

Retraction

Retracted: Plantosphere: Next Generation Adaptive and Smart Agriculture System

Journal of Sensors

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] A. Verma, M. Agrawal, K. Gupta et al., "Plantosphere: Next Generation Adaptive and Smart Agriculture System," *Journal of Sensors*, vol. 2022, Article ID 5421312, 10 pages, 2022.

Research Article

Plantosphere: Next Generation Adaptive and Smart Agriculture System

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Around 75% of the population in India is engaged in agriculture and farming. The sustainability of every economy is based on agriculture. It has a major influence on financial growth and fundamental transformation in the long run. Artificial intelligence will usher in a revolution in agricultural operations in the future. This revolution has protected crops from being negatively affected by a variety of factors such as climate change, soil porosity, and water availability. Crop monitoring, soil management, and insect identification, to name a few examples, are all conceivable uses of artificial intelligence in agriculture. The primary purpose of artificial intelligence is to close the knowledge gap that exists between inventors and farmers. Detecting disease and monitoring plant health are two of the most difficult challenges in sustainable farming. As a result, image processing technology must be used to detect plant sickness at an early stage. Photographic capture, preprocessing, segmentation, feature extraction, and sickness categorization are all part of the procedure. In reality, computer image processing was used long before human eyes were able to detect the signs and symptoms of the disease. Taking into account the climatic conditions in various parts of the world. Climate change directly affects crop output. Several soil and atmospheric characteristics are detected to anticipate the optimal crop. Sedimentation is measured by soil parameters such as pH and moisture. Today, a platform that allows farmers to advertise their products is in high demand. This paper proposes a system where farmers sell directly to clients, bypassing wholesalers and traders. A predictive analytics solution is required to maximize the farmer's profit.

1. Introduction

India is primarily an agricultural country, with agriculture providing employment to more than half of the people. As a result, the contribution of agriculture to national income in India is all the more significant, given that farming is often regarded as the country's economic backbone. Farming is the primary source of income for the vast majority of Indians [1], whether explicitly or implicitly. India has the potential to produce food grains, which might have a huge impact on the country's economic development. The principal source of income for roughly 58 percent of India's population [1] comes from agriculture [2, 3]. Agriculture,

forestry, and fisheries were anticipated to generate gross value additions of Rs. 19.4 lakh crore (277.37 \$billion) in fiscal year 2020. To put it another way, agriculture and associated industries contributed 17.8 percent of India's Gross Value Added (GVA) in fiscal year 2020 at current prices [4]. Following the pandemic-induced slump, it is expected that consumer expenditure in India would rise significantly, reaching 6.6 percent in 2021. From April 2020 through January 2021, primary agricultural exports totalled \$32.12 billion, representing a 12% increase over the previous year. In order to attain profitability and support in the rural setting, AI may give an edge for existing methods and procedures. For example, dynamic capabilities such as AI might help

recognise changes in the market value of agricultural items and provide specific planting and harvesting directions to avoid severe crop losses. Early illness identification and new water system designs may improve overall efficiency and sustainability. Weather predictions powered by artificial intelligence are continually providing accurate, surprising bits of information in day-to-day farming. Such precise information might aid in the prevention of crop losses. Farming groups may use AI apps to improve their current strong IT skills over time through learning. People have been more interested in purchasing locally produced, seasonal food directly from a farmer during the past 25 years, which has fuelled the growth of the CSA-Community Supported Agriculture model. An agricultural producer sells a finite range of “shareholdings” to members of the public in order to attract clients. In most cases, the share will consist of a box of vegetables, but additional farm products may also be included in your purchase at your discretion. In exchange for their purchase of a membership (often referred as a “subscription”), interested clients will get a box (bag, basket) of seasonal food every week throughout the agricultural season.

1.1. GDP Share of Agriculture in India. Agriculture is predicted to account for just 14 percent of India’s GDP, but it is expected to account for 42 percent of total employment in the country. Because rainfall is necessary for the cultivation of about 55 percent of India’s arable land, the rainfall received during the monsoon season is critical [1, 2]. In accordance with the Economic Survey 2020-2021, agriculture’s share of GDP has increased to more than 20% for the first time in 17 years, making it the sole bright spot in the economic picture. Agriculture was the only sector to grow at a positive rate of 3.4 percent at constant prices in 2020-21, with the rest of the economy contracting by the same amount. Agriculture’s contribution to the GDP increased from 17.8 percent in 2019-20 to 19.9 percent in 2020-21, according to the World Bank. Agricultural production contributed 20% of the nation’s gross domestic product (GDP) in 2003-04. After experiencing negative growth in 2002 as a result of the severe drought, the industry saw a 9.5 percent increase in 2003.

Manufacturing shrank by 1.4% after growing by 2.1% year-on-year. As illustrated in Figure 1, the construction industry recovered 2.2% from previous year’s 6% rise. In 2019-20, India’s real per capita income is expected to reach Rs 94,954, up from Rs 92,085 in 2018-19, a 3.1 percent increase from the previous year [2]. This is a 6.1% increase over the previous year’s per capita income of Rs 126,521.

