



# Soil Analysis and Crop Recommendation using Deep Learning

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**ABSTRACT:** Crop prediction is a task that involves using deep learning algorithms to predict crop yields and other relevant metrics based on a variety of factors, such as weather conditions, soil data, and historical crop data. The goal of this task is to provide farmers and other stakeholders with accurate and reliable information about expected crop yields, which can help them to make better decisions about planting, harvesting, and other aspects of agricultural management. The problem of crop prediction involves several challenges, including the need for accurate and timely data, the selection of relevant features and parameters for analysis, and the development of suitable machine learning models for prediction. Moreover, the prediction accuracy may also be affected by factors such as regional variations in climate and soil conditions, as well as the presence of pests and other environmental factors. To address these challenges, researchers and developers in the field of crop prediction have developed a variety of techniques, including data pre-processing, feature selection, deep learning model selection, and performance evaluation. These techniques may involve the use of different types of data, such as weather data, soil data, and crop data, as well as various deep learning algorithms, such as multi-layer perceptron algorithm and Convolutional neural network algorithm. Ultimately, the success of crop prediction depends on the ability of the system to accurately and reliably analyse data from a variety of sources, and then predict crop yields and other relevant metrics with a high degree of accuracy. By addressing these challenges, crop prediction has the potential to improve agricultural productivity and sustainability, and to support the development of more efficient and effective farming practices."

**KEYWORDS:** Soil analysis, Crop recommendation, Deep learning, Precision agriculture, Smart farming, Artificial intelligence (AI), Machine learning (ML), Convolutional neural networks (CNN)

## I. INTRODUCTION

### 1.1 PROJECT DESCRIPTION

A 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.

### **DEEP LEARNING**

Deep Learning is a subset of machine learning that involves training artificial neural networks with multiple layers to recognize patterns in data. Deep learning algorithms can be used for a wide range of tasks such as image and speech recognition, natural language processing, and even playing games like Go and Chess. The main advantage of deep learning over traditional machine learning approaches is its ability to automatically learn features from raw data without the need for manual feature engineering. This is accomplished by stacking multiple layers of neurons, each of which performs a nonlinear transformation of the input data. The output of one layer serves as the input for the next layer, allowing the network to gradually learn increasingly complex representations of the input data. Popular deep learning algorithms include Convolutional Neural Networks (CNNs) for image and video processing, Recurrent Neural Networks (RNNs) for sequential data processing such as natural language processing, and Generative Adversarial Networks (GANs) for generating realistic images and videos. Training deep learning models requires large amounts of labeled data and significant computational resources. However, recent advancements in hardware and software have made it easier to train deep learning models on a wide range of applications.

### **1.2 SCOPE OF THE PROJECT**

The scope of utilizing machine learning for soil analysis and crop recommendation encompasses the development of ML algorithms and tools to accurately assess soil properties, including nutrient levels, pH, moisture content, and texture. These algorithms leverage various data sources such as soil samples, satellite imagery, weather data, and historical crop performance records. Additionally, the scope involves the integration of predictive models to recommend suitable crop choices based on soil characteristics, local climate conditions, and agronomic practices. The application of these technologies extends to diverse agricultural settings, ranging from smallholder farms to large-scale commercial operations, with the potential to enhance crop yields, optimize resource utilization, and contribute to sustainable agricultural practices

## **II. LITERATURE SURVEY**

### **2.1 MACHINE LEARNING FOR LARGE-SCALE CROP YIELD FORECASTING, 2021**

#### **AUTHOR: DILLI PAUDEL**

Many studies have applied machine learning to crop yield prediction with a focus on specific case studies. The data and methods they used may not be transferable to other crops and locations. On the other hand, operational large-scale systems, such as the European Commission's MARS Crop Yield Forecasting System (MCYFS), do not use machine learning. Machine learning is a promising method especially when large amounts of data are being collected and published. We combined agronomic principles of crop modeling with machine learning to build a machine learning baseline for large-scale crop yield forecasting. The baseline is a workflow emphasizing correctness, modularity and reusability. For correctness, we focused on designing explainable predictors or features (in relation to crop growth and development) and applying machine learning without information leakage. We created features using crop simulation outputs and weather, remote sensing and soil data from the MCYFS database. We emphasized a modular and reusable workflow to support different crops and countries with small configuration changes. The workflow can be used to run repeatable experiments (e.g., early season or end of season predictions) using standard input data to obtain reproducible results. The results serve as a starting point for further optimizations. In our case studies, we predicted yield at regional level for five crops (soft wheat, spring barley, sunflower, sugar beet, potatoes) and three countries (the Netherlands (NL), Germany (DE), France (FR)). We compared the performance with a simple method with no prediction skill, which either predicted a linear yield trend or the average of the training set. We also aggregated the predictions to the national level and compared with past MCYFS forecasts

