Vehicle insurance checking using ML algorithm

Ambika.B[1], Amith Alfred[2]
[1]*Assistant Professor, Department of MCA, Guru Nanak Dev Engineering College Bidar, India*
[2]*Department of MCA, Guru Nanak Dev Engineering College Bidar, India*

***Abstract*—Managing traffic rule compliance has become increasingly challenging for authorities due to rapid population growth and the surge in vehicular movement. Traditional methods of penalizing traffic violators rely heavily on manual intervention, which is both time-consuming and disruptive to efficient transportation flow. This paper introduces an innovative approach for automating E-challan generation by leveraging Automatic Number Plate Recognition (ANPR) technology. The system employs strategically mounted ANPR-enabled cameras in conjunction with CCTV infrastructure, utilizing advanced image processing and Optical Character Recognition (OCR) techniques to promptly identify vehicles involved in violations by extracting their registration details. This automated framework aims to reduce dependence on manual labor while significantly improving the precision and efficiency of traffic law enforcement.**

***Index Terms*—Automated E-Challan Generation, Automatic Number Plate Recognition (ANPR), Traffic Violation Detection, Image Processing Techniques, Optical Character Recognition (OCR)**

I. INTRODUCTION

The rapid rise in population has led to a corresponding surge in vehicular traffic, intensifying the need for robust mechanisms to monitor and manage traffic rule violations. These infractions span a broad spectrum, including red light jumping, non-compliance with seat belt and helmet mandates, speeding, lack of valid insurance, vehicle fitness and pollution certification issues, and absence of proper driving credentials. To counter the increasing neglect of traffic norms, the concept of issuing challans has gained traction. Yet, enforcement agencies often struggle with tracking violations, identifying vehicle owners, and administering penalties efficiently. To overcome these hurdles, the deployment of an electronic challan system integrated with automatic number plate recognition (ANPR) offers a transformative solution. This intelligent system streamlines the detection and documentation of traffic offenses, while enabling violators to manage their penalties digitally via E-challan notifications**.**

1.1 System Overview:

- Cameras installed at strategic locations capture images of vehicles committing violations.
- The ANPR module processes these images to detect and segment license plate characters.
- The extracted plate number is cross-referenced with a centralized vehicle registration database.
- Upon successful identification, a digital challan is generated and dispatched via SMS to the mobile number linked to the vehicle's registration.

This real-time, automated approach ensures accurate identification of offending vehicles and facilitates prompt issuance of challans. It significantly reduces manual workload for traffic personnel, enhances the efficiency of challan management, and strengthens the enforcement of road safety regulations.

II. LITERATURE SURVEY

[1] This study introduces a novel framework for identifying permit number plates through the application of the ResNet-based Convolutional Neural Network (CNN). The proposed system showcases high precision in extracting vehicle registration details and retrieving ownership data from localized databases. Notably, it maintains reliable performance even when vehicles are in motion at speeds up to 10 km/h. The research places significant emphasis on character recognition—a critical component with substantial scope for advancement, particularly in the context of data-driven traffic analytics and intelligent transportation systems.

[2] This research addresses the growing concern of traffic law violations, highlighting how negligent and

indifferent behavior among drivers undermines societal discipline. Despite notable advancements in traffic regulations, the reliance on manual enforcement continues to hinder the system's effectiveness, often resulting in delayed or inaccurate issuance of both paper-based and electronic challans. The proposed solution automates the identification of traffic violators through integrated object detection and tracking techniques. Upon detecting and extracting license plate data, the system retrieves vehicle details directly from the Regional Transport Office (RTO). Offenders are then promptly notified via Email and SMS on the same day the violation is recorded. This automation significantly enhances the system's precision, operational speed, and minimizes human error.

