Integrating YOLOv8 with Fuzzy Logic System: A Novel Hybrid Approach for Efficient Parking Slot Availability Management

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Abstract: In urban areas, the challenge of finding parking spaces has become a significant concern, leading to congestion, wasted time, and increased pollution. Traditional parking management systems often lack the efficiency needed to address this issue adequately. In this paper, a novel approach was proposed to smart parking management that integrates the YOLOv8 model and fuzzy logic system. YOLOv8, a state-of-the-art object detection algorithm, enables real-time detection and tracking of vehicles within parking lots. By utilizing YOLOv8, the system can accurately identify vacant parking spaces in a timely manner. Furthermore, fuzzy logic was employed to enhance decision-making in selecting the optimal parking slot for users. Fuzzy logic enables the system to consider various factors such as proximity to the destination, parking space size, and distance from the entrance. By incorporating fuzzy logic into the decision-making process, the system can provide personalized recommendations tailored to individual user preferences and parking requirements. Based on the fuzzy inputs namely distance from entrance, proximity to exit and space, the system analyzes the best parking slot and assigns "rank" which is also fuzzy output. The decision can be made based on the rank provided to every slot of the parking lot. Slots with the highest rank should be preferred for parking because they are more suitable as they provide ease to parking the cars and can be suitable to customized needs of the users. The model can be deployed with LCD screens at various parking lots in order to save fuel and time of the commuters.

Keywords: YOLOv8 model, Internet of Things (IoT), Smart parking systems,

I. Introduction

To overcome the challenges faced for parking spaces in dense areas [1], there is a growing interest in the development of smart parking systems that leverage advanced technologies to optimize parking space utilization. Amidst this exigency, smart parking systems have emerged [2]as a promising avenue for addressing the complexities of contemporary parking management. These systems leverage cutting-edge technologies to offer real-time insights into parking space availability [3], thereby facilitating streamlined navigation and utilization of parking facilities. Among the array of technologies fueling this paradigm shift, the integration of advanced object detection algorithms, such as the YOLOv8 model, and fuzzy logic systems stands out as a particularly potent strategy. The integration of YOLOv8 and fuzzy logic offers several advantages over traditional parking management systems. Firstly, it improves the accuracy and efficiency of parking space detection, reducing the time spent searching for available spaces. Secondly, it enhances user experience by providing intelligent recommendations based on real-time data and user preferences. Lastly, it contributes to the overall optimization of parking space utilization, leading to reduced congestion and environmental impact. In summary, the proposed smart parking system represents a significant advancement in parking management technology. By leveraging the capabilities of YOLOv8 and fuzzy logic, researchers aim to revolutionize the way parking spaces are managed, ultimately leading to more efficient and sustainable urban environments. The issue of parking is getting worse these days as a result of the daily increase in traffic. There is a rush when cars are parked carelessly in public spaces like malls, markets, and other areas. Therefore, this issue was identified and provided the best solution for the unsystematic parking of automobiles with the aid of the Internet of Things (IoT). The Internet of Things (IoT) has plateaued where sophisticated solutions may be applied with ease inside frameworks and procedures related to urban governance and administration [4]. Growing car ownership rates are making it harder to find parking in cities and reducing the standard of living by producing more carbon emissions. Thus, it is imperative to develop smart parking solutions in order to cut down on greenhouse gas emissions and the time spent on parking search [5]. The social network-based analysis of online communities was obtained with mining related hashtags on Twitter to examine the conduct of users for car parking from a social media perspective. In order to map users' car parking behavior, they offered a new understandable community discovery methodology that combines the Clique, K-core, and