In 2020, the agriculture and food industries will account for 19.7 million full- and part-time jobs, accounting for 10.3 percent of overall employment in the United States as shown in Figure 2. Direct on-farm work accounted for around 2.6 million of these positions, or 1.4 percent of total employment in the United States. An additional 17.1 million jobs were supported by employment in agricultural and food-related businesses, respectively.

1.2. Challenges Faced by Indian Agriculture. Because rain is essential to the survival of around 65 percent of India’s crops

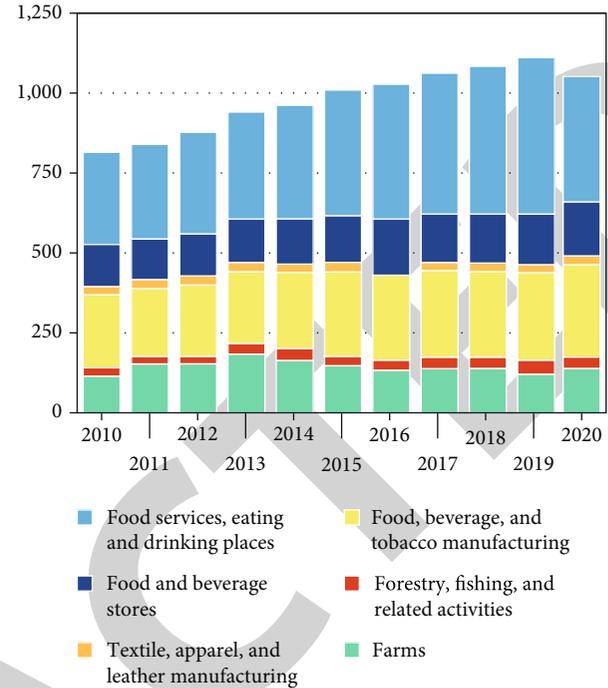


FIGURE 1: Agriculture and allied businesses contributed \$1.3 trillion to the GDP between 2009 and 2019. [5].

and more than half of its population, either too little or too much rain is typically a negative indication. A recent protest by farmers in Andhra Pradesh, Madhya Pradesh, and Punjab [2] drew widespread attention. In such circumstances, it is vital to comprehend the underlying causes of major problems in Indian agriculture.

- (i) Lack of crop rotation: crop rotation is crucial for successful agricultural operations as it helps reclaim soil fertility. Continuous grain production diminishes soil fertility, which may be restored by growing other crops like pulses, vegetables, etc. Because most farmers are illiterate, they are unaware of the benefits of crop rotation [3]. So the soil loses most of its fertility
- (ii) Lack of organised agricultural marketing: Indian farmers struggle to sell surplus harvests due to lack of established marketplaces and transportation. Dispersed and subdivided estates provide major marketing challenges
- (iii) Inadequate utilisation of inputs: Indian agriculture uses too little fertiliser and HYV seeds. Indian farmers are not applying enough fertilisers to their soils, including farmyard dung manure [3.4]. Indian farmers still use substandard seeds. They lack funds to buy high-yielding seeds of superior quality. Moreover, the country’s HYV seed supply is limited

1.3. Drawbacks of Existing System. Farmer challenges include labour availability, agricultural labour quality, agricultural labour skills, and the investment in resources (such as seeds,

