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Deep Learning-based Crop Recommendation System with IoT Integration for Agricultural Optimization

1. **Hemalatha Indukuri**, Professor, Department of IT, SRKR Engineering College(A), Bhimavaram, Andhra Pradesh, India, Email: indukurihemalatha@gmail.com.

2. Mrudhula Ruddarraju, PG scholar, Department of IT, SRKR Engineering College(A), Bhimavaram, Andhra Pradesh, India, Email: ruddarrajumrudhula@gmail.com.

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Abstract

Crop analysis and prediction have emerged as critical components in optimizing agricultural practices. Efficient crop recommendation systems are pivotal in aiding decision-making regarding suitable crops based on land and climatic conditions. Traditionally, this process relied heavily on the expertise of farmers, resulting in labour-intensive and time-consuming efforts. Leveraging machine learning and deep learning techniques can significantly streamline crop recommendations and enhance pest and disease detection, empowering farmers to maximize yield while preserving soil fertility and essential nutrients. Our proposed system employs a deep neural network model, integrating various features such as Nitrogen, Phosphorous, Potassium, Temperature, Humidity, Moisture, Rainfall, and pH to predict suitable crops for farming, serving as a crop recommendation system. This model comprises two methods: leveraging historical datasets from Kaggle and collecting real-time data through an IoT model. The IoT model incorporates sensors like DHT11 and moisture sensors to gather parameters such as Temperature, Humidity, and Soil Moisture, facilitating crop suggestions based on soil conditions. The Kaggle dataset is utilized to train and test the deep learning algorithm model, achieving an accuracy exceeding 95%. This abstract encapsulates the technical aspects of our system while addressing the need for efficient crop recommendation and real-time data collection to optimize agricultural productivity.

Keywords: Crop analysis, Prediction, Agriculture optimization, Crop recommendation, Machine learning, Deep learning, Soil fertility, Pest and disease detection

1 Introduction

India stands as a global leader in farm output, making substantial contributions to its economy. However, the agricultural sector predominantly relies on traditional techniques, which, while informed by the wisdom of experienced farmers, often entail labour-intensive processes and significant time investments. Enter smart farming: an integrated farming control system designed to address both spatial and temporal variability in crops and soil. Its aim? To maximize profitability, optimize yields, and enhance production quality. In the realm of smart farming, deep learning algorithms take center stage, tackling complex challenges where human expertise falls short. These algorithms are deployed for a myriad of tasks, from forecasting soil parameters to predicting crop yields. One of the standout advantages of deep learning is its prowess in feature learning—automatically extracting meaningful features from raw data. This ability proves invaluable in agriculture, enabling the identification of anomalies and the discovery of previously unknown elements within agricultural fields. By leveraging the homogeneous properties of these fields, deep learning models can unearth far-flung, obscured, or previously undiscovered objects, revolutionizing agricultural practices. The article "Advanced Agricultural Techniques: Harnessing Machine and Deep Learning for Intelligent Farming" delves into the forefront of agricultural innovation by examining how cutting-edge technologies can be seamlessly integrated into traditional farming methods. With the global population steadily increasing, agricultural systems are under pressure to boost productivity to meet the growing demand for food, all while minimizing environmental degradation and optimizing resource usage. In addressing these pressing challenges, the adoption of machine and deep learning technologies has emerged as a beacon of hope for revolutionizing conventional farming practices. By leveraging these advanced techniques, farmers can usher in a new era of intelligent and efficient agricultural processes. Machine learning algorithms, for instance, enable farmers to analyze vast amounts of data collected from fields, weather patterns, and crop health sensors to make informed decisions in real-time. These data-driven insights empower farmers to optimize irrigation schedules, tailor fertilization plans, and detect pest infestations early, thereby maximizing yields while minimizing resource wastage. Similarly, deep learning techniques offer unparalleled capabilities in pattern recognition and feature extraction. By training neural networks on diverse datasets, farmers can develop sophisticated models for predicting crop yields, identifying disease outbreaks, and even optimizing planting patterns. This transformative approach not only enhances productivity but also promotes sustainability by reducing reliance on chemical inputs and minimizing environmental impact. This research endeavor endeavors to delve into the complex intersections of artificial intelligence, with a specific focus on machine and deep learning, and their applications within the agricultural domain. By harnessing the power of these advanced technologies, the overarching goal of this thesis is to unearth innovative solutions that not only enhance decision-making processes but also optimize the allocation of resources, ultimately contributing to the sustainability of agricultural practices. The amalgamation of machine learning algorithms and data analytics within the realm of precision agriculture presents a profound opportunity to revolutionize crop management methodologies. This paradigm shift empowers farmers to make well-informed decisions by leveraging real-time data streams sourced from an array of outlets, including satellite imagery, ground sensors, and unmanned aerial vehicles (UAVs) or drones. These data sources collectively provide a comprehensive view of the agricultural landscape, enabling farmers to monitor crop health, assess soil conditions, and detect anomalies with unprecedented precision. By harnessing the analytical capabilities of machine learning models, farmers can extract valuable insights from this wealth of data, ranging from predictive analytics for crop yield forecasts to anomaly detection for early pest infestation alerts. Moreover, the iterative nature of machine learning facilitates continuous refinement and improvement of these predictive models, thereby enabling adaptive decision-making strategies tailored to the dynamic conditions of the agricultural environment. In essence, the integration of machine and deep learning technologies into agricultural practices represents a transformative leap towards more efficient, sustainable, and data-driven farming methodologies. By embracing these advancements, farmers stand to not only optimize their operational workflows but also mitigate environmental impact and ensure the long-term viability of agricultural production systems. These autonomous systems can execute tasks with precision and consistency, whether it's planting, irrigation, or crop monitoring, thereby streamlining operations and optimizing resource utilization. By reducing the need for manual intervention, farmers can allocate their time and resources more effectively, focusing on strategic decision-making and higher-value activities. In addition to the operational advantages, the study also delves into the transformative potential of predictive analytics within the agricultural domain. Central to this approach is the integration of machine and deep learning techniques, which empower farmers with unparalleled insights and decision-making capabilities. By harnessing machine learning algorithms, farmers can analyze vast troves of data collected from various sources, such as sensors, satellites, and drones. This data-driven approach enables real-time monitoring of crop health, soil conditions, and weather patterns, facilitating precise and informed decision-making. Moreover, machine learning algorithms can predict crop yields, optimize resource allocation, and even detect anomalies, empowering farmers to preemptively address potential challenges and enhance overall efficiency. Deep learning technologies further augment this capability by enabling advanced pattern recognition and predictive modeling. Through the analysis of complex datasets, deep learning algorithms can identify subtle correlations and trends, providing valuable insights into optimal planting strategies, pest management, and crop disease detection. This predictive analytics framework empowers farmers to anticipate market demands, mitigate risks, and optimize production processes, thereby ensuring sustainable agricultural practices. In essence, the integration of machine and deep learning technologies represents a paradigm shift in modern agriculture, offering a potent arsenal of tools to address the multifaceted challenges facing the industry. By embracing these innovative approaches, farmers can not only meet the demands of a growing population but also safeguard environmental resources for future generations, thereby ushering in a new era of intelligent and sustainable farming practices.

