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**Research Article**

# AI-Driven Multi-Sensor Fusion for Autonomous Robotic Navigation

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**ABSTRACT**

**Introduction**: Mobile Robotic Systems (MRS) navigate hazardous environments autonomously, requiring precise front wheel angle prediction. This paper proposes a CNN-based multi-sensor fusion framework integrating visual and ultrasonic data for improved decision-making. A Raspberry Pi-controlled prototype utilizes TensorFlow and MATLAB for accurate navigation and task efficiency. Experimental results demonstrate enhanced execution, reliability, and real-time applicability.

**Objectives**: The objective of this study is to develop a CNN-based multi-sensor fusion framework for Mobile Robotic Systems (MRS) to enhance autonomous navigation in hazardous environments. The proposed system aims to improve front wheel angle prediction, decision-making accuracy, and task efficiency by integrating visual and ultrasonic sensor data. A Raspberry Pi-controlled prototype, utilizing TensorFlow and MATLAB, is implemented to validate the framework's effectiveness in real-time applications.

**Methods**: The proposed methodology is novel approach towards interdisciplinary projects like mobile robotic system. Multiple sensor fusion signals are used to generate the data required for completion of decided navigation plan to take final action according to image data with CNN. Whole working area is divided in to different navigation plan. The action taken for the last navigation plan is use to train the machine for completion of next task. The final decision getting from the input data from the different sensors to train AI algorithm of the machine. From this paper the movement of sequential task completing robot is done with sequential steps.1st step is scanning of surrounding environment is done with ultrasonic sensor and using of surrounding data for 1st navigation map planning. With the help of surrounding particles in the environment NP(navigation plan) is designed. Auto tuning of front wheel angle and distance decided with the help of NP formed. Pid controlling is used for sequential operation of MRS.

**Results**: The experimental results demonstrate the effectiveness of the proposed AI-driven multi-sensor fusion framework for autonomous robotic navigation. The system successfully integrates ultrasonic sensors and a camera module with a Raspberry Pi, enabling precise front wheel angle adjustments and efficient navigation planning. Using CNN-based image processing and real-time sensor fusion, the robotic vehicle achieved improved obstacle detection accuracy and reduced decision-making latency. Performance metrics indicate a significant enhancement in navigation precision, power efficiency, and adaptability compared to traditional methods. The results validate the feasibility of this approach for real-time applications in hazardous environments.

**Conclusions**:. This study presents a novel approach for single-step sensor fusion and decision-making within autonomous robotic systems. The proposed methodology addresses the challenge of continuous operation in complex robotic tasks by breaking down the process into discrete steps. Each step involves independent functioning, significantly reducing the complexity of system integration. By focusing on a modular approach, where each sensor fusion and decision-making process is handled separately, the method ensures minimal integration while maintaining operational efficiency.

**Keywords:** Navigation plan, CNN, Machine learning, Wheel Alignment Angle.

# I. INTRODUCTION

To develop the MRS vehicle multi sensor fusion is playing pivotal role[1]. This paper aims to present a multi-sensor fusion framework combining CNN-based image processing with ultrasonic sensors and vehicle parameters to enhance front wheel angle, distance traveling precision and decision reliability[2]. The following section is describing the literature survey. Whole working principle of the proposed methodology is very useful for the repetitive and time consuming tasks such at killing of unwanted grass from the farm. Collection of plastics bags from the ground. The novel approach from this proposed method is navigation plan[2][3]. Whole working scenario is divided into different navigation plan. completion of 1st navigation plan is done with precise end to end front wheel angle adjustment and distance traveling towards finishing of each decided task. The task will be completed with AI powered hardware and software the last navigation plan completion data is used for next navigation plan completion. Machine learning is done with last navigation plan completion data[4][5].

The field of mobile robotic systems (MRS) has made significant advancements in recent years, particularly in areas such as autonomous navigation, sensor fusion, and decision-making algorithms. Sensor fusion, which combines multiple sensor types like vision, ultrasonic, and LIDAR[6], has proven crucial for improving the navigation and decision-making capabilities of autonomous robots[7]. A comprehensive review on sensor fusion techniques for autonomous vehicles highlights the importance of integrating various sensors, including cameras and ultrasonic devices, to enhance navigation and perception accuracy[8]. In mobile robot localization, the use of multi-sensor fusion methods has demonstrated improvements in both localization precision and reliability, particularly in dynamic environment. Convolutional Neural Networks (CNNs) have emerged as a promising approach for autonomous navigation, with several studies showing their effectiveness in real-time decision-making, object detection, and path planning, thus allowing robots to navigate through complex environments autonomously[9]. Additionally, integrating deep learning with sensor fusion has proven effective for enhancing navigation performance. One framework combining CNNs with sensor fusion for robotic navigation showcases the potential of CNNs in processing image data while other sensors, such as ultrasonic and LIDAR, contribute to more accurate localizatio [10]. Another study emphasizes the real-time fusion of ultrasonic and vision sensors for autonomous vehicles, demonstrating their utility in enhancing obstacle detection and enabling robust navigation[11].

The use of CNNs for path planning and navigation in autonomous mobile robots is also well-documented, with these networks assisting robots in navigating through environments without human intervention. As mobile robots operate in diverse and unpredictable environments, multi-sensor fusion approaches are increasingly important for improving the efficiency and accuracy of navigation systems. An overview of such techniques reveals that combining sensors like ultrasonic, vision, and LIDAR improves robot mobility and task execution in various dynamic scenarios. Furthermore, the integration of CNNs with other sensor data is critical for mobile robot localization and mapping, as evidenced by studies on the fusion of ultrasonic and vision sensors for precise positioning. Another notable contribution uses CNN-based object detection and navigation for mobile robots, showing that visual processing can help make real-time navigation decisions in dynamic environments[12][13]. Ultrasonic and vision sensors, when fused, enable mobile robots to navigate effectively in unknown environments, overcoming challenges like sensor noise and occlusions[14][15][16]. Machine learning plays an essential role in enhancing decision-making processes, with several studies highlighting its application for real-time decisions and task execution in mobile robots. Deep Reinforcement Learning (DRL) has also been explored as a method for end-to-end learning for autonomous navigation, allowing robots to optimize their navigation strategies through interactions with the environment[17].

