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Farm Assistant - An AI Driven Crop Recommendation System Practice

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ABSTRACT

This paper presents an AI-driven approach to enhancing agricultural productivity through a comprehensive crop recommendation system. The system integrates data from various sources, Nitrogen, Phosphorous and Potassium (NPK levels), humidity. By employing multi-label classification techniques, the system suggests optimal crops based on soil conditions, water availability, and climate patterns. Furthermore, the system continuously monitors plant growth and provides farmers with real-time insights for better decision-making. The ultimate goal of this research is to empower farmers with data-driven recommendations, improving both yield efficiency and market timing while ensuring environmental sustainability.

Keywords: random forest, sustainable agriculture, forecasting, weather, soil, crop recommendation.

INTRODUCTION

Agriculture continues to be the mainstay of the economies of many nations, particularly in developing nations where it is vital to GDP and jobs. However, a number of issues confronting modern agriculture, such as soil degradation, unpredictable weather patterns, and restricted access to useful information, limit crop yields and sustainable farming methods. Farmers frequently use conventional agricultural practices and make haphazard crop choices, which leaves production vulnerable to changes in the market and the environment.

With advances in artificial intelligence (AI) and data analytics, the potential to revolutionize agriculture through accurate, data-driven crop suggestions has grown. This paper proposes a state-of-the-art, artificial intelligence (AI)-powered crop recommendation system that combines many data sources, such as soil nutrient levels (Nitrogen, Phosphorus, Potassium, or NPK), climate patterns, humidity, and other agronomic parameters, to give farmers the best crop selections for given soil and environmental conditions.

This approach employs a variety of agronomic aspects using classification techniques to select crops that are compatible with the climatic and soil characteristics of the area. Furthermore, it incorporates information from external sources such as GGE (Google Earth Engine Team, 2017), USDA (United States Department of Agriculture, 2023) which provides high-quality environmental data, including pH, carbon content, and soil moisture. By incorporating cutting-edge artificial intelligence (AI) tools with traditional practices like crop rotation techniques, this system provides farmers with actionable insights that enable them to make wise decisions throughout the growing season, ultimately lowering resource waste, increasing yield efficiency, and encouraging sustainable farming methods.

The aim of this study is to use AI to give farmers data-driven insights that provide optimized crop selection, enhance

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agricultural planning, and promote economic stability in rural areas. This technology solves important concerns such as climate variability, soil quality, and resource efficiency by combining agriculture and AI, resulting in a more resilient, sustainable, and productive agricultural industry.

RELATED WORKS

There are some related works done by Google's DeepMind, China's FengWu and FourCastNet for accurate weather detection and SoilNet for getting soil data. By combining all these data, it can help in crop recommendation using machine learning algorithms. The approaches by those works are discussed below. Each of them perform distinct approach to find the data accurately

Google's DeepMind

Google DeepMind has developed an AI model called GraphCast (Lam et al., 2023) that revolutionizes weather forecasting by predicting weather up to 10 days in advance in less than a minute on a single desktop computer, compared to current systems that take hours on massive supercomputers. Trained on nearly 40 years of historical weather data, GraphCast outperforms 90% of traditional weather prediction systems and is particularly effective at forecasting severe weather events like extreme temperatures and tropical cyclones.

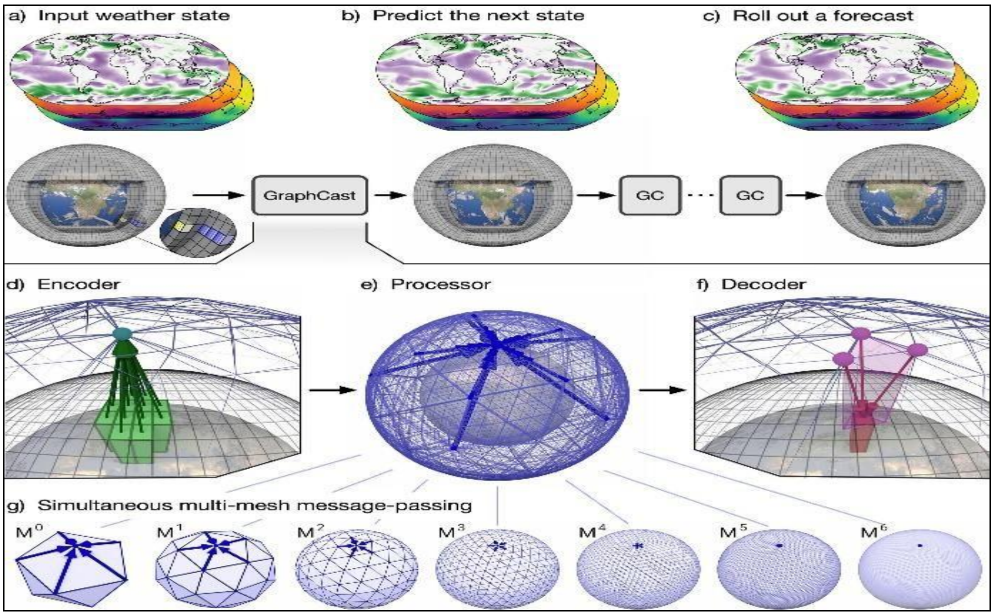

Figure 1. DeepMind - GraphCast for weather forecasting

This AI-driven approach is about 1,00 times more energy - efficient than conventional methods, making weather forecasting faster, cheaper, and more accurate. Figure 1 shows the process of GraphCast.

