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AI Portable Soil Testing for Crop Yield Using Machine Learning in Kannada

Shruthi V[1] Dr.Nuthan A C[2] Ankitha B [3], Poornima L R[4], Varshini J[5],

[1]Assistant Professor, Electronics and communication Engineering, G Madegowda Institute of Technology
[2]Professor & Head, Electonics and communication Engineering, G Madegowda Institute of Technology
[3] Student, Electronics and communication Engineering, G Madegowda Institute of Technology
[4] Student, Electronics and communication Engineering, G Madegowda Institute of Technology
[5] Student, Electronics and communication Engineering, G Madegowda Institute of Technology

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Abstract - In India, 51.09 % of Land is used as agricultural Land. More than 60% of farmers perform farming on small-scale or limited Land. To help the farmers improve their income, we are developing smart crop prediction system by performing the soil analysis using the CNN algorithm. It helps to optimize the agricultural trails. The major drawback of the existing system is that the datasets contain unreliable data, directly affecting the model's accuracy. By analyzing the soil types and temperature of the surroundings, we are forecasting the most suitable crops for that particular climate using machine learning algorithms. With this, farmers can increase the quality and quantity of their crops.

Keywords- CNN, Crop prediction, Optimize, temperature, Machine learning

1. INTRODUCTION:

Agriculture is the creative activity of growing crops and cultivating soil, which exhibits diverse methods that vary across regions. The advent of smart farming, integrating machines and automation, aids farmers in achieving sustainable crop productivity, with innovations like water-based farming, genetic modification, and organic farming playing pivotal roles in advancing agricultural practices. In the old days, farmers guessed what might happen with their crops based on what they saw and knew. Teaching computers to learn from experience and make predictions or judgments based on that learning is known as machine learning. The ability of machine learning to uncover patterns and correlations within datasets is one of its most potent aspects. The datasets, which represent the outcomes based on previous experience, must be used to train the models. This iterative training and testing process refines and improves the accuracy of machine learning models, making them valuable tools for various applications. This technique helps in crop prediction. Crop prediction has undergone a remarkable evolution and transition from the intuitive observations of early farmers to the cutting-edge innovations of modern agriculture.

Crop yield prediction is a complex and multifaceted challenge in precision agriculture. The diverse range of factors influencing crop yield, from climate and weather to soil conditions and agricultural practices, makes it a non-trivial task. By putting together many pieces, each represents a different aspect of the environment in which crops grow. Various datasets are crucial to capture the intricate interplay of these factors. By analyzing historical data, machine learning models can learn to recognize patterns and correlations among these variables, contributing to more accurate yield predictions. According to the research of Thomas van Klompenburg, Ayalew Kassahun, and Cagatay Catal , Neutral network approaches are employed to study machine learning algorithms. The accuracy of crop yield predictions often relies on the quality and quantity of available data. Agricultural systems are dynamic, and external factors can change rapidly. A prediction made at one point might become less accurate as unforeseen events, like sudden weather changes or new pest outbreaks, occur. Adopting advanced predictive technologies may be limited by factors such as access to technology, financial constraints, and the level of technological literacy among farmers.

Integrating machine learning into a smart farming system enhances the precision of agriculture by offering real-time monitoring and recommendation. Precision agriculture, while improving crop productivity, has the potential to degrade soil quality over time due to factors like increased mechanization and reliance on specific high-yield crop varieties. Crop production is becoming more cost-effective, more abundant, and of higher quality due to the broad adoption of contemporary agricultural techniques. The goal of implementing Agriculture IoT solutions is to assist farmers in addressing imbalances in supply and demand, achieving high yields, optimizing earnings, and protecting the environment. It involves leveraging smart technologies to optimize farming practices and ensure sustainable agricultural outcomes.

Many farmers lack awareness about their soil type and suitable crops, leading to uncertainties about fertilizer and pesticide requirements for the small Land. Implementing soil testing and smart farming technologies can bridge this knowledge gap, empowering farmers to make knowledgeable choices, enhance crop quality, and maximize productivity. Incorporating convolutional networks (CNN) is a prevailing trend in advancing next-generation leveraging deep learning techniques for image processing. CNN comprises convolution, pooling, and fully connected layers, excelling at spatial feature hierarchies. The new technology and corrected output data will help the farmers with smart farming. This research will help farmers select their crops in the future, which will reward them with a good income for their hard work.

