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Autonomous Machine-to-Machine (M2m) Collaboration for Indoor Search and Rescue Missions: A Multimodal Approach using Ground Vehicles and Drones

S Harsha Vardhan U[1], Vijay Kumar[2], Sampath H P[3], Rakesh Y D[4], Anil Kumar R[5]

Assistant Professors, Department of Mechanical Engineering, City Engineering College, Bengaluru, Karnataka, India[1,2,3,4,5]

ABSTRACT: Machine-to-Machine (M2M) collaboration has unlocked new possibilities for systems to autonomously and efficiently solve complex technical challenges. In recent years, M2M applications have expanded across various industries, particularly in areas where autonomous decision-making and real-time collaboration are crucial. This research project presents the development of an M2M system that enables autonomous collaboration between two ground vehicles and a drone, managed by a central base station. The system is designed specifically for indoor search and rescue operations, where traditional human intervention may be challenging or hazardous. The primary function of the drone in this system is to perform an autonomous aerial search, while the ground vehicles handle obstacle navigation and ground-level data collection. The base station serves as the control hub, managing both the drone's flight path and the vehicles' navigation, ensuring real-time coordination. A machine learning model is employed to optimize the drone's flight path, achieving near-perfect accuracy in navigating the indoor environment. This accuracy improves significantly with an increase in training data, highlighting the importance of robust training in machine learning-based navigation systems. For ground vehicles, machine learning models are also implemented to navigate complex environments with obstacles. During field testing, the integrated system demonstrated high levels of accuracy and efficiency in coordinating tasks between the drone and ground vehicles. This successful implementation of M2M collaboration showcases its potential in critical applications like search and rescue, offering a glimpse into future advancements in autonomous systems for emergency response operations. The project's findings underscore the growing importance of M2M technology in enhancing the effectiveness of autonomous systems across various domains.

KEYWORDS: Search and Rescue, Image Processing, Navigation Systems, Autonomous Systems, and Object Detection

I. INTRODUCTION

Machine-to-machine (M2M) collaboration became possible with the introduction of Cyber-Physical Systems (CPS) and the Internet of Things (IoT), together with significant advancements in networking, cloud computing, and machine learning. Road transportation, system automation, surveillance, search and rescue operations, and many other situations make use of the idea of M2M collaboration. The Internet of Things (IoT) offers a network of items with integrated sensors, software, and other technology designed to link and exchange data with other systems and devices. Machine learning is one of the key components of M2M collaboration. Researchers have used machine learning for a variety of purposes in a number of efforts. In one project, Chirra and his colleagues used face state observation to apply a behavioral technique to identify driver fatigue. In order to ascertain whether or not the driver is sleepy, it used the Viola-Jones identification algorithm to identify the face and extract the eye region from the facial image. To determine whether the driver is asleep or not, a Convolutional Neural Network (CNN) classifier employs a SoftMax layer. Better accuracy was reported by this work as compared to conventional CNN. Munawar and associates devised a categorization scheme for flooding management to organize the several technologies under examination [5]. They discovered that there were not many hybrid models—which fuse machine learning and image processing—for flood control. Furthermore, it was discovered that there was little use of machine learning-based techniques in the aftermath of a disaster. Therefore, to enable efficient and comprehensive catastrophe management throughout all phases, future efforts must concentrate on integrating disaster management expertise, image processing techniques, and machine learning tools.

Semeraro and colleagues provided a survey of the literature on machine-learning approaches used in human-robot collaboration. In order to do work grouping based on the kinds of collaborative activities, evaluation measures, and

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cognitive characteristics simulated, they have evaluated over 45 studies. Subsequently, a thorough examination of the attributes of various families of machine learning algorithms and the sensing modalities was conducted. One of the findings stressed how crucial it is for machine learning algorithms to take time dependencies into account. Numerous research projects for M2M cooperation focus on topics like time and energy efficiency, linked machines, search and rescue, etc. Zhou and his colleagues came up with an effort that suggested a way to increase the energy efficiency of M2M transmitters and receivers. After that, the preference lists are created by integrating alternating optimization, nonlinear fractional programming, and linear programming to solve the combined power control and time allocation problem. The proven simulation result attests to the suggested algorithm's ability to achieve optimal performance with minimal complexity. For cellular-enabled M2M networks, another study suggests an energy-efficient resource allocation strategy using hybrid time division multiple access (TDMA)-non-orthogonal multiple access (NOMA). When compared to the current works, the simulation result shows that the scheme can significantly reduce the total transmission time at a somewhat higher energy cost. According to Amodu and Othman, machine-to-machine (M2M) collaboration enables autonomous machine performance in sensing, processing, and actuation tasks without human intervention. The smart grid, servers, industrial or laboratory electronics systems, and other systems are a few examples of applications. The M2M systems were categorized according to their intended use. Medium access, home, mobile, LTE/LET-A, standards and service platforms, energy security, and dependability are all included in this. This study examined several described systems and attempted to offer a charting of the developments concerning architecture, security, dependability, standards, and capabilities. In a different study, Meng and colleagues offer a collaborative M2M reference architecture to improve interoperability between networked equipment. Major technical differences between M2M communications in IIoT (Industrial IoT) were also pointed out by them.

