Environmental Monitoring and Smart Irrigation for Sustainable Agriculture

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***Abstract*—Countries are collaborating to make agriculture more efficient by combining new technologies to improve its procedure. Improving irrigation efficiency in agriculture is thus critical for the survival of sustainable agricultural production. Smart irrigation methods can enhance irrigation efficiency, specially with the introduction of wireless communication systems, monitoring devices, and enhanced control techniques for efficient irrigation scheduling. As a result, this project included a wide range of topics related to irrigation methods and decision-making using agribot. Information was gathered from a variety of scientific papers. So, our research relied on several published documents which were published by authors from all over the world.**

***Index Terms*—Smart irrigation, Soil monitoring, Smart agriculture, Internet of Things (IoT), precision irrigation, Machine Learning Model.**

I. INTRODUCTION

Agriculture is the backbone of the economy in India as 50% of the population is involved in farming activities directly or indirectly. In addition, investors in the irrigated agricultural projects started sounding alarms of severe depletion of groundwater on the horizon [1] and the lack of a cost-effective real time data collection in irrigation systems in farming fields. An agricultural robot is defined as any robotic device that can improve agricultural processes, by taking over many of the farmer's duties that are slow or labour intensive. Using robots in agriculture makes many tasks simpler, faster, and more effective.

Smart Agribots are advanced agricultural robots that perform many elementary functions like ploughing the field, seed sowing, and watering, is done based on the availability of moisture content in the soil by using the sensor. It uses basic components like DC motors, Relay, Microcontroller ESP32 as the microcontroller. Automation in agriculture nowadays is the main focus and area of development for various countries. The population rate of the world is increasing rapidly and will be double in upcoming decades and the need of food is also increasing accordingly. To meet this rapid growth in demand, agriculture automation is the best solution. Traditional strategies employed by farmers are not efficient enough to fullfill the rising demand. Improper use of nutrients, water, fertilizers and pesticides disturbs the agricultural growth and the land remains barren with no fertility.[2]

Smart agriculture system (SAS) employs imaging technologies and deep learning algorithms for tasks like crop yield prediction and diseases detection, facing challenges such as international regulations and cyber security threats.[3]Wireless application protocols such as WiFi and LoRaWAN are commonly employed to collect real-time data for monitoring purposes. Embracing advanced technology is imperative to ensure efficient annual production. Therefore, this study emphasizes a comprehensive, future oriented approach, delving into wireless network protocols, and their applications in agriculture. [4] [5]

The unmanned vehicles armed with thermal sensors are used to conduct continuous assessments of the state of crops and soil. This makes the application of irrigation system and controlled watering easier. The sensors analyze the levels of the various biomes in the soil in order to ensure that the crops have a high nutritional value. Additionally, in order to select the most profitable crops, AI analyses the features of the soil.[6] Smart sensors connected to the Internet of Things can assist gather real-time weather and climate data. Farmers are able to better analyze their crop requirements with the help of a thorough projection.[7][8]

In this respect, the availability of open and interoperable architectures for the interconnection of different data acquisition and processing systems is a key issue, especially in highly dynamic and varied contexts such as agricultural settings.[9] Renewable-Energy integration promotes energy- efficient agriculture by reducing reliance on fossil fuels in water-table pumping.[10]

Overall, continuous developments are being made for monitoring soil properties accurately with the goal of making the technologies economical, and available leading to better resource management and sustainability in agriculture.[11] Precision agriculture is empowering the farmers with technology intending to get optimum outputs with precise inputs. IoT enabled smart sensors, actuators, satellite images, robots, drones are some of the key technological revolutions that boosted the agriculture industry. These components play a vital role in collecting real-time data and accordingly making decisions without human support.[12]

As a result, this paper results in Smart farming based on IoT technologies enables growers and farmers to reduce waste and enhance productivity ranging from the quantity of fertilizer utilized to the number of journeys the farm vehicles have made, and enabling efficient utilization of resources such as water, electricity, etc. These systems are more flexible than traditional systems.

