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Smart Agriculture Prediction Awaring IoT Using Recurrent Neural Network

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ABSTRACT: Mostly on agricultural research, this has a big impact on choices like pricing, distribution, and import-export of particular commodities. Utilizing cutting-edge technologies is vital for enhancing yield quality and creation, projecting crop yields, and researching agricultural illnesses and infections. The most common problem with farmers is that they don't choose the right crop according to what the soil requires. They observe a notable decline in production as a result. In order to address the farmers' problem, we proposed a deep reinforcement learning (DRL) based crop categorization system for precision agricultural selection in this study. In the crop recommendation system, DRL-based advanced agricultural approaches reduce unfavourable possibilities and increase output. We contrasted the suggested recommendation system with a number of machine learning techniques, including Random Tree, Naive Bayes, and K-Nearest Neighbor, for a site-specific crop with effective accuracy.

Keywords: Agriculture, deep neural network, IoT, recommendation system, KNN, Random Tree, Naive Bayes, reinforcement learning, SVM

I. INTRODUCTION

Crop yields are mostly predicted using crops including wheat, rice, beans, pulses, sugar cane, tea, cotton, greenhouses, corn, and soybeans. Forecasting crop yields is essential to the world's food production. Seed businesses forecast new hybrids to be employed in varied soil conditions, so they can create superior types for different environments. With the assistance of

Crop forecasts, farmers gain by preventing monetary losses. Farmers need to know which crops are appropriate for a given season and what safety measures to take based on the soil and environment conditions [1]. Farmers also need to know what kind of crops to cultivate by looking at previous years' yields.

The problems made worse by climate change and the rising demand for food brought on by the world's fastest-growing population—which is predicted to exceed 9 billion people by 2030—underline the need of an accurate crop yield forecast model at the regional level. The model needs to be improved in terms of crop management, food security, policy, and agricultural

making choices. Because of this, numerous methods have been created and used to forecast agricultural yield, including process-based models and data-driven statistical algorithms [2]. However, statistical methods offer intriguing alternatives and supplementary tools, since the process-based models for simulating the physiological mechanisms are limited by data availability for parameterization, model calibration, and validation. The development of big-data technology and high-performance computing has led to the popularity of a useful statistical technique called deep reinforcement learning (DRL). The DRL algorithm produced new possibilities to support farmers' decision-making, and guide decisions in a range of real-world scenarios with or without little assistance from humans. Using datasets generated from various sources, DRL approaches preserve the benefit of autonomously solving large nonlinear problems; they also offer a robust and flexible framework for decision-making and integrating expert knowledge into the system based on data.

II. LITERATURE REVIEW

The agricultural accuracy of the dataset created for in [4], the forecast of soybean crop production over several years is calculated by the authors to examine the effectiveness of classification algorithms. The authors of this paper use Bayes classification, random forests, neural networks, and vector machines. Authors in [5] emphasized the significance of crop prediction, and

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it can support the development of an extendable framework for agricultural yield forecast in policy-making. It enables the adaptable integration of multiple methods for yield prediction in agriculture. Additionally, a tool that uses dependent and independent variables to assist users in predicting agricultural productivity in various crops has been built.

The study [6] uses visual data mining to illustrate the agricultural data. Large-scale agricultural data is gathered for this project in order to gain understanding of the results and applications of Large-scale agricultural data is gathered for this study in order to gain understanding of input application and output (such as fertilizers). The dataset has been reduced by the use of multidimensional scaling algorithms and autonomous maps. The study in [7] highlights the significance of crop selection and talks about the factors that affect it, including market pricing, production rates, and government regulations. In order to solve the issue of crop selection and increase the crop's net return rate, this study proposes the Crop Selection Method (CSM). This suggests that the plant sequences for a season, taking into account plant species, weather, soil composition, and water density. Article [8] forecasts cereal production in Bangladesh's principal districts using data mining techniques. To compute agricultural productivity in different districts, the data set included two area-related variables, three biotic variables, and five environmental parameters. Future geospatial analytical initiatives to increase accuracy were suggested in the paper. Several classification methods are offered by the research in [9] to classify the data set for liver disease. It has been shown that naive Bayes classifiers perform better in predictions. The multi-layer perceptron is the method with the highest accuracy among the others, mentioned. The issue of food insecurity in Egypt is discussed in the article [10], which aids in determining whether or not massive food imports are required. After analysis of the paper soil datasets [11], categorization is anticipated where The crop yield is expressed as a classification rule based on the specific kind of soil. For predicting agricultural productivity, the k-Nearest Neighbor and Naive Bayes algorithms are employed. Subsequent research endeavors have yielded proficient models that employ several categorization methodologies, such as supporting vector machines.

