INTELLIGENT CROP RECOMMENDATION SYSTEM

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Abstract
Since a great deal of Indians work in agriculture, it is widely acknowledged that farmers have the perspective to plant the same crop, use more fertilizer, and follow the majority opinion. However, over the past few years, there have been notable improvements in the application of machine learning in a wide range of businesses and areas of studies. Hence, our target is to produce a system that would allow farmers to gain advantages from the application of machine learning in agriculture. India is a nation that farms, and crop productivity performs a major role in the country's economy. Thus, we may state that the foundation of all business in our nation can be agriculture. Crop choosing is an important part of agricultural planning. Many scholars have utilized machine learning strategies to examine crop yield rate estimating, prediction of weather, soil classification, and crop categorizing for agricultural planning. To improve modifications in our Indian economy, the agriculture department requires to implement multiple changes. By using machine learning systems to the farming sector, we can improve agriculture. Functional information on multiple subjects is essential for farming, together with to all developments in equipment and technologies used to perform it. This paper's goal is to utilize the crop selection strategy in a manner that will allow it contribute in finding solutions of many different problems related to agriculture. This increases crop growth levels and improves the financial security of our Indian people. In our research, the crop is predicted utilizing two algorithms: the existing Random Forest (RF) and the suggested Recurrent Neural Network (RNN). The accuracy of each technique is computed and compared with the performance of other algorithms.

I. Introduction

Agriculture plays a very important role where economic growth of a country like India is considered. The main aim of agricultural planning is to achieve maximum yield rate of crops by using little number of land resources. Many machine learning algorithms can help in raising the producing of crop yield rate. Whenever there is loss in critical situation, we can apply crop selecting method and reduce the Losses. And it can be used to acquire crop yield rate in favorable conditions. This Maximizing of yield rate helps in upgrade countries economy. Managing the interest rate benefits to boost the financial health of a country. The crop yield rate is affected by a couple of additional variables. They are crop selection and fertilizer quality. Crop selection will depend on two criteria: critical conditions and favorable conditions. Multiple investigations are done in order to improve the environment of agriculture. Generating the greatest possible production of crops is the target. Numerous methods of classification are utilized as well in order to achieve the greatest achievable crop production. Crop yield rates can be improved through the application of machine learning. Crop selection is a process used to increase crop yield. Crop construction may be impacted by the region's geography, especially locations near waterways, hills, or deep water. weather elements like as cloud coverage, temperature, humidity, even rainfall. The sort of soil can be peaty, sandy, clay, or saltwater. Copper, potassium, sulfuric acid, nitrogen, manganese, iron, calcium, pH value, carbon, and numerous harvesting strategies can all be present in soil composition. Different Crops use several kinds of criteria to generate different expectations. Using an analyzer, these prediction models may be checked. There are two categories for these predictions. Traditional statistical techniques and machine learning are the two types of methodologies. strategies. Single sample spaces can be predicted by employing the traditional method. Furthermore, machine learning methods enable with developing different predictions. Comparing to machine learning methodologies, that demand us to keep seriously the structure of data models, conventional methods have no need for us to take into account the structure of data models.

II. LITERATURE REVIEW

1. Making a choice AI-powered Harvest Turn network providing emotional support Distributer: IEEE 2023; M. Selvaganesh; E. Esakki Vigneswaran Ranchers having no concept whether an achievable yield depends upon the dirt's quality, compounds, and composition. By using an AI estimation based on Neuro-Fluffy, the work attempts to help ranchers estimate the physical makeup of their soil by estimating the proportions of Urea, potassium, magnesium, pH, and Nitrogen. The proposed framework's dataset was collected from Tamilnadan Rural University (TNAU), near Coimbatore.
For the purpose of testing, samples of soil have been taken from multiple states ranches in the Coimbatore district. For the purpose of to estimate the perfect

harvest for development and yield pivot, this algorithm analyzes the correlation of obtained datasets and scenarios, boosting yields for the year. The Coimbatore district's widely grown crops, including as corn, rice, and bananas, are selected for research. By establishing a realistic harvest for the particular trimester in light of the supplements available in the soil, the end result produces a successful harvest pivot grouping.