The implications of GraphCast extend beyond weather forecasting, with potential applications in climate crisis management, agriculture, energy, and more. As part of the World Economic Forum's AI Governance Alliance, Google DeepMind is ensuring the responsible development and deployment of AI technologies like GraphCast, which could play a crucial role in addressing global challenges by predicting extreme weather events and other critica issues driven by the climate crisis.

China's FengWu

The Shanghai Artificial Intelligence Laboratory has developed an advanced AI-based weather forecasting model called Fengwu (Xiao et al., 2024), which has successfully extended the global mid-term weather forecast time to 11.25 days. Unlike traditional models that rely on super computers, Fengwu uses machine learning to analyze atmospheric data such as wind speed, temperature, and humidity, leading to more accurate weather predictions. The model has been upgraded to include modules for severe convective weather, global mid-term meteorological forecasting, and ocean climate forecasting, enabling it to provide minute-level forecasts for severe weather and decade-long predictions for oceanic climate trends.

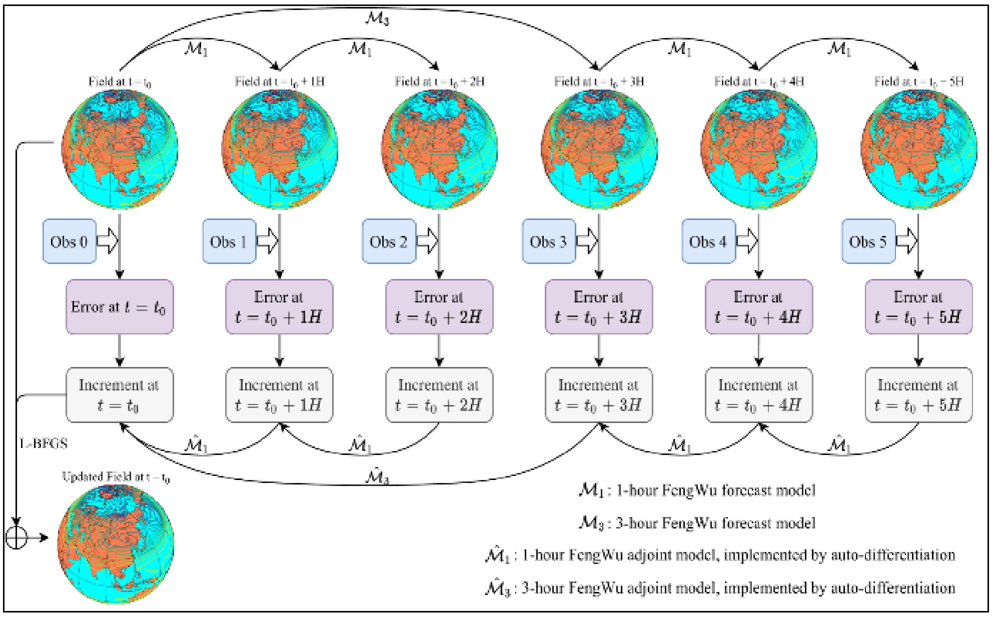

Figure 2. Implementation of 4DVar on the FengWu forecasting model

Figure 2 shows the implementation of 4DVaron the FengWu. It's breakthrough surpasses international counterparts, including Google DeepMind's AI, which delivers 10-day forecasts. The model offers precise weather forecasts from “doorstep” to “the heart of the ocean”, covering various altitudes and depths. As climate disasters become more frequent, the need for precise weather forecasting has intensified. The Chinese government is actively exploring AI's potential in weather forecasting, with initiatives like the China Meteorological Administration's pilot program, which aims to use real-time observational data to produce 15-day forecasts for various meteorological elements and hazardous weather processes

FourCastNet

The demand for designating accurate weather forecasts is on the rise all because of climate change nowadays than ever in the past. Traditional numerical weather prediction (NWP) approaches, which are built around complicated equations and massive computational power, cannot produce such high-resolution forecasts. But **FourCastNet**, a weather prediction that is driven by deep learning models. Figure 3 depicts its accuracy.

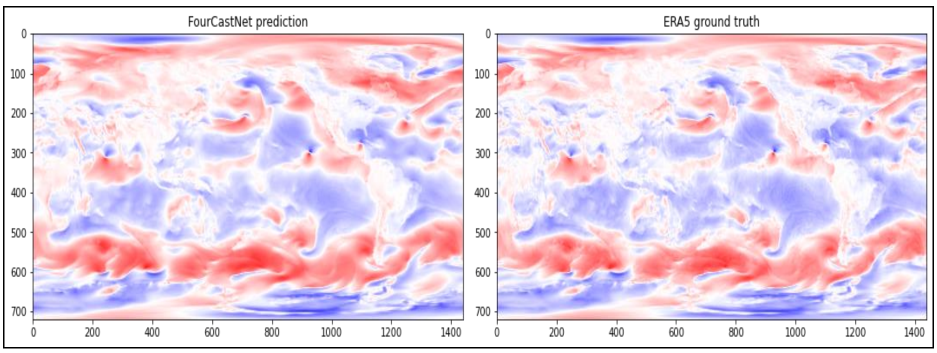

Figure 3. FourCastNet prediction vs ERA5 ground truth data

FourCastNet (Pathak et al., 2022) (Figure 3 produces surface wind velocity) weather forecasts just as most NWP models do, however it does it with great speed "within range" and produces accurate surface wind velocity weather forecasts in few seconds versus what is achievable by most NWP models. Being based on the ERA5 data set i.e. a large archival collection of atmospheric data over time, it cuts down on costs as well as improves efficiency in terms of energy use thus more ensembles are possible for better prediction of probabilities. FourCastNet is capable of simulating fine weather details including calamities such as hurricanes at the resolution of 25 km which is important for disaster management and resource allocation. Because of this, the authors have published the trained model weights, code, and datasets to the public in order to promote accessibility and foster use of the common affective research work.