II. PROPOSED SYSTEM

Overview of the system

To overcome the problem in traditional agriculture an "Smart agribot" has been proposed. The vehicle is designed with a strong chassis. The base for the agribot was made using Epoxy Resin, and E Glass Fibre for placing the hardware components like ESP32 microcontroller, motor, motor driver module. A sturdy chassis has been made using mild steel to withstand the load from the base and other components. A plougher is attached at the back side of the vehicle for ploughing. For seeding, seed drill with a hole to sow the seed is attached at the side of the vehicle. Moisture sensor for monitoring the availability of water content in the soil. Drip irrigation is proposed with various flow of water like low, medium, high according to the crop type. The vehicle is connected to our mobile through the wi-fi and Bluetooth module present in ESP32 where the agribot can be operated remotely.The major disadvantages that has been overcome in the proposed system in comparison with the already existing systems are Uneven distribution of water, Labour and cost, Data collection and analysis and Improved crop monitoring.

Block Diagram

The Block Diagram of our smart agribot is shown as,

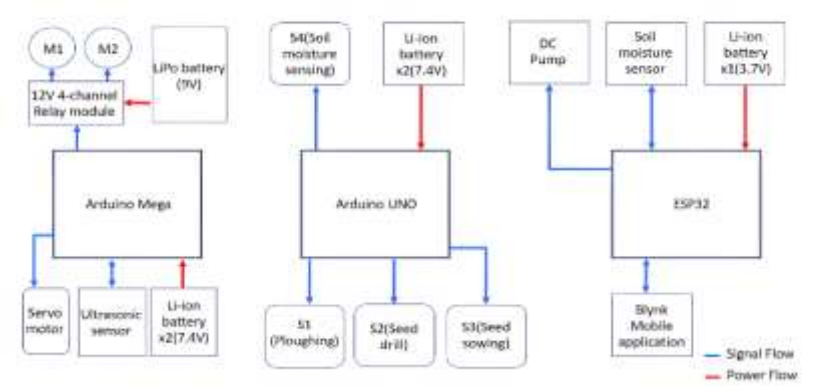

Fig.1. Block Diagram

The first block diagram includes a smart Agribot designed for autonomous movement and obstacle avoidance in fields or agricultural settings. The system integrates an Arduino Mega as the central controller, an ultrasonic sensor for detecting obstacles, a servo motor for adjusting the sensor's orientation, a 4-channel relay module to control motor movement, and LiPo batteries to power the entire setup.

The second block diagram, includes a multifunctional farming robot designed for tasks like ploughing, seed drilling, seed sowing, seed covering, and sensing soil moisture. It utilizes an Arduino UNO microcontroller, powered by lithium-ion batteries, to control four servo motors, each designated for specific operations. Motor 1 is responsible for ploughing the soil in appropriate direction, ensuring the soil is properly tilled. Motor 2 serves a dual purpose of performing the function of the seed drill to create holes for sowing seeds and covers the seeds with soil to protect them. Motor 3 manages the seed sowing process by releasing seeds into the drilled holes. Its precise movement ensures an even distribution of seeds across the field. Motor 4 controls the up-and-down motion of a soil moisture sensor. This allows the robot to analyze soil conditions at different depths, providing crucial data for optimizing irrigation.The lithium-ion batteries provide a stable power supply to drive the Arduino and the servo motors.

The Third block diagram demonstrates an automated irrigation system using an ESP32 microcontroller, an L298N motor driver, a soil moisture sensor, and a water pump powered by a lithium-ion battery. The soil moisture sensor detects the soil's moisture level and sends an analog or digital signal to the ESP32. Based on the sensor reading, the ESP32 processes the information and determines whether to activate the water pump.

