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RESEARCH PAPER

Road Sign Board Direction and Location Extraction and Recognition for Autonomous Vehicle.

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A B S T R A C T:
The problem of direction and location identification is very important in technologies used for Autonomous vehicles. while the navigation systems are that they cannot cover all areas due to a lack of signals or changes made on routes due to maintenance or upgrades. This research will focus on recognizing the sign and extracting address location names and directions from road signs. Moreover, it will help better identify road exits and lane directions for better route planning. In this paper we use YOLOv5 to identify the road board sign location and direction. Then extract the direction of each address location that are included in the road board sign and inform the car about the direction because autonomous car has no any driver so the car must decide by itself witch direction to choose to get the goal address location. This system can be used to continuously cheek the frames of the video that is taken by the car's camera for road sign boards and analyses the image to find the direction of each location that are explained inside road sign board on the road. The proposed system consists of a camera mounted on top of the front mirror of the vehicle, and also a computer to run the recorded video on the system. In experiments, yolov5 framework achieves the best performance of 98.76% mean average precision (mAP) at Intersection over Union (IoU) threshold of 0.5, evaluated on our new developed dataset. And 91.31% on different IoU thresholds, ranging from 0.5 to 0.95.

KEY WORDS: Road Sign Board, Autonomous vehicle, YOLOv5.
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1.INTRODUCTION :

A self-driving car also known as an autonomous car, driver-less car, or robotic car which is a car that is capable of traveling without human input. Self-driving cars use sensors to perceive their surroundings, such as optical and thermographic cameras , radar, lidar , ultrasound/sonar , GPS, odometry and inertial measurement units(Taeihagh & Lim, 2019) .

Nowadays, Autonomous Driving System research is gaining importance in recent decades, disrupting the automotive industry in a big way.

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Based on the road statistics data, it has been concluded that approximately 94% of road accidents are because of the driver-related faults, including inappropriate maneuvers and distracted drivers (Yurtsever et al., 2020). By automating the vehicles, Human errors can be significantly reduced by automating the vehicles. Autonomous vehicles can significantly decrease the mistake due to driver and inattention as the reason for an accident. Likewise, the vehicles can be designed to execute appropriate maneuvers that can avert the crash entirely. Therefore, Autonomous driving has the potential of saving thousands of lives by removing human error from driving. Autonomous vehicles will also benefit specific groups, people both young and old, or those that have disabilities and are not able to drive themselves, will enjoy mobility with this new technology. It can also help to make driving more efficient, resulting in lower operational fuel costs and decreased adverse impact on the environment (Bachute & Subhedar, 2021).

Autonomous vehicles use these two important technologies as follows(Team, 2021): The first one is Tracking Positions with the Global Positioning System The U.S. owns a 24-satellite-based radio navigation system called the Global Positioning System (GPS). Users with a GPS receiver can obtain geolocation and time information. Self-driving cars can use GPS to geolocate with numerical coordinates (e.g. latitude, longitude) representing their physical locations in space. They can also navigate by combining real-time GPS coordinates with other digital map data (e.g. via Google Maps). GPS data often varies around a five-meter radius. And the second one is Capturing Images with Cameras. Autonomous vehicles can visualize their environments with high-resolution digital camera images. Self-driving cars can use camera images to “see” and interpret environmental details (e.g. signs, traffic lights, animals) in ways that approximate human vision (aka computer vision). Self-driving cars can use many types of input data for computer vision.

Self-driving cars rely on machine learning, and artificial intelligence to accurately perceive and safely navigate their environments(Team, 2021). Machine learning methods based on artificial feature extraction and classifiers are used in Autonomous Driving Architectures for different tasks like Motion Planning, Vehicle Localization, Pedestrian Detection, Traffic Sign Detection, Road-marking Detection, Automated Parking, Vehicle Cybersecurity and Fault Diagnosis(Bachute & Subhedar, 2021).

Moreover, recognition and classification of traffic signs are very important, especially for unmanned automatic driving. Extensive research has been done in the area of recognition and classification of traffic and road signs. since 1989 (Gupta et al., 1989) researchers have been using machine learning techniques for sign detection. Machine learning is the study of how to make computers mimic human learning processes and the discovery of computer self-improvement techniques that collect new skills and information, categorize current knowledge, and purposefully enhance performance (Lijuan et al., 2009) Deep learning has achieved previously unheard-of levels of success in areas like speech recognition and picture classification in recent years. Deep learning is a subset of machine learning in Artificial Intelligence (AI) that focuses on learning several layers of representation and abstraction to assist make sense of data like pictures, sound, and text (Hua et al., 2009). Deep learning networks may learn unsupervised from unstructured or unlabeled data. So, it is making them very effective for traffic sign detection.

Especially when tracking any objects in a real image scene where these objects are non-rigid, the background of the scene is not fixed such as weather conditions and lighting conditions which cannot be controlled and predicted. It may contain several objects in the same scene.

Precise navigation is one of the most important requirements of a fully autonomous car. in order to navigate precisely within and through an environment (Chillingsworth, 2020). Current autonomous cars use the Global Positioning System (Swaminathan et al., 2022).

(Chillingsworth, 2020) Driverless vehicles may lose GPS mid-journey due to densely populated streets and tall skyscrapers as signals are obscured. Radio waves may also bounce off surroundings and lose contact with the vehicle, causing cars to lose GPS information. Experts warn this could have possible “safety and operation issues” for driverless vehicles which rely on satellite navigation to get to destinations. Losing this technology could see cars unable to work out a route to a destination which could cause a range of consequences. Vehicles could stop working entirely or could become confused and drive randomly until a signal is received. Oxbotica warns that a three storey building would be tall enough to create some sort of signal disruption to cars. Ben Upcroft, VP of Technology at Oxbotica says there are so many buildings that motorists would not be able to rely on GPS tools for accuracy. He said: “There are so many urban canyons and GPS ‘blind spots’ across our towns, cities and countryside, that we can't rely on GPS for accurate navigation.”

Oxbotica has warned skyscrapers are not the only issue which could derail signals to driverless vehicles. They also warn that cars at higher latitudes could also be affected as satellites are lower in the sky and may not be able to send signals. Sunspots can also cause changes in solar wind which can interfere with GPS satellites and lead to disruption(Chillingsworth, 2020).

(Haydin, 2019)Let’s sum up GPS does not require internet connection and helps to understand where the car is now. They can also navigate by combining real-time GPS coordinates with other digital map data (e.g. via Google Maps) (Team, 2021). But sometimes it fails. Like on Manhattan where the buildings are too tall, and the streets are too narrow. The signal is quite often lost in tunnels or under the bridges. It doesn’t really work when it is critical to have high precision. For sure, GPS has drawbacks. Still, it would be stupid not to use GPS for autonomous driving as the system is already working and it’s available 95% of the time. Just do not rely on it too much and always have a Plan B (Haydin, 2019). There for this research will help better identify road exits and lane directions for better route planning though extracting information about the direction of the goal location from road board singes. And also, it works as a GPS support system for autonomous vehicles while as it is clear until know the driverless car has not any support system for GPS inside their car.

The Objective of this research work is to create a GPS support system while Driverless car may lose GPS mid-journey and to achieve high accuracy in extracting the direction of the goal address location from the road sign board. And also, fast in deciding which direction to go to reduce accidents and save passengers' lives. As well as Help for better route planning to save passengers time (get to the goal address location with a minimum amount of time). At the same time reduce choosing the wrong direction and only spend the needed power consumption.

This paper is organized as follows. Section 2 mentions the works previously done that are related to the proposed work. Section 3 explains the materials and methods used in this work. Results and discussion are discussed in section 4. Finally, the conclusion and feature works are presented in section 5.

2. Related Works:

Recognizing and classifying traffic signs is critical today, particularly for unmanned automated driving. The identification and categorization of traffic signs has been the subject of much study. In 1968, an international agreement named as the Vienna Convention on Road Signs was decided upon with the goal of unifying traffic signs between states (Wali et al., 2019). This pact has been signed by 52 nations, 31 of those are in Europe. The Vienna Convention divided traffic signs into eight types, which were labeled A-H: Danger signs (A), precedence signs (B), prohibitory signs (C), necessary signs (D), specialized regulating signs (E), information, facilities, or service signs (F), directional, location signs (G), and other boards (H). As showed in Figure 1.

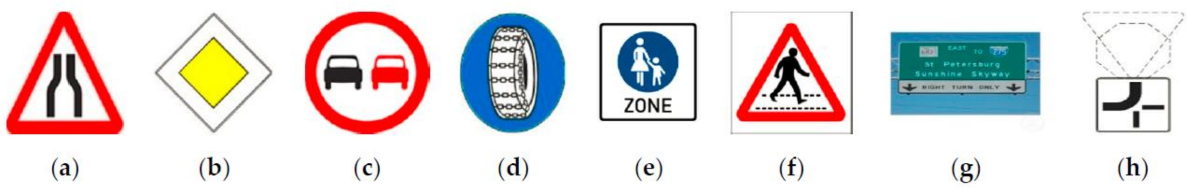

Figure 1: traffic sign types.

Considering the Vienna Treaty's well-defined provisions, there are still differences in traffic sign designs among the treaty's signatories, and in certain circumstances, significant variance among traffic sign designs may occur within the country itself. Although these variations are easy to identify by humans, they might represent a significant barrier to an automated detection system. Figure 2 shows several styles of stop signs from various nations as an example.

Figure 2: the difference between stop signs in various countries.

A lightweight and efficient ConvNet with sliding window is suggested by the authors of (Liu et al., 2001) to recognize traffic signs in high-resolution photos in light of CNN's effectiveness in categorization of traffic signs. On the German Traffic Sign Detection Benchmark dataset, the accuracy rate detection achieved is 99.89%. 3772 frames may be processed in 26.506 milliseconds using the GPU (GeForce GTX 980). This method may be applied in real-time due to the outcomes. Convolutional neural networks are used in (Nandi et al., 2018) In order to avoid the issue of color sensitivity caused by different lighting conditions, support vector machines are first used to convert the original image from RGB to grayscale. Next, the fixed layer in CNN is used to localize regions of interest that are similar to traffic signs, and learnable layers are used to extract discriminant features for classification. Although they collected 99.73% of warning signs and 97.62% of obligatory indicators using the GTSDB dataset, the program is not real-time. Recently, (HANNAN et al., 2010)employed cascaded convolutional neural networks (CNNs) to cut down on false positive areas found using the AdaBoost classifier and the local binary pattern (LBP) feature detector.