SoilNet

SoilNet (Kakhani et al., 2023) is a deep learning model, designed for analyzing soil data to assess the quality and recommend crops. It primarily uses Convolutional Neural Networks (CNNs) to process high-resolution soil data, identifying patterns in properties such as moisture, pH, and nutrient levels. SoilNet leverages real-time data from soil sensors, allowing farmers to monitor soil conditions continuously and make timely decisions. The model also integrates satellite imagery and remote sensing data to extend its analysis over larger agricultural areas, providing insights at both the field and regional levels.

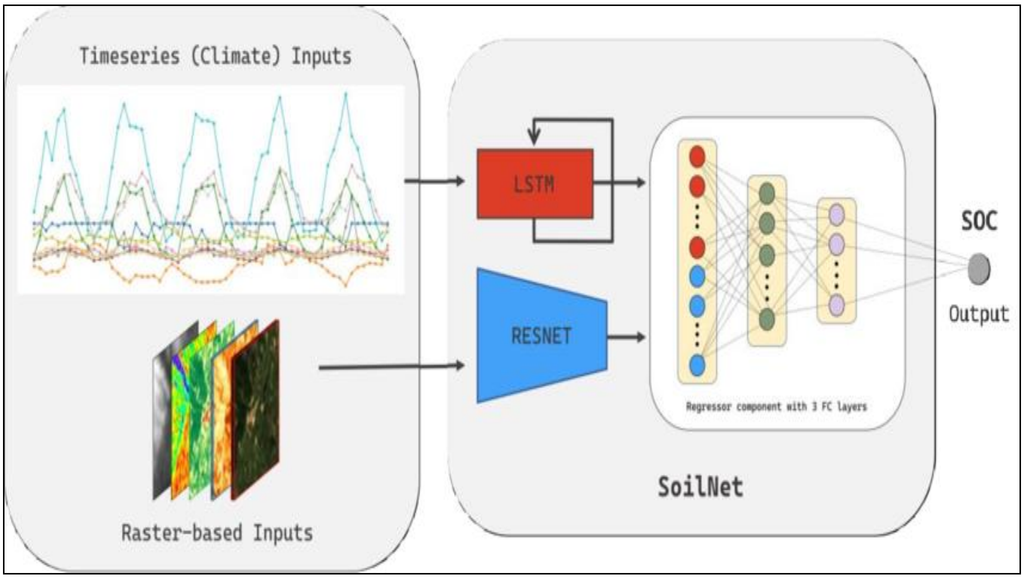

Figure 4. SoilNet Architecture

Figure 4 depicts its working of the architecture. Additionally, SoilNet offers a spatial-temporal analysis capability, allowing it to track changes in soil conditions over time and predict future suitability for specific crops. This makes it valuable in precision agriculture, where it helps farmers optimize irrigation, fertilization, and crop selection. By combining real-time monitoring with historical data, SoilNet delivers precise, data-driven crop recommendations, enabling improved yields and resource management.

METHEDOLOGY

The Figure 5 shows the use of AI in agriculture for recommending crop to analyze the data collecting and transforming into ideal crop recommendation. This uses Machine Leaning algorithms that go through the environmental and soil compatibility with each crop and recommend a specific crop for its growth. This methodology consists of several steps (Figure 6). Firstly it begins with data integration as it collects data from various sources (i.e., soil data from one source and weather related data from another source) and then transforming it into required format form processing it. It uses Machine Learning Techniques like Random Forest, Graph Convolution Network (GCN) and Support Vector Machine (Colfescu, 2024).