Regression approaches were employed by the authors in [12] to estimate yields in a specific site with satisfactory outcomes. This study has demonstrated that agricultural yields within a certain geographic area may be accurately estimated using the regression model. Uses concepts from descriptive analytics to analyze agricultural data [13]. This study offers information on which data analytics techniques are used on sugarcane harvest datasets, contingent on the investigation's findings. In [14], the ramifications of their findings are examined along with the consequences of using machine learning techniques to large datasets related to sugar cane production in Karnataka, India. Many machine learning techniques have been applied to agricultural data in an effort to determine which methodology is the most productive. Three different supervised learning algorithms were used to examine the sugar cane dataset: DT, k-NN, and SVM. DRL techniques, which integrate the ideas of deep learning and reinforcement learning to enable artificial agents to directly acquire knowledge and experience from real-world data, can be applied to anomaly detection [15].

III. PARAMETERS

In agriculture, a number of factors, including temperature, soil, moisture, rainfall, and humidity, affect crop productivity. We look into how the aforementioned factors affect the production of agricultural output. The variables are listed below.

a) Temperature: Temperature is a major factor in the crop recommendation approach. There is a maximum and minimum temperature range for each crop. Low temperatures can harm crops by smothering, freezing, and chilling them. Elevated temperatures may lead to problems in absorbing nutrients, disruption of photosynthetic processes, and death of plants.

b) Soil: When recommending crops, soil is a crucial factor. The soil contains the elements nitrogen, phosphorus, potassium, magnesium, and sulfur. The soil types that are classified by nutrients are Clay, Sandy, Salty, Peaty, Chalky, and Loamy.

c) Moisture: The most important element in plant development is the presence of moisture in the soil. In the system, crop moisture recommendations are also crucial.

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Table 1: Analysis of A Dataset

	P	N	K	TEMPERATURE	HUMIDITY	PH	RAINFALL	LABEL
0	41	90	42	21.8797444	82.002744	6.502985	202.935536	RICE
1	58	84	40	22.7724652	81.320389	7.038096	226.655537	RICE
2	54	61	44	23.004459	82.320763	7.804027	263.964648	RICE
3	37	74	42	20.491096	80.158636	6.840207	248.864034	RICE
4	43	77	41	19.130175	81.604873	7.628473	262.713874	RICE

d) Precipitation: Rainfall is a major source of water for a lot of crops. Harvesting of crops is dependent on rainfall. In regions that receive enough rainfall, crops that require more water will be planted. Rainfall also makes a wider range of water resources available, which makes it possible to grow a variety of crops.

e) Humidity: Photosynthesis cannot take place without humidity. Low humidity stunts the growth of plants, whereas high humidity can degrade the quality of plants.

IV. METHODOLOGY

4.1 Data Sets Collection

The data covers soil-specific properties that were acquired from the soil testing laboratory in Madurai District. Comparable online resources for general agricultural information have also been used. Plants that we grow include rice, millet, pulses, cotton, nuts, vegetables, sorghum, sugar cane, and coriander. One of the primary elements contained in the agricultural yield datasets shown in Table 1 are used.