Girvan-Newman community recognition algorithms with a content-based analysis that makes use of dominating topics, polarity, and relative frequency [6].A real-time occupancy identification method for car parks using a Convolutional Neural Network (CNN) classifier was provided that runs on a low-resource smart camera indicating that the method was highly efficient and resilient to variations in lighting, the existence of shadows, and partial obscured features [7].The driving challenge is one of a group of issues that rely on underlying frameworks for handling uncertainty and logical reasoning. Therefore, the elements of human intellect and behavior into vehicle computers are required to integrate in order to enable them to regulate driving actuators in a manner that is comparable to that of people, moving beyond monitoring and into duties linked to environment perception or driving. The versatility of fuzzy control allows to include a wide range of sensory data to get the desired outcomes [8]. Reverse parking is also important for the drivers as it requires much attention and skills. Fuzzy logic has been applied to reverse parking with fuzzy controllers which adjusts front as well as back alignments of vehicle's body attitude [9]. People are becoming more interested in the use of fuzzy logic in engineering technologies as automated driving systems and fuzzy theory gain much acceptance. Various researches have traditionally been focused on the automatic parking module of the automated driving system. Automatic parking modules can help vehicles park more efficiently, significantly lessen parking-related issues, and enable quicker and more convenient parking for users 10]. In another research, a near-optimal fuzzy controller was also created for automated parking of vehicle using cell mapping approach for producing trajectories which can be used to build fuzzy controllers [11]. Thus, fuzzy logic has been used in many scenarios and integrated with various models and algorithms for getting desired results.

II. REVIEW OF LITERATURE

The hybridization of Yolov8 with fuzzy logic system played an important role in object parking assistance system. Rather than mapping the parking places in a parking lot by hand, an approach was presented which was developed based on Faster R-CNN based object detection, demonstrated the reduction of the amount of human labor required by a remarkable 86% [12]. Some studies offer a reliable method for locating open parking spots for cars. The dynamic changes in light surrounding the parking lot and the inadequate quality of the webcam make it difficult to precisely identify or detect the cars. Furthermore, because it does not require learning a large number of multi-view objects, the technique based on appearance is more efficient than the one which is based solely on recognition. proposed to use. The edge orientation histogram (EOH) density and masked-area dynamic mixing features for adaptive backdrop model-based object recognition was also proposed [13]. By using both real-world settings and simulation models, the outcomes demonstrated effective management of dynamic changes in light. Using an enhanced MobileNetV3 model with unique architectural modifications, a sophisticated model was offered which pre-processed individual parking spot patches to identify occupied or available spaces and provided occupancy categorization for each patch through real-time video feeds [14]. Drivers have always been hampered by the parking issue, which is brought on by a low ratio of parking spot use. A deep learning architecture was built for vehicle detection using TensorFlow in which parking space availability was determined using the indirect Monte Carlo approach and parking space order and number were determined using the data layering method and the TimSort algorithm [15].

Parking-related issues are now increasing at a very high speed because of global industrialization, population growth, sluggish city expansion, and poor management of available parking spaces [16]. A safe, clever, effective, and dependable system that can be utilized for finding empty parking spaces, directing people to them, settling parking fee disputes, and overseeing the parking area properly is desperately needed [16]. Locating a specific open spot in the largest parking area is the primary issue with the existing parking system. An "Advanced car parking system" developed [17] helps drivers find and park their cars in designated empty spots and can quickly determine whether a parking spot is free or not. In contemporary cities, parking distribution has grown to be a significant issue, prompting the development of multiple smart parking systems (SPS). Researchers also attempted to give a thorough study, comparison, and analysis of SPSs by outlining the benefits and drawbacks of SPSs and offering a thorough understanding of their appropriateness in varied environmental settings [18]. The idea of a smart parking system developed [19] provides information to users looking for a spot online by utilizing AI and IoT. It cuts down on needless time spent figuring out parking space issues in parking lots. The system provides the website where customers may see different parking places and select a spot from available slots. The time, money, and space that the parking systems save are all added benefits to the frequently tiresome chore of parking. Over the last few decades, the population of the modern world has been continuously increasing dramatically, which has led to a rapid expansion of the car industry. The world's smooth traffic flow has been interrupted by the exponential rise, which has also created serious issues like traffic congestion and poor management. Some hardware-based and some data-driven-based solutions have already been put forth to address these problems [20]. The hardware-based solutions are less scalable, difficult, expensive to install, and maintain since they rely on various kinds of sensors placed at pertinent locations to monitor the status of parking slots. The constraints of sensor-based solutions are circumvented by data-driven solutions, which make use of the infrastructure of security cameras already present in parking lots [20]. An android based model was also developed which was used to assess the car parking slot based on fuzzy inputs like number of empty car slots, time and distance and provided the output as the recommendations to users for their personal parking needs [21]. Researchers used Google services to get the metadata for various inputs like time used in traffic situation and routes selected by the user. But they haven't considered space around parking slots. Space around the parking slot greatly affects the users' choices for parking slots as they find ease of parking with higher space around the parking slots and vice versa. An autonomous multilevel automobile parking system was proposed that used fuzzy logic controller conditions to park the car in a smaller space. It could be able to regulate traffic and prevent gridlock [22]. With its LabVIEW interface, this automated multi-level car stacking system also offered online parking space reservations. But their system also lacks customization from user's end and doesn't provide choice to users as to which parking slots are suitable for their customized needs.