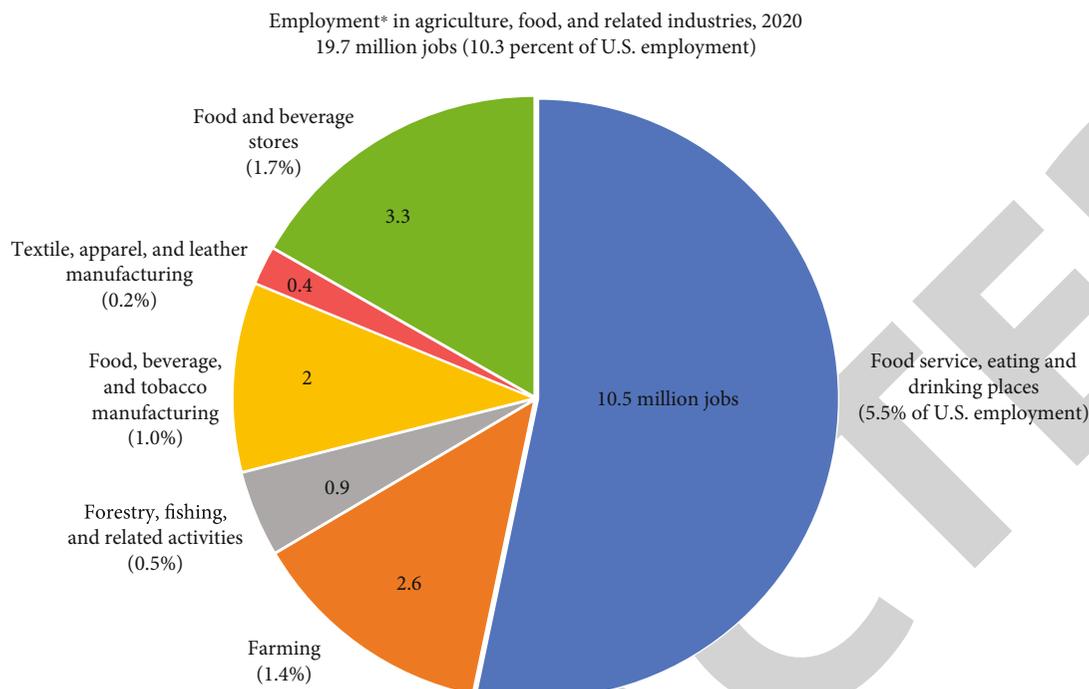


FIGURE 2: Agriculture and its related industries provide 10.3 percent of U.S. employment. [5].

fertilisers, insecticides, and other equipment, among other things). According to the USDA, these are just a few of the challenges that farmers face while working in the fields. Farmers are confronted with a variety of challenges, including the following:

- (i) Lack of awareness and education
- (ii) Poor infrastructure
- (iii) Absence of financial solutions
- (iv) Adopting new mechanisms

1.4. Existing System for Pest Detection. As the effects of climate change get more severe and unexpected, so are the risks posed by pests to crops, which are growing more severe and unpredictable. Plant-eating scale insects are phytophagous insects, which means they devour green plants. These insects feed on the sap of plant organs, particularly leaves, fruits, stems, and roots, resulting in the development of sooty mould disease in the plant. As a result of the disease's impact on photosynthesis and the subsequent tissue infection, the plants are damaged, and plant commodities' market value is reduced both in terms of quality and in terms of quantity [6]. When farmers are confronted with the problem of pest infestations, they rely on their own prior experiences and expertise to arrive at a solution.

In the absence of sufficient expertise, they may fail to utilise the most effective medications to control pests in their area. Furthermore, global issues such as an ageing population, a scarcity of agricultural labour, and migration from rural to urban regions are all major issues that require attention.

Temperatures will rise as a result of climate change, which will affect crops and pests. If CO₂ emissions cannot be curtailed, predictions for the year 2050 imply a 2°–3°C rise. Higher temperatures will affect crops and yield potential in a variety of ways. Pest range expansions and increased pest abundance due to an increase in pest cycles (generations) every cropping season and year may further expose crops to more pests. Increased insect infestations will result in increased crop losses and production gaps.

As shown in Figure 3, adaptation of IPM will be the ultimate solution to reduce pest-related losses sustainably at farm level, thereby minimizing or fully avoiding the use of pesticides. The Pest Risk Atlas will support adaptation planning to understand in which countries and regions changes in pest distribution, occurrence, and abundance will likely occur based on changes in temperature as shown in Figure 4. National quarantine systems can be reinforced, and lists of potential new entry pests are revised to reduce the probability of their invasion and spread [7].

1.5. Existing System for Crop Yield Prediction. Crop yield forecasting may be accomplished using a variety of ways. Traditionally, the appraisal of crop status by specialists has been the most reliable way of yield forecasting. Throughout the crop's growing season, observations and measurements are taken, including the number of tillers, the number of spikelet and their fertility %, the percentage of damage caused by pests and fungus, and the percentage of weed infestation. The yield may be predicted from the data gathered in this manner using regression methods or by applying information from local experts [8]. The use of remote sensing and crop simulation models are the other two ways that may be utilised to anticipate crop production.

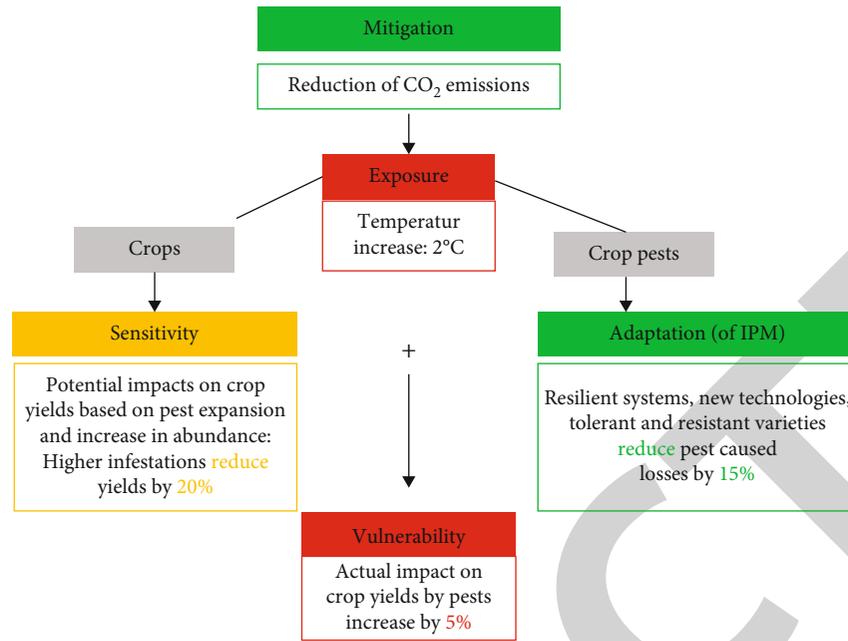


FIGURE 3: Reducing crop vulnerability to new and emerging pests by adaptation of IPM.

