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ANPR FOR PAKISTANI LICENSE PLATES: A DEEP LEARNING APPROACH USING CNN AND YOLO

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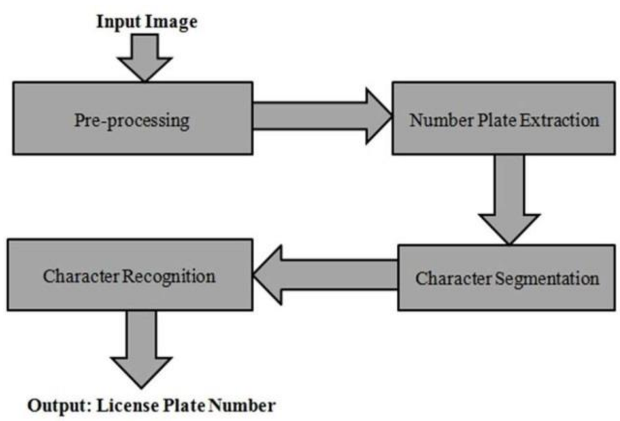
Abstract

Automatic Number Plate Recognition (ANPR) is an important technology used in various applications such as traffic monitoring, law enforcement, and parking management and used to recognize number plates in real time. . This discrepancy can be attributed to a number of difficulties Pakistan faces, such as the lack of uniform number plate sizes, the predominance of fancy number plates, a variety of fonts and a wide array of colors. These elements seriously impede the development of an effective ANPR system in the nation. The research proposal offers an effective method for Automatic Number Plate Recognition (ANPR) that is tailored to the particular features of Pakistani number plates. The method entails two main steps: Identification and localization of license plates. Using optical character recognition (OCR), convolutional neural networks (CNN), and YOLOv3 (You Only Look Once), characters from a license plate image are retrieved. In order to determine whether a license plate is genuine or fake, a special algorithm is also used. This procedure identifies the license plate precisely in an image and extracts the essential data for further processing. Utilising a dataset of 200 images of Pakistani license plates, including both bike and car plates, the effectiveness of the suggested method was assessed. The evaluation's findings demonstrated that the suggested method had a remarkable accuracy rate of 96.7%. This shows that the method is very effective at localizing and identifying Pakistani license plates.

INTRODUCTION

The use of Automatic Number Plate Recognition (ANPR), technology is essential for Real-time vehicle identification and license plate recognition. It also helps identify illegal vehicles used in crimes like kidnapping and drunk driving. In Pakistan, recognizing the vehicle license number requires less work than it does in nations like Iran, Bangladesh, and Europe. The identification of Number Plate Recognition (LPR) for all types of vehicles is the primary concern of this research paper, along with Number Plate Recognition. It is important to note that Pakistan has seen little research in the area of Number Plate Recognition in comparison to nations like Europe, India, and China. Most work involves identifying a vehicle's identification number, but in this researcher's work, a system will determine whether or not a number plate is original. The peculiar difficulties posed by Pakistani license plates, such as their non-standard sizes, elaborate designs, diverse fonts, and colours, can be blamed for this dearth of research. It is crucial to create an accurate ANPR system to handle these issues.[1] In this paper, the Iranian license plate was worked on, and [2] in this paper, Bangladesh's license plate was worked on using YOLOv3 and a custom algorithm.

An effective strategy for Pakistani license plates that is catered to the unique characteristics is proposed in this research paper. The two main steps of the suggested method are license plate localization and recognition, as well as preprocessing on images of Pakistani license plates such as resizing, removing unwanted noise, and converting to grayscale. License plate detection, character segmentation, and character recognition are the three requirements for license plate localization implementing YOLOv3, convolutional neural networks, and recognition of optical Characters (OCR). The detection of license plate images, character extraction, and authenticity assessment, including the detection of fake plates, are all made possible by this combination. In the step of recognizing license plates, with a dataset of Pakistani license plates, a deep learning model is developed.



Block diagram for character recognition and detecting the vehicle license plate

Different License plates according to the province:

Punjab latest Liense plate

Pakistan Sindh Plate

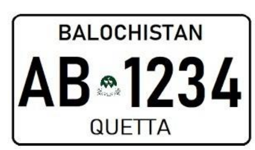
Pakistan Govt ofqSindh

Pakistan Latest Sindh

Balochistan plate

Old Punjab Plate Sindh Plate

Army plate



Balochistan

The effectiveness of the suggested method is assessed using a dataset ofq200 images that includes both bike and car license plates. The evaluation shows a 96.7% accuracy rate, which is impressive. The findings show that the suggested method recognizes Pakistani license plates with a high level of efficiency and accuracy, enabling a several uses, including as traffic control, police enforcement, and border control. This paper has proposed a vehicle recognition technology based on the general appearance characteristics of the vehicles to compensate for the restriction and shortcoming of the license plate recognition method and also system tell that license number is original or fake and also detect in weather and also improved the all challenges in this paper.

