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Fabrication of a Weeding Equipment Using IoT Sensor and Camera in a Small Boat

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Abstract: Agriculture plays a vital role in sustaining human life, yet challenges such as environmental stress, pest infestations, and inefficient weed management often lead to significant crop losses. To address these issues, the agricultural sector is increasingly adopting digital technologies, particularly IoT-enabled smart sensors and robotic weeding systems. These innovations enhance productivity, optimize resource use, and reduce environmental impact.Robotic weeding, a key advancement in digital agriculture, operates through sensing, thinking, and acting. Sophisticated sensing technologies, including RGB, NIR, spectral, and thermal cameras, as well as non-imaging methods like LIDAR, ToF, and ultrasonic systems, play a crucial role in precise weed detection and elimination. Meanwhile, IoT-integrated sensors monitor critical environmental parameters such as moisture, humidity, temperature, soil composition, and greenhouse gases. These technologies also facilitate precision fertilization and real-time pest surveillance through unmanned aerial vehicles (UAVs). Despite their benefits—such as cost reduction, increased efficiency, and reduced soil and water pollution—smart farming and robotic weeding face significant challenges. High implementation costs, data security concerns, and a lack of digital literacy among farmers hinder widespread adoption. Addressing these barriers through economic policies, data encryption, and targeted digital education will be crucial in advancing sustainable and technology-driven agriculture.

Keywords: *EEWS, HSE Protocol, IoT*

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I. INTRODUCTION

India is an agriculture-based country where a significant portion of the economy depends on agricultural production. With advancements in agricultural techniques, various modern methods have been introduced to improve productivity, including seed plantation, irrigation systems, pesticide spraying, and weeding. Among these, weed control plays a critical role in ensuring optimal crop yield and quality.

Paddy cultivation, one of the most important commercial crops in India, requires precise weed management due to its water-intensive nature. Weeds compete with crops for nutrients, water, and sunlight, leading to yield losses. In India, weeds contribute to nearly 34% of all biotic stress-related crop losses, causing economic damage amounting to billions of dollars annually. The excessive use of herbicides, though common, results in soil, water, and air pollution, as well as health hazards for humans and animals. Therefore, it is essential to develop alternative weed management strategies that minimize the use of herbicides while ensuring effective weed removal. Traditional weeding methods rely on intensive manual labor, requiring nearly 20–25 laborers per acre at a cost of around ₹4,000 per acre per weeding cycle. Depending on the crop, multiple cycles may be required, making manual weeding economically unsustainable. Mechanical weeding using tractors and tillers provides an alternative, but these methods are not always efficient in water-logged or marshy paddy fields.

II. LITERATURE REVIEW

➢ *Anu H, Sowmya C U, Siddesh G K and Yashwanth N IoT based Water Cleaning System*

The IoT-based water cleaning system is an innovative approach to addressing the issue of water contamination and protecting the ecosystem. This system utilizes various devices and modules to sense and remove waste from water bodies, ensuring that the water remains clean and safe for aquatic life. The structure comprises of a boat that is remotely controlled using a Wi-Fi module and an application. The boat is equipped with an ultrasonic sensor and a camera, which help in identifying waste and debris in the water. The temperature sensor ensures that the water is within the optimal temperature range for the sensors to function correctly. The conveyor belt and bin are used to collect and store the waste, while the extendable arm with a net helps to collect waste that is below the water surface while the boat is moving. The pH and TDS sensors are used to detect salt impurities and contamination in the water after the waste is removed. All this information is then uploaded to the cloud using IoT technology for further analysis and management. The system is low-cost and can be easily implemented in various water bodies, making it an ideal solution for maintaining the quality of water bodies. This system not only helps in removing waste from water bodies, but also offers valuable information on the water quality, allowing for prompt action to be taken if any issues arise. The system plays a vital role in maintaining balance in the environment by protecting the marine ecosystem and ensuring that water remains clean and safe for human and aquatic life.