2. Managed AI Approach for Harvest Yield Expectation in Horticulture Area Y. Jeevan Nagendra Kumar; V. Spandana; V.S. Vaishnavi; K. Neha; V.G.R.R. Devi

Distributer: IEEE 2023

AI (ML) supplies a key approach to discovering actual events and feasible solutions for the crop yield challenge. ML uses Regulated Learning for predicting an objective or event from a given set of indicators. In order to achieve the best outcomes, the correct capacity must be generated by a number of specific factors that will plan the knowledge variable to the point yield. Crop yield expectation integrates the process of estimating harvest creation using historical, dependable information that includes parameters like temperature, stickiness, ph, precipitation, and crop name. It allows us consider the best harvest to be forecasted based on field weather patterns. Irregular Woodland, an AI calculation, should be able to produce these forecasts. It will yield the best exact worth harvest as predicted. The least number of models is taken into account in order to provide the optimal harvest yield model using the arbitrary backwoods calculation. In the farming industry, knowing the harvest's yield is extremely beneficial.

3. Rice crop yield expectation in India utilizing support vector machines Niketa Gandhi; Leisa J. Armstrong; Owaiz Petkar; Amiya Kumar Tripathy

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In India, the manufacturing of food is usually affected by cereal harvests, including as rice, wheat, and other heartbeats. Reasonable temperatures are required for areas that grow rice to be economically viable and effective. Variance in periodic climate conditions could slow expansion, with periods of dryness reducing productivity. Creating expanded approaches for assessing agricultural productivity in diverse climate conditions can assist ranchers and other consumers in making greater choices about yield and agronomy. Artificial Intelligence techniques have the potential to enhance harvest output expectations in diverse climatic conditions. The audit of this AI strategy's application for rice-trimming regions in India is provided in this study. The trial results obtained by carrying out the SMO classifier with the WEKA device on the dataset of 27 location in the Indian state of Maharashtra are discussed in this investigation. The dataset used for predicting rice crop yield came from readily accessible Indian government sources. Precipitation, minimum temperature, the highest temperature, the normal temperature, reference crop evapotranspiration, region, creation, and yield for the Kharif season (June to November) for the years 1998 to 2002 were the boundaries taken into consideration for the review. The mean outright error (MAE), relative outright error (RAE), root relative square error (RRSE), and root mean square error (RMSE) were calculated for the current review. Initial results demonstrated that, in comparison to SMO, the presentation of multiple operations on the same dataset was much enhanced.

4. Brilliant Farming Expectation Framework for Vegetables Filled in Sri Lanka Rashmika Gamage; Hasitha Rajapaksa; Abhiman Sangeeth; Gimhani Hemachandra; Janaka Wijekoon; Dasuni Nawinna

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Plantation-based economies such as Sri Lanka rely primarily on agriculture for their food security and economic growth. Even if landscaping plays a significant part, there are still a few major annoyances that need to be solved. A significant cause of uncertainty for ranchers is the lack of knowledge regarding cost and yield, which influences their crop selection based on involvement. AI has tremendous potential to address these problems. In order to do this, this paper presents a novel architecture involving a flexible application, short message administration (SMS), and an API (Application Programming Connection point) with harvest streamlining, yield forecast, and value expectation. While a conventional calculation was used to improve crops, a few AI calculations were used to estimate yield and cost. While the cost has been determined with consideration for the organic market, import and product, and occasional effect, the yield was predicted taking into account ecological factors. The conclusion of yield and cost expectation has been used to select the most suitable harvests to grow. Utilizing responsive net, edge, and multilinear relapse, yield expectation has been developed. The yield expectation's R2 has increased from 0.74 to 0.89, and the RMSE esteem is now between 15.69 and 35.05. The computations of Facebook Prophet, Irregular Timberland, and Angle Supporting Tree were used to determine costs. The results of these computations show that the RMSE value ranges from 26.81 to 140.72, and the R2 value changes between 0.72 and 0.92. Crop growth has been made by employing the genetic algorithm to farming.

5.Territorial Winter Wheat Development Date Expectation Utilizing Remote Detecting Yield Model Information Osmosis and Mathematical Climate Forecast Xinran Gao; Jianxi Huang; Hongyuan Mama; Wen Zhuo; Dehai Zhu

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A forward date expectation examine is required to enhance collecting plans, prevent the impacts of adverse weather conditions, and prevent yield or quality declines due to ineffective gather plans.