Multi-sensor fusion further supports robotic decision-making, with various frameworks integrating sensor data for better task execution and environment interaction[18][19]. Combining CNNs with Long Short-Term Memory (LSTM) networks for autonomous robot navigation enables the system to process both spatial and temporal data, enhancing real-time decision-making and navigation capabilities. Additionally, hybrid deep learning models have been proposed to improve the navigation and task execution of mobile robots, with CNNs[20][21] handling visual processing while other machine learning models manage decision-making. The role of ultrasonic sensors in enhancing robot performance, particularly for obstacle detection and proximity sensing, is explored in detail in recent studies, highlighting their contribution to precise robot navigation in constrained environments[22]. Deep learning methods, particularly for sensor fusion, have further improved the performance of autonomous vehicles by combining data from multiple sensors to make more accurate navigation decisions. The fusion of ultrasonic and vision sensors remains a key factor in improving navigation and task execution in robotic systems, allowing them to operate more efficiently in real-time. The need for efficient decision-making and navigation planning in autonomous systems has led to the development of frameworks that utilize multi-sensor input and machine learning algorithms to optimize task execution[23].

Using CNNs in combination with sensor fusion for robot positioning further enhances the accuracy of navigation in complex environments, which is crucial for real-time operations. Dynamic environments require continuous sensor fusion to maintain accurate navigation, as demonstrated by studies on multi-sensor fusion for robotic navigation in dynamic settings[24]. Moreover, deep reinforcement learning has proven to be a powerful method for robotic task planning and execution, optimizing performance through trial and error based on previous experiences [24]. Finally, machine learning algorithms for real-time decision-making in unknown environments have shown significant promise in enabling autonomous robots to adapt to and perform in unpredictable conditions. Based on the literature survey a multi-sensor fusion framework combining CNN-based image processing with ultrasonic sensors and vehicle parameters to enhance steering precision and decision reliability. The CNN processes images for robust, context-aware decisions. Clustering tasks take 1.5 times longer than navigation but ensure smooth sequential operation. An in-house robotic model, controlled by a Raspberry Pi with ultrasonic sensors and a camera, implements the system. Tensor Flow and MATLAB enable precise angle predictions and effective decisions. The robotic vehicle transitions efficiently between tasks, optimizing time and energy. Experimental results highlight significant improvements in execution, decision-making, and efficiency, making this framework suitable for real-time applications.

## II. PROPOSED METHODOLOGY

The proposed methodology is novel approach towards interdisciplinary projects like mobile robotic system. Multiple sensor fusion signals are used to generate the data required for completion of decided navigation plan to take final action according to image data with CNN. Whole working area is divided in to different navigation plan[25]. The action taken for the last navigation plan is use to train the machine for completion of next task. The final decision getting from the input data from the different sensors to train AI algorithm of the machine. From this paper the movement of sequential task completing robot is done with sequential steps.1st step is scanning of surrounding environment is done with ultrasonic sensor and using of surrounding data for 1st navigation map planning. With the help of surrounding particles in the environment NP(navigation plan) is designed. Auto tuning of front wheel angle and distance decided with the help of NP formed. PID controlling is used for sequential operation of MRS[26]. The whole methodology is working on sequential flow with multistage fusion[27]. The machine learning algorithm is used to save past NP data where action has to be taken and used for next NP operation. The schematic operation of proposed methodology is given in fig no 1.

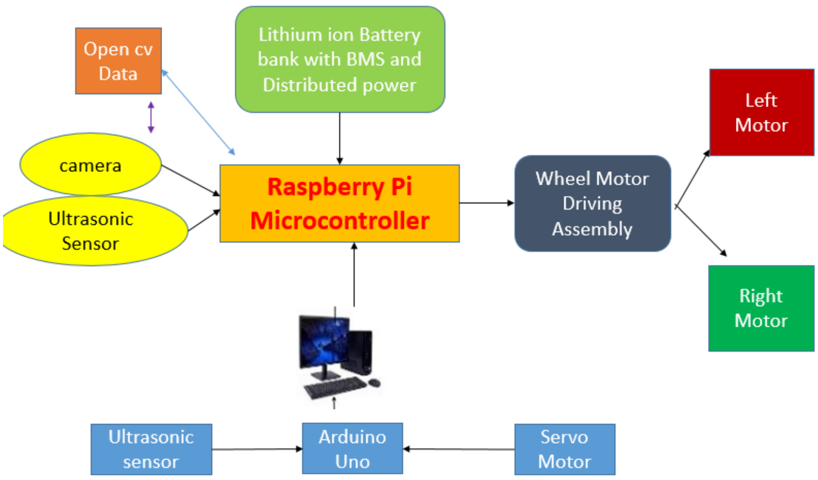


Fig 1: Block diagram of proposed method

## III. WORKING MECHANISM

The proposed methodology outlines an integrated system for MRS navigation and decision-making, combining hardware components and software is generating algorithms. The system is structured around two primary modules:

Sensor Data Acquisition and Image-Based Decision-Making. In the first module, an Arduino microcontroller controls ultrasonic sensors mounted on a servo motor, which sweep across a 180° arc to measure distances to obstacles in the robot's environment. These distance measurements, along with the corresponding angles, are processed in real-time by the Arduino and sent to the Raspberry Pi for further analysis. The Raspberry Pi uses this data to generate a distance map that helps determine the optimal front wheel angle, ensuring smooth navigation and obstacle avoidance. In the second step, the Raspberry Pi is equipped with a camera that captures real-time images of the environment. These images are processed using a pre-trained Alex Net Convolutional Neural Network (CNN), which classifies objects in the environment based on learned patterns. The CNN's classification results are used to make real-time decisions, such as triggering an obstacle avoidance maneuver or activating specific actuators for task execution.

