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An Automated Vehicle Registry System In Militaryworkshop, Nepali Army

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Abstract

"An Automated Vehicle Registry System in Military Workshop, Nepali Army" is the system designed to enhance the security and efficiency of military vehicle maintenance management by automating the processes of vehicle identification and data logging. The research employs state-of-the-art image processing techniques, notably YOLOv9 and EasyOCR, to achieve these goals. YOLOv9, trained on a custom dataset prepared by collecting a set of vehicle images in a military workshop ambience, is utilized for real-time number plate localization, offering high accuracy and speed essential for dynamic environments like military operations. Complementing this, EasyOCR, an open-source Optical Character Recognition (OCR) tool, is integrated for robust character segmentation and recognition. EasyOCR's flexibility and performance in recognizing various fonts and languages make it an ideal choice for the diverse range of military vehicle number plates. The number plate texts extracted by EasyOCR is used as query to the database stored in MONGOdB through NodeJs application. The database holds the maintenance information related to military vehicles in JSON format. All the entries that match to that query are displayed in a web application developed using html and css. The purpose of this research project is to develop an automated system that can possibly replace the current manual registry monitoring process being practiced in NA, thereby minimizing the human error, improving operational efficiency, and enabling real-time monitoring of military vehicles repair history. The system is expected to significantly improve vehicle maintenance management process and thereby enhance the operational effectiveness within the military infrastructure by automating the retrieval of maintenance history of the vehicles that appears in the military workshop.

Keywords*—YOLOV9, EasyOCR, Number plate recognition, Military workshop.*

1. INTRODUCTION

Number plate of the vehicle can be considered, the identity of the vehicle in itself. Any road vehicle registered in the department of transport management should attach it in the front and back side of the vehicle. The identification characters in these plates are used by the authorities to maintain the digital records of vehicles for taxation and other legal purposes. The number of vehicles owned by Nepali Army makes it suitable to implement the Number plate recognition system in many areas. The military vehicle drivers bring a maintenance book along with the vehicle every time they visit the workshop. The mechanics in the workshop after completion of the repair work, enter the details of the repair job manually to keep the record. If somebody has to know about the repair history of the vehicle, there is no other way than to physically verify that maintenance book. The proposed automated vehicle registry system can automate this process. The system can be implemented in the military workshops. Once the vehicle is mounted on the ramp, an imaging system acquires the image of the vehicle with the number plate as a part of it. The number plate recognition system extracts the number plate identity of the vehicle and delivers to the workshop system which links it with all the vehicle details along with the past maintenance records. The current system relies heavily on manual identification and logging of vehicle repair jobs. This process is time-consuming, prone to human error, and requires significant manpower. Lack of automated data collection hampers effective fleet management, leading to difficulties in tracking vehicle usage, maintenance schedules, and operational readiness. The absence of real-time data collection means that the army cannot easily analyze vehicle movement patterns, which is vital for strategic planning and resource allocation. The implementation of number plate recognition system for the Nepali Army offers significant benefits, including enhanced security, improved operational efficiency, data-driven decision-making, cost savings, enhanced accountability, and scalability. By leveraging technology, the Nepali Army can ensure better management of its vehicle fleet, optimize resource allocation, and strengthen overall security measures, contributing to greater operational readiness and effectiveness. Computer Vision involves developing algorithms and models to process and analyze images or videos, allowing machines to perform tasks that typically require human vision. Image Processing focuses on the manipulation and analysis of images to enhance them or extract useful information. Together, computer vision and image processing form the foundation of Number Plate Recognition systems. MONGOdB is an open-source NoSQL database management program, generally useful for working with high volume of distributed data. It’s a tool that can manage document-oriented information, to store or retrieve the necessary data. Instead of using tables and rows as in relational databases, as a NoSQL database, the MONGOdB architecture is made up of collections of documents. Documents are made up of Key-value pairs as the basic unit of data collections, the equivalent of SQL tables.

