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RESEARCH ARTICLE-COMPUTER ENGINEERING AND COMPUTER SCIENCE

AI Crop Predictor and Weed Detector Using Wireless Technologies: A Smart Application for Farmers

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Abstract

Agriculture is undoubtedly one of the biggest and most important professions in the world. Optimization of agriculture and aiming gradually and extensively toward smart agriculture are the need of the hour. IOT (Internet of Things) technology has already been successful in easing people's lives with its wide range of applications in almost all arenas. In this paper, our work takes the help of IOT devices, wireless sensor network (WSN) and AI techniques and combines them for faster and effective recommendation of suitable crops to farmers based on a list of factors such as temperature, annual precipitation, total available land size, past crop grown history and other resources. Additionally, detection of unwanted plants on crops, namely weed detection, is implemented with frame-capturing drone and deep learning methods. Naïve Bayes algorithm for crop recommendation based on several factors detected by WSN sensor nodes has been used, resulting in an accuracy of 89.29%, which has proved to be better than several other discussed algorithms in the paper, like regression or support vector machine. Deep learning using neural network successfully identifies weeds present in a specific area of crop growth extending an additional protective measure to farmers. The comprehensive application developed for farmers not only reduces the physical hardship and time spent on different agricultural activities, but also increases the overall land yield, reduces possibility of losses due to failure of crops in a particular soil and lessens the chances of damage caused to crops by weeds.

Keywords Internet of Things (IOT) · Crop recommender systems · Deep learning · Weed detection · Wireless sensor network (WSN) · Precision agriculture

1 Introduction

Farmers all around the world are required to follow an intricate practice of planting crops in rotation. This practice, which is extremely important to the well-being of the soil, is referred to as crop rotation and precision agriculture [1, 3]. In this method, different crops are planted in alternating seasons so that the soil is not constantly deprived of a particular mineral or nutrient. If the same crop is planted, season after season, then it does not give the soil a chance to regenerate the resources, hence rendering the soil barren. With multiple crops, the nutrients are regenerated at a uniform pace. However, with the concept of multiple crops comes the concern to recommend the best crops to be planted to maximize the yield. Farmers generally are not aware of the crops that should be planted on their particular field. Hence, they end up sowing the wrong seeds, which causes severe harm to the soil and their yield and thus minimizes the profits. If a crop is not suitable on a field, and still if it is planted, it yet again renders the soil barren and makes it unfit for further cultivation. Therefore, with the requirement of knowing what crops to be planted comes the need for recommending the crops by an efficient and highly accurate system. The major challenge is the accumulation of data from different fields. Only when a large dataset is collected, then a model can be trained to predict where all crops should be grown. If this is the case, then even the requirement of pesticides and herbicides will be minimized [2], as the yield will be already at its peak. This paper aims for the betterment of farmers and the

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society. It also aims for quality, uninfected and unadulterated crops, thus improving the health of the society as a whole. The main challenges involved are the collection of the dataset and the farmers knowing the characteristics of their soil, on which the computation is to be performed. This has been achieved using WSN architecture to extract the soil features and using machine learning algorithms on the input data for crop recommendation suited for the particular soil type. Also, an additional feature of this paper focuses on the crops getting damaged due to weeds. This feature has been accomplished using image processing and deep neural network techniques to detect the weed [3] present in the agricultural field. Weeds are malicious plants, which grow together with the useful and highly fertile crops. They survive by taking majority of the nutrients from the soil. This is a bad indicator toward farming, as the healthy and productive crops tend to wither due to lack of proper nutrients, hence decreasing the productivity and thus degrading the soil quality. Thus, for the betterment of the farming industry, we have also developed a flexible system to detect weeds and send the exact location to the farmers using the mobile application that we have developed. Soil moisture sensor and humidity sensors [4] connected in the WSN have been used to get the threshold readings to identify the possibility of growth of weeds. The readings, if more than threshold would prompt the farmer to launch the drone [5] which would capture the land images and send it to the controller for image processing. Thus if a weed is detected, the coordinates will be sent and the application plots a map from the farmers' current location to that of the weed location. Then, the weed can be manually extracted and this saves the crops from dying off. This is highly beneficial to the farmers and the end customers. The input data for the analysis is implemented via several machine learning algorithms [1, 6], which are initially fed into the system through multiple WSN sensor nodes, which compute and gives a full analysis of the soil [7]. With the analysis report, we can then efficiently and with precision predict the crops to be planted. The algorithm also provides an order of the crops to be planted, based on the nutrients available in the soil, thus making the task easier. The agricultural sector contributes to about 14% in India. On an average, a farmer receives 10–23% of what the consumers pays to the retail. Thus, with increased yield, we intend to eradicate the concept of intermediaries in the system of agriculture. Thus, with an outlook to benefit the society from the grassroot level to the zenith, our paper ranges to serve all purposes efficiently and with complete ease.