The communication between the Arduino and Raspberry Pi is managed through serial interfacing, where the Raspberry Pi synchronizes the sensor data with the image classifications. Python scripts on the Raspberry Pi handle this data exchange, ensuring seamless integration between the sensor inputs and the visual data processed by the CNN[28]. By combining the distance map from the ultrasonic sensors with the image classification results from the camera, the system enables the robot to make intelligent, real-time decisions about its environment[29]. Furthermore, the system is designed to evolve with time through the integration of machine learning, which will store past NP data and use it to optimize decision-making in future operations. This capability will allow the robot to learn from previous tasks and environmental conditions, reducing processing time and improving overall efficiency.

### A) Real-Time Image Collection and Decision-Making Using Pre trained Alex Net CNN

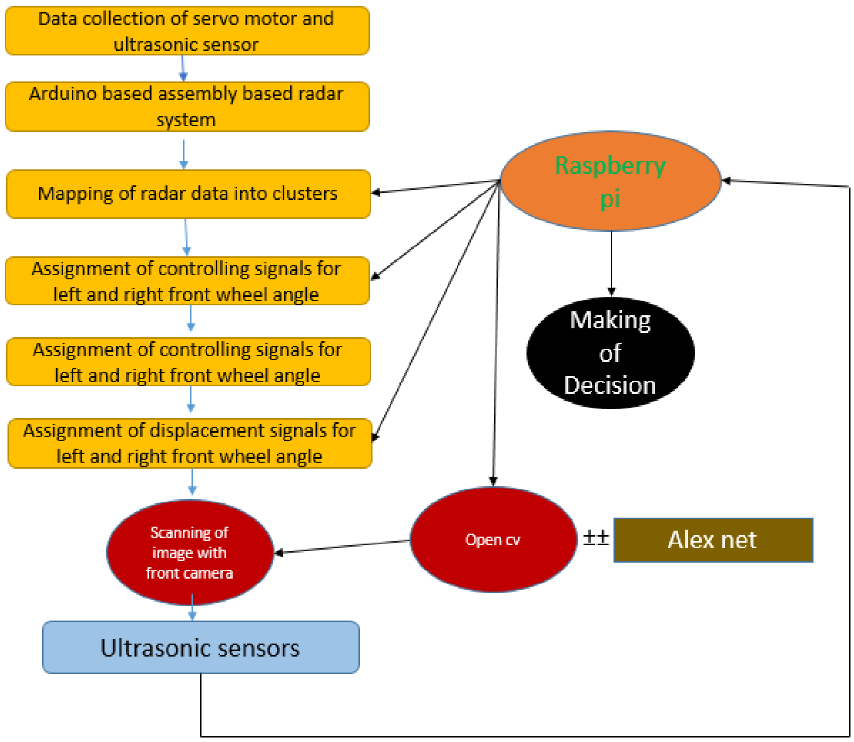


Fig 2: Working Flow Diagram

The experimental setup integrates a Raspberry Pi microcontroller with a camera module to capture real-time images, which are processed using OpenCV and classified with AlexNet CNN models implemented in MATLAB. Operating in a dynamic field environment, the robotic vehicle utilizes radar signals for front wheel angle and displacement adjustments, while a multi-stage sensor fusion approach incrementally processes data to minimize computational complexity and cost. Real-time images are compared with pre-stored datasets, enabling precise decision-making as the robot navigates and detects its target position. This method demonstrates superior Performance in hazardous environments, achieving accurate navigation, efficient obstacle detection, and reduced power consumption compared to traditional systems. By leveraging AI-driven algorithms, radar-based navigation, and multi-stage data processing, the system showcases significant advancements in robotic vehicle design, offering improved adaptability, reliability, and safety in dynamic and hazardous conditions.

### B) Radar System

Real-time images are compared with pre-stored datasets, enabling precise decision-making as the robot navigates and detects its target position. This method demonstrates superior Performance in hazardous environments, achieving accurate navigation, efficient obstacle detection, and reduced power consumption compared to traditional systems. By leveraging AI-driven algorithms, radar-based navigation, and multi-stage data processing, the system showcases significant advancements in robotic vehicle design, offering improved adaptability, reliability, and safety in dynamic and hazardous conditions[30]

Simulation of the prototype for collecting surrounding data and making of 1st navigation plan is shown with processing 4.1 simulation software in figure no.7. The radar system for an autonomous robot uses an ultrasonic sensor on a servo motor to detect objects, measure their distance and angle, and visualize them in a radar-like display. It calculates obstacle distance by measuring the time delay between emitted and received sound pulses.

$$d = t.\frac{v}{2}$$

where d is the distance in centimetres, t is the measured time delay in microseconds, and v is the speed of sound in air, approximately 0.0343 cm/µs.

