of input images. In cases of low visibility such as in fog conditions, the models would most likely suffer if images are not pretrained for enhancing their features. The Different phases of the whole development is as shown in figure 1.1.

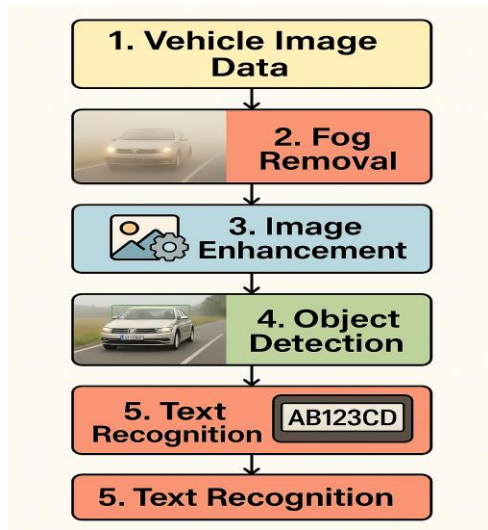

Fig 1.1 Working Phases of System

To tackle the issue of visibility degradation, pre-processing techniques such as the Dark Channel Prior (DCP)[18] have been developed. DCP is a widely used single-image dehazing method that improves contrast and restores natural color in foggy or hazy images by estimating the transmission map and atmospheric light. This enhancement makes the critical features of the number plate more distinguishable. Besides, Super-Resolution CNNs (SRCNNs) are employed to restore fine details and sharpen low-resolution images which is especially convenient when working with blurred or faraway plates recorded by CCTV cameras.

Whereas deep learning deals with the computing side of identification and enhancement, IoT is assigned the task of acquiring real-time traffic data. IoT sensors and cameras can be installed at numerous points of traffic to take snaps of vehicles and environments. IoT in this scenario is employed merely for data gathering, providing a uniform and diverse data set over multiple foggy conditions, which is extremely crucial for training and testing good deep learning models.

In incorporating DCP, SRCNN, and ODCNN under one platform aided by IoT data, this research is designed to address the issues of traditional ANPR systems during foggy conditions and help in the formation of stable, real-time vehicle recognition under poor conditions.

1.2 Motivation

Intelligent contemporary urban infrastructure increasingly relies on smart systems supporting automation, monitoring, and data-driven decision-making. Among such technologies, Automatic Number Plate Recognition (ANPR) is one of the most important ones used in usage applications such as traffic enforcement, smart tolling, parking management, and public safety. Nevertheless, the implementation of ANPR systems in real applications is typically associated with adverse environmental conditions—fog, for instance, which has been found to significantly impair visual data quality. Since fog renders light scattering and absorption, it results in decreased image contrast, obscured edges, and severe loss of fine details, all of which are critical to reliable number plate-detection.

The main driving reason behind this work originates from the very real demand that ANPR systems should withstand adversarial weather. In most of the areas-particularly hilly regions, coastal metropolises, and localities appreciating seasonally occurring fog—current ANPR technologies cannot offer accurate outcomes, thereby limiting their use. Such limitations not only impact traffic management and safety but also result in operational inefficiencies within surveillance networks and toll networks.

Although conventional image enhancement methods and optical hardware parameters have been tried, they are computationally impractical, costly, or inefficient in dense fog. Deep learning provides an adaptive as well as scalable solution, particularly when coupled with sophisticated image pre-processing methods. In particular, Object Detection Convolutional Neural Networks (ODCNNs) like YOLO and Faster R-CNN have shown very good accuracy and speed in object detection, e.g., number plates, in different conditions—considering the input images are good quality.

To make such models efficient under fog, image restoration needs to be performed. Methods such as the Dark Channel Prior (DCP) produce efficient fog removal, whereas Super-Resolution CNNs (SRCNNs) help restore fine details and improve image-resolution. However, the effective application of such models rests on the presence of true, varied, and context-dependent data-sets—something that may be created accomplished by bringing together Internet of Things (IoT)technologies.

In such an instance, IoT is being used not for complex edge processing or cloud analytics but in a concentrated manner for information collection. Utilizing IoT-connected cameras and sensors can allow for automated and scalable set of traffic images in fog, capturing true-world variation in vehicle composition, lighting, fog intensity, and angles. It is crucial while training deep learning models that generalize extremely well in many circumstances.

The motivation for this work is thus twofold: First, to bridge the performance gap in number plate detection systems under low-visibility conditions through an integrated deep learning framework; and second, to leverage IoT as a tool for building richer datasets that reflect the challenges of real-world environments. By combining DCP, SRCNN, and ODCNN in a data-driven, modular framework, this research aims at developing a firm solution to a growing significance in smart city infrastructure as shown in figure 1.2.

Fig 1.2 Detection of number plate under foggy condition [7]

Lastly, this piece of work is motivated by the vision of providing safe, effective, and reliable traffic systems regardless of the weather using cutting-edge AI methods and realistic IoT implementation.

1.3 Problem Statement

In most citywide surveillance and transport networks, visibility is taken to be optimal or just slightly compromised at best. But, in many areas likely to experience fog or haze—e.g., hilly terrain, coastal areas, or winter periods—visibility severely deteriorates. Classical ANPR systems trained on clear photographs deteriorate under these conditions, resulting in increased false alarms and-system-crashes.

Foggy weather number plate detection is a compound problem with a variety of technical-challenges:

1. Diminished contrast and detail in the image as a result of fog interference.

2. Degradation of high-frequency features of the image, including text edges and lines of license plates.

3. Varying intensity of fog, affecting the clarity of the image in different ways along time and location.

4. Real-time restrictions, since most ANPR schemes necessitate immediate reactions.

These factors necessitate a pipeline that can first preprocess and enhance images before performing accurate detection. At the same time, obtaining a large, diverse dataset of foggy images is difficult using traditional methods, making IoT a crucial enabler for scalable, real-time data collection. This thesis is motivated by the need to develop such a pipeline, leveraging the strengths of modern deep learning techniques and IoT infrastructure.

1.4 Objectives

The primary objective of this research is to design and design an IoT vehicle number detection system based on deep learning plates in real-time conditions of fog as shown in figure 1.3. Particularly, this thesis seeks to:

1. Deploy an IoT-based data acquisition system using smart cameras and environmental sensors to gather real-time vehicle image data in foggy conditions.

2. Apply Dark Channel Prior (DCP) as a pre-processing technique to remove haze
and regain scene contrast.

3. Use Super-Resolution CNN (SRCNN)[18] to super-resolve dehazed images, increasing their resolution and acuteness and improving feature visibility.

4. Train and test an Object Detection CNN (ODCNN) for accurate and precise number plate localization on enhanced images.

5. Conduct thorough performance analysis, including comparisons under different systems conditions of fog density, time of day, and vehicle distance.

6. Design modular and extensible system architecture that is reusable across other poor-weather vision applications.

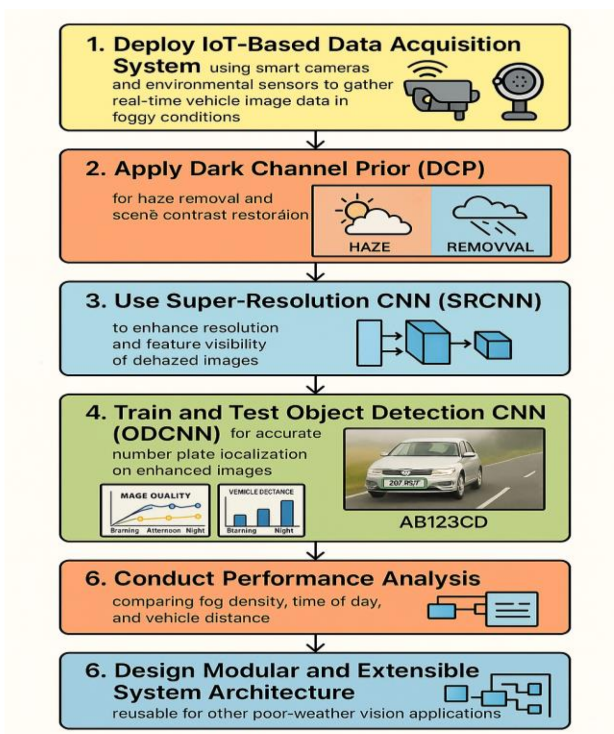

Fig. 1.3 Working overview of system

1.5 Technology Used

Multiple Technologies are used like Deep learning techniques, IoT based Techniques for Image capturing, Image enhancement, etc. for developing Vehicle number plate detection system under foggy weather condition.

- Role of IoT in the System

Whereas IoT is one aspect of this system, its purpose is restricted to sensing and data acquisition. Intelligent edge devices, like cheap cameras and fog or visibility sensors, placed strategically are used in various intersections of roads or highways. IoT devices are responsible for:

- Capturing high-frequency image streams in real-world traffic scenes.
- Logging context information like timestamp, location, and fog density.
- Transmitting information to a centralized processor or cloud storage for off-line training and model inference.

Installation of IoT improves quality and quantity of the dataset, hence the deep learning models are trained on real foggy conditions and not just on artificial data. This results in better overall generalization and better performance in real-world deployments [21].

