Enhancing Safety and Efficiency with Autonomous Navigation Systems: Integrating Real-Time Object Detection, Tracking, and Trajectory Prediction

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***Abstract*—In this study, an innovative automated navigation system for delivery vehicles was developed, leveraging real-time object detection technology. This system utilizes a bird's-eye view from high-angle cameras at traffic intersections, with the view segmented into a 7×7 grid, each grid measuring 0.5 meters. The cutting-edge YOLO (You Only Look Once) V8 algorithm is employed for precise vehicle detection in designated areas, adeptly handling various lighting and weather conditions. A key feature of this system is the use of the DeepSORT algorithm for vehicle tracking. DeepSORT excels in maintaining a consistent identification (ID) of each vehicle, crucial in complex scenarios like vehicle obscuration or close proximity of multiple vehicles. This capability ensures continuous and reliable monitoring of each vehicle's route, particularly vital in heavy traffic situations. For autonomous delivery vehicles, the system integrates real-time data from onboard sensors, ensuring accurate vehicle positioning. This integration allows for precise alignment with the vehicle's actual position. Moreover, the system employs Artificial Neural Networks (ANN) trained on diverse vehicle movement patterns. This training, based on comprehensive real-world vehicle movement data analysis, enables the system to accurately predict future vehicle locations. The system's efficacy is underscored by its high predictive accuracy, as indicated by an impressive determination coefficient (R^2) of 0.99. In conclusion, this advanced system integrates object detection, effective tracking, and trajectory prediction capabilities in real-time, offering a robust solution for enhancing the safety and efficiency of transport vehicles in high-traffic areas.**

***Index Terms*—Trajectory Prediction, Object Detection and Tracking, Artificial neural network, Autonomous Navigation Systems**

I. Introduction

The advent of automated navigation systems marks a milestone in the evolution of intelligent transportation These systems play an important role in shaping the mobility of the

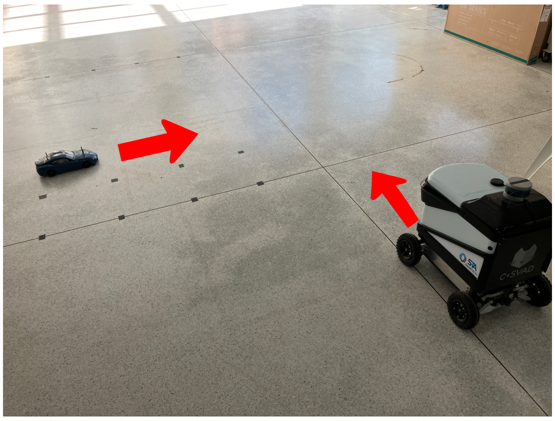

Fig. 1: The operational facet of the trajectory prediction system.

future. It requires advanced technology for precise and efficient operation. This article explores object detection integration. This is an important research that has far-reaching implications in urban traffic management and vehicle safety. The foundation of this research is based on the implementation of a bird's eye view approach using a detailed 7×7 grid system for precise vehicle locating. This approach addresses the challenges posed by the ever-changing urban environment. Accurate vehicle detection and tracking are paramount. Using the YOLO V8 model for object detection [1]and the DeepSort algorithm for tracking [2], it is a new approach to real-time data management with high accuracy and efficiency. At the heart of this study is the use of neural networks. ANN trained in a comprehensive

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dataset on vehicle motion patterns, offers insights into the future of predictive analytics in transportation. This approach not only improves the security features of automation. But it also contributes to the broader goal of intelligent traffic management. In addition, The article also delves into the collection and analysis of real-world vehicle movement data, captured through high-angle video footage. This information is at the core of our research. It allows for fine-tuning algorithms to accurately reflect real-world situations. Integration of autonomous robotic navigation systems, which are in line with vehicle tracking systems. It also shows the practicality of our research in a dynamic and unpredictable environment. The performance of the proposed system was rigorously evaluated using standard statistical measures such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2) coefficients. This article aims to support ongoing discussions about smart transit, offering insights and solutions that pave the way for safer and more efficient urban mobility. In this specific study, a system for predicting vehicle trajectories in autonomous navigation is developed, utilizing a Bird's Eye View and a 7×7 grid system. The integration of the YOLO V8 model for object detection and the DeepSort algorithm for tracking forms the core of this approach. An Artificial Neural Network (ANN) is crucial for accurate trajectory predictions. Validated with real-world data and statistical measures (MSE, MAE, R^2), the trajectory prediction system is depicted in Fig. 1.