Literature Review:

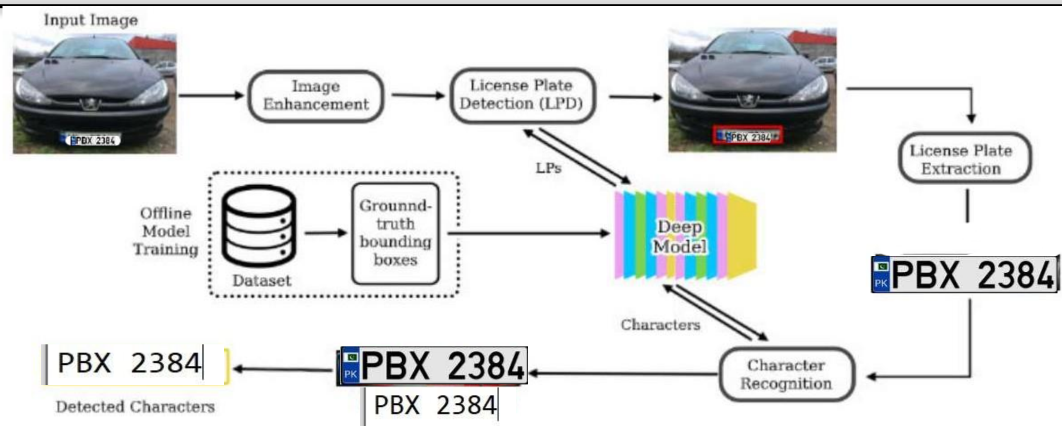
Deep architectures are DNN structures with between the input and output layers, there are hundreds or thousands of layers that are invisible. By using high-level filters, the hidden layers gradually extract useful information from their earlier layers. Research on convolutional neural networks (CNNs) has recently received a lot ofqattention from researchers in the fields of object detection and machine vision [4]. These networks provide more accurate solutions to typical machine vision issues as compared to other supervised learning models, such as Support Vector Machines (SVMs). Differentiating feature relationships [4]. Convolution layers are used to extract high-level features (i.e., kernels), fully-connected layers are used for non-linear feature learning, and pooling layers are used to reduce input tensor parameters. CNNs generate an abundance of candidate regions, which is why other extensions of these networks have been developed [4]. The selective search greedy technique is used in region-based convolutional neural networks (R-CNNs) [5] to combine neighboring regions. Faster R-CNNs [7] and Faster R-CNNs
[8] Are two further enhanced R-CNN extensions. The training procedure has been improved by
Using Fast R-CNN, indirect data feeding, a SoftMax probability layer, and Region of Interest (RoI) structures in the pooling layers. Faster R-CNN has even improved the technique by switching to Region Proposal Networks (RPNs) from Selective Search. A range of deep learning-based approaches are also available for feature extraction and classification. Among the most widely used techniques, Yolo (9), divides an input image evenly into equal-sized grids, each with a probability measure of containing a trained object. By in view of the whole image, this method—which is barely practical with R-CNN approaches—can accomplish effectiveness. After iterations, as an example YOLO models 2 and 3[1 0, 11], give even more persuasive results regarding exactness and presentation. According to an 11-layered architecture created using ImageNet education data and 19-layered contacts for classification using the current Objects in Context (COCO) dataset, the second model can classify over 9000 components [12]. An image processing and machine learning-based license plate recognition system for Bangladesh was proposed by Prashengit et al. [13]. They unveiled a dataset of 2800 images of license plates. They identified the license plate from an image using a process called shape validation in image processing. For tilt correction, they then used image processing once more. The characters on the license plate were then divided using connected components. They took the connected parts out of the license plate, each of which stands for a different character. With the Ad boost classifier, they put the recognition task into practice. They employed the Histogram of Gradient (HOG) and Local Binary Pattern (LBP) as their two primary features for recognition. Their suggested algorithm had a 97.3% accuracy rate, which appears to be the most recent cutting-edge model. However, this system mainly relies on a number of image processing methods, such as HOG, LBP, tilt correction, ROI extraction, morphological analysis, shape detection, and shape validation. Therefore, this system takes a little bit of time. An end-to-end system for recognizing Bangladeshi license plates was proposed by Nazmus Saif et al. [14]. However, their paper hasn't specifically referred to data from their dataset. Therefore, it is very difficult to assess or compare their work. Furthermore, they asserted that their dataset had accuracy of 99.5%. They made a very naive choice for this kind of task

