Research Article

Application of IoT-Based Drones in Precision Agriculture for Pest Control

Mohamad Reda. A. Refaai,1 Vinjamuri SNCH Dattu,2 N. Gireesh,3 Ekta Dixit,4 CH. Sandeep,5 and David Christopher6

1Department of Mechanical Engineering, College of Engineering, Prince Sattam Bin Abdulaziz University, Alkhurj 16273, Saudi Arabia
2Department of Mechanical Engineering, Aditya Engineering College, East Godavari, Andhra Pradesh, India
3Department of Electronics and Communication Engineering, Sree Vidyanikethan Engineering College, Tirupati, Andhra Pradesh 517501, India
4Department of Computer Science and Engineering, S. S. D. Women’s Institute of Technology, Bathinda, Punjab, India
5Department of Computer Science and Artificial Intelligence, SR University, Warangal, Telangana, India
6Department of Mechanical Engineering, College of Engineering, Wolaita Sodo University, Ethiopia

Correspondence should be addressed to Mohamad Reda. A. Refaai; drengrefaai@gmail.com and David Christopher; david.santosh@wsu.edu.et

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Unmanned aerial vehicles (UAVs), commonly known as drones, have been progressively prevalent due to their capability to operate quickly and their vast range of applications in a variety of real-world circumstances. The utilization of UAVs in precision farming has lately gained a lot of attention from the scientific community. This study addresses the assistance of drones in the precision agricultural area. This paper makes significant contributions by analyzing communication protocols and applying them to the challenge of commanding a fleet of drones to protect crops from parasite infestations. In this research, the effectiveness of nine powerful deep neural network models is measured for the detection of plant diseases using diverse methodologies. These deep neural networks are adapted to the immediate situation using transfer learning and deep extraction of features approaches. The presented study takes into account the used pretrained deep learning model for extracting features and fine-tuning. The deep feature extraction characteristics are subsequently categorized using support vector machines (SVMs) and extreme learning machines (ELMs). For measuring performance, the precision, sensitivities, specific, and F1-score are all evaluated. Deep feature extraction and SVM/ELM classification generated better outcomes than transfer learning, according to the analysis result. Furthermore, the analysis of the various methodologies tries to assess their effectiveness and costs. The different approaches, for example, confront difficulties such as investigating the region in the shortest possible time feasible, while eliminating the same region being searched by more drones, detecting parasites, and stopping their spread by applying the appropriate number of pesticides. Simulation models are a significant aid to researchers in conducting to evaluate these technologies and creating specific tactics and coordinating procedures capable of effectively supporting farms and achieving the aim. The main objective of this paper is to compare the search techniques of two distinct methods of parasitic to identify performance.

1. Introduction

Agriculture, which is a major source of income for several countries, meets two of humanity’s most fundamental requirements: food and fiber. Agriculture had changed dramatically over the last decades as a means of technological developments like the Green Movement. Agricultural research focuses on a variety of topics, including livestock management, commodities, and water depth. The drones’ ability to execute these duties is due to a variety of sensors
and devices on deck. In recent decades, modern developments have revolutionized sector managers to deal with a variety of risks, including pests and abrupt climate variability, which can significantly impair the crop or the quality of agricultural products. Because the drones have restricted fuel and pesticide supplies, they can seek assistance from other drones to accomplish pest removal. Some enrollment techniques, focused on bio-inspired ones, have been attempted to address these last concerns.

During the 1960s–1980s, the Green Revolution, also known as the third invention of agriculture, crop improvement varieties, synthetic fertilizers, pesticides, and irrigation, resulted in increased crop food production and food stability, particularly in poor countries. As a result, even though the world’s population has doubled and food production has tripled during the 1960s, agricultural production has already been responsive to the demands with a 25% increase in agricultural land.

By 2050, the consumption of agriculture and food goods is expected to rise by more than 75% [1]. Given the scarcity of arable land, agricultural expansion, or the greater use of fertilizers, insecticides, freshwater, as well as other resources, will meet a major portion of this increasing demand. However, increased agricultural input consumption has negative consequences for the ecosystem, including groundwater extraction, diminished surface streams, and eutrophication. Excessive and/or ineffective usage of environmental assets (such as water and soil), fertilizers, and insecticides for agriculture output results in economic damage as well as enhanced nutrient and water wastes, all of which lead to sustainable deterioration. The need to create approaches that could boost crop output through higher production quality and reduce environmental wastage for economic and ecologically responsible manufacturing systems [2].