The simulation environment was also created, many fuzzy operators have been tested, and the outcomes have been compared. But their system considered only limited inputs like number of maneuvers required in parking the car, starting location of the car and range to surrounding items [23]. An automobile detection network based on revamping the YOLOv5 network architecture was also proposed in order to use the YOLOv5 network and create a parking management tool based on the EfficientNet and PP-LCNet designs [24]. But the study lacks customization with parking slots and user preferences as to ease of doing parking. The two-stage approach was also proposed using fuzzy logic algorithms for maximizing the quality of performance (QoP) for electric vehicle parking lot. By regulating the charging and discharging operations of the EVs using preference variables, the second stage FIS distributes the collected energy among the EVs by evaluating many dynamic and unpredictable input factors from the electric grid and from the EVs themselves [25]. But they haven't considered the next trip distance time and fairness analysis. The work can also be modeled through neural networks instead of FIS. The self-parking system using fuzzy logic controller was proposed which gathers and processes information about available parking spaces, and positions the vehicle in a predetermined location [26]. With the aid of an LCD display, their parking system allows the user to locate the closest parking area and determines whether any spaces are available there. The parking system was also created for bay parking using fuzzy logic controllers. The developer screated and simulated kinetic model and developed two fuzzy controllers, i.e. one for speed controlling and another for steering controlling [27]. Their work can be extended through including microcontroller and actuator design which could be useful in testing real-time scenarios. In area of site selection for the car parking, the multi-criteria decision-making model (MCDM) [28] was created using fuzzy logic in which the developers considered various input variables namely the availability of land for multi-story parking, the cost of land, the distance to roadways, the travel time to attraction centers, and the population density. Their model could distinguish parking area which are in shortage of parking zones.

III. METHODOLOGY

In this research, hybrid system is proposed to optimize the problem of car parking in a particular car parking lot. Researchers have developed this system and named it "Niks ParkAssist" for simplification and other development related tasks. This system is the combination of object detection and fuzzy logic.

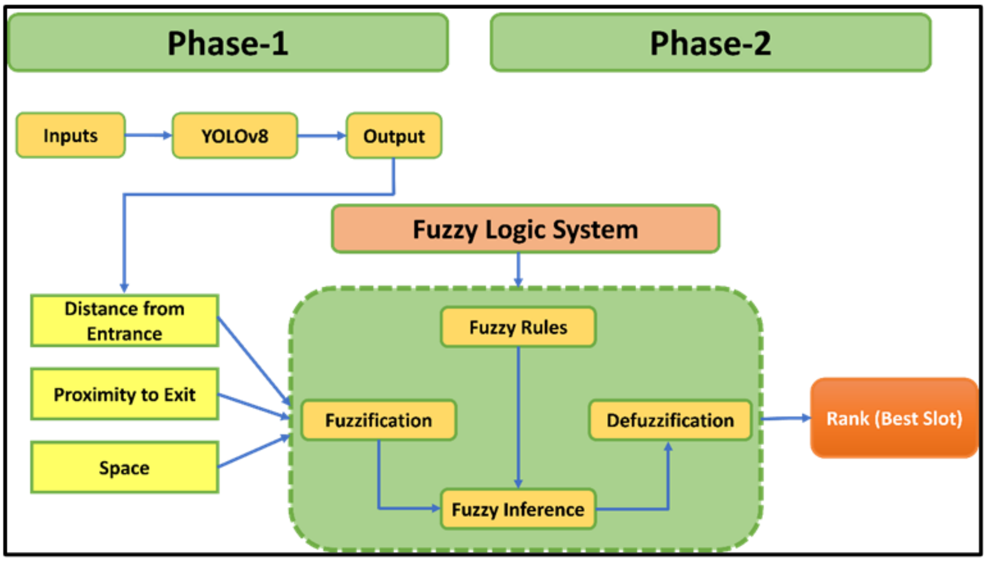

Fig. 1. Graphical presentation of the phases involved in Niks ParkAssist hybrid system

This system analyzes parking slots and provides empty parking slots based on object detection task and based on fuzzy inference system, it provides best parking slot available based on various inputs. The methodology consists of two phases: Phase-1 includes training Yolov8 model, Phase-2 includes hybridization of trained Yolov8 model with fuzzy inference system. The image of parking lot is to be fed in to Yolov8 model which provides empty parking slots with its bounding box information. This information is to be fed in to fuzzy inference system which analyzes input information and based on some fuzzy inputs, provides best parking slot which is optimized for car parking. Thus, this hybrid system provides the solution of where to park when facing the problem of congested parking lot.

