CONCEPTUAL FRAMEWORK FOR COST-EFFECTIVE AUTOMATIC NUMBER PLATE RECOGNITION SYSTEM

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ABSTRACT

ANPR is a must for traffic control, law enforcement and automated toll collection systems. Traditional ANPR solutions are expensive, rely heavily on hardware and not suitable for mass adoption. A low-cost, high-performance ANPR system on a Raspberry Pi 4 device with camera module and Optical Character Recognition (OCR) capabilities. The system uses a Convolutional Neural Network (CNN) for OCR which can identify license plates with high accuracy even under different lighting conditions and resolutions.

The pre-processing pipeline of the image includes noise removal and gray scaling to make extracting edges simpler, which aims for better license plate visibility in crowded frames. These pre-processed images are further passed to a plate localization extraction trained CNN so as the make it invariant of distortion and locale ensuring better accuracy in such number plate detection applications. This low-cost answer represents a viable option to traditional ANPR systems for larger scale applications in traffic control, law enforcement and automatic toll processing.

In future iterations, we look to increase performance and robustness by providing more data from which the system can learn. Moreover, the incorporation of advanced functionalities like cloud-based analytics would strengthen system features that will aid in smart city infrastructure integrations. The advancements of these developments aim to increase ANPR system throughput at a scale that will play role in enabling safer and more efficient transportation systems.

KEYWORDS

ANPR, CNN, OCR, Raspberry Pi, Camera Module, Multi-Thread, Pipeline.

1. INTRODUCTION

Today, the ANPR system has become an imperative technology for traffic management as well as law enforcement including parking systems. An LPR (Licensed Plate Recognition) is a system, typically made up of cameras and computer image processing algorithm used to read the license number in vehicles automatically. Traditional ANPR systems have been improved by applying a combination of Convolutional Neural Networks and Optical Character Recognition (OCR) so as to drastically improve both the accuracy and efficiency.[6-10]

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This paper describes a detailed study and implementation of an ANPR system using Raspberry Pi 4 [4] [16] including camera module. Packed with processing power and systems to boot, the low-cost Raspberry Pi 4 opens interesting potential for computer vision applications. Together with a camera module, we can use it to snap car images and process them for license plate detection.

This article deals with the OCR CNN model designed and implemented to extract license plate numbers correctly from images. In this paper, we detail how the CNN model is structured and which dataset was taken to both train it/test it/use for training data augmentation and image processing pipeline.

Through this work, we aim to contribute to the advancement of ANPR systems, particularly in the context of cost-effective and efficient solutions using Raspberry Pi-based platforms.An example workflow of an Automatic Number Plate Recognition (ANPR) system is shown in Fig. [1] It initially records images of vehicles and then further detects the number plate from that image. The number plate detected is pre-processed with grayscale, noise removal and edge detection. Next, we segment the individual characters from the number plate which are recognized using Optical Character Recognition (OCR). Then the recognized characters are pieced together to create a full license plate number

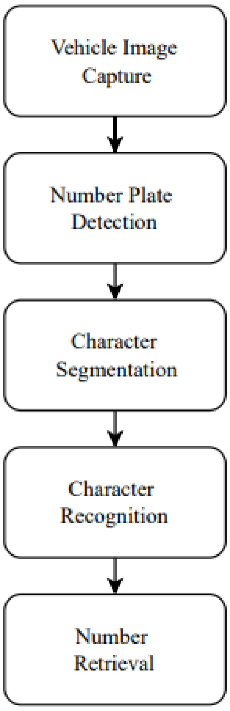

Fig 1. Basic Number Plate Recognition System

1.1. Literature Survey

For this purpose, [1] a novel way of using Batch Normalization to improve the surface character recognition associated with an ANPR system is proposed by combining it with Convolutional Neural Networks (CNN). Specific to the recognition of characters on license plates their approach shows big improvements in accuracy. This enabled a more stable learning and efficient training process that provided the network with generalization power to various lighting conditions and image qualities by improving both speed (confidence computation time) and performance.