### **2.2 CROP YIELD PREDICTION THROUGH PROXIMAL SENSING AND MACHINE LEARNING ALGORITHMS, 2020**

#### **AUTHOR: FARHAT ABBAS**

Proximal sensing techniques can potentially survey soil and crop variables responsible for variations in crop yield. The full potential of these precision agriculture technologies may be exploited in combination with innovative methods of data processing such as machine learning (ML) algorithms for the extraction of useful information responsible for



controlling crop yield. Four ML algorithms, namely linear regression (LR), elastic net (EN), k-nearest neighbor (k-NN), and support vector regression (SVR), were used to predict potato (*Solanum tuberosum*) tuber yield from data of soil and crop properties collected through proximal sensing. Six fields in Atlantic Canada including three fields in Prince Edward Island (PE) and three fields in New Brunswick (NB) were sampled, over two (2017 and 2018) growing seasons, for soil electrical conductivity, soil moisture content, soil slope, normalized-difference vegetative index (NDVI), and soil chemistry. For the growing seasons of 2017 and 2018, the data about horizontal and vertical components of soil electrical conductivity, soil moisture content, field slope, soil pH, SOM, normalized difference vegetative index, and potato tuber yield were named as PE-2017, PE-2018, NB-2017 and NB-2018 for Prince Edward Island and New Brunswick fields. Modeling techniques were employed to generate yield predictions with statistical parameters from the collected data. The SVR models outperformed all other models for all four datasets with RMSE of 5.97, 4.62, 6.60, and 6.17 t/ha, respectively. The performance of k-NN remained poor except for PE-2018.

### **2.3 IMPACT OF BEST MANAGEMENT PRACTICES ON SUSTAINABLE CROP PRODUCTION AND CLIMATE RESILIENCE IN SMALLHOLDER FARMING SYSTEMS OF SOUTH ASIA, 2021**

**AUTHOR: K.H. ANANTHA**

The study identified lack of data as a major gap in both in situ conservation measures and ex situ rainwater harvesting intervention studies. Most of the studies on in situ conservation measures were undertaken at research stations and mostly pertained to major cereals such as rice, wheat and maize along with limited data on oilseeds and pulses. Similarly, limited studies on ex situ rainwater harvesting interventions were available and within a limited time period. Data monitoring needs to be strengthened both at micro and meso scale landscape to understand the ecosystem trade-offs between upstream and downstream ecologies under different rainfall, soil type and land slope conditions. Based on the current review, we envision a huge potential to integrate in situ conservation and ex situ rainwater harvesting technologies to address water scarcity and build system level resilience. A large part of the Indian subcontinent, especially the central and eastern parts, receive medium to high rainfall (800–2000 mm/year). However, they undergo water scarcity during post- monsoon season. Integrating both the technologies has great potential to overcome these challenges and achieve sustainable crop intensification. This paper reviews peer reviewed literature on different best water management practices in different agro-ecologies of the Indian subcontinent.

### **2.4 AN APPROACH FOR PREDICTION OF CROP YIELD USING MACHINE LEARNING AND BIG DATA TECHNIQUES, 2021**

**AUTHOR: KODIMALAR PALANIVEL**

Estimating agricultural yield prior to harvest is an important issue in agriculture, as the changes in crop yield from year-to-year influence international business, food supply, and global market prices. Also, early prediction of crop yield provides useful information to policy planners. Appropriate prediction of crop productivity is required for efficient planning of land usage and economic policy. In recent times, forecasting of crop productivity at the within-field level has increased. The most influencing factor for crop productivity is weather conditions. If the weather-based prediction is made more precise, then farmers can be alerted well in advance so that the major loss can be mitigated and would be helpful for economic growth. The prediction will also aid the farmers to make decisions such as the choice of alternative crops or to discard a crop at an early stage in case of critical situations. Further, predicting crop yield can facilitate the farmers to have a better vision on cultivation of seasonal crop and its scheduling. Thus, it is necessary to simulate & predict the crop yield before cultivation for efficient crop management and expected outcome. As there exists a non-linear relationship between crop yield and the factors influencing crop, machine learning techniques might be efficient for yield predictions. Machine Learning involves problems in which the input and output relationship is not known. Learning specifies the automatic acquirement of structural descriptions. In contrast to traditional statistical methods, machine learning does not make assumptions about the exact construct of the data model, which describes the data. This feature is very helpful to describe complex non-linear behaviors such as a crop yield prediction. Machine learning is a part of artificial intelligence employed to build an intelligent system.

