"Review on A Novel deep Learning Based ANPR Pipeline for Vehicles Access Control"

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Abstract:- *Computer Vision and Deep Learning technology are playing a key role in the development of Automatic Number Plate Recognition (ANPR) to achieve the goal of an Intelligent Transportation System (ITS). ANPR systems and pipelines presented in the literature often work on a specific layout of the number plate as every region has a unique plate configuration, font style, size, and layout formation. In this paper, we have developed a smart vehicle access control system considering a wide variety of plate formations and styles for different Asian and European countries and presented novel deep learning based ANPR pipeline that can be used for heterogeneous number plates. The presented improved ANPR pipeline detects vehicle front/rear view and subsequently localizes the number plate area using the YOLOv4 (You Only Look Once) object detection models. Further, an algorithm identifies the unique plate layout, which is either a single or double row layout in different countries, and the last step in the pipeline is to recognize the number plate label using a deep learning architecture (i.e., AlexNet or R-CNNL3). The results show that our trained YOLOv4 model for vehicle front/rear view detection achieves a 98.42% mAP score, and the number plate localization model achieves a 99.71% mAP score on a 0.50 threshold. The overall average plate recognition accuracy of our proposed deep learning-based ANPR pipeline using R-CNNL3 architecture achieved a single character recognition accuracy of 96%, while AlexNet architecture recognized a single character with a 98% accuracy. In contrast, the ANPR pipeline using the OCR method is found to be 90.94%, while latency is computed as 0.99 s/frame on Core i5 CPU and 0.42 s/frame on RTX 2060 GPU. The proposed ANPR system using a deep learning requires a high-performance GPU for real-time implementation*

Keywords: *ANPR, access control, character recognition, deep learning, OCR etc.*

I. INTRODUCTION

Currently, there are 13.4 billion Internet of Things (IoT) devices. Statista predicted that this figure will increase to 29.4 billion by 2030. These devices form an interconnected network that produces extensive data in numerous social domains. Access to a large volume of data collected by various sensors makes it possible to supervise and manage different aspects of society, including evacuation systems, smart environments, and transportation. This trend boosted cities to deploy sensor networks and IoT platforms, for example, to monitor the flow of vehicles on their roads. The data obtained by these sensors have led to numerous studies in several areas, such as traffic behavior. Extracting and combining information from multiple sources, not only sensor data, but also information stored on the Internet, can lead to a better understanding of the problem to be solved. For instance, traffic in cities is partially dependent on local holidays. Some approaches have enhanced the analysis of traffic data (from vehicle counter sensors) with context information to understand the traffic conditions on roads using events data, parking information, or weather conditions.However, most solutions using License Plate Recognition (LPR) sensors did not use additional contextual datasets. Only few works combine LPR with location information, but none of them include other contextual information. They also did not explore calculated variables that enhance the raw data, such as distance traveled or visit frequency.

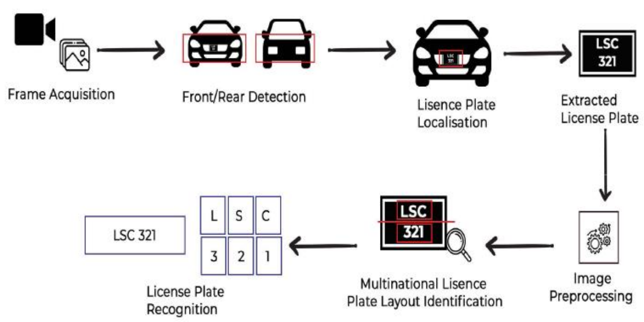


Fig. 1.1 Block Diagram of our Real Time ANPR framework

A very useful application of ANPR is Access Control Systems as it can assist to identify possible security issues and improve automation. Existing real-time ANPR works in a controlled environment. The CCTV cameras are installed everywhere but they still need human monitoring to keep a record of vehicle entry and exit from the location of the premises. ANPR system can significantly reduce the effort of service personnel, reduce the impact of human factors, and eliminate errors. In a real-time environment, there may be significant differences in vehicle orientation, speed, resolution, and lighting conditions, making number plate recognition more challenging which affects the recognition rate and accuracy.[1-3]