IV. MODEL DEVELOPMENT AND TRAINING

The methodology implemented [29] in this research (Fig.1) is the development of hybrid system which provides the solution to the parking problem, which provides best empty parking slot available from all the available empty slots.

A. Data Collection and Labelling

In order to train an object detection model, the well-known dataset PKLot was used. In order to get best optimized results, this PKLot dataset was combined with Roboflow universe dataset. Thus, total 5711 images were collected to train the Yolov8 model. For image labelling, Roboflow.ai was used which is best online tool for labelling of images. "Roboflow is a computer vision developer framework that supports many annotation formats and improves data collecting, preprocessing, and model training methods. Data augmentations, scaling, contrasting, and image orientations are some of the stages that make up data pre-processing [30]". All the images were annotated in Yolov8 pytorch format which is generally center_x, center_y, width, height format. No extra pre-processing steps were applied to images as Yolov8 automatically performs all the preprocessing steps during model training. After labelling was done, the dataset was divided into three parts: training, validation and testing. Researchers included 70 percent images into training set, 20 percent in to validation set and the rest 10 percent in to testing set.

B. Model Training and Testing

In order to achieve the objective, Yolov8 object detection model was used to detect empty car slots in the whole parking lot. The research community is interested in YOLOv8, the most recent iteration of the YOLO model, which is a sophisticated real-time object detection system. When it comes to accuracy, speed, and efficiency, YOLO is the most well-known object recognition technique among all the widely used machine learning models and methodologies, including Faster RCNN, SSD, and RetinaNet [31]. In order to train the Yolov8 model, the batch size of 16 was used with image size of 640 X 640 (default image size in Yolo). Researchers were interested in only two classes "car" and "free", thus, they changed the default configuration file (.yaml) to include only two classes instead of 80 classes (default) as they wanted the model to detect only two labels, "car" and "free" in the entire parking lot. During training, they set 'patience" = 30 epochs instead of default 100 epochs as they wanted to stop overfitting of model if it can't change the learning. Yolov8 model was trained for 300 epochs [32] as it converged early for the dataset. Researchers trained the Yolov8 from scratch as they wanted the model to learn all the basic features from scratch. Nvidia Tesla V100 GPU with 52 GB RAM was used in Google Colab Pro Notebook and trained the model with all default optimization parameters.

C. Model Evaluation

The default parameters were used to evaluate object detection model. Researchers used mAP (Mean Average Precision) as it is commonly used for object detection tasks [29]. "This metric generates a score by comparing the detected bounding box with the ground-truth bounding box. More accurate detections by the model are indicated by a higher mAP score [29]". For better evaluation of Yolov8 model, other metrics for object detection tasks namely Recall, F1 and Precision were also used.

The evaluation metrics are presented below:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (1)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (2)$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

In order to evaluate Yolov8 model, above said metrics were used. In Yolov8 model, mAP@50 was found to be 99% and mAP@50-95 was found to be 86.4%. The precision was to be 97.6% whereas Recall was to be 96.8%. "The mAPs@0.5-0.95 denotes a 0.05 step increase from the intersection over union (IoU) = 0.5 to IoU = 0.95. Ten distinct IoUs would be used to compute the AP threshold in this scenario. To provide a single value that rewards detectors with greater localization, an average is calculated [29]". Four metrics to evaluate Yolov8 model were used which were presented in Fig.2 as under. These four metrics are Precision, Recall, mAP@50, mAP@50-95.