2 Impact Statement

The proposed crop recommendation system represents a significant advancement in agricultural technology, harnessing the power of machine learning and deep learning to address critical challenges faced by farmers. By integrating various environmental parameters and historical data, this system offers precise and timely recommendations, empowering farmers to make informed decisions regarding crop selection. One of the key impacts of this system lies in its ability to streamline the crop selection process, reducing the reliance on labor-intensive and time-consuming traditional methods. By automating the analysis of diverse factors such as soil composition, climate conditions, and historical trends, farmers can efficiently identify the most suitable crops for their specific agricultural context. This not only optimizes yield potential but also minimizes the risk of crop failure due to mismatched environmental conditions. Furthermore, the incorporation of real-time data collection through IoT sensors enhances the system's accuracy and responsiveness. By continuously monitoring parameters such as temperature, humidity, and soil moisture, the system can dynamically adjust its recommendations based on evolving environmental conditions. This real-time adaptability is crucial for mitigating risks associated with sudden changes in weather patterns or emerging pest and disease threats. Overall, the proposed crop recommendation system has the potential to revolutionize agricultural practices, promoting sustainability and resilience in the face of increasingly complex environmental challenges. By leveraging advanced technologies to optimize crop selection and management, farmers can maximize productivity while minimizing resource use and environmental impact.

3 Literature Survey

Mahmudul et.al [1] addressed the pressing issue of insufficient agricultural production amidst a growing population, we focus on Bangladesh and propose a novel ensemble machine learning approach named K-nearest Neighbor Random Forest Ridge Regression (KRR). This method aims to predict crop production rates for major crops like rice (Aus, Aman, Boro), wheat, and potato. Through meticulous data preprocessing and model selection, KRR outperforms traditional and ensemble learning algorithms. Evaluation metrics including mean absolute error, mean square error (MSE), root MSE, and R2 demonstrate the superior performance of KRR, with notably low MSE values and high R2 scores across all crop predictions. This approach offers promise in optimizing crop production strategies, especially in regions with limited resources.

Singla et.al [2] In this study, the focus lies on leveraging deep learning capabilities for predicting wheat crop yield in the northern region of India. A Recurrent Neural Network (RNN) model, specifically RNN-LSTM, is utilized for its adeptness in feature extraction from extensive datasets. Comparative analysis against other models such as Artificial Neural Network, Random Forest, and Multivariate Linear Regression showcases the superiority of the RNN-LSTM model, evidenced by significantly lower Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values. Notably, the predicted crop yield values closely align with actual values, further underscoring the effectiveness of the proposed RNN-LSTM approach in agricultural yield prediction.

Madhuri et.al [3] delves into the realm of agricultural sustainability amidst challenges posed by climate change, soil erosion, and industrial emissions. Recognizing the critical role of soil health in crop productivity, the study addresses nutrient deficiencies, particularly in potassium, nitrogen, and phosphorus, which can stifle crop growth. Additionally, it highlights a common pitfall among farmers: the repetitive cultivation of the same crops without exploring diverse varieties, which can limit resilience to changing environmental conditions. To tackle these issues, the paper evaluates the efficacy of various machine learning algorithms in crop prediction. Specifically, it compares the performance of K-Nearest Neighbor (KNN), Decision Tree, and Random Forest Classifier, employing two distinct criteria: Gini impurity and Entropy. Through rigorous analysis, the study unveils Random Forest as the top-performing algorithm, demonstrating the highest accuracy among the tested methods. This finding underscores the significance of leveraging advanced machine learning techniques in addressing agricultural challenges, paving the way for more informed and resilient crop management strategies.

Ammad et.al [4] investigates, the focus is on synthesizing recent advancements in applying deep learning methodologies within agricultural contexts over the past half-decade. The study scrutinizes a plethora of research articles to discern key contributions and the resolution of significant challenges within the field. Notably, the researchers introduce an innovative intelligent agriculture system that amalgamates Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). This hybrid model exhibits proficiency in the early detection and classification of plant leaf diseases, offering potential solutions to crucial agricultural issues.