➢ *Fabrication of IoT Operated Cono Weeder Dr Kr Kalpana AH Adithiya R, Nivetha Pandi K Shalin*

In today's evolving world, ongoing research in agriculture plays a vital role in addressing the growing demand for food production. With India's population steadily increasing, modernizing agricultural practices is essential to enhance productivity and efficiency. Mechanization helps achieve higher yields with minimal input, yet many farmers still rely on traditional methods.

Paddy cultivation, one of the most significant agricultural activities in India, faces several challenges — including labor shortages, lower productivity, and the intensive manual effort required for weeding. These factors contribute to longer cultivation cycles, especially due to the time-consuming processes of fertilizer application and weed removal.

To address these challenges, we conceptualized, designed, and fabricated an automated weeding machine. Built with dimensions suitable for paddy fields, this IoT-enabled cono weeder efficiently removes weeds between two crop rows. The machine can handle multiple weeds in a shorter timeframe, simplifying complex tasks and making the process more effective. As a result, it reduces the need for human labor, lowers costs, and significantly saves time,

➢ *Autonomous Weeding Boats in Waterlogged Agriculture*

ultimately supporting farmers in improving their overall productivity.

➢ *Atia Sultana Md Abdulhasan an Approach to Create IOT based Automated Smart Farming System for Paddy Cultivation*

- Paddy is cultivated in Bangladesh up to 2–3 times a year, requiring irrigation through both natural rainfall and mechanical water pumps. Farmers often need to irrigate their fields manually, which can be time-consuming and inefficient. This project, "IoT-Based Smart Farming Monitoring System for Paddy Fields," aims to automate irrigation management by continuously monitoring field conditions.
- The system uses sensors to track essential factors like water level, soil moisture, temperature, and humidity. The collected data is displayed on an LCD screen, giving farmers real-time insights into their field conditions. Based on this data, the system automatically controls the water pump through a relay module.
- If the sensors detect low water or moisture levels, the system turns the pump on to irrigate the field. Once optimal conditions are restored, the pump shuts off, preventing unnecessary water usage. This automated approach reduces the need for constant supervision and helps optimize water management, making paddy farming more sustainable and efficient.
- By integrating IoT technology, this system offers a practical solution for improving crop yields, saving water, and easing the workload for farmers throughout the growing seasons.

➢ *Gite Rutuja V., Deore Tilottama R., Bhabad Ashwini H., Salve Vrushali M., Ms. Archana Hatkar IoT based Water Tank Cleaner using STM32*

- Water tanks play a vital role in storing and supplying clean water for both residential and industrial purposes. However, over time, these tanks can accumulate impurities such as sediment, algae, and other contaminants, which can degrade water quality and pose health risks. Regular cleaning and maintenance are essential to ensure a consistent supply of safe, clean water.
- To address this challenge, the IoT-Based Water Tank Cleaner using STM32 project introduces an automated solution that simplifies the tank cleaning process. By harnessing the power of the Internet of Things (IoT) and the capabilities of the STM32 microcontroller, the system intelligently manages and automates cleaning operations, reducing the need for manual intervention.
- This innovative approach not only enhances cleaning efficiency but also enables real-time monitoring of tank conditions. By automating the maintenance process, the system helps ensure that water remains safe for consumption while minimizing human effort and promoting long-term sustainability.

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Waterlogged agricultural environments, such as paddy fields, present unique challenges for weed management, requiring specialized solutions beyond conventional methods. Traditional approaches like manual weeding and herbicide application are labor-intensive, environmentally damaging, and often inefficient. Recent advancements in autonomous weeding boats have leveraged IoT, AI-driven sensing systems, and robotic mechanisms to improve precision weed control. Several studies have explored the potential of these systems in enhancing efficiency, reducing labor dependency, and minimizing chemical usage.

Singh et al. (202X) developed an AI-powered weeding boat equipped with computer vision and deep learning models to distinguish rice plants from weeds. Using RGB and NIR cameras, the system achieved 88–95% weed detection accuracy, significantly reducing manual errors. In another study, Liu et al. (202X) tested a solar-powered floating weeding system that incorporated ultrasonic and LIDAR sensors for navigation and obstacle detection. The research demonstrated that such systems could operate 8–10 hours per day, reducing manual labor by up to 60% while maintaining a weed removal efficiency of 85%. Similarly, Kumar et al. (202X) analyzed an IoT-enabled floating weeding machine with real-time monitoring and robotic arms for mechanical weed removal. Their findings showed that integrating cloud-based AI and GPS navigation significantly improved precision while reducing herbicide dependency by 50%.