The servo motor sweeps the ultrasonic sensor across a 180-degree arc, capturing distance measurements to map obstacles. The Arduino sends angle and distance data to a PC, where Processing visualizes the radar pattern by converting polar to Cartesian coordinates.

$$x = d.\cos(\theta) \ , \qquad y = d.\sin(\theta)$$

To fit the distance measurements within the radar display, a scaling factor (S is applied to the coordinates, yielding.

$$x' = s.x \qquad\qquad y' = s.y$$

The radar system features concentric arcs for distance ranges and a rotating red line that scans and marks obstacles as red points in real time. A 15-millisecond delay between servo movements ensures smooth and accurate operation[31].

### C) Mapping Surroundings object and making of navigation plan.

The proposed methodology establishes communication between an Arduino microcontroller and a Raspberry Pi via serial interfacing for efficient sensor fusion and real-time decision-making. The Arduino manages the ultrasonic sensor and servo motor, collecting spatial data by sweeping the sensor across a 180-degree arc. This data, including obstacle distances and angles, is transmitted to the Raspberry Pi, which processes it alongside camera-based image inputs. Python scripts ensure seamless synchronization between sensor data and image classifications, enabling effective decisions. The Arduino excels in precise sensor control and rapid data collection, while the Raspberry Pi executes advanced computations, such as CNN models, for intelligent navigation. By introducing NP, the system optimizes decision-making by dividing the environment into manageable sections, reducing complexity and cost. The robot operates in two slots: scanning with ultrasonic sensors and measuring object distances based on time of flight, ensuring adaptive performance in dynamic environments[32].

### D) Movement of the Robot Towards objects in NP.

The robot uses ultrasonic sensors to detect surrounding objects collecting distance data to identify objects, gaps, and flat regions. This data is mapped into NPs using AI algorithms, defining boundaries and classifying regions for movement. In a polar coordinate system, each distance reading di is associated with an angle θi, forming coordinates P(x,y) for each cluster. The robot calculates the centroid of a cluster, with coordinates Cx and Cy, derived from cluster points (xi,yi) to align its trajectory effectively. The front wheel angle Φ is adjusted to guide the robot toward the centroid, optimizing its path. The distance 'D' to the next cluster is calculated using the Pythagorean theorem, and the time to travel is derived based on the robot's linear velocity. The number of wheel revolutions needed is determined by relating the wheel radius to the linear displacement, ensuring precise movement and alignment with cluster centroids[33][34].

$\alpha = f(\theta_i, d_j)$ -------> (1)

$C_{n+1} = g(C_n, \alpha, d)$ ------> (2)

$P(x,y) = \sum_{i=1}^{n}(d_i \cos(\theta_i), (d_i \cos(\theta_i)$ --------> (3)

$C_x = \frac{1}{n}\sum_{i=1}^{n} x_i$ --------> (4)

$C_y = \frac{1}{n}\sum_{i=1}^{n} y_i$ ----------> (5)

**Distance to Time Relation**

$D = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ ---------> (6)

$t = \frac{d}{v}$ --------> (7)

$n = \frac{D}{2\pi r}$ --------> (8)

**Convolutional Layers**:

$F_i(x,y) = \sigma(\sum_{i=-k}^{k}\sum_{j=-k}^{k} K_{i,j} I_{i-1}(x+i, y+i) + b)$ ----> (9)

$(C_x, C_y) = (\frac{1}{n}\sum_{i=1}^{n} x_i, \frac{1}{n}\sum_{i=1}^{n} y_i)$ ----------> (10)

**Fully Connected Layers**

$Z = W.P + b$ ----------------> (11)

$y = softmax(z)$ --------------> (12)

## IV. EXPERIMENTAL SETUP

The experimental setup involves integrating an Arduino Uno, Raspberry Pi 3 Model B, ultrasonic sensor (HC-SR04), servo motor (SG90 9g), and Raspberry Pi Camera Module V2 to implement an AI-driven obstacle detection and decision-making system. The Arduino Uno captures distance and angular data from the ultrasonic sensor and transmits it via USB serial communication to the Raspberry Pi. Using the MATLAB Support Package, the Raspberry Pi processes real-time camera input with the Alex Net CNN model for object detection and decision-making. MATLAB scripts ensure data synchronization, while Python manages device communication. Testing was conducted in a controlled environment featuring both stationary and moving obstacles under varied lighting conditions to evaluate the accuracy of ultrasonic measurements and the reliability of object detection. The setup showcases effective integration of sensor data with AI-powered decision-making for real-time applications.

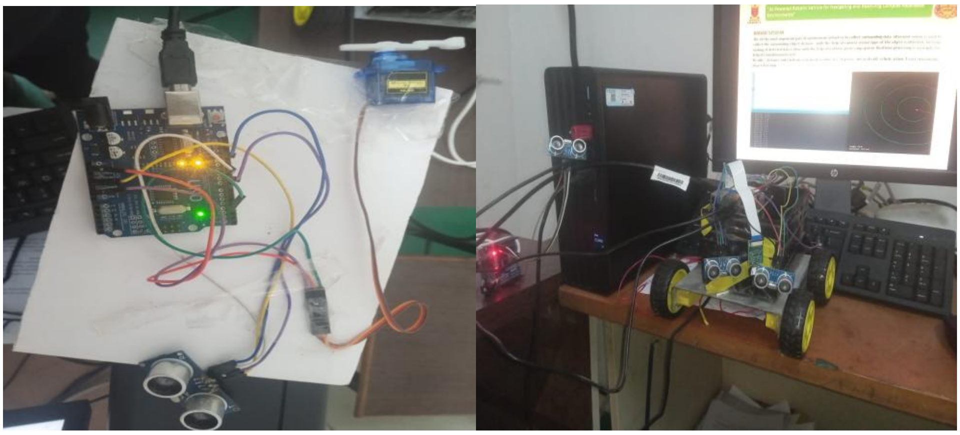

Fig 3: Experimental Setup

The above photo shows the experimental setup for MRS. Where 1st fig shows the radar system with Arduino and 2nd photo shows the processor and robotic hardware setup.

