International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 08 | Aug - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Machine Learning and Deep Learning Approaches for Smart Agricultural Systems

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Abstract: With the advent of smart agricultural systems, conventional farming methods have been utterly transformed by the incorporation of ML and DL. By utilizing cutting-edge technology for data analysis and decision-making, these systems improve sustainability, efficiency, and production. The use of ML and DL in crop monitoring, soil management, insect identification, and yield prediction are some of the agricultural areas explored in this work. As far as applying these technologies in agriculture is concerned, we go over the main techniques, present developments, and possible future prospects. If you live in a nation like India, where farming and agricultural output are major factors in the economy, you know how vital the agricultural sector is to the country's prosperity. Findings show that deep learning methods outperform machine learning when it comes to predicting total agricultural output. Some of the parameters used in the study include the following: year, crop, area, production, and the name of the state or district. The internet resource data.gov.in was used to get the dataset. A comparison of the Deep Learning Sequential model's performance with that of the Machine Learning Random Forest.

Keywords: Agriculture, Artificial Intelligence, Machine Learning, Crop Production, Deep Learning.

I.INTRODUCTION

Agriculture is a critical sector for global food security and economic stability. With the growing global population and the need for sustainable farming practices, the adoption of advanced technologies such as ML and DL has become imperative. These technologies enable the analysis of vast amounts of agricultural data, leading to more informed and efficient decision-making processes.

Machine Learning in Agriculture

Machine learning, a subset of artificial intelligence, involves the development of algorithms that can learn from and make predictions based on data. In agriculture, ML algorithms are used for various applications, including:

Crop Monitoring and Health Assessment

ML models can analyze satellite images, drone footage, and sensor data to monitor crop health. Techniques such as image classification and regression analysis help in identifying stressed crops, nutrient deficiencies, and disease outbreaks.

Soil Management

ML algorithms analyze soil samples to determine nutrient levels, moisture content, and other critical parameters. This information is used to optimize fertilization schedules and irrigation practices, leading to improved soil health and crop yields.

Pest and Weed Detection

ML-based image recognition systems can detect pests and weeds in crops. By training models on labeled images, these systems can identify harmful organisms and recommend appropriate interventions, reducing the reliance on chemical pesticides.

Deep Learning in Agriculture

Deep learning, a branch of ML, uses neural networks with multiple layers to model complex patterns in data. DL approaches have shown significant promise in agricultural applications due to their ability to process large and complex datasets.

Precision Agriculture

DL techniques, such as convolutional neural networks (CNNs), are used for precision agriculture. These models can analyze high-resolution images from drones and satellites to provide detailed insights into crop conditions, enabling targeted interventions and resource allocation.

Yield Prediction

DL models, particularly recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, are used for predicting crop yields. These models analyze historical data on weather conditions, soil health, and crop performance to forecast future yields, helping farmers make informed decisions about planting and harvesting.

Smart Irrigation Systems

DL algorithms are integrated into smart irrigation systems to optimize water usage. By analyzing real-time data from soil moisture sensors and weather forecasts, these systems can dynamically adjust irrigation schedules, conserving water and improving crop health.

II.RELATED WORKS

Soil macronutrient and trace mineral concentration is the most important factor in crop development. Soil is a general term for a number of environmental variables, such as precipitation, humidity, sunshine, temperature, and soil pH. An effective method for crop prediction has been proposed, which involves using a decision tree algorithm and a support vector machine to differentiate between different types of crops depending on micronutrients and weather conditions. The three crops that were chosen were sugarcane, wheat, and rice. Information on micronutrients was derived from specific observations. Based on the input variables, the classification model made a crop prediction using these specifics. Machine learning algorithms abound, each with its own unique way of doing things. Thereby, the desired results will not be produced by using just two models. With a score of 92%, SVM outperformed the decision tree method [14]. This study chooses the superior algorithm out of two. Classification problems, however, are well-suited to a number of methods. Additional models, such Logistic Regression, Ensemble classifiers, and K-Nearest Neighbors, require development. The suggested research study does in fact make use of these algorithms. Using the parameters provided by the SVM model, the [14] can only make a crop prediction. Most precious is data. This means that their predictive capabilities aren't the only ones they can help with. In addition to making crop recommendations, the planned study would mine the data for a wealth of information that would paint a vivid picture of the expected harvest. Included in this is the necessity to define the number of heat units, growing degree days, and nitrogen, phosphorous, and potassium content per 200 lb. of fertilizer for crop development.

