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Machine learning framework and tools in precision farming

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ABSTRACT

Farming using machine learning (ML) techniques has a role to play in the current globalization scenario due to the advantages it offers for cost-effective harvesting of the crop. The areas such as crop disease detection, soil nutrient detection, fertilizer analysis and optimization, weather and irrigation schedule prediction, are investigated utilizing a range of deep learning and ML techniques, such as K-nearest neighbors (KNNs), convolutional neural networks (CNNs), and support vector machines (SVMs). The article concentrates on preparing the recommendation system for the farmer to take a quick and timely decision for crop disease, use of optimal fertilizer for crop growth, and water requirement prediction to overcome water wastage. A massive amount of data, including image data from publicly accessible sources, such as PlantVillage, Kaggle is used to train the model. Sensor data is fed into the ML model for the nutrients analysis and water requirement analysis. An Android application is developed, which can be used from any handheld device by the farmers to take advantage of the proposed recommendation system. The result shows the promising future with better accuracy than previously available models in the same area. Parameters including recall, accuracy, precision, and F1-score are considered to gauge performance.

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1. INTRODUCTION

Agriculture crop production faces numerous challenges such as climate change, increased weed growth, pest attacks and plant diseases. Agriculture is a crucial industry for ensuring the food security of the entire world [1]. The efficient use of fertilizers and pesticides is crucial for boosting agricultural production and soil productivity. The application of these inputs must be carefully balanced to achieve optimal results, but traditional methods for determining the amount of fertilizer and pesticide to be applied are often inaccurate and wasteful [2]. The amount of fertilizer and pesticide that should be sprayed depends in large part on how plant species and weeds are classified, and advances in computer vision and machine learning (ML) have the potential to revolutionize this process. Agricultural technology is developing at a rapid rate, and with these developments comes the development of precision agricultural applications, which is accelerating the digitization of agriculture [3]. Precision agriculture management processes use a variety of ML tools and techniques to assess various factors like soil and water for optimum requirement management [4]. Agriculture can be impacted by a variety of issues, including pests and diseases that damage crops, variation in rain pattern, floods, and unexpected climate changes, to mention a few. In addition to the uncontrolled application of pesticides and fertilizers, inadequate government funding, and corruption, the bulk of these problems are mostly unplanned and cause large financial losses for the farmers in their harvesting process [5]. These factors make the farming community hostile, which results in growing debt and farmer suicides. The field can employ technological advancements like deep learning, computer vision, internet of things (IoT), and unmanned aerial vehicles (UAVs). Starting with the sowing of a seed, soil preparation, seed development, crop health monitoring, water feed metering, and harvest collecting by robots that use machine vision to determine when the crop is ready are all examples of precision agricultural tasks [6], [7]. By making quick judgments that lower costs and boost profitability, ML applications will assist to increase yield.

Numerous applications exist for ML, expert systems, fuzzy logic, and image recognition in a variety of fields. In addition to agriculture, the automation industry, robotics, e-commerce, security, and the financial and automotive sectors also frequently use ML models [8]. The issues facing agriculture can be addressed with the appropriate use of ML techniques. ML has the ability to bring in a new age in nations like India, where the primary sector is agriculture. Applications involving ML and artificial intelligence are rapidly becoming more prevalent in this industry as most of India's rural areas have embraced digitization. Farmers in the agricultural industry adhere to the measures outlined for harvest activities such as selecting a crop, getting the soil ready, planting the seeds, giving the crop fertilizer and irrigation, and keeping it healthy [6]. A smartphone is used to check ripeness of avocados by using support vector machine (SVM) model [9].

Liakos *et al.* [10] categorize ML applications in agriculture broadly as management of soil, water, crop and livestock in their study. The study covers the following categories: weather, animal welfare, livestock production, disease and weed prediction, determination of soil and water quality, and fertilizer recommendations. ML tools and techniques applicable in such an applications are SVMs, convolutional neural network (CNN), random forest (RF), K-nearest neighbor (KNN), K-means clustering, AdaBoost, and extreme gradient boosting (XGBoost) [6], [8], [10]. Using the you only look once (YOLO) algorithm, pests are identified by taking a picture with a smartphone and augmenting the data [11]. An Android application is created for soil texture analysis using CNN model developed using the flask framework and hosted on amazon web services [12].