Flowchart

The automated agricultural system is designed to optimize farming operations by integrating microcontroller-based control and the process begins with the initialization of the microcontroller and servo motors, ensuring that all components are ready for execution. The first stage involves ploughing, where the servo motor (S1) rotates 180 degrees forward to initiate the process, pauses for 15 seconds, and then rotates backward to complete the operation. Once ploughing is completed, the system moves on to seed drilling, where the second servo motor (S2) rotates 180 degrees forward to create space for sowing. During this waiting period, the third servo motor (S3) performs the seed sowing action by rotating 90 degrees back and forth to ensure precise seed placement. After this, S2 rotates backward, marking the completion of the seed drilling phase.

Fig.2. Flowchart

Following the sowing process, the system activates soil moisture sensing using the fourth servo motor (S4), which rotates 180 degrees forward to position the sensor in the soil. While waiting for 15 seconds, the sensor reads the moisture level and transmits the data to a mobile application via the Blynk IoT platform, enabling remote monitoring. Based on the sensor data, the system determines whether irrigation is necessary. If the soil moisture level is below the predefined threshold, the water pump is automatically activated to provide irrigation. Conversely, if the moisture level is sufficient, the pump remains off to conserve water resources. Throughout this process, the autonomous vehicle navigates across the field using obstacle detection sensors to ensure smooth and uninterrupted movement. Finally, a decision point determines whether the process should be repeated or terminated. If additional operations are required, the system loops back to the beginning; otherwise, it concludes, marking the end of the agricultural cycle.

This automated technique increases productivity while lowering labour expenses and preserving water. Farmers can make well-informed remote decisions with the use of IoT-enabled real-time monitoring. By detecting obstacles, safe navigation is ensured. This technology improves productivity by automating important tasks.

Development of Prototype Model

Based on the components chosen as per the requirement for the development of the autonomous smart agribot vehicle, certain calculations have been performed to build the prototype model.

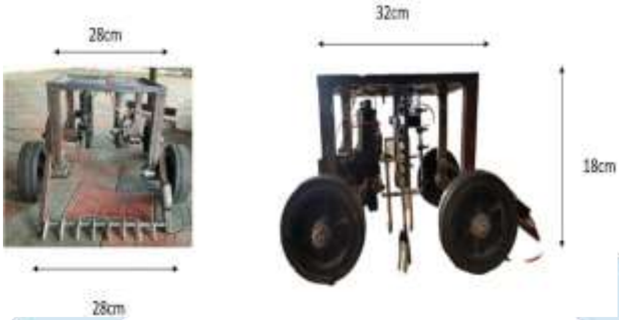

Fig.3. Prototype Model

Calculation

For choosing DC gear motor Chassis area = 546 cm2

Chassis volume = 546 cm3 = 5.46x10-4 m3

Density of mild steel = 7850 Kgm-3

Weight of chassis = Density * Volume

= 7850 * 5.46x10-4

= 4.28Kg

Weight of plougher = 2.9 Kg

Other weight = 1 Kg

Acceleration of the vehicle = 0.1305 ms-2

Force required = mass * acceleration

= 8.15*0.1305

=1.09N

Based on this motor has been chosen with a maximum torque of 13.7Nm

Stress of the material based on calculations = 1.09/0.0546

= 19.9Nm-2

Stress calculated = 19.9Nm-2

Stress mild steel = 7x10 8Nm-2

So, the strength of the material is within the theoretical calculation.

For choosing DC servo motor

Weight of plougher = 2.9 Kg

Acceleration of the vehicle = 0.1305 ms-2

Force required = mass * acceleration

= 2.9*0.1305

Force = 0.37845 N

Assume that the motor moves for 5 cm then

Torque required = force *distance moved

=0.37845*5

Torque=1.89Ncm

Based on this motor has been chosen with a maximum torque of 2.5Ncm

III. HARDWARE IMPLEMENTATION

The design of the chassis is based on the above calculations which makes the vehicle more sturdy and it will also help us to keep more objects on the surface of the vehicle. The wheels used here are non-slippery and make the vehicle move in the rough surface of the soil. The motors are attached to the front side of the vehicle and the back wheel moves with respect to the front wheel. So, the power is provided to the front wheel of the vehicle which consists of motors. The vehicle moves only if power is supplied to the driver module otherwise it remains in a braking position.