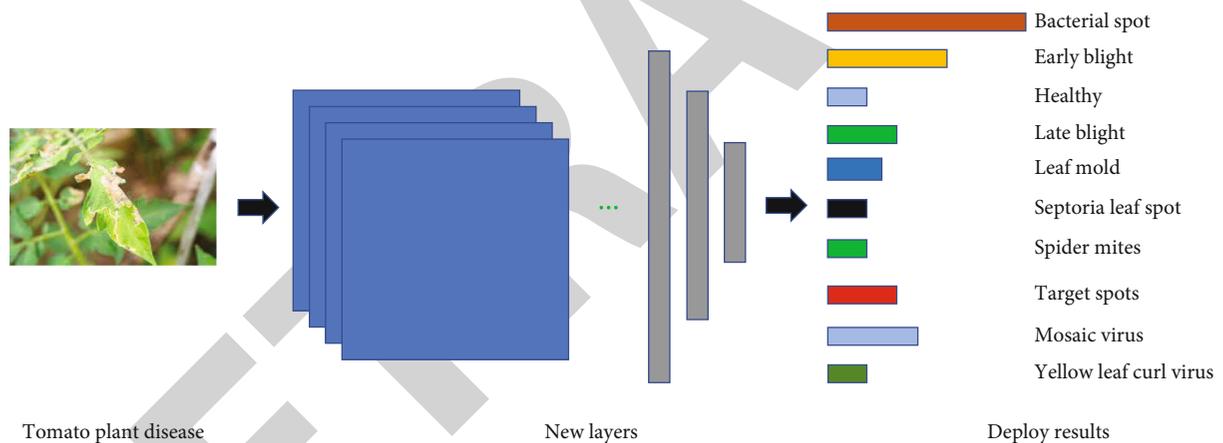


FIGURE 4: Methodology for pest detection.

In order to provide a precise, scientifically sound, and impartial estimate of crop yield as early as feasible during the crop's growth season, the yield forecast must take into account the effects of weather and climate. The gap between projections and final estimates can be traced to the time of the publication of the estimates. The difference between forecasts and estimates is that forecasts are created before the full crop is harvested, whereas estimates are made after the crop is harvested. Farmers have always made "forecasts" in order to organise their agronomic methods [9], and this has been true throughout history. For example, the planting window, the selection of a cultivar, and the amount of fertiliser to be used are all influenced by the climate in question. If farmers are aware that there is a strong likelihood of rain in the next week, they will hurry into the field to sow their seeds as soon as possible. Knowing or anticipating crop output requires knowledge of or forecasting a number of other

essential characteristics. For example, quantifying the area planted at the beginning of the growing season and measuring the area collected are two examples of quantitative analysis.

2. Related Work

In recent years, automated pest detection has been a hot topic of research. Most often, visibility, machine learning, or herb detection technology is chosen. However, in the same employment, there is rarely a comparison of options. Many computerised pesticide detection and recognition studies focus on one technical technique, while ignoring other technological choices. Computer vision and object recognition have come a long way recently. If the issue or the dataset changes, image categorization must be redone. This issue arises when using computer vision to identify plant

diseases since they use hand-made functions and algorithms for better photos. Deep learning approaches can eliminate the need for manual feature extraction [10]. Machine and deep learning advancements boost item identification and detection reliability. On one side, machine learning algorithms were employed to identify sickness. ANNs, decision trees, K -means, and KNNs were used in agriculture research projects. Vector Support Machines are one of the commonly advocated strategies in disease diagnosis (SVMs). Various methods have been used to diagnose and categorise illnesses in tomato crops. An RGB image of a tomato with yellow leaf curl disease is used to identify the illness [9, 10]. This method's average accuracy was 90%. Second, support vector machine approaches are used to identify and quantify tomato leaf miners using RGB and spectral reflection images.

Oidium neolycopersici is recognised using SVM algorithms, visual thermal, and stereo light. Fourth, powdery mildew is detected in tomatoes [9]. To obtain the dataset variability, we used just 138 photographs. Most disease detection and classification rely on image extraction to classify leaves. A large, tagged, and verified collection of ill and healthy plant images is required for successful image categorization. Until recently, no such dataset existed [11]. To solve this issue, the Plant Village effort has been collecting and categorising tens of thousands of plant pictures. The Plant Village dataset is used to train deep neural networks for crop disease detection. It is applied in contemporary pest detection and machine learning studies. Several applications exist to help farmers anticipate crop yields based on weather. Machine learning has been used to predict crops [12].