The existing architectures that use CNNs make use of the topologies or models for image classification, such as GoogleNet, AlexNet, and ResNet perform well in the tasks like image classification. AlexNet employed stacked convolutional layers, pooling layers, and rectified linear unit (ReLU) activation functions, introducing new standard practices in CNNs [13]. "Residual learning," which was made possible by ResNet, allows for the training of even deeper networks compared to previous models, evaluating the vanishing gradient problem. GoogleNet incorporated "inception modules" that combined convolutional layers with various filter sizes, improving efficiency and accuracy [14]. There is a need to do a comparative study of ML models that use CNNs [15]. Accuracy of detection varies along with crop and climatological conditions [16]. A number of ML methods were used to forecast important soil properties, such as nutrient concentration, type and moisture levels. The analysis provides a comprehensive overview of soil fertility across India at the district and block levels [17]. This data empowers farmers to make informed decisions regarding fertilizer application. It allows them to optimize fertilizer quantities based on varying fertility levels, ultimately streamlining distribution processes [18]. In irrigation prediction, sensors continuously transmit real-time data to a central unit. So, the dependency on sensor data is one more issue, along with integrating that data with the ML model. The device uses data-driven algorithms to determine the moisture content of the soil and automatically adjust water distribution. The system also boasts remote monitoring and control capabilities through a mobile or web application [19]. Integrating these crop cultivation tasks efficiently in one application for usefulness to the farmer is a challenging task that is going to be handled in this work.

To address these challenges, we come up with the mobile application which will take a real time data from the field by using the camera and the sensors which can be used by modules namely disease prediction, fertilizer prediction and irrigation prediction module. Also, the details about the implementation tools used for the development of these modules are explained so that future enhancements upon these modules will be made easy. This work proposes the novel approach of using ML models which uses the dataset of wheat for analysis of modules. The work contributes towards:

- Dataset preparation from the diverse publicly available wheat datasets.
- Presented a novel framework for crop recommendation using ML models.
- The results obtained from model were compared with a previous CNN model in this area.
- Presented various tools used in the development of ML application for the crop recommendation system.

The following is the order in which the paper is structured. In section 2, the architectural diagrams of the system framework, the dataset, the CNN model and tools for disease prediction, the SVM model and tools for soil analysis and fertilizer prediction, the KNN model and tools for weather and irrigation prediction, and the dataset are all covered. Section 3 discusses the experiment block diagram along with outcomes, such as the Android application and the results of the study with comparative analysis. Finally, the conclusion and future direction are covered in section 4.

2. MODULES AND METHOD

2.1. System framework

In the system architecture shown in Figure 1, the first crop image is uploaded, and then the user has a choice if they want to see weather prediction or pest prediction. If the user chooses weather prediction, then the weather is shown and then the market stats of any crop. And if the user chooses pest prediction, then using the CNN model, pest prediction is shown; then, pesticide is predicted, then crop recommendation is done, and at last, using multi-language support, the final report is generated in the preferred language.

The proposed framework takes the input as image data and sensor data for analysis. The disease prediction model considers image data, and fertilizer and irrigation prediction models take the sensor data. The dataset of wheat with 5k images is considered for the detection of disease, which is constructed by using publicly available datasets mentioned in the next subsection.

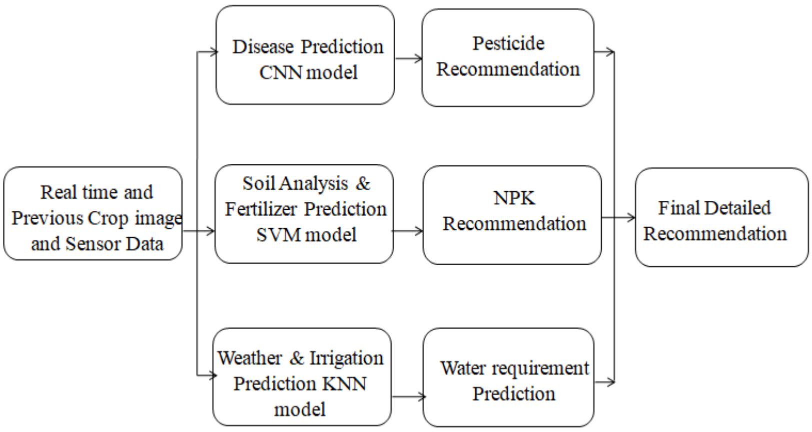


Figure 1. Proposed precision farming system framework

2.2. Dataset collection and preprocessing

The dataset is prepared from various publicly available datasets, which are mentioned in Table 1. For simplicity, only wheat crop images are considered for the experimentation purpose for the overall disease prediction module. The wheat dataset, which is considered to consist of five categories of classes, namely crown and root rot, fusarium head blight, leaf rust brown, and yellow leaf rust. The data preprocessing involves the noise removal from image and sensor data using noise removal techniques such as smoothing and averaging. Also, in the preprocessing step, data augmentation is done to increase the data availability by using the techniques of flipping, rotation, and cropping, which also increases the input data diversity. The images used in the disease detection module are made to the dimension of 224×224 in this preprocessing step.

