Crop Prediction using IoT & Machine Learning Algorithm

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Abstract -Agriculture is a primary supply of Income. It is vital for the survival of the environment. Practically every part of life, people rely on a vast range of agricultural products. Farmers must adapt to climate change while also meeting increased demand for more food of higher quality .To boost agricultural output and growth, farmers must be aware of the weather conditions, which will help them choose the best crop to cultivate under those situations. IoT-based smart farming improves the overall agriculture system by monitoring the field in real time. It keeps track of a multitude of characteristics, including humidity, temperature, and soil, and displays them in crystal clear real-time. In the agricultural sector, machine learning is utilized to increase crop output and quality. The application of appropriate algorithms to sensed data can aid in crop recommendation.

Key Words: *Agriculture, IoT, Smart farming, Machine Learning, meteorological, multidisciplinary.*

1.INTRODUCTION

One of India's most important occupations is agriculture. It is the country's largest economic sector and plays a critical part in its overall development. To meet the demands of 1.3 billion people, more than 60% of the country's land is used for agriculture, making the adoption of modern agriculture technologies essential.

This adoption will lead to a profit for our country's farmers. Crop and yield predictions were made in the past based on farmers' experience in a specific place. They prefer the previous or nearby or more popular crop in the surrounding region solely for their land, and they lack sufficient knowledge of soil nutrients such as nitrogen, phosphorus, and potassium in the soil.

In the current condition, without crop rotation and an insufficient amount of nutrients applied to the soil, yields are reduced, soil pollution (soil acidity) occurs, and the top layer is harmed.

Taking all of these issues into account, we created a system that uses machine learning to improve the farmer's situation. For the agriculture sector, machine learning (ML) is a game changer. Machine learning, which is a subset of artificial intelligence, has arisen with big data technologies and high-performance computers to open up new avenues for data-intensive study in the multidisciplinary agri-technology area. In some ways, effective farming boils down to making complex judgments based on the interconnections of many variables, such as crop specifications, soil conditions, climate change, and so on. Farming tactics have always been applied to a full field or, at best, a portion of one. In agriculture, machine learning allows for much higher precision, allowing farmers to treat plants and animals almost individually, increasing the effectiveness of their decisions.

Machine learning, for example, is not a mystery trick or magic in the agricultural industry; it is a set of well-defined models that collect certain data and use precise methods to accomplish desired results.

The methods in machine learning agriculture are derived from the learning process. To fulfil a certain task, these approaches must learn through experience. The ML is made up of data based on a set of examples. A set of attributes is used to define an individual example. Variables or features are the names given to these groups of qualities. A feature can be binary, numeric, or ordinal in nature. The performance metric is used to calculate the machine learning's performance.

1.1 Objectives

1. To make farmers' lives better.
2. To forecast the crop that will boost productivity.
3. Successful prediction approach.
4. Important for strategic decision-making.

1.2 Scope

The world will begin to believe in predictions that are based on statistical data rather than theoretical conceptions. Based on local temperature and a multitude of other characteristics, it will be easier to forecast the crop.

2. PROPOSED SYSTEM

In this technique is intended to assist farmers in making informed decisions about crop forecasting. Along with live data, historical data for temperature and humidity is also captured and stored to improve accuracy. Rainfall data from the past is also gathered and archived. The project analyses the temperature and humidity of the field live data collected using a DHT-22 sensor, historic data collected from a government website and/or Google Weather API, the type of soil used by the farmer, and historic rainfall data in order to be certain and accurate in crop prediction. It can be accomplished through the use of an unsupervised or supervised machine learning method. Datasets are trained via learning networks. Different machine learning approaches' accuracy is compared in order to determine the most accurate outcome.

The dataset is trained using learning networks. The accuracy of several machine learning algorithms is compared in order to produce the most accurate output, which is then presented to the end user. The system not only recommends the best crop, but also the best fertilizer for that crop. Farmers communicate with the system via a responsive, multilingual website.

The proposed algorithm will suggest the best crop for a given piece of land. Rainfall, temperature, humidity, and ph are examples of meteorological parameters and soil content.

The system collects data from farmers or sensors like as temperature, humidity, and PH. This data is used by machine learning predictive algorithms such as Random Forest or Decision Tree to find patterns in the data and then process it according to the input conditions.