METHODOLOGY:

The proposed system follows the CNN algorithm (convolutional neural network), a network architecture for deep learning. This algorithm learns directly from the data. Before Applying the algorithm, this system went through several levels to predict the crop using soil data.

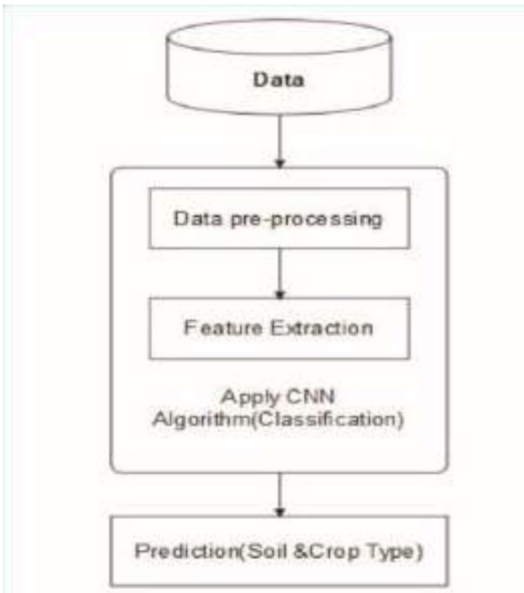

Fig:1 . Proposed System

1) Data collection: Data is sourced from various origins and tailored for specific datasets, with the primary purpose of conducting descriptive evaluations. Different online platforms, such as Kaggle, Google's weather and forestry data, and government data sources, offer datasets spanning up to a decade. These datasets encompass information on soil characteristics, ambient temperatures, and crop suitability for the respective soil types, all of which are employed in the prediction of crop outcomes.

2) Data preprocessing: Data preprocessing plays a crucial role in the machine learning phase, as it encompasses essential tasks like handling missing values, ensuring data accuracy, and many more data preprocessing steps and extracting relevant features. The format of the dataset is vital for practical analysis. In this phase, the data collected is imported into the Google Collab platform and manipulated using Python programming to preprocess and generate the desired results.

3) Feature Extraction: Feature extraction is a technique that helps reduce the amount of data needed to represent a diverse dataset comprehensively. Also, as part of data analytics and machine learning, it reduces noise reduction, improves model performance and provides computational efficiency. The attributes related to soil, crops, and weather, gathered during the preprocessing stage, form the basis for the ultimate training dataset. This method employs a correlation matrix to identify essential predictive factors for crop yield by selecting features with higher correlation values, indicating their significance in the prediction process.

4) Data Prediction: Before proceeding with this stage, it is essential to divide the dataset into two parts: a training dataset and a testing dataset. The CNN algorithm is then applied to train the model using the provided input and output data, allowing it to learn patterns and relationships within the data. The model's accuracy is assessed during the testing phase to ensure it meets the desired performance criteria.

A. Algorithms:

CNN algorithm: Convolutional neural networks (CNNs) can efficiently capture spatial patterns and feature hierarchies in visual input. They are mainly employed for image and video analysis jobs.

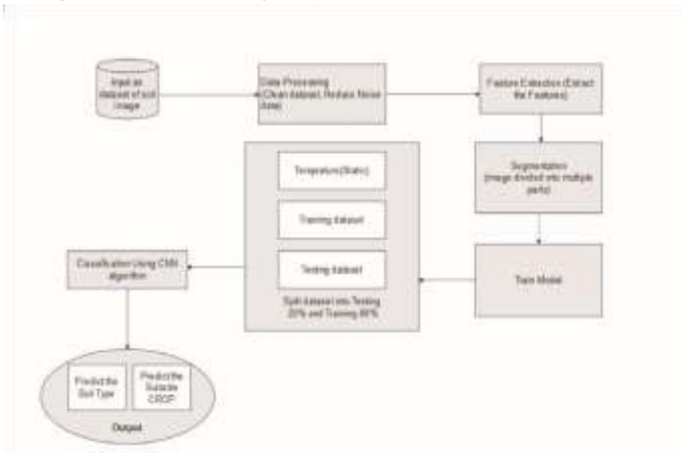

Fig. 2. System Architecture

There are Four types of layers in Convolutional Neural Networks; here are those points rephrased:

1) Convolutional Layer:

In a traditional neural network, each input neuron is directly linked to neurons in the subsequent hidden layer. In CNNs, however, only a small localized region of the input layer neurons connects to neurons in the hidden layer.