### **2.5 COUPLING MACHINE LEARNING AND CROP MODELING IMPROVES CROP YIELD PREDICTION IN THE US CORN BELT, 2021**

**AUTHOR: MOHSEN SHAHHSOEIN**

This study investigates whether coupling crop modelling and machine learning (ML) improves corn yield predictions in the US Corn Belt. The main objectives are to explore whether a hybrid approach (crop modeling+ML) would result in better predictions, investigate which combinations of hybrid models provide the most accurate predictions, and determine the features from the crop modelling that are most effective to be integrated with ML for corn yield prediction. Five ML models (linear regression, LASSO, LightGBM, random forest, and XGBoost) and six ensemble



models have been designed to address the research question. The results suggest that adding simulation crop model variables (APSIM) as input features to ML models can decrease yield prediction root mean squared error (RMSE) from 7 to 20%. Furthermore, we investigated partial inclusion of APSIM features in the ML prediction models and we found soil moisture related APSIM variables are most influential on the ML predictions followed by crop-related and phenology-related variables. Finally, based on feature importance measure, it has been observed that simulated APSIM average drought stress and average water table depth during the growing season are the most important APSIM inputs to ML. This result indicates that weather information alone is not sufficient and ML models need more hydrological inputs to make improved yield predictions. On the other hand, machine learning (ML) intends to make predictions by finding connections between input and response variables. Unlike simulation crop models, ML includes methods in which the system “learns” a transfer function to predict the desired output based on the provided inputs, rather than the researcher providing the transfer function. In addition, it is more easily applicable than simulation crop models as it does not require expert knowledge and user skills to calibrate the model, has lower runtimes, and less data storage constraints.

### III. SYSTEM ANALYSIS

#### 3.1 EXISTING SYSTEM

- 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, Naïve Bayes, and K-Nearest Neighbours
- The research focuses on the declining agricultural productivity in India due to climate changes, unpredictable rainfall, and excessive pesticide use. .
- Descriptive analytics is applied to agricultural data to assess crop yield production.
- The proposed methodology employs Principal Component Regression, a two-step process that reduces dimensionality and addresses multidimensional space and co-linearity issues for effective crop yield prediction

#### DISADVANTAGES OF EXISTING SYSTEM

- Labeled data-based classification
- Provide high number of false positive
- Binary classification can be occurred
- Computational complexity

#### 3.2 PROPOSED SYSTEM

- The proposed system leverages deep reinforcement learning to address limitations in predicting crop yield based on environmental, soil, water, and crop parameters.
- By integrating the capabilities of deep learning and reinforcement learning, the framework establishes a direct mapping between raw data and crop yield values, overcoming issues related to feature extraction quality.
- Deep neural networks are employed to predict corn hybrid yields, utilizing their ability to automatically learn complex features from genotype and environment data for enhanced accuracy.

#### ADVANTAGES OF PROPOSED SYSTEM

- Accuracy is high
- Parallel processing
- Reduce number of false positive rate
- Time and computational complexity can be reduced