[3] The foundation of this proposed Automatic Number Plate Recognition (ANPR) system lies in advanced image processing techniques. Designed primarily for traffic surveillance, the system facilitates the detection of vehicles involved in violations such as speeding and improper lane usage at signalized intersections. By enabling real-time tracking of vehicles and reporting infractions to relevant authorities, the system aims to promote smoother traffic flow and reduce the likelihood of accidents at junctions. Additionally, it offers utility in identifying stolen vehicles. The operational workflow involves detecting rule-breaking vehicles, capturing their images, and isolating the license plate region using image segmentation methods. For character extraction and recognition, the system employs optical character recognition (OCR) techniques to accurately interpret the alphanumeric content of the plates.

[4] This study focuses on enhancing the precision of bounding boxes generated during object detection in images. Leveraging YOLOv3—a state-of-the-art, real-time object detection framework—the proposed approach refines the accuracy of object localization. By integrating edge detection techniques, analyzing pixel intensity within localized regions, and utilizing the pretrained COCO dataset, the system significantly improves the delineation of object boundaries. Compared to the baseline YOLOv3 model, the enhanced method demonstrates superior performance in bounding box precision, contributing to more reliable object recognition outcomes.

[5] This research proposes a fully automated pipeline for end-to-end detection of illegal parking incidents. The system employs YOLOv3, a deep learning-based object detection framework, to achieve rapid and robust vehicle recognition. To monitor vehicle immobility, movement tracking is implemented using template matching and Intersection over Union (IoU) metrics, allowing the system to determine the duration of parking violations with built-in error tolerance. License plate extraction is performed using OpenALPR, ensuring reliable identification of offending vehicles. Empirical evaluations reveal high accuracy in both vehicle detection and movement tracking across diverse environmental conditions, while license plate recognition consistently delivers strong performance.

[6] Rather than merely cataloging prior works, this study presents a structured framework for image segmentation, organizing existing techniques into four distinct categories.

- Classical Segmentation (Dissection-Based): This traditional approach involves dividing the input image into smaller subregions, which are then classified individually. The process, referred to as *dissection*, aims to isolate distinct, classifiable components within the image.
- Window-Based or Implicit Segmentation: In contrast to dissection, these methods either explicitly segment the image by classifying predefined windows or implicitly segment it by analyzing spatial subsets derived from the entire image. These techniques bypass the need for breaking the image into discrete parts.
- Hybrid Segmentation: This third category integrates both dissection and classification. It uses classification to constrain the set of viable segmentation outcomes, while still applying dissection and recombination to define meaningful image regions.

This taxonomy provides a comprehensive lens through which segmentation strategies can be evaluated and optimized for specific computer vision tasks.

[7] This study presents an enhanced license plate recognition technique that leverages a trained neural network dataset focused on object features. A hybrid recognition algorithm is introduced to improve accuracy, with the proposed method benchmarked

against existing approaches. The system architecture is organized into three core modules: License Plate Localization**,** Character Segmentation**, and** Character Recognition**.** Evaluation was conducted on a dataset comprising 300 license plate images from both domestic and international sources. The results affirm the system's effectiveness in meeting the fundamental requirements of accurate and reliable license plate recognition.

[8] This research emphasizes the role of Automated Number Plate Recognition (ANPR) systems in mitigating traffic congestion and curbing various traffic violations. The technology is particularly effective in identifying unregistered or stolen vehicles through automated license plate detection. The study explores multiple existing algorithms for number plate recognition and introduces a novel approach aimed at enhancing detection accuracy. A concise comparative analysis of these algorithms is presented, accompanied by graphical illustrations that clarify the operational flow of the proposed method. The paper concludes with experimental evaluations and performance assessments, validating the effectiveness of the new algorithm.

[9] This research emphasizes the role of Automated Number Plate Recognition (ANPR) systems in mitigating traffic congestion and curbing various traffic violations. The technology is particularly effective in identifying unregistered or stolen vehicles through automated license plate detection. The study explores multiple existing algorithms for number plate recognition and introduces a novel approach aimed at enhancing detection accuracy. A concise comparative analysis of these algorithms is presented, accompanied by graphical illustrations that clarify the operational flow of the proposed method. The paper concludes with experimental evaluations and performance assessments, validating the effectiveness of the new algorithm.