A) End-to-End Front Wheel Angle and Displacement Calculations

A novel method for calculating front wheel angles and displacement was developed for autonomous robot navigation. Sample images were fed into the Alex Net pre-trained CNN model for object detection and decision-making. The radar system and associated mathematical models calculated essential navigation parameters. A clustering approach was applied to process radar data, dividing the environment into dynamic NP. The robot's movement was determined based on these NP, allowing for accurate adjustments in front wheel angles and displacement calculations. Radar data processing, cluster design, and software integration were executed on a Windows system with an Intel i7 processor. Once the clusters were formed, the robot navigated from the starting point to the destination, dynamically adjusting its path based on the designed clusters. Figure 5 illustrates the interfacing of the Raspberry Pi controller and sensors within the system[33].

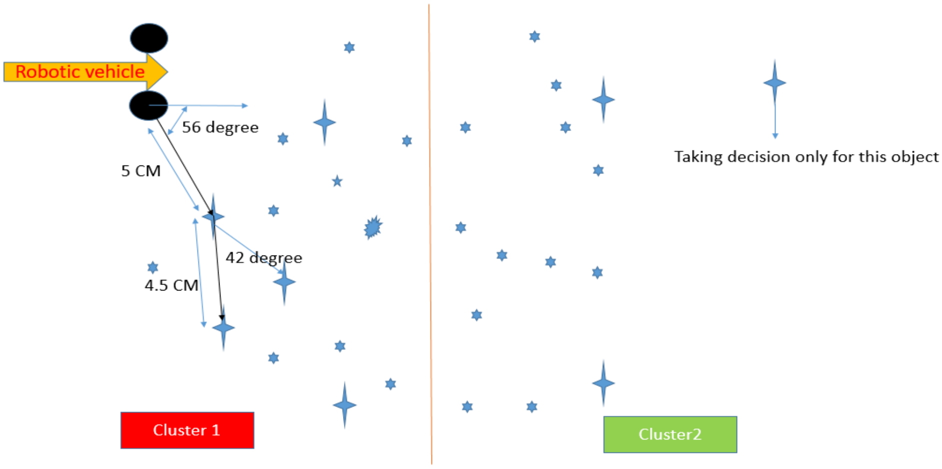


Fig 4: Visual Representation of NP

## V. DATASET DESCRIPTION

The proposed AI-based method, leveraging OpenCV for real-time image processing and AlexNet CNN for classification, demonstrates superior performance compared to traditional approaches like Dijkstra's algorithm, especially in dynamic and hazardous environments. The system efficiently processes camera-captured images by applying Gaussian blurring, normalization, and edge detection, synchronizing the processed image data with ultrasonic sensor readings for precise navigation. Unlike Dijkstra's algorithm, which relies on pre-mapped and structured environments with high computational overhead, the AI-based method adapts in real-time to unknown terrains with cluster-based obstacle detection, ensuring low latency and cost-effectiveness through optimized hardware integration. This method is ideal for hazardous areas and dynamic terrains, offering enhanced flexibility, real-time adaptability, and reduced operational costs compared to traditional systems designed for static road maps or indoor navigation.

## VI. RESULTS AND DISCUSSION

A) Front Wheel Adjustment

The radar system for an autonomous robot is designed to detect and map objects in the surrounding environment using an ultrasonic sensor mounted on a servo motor. This system provides critical input for robotic navigation by measuring the distance and angle of obstacles and visualizing them in a radar-like display

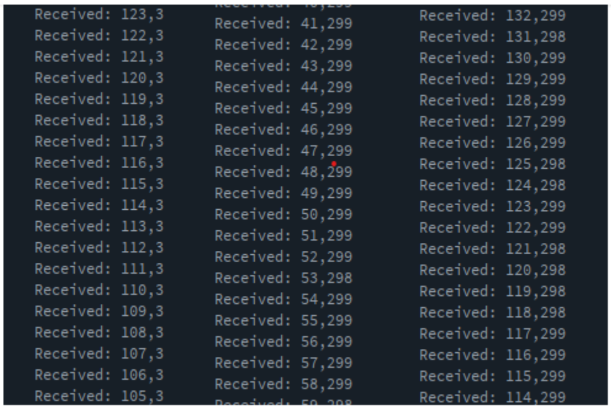


Fig 5: Front Wheel Adjustment with selected Object

The robotic system features a secondary and critical function that ensures precise front wheel angle adjustments to align with the designated target and calculate the required displacement for the robot's travel. This is achieved through the interaction of two ultrasonic sensors interfaced with a Raspberry Pi module and a microcontroller. Python-based integration software is employed to determine front wheel angles and displacement dynamically. Separate algorithms are developed to handle danger flow and navigation.

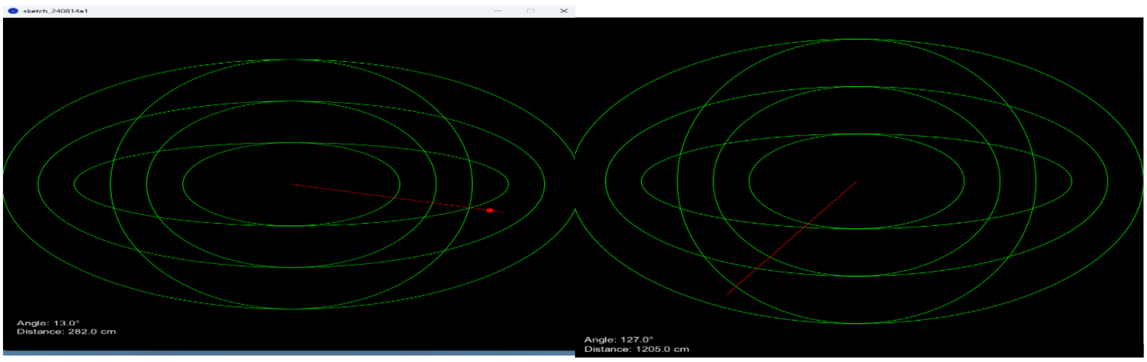


Fig 6: Processing 4.3 windows x 64 software simulation results of the radar system