2. RELATED WORK

Number plate recognition system is not a completely new domain to explore. A lot of works had already been done in this field. AHMAD et al [1] claims that the

Number plate recognition is a dependable technique for automatic vehicle identification. Number Plate Detection is an innovative use of machine learning which recognizes photos and transforms them into text. This technology can be used in military zones, apartment buildings, and traffic surveillance. DAWADI et al [2] presents a method for detecting, classifying, and recognizing Devanagari characters based vehicle's number plate (LP) in Nepalese context. The IWPOD-NET model is used in the detection phase to extract the LP from a vehicle region. After post-processing for contrast adjustment, the extracted LP is fed to a nested classifier for vehicle classification. Finally, the Devanagari LP characters are predicted/recognized using two distinct CNN models. DAHAL et al [3] used YOLOv5s that was trained on custom dataset collected by them which consisted of 2193 images of 6 classes which was augmented to extend their dataset to 5259 images and was split in the ratio of 70:20:10 for train, validation, and test respectively. SANAP et al [4] proposed that the number plate Recognition (LPR) systems commonly have framework of processing steps such as: Detection of number plate, Segmentation of plate characters and Recognition of each character. Number plate detection is a challenging task due to diversity of plate formats and environmental conditions during the image acquisition. Accuracy of character segmentation and recognition rely on the efficiency of plate detection. PANT et al [5] proposed a system in which Automatic number plate recognition is the task of extracting vehicle registration plates and labeling it for its underlying identity number. It uses optical character recognition on images to read symbols present on the number plates. Recognition system then uses Support Vector Machine (SVM) based learning and prediction on calculated Histograms of Oriented Gradients (HOG) features from each character. The system is evaluated on self-created Nepali number plate dataset. Evaluation accuracy of number plate character dataset is obtained as; 6.79% of average system error rate, 87.59% of average precision, 98.66% of average recall and 92.7% of average f-score. SHASHIRANGANA et al [6] claims that with the explosive growth in the number of vehicles in use, automated number plate recognition (ANPR) systems are required for a wide range of tasks such as law enforcement, surveillance, and toll booth operations. The operational specifications of these systems are diverse due to the differences in the intended application. For instance, they may need to run on handheld devices or cloud servers, or operate in low light and adverse weather conditions. Even though there has been a notable improvement in the current ANPR methods, there is a requirement to be filled in ANPR techniques for a complex environment. They present a critical and constructive analysis of related studies in the field of ANPR and identify the open challenge faced by researchers and developers. Further, they provide future research directions and recommendations to optimize the current solutions to work under extreme conditions.

3. MATERIAL AND METHODS

The system architecture utilized for the overall Automated Vehicle Registry System is shown in Fig. 1. The overall system is divided into five major phases; dataset preparation, yolo model training, model implementation for number plate localization, text/characters recognition and finally query to the database.

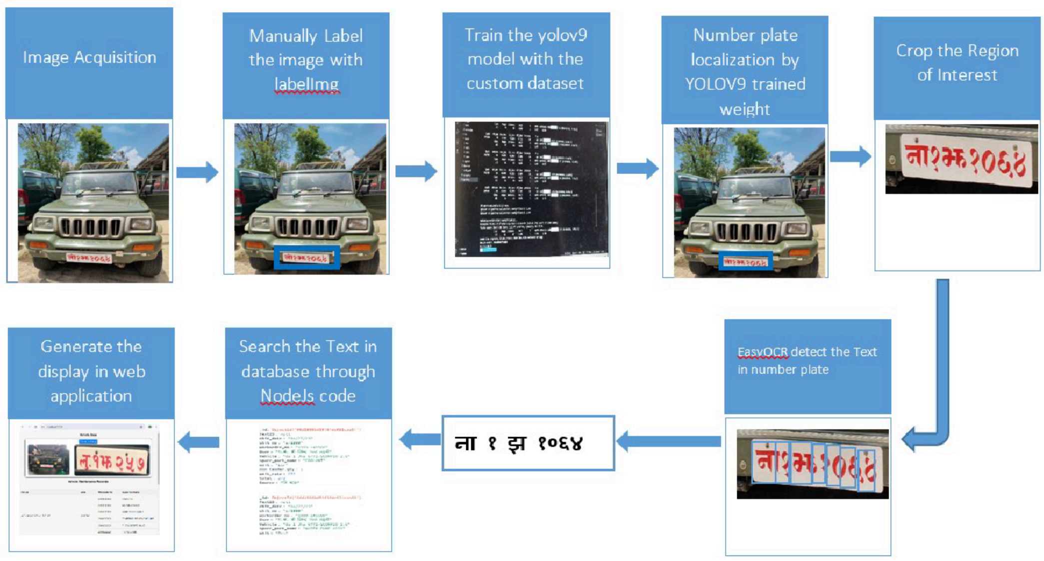

Fig. 1. System Architecture of system

Total of 564 images of vehicles that visited the EME service center, repair and maintenance workshop of Nepali army were collected during the duration of 3 months in image acquisition stage in everyday basis. The number plates were manually labelled in the dataset preparation stage. The yolov9s model was trained with the prepared dataset in model training stage which generated the weight files ready for model implementation. Dataset was split 70%, 15% and 15% as train, test and validation dataset. Using the weight files generated, the number plate detection stage is initiated

which returns the cropped image of the number plate region and fed to the EasyOCR module. EasyOCR module returns the text on the number plate and fetches it to the query to database stored in MONGOdB. All the matches to the query are returned by database and displayed in a web application developed in HTML/CSS.