3. METHODOLOGY

3.1 Algorithms

1)Random Forest

The supervised learning approach is used by Random Forest, a well-known machine learning algorithm. In machine learning, it can be applied for both classification and regression issues. It is based on ensemble learning, which is a method of combining several classifiers to solve a complex problem and increase the model's performance.

According to the name, "Random Forest is a classifier that comprises a number of decision trees on various subsets of a given dataset and takes the average to boost the dataset's projected accuracy. The random forest gathers predictions from each tree and anticipates the ultimate result based on the majority votes of projections, instead of relying on a single decision Tree. The bigger the number of trees in the forest, the more accurate it is and the problem of over fitting is avoided.

3.2 Hardware

A) Digital Temperature and Humidity Sensor:

For monitoring live temperature and humidity, the DHT22 sensor is suggested. This sensor has been demonstrated to be more precise and accurate. It uses a capacitive humidity sensor and a thermistor to detect the ambient air and sends a digital signal to the ESP32 port pin through the data pin. DHT22 features a temperature range of 40 to 80 degrees Celsius and a humidity range of 0 to 100 percent RH.

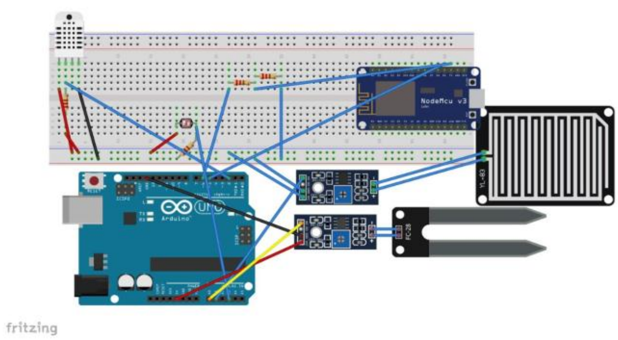
B) LDR: An LDR is a component that has a (variable) resistance that changes depending on how much light it gets. As a result of this, they can now be used in light sensor circuits. Light Dependent Resistors are another name for photoresistors (LDR). They're constructed of a semiconductor material with a great resistance to heat. Photons deliver energy to electrons when light reaches the gadget. They then leap into the conductive band, causing it to conduct electricity.

C) Rain Sensor: The presence of rain is detected using a rain sensor, which is a form of switching device. It works like a switch, and the assumption is that when it rains, the switch closes.

D) Rain Sensor Module: This board, in essence, has nickel coated lines and operates on the resistance concept. This sensor module allows you to measure moisture via analogue output pins, and it outputs a digital signal when the moisture threshold is exceeded.

E) Photovoltaic Panel: PV panels are solid-state semiconductor devices that transform light energy into electricity. PV panels will convert the sun's energy into electricity. PV panels' conversion efficiency is crucial to their development, market penetration, and energy share, despite the fact that the primary energy (solar irradiation) is free.

3.3 CIRCUIT DIAGRAM DESCRIPTION



A)Soil moisture sensor (connected to the A1 pin of Arduino)-The soil moisture sensor indicates how much water is in the soil.

Electrical resistance through the sensor is measured when a modest charge is applied to the electrodes.

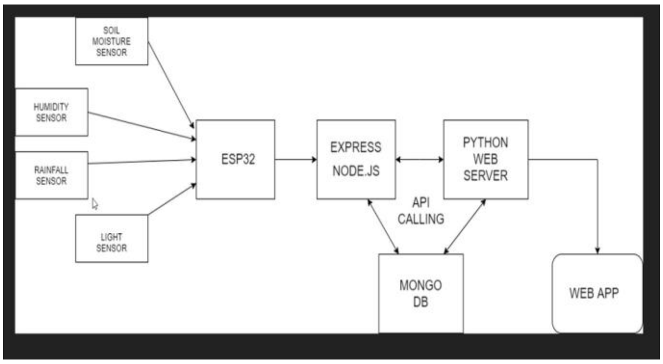
Resistance rises when water is drawn from the sensor by plants or as soil moisture lowers.

B) Rainfall sensor (connected to the A0 pin of Arduino)-By estimating the amount of water on the sensor, the rainfall sensor can tell how much rain is falling. The rain sensor detects a short circuit in the tape of the printed circuits, which is sensed by water.The sensor functions as a variable resistance that changes depending on the situation. When the sensor is wet, the resistance increases, and when the sensor is dry, the resistance decreases.