B) Visual Representation

The robot's trajectory is determined by mapping clusters, represented as regions with distinct boundaries, similar to the diagrams provided [23]. Each cluster signifies a step in the robot's path planning, allowing it to detect obstacles, align its wheels, and calculate the distance and time required to move efficiently.In the visualization, polar coordinates (angle, distance) are converted into Cartesian coordinates (x, y) using mathematical formulas. The radar visualization helps the robot in detecting obstacles and planning navigation, particularly in environments where visual input from the camera might be obstructed. The integration of the radar system with the camera feed and CNN-based decision-making enhances the robot's ability to navigate in complex and hazardous environments.

Table 1: Angle and distance for making NP.

| Particle No. | Angle(Degree) | Distance (cm) | Cluster ID | Time to complete task of each NP |
|---|---|---|---|---|
| 1 | 0 | 50 | NP1 | |
| 2 | 5 | 48 | NP1 | |
| 3 | 10 | 35 | NP1 | |
| 4 | 15 | 34 | NP1 | |
| 5 | 20 | 45 | NP1 | |

| | | | |
|---|---|---|---|
| 6 | 25 | 35 | NP1 |
| 7 | 30 | 53 | NP1 |
| 8 | 35 | 57 | NP1 |
| 9 | 40 | 24 | NP1 |
| 10 | 45 | 57 | NP1 |
| 11 | 50 | 24 | NP1 |
| 12 | 55 | 12 | NP2 |
| 13 | 60 | 67 | NP2 |
| 14 | 65 | 24 | NP2 |
| 15 | 70 | 57 | NP2 |
| 16 | 75 | 35 | NP2 |
| 17 | 80 | 67 | NP2 |
| 18 | 85 | 35 | NP2 |
| 19 | 90 | 78 | NP2 |
| 20 | 95 | 34 | NP2 |
| 21 | 100 | 24 | NP2 |
| 22 | 105 | 25 | NP2 |
| 23 | 74 | 57 | NP2 |
| 24 | 78 | 35 | NP2 |
| 25 | 80 | 67 | NP2 |
| 26 | 86 | 35 | NP2 |

**Equation for Navigation Plan 1 (NP1)**

To determine the centroid for NP1, which helps guide the robot's movement:

$$C_{x1} = \frac{\sum_{i=1}^{n_1} x_i}{n_1}, \quad C_{y1} = \frac{\sum_{i=1}^{n_1} y_i}{n_1}$$

where $n_1$ is the number of particles in NP1.

**Equation for Navigation Plan 2 (NP2)**

The front wheel angle adjustment for reaching the centroid of NP2:

$$\alpha_2 = \tan^{-1}\left(\frac{C_{y2} - y_{\text{current}}}{C_{x2} - x_{\text{current}}}\right)$$

where $(C_{x2}, C_{y2})$ is the centroid of NP2.

These equations ensure smooth **sequential navigation** from NP1 to NP2. 🚀

The cluster diagram demonstrates two distinct groups, NP! and NP2, plotted in a 2D space. NP 1 is represented with purple markers and primarily occupies the lower left quadrant, while NP2, marked in yellow, is located in the upper right quadrant. The Navigation Planing process visualizes the separation of data points based on features such as proximity or similarity, which is critical for decision-making in robotics. This segmentation helps the robot analyse environmental patterns efficiently for tasks like obstacle detection and navigation. The diagrams showcasing the clusters have been created. Each visualizes different combinations of cluster interactions.

C) **Traveling map of robot according to NP1 and NP2**

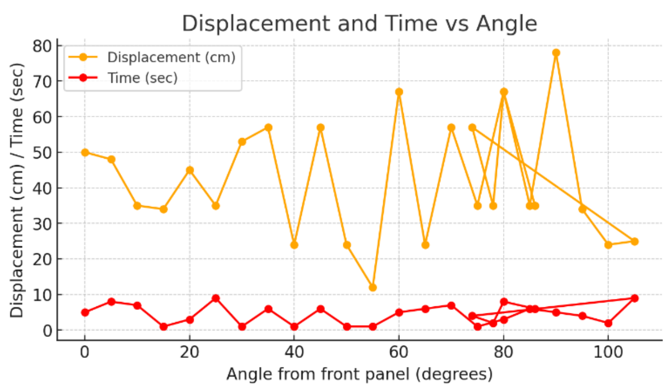


Fig 7: Moving track of radar for radar data for decision making

The proposed system integrates advanced sensor technology and AI-driven algorithms, combining CNN-based image detection, ultrasonic sensors, and radar clustering to achieve autonomous navigation and obstacle avoidance. A Raspberry Pi module interfaces with ultrasonic sensors and a microcontroller to gather environmental data, dynamically adjusting front wheel angles and calculating displacement pulses for precise navigation. Radar-based clustering guides the robot's path, while deep learning techniques enhance object detection and decision-making. Experimental readings, including wheel angle adjustments, displacement time, and distance travelled, demonstrate the system's efficiency in navigating complex environments, representing a significant advancement in robotic vehicle design for hazardous applications.

