RANI CHANNAMMA UNIVERSITY, BELAGAVI

DEPARTMENT OF COMPUTER SCIENCE

20MCAPJ4.2: Project Report on

“HSRP Number Plate Detection Using Machine Learning”

Submitted By

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MCA IV Sem

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October, 2024

RANI CHANNAMMA UNIVERSITY, BELAGAVI

DEPARTMENT OF COMPUTER SCIENCE

CERTIFICATE

This is to certify that the project entitled **“HSRP Number Plate Detection Using Machine Learning”** is a bonafide work carried by **Mr. Pramod Malgonda Patil, Reg.No: P15ZZ22S126015,** as a part of Project Work in fulfilment of the completion of MCA **IV Semester (Computer Science)** course during the year 2023-2024.

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TO WHOMSOEVER IT MAY CONCERN

A student of **Rani Channamma University Belagavi,** has successfully completed his internship from 1st June 2024 to 30th Sep 2024 at **"Infynow Software Solutions LLP",** under the careful guidance of Mr. Karthik H. (CTO) and team.

Mr. Pramod Malgonda Patil was able to successfully participate in and accomplish all of the tasks required for the project entitled **Web Application Development** through which he was able to showcase his great work and team player skills.

We at Infynow Software Solutions LLP have thoroughly enjoyed having him as an intern and we wish him all the best in his future endeavors.

For Infynow Software Solutions LLP,

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Managing Director

DECLARATION

I, Pramod Malgonda Patil hereby declare that this dissertation entitled **"HSRP Number Plate Detection Using Machine Learning "** is independently carried under the guidance of **Prof. Shivanand S. Gornale,** Professor, Department of Computer Science, Rani Channamma University, Belagavi, in partial fulfilment of the Degree of **Master of Computer Application** (**MCA**), during academic year 2023-2024.

I also declare that, I have not submitted this dissertation to any other university for award of any degree.

Date:

Place: Belagavi **Pramod Patil**

ACKNOWLEDGEMENT

The satisfaction that accompanies the successful completion of any task would be incomplete without the mention of the people who made it possible and the whose constant guidance and encouragement crown all the efforts with success.

Firstly, I thank **Dr. Parashuram Bannigidad**, Chairman & Professor, Department of Computer Science, Rani Channamma University, Belagavi, for giving me his consent to undertake this project.

My sincere thanks to project guide **Prof. Shivanand S. Gornale**, Professor, Department of Computer Science Rani Channamma University, Belagavi, who has continuously helped and gave valuable suggestions, his advice and support to guide us in the successful completion of the project work.

Besides project guide, I would like to thanks **Mrs. Amruta Unki** and **Mrs. Priyanka Kamat,** Research Scholars, Department of Computer Science, Rani Channamma University, Belagavi, for their motivation and timely support.

Finally, I would like to accolade my family, friends and other staff for their constant support guidance and encouragement during project report time.

ABSTRACT

The High-Security Registration Plate (HSRP) number plate detection using Machine Learning (ML) aims to automate the identification and verification process of vehicles through their number plates. This system employs ML algorithms to accurately detect and recognize HSRPs, enhancing security measures in traffic monitoring and law enforcement. By leveraging computer vision and machine learning techniques, the system extracts key features from vehicle images, enabling efficient detection and classification of HSRPs even in varying lighting and weather conditions. Additionally, the integration of ML models with existing surveillance systems facilitates seamless data collection and analysis, empowering authorities to detect and respond to security threats in real-time. This innovative approach not only streamlines the vehicle identification process but also contributes to the overall safety and security of roadways.

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CHAPTER 1
INTODUCTION

The HSRP number plate recognition which utilizing machine learning and image processing techniques. The HSRP (High-Security Registration Plate) Number Plate Detection project automates the identification and validation of vehicle number plates. This project's main goal is to make sure that cars have HSRP installed, as required by law of increased security. When vehicle is detected whether HSRP number plate or not then the system will notify the appropriate notify to relevant stakeholders such as the RTO (Regional Transport Office), admin, and the user.

By utilizing advanced image processing methods and pattern recognition algorithms, machine learning (ML) shows promise as a solution to these problems. Using enormous datasets of car photos to train machine learning models, these algorithms are capable of accurately identifying and categorizing HSRPs, even amid partially obscured or crowded surroundings. Additionally, the flexibility of ML algorithms enables constant development and improvement, guaranteeing reliable performance in a variety of situations.

1.1 Objectives

- Create a strong machine learning model for HSRP number plate identification and detection.
- Implement a scalable system capable of real-time processing for various traffic scenarios.
- Ensure the system handles errors gracefully and recovers properly.
- Provide timely notifications to RTO, admin, and users
- Improve compliance with HSRP regulations

1.2 Motivation

- HSRP plates are designed to prevent vehicle theft and fraud by incorporating tamper-evident features. Detecting these plates ensures vehicle authenticity and security.
- Automatic detection of HSRP plates can assist law enforcement agencies in identifying vehicles, tracking stolen cars, and enforcing traffic rules more effectively.

- Implementing automated HSRP detection systems reduces manual inspection efforts at checkpoints and parking facilities, allowing for faster processing and integration into smart traffic management systems.
- The project can help ensure vehicles comply with government regulations, as HSRP plates are mandatory in many countries to improve road safety and standardization.
- Automating number plate detection reduces human errors in reading and interpreting plates, ensuring better accuracy and efficiency.
- HSRP number plate detection can contribute to smart city infrastructure by enhancing automated surveillance systems and vehicle tracking for improved urban mobility.

1.3 Types of Number Plates

1.3.1 Non HSRP Number Plate

Non-HSRP is unregulated, lacks security features, and is customizable but less secure. Non-HSRP plates do not have security features like laser-etched codes or snap locks, they can be easily tampered with or forged.

Figure 1: Non HSRP Number Plate

1.3.2 HSRP Number Plate

HSRPs are made to be hard to copy or change, and they are intended to be tamper-proof. This lessens the chance of car fraud and theft.

Each HSRP has a unique identifying wide variety that is laser-etched on it, enabling tracking.

Figure 2: HSRP Number Plate

1.4 Problem Statement

The primary objective of this project is to design and implement an intelligent system that can automatically detect and recognize High-Security Registration Plates (HSRP) from vehicle images or live video feeds using machine learning techniques. Given the critical role of HSRP plates in vehicle identification and security, the system must demonstrate high accuracy and robustness under a wide range of environmental conditions, including varying lighting (day/night), weather (rain, fog), and angles (oblique views, different camera positions). The system is expected to overcome several key challenges inherent in real-world scenarios, such as dealing with low-resolution or blurred images, obstructions that partially occlude the plate, and reflective surfaces that can distort the appearance of the characters.

In addition to addressing environmental challenges, the system must handle variations in plate design and security features like holograms, watermarks, and fonts unique to HSRP plates. One of the primary difficulties lies in isolating the Region of Interest (ROI)—the number plate—from a noisy background, which may include other vehicles, pedestrians, and infrastructure. Furthermore, after localizing the plate, the system needs to segment the alphanumeric characters accurately, which can be impacted by issues like overlapping characters, varying font sizes, and plate damage.

Moreover, the system must be designed for scalability and efficiency, allowing for real-time detection in high-traffic environments or surveillance systems where quick identification is crucial. Another challenge is ensuring that the machine learning models generalize well across different types of cameras, resolutions, and image qualities without requiring extensive manual intervention. This involves training robust classifiers capable of recognizing alphanumeric characters under these diverse conditions while minimizing false positives and negatives. Ultimately, the system should be adaptable for integration with broader vehicle monitoring applications, such as automated toll collection, parking management, and law enforcement, making it a versatile tool for modern traffic management systems.