In (Møgelmose et al., 2012), a region proposal network (RPN) in fast R-CNN was used to train a traffic sign identification model based on deep CNNs. The average detection time is roughly 51.5 ms per picture and the detection rate is about 99% while running on the NVIDIA GTX980Ti 6GB GPU hardware environment. They employed a Chinese traffic sign database with seven basic classifications. In (Shao et al., 2018), a faster R-CNN-based model was also put out. This model had two parts: first, it used selective search to find potential areas, and then it employed CNNs to extract features, perform classifications, and change parameters. By(Zabihi & Beauchemin, 2017), a fresh method for seeing traffic indicators was uncovered. They employ the NVIDIA GTX 1070 8 GB GPU, Intel Core i5, and 16 GB RAM with Faster R-CNN based on Region Proposal Networks to achieve 90% accuracy on the GTSDB dataset.

In order to detect and identify the pictures of traffic signs that are recorded by the vehicle's on-board camera,(Chiu et al., 2021) introduces a two-stage network. They use Faster R-CNN in the detection network to find the locations of the traffic signals. They employ SVM, VGG, and ResNet for testing and validating the classification network. Additionally, for assessment purposes, the traffic signs are separated into three categories: "required," "prohibitory," and "danger." R-CNN is used in this work because of its excellent accuracy and low miss rate. They contrast the outcomes and combine the systems for detection and classification. The approach attained the mAP of 80.86% on the testing videos, compared to 53.55% from YOLOv3 and 54.92% from Mask RCNN. The findings employing Faster R-CNN for detection paired with VGG17 for classification have exhibited greater performance compared to YOLOv3 and Mask R-CNN.

(Alghmgham et al., 2019)proposed a method for instantly identifying and detecting traffic sign photos. A freshly created database of 24 unique traffic signs collected from different Saudi Arabian roads is also included in this study. The photographs, which were taken from a variety of angles, added additional variables and circumstances. The Saudi Arabian Traffic and Road Signs collection was assembled from a total of 2718 images (SA-TRS-2018). The CNN model was used with varied parameters to obtain the best recognition accuracy. According to experiments, the proposed CNN design achieved an accuracy of 100%, which is higher than that gained in other studies of the same sort. Their research contributed two things: first, it produced a brand-new dataset on Arabic traffic and road signs, and second, it built a deep CNN structure to recognize Arabic traffic signs. The photographs had to be preprocessed before being delivered to the CNN network since they were RGB images of varied sizes. The pictures' sizes were reduced to 30x30 pixels and they were made into grayscale images. The three categories of the data set were training, validation, and testing. This partitioning was designed specifically for cross-validation, a statistical approach of evaluating the efficacy of machine learning (ML) algorithms. They used a method called hold-out cross-validation, which separates the data set into three distinct sets. Their method is extensively used due to its effectiveness and ease of use. Since there is no recognized standard for how the data set should be partitioned, they chose one of the often chosen partition percentages. ReLu and Laky ReLu's activation mechanisms were used.

In(Asst, 2021), a system was suggested that was also aimed at overcoming their system. The input picture for the framework is collected from the camera attached in front of the car. A sample dataset has already been saved in the database. The input part, preprocessing part, feature extraction part, feature reduction part, and DNN classification are the parts of that system. The input picture is in RGB format and has three values. There is just one value in the grayscale. Gamma compression is used to convert RGB images to grayscale images, and gamma expansion is also used to eliminate grayscale conversion. Grayscale images only contain black and white colors, and the gray color is dispersed over the picture; the image's intensity is determined by the black and white colors.

Three processes are used in his project's prepossessing which are Grayscale, Image resizer, and apply the median filter. Feature extraction has been utilized to expand the capabilities of a system. It selects and compiles variables into features, reduces raw data, and manages additional processes. they incorporate two feature extractions into their system SURF and HOG.

Feature reduction is a technique for reducing the number of features in a system. Additional undesirable features cause the system to become overloaded, time complexity to increase, system performance to reduce, and memory space to diminish. Therefore, they removed the unwanted functionality, which caused the system to speed up and respond quickly. As the memory space rises, the system's speed rises as well. Therefore, in the system, they utilize a modified PSO. The optimization issue is solved by utilizing improved particle swarm optimization. Each particle's performance is evaluated based on its performance and pre-determined fitness. They employ an improved deep neural network (DNN) inside their system to recognize images (classification). As a result, the article found that they reduced the system's complexity while also reducing the time it takes to get a result. The system's speed has been raised, and the needed memory gap has been lowered in their proposed system.

In (Bayoudh et al., 2021) Deep learning-based driving assistance technology has already been introduced. They provide mixed 2D-3D CNN models based on the transfer learning method in order to improve performance on benchmark real-world datasets. The basic goal of transfer learning is to improve the target domain's learning process while transferring pertinent knowledge. They used a shallow 3D CNN with a pre-trained deep 2D CNN to reduce complexity and speed up the training process. The experiments' findings show that the techniques are quite useful in terms of accuracy and efficiency. Data preparation is a crucial step that entails converting, purging, and standardizing training data to improve performance. They focused on their research's part on CNN architectures, doing a parametric and hyper-parametric analysis to boost the effectiveness of their deep models. They needed large datasets to train their CNNs and increase the generalizability of their results. the capacity to combine 2D and 3D CNN to study just spatial input in order to discover more sophisticated and discriminating patterns. Additionally, the difficulty of stacking 3D convolution layers and training time are greatly reduced by employing a pre-trained 2D CNN. In other words, by processing volumetric data from various inputs and integrating pre-trained parameters with 3D convolutions, it may be possible to increase accuracy and efficiency while also overcoming missing data at each hierarchical level of the network. The spatial conversion of 2D feature maps to 3D space may be accomplished using a reshaping procedure. In their work, a deep learning-based driving assistance system is described. The Hybrid-TSR model had a testing accuracy of 99.28 percent, according to the experiments, whereas the Hybrid-SRD model got a MaxF1 score of 95.57 percent. Last but not least, they think that tighter hyper-parametric tuning could improve their performance.

In (Sudha & Galdis pushparathi, 2021)To help VIB persons cross the road safely, this study addressed the issue of traffic sign recognition. Using a unique shape-specific feature extraction approach and Random Gradient Succession with Momentum (RGSM), traffic sign detection and identification is accomplished. The trained output labels will then be classified by the CNN classifier, which will subsequently translate the traffic sign into the audio signal during both the training and testing phases. The robust audio signal processing used in their suggested traffic sign detecting system improved the performance of feature extraction and classification. The form and color of the symbol can be used to classify it. If the visually handicapped folks failed to see a stop sign, there is a high likelihood that an accident will occur. Additionally, it will help those who are visually challenged cross the highways safely. The edges are then discovered using a suitable method. In their suggested work, the preprocessing is carried out in two phases: the training phase and the testing phase. By using the shape-specific extraction approach, the features were retrieved. Finally, the classification procedure was carried out using the modified CNN classifier. By contrasting existing techniques like discriminant analysis and decision tree algorithms, the performance analysis was created.

An automated method for detecting and recognizing text and symbols on traffic signs is suggested in (A. & S., 2016). The two major components of their traffic signboard detection and identification system are detection and recognition. Text and sign detection are system components in their own right. The system has the ability to simultaneously identify text and signs. To create their system, they primarily use two modules: The first one is a module for detecting and identifying signs. The text detection and recognition module come in second. The primary emphasis is placed on text detection and identification. XML files are used to hold all of the input photos. Their proposed system will automatically test the output of previous modules and be able to show the accuracy percentage for better understanding of traffic signboards for advanced driver assistance system. The output of their project work will be the detection of text as well as symbols from real time captured images of traffic signboards. The majority of letters may be recognized from photographs of traffic signboards thanks to the text and symbol detection system with MSER. Because it quickly identifies the extremal areas from the input picture, the MSER approach has been demonstrated to produce superior results than other techniques. Candidates are lowered by imposing restrictions based on temporal and structural information. This results in more precision. To enhance OCR outcomes, perspective recitation and temporal fusion of candidate text sections were applied. OCR yields superior text recognition outcomes.

3. Methodology:

In this research work first and the most important step is to have an excellent dataset to start your work and then apply any method to perform detection and recognition. at this point we will show the flow chart of our system here to make the work that are done in this thesis clearer and more understandable. Figure 3.0 shows this clearly then we explain each step that performed.

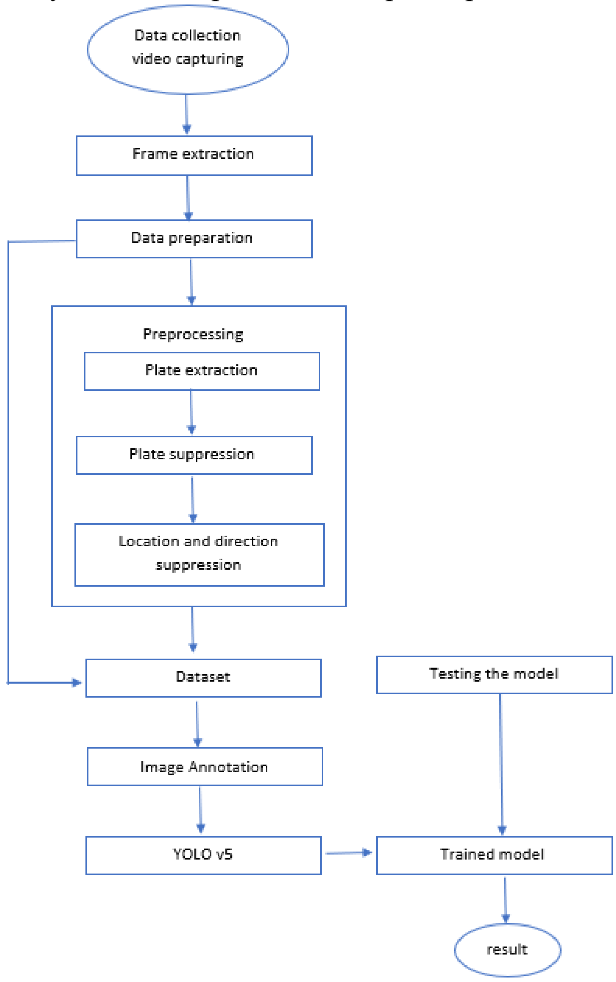

Figure 3: the flow chart of the proposed system.

3.1 Data collection (video capturing)

for Road board sign board location and direction type there is not any prepared data set until now so one of our contributions is also a newly developed dataset. First to collect data we drive a car on the 120-meter street and 150-meter street in Erbil city in Kurdistan regain. And placed a camera Infront of the car to record video of the road. The videos were taken at different times of day, and night and also from different angles, and cameras, cars, and speeds from 60km/h to 120km/h and included other parameters and conditions. we recorded 100 video which 60 of the videos are recorded at the different times of day while 40 videos are recorded at night. The reason behind the difference between the number of the videos in day and night belongs to the idea that at different times of the day videos must be recorded and also at different weather conditions like sunny and cloudy must be recorded which affects the images largely. while at the night this effect will not affect the images as the day. Then the videos are divided to two parts. the first part which %70 of the videos is used for training. And the second part which %30 for testing which %15 for the day and 15% is for the night.