II. Proposed System Design

An overview of the system is provided by this system. As depicted in Figure 2, warnings are issued by the system when vehicles entering the area are detected, and the trajectory of the detected vehicle, including the direction it will go and its location in a specified number of seconds, can be predicted.

The location of the vehicle to be detected is identified by utilizing the acquired location in the trained ANN model. This model predicts the vehicle's next position by forecasting the next 10 instances ahead. Vehicle behavior data is employed by the ANN model to learn patterns in vehicle movement. The autonomous delivery robot then takes the vehicle's position, which is the x,y coordinates, and performs the Local to Global transformation using the Homogeneous transformation matrix method [3], as demonstrated in equation (1).

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{bmatrix} S_x & 0 & d_x \\ 0 & S_y & d_y \\ 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \tag{1}$$

This equation demonstrates how the use is performed by this conversion. Scaling: which uses the S_x and S_y values for the x and y axes, respectively. Translation: uses the d_x and d_y values to convert coordinates from local to global. Given that. x, y: Local coordinates x',y': Global coordinates S_x, S_y: Magnification factor for x-axis and y, respectively. d_x,d_y Translation motion values for the x- and y-axes, respectively. This matrix is used to convert the coordinates of an object from the local coordinate system to the global coordinate system.

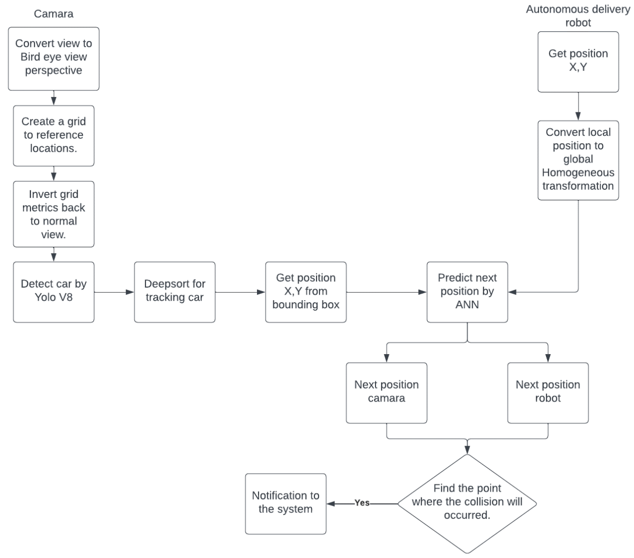


Fig. 2: Flowchart of system design.

Position based on global based on the position of the grid created by the camera side. After the position on the same coordinate, then take the acquired position into the model to predict the next position as well. After getting both positions, you will get $(x, y)_{\text{camera}}$ belongs to the camera side that detects and acquires the position $(x, y)_{\text{robot}}$ It belongs to the robot side, after which it brings the two positions $(x, y)_{\text{camera}}$ and $(x, y)_{\text{robot}}$ Enter the ANN prediction model and collect 10 points for comparison. Find the distance between them from equation (2).

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{2}$$

The equation is formulated to determine the length of a straight line between two points on a 2D plane, utilizing the principles of the Pythagorean theorem. It is assigned as follows: d represents the length of the straight line between two points. (x_1, y_1) denotes the coordinates of the first point. (x_2, y_2) signifies the coordinates of the second point. This equation calculates the length of the straight line by squaring the difference in coordinates along the x-axis $(x_2 - x_1)$and the y-axis $(y_2 - y_1)$. Then, it sums these squared differences and takes the square root of this sum to find the length of the line. If the distance after prediction is very close and the time of the two positions is closer than 3 seconds, the system will automatically notify the vehicle in advance. If there is a risk of an accident, how many seconds will the collision take place. The system automatically alerts the vehicle in advance of how many seconds a collision will occur. If there is a risk of an accident. Provided that the distance of the point after the prediction is very close, and the time of the two positions is closer than 3 seconds.

III. METHODOLOGY

A. Collect data

This research focuses on gathering real-world vehicle movement data by capturing video camera data into a bird ' s-eye view, providing a covered space for vehicle detection. The vehicle is detected by the YOLO V8 algorithm, which provides high accuracy and real-time performance required for the traffic environment.

- Detection and Data Recording Table overlays on bird's-eye view facilitate a standardized waypoint system. This ensures consistent vehicle location tracking. X and Y coordinate the detection system of each vehicle at different time intervals. Create datasets that reflect vehicle movement patterns in the area.
- Data Integrity and Preprocessing Before data can be used in an ANN model, it must be cleaned to remove outliers such as excessive data jumps. The coordinates will be normalized to help ANN Train and predict more efficiently The data obtained is x_1, y_1 as the data from the first coordinate, x_2, y_2 as the data from the second coordinate, and x_3, y_3 as the third coordinate data.