2 Literature Survey

Over the years, several researchers have studied, developed and made a significant contribution toward smart agriculture. Crop recommendation systems have evolved more and more, and increasing researches and IOT devices have added to the accuracy of crop predictions. Mythili et al. in [8] used several special sensors like humidity and PIR sensors. Arduino microcontroller is used for interfacing the hardware components, and its IDE is used by the GSM (Global System for Mobile) module to display messages on the screen for the farmers. It obviously has the advantage of not compulsorily requiring a smartphone. Farmers can get updates via the GSM network in their normal cell phones. All the data collected from the various sensors placed across the field are passed through the Arduino controller. The GSM allows messaging service to the farmers' phone to give them the updates in regular intervals. The microcontroller consists of an additional Bluetooth module that serves as the message provider to the users within the small range of the system. It provides the information to the users or farmers about the data extracted from the sensors such as temperature, water quantity in soil and smoke on GSM network or with the help of Bluetooth; 98.50% accuracy is obtained from this method. The PIR sensor is an impressive feature in this research study, which detects the presence of any animal close to the crops and notifies the farmers immediately through a LED or a buzzer. The low system cost and efficient working without Internet are a major advantage of the proposed system. The future extension of the paper is to add a water pump for facilitating irrigation when soil moisture content falls below the threshold level and take the model to the next level reducing the manual efforts of the farmers to a greater extent. Manoj Athreya et al. [9] gave a clear comparison on the different types of recommendation systems coupled with IoT technology in their research work. Mokarrama et al. in [10] work with the location of the user and the data collected from agroecological and agroclimatic areas in the Upazila regions. Modules to detect the location for data storage, similarity between location detection and recommendation have been used together to develop this system. The primary need of this system is the user location. Using the most recent Google location API, the address is collected, from which the Upazila is also identified. The database is divided into period of crop growth, thermal zone, rate of crop production, etc. Google API for location detection and analysis of the geographical statistics of the locations is followed by similarity index calculation using Pearson correlation algorithm. Finally, the best suited crops are recommended to the users. IoT devices can be amalgamated with the existing technology to improve the overall accuracy and productivity. Raja et al. [11] proposed a system for crop prediction by studying the past records. Using previous records of soil quality, crop cultivated and kinds of crops grown on the land, the crop yields and the price of crops are predicted using the sliding window nonlinear regression algorithm. Classification of dataset is done abiding the crop price in the market to find the crop demand. The total crop consumption and the quantity of crop cultivated are taken into account to suggest alternatives of crops to be grown. The proposed workflow begins with the data collection followed by conversion of data and data splitting. After data conversion, similarity index is calculated, and the split data along with the similarity are fed into the recommender system for training and prediction. Although the method is comprehensive, however, some additional soil and temperature factors may be considered for boosting the median performance. Pudumalar et al. [1] used the precision agriculture, which is rapidly increasing in popularity, for prediction of the suitable crops to the farmers in their research work. Several AI algorithms and data mining techniques, namely CHAID, KNN and Naïve Bayes, have been used in this paper for better accuracy yield. The overall working follows dataset collection and training of data by efficient feature extraction and then applies it to the ensemble model comprising of the four ML algorithms. Finally, the recommender system predicts the crop based on the model rules such as pH, soil depth, soil water content. Ensemble technique with the majority-voting model is implemented for making the precision agriculture system deliver a better result. The accuracy is fair, around 88%. However, the addition of camera and other technologies can increase the rate. Shirshivkar et al. [12] also make use of sensors such as moisture sensor, temperature and humidity sensors connected to Arduino microcontroller to develop a recommender system for crop prediction by analyzing the sensor data received via Wi-Fi module. Fertilization recommendation implemented by Hao Zhang et al. [13] analyzed factors such as soil yield and crop targets using precision agriculture. Precision fertilization coupled with a simple, efficient ArcGIS server and fertilization decision-making model made the proposed system successful in promoting technical functionalities for scientific fertilization. Weeds cause damage to the crops produced on the land, and hence there have been several techniques to detect weed; IoT robots are used for their removal. Similar study has been done in [14] to build an automated robot for detecting weed using image classification technique and spraying pesticides on the weeds. Data collection is followed by data augmentation to populate the dataset. The comparison among different algorithms of image classification proved CNN to have a higher accuracy as compared to others. Convolutional neural network model is implemented for weed detection. However, a robot comes with a lot of disadvantages too as highlighted in the paper itself, such as battery consumption, level of pesticides that can be sprayed and long-time interval between capturing and spraying of herbicides. Tang et al. [15] aim at accurate identification of weeds and properly spraying herbicides to reduce the loss of chemical fertilizers and also the environmental degradation caused by them. The paper aims at a combination of vertical projection and linear scanning techniques for finding out the central line of the row of crops. The weeds infestation rate (WIR) is analyzed and modified for improvement resulting in dynamic decision making based on the Bayesian minimum error ratio. Dataset consists of manually taken images in different conditions of light, since color is primarily an important feature of image classification. Suitable color feature and a color space are necessary for proper image classification, accompanied by Cg component to identify the predominant green in crops. The steps in this method of classification start with the original image conversion of RGB to YCrCb. It is followed by image processing, obtaining the line of center of the rows of crops and division of cells. The MWIR is then calculated within the cells, followed by real-time decision making whether to spray crops or not. Crop vertical projection identified the black portion as the soil, white pixels as the crops. The MWIR database is used to analyze the data, and then the decision is arrived at by calculating the Bayes error ratio. The accuracy of the proposed algorithm is also quite impressive, being 92.5%. In our work, we propose a unique combination of accurate crop prediction using AI and IOT coupled with weed detection using drones fitted with camera for dynamic frame capturing. Louargant et al. [16] widely focus on the spectral processing of images to distinguish between monocotyledonous and dicotyledonous plants. It uses an automated drone system to track these images and classifies them via an unsupervised learning algorithm. A positive classification of the crop field was continued with an accuracy of 80%–100%. It also successfully detected weed from the field, by running a comparison over multispectral weed images. Two types of testing were conducted, one in laboratory conditions on monocotyledonous and the other in dicotyledonous plants. They were tested with the reflectance spectra, and the field experiments resulted in multispectral images. The model in practice converts the reflectance spectra to pixelated values based on different parameters such as luminance, objects in scene, sensor characteristics which change the differentiating capability of the learning model as they serve as the learning parameters for the classification.

3 Proposed Work

The paper aims at a simple, user-friendly application for farmers, which would assist them in selecting the suitable crops for their land and also help them in detection and removal of weeds in their cropland. Wireless sensor network has been the breakthrough technology, especially in precision agriculture. Our model makes use of WSN, ML and AI working together to deliver a model with a good accuracy of 90%. The environmental factors detected using the sensors in the WSN model are fed into our system, which extracts essential features from the factors and uses Naïve Bayes algorithm to predict the suitable crop for the farmland. As an additional protection feature, our model includes a camera-fitted drone

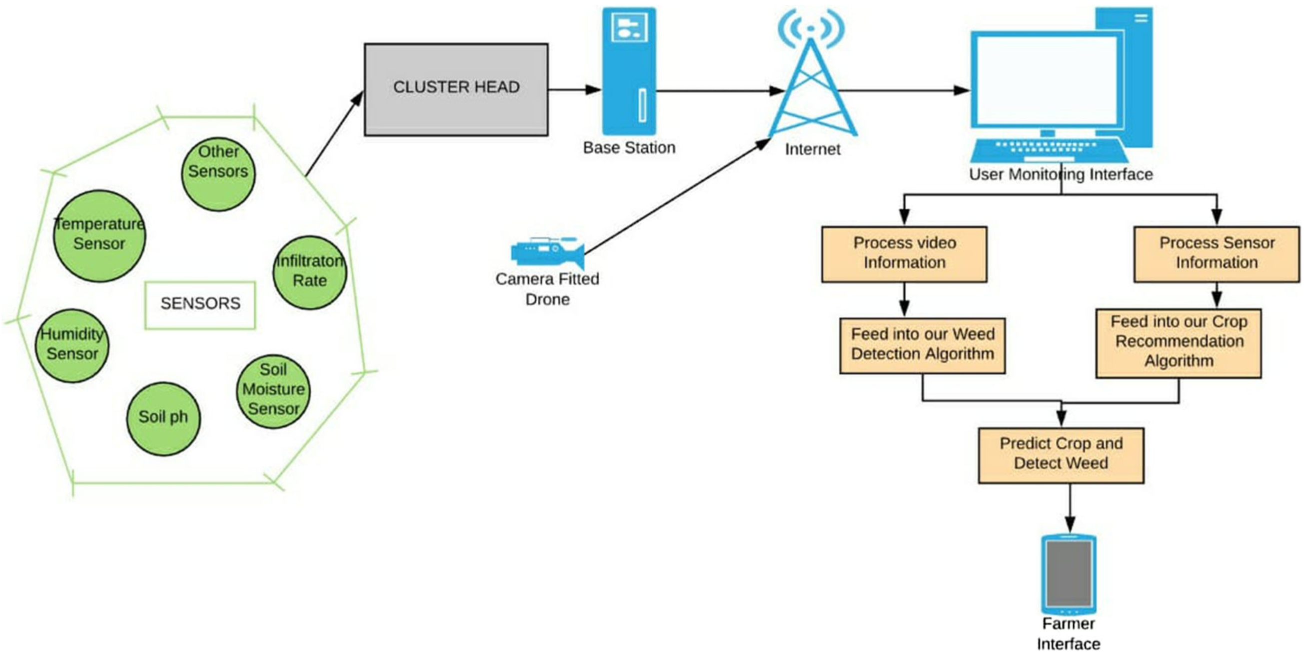

Fig. 1 Workflow for our proposed model

which will capture real-time video of the crops from a suitable height above the ground. The video fed into our system uses CNN algorithm for detection of weed growth around the crops. Weed removal has not been included in our model. But the detected frames of weed growth can be used by future add-ons to our model for weed removal. In Fig. 1, the overall workflow for our proposed model is explained. Information is collected from all the different sensors distributed across the farmland. All the sensors are connected to one cluster head, which is in turn connected to the base station. In this way, the sensor data and the data from the camera-fitted drone are collected via the Internet into the database system. After preprocessing the data, it is fed into the crop recommendation and the weed classification models. After prediction, the information is updated to the farmer's application interface.