Table 1. Dataset for disease prediction CNN model

Dataset used	Images	ULR
Wheat disease dataset - small	RGB	https://zenodo.org/records/7307816
Wheat dataset (LWDCD2020)	RGB	https://drive.google.com/drive/folders/ 1OHKtwD1Urdmhqxrp QEeF_X_ pqKotxRGD
PlantVillage dataset	RGB	https://www.kaggle.com/emmarex/plantdisease
Wheat-disease-dataset	RGB	https://www.kaggle.com/datasets/amankumar2004/wheat-disease-dataset?select=Wheat-Disease-Dataset

2.3. Disease prediction CNN model and tools

Each plant class's diseases are taught to the CNN classifiers. Results are used to activate a classifier that has been trained to categorize different plant diseases [20]. The leaves are categorized as "healthy" if they are absent. CNN model trained on 5k image dataset provided by Kaggle and plant village of different healthy and unhealthy plant image datasets [21]. Figure 2 shows various tools used for the disease prediction task.

- Keras: the Keras library includes a technique called predict that works well with any CNN or neural network model. With its qualities and factors that are properly matched with the projected class in accordance with the requirement, predict helps plan the entire model within a class [22].
- Tensorflow: TensorFlow, a framework for implementing deep learning, produced positive outcomes as well because it can simulate, train, and classify images with up to 90% accuracy [23].
- Pillow: all the fundamental image processing capabilities are available in the Pillow library. You can modify, rotate, and resize images [23].
- Numpy: a grid is used to divide the image. The feature map's cells each search for a specific object in the area of the image that corresponds to its own grid cell. Each cell contains information about three centered bounding boxes. If we have a grid that is, let's say, 3×3, then the number of boxes will be 3×3×3=27 [24].

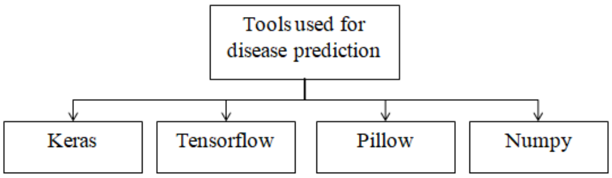


Figure 2. Tools for diseases prediction

2.4. Soil analysis and fertilizer prediction SVM model and tools

The soil's properties, which in turn depend on the temperature and topography of the land being farmed, determine which crop is selected for harvest. Precise estimation of the characteristics of the soil governs "crop selection, land preparation, seed selection, crop yield, and fertilizer selection" [17], [18]. In order to forecast the most important soil metrics, such as soil organic carbon (SOC), calcium carbonate equivalent (CCE), and clay content, digital soil mapping was utilized to correlate environmental variables. Figure 3, shows various tools used for soil and fertilizer analysis. Pandas: ML tools for data cleaning and analysis is called Pandas. The Pandas series and data frame are two Pandas data structures that can enable you modify data in a variety of ways, making Pandas data handling quick and efficient. We may conclude that a panda is the best tool for processing data based on the characteristics it offers. It supports various file formats, can manage missing data, and can clean up the data [25]. Scikit-learn: Scikit-learn offer preprocessing tools for data and the capability to create and compare ML methods. K-means clustering, RFs, SVM, and any other ML model we might wish to develop are all included in Scikit-learn. [26].

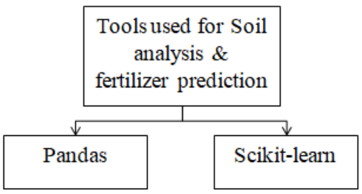


Figure 3. Tools for soil analysis and fertilizer prediction

2.5. Weather and irrigation prediction KNN model and tools

Generalized linear models and various ML techniques are utilized to forecast long-term daily rainfall with the help of climatic data. [27], [28]. As shown in Figure 4, the OpenWeatherMap and bs4 library are used for weather prediction [19]. OpenWeatherMap: with the help of this API, you may access the whole archive of historical weather data for any point on the planet. Weather information from January 1st, 1979 is included in the historical weather archive. Data are accessible in steps of one hour JSON syntax. It can provide all the meteorological information needed to make decisions for each location on earth because convolutional ML algorithms are used [29]. bs4: Web scarping using bs4 (python library) will give the 15 days weather forecast data from the vast amount of data available on the web [30].