#### IV. SYSTEM DESIGN

##### 4.1 SYSTEM ARCHITECTURE

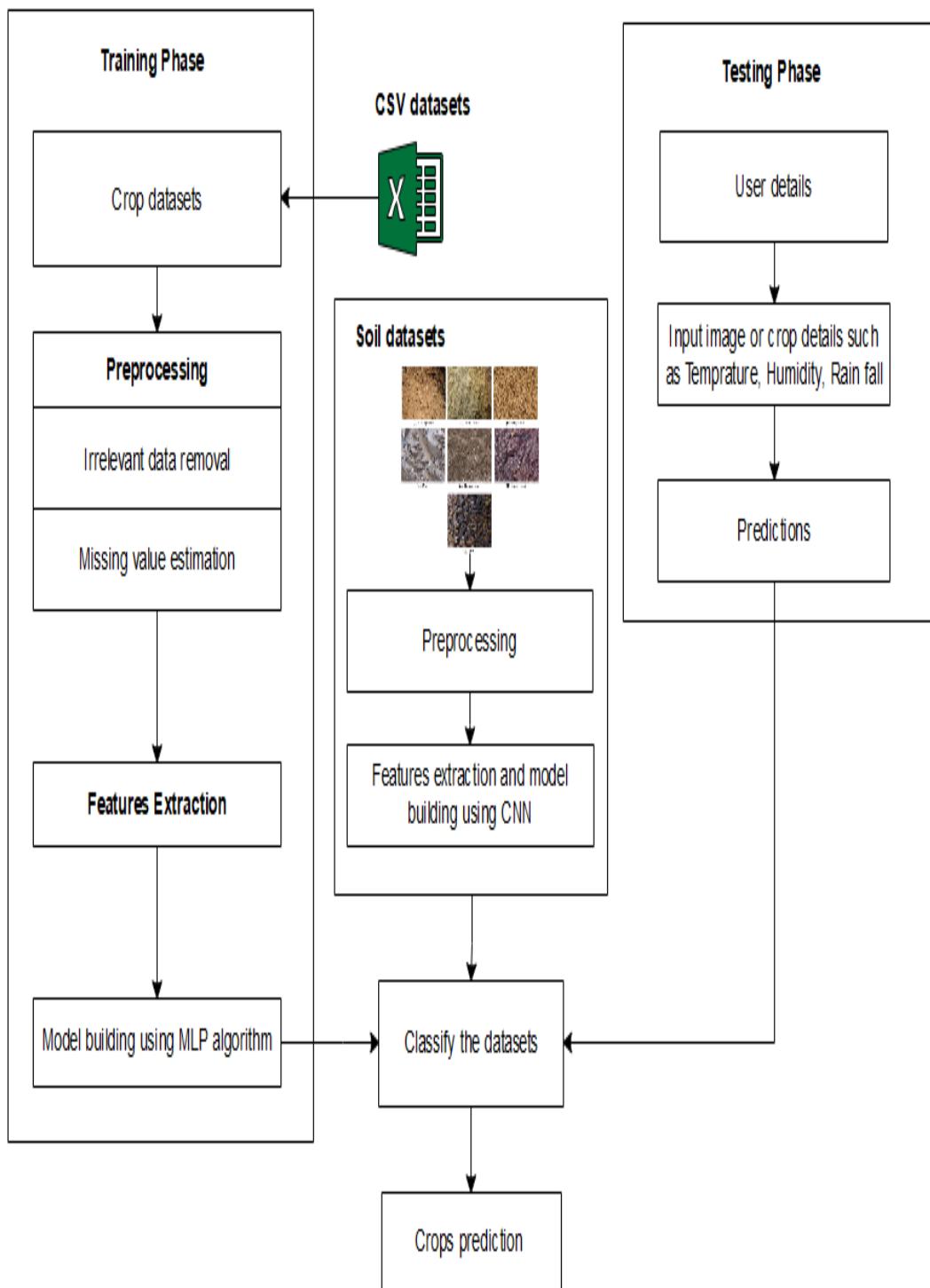
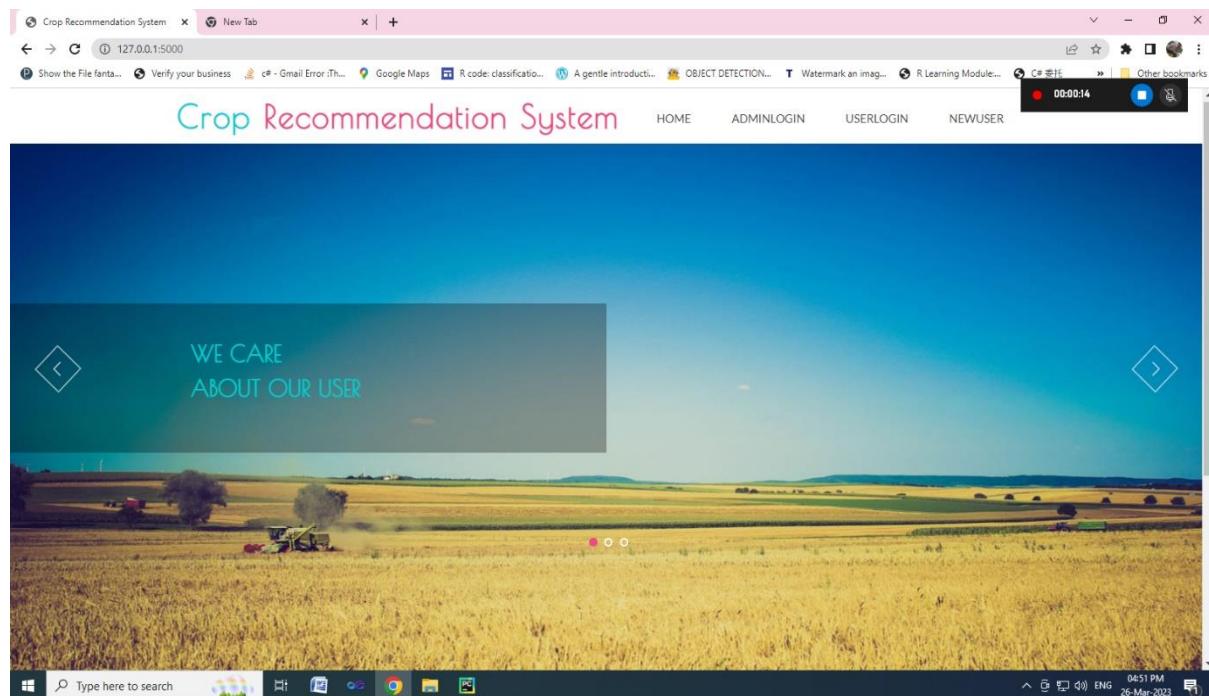