[10] The proposed system, referred to as *Unicam*, integrates advanced machine vision technologies to develop an automated video-based vehicle detection platform tailored for traffic monitoring applications. It supports real-time video and image capture, compression, digital signal processing, and data transmission through network interfaces. Leveraging specialized artificial intelligence and custom image processing modules, the system achieves highly accurate vehicle detection. Its core functionalities include monitoring speeding, red light violations, traffic data collection, and surveillance. Additionally, the system extends its utility to license plate recognition for transportation surveys, stolen vehicle tracking, and toll tag data acquisition. The integration of camera sensors with dedicated real-time processing units and networking capabilities enhances its operational efficiency. The study also explores hardware design components, networking architecture, and video detection algorithms that contribute to the system's robust performance.

III. PROPOSED SYSTEM

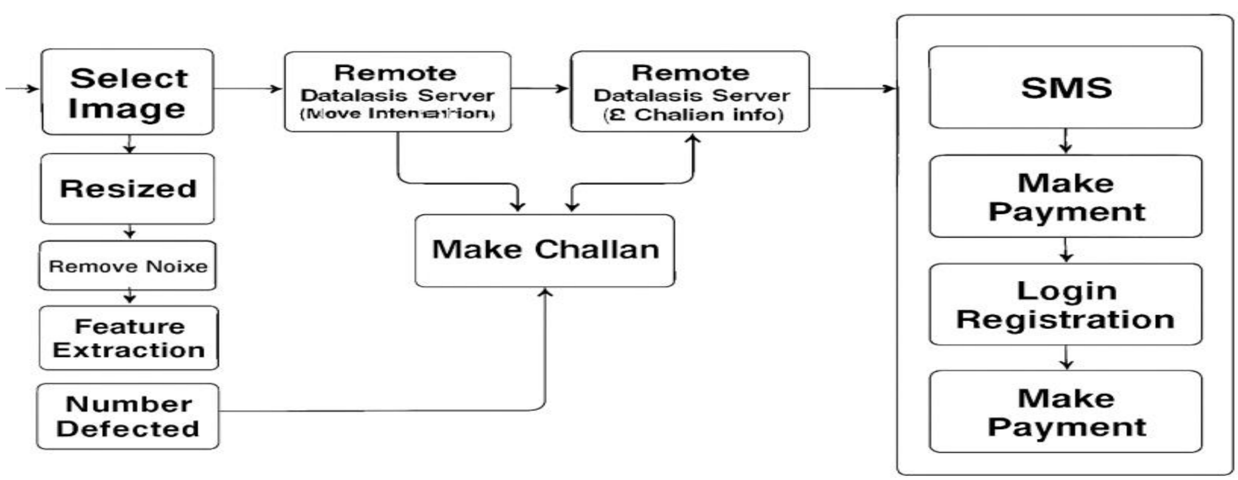

Figure 3.1: Architecture of proposed work.

- Input Image Upload: This stage involves uploading the number plate image that will be used for further analysis.
- Image Pre-processing: Before feature extraction, the image undergoes several pre-processing techniques such as converting it to grayscale and filtering out noise to enhance clarity.
- Grayscale Conversion**:** A grayscale image represents each pixel with a single intensity value, ranging from 0 (black) to 255 (white), including varying shades of gray in between. This simplifies the image while retaining essential structural details.
- Noise Reduction: This step focuses on minimizing or eliminating irrelevant visual data—commonly referred to as noise—to improve image quality and ensure accurate feature detection.
- Feature Extraction: Key visual characteristics are extracted from the image by analyzing pixel-level data. These features are essential for identifying and interpreting the number plate content.

Figure 3.2: Multi-View License Plate Detection with Pop-Up Confirmation in ANPR System

Here's a rewritten version of the two sections with improved clarity and originality, suitable for academic documentation:

- Challan Maker Module: The Challan Maker component employs Optical Character Recognition (OCR) to extract alphanumeric characters from vehicle license plates. Once extracted, these characters are cross-referenced with a centralized database to retrieve corresponding vehicle and owner details. After validating the retrieved information, the system proceeds to generate a digital challan for the identified traffic violation.
- Desktop Application Interface: Users interact with the system through a dedicated desktop application. New users must first register by creating an account. Upon successful registration, they can log in to access a personalized dashboard. Within this dashboard, users can locate their issued challans by entering their username and proceed to make payments directly through the integrated payment portal.