4 Methodology

4.1 Dataset Preprocessing

The first objective was to preprocess the dataset, as the first column included soil types, which had to be encoded using a label encoder. The next task was to ensure that these encoded soil types do not indicate any priority. Thus, one-hot encoding technique was applied on the dataset. Rest of the features was floating-point type. This ended the first phase of the data preprocessing. The next was to split the dataset into training and testing and to drop the output column. The output column was not to be encoded and kept as a string literal, as one-hot encoding would have rendered into inefficiency of the algorithms due to wide possibilities and would increase the output features by a manifold. With the data split into training and testing sets, the training part of the input features was fed into the respective classifiers. It is an important note that while fitting the training data into the classifiers, the data should always be parsed as integers. Thus, the dataset was trained with their respective training outputs and the classifier was ready to predict. In Fig. 2, the weed classification model is shown at its functional state. Higher percentage shown over an area of lands implies greater amount of weed in that area. Since we have proposed classification of weed with the help of drones, we wanted our setup to be able to properly classify based on a photograph taken from a height for which we have tested our model with some drone photographs of croplands with weeds, taken from a particular height. The crop dataset consists of the impact factors to be preprocessed for prediction of crops, namely soil moisture content, soil type, soil pH, soil infiltration level, humidity, temperature and finally the crops suitable for given values of these factors. The various factors taken into account in our dataset have been visualized using histogram to explore the variations of our dataset, which can be seen clearly in Fig. 3. After preprocessing, training and testing are carried out through our Naïve Bayes algorithm, and the input data from the farmers are fed into our model via WSN architecture, finally predicting the suitable

Fig. 2 Percentage of weed detected in cropland

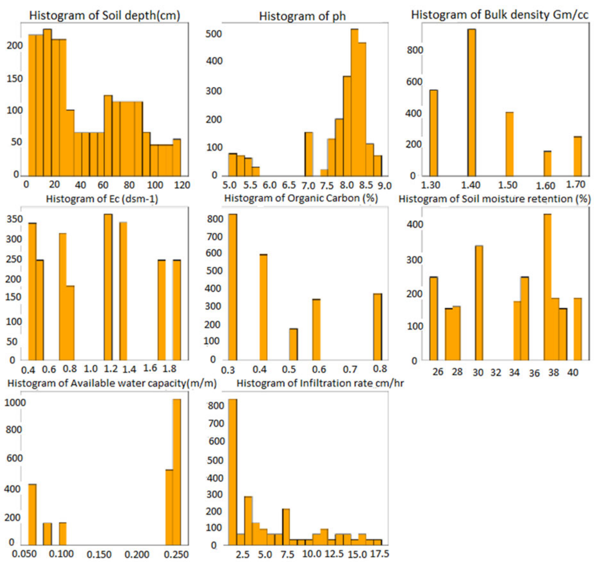

Fig. 3 Visualization of the fields of our crop dataset

crops for the land. Similarly, the weed dataset [17] consisting of weed training images has been trained by our CNN model. The video of the crop land detected by our camera-fitted drone will be fed into our model to detect weeds.

4.2 Techniques

As discussed above broadly, crop rotation and precision agriculture are the need of the agricultural sector but the inability of the farmers to predict the crops to be planted on their fields and the correct order in which the crops are required to be grown to maximize the yield and also the deficiency in the technological implementation have motivated the authors to contribute toward this social cause and make a holistic approach by a novel technique. IoT without

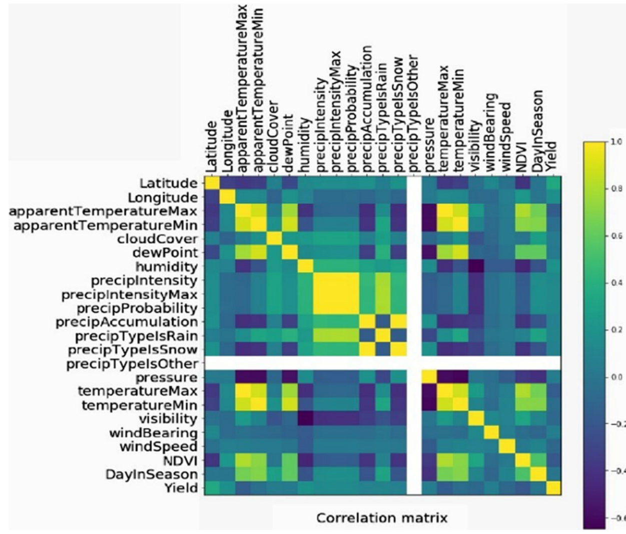

Fig. 4 Correlation matrix showing dataset features

smart processing will not be effective in processing gathered data and infer meaningful results. Hence, IoT and AI combined provide the best, innovative and effective results for our proposed application. Wireless communication technologies have become a backbone for any data retrieval, processing and communication between other devices or nodes. Zigbee is one such technology gaining popularity majorly in precision agriculture (PA) which has been used as the IoT system in our research. It has high scalability and also offers easier maintenance of the connected sensor nodes which can intercommunicate with each other. Thus, the information is collected from the various sensor nodes which communicate and transfer data via Zigbee technology to the base station. The base station receives all data, monitors each connected sensor and serves as the Zigbee Coordinator (ZC). The collected information in ZC is stored via Internet in a cloud database. The database communicates with the server to provide the information where the algorithms and predictor techniques are applied. The overall model revolves around by working on an agricultural based dataset, which has several soil types and soil conditions along with the different environment conditions. The correlation matrix between the different features such as temperature, precipitation, humidity is plotted to get a visual representation as shown in Fig. 4. The output of this dataset is the different crops that are eligible to be planted in those particular environmental situations. The main idea is to now use this dataset and predict the crops whenever some soil and environment analysis is given. These challenges were efficiently solved with several machine learning algorithms. The different algorithms, which were tested on for this dataset, were Naïve Bayes, SVM, KNN, multiple regression and K-means. Then, this classifier was used on the testing input features data. Now

