Design of automatized disease detection and fertilization system for agricultural crops

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***Abstract*- The agriculture industry has a tremendous obligation to boost productivity and food grain output due to the expanding civilization and impacts of climate change. Agriculture mechanization has become the sole choice and is urgently needed in the majority of nations where expanding cropland is inconceivable. All industries, including agriculture, have already begun to profit from the Internet of Things and artificial intelligence. Through the development of intelligent algorithms that can track, manage, and visualize numerous farming production in real-time also with intelligence comparable to that of human specialists, advancements in these digitized innovations have brought about revolutionary advances in agriculture. The invention of smart farm equipment, irrigation facilities, weed and pest extermination, application of fertilizers, greenhouse development, warehousing structures, drones for crop protection, plant health management, etc. are some of the potential uses of IoT and AI that are explored in the study. Employing artificial intelligence and the internet of things, the article's major goal is to present an overview of the customized care given to crops depending on the issues that arise in the crops and to provide appropriate fertigation so that the crops may live and yield good results.**

Keywords— Artificial intelligence, Internet of Things, Crop Protection.

I. INTRODUCTION

Our culture has always placed a high value on the agri-food industry. It is crucial because it provides us with sufficient food to meet our population's ongoing nutritional needs. It is crucial because the effects of its activities on productive capacity, employment creation, environmental conservation, and the preservation of a liveable and balanced region are substantial. Data must be accessible on a farm in order to be analysed and used to provide knowledge and information that will aid producers in making decisions and managing their business operations. This includes more precise use of agricultural inputs, the ability to predict the disease outbreaks, pests, or weather occurrences and then implement responsive strategies to mitigate risks, the mechanization of jobs, and consequently a reduction in human error.

In this regard, artificial intelligence (AI)-based solutions have become an important tool by offering mechanisms and processes to make decisions about particular jobs in the agri-food industry. Several strategies have attempted over the past few years to provide AI tools, particularly machine learning approaches, for environmental sustainability in the farming industry. In [1,2,3], a more thorough examination and other reviews are offered.

The potential occurrence of diseases and pests is one of the elements that most affect crop production. Farmers frequently use phytosanitary products to lessen their influence. This will ensure output by controlling the growth of possibly hazardous communities. Herbicides are a part of this category as well because they stop competing plants from establishing among the primary crops and competing for nutrients and water.

Farmers frequently provide precautionary remedies because it is unpredictable when the insect will come and how severe it will be. The price of these therapies shows a distinct rising trend over the past few years.

Because there are so many different types of plants and so many different diseases that can impact them, early diagnosis of phytopathogens through manual and graphical checks by experts or farmers has some drawbacks, including the dependence on a small number of people and the possibility for error. Many advantages can be derived by automating disease detection using artificial intelligence techniques, particularly deep learning [4]. Early diagnosis leads to early remediation, which lowers the demand for chemical goods, saves money by minimizing production losses, and positively impacts the environment by eliminating the long-term use of toxic phytosanitary agents. The manual method takes a lot of time and is subject to human error, while AI automation provides a more effective and dependable alternative.

As a result, it has been increasingly common in recent years to apply artificial intelligence, especially deep learning approaches, to detect plant diseases [5,6]. These methods classify and analyse plants to find potential issues. It is normal practice to use satellite and hyperspectral photography for crop research and plant disease identification. While hyperspectral pictures offer a perspective further than the visible spectrum and enable for the use of tools like the NDVI index to assess greenness and spot crop concerns [7], satellite images provide an extensive perspective of the crop and land performance. The primary disadvantage of these methods is the high cost of the necessary hardware (cameras and satellites), as well as the interpretation of huge images.

Another strategy is to analyse and categorize closer images, like leaves or plant segments, in order to find potential diseases [8,9]. The majority of the examined ideas in this category offer cloud-based diagnostic technologies. One issue we can run into is the absence of internet access in some remote areas and the requirement to send big volumes of data to carry out the categorization in these web services. In this regard, the adoption of edge computing-based equipment that can identify illnesses without requiring access to web services and minimize repeated picture uploads over the connection may be more interesting. As a result, this study introduces an EDGE device that combines the required hardware and software elements to automatically identify plant pathogens from a collection of plant leaf photos. Moreover, using many photos simultaneously rather than just one improves the classifiers' robustness, as seen in the analysis performed.

II. LITERATURE REVIEW

A review of the literature that includes works that have been published. The IEEE Explorer, journals, and works cited in the listed papers were all used in the search.

Image analysis is one of the primary methods for automatically identifying plant diseases. This examination could concentrate on several elements, such color or geometry. Other indices are also frequently employed in some specialized types of photographs. As a result, the NDVI index, which gauges an image's amount of green, is employed for hyperspectral photographs. On the other hand, there are further alternative indices for visible range pictures, including the VARI index and the vNDVI index [11].

According to the review suggested in [12], there are various difficulties in automatically detecting plant pathogens. These difficulties might include interference or mist over the camera during the picture capturing process, or undesired data in the photos such backdrop, dirt, or other crops. Pre-processing of photos, such as background delineation, texture elimination (smoothing [13,14]), or even image improvement, is one method of addressing some of these issues (e.g., contrast improvement [15]).