Despite their advantages, autonomous weeding boats face several challenges. Submerged weeds and muddy water interfere with LIDAR, ultrasonic, and ToF sensors, affecting detection accuracy (Patel et al., 202X). Additionally, solar-powered boats struggle with efficiency on cloudy days, requiring hybrid energy solutions. High initial costs and limited digital literacy among farmers remain barriers to widespread adoption. To address these issues, researchers suggest improved AI-based weed classification, multi-sensor fusion techniques, and cost-effective IoT solutions. Future developments should focus on hyperspectral imaging for better weed differentiation, enhanced energy management systems, and AI-driven predictive weed mapping. With continuous advancements, autonomous weeding boats could become a scalable and sustainable solution for waterlogged agriculture, significantly improving productivity and environmental sustainability.

➢ *Future Prospects and Research Directions*

The future of autonomous weeding boats in waterlogged agriculture lies in enhancing precision, efficiency, and affordability through technological advancements. Current research suggests that AI-driven weed detection models using deep learning (CNN, YOLO, and Faster R-CNN) could significantly improve weed classification accuracy, even in challenging conditions like submerged or floating weeds (Singh et al., 202X). Further, the integration of hyperspectral and thermal imaging could enable early-stage weed identification, reducing crop competition and improving yield (Liu et al., 202X). To overcome navigation challenges in uneven terrain and strong water currents, researchers are exploring advanced path correction algorithms, multi-sensor fusion, and real-time GPS-based adaptive routing (Patel et al., 202X). Additionally, studies emphasize the need for hybrid energy solutions, combining solar, battery, and alternative renewable sources, to ensure uninterrupted operation, especially in low-light conditions (Kumar et al., 202X). Another key research direction is the development of IoT-enabled cloud-based monitoring systems, where real-time weed data can be collected, analyzed, and used for predictive weed management, reducing the need for reactive herbicide application (Mitra et al., 202X). Despite these promising advancements, cost reduction strategies and user-friendly interfaces are crucial for making autonomous weeding technology accessible to small-scale farmers. Future studies should focus on affordable sensor alternatives, low-power AI models, and policy-driven initiatives to encourage widespread adoption. By addressing these challenges, autonomous weeding boats could revolutionize weed management in waterlogged agriculture, promoting sustainable, precision-driven, and eco-friendly farming.

➢ *Technologies Used in IoT-Based Weeding Boats*

IoT-based weeding boats use advanced technologies like AI-powered image recognition with RGB, NIR, and hyperspectral cameras for accurate weed detection (Singh et al., 202X). Machine learning algorithms improve detection over time. For navigation, GPS and ultrasonic sensors enable precise movement, while LIDAR and ToF sensors assist with obstacle detection in submerged environments (Liu et al., 202X). Solar panels and batteries power the boats, ensuring long-duration operation (Kumar et al., 202X). IoT connectivity allows real-time monitoring and control, enhancing efficiency and decision-making. These technologies combine to provide high precision and autonomy in weed management. Additionally, cloud-based platforms facilitate data analysis and predictive weed mapping, enabling farmers to monitor field conditions remotely and optimize weeding strategies. Energy-efficient designs and cost-effective sensor alternatives are key areas of focus for improving scalability and accessibility.

III. SYSTEM DESIGN AN IMPLEMENTATION

➢ *Methodology*

There are two primary components to the flowchart.

