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Soil Analysis and Crop Recommendation using Machine Learning

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***Abstract*—India is the land of agriculture and is among the top three global producers of many crops. The Indian farmer lies at the heart of the agricultural sector yet most Indian farmers remain at the bottom of the social strata. In addition, farmers find it difficult to decide which crop is best suitable and profitable for their soil, in spite of the few technological solutions that exist today, due to the variation in soil types across geographical regions. This paper proposes a crop recommendation system that uses a Convolutional Neural Network (CNN) and a Random Forest Model to predict the optimal crop to be grown by analyzing various parameters including the region, soil type, yield, selling price, etc. The CNN architecture gave an accuracy of 95.21%, and the Random Forest Algorithm had an accuracy of 75%.**

***Index Terms*—Random Forest, Image classification, Deep learning, Convolutional Neural Network**

I. INTRODUCTION

Agriculture has historically been and remains to this day one of the main pillars of the Indian economy as two-thirds of the Indian population is directly dependent on agriculture for their livelihood. An equally important fact is that it contributes to 20% of India's Global Domestic Product (GDP). At the crux of the agriculture sector lies the farmer, the Annadatta (Food Provider) of our country, who is facing many adversities today:

1) With the diversity in soil types across the country farmers usually find it difficult to decide which crop is best suitable and profitable to their soil, their conditions, their region, and hence end up facing many losses.
2) Presently it is extremely difficult for farmers to predict the yield for a particular sowing season and the profit that they can earn due to unpredictable weather conditions.
3) Dismally low profits that farmers earn for their produce because of the 'farm to market' mechanism which involves hundreds of middlemen who eat up most of the profits by transporting and selling crops.

Machine Learning and Artificial Intelligence find many applications in the modern agriculture industry. Techniques such as precision agriculture and crop recommender systems can be used to improve overall harvest quality, yield prediction, pest detection in plants and poor nutrition of farms. Deployment of AI systems can provide a shot in the arm to the beleaguered agricultural sector.

India's current agricultural suffering casts serious doubt on the future of the sector. The agricultural sector contributes 20% of GDP by hiring almost two-thirds of the workforce. Nearly 85% of Indian farmers operate with less than 5 acres of land, undertake significant product and market risks every season and are forced to rely on non-institutional credit sources due to a lack of collateral. Farmers with small holdings also account for 46% of cultivated land, half of the agricultural production, and a much higher share of high-value crops. But they are routinely excluded from modern market arrangements such as contract farming and direct purchases due to low literacy rates.

This paper describes a soil analysis and crop prediction mechanism that uses a Convolutional Neural Network and Random Forest Algorithm to solve some of the long-standing problems of the Indian agricultural sector and increase profitability for the average farmer. Additionally, it details the design and implementation of a website that serves as a marketplace for farmers and potential crop buyers, hence eliminating the need for a middleman. The remainder of the paper is divided into 4 sections as follows:

1) Section 2 details past work done in Crop Prediction and Soil Classification.
2) Section 3 describes the flow of the proposed system and its implementation.
3) Section 4 summarizes observations and results.
4) Section 5 mentions the conclusion and future scope

II. BACKGROUND AND RELATED WORK

In this section, we review, summarize and analyze work related to Crop Prediction and Soil Classification in agriculture.

Babu et al. [1] described a model that applies Precision Agriculture (PA) principles to small, open farms at the individual farmer and crop level, to affect a degree of control over variability. The goal of the model was to recommend crops to even the smallest farmer at the level of his/her smallest plot of the crop, using the most accessible technologies such as SMS and email. The model was designed for the state of Kerala.

Pudumalar et al. [2] proposed a recommender system on precision agriculture using data mining techniques. Crop recommendation was based on the research data of their soil types, soil characteristics, and crop yield. Their system used an ensemble method using majority voting, consisting of four individual models, namely, CHAID, Random tree, Naive Bayes, and K-Nearest Neighbours.

Rajak et al. [3] proposed an ensemble model with a majority voting technique, where the ensemble model comprises four individual models, namely, Support Vector Machine, Artificial Neural Network, Random Tree, and Naive Bayes. Their dataset included various attributes of soil like pH, water density, etc. as features collected from soil testing labs and universities.

