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# SMART FARMING USING IMAGE PROCESSING AND MACHINE LEARNING

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**Abstract -** Any country's economic development depends heavily on agriculture. Many emerging nations economies are boosted by agriculture. India is one of the top producing nations in the world for a wide variety of crops, and it continues to use traditional farming methods. Smart farming is an advanced technology that uses various technologies ,improve the agriculture productivity and efficiency. Among these technologies, Image Processing and Machine Learning are emerged as powerful tools that can help farmers better crop yields and reduce costs. Image Processing allows farmers to analyse ground based images of crops to monitor their growth and health. While Machine Learning algorithms can be trained on large datasets of crop data to predict yields, identifying diseases, fertilizer use. The accuracy we got for identifying the best crop to grow is 0.9901.The combination of these technologies can provide farmers with real time data into their crops, enabling them to make more informed decisions about managing their crops. So, Smart farming using image processing and machine learning has the potential to transform the agricultural by improving yields, reducing costs.

**Key words:** Smart farming, Image Processing, Machine Learning, cost reduction, real time data.

## 1. INTRODUCTION

Agriculture plays a crucial role in driving economic growth, especially in developing countries. India is a major global producer of crops, but its farmers still rely on traditional methods. They face challenges due to changing weather conditions and the need to meet rising demands for high quality food. To overcome these challenges, farmers need to stay updated on changing climate patterns to produce quality crops. One solution is to implement a Smart Agriculture system that employs Image Processing and Machine Learning to monitor crops in real-time and offer recommendations to farmers. The system would provide advice based on factors such as humidity, temperature, pH, moisture, and rainfall, and suggest fertilizers based on soil factors like nitrogen, phosphorus, and potassium levels. The proposed solution involves developing an ML-based web application that offers informed decisions to farmers on farming strategies. The process involves problem definition, data collection, data pre-processing for ML algorithms, developing ML models for predicting crop yields and fertilizer recommendations, deploying the web application for farmers to access recommendations, continuously updating the models based on new data, and evaluating the system's performance to enhance crop yields and quality continually. Agriculture comprises seven essential steps, including Land Management, Soil Preparation, Water Monitoring, Identifying weeds, Pesticides Recommendation, Identifying diseased crops, and cost estimation. Land management requires keeping an eye on external factors like the weather, geological features, as these variables fluctuate between different sites and have an impact on crop output. The variability of rainfall, a key component of the earth's climate that directly affects agriculture and biological systems

## 2. LITERATURE SURVEY

In [1], Rushika G, Juliee K, Pooja M, Sache N, and Priya R used KS Organising Maps and BP Networks among other machine learning techniques. The network used to train the model was instructed to categorise soil types as either organic or inorganic. The most accurate model was picked as the final model after they had compared numerous other learning techniques. The application also evaluates the soil's quality and forecasts the yield based on that quality. In [2], Radhika N used MSVM to decide how to sample various soil properties in real-time. The programme she suggested was broken down into four modules: a sensor interface with an Internet of Things device, a cloud, an analysis of real-time data, and a user interface. Actually, by using this method, farmers will be better able to choose the right crop to grow depending on the local soil's features. An ARIMA model was created by Shridhar M, Chinmay P, Piyush W, Aniket P, and Vaishali D in [3] to forecast temperature, pH, and moisture. The historical data is used to forecast time series.

Once again using K-means, the projected values are then used to categorise the crops according to their pH levels.The most appropriate set of crops for the farmer are predicted using the KNN model.A KNN model was developed by Raghav K, Bhagavatula A, Aashish S, Drishti J, Natesh B, and Varshini S in [4]. It calculates the features and suggests the crop that is suitable for growing in that specific place. A standardised dataset is maintained with all of the minimal specifications for a crop. The area where crop prediction is needed is equipped with a number of sensors, which feed real-time data to the cloud. In [5], Akash R, Balaji S, Deepit A, Sarath J, and Vinith K created a technique that assesses the crop's quality. Numerous machine learning algorithms operate in various ways. Consequently, using just two models will not produce the needed results. The SVM accuracy score was higher.by 92% [6] compared to the decision tree algorithm. Out of two algorithms, the best one is chosen in this study. However, a number of algorithms are specifically designed for categorization jobs. Other models such as the K Neighbors classifier, Logistic Regression, and Ensemble classifiers need to be worked on. The planned research work does in fact use these algorithms. Based only on the information that was entered into the SVM model, the [6] forecasts a single crop. Data has the highest value. Consequently, in addition to using them for prediction, further information can be collected.