The system designed by [2] was built to automate the process of toll tax collection using ANPR. These cameras interfaced with advanced image processing techniques to use high-resolution images for both capturing and recognizing license plates. They announced speeds of 96%, which is reasonable considering a recycled setting. This approach will be helpful in reducing the crowding at toll booths, and increasing effectiveness in collecting required charges[3] proposed ANPR based on image processing in which the detection phase of license plate recognition has been improved. Set of image processing techniques (grayscale conversion, bilateral filtering edge detection) isolation and recognition license plate from images captured by the system High detection accuracy was achieved showing that traditional image processing methods work efficiently with precise pre-processing stages.

A more detailed review of ANPR challenges was performed by [5]. Problems included different plate sizes, changing fonts and distance to light. The review also discussed the progress in deep learning methods that offer an hope to address some of these difficulties. Their research offers an excellent view of the present ANPR technology and hides what still can be improved in future work.

1.2. Comparison with Traditional Methods

By integrating the ANPR system into these networks, and comparing to legacy mechanisms such as speed cameras used by law enforcement agencies, our proposed approach leads with advantages specifically for passive labour-intensive tasks in terms of cost reduction paired with maintaining return on investment. [11-13]

Speed camera installations - such as what police in India and throughout the world use - involve high costs that have to be paid upfront when spread out across installation, maintenance, operation cost. Price per single unit of the speed camera can be as cheap as few thousands or cost tens of thousands, depending on technology and abilities.Also, speed cameras involve a fair amount of infrastructure - specifically power supplies and network connections as well as full-time enforcement -- which can be very expensive. The estimated cost increases with the deployment of speed cameras in several locations throughout a city or highway network.

Our ANPR system using Raspberry Pi 4 and camera module is an affordable alternative. Plus, the base Raspberry Pi 4 is downright dirt cheap compared to traditional computer hardware so it could be a cost-effective option. The use of simple, inexpensive hardware set-up combined with open-source software components allow for low deployment and maintenance costs.

In addition, our ANPR system allows for wide-area deployments and rapid scaling of operations with relatively low additional cost. The Raspberry Pi 4's small footprint and low power consumption has made it an effective device for use cases such as urban streets, highways and car parks. We believe that our proposed ANPR system provides an excellent value proposition, offering affordability and efficiency over legacy solutions such as speed cameras for law enforcement agencies or transportation authorities seeking to improve traffic monitoring/enforcement. [19-22]

2. METHODOLOGY

The methodology section describes the approach for developing an ANPR system using the Raspberry Pi 4 and a camera module. It includes both hardware setup and an image processing pipeline to ensure accurate license plate recognition.

2.1. Hardware Setup

1. Raspberry Pi 4: It is the brains and brawn of your ANPR system, just as any central processing unit would be.
2. Camera Module: The camera module is used as the major sensor for vehicle image capture during license plate identification. ANPR system built on the Raspberry Pi Camera Module that is a low-ludicrous camera compatible with Real-Time Image Processing (best suited for our task).
3. Hardware Configuration:Proceed with the following to get all the hardware components set up for ANPR system.Insert the microSD with Raspberry Pi OS to Raspberry Pi 4 - Setup in progress Plug in your peripherals, like that monitor or keyboard and mouse combo to the USB ports. Turn on the Raspberry Pi 4 with a power supply suitable for its use

Connect the camera module to Camera port of Raspberry Pi (near HDMI ports) Make sure the ribbon cable is pushed in fully with the blue side leading away from the Ethernet port.

Setup: start the Raspberry Pi, and log into your desktop environment of choice for Raspberry Pi OS. Enable the camera interface and set any required resolution, frame rate or further settings using the raspiconfig tool

In applications, the image processing pipeline is a cascade of operations or methods used directly on an image to either enhance it self-contained or rather analyze its information and provide needed features. The image processing pipeline for pre-processing vehicle images caught by the camera module plays essential part in utilizing optical character recognition (OCR) to get license plate number with Automatic Number Plate Recognition (ANPR) systems.