Agriculture has been one of the areas that make use of the Internet of Things to promote smart cultivation. A wide range of plant behavior research and understanding is required to cope with changing climate and to understand exactly crop production in specialized small-scale habitats. The word itself implies that the Internet of Things paradigm will usher in a mechanical cosmos in which everyday instruments and equipment will be enhanced with the help of computing capabilities. Sensing, as well as network and system capabilities, would be included in these devices. To look at it another way, physical items that may be assigned as “things” will be able to operate as solitary units or as a fusion of concerted action from disparate devices. Drones could be used to optimize crop choice, availability of water, fertilization, and insecticides in farming. Drones will aid in the lowering of overall agricultural manufacturing costs while also ensuring decent yield and grain quality [3]. Different challenges arise as a result of the growing population and agricultural production. Drones are being utilized in improved agricultural productivity, precision, and the capacity to overcome challenges, as well as to boost precise measurement, real-time information gathering, and productive farming development. Producers could distinguish between high and poor-yielding plants on the farms by employing drones. In agriculture, IoT mostly aids producers in bridging the gap between demand and supply. IoT concepts have been applied to drone farming, and it has the potential to increase the area [4].

Naturally, the responses to these issues rely on quick and efficient manufacturing. Robotics, computer programming, machine intelligence, the Internet of Things (IoT), and other technologies could help smart farmers create smart, effective, and rapid goods. Precision agriculture attempts to create valuable outcomes for comprehending the soil and also to gather and process data from different sources using information and communication technology (ICT) solutions. Humidity, Irrigation, pesticides, vegetation, and other variables change over time and location, necessitating ongoing product assessment in regards to watering and spray. This method attempts to utilize agricultural chemicals better effectively, conserve fuel and commodities, avoid agriculture pollution, employ smart technological solutions, and produce environmentally responsible goods in this manner. Every one of these factors has a substantial impact on crop yield. Precision farming, in this sense, could combine different analytical techniques and technical instruments that are relevant to all steps of manufacture, from planting to harvesting [5].

Precision agriculture (PA) is rapidly gaining traction in today’s modern technology-driven world, and it is been dubbed “the farmer of the century.” This is a computerized farming administration approach that uses advanced technologies to monitor and optimize agriculture manufacturing activities. To improve farm productivity, PA employs current technology and concepts to regulate temporal and spatial variations in all elements of agricultural output. A variation that has a substantial impact on agriculture is referred to as spatial and temporal distribution. Soil variability, yield variability, crop variability, field variability, and management variability are all examples of spatial and temporal distribution. To accomplish these objectives, unmanned aerial vehicles (UAVs), sensor technologies, satellite tracking, location systems, and the Internet of things (IoT) is commonly utilized [6]. As it finds its way into farms throughout Europe, PA is rapidly assisting producers with their work. Larger harvests necessitate a larger capital commitment since they necessitate a higher proportion of fertilizers, insecticides, water, and other commodities. Producers, on the other hand, can save a lot of money by properly managing their expenses. Furthermore, in addition to improving output through careful monitoring, producers may improve plant performance and wellbeing at the same time, allowing them to accomplish things [7].

Figure 1 shows documentation produced by scientists, professors, and farmers during the previous 10 years, proving that PA is becoming more popular every day [8]. PA has developed a digital-based farm management model for monitoring and optimizing agriculture manufacturing processes. Wheat, rice, soybean, maize, barley, potato, orange, olive, and a variety of other crops have all used PA in their production, tracking, and harvest. The challenges of agricultural needs and desires are highlighted in this context. Drones to Improve Insect Pest Administration is a special
accumulation that showcases research and innovation of autonomous drones (or uncrewed) airframe scheme (UAS, or drone) advanced technologies for control of insect pests, ranging from identification and demarcation of insect infestation harm and pest ecosystems to delivering of microbes and equipment to alleviate pest fears. The articles range from more fundamental research (testing and enhancing drones’ capacities to identify pest issues or transport pest control products) to test hypotheses (operational potential and problems of drones utilized n pest control systems) [9].

To sense the presence of insects and pests on farmland, remote-sensing technology such as satellites and UAVs are used to locate predatory insects and quickly notify farmers of the situation. The benefits of agriculture sensing technologies based on satellites, known as high-altitude remote-sensing technologies, include a large tracking area, fine responsiveness, a short return interval, and low cost. A satellite device, on the one side, could span a large region and is useful for a variety of disaster tracking. Satellite surveillance, on the other side, is weather-sensitive and also has a lower resolution, making it more difficult to fulfill this need for pests and pest tracking in agricultural areas [9]. Identification technique based on drones or unmanned aerial vehicles (UAVs), known as low-altitude distant location technologies, is now commonly used in modern fields, ensuring high reliability of obtained data. Whenever drones are being used to indicate the existence of insects and pests, agricultural diseases and pests monitoring must be standardized and digitized. Nevertheless, a drone on a distant large-scale farm confronts issues such as short flying time and regular charge change due to its restricted carrying mass and storage capacity. These qualities now influence the development and use of drones in modern farming [7].