Cedric et.al [5] study focuses on developing a predictive system using machine learning techniques to forecast crop yields in West African countries. The analysis encompasses six key crops: rice, maize, cassava, seed cotton, yams, and bananas, operating at a country-level granularity throughout the year. Employing a combination of decision tree, multivariate logistic regression, and k-nearest neighbor models, the researchers construct a robust predictive framework. The outcomes demonstrate promising performance across all three models. Particularly noteworthy are the decision tree and K-Nearest Neighbor models, which exhibit strong correlation with expected data, underscoring the efficacy of the predictive approach. This research contributes to the advancement of agricultural forecasting in West Africa, offering valuable insights for improved crop management and productivity in the region.

Bini et.al [6] This review underscores the efficacy of deep learning methodologies in enhancing accuracy for smart agriculture applications. Focusing on a diverse array of crops including fruits like grapes, apples, citrus, and tomatoes, as well as vegetables such as sugarcane, corn, soybean, cucumber, maize, and wheat, the study investigates the recognition of bloom/yield in crop images. Notably, conventional deep learning techniques have yielded an impressive average accuracy of 92.51%. This highlights the potential of leveraging advanced technology to bolster precision in crop monitoring and management, offering promising prospects for sustainable agricultural practices.

Kalimuthu et.al [7] This research endeavor aims to support novice farmers by employing machine learning techniques for crop prediction, a pivotal aspect of modern agricultural practices. By harnessing the power of advanced technology, particularly the Naïve Bayes algorithm, the study facilitates informed decision-making in crop selection and sowing. Essential seed data, inclusive of pertinent parameters such as temperature, humidity, and moisture content, is collected and analyzed. This comprehensive approach enables farmers to optimize crop choices, thereby fostering conditions conducive to successful growth and yield.

Suchithra et.al [8] This study focuses on enhancing the accuracy of soil nutrient classification, particularly at the village level, thereby reducing unnecessary expenditure. Five different problems are addressed, including Gaussian radial basis, sine-squared, hyperbolic tangent, triangular basis, and hard limit functions. Among these, the Gaussian radial basis function emerges as the most effective, consistently achieving accuracy rates exceeding 80% in various performance evaluations. This research contributes to the optimization of Extreme Learning Machine parameters, offering valuable insights for improved soil nutrient classification and resource allocation in agriculture.

4 Methodology

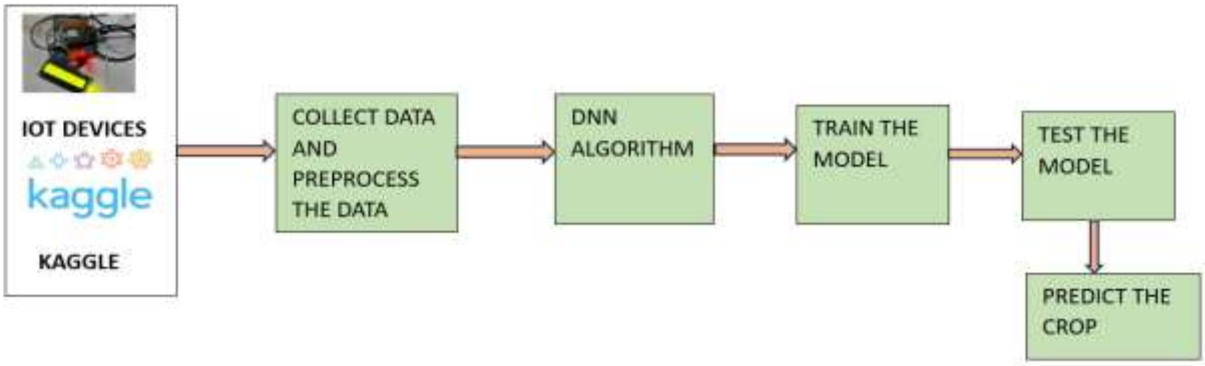

Fig 1 System architecture

To facilitate efficient environment monitoring and provide real-time data to farmers, our project utilizes IoT devices to collect essential parameters such as temperature, humidity, soil moisture, and soil temperature. The system, powered by Node MCU, integrates sensors like the DHT11 and moisture sensor to gather these data points.

To set up the IoT-based agriculture monitoring system, we follow these steps:

1. Installation of Arduino IDE:
   - Download and install the Arduino IDE software on your PC.
   - Open the software and navigate to the "File" option in the upper-left corner, then select "Preferences."
   - Paste the given link into the "Additional Board Manager URL" field: `http://arduino.esp8266.com/stable/package_esp8266com_index.json`
   - Click on the board manager, search for "esp8266," and install the board to the software.
   - Choose the appropriate board and select the system port where the Node MCU is connected.
   - Upload and run the code to the Node MCU.
2. Setting Up Thing Speak:
   - Sign up for Thing Speak, which serves as the cloud storage for our IoT data.
   - Log in with the provided credentials (iotproject194@gmail.com and password Project@123).
   - Create a channel named "IoT-based Agriculture Monitoring System."

Once the system is set up and the code is successfully compiled and uploaded, the IoT devices begin collecting data and transmitting it to Thing Speak for live monitoring. The collected data is stored in a CSV file, which can be downloaded and utilized as our dataset for further analysis and model training.

