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A Machine Learning-Driven Crop Recommendation System with IoT Integration

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***Abstract*—Bangladesh's economy depends heavily on agriculture, yet farmers confront a significant obstacle in choosing the best crop which affects production and regrettably causes financial hardships, migration, and suicides. Because climate and ingredients of soil are changing continuously. This paper proposes a system that utilizes several types of soil and environmental characteristics to determine the ideal crop for a particular land. Via Internet of Things (IoT) devices, environmental characteristics that include temperature and humidity, as well as soil parameter that is pH will be immediately retrieved from the land, enabling instantaneous data gathering. Using a variety of algorithms, the suggested approach Gaussian Naive Bayes which we got 99.55% validation accuracy, determines which crop would be best for cultivation. Following the integration of the model into an intuitive interface, farmers are provided with a useful tool to improve decision-making and eventually support Bangladeshi agriculture's sustainability. The most efficient and accurate method is selected to build a machine-learning model after undergoing extensive testing on several different algorithms. In order to provide farmers with exact recommendations for choosing the most suited crop for cultivation which is integrated into an easy-to-use interface.**

***Index Terms*—IoT, Machine-Learning, Accuracy, Website, Crop Recommendation.**

I. Introduction

Agriculture is an essential aspect of the world economy, producing food, fiber, and other vital commodities for the benefit of humanity [1]. Approximately 66% of the workforce in the continent is engaged in agriculture-related activities [2]. Bangladesh is one of the oldest countries that continues to engage in agricultural practices [3]. However, agriculture has seen significant changes in recent years as a result of globalization [4]. Several variables have impacted the agricultural well-being in Bangladesh [5]. Several innovative technologies have emerged to restore and improve the health of the agricultural economy [6]. The traditional methods employed are inherently detrimental and labor-intensive [7]. The primary challenges encountered by farmers are crop selection and the impact of changing climatic conditions [8]. By adopting smart technology, a nation may significantly enhance its agricultural output [9]. The use of accessible technology will empower farmers to improve their practices and achieve higher results [10]. To improve crop selection several aspects must be considered, including soil and environmental entities. Hence, a website and IoT sensor can be applied to gather soil attributes such as phosphorus, nitrogen, potassium, soil pH, temperature, humidity, and rainfall [11].

Fig. 1. System Objective Overview: Charting the Course for Smart Farming Excellence.