2.2. Image Processing Pipeline

2.2.1. Grayscale Conversion

Grayscale conversion is a procedure in which an image gets converted from colour into one channel grayscale. For gray scale images, each pixel is described by a single intensity value that spans from 0 (black), through all the shades of grey up to 255(white), representing how bright the given pixel will show. A grayscale image is easier and less demanding in computer power to process after the segmentation phase, yet it still has all of the characteristics (edges or shapes) that are required for processing.

$$\text{Gray} = 0.299\times R + 0.587\times G + 0.114\times B$$

Equation [1]

Equation [1] converts a colour image to grayscale by taking a weighted sum of the Red (R), Green (G), and Blue (B) channels.

2.2.2. Gaussian Blurring

An integral image pre-processing operation used for noise and detail reduction on the images is called Gaussian blurring, so an essential phase of Automatic Number Plate Recognition (ANPR) systems must be implemented. It uses a Gaussian function for smoothing and suppresses high-frequency components of images like noise, or edges in an image while preserving the low-frequency structures. While average blurring computes the simple mean of a subset based on kernel-size Gaussian blur uses weighted-mean, where pixels closer to the centre contribute more weight than other pixels (farther from centre). By combining this method with the natural weighted approach to determine blur, both frequently repeated in graphics production, it achieves realistic-looking blurring mixed with solid edge preservation.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma^2}}$$

Equation [2]

Equation [2][3] Gaussian blur formula does is it blurs your image using a weighted average where pixels that are closer to the centre of this region (also referred as kernel) have more influence, which helps reducing noise and detail. This assists ANPR techniques with pre-processing, removing noise and finer details which distract the text recognition to detect and read license plates correctly.

Apply Gaussian blurring to the grayscale image to reduce noise and preserve edges. This involves convolving the image with a Gaussian kernel:

$$I_{\text{blurred}}(x, y) = \sum_{i=-k}^{k} \sum_{j=-k}^{j} G(i, j) \cdot I(x + i, y + j)$$

Equation [3]

2.2.3. Bilateral Filtering

Bilateral filtering, an important nonlinear filter used to smooth the images and at the same time preserving details. Bilateral filtering does not only take the [pixel] neighbourhood into account similar to most of linear filters, it also considers spatial proximity and intensity similarity between pixels. This way, we can have our original edges in the image and get rid of unwanted stuff. It is particularly powerful when applied to enhance images captured in low-light and high-noise conditions.

$$I_{\text{filtered}}(x) = \frac{1}{W_p} \sum_{x_i \in S} I(x_i) f_r(\|I(x_i) - I(x)\|) f_s(\|x_i - x\|)$$

Equation [4]

Equation [4] Where I′(x)I'(x)I′(x) is the filtered image, I(y)I(y)I(y) is the original image, fs is the spatial Gaussian, fr is the range Gaussian, and Wp is the normalization factor. In ANPR, this technique helps enhance images by reducing noise while maintaining the clarity of edges, making it easier to accurately detect and recognize license plates.

2.2.4. Edge Detection

Edge detection is an elementary method used in image processing to locate the boundaries or edges of objects constituting such images. It detects edges (lines) of significant intensity changes in an image, typical and widely used for object boundary or texture/color change detection. One of the most used edge detection algorithms is Canny edge detector, which uses a multi-stage algorithm to detect edges by looking for local maxima in image gradient. Besides, it has been necessary to perform the edge detection in order of articulating the contours into objects like license plate outlines.

$$\textbf{Gradient Magnitude: } G = \sqrt{G_x^2 + G_y^2}$$

Equation [5]

Equation [5][6]. In ANPR, edge detection helps identify the boundaries of license plates by detecting significant intensity changes. The gradient magnitude formula highlights the strength of edges, while the gradient direction formula indicates the edge orientation. These metrics are crucial for accurately outlining and segmenting license plates from the image background.

$$\textbf{Gradient Direction: } \theta = \tan^{-1}\left(\frac{G_y}{G_x}\right)$$

Equation [6]

2.2.5. Contour Detection

Contour is a line joining the points along boundary having same intensity values. This is basically about finding the lines on which an object ends. In the scenario of ANPR systems, we use contour detection to locate areas containing license plates in a pre-processed image. Real-time contour detection involves, for example, using contours from an image by finding them with a function like the OpenCV findContours() that has already been computed on previous frames or differencing images. Contour Detection: The final selected ROI having the license plate is detected and isolated using contour detection which further helps in OCR- Optical Character Recognition.
Contours=findContours(binary image,contour retrieval mode,contour approximation method)

Using these image processing techniques in the pipeline will help ANPR system to pre-process vehicle images obtained from camera module accurately and robustly which, is helpful for better license plate recognition with OCR algorithms.