IV. ALGORITHM

4.1. Optical Character Recognition (OCR)

Optical Character Recognition (OCR), often referred to as text recognition, is a technology designed to extract and digitize textual content from scanned documents, camera-captured images, and image-based PDFs. By detecting individual characters within an image, OCR systems reconstruct words and sentences, making the original content accessible for editing and reuse. This automation significantly reduces the need for manual data entry. OCR solutions typically combine hardware and software components. Hardware such as optical scanners or dedicated circuit boards captures the physical text, while software performs the complex task of interpreting and converting it into machine-readable format. Modern OCR systems increasingly incorporate artificial intelligence (AI) to enhance recognition capabilities. Through intelligent character recognition (ICR), these systems can adapt to various languages, fonts, and even styles of handwriting.

4.2. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a highly effective deep learning architecture widely used for image analysis and pattern recognition tasks. It operates through a layered structure, primarily composed of a feature extraction stage and a feature mapping stage. In the feature extraction stage, neurons are connected to localized regions—known as receptive fields—within the preceding layer. This localized connectivity enables the network to detect spatially relevant features, preserving the positional relationships among elements in the input image.

The feature mapping stage consists of multiple layers, each containing several feature maps. A feature map is a two-dimensional grid where all neurons share identical weights, allowing consistent detection of specific patterns across the image. Activation functions, such as the sigmoid function, introduce non-linearity and help the network learn complex transformations. The shared weights across neurons in a feature map significantly reduce the number of trainable parameters, enhancing computational efficiency. Each Convolutional layer is typically followed by a sub sampling or pooling layer, which performs operations like local averaging or max pooling. This secondary feature extraction step reduces the spatial resolution of the input, helping the network focus on the most salient features while minimizing computational load.

4.3. The Convolution Layer

The convolution layer serves as the foundational component of a Convolutional Neural Network (CNN), responsible for the initial phase of feature extraction from input images—such as leaf imagery in agricultural applications. It operates by applying a set of learnable filters (kernels) across localized regions of the image, enabling the network to capture essential visual patterns. Through this Convolutional operation, the layer analyzes small patches of pixel data to identify features like edges, textures, and contours. Depending on the filter used, the layer can perform various image transformations, including edge detection, sharpening, and blurring. Common filters include the identity filter, edge detection kernel, sharpening filter, box blur, and Gaussian blur, each contributing to the enhancement or suppression of specific image characteristics. This localized feature extraction is critical for enabling deeper layers of the network to build hierarchical representations of the input, ultimately supporting tasks such as classification, segmentation, or object detection.

4.4. Pooling Layers

Pooling layers are integral to reducing computational complexity in CNNs, especially when processing high-resolution images. Spatial pooling—also referred to as sub sampling or down sampling—compresses the dimensions of each feature map while preserving the most salient information. This dimensionality reduction helps prevent over fitting and improves the model's efficiency.

4.5. Fully Connected Layer

Following the Convolutional and pooling stages, the fully connected layer transforms the reduced feature maps into a one-dimensional vector (e.g., x1,x2,x3,…x_1, x_2, x_3, \ldots). These vectorized features are then combined and processed to form a predictive model capable of interpreting the input data. This layer plays a crucial role in learning complex patterns and relationships for tasks such as classification.

4.6. Softmax Classifier

To finalize the prediction process, activation functions like softmax or sigmoid are applied to the output layer. The softmax classifier is particularly effective for multi-class classification problems, such as identifying specific leaf diseases. It converts the model's raw output scores into probability distributions, allowing the system to assign the input to the most likely category based on the learned features.