CHAPTER 2

LITERATURE SURVEY

2.1 Paper Survey

The detection and recognition of High-Security Registration Plates (HSRP) using machine learning techniques have gained considerable momentum in the past five years, driven by advances in deep learning, especially Convolutional Neural Networks (CNNs). These models have proven to be effective in recognizing alphanumeric patterns and handling the complexities associated with HSRPs, such as varying fonts, designs, and security features. In 2019, Li et al. introduced the use of attention mechanisms in CNNs specifically for vehicle registration plate detection. By focusing the model's attention on key areas of the number plate, their method improved both the accuracy and interpretability of the results. This study was pivotal in addressing the challenges posed by complex HSRP designs, which often include holograms and watermarks. The attention-based approach allowed the model to ignore irrelevant background information and concentrate on the important details of the plates [1]. The issue of limited labeled data in the domain of HSRP detection was tackled by Uddin et al. in 2020, who employed transfer learning techniques. By fine-tuning pre-trained models on large-scale datasets and then adapting them to the specific task of HSRP recognition, they demonstrated significant improvements in both speed and accuracy. Their research also explored techniques such as data augmentation to enhance the generalization capability of the models when applied to different HSRP formats [2]. In 2021, Shah et al. introduced multi-resolution CNN architectures to improve the detection of HSRPs under diverse conditions, such as varying image resolutions, angles, and environmental factors. Their approach allowed the network to process images at multiple scales, thereby improving robustness, especially in real-world scenarios where plates may be captured from different angles or in low-light conditions. This method was especially useful for handling blurred or distorted images commonly encountered in surveillance footage [3]. In 2022, Patel and Rao developed a hybrid system combining CNNs with Optical Character Recognition (OCR) technology for the detection and recognition of HSRPs. Their approach leveraged CNNs to localize and detect the plate, while OCR was employed to read the alphanumeric characters on the plate. This integration resulted in more accurate detection and recognition of HSRPs, particularly in cases where the security features or fonts varied significantly [4]. Kumar et al. (2023) focused on overcoming the challenges posed by the lack of large-scale datasets for HSRP detection. Their research introduced novel data augmentation techniques and synthetic dataset generation, where artificially generated HSRP images were used to train CNN models. This approach not only expanded the dataset but also improved the model's ability to generalize across various plate styles and environments. Their findings highlighted the importance of dataset diversity in achieving high accuracy in real-world applications [5]. In 2024, Gupta and Singh explored the application of edge AI for real-time HSRP detection. Their study focused on deploying lightweight CNN models on edge devices such as cameras and mobile devices, enabling real-time processing of HSRP images. By optimizing the model for low-power devices, they made significant progress in ensuring fast and efficient detection without the need for heavy computational resources. This innovation is crucial for practical applications in traffic monitoring and law enforcement [6].

In this chapter High-Security Registration Plate (HSRP) detection and recognition has advanced dramatically in recent years, owing mostly to advances in machine learning and deep learning, namely Convolutional Neural Networks (CNNs). Early research aimed to improve model accuracy and handle complicated HSRP features such as variable fonts and security aspects. Li et al. (2019) used attention mechanisms to focus on crucial portions of the number plate, resulting in higher detection accuracy. Uddin et al. (2020) used transfer learning to overcome the difficulty of insufficient data, whereas Shah et al. (2021) created multi-resolution CNN architectures to improve performance under a variety of environmental situations. In 2022, Patel and Rao demonstrated that the coupling of CNNs with Optical Character Recognition (OCR) improved the precision of HSRP. Kumar et al. (2023) addressed dataset restrictions by generating synthetic data and increasing generalization across diverse plate types, while Gupta and Singh (2024) used edge AI to detect HSRP in real time and at low power. Collectively, this research highlight major advances in automating and improving HSRP identification, paving the path for real-world applications in traffic monitoring and enforcement systems.

CHAPTER 3

MATERIALS AND METHODOLOGY

3.1 Data Set Description

3.1.1 Number Plate Images

In this the dataset primarily consists of images of vehicle number plates which are real time images in various lighting and environmental conditions.It has 300 images of vehicle number plates which are some hsrp number plates and some are non hsrp number plates and these all images are captured by mobile phone camera. In this data set each images are labeled as either HSRP-Compliant or non compliant.In the collected data set out of 300 images 150 number plates are HSRP number plates and another 150 images are non Hsrp number plates with there vehicle registered email address.

3.1.2 Vehicle Information

Metadata associated with each image, including vehicle type, registration number, and owner details.

3.2 System Requirements

3.2.1 Hardware Requirements

Processer : Intel Atom or higher

Hard Disk : Min 500GB or More

Architecture : 64-bit

RAM : Min 4GB or More

CPU : 2GHZ or Faster

3.2.2 Software Requirements

Coding Language: HTML, CSS, Bootstrap and Python

Algorithms : Tensor flow

Library : Open CV

Code Editor : Visual Studio Code

3.3 Proposed and Existing System

3.3.1 Existing System

The current system relies heavily on manual verification methods, which are labour-intensive and error-prone. Although HSRPs offer increased security features, the lack of automated detection systems limits their effectiveness. Manual intervention also leads to delays in processing and increased chances of human error.

Additionally, there may be delays in identifying vehicles without HSRP, leading to potential security risks. The current system lacks automation and real-time notification features, making it inefficient for large-scale implementation

DISADVANTAGES OF EXISTING SYSTEM.

- Constant human mediation.
- High cost
- More Manpower is required

3.3.2 Proposed System

The proposed HSRP Number Plate Detection System will provide an efficient, automated solution for monitoring and enforcing the installation of HSRP on vehicles. The system will capture images of number plates using a camera, analyse the images using Machine Learning algorithms to detect the presence of an HSRP, and send notifications based on the results.

ADVANTAGES OF PROPOSED SYSTEM.

1 Computerized system requires less labour.
2 This system detects easily the number plate is HSRP or not.
3 The included number plate is naturally trimmed and shown separately.

3.4 Methodology Diagram

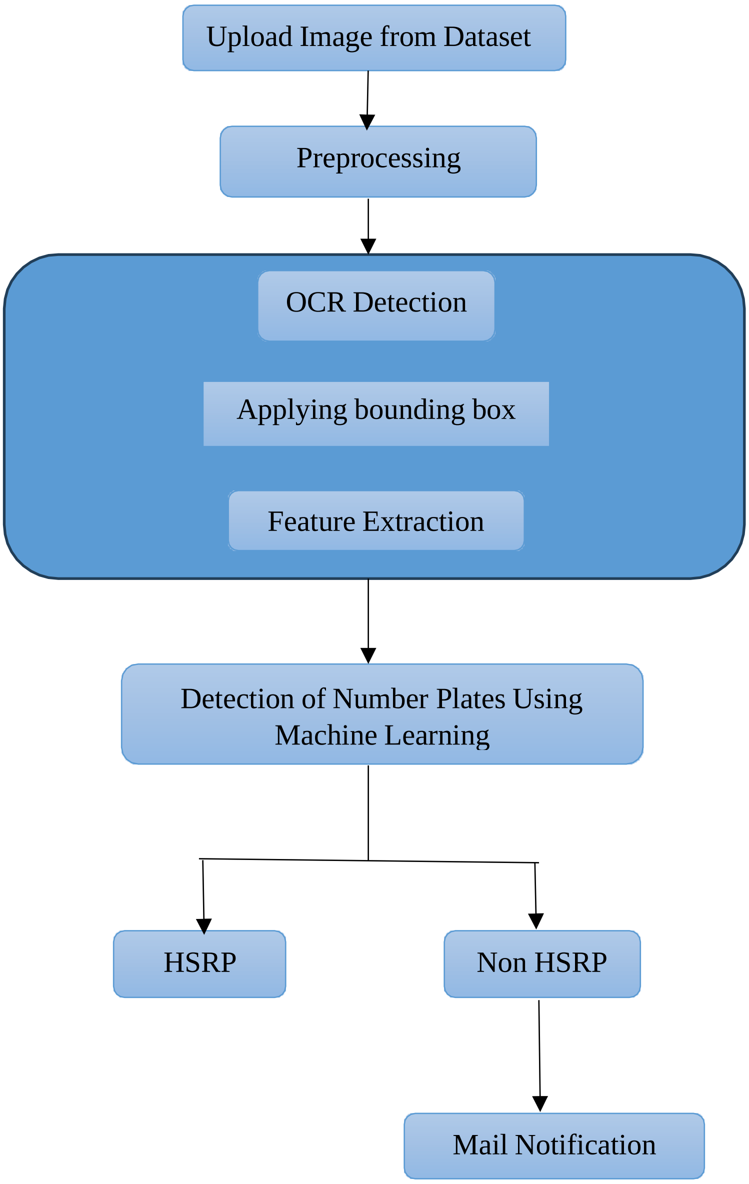

Figure 3: Proposed Methodology Diagram

1. Image Input (Vehicle Number Plate Image)

The process starts with capturing an image of the vehicle's number plate. This image serves as the raw input to the system. It could be acquired via a camera at checkpoints, parking areas, or toll booths. The image is then passed on to the next stage for further processing. At this point, the image contains all the details required for identification, but it is not yet usable by the machine learning model until it is pre-processed.