- Dark Channel Prior (DCP) for Haze Removal

The initial critical phase of the processing pipeline is dehazing, as fog has especially important impacts on image contrast and visibility. One of the best individual-image dehazing algorithms is the Dark Channel Prior of He et al. It exploits the observation that in many non-sky non-hazy outdoor windows, there are pixels with extremely low intensity in at least one of the color channels. In fog, the dark channel is darker because of the veil of scattering particles in the air.

DCP is using this figure to estimate the thickness of the fog and restore the scene brightness. The dehazed image obtained is far greater contrasted and restores clarity in-obstructed-areas.

Notably, this approach does not need training data, which makes it suitable for real-time pre-processing across different intensities of fog.

- Super-Resolution CNN (SRCNN) for Image Enhancement

Following dehazing, the image is subjected to a Super-Resolution CNN (SRCNN)[18] to restore details and enhance resolution. Fog not only reduces contrast but tends to blur finer structures, like a character's edges and characters of number plate. Furthermore, the majority of IoT cameras can function at low resolutions to save energy and bandwidth.

SRCNN is a deep neural network that reconstructs a high-resolution image from a low-resolution input by learning a mapping between the two domains. It consists of convolutional layers which perform patch extraction, nonlinear mapping, and reconstruction. SRCNN is applied in this system learned on low- and high-resolution car image pairs to improve plate regions and improve feature discriminability as shown in fig 1.4

Fig 1.4 Before DCP vs After DCP [19]

Enhanced output of images facilitates the following detection network to obtain informative features with increased confidence, leading to more accurate number plate position.

- Object Detection CNN (ODCNN) for Plate Localization

The key to the number plate recognition system is the Object Detection CNN (ODCNN) module. The work of this module is to detect and localizing the number plate in the improved image. Such popular models as YOLOv5, Faster R-CNN & SSD are being looked at for this purpose, based on the computational complexity vs. accuracy-trade-off.

For this research, YOLOv5[2,11,14] is selected since it can carry out high-accuracy real-time detection. It splits the input translates image to grids and generates bounding boxes and confidence scores of number plate regions. The model is trained on a labeled data set of car images under different fog scenarios, e.g., real images taken by the IoT system and enhanced data.

The final output consists of bounding boxes around the number plates, which can be optionally passed to an OCR engine for character recognition if desired.

1.6 Research Contribution and Application

This thesis gives a robust and stable solution for the number plate detection problem in foggy weather using deep learning and IoT. The primary contributions of this study are:

- A deep learning pipeline-based modular framework that combines DCP, SRCNN, and ODCNN for image restoration, enhancement, and detection.
- A dataset of actual foggy car images collected via IoT-enabled cameras.
- Comparative performance of the system in different fog levels, comparing the performance of every module.
- Demonstration of real-time capability, in that the system can be used in traffic monitoring, toll collection, and intelligent transportation networks.

- Applications and Impact

  - The solution worked out in this research can find applications in various sectors, including- Enforcement of traffic: Detection and identification of cars violating traffic rules in fog areas.

  - Toll collection systems: Reliable collection of tolls regardless of unfavorable weather.

  - Smart city systems: Facilitating weather-independent surveillance and public security-monitoring.

In addition to number plate recognition, the pipeline module (DCP + SRCNN + ODCNN) can be applied to other object detection tasks with visibility issues—pedestrian detection, road sign detection, or driver vision systems in autonomous vehicles.

1.7 Thesis Structure

The remaining part of the thesis is structured as follows:

- Chapter 2 – Literature Review: Explains prior work on number plate detection, dehazing, super-resolution, and object detection using deep models.

- Chapter 3 – Methodology: Explains the IoT data collection framework, describes the dataset used, evaluation measure used, model structure, training process, and module integration.

- Chapter 4 – Experimental Setup: Tools and frameworks.

- Chapter 5 – Discussion and Analysis: Examines results, considers limitations, and discusses possible extensions and improvements.

- Chapter 6 – Conclusion and Future Work: Provides an overview of conclusions and some possible future research directions.

CHAPTER 2

LITERATURE REVIEW

This section provides a concise summary of the articles listed in the table above, together with their respective results.

2.1 Review of techniques based on CNN

Muhammad Gufran Khan et al. introduced a novel deep learning-based Automatic Number Plate Recognition (ANPR) pipeline for automotive access control systems in 2022, [1]. The process eliminates problems occurring due to ecu and Asian heterogeneous plate designs. YOLOv4 was redeveloped to be listed for front/rear vehicle view detection and license plate localization, which achieved suggest common precision (mAP) rankings of 98.42% and 99.71%, respectively. For character popularity, the tool utilized AlexNet and R-CNNL3 deep learning models, which resulted in 98% one-character popularity accuracy. OCR Tesseract also found its application as a comparative technique with an overall accuracy of 90.94%. Pipeline operations are responsible for processing the video frames in real-time, utilization of preprocessing techniques such as grayscale conversion, binarization, and histogram equalization for detection accuracy improvement. The model tested robustness under many lights and ambient conditions and adapted to best suited for GPU deployment.

It's highly suitable for more than one ANPR scenarios beyond vehicle access control. Uma K. Kesava Pillai et al. offered deep CNN-based method for vehicle color and type recognition to aid Amber and Silver Alerts in 2021, [2]. With the intention to work towards fulfilling the urgent requirement of quick identification during the emergency scenario, they developed a model with the use of convolutional neural networks (CNNs) for the classification of vehicles based on their type and color. In order to combat the environmental issue and learn best, the device utilized fact pre-processing methods such as haze removal and data enhancement. In comparing shallow and deep CNNs, it was evident that the deep CNNs outperformed shallow models with an accuracy of 89% and 95% in car type and color class respectively. The use of batch normalization and dropout layers which were also among the primary features were needed to avoid overfitting. Uploaded on OpenCV and Python, destiny dreams involve enhancing this device for vehicle recognition and number plate reading format. Shenghui Wang et al. suggested a deep learning-supported method to license plate recognition in smart building security systems in 2021, [3]. They created an application using convolutional neural networks (CNN) in image processing to search for license plates, identify characters, and read license plate numbers. It applies preprocessing techniques such as denoising and binarization to improve performance in harsh conditions such as bad weather and nighttime. For the recognition part of the main character, Inception-V3 is the backbone network that allows us to achieve features for character recognition very efficiently. Training the network was conducted with real but noisy and warped images and it was able to identify with 98.44% accuracy. The system assists in access management to structures by car recognition with a history of the car captured that boosts security and efficiency in utilization of smart buildings.

Irina Valeryevna Pustokhina et al. proposed an advanced computational approach for Vehicle License Plate Recognition (VLPR) using Optimal K-Means clustering integrated with a Convolutional Neural Network (CNN) in 2020 [7]. They explained that the system is divided into three stages named the OKM-CNN; the first stage involves locating a license plate, the second stage involves optimal K-mean clustering of the characters using the Krill Herd (KH) algorithm and finally the third stage is character recognition using CNN. Such a system has been validated on the Stanford Cars, FZU Cars datasets and in the HumAIn 2019 Challenge and had higher levels of accuracy when utilized as opposed to standard methods. The OKM-CNN model showed an accuracy of 98.1% which goes to show its true worth in terms of intelligent transportation applications such as toll collection, parking management as well as traffic monitoring. Other improvements will include the use of various languages on license plates and the optimization of parameters based on bio inspired algorithms. Mohit Kumar Kushwaha et al. proposed a deep learning-based approach for car number plate detection using convolutional neural networks (CNN) in 2022 [8]. The researchers created an Automatic Number Plate Recognition (ANPR) system designed for overcoming the problems of noise, poor illumination, oblique view angles, and non-standard typefaces. Some noise reduction methods such as Gaussian blurring and converting the image to grayscale were utilized to assist the recognition. Using character segmentation and recognition CNN, the f1-score was 94.94% on the Kaggle dataset after another 80 epochs of training. Practical applications of the proposed model were found in parking system, collection of tolls, and enforcement of traffic rules. It's true that the system had a number of shortcomings, yet its usability and effectiveness in the everchanging real world setting of intelligent transport systems were more than apparent. Manik Rakhra et al. proposed a method for classifying and detecting vehicle license plates using deeply learned convolutional neural networks (CNNs) in 2022 [9]. Among the CNN architectures used for this task are the DenseNet201, InceptionResNetV2, EfficientNetB5, and Xception, which specialize in image processing of license plates with specific attention to their originating state. The training and testing accuracies for the DenseNet201 model were reported as 99.96% and 90.38 respectively. The interest of the research was targeting US license plates and data from the Kaggle website was used, and sample imbalance Correction methods such as augmentation were applied. The approach proved to effectively classify the individual classes with the highest derived percentage of 91.5% for EfficientNetB5. The research adds to the body of knowledge in intelligent transportation systems specifically in automatic license plate recognition by demonstrating its potential in the field by dealing with variations in the illumination and the environment. Gamal Alkawsi et al. reviewed deep learning methods for Arabic vehicle license plate recognition (ALPR) in 2021, [4]. They explored some methods of detecting, segmenting, and recognizing license plates with attention on factors such as plate designs, languages, and the relevant environment in different countries. The ALPR process involves image acquisition time, license plate detection, segmentation and character recognition. Recent methods such as Mask-RCNN and YOLOv2, for example, provided a highly accurate system, having obtained up to 97.9 percent for the case of Mask-RCNN and 99.37 with Convolutional Neural Network for specific tasks. Nevertheless, factors such as sensitivity towards noise, light, and even computational complexity emerged. The investigation stressed making use of effective pre-processing techniques and more sophisticated algorithms to cope with difficult situations, in particular in the case of images taken at night or with difficult backgrounds. It recommended solutions to the identified shortcomings and accented the need for further improvement of existing ALPR systems with focus on license plates bearing Arabic characters.