NLTK Python Library was deployed to classify and was stored for further accuracy calculations. Then, the predicted output is compared with the test output feature. A confusion matrix is plotted, and the accuracy is found out. By changing hyperparameters, the algorithms were tested and verified for production. Now these algorithms were implemented in a Django framework, which would serve as an interface for the users. The users would pass in the data as a form and run their choice of predictions. The output would efficiently predict the crops to be planted. However, the major concern was the way users can gather the information about their soil. The main idea of setting up an IOT device was to resolve this issue. We used a WSN, which requires a centralized unit which could be controlled by user interface embedded in the Django app. Whenever the user clicks the button, it would activate the sensors and would upload the feed from the cloud network. The Web application would automatically fill in the required details in the Django form, and the analysis would be performed according to the algorithm selected. IGMS can be incorporated in a Web application. IGMS sensors incorporated are primarily humidity, pH scale, salinity, temperature. Data collected will be stored remotely in a server, and then a copy is sent to the cloud. The cloud is again requested with a GET request, by the application. The cloud inputs the required values in the form, and the result is found by using the desired algorithm. Thus, an efficient user-friendly two-click automated system is developed, which has a vision to be a boon to the agricultural sector. Firstly, we have implemented a large number of crop varieties in the dataset so that all the types of crop pools were filled with a high number of instances in every crop pool. A crop pool as used in our algorithms is the possibility of certain types of crops belonging to a same class as predicted and guided by the machine learning algorithms which runs on the massive dataset and hence setting up various rules for each crop, and justifying any crop which is provided by the user while testing to allocate the crop to a particular crop pool class. This classification is not based on the properties of the crops; rather, it feeds on the environment conditions and other dataset attributes. Now, the biggest challenge was to allocate a crop, which was never encountered in the dataset before. Therefore, to overcome that challenge, machine learning algorithms were applied to generate a set of rules. The rule set would take all the types of crops available, including crops which weren't ever encountered in our training dataset. Based on the intrinsic properties of these crops and also several other environmental factors pertaining to the particular crop type, correlation checks of the identified crop were performed against the crops available in our dataset to find the closest correlated crop type. If the correlation value passes the barrier limit, the unknown crop is readily placed in the crop pool of that of the highest correlation crop. This also helps in future adding and updating of the crop dataset and hence is a robust and innovative technique in assigning to even unknown crops. Now this unknown crop belongs to a crop pool class, and thus, it is highly user-friendly if the user wants to add other crops into their consideration, which does not belong to the dataset. Hence, this alternative is provided which makes the application highly scalable and flexible for any type of crop, whether known as well as the unknown crops based on the users discretion and priorities, thus accurately recommending the crops which are optimum for getting sown in the area based on the users environmental conditions and other dependent factors, thus establishing an efficient and highly productive system. Another important add-on feature of this is the drone-based weed detection, which we have tried to implement as a secondary feature. It incorporates a 360-degree camera fitted underneath it. It uses a complex CNN technique, which takes a video frame as input and processes it in several deep neural layers. It also has implemented inception network techniques. It marks the regions where it detects weed plants and using the drones' gyroscope plots a map between the user's current location and the different location of weed found in the crop fields. There is a threshold value for the distinction between classification of weed and nonweed, by tuning several hyperparameters and learning this threshold on repeated training in batches. Thus, in the end, the weed plants can be plucked out. This system is hence maximizing the crop yield and has a high impact factor.

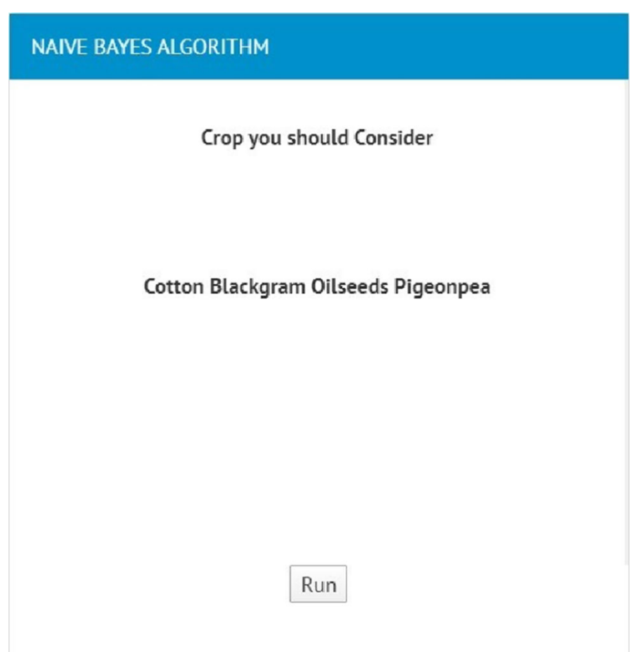

Fig. 5 Crop prediction by our model

4.3 Model Implementation

This whole analysis model was deployed on a python-based framework. Django has been used to serve as the user interface. The user interface contains a form which can either be filled by the user or with a button click, and a full analysis can be done by the IOT sensor which uploads its analysis reports on a remote cloud database, and the respective form inputs, i.e., pH, temperature, humidity, temperature, etc., will be populated from the same. These inputs are passed into the machine learning models, which first train the dataset and immediately process the predicted output. They also take into account the previous history of the crops and optimize the output. Naïve Bayes, SVM, KNN algorithms have been implemented, and the user is free to choose any to compare the accuracy and to avoid biasness. Figure 5 shows an illustrative snapshot of the Django-based HTML processor Jinja template. The output is of the Naïve Bayes algorithm running and predicting the possible crops to be planted in the particular soil. sklearn.svm.SVC, sklearn.naive_bayes, sklearn.clusters.KMeans and other various python libraries were used to make this implementation a success.

Genetic mathematical modeling of our research:

1. START
2. Take sensor reading inputs $a_1, a_2, a_3, a_4 \ldots a_i$ from sensors in WSN
   - 2.1 $A(a_1, a_2, a_3, a_4 \ldots a_i)$ send to base station via cluster head
3. Images $I(i_1, i_2, i_3, \ldots i_i)$ from frame capturing drone taken input
4. Send Step 2.1 and 3 via Internet over to the database system
5. Processing
   - 5.1 Encoding the sensor inputs $a_1, a_2, a_3, a_4 \ldots a_i$
     OneHotEncoder[Data($a_1, a_2, a_3, a_4 \ldots a_i$)]
   - 5.2 Split sensor input Data into Training and Testing sets (T_r and T_e respectively)
     T_r = TrainingSet[Data($a_1, a_2, a_3, a_4 \ldots a_i$)]
     T_e = TestingSet[Data($a_1, a_2, a_3, a_4 \ldots a_i$)]
   - 5.3 Loop j → length(I):
     Resize(I[j],(Dimension),interpolation)
   - 5.4 Loop j → length(I): Blur → GaussianBlur(I[j])
   - 5.5 ImageFinal →image[1]
   - 5.6 grayImage = ConvertColor(image, RGB TO GRAY)
   - 5.7 transformation =
     Call[distanceTransformFunction()]
   - 5.8 result = Threshold(transformation , 0.7 * Max(transformation) , 255, 0)
6. Classification
   - 6.1 Deploy the T_r into classifiers
   - 6.2 Classifier_k.classify (Features(T_r)) ; k belongs to { Naïve Bayes, SVM, KNN, Multiple Rgression, K-Means} -> Return result_k
     - 6.2.1 NLTK for classification accuracy
       nltk.accuracy(result_k)
   - 6.3 Note the highest accuracy value for classifier.
   - 6.4 Feed the pre processed image into the YOLO network
   - 6.5 $L_1 \rightarrow \alpha_{coord} \Sigma_{i=0}^{s^2} \Sigma_{j=0}^{B} \omega^{obj}{}_{ij}$[Square(Difference(($x_i, \hat{x}_i$) + Square(Difference ($y_i, \hat{y}_i$)] + $\alpha_{coord} \Sigma_{i=0}^{s^2} \Sigma_{j=0}^{B} \omega^{obj}{}_{ij}$[Square(Difference(Root($w_i$),Root($\hat{w}_i$)) + Square(Difference (Root(h_i) ,Root($\hat{h}_i$))]
   - 6.6 $L_2 \rightarrow \Sigma_{i=0}^{s^2} \Sigma_{j=0}^{B} \omega^{obj}{}_{ij}$ [Square(Difference($C_i, \hat{c}_i$)] + $\alpha_{coord} \Sigma_{i=0}^{s^2} \Sigma_{j=0}^{B} \omega^{noobj}{}_{ij}$ [Square(Difference ($C_i, \hat{c}_i$)]
   - 6.7 $L_3 \rightarrow \Sigma_{i=0}^{s^2} \omega^{obj}{}_{i} \sum_{c\epsilon classes}$ [Square(Difference($p_i(c), \hat{p}_i(c)$)]
   - 6.8 Total Loss Computation → $\mathbf{L_1 + L_2 + L_3}$
7. END

4.4 Neural Network in Weed Detection

The weed detection mechanism is largely dependent on the neural network feed. The process is majorly based on taking images of several parts of the field, which will serve as the input for the neural network. Before passing them through the network, the images have to be resized into 608 × 608 pixels resolution, which were visualized to fit the neural architecture with the highest accuracy. The resolution of the resulting image must be of very good quality, as every layer will extract different properties from the RGB layers, which will cumulatively be assessed for the prediction and detection.