Convolutional networks are effective as fundamental deep learning techniques in several plant disease diagnosis investigations. The research employed the LeNet design as a fully convolutional to categorize picture collections, which allowed it to distinguish between normal and infected banana leaves. Learning techniques perfectly alright by learning algorithms have been used to assess these [4]. A database of 54,305 photos of sick and normal leaf tissue has been used in the study. AlexNet and GoogleNet networks based on a thorough CNN were used to assess their effectiveness in identifying 14 different crops and 26 illnesses. They created a novel prevention and detection method that included seven different disease categories. They employed CNN-based classification techniques, an accuracy rate of 82.3% using a four-fold cross-validation technique. Using a deep convolutional neural network, they suggested a new method for recognizing 13 multiple variations of plant illnesses. They created a strong profound sensor that could identify 9 distinct vegetable diseases and pests instantaneously [10].

Antibiotic resistance is posing a growing challenge to the successful management and cure of a wide spectrum of human infections. To prevent cross-resistance, newer and better medicines with unique different mechanisms of action are urgently needed. Existing fibroblast pharmacological screens, on the other hand, are limited to basic live/dead data logging with no mechanisms of effect prediction capability [11]. The use of learning algorithms approaches to increase the extraction of information using visual input is becoming more common. Unfortunately, these techniques struggle with varied biological morphologies and typically necessitate time the world training. Combining human or human and computer data for training from mixed human Plasmodium species farms, researchers proposed a semi machine learning approach.

2. Related Work

With the rise of big data technology and information computers, machine learning has opened up new possibilities for information research in the multi-disciplinary agri-technology arena. Researchers offer a complete assessment of studies on machine learning techniques in agricultural systems in this study. Crop leadership included applications on yield prediction, detection of diseases, weed recognition, grain quality, and features are available; livestock organization included application forms on animal protection and animal agriculture; wastewater reuse included implementa- tions on irrigation systems, and soil compaction included implementations on soil quality. The materials offered have been filtered and classified to show how machine learning management systems will assist farming. Agricultural production solutions are turning towards real-time artificial intelligence empowered software that would provide comprehensive suggestions and analyses for farmers’ decision-making and activity by using machine learning to sensor information. In the research of machine learning for the detection of pests, they fail to detect the pests and different weeds that cause damage to the yielding crops proposed by [12].

The possibility of machine learning techniques for weeds and agricultural categorization from drone photos is investigated in this research. Weed detection in fields is a tough challenge that has been tackled by using ortho-mosaicing, extraction of features, and picture labeling to train machine learning systems. The effectiveness of multiple machine learning approaches, including support vector
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machine (SVM), random forest (RF), and k-nearest neighbors (KNN), is examined in this research to identify weeds utilizing drone photos gathered from an Australian chili farm field. Precision, accuracy, recall, false-positive rate, and kappa statistics were the assessment criteria utilized to compare the performances. The machine learning techniques are simulated in MATLAB, and the obtained weed identification prediction accuracy is 96% utilizing RF, 94% using SVM, and 63% using the classification technique. According to this research, the random forest algorithm and support vector machine are efficient to utilize and could be simply deployed for weed detection in UAV photos. The major drawback of early weed detection is they could only detect the weed among the crops and the time consumption is high when compared to other techniques [13].

The Internet’s excellent technologies and widespread agricultural conversion and upgrade have improved the entire agricultural industrial chain and intensive farming. Due to the increasing price and hardship associated with the traditional agricultural planting planning, IoT devices are being used in agricultural production to enable real-time identification and intelligent management of crop development circumstances, navigation systems, and a shift in traditional agricultural device planting methods. The goal of this paper is to develop and study an intelligence agricultural IoT automation solution. This paper begins by providing an introduction to IoT fundamental concepts before moving on to the core technologies of the Internet of Things. The present challenges and inadequacies are assessed in conjunction with the present state of agriculture mechanization in the nation. On this foundation, augment and strengthen it with an IoT technology platform. The general scheme design, modules functionality layout, and AC method realization of the IoT braking control scheme are fully detailed in this paper. And conduct a study on the subject of the article using investigation, comparative evaluation, and other research techniques. The greenhouses sample information is picked as the sampling, the appropriate initial function is chosen, and the proposed fuzzy rules acquired by the training of the fuzzy neural network method are reasonably right, according to experimental research. The automatic temperature control system’s output result is largely compatible with the real data on-site. Generally, the heat AC system proposed in this paper may match the agricultural AC criteria. Based on the research it is noted that the technology could not stand the high temperature in the field and this is considered the limitation of research proposed by [14].