A key hurdle is the possibility for numerous illnesses to exist in a single crop, in addition to material-specific problems that might occur during picture collection. Predictive diagnosis of plant pathogens requires categorization after image analysis, which may be done in two ways. In the first, a collection of characteristics from the photos are selected and extracted using traditional Machine Learning (ML) methods. These methods include Support Vector Machines (SVM) [16,17], K-Means algorithm [18], and Random Forest [19]. For these methods to be effective, a highly accurate human-made answer (ground truth) is required. Also, they need to function adequately with less data. Second, and presently one of the most used methods, is to develop a model to recognize the dataset classes using Deep Learning (DL) [20], notably Convolutional Neural Networks (CNN) [21,22]. As is widely known, the amount and quality of pictures accessible for use are only sufficient for understanding in a particular task. In certain circumstances, a connectivity founded on previously acquired knowledge and customized to the relevant job is built via transfer learning. Large datasets, like ImageNet, are used to pre-train these networks [23]. In this method, the very first tier of the learning algorithm is removed, the last layers are modified for the particular job, and only the final steps are learned. In this manner, the computation time is decreased, and the specific job does not require initial training. In the literature, Alexnet [24], ResNet50 [25], VGG16 [26], and Inception V3 [27] are the most popular and effective networks. As EfficientNet [28] has eight different subnet configurations, it may also be seen as a collection of channels.

Capsule Networks [29] offer an alternate strategy to the most common network design and address one of the major shortcomings of conventional CNN. CNNs treat comparable pictures as equivalent regardless of their differences, disregarding the potential attribute organization in an image. The Capsule Network technique is employed in the study reported by Samin et al. [30] without the use of Transfer Learning, yielding a reliability of 93.07%.
A lighter version of CNN has recently been developed [31] and is centered on Inception and Remnant connection. Better features are extracted from the input photos using the suggested method. This is accomplished by switching out the traditional convolution with a combination of a complexity separable convolution and a juncture convolution, which requires less parameters and speeds up computation. 99.39% accuracy is the final performance with the suggested technique.

After reviewing the state-of-the-art, it is clear that there are several recommendations now being made, the most of which are based on methods of deep learning and give promising outcomes using the datasets already available. Yet, there are several particular gaps that we believe need to be examined. On the one hand, certain studies imply that picture pre-processing is necessary before categorization; in our opinion, this feature should be researched more as it would enable an enhancement in the classification phase. Yet, the majority of the papers are assessed using an alleged perfect dataset. It would be feasible to analyze the potential resilience of current models by validating them using more realistic dataset. Ref. [32] takes an intriguing tack, but since they're dealing with infrared pictures, any real-world implementation would necessitate the exorbitant deployment of infrared cameras.

In addition to filling up the aforementioned holes, our goal is to create a solid model that can be used on an edge framework. In fact, our approach, which will be discussed in more detail in the next part, places equal emphasis on developing the mechanical framework to support it as well as the software.

III. PROPOSED SYSTEM

The proposed framework is composed of the following two modules:

1. The AI module is in charge of identifying diseases in crops by scanning their leaves.
2. IoT Module: Using the information from the AI Module, this module oversees fertigating the crops. For use, these two components need to be combined and coordinated.

To forecast crop diseases, the AI Module uses any of the possible techniques listed below:

1. learning strategy under supervision.
2. Method of unsupervised learning.
3. Technique of semi-supervised learning.
4. Method of reinforcement for learning.

In an IoT module holds the following units in its framework to provide the desired function:

1. Recording the humidity and temperature.
2. Measuring soil moisture humidity (DHT22 sensors keep an eye on the air's temperature and humidity). The soil humidity is recorded via the YL-69 sensor and LM393 Comparator.
3. Solenoid Valve.
4. Fertilizer tank. (Tank holding Nitrogen, phosphorus and potassium fertilizers)

IV. METHODOLOGY

The following Fig.1.1 demonstrates the overall sequence of the AI Module with IoT:

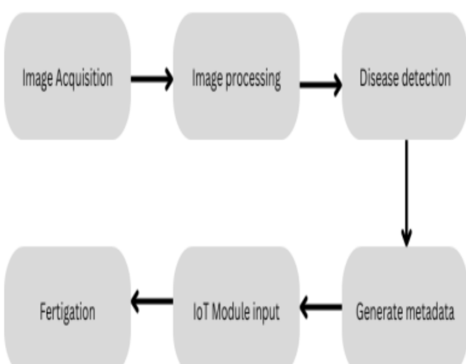

Figure. 1 Proposed Block Diagram

The processes that occur at each level of the framework are as follows:

Image Acquisition: The photograph of the crop leaves is captured using either an automatic ESP32 Cam module or, if the farmer so chooses a manual option that overrides the automation.

Image processing: The captured picture is analyzed at this point, and in most cases, it is divided piece by piece and the potential illnesses are paired.

Disease detection: In this stage, the illness that most closely resembles the state of the plant or the status of the leaves is found.

Produce Metadata: The metadata created as the feed for the IoT Module includes the illness identified and the anticipated quantity of fertilizer that should be applied to the plants to rehabilitate the crops.

IoT module Input: The IoT Module starts controlling at this phase. It receives the information input and, while the soil condition is being watched, determines the appropriate quantity of fertigation to be applied to the vegetation.

Fertigation: This is the last stage of the process, in which fertilizer and water are combined and then applied to the crops using an organized process. With simply a press of a button, this procedure is repeated each time, saving the producers time and enhancing agricultural accuracy for higher-quality, better-yielding crops.

V. RESULTS

[Input to be added]

VI. CONCLUSION

[Input to be added]

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