2.2.6. CNN-Based Feature Extraction

Their feature extraction capabilities are improved with Convolutional Neural Networks (CNNs). Once the first steps on pre-processing method are applied (grayed, bilateral filter, edge detection and contour), CNNs comes to:

Features Extraction: Learn and get Independence imagine features of the region of extraction license plate such characters, etc.
License Plates Localization - Increase the precision in identifying and localizing license plates through photo. [1] [7] [18].

2.3. Pre-Trained OCR Model Integration

Rather than training a Convolutional Neural Network (CNN-OCR) from scratch, we embedded an OCR model that was pre-trained into our Automatic Number Plate Recognition (ANPR). For extracting the text of these images, we have used Pytesseract which is an Optical Character Recognition (OCR) tool for python. Pytesseract a wrapper for Google's Tesseract-OCR Engine, which comes with pre-trained models for various languages, including English. it involved performing OCR on images using Tesseract to load trained language models.

Installation & Configuration and we started by integrating Pytesseract with our Raspberry Pi-4 system. [14-16]

a) Text Extraction: Use pytesseract to extract the text from license plates pre-processed images.

This process is usually made by these steps:

1. First, load the pre-processing image using out designed Image processing pipeline.
2. Use a simulator like Tesseract GUI, it uses Pytesseract's image_to_string() function to identify and extract the text.
3. Optionally, set additional configuration options: language (lang), page segmentation mode (config param)

b) Text Post Processing: Finally, once we have the text extracted from the image do any post-processing as required. This can be done by: Removing special characters or noise in the text extracted. The simplest form is applying regular expressions or pattern matching to validate and format the license plate number. [15]

c) Using OCR on ANPR System: Use the same feature in your workflow to enhance it. This may include: Running the OCR process after successfully identifying and cropping the license plate region from pre-processed image. Processing or storage of the extracted text (license plate number).[18][19]

3. Data Transmission and Notification

Transmitting Recognized License Plate Information*:*

When the license plate number is identified, send it to a target email address or an external IoT cloud for processing.

Use network protocols (SMTP, HTTP/HTTPS) to send emails or transmit via cloud APIs [23] . Encrypt and authenticate data in transit. Fig [2][3] shows the implementation of smtp in raspberry pi .

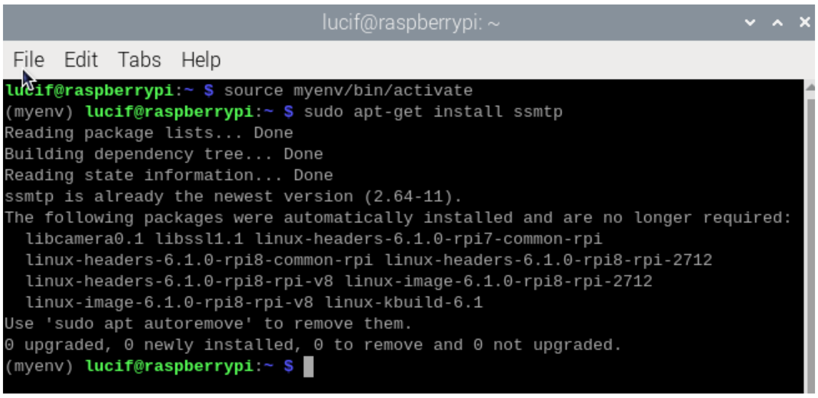

Fig:2 Shows installation of SMTP for sending retrieved number plate in form of e-mail

