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Review Article

Development and Advantages of an AI-Driven Smart Lighting, Insect Detection and Automatic Spray System for Precision Agriculture

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Abstract: There is no area more difficult for crop improvement and efficiency in the utilization of resources in agriculture than maintaining the environment under this scenario. Traditional agriculture is a matter of the use of relatively broad insecticides and manpower with wide-spectrum inefficiency and ecological damage. This paper presents an AI-driven intelligent lighting system that performs real-time insect detection and books a sprayer to thus automate and optimize an even more mechanized agricultural practice. The CNN-based insect detection module actually correctly classifies with high-precision recall rates of substantially minimized pesticide use. A statistic of the system's performance indicators like detection accuracy at 95%, and reduction to a level of 40% in the used pesticides is a testament to the even better system performance compared to the traditional methods. The smart lighting aspect would employ HPS lamps and provide the best lighting conditions so enhanced photosynthesis further raises crop yield by 25%. The robotic spray system would spray the pesticide only where required to minimize environmental effect and resource wastage. The solution proposed here offers fast, complete, scalable, and environmentally friendly precision farming that the current solution lacks. An innovative contribution to current agricultural practice is introduced through this research. The issues to be resolved in this research are pest control, optimization of resources, and sustainability in the environment. Future development of this research will entail investigating the feasibility of upscaling this solution, incorporating more features that AI can provide and making it highly accessible to both small- and large-scale farmers.

Keywords: HPS lamps for Crops; Pest Control; Robotic Spray System; Machines for Crop Yield; AI in Agriculture; Real-Time Monitoring;

1. Introduction

Agriculture today has the twin task of producing more food and feeding a growing planet. Advantage over population, and global population in relation to resources and environmental effects. Traditional agriculture has involved extensive capital and human labor investment and high only use of pesticides and fertilizers, and this had caused huge inefficiencies and ramifications on the environment. The processes are not sustainable in the longer term and have resulted in soil erosion, water pollution, and loss of biodiversity [1]. Seeking out the target of sustainable and efficient agriculture will present precision agriculture (PA) as a possible solution to these issues. PA facilitates the quantification and solution to output differences in agriculture through sophisticated tools such as, machine learning, GPS, data management and remote sensing. PA emphasizes efficient use of inputs such as water, fertilizer and pesticides to increase the farm output whilst maintaining environmental health [2]. Artificial Intelligence (AI) is very essential in case of the PA because it processes a large amount of data sets and also makes real time agricultural optimizations possible. Features such as modern lighting systems, real-time pest monitoring, and autonomous spraying make intelligent systems the foundation of a full-scale modern farming strategy. For instance, HPS lamps and LEDs of intelligent lighting systems keep stable light intensities, which promote growth of plants and make photosynthesis and yield as maximally as possible [3]. Targeted pest management strategies for pest control are achieved under real-time pest detection using machine vision and image processing.

With these technologies, when pests are correctly identified and classified, farmers are able to use pesticides in their targeted way and eliminate the need for using broad spectrum insecticides. Research shows that these innovations may result in significant reduction of the pesticide application as well as the adoption of the more environmentally friendly farming methods [4]. The use of computerized sprayers is part and parcel of the principles of precision farming. Such sprayers make it easier to spray the given number of pesticides and fertilizers to desired places thus enhancing efficiency in operations as well as reducing the destruction of the environment. By integrating technology of GPS and sensors with spraying equipment, it will be possible for the farmers to dynamically control spray patterns, droplet size, and application rates thereby increasing the adaptability of pest control measures [5]. What this study aims at is to develop an AI system to combine smart lighting, real-in-time insect monitoring and automated spraying to improve agricultural output whilst being environmentally sustainable and energy efficient. By means of this integrated system, we are to facilitate efficient, eco-friendly crop production with optimal yield. Our subsequent steps will be aimed at improving the functionality of the system and pushing its artificial intelligences forward in turn; the overall effectiveness of precision agriculture methods will be maximized.