Reddy et al. [4] proposed a two-step model - the first step for soil classification and a second step for crop suggestion. The first step used chemical features of soil such as moisture, the content of potassium, magnesium, etc. to predict the soil series or the soil type. The second step used features such as the soil series, temperature, humidity, rainfall, and pH. Classification algorithms like Support Vector Machine, K-Nearest Neighbours, and Bagging were utilized to suggest crops. Although this paper did not implement the system proposed by them, its' two-step model inspired us to use different machine learning algorithms to achieve different goals of the system by using a two-step model.

Savla et al. [5] compared classification algorithms and their performance in yield prediction in precision agriculture. These algorithms were implemented on a data set collected for several years in yield prediction on the soya bean crop. The algorithms used were Support Vector Machine, Random Forest, Neural Network, REPTree, Bagging, and Bayes. The authors concluded that bagging was the best algorithm for yield prediction as the error deviation was minimum.

Manjula et al. [6] developed a framework called eXtensible Crop Yield Prediction Framework (XCYPF) that enabled the flexible inclusion of various techniques towards crop yield prediction. They also developed a tool that would help people to predict crop yield for various crops with dependent and independent variables.

Kumar et al. [7] proposed a Crop Selection Method (CSM) to solve the crop selection problem and improve the net yield rate of the crop. The method suggested a series of crops to be selected over a season considering factors like weather, soil type, water density, and crop type. The predicted value of influential parameters determined the accuracy of the model. They also illustrated the significance of crop selection and the factors affecting crop selection like production rate, market price, and government policies.

Ahamed et al. [8] used data mining techniques to estimate the crop yield for cereal crops in major districts of Bangladesh. They proposed a system that consisted of two parts: Clustering (for creating district clusters) and Classification using KNN (k-nearest neighbor), Linear Regression, (ANN) artificial neural network in rapid miner tool. Their data set included 5 environmental variables, 3 biotic variables, and 2 area-related variables to determine the crop yield in different districts.

Paul et al. [9] analyzed soil datasets to predict soil categories/types. They identified crop yield from the predicted soil categories as a classification rule. Naive Bayes and K-nearest neighbor algorithms were used for predicting crop yields

Khedr et al. [10] tried to solve the problem of food insecurity in Egypt. They proposed a framework to predict the production, and import for a particular year. The model used Artificial Neural Networks along with Multi-layer perceptrons in WEKA to build the prediction. At the end of the process, one would be able to visualize the amount of production import, need, and availability. The goal was to make decisions on whether food needs to be imported or not.

Venugopal et al. [11] used three machine learning algorithms i.e. Logistic Regression, Naive Bayes algorithm, and Random forest algorithm to recommend suitable crops and predict yield value and then compared the results of those algorithms. They collected past data on weather, temperature, and a number of other factors to train their models. The Random Forest Algorithm gave the highest accuracy among all those three algorithms.

Mahendra et al. [12] proposed a system that predicted the most suitable crop based on soil contents, soil PH, weather, and rainfall. They used a Support Vector Machine(SVM) algorithm for rainfall prediction. The result was used for crop prediction using the Decision Tree Algorithm.

Priya et al. [13] used Random Forest Algorithm to predict crop yield for the state of Tamil Nadu, India. Their model consisted of parameters like rainfall, maximum temperature, season, and production.

Champaneri et al. [14] used Random Forest Algorithm for crop yield predictions for the state of Maharashtra. They gathered data from different government websites and data related to the climatic parameters (precipitation, temperature, cloud cover, vapor pressure) at a monthly level which was used to train a machine learning model.%.

Bharath et al. [15] proposed a system to recommend the most suitable crops for a farmer based on nutritional features of land. These features would be calculated in a lab from a soil sample collected by the farmer. The Naive Bayes algorithm was used for prediction and the model's accuracy was 75%

The systems proposed by the above papers have a few drawbacks:

1) References [1], [2], [3], [4], [5], [6] and [7] require site-specific features like chemical properties of the soil, such as the content of minerals, pH, etc and other properties such as wind speed which may be tough and/or expensive for farmer to collect.
2) References [1], [2], [4], [12] and [15] focus only on recommending crops that are best suited to the soil without considering their yield or gross revenue.