A. Custom Dataset Preparation

As the very first stage of this system, total of 564 images of the military vehicles were collected. The military vehicles were mainly agency assigned vehicles to the high-ranking officials above the rank of Colonel in Nepali army and they were actually visiting the military workshop, EMESC for necessary servicing, repair and maintenance. So, most of the images are of light vehicles category. In addition, some images of the pickup trucks were also acquired which are unit vehicles of the NA units and formations. Hence all of the images are taken from the workshop floor with necessary permission of EMESC officials. For image acquisition a normal cell phone camera of 50MP was used. It took the time period of approximately 3 months' duration to collect aforementioned number of images. Images of the vehicles were taken in day-to-day basis since all of the vehicles could not be summoned for this purpose only and opportunity was taken while they visited the workshop. Hence, there are more than a single image of the same vehicle in the dataset but acquired at the different time period. Moreover, the images were taken from both the front side and rear side to collect the diverse formats of number plates in practice.

Fig. 2. Image Acquisition

In all the images acquired, number plate region is actually the RoI and it is manually labeled after the image acquisition using the open-source tool labelImg. It is used to manually label the regions in the images for the training procedure of the machine learning algorithms. In this case, the labelImg generates the .txt label file which contains only the LP (license plate) class label, center coordinate (x,y) of the rectangular selection, and the width and height of the rectangular selection. The label file: .txt thus generated is appropriate for training the yolo algorithm**.**

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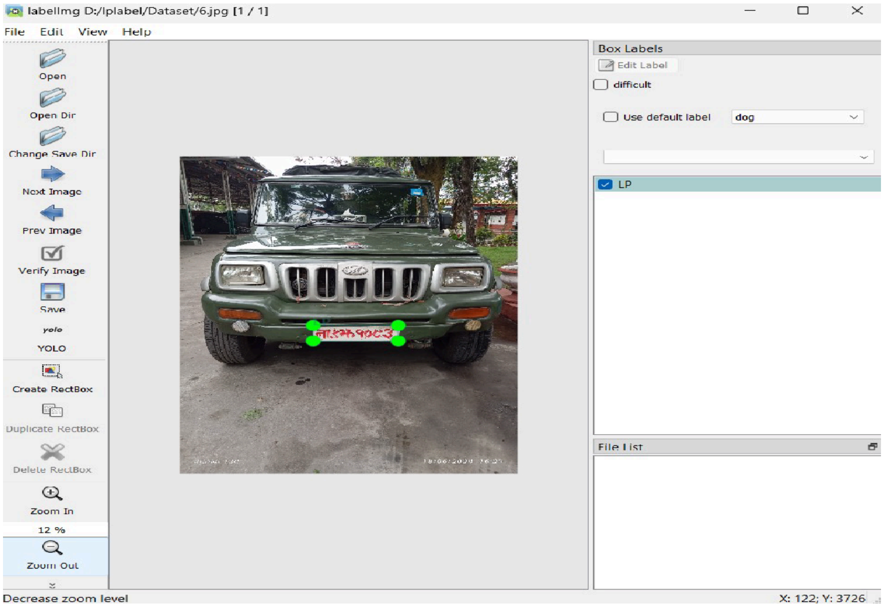

Fig. 3. Manually Labeling ROI

B. Training Yolo model

After the custom dataset is prepared, the dataset is split into train, test and validate data. Python code divided the entire dataset into 70% train 15% test and 15% validation dataset, randomly. Thus, prepared dataset is input to the YOLOv9s model for the model training. The model is run for 300 epochs and it took 31.217 hours to complete in the pc with intel 11th gen i7 processors and the base level GPU Nvidia MX 350. After the completion of training yolov9s model, it resulted into the output of two weight files namely best.pt and last.pt. last.pt is the weight of the training the dataset obtained at the last epoch i.e., 300th epoch and best.pt is the best weight file obtained within the 300 epochs. For the automated military vehicle registry system best.pt file is used for further implementations.