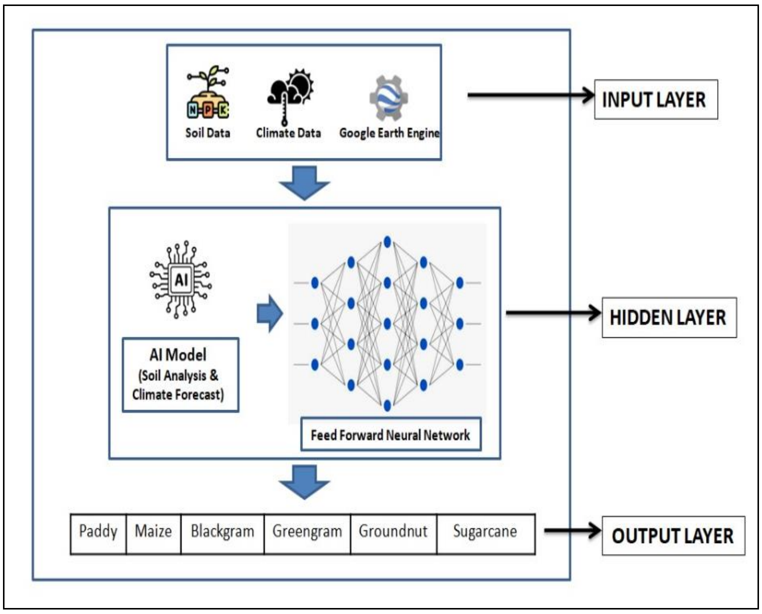

Figure 5. Architecture for Farm Assistant

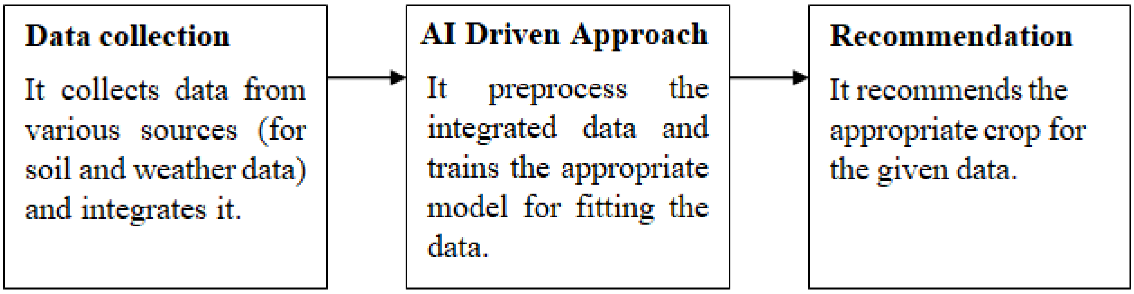

Figure 6. Methodology

Data Gathering

Data gathering is the foremost and primary step in building the crop recommendation system as it summarizes crucial information about soil, weather and other environmental factors which influences the soil growth. In this paper the data is collected from Kaggle for the training purpose. For accessing with real time data Google Earth Engine (GEE) provides the accurate data on all the necessary features. It provides various features and updated records for the necessary attributes.

Agricultural Data (Soil and Crop Growth)

There are various types of soil on Earth, each possessing unique characteristics. These characteristics play a crucial role in determining how well plants grow in them. Google Earth Engine (GEE) is a powerful cloud-based geospatial (Google Earth Engine Team, 2017) analysis platform that allows researchers and developers to access, process, and visualize large datasets for environmental monitoring, agricultural management, and climate research.

In the field of agriculture, GEE provides various datasets for moisture level, organic carbon content and other important factors of soil which impacts soil growth. With the help of GEE researchers can access data set like Soil Moisture Access Passive (SMAP) Mission, USDA (United States Department of Agriculture, 2023). This dataset provides various properties of soil include soil textures, humidity, pH and organic carbon. For instance, soil moisture data from SMAP helps monitor water availability, while soil organic carbon from SoilGrids gives insight into soil fertility, enabling optimized crop selection and improved yield predictions (Islam et al., 2018).

Cultural and Seasonal Factors

Cultural variables such as traditional crop selection, irrigation methods, and timing of planting were collected via surveys from local farmers. Seasonal variables, including average monthly temperature, rainfall, and frost-free days, were obtained from meteorological stations and satellite data from Google Earth Engine (Porter et al., 2005). These variables were analyzed to assess their impact on crop productivity in the region. Cultural factors such as crop rotation practices, traditional irrigation techniques, and seed selection were collected through field surveys of local farmers and historical records from the region. Seasonal factors, including average monthly temperatures, rainfall distribution, and frost periods, were sourced from meteorological data and satellite observations using Google Earth Engine. The data was analyzed to understand the interaction between these factors and their impact on agricultural productivity. On such traditional methodology for getting information is through their traditional calendar which specifies the auspicious time. For example, in South India, Panchangam is a traditional Hindu calendar that provides detailed astrological and astronomical information used for various purposes like determining auspicious days, performing rituals, and understanding the cosmic influence on human lives. It is deeply rooted in Vedic astrology and is widely used in India.

AI driven Crop Recommendation

In order to analyze large agricultural datasets and produce accurate crop predictions, an AI-driven crop recommendation system uses advanced cutting-edge algorithms. This approach can recommend the best crops for a site by taking into account several variables, including soil quality, climatic, and seasonal patterns. An AI-driven strategy offers data-backed insights, optimizing land use, boosting crop diversity, and improving total yield (Cunha et al., 2018) in contrast to conventional farming methods that rely on incomplete information and unguaranteed yield.

The recommendation system can recommend several crops that are compatible with area based on the set of input conditions since it uses a multi-label classification approach. This adaptability, which enables farmers to grow complementary crops in the same space, is essential for promoting a variety of cropping systems. Moreover, by including seasonal data and ongoing feedback from environmental sensors, the system can modify its suggestions in real time, increasing adaptability. As a result, this AI-powered crop recommendation system backs a robust, sustainable agriculture model that gives farmers precise, timely advice.

Multi-label classification

In the context of AI-driven crop recommendation systems, multi-label classification plays a pivotal role in providing precise and effective crop suggestions. Unlike traditional single- label classification, where each input is associated with only one output, multi- label classification allows the system to assign multiple crops to a given set of input conditions.