2.Preprocessing the Image

Once the image is captured, it undergoes preprocessing using OpenCV. This stage typically involves converting the image to grayscale, resizing, noise reduction, and enhancing the image for better recognition. Preprocessing is critical because it ensures the number plate features are clearly defined for both the OCR and the machine learning model. This step ensures consistency in the image quality and format, which boosts the accuracy of the detection system.

3.Machine Learning Classification (HSRP Detection)

After preprocessing, the image is fed into the trained machine learning model, which classifies the number plate as either HSRP or non-HSRP. The ML model, built using libraries such as TensorFlow or scikit-learn, has been trained on a dataset of HSRP and non-HSRP number plate images. It identifies patterns and features unique to HSRP plates, such as the reflective background, chromium hologram, and laser-etched code. If the number plate is classified as HSRP, the process ends here. If it is non-HSRP, the system proceeds to the next step.

4.OCR (Extracting Number from Plate)

If the plate is classified as non-HSRP, Tesseract OCR is used to extract the vehicle's registration number from the image. OCR (Optical Character Recognition) converts the image-based number into machine-readable text. This step is crucial for identifying the vehicle based on the extracted registration number, which will later be used to query the database.

5.Database Query (User Identification)

Once the number plate has been extracted, the system queries a database to retrieve the email address associated with that registration number. The database contains entries with number plates and corresponding user details, such as emails and other contact information. If the system finds a matching number plate in the database, it retrieves the user’s email address for further action.

6.Email Notification (Non-HSRP Alert)

If the vehicle is identified as having a non-HSRP plate, the system sends an email notification to the user. This is done using Python’s smtp lib or an external email service like SendGrid. The email informs the user that their vehicle does not have an HSRP-compliant number plate and may include instructions or regulatory information. The email is generated automatically, providing a seamless notification system to users, ensuring compliance with the latest vehicle number plate regulations.

7.End of Process

Once the email notification is sent, the process ends. The system has now identified a non-HSRP vehicle, extracted the number plate, queried the database for the owner's information, and sent the necessary notification.

3.4.1 METHODOLOGY ADOPTED

- **Segmentation of Predicted Regions**

In machine learning, the process of breaking an image up into meaningful sections or regions for in-depth examination is known as segmentation of expected regions. Segmentation is employed in the context of vehicle number plate detection to separate the area of the image containing the number plate from other unimportant parts. Techniques like thresholding, edge detection, and deep learning-based methods like K-Nearest Neighbours (KNN) can be used to do this. The model can concentrate on the number plate region for additional processing, like text extraction via OCR and classification (HSRP or non-HSRP), once the region has been precisely segmented. By focusing the machine learning model's predictions on the pertinent portion of the image, proper segmentation increases accuracy and lowers noise from surrounding objects.

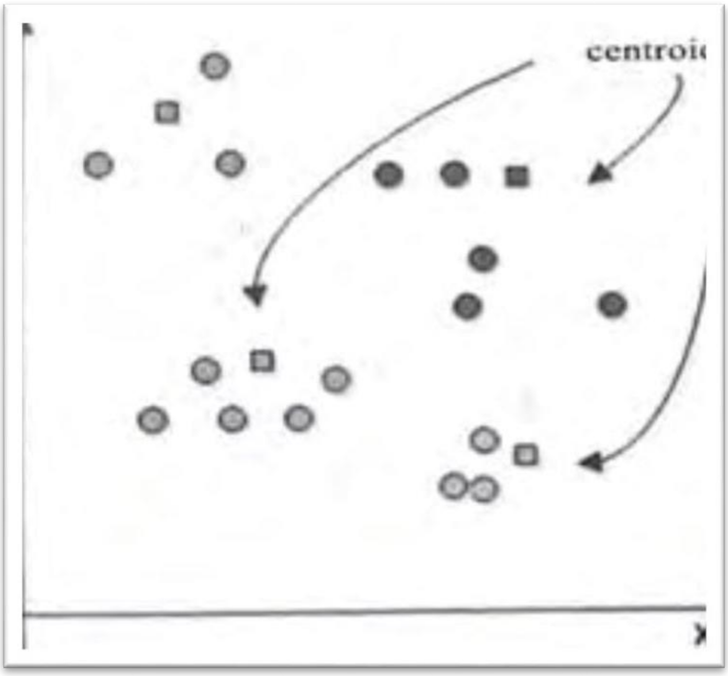

Figure 4: Segmentation of Predicted Regions

Obtaining a Single Bounded Box

Finding and drawing a rectangular border around the particular region of interest in an image—such as a car's license plate—is the first step in creating a single bounded box. This method is frequently applied to object detection tasks, in which the coordinates of the box enclosing the object are predicted by an algorithm, such as a K-Nearest Neighbours (KNN). Prior to detecting the car number plate, the algorithm analyses the image to identify edges and contours. It then determines the bounding box that encircles the number plate area securely. This bounded box is crucial because it keeps the area with the license plate separate, enabling other processes, such as text extraction or classification, to concentrate only on the pertinent part of the picture.

Figure 5: Obtaining a Single Bounded Box

- ## Segmentation of Predicted Regions

Predicted region segmentation entails breaking up an image into discrete, significant sections using the results of a machine learning model, paying particular attention to the areas that have pertinent items or attributes. Segmentation is used in car number plate detection to separate and pinpoint the precise region of the image containing the number plate. An object detection model that forecasts bounding boxes around possible number plate locations usually serves as the first step in this procedure. Machine learning-based approaches and thresholding are examples of segmentation techniques that improve these predictions by separating the license plate from other areas of the picture. After segmented, the areas are utilized for additional analysis, like optical character recognition (OCR) text extraction. Accurate segmentation ensures that subsequent steps, like classification and text extraction, are performed only on the relevant portion of the image, thereby improving the overall accuracy and efficiency of the detection system.

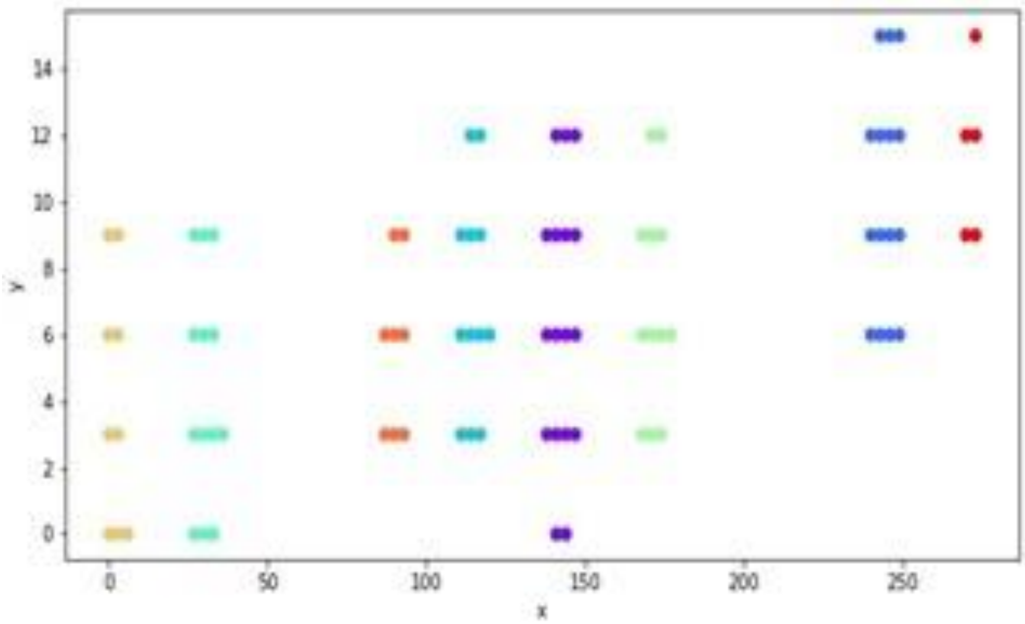

Figure 6: Segmentation of Predicted Regions

CHAPTER 4
OVERVIEW OF TECHNOLOGIES

4.1 Machine Learning

Machine learning is a subfield of computer science that originated from the study of pattern recognition and computational learning theory in artificial intelligence. Machine learning research focuses on developing and analysing algorithms that can learn from data and forecast future events. These algorithms work by building a model from sample inputs in order to generate data-driven predictions or judgments, as opposed to strictly adhering to static program instructions.