Ploughing

The overall process is controlled automatically by using DC servo motor MG995 which is integrated with Arduino UNO. Here rod like structure made up of mild steel are used to attach the wings of plougher . The plougher is connected by an extended angle that comes out from the vehicle, DC servo motor is mounted on it to control the plougher movement.

Seed Drilling and Seed Sowing

The seed drill digs the soil continuously in a straight line and the seeds are sowed from the seed storage container. The dimensions are 19cm length and 6.5cm breath. The seed storage container sows the seeds at the proper seeding rate. The seeds are dropped into furrow lines in a continuous flow and are then covered with soil.

Moisture Sensing

The vertical movement of the sensor, allows the robot to gather data on soil moisture at different depths. The system continuously monitors the data from the soil moisture sensor and compares the current moisture level with a preset threshold value. If the moisture level is detected to be low, the ESP32 microcontroller signals the app (Blink) to activate a pump for irrigation, ensuring that the plants receive the necessary water for growth. This automated system helps maintain optimal soil moisture, preventing over or under-watering, and ultimately improving the efficiency of irrigation in agricultural operations.

IV. IRRIGATION SYSTEM

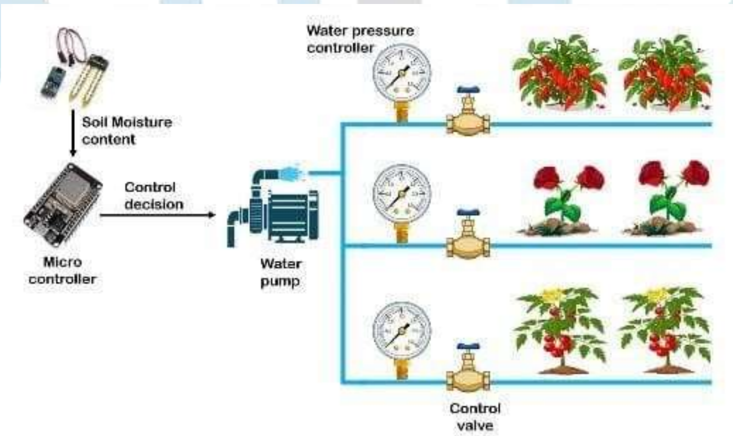

Fig.4. Automatic Irrigation System

The proposed system also provides solution for the irrigation problem by integrating automatic irrigation system. The plant is chosen based on the user's choice and also the water required for irrigation purpose is approximated based on the plant type. As each plant has different water requirements the pressure gauge is operated according to the water requirement.

The pressure gauge is used to control the level of water needed to irrigate the crops. The microcontroller receives the data about the moisture content of the soil with the help of soil moisture sensor and makes decision and turns on the water pump accordingly. Also, the control valve ensures that the crops do not receive any unnecessary water when the soil is high in moisture content.

Evaluation of Crop Cultivation Patterns

The selection of crops for this agricultural study are Rice, Cotton, Tomato, and Banana based on seasonal adaptability, water needs, and growth duration across various districts. Rice and Cotton need moderate irrigation, Tomato is water-efficient, and Banana demands the most due to its long growth period. Shorter-duration crops like Tomato boost productivity, while long-duration crops like Banana require extensive management. Optimal districts like Coimbatore and Thanjavur support multiple crops due to favorable conditions. These crops play key roles in agriculture—Rice for food security, Cotton for textiles, Tomato for markets, and Banana for the fruit trade.