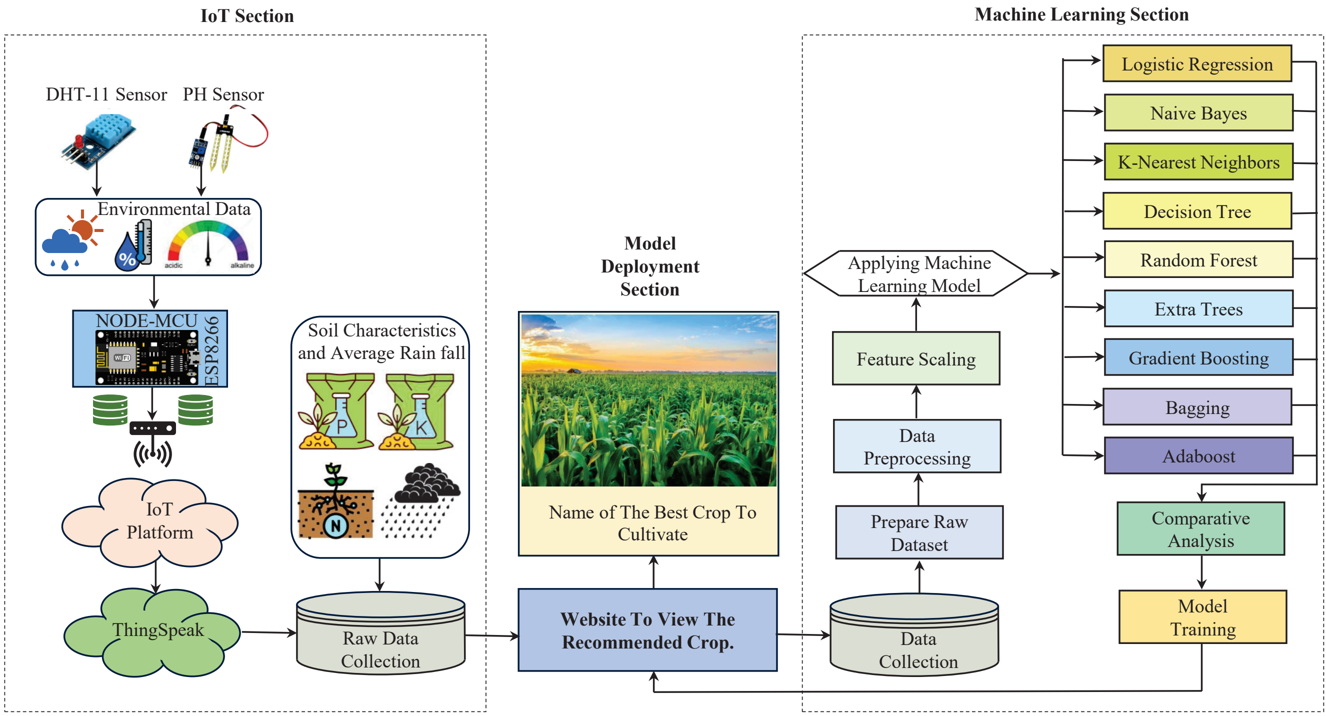

Fig. 2. Functional block diagram of the proposed prototype.

This data enables the suggestion of crops based on their optimal requirements. However, the utilization of these sensors necessitates substantial investment and specialized knowledge to operate them effectively, in addition to regular maintenance [12].

A model will be created by a Machine Learning algorithm to autonomously choose crops [13] The combination of the Internet of Things (IoT) and Artificial Intelligence (AI) in agriculture has shown substantial expansion in recent times [14]. The key purpose of this study has been illustrated in Fig. 1. The main contributions of this work are emphasized as follows:

- Real-world Implementation of IoT: Environmental entities were collected using IoT sensors.
- User-friendly interface: A website to manually manipulate the entities has been provided.
- Crop Recommendation: A very precise machine learning model with an accuracy of 99.55% to recommend crops has been created.

II. RELATED STUDIES

In 2021, Mamata Garanayak, Goutam Sahu, and Sachi Nandan Mohanty introduced a system designed to aid agronomists in selecting the most suitable crop for their farmland. The system utilizes essential variables related to five different crops: rice, ragi, gramme, potato, and onion. The selection process is based on the majority voting (MV) method, resulting in accuracy rates of 94.78%, 93.60%, 92.04%, 87.69%, and 85.43% for each respective crop [15]. A Deep Neural Network is utilized to provide crop recommendations to farmers based on specific chemical conditions including pH, nitrogen, phosphorus, and potassium levels, as well as numerous climate aspects such as rainfall, temperature, and humidity which took place in 2022. This study employed a deep learning strategy based on grey wolf optimization [16].

Takalani Orifha Mufamadi and Ritesh Ajoodha have created a crop recommendation system in 2023. This system is capable of determining the most suitable crop to cultivate, considering the soil's attributes such as pH level, phosphorus content, potassium content, nitrogen content, and magnesium content. The available crop options include maize, kidney beans, banana, mango, grapes, watermelon, apple, orange, papaya, and cotton. Their ultimate solution employs the RF algorithm and achieved an accuracy of 91.1% [17]. In 2023, a crop recommendation system was implemented in India. This system utilises many elements like as soil nitrogen, phosphorous, and potassium levels, as well as the season and district, to select suitable crops and anticipate their production. The K-Nearest Neighbour algorithm achieved an accuracy of 98% for recommendation and 96% for yield prediction [18].

Based on the aforementioned investigations, it appears that my work is likely to surpass them in terms of accuracy. Moreover, the absence of IoT devices for immediate data capturing from the field was noticeable. Furthermore, a user-friendly interface was not established to assist all sorts of farmers, hindering their ability to effectively use their resources and increase productivity.