There are many parallels and similarities between machine learning and computational statistics, a science that similarly focuses on prediction. It shares many similarities with mathematical optimization, which gives the field its methodology, theoretical underpinnings, and application domains. Machine learning is utilized in many computing activities when it is impractical to build and write explicit methods. Examples of applications are spam filters. computer vision, search engines, and optical character recognition (OCR). Data mining and machine learning are occasionally confused, despite the latter's greater emphasis on exploratory data processing. Pattern recognition and machine learning "may be seen as two sides of the same field. Machine learning techniques may be referred to as predictive analytics or predictive modelling when used in industrial applications.

4.2 OCR (Optical Character Recognition)

Traditional OCR methods have been used extensively for character recognition in number plate detection. However, these methods may struggle with the varying conditions of number plates, such as different fonts, sizes, angles, and lighting conditions.

Optical Character Recognition (OCR) plays a crucial role in an HSRP (High-Security Registration Plate) number plate detection project as it is responsible for extracting the alphanumeric characters (vehicle registration details) from the detected number plates

After detecting the number plate, the characters (letters and numbers) on the plate need to be extracted and recognized.

4.3 PYTHON

Python plays a crucial role in enabling machine learning for detecting HSRP (High-Security Registration Plate) in vehicle number plates. Using libraries like TensorFlow or scikit-learn, Python allows you to train and deploy an ML model that classifies plates as HSRP or non-HSRP based on image features. Preprocessing with OpenCV ensures images are optimized for model input, improving classification accuracy. Post-classification, Tesseract OCR extracts the text from non-HSRP plates for further use, such as querying a database to retrieve user details. Python also integrates seamlessly with databases (e.g., via MySQL Connector) and automates notifications through email when a non-HSRP plate is detected. Thus, Python bridges the entire workflow—from image preprocessing and ML model predictions to post-processing, database interaction, and user notification.

CHAPTER 5
EXPRIMENTAL RESULTS

5.1 Plate Detection

In the final stage, the trained model is applied to new photos to detect vehicle number plates. This requires KNN to recognize and reliably localize number plates within images, derive bounding box coordinates, and read the text from these plates using Optical Character Recognition (OCR). The model also uses learnt features to determine whether the detected number plate is HSRP (High-Security Registration Plate) or non-HSRP. If the number plate is categorized as non-HSRP, the algorithm takes the details and searches a database for the relevant email address. An email is subsequently sent to the appropriate user with information about the number plate. The KNN technique includes detecting the number plate region using nearest neighbours, extracting bounding boxes, and extracting text using OCR. The model also uses classification to determine whether the number plate is HSRP or non-HSRP. If the number is not HSRP, it is retrieved and forwarded to the user via email with the required information. The accuracy of detection and classification, as well as the efficiency of email communication, demonstrate the system's usefulness.

5.2 Plate Information

Several critical steps are involved in extracting plate information from photos in order to effectively identify and process vehicle number plates. Once a number plate has been discovered and located using methods such as K-Nearest Neighbours (KNN), the text on the plate is read and extracted using Optical Character Recognition (OCR). The retrieved text is next evaluated to identify whether the plate is a high-security registration plate (HSRP) or not. This classification is critical for future processing. If the plate is identified as non-HSRP, the system retrieves the vehicle's registration number and compares it to a database to determine the associated user's email address. An email is then sent to the appropriate person, containing pertinent information or alerts about their number plate. This procedure provides correct identification and timely transmission based on identified plate information.

5.3 Images of Results

5.3.1 RTO SIGN IN PAGE

The RTO Sign in page is the system's entry point, where users securely provide their credentials—usually a mobile number and password. Robust encryption safeguards this information, and for added security, we may user two-factor authentication. It ensures a smooth, secure user experience while protecting sensitive cardiac data.

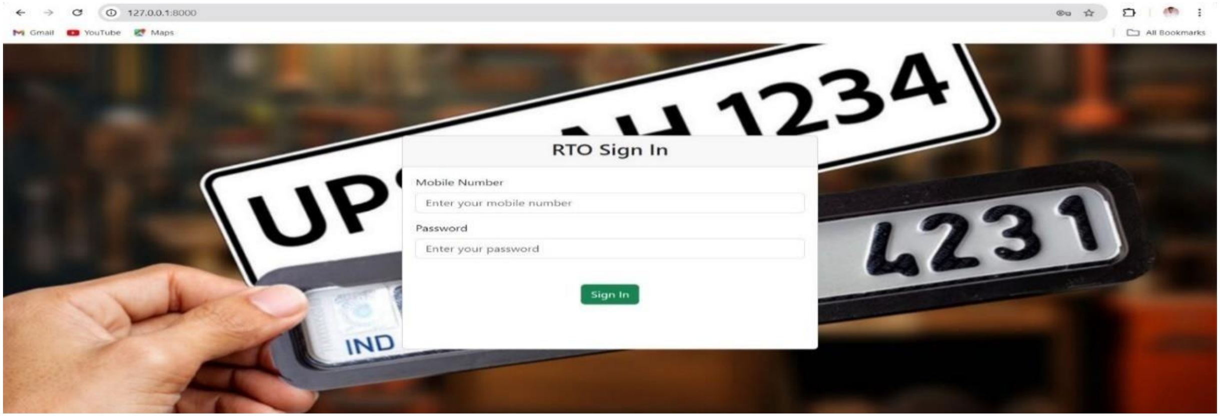

Figure 7: RTO Sign in Page

5.3.2 UPLOAD THE NUMBER PLATE IMAGE

The Upload image is where users can easily add their images to our system. It's like a virtual gallery where you can contribute your valuable number plate photos. Users simply select the images they want to upload from their devices for know the number plate is HSRP or NOT.

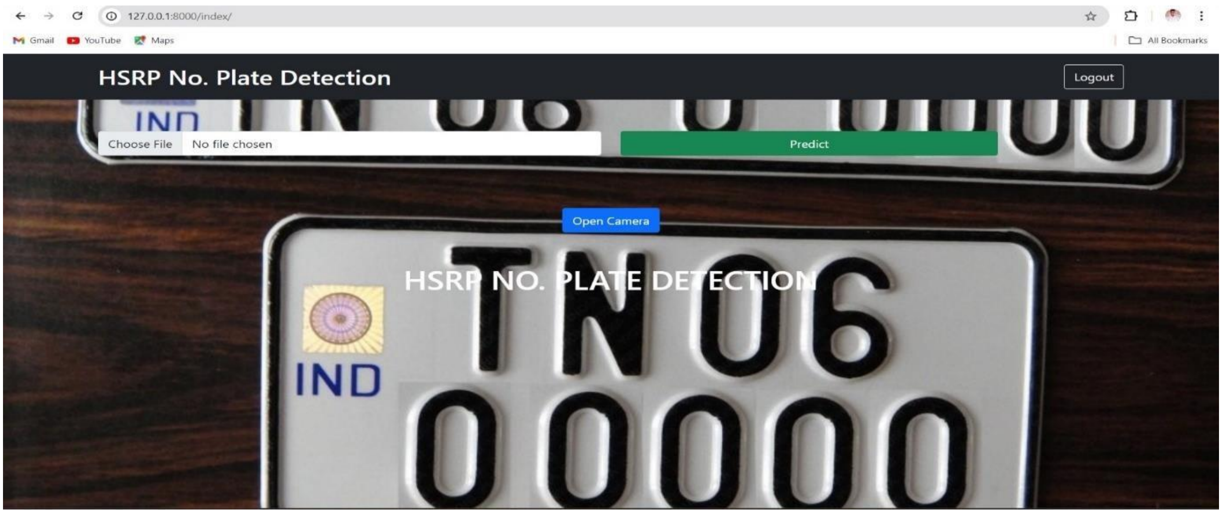

Figure 8: Upload the number plate images

5.3.3 UPLOAD NUMBERPLATE IMAGE USING CAMERA

The Upload image using the open camera button is where users can easily capture their number plate images to system. It's like a virtual gallery where you can contribute your valuable number plate photos. Users simply select the images they want to upload from their devices for know the number plate is HSRP or NOT.