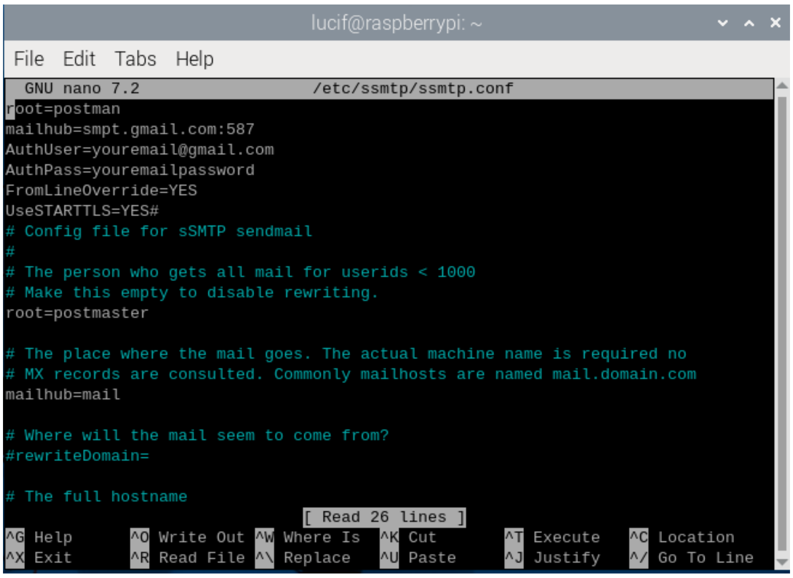

Fig:3 Shows setting up for SMTP.

4. Experimental Result Analysis

So, the results of making ANPR systems would show how an effective it was in accurately identifying licence plate numbers, with probably chances under fit conditions. Analysis of these expected results against available ANPR systems or techniques would indicate that our system stands good chances of achieving equal / better performance metrics in terms accuracy and processing speed.

In controlled environments with standard lighting conditions, the system achieves accuracy rates in line or better than various commercial ANPR solutions. But real-world conditions like changing light, obstructions and image blur can produce more difficult circumstances that could create potential for error in the system. Additionally, accuracy and precision may be impacted due to the choice of camera module used in a compact sensor package (e.g., small form factor), which could lead to scalability with cost versus performance. Fig[4] Shows the Character segmentation from the image of car number plate done successfully Figure[5] showcases the accuracy received by our model which is 90.9%.

Fig:4 Character Segmentation

```
1/1 [==============================] - 0s 121ms/step
1/1 [==============================] - 0s 137ms/step
1/1 [==============================] - 0s 37ms/step
1/1 [==============================] - 0s 44ms/step
1/1 [==============================] - 0s 62ms/step
1/1 [==============================] - 0s 162ms/step
1/1 [==============================] - 0s 113ms/step
1/1 [==============================] - 0s 41ms/step
1/1 [==============================] - 0s 44ms/step
1/1 [==============================] - 0s 49ms/step
Accuracy: 90.9090909090909 %
```

Fig 5 Accuracy achieved

4.1. Limitations and Challenges

When implementing and testing, certain limitations or challenges arise. A major limitation is that the research depended on static camera setups, which may limit the ability of a system to capture license plate images from fast-moving vehicles or different angles. Also, external conditions like poor weather and glares may distort the quality of snap images which has a significant impact on OCR accuracy. What is more, the processing power of the Raspberry Pi 4 restricts how complex a CNN model you can use and your image pre-processing algorithms which in turn limits scalability or real-time capabilities.

