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A Study On Carrot Care Of Automated Weed Removal For Optimum Growth

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Abstract: Plants that are deemed undesirable in a certain circumstance are known as weeds; they are essentially "plants in the wrong place." It is necessary to control weeds because they contaminate the crop and lower its quality. Weeds hinder agricultural output, suffocate pastures, infiltrate crops, and occasionally endanger cattle. Their fierce competition for sunlight, water, and nutrients lowers agricultural productivity and degrades crop quality. On an agricultural farm, controlling weeds is one of the most challenging duties. After they are convinced of its benefits, farmers readily adopt mechanical weed control.Agricultural weeding machines with motors not only remove weeds between crop rows but also keep the soil surface loose, which enhances soil aeration and water-intake capacity. By using a motorised weeder, you can save time and labour costs. Because human-operated Weeders need muscle effort, they cannot be used for extended periods of time. Hand weeding by hand is a time-consuming process. This battery drive motorised weeder uses a battery-powered motorised mechanism. An agricultural tool used to eradicate weeds that impede crop growth is called a weeder. Petrol-powered power weeders frequently produce excessive vibration and emissions. An electric system is being installed in the weeder to solve these problems. The current 2-stroke gasoline engine provides the power. Due to a lack of personnel for fieldwork, the weeder is made to be manually operated and is positioned at the roots of weeds. The entire cultivated land is cleared of undesired plants once the instrument has been moved and the weeds are clipped.

Index Terms - weeder, motor, battery, mounts and joints, weed cutter, two-stroke engine, and petroleum engine.

I. Introduction

The problems and necessity for innovative technology to optimize herbicide use and enhance real-time weed control are highlighted by recent studies on sensing approaches for robotic weed detection(Jindal,2018). In organic tomato fields, a ground-based weeding robot equipped with a pulsed-jet thermal micro-dosing system and a hyper-spectral sensor can eradicate intra-row weeds with 95.8% accuracy(Grichar,2006). Despite the prevalence ofmechanised farming, pesticides, and human weeding crop spacing and operational limitations limit the use of current mechanical and thermal technologies. Concerns about food safety and yield improvement have been addressed by the increased demand for organic food, particularly in Europe, which has sparked interest in safer, sustainable weed management techniques(Downey et al.,2003)

Crop production is significantly hampered by weeds, which must be effectively controlled to increase yields and satisfy the world's food needs. Although herbicides are effective, they frequently pollute the environment because only a small portion of them actually target weeds; the remainder either impact the ground or drift. In addition to harming useful creatures like earthworms and spiders, mechanical approaches can cause soil erosion. Only weeds that have a low environmental impact should be the target of sustainable weed control techniques.Real-time weed location and identification prior to the use of control measures could enhance crop management practices overall and boost sustainability and efficacy by reducing inadvertent ecological damage.

Weeds reduce crop yields by absorbing sunshine, water, and soil fertility, obstructing water flow, and increasing crop damage, pests, and diseases. Herbicides are frequently used on entire fields, increasing prices, polluting the environment, and taking a lot of time. Farmers spend 35% of their overall cultivation expenditure on weed elimination. There are two parts to crop protection: weed identification and control. Shape-based classification works well when weeds and crops can be precisely distinguished by their varied shapes. By reducing the use of herbicides, minimizing their negative effects on the environment, and boosting weed management effectiveness, this strategy eventually increases crop yields and lowers cultivation expenses overall.

One of the most crucial jobs in the field is weed eradication because agriculture is the backbone of India. To reduce the impact of weeds on crops and enhance crop quality, weeds must be removed from all fields. Weeds are the biological barrier that most limits agricultural production since they destroy crops irreversibly until they are harvested.The characteristics of weeds are influenced by crops, management, soil, and climate. Farming also lacks many technical developments, and labour migration from rural to urban regions has reduced the number of labourers available to work in the fields. To get over these challenges, the research aims to create a weeder.

Approximately 75% of India's population is directly or indirectly dependent on farming, making the country an agricultural one. Seeding, spraying, weeding, and other practices have been carried out by our farmers using the same tools and techniques for generations. Customers are demanding high-quality food products and are paying close attention to food safety. In particular, no power-operated mechanical weed management technology is available for crops like soybeans, maize, or gram. A cheap weeder is therefore necessary for small and medium-sized farmer

One of the most challenging duties in agriculture is weed control, which also contributes significantly to the production costs of the sector. Effective weed management methods to stop weed development and spread were generally a source of concern for farmers. Eliminating undesirable plants by hand and using bullock-operated equipment is a highly challenging task in Indian agriculture, and it may further harm primary crop.