However, as most expectation models are fact-based, they are inappropriate for use in a territorial setting, and consistency is crucial for far away detection-based models. The WOrld FOod Studies (WOFOST) crop development model was modified by including a system that integrated leaf region record (LAI) data from the MODerate Goal Imaging Spectroradiometer (MODIS). Gauge meteorological data from THORPEX Intelligent Stupendous Worldwide Outfit (TIGGE) was used as a climate information input for the future time frames. We chosen the Henan Territory's wheat-establishing region over the colder months as our study area, and we changed the WOFOST model based on perception results. A standardized expense capability was created to quantify the difference between MODIS LAI items and replicated LAI items. Savitzky-Golay (S-G) channel was used to smooth the MODIS LAI profile first. These two LAI profiles were then normalized in order to preserve their pattern data. Next, we chosen as improvement boundaries in the WOFOST model boundaries that are sensitive to development date, such as rise date (IDEM), strong temperature aggregate from anthesis to development (TSUM1), and persuasive temperature aggregate from development to anthesis (TSUM2).). These borders lack unambiguous geographical in nature and transitory examples and have extreme year-to-year contrasts. Rearranging Complex Advancement near developed at the University of Arizona (SCE-UA) computations allowed us to reconstruct each pixel in the review region and retrieve its ideal bounds. At that point, we propose WOFOST to this optimal boundary set in order to replicate the growth and improvement of winter wheat. Furthermore, we converted TIGGE data into a CABO-design weather record in order to trigger WOFOST to simulate the development of winter wheat throughout the course of the next 16 days. This allowed us to obtain a spatial distribution of the winter wheat development date within the review area. By matching the estimated date with the observed date from agrometeorological locations, it can be seen that this method was highly accurate when forecasting the provincial development date, with a root mean square error (RMSE) of 1.93 days and a connection coefficient (R2) of 0.90. Apart from that, there was obvious geographic variability in the development forecast's dispersion guidance.

6. Utilizing double polarimetric TerraSAR-X stripmap artwork, different harvest yield estimates Carl Menges, Doug Dark, and Tishampati Dha Released by IEEE 2023

The results of a study designed to tie the production from various harvests to the double polarimetric symbolism of TerraSAR-X are provided in this research. Since X-band frequency is more averse to small harvest structures—specifically, thickness of the stem and head—it takes sense to relate respect backscatter. In addition, the volume transpiring via double polarimetric entropy/alpha decay was highlighted by means of TerraSAR-X's intelligent double polarimetric technique. In addition, the volume vaporizing via double polarimetric entropy/alpha decay has been highlighted by means of TerraSAR-X's intelligent double polarimetric technique. Strong correlations were found to provide information collected through gatherer telemetry.

7. Assessing Harvest Using Information Analysis Distributer: IEEE 2023; Manish Kumar Sharma; Shashank Agrahari; Shivam Tyagi; Shivam Punia

Food is a basic human need for growth and survival. The demand for the food also rises as the population grows. The techniques used in agribusiness must be upgraded in order to care for a wider range of people. One such tactic involves identifying the appropriate harvest, which can help minimize waste and let the rancher select a reasonable output based on his situation. This paper proposes a process that can help ranchers forecast and determine the most reasonable harvest for their land by using information investigation methods and effectively accessible elements. The model creation process wrapped up the information examination via which information is completed. The method called crop scoring, which measures the yield in relation to the model and harvesting with a level score that is shown as most reasonable for the rancher, is presented in the study

. 8. Harvest as well as yield prediction for farming using artificial intelligence Vineela Chandra Dodda, Lakshmi Kuruguntla, Jaswanth Singamsetty, and Akshay Kumar Gajula Distributor: 2023 IEEE

In order for any nation to succeed, horticulture should be cultivated on a transcendent basis. However, there is an important danger to the harvest output due to unpredictable and mismanaged climate changes, traditional farming practices, and unlucky water system management. In the past, crop yield was predicted based on rancher wisdom. The current challenge is to increase harvest while taking into account the concerns of a growing population. AI (ML) techniques are currently being applied in a variety of disciplines to come up with practical and useful arrangements. ML offers multiple calculations related to a company, clustering, and neural networks that can be applied for forecasting crop yield. In this work, we offer a method that projections the appropriate harvest for development and identifies the soil quality in light of the K-Closest Neighbors (KNN) calculation. We consider both soil quality and temperature as inputs to our algorithm. Moreover, our method suggests the manure based on the expected yield. The results of the experiments demonstrate the efficacy of our method works exactly estimates for production and choice of harvest, greatly helping ranchers

III. Existing system

To identify the purpose of regression, classification, and other tasks, random forests, referred to as random decision forests, are ensemble learning techniques that work by creating an extensive number of decision trees during training and producing a class that represents the mean/average prediction (regression) or the mode of the classes (classification) of the individual trees. The risk of decision trees to overfit to their training set has been accounted for by random decision forests. Despite they are less accurate than gradient boosted trees, random forests still perform better than choice trees in most cases. Their performance, however, may be altered by the unique qualities of the data.