Michael Kročka et al. proposed an Automatic License Plate Recognition (ALPR) system using OpenCV for image processing in 2022, [5]. They put in place a system that scans parking lots in order to identify and read vehicle plates. The system applies basic functions such as Gaussian blurring, adaptive threshold and edge detection in order to find a license plate. For the recognition of text, PyTesseract OCR was used.

Their work was primarily aimed at low-power computing devices such as Raspberry Pi and focused on light-weight computational methods. The system managed to detect number plates in 96.2% of cases and recognized textual data in 90% of cases from a out 500 vehicle portraits. Among the problems were colored plates with low contrast, which perhaps may be avoided by contrast enhancement and some adjustment of adaptive thresholds. Prospective improvements are aimed at increasing the recognition accuracy and widening the range of the datasets and colored license plates associated with them.

Chen Geng et al. proposed a deep learning-based anti-occupation system for New Energy Vehicle (NEV) charging piles to prevent illegal occupation and improve efficiency in 2024 [12]. They have invented a new model for real-time observation of charging piles which includes both Convolutional Neural Networks (CNN) and a Recurrent Neural Networks (RNN) that is capable of high license plate recognition and classification of vehicles accurately. The system design has cameras for real-time identification of the vehicle, preprocessed modules handling standardizes the process of photographing, and data analysis programs utilized to sort out. Analyze data and calculate the occupancy level. The hybrid model method also proved to be more accurate than the previous method and managed to reach 95% on the training set and over 92% recognition accuracy in both cross-validation and testing sets. The image processing is done in less than 0.3 seconds, which is appropriate for real-time use due to its quickness and dependability. This system is an appropriate solution in solving NEV charging pile occupation management plagued by image deformation and changing environments in ensuring smart transport and green energy.

2.2 Review on techniques based on YOLO

Dzinaishe Mpini et al. in 2023 [6] have compared Automatic Number Plate Recognition (ANPR) methods specifically for Zimbabwean number plates. They have applied and tested plate detection methods with OpenCV and YOLOv8 and further tested character recognition methods which are PyTesseract, K-Nearest Neighbors (K-NN), and Random Forest (RF) classifiers. From their findings, it was established that of the two methods, YOLOv8 was accurate compared to the others with a mean processing time of only 0.10 seconds whereas plate detection with OpenCV had a mean accuracy of 77.78 with a very high mean time utilization of 12.36 seconds When comparing K-NN with other character recognition methods, K-NN was more accurate at 66.67% and had a faster processing speed of 0.19 seconds per character. Other character recognition techniques like PyTesseract had an accuracy of 55.56%, where the performance was best with rectangular plates, but it did not work as well with square and indistinct fonts. Performance of RF classifiers was very weak as they recognized only plates, they were trained on and did not perceive untrained data. The research revealed the feasibility of combining YOLOv8 and K-NN as technical prerequisites for the development of high-speed productive end to end ANPR system for Zimbabwe. Recommendations included extending training duration with various datasets and some different climates to increase strength and applying better techniques such as and YOLOR to increase the system reliability.

Sushant Poojary et al. presented a deep learning technique for automatic number plate recognition (ANPR) based on YOLO and Convolutional Neural Networks (CNN) in 2022, [10]. The system was deployed in 3 major sections: detection of number plates, character segmentation, and detection of detected characters. It is on images taken under difficult light and angle conditions that the number plates localized using YOLO with minimal pre-processing. On character segmentation, image structures were used in contour segmentation, contrast improvement, and conversion to grayscale. Character recognition was performed with the help of CNN and characters were assigned to 37 classes with high accuracy (10 digits, English 26 letter capitalized alphabets, and non-character). It is useful in application such as traffic control, toll, and security and illustrates how deep learning is applied in ANPR systems to make them accurate and trustworthy.

Twana Mustafa et al. introduced an ANPR system based on deep learning for campus gate number plate recognition in 2023 [11]. It made use of OpenCV and YOLO for recognizing the license plate and Tesseract OCR and PaddleOCR for identifying sunlit, rain or night conditions license plates. The suggested approach consisted of four consecutive modules: image preprocessing module, license plate detection module, character segmentation, and optical character recognition module. For effectively detecting the area of the license plate, YOLO was used in the system and OCR was utilized for recognizing and extracting the texts. The system was highly effective with accuracy rates under different light and climate conditions. This entered into view with this strategy that, deep learning as well as OCR technologies are ideally suited to graphical applications like traffic law enforcement as well as parking management systems.

Qudes MB Aljelawy et al. proposed a license plate detection and recognition system using the YOLOv4 algorithm, EasyOCR, and Raspberry Pi 4 with a camera in 2022, [13]. The system consisted of the steps of license plate cloning through image preprocessing, segmentation, noise removal, and efficient deep learning methods. YYOLOv4 came in handy in improving efficiency in the tasks and was responsible for high-accuracy license plates detection while EasyOCR was responsible for text character extraction. The system achieved 99 % accuracy for short distances of under 6 meters and there was a decline as the ranges increased. The setup also gave Cascade Classifiers for comparison and the comparative results were different depending on distance and angle. The image resolution used by the Raspberry Pi's camera was 2592x1944 which improved detection. The study suggested possible use of the models in parking system, surveillance and traffic monitoring and prospects of improving kinematics through parallel implementations in future research were unquestionable.

Shashi Kant Gupta et al. proposed a deep learning-based model for vehicle number plate detection using an Image Labeler model in 2023, [14]. The system was designed with the intent of enhancing road safety and traffic control through effective detection and recognition of vehicle registration number plates. In this context, the model applied the relevant knowledge and instinct gained by utilizing deep learning algorithms that were created previously through segmentation of images into the numeric and alphabet segments in images for training and recognition. This included preprocessing the images to grayscale, denoising the images and active contours to emphasize areas of interest. The Image Labeler took the logo of the number plate and learned the characters involved and their relative positions. Testing results showed 98.25% success in detection of the plates while that of characters was 79%. This system was relevant in crime prevention, traffic control, and automatic toll collection. Work is in progress to increase the processing speed and scalability by means of graph convolution methods.

Haziq Danial Bin Ihsanul Wildan et al. proposed a system for vehicle license plate recognition using a combination of deep learning methods in 2023,, including TensorFlow, Tesseract-OCR, and YOLO models [15]. The method included image processing for dividing letters into reasonable parts that can be read and understood, localizing the areas which contain pictures of the car license plates as well as character recognition with OCR technology. The model reached an accuracy of 90% on 225 images dataset for training and utilized a web-based application which was developed based on Flask for real-time deployment. The system was able to detect and recognize vehicle license plates in poor or bright lighting as well as in busy backgrounds. It was designed to improve the efficiency of already developed applications for intelligent transport systems, traffic control, and the relevant law enforcement agencies incorporating newest technologies of machine learning and frameworks based on Python. Future work deals with the enhancement of real-time processing of the system to retrieve results and expansion of the model's applicability for more datasets.

Xianli Jin et al. proposed a Vehicle License Plate Recognition algorithm based on deep learning named Fog-Haze LPR (LPRFH) in 2021 to alleviate low-visibility-caused problems [18]. Their design involves a series of top-level modules: a dark channel prior-driven atmospheric light value-led local dehazing initial, an Object Detection Convolutional Neural Network (ODCNN)-driven Joint Further-dehazing and Region-extracting Model (JFRM) for later local plate detection, and a Super-Resolution Convolutional Neural Network (SRCNN)-sponsored convolution to capture subtle plate character details. JFRM also improves plate detection and dehazing using YOLOv3 detection mechanism and bounding box accuracy is improved using WPOD-NET for slanted license plate correction. Separation of characters is performed by connected components and character recognition is performed by an Artificial Neural Network (ANN) for character recognition improvement. Experiments on actual and virtual datasets under different fog-haze conditions produced robust detection with high accuracy and character recognition rate of up to 94.1% with a six-layer SRCNN. The system was also robust against distortions like motion blur, tilt, and partial occlusion and therefore is well-suited for real-world practical intelligent traffic monitoring in harsh weather conditions.

Pei Liu and Wanhai Yao introduced a fog-resistant vehicle license plate recognition scheme in 2024 to optimize vehicle recognition under low fog visibility [18]. The process begins by de-fogging the license plates' images using an enhanced Dark Channel Prior (DCP) with an adaptive window to accurately compute the dark channel in size and entropy in the image. This defogging significantly impacts image acuteness, as verified through high information entropy values. License plate regions are subsequently detected after defogging by the system through color thresholding in HSV space followed by grayscale conversion and Radon-based tilt correction for plate size and orientation normalization. Plate area binarization is done with Otsu's thresholding along with morphological processing and border removal to separate the plate area. Vertical projection is subsequently used to carry out character segmentation, and template matching is used to perform final recognition. Experiments in light fog, medium fog, and heavy fog environments validated the enhanced DCP algorithm more effectively, improved the recognition rate from 54% (original image) to 82% in light fog, and proved to be usable and feasible for real-time traffic detection in adverse weather conditions.