The articles range from more basic research (testing and enhancing drones’ capacity to identify insect issues or distribute pest control products) to case studies (identifying challenges and opportunities of UAV use in pest control schemes). The selection also aims to spark debate about JEE’s position as a publishing venue for future posts on the drone, as well as many other cyber-physical devices, big data analysis, and deep learning processes. Whereas these techniques originated in sectors that are undoubtedly unrelated to entomology, we believe that the interprofessional approach is the best path for the implementation of technology and research transmission, resulting in a faster pace of research and innovation of these innovations to enhance pesticides. Drone to enhance insect pest control is a special compilation that showcases research and innovation of unmanned aviation systems (unmanned aircraft systems, or drones) technologies for the control of insect pests. The selection also aims to spark debate about JEE’s position as a publishing venue for future posts on UAVs, as well as many other cyber-physical devices, big data analyses, and profound learning processes. Whereas these techniques originated in areas that are undoubtedly unrelated to anthropology, we believe that an interdisciplinary team is the best path for applied research and technology transfer, resulting in a faster pace of research and development of these innovations to enhance pest management. The article failed to improve the robustness of the drone, hence, a lot of enhancement is needed in the drone usage proposed by [15].

Artificial intelligence (AI) has lately made an appearance in the agriculture industry. Inadequate fertilization, pest and disease infestations, massive data demands, reduced performance, and a gap in knowledge among farmers and technologies are just a few of the issues the industry is facing to increase its production. The adaptability, excellent quality, precision, and expense of AI in agriculture are the primary elements. The implications of AI in soil conservation, cultivation practices, weed control, and disease organization are discussed in this study. A significant emphasis is placed on the application’s advantages and weaknesses, as well as how to use expert systems to increase productivity. Because they could offer site-specific, linked, and interpreted guidance, expert systems are useful tools for crop cultivation. Expert systems for farming, on the other hand, are a relatively discovery, and their usage in agricultural production is still uncommon. While AI has improved the farming industry significantly, it does have a lower-than-average influence on farming production as contrasted to its possibilities and effects in those other industries. There is still work that can be done to improve farming production utilizing AI because it has many limitations [16].

3. Methodology

In this research, precision agriculture for pest control is detected using the IoT application. The main aim of the research is to control the pest in precision agriculture using unmanned aerial vehicles (UAV). At first, the detailed account of precision agriculture is described and then the pest classification is done using the pretrained deep learning model and transfer algorithm. Following the pest classification, the researchers used the pest search algorithm and drone communication to eradicate the pest in three different cases. Finally, the performance evaluation is done for both the proposed method.

3.1. Precision Agriculture. In recent years, smart farming and precision agriculture have sparked even more interest. New information and communication technology enable new options for active tracking of farmland, cattle, and water infrastructure, with the ultimate goal of reducing living
being. Among the most significant aspects of precision farming are managing resources [17]. Making better use of resources encourages better performance. Image-based measurements and smart data mining are necessary to obtain additional information and expand understanding of the situation. Drones may capture aerial photographs of agriculture fields and animal farms. Precision agriculture reflects the efficiency and productive utilization of restricted input and produces impactful output. It is a fresh approach to using digital technologies to enhance agricultural methods. The characteristics and geometries of smart agriculture are evolving as a result of many technological advances. IoT, meteorology, and advanced analytics technology are all key trends. In all industries, the Internet of Things does have a massive effect; it provides additional technologies. It refers to innovative ways for academics to put their research into practice. It enhances the productivity of operational functions in particular. It is an implementation of farming in agriculture. It enabled, for instance, the collection of actual field information on soil and air temperature. Aerial imaging, drones, and spacecraft are used as precision farming tools on a wide scale. Researchers used machine learning and statistical analysis to positively influenced decisions to make precision farming more viable, dependable, optimized, and efficient. Detection of pests in farmlands is yet another key subject of study and implementation situation in which video review may aid in the development of plantations. The proper identification of this type of plant is still a work in progress. Herbicides are the most commonly used method for controlling weed infestations [18]. Drones are employed in precision agriculture to detect plant development data, soil humidity, fertilizer in the field or to release precisely and precisely inside the ground has been adjusted for diseases, parasitic infections, or harvest monitoring. UAVs are commonly used for surveillance, dusting, and crop insurance surveys. The utilization of a UAV outfitted with a high-resolution camera is widely used to survey an area of interest.