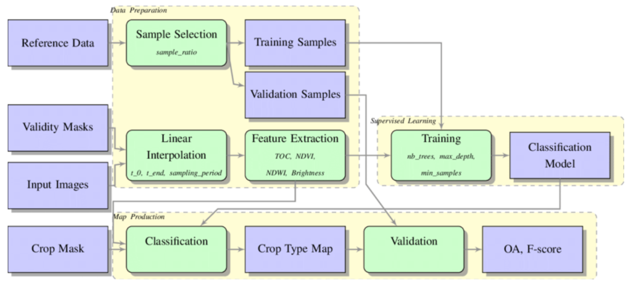
A common approach for solving different kinds of issues related to machine learning is the use of decision trees. Hastie et al. state that tree learning "come[s] closest to meeting the requirements for serving as an off-the-shelf procedure for data mining" because it is robust to the inclusion of irrelevant features, produces inspectable models, and is invariant under scaling and various other transformations of feature values. They are rarely accurate though.

Thoroughly established trees in particular have a propensity to learn extremely erratic patterns; they overfit their training sets, result in low bias but enormous variation. In order to lower the variance, random forests are an algorithm for averaging several deep decision trees that were trained on various portions of the same training set. This often considerably improves the final model's performance, but at the cost of a slight increase in bias and some interpretability loss. Forests are similar to the fruition of efforts made by decision tree algorithms. using the collaborative efforts of different trees to improve the performance of a single random tree. Forests provide the effects of a K-fold cross validation, albeit not exactly similarly.

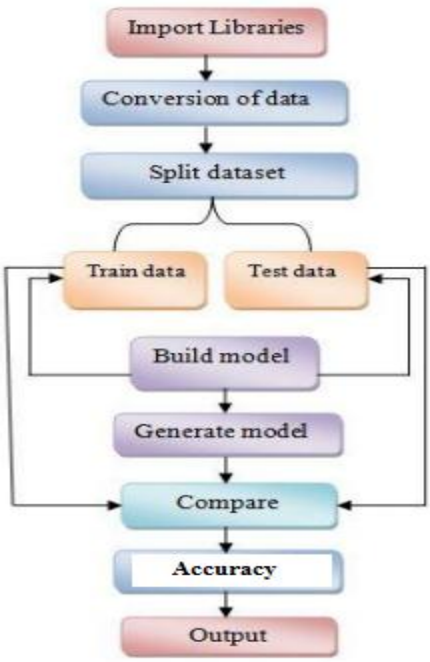
IV. Proposed system

A class of artificial neural networks referred to as a recurrent neural network (RNN) has connections between nodes which generate a graph along a temporal sequence. It can now display dynamically dynamic behavior as a result. RNNs, which are derived from feed forward neural networks, have the capacity of processing input sequences of varying length using their internal state, or memory. They can thereby be used for tasks like speech recognition or unsegmented, corresponding handwriting recognition. When we refer about two broad kinds of networks with equivalent general structures—one that has limited impulse and the other with infinite impulses—we call them "recurrent neural networks" without distinction. Networks in both groups behave continuously over time. An infinite impulse recurrent network is a directed cyclic graph that cannot be unrolled, whereas a finite impulse recurrent network is a directed acyclic graph that can be unrolled and replaced it with a strictly feedforward neural network.

SYSTEM ARCHITECTURE



Flow chart



Additional stored states can be included in both finite impulse and infinite impulse recurrent networks, and the neural network may directly control the storage. If the storage has feedback loops or time delays, it can also be changed out for another network or graph. These regulated conditions, which are an important part of gated recurrent units and memory networks (LSTMs), are known as gated states or gated memory. A different designation for this is a Feedback Neural Network (FNN).