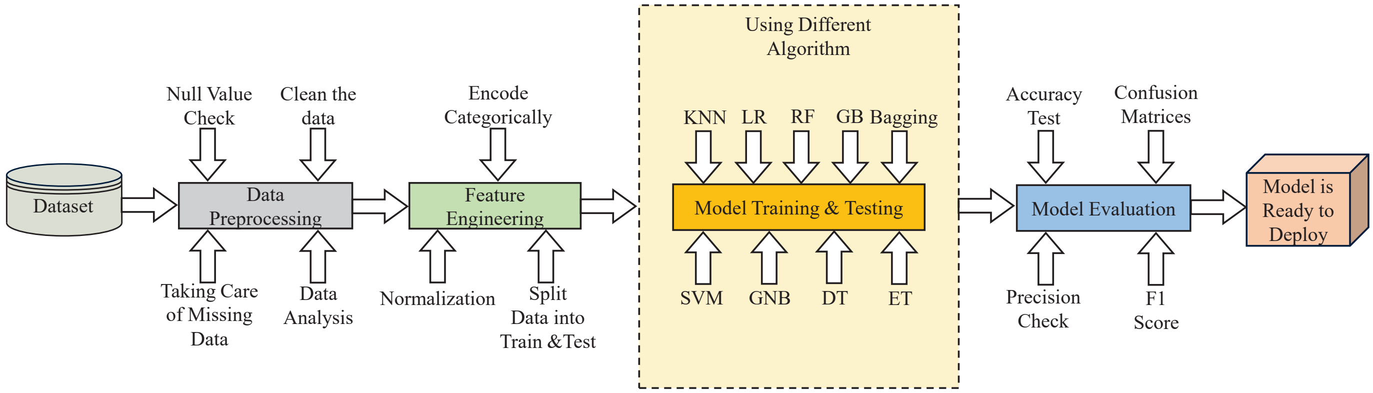

Fig. 3. Proposed workflow of Machine learning classifier designing procedure.

III. PROPOSED SYSTEM

The functional workflow of this prototype under consideration is illustrated in Fig. 2. The approach will choose the most suited crop for the given spot based on seven parameters. The three parameters (Temperature, Humidity, pH) will be collected automatically from the field using sensors and IoT technology.Data will be sent to the server. The server website will automatically retrieve the entry. The remaining four parameters(Nitrogen, Phosphorus, Potassium, and Rainfall) will be provided by the user as manual input. The user has the ability to adjust all seven input parameters. Once all the criteria have been entered, the optimal crop to produce will be displayed by clicking the ”Get Recommendation” button.

IV. DETAILS DESCRIPTION OF THE PROPOSED SYSTEM

The proposed system consists design of machine-learning model illustrated in Fig. 3, sensors connected with an IoT platform, and a user-friendly interface(website).

A. Data Collection

The DHT-11 sensor will provide the temperature and humidity of the environment and pH sensor will provide the pH of soil, The circuit connection is illustarted in Fig. 4.

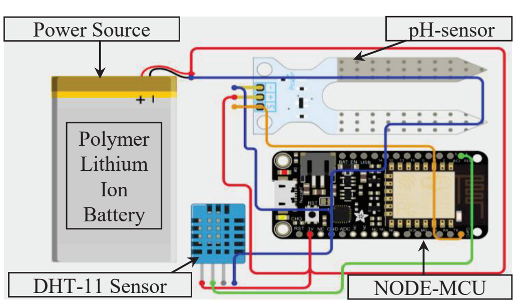

Fig. 4. Schematic representation of the innovative system capturing agricultural data for smart farming applications.

These three entities will be transferred to the ESP-8266 module that is connected to the internet. This module will push the data into a server named ”ThinkSpeak”.

Data will be retrieved automatically from the ThinkSpeak server and the other entities(Nitrogen, Phosphorus, Potassium, and Rainfall) will be provided by user manually on the website.

B. Data Preprocessing

To ensure the efficacy of the crop recommendation system, a wide range of data is gathered from Kaggle, encompassing details on soil nutrient levels and environmental conditions. The crop suggestion dataset has been primarily obtained from Kaggle [10]. The dataset had entries for nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, rainfall, and a label column (crop name). The current stage of the proposed system entails a review of the dataset and the analysis of correlations. Initially, a check was performed to verify the presence of any null value, and it was determined that none was present. If any data is missing, it will be replaced with an assumed value derived from the average of all values in that column. Alternatively, the row containing the missing data can be deleted.