4. Proposed Method

4.1. Deep Learning and CNN Model (Pretrained). Deep learning is a class of machine learning techniques that learns data properties by using mathematical models made up of numerous processing elements. Attention to this topic has resulted in the growth of substantial-high successes in fields including such recognition and classification utilizing machine learning. Such algorithms have lately been applied in a variety of applications, including voice recognition, optical object recognition, and object detection. While the first research on deep learning had a long record, the production of vast data and the development of powerful processors with massive scale storage are the major reasons for its current advancement. Again, for the problem of crop disease detection, this research evaluates alternative ways of the nine more effective designs of deep learning techniques. The AlexNet design is a deep learning system with 25 levels and parameters that could be learned on only eight of them. The GoogleNet design, which is predicated on a network-in-network technique, employs design components that retrieve distinct local features using multiple convolution layers simultaneously. The Oxford Visual Geometry Group (VGG) developed the VGG system, which is a homogenous structure that was utilized to improve outcomes in the ILSVRC-2014 contest. They created the ResNet network to train systems with even more complexity.

Standard successive networks like VGGNet and AlexNet vary from in this structure, which is based on micro-architecture components. Research presented the Inception system as a form of the CNN model. There are a lot of convolution and max-pooling phases in this system. This has a fully linked computational model in the final step. The remaining interconnections and structure of the network of the InceptionResNetV2 system were predicated on the Inception-based underlying network [20]. Although InceptionResNetV2 operates roughly identically to other Inception designs, it achieves sufficient training speed by using convolution layers. SqueezeNet is a smart structure developed by research that delivers AlexNet-level accuracy on ImageNet with 50 times fewer variables. Table 1 summarizes the parameter utilization properties of various designs.

4.2. Classifier. In this research, the standard classifier technique of the support vector machine and the extreme learning method are utilized to design deep features from a specific layer of the pretrained deep network.

4.3. Support Vector Machine. Support vector machine is a statistical training theory-based technique invented by Vapnik. The goal of the SVM approach is to create a linear discriminant functional with the biggest marginal dividing the groups. Support vectors are the training data that are nearest to the hyper-plane. Support vector machine can discriminate between linear differentiated and undifferentiated large datasets [21]. This classification is used to address issues in a variety of fields, including image and item identification, speech recognition, fingerprint recognition, and handwriting recognition.

4.4. Extreme Learning Machine. ELM is a research-based learning method for Single Hidden layer Feedforward Networks (SLFNs). In ELM, outcome values are adjusted using the least-squares method, whereas hidden state values are produced randomly. ELM can be described using the equation provided in equation (1)

$$\sum_{\alpha \in H} a_u(x_u \ast y_v + g_u) = Z_v, v = 1, 2, \ldots, J,$$

where \(y_u, z_v\) denotes the input and output, the number of the training sample is denoted as \(J\), and \(\alpha\) is the weight input and the hidden layer is denoted as \(\alpha\). \(Z = T T^T\) can be represented in the matrix if the output of the network implies
Table 1: Parameter utilization.

| System          | Deepness | File size | Variables | Data capacity |
|-----------------|----------|-----------|-----------|--------------|
| Inceptionv3     | 46 s     | 87 Mb     | 23.8      | 299 × 299    |
| AlexNet         | 16       | 228 Mb    | 62        | 228 × 228    |
| VGG19           | 19       | 535 Mb    | 144       | 224 × 224    |
| InceptionResNetv2 | 164     | 209 Mb    | 55.9      | 299 × 299    |
| VGG16           | 16       | 515 Mb    | 138       | 224 × 224    |
| ResNet101       | 101      | 167 Mb    | 44.6      | 224 × 224    |
| SqueezeNet      | 16       | 4.6 Mb    | 1.25      | 228 × 228    |
| GoogleNet       | 22       | 27 Mb     | 7         | 224 × 224    |

4.6. Transfer Learning. Transfer supervised machine learning method that uses information gained from a model generated to solve an issue as a preliminary step for tackling a different challenge. Pretrained models convolution neural network models are developed based on transfer learning and were used in the present study to fine-tune the approach. The advantage of employing pretrained convolution layers over convolutional networks with random initialization parameters is that they have been faster and more efficient to learn [23]. Furthermore, rather than moving the last three levels of the pre-trained model’s networks to their categorization job, the fine-tuning process is based on the transfer extra layer, as seen in Figure 2, and it is shown in Algorithm 1.

4.7. Feature Extraction. Deep extracted features are focused on features extracted from a deep learning model that has been pretrained. Machine learning classification is performed using these parameters. To put it another way, this approach works by extracting feature representations from the fully-connected level of pretrained models’ networks. Effective deep characteristics were retrieved from ResNet50, ResNet101, InceptionV3, GoogleNet, InceptionResNetV2, and SqueezeNet and fc1000, fc1000, forecast, predictions, and pool10, accordingly, from a specific layer of deep learning models [25].