The Amazon warehouses, which handle about 1.6 million deliveries every day with very minimal human intervention, are one of the most popular examples of M2M collaborations. With very little assistance from humans, the majority of Amazon warehouses process orders using mobile robots. They are able to be both cost-effective and client-responsive thanks to the system, which heavily leverages M2M communication. With more than 600 million listed products and over 310 million active users, this puts them in a 38% share of the e-commerce business. Figure 1 demonstrates how M2M communication is used at the Amazon warehouses in real life. It displays a group of robots that the Amazon warehouse uses to distribute materials. These are able to retrieve items from their inventory and prepare them for distribution, as well as move various shelves across the warehouse in accordance with their placement protocol. The entire procedure is automated, and mobile robots exchange information and coordinate their paths and routes.

Unmanned aerial vehicles (UAVs) have been employed for outdoor search and rescue operations in a number of documented works; in the majority of these situations, the search was launched automatically by the UAV, but the rescue was carried out by humans. However, for a variety of reasons, individuals may find it challenging to carry out rescue operations in specific situations. The location may be hazardous, the place may be difficult to access, or there may not be enough skilled labor. Search and rescue operations might become more complex in indoor facilities. This article discusses a trial study for an indoor search and rescue system that uses GPS signal interference to overcome this problem. The potential of machine learning and recent advancements in the Internet of Things (IoT) allowed for the implementation of the M2M cooperation. In the system, two ground vehicles and a drone cooperate to locate a certain object and then direct the ground vehicles to the location on their own. The coordination techniques between the two vehicles, the sensors and algorithms employed, the interior environment mapping techniques, the navigation techniques in the GPS-denied environment, and the obstacle avoidance mechanism will all be covered in this paper. It shows how machine learning may be used to develop and control an M2M system within an IoT framework. The structure of the base station, the drone's machine learning model and its object detection method, and the ground vehicles' navigation plan are all explained in the part that follows, which covers the system design. A client can use the graphical user interface described in the third part to operate the system. Section 4 displays the data analysis and system assessment. Future growth ideas are presented in the next part, which is followed by concluding remarks.

II. SYSTEM DESIGN

The design and development of a prototype M2M collaboration system that uses two ground vehicles and a drone to conduct search and rescue operations is covered in the article (Figure 2). The ground vehicles, drones, and base station make up the three main parts of the created system. The base station oversees the operation and handles the majority of the computations, communication, and ground vehicle and drone control. The base station does machine learning activities and houses various wireless networks for communication with the drone and ground vehicles. The way the system operates is that a drone locates a specific object inside a building, and then two ground vehicles are sent out to retrieve the object. In order to put this into practice, a drone is assigned to fly over a predetermined area (where the

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object is expected to be) and look for the object according to the user's specifications. After that, the location data was transmitted to the base station. The ground vehicles are situated at two distinct places, and the base station determines the best way and transmits the navigation route to them. After then, the cars go in the direction of the designated item. In this experiment, two identical wirelessly linked autos are employed, and a drone is used for search operations.