The production value was predicted using a linear regression model in relation to environmental variables like rainfall, temperature, and humidity. All of these algorithms' results were below 90% [7]. This effort consisted solely of the model's dataset implementation. It is necessary to design a web interface that even regular people can utilise effectively. For the model to forecast the crop, all the values must be manually entered. Utilizing web scraping, the suggested method assists in obtaining temperature and humidity information. Therefore, it is not necessary to manually enter the values. The suggested approach offers a user-interactive web interface where they can enter the average rainfall and soil pH.

The GDD Growing Degree Days can be computed using the base temperature of a certain crop. This study's primary goal is to develop simple, mathematically sound formulas for determining the basal temperature of the GDD. Mathematical formulas are proposed, shown to be true, and tested using temperature data for snap beans, sweet corn and cowpea. In contrast to past methods, these new mathematical formulae can quickly and accurately produce the base temperature.These equations can be used to determine the GDD base temperature for every crop at any stage of growth [8]. This paper offers a formula to figure out the crops' GDD. As a result, the formula given in [8] was used in the proposed work to estimate the GDD of the expected crop. The same dataset utilised by other researchers and the fundamental CNN model were employed in this study [9].

Therefore, the Pests dataset from the Kaggle website was employed in the suggested model. Nine different insect classes make up this dataset. Each photograph was captured from a unique angle. The suggested model was chosen for this dataset because it was trained on photographs from multiple places, which provided more information for the model to analyse the images and distinguish between them. The suggested model classifies data using the Resnet152V2 model. The Resnet152V2 model serves as the foundation, on top of which additional hidden layers such as Global Average Pooling 2D and Dropouts are added. The base pre-trained model is being fine-tuned in this sentence.

This study looked into the relationship between the identification key and the level of difficulty in classifying insects. The SPIPOLL database was used to create 193 typical value pathways for a group of 134 insects. Based on the characteristic value of the average IES of all insects, a formula was developed. The estimated IES for each beetle was then produced using the derived IES from the CV, creating a ranked list of insects. The expected bug ranking list and the actual bug ranking list were then

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compared. Indicating that the CV can be used to estimate the IES of SPIPOLL insects, the results revealed a significant correlation between the estimated and real truth IES [10]

## 3. METHEDOLOGY

In this work, three modules—crop recommendation, disease identification, pest identification, and pest recommendation— are proposed. The Web application that is being suggested was created using the Django framework. The user login screen is where the Web

Interface begins. Users must first register with their basic information, such as name, address, country, state, zip code, phone number, username, and password, in order to access these modules. The user must check in using their credentials after being led to the login page after the account has been created. The modules are thoroughly explained in the section that follows.

### 3.1.Crop recommendation:

The crop Recommendation module utilized three datasets obtained from Kaggle, namely Crop Recommendation. csv,soil.csv. csv and scientific names .csv.These datasets were chosen for their relevant attributes, which include temperature, humidity, average rainfall, soil pH, nitrogen, phosphorous, and potassium requirement ratios, all of which are crucial for crop prediction. The crop reccomender.csv was primarily used to train the model, while the soil names and crop names datasets were utilized to obtain crops, such as soil type and scientific names.

After giving respective details this module works on classifiers like Decision tree, Naïve Bayes, SVM ,Logical

Regression, Random Forest, XGBoost.

After all the models trained their accuracy is compared, then the model with highest accuracy is used for output.