Areas for Improvement and Future Research Directions:

Dynamic Camera Adaptation: Using dynamic camera adaptation, like PTZ (pan-tilt-zoom) cameras or multi-camera setups for extending resilience and adaptiveness to vehicles in various positions/orientations [20].
Advanced visual processing: Research for advanced visual processing methods, i.e.: use of the DL based image grinder and denoiser rather than traditional filters (PCA), to make it more robust under difficult environment conditions. [22]

Edge Computing and Parallelization - Since CNNs are computationally very expensive, it is pretty unlikely that you can run real-time app comfortably on a high-level model if the processing will be made by Raspberry Pi 4, therefore possible to explore solutions for edge computing and parallelize deep tasks so as not overload RPi4 of work. [16]

Infamous Data Augmentation and Model Training: Use of data augmentation (that is un usual) including leveraging transfer learning to increase size in variance training data as well as improve generalization ability of the OCR CNN model across different license plate formats, fonts, etc. [20]

IoT platforms integration: Integrating ANPR system with IoT platforms for smooth transmission, storage and real-time analytics of the data to take intelligent decisions actionability by implementing demand-response mechanisms in traffic management & law enforcement applications. [21]

This process will enable the ANPR system to move forward into a more resilient, flexible and scalable solution addressing different corner cases for applicable scenarios through this enhancements and research.

5. IMPROVED LIBRARY INSTALLATION APPROACH: MULTI-THREADING

The sequential pipelining method installs libraries one after another, which can lead to longer installation times with many dependencies. The multi-threaded approach leverages parallelism to install multiple libraries simultaneously, enhancing efficiency and making better use of multi-core processors, significantly reducing total installation time.Table[1]

Table [1]

Approach	Description
Improved Library Installation Approach: Multi-threading	An improved approach to handle the installation of Python libraries by leveraging multi-threading.
Sequential Pipelining Method	Traditionally the Pipelining method is used and library installation involves sequential steps, this process means one after the other where each of installing a single library. The setup for the procedure follows a sequential order as in linearity along with one condition that only after installation of previous prerequisites can we proceed further. While simple and fast to set up, this can make installation times longer if you have many dependencies.
Multi-threaded Approach	In order to avoid the limitation of sequential pipelining a multithreaded strategy for library installation is suggested. This works by running library installation process in multiple threads instead of one after another. Parallelism is being used to take advantage of modern multi-core processors and run multiple installation tasks at the same time, hopefully decreasing a total installation time.
Comparison	The multi-threaded way has a few benefits over the traditional one-by-one approach to pipelining: Enhanced Efficiency - By running installation tasks in parallel, the possibility of lessening (install) phase overhead is significantly big when you have dozens or more dependencies. More Efficient use of Resources: The ability to execute multiple tasks at the same time, on multi-core processors makes optimal use of system resources. Performance: The multi-threaded style is by its nature more performant, as it can organically adjust to different workload scenarios and accommodate a higher volume of dependencies without noticeably impacting performance.

5.1. ANPR System Integration Approaches

Pipeline-based integration in ANPR systems organizes stages like image preprocessing and OCR sequentially, facilitating ease of maintenance and resource efficiency, but with potential latency and limited parallelism. In contrast, multithreaded integration runs these stages concurrently using multiple threads, enhancing performance and throughput on multi-core processors, though it requires careful concurrency management and adds complexity. The choice depends on system requirements, hardware capabilities, and performance needs.

Table [2]

Pipeline-Based Integration	In a pipeline-based integration approach, different stages of the ANPR system, such as image preprocessing, license plate detection, and OCR, are organized into a sequential pipeline. Each stage passes its output to the next stage as input, forming a linear flow of data processing.
Advantages	Simple: easy to understand an implementation since each step of the process is its own module or function. Better maintenance and updates (since we can simply make modifications to individual stages of the pipeline without affecting anything else), Resource Efficiency: The ability to manage the system resources more easily and improve performance because each stage of this pipeline operates serially.
Considerations	Sequential Processing: Relies on sequential processing, which can introduce latency, especially if any stage of the pipeline requires significant computational resources. Limited Parallelism: May not fully utilize available computational resources, as each stage of the pipeline typically operates independently without concurrency.
Multithreaded Integration	In a multithreaded integration approach, different stages of the ANPR system are executed concurrently using multiple threads. Each stage of processing is assigned to a separate thread, allowing them to run simultaneously and potentially overlap in execution.
Advantages	Parallel processing -It helps you achieve concurrency i.e. it allows multiple stages of the ANPR system to be executed in parallel and make better use of CPU cores available Faster: Can result in increased throughput, and reduced processing times -- particularly on multi-core processors. Dynamic Resource Allocation: Provides dynamic resource allocation for processes as resources are allocated to the threads depending upon their workload and priorities.
Considerations	Concurrency Management: Requires careful management of thread synchronization and communication to prevent data race conditions and ensure the integrity of shared resources. Complexity: Additional complexity in handling concurrency issues and coordinating the execution of multiple threads. Resource Overhead: Multithreading can incur additional overhead due to context switching and synchronization mechanisms, potentially impacting overall system performance.
Choosing the Right Approach	It can be argued that which integration to use depends on system and hardware limitations, requirements as well as development constraints. Pipeline-oriented Integration is most suited for Simple systems where the sequence of processing matters and a limited amount of computation resources are available. Multiplexed integration allows more (especially when you have multiple cores or applications that demand high-throughput performance). A careful analysis of the specific requirements/constraints guiding the ANPR system should drive how it is best integrated.