Thus trade-offs between quality and revenue are ignored which may have a great impact on income of the farmer. The proposed system recommends crops that are most appropriate for a given soil type and region simultaneously considering the revenue that the crops could potentially generate.

III. Methodology

This section describes a two-step model solution based on machine learning. A user clicks a picture of soil, sets location and area parameters and feeds these inputs to the system. The output will be a list of crop recommendations based on predicted quality, quantity(yield), and gross revenue.

A. System Overview

Step 1: Soil Classification using Convolutional Neural Networks

In the first step, we process the image of the soil that is fed into the system by the user and classify it into one of the four classes of soil, namely Red, Alluvial, Black, and Clay. This is done by a Convolutional Neural Network whose implementation details are discussed in the following subsections. After the soil type is predicted, a few crops are shortlisted that are suitable to be cultivated in that soil type. Hence, this step ensures that the quality of the crops recommended is good, as only crops suitable to the soil type are shortlisted.

Step 2: Yield and Income Prediction

In the second step, our system considers features such as soil type (predicted by the first step), Area of land to be cultivated (in hectares), State, District, crop, and season of cultivation and predicts the yield of all the shortlisted crops given the above features (in quintals). This is done by the Random Forest Algorithm whose implementation details are discussed in the following subsections. After the yield is predicted, the system uses an API developed by the Government of India [16] to retrieve the price of each crop in the shortlist in the given region. This is used to estimate the income generated by a crop using the unitary method. The crop which generates the highest income is then recommended to the user. Hence, this step takes into account the quantity and the profitability of the crop.

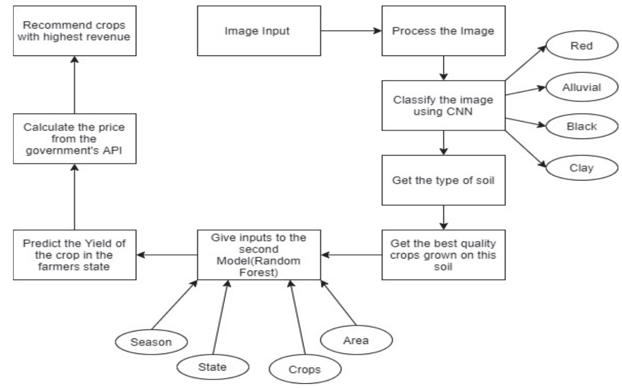

Fig. 1. System Workflow

B. System Architecture

1) Convolutional Neural Network:

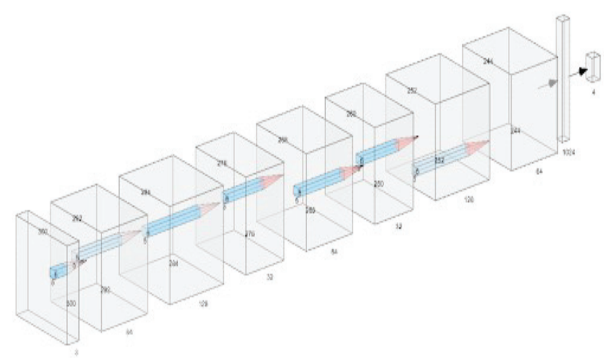

Fig. 2. CNN Network Architecture

i) Dataset Collection:

The dataset used in training the parameters of this algorithm comprises images of the different soil types namely, Red Soil, Black Soil, Clay Soil, and Alluvial Soil. The dataset includes 150-200 images of each soil type in the training set and about 50 images in the test set. This data is collected from the Soil Classification Image Dataset [17] on Kaggle and from similar other online sources.

ii) Data Pre-Processing and Algorithm Implementation:

The images in the dataset are of various sizes and dimensions, and hence need to be resized and pre-processed before they are fed into the model. The algorithm needs to read a colored image for our use case, and every colored image in RGB format has three channels, one for each color, Red, Green, and Blue. Hence, the images are first resized to 300x300x3 images. The images are then converted into numerical (pixel intensities) arrays so that the model can process the data. This numerical data is then fed into the Machine Learning model.

The machine learning model used to classify these images into the different soil types is a Convolutional Neural Network. The network architecture of the same can be seen in Fig 2.