4.2 Learners Used In The Model

4.2.1 Random Tree

A decision tree and a random tree are similar. As each split has only a random subgroup of features, it differs from a random tree. It is possible to construct random trees with both nominal and numerical data. The Random Tree is C4.5 or similar to CART. But during training, it differs by selecting only a random subset of characteristics. It considers K. Attributes chosen at random for every node. The subset size is determined by the subset ratio argument.

4.2.2 K-Nearest Neighbor

K-Nearest Neighbor is determined using both classification and regression. K-Nearest Neighbors is a simple technique that uses similitude measures to categorize new cases and stores all of the examples that already exist. The sample set is divided into groups based on "close-down" metrics, which include Manhattan and Euclidean distances.

4.2.3 Naive Bayes

Based on the Bayesian classification technique, the Naive Bayes classifier is a main probabilistic model that applies the Bayes theorem with naïve strong assumptions of autonomy. A method for creating classification models called Naive Bayes uses problem instances as vectors of characteristic values, and a class label is given to every scenario. Class labels are selected from a limited set of possibilities. It is actually a group of algorithms built around the same fundamental idea rather than a single method. When the class variable is present, all Bayes classifiers incorrectly assume that the value of a particular feature is independent of the significance of any other feature.

i) Collection of data
ii) Pre-processing of data
iii) Divide the data into test data and train data
iv) Apply training data set to the classifiers, KNN, Random tree, naives bayes, DRL
v) Predict the accuracy of the yield prediction of the crop
vi) Trained model and crop recommendation

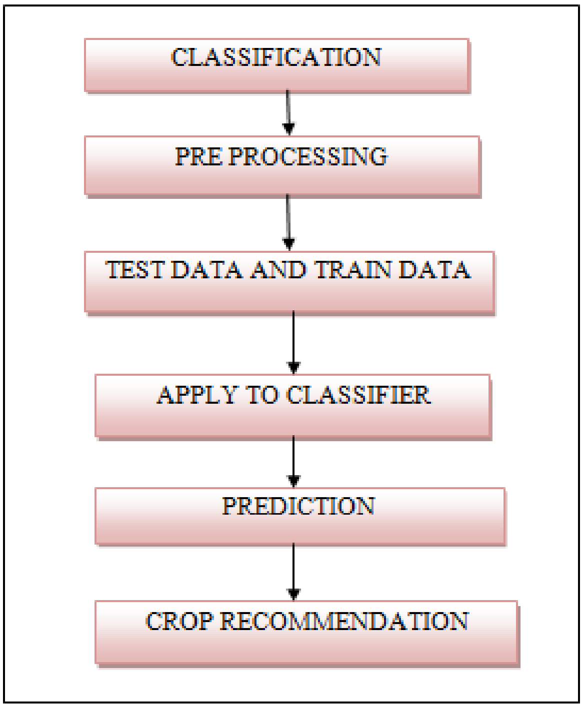

Figure 1: Flow Chart of The Proposed Algorithm

4.2.4 DRL

Deep reinforcement learning is able to create an end-to-end architecture that can predict the crop by combining the benefits of deep learning and reinforcement learning. Thus, a fresh intelligent method that can overcome the disadvantages of the previously mentioned machine learning methods is given, based on deep reinforcement learning. The environment evaluates the categorization action the agent performs on a single sample at each time step and awards the agent. Given that the minority class sample offers a bigger reward, the agent responds to the minority class more strongly.