Carrots are classified as members of the Apiaceae family by their scientific name, Daucus carota L. It is classified as a biennial annual crop, which means that even while it is grown, it often takes two years to complete its life cycle.It appears that carrots mature more slowly in warmer climates because their growth slows down as the temperature rises.Among other medical benefits, this vegetable is believed to relax the body, strengthen the heart and brain, prevent constipation, and act as a diuretic.Carrots have been grown for a long time, but their poor yield per acre means that their potential remains unrealised. Therefore, there is an urgent need to raise production in order to meet demand and boost agricultural output. The global output of carrots varies from 30 to over 100 tonnes per hectare due to a number of growth variables, including climate, soil quality, and other elements.

There is not enough food produced worldwide to meet the demands of the expanding population. In agriculture, weed infestations, illnesses, and insect pests drastically lower crop output and land value. Climate change, intensive management techniques, and ecological changes that modify weed behavior provide problems for modern farming. Weeds can be controlled by targeted cultivation and mechanical means, but the current weed control system is imprecise, which puts both efficacy and safety at risk. With approaches that rely on traditional image processing, deep learning algorithms, and chemicals, weed management is a significant financial burden for farmers. However, heavy machinery use exacerbates soil erosion, which further reduces agricultural production and soil fertility.

Carrots are a versatile vegetable, and its meaty roots are commonly used in many different types of cooking. They can be boiled or steamed as a side dish in many vegetable-based cuisines, eaten raw in salads, or added to soups for flavour and nutritional value [6]. It is said to have a number of health benefits, including preventing constipation, strengthening the heart and brain, calming the body, and acting as a diuretic [7]. Purple and black carrots are used to make Kanjal, a beverage valued for its extraordinary delectable qualities [3]. Carrots have been cultivated for a long time, but their low yield per acre means that their potential remains untapped; consequently, production needs to be enhanced immediately to meet demand and boost agricultural output [8].

It is easy for weed competition to lower crop output. To avoid crop losses, early weed removal is very crucial. Reduced options for herbicides and rising weed control expenses are endangering crop profitability. By precisely measuring the distribution of weeds in the field and carrying out weed control operations in specific regions, smart agriculture can leverage intelligent technology to boost the economic benefits of agricultural goods while simultaneously increasing the efficacy of pesticides. In order to accurately distinguish weeds from crops at particular points in the field, an automatic system that removes weeds within crop rows must make use of dependable sensing technologies. There have been numerous noteworthy advancements in crop differentiation in recent years.

A weeder cycle is a piece of machinery used in agriculture. This apparatus consists of a handle, chain, rotor, sprocket wheel, and planet gear, among other components. Connecting the rotor and wheel is a chain that is fastened to a frame. A chain connects the sprocket and planet gear, and the wheel is fastened to the sprocket wheel and the rotor to the planet gear. The frame holds that component in place. The wheels were spun by pushing the weedier cycle. Following this, the wheel-joined sprocket will rotate. The chain attachment assembly will rotate it in addition to the planet gear. Due to the Planet gear being coupled to the rotor, the rotor will rotate.

II . WORK RELATED

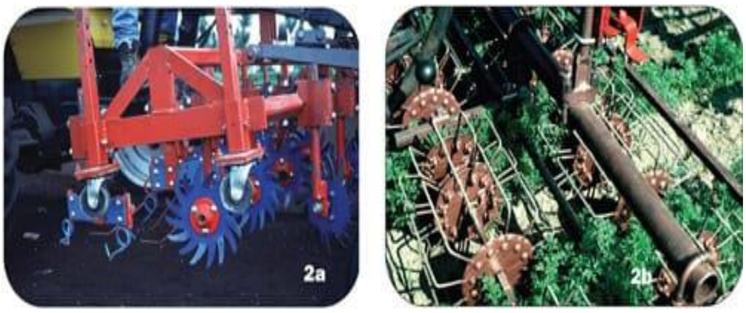
The references for this research were derived from our investigation of the pertinent literature on intelligent weeding technology. A few related studies are presented and discussed in this section. Roberts et al. [80] presented the use of weed identification in agriculture and examined the advantages, difficulties, and restrictions of different imaging, sensor, and detection techniques. Additionally, their analysis examined the prospects and obstacles for the field's use of new weed management technologies, including comprising laser, electric, mechanical, thermal, and chemical weeding that is done automatically. This review does not provide a detailed introduction to the process or associated methods for weed detection.