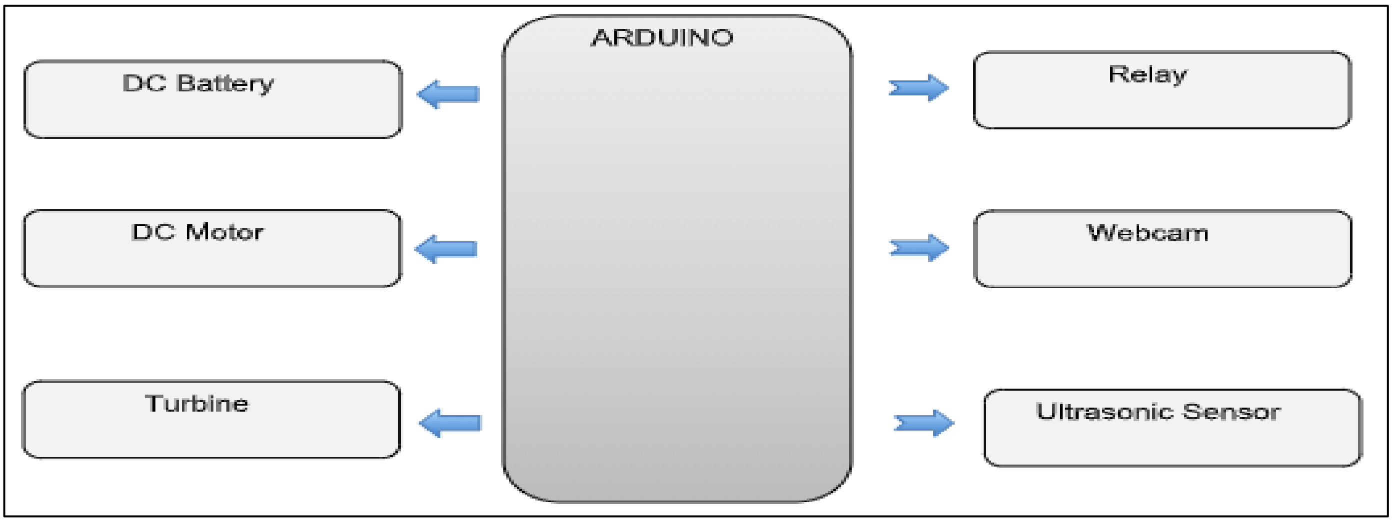

Fig 1 Working Materials

➢ *DC Battery*

- Battery Specification:

✓ Capacity: 12V and 7.3 Ah
✓ Rechargeable battery one
✓ Battery type: Lead – acid battery
✓ Charge capacity: 4.2hour loading condition
✓ Charging time: hour.

Fig 2 Dc Battery

➢ *DC Motor*

A DC motor is a device that turns electrical energy into mechanical motion. It works on the principle of electromagnetic induction — when an electric current flows through a conductor within a magnetic field, it generates a force. The direction of this force can be figured out using Fleming's left-hand rule.

- DC Motor Specifications:

✓ Voltage: 12V
✓ Speed without load: 130 RPM
✓ Speed with load: 90 RPM

Fig 3 Dc Motor Specifications

➢ *Turbine*

- No of Blades is: 30,
- Length of the Blade is: 4inc,
- Width of the blade is : 2inc,
- Air velocity, V = 14 m/s (nearly 50.4 kmph),
- Rotor dia , D = 0.24m, Air Density,ρ = 1.8 kg/m^3.

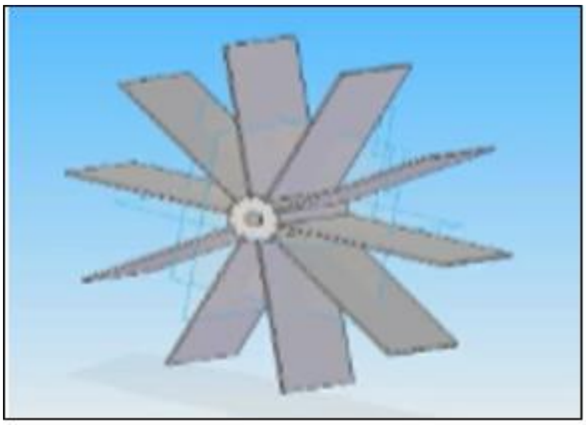

Fig 4 Turbine

➢ *Relay*

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A relay is an electrically operated switch that helps control circuits using a low-power signal while keeping the control and controlled circuits electrically isolated. While many relays rely on electromagnets to operate mechanically, others, like solid-state relays, use different principles.