3.2 Frame extraction

At this point we want to focus on the first part which is 70 videos. First, we performed frame extraction. The extraction used the gap equals to 10 mains that it only extracts the frames that are equals to 0 and 10times to get frames that have more different from the previous one. The result of frame extraction we get 22,946 frames for day from the 45 videos that are recorded at day times. Also 11,630 frames from 25 videos that are recorded at night time. at this point the total number of frames are 34,576 frames. 66.4% is for day time and 33.6% for the night.

3.3 Data preparation

From the 34,576 images we selected 1000 images to make our dataset less and contains many information. Figure 4 illustrates some images inside our dataset as a sample of different whether condition. Later 150 images which 15% are used for validation and 200 images which 20% are used for testing and 65% are used for training. but before training our system we performed some preprocessing step to make our model learn better with lesser data. 330 images are gone through the preprocessing step.

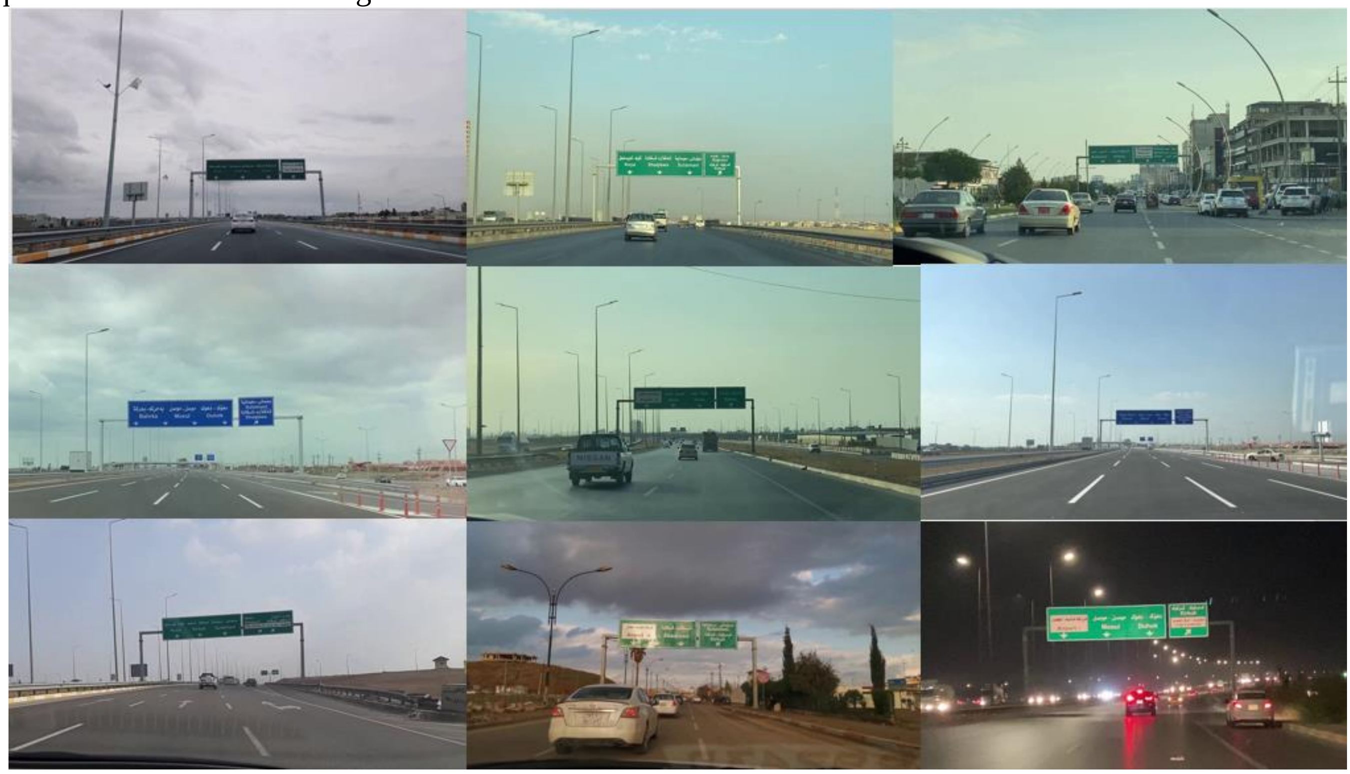

Figure 4: some images inside our dataset

3.4 preprocessing

In this research work, we performed preprocessing based on extracting the regain that are (green and blue) color and scanning the images looking for blue and green color exotically using RGB value that are in green and blue plates so we performed plate extraction. as in Figure 5 and Figure 6 shows the real time image and Figure 7, and Figure 8 are show their plat extraction.

Figure 5:Blue Road sign board location and direction plate in real image.

Figure 6: green road sign board location and direction plate in real image.

Figure 7: green plate extraction.

Figure 8: Blue plate extraction

Then converting the color image to a black and weight image and scanning the image to know if the image contains two plates or just one plate. if it contains two plates surely, we can find the edges between the two plates so at that point we perform plate suppression on the RGB image that achieved from plate extraction. Later location and direction suppression will be performed so we get as In Figure 9. Finally, the images are preprocessed and we get 880 preprocessed images with 620 real-time images without any preprocessing used to create a newly developed dataset.

a) Location and direction suppression for green plates

b) Location and direction suppression for blue plates

Figure 9: location and direction suppression.

3.5 Dataset

At the output of the preprocessing step, we get 880 images with the extra 320 image to produced our training part witches 1200 images to train our model. and 150 images for validation. And another 200 for testing. As a result, our dataset contains 1550 images for training, validation and testing also 30 extra videos for testing. Finally, a total of 1550 images with 30 videos were collected to form the dataset which we named Kurdistan Regin Government Traffic and Road Signs Board Direction and Location (KRG-TRSBDL-2023). While the testing video part are 30 videos which 15 for night and 15 for deferent times of day.

This research work selects 20 different classes that noticed on the location and direction road sign boards on the 120-meter and 150-meter street in Erbil city in Kurdistan regain. And also trains our newly developed system which's GPS Support System to recognize and classifies them for autonomous vehicle. The labels are mentioned in the Table1.

Table 1:Name of all the classes.

Airport right	Airport stright	Koya right	Koya stright
Baghdad right	Baghdad stright	Shaqlawa right	Shaqlawa stright
Bnaslawa right	Bnaslawa stright	Sulaimani right	Sulaimani stright
City center right	City center stright	Kirkuk right	Kirkuk stright
Duhok stright	Bahrka stright	Mosul stright	Makhmur stright

3.6 Image annotation:

All images that get from the preprocessing step are annotated using an online application named Roboflow which helps you to label all images inside your dataset to get the Yolo format file for each image in your dataset.

3.7 YOLO (You Only Look Once)

YOLO is used in this project. This research work analyzes and discovers various elements in a picture (in real-time). The object identification procedure in YOLO, which is carried out as a regression problem, provides the categorization probabilities of the discovered photographs. The YOLO approach uses convolutional neural networks (CNN) to detect objects quickly. As the name would suggest, the method only requires one forward loop through a neural network to recognize objects. This implies that the entire scenario is predicted using a single run of the algorithm. Using the CNN, several class frequencies and bounding boxes are simultaneously predicted. The YOLO algorithm comes in numerous forms.

The YOLO algorithm is crucial for the following reasons:

- Speed: Because it can anticipate objects in real-time, this method increases the speed of detection.
- High accuracy: The YOLO prediction method yields precise findings with little background mistakes.
- learning capability: The algorithm has great learning capabilities that allow it to pick up on object representations and use them for object detection.

In driverless vehicles, the YOLO algorithm can be used to find nearby things like other cars, pedestrians, and parking signals. Since there is no human driver in an autonomous vehicle, object detection is done to prevent collisions. In this study YOLOv5 employed to extract the location and directions of the address locations that are on the road sign boards. For this project, PyCharm is used as a tool and Python is used as the programming language. Opencv is a free software library for image processing, machine learning, and computer vision. It currently plays a significant part in real-time operation.

4. Result and Discussion:

Since the introduction of R-CNN (recurrent convolutional neural network), the YOLO method has been created to increase computational processing speed. It is a model that, by incorporating the full image into a single neural network structure, is capable of simultaneously detecting several objects in real time. YOLO is quicker than the existing R-CNN, although its accuracy is somewhat lower. However, accuracy improves with each new version of YOLO. The benefit of YOLO is that because the processing is rather straightforward, the procedure happens extremely quickly. In addition, MAP (Mean Average Precision) is nearly twice greater than that of the existing real-time object identification method, and the class specified in YOLO has a low background error rate due to good comprehension of input data in a way that the full image comes in at once.

The class distribution in the dataset is shown in the Figure 10 which shows the number of each label inside the dataset. Also, the height and the width of the images that are utilized to learn the model. which is clear that a part of the images is in small size because they are the images that we get from our preprocessing step and the other part is real time image without performing any operation on them. However, it clearly shows the location of the labels inside the images after annotating the images in one hand there are some images that a single label takes whole the image and in other hand in some images one label takes a small part of the image.

While a confusion matrix presents a table layout of the different outcomes of the prediction and results of a classification problem and helps visualize its outcomes and it plots a table of all the predicted and actual values of a classifier. Figure 11 shows the confusion matrix of our model witch clearly the percentage of the accuracy of each class are presented. The diagonal of the chart shows that the accuracy of ten of the classes are 100% and the other ten class have lower accuracy rate.