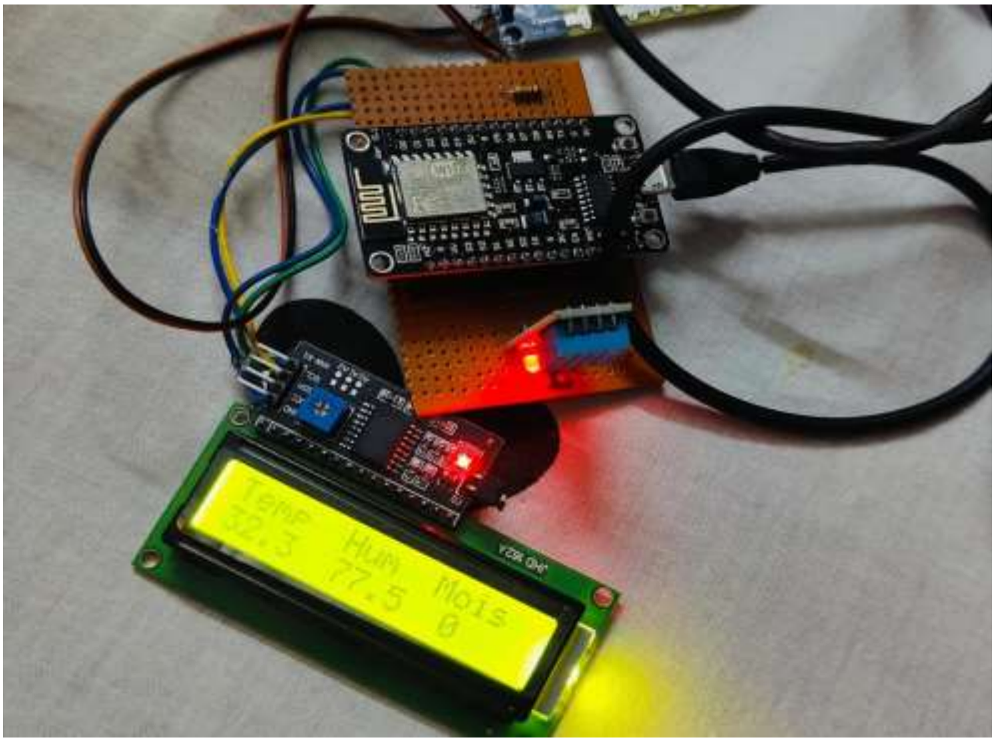

Fig 2 Working of Sensors

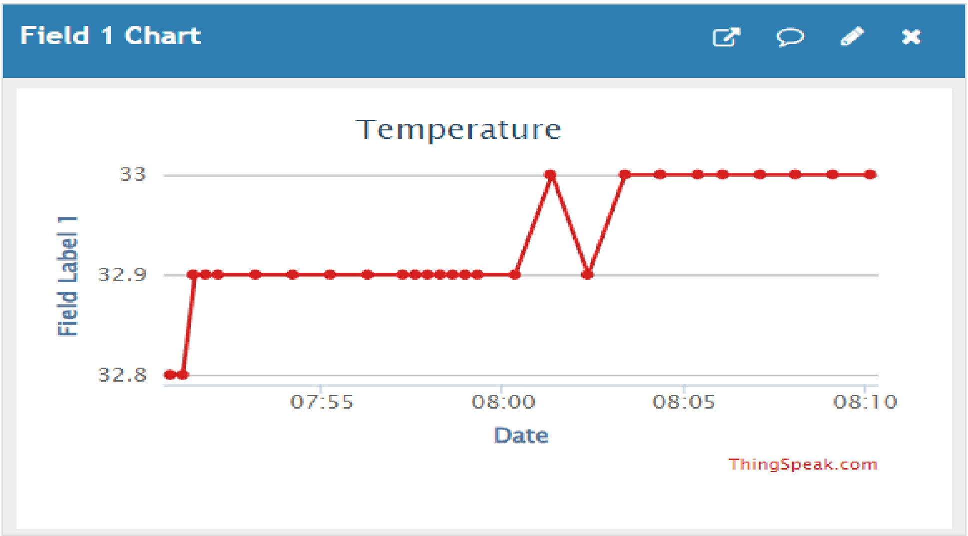

Fig 3 Graph for Temperature

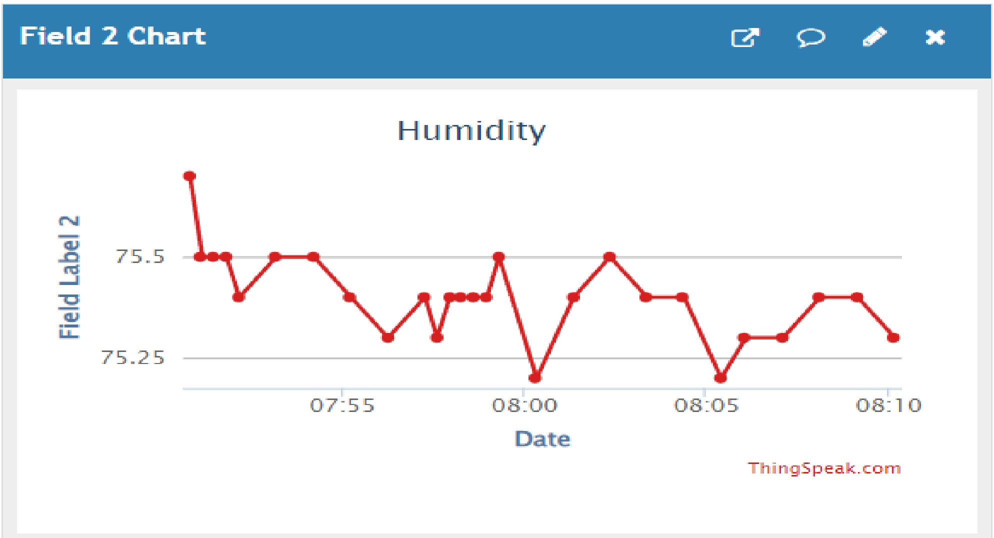

Fig 4 Graph for Humidity

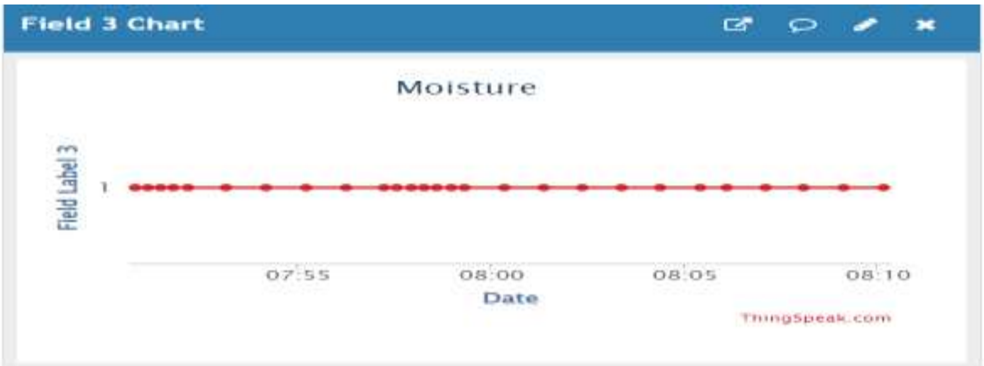

Fig 5 Graph for Moisture

This approach not only enables farmers to access real-time environmental data crucial for decision-making but also empowers them to optimize their agricultural practices to enhance overall yield and product quality. By integrating IoT technology into agriculture, we aim to revolutionize traditional farming methods and contribute to sustainable and efficient food production.

The flowchart outlines a crop prediction process using machine learning. It begins with collecting data from the sensors in the field and from the Kaggle website. This data is then pre-processed to prepare it for analysis. Next, a machine learning model is configured and trained on the data. Once trained, the model can be used to predict crop yields for new data inputs. Here's a breakdown of the steps:

Data collection through sensors: This block refers to gathering data from sensors in the field. This data might include soil properties, weather conditions, and plant health indicators.

1. **Data collected from the Kaggle website:** This block indicates that the data used for

this specific example is being obtained from the Kaggle website, a popular repository for machine learning datasets. In a real-world scenario, the data would likely come from farm sensors. We have taken the data set with features like nitrogen, phosphorous, potassium, temperature, humidity, rainfall, pH, and labels. Table 1 shows the feature's importance and data type.

2. **Preprocessing the data:** This step involves cleaning and preparing the data for use in the machine learning model. This may include tasks like handling missing values, formatting the data, and normalization. Outliers are also eliminated in this step. We have used the IQR technique and boxplots to remove the outliers. We primarily removed the null values and duplicate records and segregated features from the label column. Table 2 shows the first few values of the data set after preprocessing the data. Table 3 shows unique labels.
3. **Configure the model:** In this block, the machine learning model is chosen and configured. This includes selecting the type of model (e.g., decision tree, random forest) and setting its hyperparameters (e.g., number of trees, learning rate). We have decided on the deep learning model. A Deep Neural Network algorithm is used in this model. To achieve the highest test and validation accuracy, we used one of the configurations such as epochs.