Table 1. Crop Cultivation Pattern

CROP	**MONTH OF PLANTING**	**DURATION** (days)	**WATER REQUIRED**	**DISTRICTS**
Rice	Dec – Jan (Navarai)	< 120	74 cm	Coimbatore, Salem, Cuddalore, Vellore
Cotton	Feb – Mar (Rice Fallow)	125 - 135	83 cm	Thanjavur, Karur, Cuddalore, Villupuram
Tomato	Aug - Sep	60 - 100	30 cm	Dharmapuri, Salem, Krishnagiri
Banana	Apr – Mid June (Summer)	100 - 150	176 cm	Coimbatore, Erode, Thanjavur

This study provides a comprehensive understanding of crop cultivation strategies, helping to optimize resource utilization and enhance agricultural sustainability. The findings may serve as a reference for improving water management, crop planning, and productivity enhancement in the selected regions.

Drip irrigation is a transformative solution in modern agriculture, offering precise water delivery to plant roots, reducing evaporation and runoff, and optimizing resource use. It significantly lowers water consumption while boosting crop productivity, with studies showing water savings of 39%-66% and yield increases of 14%-52%. By preventing overwatering, reducing soil erosion, and minimizing nutrient loss, it enhances efficiency and lowers irrigation costs. In the face of water scarcity and climate change, widespread adoption of drip irrigation is crucial for sustainable farming, ensuring food security while conserving water resources. conserving water resources.

Table 2. Water Use Efficiency in Drip Irrigation

CROP	METHODS OF IRRIGATION	WATER REQUIREMENT (cm)	% WATER SAVING	YIELD (Kg ha^{-1})	% INCREASE IN YIELD	WATER USE EFFICIENCY (Kg ha mm)
Rice	Conventional transplanted	120.00	-	5200	-	4.33
	Surface drip	61.90	48.40	5940	14.20	9.60
Cotton	Furrow	83.00	-	2600	-	31.33
	Drip	28.00	66.26	3250	25.00	116.10
Tomato	Surface	30.00	-	32000	-	106.66
	Drip	18.40	39.00	48000	50.00	260.86
Banana	Surface	176.00	-	57500	-	32.67
	Drip	97.00	45.00	87500	52.00	90.20

V. DEVELOPED MACHINE LEARNING MODEL

Data Acquisition

The dataset used in this study is collected from publicly available agricultural and environmental monitoring websites, providing real-time data on soil moisture, temperature, humidity, and irrigation control parameters. Web scraping techniques were employed to extract relevant features, ensuring a diverse and representative dataset for various soil conditions. The dataset comprises 5000 entries with seven key features essential for optimizing irrigation. These include moisture, indicating soil water content; temperature and humidity and valve position , controlling the irrigation flow. additionally, pump water flow and time to fill 1 acre help assess water distribution efficiency, while soil type determines absorption and retention properties. These features serve as critical inputs for training the ML model to enhance irrigation management and resource utilization.

Data Preprocessing

To enhance the accuracy and efficiency of the machine learning model, the dataset underwent a series of preprocessing steps. Initially, missing values were checked and handled appropriately, although this dataset contained no missing entries. Next, data types were verified to ensure numerical and categorical features were correctly formatted. Feature selection was then performed to identify the most relevant variables contributing to the model's predictive performance. Key attributes such as moisture, temperature, humidity, valve position, pump water flow ,time to fill 1 acre and soil type are retained as they are critical for irrigation management.

To ensure uniformity in data representation, feature transformation techniques were applied Numerical features such as moisture, temperature and humidity were standardized using min-max scaling to bring them within a uniform range. The categorical feature like soil type was encoded using one-hot encoding, converting it into binary variables to allow the model to interpret different soil classifications for optimizing the model performance.

Model Selection and Training

Linear Regression was selected for this study due to its effectiveness in predicting continuous variables based on independent features. Given the nature of the dataset, this method was well-suited for modelling irrigation needs by analysing the factors.Linear Regression establishes a relationship between different variables by fitting a linear equation to the data. This minimizes errors using the least squares method, which reduces the sum of squared differences between actual and predicted values.