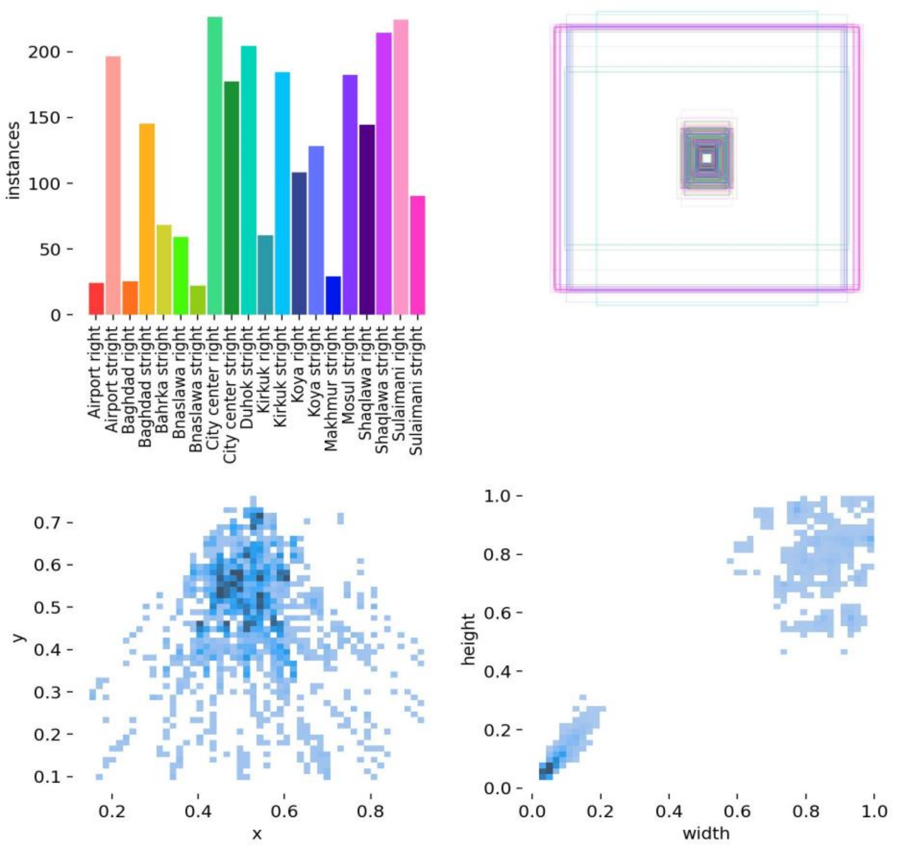

Figure 10: Label distribution in the dataset.

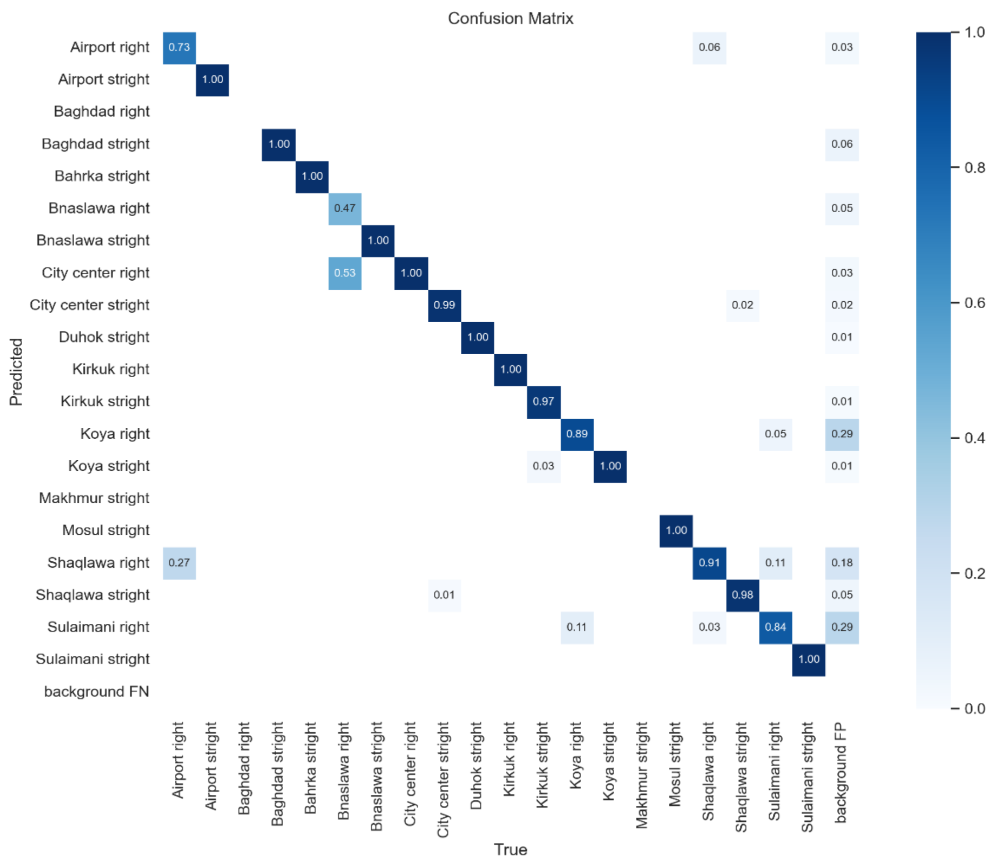

Figure 11: confusion matrix presents the accuracy of all classes.

To summarize YOLOv5 losses and metrics. All explanation is in the Figure 12. YOLO loss function is composed of three parts:

1. **box_loss** — bounding box regression loss (Mean Squared Error) is 1.5% for train and 1.6% for validation box_loss.
2. **obj_loss** — the confidence of object presence is the objectness loss (Binary Cross Entropy) is 0.5% for train and 0.6% for validation object_loss.
3. **cls_loss** — the classification loss (Cross Entropy) is 0.6% in the train and 0.5% in the validation class_loss.

Precision measures how much of the bbox predictions are correct (True positives / (True positives + False positives)) is 95.37% and **Recall** measures how much of the true bbox were correctly predicted (True positives / (True positives + False negatives)) is 97.49%. 'mAP_0.5' is the mean Average Precision (**mAP**) at IoU (Intersection over Union) threshold of 0.5 is 98.76%. ' mAP_0.5:0.95' is the average mAP over different IoU thresholds, ranging from 0.5 to 0.95 is 91.31%.].

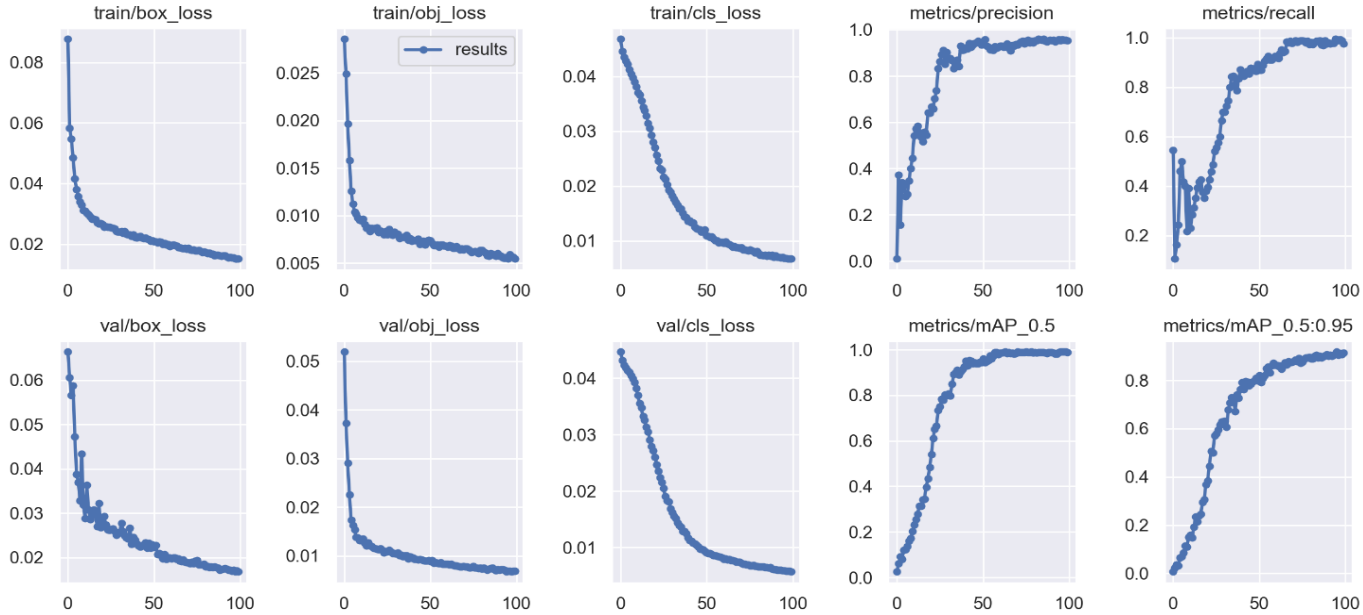

Figure 12: Results of 'feature extraction'.

4.1 Testing the system for the Day Time

To evaluate the system, the result of the systems accuracy must be calculated based on the location of the address on the plate. For this purpose, thirty videos are prepared for testing the model. the bellow Figure 13 shows an example of the plates for location and direction plates and also worked on in this paper.

Figure 13:an example of the plates for location and direction plates.

So divided the plate to five parts from the left to right which we named the first address location at the left as First address location and the second Address at the left as second Address location. also, the third one at the left as Third address Location. the last one which contains two addresses named the upper address as the fourth upper address location and the lower address as fourth lower address location. The result is cleared in figure 14. the result is calculated for deferent times of day with deferent whether condition like sunny and cloudy day then take the average accuracy while the speed of the car is fixed at the speed of 60km/h.

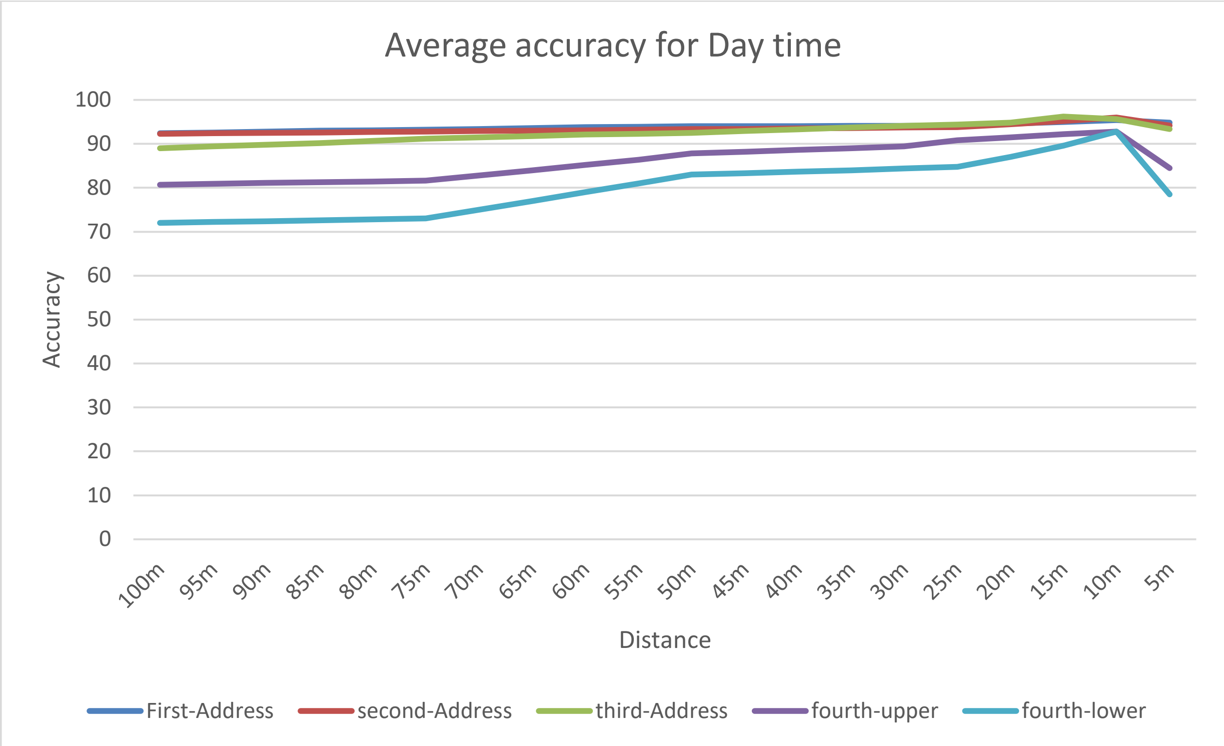

Figure 14: average accuracy of each address location on the plate based on their location on the plate from different distance from the plate while the car has the speed of 60km/h.