The architecture in Fig. 6 is comprised of five convolution and max-pooling blocks. In each of the layers, the pixels of the image provide different pieces of information pertaining to the features, which are associated with classification. Max pooling is an important feature in each layer which allows to reduce the number of features and hence the pixels and pass it down to the next layer. Thus, according to the convergence theorem, with each progression in the neural network, we slowly converge toward a particular weight matrix by repeated forward and back-propagation in the series of number of epochs and batch processing. The neural network started with initially 16 filters and was then successively doubled in the forthcoming layers. Downsampling by a factor of 32 was contributed by each of the max-pooling layers. A feature map of 19 × 19 × 256 was created at the end of the five convolutional layers and pooling layers. After this step, we

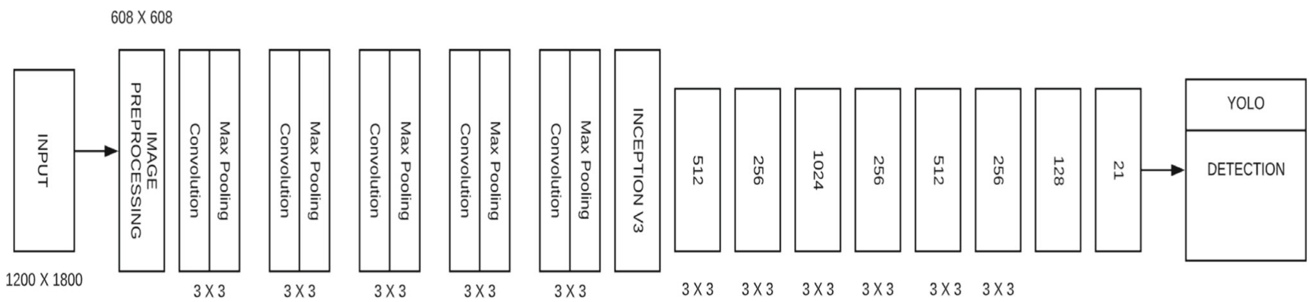

Fig. 6 Neural network architecture layers

pass the resultant image into a layer of Inception V3 network layer. Again, it is passed into a wide range of convolutional operations, finally resulting in a $19 \times 19 \times 21$ resolution. This is a methodology used to convert the two-dimensional tensor to three-dimensional tensor, so that bounding boxes can be established. We then use the YOLO v3 algorithm to create the bounding boxes, which were encoded to surround on weed-laden areas via other algorithms and annotation processes. Also it is to be noted that the bounding boxes also have the accuracy with which it predicted the possibility of a weed infestation. With this methodology, the camera can be fit into a drone and a top-view image taken and the weed detection process is thus implemented. This neural network does not use the default anchor boxes; rather, as mentioned above, it is calculated based on our training weed data. Various machine learning algorithms were tested to predict the bounding boxes, and it was observed that K-means algorithm gave the highest accuracy.

$$
\begin{aligned}
L_1 = {} & \alpha_{\text{coord}} \Sigma_{i=0}^{s^2} \Sigma_{j=0}^{B} \omega_{ij}^{obj} [(X_i - \hat{X}_i)^2 + (Y_i - \hat{Y}_i)^2] \\
& + \alpha_{coord} \Sigma_{i=0}^{s^2} \Sigma_{j=0}^{B} \omega_{ij}^{obj} [(\sqrt{\mathrm{W}_i} - \sqrt{\hat{W}_i})^2)^2 \\
& + (\sqrt{\mathrm{h}_i} - \sqrt{\hat{\mathrm{h}}_i})^2] \\
L_2 = {} & \Sigma_{i=0}^{s^2} \Sigma_{j=0}^{B} \omega_{ij}^{obj} (C_i - \hat{c}_i)^2 \\
& + \alpha_{coord} \Sigma_{i=0}^{s^2} \Sigma_{j=0}^{B} \omega_{ij}^{noobj} \left[(C_i - \hat{c}_i)^2 \right] \\
L_3 = {} & \Sigma_{i=0}^{s^2} \omega_i^{obj} \sum_{c \in classes} \left(p_i(c) - \hat{P}_i(c) \right)^2 \\
L_{loss} = {} & L_1 \\
& + L_2 \\
& + L_3
\end{aligned}
\tag{1}
$$

The mathematical calculation of the bounding boxes as prescribed by YOLO algorithm mainly is classified into L_1, which indicates the error in the bounding box. L_2 indicates the error in confidence of the system. L_3 indicates the loss function of the system. In the calculation shown in Eq. 1, α_{coord} and α_{noobj} are taken as 6 and 0.5. The number of grid cells is indicated by S, and that of bounding boxes is indicated by B:

$$\omega_{ij}^{obj} = \text{ denotes the } j\text{th bounding box in the grid cell} i$$

$$\omega_{ij}^{noobj} = -\omega_{ij}^{obj}$$

$$\alpha_{coord} = 6$$

$$\alpha_{noobj} = 0.5$$

$$\alpha_{coord} = 10 * \alpha_{noobj}$$

w_i, h_i, x_i, y_i are the width, height and centroid coordinates of the corresponding anchor box. The final loss function is calculated by summing up the L_1, L_2 and L_3.

c_i is the calculated confidence score of object p_i (c) pertaining to the classification loss. The parameters with hats are the corresponding estimated values. c here denotes the classes. ω_{ij}^{obj} is 1 if there is an object in cell and 0 otherwise.

4.5 Machine Learning Algorithm in Crop Recommendation

Several machine learning algorithms have been developed to predict which crop is suitable based on the environmental conditions. The Naïve Bayes algorithm outputted the best accuracy. Naïve Bayes is a probability-based algorithm which is based on Bayes algorithm. It functions in developing the classifier models and is responsible for assigning the class labels. In this case, a set of crops which are in the data pool are selected and assigned accuracy based on prior training on a dataset. In this algorithm, a particular set is equally compared with all the attributes in the dataset, without discrimination or biasness. The algorithm assures that only one crop set will be left in the pool. After the accuracy calculation, the crop pool with the highest probability is outputted by the pipeline. Support vector machine (SVM) is an algorithm which isolates a hyperplane to a value of unity, hence regarding itself as a discriminative classifier. It is a collection of directed procedures of learning, relapse, order and exception's revelation. Each attribute is plotted on a hyperplane, in N-dimensional space with the value of each attribute serving as the component established in that particular chosen plan. KNN is another algorithm implemented. Predictions are made directly on the dataset while using this algorithm. For a new instance namely x, by traversing through the entirety of the training dataset, prediction is made by grouping the K most correlated instances and then summarizing the output variable for all of the K instances. It is generally based on the centroid of all the classes, or a median or mode, which constantly shifts indicating which class the crop sets belong to. To determine this, we find out the Euclidean distance between all the instances. Euclidean distance is calculated as the square root of the sum of the squared differences between a new point (x) and an existing point (xi) across all input attributes j:

$$ED(x,\ x_i)\ = \sqrt{\left(\Sigma\,\Sigma_{i,j}\left(\left(x_j - x_{ij}\right)^2\right)\right)} \tag{2}$$