C) Humidity sensor (connected to the A2 pin of Arduino)-The humidity sensor determines the amount of moisture and temperature in the air.It uses a capacitive humidity sensor and a thermistor to monitor the ambient air and delivers a digital signal on the data pin(There are no analogue input ports required).It's simple to use, but data collection necessitates careful timing.

D) Light dependent resistor (connected to the A3 pin of Arduino)-When light falls on the LDR, the resistance lowers, and when light falls on the LDR, the resistance increases. When an LDR is kept in the dark, it has a high resistance, but it has a lesser resistance when kept in the light.

3.2 BLOCK DIAGRAM DESCRIPTION



1.The ground pin of the Arduino is linked to the GND pin, and all of the VCC pins are connected to the 5v pin.

2.All of the data from these sensors is sent to Arduino, which uses NODEMCU to deliver the data to the server.

3.We're using an ARDUINO instead of a NODEMCU esp8266 because the Arduino doesn't have enough analogue pins.

4.We use the UART protocol to communicate data from Arduino to Nodemcu (TX RX pins).

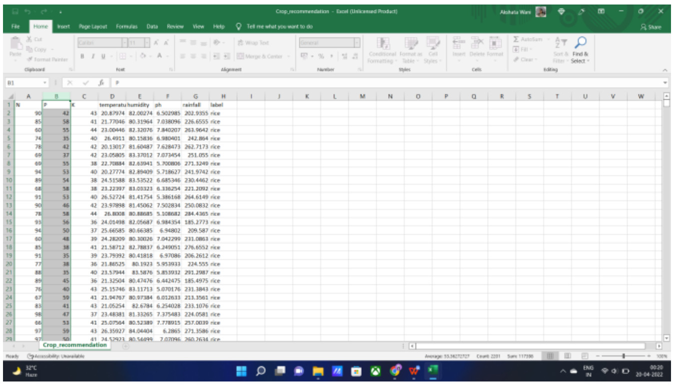
5.After delivering data to nodemcu, the data is sent to the server and saved in our database (MongoDB).

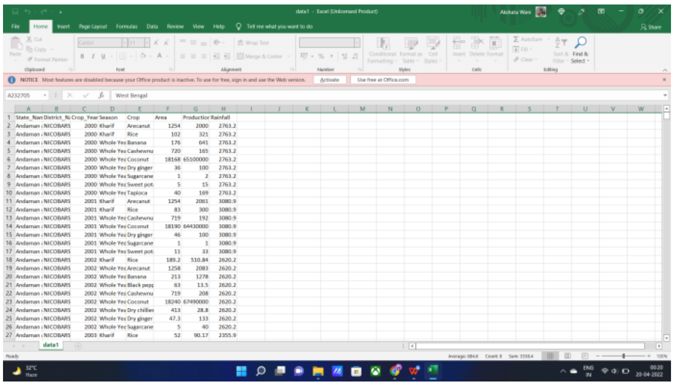
6.Data is retrieved from the MongoDB database and processed using the Decision tree algorithm in the TensorFLow Framework.

7.After TensorFLow has processed the data, the outcome is displayed to the farmer via the frontend application (JavaScript or Django).

4. DATASET

The dataset is collected from Kaggle, For crop prediction dataset consists of 2201 number of rows and 8 columns over which different techniques are applied and 4 characteristics are selected And for area wise crop prediction dataset consists of 232705 number of rows and 8 columns.