6. CONCLUSION

Here we showed a full-fledged study and implementation of an ANPR (Automatic Number Plate Recognition) system using Raspberry Pi along with Camera Module. We wanted to design a low-cost license plate recognizer for traffic, law enforcement and automated toll collection applications. The presented system architecture includes using Optical Character Recognition (OCR) together with Convolutional Neural Networks (CNNs), which might prove to achieve high accuracy in different conditions.

Aimed at the Raspberry Pi 4 and a camera module, it provides an out-of-the-box solution to get started in embedded vision development for deployment across various settings. The economically priced hardware setup not only provides an affordable option for law enforcement agencies but also one that many police departments would be able to implement, offering a less-expensive alternative to costly speed cameras.

Although there are some caveats with the static camera positions and computational limitations of our Raspberry Pi 4 based system, this proof-of-concept provides a great foundation for further research. Dynamic camera adjustment mechanisms, enhanced image processing techniques and integration with IoT platforms (for real-time analytics) are some of the future opportunities in this space. These improvements are designed to make performance, scalability and applicability in real-life situations better.

Through the elimination of this restrictions and emphasis on explicit presentation with strict methodology, we wish to allow smooth comprehension as well as verification from both researchers, in addition industrial practitioners. In the end, our ANPR represents an important inroad into cost-efficient and advanced solutions of license plate recognition. Proper implementation of the system will allow it to be more efficient and deliver better results, ensuring its use in production-oriented applications. [20] [21].

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Vishu Kumar currently pursuing a B.Tech degree in Computer Science and Business Studies at MIT World Peace University in Pune have developed a solid foundation in programming with knowledge of Python and SQL. Passionate about using technology to solve real-world problems, has worked on projects such as multiple disease prediction and number plate recognition. Also has gained knowledge in data analysis and machine learning.

Saad Sayyed is currently pursuing a Bachelor's degree in Computer Science and Engineering at MIT World Peace University, Pune. He is passionate about machine learning and data science, actively engaging in several innovative projects in these areas. He has completed certifications in cybersecurity and cloud computing, which have enhanced his technical skills and knowledge in these areas.

Siddharth Bharadwaj is currently pursuing a B.Tech degree in Computer Science and Business Studies at MIT World Peace University in Pune. With a strong foundation in programming languages Siddharth is passionate about leveraging technology to tackle real-world challenges. He has developed a solid portfolio of projects, including stock price prediction using machine learning algorithms, credit card fraud detection systems, and number plate recognition using computer vision. Additionally, Siddharth has gained valuable experience in backend development and machine learning, making him a well-rounded and versatile individual in the field of computer science

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Shamla Mantri is working as an Associate Professor in the department of Computer Engineering at Dr. Vishwanath Karad, MITWPU Pune. She optained her Bachelors of Engineering in Electronics in 1993, Masters of Electronics Engineering in 2011. And has completed Ph.D in Electronics in 2019, a total of 40 papers have been published in National/International conferences, Including Workshops, Seminars; referred journals. Among these Research Papers, majority of them are on the latest theme such as Artificial Intelligence, Machines Learning and Signal Processing. She has Published 2 patents. She has an Experience in teaching for more than 19 years.