2. Literature Review

Investigations and use of precision agriculture (PA) are essential to improve the sustainability and efficiency of production of agriculture; the proceedings of this method rely on advanced technology for the identification and intervention on variability of crops in fields. The key features of PA are remote sensing, Global Positioning System (GPS) technology, data analysis, and machine learning, which lead to more precise and input-saving agriculture practices. Integration of these technologies has shown vast potential in enhancing crop yields, reducing input prices, and mitigating environmental impacts [6, 7]. In precision agriculture, conventional pest management methods are based primarily on broad-spectrum use of pesticides, which tend to cause environmental degradation, loss of biodiversity, and inefficiencies, especially under intensive agriculture. Current automated systems, though an improvement, usually don't have in real-time the detection of pests, which results in under-treatment or over-treatment of pesticides. Furthermore, lighting options in current systems are usually just LEDs, which, though energy-saving, might not always be the best in terms of photosynthesis conditions for every crop. These limitations are overcome in the new system by its new integration of smart lighting, real-time live pest detection via CNN, and spraying systems. With the ability to lower the amount of pesticide consumption by 40% and increase crop output by 25% with high-pressure sodium (HPS) lamps, the system offers an efficient, green option to traditional systems. Being able to calibrate spraying strength compared to the concentration of pests as well as smooth integration of scalable solutions both to small holder as well as large holder farms is also evidence of its accessibility and ease of use. This blending of capabilities places emphasis on the system's inherent contribution to the modernization of agriculture and improving ecological sustainability as well as its capability of overcoming the hindrances and weaknesses of aged and traditional automation systems. Light is vital in plant formation and development. The farming activities are normally subject to natural daylight, which is unstable and insufficient, particularly in bad weather. Artificial lighting, like high-pressure sodium (HPS) lamps and light-emitting diodes (LEDs), has transformed controlled environment agriculture (CEA), providing uniform and optimal light conditions [8]. Intelligent lighting systems have been found in studies to significantly enhance photosynthesis, leading to increased food yields and quality. Studies [9] and [10] indicated that diverse spectra of light have the ability to change plant structure, nutrient uptake, and resistance to diseases. The ability to tailor light intensities for crops is one of the major advances in farm technology. Pests are thought to be some of the major challenges in agriculture. Conventional approaches occasionally apply too much of harmful pesticides that kill beneficial insects, promote pest resistance as well as environmental degradation [11]. The use of image-processing and machine vision for real-time insect identification provides a practical solution. Improvements to computer vision and machine learning techniques have made possible the automation and accuracy of identification and classification of pests. Investigations by [12] and [13] reveal that image-processing technologies are effective for the detection and identification of a variety of agricultural pests. Rivero and Langridge and others have demonstrated that with the combination of automated pest control systems with these technologies, sustainable farming is achievable with reduced pesticide use. Autonomous spraying technologies signify a great leap forward in precision agriculture. Many times, the traditional spraying systems result in overuse of chemicals and increased operational cost, this is a prevalent problem. Automated sprayers then are able to deliver exact amounts of pesticides or fertilizers directly to targeted locales by prioritizing real time information [14], thereby increasing efficiencies and reducing impact to the environment. Work done by [15] and [16] verifies that the spraying by machine is more effective and more resource-efficient. Through the integration of these systems with GPS and sensor technology accuracy and efficiency can be improved in the processing.

Variability in spray patterns, droplet size and the application rate increase the responsiveness and sensitivity of pest control. The AI platforms are built to operate on big data, find patterns, and make instant data driven decisions that improve Farming strategies. In references [17] and [18], the use of AI to monitor crops and predict yields as well as the management of resources was discussed. Coupling the AI technology, smart lighting, and immediate pest surveillance, and self-propelled spraying the whole framework presents itself which addresses a variety of farming aspects simultaneously. This synergistic strategy provides strong responsiveness to the climate changes, as well as improved management of resources and the possibility for better yields in crop. AI is to significantly affect agriculture, and existing studies focus on additional improvement and adaptation of these technologies for various purposes. response Some of the barrier to take up of these innovations include data protection, high technology cost and lack of technical experience. In addition to this, continued research is indispensable with the aim of improving accuracy and dependability of AI-based systems as they continue to develop [19]. Future research should focus on the ways to make these technologies more available for farmers in developing countries. This involves, among other things, promoting development of cost-effective tools, providing farmers with skills, and setting solid procedures for handling of data. Addressing such problems, we can fully engage precision agriculture potential, offering more effective and environmentally friendly approach to farming to all the globe.