The network contains 9 layers, with 7 convolutional+pooling layers followed by 2 fully connected layers which includes 1 softmax layer. Each convolutional layer has filter size(f) =3, stride (s)=1 and padding (p)=0. Max-pooling is used in all the pooling layers with filter/kernel size(f) =3, and stride (s)=1. The convolutional layers and one fully connected layer use the ReLU activation function. Hence, the network contains 2,365,636 trainable parameters. This network was trained with the Adam Optimization Algorithm and with the learning rate set to 10^{-3} for 20 epochs. The model gave an accuracy of 95.21% on the test set. The training results can for this model can be seen in the Accuracy and Loss graphs in Fig 3 and Fig 4 respectively.

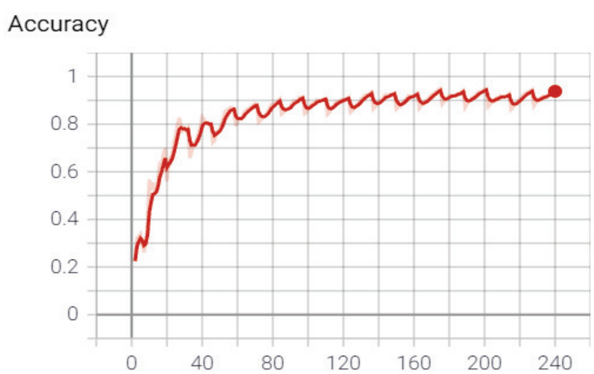

Fig. 3. Graph of Accuracy of CNN Vs No. of Training Steps

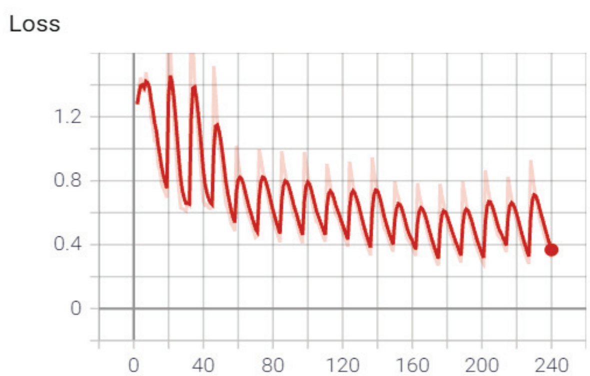

Fig. 4. Graph of Loss Function of CNN Vs No. of Training Steps

2) Random Forest Algorithm:

i) Dataset Collection:

The dataset used in training the parameters of this algorithm is used to predict the yield of a particular crop in a region, and hence it comprises features such as the State, District, Season of Cultivation, Crop, the Area of the land to be cultivated, and the yield of the crop. This data is collected from the Crop Prediction in India [18] dataset on Kaggle and other online sources such as news articles.

ii) Data Pre-Processing and Algorithm Implementation:

This dataset contains dirty data, hence our first pre-processing step was to clean the data, we did this by removing entries/rows with one or more missing/null values. Our dataset also contains categorical string data, which needs to be encoded in numeric form so that the Random Forest algorithm can process it. Hence, our second step was to encode categorical string data using One-Hot Encoding.

Using the One-Hot Encoding method, all unique values from a single column were considered as a separate feature. The dataset had 124 unique values of crops, 6 unique values of Seasons, 33 unique values of States, so a total of 164 features with Area. Suppose we have to provide Coconut as input to the model, then the column name Coconut will be set to 1 and the rest of the columns having crop names will be set to 0. The same applies to states and seasons.

Random Forest builds multiple decision trees and combines them together by using a bagging method, which selects a random sample of data from a training set. As a result for a dataset that requires such robust features a Random Forest Algorithm works best and better than many other regression methods like Linear Regression. Random Forest gave a 75.67% score. The numeric output of yield was predicted best by Random Forest and the end result matched for many crops of different states.

