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Smart Farming using Machine Learning and Deep Learning Techniques

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Abstract: **Agriculture is defined as the practice of growing crops, raising livestock and cultivating plants. As we all know agriculture is key in growing the economy of any nation. About 58 percent of a country primary means of survival is agriculture. Farmers till date had adopted conventional farming techniques. These techniques were not exact thus lowered the output and were time-consuming. Specific agriculture assists in improving the output by accurately expecting the steps that need to be performed at the right time. Weather forecasting, soil assessment, crop selection, fertilizer and pesticide management are some components of precision farming. IOT, Data Mining, Data Analytics, Machine Learning are some advanced technologies that can be employed in doing Precise Farming. It helps to know how much manual efforts are necessary and how productivity can be enhanced. Farmers have been facing various challenges in these recent times, this includes crop failure due to less rains, infertility of the soil etc. Because of the changing conditions most recently, the proposed work helps to understand how crops and harvest can be managed intelligently and one does not compromise with the yield.**

Keywords: **Data Mining, Machine Learning and Smart Farming**.

1. INTRODUCTION

Agriculture which is also widely known as farming can be simply defined as the growing of crops as well as the rearing of livestock. Its significance in the economy of a nation is considerable. Many raw materials and food products are produced by agriculture. Cotton and jute that are grown are raw materials used in industries to manufacture various goods for consumers. The resources which can be utilized for making value added products are also souring from Agriculture in addition to the food resources. Agriculture is carried out by using some cultural practices on the growth of the crops. Conventional or traditional farming is still the commonest of agricultural practices in most parts of the world. There are techniques that are employed and advocated by experienced farmers. These techniques are not accurate so therefore do take quite a lot of effort and time to achieve the end results.

Precision Agriculture is the application of digital technologies which includes robots, electronics devices, sensor and automation technologies. Its purpose is to reduce the amount of work needed to complete an activity, improve profitability, and improve decision control. These technologies aim to optimize farming inputs and durable maximization of output. Apart from being known as Precision farming, It is a farming management system which allows for monitoring and control of variability in farming practices for the purpose of improving the overall production efficiency of the whole system [?].It may be worthwhile to note that if we discuss the adoption rate of precision agriculture, the adoption rate in high value enterprise dimension farms langauage is higher as compared to the low value enterprise dimension farms. Moreover, the rate of adoption of precision agriculture is also correlated with the country and area places. The adoption of the Zone With greater location in mountain sowever, is lower adoption compared with valley for farmers of the farmers in the valley [2]. This change in practice is however expected because of the low costs required to. There- fore, there is need to come up with a way in order to reduce the cost on machineries so that the small farmers can also practice precision farming.

However, a much more precise definition is that precision agriculture is all about the application of high technology equipments to include: IoT, Innovation based on Large data analysis, Artificial Intelligence, Data Science and the likes. Internet of Things (IOT) here refers to a system of interconnected computing devices, sensors, and other smart devices that can communicate and exchange data with one another [3]. In agricultural uses, wireless sensor networks are used to monitor temperature and other soil attributes remotely for the purpose of determining the status of the crops. WSN as a forecasting technique can also be used to forecast when agricultural fields will be watered. Wireless Sensor Networks measure external variables like pressure; humidity; tem perature; and soil moisture-high frequency of salinity and conductivity [4].