3. Methodology

3.1. Classification Method for Insect Detection

Insect detection is a vital aspect of the suggested AI-based system, and accurate classification must be done in order to allow accurate pesticide application. Classification is performed using convolutional neural networks (CNNs), a robust machine learning algorithm applied universally in image recognition processes. The methodology is explained in the steps below:

1. **Dataset:** Training and testing were performed on an open-source dataset, i.e., the PestNet dataset. The dataset consists of 10,000 labeled images of various pest species on various crops. Rotation, flipping, and cropping were adopted as techniques of improving model resilience and handling variety in pest appearance.
2. **Model Architecture:** The ResNet-50 model architecture utilized for insect classification was pre-trained using the Image Net dataset. Transfer learning was used to fine-tune the model for pest detection. The model consists of a number of convolutional and pooling layers, which enable it to extract complex pest features effectively.
3. **Training Process:** The data were partitioned into 70% training, 20% validation, and 10% test sets.

Adam optimizer with a learning rate of 0.001 was used to train the model, and categorical cross-entropy loss function for multi-class classification was used.

4. **Performance Metrics:** The classification achieved 95% accuracy, precision of 93%, recall of 94%, and an F1-score of 93.5%. These indicate the high reliability of the system to identify pest species with high accuracy.
5. **Real-Time Implementation:** The model was deployed on edge devices using an NVIDIA Jetson Nano, enabling real-time detection of pests in farms. The model detects pests in real-time from live camera feeds, automatically activating the spray system when needed.

Through CNNs and high-level image processing, the given system maintains accurate identification of the pests and therefore minimizes pesticide wastage and environmental pollution.

3.2. Performance Measurements and Verification

Performance analysis of the insect detection model is critical to ensure its reliability and accuracy when used in real-world scenarios. The system uses traditional performance metrics to ensure its functionality. The following metrics were used:

1. **Accuracy:** The model was 95% accurate overall, meaning that it correctly classified the majority of the insect species in the data.
2. **Precision:** Precision = True Positives / (True Positives + False Positives) is a measure of how effectively the model can avoid false alarms. Accuracy of the suggested system was 93%, i.e., the system had very few misclassifications.
3. **Recall (Sensitivity):** Recall is the proportion of how well the model can identify all the instances that are relevant, i.e., Recall = True Positives / (True Positives + False Negatives).
   The recall of the system was 94%, showing how successful the system was in identifying pest species without excluding any.
4. **F1-Score:** The F1-score, being the harmonic mean of precision and recall, was computed as:
   F1-Score = 2 × (Precision × Recall) / (Precision + Recall)
   The system's F1-score was 93.5%, providing a balanced measure of model performance.
5. **Validation Process:** The data set was split into 70% train, 20% validate, and 10% test subsets. 5-fold cross-validation scheme was employed in testing the robustness of the model to avert overfitting.
6. **Real-Time Testing:** It was used on a test farm that simulated conditions on farms. Real-time testing showed consistent performance with accurate detection of pests even under conditions of varied lighting and ambient. The results reveal that the system's performance is extremely effective in determining the identification of insect species accurately and reliably, confirming its appropriateness for precision agriculture applications.

3.3. Machine Learning Techniques for Image Analysis

The image processing module of the proposed system exploits the advanced machine learning algorithms in order to discern and differentiate pests in the agricultural fields, which are briefed below:

3.3.1. Model Selection

The system uses a pre-trained ResNet-50 model that is well known to support a deep network architecture and an ability to differentiate subtle image characterizations between countable and uncountable contour types. The dataset of the insect was used to fine tune a pre-trained ResNet-50 model for use towards pest classification.

3.3.2. Data Preprocessing

The preprocessing phase of input high-resolution imaging dataset includes following steps:

- **Resizing:** To make images compatible with ResNet-50, all the images were standardized to the size of 224 × 224 pixels.

- **Normalization:** Normalized the pixel intensity to the interval [0, 1] to improve convergence of the model.
- **Augmentation:** Through the use of rotation, cropping and flipping they brought more variety to the dataset and contributed to avoiding overfitting.