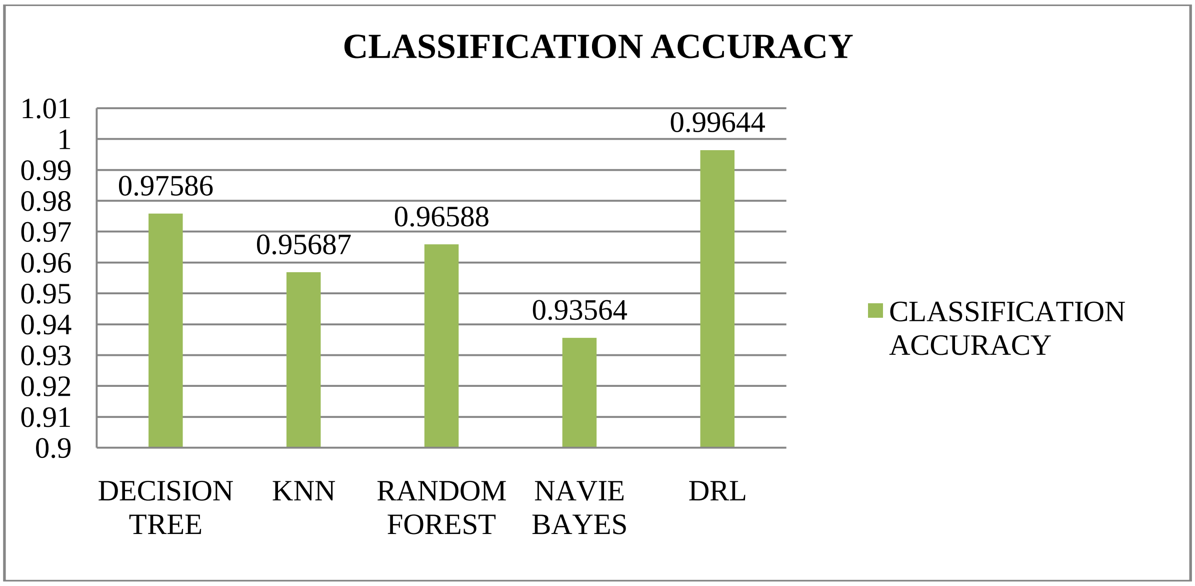

FIGURE 2: ACCURACY OF VARIOUS CLASSIFIERS

V. RESULTS AND DISCUSSION

The crop can view different settings for different parameters in any of these options at any one time. The system will be able to use these possibilities to make decisions, which is why there are so many of them. In other words, every system is sufficiently trained to function independently. Each crop's specific needs for nitrogen, phosphate, and potassium are taken into consideration, along with temperature, humidity, rainfall, and crop type labeling. After the entire data set has been collected, the system must produce an input, which is determined by training. The system assigned all of the parametric values for each crop based on the training and data collection procedures previously outlined. The crop label can now be used by the system to modify all of the numbers. The actuators will adjust these values and maintain the value of each parameter sufficiently stable to prevent overflow or negligence after all sensor data has been gathered, processed, and stored in the system.

The technology will be able to calculate the quantity of humidity and temperature for each crop based on these facts. While adding more values to other elements, the system is refined enough to observe the current state and outcome of the crop. These data can be used by the system to make judgments. The amount of N, P, and K, among other parameters not shown in this graph, has also been graphed and data logged in a comparable manner. The outcomes are displayed in Figure 4, where we can observe that the highest accuracy (DRL) of the random forest-based classifiers and the DRL-based classifiers are nearly equal. The rationale is that a deep neural network's overall performance grows with dataset length. Nonetheless, based on the existing dataset, DRL's accuracy surpasses random forest's as the dataset lengthens. Next, the accuracy of different machine learning systems are presented, including KNN, Naïve Bayes, and decision tree classifiers.

VI. CONCLUSION AND FUTURE WORK:

In this study, we investigated a number of agricultural data analysis methods offered by various academics. With the least amount of input, precision agriculture leverages technology to give farmers the best potential results. The automation of intelligent behavior, or artificial intelligence, is continuously improving our society and helping humanity in a variety of ways. The impact of IoT and AI on creative farm management is examined, and a brief introduction is given to the most popular machine learning methods in precision agriculture. We used decision tree, random forest, KNN, Naïve Bayes, and DRL based classifiers. Among the remainder, random forest and DRL networks based on neural networks perform the best.

Based on prior considerations and discoveries, the current research may serve as inspiration for a number of future works. In order to mitigate the effects of over fitting, we first wish to widen the network structure. For instance, we think that incorporating older data, like Long Short Term Memory, into the new pipeline could enhance the results. We also like to observe the impact of optimization tactics on the outcomes.

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