Figure No.:1 System Architecture



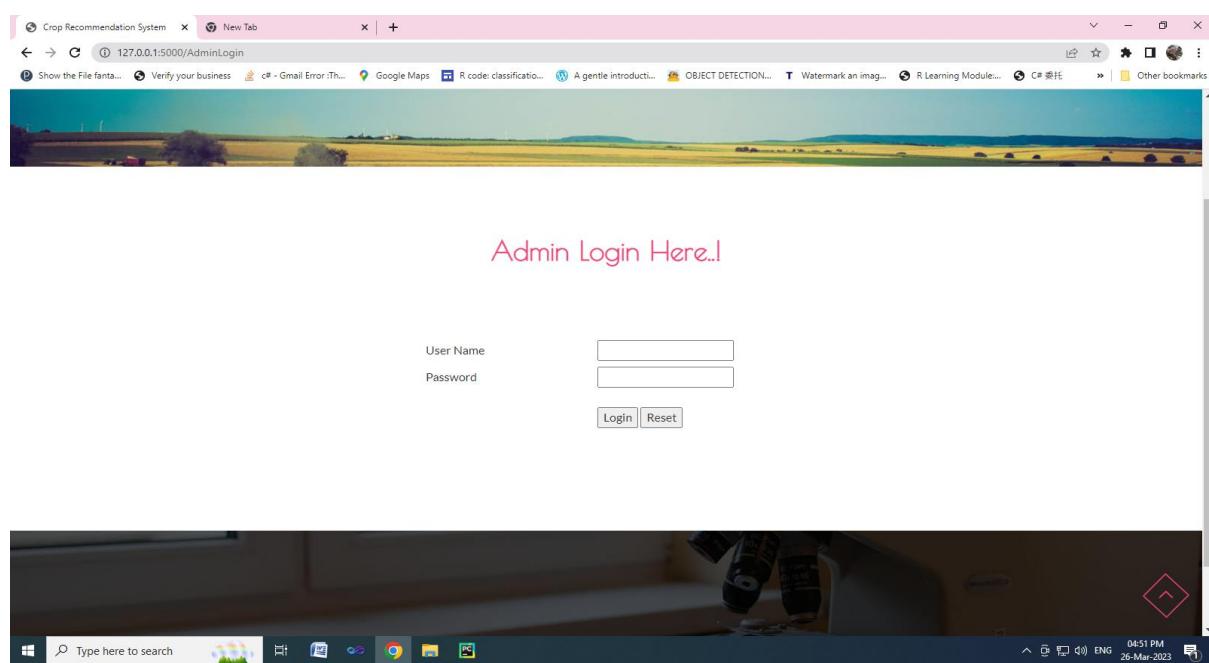
## V. RESULTS

### HOME PAGE



Here is the home page of our Python mysql web application. When you access the localhost URL (<http://127.0.0.1:8000/>), this is the first page you will see.

### ADMIN LOGIN



After selecting "Admin Login," this page appears, allowing admin to log in with their username and password.



## USER INFORMATION

The screenshot shows the homepage of the Crop Recommendation System. The title 'Crop Recommendation System' is at the top. Below it is a navigation menu with links: HOME, UPLOADDATASET, CROP RECOMMEND, RECOMMENDINFO, and LOGOUT. A large landscape image of a field under a blue sky is centered on the page.

**User Information**

Name	Gender	Age	EmailId	Phone	UserName
jai	male	20	jai@gmail.com	9894637541	jai
san	male	20	sangeeth5535@gmail.com	9486365535	san
swathi	female	20	sangeeth5535@gmail.com	9486365535	swathi
richdevos	male	20	sangeeth5535@gmail.com	9486365535	richdevos
nishanthi	female	20	nishanthi@gmail.com	7904902206	nishanthi
aswin	male	20	sangeeth5535@gmail.com	9384410144	aswin
dhana	female	20	dhana@gmail.com	9087090653	dhana
maha	female	20	sangeeth5535@gmail.com	9486365535	maha

The registered user can view their profile details in this page.

## UPLOAD CROP DATASET

The screenshot shows the 'Upload Crop Dataset' page. It features a large landscape image at the top. Below it is a form with the text 'Upload Crop Dataset' and a file input field labeled 'Choose file'. The placeholder text 'No file chosen' is visible in the input field. A 'Submit' button is located below the input field.