2) Pooling Layer:

The pooling layer's role is to decrease the complexity of the feature map. Typically, you'll find multiple layers of activation.

And they were pooling within the hidden layers of the CNN. These layers help in downsizing and summarizing the information in the feature maps.

3) Flatten:

Flattening involves transforming the data into a onedimensional array before passing it to the next layer. Specifically, the output produced by the convolutional layers is reshaped into a single elongated feature vector. This aids in the transition from convolutional layers to fully connected layers.

4) Fully-Connected Layer:

Fully connected layers make up the final layers in the network. The input to these fully connected layers

comes from the output of the last pooling or convolutional layer. This input is flattened and fed into the fully connected layer, allowing for the network's final decision-making and production.

The CNN-based crop prediction system employs advanced image processing techniques to analyze agricultural images retrieved from a database, ultimately predicting the most suitable crop based on soil type. This innovative architecture integrates computer vision, machine learning, and agricultural expertise to enhance precision farming practices.

Data Retrieval and Image Processing: The system begins by retrieving agricultural images from a database that contains a comprehensive collection of soil samples. These images serve as the input dataset for the prediction model. Raw images undergo preprocessing steps such as resizing, normalization, and data augmentation to enhance the quality of input data. This ensures that the model is trained on a diverse and representative set of images.

Convolutional Neural Network: The system's heart is a CNN architecture that extracts intricate features from the input images. Multiple convolutional and pooling layers capture hierarchical features, enabling the model to recognize patterns associated with different soil types.

Feature Extraction and Selection: Extracted features from the CNN layers are subjected to a feature selection process. Relevant features, such as colour distribution, texture, and spatial characteristics, are identified to improve the efficiency of the subsequent prediction model.Soil Type Prediction: A machine learning model, potentially a classifier, is trained using the selected features to predict the soil type based on the input images. This model is fine-tuned to accurately classify soil types, providing crucial information for crop suitability assessment.

2. WORKING PRINCIPLE:

The working principle of AI portable soil testing for crop yield using machine learning involves collecting soil data through portable sensors and analyzing it with intelligent algorithms to provide real-time insights. The system uses various sensors to measure key soil parameters such as pH, moisture, temperature, nitrogen, phosphorus, and potassium levels. This data is then fed into a machine learning model trained on large datasets of soil and crop yield information. The model analyzes the input and predicts the soil’s fertility, suitability for specific crops, and potential yield. It also offers recommendations on fertilizers, irrigation, and crop selection to optimize productivity. The use of AI ensures that the system continuously learns from new data, improving its accuracy and decision-making over time, making it highly efficient for precision agriculture.

Fig.3 Model Picture

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1. SoilInsertion:

The Soil NPK Sensor is inserted into the soil to measure the levels of Nitrogen (N), Phosphorus (P), and Potassium (K)—key nutrients for plant growth.

2. DataCollection:

The sensor collects real-time data from the soil and sends it as electrical signals.

3. Microcontroller Processing: The microcontroller (ESP32 or Node MCU shown in the image) receives the sensor data through GPIO pins and processes the information.

4. DisplayOutput:

The data is displayed on the OLED screen connected to the microcontroller, allowing the user to view soil nutrient levels instantly.

5. Wireless Data Transmission (Optional): The microcontroller can also transmit the data wirelessly (via Wi-Fi/Bluetooth) to a smartphone or cloud for further processing.

6. MachineLearningAnalysis:

A machine learning model (either onboard or cloud-based) analyzes the soil data to:

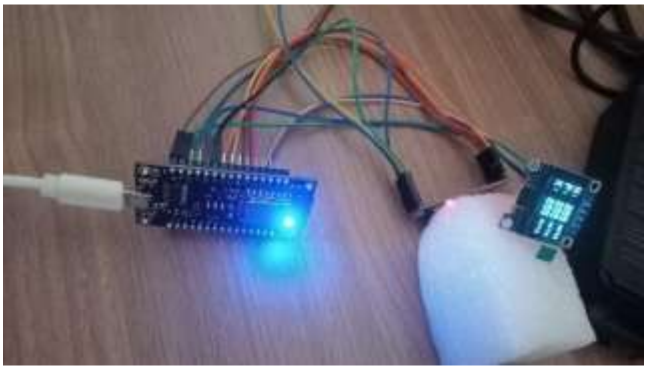
- Predict soil fertility
- Suggest suitable crops
- Recommend fertilizers and corrective actions

7. DecisionSupport:

The processed results help farmers make informed decisions to optimize crop yield and soil health.