1. YOLOv9

YOLOv9 is one of the last iterations of the YOLO series by Chien-Yao Wang et al., released on 21 February 2024. It's an advancement from YOLOv7, both developed by Chien-Yao Wang and colleagues. YOLOv7 made significant steps in optimizing the training process with what's called a trainable bag-of-freebies, effectively enhancing training efficiency to boost object detection accuracy without adding to the inference cost. However, YOLOv7 didn't specifically address the problem of information loss during the input data's feed forward process, a challenge known as the information bottleneck. This issue arises from downscaling operations in the network, which can dilute important input data. Advancing object detection technology, YOLOv9 stands out as a significant development in Object Detection, created by Chien-Yao Wang and his team. This new version introduces innovative methods such as Programmable Gradient Information

(PGI) and Generalized Efficient Layer Aggregation Network (GELAN) to effectively address issues related to information loss and computational efficiency. These advancements ensure that YOLOv9 delivers top-notch performance in detecting objects in real- time, setting a new standard for accuracy and speed in the field.

2. Architecture of YOLOv9

YOLOv9 combines Programmable Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN) to create a unique architecture that significantly improves gradient flow and information retention. This combination addresses the challenges of information bottleneck and gradient reliability, enabling the model to learn more efficiently and accurately from complex data patterns without losing any information.

C. Model Implementation

The best model output of the training is utilized for the model implementation. A HTML/CSS based web application is built which can accept the image file as an input. NodeJS script is used to accept that input image from the port: 3000 and run the python script implementing the yolov9 model with the best weight file. yolov9 implementation localizes and gives the cropped number plate region output from the input image. For the localization of the number plate, we initially detect the presence of vehicle in the image frame using yolov9. Then the region of interest in inferred by the model and cropped from the input image as an output of the model.

D. Character Recognition

After segmenting the region of interest form the input image i.e., localized plate, the cropped image is passed into the OCR system for the prediction.

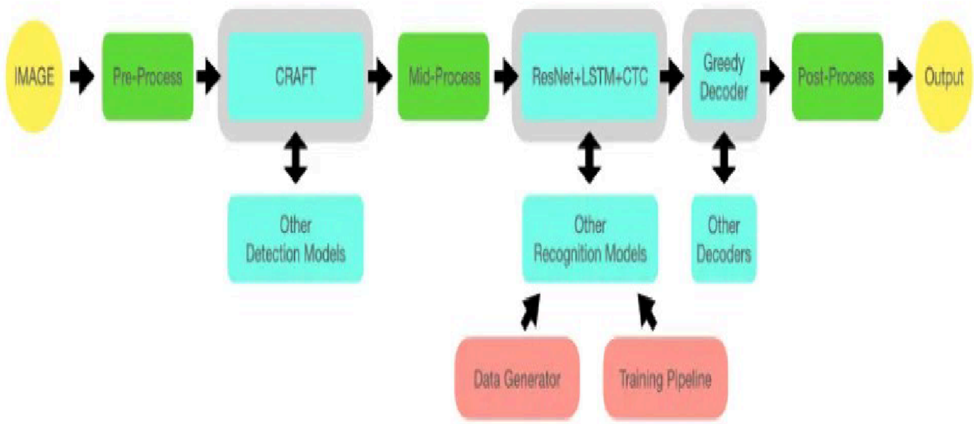

Fig. 4. EasyOCR Framework

EasyOCR is a Python computer language Optical Character Recognition (OCR) module that is both flexible and easy to use. OCR technology is useful for a variety of tasks, including data entry automation and image analysis. It enables computers to identify and extract text from photographs or scanned documents. EasyOCR stands out for its dedication to making OCR implementation easier for developers. It’s made to be user-friendly even for people with no background in OCR or computer vision. Multiple language support, pre-trained text detection and identification models, and a focus on speed and efficiency in word recognition inside images are all provided by the library. EasyOCR is a dependable option for Python developers because of its versatility in handling typefaces and text layouts, as well as its focus on accuracy and speed. EasyOCR simplifies the process of extracting text from photos for use in various Python researches, including desktop software, online applications, and others.

E. Registry System

After the successful retrieval of the characters in the number plate of the vehicle, it is input as the query to the vehicle registry system database holding the maintenance history. This system records the date, workorder no., chit no., spares used for maintenance as the JSON object. For the database, the repair maintenance data of last one year in EMESC was collected and entered in a excel file.