The AI model, trained on a diverse dataset that includes soil properties (such as pH, organic content, and moisture levels), meteorological data (rainfall patterns, temperature, frost days), and historical market trends, can recommend several crops that can thrive in the same conditions. For example, in a region with moderate soil fertility and good water availability, the model might recommend both maize and wheat, as they can grow under similar conditions but offer different market opportunities.

Multi-label classification enables a more flexible approach to agricultural planning. It allows farmers to diversify their crop portfolio (Bhardwaj et al., 2023), minimizing risk and optimizing land use by growing complementary crops. Additionally, by incorporating traditional knowledge, such as crop rotation practices or seasonality data from sources like Panchangam, the system enhances the accuracy of its recommendations, aligning crop suggestions with both modern data insights and time-tested agricultural practices.

As, India is the second largest country in contributing to the agriculture sector and is one of the country affected most due to natural disaster. The crop growth is tremendously affected by the climate and weather and it should focus on the natural disaster too. So, it is essential to focus the growth of a crop based on climate and weather and the crop can't be grown on any places it depends on various properties of the soil (E.g., Alluvial soil in India is mainly found in the Indo-Gangetic plains and the coastal regions which yields rice and wheat) and it depends on humidity, Nutrient and pH content of the soil.

Being a developing country, India should make use of the AI to increase the growth of the crop by using soil and weather data. The parameters going to consider in this paper are NPK (Nitrogen, Potassium, Phosphorous), Humidity and pH of the soil and rainfall.

MODELS

Random Forest

Random forest is an ensemble algorithm that builds multiple decision trees and each tree predicts a particular crop, final result is identified by the majority voting of all the trees. After training it identifies the importance of all the attributes in predicting crop.

Graph Convolution Networks

Graph Convolution Networks (GCNs) (Barvin and Sampradeepraj, 2023) used to model relationships between environmental factors, soil properties, and crops in the neural network architecture and shown in Figure 7. GCNs allow for the effective handling of structured data where relationships (edges) between different geographical locations (nodes) play a critical role in predicting the most suitable crop for a given region. Its architecture used for training this model is given in the Table 1 below.

Table 1. Layered Table

Model: "sequential"

Layer (type)	**Output Shape**	**Param #**
dense (Dense)	(None, 64)	512
dense_1 (Dense)	(None, 32)	2,080
dense_2 (Dense)	(None, 22)	726

Total params: 9,956 (38.89 KB)
Trainable params: 3,318 (12.96 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 6,638 (25.93 KB)

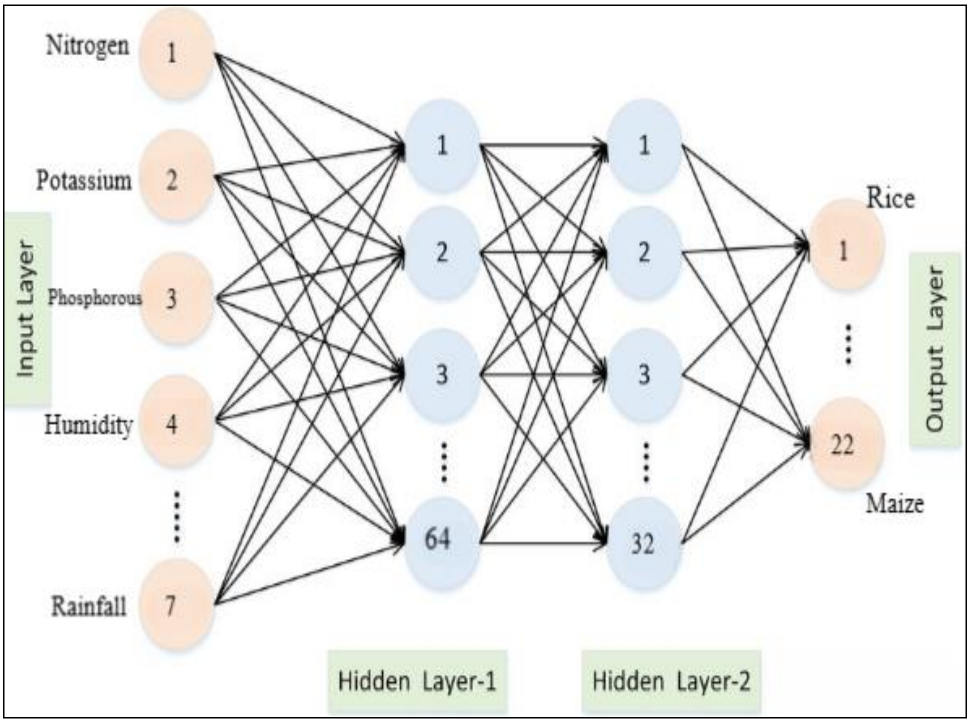

Figure 7. Neural Network Architecture

<u>*Data Representation and Graph Construction*</u>

The core of the system relies on constructing a graph-based (CSIRO's Data61, 2018) representation of the data:

- Nodes represent geographical locations or farmland areas.

- Edges represent the relationships or similarities between these regions, such as proximity, similarity in soil composition, climate, or historical crop yields.

The adjacency matrix A is constructed to encode these relationships, while feature vectors for each node consist of environmental, soil, and historical data, such as:

- Soil properties: pH, nitrogen, phosphorus, potassium levels.