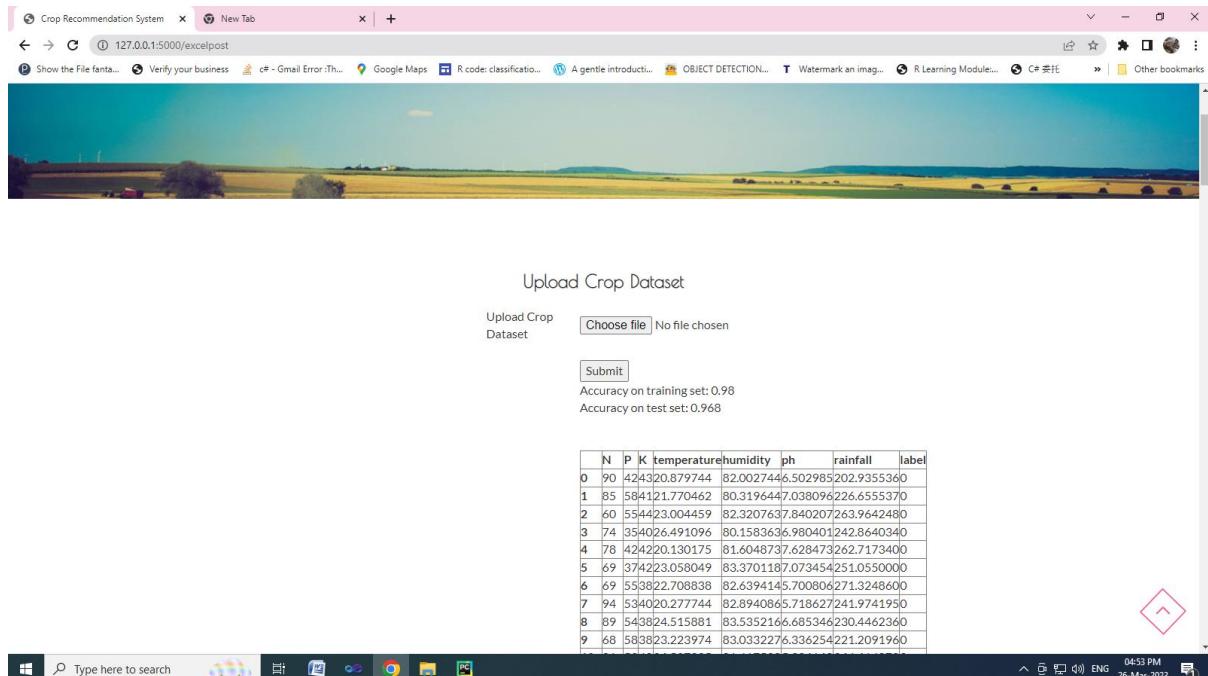
**Upload Crop Dataset**

Upload Crop Dataset  No file chosen

Admin will upload crop recommendation dataset here so that training will start in this page