The metric "box_loss" in the above figure for train set and validation set is continuously decreasing. This indicates that the model has learnt perfectly. It indicates that the model is capable in predicting all the bounding boxes perfectly. Another metric "cls_loss" also decreasing in both, training set and validation set respectively. This also indicates that the model is capable in predicting classes accurately [33]in parking lot. Another metric "dfl_loss" (Distributed Focal Loss) is intended to handle some rigorous class imbalances in object detection tasks. In Yolov8 it is also used to improve bounding box regression, especially for objects with blurry or unclear boundaries which are difficult to predict. Both the metrics, Precision and Recall in the Fig.2 are increasing and both are 97.6% and 96.8% respectively. Researchers also calculated F1 score for overall measurement of precision and recall. F1 score calculated as per the above formula (3) is 0.941, i.e. 94.1%. Thus, the model has been trained perfectly with the train set to predict the objects in parking lot. Metric "mAp@50 is the mean average precision calculated at an intersection over union (IoU) threshold of 0.50. It's a measure of the model's accuracy considering only the "easy" detections" [34]; whereas "mAP@50-95 is the average of the mean average precision calculated at varying IoU thresholds, ranging from 0.50 to 0.95. It gives a comprehensive view of the model's performance across different levels of detection difficulty [34]". Both the metrics in the Fig.2 are increasing and thus, indicate that the model performed well with training and validation sets.

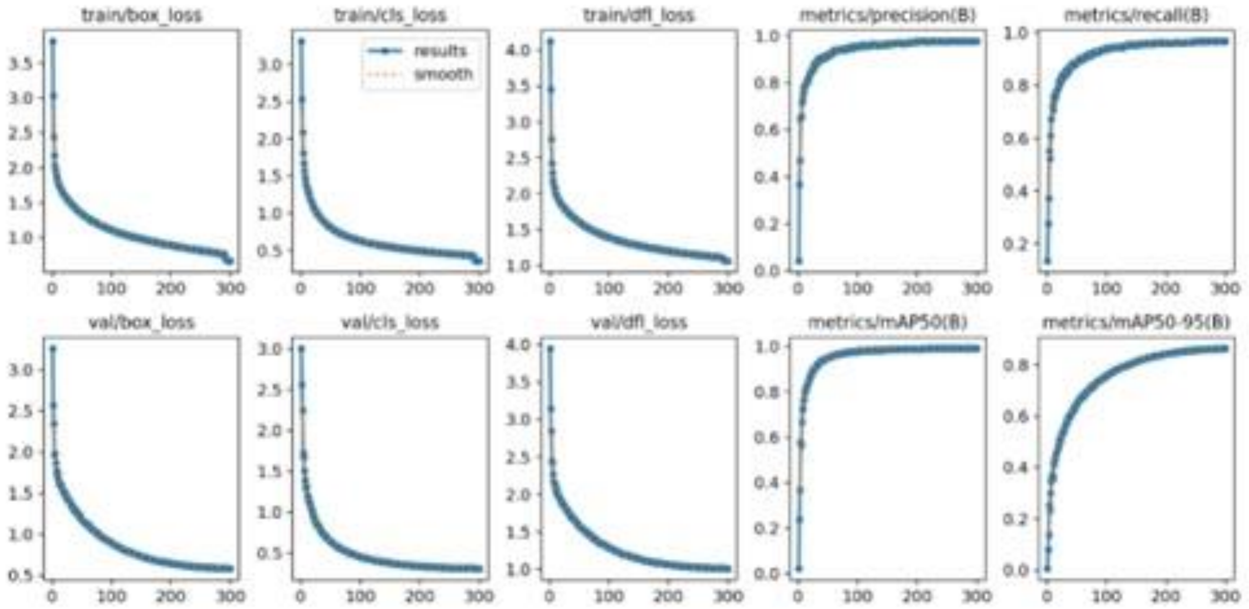

Fig. 2. Performance evaluation of YOLOv8 on training and validation datasets

V. DEVELOPMENT OF HYBRID SYSTEM WITH FUZZY LOGIC

A. Pre-processing Inputs

After training of Yolov8 model, the hybrid system was developed for identifying free parking slots and analyzing them for providing optimum slot available with fuzzy logic system. This hybrid system (Niks ParkAssist) fetches input data from the Yolov8 model's output, preprocess them and feds them into fuzzy inference system to provide best free parking slots. The study parking lot used for the research has 15 parking slots which all are perpendicular. This parking lot is depicted in Fig.3.