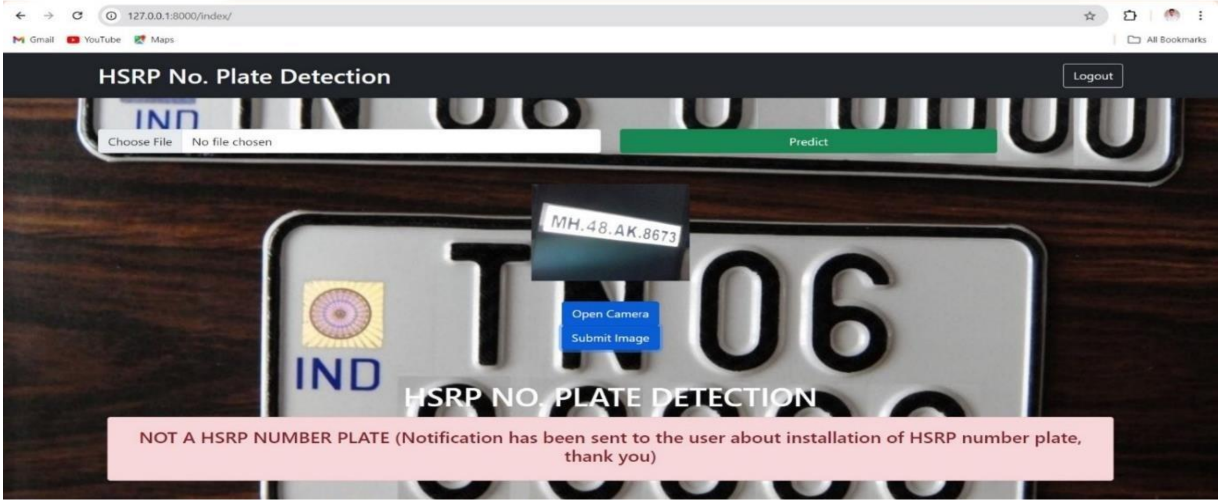

Figure 9: Upload the number plate image using camera

5.3.4 REGISTRATION OF USERES VEHICLE INFORMATION

In this RTO can register the information about the vehicle user and detect the number plate and give the result from registered vehicle information

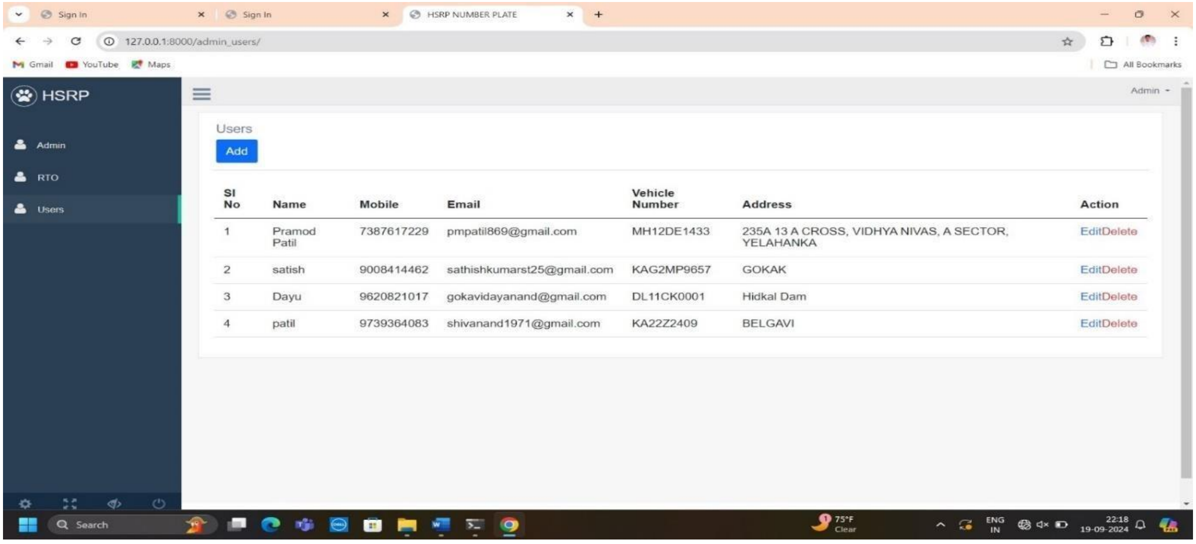

Figure 10: Registration of Users Vehicle Information

5.3.5 IDENTIFYING HSRP NUMBER PLATE

After detecting number plate, the uploaded images is hsrp then its give message like as below.

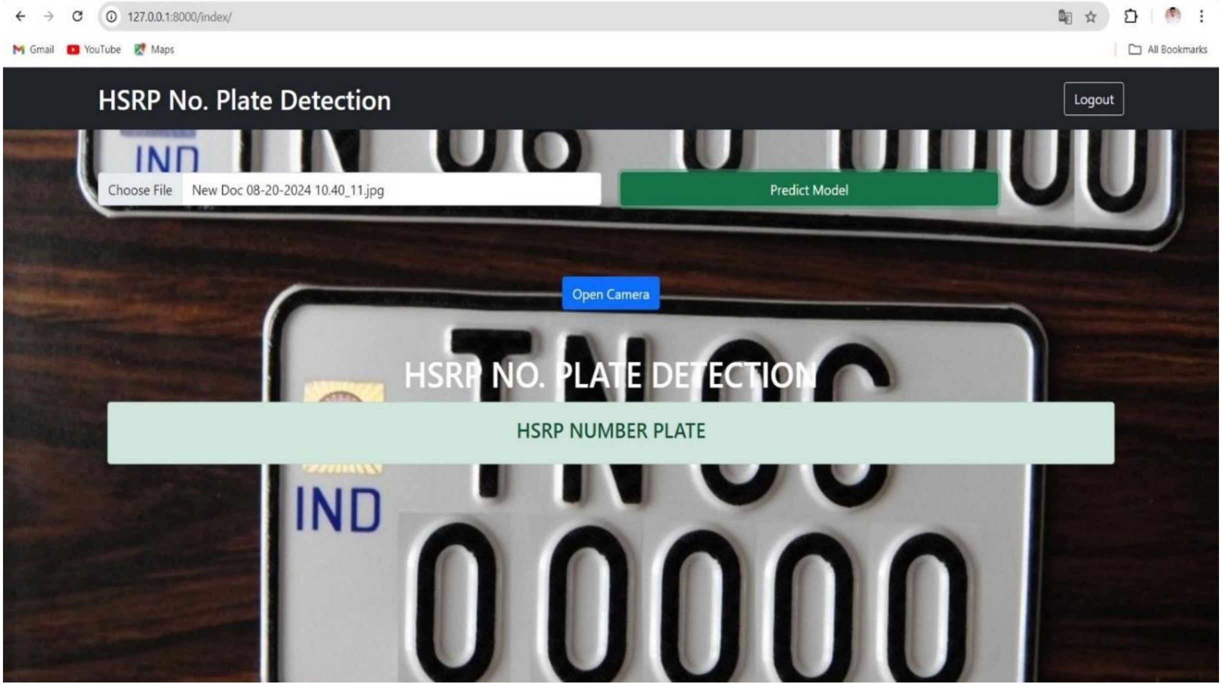

Figure 11: Identifying HSRP Number Plate

5.3.6 IDENTIFYING NOT HSRP NUMBER PLATE

After detecting number plate, the uploaded images is not HSRP then its give message like as below. And send mail to the registered vehicle owner email address.