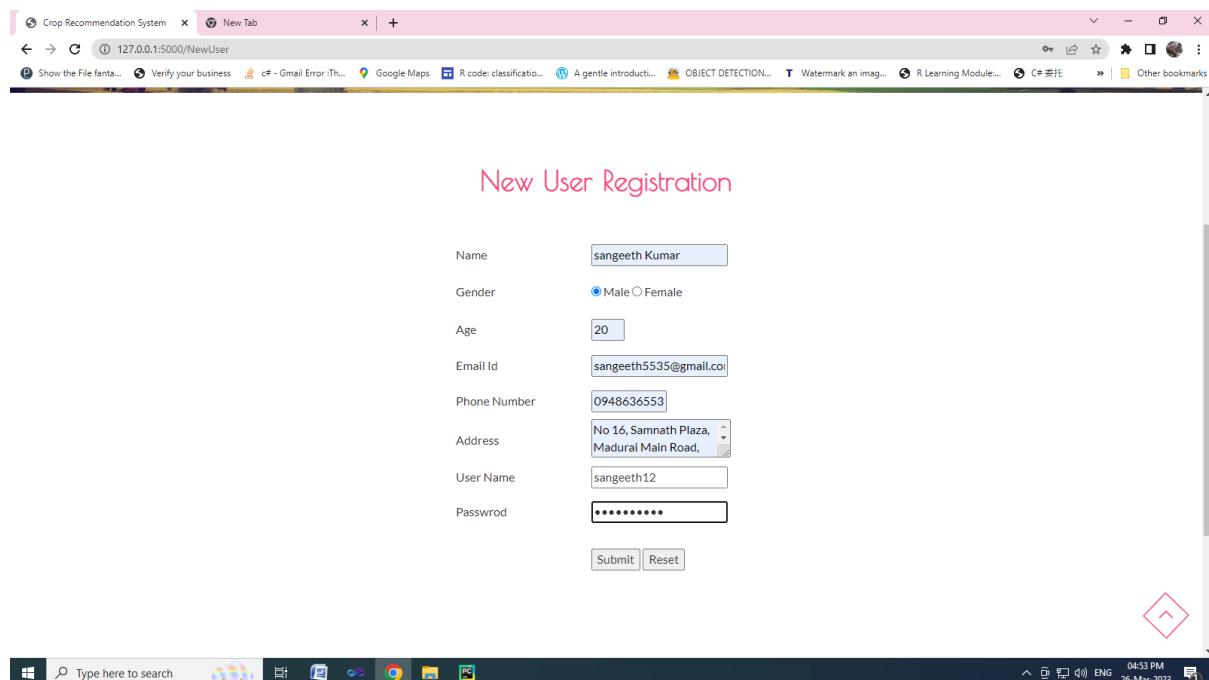


## TRINING DATASET



The accuracy results of training and testing dataset will be shown here

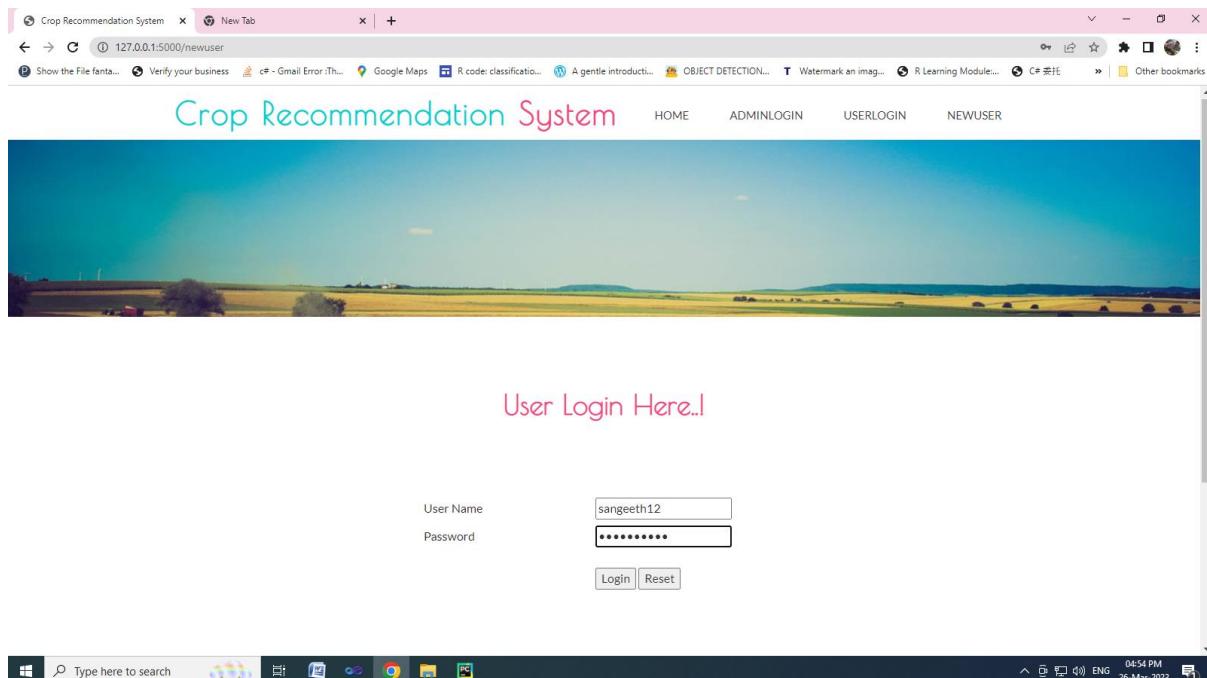
## USER REGISTRATION



This is the new user registration page of our web application. Users must register by providing their email, password, and general details