by using the YOLOv3 for both license plate detection and recognition. However, we recreated their model to assess their claim before they were finished. Unfortunately, using YOLOv3 on our dataset, we were unable to achieve that accuracy. We believe they encountered this issue as well and added it to the restriction. In conclusion, their dataset was not diverse enough and could not be used for real-life scenarios, which is why their model had such a high accuracy. A sensor-based system for vehicle recognition has also recently been suggested [15].In this paper, the authors present a number of published works in the area of ITS applications based on deep learning. Similar to the strategy used in this paper, we have put forth a license plate localization method based on YOLO v.3 in [16]. With precision and recall figures of 0.979 and 0.972, experimental findings demonstrated the robustness of our methodology. For the purpose of detecting vehicles, we also proposed a deep model based on Faster R-CNN. Which can recognize vehicles based on their outward appearance [17]. For the purposes of this study, we used the Stanford University-provided Cars Dataset for testing and training. In addition, [18] included a review of various deep neural network-based ALPR strategies. In the aforementioned paper, we covered a range of techniques and methods along with their corresponding benefits and drawbacks for creating an ALPR system that is well-designed, has a high degree of accuracy, and performs admirably.

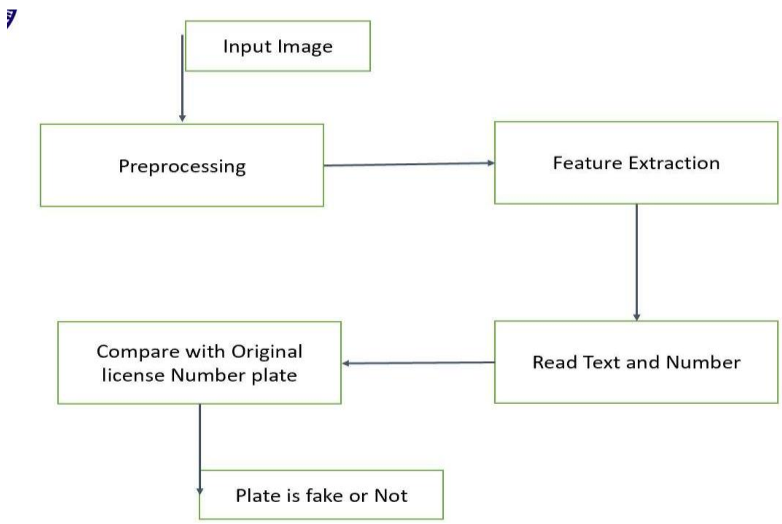
Proposed Methods:

Proposed Model si YOLO and CNN Na OCR along with custom Algorithm and flowchart that was utilized to extract the character order from license plates is clarified in this allotment. Our education endeavors have been primarily geared towards those circumstances because the put forward method is intended to be utilized as automatic commercial application for driveway security gates. The method composed of two profound thing detection layers, both of that are executed by YOLO architectures. We required to proposition a real-time program with elevated precision in LPD and CR, so the 3rd model of YOLO was chosen for both stages. The majority of the characters on license plates are small, and the localization procedure should be carried out in real-time, so YOLO v.3 has an advantage over the suggested method, according to the descriptions in Section II. In Fig. 2, a brief summary of the proposed approach is presented. In this diagram, the input is represented by a picture, a group of pictures, or a video frame, and the output is represented by a string of characters that refers to the context of the vehicle license plates.

When a vehicle diagram is fed into the system several diagram enhancement methods have been utilized to enhance the quality of the common illustration and produce a new illustration that is, in several ways, greater than the unique. The LPD juncture then kicks off and searches for any sub item(s) that resemble a vehicle's license plate(s). In this stage, the treat searches for any available license plate applying a pre-trained YOLO v. 3 profound architecture. It is necessary for CR to activate a second YOLO v.3 deep network in order to recognize the letters and numbers on the cropped license plates. A classification approach for CR is developed using the character segmentation and OCR processes that treats each character or digit as an independent object. In the event that no license plates are found during the LPD stage, the programmer moves on to the next modules, such as character recognition and license plate cropping, and waits for further picture input. Here, the input image is first processed using various image-enhancement techniques in order to further explain the diagram. The most frequent intensities in the input image are distributed in this step using the Histogram Equalization (HE) method, standardizing the intensities and enhancing contrast.



Propose methodology diagram of ANPR Pakistani license number Pate [1]



Propose methodology diagram Flow charts of Pakistani license number plate

After the image quality has been enhanced, the second stage, which uses deep learning-based license plate detection, will be turned on. Fig. 4 depicts the organization of the YOLO v.3 networks mentioned in the suggested method. Because the input resolutions for YOLO v.3 range from 320 by 320 to 416 by 416 and other multiples of 32, it is clear that each deep network's input images are scaled to a 1:1 square image. YOLO keeps the images' aspect ratio intact. Black bars are automatically added to an image to make it square if the input image is not square.

