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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

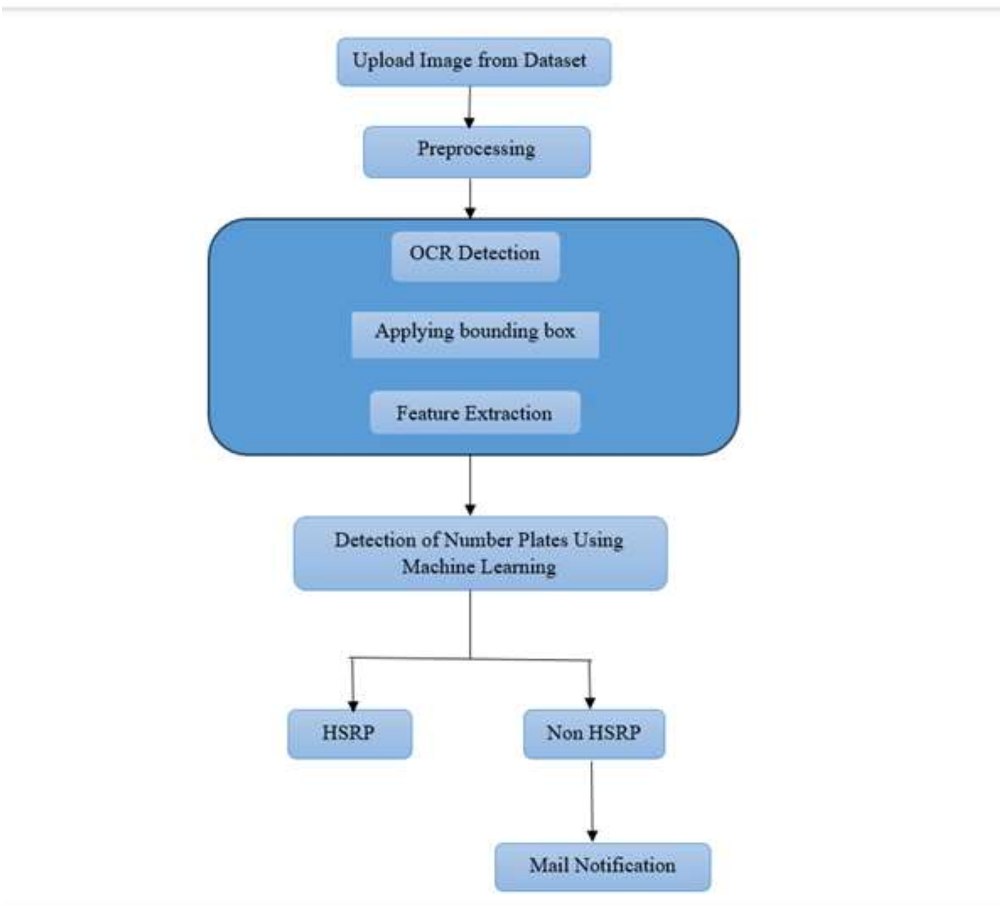

Figure 1: General architecture of the proposed work

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. 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.

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

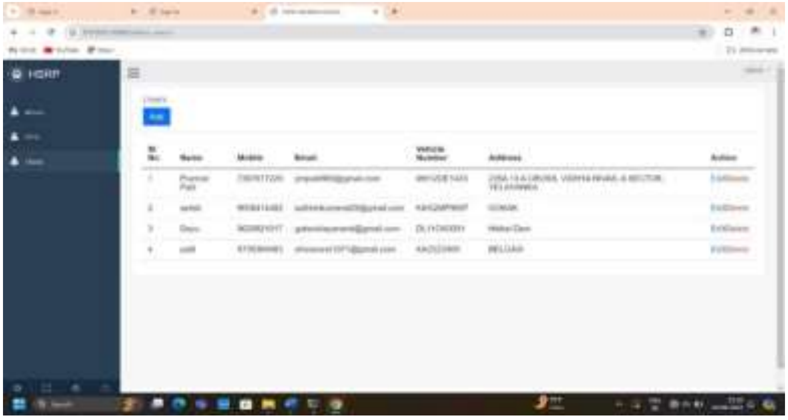

Figure 7: Registration of Users Vehicle Information

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

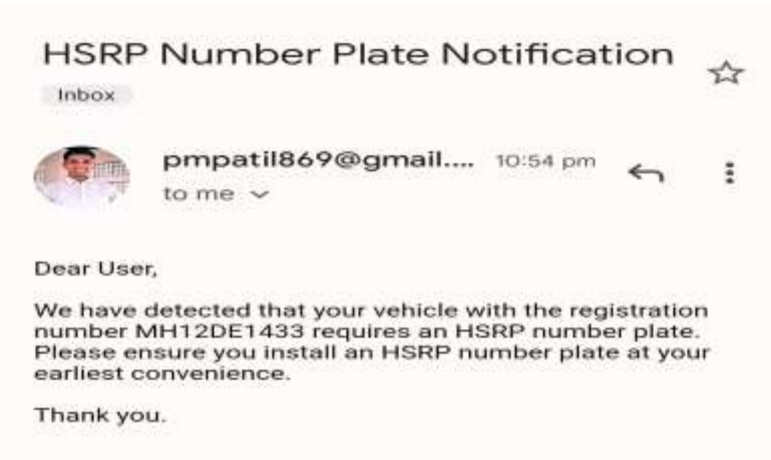

Figure 10: Mail Notification To Not HSRP Vehicle Owner as Output

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.

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