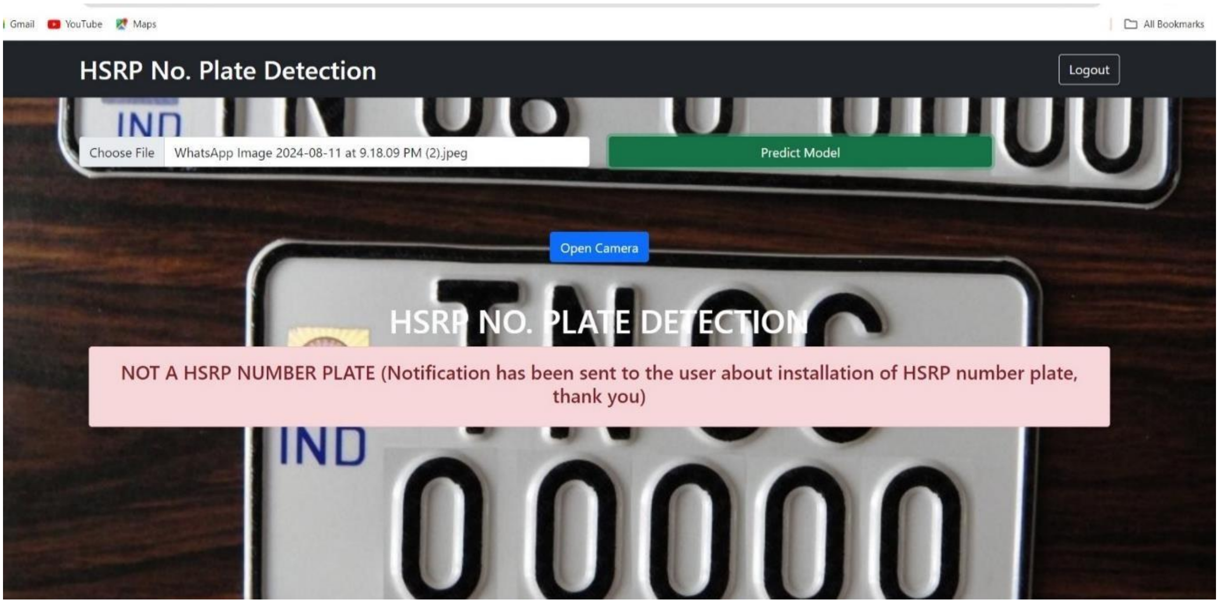

Figure 12: Identifying Not HSRP Number Plate

5.3.7 MAIL NOTIFICATION TO NOT HSRP VEHICLE OWNER AS OUTPUT

Sending mail to the vehicle owner whose number plate is not hsrp

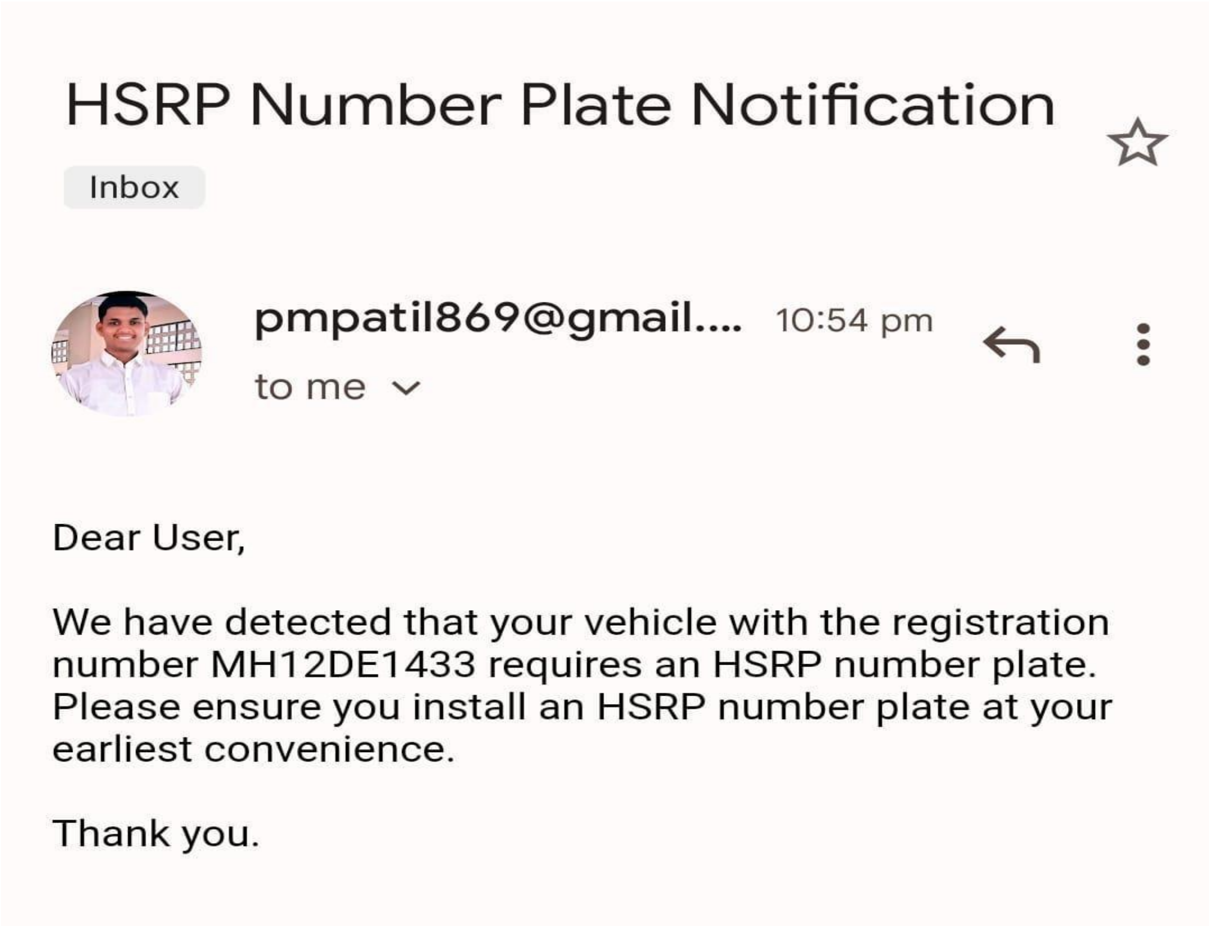

Figure 13: Send Mail Notification to Not HSRP Vehicle Owner as Output

CHAPTER 6
CONCLUSION AND FUTURE WORK

CONCLUSION

Vehicle number plate detection employing modern machine learning techniques such as K-Nearest Neighbors (KNN) offers a reliable and efficient solution for reliably detecting and processing vehicle plates. The system excels at feature extraction and classification thanks to machine learning capabilities, ensuring exact detection and text extraction. KNN provides a simplified, distance-based technique to feature classification that, while less sophisticated, accurately recognizes and locates number plates. The inclusion of Optical Character Recognition (OCR) improves the system's ability to read and interpret plate text. Furthermore, the system's capacity to classify plates as HSRP or non-HSRP and then send notices via email to non-HSRP plates adds substantial value by allowing for timely and relevant communication. Overall, this combination of methodologies provides a comprehensive, accurate, and practical solution for detecting and managing vehicle number plates.

FUTURE WORK

Future research in vehicle number plate detection can concentrate on improving the system's accuracy and adaptability by combining sophisticated approaches like Transfer Learning and attention mechanisms. Transfer Learning can use pre-trained models on large-scale datasets to improve detection performance while reducing training time. Integrating attention mechanisms could help the model focus on crucial portions of the number plate, increasing text extraction precision. Furthermore, enabling the system to accommodate a wider range of climatic conditions and plate designs by more extensive data augmentation and synthetic data synthesis can improve its robustness. Incorporating real-time processing capabilities, as well as creating a more intuitive user interface for improved interaction and feedback, could help to make the system more effective and usable. Investigating cross-modal data integration, such as merging visual data with contextual information from other sensors, may yield new insights and increase overall system reliability.

CHAPTER 7

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Paper/Submission ID	2362563
Submitted by	plagiarismrcub@gmail.com
Submission Date	2024-09-28 07:11:22
Total Pages, Total Words	23, 4212
Document type	Others

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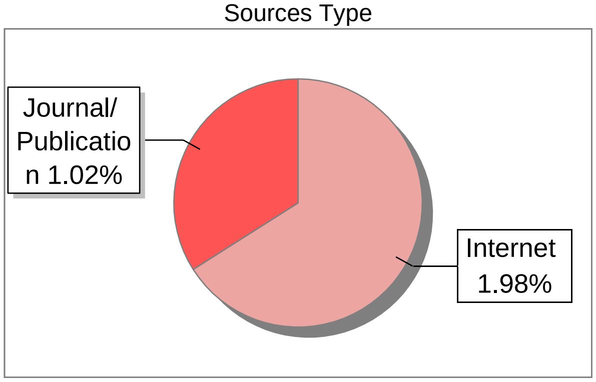

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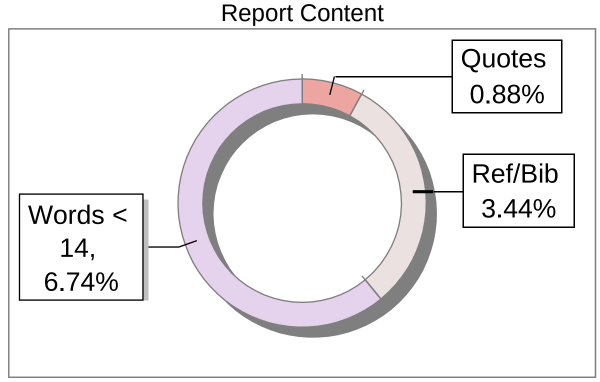

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International Journal of Research Publication and Reviews
(Open Access, Peer Reviewed, International Journal)
(A+ Grade, Impact Factor 6.844)
ISSN 2582-7421
Sr. No: IJRPR 120741-1

Certificate of Acceptance & Publication

This certificate is awarded to "Pramod M Patil", and certifies the acceptance for publication of research paper entitled "HSRP Number Plate Detection Using Machine Learning" in “International Journal of Research Publication and Reviews”, Volume 5, Issue 10 .