2. LITERATURE SURVEY

The salt and the mineral concentration within the soil, together with other nutrients, primarily determines the production of crops. Considering soil as a generalized reflection of many of the environmental factors, such factors include the amount of rainfall, humidity, sunlight, temperature, and the soil's PH. It has been proposed that the classification of the type of crop from micronutrients and metrological characteristics using a decision tree algorithm and a support vector machine is an effective solution for predicting the crop. Three selected crops include wheat, rice, and sugarcane. from certain observations about the details of specific micronutrients were obtained. These details were used to train the classifier model which in turn gave the output crop as per the values passed. There exist many Machine Learning algorithms, which are capable of performing similar tasks in different ways. So just two models will not execute the desired output. The performance of the algorithmic components in the 12th is ranked, 91 percent for SVM as opposed to the decision tree algorithm. In this work we pick one of the two algorithms, the best performing algorithm. Different algorithms exist for classification tasks. The need to combine And looking for working other models classifiers, K Neighbors classifier, Ensemble classifiers, or Logistic Regression is emphasized. These algorithms are indeed applied in proposed research work. The data mining in the [9] models only makes a prediction, i.e., a crop that can be the output value given to the SVM model. Such data is highly essential. Therefore, more value could be derived beyond their scope of usage for predictive purposes. The proposed research work not only recommends the crops and also harnesses that enterprise information to obtain some details that were used to explain the predicted crops this includes the amount of Growing Degree Days such as heat units, Mean quantity of heat required by the crop development and the mean quantity of nitrogen, phosphorous and potassium content that can be supplied for the growth per 200 lb. fertilizer.

Such machine Learning algorithms as SVM and decision tree classifiers were employed [14] but in this work Machine Learning algorithms such as Decision Tree, K Nearest Neighbor, Linear Regression model, Neural Network, Naive Bayes and Sup- port Vector Machine have been employed for crop recommendation to the users. It has provided an exposure to other algorithms compared to [09]. Linear Regression model was applied to estimate the rate of production with regard to certain weather conditions such as rainfall, temperature and humidity atgression the values where all less than 90 percent, [9]'.For the present study, a model implementation based on given data was done. A web interface needs to be developed so that even common people can exploit it efficiently.

The input values should be moderated for the model to predict the crop. The pro- posed work uses web scraping to extract temperature and humidity values, for which the manual input is not needed. The proposed work provides an interactive web inter- face, where a user specifies the average rainfall and soil pH values. The temperature and humidity details are automatically extracted and fed into the best model that consists of 10 algorithms with hyper parameter tuning. The proposed work aims to maintain an accuracy of 95.45 percent with hyper parametric tuning algorithms, which, to date, has not been reported in [10]. The predicted results with some handy information are displayed in the web interface, enabling the user to understand the results more efficiently. Growing Degree Days GDD can also be calculated on the base temperature of a crop. This study strives for viability and mathematically acceptable formulas that will assist in GDD's base temperature calculations. Temperature data for snap beans, sweet corn, and cowpeas are used to develop, prove, and test mathematical formulas.

3. CHALLENGES AND EVOLUTION

Precision agriculture with machine learning and deep learning is held with great promise but also involves several challenges. Firstly, popper investments in the technologies of precision farming would limit one adoption, especially those smaller farms that could not muster sufficient financing. In tandem, additional massive amounts of data cover various fields of dimensions, such as those observed from the soil and weather or those dealing with crop health. Another perturbing factor in precision is to obtain consistent data sources and ensure that every other categorical prediction provides reliable information. Most models may not yield accurate results because of mismatched data sources resulting in discrepancies in predictions. Models fear obstacles in terms of specificity, as there are farming environments they differ to. For example, some machine learning models may be tailored to one climatic condition and soil type. These models may be expected to perform inaccurately in many other regions due to environmental variations.

Since weed and pest identification are still difficult, the adaptation of most current models to real-time variations in crop appearance is limited in development regions, thus limiting advanced algorithms that farmers may use at larger scales. Further, the absence of standardized datasets in agricultural AI means model training is erratic and results are less reliable.

4. FUTURE DIRECTIONS

Increased affordability and adaptability to different operating scales should be at the forefront of precision agriculture research. The reduced cost of IoT sensors, coupled with an open, standardized platform, may become key drivers for adopting such technology on a wider scale. For example, harnessing edge computing rather than cloud-based solutions may help make data processing cost-effective, as it would allow for processing of data at a farm level. Further, model generalization across diverse crop- ping systems and weather conditions needs to be improved to raise the effectiveness of AI models .

Advanced machine learning techniques, including transfer learning and federated learning, offer some solutions to all these challenges arising from data. These strategies enable the adaptation of models to a new data set with minimal retraining, thus supporting a range of applications. By integrating blockchain technology with IoT in agriculture, concerns about data security and reliability could also be addressed by providing a decentralized platform for real-time monitoring and integrity of data . Research institutions and agricultural technology are refining algorithms to ensure accuracy and reliability while also developing user-friendly interfaces that render insights derived from AI simpler for non-technical users to digest.