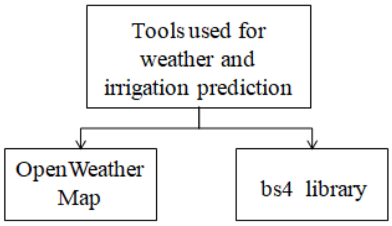


Figure 4. Tools for weather and irrigation prediction

3. RESULTS AND DISCUSSION

This section describes experimentation and output for the implementation of the system framework discussed in the previous section. The overall system architecture for crop protection depends on the IoT components such as Node MCU, Android application, and cloud system as shown in the block diagram in Figure 5. The Android application in the first block allows users to select the disease prediction option. It is controlled by a user interface that comprises a monitoring and control system page, soil analysis, fertilizer prediction, and irrigation prediction modules. The application contains a dedicated user interface page for every module; a disease prediction module takes a crop image as an input and predicts the particular diseases on it or otherwise classifies it as healthy. Similarly, soil analysis and the fertilizer prediction module work. The irrigation prediction module controls and monitors the motor pump, sensor, and robotic arm. After the user enters data through the Android app, Firebase uploads the output, which Node MCU processes to function. The Node MCU serves as the main board and is the next block. Using the built-in WiFi on the board, the board processes each piece of data that the sensor reads and uploads it to firebase. The Node MCU block and firebase real-time database communicate in both directions in order to update and get processed data from the cloud and raw data from the field.

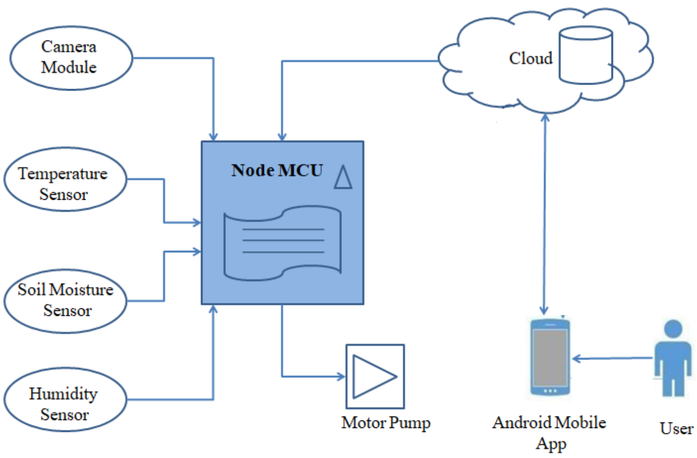
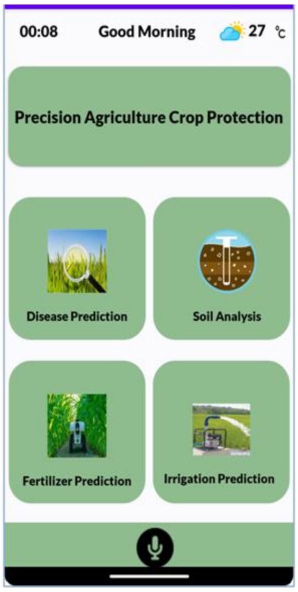


Figure 5. Block diagram with IoT components

The mobile application, which is developed in Android, makes use of the ML model, which is developed in Python. Modules that are described in the architecture, such as disease prediction, soil analysis and fertilizer prediction, and weather and irrigation prediction, are developed in Python and called from the Android application. Figure 6 shows the application views where Figure 6(a) shows first page of our Android application for precision agriculture crop protection which has four different icons for disease prediction, soil analysis, fertilizer prediction, and irrigation prediction. Figure 6(b) shows the disease prediction Android application page, which is launched when the user clicks on the disease prediction icon in Figure 6(a).



(a)

(b)

Figure 6. View of Android application developed for crop protection (a) First page of the application and (b) A page for the disease prediction module for the uploaded image with detected disease description

The disease prediction Android application page is divided into three parts: first, crop image; second, crop details; and third, detailed recommendation. Once the crop image is captured in the first part, the details about it will appear in the section below with the name of the crop disease and disease symptoms, and the third section gives the detailed analysis and recommendation regarding which pesticides to use and in what amount. Thus, the android application developed can be made available to farmers to take informed decisions based on the detailed recommendation provided.

The disease prediction module just discussed above with a CNN has an accuracy of 96.25%. This can be seen in Figure 7, where we compare the training and validation loss and accuracy of the model created. The number of epochs boosts the training accuracy; however, the validation accuracy fluctuates as the number of epochs increases yet still produces higher classification results. The loss, on the other hand, decreases with the increasing epochs, and the same pattern is followed in reverse order for training, and validation loss both decreases with the number of epochs, but the validation loss is fluctuating while decreasing with the increasing epochs.