As seen in Figure 3, the generated deep features are used in the classification stage by employing standard models such as SVM and ELM as shown in Algorithm 2.

4.8. Pest Moving Algorithm. The pest can be transported in a variety of ways, such as randomly determining routes or searching for crops. Irrespective of the activity of other insects, the pest is led by the existence of vegetation when traveling. It has a restricted view of the area in which it is located [26]. If a pest is attached to a host, it will keep feeding till the plant dies. Rather, if it is in a part of the pitch where there are no plants, it goes in quest of one.

Pests can be identified in three different situations when performing mobility:

(i) If the pest could see more than one plant, it could pick which one to attack

(ii) If the pests could see a plant near it, this would target it; if it can have seen more than a plant, it would choose one to attack

(iii) If no visible region around the insect includes a plant, it will travel until it discovers one

Drones employ a distributed approach for pest search that is controlled by message passing. Every UAV has a storage that is utilized to store records about already visited attractions (which is encrypted and kept in this storage). At each passage, the drone maintains its mapping by inputting additional information (such as the existence of normal or sick crops) and discarding inaccurate data. This mapping aids the UAV in determining the next course of action. In addition, to save time and attention, the drones will not return to an area that has already been examined and sterilized. As a result, the next path is selected at random from nonunknown places. The drone then selects a traveling orientation and a distance [27]. Naturally, the locations nearest to the drone which have yet to be examined will be prioritized. The drone takes account of its original orientation in place to avert returning to it if it chooses this path. To recreate the overall map, UAVs communicate local views of the map. The drone’s information mapping can be shown
as a grid of regions with the drones in the center as illustrated in Figure 4.

The distance covered by the UAV determines the shift at each move. The drone’s database is shared with neighboring drones within the Wi-Fi distance, allowing these drones to learn about regions explored by the other UAVs without having to visit them individually. This cuts down on time complexity and eliminates waste. The transfer of these images can take place regularly or in response to map changes. Whenever a UAV receives a mapping from some other drone, it adds the data to its database [28]. This distributed approach employs a distributed search message, which contains information about an original thought field region. From every new location, knowledge must be memorized in every drone to store information that is connected to that region in its memories, which is represented by a distributed search message. This implies that drones swap DSMs in interchange for their existing mappings. Distributed search message is 25 bytes in size. The location of the region is represented by the A and B field values. Each region is depicted by 10 square meters with these dimensions according to the square’s northwest orientation. In the Time to Live field, the deadlines data are shown in milliseconds (Table 3) [29].

The State field, on the other hand, refers to the region that is being considered as:

(i) Lack of plants and lack of pests: “0000000”
(ii) Existence of plant health: “0000001”
(iii) Existence of a pesticide-treated plant: “0000010”
(iv) Existence of an infected plant: “0000011”
(v) Despite the lack of a plant, pestered present: “00000100” the remaining combinations will be used for future projects.

4.9. Drone Communication. The drone that produced the package will send it to the targeted drone or all drones. Upon reception, the kind of packet influences the drone’s implementation of a certain process based on the type of

| S. no | Type               | Training set | Testing Set | Overall |
|-------|--------------------|--------------|-------------|---------|
| 1.    | Shot Hole          | 550          | 50          | 600     |
| 2.    | Blossom Blight     | 72           | 14          | 86      |
| 3.    | Oak root fungus    | 65           | 8           | 73      |
| 4.    | Plum lecanium      | 312          | 33          | 345     |
| 5.    | Black Cherry Aphid | 180          | 20          | 200     |
| 6.    | Bacterial canker   | 130          | 15          | 145     |
| 7.    | Fire Blight        | 190          | 20          | 210     |

Figure 2: Transfer learning Schematic Diagram.

Figure 3: Traditional classifier and feature extraction schematic diagram.

Table 2: Data of pest disease collection.

| S. no | Type               | Training set | Testing Set | Overall |
|-------|--------------------|--------------|-------------|---------|
| 1.    | Shot Hole          | 550          | 50          | 600     |
| 2.    | Blossom Blight     | 72           | 14          | 86      |
| 3.    | Oak root fungus    | 65           | 8           | 73      |
| 4.    | Plum lecanium      | 312          | 33          | 345     |
| 5.    | Black Cherry Aphid | 180          | 20          | 200     |
| 6.    | Bacterial canker   | 130          | 15          | 145     |
| 7.    | Fire Blight        | 190          | 20          | 210     |
Stage 1: Data set of crops in the field is collected
Stage 2: The data size is resized based on the deep network utilizing bilinear interpolation.
Stage 3: By the use of a fully-connected layer of deep learning algorithm the features were extracted.
Stage 4: Using the support vector and extreme learning machine the classification is performed.