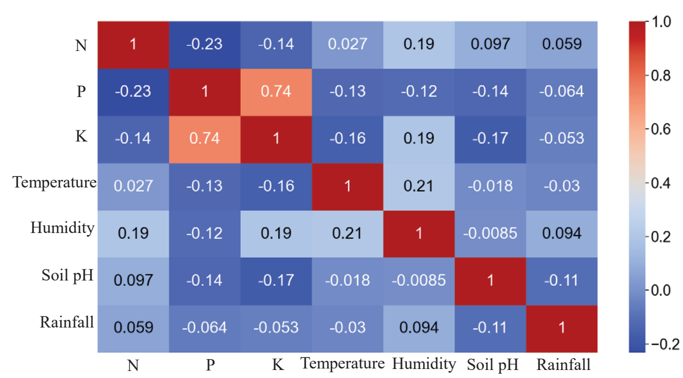

Fig. 5. Correlation Analysis of Soil Nutrients and Environmental Parameters in Agricultural Contexts.

The correlation analysis utilizes Fig. 5 to display a heatmap, providing a valuable understanding of the link between various soil nutrients and environmental parameters. Here 1 indicates a strong positive correlation, -1 represents a significant negative correlation and 0 represents no connection. For instance, Nitrogen (N) has a weak positive association with Humidity, Temperature, pH, and Rainfall, whereas it demonstrates a weak negative interrelation with Phosphorus and Potassium. In this manner, the other parameters can be interpreted with each other.

C. Feature Engineering

The dataset is partitioned into two distinct categories: numerical data and category data. The category data must be transformed into numerical values. The column representing the crop name has been transformed into a numerical number ranging from 1 to 22, as there are a total of 22 crop names in the dataset. The dataset's features are normalized through the process of feature scaling. Feature scaling can restrict the range of the feature. To normalize all the features within the range of 0 and 1, the min max scaler () function can be utilized.

$$X_{\text{scaled}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$$

where,

- X_{scaled} is the scaled value of the feature.
- X is the original value of the feature.
- X_{min} is the minimum value of the feature in the training data.
- X_{max} is the maximum value of the feature in the training data.

and then 80% of were split for training and 20% for the testing purpose.

D. Model Training and Testing

Now 80% of the data will be used for the training of models and the rest will be for testing. Here KNN: K-Nearest Neighbors, LR: Logistic Regression, RF: Random Forest, GB: Gradient Boosting, Bagging: Bootstrap Aggregating, SVM: Support Vector Machine, GNB: Gaussian Naive Bayes, DT: Decision Tree and ET: Extra Trees algorithms have been used to train the model, as shown in Fig. 3. The algorithm having the best accuracy in percentage will be picked for deployment.

E. Model Parameters and Evaluation

In this section model accuracy, precision, recall and f1 score is going to calculated for the ultimate algorithm selection to train the model using equations [19],

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives + False Positives}} \tag{1}$$

$$\text{Accuracy} = \frac{\text{True Positives + True Negatives}}{\text{Total Population}} \tag{2}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision + Recall}} \tag{3}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}} \tag{4}$$

The Gaussian Naive Bayes (GNB) algorithm has proven to be highly effective based on these equations. This algorithm will be used to construct the model, and the model parameters such as, class prior as well as mean of feature per class has been displayed in table.I and the variance of features per class has been shown in table.II. There are a total of 22 crops, only one crop will be selected, resulting in 22 classes.