4. **Train the model:** The model is trained on the pre-processed data. During training, the model learns the relationships between the input data (e.g., sensor readings) and the target variable (e.g., crop type).
5. **Test the model:** The model's performance is evaluated on a separate dataset to assess its accuracy and generalizability. We evaluate the accuracy of the created model against the test data. We have tested the data over different splitting ratios such as 50:50, 60:40, 70:30, and 80:20.
6. **Predict the crop:** Once trained and tested, the model can be used to predict the crop type for new data inputs.

Index	Feature Name	Feature Description	Data type
1	Nitrogen	Nitrogen is largely responsible for the growth of leaves of the plant	Int64
2	Phosphorus	Phosphorus is largely responsible for the root growth and flower and fruit development	Int64

3	Potassium	Potassium is a nutrient that helps the overall fractions of the plant perform correctly	Int64
4	Temperature	Temperature in degrees Celsius	Float64
5	Humidity	Relative humidity in %	Float64
6	pH	Ph value of the soil	Float64
7	Rainfall	Rainfall in mm	Float64
8	Label	Name of the crop	object

Table 1 Main Features

N	P	K	Temperature	Humidity	Ph	Rainfall	Label
90	42	43	20.87974	82.00274	6.502985	202.9355	Rice
85	58	41	21.77046	80.31964	7.038096	226.6555	Rice
60	55	44	23.00446	82.32076	7.840207	263.9642	Rice
74	35	40	26.4911	80.15836	6.980401	242.864	Rice
78	42	42	20.13017	81.60487	7.628473	262.7173	Rice
69	37	42	23.05805	83.37012	7.073454	251.055	Rice

Table 2 First rows of data

Index	Label
1	Apple
2	Banana
3	Blackgram
4	Chickpea
5	Coconut
6	Coffee
7	Cotton
8	Grapes
9	Jute
10	Kidneybeans
11	Lentil
12	Maize
13	Mungbean
14	Mango
15	Mothbean
16	Muskmelon
17	Orange
18	Papaya
19	Rice
20	Pigeonpea
21	Pomegranate
22	watermelon

Table 3 All Unique Labels

4.1 Experimentation:

The deep neural network is a multi-class neural network, it can be used to classify data into multiple classes. This is in contrast to a single-class neural network, which can only classify data into one category. We created a four-layered neural network using the TensorFlow framework. The first layer is a sequential layer that acts as an input layer, the second layer consists of 128 neurons, the third includes 64 neurons, and the fourth layer (output layer) includes 32 neurons. The second and third layers are called hidden layers. A common starting point is a dropout rate of 0.5, meaning half of the neurons in the layer are randomly dropped out during training. This dropout layer helps us to overcome the overfitting.