Text25	chit_date	chit_no	workorder_no	User	Vehicle Type	Vehicle Number	spare_part_name	unit	non-tencer_qty	unit_rate	total	Source
6753							CROSS BEARING	Pcs	1	1875	1875	ख स्टक
6754							FOG LIGHT BULB	Pcs	2	150	300	ख स्टक
6755							TYRE VALVE PIN (BIG SIZE)	SET	0.083	3	0.249	BG SUPPLIERS
6756							ABC RUBBER PAD	Set	1	375	375	ख स्टक
6757							BRAKE PAD	Set	1	2250	2250	ख स्टक
6758							CABLE TIE	Set	1	80	80	ख स्टक
6759							CAR SCENT	Pcs	1	150	150	ख स्टक
6760							CENTER BOLT	PCS	1	49	49	BG SUPPLIERS
6761		591	591/164101	म.के. बिष्णु बहादुर कार्की	BOLERO	Ba 2Jha 4312 (EAB 7388)	DOOR VISOR	Set	1	900	900	ख स्टक
6762							DOUBLE TAPE	roll	1	450	450	ख स्टक
6763							ENGINE OIL	Ltr	7	360	2520	डि स्टक
6764							FUEL FILTER	Set	1	473	473	ख स्टक
6765							OIL FILTER	Pcs	1	750	750	ख स्टक
6766							OIL PUMP GEAR	PCS	1	88	88	BG SUPPLIERS
6767							SEAT CUSION	Set	0.5	5500	2750	ख स्टक
6768	30-Aug-23						GALAICHA	Set	1	3888	3888	ख स्टक
6769							RUBBER MAT	Set	1	4500	4500	LP
6770		599	599/114452	उ.र. श्री योग राज शर्मा	SCORPIO S11	Ba 2 Jha 4614 (BAB 7134)	SEAT CUSION	Set	1	8500	8500	ख स्टक
6771							WATER BAG (SEAT POCKET)	Pcs	2	3000	6000	LP
6772							AXLE OIL SEAL (FRONT/REAR)	PCS	1	633	633	BG SUPPLIERS
6773							DOOR OPEN HANDLE INNER RIGHT	PCS	1	389	389	BG SUPPLIERS

Fig. 5. Maintenance history entry

All together 31550 entries were input to the excel file as the maintenance activity carried out over the different vehicles in EMESC workshop. The data contained chit-date, chit-no, vehicle number, vehicle category, user assigned with the vehicle, spare parts consumed in the repair job etc. The excel entries thus collected are stored in MONGOdB database where each entry are converted to the MONGOdB database. Query made to the database are returned to the requests matching the vehicle identification numbers.

4. Experimental Setup

YOLOv9 and EasyOCR are the backbone of this Automated vehicle registry system in Military workshop. Both of which are implemented in the python environment of version 3.12.4. The image acquisition is carried out in the military workshop of EMESC, NA with a normal cell phone camera of 50MP. The imaging location is from a workshop ambience hence the mechanics, vehicle ramps and other tools might also be present in the image background. Labelimg is used as a labeling tool for training yolo model. Labelimg is an open-source tool implemented in python. To train the yolo model with the custom dataset a normal laptop with 11th gen core i7 processor, base model NVidia GPU GeForce MX350, and the primary memory of 16gb is used. Windows 11 operating system, Nvidia driver version 32.0.15.5612, Cuda compilation tools V12.5.40, are installed in the laptop to make use of the GPU available in the system as yolov9 and EasyOCR both need GPU for the faster processing. With the aforementioned system, it took approximately 31 hours to train the yolov9s model with the dataset of 564 images. A Web application developed in HTML/CSS is designed that takes input of the image from the user. The web application is hosted by Nodes Server in Localhost 3000. NodeJS script accepts the input image from the user and activates the yolov9 model implementing python script. It produces the cropped image of the RoI and saves the cropped image in ./yolov9/runs/detect/cropped/*.jpg. The cropped image is input to EasyOCR python script which returns the all the text of the number plate. Out of all text last 3 or 4 digits are stored as the plate number text and used to generate the query in database. Nodejs scripts access the database stored in MONGOdB through mongoose. All the matches to the query in database are displayed in the web application.