- Weather conditions: Temperature, rainfall, humidity.

- Geographical information: Elevation, latitude, longitude.

- Historical data: Crop yields, seasonal variations.

<u>*Graph Convolution Network Architecture*</u>

The GCN architecture forms the foundation of the crop recommendation system. It operates in the following steps:

a. Graph Laplacian Calculation

The graph's Laplacian matrix L is calculated to capture the structural properties of the graph. The Laplacian is normalized as follows:

$$\boldsymbol{L} = \boldsymbol{I} - \boldsymbol{D}^{-\frac{1}{2}} \boldsymbol{A} \boldsymbol{D}^{-\frac{1}{2}} \quad (1)$$

where:

D is the degree matrix and ***A*** is the adjacency matrix of the graph.

This step ensures that the features from neighboring nodes are aggregated in a balanced manner.

b. Feature Propagation through Convolution Layers

The GCN applies convolution operations to propagate features across the graph. Each layer in the GCN takes the node features X and propagates them using the adjacency matrix ***A***:

$$\boldsymbol{H}^{(l+1)} = \sigma(\boldsymbol{D}^{-\frac{1}{2}} \boldsymbol{A} \boldsymbol{D}^{-\frac{1}{2}} \boldsymbol{H}^{(l)} \boldsymbol{W}^{(l)}) \quad (2)$$

where:

- ***H*** is the hidden layer representation of the nodes.

- ***W*** are the trainable weight matrices.

- $\boldsymbol{\sigma}$ is the activation function (e.g., ReLU).

This step captures the influence of neighboring regions, enriching the feature representation of each node by aggregating information from its neighbors.

c. Crop Suitability Prediction

The GCN's final layer outputs a prediction for each node (region), classifying the suitability of various crops based on the learned graph representation. The output layer is defined as:

$$Z=softmax(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}H^{(l)}W^{(l)}) \qquad (3)$$

where:

Z is a probability distribution over the crop classes, and l represents the number of layers in the network.

Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning algorithm which tries to identify the hyperplane which tends to separate the crops. This algorithm works wellifit has less number of attributes. In this example as the dataset has 7 attributes, it will create a 7 dimensional hyperplane which will separate the crops where each feature represents a dimension.

Dataset Overview

The dataset we used to train the model consists of several data which are augmented of 2200 data with crops going to be trained are Rice, Apple, Banana, Black gram, Chickpea, Coconut, Coffee, Cotton, Grapes, Jute, Kidneybeans, Lentil, Maize, Mango, Mothbeans, Mungbean, muskmelon, Orange, Papaya, PigeonPeas, Pomegranate, Watermelon with each crop consists of 100 data and the attributes are Nitrogen, Potassium, Phosphorous each data is splitted into 80% for training and remaining is for testing data shown in Table 2.

Table 2. Overview of Dataset

Nitrogen	Phosphorus	Potassium	Temperature	Humidity	pH_Value	Rainfall	Crop
90	42	43	20.88	82	6.5	202.94	Rice
62	52	16	22.28	58.84	6.97	63.87	Maize
28	72	84	18.73	19.18	6.48	71.58	Chickpeas
34	60	22	17.66	18.15	5.64	100.67	Kidney Beans
34	56	17	33.41	35.43	4.55	139.67	Pigeon Peas

Data augmentation is a common method in machine learning which involves modifying current data to artificially increase the size of a training dataset. Data augmentation aims to increase the variety and variability of the training data in an effort to improve the effectiveness and adaptability of machine learning models.

The Figure 8 shows how each pair of data affects the crop prediction. e.g., the relation between nitrogen and potassium for apple shows that both high level of potassium and phosphorous might result in prediction of Apple. This is used to identify contribution of a pair of data in predicting crop. The relation between two attributes can be viewed by the following correlation graph represent in Figure 9. Negative value indicates that they are independent of each other, and high positive value denotes that they are highly depend on each other.