SVM-Support Vector Machine and RF-random forest approaches are used for accuracy. Thus, crop yellow yields are predicted as the optimal bio condition [6, 11]. Smart farming is difficult in undeveloped nations because many farmers lack knowledge and education. Agricultural yield prediction techniques or combinations: Field research, plant growth modelling, remote sensing, and statistical models. Agricultural yield prediction techniques or combinations: Field research, plant growth modelling, remote sensing, and statistical models; these approaches' have their own benefits and drawbacks. Four farmers' reports and objective surveys are used to gather data on the ground. Respondents, resource restrictions, and reliability deteriorate due to sampling errors and non-sampling. Process-oriented crop models enhance and develop crops based on crop attributes and environmental conditions. They apply universal agrodevelopment ideas [13]. However, not all yield drop causes are included, and substantial data and validation are necessary. Remote sensing uses satellite photos to acquire crop information. Remote sensing data is open source and devoid of human mistake [6]. As a result, satellite data readings may only be utilized to predict agricultural yields based on physicochemical or analytical models. Statistics models employ weather indicators and predictors to forecast the three options outlined. For genetic development and management, these models fit linear models between predictors and residues. They are exact but cannot be stretched in space or time.

3. Proposed Methodology

The key components of the proposed solution, which is an android application, are pest detection and crop yield prediction. In the pest detection module, it is simple to take a photo of the plant and send it to the mobile device for further analysis. The picture is subsequently provided by a convolutional neural network, which encodes the image in a numerical array that is classified with the other numerical arrays in the model, which is then used to generate the picture.

The model is a TensorFlow model [14], which is constructed from the massive size of a traditional TensorFlow model. This model aids in the classification of the image's numerical value into datasets. The trust value is calculated and shown when a numerical array matches. We took soil and climatic parameters into account when developing the crop yield prediction model. Our prediction model is constructed using artificial neural networks [13] in our effort to deliver the proper crop to be cultivated. As a result, we can guarantee that the results are always accurate.

3.1. Pest Detection. The newly developed technology is linked to a smartphone, allowing farmers to increase their productivity. An implementation of a CNN object detection model [15] utilising the Keras platform on a mobile device is demonstrated in order to detect pests in a photograph using the suggested approach. It is necessary to perform five important processes in order to identify plant disease: capture of images, image preprocessing, segmentation of images, feature extraction, and classification. In image processing, the usage of a digital camera or scanner is demonstrated in the figure. Enhancing image processing, segmenting photos into affected and healthy parts, extracting the feature that defines the location of infection, and aiding in the categorization of illness are all examples of preprocessing techniques [16].

3.2. Dataset. We utilised the Plant Village dataset to detect pests. It has 18 groups and 54306 images of diverse plant leaves: 13 plant species and 26 plant disease categories. The data collection comprises images of healthy and unhealthy crops. On display are fourteen different types of crops such as apples and blueberries as well as citrus fruits and vegetables. Each class has two areas: plant name and sickness name. See Figure 5 for scaling and dividing images for further classification and preprocessing.

3.3. Crop Yield Prediction. The proposed system establishes a recommendation system that proposes an appropriate crop by taking into account the physical features of soil, climate, and crop attributes. The selection of the correct crop for particular conditions helps to enhance agricultural production. It allows farmers to pick an appropriate crop for planting. It also helps public agencies develop efficient soil management methods to improve production and preserve soil fertility. The necessary data for the study include climatic factors, soil physical features, and crop characteristics. Meteorological survey in India obtains climate parameters [17].