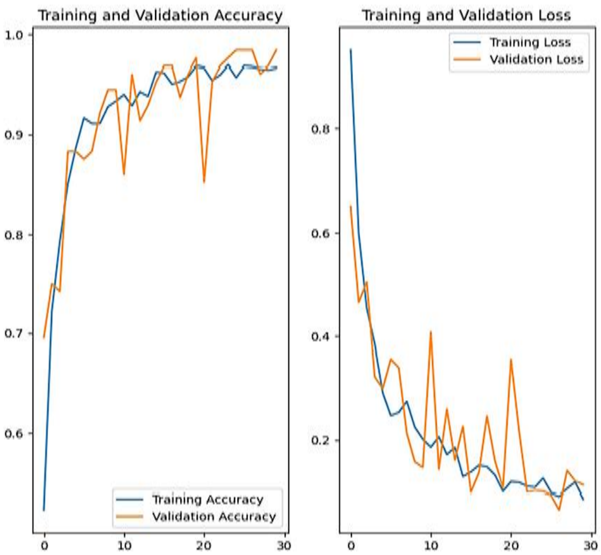


Figure 7. Accuracy and loss (training and validation)

A comparison of diverse ML models for disease detection, derived from prior research, is detailed in Table 2. The table illustrates that various CNN designs yield differing levels of effectiveness. Specifically, models such as faster R-CNN [31], a standard CNN [32], DenseNet-121 [33], a pre-trained CNN augmented with SVM [34], and our developed pre-trained CNN utilizing ResNet50 were applied to detect diseases in crops like tomatoes, maize, apples, rice, and wheat. Notably, the ResNet50-based model we proposed achieved the highest accuracy, reaching 96.25%. This represents a 2.54% increase in accuracy compared to the DenseNet-121 model [33] and a 10.25% improvement over the faster R-CNN [31]. These results emphasize the superior precision of our model in classifying crop diseases, indicating its strong potential for applications in agricultural disease detection. The limitation of pre-trained CNN utilizing ResNet50 is large computing power, as it mostly requires a T4 GPU with 16 GB RAM and a 1 TB disk for the processing of input data, so it's difficult to compute on small handheld devices. Also, overfitting is one more risk where the model fits on training data but deviates on new data.

Table 2. Comparative analysis

Model used	Dataset	Crop	Performance
Faster R-CNN	Self-generated database	Tomato	Accuracy: 85.98% [31]
CNN	Plant village dataset	Maize	Accuracy: 92.85% [32]
DenseNet-121	AI-challenger plant disease recognition	Apple	Accuracy: 93.71% [33]
Pre-trained CNN with SVM	Self-generated database	Rice	Accuracy: 91.37% [34]
Pre-trained CNN with ResNet50 (proposed)	Wheat-disease- generated database dataset	Wheat	Accuracy: 96.25%

4. CONCLUSION

The proposed system combines the three modules, such as disease prediction, soil/fertilizer analysis, and irrigation/weather prediction for pesticide recommendation, NPK recommendation, and water requirement recommendation, respectively. By utilizing ML to classify crop diseases, farmers can expect a potential 15-20% reduction in pesticide usage, leading to significant cost savings and reduced environmental impact. Also, the system's ability to accurately guess how much fertilizer is needed, using methods like SVM-based soil analysis, could lead to a higher crop yield by making the best use of nutrients. Real-time weather and irrigation predictions, powered by KNN, enable farmers to reduce water consumption, ensuring efficient resource management. This precision agriculture method uses CNN to classify diseases and weeds, analyze soil, and predict the weather. It gives farmers a way to use fertilizer and pesticides more efficiently, make the soil more productive, and make sure they water their crops at the right time, all of which lead to a more sustainable and profitable farming experience. This work gives the framework and simple mobile application that facilitates farmers in decision-making during farming. In the future, the transfer learning approaches can be implemented by freezing and unfreezing the different layers in the CNN for the disease detection module using the predefined ML models such as ResNet, GoogleNet, and AlexNet. Also, the input data can be extended to multiple crops, and the impact of that can be analyzed under different execution conditions and treatments. Furthermore, mobile applications will be developed upon our system, which monitors the crop at regular intervals and gives notifications to farmers over the mobile phone.

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R. B. Kulkarni		✓				✓	✓		✓	✓	✓	✓		
Suchita S. Patil			✓	✓	✓		✓			✓	✓			

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, Patil S. B., upon reasonable request.

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