Signed Ashish Agarwal

Editor-in-Chief
International Journal of Research Publication and Reviews

Date 02-10-2024

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

HSRP Number Plate Detection Using Machine Learning

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A B S T R A C T

The High-Security Registration Plate (HSRP) number plate detection using Machine Learning (ML) aims to automate the identification and verification process of vehicles through their number plates. This system employs ML algorithms to accurately detect and recognize HSRPs, enhancing security measures in traffic monitoring and law enforcement. By leveraging computer vision and machine learning techniques, the system extracts key features from vehicle images, enabling efficient detection and classification of HSRPs even in varying lighting and weather conditions. Additionally, the integration of ML models with existing surveillance systems facilitates seamless data collection and analysis, empowering authorities to detect and respond to security threats in real-time. This innovative approach not only streamlines the vehicle identification process but also contributes to the overall safety and security of roadways.

Keywords: K-Nearest Neighbors (KNN), Number plate detection, Optical character recognition, HSRP.

1. Introduction

The HSRP number plate recognition which utilizing machine learning and image processing techniques. The HSRP (High-Security Registration Plate) Number Plate Detection project automates the identification and validation of vehicle number plates. This project's main goal is to make sure that cars have HSRP installed, as required by law of increased security. When vehicle is detected whether HSRP number plate or not then the system will notify the appropriate notify to relevant stakeholders such as the RTO (Regional Transport Office), admin, and the user.

By utilizing advanced image processing methods and pattern recognition algorithms, machine learning (ML) shows promise as a solution to these problems. Using enormous datasets of car photos to train machine learning models, these algorithms are capable of accurately identifying and categorizing HSRPs, even amid partially obscured or crowded surroundings. Additionally, the flexibility of ML algorithms enables constant development and improvement, guaranteeing reliable performance in a variety of situations.

2. Literature Survey

The detection and recognition of High-Security Registration Plates (HSRP) using machine learning techniques have gained considerable momentum in the past five years, driven by advances in deep learning, especially Convolutional Neural Networks (CNNs). These models have proven to be effective in recognizing alphanumeric patterns and handling the complexities associated with HSRPs, such as varying fonts, designs, and security features. In 2019, Li et al. introduced the use of attention mechanisms in CNNs specifically for vehicle registration plate detection. By focusing the model's attention on key areas of the number plate, their method improved both the accuracy and interpretability of the results. This study was pivotal in addressing the challenges posed by complex HSRP designs, which often include holograms and watermarks. The attention-based approach allowed the model to ignore irrelevant background information and concentrate on the important details of the plates [1]. The issue of limited labeled data in the domain of HSRP detection was tackled by Uddin et al. in 2020, who employed transfer learning techniques. By fine-tuning pre-trained models on large-scale datasets and then adapting them to the specific task of HSRP recognition, they demonstrated significant improvements in both speed and accuracy. Their research also explored techniques such as data augmentation to enhance the generalization capability of the models when applied to different HSRP formats [2]. In 2021, Shah et al. introduced multi-resolution CNN architectures to improve the detection of HSRPs under diverse conditions, such as varying image resolutions, angles, and environmental factors. Their approach allowed the network to process images at multiple scales, thereby improving robustness, especially in real-world scenarios where plates may be captured from different angles or in low-light conditions. This method was especially useful for handling blurred or distorted images commonly encountered in surveillance footage [3]. In 2022, Patel and Rao developed a hybrid system combining CNNs with Optical Character Recognition (OCR) technology for the detection and recognition of HSRPs. Their approach leveraged CNNs to localize and detect the plate, while OCR was employed to read the alphanumeric characters on the plate. This integration resulted in more accurate detection and recognition of HSRPs, particularly in cases where the security features or fonts varied significantly [4]. Kumar et al. (2023) focused on overcoming the challenges posed by the lack of large-scale datasets for HSRP detection. Their research introduced novel data augmentation techniques and synthetic dataset generation, where artificially generated HSRP images were used to train CNN models. This approach not only expanded the dataset but also improved the model's ability to generalize across various plate styles and environments. Their findings highlighted the importance of dataset diversity in achieving high accuracy in real-world applications [5]. In 2024, Gupta and Singh explored the application of edge AI for real-time HSRP detection. Their study focused on deploying lightweight CNN models on edge devices such as cameras and mobile devices, enabling real-time processing of HSRP images. By optimizing the model for low-power devices, they made significant progress in ensuring fast and efficient detection without the need for heavy computational resources.

In this chapter High-Security Registration Plate (HSRP) detection and recognition has advanced dramatically in recent years, owing mostly to advances in machine learning and deep learning, namely Convolutional Neural Networks (CNNs). Early research aimed to improve model accuracy and handle complicated HSRP features such as variable fonts and security aspects. Li et al. (2019) used attention mechanisms to focus on crucial portions of the number plate, resulting in higher detection accuracy. Uddin et al. (2020) used transfer learning to overcome the difficulty of insufficient data, whereas Shah et al. (2021) created multi-resolution CNN architectures to improve performance under a variety of environmental situations. In 2022, Patel and Rao demonstrated that the coupling of CNNs with Optical Character Recognition (OCR) improved the precision of HSRP. Kumar et al. (2023) addressed dataset restrictions by generating synthetic data and increasing generalization across diverse plate types, while Gupta and Singh (2024) used edge AI to detect HSRP in real time and at low power.

3. Proposed Methodology

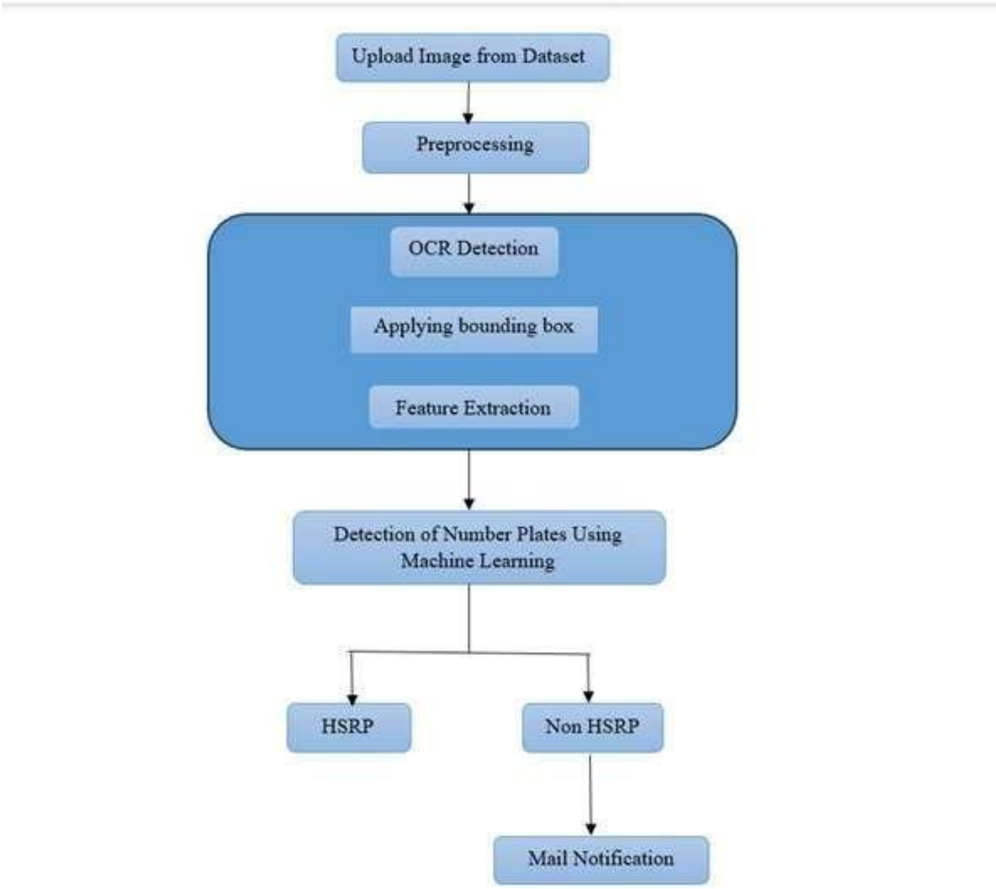

Figure 1: General architecture of the proposed work

The suggested process for HSRP Number Plate Detection using machine learning identification entails the following steps:

Image Input (Vehicle Number Plate Image)

The process starts with capturing an image of the vehicle's number plate. This image serves as the raw input to the system. I t could be acquired via a camera at checkpoints, parking areas, or toll booths. The image is then passed on to the next stage for further processing. At this point, the image contains all the details required for identification, but it is not yet usable by the machine learning model until it is pre-processed.