II. LITERATURE REVIEW

- **Fakhar et al.(2018):-** It proposed an affordable ANPR system using Raspberry Pi, in which the model uses a real-time image captured from a camera. The image is denoised, filtered, and segmented, and the characters on the plate are recognized.
- **Virakwan and Nui Din et al. (2017):-** He suggested an ANPR System in POLIMAS, which verifies that only registered automobiles are permitted to enter the specific place. A webcam is installed using four different orientations: front, back, front top, and rear top. The captured image is converted to grayscale, and the intensity and contrast are adjusted using the histogram equalization approach.
- **Mr. Ankit Darade, Mr Mayak et al. (2017):-** The results are collected in a string configuration and compared to the database's reserved entries. As the recognition remained a challenge due to the various formations of plates in different regions.
- **Chou and Liu et al. (2019):-** He presented a real-time truck number plate recognition (TNPR) system which reduces the labor force and time spent in identifying number plates. Their system effectively reduces the risks of crime and improves the transparency, automation, and efficiency of frontline human labor. Using YOLO and CNN based DL architectures, the system achieved a single character identification rate of 97.59 %, an overall recognition rate of 93.73 %, and an inference time of 0.3271 seconds per image.
- **Chen and Hu in et al. (2019):-** An ITS was introduced where they focused on video-based vehicle identification and classification techniques, that are based on both static and motion features to achieve improved results. The proposed technique localizes vehicle number plate area and classifies vehicle plate characters with 95% confidence accuracy under environmental conditions such as different illuminations.
- **S. Tenzin, P. Dorji et al. (2018):-** A vehicle plate recognition system based on OCR and Wireless Sensors Network (WSN) is described in. The proposed system uses a Smart Parking Service (SPANS) framework to capture images of parking spaces and recognizes moving or parked vehicle number plates. Furthermore, the system's performance is measured using real-time images.
- **R. N. Babu et al. (2020):-** In for plate recognition used state-of-the-art DL techniques. Their image dataset comprised 6500 Indian car number plates that are divided into 90:10 training and testing sets. The images were acquired by three different cameras with different specifications, such as bit rate and focal length. A 37-class CNN model was trained for character recognition.
- **Ariff et. al. et al. (2021):-]** used various segmentation techniques for the processing of the noisy license plate images. To remove undesired pixels, 100 Malaysian vehicle plates with a resolution of 1932 - 2576 pixels were processed using threshold approaches such as Savoula and Niblack. In this case, Savoula segmentation has an average accuracy of 83%. The template matching technique is used to classify characters.[3-6]

III. THEORETICAL DESCRIPTION

The concept of information fusion has been applied to the specific problem of tourism flows and smart cities. These approaches used data analysis techniques to combine multiple sources of information, providing valuable insights for developing smart tourism applications in cities and designing sustainable environments. Smart city applications were built on top of data, and data fusion provided a wide variety of techniques to improve the input data for an application. Examples of these techniques included data association, state estimation, unsupervised machine learning, or statistical inference. For example, combining different tourist information was used to predict the tourist flow with graph neural networks. The data used in the solution were composed of tourist infrastructure information, such as camping and tourist housing from Open Street Map and the National Statistics Institute reports released by the Ministry of Transportation; and human mobility data, including the number of movements between administrative areas per hour extracted from geo tagged Twitter data. Most of these applications were focused either on user recommendations or tourist flow, but little attention was paid to studying the individual behavior of the tourist inside an area

3.1. Main Clustering Algorithms:-Unsupervised machine learning automates the knowledge discovery process without needing labeled or previously classified data. Most taxonomies group the algorithms into at least five categories, although we have identified seven, as some of them did not fit in the 5 elements taxonomy:

- **Partitional Clustering:** decomposes a dataset into distinct clusters through an iterative process of distance calculations between individuals.
- **Hierarchical Clustering:** constructs clusters in either an agglomerative or divisive manner by adding or removing individuals, respectively.
- **Density-based Clustering:** identifies dense regions of objects in the data space separated by low-density regions.
- **Distribution-based Clustering:** creates clusters based on the probability that each individual belongs to the same distribution.
- **Grid-based Clustering:** divides the space into a finite number of cells.
- **Message-Passing Clustering:** creates clusters by exchanging messages between different data points until convergence.
- **Spectral Clustering:** uses the spectral radius of a similarity matrix of the data in a multidimensional problem.