3. RESULT:

From the image, the OLED display is showing real-time soil nutrient readings for the threeprimary macronutrients: **Potassium (K)**, **Phosphorus (P)**, and **Nitrogen (N)**.



Fig,4: Result Picture

The image shows a working AI-based portable soil testing system that displays real-time soil nutrient data on an OLED screen using a microcontroller and sensors. The key result visible on the OLED screen includes the measured values of the three essential macronutrients: Nitrogen (N), Phosphorus (P), and Potassium (K), all showing a reading of 255. These values are crucial for understanding soil fertility and determining the suitability of soil for specific crops. In this particular setup, the readings of 255 for each nutrient suggest that the sensor is either operating at its maximum measurable capacity or is in a testing or calibration state. These values might also indicate sensor error or a lack of proper soil contact, as real-world soil rarely contains all nutrients at peak levels simultaneously.

This result is displayed using a compact and low-power OLED screen connected to a microcontroller, likely an ESP32 or NodeMCU, which is responsible for processing the sensor data and displaying it in human- readable form. The sensor involved in this setup is a Soil NPK sensor, which is capable of detecting the concentration levels of Nitrogen, Phosphorus, and Potassium directly from the soil. The data collected is transmitted via jumper wires to the microcontroller, which interprets and displays the output. This kind of setup is particularly useful in smart agriculture, where real-time and portable testing of soil quality can significantly aid decision-making processes for farmers.

Using this system, farmers can quickly identify nutrient deficiencies and determine the most appropriate fertilization strategy to boost crop yield. If integrated with machine learning, the soil data can be used to train models that predict soil health trends, recommend suitable crops for a specific region, and suggest corrective actions for poor soil conditions. For example, if the nitrogen level is too low, the system can alert the user and suggest nitrogen-rich fertilizers or crop rotation practices. Additionally, by collecting and analyzing data from multiple fields over time, the system can learn patterns and improve its prediction accuracy, providing a strong basis for precision agriculture.

In practical use, the AI model can also take environmental factors such as temperature, humidity, and previous crop history into account, making its recommendations more robust. The use of IoT- enabled microcontrollers allows for wireless data transmission to cloud platforms or mobile applications, enabling remote monitoring and analysis. This enhances the usability and accessibility of soil testing tools, especially in rural areas where access to lab-based soil analysis is limited. Ultimately, this AI portable soil testing system can reduce costs, save time, and increase productivity for farmers, making agriculture more efficient and sustainable.

In conclusion, the results displayed in the image demonstrate the capability of a basic AI-powered soil testing system to capture, display, and potentially analyze soil nutrient data. The use of machine learning and IoT technologies in agriculture is a step forward in achieving smart farming goals. However, the accuracy and reliability of sensor readings need to be validated in real soil conditions, and the system should be properly calibrated to provide actionable insights for real-world farming applications.

4. CONCLUSIONS:

Any nation must prioritize agriculture if it is to have sustained growth over the long term. Based on the properties of their soil, farmers may use this kind of model to assist them in choosing the best crops to grow, which will eventually increase crop output and promote sustainable agriculture. The model is tested by applying a different machine-learning algorithm. Here, we use the CNN algorithm, which shows the highest accuracy for soil classification within a shorter period. It gives more accuracy and offers more benefits to farmers. This method would provide real-time data to guarantee higher crop output productivity.

adopting AI-powered soil testing systems integrated with machine learning algorithms like Convolutional Neural Networks (CNN) can significantly transform traditional farming into a more data-driven and efficient practice. The use of CNN in soil classification not only improves the accuracy of predictions but also speeds up the decision-making process, allowing farmers to act promptly based on real-time insights. By accurately identifying soil nutrient levels and classifying soil types, this model helps farmers select the most suitable crops for their land, leading to optimized resource usage, reduced input costs, and increased yields. Additionally, this approach supports sustainable agriculture by minimizing over-fertilization and preventing soil degradation. The real-time capability of the system ensures that farmers are equipped with up-to-date information, enabling adaptive planning and precision farming practices. As agriculture continues to face challenges from climate change, population growth, and resource limitations, integrating such intelligent systems will play a crucial role in achieving food security and long-term agricultural sustainability. Overall, the combination of AI, portable hardware, and machine learning like CNN offers a powerful toolset for revolutionizing the way farmers manage and cultivate their land.

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