From the Yolov8 model's predictions on the said parking lot, these predictions were preprocessed for features extractions. Researchers extracted important features from the predictions namely center_x, center_y, width and height of predicted bounding boxes with their confidence and class labels. Co-ordinates center_x and center_y, are useful for localizing objects in the parking lot. Yolov8 model provided bounding box center co-ordinates and thus, there is no need to calculate these center co-ordinates of each predicted bounding box. From all these predicted classes, researchers segregated "free" classes from the entire prediction as they needed only free class labels. For the parking lot, seven parking slots were inferenced as "free" from the model's prediction.

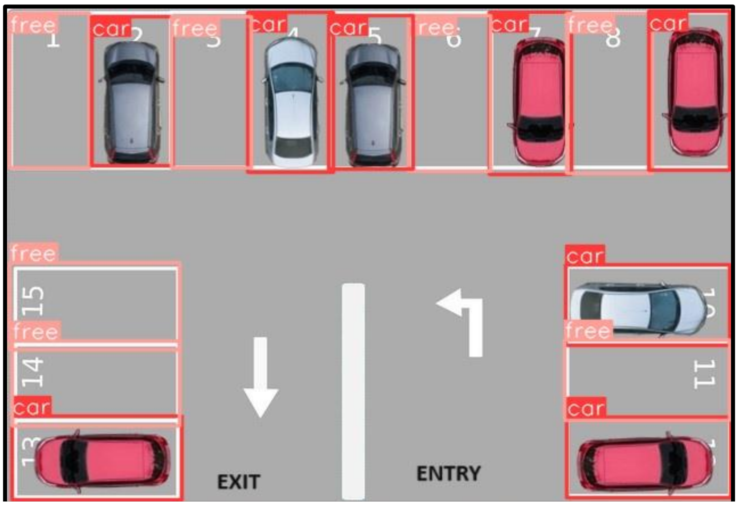

Fig. 3. YOLOv8 model's predictions on study parking lot. This parking lot also shows the distance from entrance and distance from exit

In order to calculate distance of each parking slot from its entrance and exit points, researchers used Euclidean distance to calculate their entrance and exit points. Following is the calculation for slot-1:

$$\text{Distance} = \sqrt{(x_{slot1} - x_{entrance})^2 + (y_{slot1} - y_{entrance})^2} \quad (4)$$

Where, x_{slot1} and y_{slot1} are center coordinates of slot1, and $x_{entrance}$ and $y_{entrance}$ are center coordinates of entrance points. This process was carried on for all parking slots to get their distance coordinates. Similarly, exit coordinates for all the parking slots were calculated with their exit point coordinates. Then, researchers identified Euclidean distance of each parking slot with its exit point distance as follows:

$$\text{Distance} = \sqrt{(x_{slot1} - x_{exit})^2 + (y_{slot1} - y_{exit})^2} \quad (5)$$

Where, x_{slot1} and y_{slot1} are center coordinates of slot1, and x_{exit} and y_{exit} are center coordinates of exit points. Based on the Euclidean distance formulae (4) and (5), researchers calculated “distance from entrance” and “proximity to exit” for each empty parking slot. The space variable (Table-2) was calculated using MATLAB ImageView in pixels format which was rescaled to 100 points in order to ease the calculations. The summary of other variables is presented as below:

TABLE 1.
YOLOV8 MODEL'S OUTPUT (X, Y COORDINATES) PRESENTED AS TABULAR FORM

Slot No.	X Coordinate	Y Coordinate	Distance From Entrance	Proximity To Exit
1	39.5	74.5	465.98	376.81
3	178.0	78.0	378.19	336.92
6	389.5	78.5	327.20	383.85
8	531.0	75.5	367.61	471.34
11	563.5	341.5	205.55	367.71
14	78.5	344.5	295.75	142.58
15	79.0	272.0	318.13	188.52

B. Fuzzification

The fuzzification step converts inputs obtained from the previous step (bounding box coordinates) in to fuzzy sets. Three linguistic variables namely “distance from entrance”, “proximity to exit” and “space” which are input variables were used. The output variable “rank” was defined as the fuzzy score which provides rank to the best available parking slot. Two inputs were used from the Yolov8 model’s output and one input “space” was defined as new linguistic variable for the fuzzy inference system.