License Plate Detection:

We suggest using the YOLOv3 (You only look once), algorithm, a cutting-edge object detection algorithm, to find license plates in complex scenes. YOLO is extremely effective and appropriate for real-time applications because it uses a single neural network to carry out object detection and localization at the same time. Our annotated dataset of images of Pakistani license plates is used to train the YOLO model. The license plate designs, fonts, colors, and backgrounds in the dataset come in a wide variety. Using this dataset as training data, the YOLO model gains the ability to precisely detect and localize license plates in a variety of scenarios. The YOLO algorithm is strong and capable of handling challenging ANPR conditions like low lighting, occlusions, and various viewing angles. Even when partially obscured or surrounded by other objects, it can still recognize license plates.

YOLOv3 Bounding Box Prediction

YOLOv3 divides an image into an S×S grid and predicts B bounding boxes for each cell. Each bounding box contains the following components:

Equation 1: YOLOv3 Prediction [1]

$$\text{Prediction} = (x, y, w, h, \text{confidence}, \text{class scores})$$

Where (x, y) is the center of the box, (w, h) is the width and height relative to the image dimensions.

The confidence score is calculated as:

Equation 2: Confidence [1]

$$\text{confidence} = P(\text{object}) \cdot \text{IOU}_{\text{pred, truth}}$$

Where P(object) is the probability of an object being present, and IOU is the Intersection Over Union between the predicted and ground truth bounding boxes.

CNN Feature Extraction (Convolution Operation)

Convolutional Neural Networks (CNNs) extract features using kernels applied over input pixels. The operation for a single output pixel is:

Equation 3: CNN [2]

$$\text{Output}(i, j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \text{Input}(i+m, j+n) \cdot \text{K}$$

Where Kernel (m, n) is the filter matrix, and Input(i + m, j + n) are the local image pixels.

Softmax Function for Character Classification

The softmax function is used in OCR for classifying one character among multiple classes (A–Z, 0–9):

Equation 4: Softmax [2]

$$P(y = j \mid \mathbf{z}) = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}$$

Where z_j is the logit (raw score) for class j, and the denominator sums the exponentials of all class scores.

YOLOv3 Loss Function

The overall loss in YOLOv3 includes bounding box localization, confidence, and classification loss:

Equation 5: YOLOv3 Loss FUnction [1]

$$\mathcal{L} = \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] + \ldots$$

This includes:

- Localization loss (difference between predicted and actual bounding boxes)
- Confidence loss
- Classification loss

Intersection Over Union (IoU)

IoU measures the overlap between predicted and actual bounding boxes:

Equation 6: IOU [1]

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

It is used both in the loss function and for measuring accuracy during detection.

Greedy Graph-Based Segmentation

This technique identifies connected components (characters) in a binarized image:

Equation 7: Greedy Graph [6]

$$\text{Label}(p) = \text{Label}(q)$$

This is used to group white pixels representing characters into bounding boxes for OCR.

Dataset:

In order to recognize license plates at night, illumination sources must illuminate the surveillance zone and the training data, which are color samples with varying resolutions. However, in low- light conditions, like at night or in the late afternoon, infrared cameras can create grayscale images that can provide a better representation of the photographs. A total of 200 images are included in the datasets, 100 of which are real number plates and 100 of which are fake. This section is divided into two parts to introduce the datasets to both train and test.

Character Detect Dataset:

In the character recognition stage, we used a dataset of all digits and typical characters found on Pakistani license plates. Accordingly, we used every cropped license plate generated by the LPD deep network. Each image in the dataset has been painstakingly annotated with the bounding box coordinates surrounding specific characters. This annotation offers real-world data for model training and evaluation, enabling developers to precisely assess model performance.

Image Id	Character	Label
1	A	0
2	B	1
3	C	2
4	D	3
5	E	4
6	F	5
7	G	6
8	H	7
9	I	8
10	J	9
11	K	10
12	L	11
13	M	12
14	N	13
15	O	14
16	P	15
17	Q	16
18	R	17
19	S	18
20	T	19
21	U	20
22	V	21
23	W	22
24	X	23
25	Y	24
26	Z	25
1000	0	26
1001	1	27
1002	2	28
1003	3	29
1004	4	30
1005	5	31
1006	6	32
1007	7	33
1008	8	34
1009	9	35

Image ID : Each image in the dataset has a specific identifier .