V. SYSTEM DESIGN

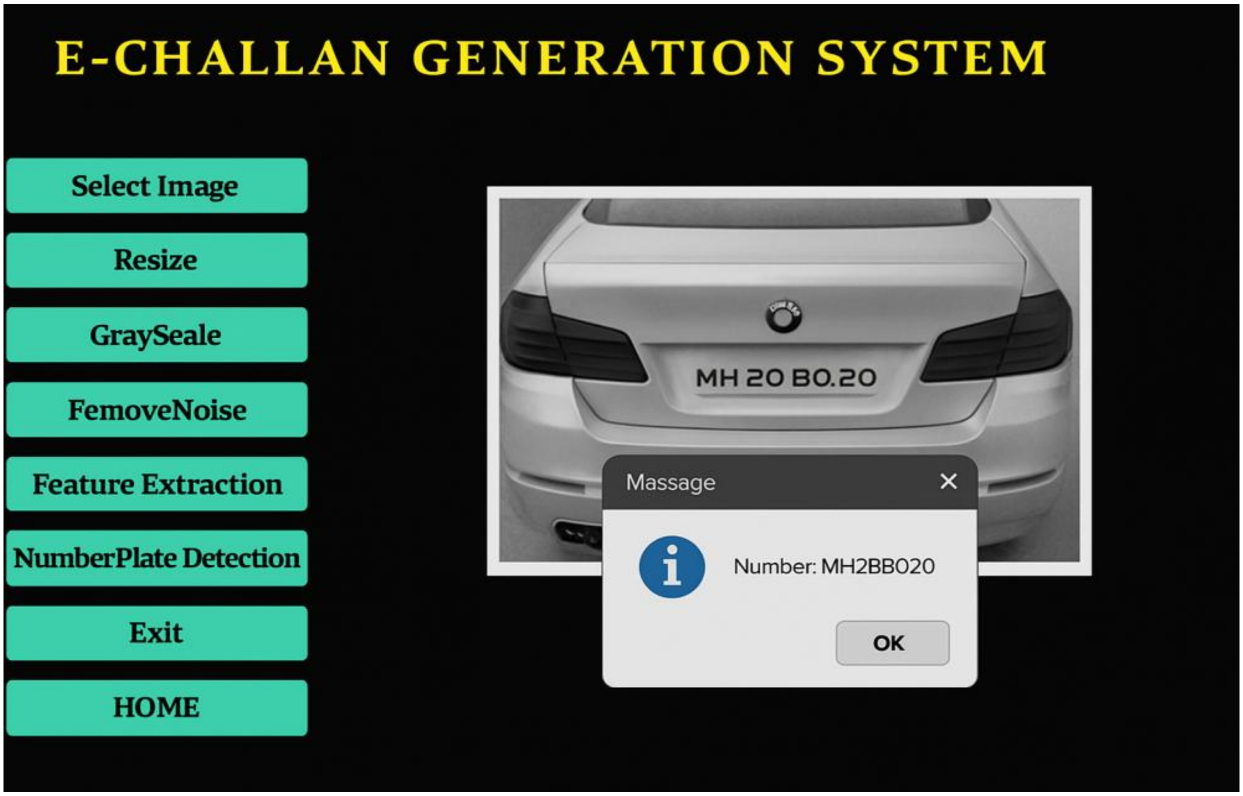

Figure 5.1: E-Challan System Interface with Number Plate Detection

Field	Information
Input File	6.png
User Name	Pranaav Chaudhari
Resized File Path	`C:\Users\pranav chaudhari\Desktop\newworkspace\Challan\src\com\project\images\resi`
Owner Name	Shambhavi Surve
Mobile Number	9989097736
Message Status	Message sent successfully to +91 98890 97736

Figure 5.2: File and Message Transmission Details

Table 5.1: Traffic E-Challan Notification Details

Field	Details
Recipient Name	Shambhavi Surve
Vehicle Number	MH20BQ20
Offense Type	Overspeeding
Date & Time of Offense	11-05-2023 12:27:43
Fine Amount	₹300
Payment Deadline	Within 15 days of receipt
Consequences of Non-Payment	Further penalties and legal action
Payment Link	https://rzp.io/l/qqO2T7zp
Message Source	Sent from Twilio trial account

VI. RESULTS AND DISCUSSIONS

This section presents the overall accuracy achieved by the CNN-based classification technique, demonstrating its superior performance in leaf disease prediction compared to previously established methods.