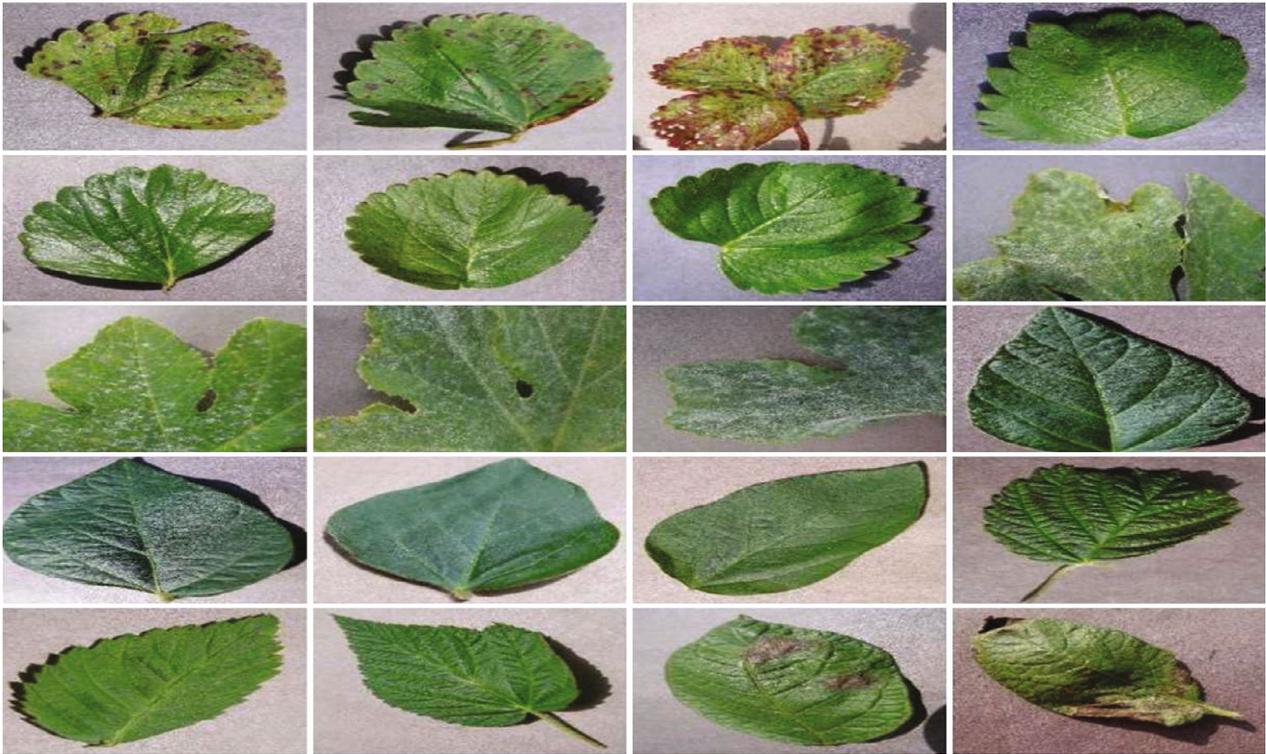


FIGURE 5: Dataset of pest detection.

The crop yield prediction system comprises climatic factors, soil physical attributes, and crop properties. Meteorological surveys from India have yielded climate parameters. The crops are examined for the study, including maize, finger millet, rice, and sugarcane.

These crops are the main economic cultures cultivated in the region. Artificial neural networks are the machine learning approach employed throughout this investigation. In the appropriateness measures, namely, specific location crop is recommended as follows: 1—highly appropriate, 2—moderately appropriate, 3—marginally appropriate, and 4—inappropriate.

The crop yield prediction system [18] as shown in the above figure follows the following steps:

- (i) Collection of data: the majority of the papers used chemical parameters, water content, electrical conductivity, organic content, and fertility to implement the model. These values are considered the algorithm inputs.
- (ii) Data preprocessing: a large amount of data is needed to successfully complete a model. Real-world data can be gathered in raw format. It may have certain values which are lacking, inconsistent, and loud. This step should be followed by filtering such unnecessary values. The data are standardised.
- (iii) Data categorization: it is one of the techniques of mining of information. This is used for analysing

and dividing the data into a single class. A prototype is developed during preprocessing. The deleted prototype is evaluated against the present dataset in the categorization. The prototype performance and accuracy should be quantified.

- (iv) Forecast: the presentation of the related classification algorithm based on the precise analysis and performance will provide farmers a proposal to grow in a certain soil type.
- (v) Findings: the end result shows that the crops are suggested.

4. Design and Implementation

This section includes the detailed description of the work.

4.1. *Pest Detection.* The module detects pests by the following.

- (1) Image capture: image acquisition is the process of collecting plant leaf images with or without sickness. The system's accuracy depends on the image types used during training. On the farm, images are captured with a digital camera. The image quality is determined by the digital camera's kind and position. The first stage is to gather the visual data that will be utilised as the computational input. It is necessary to use images in the .bmp, .jpg, .png, and .gif formats.

- (2) Preprocessing: after image capture comes preprocessing. Photo editing software can improve, resize, and smooth photos. The recorded leaf photos may indicate insects, insect excrement, dust, squirrels, and other noise-reducing agents. Enhanced distorted images using noise reduction filters. Poor picture contrast necessitates contrast enhancing techniques. The task requires only sheet photographs, with the rest as the backdrop. Hence, methods to eliminate backdrop leaves from whole photos are used.
- (3) Segmenting images: in order to identify leaf diseases, preprocessed photographs from the region of interest must be segmented. The image must be divided into discrete leaf parts. Segmentation may be done using Otsu, k -means, thresholding, region, edge, etc. This is an example of edge detection using deformation segmentation. Infected leaves show colour variations, which are removed using the clustering procedure k -means [19].
- (4) Extract features: it includes locating and extracting inherent traits called as image illness descriptive features. Colour, texture, and shape are usually retrieved. Colour elements of the histogram and moments identify between illnesses based on colour. Textures that show how image textures are spread are retrieved to categorise illnesses. Entropy, uniformity, and contrast are some of the characteristics of texture. The form illustrates how the symptoms of the disease differ from one another. When it comes to leaf diseases, colour and texture extraction are preferable.
- (5) Identifiers for diseases: leaf diseases [11] are classified according to these characteristics. Classification is a monitoring approach for mapping leaf pictures to illnesses that may be used in disease mapping. Photos with illness labels are used to train the classifier, which then specifies a predefined set of disease classifications. Training is the term used to describe this degree of learning. To put the pictures through their paces, the trained classifier is employed [20].
- (iii) Data categorization: it is one of the techniques of mining of information. This is used for analysing and dividing the data into a single class. A prototype is developed during preprocessing. The deleted prototype is evaluated against the present dataset in the categorization. The prototype performance and accuracy should be quantified.
- (iv) Forecast: the presentation of the related classification algorithm based on the precise analysis and performance will provide farmers a proposal to grow in a certain soil type.
- (v) Findings: the end result shows that the crops are suggested.