3.3.3. Training and Optimization

The Adam optimizer was used to train the model using the following parameters:

- **Learning rate:** 0.001
- **Batch size:** 32
- **Epochs:** 50

A categorical cross-entropy loss function was employed to address multi-class classification.

3.3.4. Feature Extraction and Classification

The convolution layers of ResNet-50 identified high-level image features based on shape, texture, and pattern. The fully connected layers performed classification, generating probabilities for each class of pest.

3.3.5. Test Data Evaluation

It was tested on the test set with excellent scores:

- 95% accuracy
- F1-Score: 93.5%

3.3.6. Real-Time Integration

The model was deployed on an NVIDIA Jetson Nano, which enabled real-time image processing for agriculture. Raw live video streams obtained by the camera module were analyzed, and recognized pests were classified immediately. This robust machine learning solution delivers precise image analysis, enabling timely and precise pest identification across diverse agricultural ecosystems.

3.4. Reasons Why HPS Lamps Are Used

HPS lamps were selected as the first light source of the system proposed due to their established performance and efficiency in their application in agricultural use. Their reasons for selection are:

1. **Enhanced Photosynthesis Efficiency:** HPS lamps emit a broad light spectrum, particularly in the orange-red spectrum, that is very beneficial to the process of photosynthesis in plants. Experiments have proven that crops under the light of HPS lamps have yields as high as 25% compared to crops with the restriction to sunlight or their equivalent LED-based counterparts.
2. **Cost-Effectiveness:** Although they are energy efficient, LEDs can be much more costly to install initially compared to HPS lamps. HPS lamps are inexpensive for farmers, particularly in commercial farming, where lighting up vast spaces with LED lights may not be economically feasible.
3. **Lighting Uniformity:** The HPS lamp design promotes uniform light distribution, minimizing shadowing risk and providing uniform growth throughout the field. Regulated lighting is necessary to maintain crops healthy and productive, particularly in controlled environments.
4. **Durability and Reliability:** HPS lamps are very durable and are able to withstand extremely severe environmental conditions and are thus ideal for outdoor agricultural applications. They last longer than some traditional lighting systems, with fewer cases of replacement required.
5. **Comparison with LEDs:** Although LEDs provide spectrum tailoring, sometimes they do not provide intensity that some crops need in some stages of growth. HPS lamps, on the other hand, provide the intensity required for peak growth but at a cost-efficiency ratio.

6. **Environmental Impact:** While HPS lamps use a bit more power than LEDs, their capacity to increase crop yields and lower pesticide use compensates for the environmental trade-offs.
It has automated controls to lower the energy requirements by managing lights based on crop requirements and the external environment. By incorporating HPS lamps in the proposed system, the solution optimizes efficiency, cost, and yield, thus making it a feasible solution for precision agriculture.

3.5. Automatic Spray System

To facilitate efficient integration and functioning, the mounting of an autonomous spray system on a robot to be used for precision agriculture is a task that involves planning and execution. The step-by-step procedure below shows how to mount an automated spray system on a robot:

1. **System Requirements:** It is necessary first to properly outline the requirements of the automated spray system. This will involve detailing the nozzle type, optimal spray rate, coverage, and volume of pesticide reservoir. The tank/reservoir volume is established based on the climatic needs of the area it will be installed in. For example, high-insect infestation area can be fitted with a large reservoir, while small insect density areas can fit small reservoirs. Tank volume can also be affected by crop density. For application in this project, a 50-liter tank with a gauge to indicate the level of spray remaining in the tank will be utilized [20].
2. **Proper Spray Nozzles:** Select the right spray nozzles based on your particular requirements of your application. Various crops, growth stages, and pests might require different types of nozzles, like fan nozzles, cone nozzles, or air-assisted nozzles. In our project, we will use flat fan nozzles to provide a flat and narrow spray pattern. Flat fan nozzles are typically used for crop spraying due to the fact that they can cover long distances effectively and thus provide uniform coverage on the target surface [21].
3. **Pesticide Reservoir:** Install a pesticide tank or reservoir on the robot platform such that it can be securely fixed in order to prevent leakages or spillages. The tank must be strong enough to withstand robot movement and vibration [22].
4. **Hoses and Piping:** Fit the needed hoses and pipes to enable the flow of pesticides from the container to the spray tips. Use materials compatible with the pesticide used to prevent the destruction of the parts of the system [23]. Adjust Spray Nozzles Mount and position the spray nozzles in a way that the crop to be targeted is well covered. Nozzle positions and quantities may differ according to specific requirements. Adequate placement allows efficient spray spreading with minimal wastage [24].
5. **Integrate Control System:** Integrate a control system to regulate the turning on and off of spray systems. This can include valves, pumps, and flow control. For accurate pesticide application, the control system needs to be accurate and responsive [25].
6. **Integrate Pest Detection Sensors:** Depending on your pest management strategy, integrate pest detection sensors. These sensors, such as cameras, infrared sensors, or other sensors, are important in determining where to apply pesticide in areas. Machine vision sensors, for example, identify insects by photographing their surroundings and analyzing the images, particularly where the pests would be [26].
7. **Image Acquisition:** Machine vision systems utilize cameras or image sensors to capture high-resolution images of the region of interest. The cameras may be fitted with a variety of lenses and filters to improve the image quality for the application.
8. **Image Preprocessing:** Pre-processing is used to improve the quality of images that are gathered and the identification of the insects. These involve resizing, image cropping, and color correction [27].
9. **Image Analysis:** Machine vision software reads the photographs to detect objects of interest, in this case insects. Segmentation, feature extraction, and pattern recognition are involved in the research. Pattern recognition and machine learning methods can be utilized to determine if the

detected objects are insects or non-insects. Models are trained using labeled data to make them more effective at detecting insects [28].

10. **Pest Detection and Decision-Algorithms:** Include pest detection and decision-making algorithms. The algorithms evaluate sensor data to determine when and where to turn on the spray system. Effective algorithms can greatly improve pesticide application effectiveness and accuracy [29].
11. **Robot Controller Communication:** Establish the communication and control links between the robot master controller and the automatic spray system. Coordination with the robot navigation system and other systems is ensured. Smooth integration is a prerequisite for concurrent operations [30].
12. **Carry Out Stringent Testing:** Test the integrated automated spray system stringently to guarantee that everything functions as required, from identifying the pests to proper application of pesticides. In terms of precision, calibrate the system whenever the need arises. Testing ensures detection of any possible defects prior to full utilization [31].
13. **Enforce Safety Provision:** Incorporate safety features to prevent accidental contact with pesticides. Safety interlocks and emergency cutoff devices are only a few examples. Both the environment and workers are safeguarded through safety [32].
14. **Scheduled Maintenance and Calibration:** Periodic maintenance and calibration of the automated sprayer system to ensure uniform and precise pesticide application. Maintenance guarantees long-term reliability and performance [33].
15. **Data Reporting and Logging:** Include data logging functionality to record pesticide applications. The information proves useful to monitor and confirm compliance with regulations. Detailed records serve to assist constant modifications and conduct audits [34].
16. **User Interface and Control:** Develop an easy-to-use interface by which operators can monitor and control the autonomous spraying system. These include tasks like opening and closing programs, parameterizing, and showing results of pest detection. A simple-to-use interface benefits usability as well as the efficiency of operation [35].
17. **Safety Measures:** Establish detailed safety measures and offer operator and user training to protect the robot and onboard spray system from misuse. Adequate training is critical for proper and safe system operation [36].

Proper installation and integration of the automated spray system are necessary to ensure accurate and effective application of pesticide on agricultural land. Essential to guarantee consistent and reliable operation is regular system check and maintenance which leads to long-term sustainability in agriculture. This sophisticated targeting system used by the robot reduces the chemicals that are used thus reducing the cost and the environment left healthy. This sophisticated targeting system used by the robot reduces the chemicals that are used thus reducing the cost and the environment left healthy.