Figure 14 shows graphs of the accuracy for the first address location, the second address location, the third address location, and also the fourth upper address location and fourth lower location at 20 deferent distances from the plate. As it is clear that the accuracy of the first address location at the 100m distance from the plate is equal to 92.4 percentage and the second address location have the 92.3 percentage. Also, the third address location got the 89 percentage. Moreover, the prediction accuracy of the fourth upper and lower achieved 80.7 and 72 percentage respectively. However, the accuracy of the five-address location is high at the distance 100m from the plate and also however the car gets near from the plate the accuracy well be rise more. as it is visible from the graph when the distance is 50m from the plate, accuracy of the first address location rises to 94 percentage, the second address location to 93.4 percentage, and also the third address location is gets to 92.5 percentage. while the fourth upper and lower address location rises to 87.8 and 83 percentage respectively.

However, the autonomous vehicle gets near and near form the plate the percentage of recognition will be better as it is noticeable from the result graphs. while the distance arrives to 10m distance from the plate, accuracy of the first address location archives 95.6 percentage, the second address location rise to 96 percentage and the third address location gets 95.6 percentage. Moreover, the fourth upper and lower address location gets 91.4 and 90 percentage respectively. it noticeable, the result of accuracy for the first address location, the second address location and the third address location are more similar because they have the same size in the plate and they are clearer inside the plate. but the fourth upper and lower address location get lower accuracy percentage than the other three address location.

Because these two-address location take the size of one address location as in the other three. The fourth lower location will be inside the fourth upper location to rightly select specific class for the upper address location. So, the result of the first and second and the third address location will be better at every distance than the fourth upper and lower address location however, all address locations get a good accuracy in all distance.

While the distance will get near the plate to 5m the accuracy of the first address location gets down to 94.8 percentage and the second address location also to 94.2 percentage and the third address location to 93.4 percentage. Moreover, the accuracy of the fourth upper and lower address location gets down to 84.5 and 78.5 percentage respectively. This result achieved at this point of view because the car is so near the plate and the plate is placed at the high of 5m from earth.so at this point of view the accuracy percentage of all address locations will gets lower. To summaries this part, it clear that the result of the first three address locations is more similar and the result of the fourth upper and lower address location are similar to each other. Also, the accuracy percentage of all address locations will get higher however the car gets nearer from the plate until it arrives to its maximum accuracy percentage at the 10m distance from the plate while the plate is more near and clearer. But after this point however the car gets near from the plate the point of view for the plate will change and step by step the plate will disappear from the camera vision so the accuracy gets down until the car passes the plate. Figure 15 shows the result of a frame inside the videos.

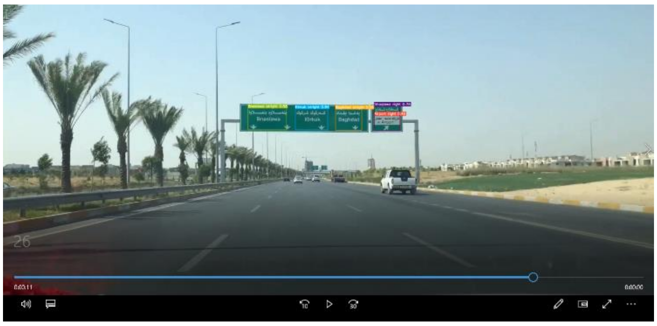

Figure 15: shows the result of a frame inside the videos of day.

4.2 Testing the result of Night

In this paper the same things that have been done for the day time are repeated for the Night videos mains that we tested the night videos and Figure 16 shows an example of the frames inside the Night videos.

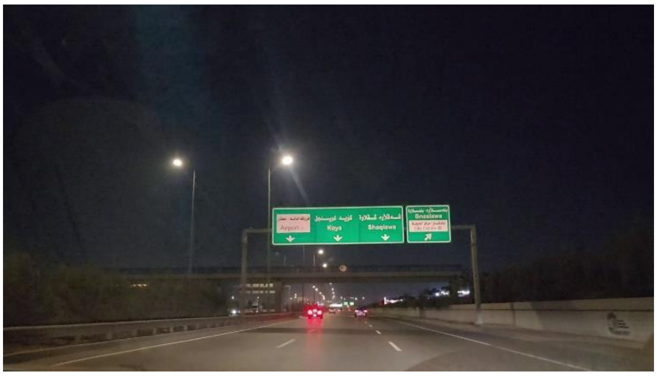

Figure 16: an example of the frame inside the Night videos.

To evaluate the system on the night data based on the location of the address on the plate, we divided the plate to five parts from the left to right which we named the first address location at the left as First address location and the second Address at the left as second Address location. also, the third one at the left as Third address Location. the last one which contains two addresses named the upper address as the fourth upper address location and the lower address as fourth lower address location. The result is cleared in Figure 17. the result is calculated for night and take the average accuracy while the speed of the car is fixed at the speed of 60km/h.

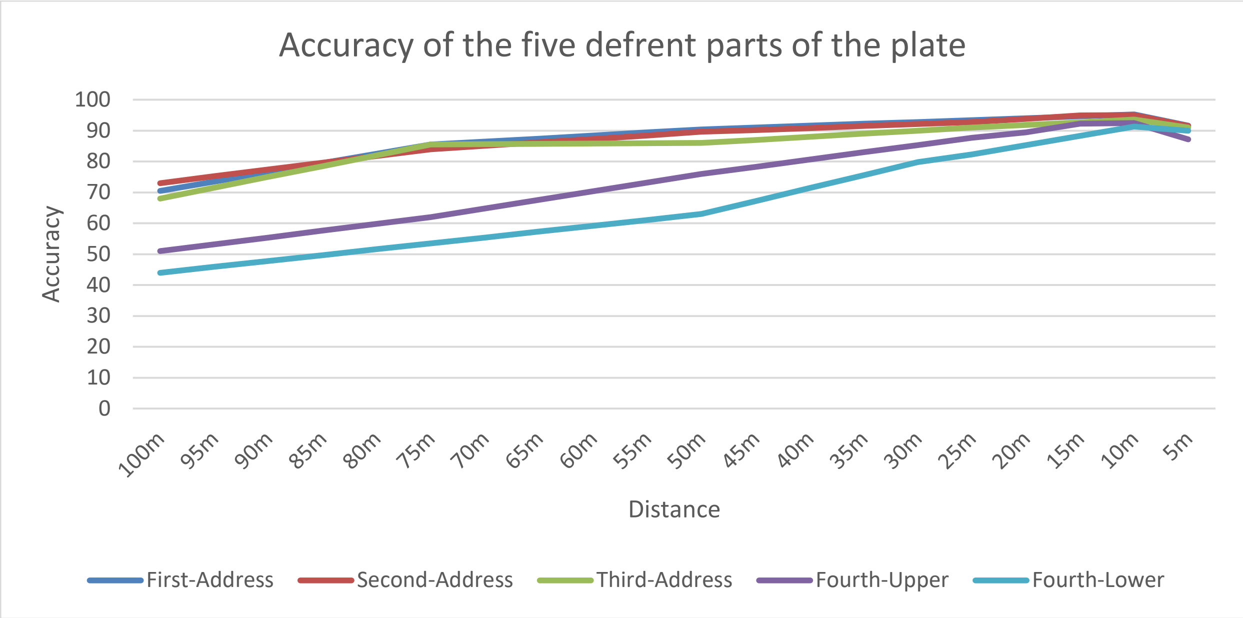

Figure 17: graphs of accuracy per distances for the first address location, the second address location, the third address location, and also the fourth upper address location and fourth lower address location.

Figure 17 shows the graph of the accuracy for the first address location, the second address location, the third address location, and also the fourth upper address location and fourth lower address location at 20 different distances from the plate. As it is clear, accuracy of the first address location at the 100m distance from the plate is equal to 70.5 percentage and the second address location have the 73 percentage. Also, the third address location got the 68 percentage. Moreover, the prediction accuracy of the fourth upper and lower achieved 51 and 44 percentage respectively. However, the car gets near from the plate, the prediction accuracy will be rise. as it is visible from the graph, when the distance is 50m from the plate the first address location rises to 90.4 percentage, the second address location to 89.6 percentage, and also the third address location is gets to 86 percentage. while the fourth upper and lower address location rises to 76 and 63 percentage respectively.

However, the car gets nearer form the plate the percentage of recognition will be better as it is noticeable from the result graphs. while the distance arrives to 10m distance from the plate the accuracy of the first address location archives 95.2 percentage, the second address location rise to 95 percentage and the third address location gets 93.6 percentage. Moreover, the fourth upper and lower address location gets 92.4 and 91.3 percentage respectively.it noticeable that the result of the first address location, the second address location and the third address location are more similar because they have the same size in the plate and they are clearer inside the plate but the fourth upper and lower address location gets lower percentage than the other three address location. Because these two-address location take the size of one address location as in other three. The fourth lower location will be inside the fourth upper location to rightly select specific class for the upper address location. So, the result of the first and second and the third address location will be better at every distance than the fourth upper and lower address location however, all address locations get a good accuracy in all distance.