4.6 WSN Architecture Implementation

Wireless sensor network (WSN) architecture is currently the most widely used remote sensing technology in precision agriculture (PA). The advantages of using WSN are manifold as nowadays in current agricultural requirements, the optimum use of fertilizers or pesticides or water needed for irrigation is yet not known clearly to famers. There is still a prevalent deficiency of laboratories for soil testing in many areas of the world for which proper crops for a particular soil type are often not chosen correctly [18]. The amount of requirements for improving soil health is still ambiguous to farmers in several areas. And also, less than normal or more than normal use of pesticides and fertilizers for specific crops can adversely affect the nutrition of soil and health of farmers, respectively [19]. Hence, rapid data collection, prediction of correct crops for a specific soil type and environmental conditions and monitoring of the data at a low cost but a higher efficiency are the need of the hour. WSN is one such important technology, which helps in accurate spatial data retrieval via different sensors placed at different strategic positions spread throughout the farmland and then applying decision algorithms to derive useful results.

The WSN architecture targeted in our paper uses Zigbee technology as it offers all the basic and important requirements, namely less consumption of power and higher lifecycle, low data rate and moderate to high coverage area. Placement of WSN sensor nodes is a challenge; hence, this paper aims at terrestrial WSN using different network topologies, like mesh, tree for sensor placement, based on farmer requirements. And again, alternative solar energy power as a

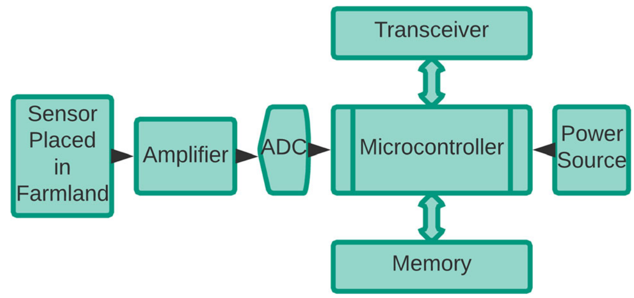

Fig. 7 Sensor node architecture

secondary battery source power offers longevity to our WSN. The different sensors that are being used in our model, namely relative humidity, temperature, soil water capacity and soil porosity sensors, are placed at strategic position throughout the agricultural land to retrieve the signals efficiently and provide accurate input data to our crop recommendation engine to perform data analysis on the data and predict the crops suitable for the land. The WSN sensor node architecture is shown in Fig. 7. Sensors convert the specified quantity to be measured into an analog signal, which is amplified and fed to processor via ADC. The transceiver section uses Zigbee for network establishment and communication in WSN.

Temperature Sensor—Different crops have different levels of tolerance toward both soil and environmental temperatures. For example, broccoli seeds germinate in cooler climates whereas marigolds germinate in relatively warmer ones. Hence, before selecting a crop for a farmland, the temperature is a crucial thing to monitor. The temperature sensor is hence used to determine the temperature in the farmland where it is implanted, sending off any abnormal conditions. The sensor is primarily a diode where the value can be measured based on the change in voltage between the terminals of the diode, which is used to calculate the temperature:

$$T\ =\ Q\ \times\ \left(V_f / nk\ \times\ log I_f\right) \tag{3}$$

where

T is the temperature measured,
I_f is the forward current,
k is the Boltzmann's constant,
T is the absolute temperature,
Q is the magnitude of electronic charge,
n is the value between 1 and 2

pH Sensor—Another major regulator of crop nutrients and an important factor to be considered for crop selection is the soil pH level. It is also related to the climatic conditions of that area; hence, the use of both pH sensor and temperature sensor would allow better decision making for the ML model to identify the relevant crop accurately. Plants like asparagus prefer a slightly alkaline soil to grow on, while blueberries grow well on more acidic soil. A pH sensor works based on the principle of hydrogen-ion concentration measurement in the soil:

$$pH\,(\text{soil}) = pH\,(\text{solution}) + \left((E\,(\text{solution})\;\;E\,(\text{soil}))\,/\,\left(R \times T/F\,\log 10\right)\right) \tag{4}$$

where,

pH(soil) is the pH value to be calculated

pH(solution) is the known pH value of standard solution

R is the gas constant (joules per kelvin per mole)

T is the temperature in kelvin

F is the Faraday constant value (coulombs per mole)

$E(X)$ is the electrode potential

Environmental factors affecting sensor readings such as temperature at its extreme values provide tension to the sensor electronics and would reduce longevity. In places where temperature varies almost more than frequently the temperature sensor used as a WSN sensor node, data value should be periodically fed into the pH sensor to result in more accurate readings. Also extreme pressure changes cause material of the sensor to be affected and provide faulty readings. The glass membrane for pH measurement can be affected if exposed to frequent dusty air conditions and would develop a coating which has to be chemically cleaned in specified time intervals.

VWC (volumetric water content) soil moisture sensor—It is an important measurement to be considered while crop farming as it is very closely related to the amount of irrigation required for the crop too. If the soil moisture content can be measured correctly, then it would aim at a possibility of saving water as many farmers are unaware of the exact water content their type of soil needs:

$$\Theta = \left(\varepsilon_b^a + \left(\left(1 - \varepsilon_m^a\right)(\rho b/\rho s)\right) - 1\right)/\left(\varepsilon_w^a - 1\right)) \tag{5}$$

where

Θ is the water content in VMC measurement

εb is the bulk soil permittivity

εm is the mineral permittivity

ρs is the particle density

ρb is the soil bulk density

εw is the water permittivity

Environmental factors affecting sensor readings—The permittivity of water is inversely dependent on temperature, and also conductivity of soil is directly correlated with temperature. Bulk density of soils can result in +- 2% error in the water content sensor readings.

Humidity sensor—Exposure to sunlight and temperature is joined with humidity of a region as one of the other main important factors affecting crop growth. Increased humidity allows crop growth having longer and wider crop parts. Vegetables ideally grow in room humidity, while flowering plants need lesser humid conditions. Such a sensor mainly works based on the change in the capacitive or resistive value of the dielectric element used to measure relative humidity values. The capacitive-type humidity sensor is proposed in the WSN network sensor node connection, as it is known to provide better results than the resistive and thermal ones, when tested across a varied range of temperatures

$$R_h = 100 \times \left(exp\,\left(\left(17.625 \times T_d\right)/\left(243.04 + T_d\right)\right)\,/\,exp\,\left(\left(17.625 \times T\right)/\left(243.04 + T\right)\right)\right) \tag{6}$$

where

T is the temperature

T_d is the dewpoint

Environmental factors affecting sensor readings—Humidity sensor readings are affected by altitude of the region due to the change in vapor pressures. It is also affected by the temperature. As temperature increases, the relative humidity decreases. Hence, sometimes calculation of dewpoint instead gives a better air moisture content reading as it is independent of temperature.