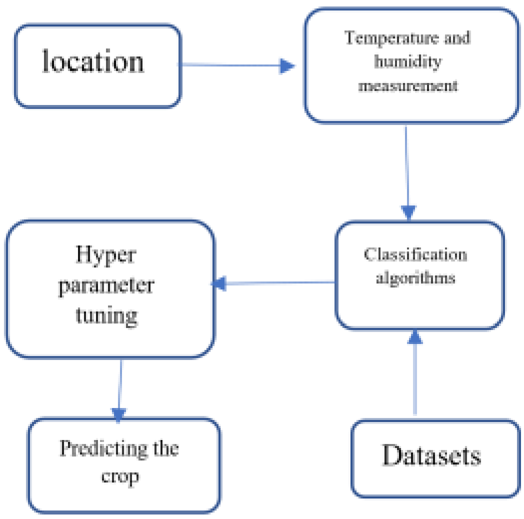


Fig1 : flowchart for crop recommendation

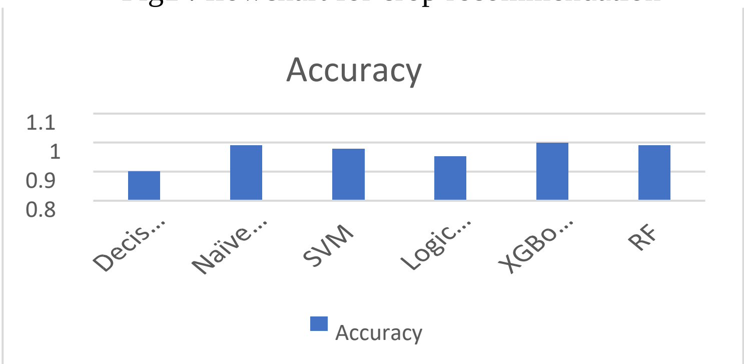


Fig2: Accuracy comparison of different models.

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**3.2.Disease Identification:**

To identify plant diseases, the V2 disease_identification dataset from Kaggle was used. This dataset comprises images of various disease stages for all types of plants, and any plant leaf at any disease stage can be captured and uploaded onto the webpage.

The dataset contains approximately 89.9k images of size 3GB, which were imported into the RESNET machine learning model. RESNET is a neural network that employs an "identity shortcut connection" allowing the model to skip one or more layers.

This approach enables the network to be trained on thousands of layers without affecting performance, making it suitable for predicting the images.

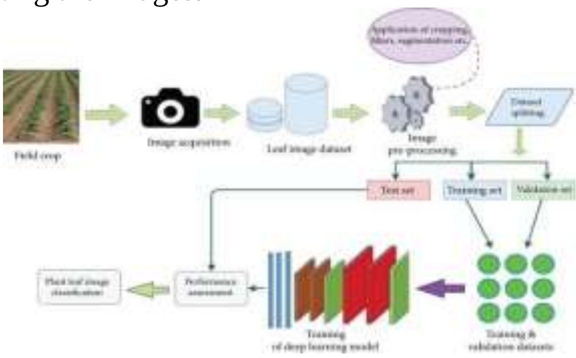


Fig2:Architecture diagram for disease identification

**3.3.Pesticide Identification**

The pests dataset from Kaggle, which includes pictures of numerous insects photographed in various locales, is the data source used for this module. This dataset was chosen because it contains insects that come into contact with crops, a situation where it can be challenging to tell an insect from a crop. Due to the model's training on the pest dataset, the suggested approach can efficiently categorise insects. Training, testing, and validation sets were each given a portion of the dataset to work with. The testing set contained 945 photos, the validation set contained 441 images, and the validation set was used during the execution of the epochs. The training set contained 1764 images. To increase the amount of training photos, data augmentation was used to resize all of the images to 224x224 pixels. For the purpose of obtaining extra images that were then utilised for categorization, this required rotating, flipping, and rescaling the original image. A Resnet152V2 pretrained Keras model was used to categorise the photos. Convolutional, pooling, activating, and fully linked layers are stacked on top of one another in deep residual networks. The identity link between the layers is the single structure that transforms an established into a recurrent neural network.