To ensure effective training, the dataset was partitioned into 4000 records for training and 1000 records for testing.The training phase involved feeding the model with labelled data, allowing it to learn patterns and relationships between the input features and target variable. Hyperparameter tuning was applied to enhance model accuracy and prevent overfitting. Once trained, the model was evaluated on the test set using performance metrics such as Mean Squared Error (MSE) and R-squared (R^2) values, ensuring its reliability in predicting irrigation parameters. The results confirmed that Linear Regression was a suitable approach for improving water resource management in agricultural applications.

Performance Evaluation

The trained Linear Regression model performed successfully during testing, demonstrating high accuracy in predicting irrigation parameters. When evaluated on 1000 unseen records, the model's predictions closely matched the actual values, confirming its reliability. The R-squared (R^2) score showed that the model effectively captured the relationships between key factors such as moisture, temperature and humidity. The consistency of results across both training and testing datasets proved that the model was well-generalized and did not suffer from overfitting.

Regression equation

To further illustrate the model's predictive capabilities, two regression equations are included.These equations highlight the contribution of each variable and demonstrate how the model effectively estimates irrigation requirements based on real-world conditions.

The overall relationship between irrigation parameters and environmental factors are given "Equation 1".

$$\text{Flow Rate} = 22.6103 + (-0.0026 * \text{Moisture } (\%)) + (0.0054 * \text{Temperature } (^\circ\text{C})) + (-0.0039 * \text{Humidity } (\%)) + (-0.0011 * \text{Valve Position } (\%)) + (-0.0010 * \text{Time to Fill 1 Acre (min)}) \tag{1}$$

	Moisture (%)	Temperature (°C)	Humidity (%)	Valve Position (%)	Time to Fill 1 Acre (min)	Pump Water Flow (L/min)
0	33.773375	30.008318	87.413265	83.835046	9205.143024	13.046261
1	83.283837	39.555588	65.758221	83.824620	19816.368283	2.533330
2	56.963023	38.097437	68.411529	53.248907	5375.413230	16.966830
3	53.886736	35.359457	64.630371	50.371539	6396.091893	15.957577
4	32.546812	23.782830	62.113574	70.232697	18542.193886	3.792413

Fig 5. Performance Evaluation of Equation 1

The trained Linear Regression model demonstrated high accuracy with R^2 score of 0.8770 during testing, with predictions closely aligning with actual values ensuring reliable performance. To validate its accuracy, a set of tested values is included showcasing the predicted flow rate for different conditions. The strong correlation between predicted and actual values reinforces the model's effectiveness in optimizing water management.

"Equation 2" focuses on a specific subset of features that had the highest impact on predictions.

$$\text{Pump Water Flow} = 22.154 + (-0.00103 * \text{Time to Fill 1 Acre}) + (0.00483 * \text{Temperature}) \tag{2}$$

	Time to Fill 1 Acre (min)	Temperature (°C)	Pump Water Flow (L/min)
0	9205.143024	30.008318	12.817643
1	19816.368283	39.555588	1.934194
2	5375.413230	38.097437	16.801335
3	6396.091893	35.359457	15.736812
4	18542.193886	23.782830	3.170411

Fig 6. Performance Evaluation of Equation 2

The trained Linear Regression model demonstrated strong predictive performance, achieving a high R^2 score of 0.8776 during testing. The model's predictions closely matched the actual values, ensuring accuracy and reliability. To further validate its effectiveness, a set of tested values has been included, showcasing the predicted flow rate under various conditions. The strong correlation between predicted and actual values reinforces the model's capability in optimizing water management and improving irrigation efficiency.