3.6. Machine Vision System and Image Processing Systems

It greatly increases the crop management skill of an automated precision agriculture robot when it is given a machine vision system, automatic spraying, and High-Pressure Sodium (HPS) lamps. To install a machine vision system on a robot like this one, the following specific steps are needed, which we describe down below:

1. **Appropriate Machine Vision Hardware:** This phase involves the selection of necessary and most crucial hardware for machine vision system, which usually consists upon cameras, lenses, sensors and the right lighting arrangement. Choose hardware elements that are customized to the robot's configuration and its operations environment. The chosen machine vision cameras are designed to accommodate the requirement of precise timing, ramped imaging, and specialized image processing software for great application performance. Such cameras are an important component of automated quality control systems. [37]

2. **Appropriate Image Processing Equipment:** This phase involves selection of relevant image capturing devices like cameras, image sensors and custom vision solutions designed for farm use. The type of camera used will depend on the task at hand, the environment and needs of the specific system. In order to ensure best image quality in this project, we have chosen to use Charge-Coupled Device (CCD) cameras, which are reputed for their low noise and quality image production. They are especially suitable for the applications little image quality oriented, such as scientific photography, microscopy; industrial inspection of high quality [38].
3. **Lens Filters and Covers:** To protect camera lens from possible damages and environmental dust, cover the camera lens with a lens cover or filter. It will be possible to eliminate the buildup from the water and dust by using a non-reflective material when coating the lens [39].
4. **Image Sensors:** CCDs are arranged in arrays in a grid like arrangement or a defined pattern. Every CCD sensor in the array takes part of the whole picture. CCD arrays are variable, being used for scientific imaging, astronomy, and design of high-tech digital cameras [40].
5. **Mounting and Positioning:** Choose the best places on the robot for camera and imaging vision placement for clear sight. Ensure that the cameras can provide a straight and no charge view of the crops and targeted areas. We place cameras on the robot's top, to ensure an unobstructed view, in our project [41].
6. **Connections and Wiring:** Include image-processing equipment in the robot's control system. Establish the cabling for signaling, sharing data and handling power on the system. A stable wiring can ensure seamless performance and data consistency [42].
7. **Calibration and Alignment:** It is therefore important to calibrate the image processing system to ensure the accurate and reliable picture recording and measurement. The precise alignment of lens and camera is highly crucial to get high quality and precise imaging. Calibration measures need frequent measures to verify the system's accuracy [43].
8. **Camera Settings and Parameters:** Adjust the exposure time, aperture, the focus and the camera white balance to achieve maximum image quality in your agricultural fulfilment. The adjustment of these settings could be made essential due to variations in lighting condition. Properly setting the system allows it to properly react to the change of situations [44].
9. **Software Integration:** Adopt or purchase a program to process images that is capable of handling and processing data generated from camera recordings. Subsequent to it, deploy a software, which is capable of monitoring the health of crops, detect pests, and identify weeds. Real-time assessments and decision-making processes are enhanced with state-of-the-art software integration [45].
10. **Testing and Validation:** To assess the effectiveness of the system for image processing, extensive testing should be carried out under conditions of laboratory and practical field research. The technology should be able to detect accurately the farming conditions and pests, and respond appropriately to such observations. Much testing is required in order to diagnose and remedy any issues before the system is fully launched [46].
11. **Maintenance and Repair:** Create an upcoming maintenance plan for the correct running of the image processing system. Calibrate frequently to verify continuous accuracy in the system. System performance and durability can only be maintained over the long-term by regularly performing maintenance [47].

With the installation of an image processing system, the robot can then receive, interpret and control visual input on the fly. By adding this feature, the robot's ability to estimate the health of the crops, and to identify pests and diseases among them to make some changes in order to improve the precision agriculture methods is greatly supported. The robot must be set-up and maintained accurately to ensure it functions properly, this will promote the adoption of sustainable and efficient agriculture methods. Through monitoring and treating crops, the robot helps the production of healthier plants, higher crop yields. Quick seismological response to pests and diseases reduces crop loss rates. Continuous monitoring and treatment of crops result in an increased quality factor of crop. Making the illumination more uniform, accurate spraying methods and the identification of problems before they get worse are all some of the factors resulting in improved quality of crops.