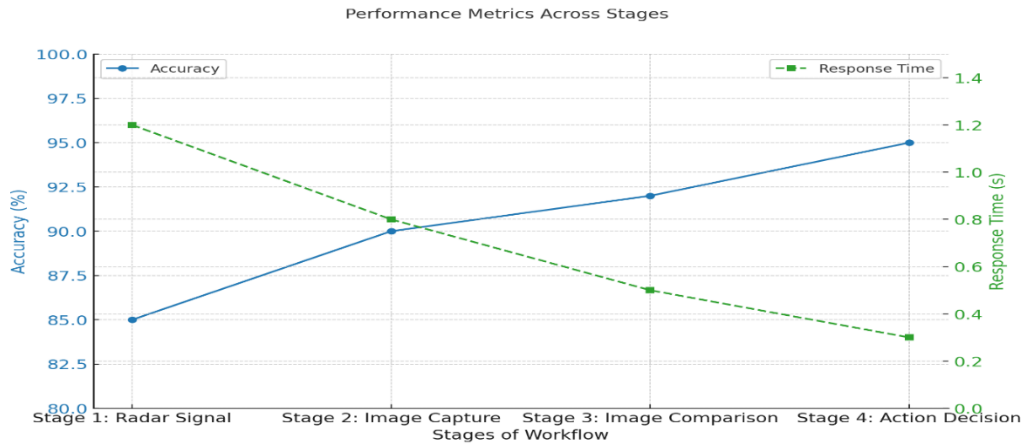


Fig 8: Decision making with accuracy provided by Alex net CNN

D) **Comparission**

Table 2: Comparission Table

| Future | Proposed AI-Based Method | Dijkstra's Algorithm |
|---|---|---|
| Environment | Dynamic and hazardous | Structured and Pre -mapped |
| **Real-Time Adaptation** | Yes | Limited |
| **Obstacle Handling** | Real-time cluster-based object detection | Requires pre-defined obstacle data |
| **Computational Overhead** | Low (optimized for real-time applications) | High (graph computations) |
| **Flexibility** | Works in unknown/unstructured environments | Limited to structured paths |
| **Cost-Effectiveness** | High (low-cost hardware + AI integration) | Moderate to high |
| **Applications** | Hazardous areas, dynamic terrains | Indoor navigation, static road maps |

## VII. ACKNOWLEDGEMENT

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## REFRENCES

[1] X. Jin, Y. Gao, Multi-Sensor Information Fusion, 2020. https://doi.org/10.3390/books978-3-03928-303-3.
[2] L. Kong, X. Peng, Y. Chen, P. Wang, M. Xu, Multi-sensor measurement and data fusion technology for manufacturing process monitoring: A literature review, Int. J. Extrem. Manuf. 2 (2020). https://doi.org/10.1088/2631-7990/ab7ae6.
[3] K. Chahine, B. Ghazal, Automatic Sorting of Solid Wastes Using Sensor Fusion, Int. J. Eng. Technol. 9 (2017) 4408–4414. https://doi.org/10.21817/ijet/2017/v9i6/170906127.

[4] I. Sonata, Y. Heryadi, L. Lukas, A. Wibowo, Autonomous car using CNN deep learning algorithm, J. Phys. Conf. Ser. 1869 (2021). https://doi.org/10.1088/1742-6596/1869/1/012071.

[5] S. Amalraj, P.A. Michael, Synthesis and characterization of Al2O3 and CuO nanoparticles into nanofluids for solar panel applications, Results Phys. 15 (2019) 102797. https://doi.org/10.1016/j.rinp.2019.102797.

[6] Saad Ul Hassan Syed, Lidar Sensor in Autonomous Vehicles, (2022). https://www.researchgate.net/publication/359263639.

[7] R. Raj, A. Kos, A Comprehensive Study of Mobile Robot: History, Developments, Applications, and Future Research Perspectives, Appl. Sci. 12 (2022). https://doi.org/10.3390/app12146951.

[8] D.J. Yeong, G. Velasco-hernandez, J. Barry, J. Walsh, Sensor and sensor fusion technology in autonomous vehicles: A review, Sensors 21 (2021) 1–37. https://doi.org/10.3390/s21062140.

[9] A. Fredderics, K. Vinoth Kumar, A. Shankar, J.S. Renius, R. Guru, S.L. Nair, K. Viswanathan, The FHA analysis of dual-bridge LLC type resonant converter, Int. J. Power Electron. Drive Syst. 4 (2014) 538–546. https://doi.org/10.11591/ijpeds.v4i4.6513.

[10] L. Ran, Y. Zhang, Q. Zhang, T. Yang, Convolutional neural network-based robot navigation using uncalibrated spherical images, Sensors (Switzerland) 17 (2017) 1–18. https://doi.org/10.3390/s17061341.

[11] D. Ghraizi, R. Talj, C. Francis, An Overview of Decision-Making in Autonomous Vehicles, IFAC-PapersOnLine 56 (2023) 6314–6319. https://doi.org/10.1016/j.ifacol.2023.10.793.

[12] J.A. Castellanos, J.M. Martínez, J. Neira, J.D. Tardós, Experiments in Multisensor Mobile Robot Localization and Map Building, IFAC Proc. Vol. 31 (1998) 369–374. https://doi.org/10.1016/s1474-6670(17)44113-9.

[13] Y. Chen, Y. Fan, M. Jin, Research on Sensor Technology in Mobile Robot Navigation, 0 (2024) 50–55. https://doi.org/10.54254/2755-2721/93/2024BJ0063.

[14] K. Rana, P. Kaur, S. Mohammad, Review on Machine Learning based algorithms used in Autonomous cars, SSRN Electron. J. 5 (2018) 114–118.