While the distance will get near the plate to 5m, the accuracy of the first address location gets down to 91.6 percentage and the second address location also to 91.5 percentage and the third address location to 91 percentage. Moreover, the accuracy of the fourth upper and lower address location gets down to 87.2 and 90 percentage respectively. This result achieved at this point of view because the car is so near the plate and the plate is placed at the high of 5m from earth.so at this point of view the accuracy percentage of all address locations well gets lower.

To summaries this part it clear that the result of the first three address locations is more similar and the result of the fourth upper and lower address location are similar to each other. Also, the accuracy percentage of all address locations will get higher however the car gets nearer from the plate until it arrives to its maximum accuracy percentage at the 10m distance from the plate while the plate is more near and clearer. But after this point however the car gets near from the plate the point of view for the plate will change and step by step the plate will disappear from the camera vision so the accuracy gets down until the car passes the plate. Figure 18 shows a result of a frame inside the videos of the night.

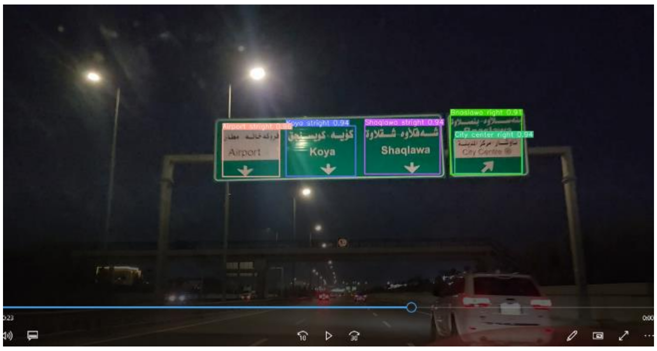

Figure 18: result of a frame inside the videos of the night.

4.3 The effect of car view angle and distance on accuracy.

1. When the car is driven on the left lane of the street, the view of the direction sign will be affected when the car is too far or too near. This will happen as the car distance to the far-right address on the direction sign will fall more under light reflection and letter blurring.
2. When the car is too close to the direction sign, the angle of view for the far address will decrease, hence, the letter will look almost overlapped and the view angle will fall under the light reflection from the address plate. This will decrease the recognition rate of the addresses on the plate which have a worse viewing angle than the others.
3. The addresses on the direction sign which are straight or in direct view with the car camera will have a higher recognition rate, as it will be normally visible all the time and have a clearer view for recognition.

4.4 Comparison between accuracy of day and night

now at this step it is needed to compare the result that we get at the day and night. The bellow Figure 19 show the average accuracy in percentage for the night and the day. For this step we calculated the average accuracy for the first address location and the second address location, the third address location, the fourth upper and lower address location to get the average accuracy in percentage for day time. The same idea used for calculating the average accuracy for night. As a result, we get the graphs bellow to compare these two parts and evaluate the difference between them.

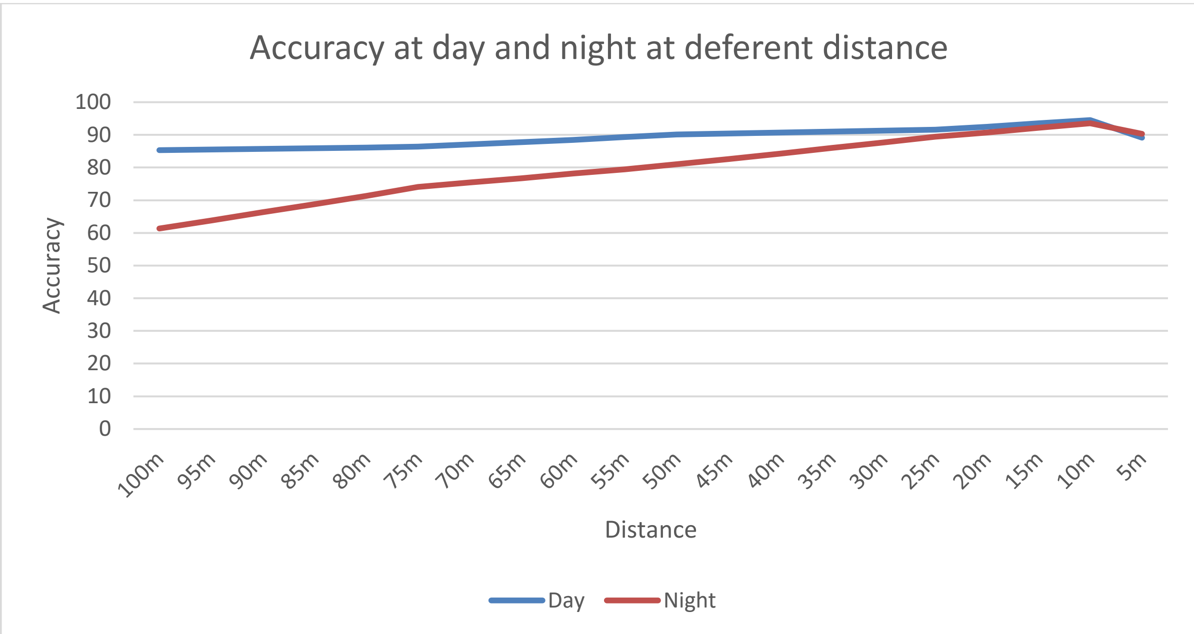

Figure 19: Average accuracy per distance for the night and the day.

Figure 19 show graphs of accuracy at the day and the night for the system.as it is clear from the graph the accuracy at the distance 100m distance from the plate at the day is equal to 85.3 percentage while the accuracy for the night is 61.3 percentage. Moreover, the accuracy percentage at 50m distance for day rise to 90.1 percentage and the accuracy for night gets to 81 percentage. The reason behind this big difference in accuracy percentage between day and night is that at the night time the plates will be affected by so many eliminations of the lights on the road and also the lights of the cars on the road these so many eliminations makes that the address location difficultly be classified and gets lower accuracy rate.

This difference will still be noticed until the car reaches to 25m distance from the plate then the accuracy of the day gets 91.6 percentage and night reaches to 89.4 which the difference gets lower between them and at the distance of 10m from the plate the day gets 94.5 percentage and the night achieves 93.5 percentage. Also, at the distance of 5m the accuracy of the day and night gets down to 89.1 and 90.3 respectively.to summarize this part, it is clear that the accuracy of the day is better than the night time because of so many eliminations that the plate will be affected by at the night time. Moreover, the accuracy of both day and night increases as the car gets nearer from the plate until it reaches to the 10m distance from the plate witch the plate is clearer from the camera vision. Then the accuracy goes down for both day and night because at this point of view the plate step by step will be disappear from the vision of the camera.

4.5 How the system will be affected by the speed of the car at the day

At this part the speed of the car will be taken into count. So now we want to test our system under different speed of the car. For this purpose, at first step, we tested five videos at different times of day and different weather condition like sunny and cloudy while the car has the speed of the 60km/h and extracted the average accuracy in percentage of the five videos. so, we get the accuracy of the first address location, second address location and third address location. Moreover, the accuracy of the fourth upper address location and fourth lower address location at 20 different distances from the plate which are from 100m to 5m distance from the plate. Then extracting the average prediction accuracy of the five-address location in each distance from the plate to get the average accuracy at each distance from the plate at the speed of 60km/h.

At second step, we tested five videos at different times of day and different weather condition like sunny and cloudy while the car has the speed of the 90km/h and extracted the average accuracy of the five videos. so, we get the accuracy of the first address location, second address location and third address location. Moreover, the accuracy of the fourth upper address location and fourth lower address location at 20 different distances from the plate which are from 100m to 5m distance from the plate. Then extracting the average accuracy of the five-address location in each distance from the plate to get the average accuracy at each distance from the plate while the car has the speed of 90km/h.

At the third step, we tested five videos at different times of day and different weather condition like sunny and cloudy while the car has the speed of the 120km/h and extracted the average accuracy of the five videos. so, we get the accuracy of the first address location, second address location and third address location. Moreover, the accuracy of the fourth upper address location and fourth lower address location at 20 different distances from the plate which are from 100m to 5m distance from the plate. Then extracting the average accuracy of the five-address location in each distance from the plate to get the average accuracy at each distance from the plate while the car has the speed of 120km/h. the result that achieved from each step are showed in Figure 20.

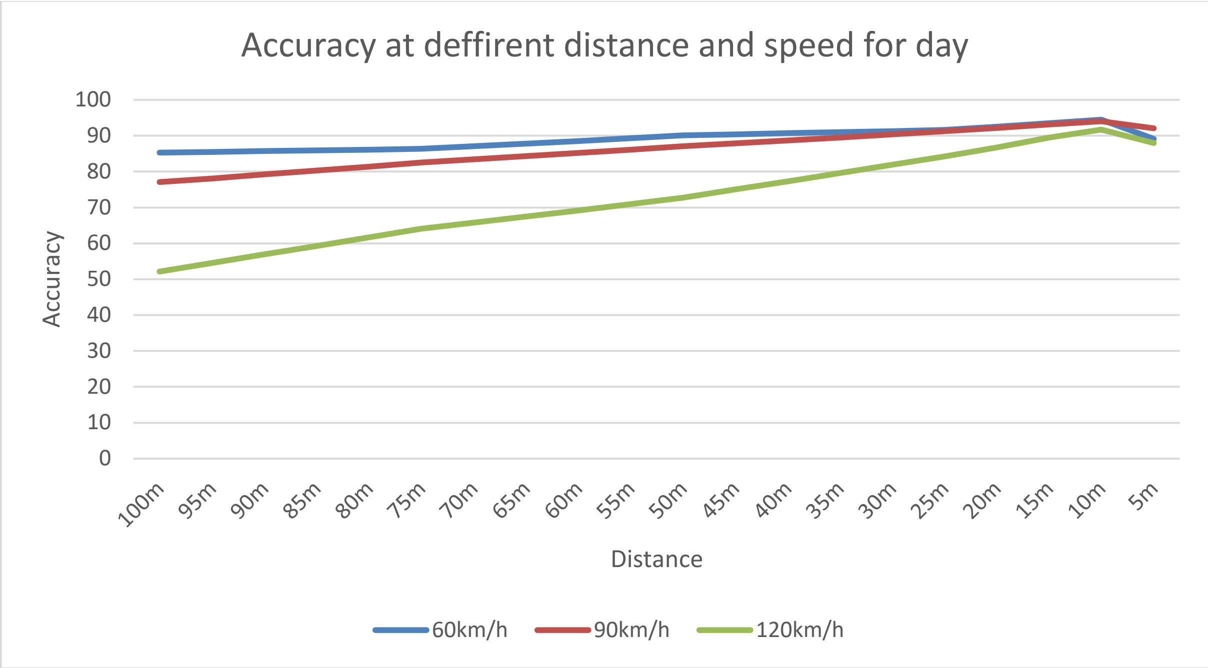

Figure 20: graph of the accuracy per distance while the car has the speed of 60km/h and 90km/h and also 120km/h at the day.