Using standard weeding robots from the past three decades, Li et al. provided a comprehensive overview of machine learning and deep learning-based weed detecting techniques. For the scholars and practitioners, it acted as a guide. Zhang et al. introduced machine learning and deep learning-based weed detection methods together with some new weeding robots, while also talking about the drawbacks and development patterns of current systems.

For researchers, these reviews can offer useful information. Few literature evaluations, meanwhile, are able to offer comprehensive details on weed identification and management methods in vegetable fields.This paper reviews and compiles the literature and research findings in the field of intelligent vegetable weed control. We go over weed detection technologies in detail, including crop-row detection, global weed detection, and precise vegetable and plant identification. The development and application of weed detection technologies in the field of vegetable weed control can be learnt by researchers from this review, as well as identify the shortcomings of the technology.

This article discusses image collection tools, image processing methods, detection algorithms, and the precision of weed and vegetable identification. Researchers and vegetable growers can learn which weed control actuators and robots have been employed in the vegetable weed control industry. For researchers, knowing which crops and weeds have been studied for detection and weed control techniques is essential. The paper's conclusion also discusses the difficulties and future directions of weed control and vegetable detecting technology. In summary, this review might serve as a resource for vegetable growers and researchers doing studies and practices related to vegetable weed control.

Fig 1-Type of Weeders



It might take up to 20 days for carrot seedlings to recover from root damage or relocation. Cultivation of cotyledons may reduce carrot output and stand. Mechanical weeders also damage carrot rows, leaving less than 12 cm of undisturbed space. The kind of soil and the size of the weeds are two of the numerous variables that might affect how well mechanical weeders (Figure 2) work. For instance, the torsion weeder with spiked discs and the basket wheel hoe are both efficient weeders on mineral soils, however they vary in a few ways:

Speed of operation: (torsion > basket) violence (torsion > basket) quantity of cultivation during the season (torsion > basket) The basket wheel hoe works well on weeds with two leaves or less, while the torsion weeder works best on weeds with four leaves or fewer. But the basket wheel hoe works better on muck soil, which is more easily disturbed and has looser roots for weeds.

Benefits

i. Increased crop yield

ii. Reduced labour cost

iii. Improved crop health

iv. Increased efficiency

v. Environmental benefits

Benefits Enhanced yields of crops Power weeders help crops get more sunlight, nutrients, and water by pulling weeds, which can increase agricultural yields. lower labour expenses Power weeders can eliminate the need for manual labour by automating the weed-removal operation. By eliminating weeds that can compete with crops for resources, power weeders can contribute to the maintenance of better crop health. benefits to the environment Because power weeders don't require fuel or herbicides, they help lessen environmental pollution and soil degradation. Enhanced productivity Larger areas may be effectively covered by power weeders, which can boost output overall. Power weeders are useful for organic farming, row crops, and small crops including fruits, vegetables, and some seed crops.

III . MATERIALS USED

3 . 1 Battery weeder

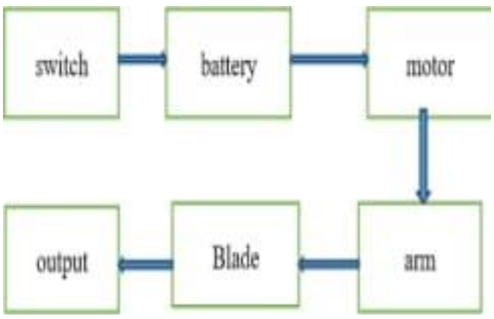


Fig 2.Block diagram

Fig 3. Fabrication diagram

3 . 2 .Brushless dc motor

Fig 4. Dc motor

Its additionally known as electronically commutated motors (ECM or EC motors), brushless DC electric motors (BLDC motors or BL motors), and synchronous DC motors, are synchronous motors that are powered by direct current (DC) electricity via an inverter or switching power supply that produces alternating current (AC) via a closed-loop controller to drive each vehicle phase. Current pulses are sent to the motor windings by the controller to control the motor's speed and torque.Brushless motors are superior to brushed motors in a number of ways, such as fast speed, electronic control, low maintenance, and a high power-to-weight ratio.Handheld gadgets and computer peripherals like printers and disc drives employ brushless motors. In general, brushless motor systems are built similarly to permanent magnet synchronous motors (PMSMs), though they can also be power tools, switching reluctance motors, induction (asynchronous) motors, and vehicles such as cars and model aeroplanes.