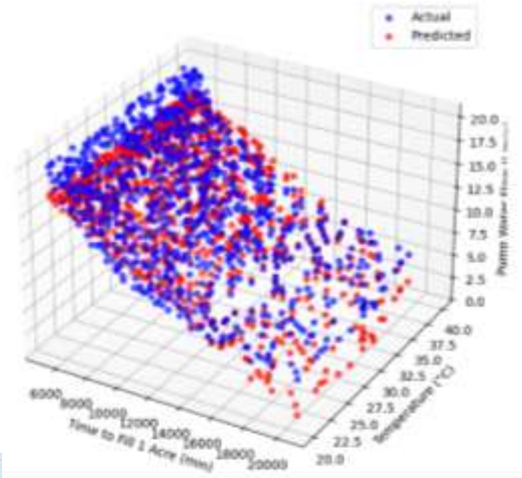

Fig 7. 3D Plot:Pump Water Flow Prediction

The 3D scatter plot of the equation provides insights into the model's predictions. In the plot, blue dots represent actual values, while red dots indicate predicted values from the Linear Regression model. The close alignment of red and blue dots with the surface suggests a strong correlation, demonstrating the model's accuracy in predicting water flow under varying conditions.

VI. CIRCUIT DIAGRAM

For the project, three circuit diagram connection are given for the separate function of the vehicle. The first circuit diagram connection is for movement of the vehicle according to the obstacle detection sensed by the ultrasonic by using Atmega. The second circuit diagram is used for performing the agriculture tasks using Arduino UNO. The third circuit diagram connection is for controlling the water pump with Blynk app according to the soil condition by using ESP32.

Movement of Vehicle

The diagram represents a smart Agribot designed for autonomous movement and obstacle avoidance in fields or agricultural settings. The system integrates an Arduino Mega as the central controller, an ultrasonic sensor for detecting obstacles, a servo motor for adjusting the sensor's orientation, a 4-channel relay module to control motor movement, and LiPo batteries to power the entire setup.

The ultrasonic sensor (HC-SR04) is mounted on a servo motor at the front of the vehicle. When the sensor detects an object within a predefined range, it signals the Arduino to initiate corrective actions. When an obstacle is detected, the servo motor rotates to scan for a clear path, allowing smooth navigation. The Arduino Mega processes sensor input and directs the relay module to control the DC motors, adjusting movement accordingly. The 4-channel relay module alters motor polarity, enabling the robot to move forward, backward, or turn efficiently. This precise motor control ensures the robot can effectively navigate around obstacles without manual intervention. LiPo batteries provide stable power to all components, ensuring the motors have adequate current to drive the wheels, even during complex operations.

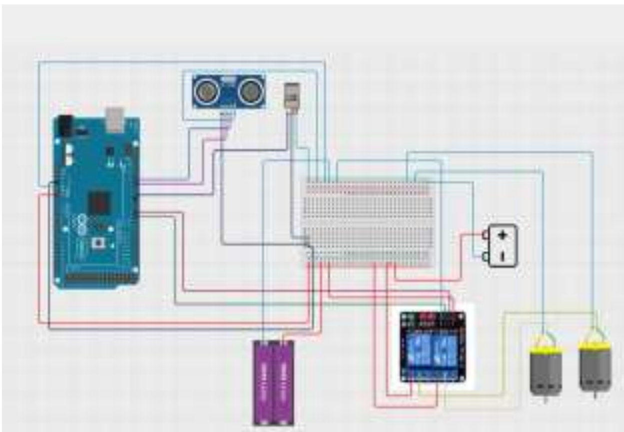

Fig 8. Vehicle Movement Circuit connection

This autonomous system is particularly useful in agricultural applications where the robot can traverse fields, avoid obstacles like rocks or crops, and perform its tasks with minimal human supervision.

Agricultural Tasks

This circuit diagram represents a multifunctional farming robot designed for tasks like ploughing, seed drilling, seed sowing, seed covering, and sensing soil moisture. It utilizes an Arduino UNO microcontroller, powered by lithium-ion batteries, to control four servo motors, each designated for specific operations.