Figure 20 clearly shows the graphs of the accuracy in percentage at 20 deferent distances from the plate while the autonomous car has three different speeds which are 60km/h and 90km/h and also 120km/h. It can be noticing the accuracy of recognition will be affected by the speed of the car. while the car is at the distance of 100m from the plate and the speed of 60km/h the accuracy will be 85.3 percentage while when the speed increased to 90km/h the accuracy will be 77.1 percentage. While the speed changes to 120km/h the accuracy achieved is 52.1 percentage. For more declaration the Figure 21 shows this result in graph

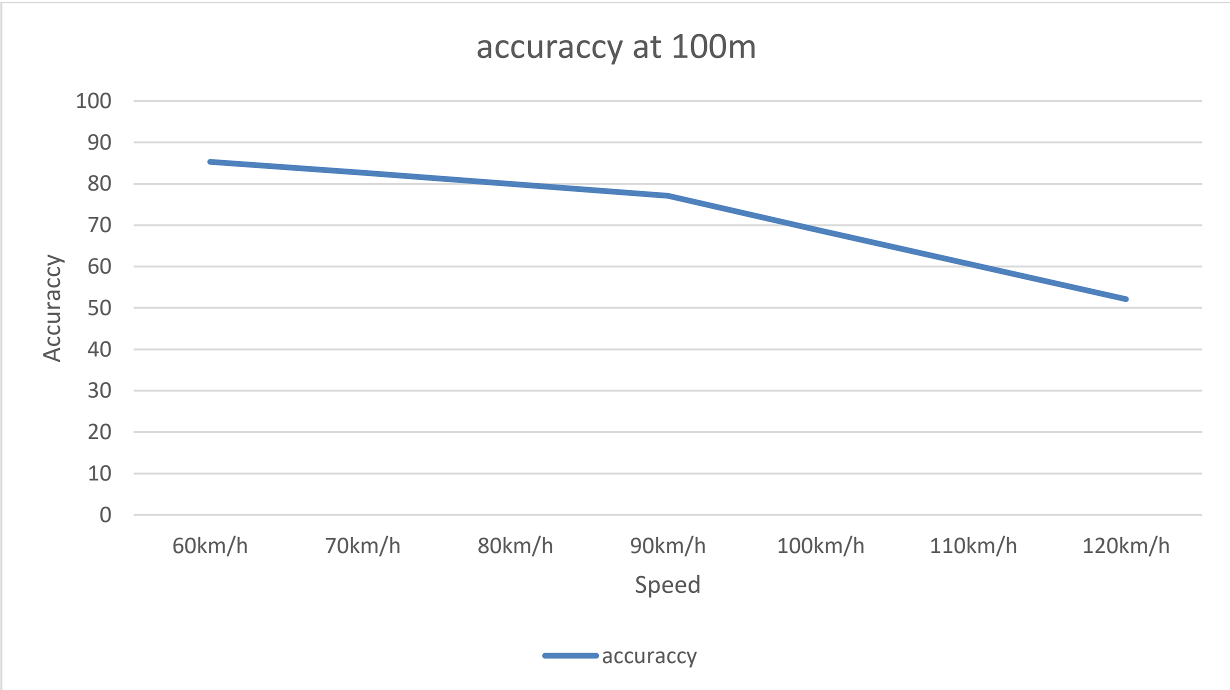

Figure 21: Accuracy of prediction per speed at the distance of 100m from the plate at the day.

To evaluate the system, it is visible from Figure 20 that at the 50m distance from the plate and at the speed of 60km/h the accuracy rises to 90.1 percentage while the speed increases to 90km/h the accuracy that will be achieved is 87.1 percentage. Also, while the speed rises to 120km/h the accuracy is 72.7 percentage. This result can be showed as a graph as in Figure 22.

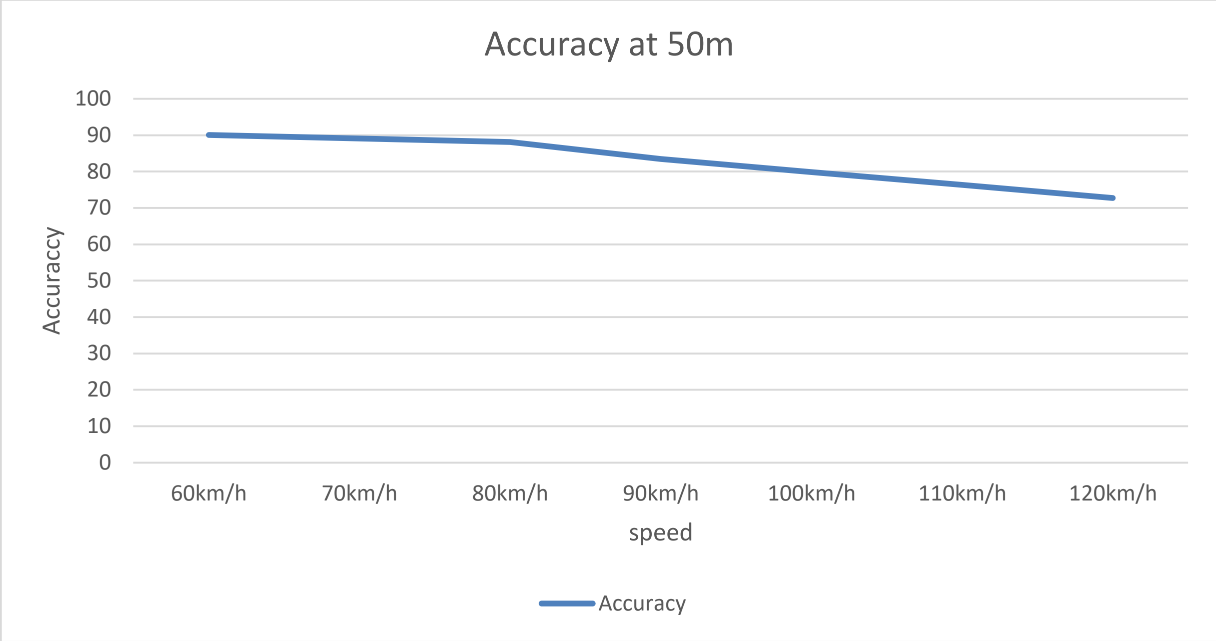

Figure 22: Accuracy of prediction per speed at the distance of 50m from the plate at the day.

To summaries this result it can be decided that the speed will affect the accuracy of the recognition of the system because however the speed increases the data will be more blurred. Then the accuracy will be lower. And this blurring that will be created by the effect of the speed is more effective at the 100m distance from the plate than 50m distance from the plate. Because however the vehicle gets near from the plate the plate will be clearer in the vision of the vehicle's camera and the effect of the speed will be lower until at 10m from the plate the accuracy that achieved at the speed 60km/h is 94.5 percentage and at the speed 90km/h the accuracy is 94 percentage. While the speed is 120km/h the accuracy is 91.7 percentage. This result can be clearly represented as a graph as it is showed in Figure 23 so at this distance the effect of the blurred data that made by increasing the speed is very low and can be neglected.

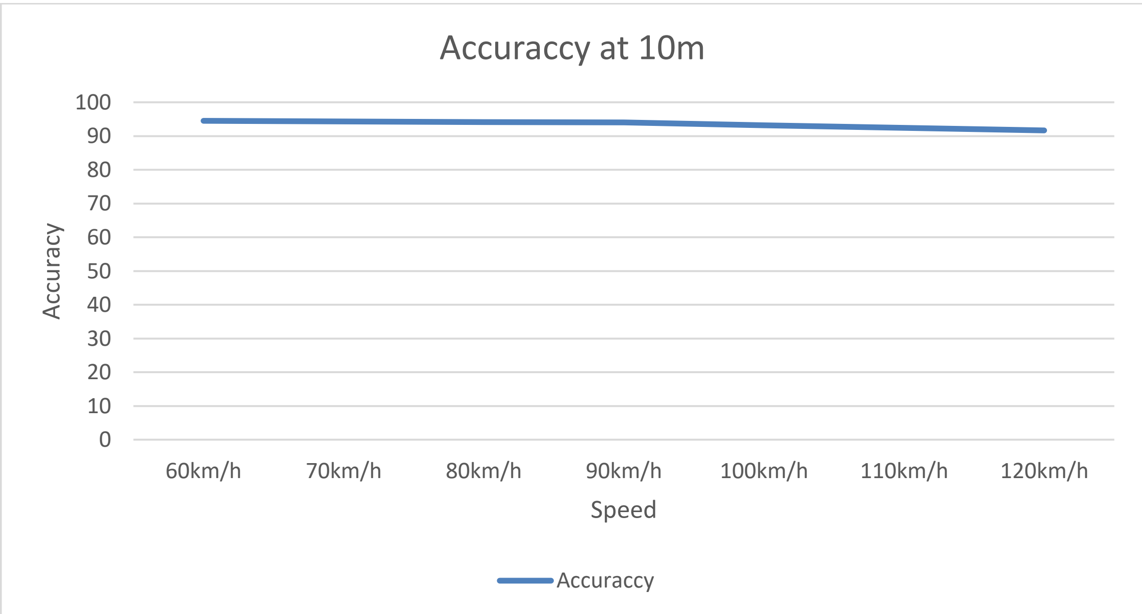

Figure 23: Accuracy of prediction per speed at the distance of 10m from the plate at the day.

4.6 How the system will be affected by the speed of the car at the Night

Now it is time to test the system under different speeds for the night data. For this purpose, at first step, we tested five videos at the night while the car has the speed of the 60km/h and extracted the average accuracy in percentage of the five videos. so, we get the accuracy of the first address location, second address location and third address location. Moreover, the accuracy of the fourth upper address location and fourth lower address location at 20 different distances from the plate which are from 100m to 5m distance from the plate. Then extracting the average of the five-address location in each distance from the plate to get the average accuracy at each distance from the plate at the speed of 60km/h.

at the second step the same scenario is repeated while the vehicle has the speed of 90km/h to get the average accuracy in percentage for the system at the speed of 90km/h and at each distance from 100m to 5m from the plate. Moreover, at the third step all things are repeated but at this time the speed changed to 120km/h to get the average accuracy of the system at the night with the speed of 120km/h at each distance from 100m to 5m from the plate. As a result, three graph achieved as it showed in Figure 24. each graph is related to a result accuracy in recognition of a specific speed of the car.