3.3. Screws

Fig 5 . screws

A screw is a kind of fastener that is somewhat similar to a bolt (see the section below on the differences between a bolt and a screw). It is usually made of metal and is distinguished by a helical ridge called a male thread (external thread). When screwed into a substance, the thread creates grooves that may help pull the connected material together and prevent pull-out, while the screw itself digs in and wedging into the material when rotated. A wide range of materials can be secured using screws; wood, sheet metal, and plastic are among the most often used materials.

3. 4. Mount and joints

Fig 6. Mount and joints

An area of a machine that joins one or more mechanical components is called a mechanical junction. Temporary or permanent, the majority of mechanical joints are made to be disassembled. The majority of mechanical joints are made to permit relative motion in one degree of freedom while limiting movement in one or more other degrees. Typically purchased pre-assembled, mechanical joints are significantly less expensive. The foundation or substrate can be isolated from the dynamics of the mounted equipment by using shock mounts. Silence is essential to the effectiveness of submarine missions, hence this is crucial.

Almost all current cars have motor and transmission mounts, which serve as another common example of this. Without isolation mounts, current cars would have a significantly different noise and comfort level than we are accustomed to.

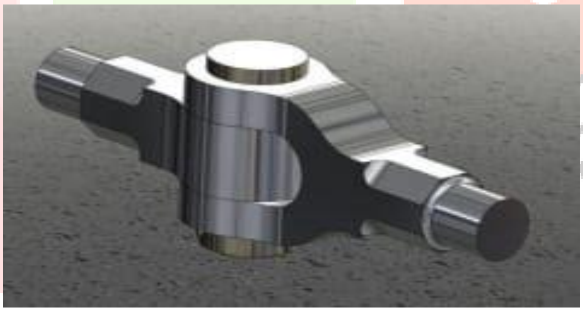
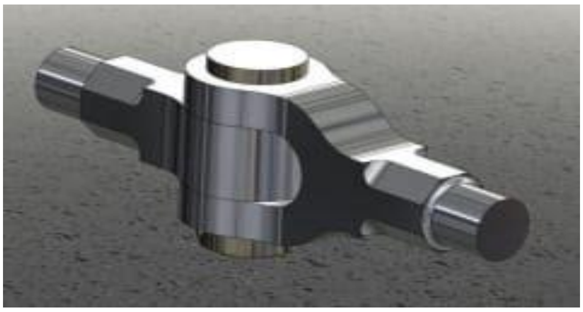


Fig 7. Mechanical joint



3.5. Wheels and rods

Fig 8. Wheels

A wheel rotates when it is subjected to torque or gravity about its axis. A wheel is essentially a circular block of sturdy, hard material with an axle bearing located in the center of the block. These parts come together to build one of the six simple machines.

One can control the direction of a vehicle or vessel by placing it horizontally on a column that is connected to a rudder or a chassis that is mounted on other wheels (e.g., a steering wheel or ship's wheel); transport heavy loads by placing it vertically beneath a load-bearing platform or case; control the spinning motion used to shape materials (e.g., a potter's wheel); or store, release, or transmit energy by placing a wheel on a crank or engine.

3. 6. Battery

Fig 9.battery

In order to power electrical devices such as cell phones, torches, and electric cars, a battery is a device consisting of one or more externally connected electrochemical cells [1]. In a battery that is producing electricity, the cathode is the positive terminal and the anode is the negative terminal. From the terminal designated as negative, electrons will move to the positive terminal through an external electric circuit. When an external electric load is connected to a battery, a redox process transforms high-energy reactants into lower-energy products. Electrical energy is subsequently transferred to the external circuit from the free-energy differential. Initially intended to describe only multi-cell devices, the term "battery" has recently been used to describe single-cell devices as well.

The electrode materials in primary (single-use or "disposable") batteries are used just once before being discarded since they undergo irreversible changes after discharge. An alkaline battery is a common example, used in torches and many other portable electrical gadgets. It is possible to repeatedly discharge and replenish secondary (rechargeable) batteries by applying an electric current; reverse current can return the electrodes to their initial composition. Examples include the thin, tiny cells found in smartphones, the massive lead acid or lithium-ion batteries found in cars, and the lithium-ion batteries found in portable gadgets such as laptops, smartphones, and cell phones.

3.7. Power weeder

Fig 10. Power weeder

3.8. Two storke power engine

The engine is the most crucial part of the power weeder's construction. A two-stroke petrol engine was employed for this project.Two-stroke gasoline engine Petrol engines employ a mixture of gasoline and air to compress to less than 1275 kpa. The piston head in each cylinder then uses a spark plug to ignite the mixture.