C. Membership Functions

Researchers defined membership functions for three antecedents (input variables) and one consequent (output variable). The first input variable “distance from entrance” was defined with three triangular membership functions “close”, “medium” and “far”. Input “distance from entrance” has three membership functions with range (universe of discourse) of 0-550. The “close” membership function has values of 0-250, medium 200-400 and far 350-550. The second input variable “proximity to exit” was also defined by three triangular membership functions “close”, “medium” and “far”. The membership function “close” has the value of 0-250, with high on 150. The “medium” membership function has value of 200-400 with high on 300. The last membership function “far” has value of 350-550 with high on 450.

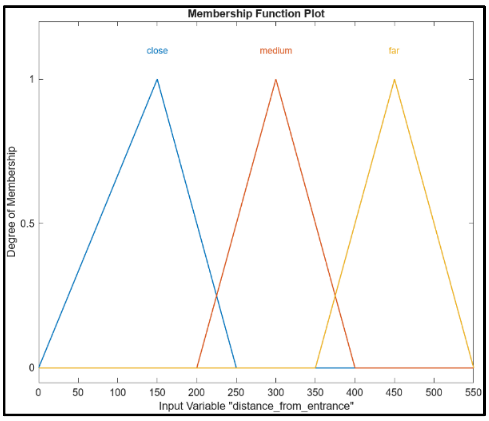

Fig. 4. Distance to entrance variable

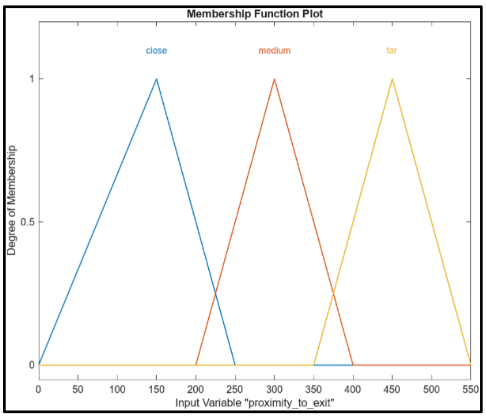

Fig. 5. Proximity to exit variable

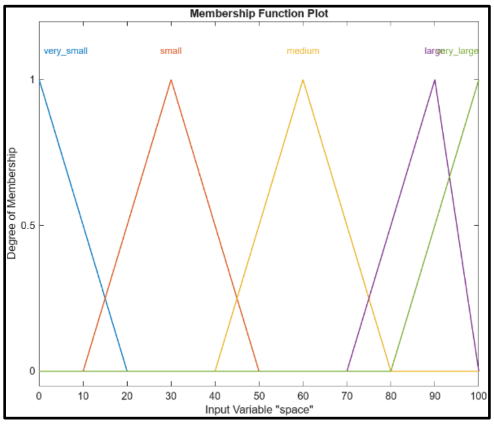

Fig. 6. Space variable

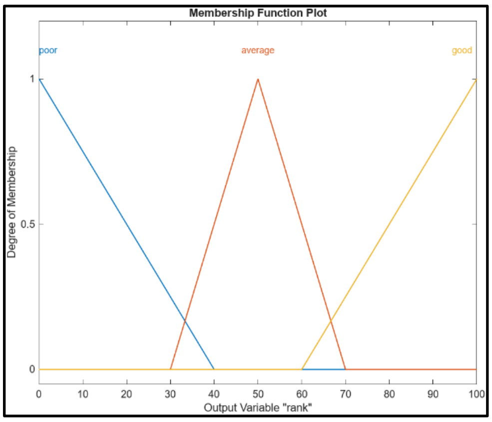

Fig. 7. Rank variable

The third input variable "space" indicates the available space around the empty parking slot. It was defined with five triangular membership functions as "very small", "small", "medium", "large" and "very large". The first membership "very small" was defined with 0-20 with high on 0. The "small" membership function was defined with a range of 10-50 with peak value of 30. The "medium" membership function was defined with a range of 40-80 with its peak value of 60. The "large" membership function [35] was defined with the range of 70-100 with the peak value of 90. The last membership function "very large" was defined with a range of 80-100 with the peak value of 100. The membership functions of last variable (consequent) "rank" was defined by triangular membership functions namely "poor", "average" and "good". The first membership function "poor" was defined with the range of 0-40 with the peak value of 0 indicating the membership function is high for the score of 0 or nearly 0. The second membership function "average" was defined with the range of 30-70 with the peak of value of 50. The last membership function "good" was defined with the range of 60-100 with the peak value of 100.