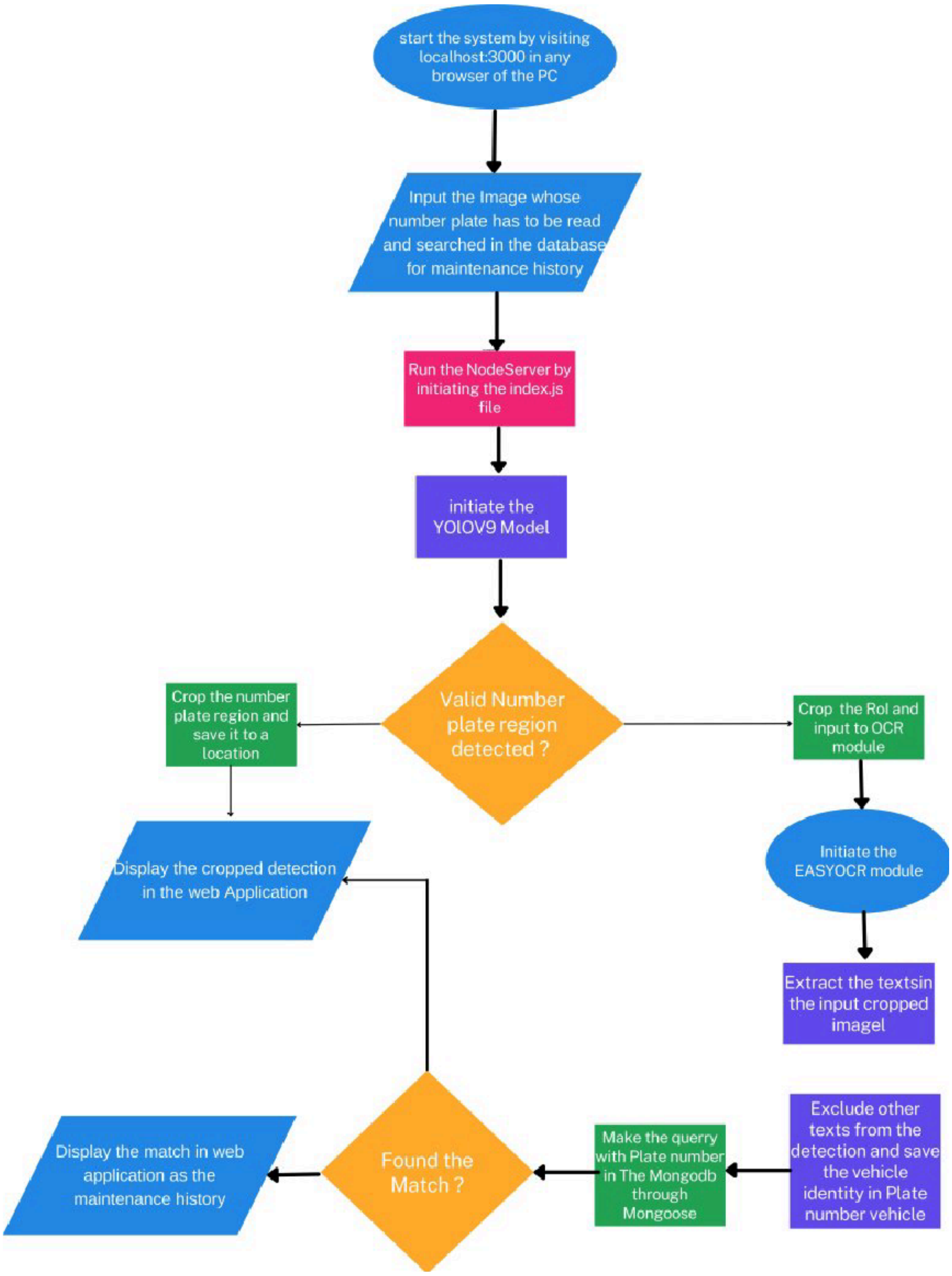

Fig. 6. flowchart of Automatic Number plate Registry system

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5. RESULTS AND DISCUSSION

Fig. 7. yolov9 model training

Fig 7 shows the prediction of license plate detection with the confidence score of the validation dataset. Which shows that the license plate region from the vehicle image is detected with the confidence score 0.9 if any unseen image is input to the yolov9 model. License plate region can both be from the front side or the back side of the vehicle. Generally, front side number plate is of the aspect ratio 4:1 and the rear side number plate aspect ratio is 4:3. The image acquired by the imaging system of number plate recognition system is prone to different illumination and camera angle since they are collected from the military workshop floor, which makes it challenging to detect the number plate of the vehicle from the frame. Moreover, the condition with the image having more than one number plate in a single frame can pose the complexity to the system. Similarly, presence of the region similar to license plate in the image and the characters other than number plate markings in the image might also prove to be the noise for the system. Detection of the vehicle in the image frame and localization of the number plate is carried out by using yolov9 and the result obtained is as shown in Fig.8.

Fig. 8. Number plate localization by YOLOv9

A. Confusion Matrix

The confusion matrix offers a detailed view of the model's prediction capability across different classes. In this case, the classes are 'LP' (License Plate) and background.