Label: Each character is given a numerical label for training purposes. As an illustration, A = 0, B

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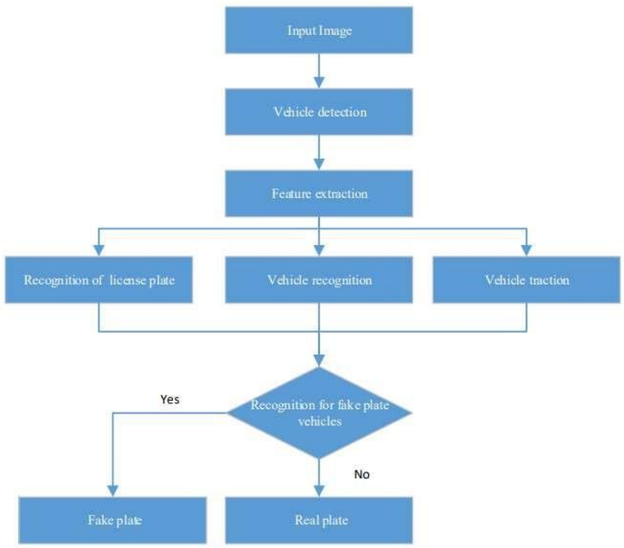
= 1, C = 2, and so forth. During model training, the character can be represented numerically using the label.

Character: The persona depicted in the picture.
Custom General Algorithm:

Steps:

1: Take Image
2: Preprocessing applied
3: CNN Used For feature extract
4: Extract text and Numbers Using OCR
5: Next Step is Compare License plate with Original License Number Without Text only Texture Compared.
6: System will tell is Original or Fake and Also write the character.



Vehicle Recognition Flow Charts

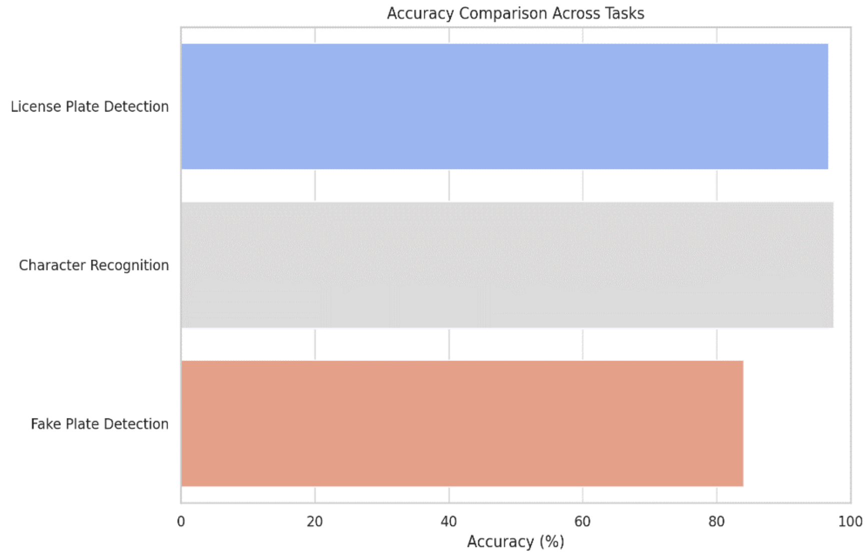
Greedy Graph-based Segmentation [19]:
1. Include a 24-bit RBG colour license plate picture. Set of persona from the license plate as product 2
3. alter the characterize to an 8-bit grayscale model.
4. alter the grayscale characterize into a binary characterize made up of 0 and 255.
5. transform 255 to 0 and map 1 to 0. 0 indicates a white pixel, whereas 1 indicates a black-colored pixel.
6. In column for a For b in a row.8. If visited[b][a] = 0 and image[b][a] = 1, then
9. Visited[b][a] equals 1
10. shove(b, a) into the apogee queue, r into the R list, and c into the C list
11. whereas apogee row is vacant
12. confirm in-case the pixel's(b, a) close to close by 8 neighbours have ever visited black-colored.
13. shove the coordinates(b,a) ,if found, into the row Vertex, with b balancing for R and a for C.
14. max a = C's highest worth
15. max b = R's highest worth
16. min a = C's minimum
17. min b equals R's minimum
18. crystal-clear C and R
19. Enter the after into a list character box:(min a,min b,max a,max b)
20. For each character box element:
21. Use(min a , min b)and(max a, max b) to chop the rectangular segment, that spell the top left corner and backside right corner of a rectangle , respectively.