3.2. Clustering performance:- The three most popular internal evaluation metrics in the literature are silhouette coefficient, Calinski Harabasz score, and Davies Bouldin index. All of these metrics are based on distances between data points and are commonly used to evaluate the effectiveness of virtually any clustering algorithm, working especially well in algorithms that work with distances, such as those included in the hierarchical, partitional, or spectral categories. These distance-based metrics may not be suitable for algorithms that use the Expectation Maximization (EM) method, such as the Gaussian Mixture algorithm. This is because the EM method models the data using probability distributions rather than distances between data points.

3.3. Principal Component Analysis:- The Principal Component Analysis (PCA) method condenses the information provided by multiple variables ($X1,\ldots,Xp$) from a given sample into a smaller number of variables, finding a number s of underlying factors that explain approximately the same variance as the original variables with $s < p$. Each of the new variables ($Z1,\ldots,$) are called principal components, which are linear combinations of the original variables. We define each Zi as:

$$Zi = \Phi 1iX1 + \Phi 2iX2 + \cdots + \Phi piXp$$

Each Φ represents the weight or importance that each variable Xi has in each Zi and, explains the information collected by each of the principal components. It is advisable to apply prior normalization to the data, since this method is highly sensitive to variables of different scales. Furthermore, the PCA only works with numerical data, so it is necessary to perform a previous preprocessing on categorical variables that may exist in the input dataset.

3.4. Normalization:- Normalization compresses or expands the values of each variable to fit them in the same range of values, normally [0,1], or [−1, 1], making them comparable in subsequent processes (PCA or ML algorithms). The choice of the normalization algorithm usually depends on the specific application and the dataset used, as different methods may yield different results and interpretations. For example, in clustering analysis, normalization can be particularly important for comparing similarities between characteristics based on certain distance measures. Among the most commonly used normalization methods are min–max normalization and z-score standardization. We have also tested two other methods that are commonly used in the literature and occasionally produce better results than min–max or z-score.

- **Min–max normalization:** Uses the minimum and maximum in the attribute domain to normalize the values to the interval, [0, 1] keeping the distances for each data point X.

$$x = \frac{x - x_{Min}}{x_{Max} - x_{Min}}$$

- **Z-score standardization:** scales the values so that the mean (μ) of the data domain is 0 and the standard deviation (σ) is equal to 1.

$$x = \frac{x - \mu}{\sigma}$$

- **Median Absolute Deviation (MAD) normalization:** normalizes the data such that the median of each attribute is 0 and the median absolute deviation is equal to 1.

$$x = \frac{x - Medium\ (x)}{MAD\ (x)}$$

Where $median\ (X)$ is the median of the values in attribute X, and $M(X)$ is the median absolute deviation of X.[6-7]

IV. CLUSTERING PIPELINE

4.1. Background:- Recent years have seen a growing trend of urban exodus, with many people leaving the cities searching for a quieter life. This trend has been boosted by COVID-19. With the rise of telecommuting, this trend is likely to continue in the future. These migratory flows include both foreign immigrants and the arrival of resident citizens from other parts of the country. In our use case, we take data from 3 small villages in the Alpujarra, an area close to a national park, and attracting tourists from diverse backgrounds. It is especially favored by local and foreign retirees and "neo-rurals", individuals drawn by environmental concerns or a quieter lifestyle, often becoming residents for extended periods.

4.2. Data Collection :- The main source of information for our work was the vehicle tracking system, particularly the license plate recognition (LPR) cameras. The data were collected by four vision LPR IP devices with Automatic number-plate recognition (ANPR) based on Deep Learning. The devices have a 2MP resolution, 2.8–12 mm varifocal optics, and IR LEDs with a range of 50 m. To cover the entrances and exits of each village in the target area, we strategically positioned the four cameras By taking advantage of the road structure, we could monitor the mobility of all vehicles in the area using only four LPRs, minimizing the cost and complexity of the system. The information collected by the cameras was stored on a cloud platform.

4.3. Data Cleaning:- In the field of the IoT, the production of sensor data can often be inaccurate and lead to the loss of some records. In our case, we presented two cleaning steps for the main dataset (LPR cameras). The first step, "license plate matching", aimed to reduce the error rate of incomplete or wrongly detected license plates by the LPRs. About 2% of the stored 1,050,760 records had missing values in the license plate number. For example, if we had a record with a correct license plate 0000AAA, and another record with the value 0#00AAA, missing the second digit, we could, by probability, infer that both records belong to the same plate number and assign the correct value, 0000AAA, to both records.