In addition, we experimented with different combinations of “relu”, “softmax” , and activation functions to tune the model for better accuracy and performance. **Softmax** is typically used in the last layer of a neural network to predict the class of an input image. It is also used in other applications, such as natural language processing and machine translation. ReLU is typically used in the hidden layers of a neural network to add non-linearity. It is very efficient and can help neural networks learn more complex relationships between the input and output data.

Finally, we experimented with the network with multiple epoch values until we found the optimal ones. Increasing epoch value decreases the performance of the neural network. Finally, we use an optimizer called Adams optimizer. Adam is a popular optimization algorithm for training deep learning models. It is an extension of the AdaGrad and RMSProp algorithms, and it is effective for a wide range of problems.

```
model = Sequential ()
model.add (Dense(128, input_dim=X_train.shape[1], activation='relu'))
model.add (Dropout(0.5))
model.add (Dense(64, activation='relu'))
model.add (Dropout(0.5))
model.add (Dense(32, activation='relu'))
model.add (Dropout(0.5))
model.add (Dense(len(np.unique(y_train)), activation='softmax'))


model.compile(loss='sparse_categorical_crossentropy', optimizer='adam',
metrics=['accuracy'])
```

Results

The table shows the results of our experiments. We tried different splits for train and test data and it settled down for 80% training data and 20% testing data. For all the split ratios, we achieved at least 95% accuracy.

We have compared our deep neural network algorithm with four other existing algorithms. The compared algorithms are KNN, Naïve Bayes, Logistic Regression, and Gradient Boosting Algorithm. These algorithms have accuracy of about 84.2727,94.7272,63.9090,90.4545 respectively. This clearly states that the proposed work has the highest accuracy among all these algorithms. Table 4 shows the comparison of the proposed model and the existing model's accuracy.

For, the deep neural network, we observed that the number of epochs plays a crucial role in the accuracy and performance. We achieved an accuracy of 96.90% with 500 epochs.

For this model, we used one metric i.e., accuracy. Accuracy is given by

Accuracy = (True Positive + True Negative) / (True Positive False Positive + True Negative + False Negative).

We believe that, this work will help other developers or researchers understand the importance of accuracy and performance of the deep neural network algorithm.

Index	Algorithm	train_score	test_scores	Accuracy
1	KNN	89.636364	84.272727	84.272727
2	NaiveBayes	96.363636	94.727273	94.727273
3	LogisticRegression	66.454545	63.909091	63.909091
4	GradientBoostingClassifier	95.727273	90.454545	90.454545
5	**Deep neural network**	**97.410714**	**96.904761**	**96.904761**

Table 4 Accuracy Comparison

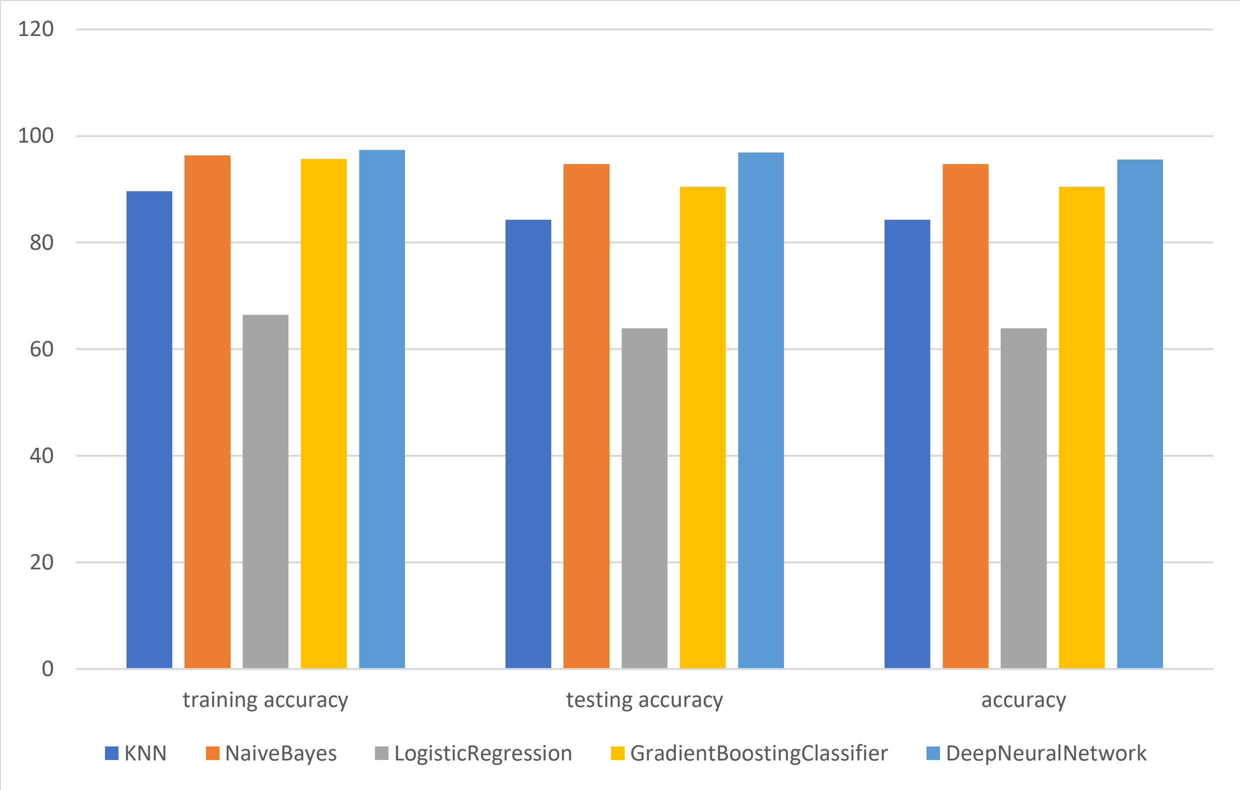
120
100
80
60
40
20
0
training accuracy
testing accuracy
accuracy
KNN
NaiveBayes
LogisticRegression
GradientBoostingClassifier
DeepNeuralNetwork