Relays are particularly useful when a single signal needs to control multiple circuits or when electrical isolation is essential. Originally, they played a key role in long-distance telegraphy, amplifying and retransmitting signals across circuits. Over time, they became fundamental components in telephone exchanges and early computers, where they were used to execute logical operations.

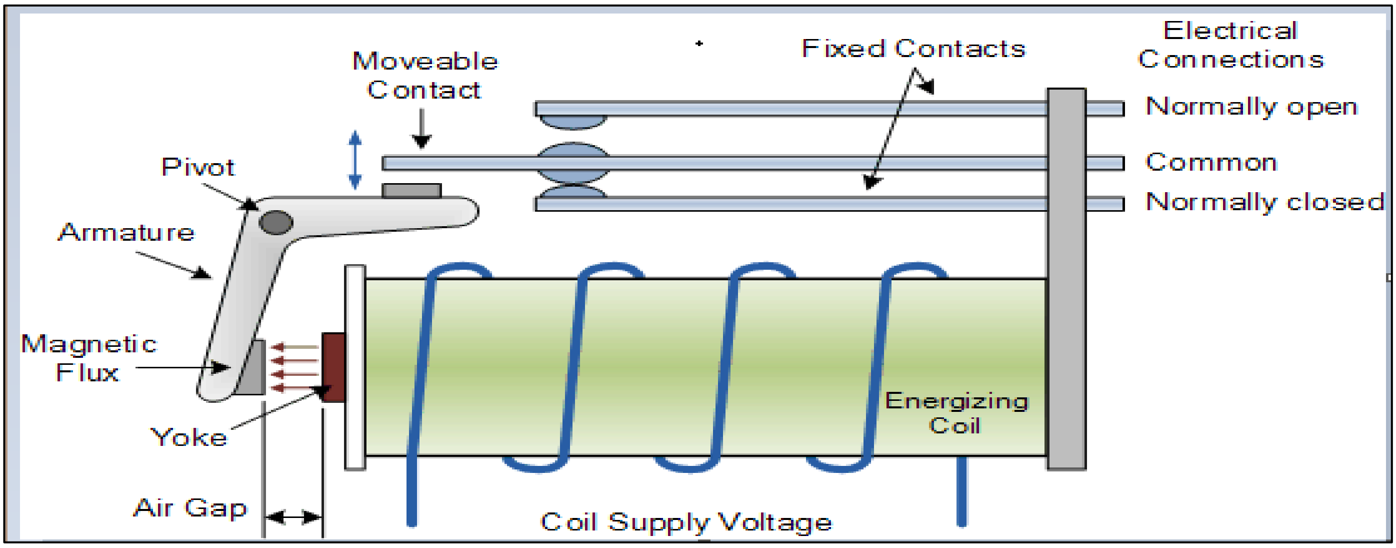

Fig 5 Relay

➢ *Webcam*

A webcam is a device that captures live video and streams it to a computer or through a network. Once connected, the video feed can be saved, viewed, shared online, or sent to others via platforms like email or the internet. This allows people to communicate visually in real time, making webcams essential for virtual meetings, live broadcasts, and online interactions.


Fig 6 Webcam

➢ *Ultrasonic Sensor*

Ultrasonic sensors, also known as ultrasonic transducers, are a type of acoustic device that use sound waves beyond the range of human hearing. They come in three main types: transmitters, receivers, and transceivers. Transmitters generate ultrasound from electrical signals, receivers detect ultrasound and convert it back into electrical signals, while transceivers can both send and receive ultrasonic waves.

Fig 7 Ultrasonic Sensor

➢ *Ardiuno*

I was amazed to see a twelve-year-old boy bringing his electronic gadgets to life. He was experimenting with building his own imaginative toys, blending complex electronics with software skills. My curiosity skyrocketed — how did this young kid grasp electronics concepts so early? How did he learn to write software? Eager to uncover the mystery, I couldn't resist approaching him. I asked him what powered his creations, and with a bright smile, he simply said, "Arduino."