1. True Positives (TP): The model successfully identified 85 license plates correctly.
2. False Negatives (FN): Only 3 license plates were missed by the model, indicating a high sensitivity.
3. True Negatives (TN) and False Positives (FP): The matrix indicates an exemplary specificity as nearly all background predictions were correct, evidenced by a high number of true negatives and an insignificant count of false positives.

The high TP rate alongside low FN suggests that the model is highly effective in recognizing license plates with minimal misses.

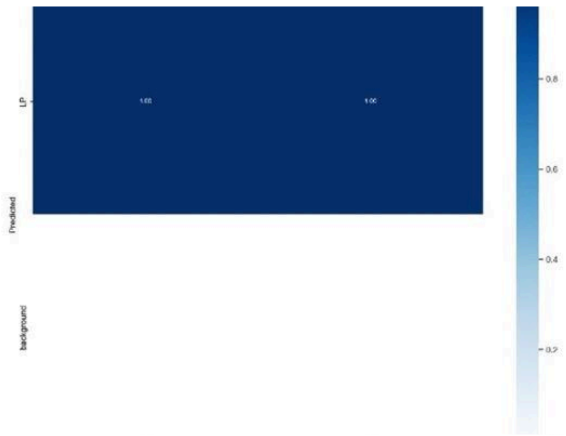

Fig. 9. Confusion Matrix of training YOLOV9

B. F1-Confidence Curve and precision-confidence curve

The F1-confidence curve illustrates the F1 score across different confidence thresholds and the precision-confidence curve measures the precision across different confidence thresholds:

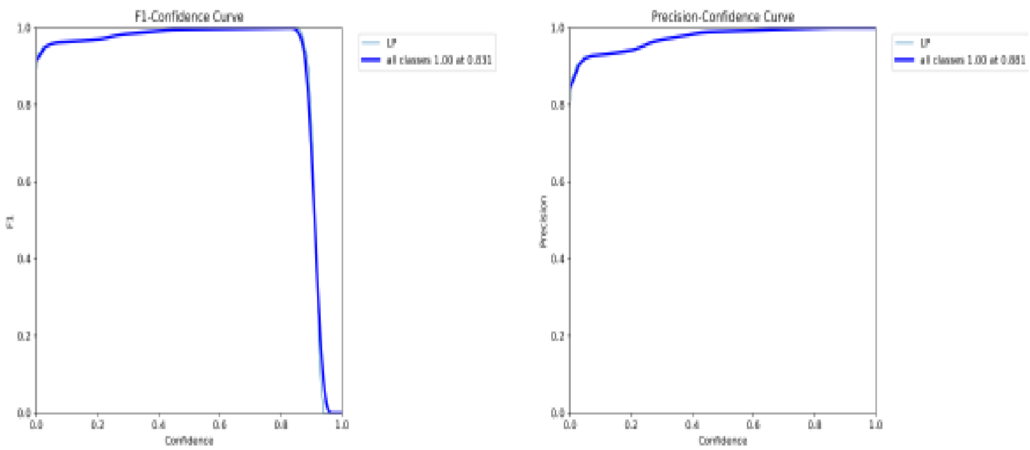

Fig. 10 (a) F1-confidence curve (b) precision-confidence curve

1. Stable Performance: The F1 score remains stable and close to 1.0 for confidence thresholds up to approximately 0.831. This indicates that the model maintains a high precision and recall balance for most confidence levels.
2. High Precision: The model consistently shows high precision (above 0.8) across confidence levels up to 0.881, affirming the accuracy of its predictions in identifying license plates.
3. Sharp Decline: There is a noticeable drop in the F1 score as the confidence threshold approaches 1. This could be due to overfitting at very high confidence levels where the model is too stringent, leading to an increase in false negatives.

Moreover, Fig. 11 suggests that the model gets fine-tuned in less than 100 epochs and is a suitable choice to localize the license plates from the images of the vehicles.

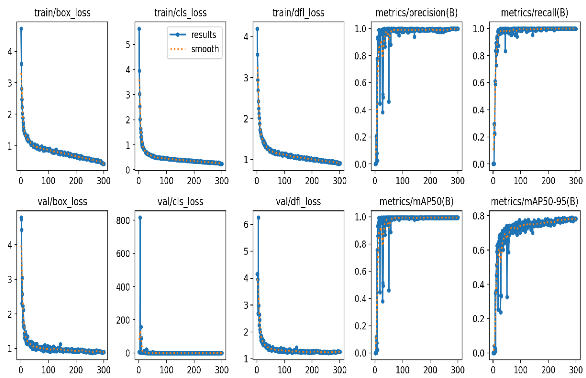

Fig. 11. Metrics over Epoch

The localized number plate region of the image frame is cropped and input to the EasyOCR. EasyOCR returns the text in input cropped number plate image in the form of string and again writes it over the image itself. The result achieved is as shown in Fig. 12.