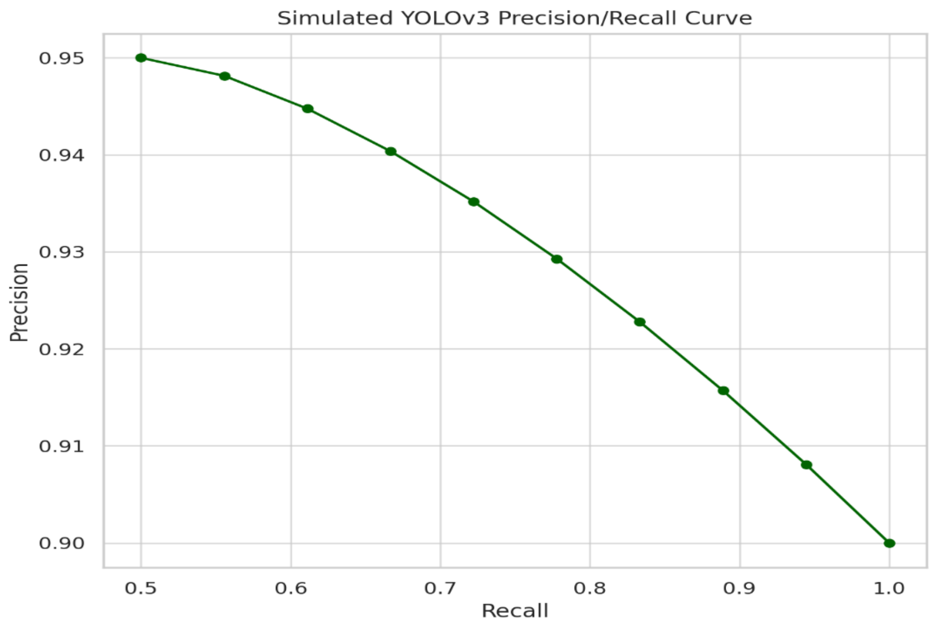
Results and Analysis:
Two sets of experiments of the same types and different types are conducted to demonstrate the efficacy of the method of identifying vehicles with fake license plates. 200 images of typical vehicles and 100 images of vehicles with fake license plates, including those with missing license plates, defaced license plates, and forged license plates,

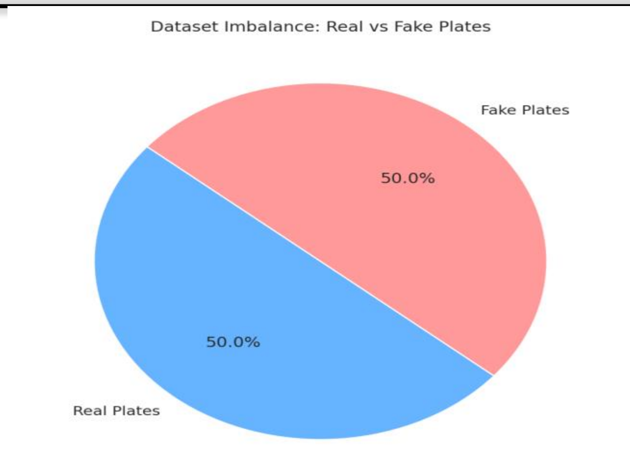
are recognized. In Table 1, the experimental findings are displayed. The accuracy rate for fake license plate detection is 84%.To train and test our model, we used a diverse dataset. We still hold the record for the highest accuracy in this field with our character recognition accuracy of 97.5%. We compared our system to those that were already in place, and it turned out that our system was superior.