Table 2.1 Comparison of Different techniques and its accuracy

Year	Title	Models Used	Dataset	Accuracy
2020	Automatic Vehicle License Plate Recognition Using OKM-CNN [1]	Optimal K-Means clustering, CNN	Stanford Cars, FZU Cars, HumAIn 2019	98.1%
2021	Arabic Vehicle Licence Plate Recognition [2]	Mask-RCNN, YOLOv2	Arabic-Car Dataset	97.9% (Mask-RCNN), 99.37% (CNN)
2021	Vehicle Color and Type Identification [3]	Shallow and Deep CNNs	Own dataset with augmentation	95% (color), 89% (type)
2022	Automatic License Plate Recognition Using OpenCV [4]	OpenCV, PyTesseract OCR	500 Image Rear View dataset	96.2% (detection), 90% (recognition)

2022	Deep Learning Methods for Number Plate Recognition [5]	YOLO, CNN	Dataset with augmentation	High performance reported
2022	Car Number Plate Detection using Deep Learning [6]	YOLO, CNN	Kaggle dataset	F1-score: 94.94%
2022	Classification of License Plates [7]	DenseNet201 ,InceptionResNetV2, EfficientNetB5, Xception	US License Plate dataset (Kaggle)	90.38% (DenseNet 201), 91.5% (EfficientNetB5)
2023	Zimbabwean Number-Plate Recognition [8]	YOLOv8, K-Nearest Neighbor (KNN)	Zimbabwe Vehicle dataset	100% (detection), 66.67% (recognition)
2023	Vehicle License Plate Recognition for Intelligent Systems [9]	YOLOv4, EasyOCR	Not specified	99% (short distance detection)

2023	Campus-Gate License-Plate Recognition [10]	YOLO, PaddleOCR, Tesseract	Real-time captured data	High performance
2023	Detection of Number Plate in Vehicles Using Deep Learning [11]	YOLO, Tesseract OCR	225 manually labeled images	90% recognition
2023	License-Plate Reader with PUC Details [12]	Tesseract OCR, TensorFlow	Custom dataset	High performance reported
2024	License-Plate Detection Using YOLOv5 [13]	YOLOv5, MobileViTv3, Biformer	CCPD dataset	99.8% detection accuracy
2024	Vehicle Charging Pile Anti-Occupation System [14]	CNN, RNN	Not specified	95% (recognition)

2024	Enhancing Vehicle Entrance and Parking Management [15]	YOLOv8, Tesseract OCR, Haar Cascade Classifier	Custom datasets for vehicle/plate images	Precision: 99.8%, mAP@50: 99.4%
2024	License Plate Recognition Using YOLOv5 [16]	YOLOv5, Improved WIoU, MobileViTv3	CCPD dataset	99.8% (precision), 99.9% (recall), mAP: 99.5%
2024	A Computer Vision-Based Vehicle Detection System Leveraging Deep Learning [17]	YOLOv8 Ultralytics, TensorFlow, OCR	Custom datasets (1,200 for vehicles, 1,000 for plates)	95% accuracy

A dataset is a collection of logically consistent data, generally used at train and test levels for machine learning algorithms. In the case of vehicle license plate recognition (VLPR), datasets typically consist of plate and vehicle images in varying conditions like lighting, weather, and orientation good annotation in rich datasets, such as bounding boxes surrounding plates and character labels, ensures accurate detection and recognition. The set's quality, variety, and quantity of annotations directly influence VLPR system performance and overall generalizability, making dataset preparation and selection a very important research and development task. Below we have a comparison table, Table 2.2, for different datasets of vehicle number plate under different adverse conditions which was earlier collected through IoT- based setup.

Table 2.2 Comparison of different datasets based on its pros & cons

Dataset Name / Source	Size of Dataset	Year	Pros	Cons
Foggy-Hazy License Plates Images (Mendeley Data) [18]	1,001 foggy-hazy images	2023	Specifically targets foggy/hazy conditions; manually collected; includes ground truth; multiple locations (India)	Limited to Indian regions; relatively small; may lack vehicle and plate diversity
Foggy License Plates Worldwide (Mendeley Data) [2]	4,420 images (Bangladesh: 2,754 annotated, Thailand: 388,English plates:	2023	Global coverage; diverse vehicle types and regions; varying fog levels using depth estimation; YOLO-format annotations	Some subsets lack annotations; fog is artificially simulated
Car-1000 (arXiv) [3]	140,312 images, 1,000 car models, 165 automakers	2022	Very large and diverse; fine-grained, hierarchical labels; covers vehicles from 1960s–2020s; global coverage	Not specific to license plates or foggy conditions; focused on car model classification
TAU Vehicle Type Recognition Competition Dataset [7]	Not specified (TAU: ~17 types, CompCars: thousands of images)	2019–2020	Used for vehicle type/classification; includes multiple viewpoints, weather conditions, and haze	Not focused on license plates; class imbalance; annotation quality

Chars74K (for character recognition in ANPR pipelines) [10]	74,000 images (64 classes)	2009	Large, includes natural, hand-drawn, and computer-synthesized characters; used for robust OCR training	Not specific to license plates; may not reflect real-world plate fonts/styles
Irani Vehicle Dataset [11]	313 images	2022	Used for front/rear detection;	Small size;limited to Iran
Croatia Vehicle Dataset [14]	636 images	2021	Real-world Croatian plates; annotated; used for detection/localization	Small size; limited to one country; not focused on adverse weather
Brazilian Vehicle Dataset [13]	2,925 images (public video monitoring), 620 parking lot images	2018	Real-world, various scenarios; annotated for detection/localization	Not focused on fog/haze; annotation details may vary
Indian Number Plate Dataset [1][3][6]	10,000 images	2021	Large size; real-world Indian plates; used for detection and recognition	Limited to India; may lack adverse weather scenarios
Pakistani Number Plate Dataset (custom, see Khan et al.,	1,000 images (823 for detection, 200 for character recognition)	2021	Diverse plate types, fonts, orientations; includes images with dust, fog, and varying lighting	Limited in size; regional focus; annotation details not fully specified

The literature reviewed shows substantial improvement in number plate detection through deep learning, and most notably object detection CNNs such as YOLO, Faster R-CNN, and SSD. These have been seen to be extremely accurate under ideal conditions but suffer from performance drops in adverse weather, and notably fog. The image dehazing algorithms such as Dark Channel Prior (DCP) [17] show successful removal of fog for visibility recovery, and SRCNNs have been shown to improve image quality and restore detail loss. There are fewer studies, nonetheless, that integrate these algorithms in a single pipeline that is specifically designed for fog images.

In addition, while IoT has discussed in ANPR systems, its application has mainly been on processing transmission rather than strategic acquisition of information. There is a definite research lacuna in applying IoT to specific, condition-specific dataset generation, particularly under actual-world fog conditions.

Thus, integrating DCP, SRCNN [18], and ODCNN with IoT-data[21] collection provides new and promising direction. It remedies both the disadvantages of low visibility and the lack of adequate appropriate training data. This thesis will fill this gap by suggesting a robust, real-time fog-resistant number plate system detection through a deep learning-based, IoT-enabled platform.

CHAPTER 3

METHODOLOGY

This chapter introduces the envisioned model for license plate recognition under foggy conditions on the basis of multi-stage deep learning-based architecture consisting of dehazing, detection, and recognition stages. The methodology includes Dark Channel Prior image defogging, Super-Resolution Convolutional Neural Network improvement of character clarity, YOLOv5[2,5,6,8] object-level detection of license plates, and Optical Character Recognition reading of alphanumeric characters.

In the first phase, DCP is performed pixel-wise to remove fog interference. The algorithm computes the transmission maps with an adaptive filter window based on image entropy and local light estimation of the atmosphere. The estimates are used to reconstruct fog-free images by removing color distortion and contrast loss. This significantly enhances visual quality and sets the image ready for precise downstream detection.

In stage two, YOLOv5, a cutting-edge object detection model, is employed for rapid and precise license plate localization. YOLOv5 is trained on annotated license plate images and identifies the license plate bounding box in real-time.

When detected, the detected license plate area is processed by SRCNN, which increases the resolution and sharpness of low-resolution foggy images. The six-layer SRCNN recovers high-resolution features with distinct edges and fine character details required for effective OCR performance. In the final step, OCR is employed for image-based character recognition to machine-readable text. Projection profiling is applied to character segmentation, and single-alphanumeric detection is performed by using OCR engines such as Tesseract[13]. The pipeline consisting of DCP, YOLOv5, SRCNN, and OCR provides a strong and effective license plate recognition system for intelligent transportation systems under low-visibility conditions.

3.1 Dataset

We used a secondary dataset consisting of 2,754 annotated samples, placed deliberately to support the development and testing of a license plate reading system on diverse real-world conditions. The dataset was divided into three categorically distinct subsets to support intensive training, testing, and validation. To the specific extent of 70% of the data amounting to 1,928 images, the data was divided into the training set to enable the model to learn strong features. The rest of the 30% roughly divided between the validation and test sets, each containing 413 images, to allow for unbiased performance assessment and calibration of the model parameters.

The data is also extremely heterogenous, and it covers the full range of image characteristics. It covers different degrees of blur and sharpness, which cover realistic situations in real life where motion blurring, low resolution, or atmospheric phenomena like fog would be encountered.