5. Results and Discussion

This section includes the results and the discussion of the work.

5.1. Pest Detection. When using the pest detecting module on an Android mobile [21], it is possible to take a picture of the leaf and send it to the device. Following that, the programme will forecast the sort of bug that is present in the leaf. As indicated in Figure 6, the accuracy of the pest detection model acquired is 95.16 percent, which corresponds to the accuracy of the model obtained. It is also decided what the confidence level is, and when a numeric array matches, the confidence level is provided with its value.

5.2. Crop Yield Detection. The forecast of crop yields is a crucial national and regional decision-makers' responsibility in order to make quick decisions. A precise model of crop production can aid farmers determine what to cultivate and when to plant. There are several techniques to predict agricultural production. This paper concludes that rapid advancements in ML technology will result in cost-effective agricultural solutions. As seen in Figure 7, the accuracy of the crop yield forecast model achieved is 95.83 percent, according to the model. The accuracy of the validation procedure was 96.44 percent, while the accuracy of the test procedure was 92.93 percent [22]. A crop yield prediction system for a suitable crop is developed in the proposed system, taking consideration of the physical characteristics of the soil, the climate, and the crop.

5.3. Farmers Community and E-Mandi. An agricultural cooperative is comprised of individuals who pledge their support to a farm operation in order for the farmland to become, either legally or spiritually, a communal farm where growers and consumers work together to provide mutual support while sharing in the risks and rewards of food production. Farmers and customers collaborate to support a farm operation in a community supported agriculture (CSA) model [23]. Aside from that, it will have agricultural and farming-related news, along with a community post where individuals can ask questions and share their experiences. Additionally, government programmes will be

4.2. Yield Prediction of Crop. The crop yield prediction system follows the following steps:

- (i) Collection of data: the majority of the papers used chemical parameters, water content, electrical conductivity, organic content, and fertility to implement the model. These values are considered the algorithm inputs.
- (ii) Data preprocessing: a large amount of data is needed to successfully complete a model. Real-world data can be gathered in raw format. It may have certain values which are lacking, inconsistent, and loud. This step should be followed by filtering such unnecessary values. The data are standardised.

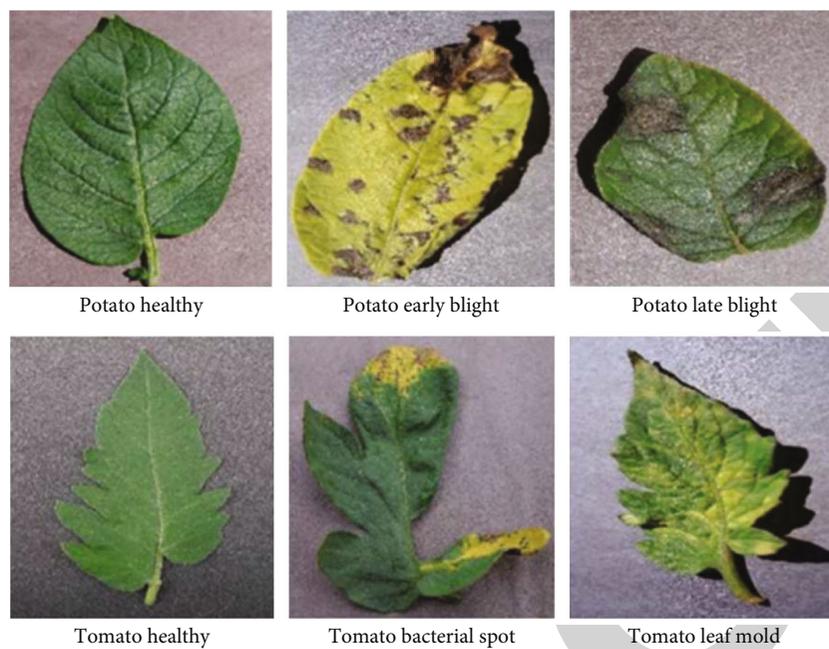


FIGURE 6: Pest detection.