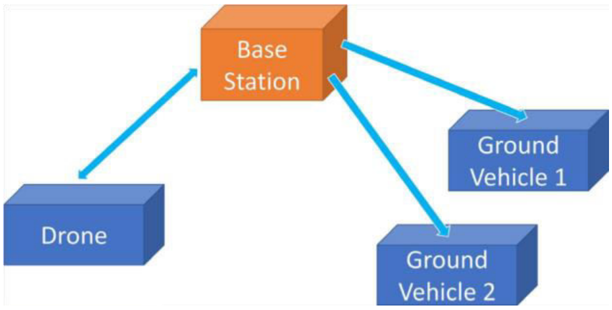

Figure 1. System Design

2.1. Base Station

The machine learning for drones and ground vehicles is operated by an NVIDIA Jetson TX2 board, which serves as the processor in the base station. One of the most effective, potent, and quick embedded artificial intelligence (AI) computing boards is the Jetson TX2. Its foundation is an NVIDIA PascalTM-family GPU with 59.7 GB/s of memory bandwidth and 8 GB of RAM. It can be easily integrated into a wide range of products and form factors thanks to its multitude of common hardware interfaces. The board has 32 GB of eMMC storage, an ARM 128-bit CPU, a 256-core NVIDIA Pascal GPU, Wi-Fi, and Bluetooth. Two distinct wireless networks—one for the drone and one for the ground vehicles—were used to designate the network connectivity for the base station Figure 2. The base station and drone connected via the initial wireless network. The drone was connected to the base station (NVIDIA) via a proprietary Wi-Fi access point that it comes with. The drone uses this communication channel to communicate with the base station, sending images captured by its camera and receiving directions to fly. Utilizing a Wi-Fi router, the second wireless network allowed for communication between the ground vehicles and the base station. An Ethernet wire was used to link the router straight to the NVIDIA TX2 board. A Wi-Fi access point was established by the router and was applied by land vehicles. The MAC addresses of the NVIDIA TX2 board and ground vehicles were mapped to their corresponding IP addresses, which were fixed in the network settings. Hence making it possible for both ground vehicles to instantly connect to the base station using Raspberry Pis. In order to guide the ground vehicles and operate the drone, machine learning algorithms are housed in the base station. It takes input from the user for an object's description, directs the drone to take pictures of the thing, and provides ground vehicle navigation data. The method uses machine learning techniques to create a model for the flight path, direction, and object color identification. It also calculates the best route for the ground vehicles.

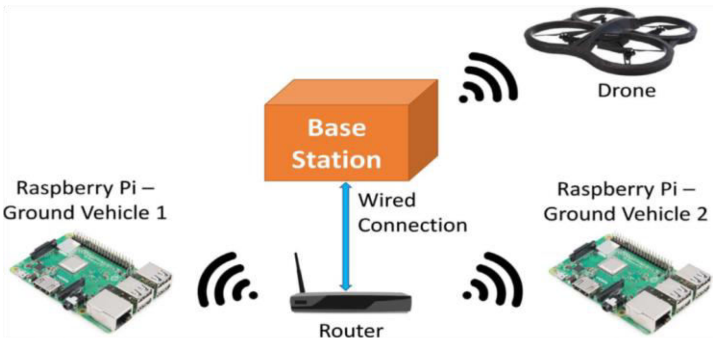

Figure 2. Wireless network connectivity between the base station and machines.

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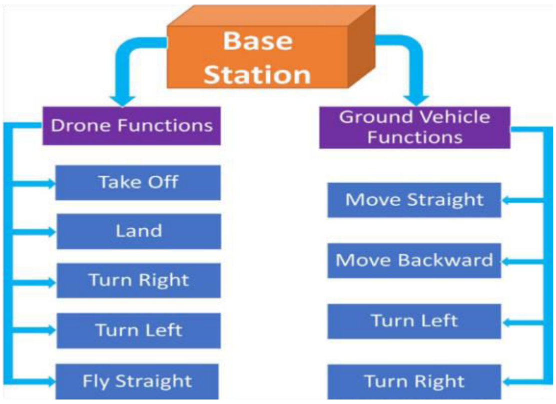

Figure 3. Functions called from the base station.

The main server, which uses a Flask server with a Python foundation to communicate with all of the machines—both land vehicles and drones—is also housed at the base station. The functions that controlled the machines could be initiated from the base station thanks to the Flask server's ability to transmit and receive commands between the base station and the machines. Figure 4 displays the base station's activity plan.

2.2. Autonomous Drone Flight and Object Identification

The drone used for this project is an open system that allows a Python library to program the drone's navigation services. The drone's task is to fly autonomously within a given space and search for an object as specified for a mission. The first part of the activity involves training the drone with flight path so that it can learn about surroundings for a safe flight. With this capability it can then gather data to search for a desired object so that ground vehicles can launch a rescue operation.

III. DRONE DETAILS

Open programming access, a dual camera for both forward and downward vision, low weight, a respectable battery life, and affordability are all necessary for a drone. In order for it to be seamlessly integrated into the project without requiring any changes, the open access feature is crucial. The majority of commercial drones are pricey and do not allow users to program them. A Parrot AR Drone was chosen for the project following a thorough search (Table 1).