TABLE I
CLASS PRIORS AND MEAN PER CLASS

Class	Prior	Mean of features per class
1	0.046	0.78, -0.19, -016, -0.36, 0.49, -0.19, 2.46
2	0.045	0.72, -0.15, -0.55, -0.68, -0.31, -0.26, -0.31
3	0.044	0.76, -0.19, -0.16, -0.12, 0.38, 0.34, 1.30
4	0.047	1.81, -0.23, -0.56, -0.30, 0.38, 0.57, -0.41
5	0.041	-0.78, -1.08, -0.34, 0.34, 1.06, -0.69, 1.32
6	0.044	-0.02, 0.16, 0.04, 1.56, 0.94, 0.34, 0.67
7	0.049	-0.85, -1.12, -0.75, -0.53, 0.93, 0.69, 0.14
8	0.044	-0.82, 2.44, 2.97, -0.59, 0.94, -0.72, 0.17
9	0.047	1.33, -1.08, 0.04, 0.60, 0.95, -0.15, -1.42
10	0.046	1.29, -1.09, 0.04, -0.00, 0.61, 0.02, -0.95
11	0.049	-0.75, 2.39, 2.98, -0.40, 0.47, -0.60, -0.60
12	0.046	-0.84, -0.79, -0.36, 1.09, -0.97, -0.95, -0.15
13	0.045	1.33, 0.86, 0.04, 0.36, 0.40, -0.64, 0.04
14	0.044	-0.90, -1.05, -0.16, -0.76, 0.85, -0.06, 0.08
15	0.051	-0.85, 0.45, -0.56, -0.22, -0.31, 0.57, -1.03
16	0.045	-0.26, 0.43, -0.57, 0.85, -0.28, 0.81, -0.63
17	0.046	-0.81, -0.18, -0.55, 0.59, 0.63, 0.30, -0.99
18	0.043	-0.78, -0.15, -0.55, 0.51, -0.85, 0.74, -0.94
19	0.044	-0.81, 0.44, -0.54, 0.50, -1.12, -0.87, 0.89
20	0.045	-0.79, 0.43, -0.55, -1.09, -2.27, -0.94, 0.05
21	0.042	-0.26, 0.43, 0.62, -1.32, -2.47, 1.19, -0.42
22	0.047	1.36, -0.75, -0.36, -0.02, -0.60, 0.43, 1.03

TABLE II
VARIANCE OF FEATURES PER CLASS

Class	Variance of features per class
Class 1	0.103, 0.058, 0.003, 0.16, 0.004, 0.997, 0.372
Class 2	0.094, 0.058, 0.003, 0.285, 0.059, 0.293, 0.076
Class 3	0.086, 0.044, 0.004, 0.054, 0.062, 0.358, 0.079
Class 4	0.095, 0.047, 0.004, 0.049, 0.019, 0.642, 0.042
Class 5	0.11, 0.061, 0.003, 0.076, 0.014, 0.135, 0.3
Class 6	0.114, 0.047, 0.004, 1.532, 0.004, 0.036, 1.309
Class 7	0.102, 0.052, 0.004, 2.024, 0.004, 0.518, 0.011
Class 8	0.107, 0.06, 0.004, 0.029, 0.004, 0.127, 0.016
Class 9	0.11, 0.045, 0.004, 0.027, 0.005, 0.091, 0.003
Class 10	0.116, 0.05, 0.004, 0.029, 0.017, 0.136, 0.011]
Class 11	0.113, 0.05, 0.004, 3.663, 0.003, 0.156, 0.003
Class 12	0.11, 0.051, 0.003, 0.28, 0.016, 0.872, 0.004
Class 13	0.088, 0.051, 0.005, 0.073, 0.016, 0.13, 0.031
Class 14	0.102, 0.05, 0.003, 0.177, 0.017, 0.414, 0.003
Class 15	0.106, 0.049, 0.003, 0.421, 0.017, 0.475, 0.01
Class 16	0.114, 0.046, 0.004, 0.275, 0.016, 0.222, 0.006
Class 17	0.101, 0.056, 0.004, 0.026, 0.016, 0.127, 0.017
Class 18	0.094, 0.05, 0.003, 0.186, 0.095, 5.475, 0.058
Class 19	0.1, 0.049, 0.003, 1.291, 0.22, 1.171, 0.334
Class 20	0.08, 0.053, 0.004, 0.261, 0.01, 0.036, 0.209
Class 21	0.102, 0.045, 0.004, 0.051, 0.005, 1.014, 0.019
Class 22	0.103, 0.047, 0.004, 0.086, 0.069, 0.274, 0.224

Class priors represents prior probabilities of each class occurring in the dataset, Mean per class denotes the mean value of each feature within each class. In GNB, it is assumed that each feature within each class follows a Gaussian (normal) distribution. Variance per class quantifies the dispersion of feature values around the mean within each class.