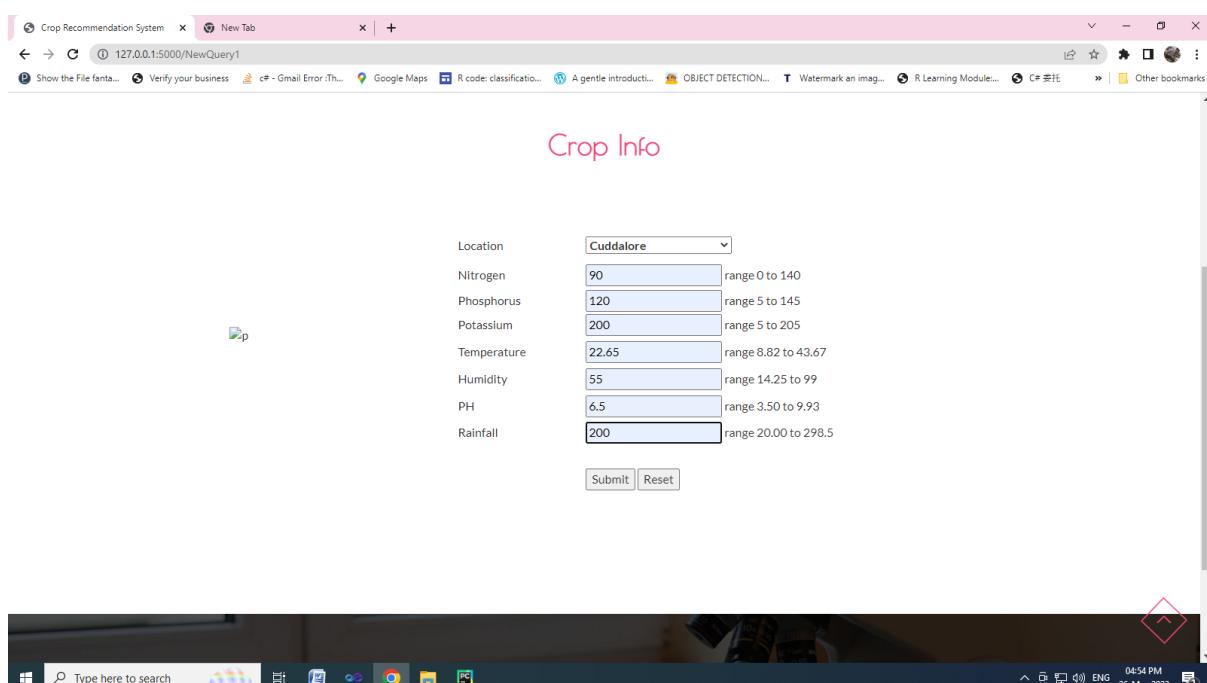


## USER LOGIN



This page where user can login

## CROP INFO



The user has to fill the required data in this page



## CROP INFORMATION

The screenshot shows a Microsoft Edge browser window with the title 'Crop Recommendation System'. The main content area displays a table titled 'Your's Crop Information' and 'Your's Crop Status'. The table includes columns for UserName, Location, Nitrogen, Phosphorus, Potassium, Temperature, Humidity, PH, Rainfall, Result, and Fertilizer. A row for 'sangeeth12Cuddalore' is shown with values: Nitrogen (90), Phosphorus (120), Potassium (200), Temperature (22.65), Humidity (55), PH (6.5), Rainfall (200), Result (Predict), and Fertilizer (chickpea). A note in the Fertilizer column states: 'The generally recommended doses for chickpea include 20–30 kg nitrogen (N) and 40–60 kg phosphorus (P) ha<sup>-1</sup>. If soils are low in potassium (K), an application of 17 to 25 kg K ha<sup>-1</sup> is recommended'. Below the table, a camera interface shows a soil sample with the text '© All rights reserved | Design by Crop Recommendation System'. The bottom of the screen shows a Windows taskbar with the date and time (26-Mar-2023, 04:59 PM).

In this page results regarding the recommended crops will be shown here

## SOIL PREDICTION

The screenshot shows a Microsoft Edge browser window with the title 'Crop Recommendation System'. The main content area displays a process flow for soil prediction. On the left, there are four steps: 'Upload Image' (with a placeholder image of a soil sample), 'Grayscale' (a grayscale version of the image), 'Invert' (an inverted color version of the image), and 'Noise Removal' (a processed version of the image). To the right, the 'Result' section shows the prediction 'Red soil' and the note 'Marsh soils are not suitable for crop cultivation due to their high acidic nature'. Below the result is a 'Predict' button. The bottom of the screen shows a Windows taskbar with the date and time (26-Mar-2023, 05:03 PM).

In this page pictures regarding the recommended crops will be shown here



## VI. CONCLUSION

Deep Learning Algorithm has been incorporated for crop prediction, which demonstrated superior performance in Crop Challenge using large datasets of products. The approach used deep neural networks to make crop datasets such as soil and textual datasets. In conclusion, deep learning models offer a promising solution for predicting crop yields based on environmental variables such as temperature, pH, rainfall, and soil data. By using neural networks to analyse large and complex datasets, these models can identify patterns and relationships that would be difficult or impossible for humans to discern. By training the model on historical data and then using it to make predictions on new data, farmers and researchers can gain valuable insights into which crops are most likely to thrive under certain environmental conditions. However, there are still some challenges to overcome, such as the need for high-quality and diverse data, the difficulty of interpreting complex neural networks, and the potential for bias and errors in the training data. Overall, deep learning holds great promise for revolutionizing the field of crop prediction and helping to feed a growing global population

## VII. FUTURE ENHANCEMENT

In the future, soil analysis and crop recommendation systems using deep learning can be significantly enhanced by integrating multi-spectral and hyperspectral imaging technologies, which provide detailed insights into soil properties beyond the visible spectrum. This can be combined with real-time IoT sensors to continuously monitor soil conditions, enabling dynamic and adaptive crop recommendations. Furthermore, leveraging advancements in transfer learning and federated learning can enhance model accuracy and efficiency by allowing models to learn from diverse datasets across different regions without compromising data privacy. Additionally, incorporating predictive analytics for weather patterns and climate change impacts can optimize crop selection and farming practices, thereby improving yield and sustainability. These enhancements will make soil analysis and crop recommendation systems more robust, precise, and tailored to the specific needs of individual farms.

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