5. CONCLUSIONS

Precision agriculture has the potential to define the very future of farming on the counts of productivity, sustainability, and, indeed, profitability with cutting-edge machine learning and IoT technologies. A few other challenges of cost, complexity of the data in terms of that goes into agri-production, and the adaptability of the environment are said to be some but not all of the challenges that would need to be met in order to benefit from this effort. Future research should involve addressing the standardization of data collection, reduction of technology costs, and enhancement of model adaptability upon agricultural landscapes for effective utilization. Transfer of learning emerging techniques and integration with blockchain could additionally facilitate introducing secure, scalable, and adaptable solutions for precision agriculture. Collaboration among researchers, farmers, and technology developers in freely exchanging the experiences derived to build accessible, effective, and resilient agriculture technologies may elements necessary for the future of farming.

Table 1 Comparison outlining each study's authors, techniques, advantages, and disadvantages.

Authors	Methodology Used	Strengths	Limitations
Rubina Rashid et al. (2024)	The paper proposes a Multi-Model Fusion Net- work (MMF-Net) based on CNN	High accuracy (99.23 percent)	Real-time constraints, reliance on environmental data quality.
Vasileios Balafas et al. (2022)	Review of ML/DL techniques in plant disease classification (binary/multi-class) and object detection	Comprehensive review (79 studies), latest works included (until 2022)	Limited real-world analysis, dataset dependency challenges with object detection in complex environments
Jorge Fuentes-Pacheco et al. (2024)	Curriculum by Smoothing (CS) with ResNet50V2, testing nitrogen levels in basil plants using 144 RGB images per class;	Achieves 7 percent higher accuracy than traditional transfer learning, effective with small datasets, pro- vides new dataset available for the scientific community.	Focuses on a controlled environment , limited generalizability, small dataset increases model susceptibility to variance.
Youssef N et al. (2024)	RF-sensing-based moisture estimation in grapes, using machine learning models (LSTM, GRU, Bi- LSTM)	Improves RMSE and MAE by 12 percent, enhances sustainability in agricultural practices through optimized ML models, non-invasive RF sensing.	Limited to grape moisturedata, requires specialized sensing equipment, some methods are computationally intensive
Nabila Elbeheiry et al. (2023)	A systematic review of 588 research articles using Cochrane methods to ensure structured analysis.	Detailed coverage of technological components in smart farming	Limited focus on non-technical aspects (e.g., social or economic challenges.
Muhammad Umar et al. (2024)	Developed a YOLOv7-based model for detecting and classifying tomato leaf diseases. Integrated SIFT for image segmentation and CNN for classification.	High accuracy (98.8 percent) in disease classification using advanced CNN and YOLOv7 models.	Limited by the quality of the training dataset (e.g., stable environment images).
Rayner Alfred et al. (2022)	Systematic literature review (SLR) focusing on the applications of Big Data, Machine Learning, and IoT in rice 6production	Comprehensive analysis of data sources, algorithms, and processes in rice smart farming.	The review is limited to paddy rice applications, which narrows generalization to other crops

Gabriele Patrizi et al. (2022)	Utilizes Long Short-Term Memory (LSTM) neural networks to develop virtual soil moisture sensors.	Reduces cost by eliminating the need for expensive soil moisture sensors.	LSTM models require significant computational resources and complex training.
Mahrin Tasfe et al. (2024)	Surveys deep learning architectures such as CNNs, Vision Transformers (ViTs), and lightweight models.	Provides a detailed survey with performance metrics, datasets, and architectures..	Some models (e.g., ViTs) require high computational resources.
Jalal Uddin et al. (2024)	Analyzes over 100 research papers on deep learning for greenhouse applications, including disease detection, yield estimation, and growth monitor-	Fills a literature gap by focusing on greenhouse environments.	Limited labeled data for greenhouse-specific applications.

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