Fig 6

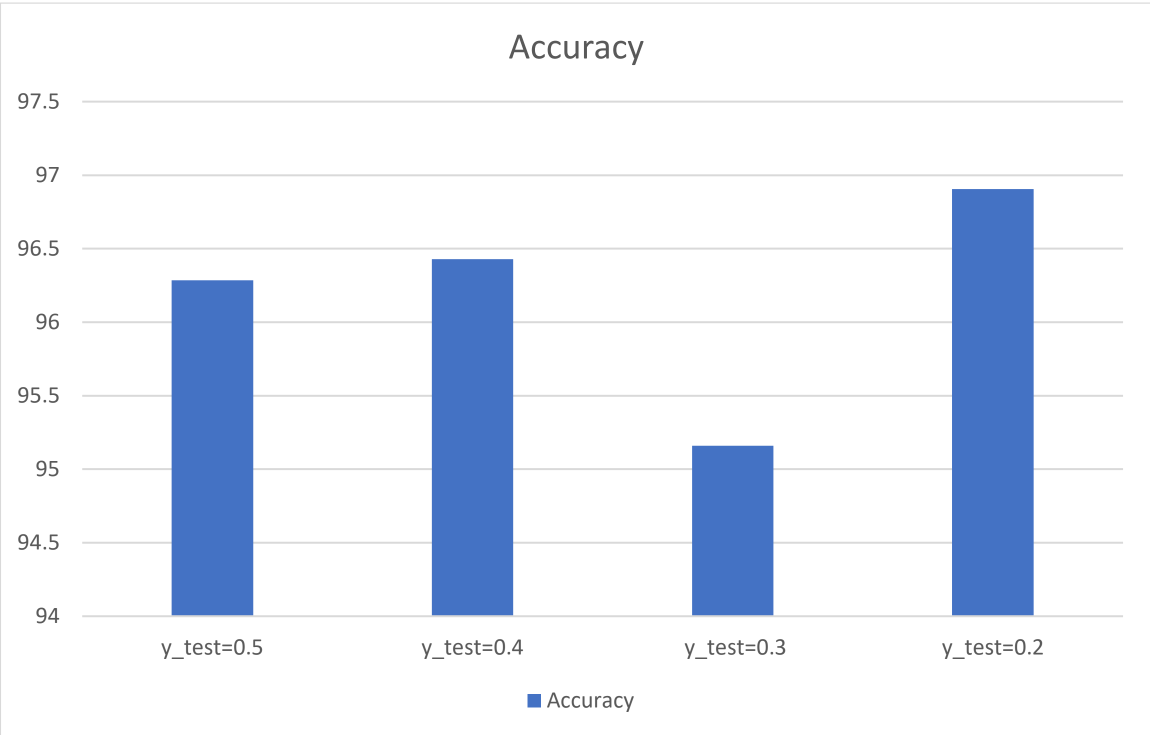
Accuracy
97.5
97
96.5
96
95.5
95
94.5
94
y_test=0.5
y_test=0.4
y_test=0.3
y_test=0.2
Accuracy

Fig 7

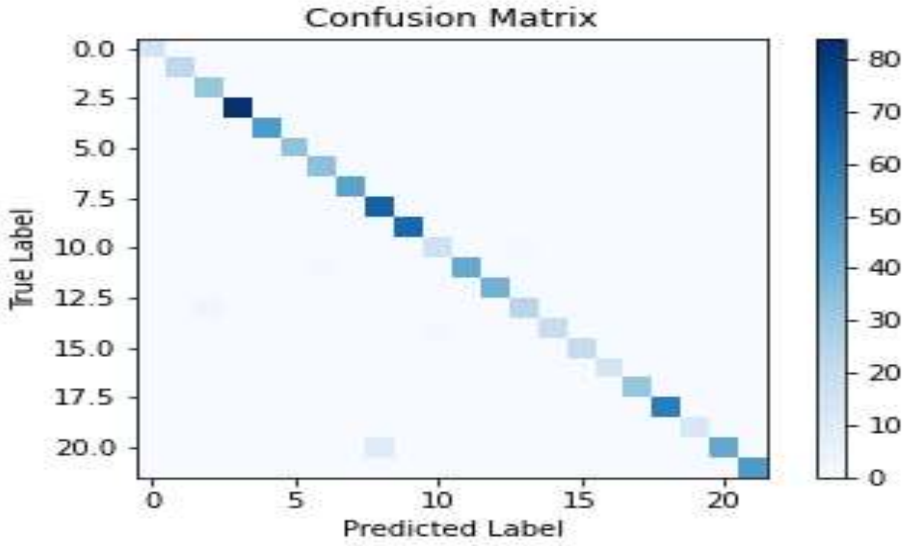

Fig 8

Confusion matrix is a metric for summarizing the model performance with the given entries.