C. Web Portal

To assimilate all the components of the system we have discussed so far, we decide to create a prototype of a web portal that would use the Crop Recommendation System proposed by this paper. This portal has a very attractive, and user-friendly, user interface. This web portal can be used by two types of users, farmers, and wholesalers. Farmers can feed in the inputs of the two models of the system and get crop recommendations based on those inputs. Once a farmer decides to grow a crop, he/she can create a crop listing on the "Farmer's Market" section of the portal. Wholesalers can view these listings on the "Farmer's Market" section and can send requests to connect with the farmer of their choice to continue further dealings. Once the farmer accepts the request, then the farmer and wholesaler can reach out to each other using the WhatsApp feature of the portal and continue their dealings. This feature of the portal solves the middleman problem so that a farmer can keep the entirety of his profits. Snapshots of the Recommendation feature and the 'Farmer's Market' section can be seen in Fig 5 and Fig 6 respectively.

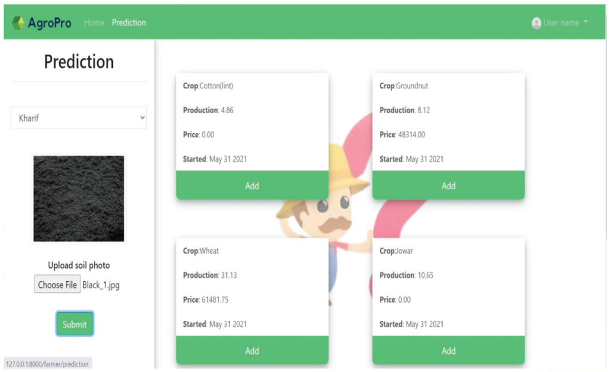

Fig. 5. Recommendation System on the Web Portal

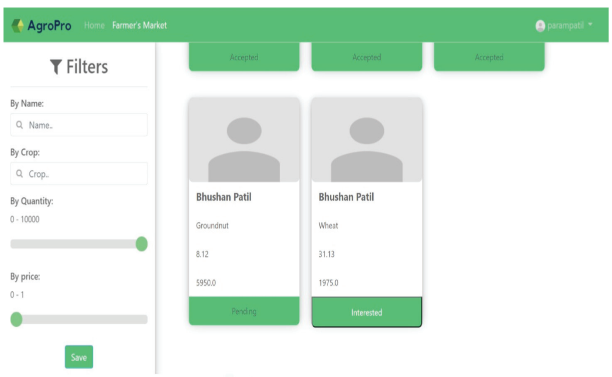

Fig. 6. Farmer's Market Section on the Web Portal

IV. Observations and Results

This section describes the various image classification algorithms and architectures we experimented with and how they compare with each other.

A. Support Vector Machine (SVM)

For this algorithm, the images are first resized to 200 x 200 x 3 images. The images are then converted into numerical (pixel intensities) arrays and then flattened to a 120000 x 1 feature vector. This feature vector is then fed into the SVM model.

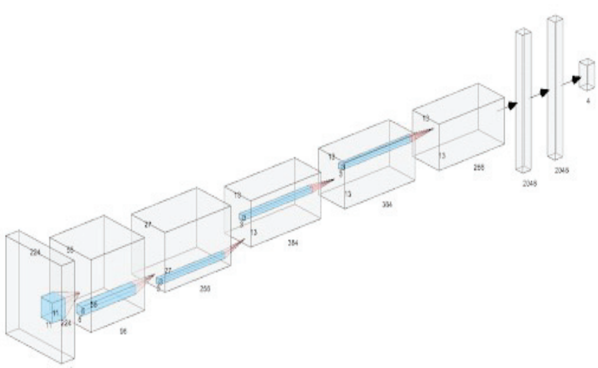

Fig. 7. Alexnet Network Architecture

The SVM model was trained using two kernels, namely the linear and the Radial Basis Function(RBF) Kernel. The model with a linear kernel gave an accuracy of 83.5% and the RBF kernel gave an accuracy of 86.7% on the test set.

B. AlexNet

This is a classical network architecture for the Convolutional Neural Network Algorithm, this architecture was proposed in the paper [19]. To replicate the dimensions for this architecture the images were first resized to 224 x 224 x 3 images. The images are then converted into numerical (pixel intensities) arrays, this numerical data is then fed into the CNN model. This architecture can be observed in Figure 3.
We implemented the exact architecture suggested by the paper [19] with just a minor modification in the output layer, where we have 4 units as opposed to 1000 units since we have only 4 classes. Hence, the network contains about 59 million trainable parameters. The model was trained using the Adam Optimization Algorithm with the learning rate as 10^{-3} and epoch as 25. This architecture gave us an accuracy of 25% on the test set.