In object distribution, the data set offers a wide variety of vehicle types. The majority are cars with 46.6%, followed by motorcycles and bicycles with 39.4%. Compressed natural gas vehicles account for 3.3%, and trucks and buses account for 8.1%. The data set further comprises 2.6% as isolated license plate images, which may come in very useful when training models preferred standalone plate detection and character identification. This complete and balanced dataset structure enables the development of a robust and adaptable license plate reading system applicable in various traffic surveillance and intelligent surveillance systems. The samples of dataset is shown in figure 3.1.

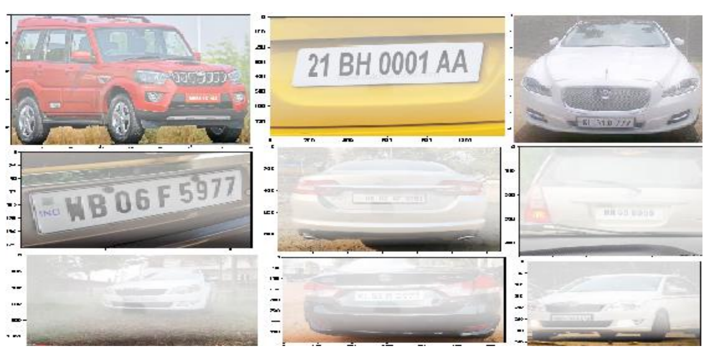

Fig 3.1 Sample of Dataset

3.2 Data Preprocesing

Data preprocessing in this thesis is to improve image clarity of the fog scenes using the Dark Channel Prior (DCP)[17] method. The fog images are decomposed initially into RGB channels and then a dark channel is derived based on minimum intensity over channels. Atmospheric light is estimated from the darkest channel or brightest area of dark channel. Transmission map is computed and enhanced by guided filtering in a bid to preserve edge information. Finally, dehazed image is reconstructed using better transmission and atmospheric light estimation. Preprocessing significantly helps in image contrast and visibility with a view to making proper license plate detection and reading easier.

3.2.1 Dark Channel Prior Algorithm

In this thesis, the Dark Channel Prior (DCP) algorithm is employed as a crucial preprocessing technique to enhance license plate visibility under foggy conditions. Originally proposed by He et al., the DCP algorithm effectively removes haze from single images by leveraging a statistical observation: in most natural, haze-free images, at least one-color channel contains very low intensity values in non-sky regions. This principle is exploited to estimate the thickness of haze and restore the original scene visibility.

DCP processing starts by breaking down the input blurred image into its RGB channels. At each pixel location, the algorithm calculates the minimum intensity among the three channels to create a "dark channel" image of the least hazy regions. Then, an erosion operation is applied using a small kernel that continues to refine the dark channel by highlighting the darkest areas of the image. This serves to localize shadowed or blocked areas, for example, by fog.

The second is to estimate atmospheric light (A)—the image region most affected by haze. This is usually performed by averaging the brightest pixels in the dark channel and picking a high percentile (e.g., 0.2%) to calculate the ambient light value, since the areas are most indicative of haze effect. Correct estimation of A is crucial to successful haze removal. Image Processing: Basis and Applications.

Subsequently, the transmission map (t) is calculated. This map measures the extent to which light is attenuated as it travels through the haze. The transmission is estimated using the normalized input image and atmospheric light values. Mathematically, this is expressed as in equation 3.1:

$$\tilde{t}(x) = 1 - \min_{c}\left(\min_{y\in\Omega(x)}\left(\frac{I^c(y)}{A^c}\right)\right)$$

Eq 3.1

where $\Omega(x)$ is a local patch around pixel x, and $I^c(y)$ is the intensity of channel c at position y.

In order to sharpen the transmission map and maintain the edge information required to accurately localize license plates, a guided filtering process is performed. Sharpening is carried out using the grayscale as a guide, which reduces a cost function in terms of the Laplacian matrix. Resulting is the smooth but edge-preserving transmission map that is retaining significant object boundaries as shown in Fig 3.2.

Fig 3.2 Edge preserving transmission map of image

Lastly, the scene radiance (dehazed image) is restored based on the refined transmission map and atmospheric light. Each color channel uses the following equation 3.2:

$$J(x)' = \frac{I(x) - A}{\max(t(x), t_0)} + A$$

Eq 3.2

where J(x) is the recovered pixel value, t0 is a lower bound to prevent division by near-zero values, and I(x) is the original pixel value.

This algorithm significantly enhances contrast and sharpness of the image and hence feature recognition on license plates. Better visibility also highly enhances the performance of subsequent tasks such as detection of license plates through YOLOv8 and character identification through EasyOCR. Experimental results conducted in the research showed that DCP performed better than other dehazing algorithms in terms

of structural similarity (SSIM = 0.8188) and peak signal-to-noise ratio (PSNR = 19.71), thus confirming its applicability in fog-resistant vision systems. The working of the DCP is shown in Fig 3.3 .

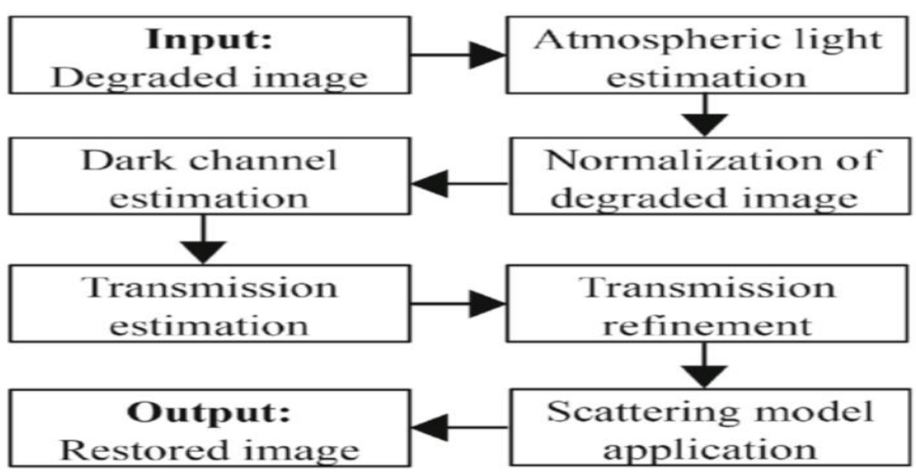

Fig 3.3 Working flow of DCP algorithm

DCP estimates the atmospheric light and transmission map and based on that it intensifies the low intensity pixel of RGB which is shown in Fig 3.4

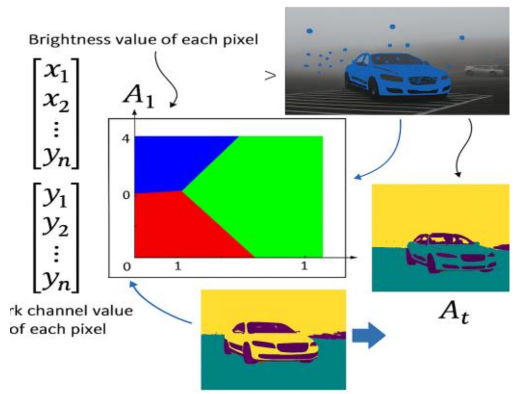

Fig 3.4 Feature extraction with the help of DCP

3.3 Proposed Work

This section depicts a complete deep learning-based approach for reading and recognizing vehicle number plates in challenging foggy conditions. Following preprocessing of the images by the Dark Channel Prior (DCP)[17] technique (this section does not cover), which is used before feeding the inputs to the suggested system, it has three very fundamental steps:

- Object Detection using YOLOv5
- Image Enhancement using SRCNN
- Character Recognition using Tesseract OCR

Each phase solves particular problems caused by fog image degradation and attempts to provide accuracy, speed, and robustness.

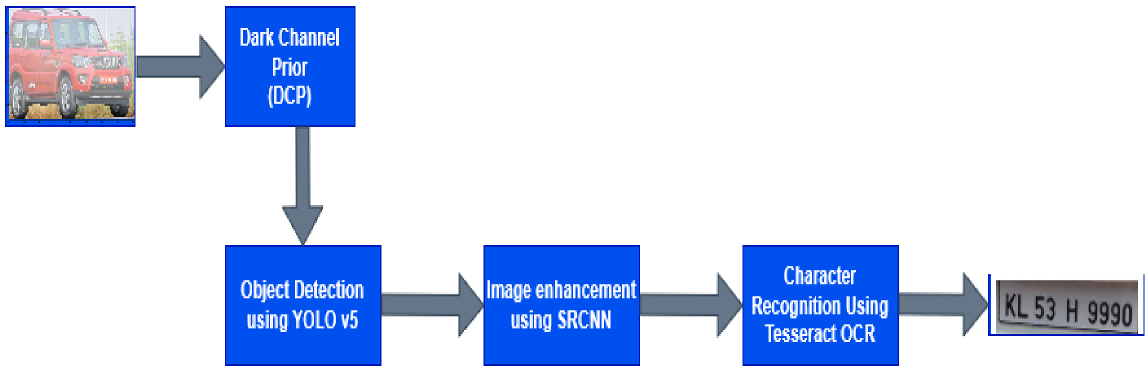

Fig. 3.5 Proposed Working of ANPR system under Foggy condition

The proposed alogirthm for the system we have developed is shown in Algorithm 1.