V. Result and Discussion

Accuracy, precision, recall, and f1-score have been calculated using equations (1) to (4) and the comparison of several algorithm behaviors has been demonstrated in the table.III breifly.

TABLE III
COMPARISON OF DIFFERENT ALGORITHMS USED FOR MODEL SELECTION.

Name of Used Algorithms	Accuracy	Weighted average		
		Precision	Recall	F1 Score
Logistic Regression	96.36%	96.44%	96.36%	96.35%
Gaussian Naive Bayes	**99.55%**	**99.58%**	**99.55%**	**99.54%**
SVM	96.82%	97.15%	96.82%	96.80%
K-Nearest Neighbors	95.91%	96.54%	95.91%	95.90%
Decision Tree	98.41%	98.45%	98.41%	98.41%
Extra Tree	88.86%	89.21%	88.86%	88.63%
Random Forest	99.32%	99.37%	99.32%	99.32%
Bagging Classifier	98.41%	98.47%	98.41%	98.41%
Gradient Boosting	98.18%	98.43%	98.18%	98.19%

A total of nine algorithms were employed for training the model. Among these nine algorithms. The LR, KNN, RF, SVM, GB, GNB, DT, ET, and Bagging Classifier algorithms exhibit accuracy scores of 96.36%, 95.91%, 99.32%, 96.82%, 98.18%, 99.55%, 98.41%, 88.86%, and 98.41% respectively. Thus, it is obvious that Gaussian Naive Bayes(GNB) offers the highest accuracy score, whereas Extra Trees Classifier offers the lowest accuracy score. GNB outperforms other algorithms in terms of accuracy, weighted precision, weighted recall, and weighted F1 score while training and testing the model. The confusion matrix depicted in Fig. 6 similarly illustrates the same outcome. The Gaussian Naive Bayes algorithm will be employed to construct the machine learning model considering its superior accuracy score. The confusion matrix of Gaussian Naive Bayes algorithm has been provided in Fig. 6.

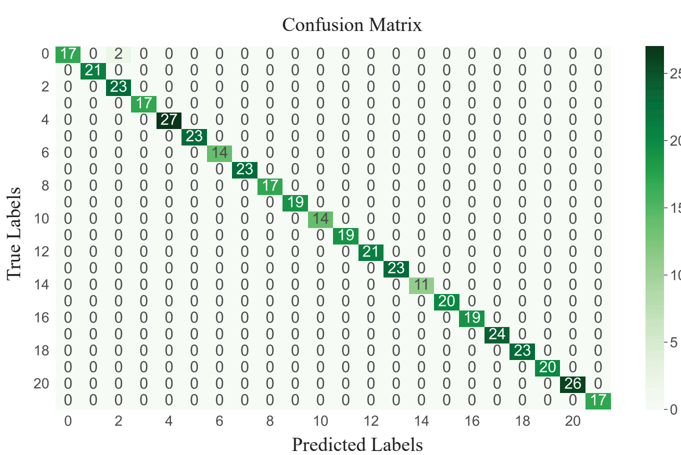

Fig. 6. Confusion Matrix of Gaussian Naive Bayes Algorithm.

The hardware component of the Internet of Things (IoT) segment is shown in Fig. 7. The components utilized in this case have been integrated into the printed circuit board (PCB).

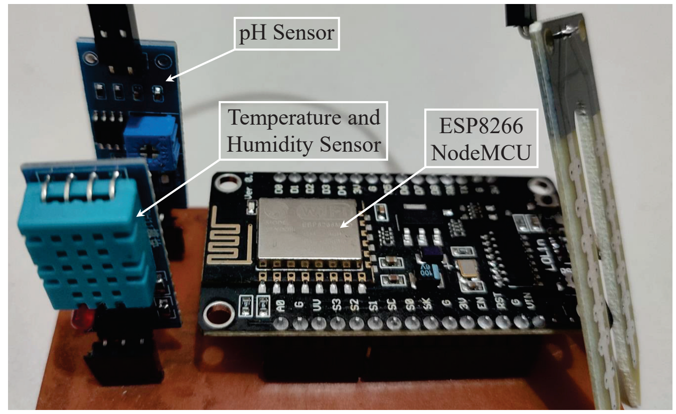

Fig. 7. PCB Design of the IoT Section.