4.4. Data fusion:- Combining data from provenance, mobility in the area, and the holiday calendar offered the opportunity to gain an understanding of the region, its inhabitants, and visitors. This section explains each source of information and the feature extraction and construction process of each dataset to allow the merging.

- **License plate recognition data:-** The LPRs return information on four variables: the vehicle license plate (license_plate), the time stamp (time_stamp), and a variable (direction) indicated as ''IN'' when a vehicle enters the village or ''OUT'' when it exits
- **Vehicle information data:-** The Spanish Directorate-General for Traffic (DGT) provided us with data relating to vehicle information including details such as the vehicle's CO2 emissions (co2_emissions), the number of seats (num_seats), and the postcode of the vehicle's address (postcode).
- **Demographic and economic data:-** We accessed data regarding population size (population), average gross income (gross_income), and average disposable income (disposable_income) per person for each region linked to a postcode (postcode). This information came from the National Statistics Institute The data were available for regions with more than 1000 inhabitants and were updated until 2020. The information collected in this database allowed us to understand each region's economic and demographic characteristics, which was valuable for analyzing patterns in the data related to the drivers' economic capacity and willingness to travel. We obtained a database with 11,752 postcode records from India and four attributes.
- **National calendar data:-** We obtained the holiday data using a holiday library, which also allowed the creation of custom calendars for local holidays, long weekends, and bank holidays. The library was designed to quickly and efficiently generate holiday sets specific to each country and subdivision (such as state or province). It aimed to determine whether a particular date was a public holiday and to set national and regional holidays for multiple countries.
- **Geographic data:-** We obtained the geographic origin of the vehicles using the postcode and two libraries: pgeocode and geopy. pgeocode allowed fast and efficient

queries of GPS coordinates, region name, and municipality name from postcodes. geopy is a Python client that provided access to several popular geocoding web services. We used data from both sources to validate and complement each other's vehicle location information at different levels, such as municipality, county, or suburb.

- **Merge of all the processed datasets:-** Finally, we fused all constructed databases, crossing the information from the license plate and postcode variables. After merging the tables, we eliminated records with any of the aforementioned attributes null. The information from the national calendar allowed us to add to the vehicle database information related to the stay and its total number of holidays (total_holiday), workdays (total_workday), high season (total_high_season), low season (total_high_ season) and a binary variable indicating whether the vehicle enters the area on a holiday or a workday (entry_in_holiday). The resulting dataset contains information on the behavior in the area for 49,224 vehicles and 27 attributes.

4.5. Preprocessing:- Our dataset contains 27 attributes with different scales and units. Hence, some variables may be more influential than others in our analysis. To solve this problem, we will apply normalization to the data. Normalization must be applied to numerical data, so we must first convert the categorical variables (in our use case: route, postcode, autonomous_community, province, county, district, town) to numerical values. In particular, the numeric variable, total_distance, kept the information of the kilometers traveled in the variable route. The rest of the categorical variables related to the provenance: town, postal code, etc., and we converted them into the variable km_to_dest.

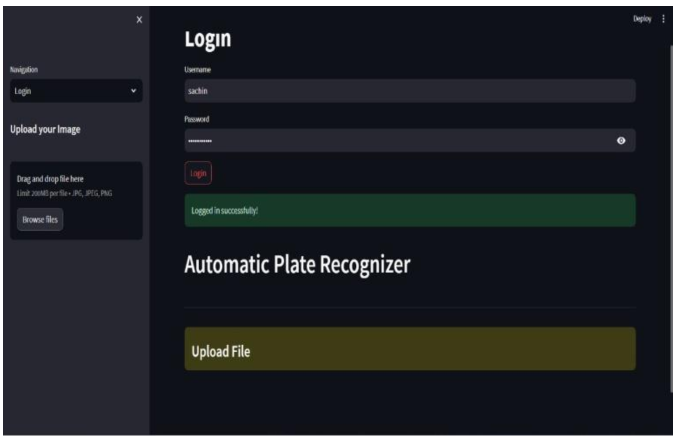
4.6. Dimensionality Reduction:- We reduced the dataset's dimensionality to improve efficiency in clustering. This involved simplifying the feature matrix by removing low-variance features that would not contribute much to our goal of clustering different vehicle behaviors. We used PCA to reduce dimensionality. We found that removing variables with very high correlation substantially improved the results and the performance of the clustering models for our data. Furthermore, correlated variables increased the data's variance, making the visual interpretation of the PCA results difficult, as the first principal components might not have accurately reflected the underlying structure of the data.