V. Conculsion

Multiple research studies and analyzes have taken us to the conclusion that utilizing a number of machine learning algorithms will not just help farmers achieve greater success, but also increase their revenue—for many, this is a matter of life and death. Farmers currently make educated predictions based on previous performance and plan accordingly; but, employing machine learning (ML) will reduce error margins and yield superior results. The suggestions that this planned system would offer are certain to help farmers in growing better and higher-yielding crops.

REFERENCES

[1] Mayank Champaneri, ChaitanyaChandvidkar, DarpanChachpara, MansingRathod, “Crop yield prediction using machine learning” International Journal of Science and Research, April 2020.

[2] Pavan Patil, VirendraPanpatil, Prof.ShrikantKokate, “Crop Prediction System using Machine Learning Algorithms”, International Research Journal of Engineering and Technology, Feb 2020.

[3] Ramesh Medar, Shweta, Vijay S. Rajpurohit, “Crop Yield Prediction using Machine Learning Techniques”, 5th International Conference for Convergence in Technology, 2019.

[4] TruptiBhange, Swati Shekapure, Komal Pawar, HarshadaChoudhari, “Survey Paper on Prediction of Crop yield and Suitable Crop”, International Journal of Innovative Research in Science, Engineering and Technology, May 2019.

[5] E. Manjula, S. Djodiltachoumy, “A Modal for Prediction of Crop Yield”, International Journal of Computational Intelligence and Informatics, March 2017.

[6] Nishit Jain, Amit Kumar, SahilGarud, Vishal Pradhan, Prajakta Kulkarni, “Crop Selection Method Based on Various Environmental Factors Using Machine Learning”, International Research Journal of Engineering and Technology (IRJET), Feb 2017.

[7] Rakesh Kumar, M.P. Singh, Prabhat Kumar, J.P. Singh, “Crop Selection Method to Maximize Crop Yield Rate using Machine Learning Technique”, 2015 International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM), Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, T.N., India., May 2015.

[8] Liu Qingyuan, and Wang Tianchuan, “Market price theory and practice”. Dalian: Northeast University of Finance and Economics Press, 1998, pp. 15-20.

[9] R. S. Pindyck, and D. L. Rubinfeld, “Econometric Models and Economic Forecasts”, The McGwar-Hill Companies, Inc, 1998, pp. 251-260.

[10] Yao Xia, Peng Hangen, and Zhu Yan, “ARIMA Time Series Modeling and Applying on Fresh Agricultural Products”, System Sciences and Comprehensive Studies in Agriculture, vol. 23, Feb. 2007 , pp. 88-94.

[11] Nie Rong, Qin Keming, and Zhang Xiaohong, “Stochastic Model and Risk Measuring on the Farm-produce′s Price”, Mathematics In Practice and Theory, vol. 34, Nov. 2004, pp. 108-112.

[12] Zhang Xiaioshuan, “Research of Aquatic Products Price Forecasts Support System”, Beijing: China Agricultural University, 2003, pp. 10-15.

[13] Yu Shouhua, Huang Haoran, and Ou Jingying, “Vegetables Prices Prediction Research of Regional Agricultural Products Wholesale Market”, Research of Agricultural Modernization, 27 monog, Dec. 2006, pp. 118-120.

[14] Cheng Xianlu, “Vegetables Prices Forecast and Predict System Research of Beijing's Agricultural Products Wholesale Market”, Beijing Agricultural Sciences, Feb. 2002, pp. 1-10.

[15] Yuan Zenren, “Artificial neural network and applications”, Beijing: Qinghua University Press, 1998, pp. 13-14.

[16] MT Hagan, and MB Menhaj, “Training Feed Forward Networks with Marquart Algorithm”, IEEE Trans.on Neural Networks, vol. 5, June 1994, pp. 989-993.

[17] Xu Dong, and Wu Zhen, “System analysis and design-neural network based on the MATLAB6.X” (the 2nd version), Xi’an: Xi’an Electronic Technology University Press, 2002, pp. 30-33.

[18] Li Xiaofeng, “New improvement of BP neural network and its application”, Journal of Jilin Institute of Chemical Technology, vol. 17, Dec. 2000, pp. 48-51.

[19] Gao Ling, “The crop pest situation forecasting and achieving in MATLAB based on BP neural network”, Hefei: Anhui Agricultural University, 2003, pp. 45-52.