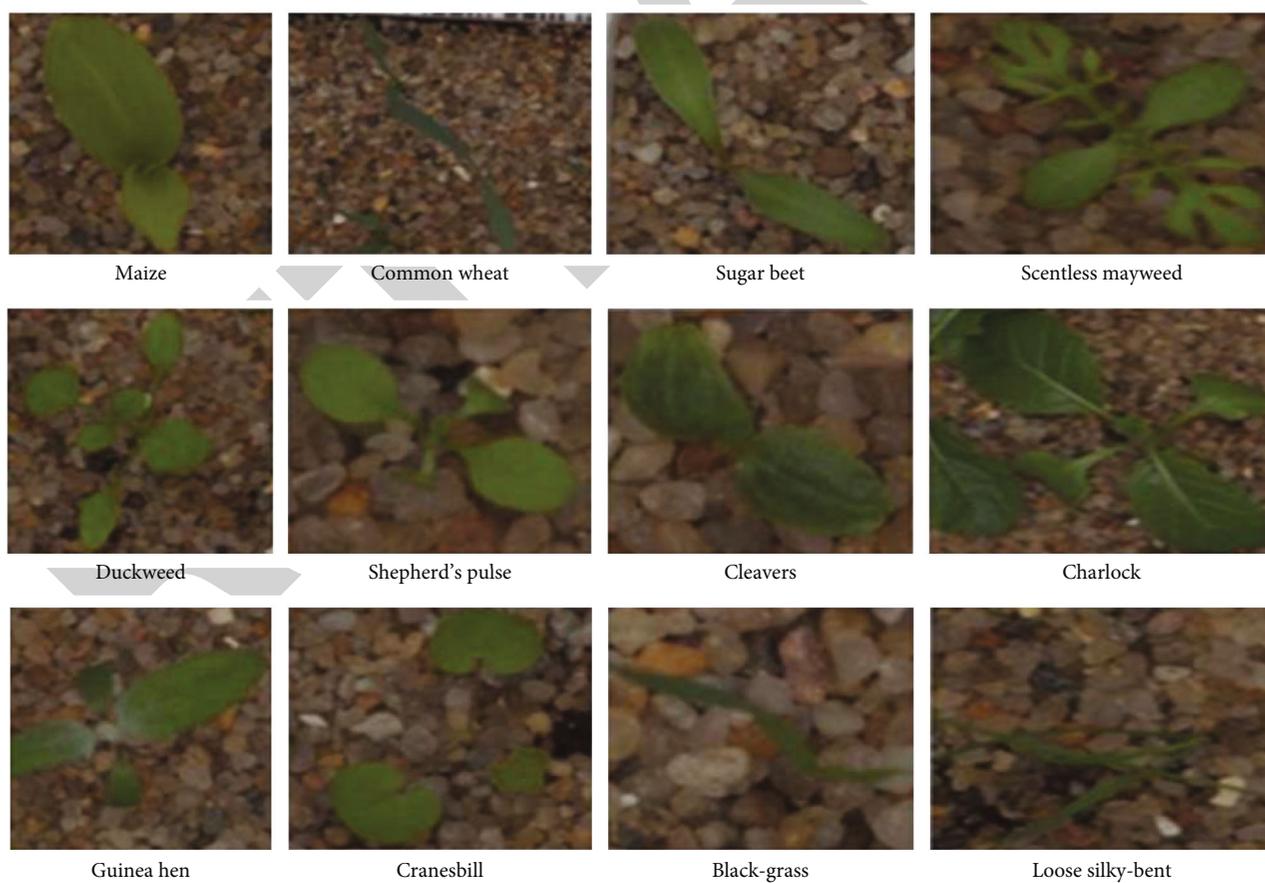


FIGURE 7: Crop yield detection.

provided on the applications so that users may take a quick glance at them while on the go.

In E-Mandi, farmers can check real-time Mandi Rates and can directly connect with the consumers. E-Mandi will provide real-time market rates of different fruits and vegetables. Farmers can also check the commodity rates. E-Mandi will help the farmers to know the fluctuations in the market rates so that he can sell his product at a better rate.

6. Conclusion and Future Work

The suggested system uses deep learning to diagnose agricultural diseases using convolutional neural networks. The model is assessed for particular plant species with specific plant diseases. Overall, the Mobile Net model outperforms competing models in terms of functionality and disease detection accuracy. The project will incorporate more plant kinds and illnesses.

Farmers may sell/buy agricultural items cheaply without utilising middlemen. Farmers knowing about current farms will be more helpful and safer. Farmers plant the proper harvest according to soil conditions, which the framework records. The suggested methodology helps farmers choose the right crop throughout harvest season. The model was evaluated and verified using data from an Indian data area. The approach that has been proposed detects all of the potential agricultural crops that might be grown in a specific location and assists farmers in deciding which crop to plant in their fields. Farmers in India mostly rely on manual monitoring and a few applications that are limited in terms of database size and are only capable of doing the detection portion of the job. Because prevention is preferable to treatment, our initiative attempts are to forecast the assault of pests/diseases in the future, so enabling farmers to take precautionary measures to avoid such attacks. In our future work, we hope to expand on the findings of this study and concentrate on the construction of a crop production forecast model that is based on DL data. We anticipate that additional study will be undertaken on the application of DL techniques in agricultural production prediction in the near future, owing to the higher performance of DL algorithms in other problem domains such as signal processing.

Data Availability

No standard published dataset is used. The dataset used is the curated one for the demonstration and study purpose.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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