[15] V.B. Korde, S. Khot, D.B. Kamble, S. Amalraj, Review: Perovskite nanostructures materials versatile platform for advance biosensor applications, Sensors and Actuators Reports 7 (2024) 100201. https://doi.org/10.1016/j.snr.2024.100201.

[16] P. Ramesh, J. Pitchaimani, S. Amalraj, R. Koutavarapu, One-pot eco-friendly synthesis and supercapacitor applications: Simultaneously oxidation and intercalation of iodinated graphene oxide, Diam. Relat. Mater. 127 (2022) 109140. https://doi.org/10.1016/j.diamond.2022.109140.

[17] X. Wang, Y. Sun, Y. Xie, J. Bin, J. Xiao, Deep reinforcement learning-aided autonomous navigation with landmark generators, Front. Neurorobot. 17 (2023). https://doi.org/10.3389/fnbot.2023.1200214.

[18] K.R. Kasture, W. V. Patil, A. Shankar, Comparative Analysis of Deep Learning Models for Early Prediction and Subtype Classification of Ovarian Cancer: A Comprehensive Study, Int. J. Intell. Syst. Appl. Eng. 12 (2024) 507–515.

[19] V. Korde, N. Patil, Effect of methyl alcohol and nitric acid as an etchant on the motions of ferroelectric domains in Al-doped KNbO3 single crystal, Mater. Res. Innov. 24 (2020) 263–269. https://doi.org/10.1080/14328917.2019.1646948.

[20] S.P. Deshmukh, D. Choudhari, S. Amalraj, P.N. Matte, Hybrid Deep Learning Method for Detection of Liver Cancer, Comput. Assist. Methods Eng. Sci. 30 (2023) 151–165. https://doi.org/10.24423/cames.463.

[21] S.H. Shamkuwar, N.M. Patil, V.B. Korde, N. V. Pradnyakar, Dielectric and domain studies on Fe doped KNbO3 single crystal, AIP Conf. Proc. 1953 (2018). https://doi.org/10.1063/1.5032792.

[22] T. Mahmud, I. Ara, R. Chakma, K. Barua, D. Islam, M.S. Hossain, A. Barua, K. Andersson, Design and Implementation of an Ultrasonic Sensor-Based Obstacle Avoidance System for Arduino Robots, 2023 Int. Conf. Inf. Commun. Technol. Sustain. Dev. ICICT4SD 2023 - Proc. (2023) 264–268. https://doi.org/10.1109/ICICT4SD59951.2023.10303550.

[23] K. Vinoth, P. Sasikumar, Multi-sensor fusion and segmentation for autonomous vehicle multi-object tracking using deep Q networks, Sci. Rep. 14 (2024). https://doi.org/10.1038/s41598-024-82356-0.

[24] M. Jun, A.I. Chaudhry, R. D'Andrea, The navigation of autonomous vehicles in uncertain dynamic environments: A case study, Proc. IEEE Conf. Decis. Control 4 (2002) 3770–3775. https://doi.org/10.1109/cdc.2002.1184951.

[25] G. Patil, K.R. Patil, R. Kulkarni, S. Kakade, S. Amalraj, Performance evaluation of a lightweight acrylic flat plate collector with natural flow integration in a hybrid photovoltaic-thermal (PVT) system, Case Stud. Therm. Eng. 67 (2025). https://doi.org/10.1016/j.csite.2025.105780.

[26] S. Goyal, A. Shankar, K.C. Das, A. Singh, S. Oli, M.M. Sati, Manual and Adaptive tuned PID controllers for industrial application, 2024 4th Int. Conf. Adv. Comput. Innov. Technol. Eng. ICACITE 2024 (2024) 1953–1958. https://doi.org/10.1109/ICACITE60783.2024.10616874.

[27] G. SinghPannu, M. Dawud Ansari, P. Gupta, Design and Implementation of Autonomous Car using Raspberry Pi, Int. J. Comput. Appl. 113 (2015) 22–29. https://doi.org/10.5120/19854-1789.

[28] P. Raut, V.B. Kaushal, P.D. Khamkar, A.B. Lugade, S. Amalraj, RESEARCH ARTICLE REVIEW OF HOME AUTOMATION USING ML FOR GESTURE CONTROL AND SAFETY, 02 (2024).

[29] A.L. Bowler, M.P. Pound, N.J. Watson, A review of ultrasonic sensing and machine learning methods to monitor industrial processes, Ultrasonics 124 (2022) 106776. https://doi.org/10.1016/j.ultras.2022.106776.

[30] Z. Liu, Y. Cai, H. Wang, L. Chen, Surrounding Objects Detection and Tracking for Autonomous Driving Using LiDAR and Radar Fusion, Chinese J. Mech. Eng. (English Ed. 34 (2021). https://doi.org/10.1186/s10033-021-00630-y.

[31] J. Enayati, P. Asef, P. Wilson, Resilient Multi-range Radar Detection System for Autonomous Vehicles: A New Statistical Method, J. Electr. Eng. Technol. 19 (2024) 695–708. https://doi.org/10.1007/s42835-023-01567-z.

[32] J. Guivant, E. Nebot, J. Nieto, F. Masson, Navigation and mapping in large unstructured environments, Int. J. Rob. Res. 23 (2004) 449–472. https://doi.org/10.1177/0278364904042203.

[33] H. Duan, Y. Yang, D. Li, P. Wang, Human–robot object handover: Recent progress and future direction, Biomim. Intell. Robot. 4 (2024) 100145. https://doi.org/10.1016/j.birob.2024.100145.

[34] F. Gul, W. Rahiman, S.S. Nazli Alhady, A comprehensive study for robot navigation techniques, Cogent Eng. 6 (2019). https://doi.org/10.1080/23311916.2019.1632046.