B. System Design and Implementation

The research uses a sequential approach to system design. By developing and integrating detection, tracking, and prediction components into a coherent framework that can facilitate robot navigation alongside traditional vehicle

- Vehicle Detection with YOLO V8 [4], [5]. The first phase is about deploying the YOLO V8 algorithm. For vehicle detection, The algorithm's architecture is finely tuned to process images from a bird's eye view. Optimize vehicle identification and locating capabilities within the grid reference system.
- Vehicle Tracking with Deep SORT [1], [2], [6] After detection Deep SORT algorithms are used to track Deep SORT vehicles, consolidate motion data maintain tracking identifiers, and separate individual IDs even in cases of temporary obscuration or proximity of multiple vehicles.
- Autonomous Robot Navigation The automated delivery robot is equipped with sensors that provide real-time location information. This data is converted into the same coordinate using homogeneous transformation to manage on the same system used for vehicle tracking.

C. Trajectory Prediction and Collision Avoidance

The focus of the system lies in its ability to predict the location of future vehicles and robots and identify potential collision points in advance.

- ANN for Trajectory Prediction [7]–[14] ANN was developed and trained to predict the future position of a vehicle based on where it collects data on vehicle behavior. ANN's architecture consists of 2 dense layers, each using a linear function, with a total of 4 inputs: x_1, x_2, x_3, x_4 Given that x_1 is the value x from the first position, x_2 is the y value from the first position, x_3 is the value x from the second position, x_4 is the y value from the second position, and there are two outputs of y_1, y_2 each given as follows: y_1 is the x value from the third position, y_2 is the y value from the third position.

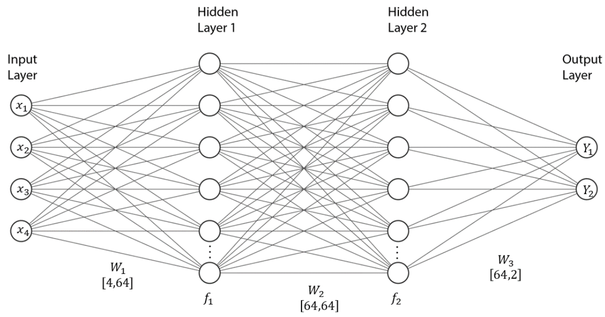


Fig. 3: Proposed ANN Design.

- Performance Evaluation Metrics ANN's predictive performance is quantified using various indicators, including Mean Squared Error (MSE), Mean Absolute Error (MAE), and Determination Coefficient (R^2).

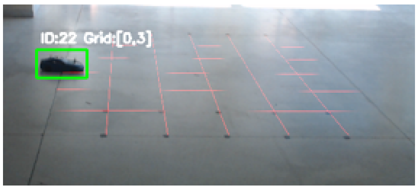
IV. INTEGRATION AND SYSTEM TESTING

The final stage involves the development of sensing, tracking, and prediction models. The overall performance of the system is tested in a simulated environment that closely mimics real-world conditions. Potential collisions are flagged, and the system response here is the accuracy value of the ANN model.

TABLE I: Comparison of Key Performance Metrics Values for ANN Model

Metric	Value
Mean Square Error (MSE)	3.79E-13
Mean Absolute Error (MAE)	5.05E-7
R-Square (R^2)	0.99

- Mean Squared Error (MSE): 3.79e-13 This value is very close to zero, which suggests that the predicted positions from the ANN are almost identical to the actual positions. The errors between the predicted and actual values are minuscule on average.
- Mean Absolute Error (MAE): 5.06e-07 The MAE being a small number indicates that the average absolute error between the predicted and actual values is extremely low. This means that on average, the predictions are very accurate.
- R-squared (R^2): 0.99 The R^2value is essentially 1, which means the model explains virtually all the variability of the response data around its mean. In other words, the model's predictions match the actual data almost perfectly.



(a) Position (0,3)

(b) Position (3,0)

(c) Position (1,1)

Fig. 4: The Position of the Vehicle as Detected by the System.

The results of the robot location is illustrate in Fig 4.

- From the inspection test of 49 points, it was found that only 4 points were misplaced: (2,5),(2,6),(3,5),(3,6). This means that only 8.16 % of test points misidentified locations, and the remaining 91.84 % of test points indicate the correct location.