Algorithm 1 Proposed method

Input: *P={p1,p2,…,pn} a set of vehicle images captured in foggy weather*
Output: *R, a set of detected license plate characters*

```
if len(P) == 0 then
    return Ø
else
    for pᵢ in P do
        I ← IoT_Acquire(pᵢ)
        D ← ApplyDCP(I, ω = 0.95, patch = 15)
        B ← YOLOv5_Detect (S, conf = 0.5, iou = 0.5)
        S SRCNN_Upscale(D, lr = 1e−4, epochs = 100)
        L ← CropLicensePlate(S, B)
        C ← SegmentCharacters(L)
        result ← RecognizeCharacters(C)
        R ← R ∪ {result}
    end for
end if
return R
```

➢ License Plate Detection Using YOLOv5

The second process after dehazing of the image is to detect and find the area of the license plate using YOLOv5, a real-time object detector. YOLOv5 casts object detection as a problem of single regressions, estimating bounding box corners and class predictions directly from an image without conducting region proposals.

The input image is masked with an SXS grid, and each grid cell makes C class predictions and B bounding box predictions. Each bounding box prediction consists of:

Each phase solves particular problems caused by fog image degradation and attempts to provide accuracy, speed, and robustness.

- x,y: Center coordinates (relative to the grid cell)
- w,h: Width and height (relative to the whole image)
- Pobj: Object confidence score
- Pclass: Class probabilities (for "license plate")

The **final confidence score** for a bounding box is calculated as in equation 3.3:

$$\text{Confidence} = P_{\text{obj}} \times \text{IoU}_{\text{pred}}^{\text{truth}}$$

Eq 3.3

Where:

- P_{obj} = probability that the object exists in the box
- IoU $^{\text{Truth/pred}}$ = Intersection over Union between predicted and actual box

$$Intersection\ over\ Union(IoU) = \frac{Areao\ fOverlap}{Area\ ofUnion}$$

Eq 3.4

This is a crucial requirement in foggy conditions scenarios since edge contrast and clarity are compromised. YOLOv5 architecture consists of:

- CSP-Darknet as the feature extraction backbone
- PANet for feature aggregation
- PANet for feature aggregation
- Head layers for classification and bounding box regression

This robust architecture makes YOLOv5 able to identify number plates successfully even during visibility loss, changing lighting, or part occlusion scenarios as shown in Fig 3.6.

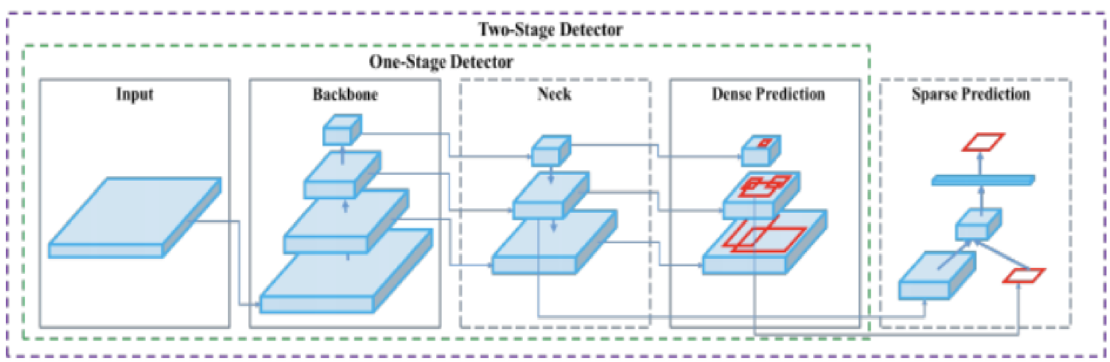

Fig 3.6 Working Architecture of YOLOv5 [15]

To train YOLOv5, we employ an image set of cars delineated with a box around a license plate as shown in Fig 3.7. They are annotated in the YOLO style (class, x-center, y-center, width, height) normalized relative to image size and save in .xml file.

Fig 3.7 Bounding Box around Number plate

Training is reduced to tuning model weights to optimize a combination loss function made up of as shown in equation 3.5:

- Bounding box regression loss
- Objectness loss (binary cross-entropy)
- Classification loss

$$\text{Total Loss} = \lambda_1 L_{\text{box}} + \lambda_2 L_{\text{obj}} + \lambda_3 L_{\text{cls}}$$

Eq 3.5

Where λ values are scaling weights for each component.

- Image enhancement using SRCNN

Once YOLOv5 recognizes the license plate, region cropping is done for improvement with Super-Resolution Convolutional Neural Network (SRCNN)[18] for transition. Since the plate will be blurry due to fog, low light, and sensor deterioration, direct OCR does not improve well. SRCNN is used to restore high frequency details and refine edges for character observation with higher clarity.

SRCNN is a shallow network consisting of three layers:

1. Patch extraction layer

$$\text{Applies } f_1(x) = \max(0, W_1 * x + b_1)$$

Eq 3.6

Extract overlapping patches and convert in high dimensional space

2. Nonlinear mapping layer

$$\text{Applies } f_2(x) = \max(0, W_2 * f_1(x) + b_2)$$

Eq 3.7

Map patches feature from low resolution to high resolution

3. Reconstruction Layer

$$\text{Applies } f_3(x) = W_3 * f_2(x) + b_3$$

Eq 3.8

Reconstruct final high-resolution image from mapped feature

The network is trained to minimize the **Mean Squared Error (MSE)** between the ground truth high-resolution image Y from reconstruct image Y'.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widehat{Y_i}\right)^2$$

Eq 3.9

SRCNN's improvement phase renders hitherto illegible, obscured characters readable, particularly under environmental conditions such as grime or fog. The model is compact, which implies that the process does not slow down and can be applied in real-time systems.

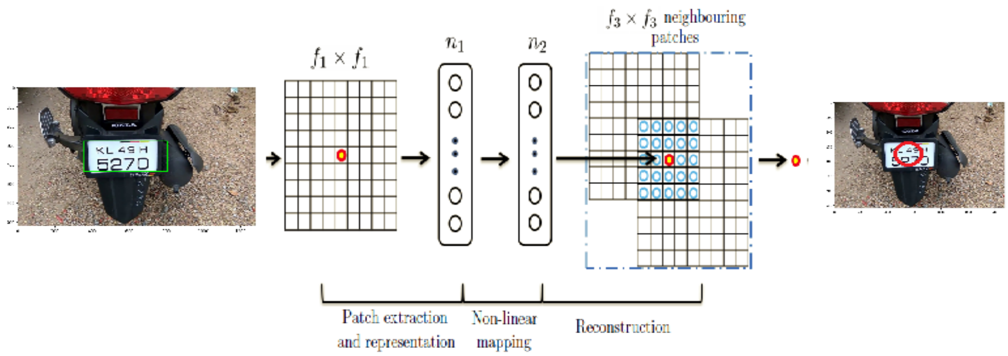

Fig 3.8 Working Architecture of SRCNN

➢ Character recognition Using Tesseract

After the license plate area has been super-resolved, it is then forwarded to Tesseract OCR for recognition of text. Tesseract is open-source OCR software developed by Google that is capable of reading many languages as well as alphanumeric pattern recognition.

Tesseract uses a Recurrent Neural Network (RNN) based on an LSTM architecture, which is particularly well suited for sequence prediction such as text. The segmented one character at a time is worked through and compared against a bank of trained characters with probability scoring.

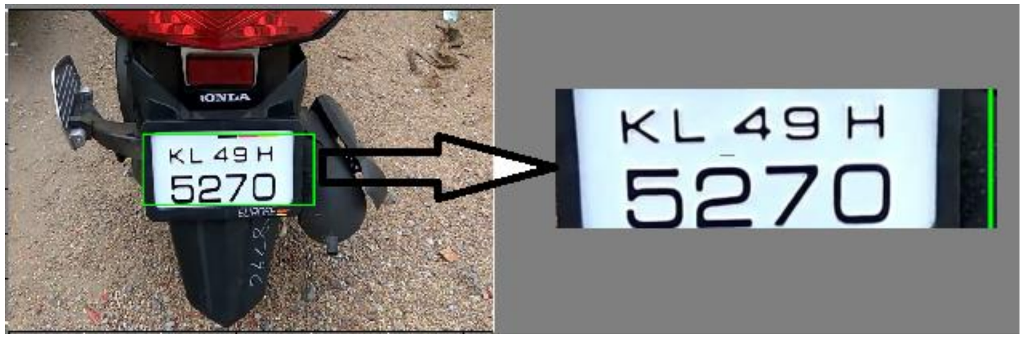

Fig 3.9 Extraction of character from Number plate through OCR

CHAPTER 4

EXPERIMENTAL SETUP

In this chapter we will discuss the requirements of different tools, library, framework that has been used while developing the project.

Jupyter Notebook: It is used for a wide variety of tasks of data science, including exploratory data analysis (EDA), data wrangling (cleansing) and transformation, data visualization, predictive modelling, machine learning, and deep learning.

- Pandas: It is a Python toolkit for working with data collections. It includes functions for analysing, wrangling, cleansing, and modifying data. The word "Pandas" refers to both "Panel Data".

- Matplotlib: Matplotlib is a comprehensive Python package that permits you to create static and interactive visualizations. Matplotlib allows for both easy and difficult tasks. It helps us create plots that are suitable for visualization. It helps us create reciprocal figures that can zoom, pan, and update.