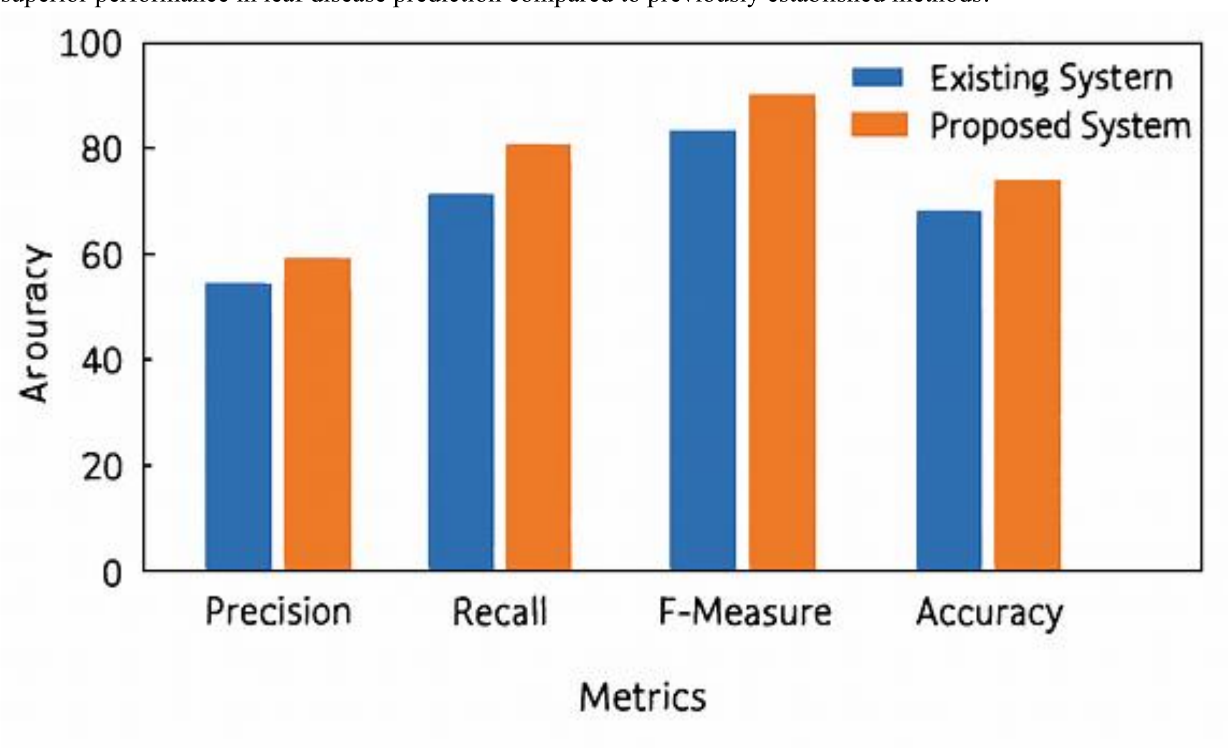

Figure 6.1: CNN-Classification accuracy graph.

Table 6.1: *Performance Metrics Comparison between Existing System and Proposed CNN-based ANPR Model*

	Existing System	Proposed System(CNN)
Precision	60.6	52.70
Recall	75.1	87.64
F-Measure	68.8	74.31
Accuracy	78.29	86.26

VII. CONCLUSION

Law enforcement, toll collection, vehicle theft detection, traffic regulation, road safety, security and surveillance, as well as traffic management and monitoring, can all benefit substantially from the proposed system. A key advantage lies in its ability to automate and streamline traditionally manual tasks performed by authorities, thereby expediting the inspection and verification of vehicle details. This enhanced efficiency directly contributes to more effective and timely management of traffic challans.

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