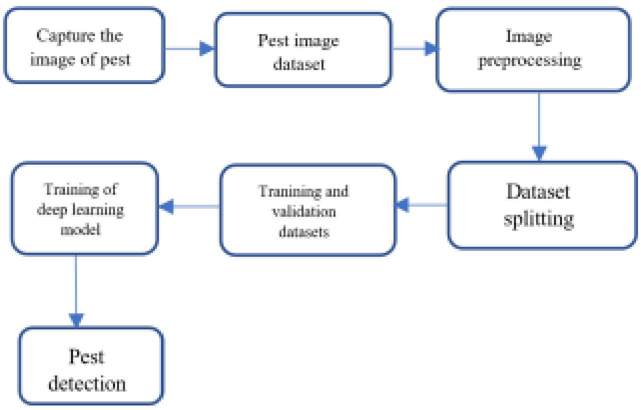


Fig 3.3 Flowchart for pest identification.

**4.WEB APPLICATION**

The web application we developed here is based on Django framwork using html,css,javascript.

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**5.Data Sets:**

**Module 1: Crop Recommendation**

The data set for crop recommendation is a csv file which consist of almost 2400 entries.in which it has different column as nitrogen, phosphorous, potassium ,temperature humidity ,ph,rainfall.

| Nitrogen | Phosphorous | Potassium | Temperature | Humidity | Ph | Rainfall | Label |
|---|---|---|---|---|---|---|---|
| 90 | 42 | 43 | 20.87974 | 82.00274 | 6.502985 | 202.9355 | Rice |
| 85 | 58 | 41 | 21.77046 | 80.31964 | 7.038096 | 226.6555 | Rice |
| 60 | 55 | 55 | 23.00446 | 82.32076 | 7.840207 | 263.9642 | Rice |
| 74 | 35 | 35 | 26.4911 | 80.15836 | 6.980401 | 242.864 | Rice |
| 78 | 42 | 42 | 20.13017 | 81.60487 | 7.628473 | 262.7173 | Rice |
| 69 | 37 | 37 | 23.05805 | 83.37012 | 7.073454 | 251.055 | Rice |
| 69 | 35 | 55 | 22.70884 | 82.63941 | 5.700806 | 271.3249 | Rice |

Fig5.1 dataset sample for crop recommendation

**. Module 2: Disease Identification:**

The disease detection data set consist of nearly 90,000 images in which contain different plants like apple ,corn ,maize ,tamato etc.It has its leaves with diseases at every stage of its life.

**Fig 5.2.a dataset image for disease detection**

| Plant Name | Disease Name | Leaf Image | Preventive measures |
|---|---|---|---|
| Apple | Scab |  | Rake under trees and destroy infected leaves to reduce the number of fungal spores available to start the disease cycle over again next spring. |
| Corn | Grey Leaf Spot |  | limiting the amount of secondary disease cycles and protecting leaf area from damage until after corn grain formation. |
| Potato | Early Blight |  | Plant only disease-free, certified seed. |
| Tomato | Mosaic virus |  | Avoid planting in fields where tomato root debris is present, as the virus can survive long-term in roots. |
| Orange | Citrus Greening |  | the most common practices are avoiding the spread of infection by removal of symptomatic trees, protecting grove edges through intensive monitoring, use of pesticides, and biological control of the vector ACP. |

Fig 5.2.b Tabular form of disease identificaiton

**Module 3: Pest identification:**

It has collection of 56,685 high-quality images featuring 132 pests commonly found in India . It also contains pesticides, which are commonly used to control them.