3.9. Weeder tool

Fig 11. Weeder tool

Made of mild steel with a typical length of 203.2 mm and width of 25.4 mm, the weeder tool used to fabricate the power weeder is assembled on a chassis using bolts and lock nuts and is welded elsewhere as needed. The blade on disc is assembled using lock nuts and bolts that have a diameter of 10 mm for the hexagonal head. The primary goal of lock nuts is to prevent slippage while the machine is operating.

3.10. Chassis frame

The angles used to form the chassis are composed of mild steel, which is cut to the proper length and then joined using an arc welding flame. Every component of the machine, including the engine, wheels, gearbox, tools, etc., are mounted and loaded by the chassis. It maintains every component joined.

3.11. Shaft & chain

Fig 12. Shaft used for fabrication weeder

3.12. Chain used for fabrication weeder

The shaft is composed of cast steel. It supports wheels and gives them motion with the aid of an appropriate gearbox system. A single sprocket is fastened to the shaft, which is moved by the engine via a chain. The shaft used to make the weeder Power transmission and motion from the engine shaft to the shaft supporting the wheels are provided by the chain. The chain is fixed to attached, correctly aligned sprockets. Chain makes sure that there is less loss during transmission. The chain is single-stranded.

Fig 13 . Chain used for fabrication weeder

3.13. **Handel & wheel**

The handle directs the car in the desired direction. Because an accelerator is attached to the handle, it is also used to change the machine's speed as needed. The handle is made with human comfort in mind, taking into account both machine handling and height. On the machine, there is only one wheel. The position of this front wheel is beneath the chassis.

IV. METHODS

Results from Sensors Computer vision and image processing use cameras and machine learning algorithms to differentiate between carrot plants and weeds. Using photos of plants and soil, the approach identifies weeds by size, form, or colour.

4.1. Sensor Based Detection:

Findings Using Sensors To distinguish between weeds and carrot plants, computer vision and image processing employ cameras and machine learning algorithms. To detect weeds by size, shape, or colour, the method makes use of photographs of plants and soil.

Fig 14. Detection

4.2. Deep learning (cnn):

Infrared or multi-spectral cameras:Sensors known as infrared or muto the naked eye. Because carrots and weeds reflect light differently, thlti-spectral cameras are able to identify light wavelengths that are invisible ese cameras can help distinguish between the two.

Lidar:A technique called Light Detection and Ranging, or LIDAR, uses high-resolution three-dimensional photographs of a field to help identify weeds by analysing their structure and height.

4.3. Mechanical weeding mechanisms:

Mechanisms for Weeding Mechanically After weeds are identified by the system, they must be manually removed without damaging the carrot plants using an automated weeding method.

Rotary Blades or Tines: Weeds can be pulled out of the ground by using these revolving or oscillating tines or blades. You can modify the system such that it targets the weeds and stays away from the carrots.

Finger Weeders: These rotating tools, which resemble mechanical fingers, are used to carefully pull weeds from between rows. Strong enough to pluck weeds, the fingers are flexible enough not to harm the carrot plants.

Suction or hoover mechanisms: Certain systems pull and remove weeds from the soil using suction or a hoover, enabling precision without also upsetting the nearby soil.

Fig 16 . Machine

4.4. Actuators and robotic systems

Robotic arms or rigid actuators: Weeds can be targeted and removed using robotic arms equipped with revolving blades or brushes, among other specialized equipment. Sensor inputs are used to inform the algorithms that control these arms.

Linear actuators:Based on the location of the weeds and carrots, linear actuators can regulate the depth or motion of mechanical weeding instruments, enabling more accurate control of the weeding activity.

Grippers and pinches: Grasping and removing weeds could be done by automated systems using grippers or pinches. The purpose of these grippers is to capture weeds by their stems or leaves without damaging the roots of carrots.

Fig 17 . Actuators

4.5. Data gathering and machine learning

Data Collection: Information about the distribution of weeds, their growth stages, and the surrounding environment can be obtained by the system. Through the improvement of weed detection algorithms, this data can eventually aid in the optimization of the weeding process.

Adaptive algorithms and machine learning:The weeding process could be continuously improved by machine learning models. The system might "learn" which sensors or methods work best in particular situations, enhancing its approach to weed detection and eradication over time.