The drone has a 50-meter control range and may be linked to the base station using Wi-Fi, which is sufficient for the project. The system's ability to receive orders from users and provide access to the camera outputs for additional processing is what makes it so beautiful. Figure 4 provides a photo of the camera.

Table 1. System Architecture

Feature	Description
Processor	ARM Cortex A8 1 GHz 32 bits
Video	800 MHz video DSP TMS320DMC64x
RAM	1 GB of DDR1 at 200 MHz
Operating system	Linux 2.6.32
Camera	Two 720p HD with 93-degree field of view and 30 frames per second. H264 encoding and has low latency streaming

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Figure 4. System Design

The ultrasonic sensors on the frame are coated with a liquid-repellent nano-coating made from expanded polypropylene hulls. Although the system can be used with smart devices, this project has developed unique programs to make it work. With its 1000 mAh lithium polymer battery, it can fly for up to 12 minutes. For this purpose, the battery life is adequate and quite good. When hovering, the four brushless motors run at 14.5 W and 28,500 rpm. It uses eight MIPs AVR CPUs per motor controller and features a self-lubricating bronze micro ball bearing. It makes use of minimal sound nylatron propeller reducer gears for an 8.6 propeller. Without a doubt, brushless motors are more dependable and long-lasting than brushed motors. The frames are simple to install around the drone's frame to provide protection. Because of all these capabilities, this drone is ideal for the project since it can fly for the necessary amount of time on a single charge while producing minimal noise. What's more, it provides access to the motor controller for flight control and camera movies.

IV. AUTONOMOUS FLIGHT USING MACHINE LEARNING

The drone must fly over a specific region within a building while on a search operation. Initially, a test area where the drone will fly itself was chosen to be an open corridor of an academic building. Making a map of the drone's working area and visualizing its surroundings and obstacles is the first step. For this project, an open corridor of 1.5 meters in width, 6.7 meters in height, and 50 meters in length was utilized. The drone comes into contact with three objects while staying at a safe altitude of around two meters: the wall to its left, the wall to its right, and the path in front of the drone. The training process for the machine learning drone to categorize these three factors and adjust its flight path accordingly.

Two built-in cameras are included with the drone: one faces forward, while the other faces the earth. For this project, both cameras are used, and real-time photos are sent to the base station. Approximately 8000 photos were first gathered for training purposes for the front route, the left wall, and the right wall. These were given to a convolutional neural network (CNN) - based machine learning system that was tasked with classifying photos. Half of the data is utilized for training and the other half is used for validation. The model was trained to a 99% efficiency.

Utilizing TensorFlow, the image recognition system was created. Google has released this machine-learning package as open-source. The process of picture recognition was implemented through a series of processes, including database creation, noise reduction, CNN model creation, identification of model features, model training, and model testing (Figure 6).

Database Development: Having a trustworthy data set is essential for a high-quality machine learning system. Even the most advanced machine learning algorithms cannot compare to a model that has been trained on a trustworthy dataset. Three different kinds of datasets were gathered for this study. These depictions include the front path, the left side of the way's obstacles, and the right side of the path's obstacles. The goal of this strategy was to create a model that could recognize any of these three categories of photos and, while the drone was in object search mode, give it the proper command for its next flight path.

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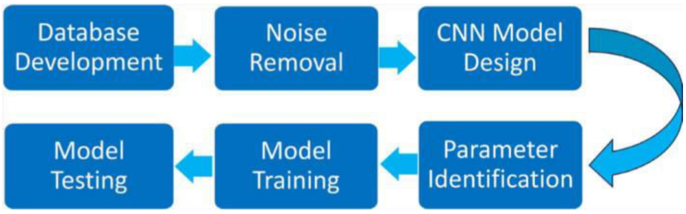

Figure 5. Steps of image recognition system.

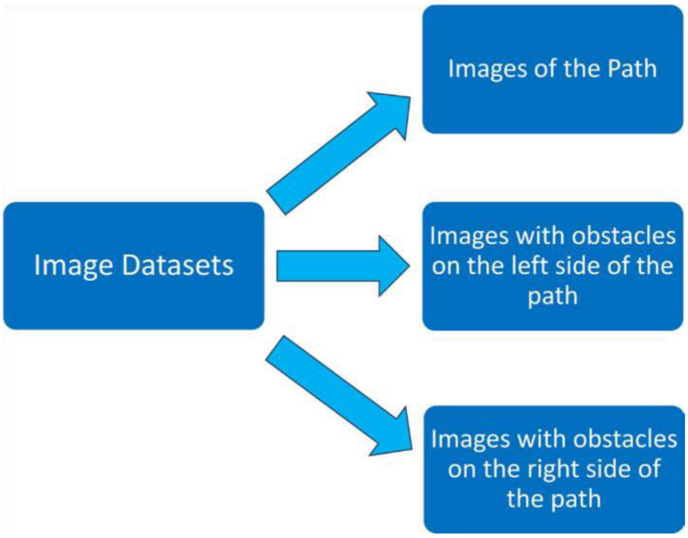

Figure 6. Dataset of images for training.