Algorithm 1: Proposed Transfer Learning Algorithm.

Algorithm 2: Proposed Feature Extraction Algorithm.

Table 3: Distributed search message.

| A direct | B Direct | Time to Live | Stage |
|----------|----------|--------------|-------|
| 8 Bytes  | 8 Bytes  | 8 Bytes      | 1 Byte|

packets transmitted [30]. Drones communicate with each other for three basic purposes:

4.9.1. Enrollments. When a UAV detects a pest and one of the following circumstances applies, it transmits a call for assistance over the Internet. (a) The pest container is low; (b) The residual battery’s capacity, except for the reserves, is such that it can only approach the base for recharging.

4.9.2. Transferring Data of Previously Performed Identification. The drones can communicate about their current states, such as the amount of insecticide left and the amount of energy they have left.

4.9.3. Transferring Data regarding Some UAVs Condition. The drones transmit messages on previously controlled territory periodically in order to prevent visiting the very same area multiple times and also to coordinate efforts the UAVs, speeding up a search and eradication of pests [31].

5. Result and Discussion

Throughout this research, they measured the effectiveness of nine powerful deep neural network models for the detection of plant diseases using diverse methodologies. The MATLAB deep learning package was used to carry out the experiments. All of the programs were run on a system with a dual-core Intel Xeon E5 processor and 64 GB of RAM. To examine the classification
performance of the feature representation, researchers employed the SVM and ELM techniques [32]. Again, for support vector machine classification variables, the research utilized a one-versus-all strategy and a quadratic SVM as the classification category. In particular, for the ELM classification characteristics, researchers utilized a sigmoid activation function as an activation function and a hidden layer neuron frequency. Researchers used a database including their plant pest photos to evaluate the suggested product’s effectiveness. There are several 1965 photos in this database, which represent eight different plant diseases. Pest disease data were gathered. A 10-fold cross-validation test has been used to evaluate the efficiency of the suggested approaches. In particular, we employed accuracy, sensitivity, specificity, and F1-score as performance metrics for experimental research categorization. Under the following subheadings, the obtained measurements and efficiency evaluations are presented.

5.1. Results Related to Deep Feature Extraction. For deep extracting features in this part, we use three different fully connected layers depending on pretrained models AlexNet, VGG16, and VGG19 models. Deep characteristics were recovered from the FCL [1], FCL [2], and FCL [3] layers for each of these systems. The efficacy of these features was then evaluated utilizing SVM and ELM techniques. Table 4 shows the accuracy rate of different experimental experiments. The expected total precision rating from across folds and associated mean and standard deviation have been used to assess those accuracy results [33].

The effectiveness of the deep feature extracted from the FCL [1], FCL [2], and FCL [3] levels in each of the AlexNet, VGG16, and VGG19 models was evaluated using SVM, ELM, and KNN approaches, as seen in Table 4. The FCL [1] layer was judged to have the best feature representations for these projections based on the precision ratings. Using the Support vector machine the maximum degree of accuracy for the AlexNet model was 95.5%. The accuracy rate for the VGG16 model using the Support vector machine classifier was 95%, whereas the precision value for the VGG19 model using the ELM classifier was 94.74%. Including these findings, AlexNet had the shortest training time of the three approaches for all fully-connected layers, whereas VGG16 and VGG19 had nearly similar training schedules. Table 5 also includes the sensitivities (Sens), specificity (Spec), and F1-score (FS) performance indicators for these experiments conducted.

In this part, the performance is the measure of pests eliminated over duration, place, and amount of recharging grounds. The simulation includes a set of fixed settings as well as a range of experimental factors. It has a graphical user interface (GUI) that allows you to adjust the model parameters to replicate a particular circumstance. The contrast between the randomized and distributed search algorithms would be illustrated in particular. As stated in Table 6, the two techniques are evaluated in three different scenarios.