3.7. High-Pressure Sodium (HPS) Lamps

When it comes to a precision agriculture robot being in the position to provide nighttime artificial lighting to crops with the use of HPS lamps, the planning is of a meticulous nature and the execution is careful. Strong management of artificial lighting, water, etc., through the robot helps achieve sustainable and environmentally responsible agriculture. Do the following steps to install HPS lamps in the robot:

1. **Lamp Fixture Selection:** Choose an HPS light fixture that can accommodate the robot's structure as well as support the HPS lamp tight. An effective fixture guarantees that lamp weight is evenly distributed and has got a good electrical connection [48].
2. **Mounting Position:** What area of the robot is most ideal for the HPS light fixture? Make sure that the entire crop gets the light evenly. Bear in mind the robot's movement and its flexibility in terms of the adjustment of the angle or the height of the lamp [49].
3. **Power Supply Infrastructure:** To make the HPS light capable to work properly, it is crucial to ensure that the robots are getting necessary amount of electricity. As HPS lights need great number of electrical currents, it is necessary to pay close attention to safety measures and connections. Therefore, it is crucial to install a reliable source of power for lamp overnight [50].
4. **Wiring and Connections:** Turn the HPS light fixture on by having it interfaced with the electrical components of the robot. Properly fit the HPS light with safe and accurate wiring to provide a stable electrical link. Check all electrical connections for safety and fit all the safety and legal standards [51].
5. **Safety Measures:** Make electrical practices safe by installing barriers and checking the HPS lamp operates safely. Measures such as affixing safety covers, grounding the wiring, and posting of clear warning signs or markers are necessary [52].

Figure 1: Front view of 3D model

6. **Testing and Validation:** Completely test the HPS lighting system as a part of the facility to ensure its dependability. Examine the lamp in various operational situations in order to ensure that it outputs constant light and functions at its maximum capability. Establish whether the system is capable of effectively complementing light for crops during night [53].
7. **Maintenance and Monitoring:** Create an outline of planned maintenance plan to maintain the

HPS lamp system. Keep up the state of all components and fix wear or damage immediately by replacing required components. Monitor the lamp's functioning regularly to address possible problems quickly and to maintain the sustainable operation [54].

After these installation guidelines and thoughtful deliberations, the precision agriculture robot is able to take advantage of HPS lamps to make up it loses during night time and a larger crop yield and output can be seen. By doing so, the precision agriculture robot will be able to accurately exploit the HPS lamp to enhance additional nighttime lighting to crops to facilitate an increased growth and productivity.

4. Results and Discussion

The AI-based systems could be practically employed in various farming fields i.e., from small to large-scale farms. The subsequent subsections depict its viability:

4.1. Cost and Accessibility

The system reduces costs by using readily available materials such as HPS lamps and NVIDIA Jetson Nano for real-time monitoring of pest infestation. Small scale farmers can adapt to modular versions of the system and would be able to incorporate only vital components such as pest detection and pest spraying and reduce costs.

4.2. Scalability *y*

Scaling up the system would be possible for large farms through multiple units working all together. The central monitoring system is helpful in managing many units, which is very advantageous to the large farm operation.

4.3. Ease of Maintenance

The design guarantees that the components are reliable with low requirement for maintenance. The system offers rapid, automated notification to farmers in case of faults, complementing reliable continuous use.

4.4. Farmer Training and Support

Farmer training exercises and readily available guidebooks will guide the farmers on the use of the system. All in all, complete after-sales service and technical refinement advice will guarantee that farmers will be able to address issues and adjust the system according to certain needs.

4.5. Energy Efficiency

The system includes real-time adaptive lighting and spraying technologies that help save both energy and resources automatically according to different conditions. The use of solar power is a primary strategy of enhancing environmental sustainability of the system, especially with respect to farmers off the main electrical network.

4.6. Field Tests and Results

The effectiveness of the system was established early, with its field tests confirming a 40% reduction in pesticide utilization and 25% increase in crop yield, clearly not an unattractive system. These results highlight its potential

4.7. Context-Specific Adaptations

The system is flexible to fit specific needs of various crops and environments. Calibrating the spraying parameters to suit the types and densities of pests, the mechanism guarantees optimal pesticides use. Through cost management, scalability, maintainability, and flexibility, the proposed system demonstrates the ability to address the existing needs in agriculture, as specific demands of farming communities are satisfied. A farm can best use the robot with a spray system, HPS lamps, image processing, and machine vision systems if the robot follows a specific workflow. The functioning of the robot in a farm is briefly discussed below.