V. OBJECT SEARCH WITH MACHINE LEARNING AND IMAGE PROCESSING

For this, a trained model built on the ImageNet database was employed [21]. The two primary responsibilities of object detection are object localization and image classification. First, the image's pixels must be categorized into one or more classes. Next, an item must be localized to produce a bounding box that indicates the object's location within the image. This instance used object detection using R-CNN. An extension of CNN with an emphasis on object detection is called an R-CNN. An R-CNN is a based on regions CNN. It's a convolutional neural network-based visual object recognition system that blends rich feature computation with bottom-up region suggestions. R-CNN presents a number of boxes in the picture and determines which ones match up with objects. It uses a selective search technique to compute these proposal zones. R-CNN uses a three-step procedure to accomplish this goal [22]. It uses selective searching to build zones in each image in the first stage [23]. Selective searching creates regions that may correspond to an object in the image by using attributes like colour, scale, location, and so on. After that, these regions are routed to a feature the extraction stage (the second R-CNN step) finds and names the region that it relates to. In order to extract pertinent information from the areas, the inventors of R-CNN employed AlexNet, a deep convolutional neural network [24]. After that, a linear Support Vector Mechanism (SVM) that has been trained for each SVM class receives these features. Unfortunately, because each region is submitted to the linear SVM, which does object detection by iteratively going through each SVM class, this is an extremely time-consuming procedure.

VI. GROUND VEHICLES AND NAVIGATION

For this project, two ground vehicles that run Raspberry Pi modules for control and communication were used. The objective for the ground vehicles is to approach the target while dodging obstructions on the ground. The base station is equipped with this obstacle data, which is utilized by the navigation algorithm to determine the best route for the ground vehicles. The ground vehicles follow instructions from the base station to steer clear of obstacles on the ground and approach the target. To help the ground vehicles maneuver toward the target, a variety of path planning (navigation) algorithms were tested and examined [27]. The A-Star algorithm, Dijkstra Search, Depth First Search, and Breadth First Search were the algorithms examined for this project.

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6.1 Vehicle Design

The two ground vehicles are the same and were created using an RC car chassis kit that included a Raspberry Pi board, a motor driver, two driving wheels, one caster wheel, a speed encoder, and a battery box (Figure 16). The vehicle is 21 cm by 10 cm (L by W), and its wheels measure 6 cm by 2.7 cm (D by H). The L298 motor drive controller board with a twin H-bridge powers the motor, which needs between 3 and 6 volts. The driver board is capable of vigorous driving strong anti-interference capabilities and minimal power usage. Approximate weight of the board is 3.5 ounces. Every ground vehicle has a Raspberry Pi 3 module installed in order to produce motion commands for the motors through the motor driver and enable a wireless connection between the vehicle and the base station. The two ground vehicles are the same and were created using an RC car chassis kit that included a Raspberry Pi board, a motor driver, two driving wheels, one caster wheel, a speed encoder, and a battery box (Figure 16). The vehicle is 21 cm by 10 cm (L by W), and its wheels measure 6 cm by 2.7 cm (D by H). The L298 motor drive controller board with a twin H-bridge powers the motor, which needs between 3 and 6 volts. The driver board is capable of vigorous driving strong anti-interference capabilities and minimal power usage. Approximate weight of the board is 3.5 ounces. Every ground vehicle has a Raspberry Pi 3 module installed in order to produce motion commands for the motors through the motor driver and enable a wireless connection between the vehicle and the base station.

VII. PATH PLANNING AND NAVIGATION

The next step is to direct the ground vehicles through obstructions to reach the target when it has been located. The passage between the ground vehicles and the target is lined with a number of tiny blocks. Planning is key to navigating over obstacles without colliding with anything.