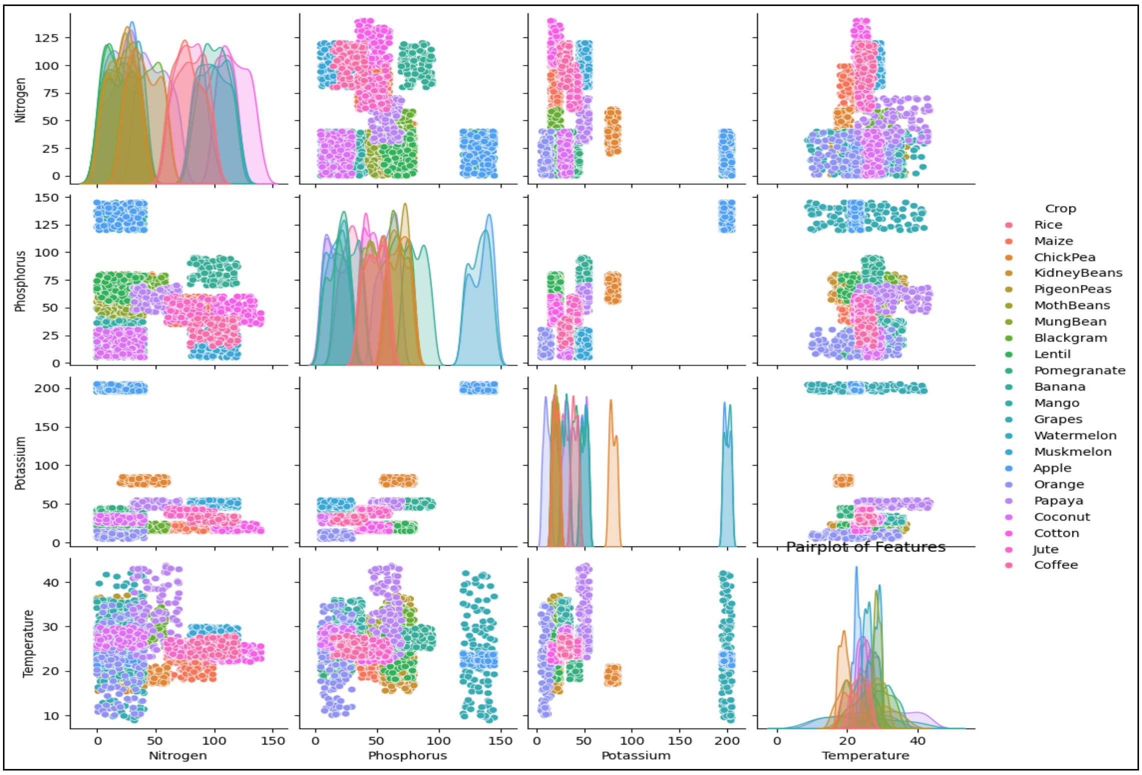

Figure 8. Relationship between the attributes

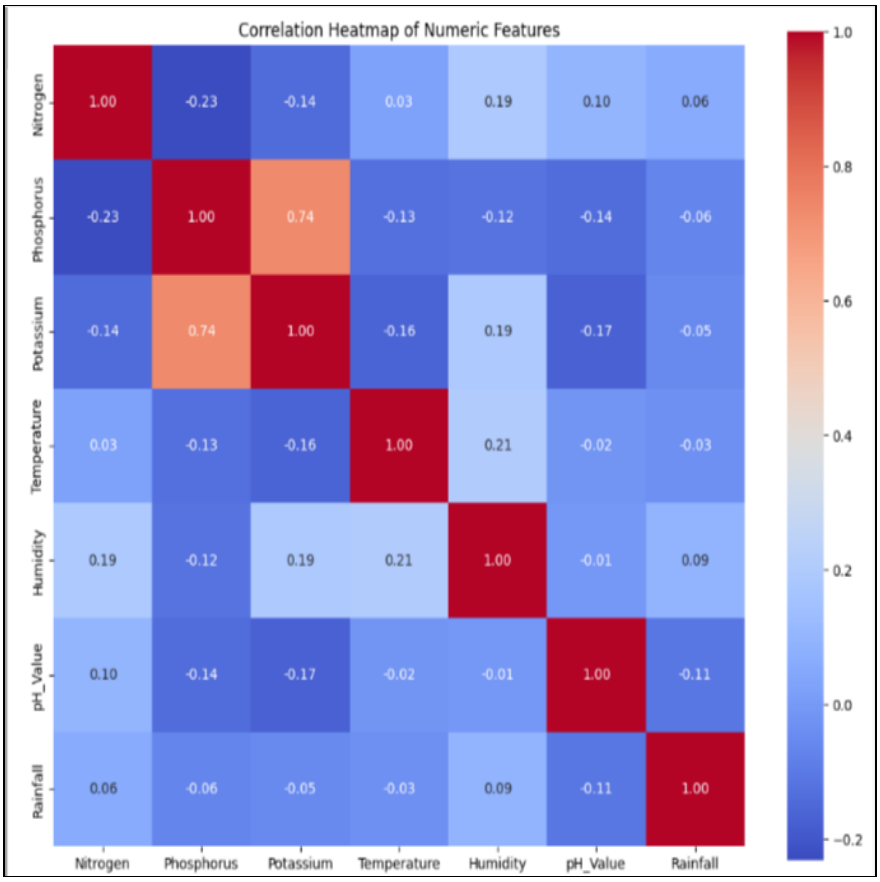

Figure 9. Correlation Matrix Showing Relationships - Soil and Environmental Factors

This data is trained using Neural Network, Random Forest, Support Vector Machine to use the better accuracy in the crop prediction.

PERFORMANCE ANALYSIS

Three models were created based on Neural Network, Random forest, Support Vector Machine (SVM). All these are having ideal accuracy and loss value. The accuracy and loss value of the neural network is shown below in Figure 10 for every epochs.