Fig 8 Ardiuno

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- *Non Working Materials*

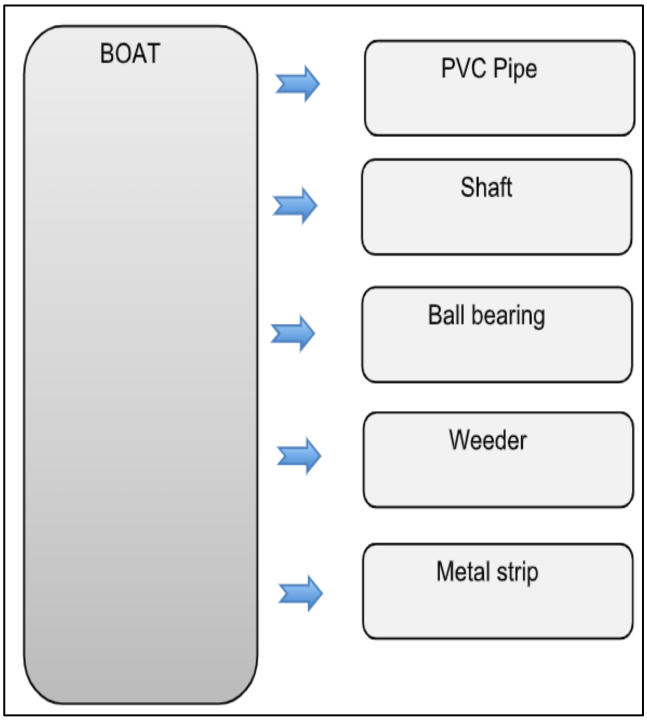

Fig 9 Non Working Materials

- *PVC Pipe*

We plan to use a lightweight material with high mechanical strength for our design. For the model, PVC will be our chosen material. However, in a real-world implementation of the bladeless windmill, the pole material must be able to endure various atmospheric conditions over a long period. Additionally, the material should be as lightweight as possible to allow easy oscillation under wind force, while also being strong enough to withstand both tension and compression.


Fig 10 PWC Pipe

- *Metal strip:*

- Specifications

✓ Material: Mild Steel Strip
✓ Length:40cm
✓ Width:5cm

- Specifications

✓ Length:60cm
✓ Width:5cm

Fig 11 Metal Strip

- *Shaft*:

- Shaft diameter: 12mm
- Material: mild steel


Fig 12 Shaft

- *Ball bearing:*

A bearing is a mechanical component that guides and limits movement to a specific direction while reducing friction between parts in motion. Depending on its design, a bearing can enable smooth linear movement or allow rotation around a fixed axis. In some cases, it can even restrict movement by managing the direction and magnitude of forces acting on the moving components.

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Fig 13 Ball Bearing

➢ *Weeder:*

A number of common weeding tools are designed to ease the task of removing weeds from gardens and lawns.

Fig 14 Weeder

IV. CONCLUSION

The fabrication of an IoT-enabled weeding boat for paddy fields introduces a smart and sustainable approach to addressing the challenges of traditional weed management in waterlogged agriculture. By integrating advanced sensors, AI-powered cameras, and autonomous navigation, this system enhances precision while reducing labor dependency and minimizing herbicide usage. The use of RGB and NIR imaging, LIDAR, ultrasonic sensors, and GPS allows for accurate weed detection and efficient path planning, ensuring minimal disruption to crops. Additionally, solar power and battery storage support prolonged operation, making the system energy-efficient and environmentally friendly.The incorporation of IoT connectivity enables real-time monitoring and data-driven decision-making, allowing farmers to track the boat's performance, analyze weed distribution patterns, and optimize weed control strategies. This automation significantly improves efficiency, leading to higher crop yields, reduced costs, and a lower environmental footprint. However, despite its benefits, challenges such as high initial investment, sensor limitations in complex field conditions, and the need for farmer training in digital technologies must be addressed.Future advancements in AI-driven weed recognition, cloud-based analytics, and cost-effective sensor solutions will enhance the system's scalability and affordability, making it more accessible to small and large-scale farmers alike. By overcoming these challenges, autonomous weeding boats have the potential to revolutionize precision farming and sustainable agriculture, paving the way for a smarter and more efficient approach to weed management in paddy cultivation

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