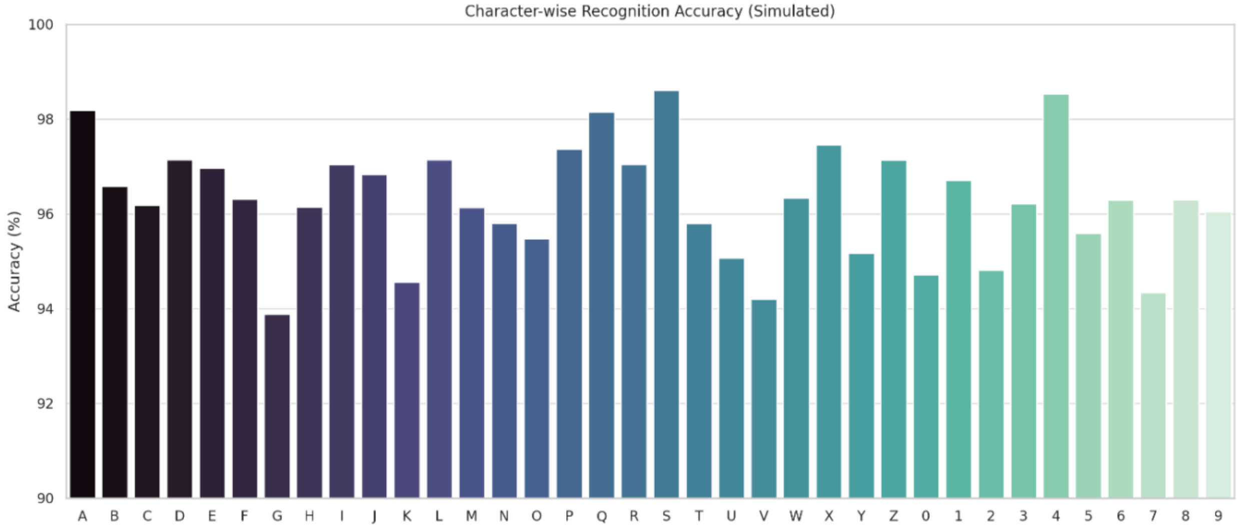
Extracted Results Table

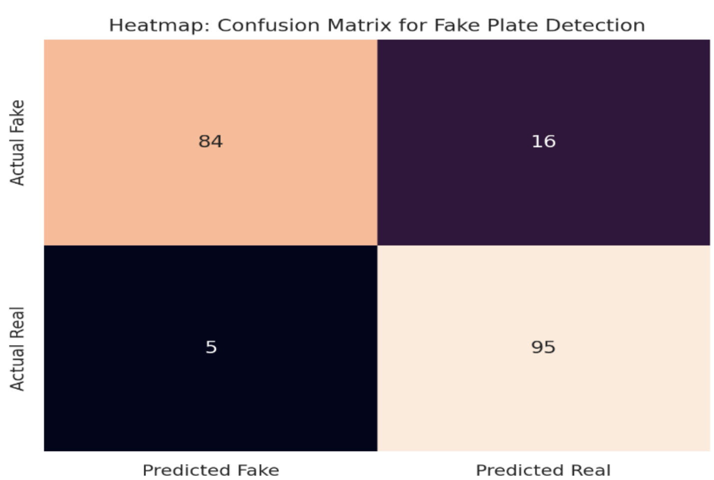
Task	Model/Method	Accuracy	Dataset Size	Notes
License Plate Detection	YOLOv3	96.7%	200	Works on real + fake plates (cars/bikes)
Character Recognition	CNN + OCR	97.5%	Cropped plates	Letters & digits isolated with bounding box
Fake Plate Detection	Custom algorithm	84.0%	100 fake only	Texture-based matching











Conclusion:
In ANPR process, this system can be made more effective in the future. Additionally, the registration process at points of entry or exit within an organization can be fully automated and also implement the greedy graph-based segmentation

approach. The research in this paper addressed issues with foreground extraction and the identification of vehicles with fake license plates, and it established a solid framework for the development of a system for the identification and retrieval of vehicles with fake license plates in the future. The use of this system for smart parking management in the future could be a positive step towards a more intelligent India. Where there won't be a need for security personnel to register at entry or exit check points, and there won't be any trouble finding parking.

The suggestion of the Automatic Number Plate Recognition (ANPR) research on Pakistani license plates will serve as a great representation of intelligent transportation systems in the field that other research organizations in different countries of the global community tend to ignore. As compared to developed nations where the design of number plates has a rule-book to follow, Pakistan is a challenge since there is no consistency in the size of plates, fonts, and plate color as well as the alignment. It is this heterogeneity that has in the past presented challenges in ensuring that competent ANPR systems are rolled out; it has also been a source of inaccuracy in such systems. As such, the solution proposed in this paper, that relies on a deep learning based model that uses YOLOv3 to drive the detection, convolutional neural networks (CNN) to extract features, and OCR to recognize those features, shows that even in such chaotic data setting, contemporary AI models can be made to be adapted to produce useful solutions.

The advantage of the suggested methodology is that it is very simple, easy enough to understand, and effective use of well-known machine learning techniques. The two-level architecture based on use of YOLOv3 with the license plate localization and subsequent character segmentation enables real-time work with high accuracy. Other decision targets such as the CNN and OCR also adds on to the advantageous nature of the system ability to recognize characters effectively, even in the noisy or low-resolution situations. It is also interesting to note that the custom algorithm created to identify cloned and counterfeit license plates provides another practical relevancy in particular of the law enforcement agencies that come across cloned or tampered license plates on the roads on a regular basis.

Model evaluation is encouraging. The accuracy of the license plate detection was 96.7 percent, whereas the accuracy of character recognition was 97.5 percent. Such results are quite remarkable since the size of the training set is minimal (200 images: 100 original and 100 fake license plates). Also, it could identify fake license plates accurately using a texture comparison technique at the rate of 84 percent accuracy which is a new feature in standard ANPR systems. These figures indicate that the model can be more than merely functional, and it could be effectively applied in the small-scale domain in real life, i.e., parking garages, gated communities, and Highway turnstiles.

Nonetheless, the study does not happen without limitations. The pressing problem is the small amount of data. Although 200 images might be adequate as proof of concept, those are nowhere close to train a system to generalize well with regards to the large variability in the visual attributes of the Pakistani license plates. A small data set raises the probability of overfitting, that is, the model will adapt to usage patterns particular to the training ones but perform miserably on new ones. What is more, there are no detailed performance evaluation metrics like precision, recall, F1 score, and ROC-AUC curves as commonly used in machine learning to get the full picture about the behavior of the model, which can also be found in the paper. Transparency is also limited by the lack of the confusion matrix patterns and the break-downs according to classes.