- Seaborn: It is a Python package for plotting statistical graphs. It is built atop of matplotlib and combines seamlessly with Pandas data structures.

- Scikit-learn: It is one of the most helpful machine learning libraries in Python. The sklearn package includes several beneficial methods for machine learning and statistical modelling, like classification, regression, clustering, and dimensionality reduction.

- TensorFlow: It is an open-source library created by Google, mainly used for deep learning applications. It also reinforces conventional machine learning. It was primarily built for huge numerical computations without taking deep learning into consideration.

Fig 4.1 IoT tools for capturing Data

CHAPTER 5

DISCUSSION AND ANALYSIS

In this section we will show the result we have obtained after model training based on YOLOv5. We have provided input after processing from DCP network. The detected image passed from SRCNN network so that it would enhance the image resolution.

5.1 Detected number plate

After the YOLOv5 model was trained on a confiscated batch of car images number plates marked for 50 epochs, the model was upgraded. The new test scored a mean Average Precision (mAP@0.5) of 95.6% with a good ratio of recall and precision. The model effectively located and detected number plates under varied conditions like foggy environments, angles, and partial coverages. The bounding boxes were precise and well aligned with real plate areas. The model achieved very good generalization to new test images, substantiating its robustness and consistency to actual number plate localization in real-world conditions**.**

The image below with fig 5.1 ,5.2, 5.3 shows the number plate detection after trained from YOLOv5 model.

Fig 5.1 Sample 1 for plate detection

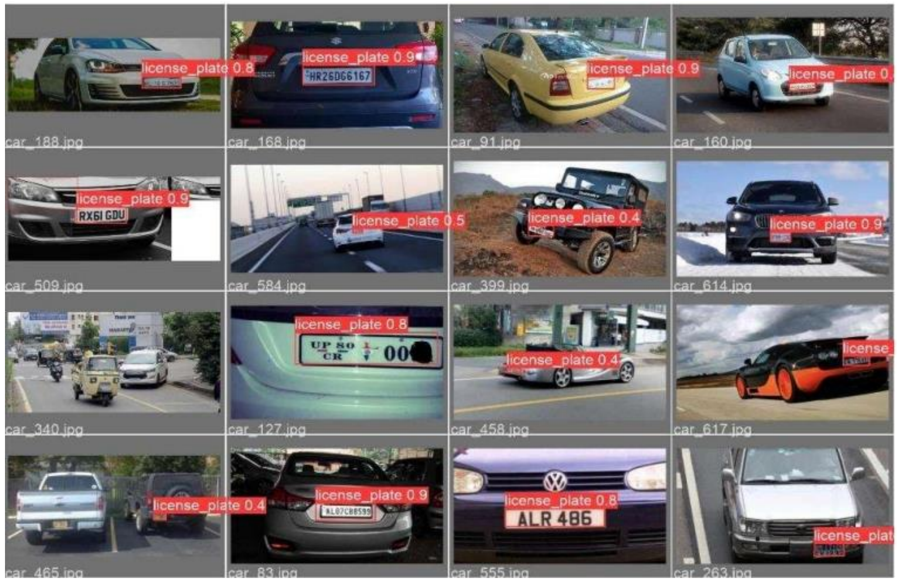

Fig 5.2 Combined sample test image for detected plate

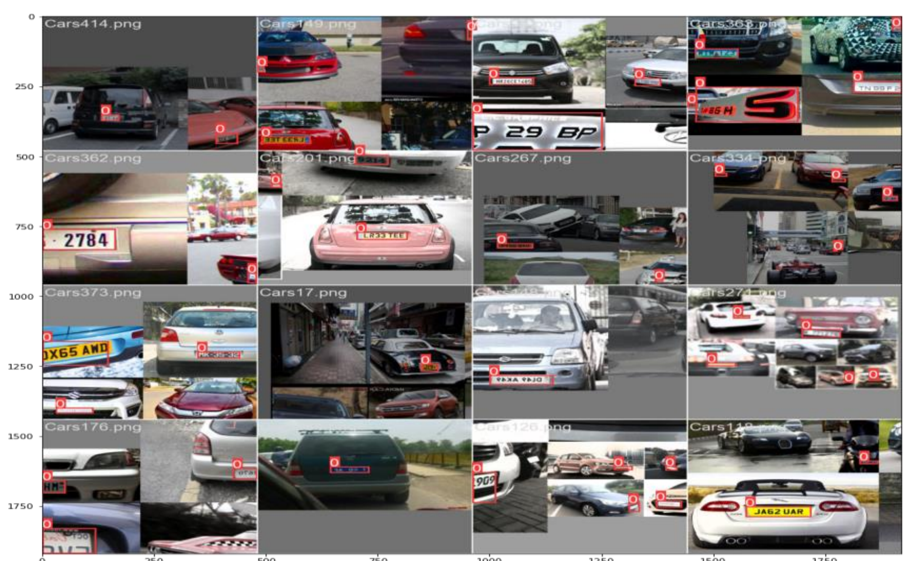

Fig 5.3 combined-2 sample test image for detected plate

5.2 Performance analysis

The below image shows the following at 20 epochs (Fig 5.4):

- Training **and validation losses** are consistently decreasing.
- Precision **and recall** are both high (>0.95).
- mAP@0.5 is excellent (~0.975), and **mAP@0.5:0.95** (~0.65) indicates decent localization quality.
- Model **shows no overfitting or underfitting** during these epochs.

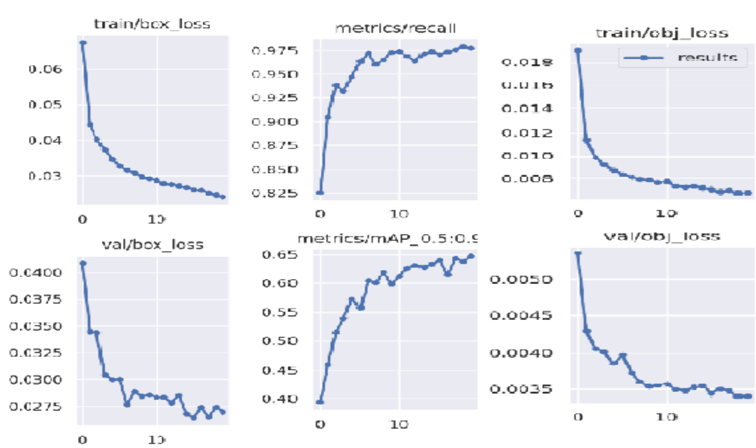

Fig 5.4 Analysis of model performance at 20 epochs

The below image shows the following at 50 epochs(Fig 5.5):

- The YOLOv5 model is learning well (all training and validation losses are decreasing).

- There is **no sign of overfitting** (validation metrics improve consistently).
- The model reaches **high precision and recall (~1.0)**.

- **mAP@0.5 > 0.95** and **mAP@0.5:0.95 ~ 0.68**, which is very good for practical applications like license plate detection.

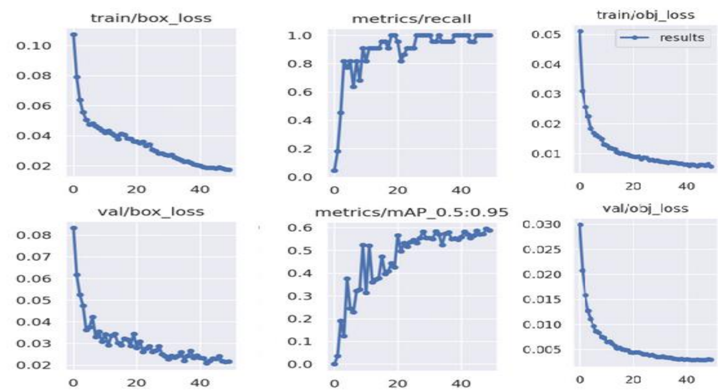

Fig 5.5 Analysis of model performance at 50 epochs

YOLOv5 model has better performance in car number plate detection. Objectness and box losses decrease over time, showing proper learning and generalization. Classification loss is constant since it's a one-class problem. Precision and recall grow very fast and approach 1.0, showing exact and perfect detection. The mAP@0.5 is more than 0.95, which shows high detection accuracy, while mAP@0.5:0.95 levels off at 0.65–0.70, which confirms correct localization for different IoU thresholds. In general, the model is consistent in spotting license plates even in adverse weather conditions and thus can be applied in real-time traffic monitoring and automatic surveillance systems.

CHAPTER 6

CONCLUSION & FUTURE WORK

This paper presented a strong deep learning-based approach of automatic number plate detection and recognition under very foggy weather conditions. The architecture was utilized with four steps: Dark Channel Prior (DCP) preprocessing, YOLOv5 detection, SRCNN enhancement, and Tesseract OCR recognition. Each step was selected to address some low-visibility conditions' problems such as image deterioration, low contrast, and poor edge definition.

The YOLOv5 model performed well in license plate detection. With steady decrease in training loss and validation loss and precision (≈1.0) values, recall (≈1.0) values, and mAP@0.5 values (>0.95), the model was accurate and efficient. The precision-confidence curve also supported the correctness of predictions at high precision = 0.909. The SRCNN module improved the visual quality of cropped number plate regions, making the previously unreadable characters readable to be recognized. Tesseract OCR successfully pulled textual data from the enhanced plates, thereby finishing the end-to-end pipeline.