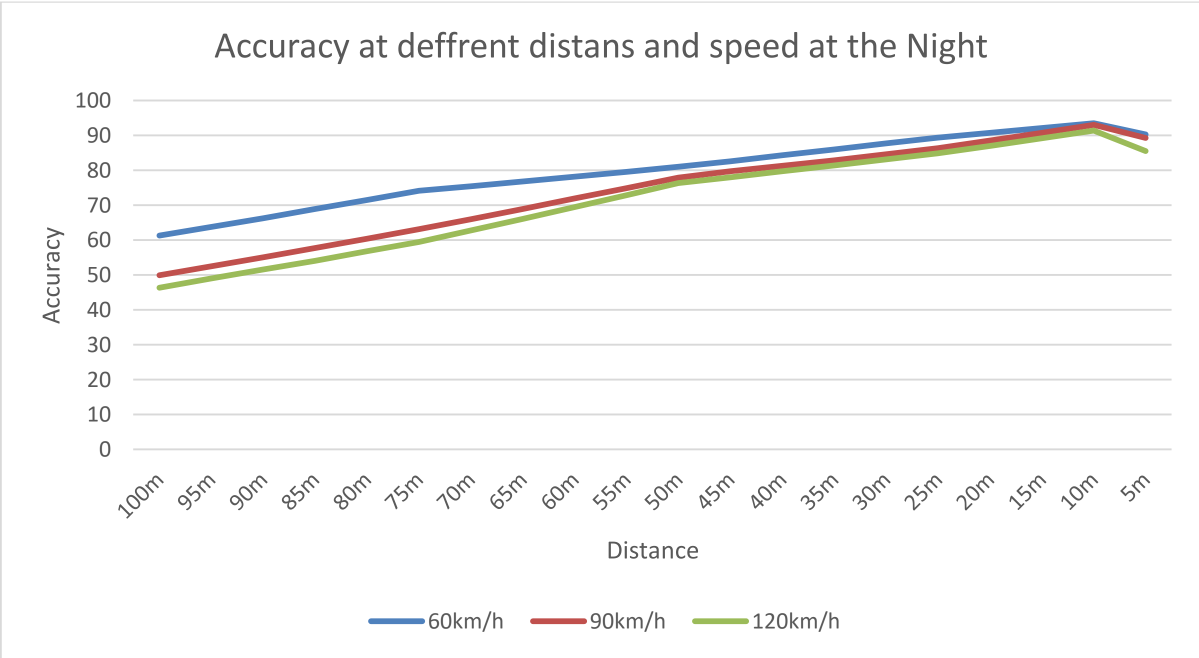

Figure 24: graphs of the accuracy per distance while the autonomous car has the speed of 60km/h and 90km/h and also 120km/h at the night.

Figure 24 clearly shows the graphs of the accuracy in percentage at 20 different distances from the plate at the night while the autonomous car has three different speed which are 60km/h and 90km/h and also 120km/h. It can be noticing the accuracy of recognition will be affected by the speed of the car. while the car is at the distance of 100m from the plate and the speed of 60km/h the accuracy will be 61.3 percentage while when the speed increased to 90km/h the accuracy will be 49.9 percentage. While the speed changes to 120km/h the accuracy achieved is 46.4 percentage. For more declaration the Figure 25 shows this result in graph.

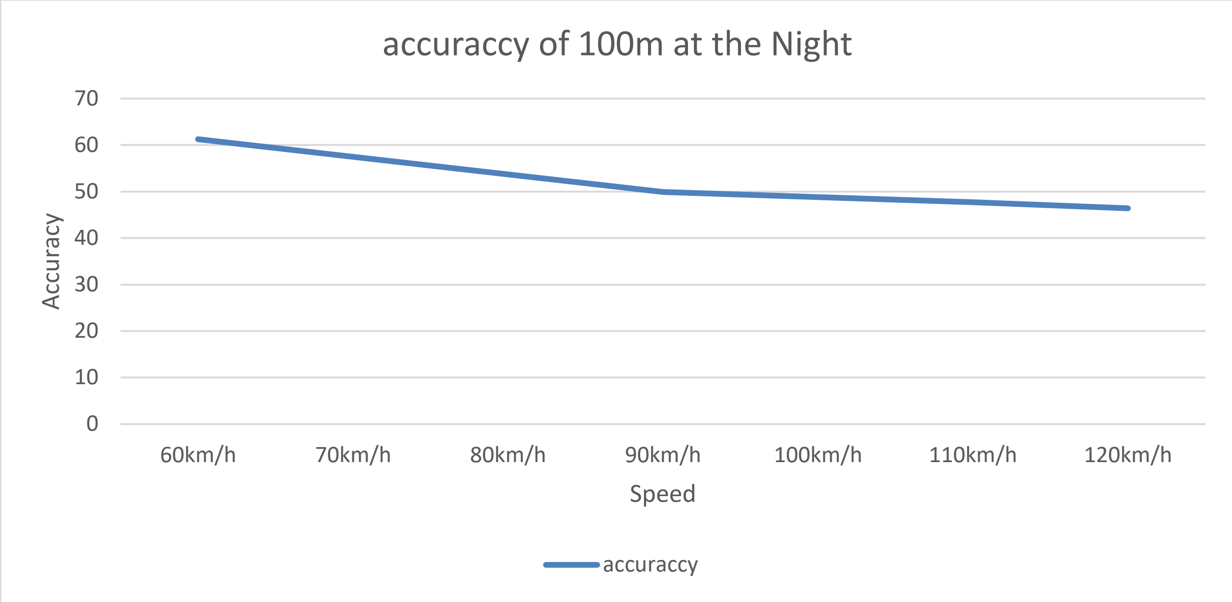

Figure 25: Accuracy of prediction per speed at the distance of 100m from the plate at the night.

To evaluate the system at the night under different speed of the car, it is visible from figure 24 at the 50m distance from the plate and at the speed of 60km/h the accuracy rises to 81 percentage while the speed increases to 90km/h the accuracy that will be achieved is 77.9 percentage. Also, while the speed rises to 120km/h the accuracy is 76.3 percentage. To summaries this result it can be decided that the speed will affect the accuracy of the recognition of the system because however the speed increases the data will be more blurred. Then the accuracy will be lower.

And this blurring that will be created by the effect of the speed is more effective at the 100m distance from the plate than 50m distance from the plate. Because however the vehicle gets near from the plate the plate will be clearer in the vision of the vehicle's camera and the effect of the speed will be lower.

For more explanation in this paper the result of a frame inside the testing videos are showed in Figure 26.

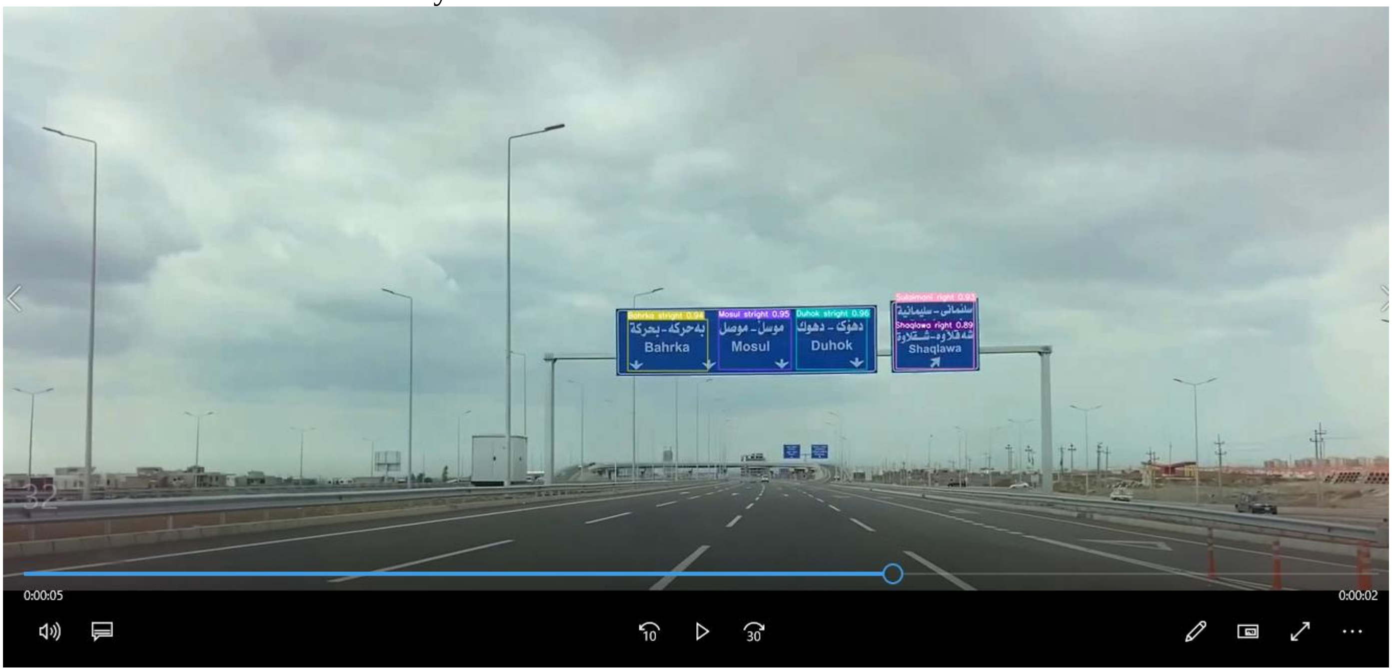

Figure 26: Result of a frame inside the testing videos.

5. Conclusion

A deep learning-based driving assistance system is described in this study. we proposed a strong traffic sign location and direction detection and recognition using YOLOv5. This technique is more cost-effective than earlier methods in terms of computing efficiency. the system's performance can be improved on real time image datasets. When these strategies are used, models' generalization capabilities improve, training time is reduced, and overfitting issues are avoided. we also discovered that learning rate is perfect in using this model. This algorithm improves the speed of detection because it can predict objects in real-time and also provides accurate results with minimal background errors. The proposed system can operate under a various condition. Also, our proposed system will save the valuable life by preventing accidents due to the late in making decision about which direction to go on the road. The project is mainly focus on majority of the society who used to travel especially the night travelers and it also helps traffic police to reduce the traffic issues. The main idea for this project is from the road accidents that take place due to the autonomous car error in taking direction to get the goal address location or any changes in the road due to maintenance or upgrade. People die in these road accidents which is a great loss for the family. It provides maximum efficiency. The Result Showed that the accuracy of bounding box prediction is 95.37% and the accuracy of the true box were correctly predicted is 97.49%. And also, the framework achieves the best performance of 98.76% mean average precision (mAP) at Intersection over Union (IoU) threshold of 0.5, evaluated on our new developed dataset. And 91.31% on different IoU thresholds, ranging from 0.5 to 0.95.

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