4.8. Navigation and Localization

The robot comes equipped to autonomously traverse the field with GPS, sensors, and computer vision, thereby preventing it from encountering any impediments. As soon as the field is marked out with the help of localization mechanisms, the robot may manage to localize itself in the field precisely, and it ensures that when tasks are performed, it is done with maximum accuracy.

4.9. Data Collection and Image Processing

As the robot circuits around the field, the image processing system continuously receives photographs of the crops. The image processing program analyzes these images in real-time to find out about crop health, growth stage, and pest or disease infestation.

4.10. Decision Making

In relation to the data collected and assessed, the inner computer of the robot makes decisions on specific activities. For instance, if it senses signs of insect infestations or disease, it could trigger the spraying system to control the issue. When pests or diseases are detected, the robot activates the spray system. The spray system features nozzles that accurately dispense pesticides or treatments to targeted areas, minimizing chemical use and providing sufficient coverage.

4.11. HPS Lamp Operation

When the robot works at night or in dim light, it activates the HPS lights. The lamps provide artificial light for the crops in order to excite growth and photosynthesis and extend the photoperiod whenever necessary. The connection between daylight and the ontogenetic periods of plants like wheat is extremely important and stipulates most factors of their ontogenesis: Light stimulates seed germination, with root and shoot growth. But direct sunlight is not always necessary during the initial phase. Once plants reach the vegetative stage, sunlight is needed for photosynthesis. Photosynthesis generates energy and facilitates structural growth, forming leaves and stems and expanding plant life. Sunlight is necessary during reproductive stages like wheat flowering and grain filling. It encourages the development of reproductive structures and results in healthy grain filling. Poor sunlight in these periods might affect the quality and production of grain. Plants, nearing maturity, need proper sunshine to enable the final stages of growth and ripening of grain. Good exposure during this time fosters good grain growth and quality. Every stage of development requires various sunshine requirements. Proper management of solar exposure is essential for optimizing crop production, quality, and health. Excessive sunshine, however, tends to stress the plants and inhibit their growth, especially at hot temperatures or critical growth stages. Therefore, management of solar exposure to every development stage is vital to maximize growth and production as well as minimize crop damage.

4.12. Machine Vision and Path Planning

The machine vision system continuously monitors the field and provides input to the robot path-planning algorithms. The robot has the ability to adjust course in real time to miss damaged or unhealthy sections of crops while also optimizing spray and light distribution.

4.13. Data Logging and Reporting

During operation, the robot logs crop conditions, treatments, and environmental factors. This data can be used to analyses performance, optimize, and report for making future farming decisions. A central control system enables farmers or agricultural experts to remotely track and control the working of the robot.

4.14. Safety Features

The robot is equipped with safety features to prevent accidents with obstacles and safe working in the field.

4.15. Battery Management

The power source of the robot, typically a battery, is checked to make sure that it has sufficient charge to complete its tasks. When the battery charges are low, they will be replaced and sent for charging.

4.16. Maintenance

The robot and its parts, including the spray system and HPS lights, need to be regularly maintained to keep it in top working condition. This combined system allows the robot to maintain crop health on its own and wisely, manage pest and disease issues, and provide extra light at night or in low-light conditions. It optimizes the use of resources and minimizes the need for human work in the field. The capabilities of the robot can greatly enhance crop yield and quality while decreasing the environmental impact of farming practices.

5. Conclusion

In the face of contemporary farming where sustainable and high-yielding production of crops takes center stage, the growth and benefits of our AI-powered smart lighting and insect detection system mark a landmark progress. Such advanced system involving smart lighting solution paired with live insect detection and feedback has already proved to deliver potential solutions in terms of confronting the challenges posed by precision farming. By maximizing crop growth while minimizing the use of pesticides and environmental destruction, we have demonstrated the value of this multi-faceted approach. Going forward, subsequent research will build on system advancements and the implementation of other AI features to evolve the discipline of precision agriculture and encourage sustainable farm practice.

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