The entire system is running smoothly even during days with fog, breaking vision boundaries and improving real-time plate recognition. Its combination of dehazing, object detection, super-resolution, and OCR illustrates the efficiency in adopting legacy image processing methods with state-of-the-art deep learning models.

➢ Future scope

While the existing system provides a high level of accuracy and generalizability, the following areas of improvement and extension are available for future work:

- Multi-Language and Regional Plate Recognition-

  The Tesseract (default OCR engine) works well for alphanumeric plates but can be optimized for multi-language or regional plate types (e.g., Chinese, Arabic, or ornamented fonts). Adding a more sophisticated or specialized

OCR engine with training from varied data sets may provide higher recognition rates.

- End-to-End Deep Learning Approach-

  Future works can try out end-to-end models which consolidate detection, enhancement, and recognition into a one-pipe setup. YOLOv8 (with OCR support) or transformer-based models may assist in reducing latency with utmost consistency among modules.

- Weather-Adaptive Detection Systems-

  The system is now optimized to work in fog. The directions for the future can involve training under various weather conditions like rain, snow, and night by utilizing the integration of weather classifying modules and adaptive preprocessing pipelines.

- Real-Time Embedded Deployment-

  Hosting the system on edge devices (e.g., Raspberry Pi, NVIDIA Jetson) would support real-time computation for smart city solutions. Quantization, model pruning, or applying small variants of YOLO (e.g., YOLOv5n or YOLOv7-tiny) can be utilized to reduce the system in order to make it leaner and deployable.

- License Plate Forgery Detection-

  Future work can also include enhancing security by detecting spoofed or tampered license plates using adversarial detection models or image integrity tests.

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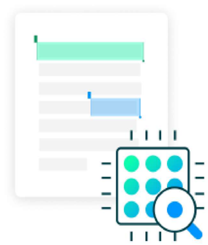

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Title of Paper: Vehicle Number Plate Detection and Identification System: A Review

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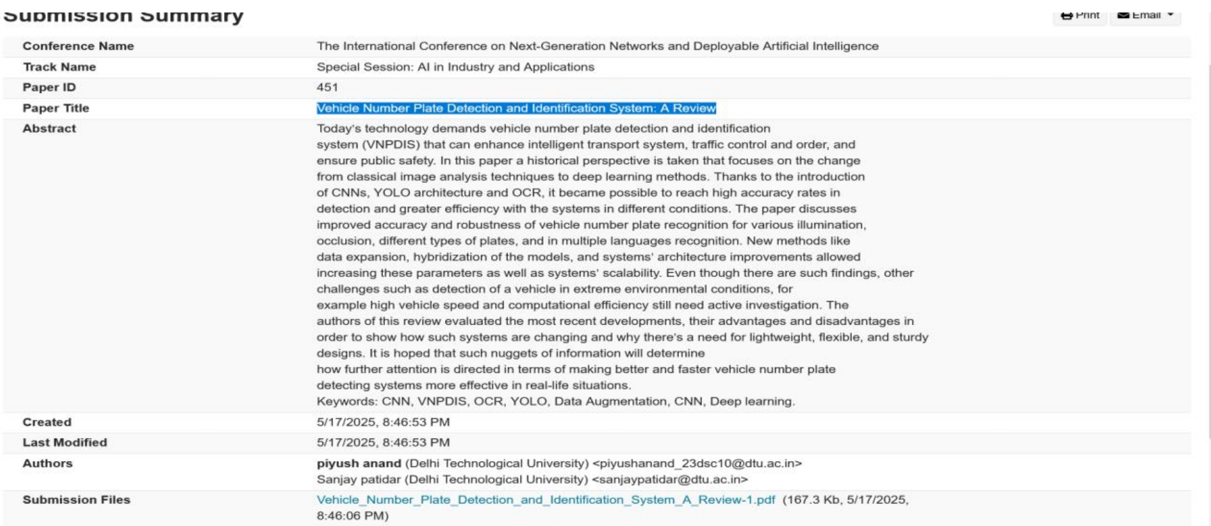

Submission Summary

Conference Name	The International Conference on Next-Generation Networks and Deployable Artificial Intelligence
Track Name	Special Session: AI in Industry and Applications
Paper ID	451
Paper Title	Vehicle Number Plate Detection and Identification System: A Review
Abstract	Today's technology demands vehicle number plate detection and identification system (VNPDIS) that can enhance intelligent transport system, traffic control and order, and ensure public safety. In this paper a historical perspective is taken that focuses on the change from classical image analysis techniques to deep learning methods. Thanks to the introduction of CNNs, YOLO architecture and OCR, it became possible to reach high accuracy rates in detection and greater efficiency with the systems in different conditions. The paper discusses improved accuracy and robustness of vehicle number plate recognition for various illumination, occlusion, different types of plates, and in multiple languages recognition. New methods like data expansion, hybridization of the models, and systems' architecture improvements allowed increasing these parameters as well as systems' scalability. Even though there are such findings, other challenges such as detection of a vehicle in extreme environmental conditions, for example high vehicle speed and computational efficiency still need active investigation. The authors of this review evaluated the most recent developments, their advantages and disadvantages in order to show how such systems are changing and why there's a need for lightweight, flexible, and sturdy designs. It is hoped that such nuggets of information will determine how further attention is directed in terms of making better and faster vehicle number plate detecting systems more effective in real-life situations. Keywords: CNN, VNPDIS, OCR, YOLO, Data Augmentation, CNN, Deep learning.
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Authors	**piyush anand** (Delhi Technological University) <piyushanand_23dsc10@dtu.ac.in> Sanjay patidar (Delhi Technological University) <sanjaypatidar@dtu.ac.in>
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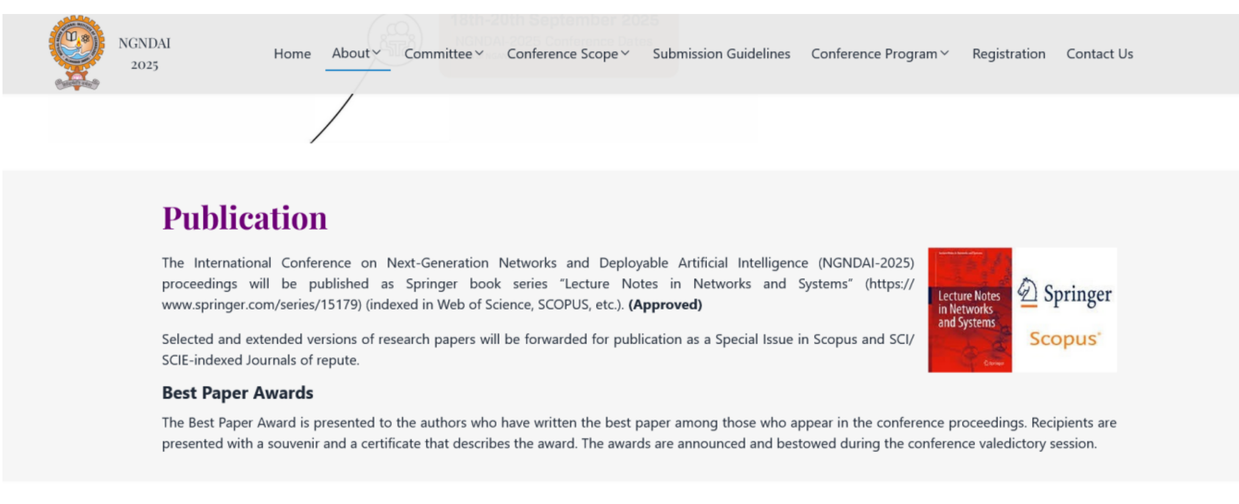

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Title of Paper: Development and analysis of Vehicle number plate detection system in Foggy condition

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Conference Name	The International Conference on Next-Generation Networks and Deployable Artificial Intelligence
Track Name	Special Session: AI in Industry and Applications
Paper ID	455
Paper Title	Development and analysis of Vehicle number plate detection system in Foggy condition
Abstract	Number plate recognition of automobiles is a crucial aspect in smart transport systems supporting automatic vehicle tracking and identification. License plate recognition during foggy and hazy weather conditions, however, still poses a challenge due to visibility issues and fuzzy image features. The objective of this research is to suggest an in-real-time number plate recognition system by deep learning for identification under adverse weather conditions with datasets collected using IoT devices. The proposed approach is three-pronged: image dehazing via dark channel prior algorithm for enhancement as step one, license plate detection through a CNN-based object detection model, and recognition of characters using Optical Character Recognition (OCR) techniques with super-resolution enhancement. Although in this instance the IoT system is not being created, for simulation of real-world conditions, the research utilized IoT-source image databases. Experimental results show that high identification rates were achieved even in heavy haze and fog by the proposed approach, which attests to its effectiveness under adverse weather conditions and future implementation in smart surveillance systems. The technique is a low-cost, flexible method that can be trained and tuned for many real-time traffic and security tasks, particularly in areas most affected by poor weather. In addition, the method reduces reliance on human observation, maximizes operational effectiveness, and can be adapted to existing traffic infrastructure with minimal change. Its flexibility also makes it possible to be coupled with cloud-based solutions for continuous learning and remote monitoring to ensure maximum long-term system performance and responsiveness. The accuracy of the model at 20 Epochs is 93% and with trained on 50 epochs it reached to 96%.
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