Preprocessing the Image

Once the image is captured, it undergoes preprocessing using OpenCV. This stage typically involves converting the image to grayscale, resizing, noise reduction, and enhancing the image for better recognition. Preprocessing is critical because it ensures the number plate features are clearly defined for both the OCR and the machine learning model. This step ensures consistency in the image quality and format, which boosts the accuracy of the detection system.

Machine Learning Classification (HSRP Detection)

After preprocessing, the image is fed into the trained machine learning model, which classifies the number plate as either HSRP or non-HSRP. The ML model, built using libraries such as TensorFlow or scikit-learn, has been trained on a dataset of HSRP and non-HSRP number plate images. It identifies patterns and features unique to HSRP plates, such as the reflective background, chromium hologram, and laser-etched code. If the number plate is classified as HSRP, the process ends here. If it is non-HSRP, the system proceeds to the next step.

OCR (Extracting Number from Plate)

If the plate is classified as non-HSRP, Tesseract OCR is used to extract the vehicle's registration number from the image. OCR (Optical Character Recognition) converts the image-based number into machine-readable text. This step is crucial for identifying the vehicle based on the extracted registration number, which will later be used to query the database.

Database Query (User Identification)

Once the number plate has been extracted, the system queries a database to retrieve the email address associated with that registration number. The database contains entries with number plates and corresponding user details, such as emails and other contact information. If the system finds a matching number plate in the database, it retrieves the user’s email address for further action.

Email Notification (Non-HSRP Alert)

If the vehicle is identified as having a non-HSRP plate, the system sends an email notification to the user. This is done using Python’s smtp lib or an external email service like SendGrid. The email informs the user that their vehicle does not have an HSRP-compliant number plate and may include instructions or regulatory information. The email is generated automatically, providing a seamless notification system to users, ensuring compliance with the latest vehicle number plate regulations.

End of Process

Once the email notification is sent, the process ends. The system has now identified a non-HSRP vehicle, extracted the number plate, queried the database for the owner’s information, and sent the necessary notification.

4. Experimental results and discussion

4.1 Types of Number Plate

Figure 2: HSRP Number Plate samples **Figure 3: Non HSRP Number Plate sample**

HSRP Number Plate

HSRPs are made to be hard to copy or change, and they are intended to be tamper-proof. This lessens the chance of car fraud and theft.

Each HSRP has a unique identifying wide variety that is laser-etched on it, enabling tracking.

Non HSRP Number Plate

Non-HSRP is unregulated, lacks security features, and is customizable but less secure.

Non-HSRP plates do not have security features like laser-etched codes or snap locks, they can be easily tampered with or forged.

4.2 Plate Detection

In the final stage, the trained model is applied to new photos to detect vehicle number plates. This requires KNN to recognize and reliably localize number plates within images, derive bounding box coordinates, and read the text from these plates using Optical Character Recognition (OCR). The model also uses learnt features to determine whether the detected number plate is HSRP (High-Security Registration Plate) or non-HSRP. If the number plate is categorized as non-HSRP, the algorithm takes the details and searches a database for the relevant email address. An email is subsequently sent to the appropriate user with information about the number plate. The KNN technique includes detecting the number plate region using nearest neighbors, extracting bounding boxes, and extracting text using OCR. The model also uses classification to determine whether the number plate is HSRP or non-HSRP. If the number is not HSRP, it is retrieved and forwarded to the user via email with the required information. The accuracy of detection and classification, as well as the efficiency of email communication, demonstrate the system's usefulness.

4.3 Plate Information

Several critical steps are involved in extracting plate information from photos in order to effectively identify and process vehicle number plates. Once a number plate has been discovered and located using methods such as K-Nearest Neighbors (KNN), the text on the plate is read and extracted using Optical Character Recognition (OCR). The retrieved text is next evaluated to identify whether the plate is a high-security registration plate (HSRP) or not. This classification is critical for future processing. If the plate is identified as non-HSRP, the system retrieves the vehicle's registration number and compares it to a database to determine the associated user's email address. An email is then sent to the appropriate person, containing pertinent information or alerts about their number plate. This procedure provides correct identification and timely transmission based on identified plate information.

4.4 RTO SIGN IN PAGE:

The RTO Sign in page is the system's entry point, where users securely provide their credentials—usually a mobile number and password. Robust encryption safeguards this information, and for added security, we may user two-factor authentication. It ensures a smooth, secure user experience while protecting sensitive cardiac data.

Figure 4: RTO Sign in Page

4.5 UPLOAD THE NUMBER PLATE IMAGE

The Upload image is where users can easily add their images to our system. It's like a virtual gallery where you can contribute your valuable number plate photos. Users simply select the images they want to upload from their devices for now the number plate is HSRP or NOT.

Figure 5: Upload the number plate images

4.6 UPLOAD NUMBERPLATE IMAGE USING CAMERA:

The Upload image using the open camera button is where users can easily capture their number plate images to system. It's like a virtual gallery where you can contribute your valuable number plate photos. Users simply select the images they want to upload from their devices for know the number plate is HSRP or NOT.

Figure 6: Upload the number plate images using camera

4.7 REGISTRATION OF USERES VEHICLE INFORMATION

In this RTO can register the information about the vehicle user and detect the number plate and give the result from registered vehicle information

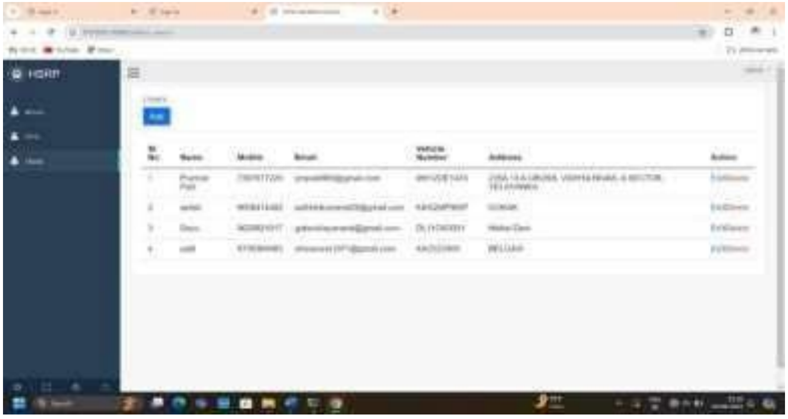

Figure 7: Registration of Users Vehicle Information

4.8 IDENTIFYING HSRP NUMBER PLATE:

After detecting number plate, the uploaded images is HSRP then it’s give message like as below.

Figure 8: Identifying HSRP Number Plate

4.9 IDENTIFYING NOT HSRP NUMBER PLATE:

After detecting number plate the uploaded images is not HSRP then it’s give message like as below. And send mail to the registered vehicle owner email address.

Figure 9: Identifying Not HSRP Number Plate

4.10 MAIL NOTIFICATION TO NOT HSRP VEHICLE OWNER AS OUTPUT

Sending mail to the vehicle owner whose number plate is nopt hsrp

Figure 10: Mail Notification To Not HSRP Vehicle Owner as Output

5. Conclusion

Vehicle number plate detection employing modern machine learning techniques such as K-Nearest Neighbors (KNN) offers a reliable and efficient solution for reliably detecting and processing vehicle plates. The system excels at feature extraction and classification thanks to machine learning capabilities, ensuring exact detection and text extraction. KNN provides a simplified, distance-based technique to feature classification that, while less sophisticated, accurately recognizes and locates number plates. The inclusion of Optical Character Recognition (OCR) improves the system's ability to read and interpret plate text. Furthermore, the system's capacity to classify plates as HSRP or non-HSRP and then send notices via email to non-HSRP plates adds substantial value by allowing for timely and relevant communication. Overall, this combination of methodologies provides a comprehensive, accurate, and practical solution for detecting and managing vehicle number plates.

Acknowledgements

I am grateful to Prof. Shivanand S. Gornale Department of Computer Science, Rani Channamma University, Belagavi for his valuable guidance for completion of this work

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