The actual website that has been created and in the back-end part of the website machine learning model of the proposed prototype has been implemented as visualized in Fig. 8. The website will automatically collect temperature, humidity, and pH readings through the IoT section of the system.

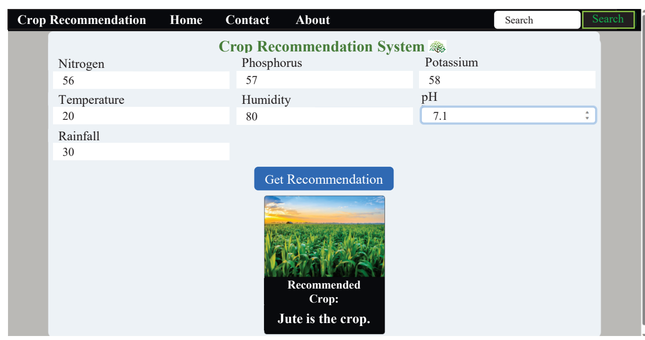

Fig. 8. Website as The User Interface of System for Input and Output Purpose.

VI. Comparative Analysis

TABLE IV
A COMPARISON BETWEEN THE PROPOSED MODEL AND OTHER WORK OVER VARIOUS CROPS CLASSIFICATION.

Year	Datasets	Types of crops	Methods(accuracy)	Ref.
2023	Kaggle	Various crops	RF (78.79%), DT (73.61%)	[20]
2022	Karnataka, India	Various crops	DNN (87%), GNB (72%)	[18]
2023	Kaggle	Various crops	KNN (98%), RF (96%)	[21]
2021	Andra Pradesh, India	Rice, ragi, Gram, Potato, Onion	MV (94.78%)	[22]
2017	Tamilnadu India	Various crops	RF (88%)	[23] , [24]
2024	**Kaggle**	**Various crops**	**GNB (99.55%)**	

Many previous works have been conducted on Rice, Ragi, Gram, Potato, onion, and various other crops in similar topics.

The accuracy that previous work provided was as good as table.IV represents. These works have utilised the Random Forest (RF), Decision Tree (DT), Deep Neural Network (DNN), k-Nearest Neighbour (KNN), Majority Voting (MV) and Gaussian Naive Bayes (GNB) classification techniques. All the works has less accuracy, didn't offer instantaneous integrated data collection and a user-friendly platform for farmers to benefit from it directly. But this proposed prototype exhibits superior performance due to,

- This study achieved a high accuracy rate of 99.54% for selecting the best crop.
- Simultaneous data collection through IoT technology.
- Connecting the Internet of Things (IoT) with Machine Learning (ML) in the realm of smart agriculture through a easy to use interface.
- Offer personalized consultation services to even the most minor agricultural producers, addressing the individual requirements of their smallest farmed areas.

VII. Conclusion

This research introduces an innovative approach merging IoT technology with machine learning, revolutionizing traditional farming into smart agriculture. Leveraging IoT devices enables real-time data collection, empowering our machine-learning algorithms to deliver precise crop recommendations promptly. As a result, the validation accuracy was obtained 99.55% using the Gaussian Naive Bayes classifier which was the best accuracy among the others classifiers. This user-friendly system empowers farmers to optimize resource utilization and increase production by selecting the most suitable crops for their fields. Our study demonstrates the high effectiveness of this approach in enhancing agricultural yields and resource optimization. Looking ahead, the potential for further advancements is substantial, with opportunities to enhance reliability and precision through advanced sensor technologies, improved scalability, and additional data sources. Ongoing collaboration with farmers, agronomists, and stakeholders remains crucial for refining our system to accommodate diverse agricultural settings

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