4.6. Efficiency in energy use and power supplies

Solar power: In order to give autonomous weeding robots a sustainable power supply, particularly in big fields, solar panels can be incorporated into the system.

Electric motors:weeding systems, and movement are the usual applications for electric motors. They use less energy and are quieter than petrol engines.

Battery storage: The weeder may work in the field for longer stretches of time without needing to be recharged because high-capacity batteries have a long-term energy storage capability.

4.7. The power source for automated weed eaters

Effective power systems are necessary for automated weeders. Long lifespan and excellent energy density make lithium-ion batteries perfect for battery-operated weed eaters. For dependable power, lead-acid batteries are frequently found in larger versions.Solar panels can be used in certain systems to supply supplementary power or recharge batteries.

V. DISCUSSION

Limitation

Carrot weeders, particularly automatic ones, have a number of drawbacks despite their many benefits. First, small-scale farmers may find it difficult to afford the hefty initial costs. Some farms may not be able to afford the significant technological investment required for automated weeders. Furthermore, because of their complexity, they may break down frequently and need specialized maintenance and repair, raising operating expenses. Automated systems' accuracy is another drawback. Identifying and distinguishing between immature carrot plants and weeds can be difficult, particularly when the seedlings are tiny and resemble weeds, which could harm the crop. Furthermore, weather-related factors like muddy, damp, or severely dry soil can limit the weeder's effectiveness. Another issue with battery-operated models is their power consumption, which can have limited operational.

Soil Type Sensitivity: Loose soils with good drainage are usually ideal for carrot weeders. A weeder may have trouble penetrating clay-heavy or compacted soils, which reduces its ability to eradicate weeds without harming the nearby plants or soil. In addition to being challenging to use in rocky or uneven soil, it may clog or harm the equipment.

Size &Maneuverability: Although the weeder is often made for small-scale jobs, it might be difficult to use for bigger garden beds or rows. Additionally, the design may make it more difficult to manoeuvre around delicate plants like carrots, particularly if the weeder's tines or blades are very hard, increasing the possibility of inadvertent crop injury. The weeding procedure may take longer in dense or overgrown areas if the instrument needs to make several passes.

The inability of many carrot weeders to precisely manage depth makes it more difficult to make sure that the weeds are being pulled out by their roots. If the tool is too deep or too shallow, it may damage nearby crops like carrots that grow near the surface or leave weed roots behind.

Manual Labour: Depending on the model, some carrot weeders could need a lot of hand labour. This can be taxing on the body, particularly for people who are weak or have poor mobility. This may reduce the weeder's effectiveness for bigger areas when compared to more mechanical or automated options.

Weed Variety Limited: Certain models may not be successful against all weeds, especially those with deep or robust root systems, because they are designed for particular weed species or sizes.

Future Work

1. Two rotors, a float, a frame, and a handle make up the weeder.
2. The entire length of the cone-shaped rotors is covered in welded strips that are smooth and serrated.
3. The rotors are orientated in opposition to each other and positioned in tandem.

Future Scope

1. High performance will result from the use of new material
2. In order to lower the cost of production and the usage of chemicals for weed control, farmers require alternatives.
3. As of right now, there isn't a method in place to get rid of weeds that are in the seed line between crop plants.

V. RESULT

The purpose of the compact and effective weed removal equipment is to eradicate weeds. The machine was put to the test in a field to see how well it could weed. The machine operated flawlessly, indicating that the test was successful. Thus, it can be said that the machine is manageable and relatively small. Farmers have less work to do because of this machine's uncomplicated field operation. Compared to hand weeding, this machine's cost of weeding is significantly lower. It has decreased by 66.66%.This may be the greatest device for farmers with little land because the weeders currently on the market are appropriate for huge fields.

VI. CONCLUSION

Agricultural development has a major impact on the reduction of rural poverty. The effort required to make a weeder will ensure that farmers' demands are met. The weeder need to be user-friendly and somewhat efficient. Compared to the traditional method of weed removal, it was faster. It is more economical and requires less labour than manual weeding. Don't use petrol or electricity here.

The molecular structure, soil condition, and moisture content all have been found to have a complete impact on the tool's depth. The purpose of this effort is to integrate mechanical systems into agricultural fields for agricultural activities. There are other tasks that can be completed, such as weed eradication, ground softening, and plowing. Applying various mechanisms to the machine is a common way to adopt diverse agricultural equipment. It is therefore a multifunctional tool that has practical applications in various disciplines. The materials used to fabricate the Low Cost Weeder are found locally. Overall, the weeder's performance was adequate

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