Ma has researched the graph-based optimization problem known as multi-agent path finding (MAPF) and has presented a graph-based route planning technique to create collision-free paths for several robots in a real-world multi-robot system. This paper examines many classifications of both traditional and modern MAPF algorithms, as well as various research endeavours aimed at addressing the difficulties associated with applying MAPF methods to actual situations. Algorithmic methods for important parts of various multi-robot applications, such as automated train scheduling, automated warehouse fulfilment and sorting, and navigation of non-holonomic robots and quad copters, have been handled via MAPF issues. This demonstrates their potential for large-scale multi-robot systems applications in the real world. Qin and his colleagues presented a novel path planning methodology for the Automated Valet Parking (AVP) system that is based on the geometry curve and the directed graph search. The global path planning, the path coordination technique, and the parking path planning comprise the three components of the overall path planning methodology. According to simulation results, compared to the general planning algorithm, the suggested route planning algorithm generates a suitable path for the AVP system in a shorter amount of time.

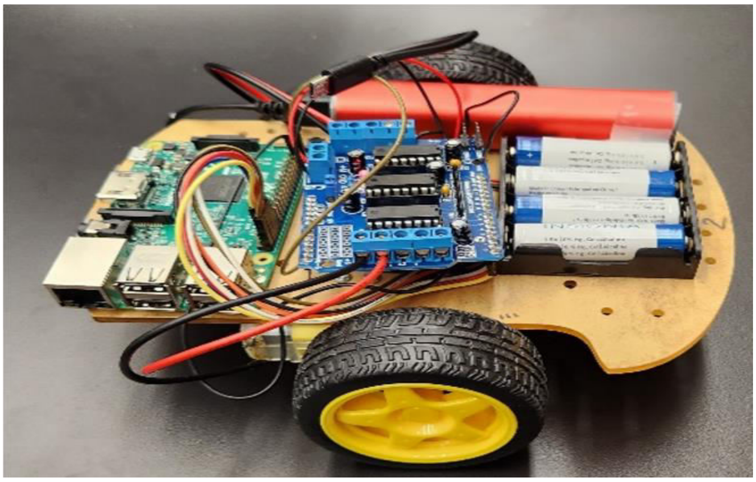

Figure 7. Navigation System

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Figure 8. Path Planning and Navigation

We have applied the popular graph-based path planning technique for robotic applications in this project. There are various methods for path planning based on graphs. The A-Start algorithm, Dijkstra's Search, Depth First Search, and Breadth First Search are important ones. This section will discuss the final algorithm selection and emphasize their respective performances. When it comes to searching the node, Depth First Search and Breadth First Search can work well together. Nonetheless, it is important to check for all of the nodes in the tree beforehand, as there is needless energy use in locating the desired object. Dijkstra's method performs well in determining the best route for locating the desired object. It was discovered, although, that this was not the most effective method of path finding.

VIII. CONCLUSION

A Multimodal Approach Using Ground Vehicles and Drones" demonstrates the immense potential of integrating multiple autonomous systems to address complex challenges in search and rescue operations. By combining the capabilities of drones and ground vehicles through a base station, this study successfully establishes a system where machine-to-machine communication enables real-time coordination and efficient task management in environments where human intervention may be difficult or hazardous. The use of machine learning for drone flight path optimization and ground vehicle navigation is particularly noteworthy, as it allows the system to adapt to dynamic and unpredictable environments commonly encountered during search and rescue missions. The system's ability to improve accuracy with additional training data underlines the importance of robust training models in achieving effective autonomous navigation. As demonstrated during field testing, the collaboration between the drone and ground vehicles resulted in high levels of precision, highlighting the advantages of utilizing M2M communication in ensuring that all autonomous agents operate in synchrony. One of the key contributions of this research is the development of a conceptual framework that integrates multimodal agents to enhance the overall efficiency of search and rescue missions. The ground vehicles can navigate through obstacles, while the drone provides an aerial perspective, creating a comprehensive solution to search and rescue in indoor environments. This division of labour allows for greater coverage and faster decision-making, which is crucial in time-sensitive missions. The successful implementation of this system during field tests underscores its practical applicability and points toward the future of M2M collaboration in emergency response. This research opens up new possibilities for expanding such systems to other domains beyond search and rescue, such as disaster relief, industrial inspection, and military operations. Future work could focus on refining the algorithms to further enhance the decision-making capabilities of each autonomous agent, improving the overall system's scalability, and ensuring its robustness in more complex environments. This study offers a promising step forward in the application of autonomous systems and M2M communication, showcasing how technology can be leveraged to create effective solutions for critical real-world challenges.

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