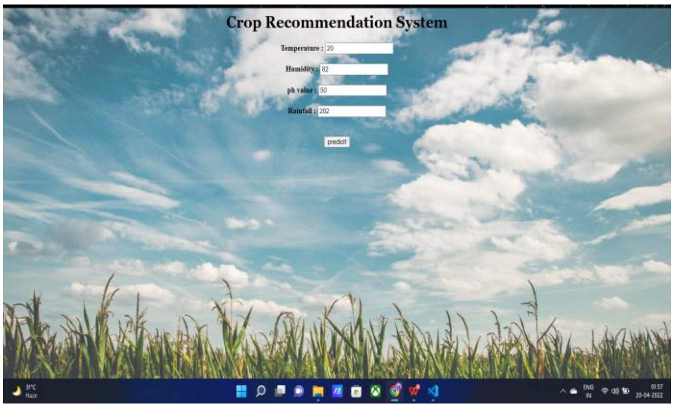


5. RESULT

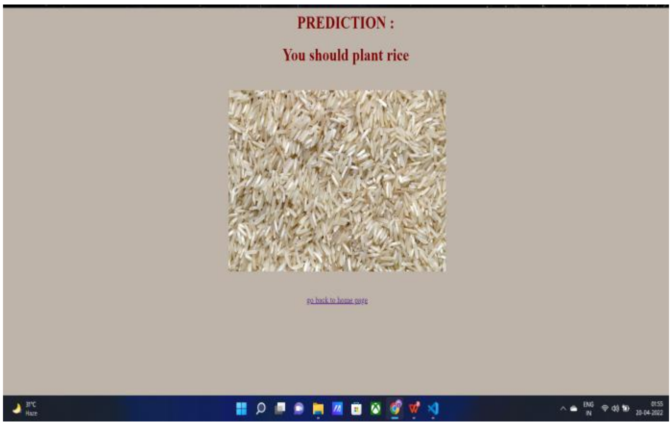
The Graphical User Interface(GUI) has been developed for the machine learning models using the Flask Framework. For the backend of the site we have used Python. This site will predict the best suitable crop for cultivation.

First, on our home page ,we get information about our system and also option whether to predict the crop by using the sensors value or by the area.

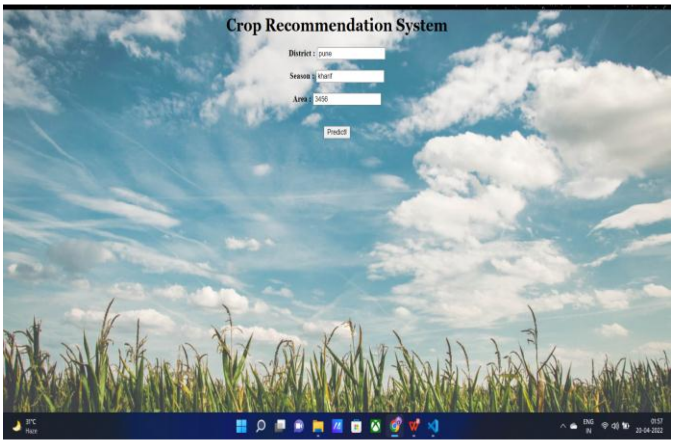
The next page is decided on what we select if we select by using sensors value then the user have to give inputs like temperature , Ph value, humidity and rainfall to forecasting the harvest



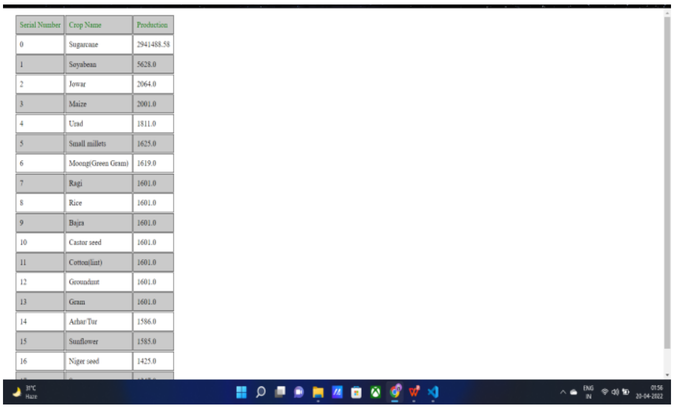
By entering this values we will get a image of predicted crop. It will also deliver a message that you should plant predicted crop.



After that, the next one is by using Area section, here the user have to give the inputs like District ,season and area to predict the yield of the crop for that particular area.



By entering this values we will get the predicted crop name and how much production can we expect from entered area and location.



Serial Number	Crop Name	Production
0	Sugarcane	2941488.58
1	Soyabean	5628.0
2	Jowar	2064.0
3	Maize	2001.0
4	Urad	1811.0
5	Small millets	1625.0
6	Moong(Green Gram)	1619.0
7	Ragi	1601.0
8	Rice	1601.0
9	Bajra	1601.0
10	Castor seed	1601.0
11	Cotton(lint)	1601.0
12	Groundnut	1601.0
13	Gram	1601.0
14	Arhar/Tur	1586.0
15	Sunflower	1585.0
16	Niger seed	1425.0

6. CONCLUSION

The objective of this project is to predict the crop using historical data. We propose a smart agricultural strategy in this paper, which is based on two developing technologies: the Internet of Things and machine learning. The accuracy of the result is improved by using both real-time and historical data. The accuracy of the system is also improved by comparing multiple machine learning techniques. This strategy will be utilized to assist farmers in overcoming hurdles and increasing the quantity and quality of their products.

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