Wireless sensor networks can be extended to other applications such as:

1) Drone automation for weed detection—Wireless sensor networks have a huge impact in precision agriculture as seen in the literature survey of our paper. The prediction and recommendation of crops have highly benefitted due to the WSN techniques collaborated with ML and DL. As a future prospect of our research, it is aimed for drone automation using WSN. Weed growth depends on several factors such as the climatic influences of a particular area followed by soil fertility, soil moisture capacity, etc. In our research for crop recommendation, all the sensors placed throughout the field are already monitoring several climatic and soil content features. Those features recorded by the sensors in the WSN can be exploited to get a boundary limit condition for discharging or activating the drones for weed detection mechanism. Hence, it would save the unnecessary battery wastage of drones as they would be deployed only at the right and specific time, more toward the early growth of the crops, and would in turn develop a fully automated drone monitoring system.
2) Prevention and controlling of forest fires—Forest fires are becoming very common in today's world due to increasing drastic climatic changes. And it is till date a very uncontrollable disaster and results in a huge loss of forest resources, degradation of environment, and loss of human habitat too. Forests are an integral part of our survival, and protecting and conserving our forests is a global concern. WSN sensors tracking the smoke and the

heat can send off alarms to the nearby controlling unit and help in regulation and faster controlling of erupted wildfires.

3) Smart home applications—WSN can also be widely applied to our home and daily lives in the modern cities. The very notion of saving electricity can be efficiently executed by WSN and IOT devices continuously tracking user moment using vibration and heat transfer energies. The IOT and WSN can together communicate via infrared frequencies and switch off the electronic applications whenever the sensors are not in use. This combined with all the devices combined can play a key role in turning a modern city into a smart city.
4) Prevention and detection of wastewater contamination—Due to aggressive use of pesticides, there is an immense amount of pesticides, herbicides and insecticides that get heavily dissolved. This results later in phenomenon called as algae bloom which reduces the oxygen content of the nearby water bodies. Most agricultural water is disposed in some river or seeps into the groundwater, which later is consumed by the human population. Thus, it becomes a necessity to track the purification status, as the agricultural wastewater is totally untracked of. Thus, with the help of WSN and IOT devices and sensors placed at every checkpoint, the water is checked for the percentages of this contamination. If these amounts are found excessively high, then the wireless network sends a signal to channel this water into containment shells for further purification.

```
def run_naive_bayes_algorithm(self,test_records):
    training_set = nltk.classify.apply_features(self.extract_features, self.records)
    classifier = nltk.NaiveBayesClassifier.train(training_set)
    result = classifier.classify(self.extract_features(test_records.split(",")))
    return result


if __name__=="__main__":
    naive_bayes = NaiveBayes()

    result=naive_bayes.run_naive_bayes_algorithm()
    print("Result :: ",result)
```

Fig. 8 Naive Bayes code snippet

```
Accuracy:: 89.29%
Result :: Cotton Jowar Pigeonpea Blackgram
```

Fig. 9 Crop prediction accuracy

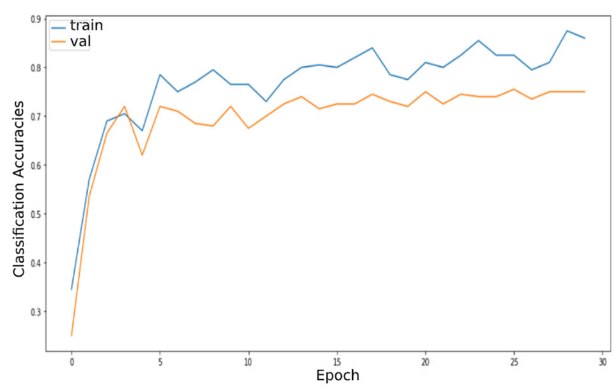

Fig. 10 Classification accuracy

5 Results Analysis and Discussion

The model showed an impressive accuracy of approximately 90% when trained on our dataset (training/testing: 3:1) using Naïve Bayes. The Bayesian code implemented in our research for prediction of crops has been shown in Fig. 8. The run_naive_bayes_algorithm runs the Naive Bayes Classifier model on the trained dataset and returns the result accuracy which is printed in the main function. The main concept revolves around the information gathered from sensors via WSN and proper ML fitting model to our dataset coupled with proper CNN detection of weed images captured from the drone. In this era of revolutionizing agriculture, our proposed model will definitely ease the lives of farmers and help them tackle with the huge losses incurred due to lack of knowledge of the appropriate crops to be grown on a land and also due to the weeds affecting their crops. Figure 9 illustrates the accuracy of the dataset using the Naïve Bayes algorithm. The dataset is randomly split into a training set and testing set. The algorithm is then trained on the training set by the classifier. This classifier is then passed into the testing dataset, and a confusion matrix is extracted. This confusion matrix is then computed, and the score and accuracy are predicted. As visible in Fig. 9, the accuracy is predicted to be 89.29%. There is an added validation set which is kept separately. Also in the image, a prediction of crop is also made for a particular tuple in the test data. Again, in Fig. 10, a graph between training and validation set is plotted based on the progress of training and testing of the data. The accuracy at every point is noted and hence plotted. It can be seen that both the curves are at par with each other; hence, the algorithm is highly capable and successful in predicting the accuracies. Moreover, the hyperparameters are correctly set to avoid overfitting and underfitting. This trade-off is the key factor in determining the accuracy and legitimacy of an algorithm.

In Table 1, a comparison between different ML techniques based in their prediction accuracy is depicted. Although all techniques are fairly having a good accuracy score, we chose to commence with Naïve Bayes, as it has proven to give higher accuracy and closer prediction results as compared to others. The ensemble technique which was used in this paper is random forest. It matched our study requirements. Random

Table 1 Comparison between different techniques for crop prediction

Techniques	Accuracy (%)
Naïve Bayes	89.29
Ensemble	88.7
KNN	88
SVM	87
Regression	84.8

forest basically is a highly nonparametric algorithm except the hyperparameters, namely feature subspace ratio, number of trees and a few others. It was an optimally robust classifier owing to our dataset, which matches the requirements of the algorithm but ensemble learning is not immune to overfitting, which significantly penalized the accuracy during testing phase, thus resulting with an accuracy score of 88.7% (Table 1.). The Naïve Bayes algorithm is immune to overfitting and hence was declared superior in accuracy and other metrics to the other algorithms, thus resulting as the best algorithm for our use-case scenario and dataset.

A minute difference between Naïve Bayes and KNN algorithm is that the former is a generative classifier, while the latter is a discriminative classifier. KNN is actually a lazy classifier, which operates on supervised learning. The main reason KNN did not give the desired results as being a lazy classifier becomes difficult to predict which is exactly the scenario provided in real time. While implementing the algorithms, variable clustering sizes were used, and with the increase in clustering size till 5, the accuracy increased and then progressively degraded. Hence, the maximum accuracy KNN provided was that of 88%. The Naïve Bayes is on the other side coined as an eager learning classifier, and it being much faster than KNN makes it easier to compute the huge crop dataset with a number of attributes. In this case, we took probabilistic estimation methodology, generating probabilities for each crop pool class. The algorithm learns over time, and moreover it automatically takes care of the high dimensionality pertaining to the different attributes in the dataset. In KNN, a further dimensionality reduction technique had to be applied to make the accuracy viable to our test scenario, taking significantly more time in prediction and also reducing the accuracy as the dataset attributes need not be highly correlated with each other. This makes the KNN algorithm gullible and makes it predict wrong results. Thus, the Naïve Bayes gave an accuracy score of 89.29%, whereas KNN gave a score of 88% (Table 1).