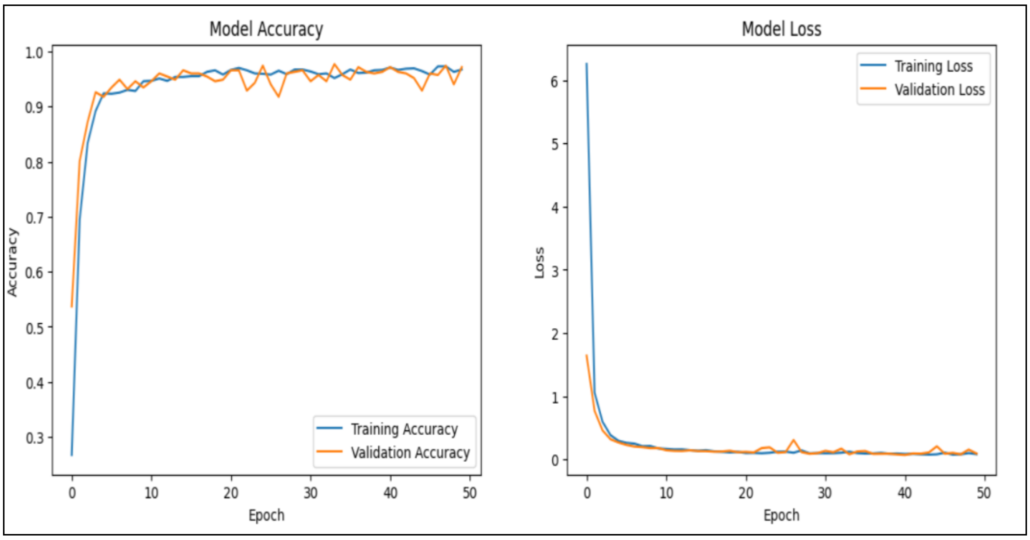

Figure 10. Performance of GCN Model over Training Epochs

Confusion map: A confusion Matrix is tabular representation in Figure 11 to evaluate the performance of the model. It depicts how the model predicted value matches/differs with the actual value.

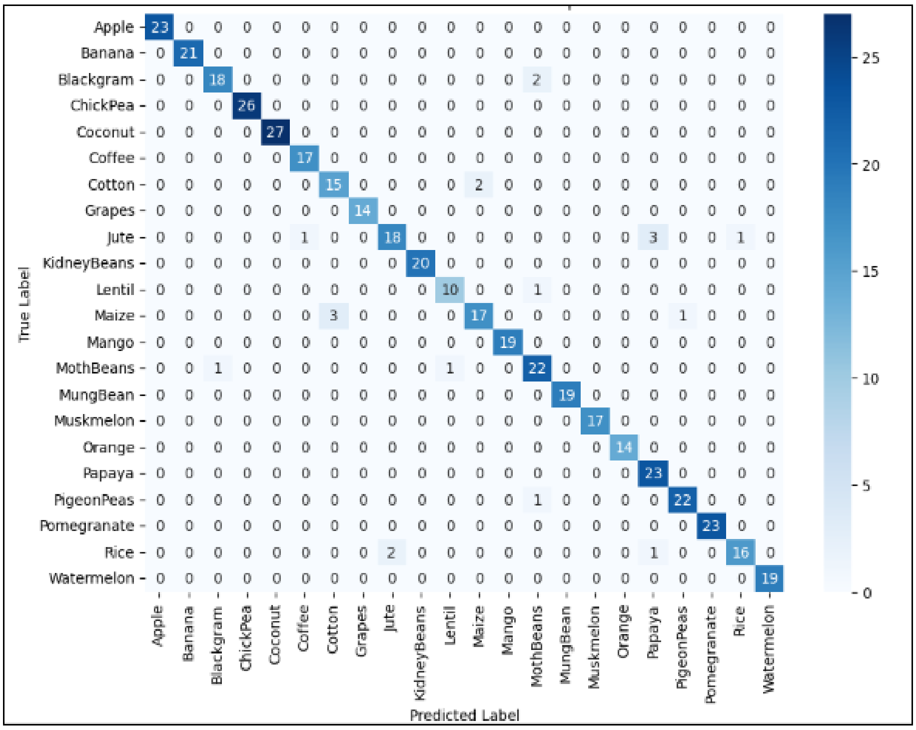

Figure 11. Confusion Matrix for Multi-Label Crop Classification

For a multi-class classification with 'n' label, it will have 'n' rows and 'n' column each value in the table specifies the true value and predicted value. The above confusion matrix denotes the matrix for neural network.

Table 3. Performance Analysis across Different Algorithms (GCN, Random Forest, SVM)

Method	Training	Testing	Accuracy
GCN	80%	20%	95.63%
Random Forest	80%	20%	99.03%
SVM	80%	20%	96.95%

By comparing the above Table 3 data, Random forest give better accuracy than all the other algorithms. It is due to handling of relatively less data and handling only numerical value. On the other hand SVM and neural network requires more data to be trained effectively. At the same time, Neural network can handle any type of data effectively (Random forest and SVM can't handle it).

CONCLUSIONS

In the agriculture domain, crop prediction for a particular land is a major issue. By integrating ML tools it can significantly improve the growth of crop and create some huge impact in agriculture. By analyzing key environmental factors such as soil nutrients (Nitrogen, Phosphorus, Potassium), weather parameters (temperature, humidity, rainfall), and soil pH, machine learning models can effectively recommend optimal crops for specific regions.

Various algorithms such as Support Vector Machine (SVM), Random Forest, Neural Network have been implemented for this (Roßbach, 2018). Among these Neural networks yield higher accuracy for this problem. The integration of data from sources like satellite imagery (Google Earth Engine) further enhances the precision of these predictions. By integrating agriculture with Machine Learning tools can addresses problems like fluctuating weather, Soil degradation. This ensures the sustainability and efficiency in agriculture for both large and small scale farmers. These advancements will help improve food security, reduce crop failures, and contribute to the economic stability of rural India.

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