| Pesticides | Image | Insecticide used |
|---|---|---|
| Adris tyrannus |  | Spinosad , Admire , Agrovet. |
| Black hairy |  | Sparys containing cyphermethrin, deltamethrin |
| Gall fly |  | Acephate , Confidor |
| Jute hairy |  | Missile , Keefun , Snailkill , Vollam Targo. |
| Apolygus |  | Rogor , Exponus , Godrej gracia. |
| Field cricket |  | Phoskill , Regent , Monostar. |
| Jute aphid |  | Confidor ,Ekalux , Actara. |
| Indigo caterpillar |  | Econeem , Rimon , Alecto |

Fig 5.3.a Tabular column for pest

Fig 5.3.b dataset image for pest identification

## 6.RESULT AND DISCUSSION

After opening the website in localhost the web interface obtained is shown below with login and sign up options.

### 6.1 Web Application:


Fig 6.1.a web interface

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Fig 6.1.b Dashboard pages

**6.2 Crop Recommendation :**

The parameters covered by the Crop Suggestion include humidity, average rainfall, soil pH, nitrogen need ratio, potassium requirement ratio, and phosphorous need ratio. These factors are all essential for crop prediction.


Fig 6.2.1 frontend and result for crop recommendation

**6.3 Disease identification:**

In disease identification web page it ask for the image of the leaf to upload to the website ,whose disease is to be detected.Then it detects the image and displays the disease identified and the respective measures to be taken as foolow


fig 6.3.1 frontend and result for disease identification

Industrial Engineering Journal
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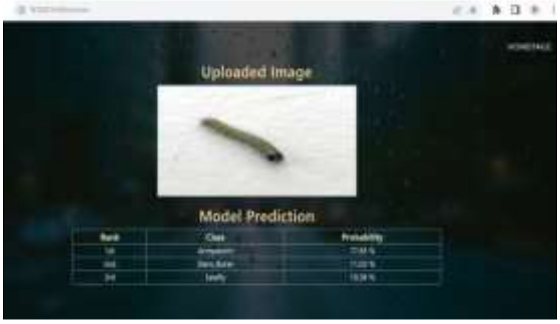


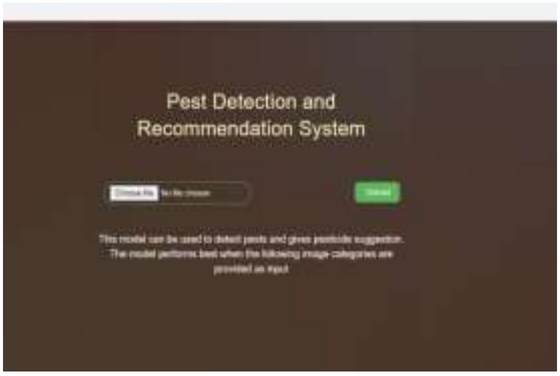

fig 6.4.1 frontend and result for pest identification

**6.4 Pest Identifaction:**

This module assists in detecting the insects and pests that are present in farms and also makes pesticide recommendations for the anticipated insect. The Weeds RESNET pretrained algorithm was used to predict. The outcome was an accuracy of 0.98.

**6.5 Pest Recommendation:**

Based on the pests identified in above module the respective pesticides will be recommended with the help of data in the datasets.




## 7.CONCLUSION AND FUTURE SCOPE

Since agriculture plays a significant role in our economy, it is crucial to make sure that even the smallest expenditure is made with care. When it comes to farming, crop recommendation and disease identification are two examples. Therefore, in order to benefit the farmer, it is essential to verify that the appropriate product has been chosen for the appropriate soil and that it complies with its criteria. Farmers would be better able to select the ideal crop to cultivate with the aid of this technology based on a range of geographic and environmental factors and also able to identify the diaseases and respective measures to be taken by the farmers. The ML based recommendations would greatly inform the farmer and help them in minimising expenses and making strategic decisions by replacing intuition and passeddown knowledge with more reliable datadriven ML models.Our future work aims at developing this model with adaptive learning in pest recommendation module and add an extra module of weed identification and Herbicide recommendation and also cost estimation.

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