V. Conclusion

In this study, great progress has been made in autonomous navigation, contributing to the expansion of knowledge in the field of intelligent transportation. The YOLO V8 model is used to detect objects in real-time. Integration of DeepSort algorithms for tracking and neural networks For accurate trajectory prediction, it represents a new way to increase vehicle safety and optimize traffic. The use of grid systems derived from positional conversion to Bird's-Eye View has proven to be effective in accurately detecting and tracking vehicles, addressing environmental challenges in a given autonomous vehicle space. The experimental results demonstrate the high efficiency of the proposed automated navigation system in vehicle detection and tracking. The system achieves accuracy in predicting satisfaction based on evidence from statistical measurements. R-squared (R^2) 0.99 Test-based system crash alert accuracy (81% accuracy in 100 tests) This may be because the processor or algorithm created cannot keep up with the computational speed sometimes. It uses the processor on an Intel Core i5 gen10 because ANN runs in the CPU. The processor can be improved to have increased computational speed. The inclusion of autonomous robotic navigation systems in this framework demonstrates its practical application. Real-time alignment of sensor data with vehicle tracking systems has been achieved with a focus on intelligent traffic management. Future research suggests focusing on increasing the scalability of this system for metropolitan areas and improving algorithms in a variety of environments, including transmitting more complex data

References

[1] N. S. Punn, S. K. Sonbhadra, S. Agarwal, and G. Rai, "Monitoring covid-19 social distancing with person detection and tracking via fine-tuned yolo v3 and deepsort techniques," *arXiv preprint arXiv:2005.01385*, 2020.

[2] Y. Du, Z. Zhao, Y. Song, Y. Zhao, F. Su, T. Gong, and H. Meng, "Strongsort: Make deepsort great again," *IEEE Transactions on Multimedia*, 2023.

[3] J. J. Craig, *Introduction to robotics*. Pearson Educacion, 2006.

[4] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 779–788.

[5] G. Wang, Y. Chen, P. An, H. Hong, J. Hu, and T. Huang, "Uav-yolov8: a small-object-detection model based on improved yolov8 for uav aerial photography scenarios," *Sensors*, vol. 23, no. 16, p. 7190, 2023.

[6] Y. Ge, S. Lin, Y. Zhang, Z. Li, H. Cheng, J. Dong, S. Shao, J. Zhang, X. Qi, and Z. Wu, "Tracking and counting of tomato at different growth period using an improving yolo-deepsort network for inspection robot," *Machines*, vol. 10, no. 6, p. 489, 2022.

[7] N. Nikhil and B. Tran Morris, "Convolutional neural network for trajectory prediction," in *Proceedings of the European Conference on Computer Vision (ECCV) Workshops*, 2018, pp. 0–0.

[8] G. Debat, T. Chauhan, B. R. Cottereau, T. Masquelier, M. Paindavoine, and R. Baures, "Event-based trajectory prediction using spiking neural networks," *Frontiers in computational neuroscience*, vol. 15, p. 658764, 2021.

[9] D. Singh and R. Srivastava, "Graph neural network with rnns based trajectory prediction of dynamic agents for autonomous vehicle," *Applied Intelligence*, vol. 52, no. 11, pp. 12 801–12 816, 2022.

[10] S. Zamboni, Z. T. Kefato, S. Girdzijauskas, C. Norén, and L. Dal Col, "Pedestrian trajectory prediction with convolutional neural networks," *Pattern Recognition*, vol. 121, p. 108252, 2022.

[11] J. Zaghir, J. F. Rodrigues-Jr, L. Goeuriot, and S. Amer-Yahia, "Real-world patient trajectory prediction from clinical notes using artificial neural networks and umls-based extraction of concepts," *Journal of Healthcare Informatics Research*, vol. 5, no. 4, pp. 474–496, 2021.

[12] D. Choi, K. Min, and J. Choi, "Regularising neural networks for future trajectory prediction via inverse reinforcement learning framework," *IET Computer Vision*, vol. 14, no. 5, pp. 192–200, 2020.

[13] Y. Cao, D. Xu, X. Weng, Z. Mao, A. Anandkumar, C. Xiao, and M. Pavone, "Robust trajectory prediction against adversarial attacks," in *Conference on Robot Learning*. PMLR, 2023, pp. 128–137.

[14] Y. Wang, D. Zhang, Y. Liu, and K.-L. Tan, "Trajectory forecasting with neural networks: An empirical evaluation and a new hybrid model," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 10, pp. 4400–4409, 2019.