SVM can be equally considered as a best fit for this use-case as it automatically takes into account the high-dimensionality problems and computes each hyperplane, thus perfectly giving the accuracy metrics. Moreover, it is a perfectly balanced dataset which gives SVM an edge-over KNN algorithm. Moreover, it is a perfectly balanced dataset which gives SVM an edge-over KNN algorithm. However, it was probably due to fact that our dataset was heavily pre-processed and also the unconditional change in environment conditions resulted in Naïve Bayes better than SVM. KNN can actually quickly learn the classes as it uses median, centroid and mode calculations, thus giving a slightly better accuracy than SVM. At the end, SVM gave an accuracy score of 87% (Table 1).

Regression algorithm too is designed to output well-calibrated class probabilities. It has a smooth unconstrained loss function which also supports Bayesian cases, but generally is focused on the linearity. The dataset is not so much linear with lots of attributes and hence may give rise to multi-dimensional planes getting involved where regression-based methods fail to comprehend with ease. Thus, it resulted in a lesser accuracy metric score of 84.8% (Table 1.).

Future scope of improvement includes better management of network longevity for WSN, addition of more possible sensors for more accurate crop prediction and a drone with robotic arms which enables autoplucking of weeds based on real-time weed detection.

6 Conclusion

Precision agriculture has helped in revolutionizing the agricultural industry to a great extent. Our proposed model of using wireless sensor networks and AI models for crop prediction and weed detection has also added its bit of increasing agricultural efficiency. In contrast to traditional agricultural methods consuming more time, hard work and sometimes leading to improper outputs, losses, modern agricultural methods involving the concept of AI and IoT will definitely help farmers worldwide in taking better decisions and help them in increasing the overall crop yield and efficiency. The proposed model can harness possibility of precise management of farm sector.

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Authors' Contributions Ishita Dasgupta was involved in conceptualization, resources, methodology, software, investigation, writing—original draft, writing—review and editing and visualization. Jayit Saha supported conceptualization, resources, methodology, software, formal analysis, writing—original draft, writing—review and editing and visualization. Pattabiraman. V was involved in validation, data curation, writing—review and editing, supervision, project administration and funding acquisition. Parvathi. R contributed to validation, data curation, writing—review and editing, supervision, project administration and funding acquisition.

Compliance with Ethical Standards

Conflicts of interest The authors declare no conflicts of interest.

References

1. Pudumalar, S.; Ramanujam, E.; Rajashree, R. H.; Kavya, C.; Kiruthika, T.; & Nisha, J.: Crop recommendation system for precision agriculture. In: 2016 Eighth International Conference on Advanced Computing (ICoAC) pp. 32–36. IEEE (2017)
2. Perez, A.J.; Lopez, F.; Benlloch, J.V.; Christensen, S.: Colour and shape analysis techniques for weed detection in cereal fields. Comput. Electr. Agric. **25**(3), 197–212 (2000)
3. Burgos-Artizzu, X.P.; Ribeiro, A.; Guijarro, M.; Pajares, G.: Real-time image processing for crop/weed discrimination in maize fields. Comput. Electr. Agric. **75**(2), 337–346 (2011)
4. Banavlikar, T.; Mahir, A..; Budukh, M.; Dhodapkar, S.: Crop recommendation system using Neural Networks. In: International Research Journal of Engineering and Technology (IRJET) (2018)
5. Bah, M.D.; Hafiane, A.; Canals, R.: Deep learning with unsupervised data labeling for weed detection in line crops in UAV images. Remote Sens. **10**(11), 1690 (2018)
6. Rajak, R.K.; Pawar, A.; Pendke, M.; Shinde, P.; Rathod, S.; Devare, A.: Crop recommendation system to maximize crop yield using machine learning technique. Int. Res.J Eng. Technol. **4**(12), 950–953 (2017)
7. Na, A.; Isaac, W.; Varshney, S.; & Khan, E.: An IoT based system for remote monitoring of soil characteristics. In: 2016 International Conference on Information Technology (InCITe)-The Next Generation IT Summit on the Theme-Internet of Things: Connect your Worlds (pp. 316–320). IEEE (2016)
8. Mythili, R., Meenakshi K.; Apoorv T.; Neha P.: IoT Based Smart Farm Monitoring" System International Journal of Recent Technology and Engineering (2019) (IJRTE)ISSN: 2277-3878
9. Manoj Athreya A..; Hrithik Gowda,; S., Madhu, S.; Ravikumar, V.: Agriculture Based Recommender System using IoT-A Research, IJRTE, ISSN: 2277-3878 (2019)
10. Mokarrama M. J.; Arefin, M. S.: RSF: A recommendation system for farmers. In *2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)* (pp. 843–850). IEEE (2017).
11. Raja, S. K. S.; Rishi, R.; Sundaresan, E.; Srijit, V.: Demand based crop recommender system for farmers. In: 2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR) (pp. 194–199). IEEE (2017)
12. Recommender System For Smart Agriculture Using Iot" Prathmesh Shirshivkar, Mayur Solaskar, Ramesh Borkar, Sameer Sawant, Smita Patil, International Conference on Innovative and Advanced Technologies in Engineering (ICIATE-2019), 2019, ISSN (e): 2250-3021, ISSN (p): 2278–8719 PP 42–44
13. Design and Implementation of Crop Recommendation Fertilization Decision System Based on WEBGIS at Village Scale", Hao Zhang, Li Zhang, Yanna Ren, Juan Zhang, Xin Xu1, Xinming Ma1, and Zhongmin Lu, 4th Conference on Computer and Computing Technologies in Agriculture (CCTA), Oct 2010, pp.357–364, https://doi.org/10.1007/978-3-642-18336-2_44
14. Ngo H.C.; Hashim, U.R.; Sek, Y. W.; Kumar, Y. J.; Ke, W.S.: Weeds Detection in Agricultural Fields using Convolutional Neural Network. In: International Journal of Innovative Technology and Exploring Engineering (2019), (IJITEE)ISSN: 2278-3075
15. Tang, J.-L.; Chen, X.-Q.; Miao, R.-H.; Wang, D.: Weed detection using image processing under different illumination for site-specific areas spraying. Comput. Electr. Agric. **122**, 103–111 (2016). https://doi.org/10.1016/j.compag.2015.12.016
16. Louargant, M.; Villette, S.; Jones, G.; Vigneau, N.; Paoli, J.N.; Gée, C.: Weed detection by UAV: simulation of the impact of spectral mixing in multispectral images. Precis. Agric. **18**(6), 932–951 (2017)
17. dos Santos Ferreira, A., Pistori, H., Matte Freitas, D.,; Gonçalves da Silva, G.: Data for: Weed Detection in Soybean Crops Using ConvNets", Mendeley Data, v2 (2017) http://dx.doi.org/10.17632/3fmjm7ncc6.2
18. Methods for Rapid Testing of Plant and Soil Nutrients", Christian Dimkpa, P.S. Bindraban, Joan E Mclean, Lydiah Gatere, https://doi.org/10.1007/978-3-319-58679-3_1, July (2017)
19. Excessive use of nitrogenous fertilizers: an unawareness causing serious threats to environment and human health", Moddassir Ahmed, Muhammad Rauf, Zahid Mukhtar, Nasir Ahmad Saeed, Environ. Sci. Pollut. Res., 14 (2017)