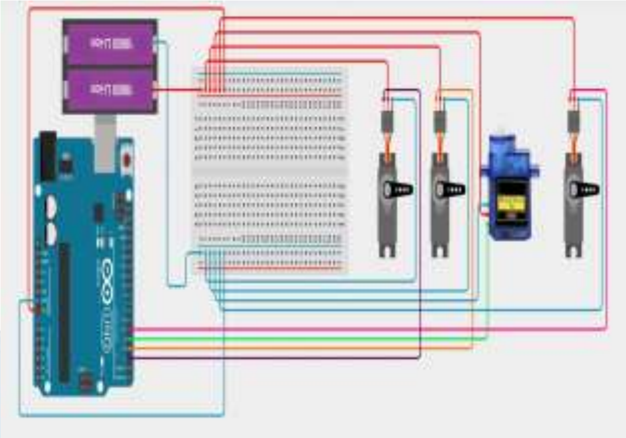

Fig 9. Agricultural Task Circuit connection

Motor 1 is responsible for ploughing the soil as it moves the plougher in appropriate direction, ensuring the soil is properly tilled. Motor 2 serves a dual purpose of seed drilling for sowing seeds covers the seeds with soil to protect them.Motor 3 manages the seed sowing process by releasing seeds into the drilled holes.Motor 4 controls the up-and-down motion of a soil moisture sensor which allows the robot to analyze soil conditions at different depths, providing crucial data for optimizing irrigation.The Arduino UNO executes the programmed instructions to coordinate the motors based on the sequence of operations. The lithium-ion batteries provide a stable power supply to drive the Arduino and the servo motors.

Irrigation and Water Pump Control

This circuit diagram demonstrates an automated irrigation system using an ESP32 microcontroller, an L298N motor driver, a soil moisture sensor, and a water pump powered by a lithium-ion battery.

The soil moisture sensor detects the soil's moisture level and sends an analog to the ESP32. The sensor's output pin is connected to the ESP32's input pin to read the data. Based on the sensor reading, the ESP32 processes the information and determines whether to activate the water pump. The motor driver (L298N) acts as an interface between the ESP32 and the water pump.The motor driver's input pins are connected to the ESP32's pins to receive control signals. The ESP32 and other components share a common ground connection for stable operation.

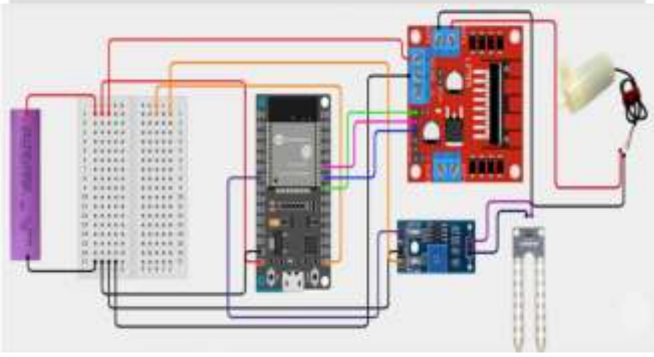

Fig 10. Water Pump Circuit connection

VII. CONCLUSION

These papers represent a tremendous leap in agricultural technology, with various benefits that have the potential to change existing farming operations. Smart farming based on IoT technologies enables growers and farmers to reduce waste and enhance productivity ranging from the quantity of fertilizer utilized to the number of journeys the farm vehicles have made, and enabling efficient utilization of resources such as water, electricity, etc. These systems are more flexible than traditional systems. This system helps to reduce human efforts. Thus, it has made possible to automate the most significant working routines. Multipurpose autonomous agricultural robot has successfully implemented and tested for various functions like ploughing, seeding, check moisture content of soil and water irrigation.Moreover, this paper demonstrates how emerging technologies can be seamlessly integrated into existing agricultural practices. Real-time implementation not only improves reliability and scalability but also allows for better crop productivity and real time monitoring

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