Fig. 12. EasyOCR Character Recognition

Number plate characters thus extracted using EasyOCR either, Nepali or English manuscripts are used as the query to the database stored in MONGOdB. The database holds the maintenance history and other detail of the input image vehicle. The database match is displayed in the HTML/CSS web application in a tabular format easy to be viewed at the first glance as shown in Fig 13.

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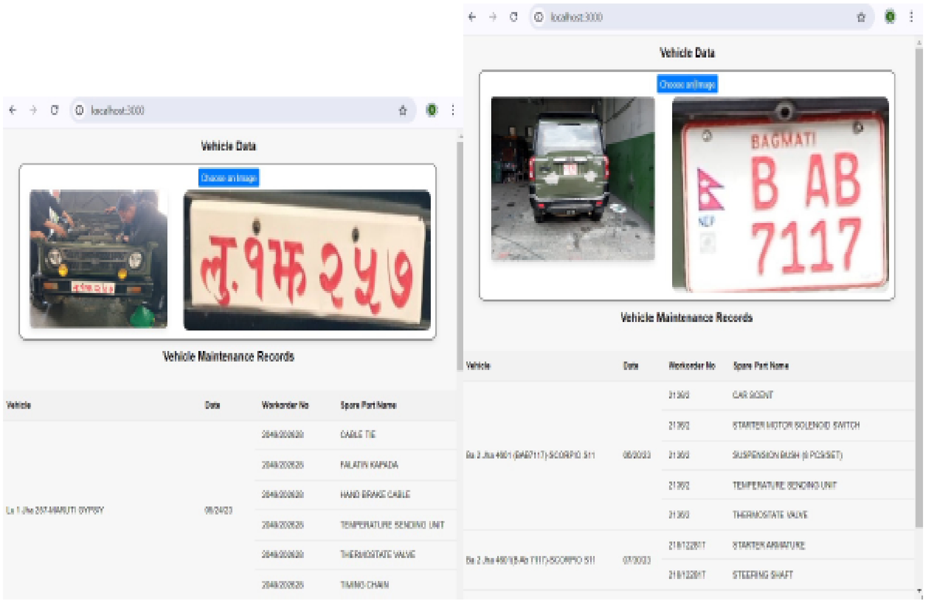

Fig. 13. Maintenance History retrieval

6. CONCLUSIONS AND FUTURE WORK

The license plate region is detected from the vehicle image in this research using yolov9 accurately in many of the instances. Even in the noisy background, skewed image and uneven illumination to the image or the different size and dimension of the number plate, yolov9 accurately detects the number plate region. EasyOCR extracts the text in number plate and delivers it for the query to the database. In EasyOCR part, there are limitations in the research especially in recognizing the handwritten scripts. Moreover, B written in embossed number plate are sometimes decoded as 8 and A is decoded as 4. Additionally, EasyOCR detects all the text in the license plate and it not only carries the vehicle identity numbers. Plus, the number at the last part of handwritten number plate is sometimes with 3 digits and sometimes 4 digits. Hence to identify the vehicle in the database it poses a challenge which is addressed by isolating the plate numbers only for the number plate text i.e last part of numerical digits only. Then configuring the search for exactly 4 digits first or 3 to 4 consecutive numerical digits in the number plate characters are carried out. One more limitation in the research is due to the dataset of the military vehicles. There are two types of vechicle number plates in practice in military vehicles. Once it was instructed to replace all the handwritten number plates with the standard Embossed number plates one, and even the process was initiated to some of the agency assigned vehicles to high-ranking officials. But the decision was taken back and the process halted resulting in existence of both format number plates. EasyOCR returned texts are not always accurate and often leads to misinterpretation of the number plate characters. The same letter written in different handwritten style are recognized as the different letters. Due to the 3 or 4 consecutive last digit search in detected number plate text, it may result in match with more than one vehicle identities in database and are displayed in the html application. Hence as the future work, EasyOCR part can be fine-tuned with the custom defined dataset rather than the standard one. Once the license plate characters are accurately recognized, the whole of the vehicle identity text can be used as the query to the database. That results in the exact vehicle image input to the system with the corresponding exact repair history. However due to the limited number of vehicles available to NA, the technique used in this research is sufficient with the considerable accuracy.

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