The other limitation is linked to the environment conditions. There is a wide range of lighting and resolution variations in the data, however, it is not known how the model would work in extreme cases when visibility is low at night, glare, extreme rain or camera contentious. Temporal stability is not mentioned either, i.e. whether this system can be used to create systems that keep the accuracy over several frames in a video sequence or whether it is robust against motion blur. In real-life installations, one would need to know how to manage run-time conditions. Besides, the study fails to address the computing ability of the model. There is the implication of real-time processing which is not demonstrated quantitatively. Latency and memory requirements become critical bottlenecks in resource-limited systems like embedded systems or the low-cost-surveillance-oriented hardware. These are the facts that were not discussed in the study.

Though these are the limitations, the paper provides very convincing points about the ANPR system in a developing country with the possibility of using deep learning. It demonstrates that with very few resources, limited infrastructure, customizing the existing architecture, and training pipelines, it is not a difficult task to construct a system with high accuracy. YOLOv3 is already characterized by a reasonable trade off between speed and accuracy, and the transfer to the present case indicates that out-of-the-box approaches can be tuned locally to the demands of the country. Also, including the fake plates detection into the pipeline, the authors have managed to extend the capabilities of the ANPR system beyond the usual character recognition.

The potential of future research in the field is wide. An increase in the dataset would be among the expediency of the improvements. Cooperation with the government agencies like the Motor Vehicle Registration Authorities or Traffic Police may contribute to the development of the large annotated funds covering all the areas of Pakistan. Such datasets ought to be very diverse in terms of license plate designs, light situations, occlusions and qualities of images among others. Additional tricks that might assist in making training set more diverse and robust include random cropping, rotation, color jittering, and synthetic image generation techniques (e.g., GANs).

In addition to the expansion of the data set, it would be valuable to combine the model with the video-based tracking systems. Temporal modeling may be applied, in this case, instead of treating each individual frame as a separate image, a vehicle may be tracked by multiple frames, which would allow more reliable plate detection and limit false positives. To keep object identities between frames and to increase tracking stability, it is possible to augment YOLO with algorithm like Deep SORT or ByteTrack. Such a system would be applicable in such applications as traffic control, tolling and policing.

The other improvement aspect is on models optimized towards deployment at edges. Whereas, even though YOLOv3 offers decent performance, it is, never the less, a computationally demanding algorithm, especially when two different copies of it (one to detect plates and another one to separate character sequences) are used. In future, the author could consider running lightweight architecture models like YOLOv5n, YOLOv8n or MobileNet-SSD, specifically developed and optimized to run on developmentally-restricted devices. Such methods as knowledge distillation, quantization and pruning could be utilized to minimize model size what would not significantly decrease the accuracy.

One of the most notable features of this system is the fake plate detection and should be looked into more. This system relies on comparing textures and this might not be enough in forgery carried out in a complex way. In the future, the models might be made to interface data with other databases, including vehicle registration APIs, to compare plates identified with official records. There are the possibilities of verifying authenticity through multi-modal methods which employ RFID tags, NFC chips or even acoustic signatures. Machine learning can also be trained to recognize indications of a tampered machine learning model: uneven spacing, mismatched fonts, damaged plates, etc.

Still, one should consider a linguistic aspect as well. In Pakistan, there are license plates with pieces of urdu script, local symbols or fancy designs. These variations might cause challenge to the current OCR system. Future research can employ training multilingual OCR models to deep learning models like CRNN, or transformer-based models like TrOCR which have demonstrated promising results in character recognition challenges on mixed scripts.

System intelligence would also be improved by incorporating metadata GPS and other context related data. Combined with geographical coordinates, time stamps and environmental measurements, the tracking and profiling system of vehicles can be developed on a greater scale, as their movements to plate detection events can be tracked. This may be especially helpful in police-detective and urban development.

Behavioral analysis and anomaly identification are another interesting prospect. Instead of letting citizens passively identify plates, the program would become an observer of vehicle dynamics and instead of relying on the passive notice of license plates, the program would recognize repeated U-turns, docking near sensitive areas, or frequent visits to restricted areas. These revelations could be injected into future policing algorithms or offence detection programs.

Lastly, in terms of research and academia, it would be very useful that the authors release their model and dataset as open-source. By so doing, it would be possible to create a cooperative ecosystem by other researchers benchmarking, replicating, and beyond, and extending the work. It would also enable practitioners and policymakers to test the model with their own environment, hence hastening the time to adoption and innovation in the field.

To sum up, the present study has shown that the ANPR system based on deep learning is certainly possible to implement in the Pakistani situation and that it can certainly be effective enough. Although the dataset is small and it faces a number of challenges, the model also exhibited high accuracy in the detection of plates, recognition of characters and detecting of fake notes. The provided system provides a solid base towards further developments, and once larger datasets are utilized, video processing is performed in real-time, models are lightweight, and there is integration across the domains, it might become a go-to technology of intelligent vehicle monitoring in Pakistan and other related areas. This piece of work preconditions the convergence of AI, surveillance and transportation policy in one of the most vital but under served elements of contemporary urban infrastructure.

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