D. Rules Base

After defining membership functions for each input and output variables, the fuzzy rules were defined in the fuzzy inference system. These fuzzy rules map the input variables defined with the output variable which is fuzzy score. Total 35 rules were defined for each fuzzy input variable.

E. Creating Fuzzy Control System

After defining fuzzy rules, the fuzzy control system was created through passing defined fuzzy rules in to the control system. Then after, a control simulation was created through "Control System Simulation". The input values of fuzzy input variables "distance from entrance", "proximity to exit" and "space" were set to represent a particular parking slot. These values were the outputs from the Yolov8 model's predictions. The fuzzy control system was used to calculate fuzzy score as the output of the system from provided fuzzy inputs. Thus, the system generated the fuzzy scores as the output for each fuzzy input. Finally, the system printed all the fuzzy scores for each parking slot and provided the best parking slot with the highest rank. The best parking slot was "Slot-15" with the highest rank of 85.24.

Based on bounding box coordinates of Yolov8 model's output and fuzzy linguistic variable "space" as depicted in Table-2, researchers determined Slot-14 and Slot-15 as the best slots to park the car as these both the slots were optimized for car parking space. Slot-14 has the fuzzy score of 84.44 and Slot-15 has the fuzzy score of 85.24. Slot number 1, 3 and 8 have the lowest fuzzy score as they are far from the center coordinates with entry and exit distance as well as the space around them is also very low. Thus, they have the lowest fuzzy score as they are not suitable for parking. If the best slots are not available for car parking, then the drivers can use these slots for parking their cars but, they do have some skills for parking and they have to sacrifice some ease of parking there might be some traffic while entering the parking or exiting the parking. The system has classified these two slots as the best based on their entrance and exit distance from their center coordinates and space available around them. Thus, the system has perfectly classified slots available for car parking and provided the best slots available.

TABLE 2.
RESULT ANALYSIS OF HYBRID YOLOV8 AND FUZZY LOGIC SYSTEM

Slot No.	X Coordinate	Y Coordinate	Distance From Entrance	Proximity To Exit	Space	Rank
1	39.5	74.5	465.98	376.81	10	17.46
3	178.0	78.0	378.19	336.92	20	17.33
6	389.5	78.5	327.20	383.85	85	50
8	531.0	75.5	367.61	471.34	15	18.29

11	563.5	341.5	205.55	367.71	100	70.94
14	78.5	344.5	295.75	142.58	80	84.44
15	79.0	272.0	318.13	188.52	90	85.24

The above results are for one input image. Researchers developed an automated fuzzy system (Niks Park Assist) which captures images from CCTV camera at 60 seconds of interval (which can be customized), preprocess these images and based on trained YOLOv8 model, predictions are to be made. Then based on these predictions, fuzzy system calculates "rank" for free parking slots using fuzzy inputs and predefined rules in order to evaluate best parking slots. The system is capable of providing best parking slots based on the fuzzy inputs. The effectiveness of the system has been checked by implementing on various images and videos and it excels on all the images and videos taken. After developing the system, researchers developed simple lightweight Flask web-based application in order to deploy this system later on. The Flask app uses "NiksParkAssist" system on CCTV camera video feeds and makes the predictions based on trained model. These predictions are to be fed in to the fuzzy system in order to give rank to the free slots available.

VI. CONCLUSION

The integration of a YOLOv8 object detection model with a fuzzy logic control system for car parking space prediction is a promising approach to optimize parking space utilization. By leveraging advanced computer vision techniques, the system accurately identifies empty parking slots, providing crucial input variables for the fuzzy logic system. In this specific implementation, three key input variables were considered: the distance from the entrance, proximity to the exit, and the space surrounding the parking slot. These factors are essential in determining the desirability and accessibility of a parking spot. Overall, this approach offers a sophisticated solution for optimizing parking space selection, enhancing user experience, and potentially reducing traffic congestion that results in wastage of time. Further refinements and real-world testing could lead to even greater efficiency and effectiveness in parking management systems. This system can be extended by including other fuzzy inputs and applying other techniques such as computer vision techniques. Thus, this system can be deployed at various basement parking with CCTV camera and LCDs installed where drivers can't see how many slots are available for them to park the cars or they are totally unaware about whether there are free slots available for them.

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