C. Convolutional Neural Networks with Other/New Architectures

After getting decent results from the SVM model and disappointing results from AlexNet, we decided to experiment with different architectures in the CNN algorithm. For all the following architectures the images are first resized to 300x300x3 images. The images are then converted into numerical (pixel intensities) arrays, which is then fed into the CNN model. The model is trained using the Adam optimization algorithm with learning rate for all architectures as 10^{-4} and no. of epochs as 25.

1) 32-64-128-64-32 Architecture:

In this architecture there are 7 layers with 5 convolutional + pooling layers, of sizes 32,64,128,64, and 32, with ReLu activation, followed by one fully connected layer of size 1024, with ReLu activation and one fully connected layer of size 104, with softmax activation. The filter size was kept the same for all convolutional and max-pooling layers. We experimented with three filter sizes, the accuracy obtained in each case is summarized in Table 1.

TABLE I
Comparison between filter sizes in the 32-64-128-64-32 architecture

Filter Size	Accuracy
f=3	88.75%
f=5	87%
f=7	82.44%

2) 64-128-256-128-64 Architecture:

In this architecture there are 7 layers with 5 convolutional + pooling layers, of sizes 64,128,256,128 and 64, with ReLu activation, followed by one fully connected layer of size 1024, with ReLu activation and one fully connected layer of size 4, with softmax activation. The filter size was kept the same for all convolutional and max-pooling layers. We experimented with three filter sizes, the accuracy obtained in each case is summarized in Table 2.

TABLE II
COMPARISON BETWEEN FILTER SIZES IN THE 64-128-256-128-64 ARCHITECTURE

Filter Size	Accuracy
f=3	25%
f=5	90.95%
f=7	79.2%

3) 64-128-32-64-32-128-64 Architecture:

In this architecture there are 9 layers with 7 convolutional + pooling layers, of sizes 64,128,32,64,32,128 and 64, with ReLu activation, followed by one fully connected layer of size 1024, with ReLu activation and one fully connected layer of size 4, with softmax activation. The filter size was kept the same for all convolutional and max-pooling layers. We experimented with three filter sizes, the accuracy obtained in each case is summarized in Table 3:

TABLE III
COMPARISON BETWEEN FILTER SIZES IN THE 64-128-32-64-32-128-64 ARCHITECTURE

Filter Size	Accuracy
f=3	81.38%
f=5	95.21%
f=7	69.68%

The results of all algorithms are summarized in the table 4.

TABLE IV
COMPARISON BETWEEN VARIOUS ALGORITHMS AND ARCHITECTURES

Sr. No.	Algorithm /Architecture	Hyperparamters	No. of trainable parameters	Accuracy
1	SVM	RBF Kernel	120,000	86.7%
2	AlexNet	Adam, Learning Rate=10^{-3}, $Epochs = 25$	59 Million	25%
3	CNN (32-64-128-64-32)	Adam, Learning Rate=10^{-4}, $Epochs = 25, f = 5$	1.33 Million	87%
4	CNN (64-128-256-128-64)	Adam, Learning Rate=10^{-3}, $Epochs = 25, f = 5$	3.7 Million	90.95%
5	CNN (64-128-32-64-32-128-64)	Adam, Learning Rate=10^{-3}, $Epochs = 25, f = 5$	2.3 Million	95.21%

V. CONCLUSION AND FUTURE SCOPE

A flourishing agricultural sector is key for India's sustained economic growth. Our aim was to empower farmers with small land holdings by increasing profitability and maximising crop yield. In our experiments Convolutional Neural Networks with symmetrical architectures gave significantly better results for image classification for the selected soil classification dataset. The final CNN architecture had an amazing accuracy of 95.21%. The Random Forest Algorithm had an accuracy of 75%. Future experiments can adapt this system to a mixture of soil types, by accounting for the composition present in the minority of the mixture. The system can be further improved by expanding the crop production dataset to get more accurate results for yield prediction

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