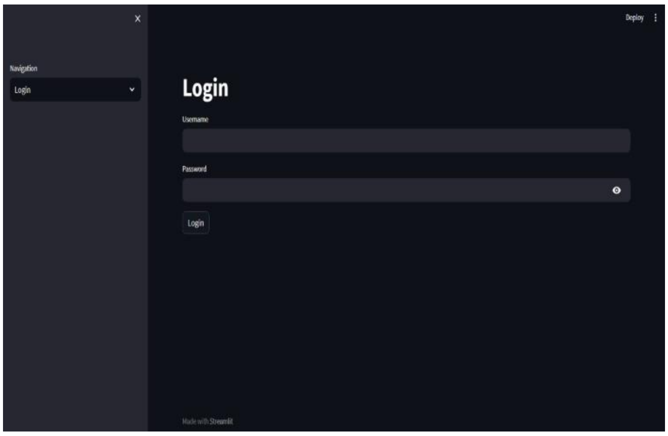
4.7. Clustering And Evaluation:- Our study explored all the algorithms mentioned in Section to determine the optimal approach for pattern recognition and evaluated whether they could find a realistic solution.

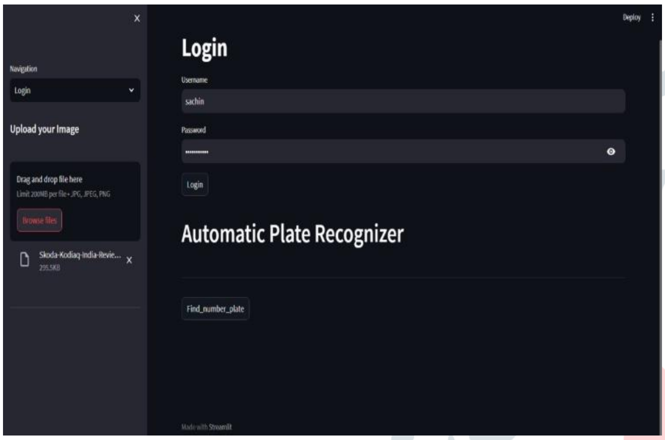
4.8. Visualization:- Data visualization was essential in our work, as it helped to determine and make decisions about parameter settings, algorithms, and normalization methods. It also made our machine learning results more understandable. For instance, we used the elbow method to find the best number of clusters for various algorithms. This method plots the number of clusters and a given evaluation metric. The number of clusters at the curve's bend ("elbow") balances the model's complexity and accuracy. We used scatter plots to visualize the first two principal components for each normalization method, helping us grasp the data's structure and cluster distribution.

4.9. Data privacy and security:- The LPR cameras sent the license plates to a secured server on our provider's premises. We only used the anonymized dataset. The other datasets were public, except the DGT dataset. The DGT shared with us sensitive data with license plates and its associate owner's postal code only for research purposes. This information was stored encrypted and was accessible only to authorized researchers. Furthermore, we used clustering, which means that we did not evaluate the individual behavior of each person but considered them part of a group. Hence, the privacy of the activities of the individuals is not compromised.[8-9]

Screenshot of Project:-







V. CONCLUSIONS

This paper presents a novel deep learning-based ANPR pipeline that is implemented and tested for automatic vehicle access control applications. By using object detection and DL models, we counter the heterogeneity and assortment problem of number plates across various Asian and European region number plates. The proposed real-time ANPR pipeline is tested using an IP camera video frames collected by considering the variations in the environment illumination and frame orientation. The obtained mAP score for plate extraction using YOLOv4 is 99.71% on a 0.50 threshold. In addition, for vehicle front/rear-view, we used another YOLOv4 which gives a 98.42% mAP score. The preprocessing techniques ar applied to the localized plate, and after the identification of the plate layout, the last step is to pass the frames to the DL character recognition model namely AlexNet or R-CNNL3. Our ANPR pipeline with the YOLOv4 model and OCR gives an overall average plate recognition accuracy score of 90.94%. Furthermore, DL-based architectures namely R-CNNL3 gives 96% on single characters recognition and 87.24% average accuracy on overall character recognition on different datasets. Meanwhile, the AlexNet architecture gives 98%-single character recognition accuracy and 87.56% as overall character recognition accuracy on different datasets.

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