The graphs (Figures 5–7) show that many Pest were destroyed in each of the 3 scenarios studied. Figure 5 shows

| Classification Algorithm | Support Vector Machine | k-nearest neighbor | Extreme Learning Machine | Time |
|--------------------------|------------------------|--------------------|--------------------------|------|
| VGG19                    |                        |                    |                          |      |
| FCL [1]                  | 95.46                  | 89.02              | 94.75                    | 1 min 16 sec |
| FCL [2]                  | 94.98                  | 87.95              | 94.39                    | 1 min 17 sec |
| FCL [3]                  | 91.76                  | 85.6               | 93.02                    | 1 min 20 sec |
| AlexNet                  |                        |                    |                          |      |
| FCL [1]                  | 95.5                   | 89.42              | 93.42                    | 30 sec |
| FCL [2]                  | 94.2                   | 89.02              | 92.30                    | 31 sec |
| FCL [3]                  | 92.3                   | 84.6               | 91.54                    | 35 sec |
| VGG16                    |                        |                    |                          |      |
| FCL [1]                  | 95.1                   | 88.56              | 94.85                    | 1 min 5 sec |
| FCL [2]                  | 93.8                   | 87.1               | 93.58                    | 1 min 6 sec |
| FCL [3]                  | 92.6                   | 84.8               | 92.12                    | 1 min 8 sec |

| Classification model | K-nearest neighbor | Support Vector | Extreme learning machine |
|---------------------|--------------------|----------------|--------------------------|
| Performance         | Spec Sens FS Spec Sens FS Spec Sens FS Spec Sens FS Spec Sens FS Spec Sens FS |
| VGG19               |                    |                |                          |      |
| FCL [1]             | 98.24              | 87.29          | 85.45                    | 99.20 | 92.23 | 92.48 | 99.24 | 92.68 | 93.05 |
| FCL [2]             | 98.24              | 85.44          | 82.70                    | 99.14 | 92.42 | 92.45 | 99.13 | 91.88 | 91.94 |
| FCL [3]             | 97.86              | 82.89          | 80.95                    | 98.80 | 89.35 | 94.11 | 98.98 | 99.99 | 90.64 |
| AlexNet             |                    |                |                          |      |
| FCL [1]             | 98.39              | 87.95          | 86.34                    | 99.36 | 94.35 | 94.59 | 90.01 | 90.76 | 91.30 |
| FCL [2]             | 98.34              | 87.06          | 84.88                    | 99.24 | 93.04 | 93.50 | 98.85 | 89.45 | 90.24 |
| FCL [3]             | 97.39              | 76.32          | 82.04                    | 98.79 | 89.62 | 90.03 | 98.72 | 88.22 | 89.32 |
| VGG16               |                    |                |                          |      |
| FCL [1]             | 98.01              | 86.55          | 87.34                    | 99.32 | 93.03 | 93.20 | 99.23 | 92.13 | 92.45 |
| FCL [2]             | 97.76              | 83.88          | 86.34                    | 99.13 | 91.92 | 91.70 | 99.09 | 91.52 | 91.98 |
| FCL [3]             | 98.41              | 82.62          | 78.04                    | 98.87 | 89.98 | 89.88 | 98.88 | 89.86 | 90.35 |
that the base amount increased from 32 to 48 units compared to the second version. Following these graphs, it is feasible to determine that to achieve excellent efficiency, it is required to adhere to the proportions shown in the first scene when the pests are nearly all eliminated.

As can be shown, drones that utilize the distributed search algorithm attain resolution significantly faster than those that employ the randomized selection method. Here the last two, in addition to ending longer, kill far fewer pests in all three scenarios. Furthermore, because the quantity of drones does not rise proportionally with the size of the field, plenty more pests will be active, causing crop difficulties. When looking at Figure 6, it is clear that perhaps the proportion of living pests is extremely low.

In Figure 7, however, the proportion rises due to the large field size; it is nearly four times larger than the first scenario, even though the bases are only tripled and the quantity of drones is increased from 20 to 35.

6. Conclusion

The outcomes of deep extracting features and transfer learning for the identification of plant pests and diseases were evaluated in this research. Both for deep extracting features and transfer learning, this research utilized nine powerful deep neural network designs.

(i) First, researchers gathered feature representations from these deep models’ fully-connected layers. SVM, ELM, and KNN classifications were used as performance parameters of the feature representation that were generated. These neural nets were then fine-tuned using photos of plant pests and diseases. Lastly, researchers used conventional techniques to evaluate the results of deep learning techniques.

(ii) As a consequence, the ResNet50 models and Support vector machine achieved the highest level of accuracy of 97.86%. Furthermore, the computed running time for deep extracting features and transfer learning development of deep learning models, as well as the proposed architecture based on thorough extracting features, were lower-than approaches that rely on transfer learning. For the experiments, researchers used three various situations with a base number, field dimension, pest number, and various numbers of drones.

(iii) The behavior of two alternative search algorithms, one based on random preferences and the other depending on a disseminated one, was demonstrated in the simulation sessions. The outcomes
showed the effectiveness of the various methods, demonstrating that the distribution method is more appropriate and suggested for pest combat.

Data Availability

The data used to support the findings of this study are included in the article. Furthermore, data or information are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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