The diagonal of the confusion matrix shows the how many times the prediction was correct.

Accuracy = (True Positive + True Negative) /(True Positive +False Positive + True Negative + False Negative) .

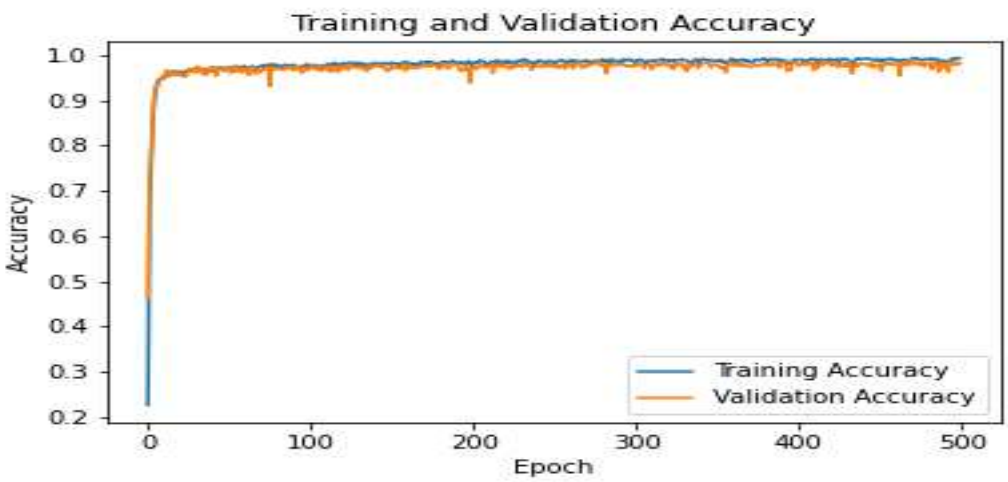

Fig 9

Fig 9 shows how the training and validation accuracy fluctuated while iterating through each epoch. As the epochs increase the accuracy also increases

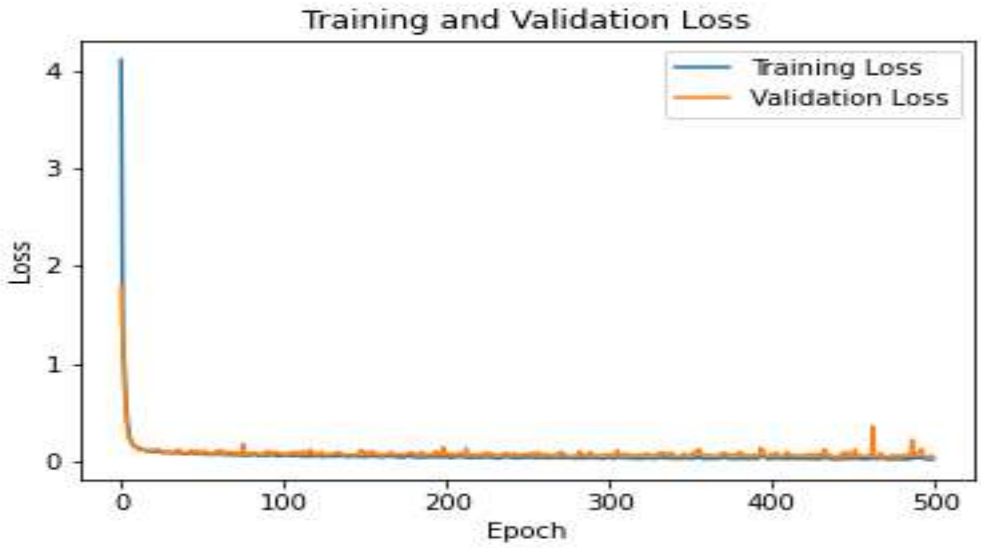

Fig 10

Fig 10 shows the loss details are decreasing as the epochs increases. This shows that the model is learning progressively as the epochs increases.

Conclusion

In conclusion, the integration of machine learning and IoT technologies presents a promising solution to the challenges faced in traditional crop analysis and recommendation systems. By harnessing the power of deep neural networks and real-time data collection through IoT devices, farmers can access accurate and timely information to make informed decisions about crop selection and management practices. This proposed system not only streamlines the process of crop recommendations but also enhances pest and disease detection, contributing to improved agricultural productivity and sustainability. With an accuracy exceeding 95%, the deep neural network model trained on historical datasets demonstrates its effectiveness in predicting suitable crops based on diverse environmental factors. Moving forward, the adoption of such advanced technologies in agriculture holds the potential to revolutionize farming practices, empowering farmers to maximize yield while conserving resources and minimizing environmental impact. As we continue to refine and expand these systems, the future of agriculture looks increasingly promising, with optimized crop production and improved livelihoods for farmers worldwide.

Future scope

The project features a deep neural network model that predicts suitable crops by analyzing various factors such as Nitrogen, Phosphorus, Potassium, Temperature, Humidity, Moisture, Rainfall, and pH. It leverages historical datasets from Kaggle for model training and testing, achieving over 95% accuracy. The system also integrates IoT technology with sensors like DHT11 and soil moisture sensors to collect real-time data, enhancing crop recommendations based on current soil conditions. Additionally, it includes machine learning techniques for early pest and disease detection, all accessible through a user-friendly interface aimed at maximizing yield while preserving soil fertility and essential nutrients.

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