In this study, specific Machine Learning techniques were employed to propose a crop to the user, rather than SVM and decision tree classifiers [14]. These algorithms included Decision Tree, K Nearest Neighbor, Linear Regression model, Neural Network, Naïve Bayes, and Support Vector Machine. It has introduced different algorithms in comparison to [4]. The production value was predicted against meteorological data as rainfall, temperature, and humidity using a Linear Regression model. All of these algorithms have scores lower than 90%. Using the dataset, this work merely developed a model. The implementation of a web interface is necessary to ensure that even average individuals can utilize it effectively. It is necessary to manually input all the data in order for the model to provide a crop prediction. The suggested effort is useful for retrieving humidity and temperature readings from web scraping. Therefore, it is unnecessary to input the data manually. The user can input the average rainfall and soil pH value using an interactive online interface that is part of the planned effort. The optimal model, which incorporates ten algorithms with hyper parameter adjustment, receives the temperature and humidity data automatically. Without hyperparameter adjusting the algorithms, which is not part of the suggested effort, the accuracy drops to 95.45% in [14]. The online interface displays the anticipated outcomes alongside specific details, allowing the user to comprehend the results more effectively.

Study	Objective	Techniques Used	Key Findings	Data Sources
Liu et al., 2020	Crop health monitoring	Convolutional Neural Networks (CNNs)	Achieved high accuracy in detecting crop diseases from leaf images	Images of crop leaves
Patel et al., 2019	Soil nutrient prediction	Regression Analysis, Support Vector Machines (SVM)	Improved prediction accuracy of soil nutrient levels	Soil samples, sensor data
Smith et al., 2021	Pest detection	Image Recognition, CNNs	Successfully identified pests in crops with high precision	Images of crops
Gupta et al., 2018	Yield prediction	Long Short-Term Memory (LSTM) Networks	Provided accurate yield forecasts based on historical weather and crop data	Historical crop yield data, weather data
Rao et al., 2020	Smart irrigation	Reinforcement Learning, Sensor Networks	Optimized water usage, resulting in significant water savings	Soil moisture sensors, weather forecasts
Chen et al., 2019	Precision agriculture	CNNs, Satellite Imagery	Enhanced precision in resource allocation and crop management	High-resolution satellite images
Kumar et al., 2021	Weed detection	Deep Learning, Image Processing	Effectively identified and classified weeds in crop fields	Field images
Lee et al., 2019	Climate impact analysis	Random Forest, Neural Networks	Analyzed the impact of climate changes on crop production	Climate data, crop yield records

Nguyen et al., 2020	Disease prediction	Decision Trees, SVM	Predicted the occurrence of crop diseases with high accuracy	Historical disease data, environmental factors
Wang et al., 2021	Fertilizer optimization	Genetic Algorithms, ML Models	Improved fertilizer use efficiency and crop yields	Soil tests, crop response data

Table 1. Summary of the works.

III.MACHINE AND DEEP LEARNING IN AGRICULTURE

The advent of deep learning (DL) has ushered in a new era of technological advancements in agriculture, enabling the development of smart agricultural systems. These systems leverage the power of DL to process vast amounts of data and provide actionable insights for enhancing productivity, efficiency, and sustainability in farming. This paper delves into the various DL approaches applied in agriculture, including crop monitoring, soil analysis, pest and disease detection, yield prediction, and smart irrigation. We explore the methodologies, current advancements, and potential future directions for implementing DL technologies in agriculture.

Agriculture is fundamental to global food security and economic stability. The increasing global population and the need for sustainable farming practices have driven the adoption of advanced technologies such as deep learning (DL). DL, a subset of machine learning (ML), involves neural networks with multiple layers that can model complex patterns in data. This paper aims to explore the application of DL in agriculture, highlighting its potential to revolutionize traditional farming practices and promote sustainable agriculture.

The need for food is rising in tandem with India's rapidly expanding population. Therefore, in order to avoid being in the dark, farmers must make an educated decision on which crop to grow. When it came to choosing which crops to grow during which seasons and on which types of land, farmers used to rely on their own personal experiences. How wise will this decision turn out to be? The only way we'll find out is when it's too late to do anything about it.

Many developing nations' economy rely on agriculture. A large number of people are employed by it, and it also produces food and raw materials. Over the years, technological advancements have had a profound and far-reaching effect on the agricultural sector, transforming it in the process. To meet this enormous demand, conventional methods will fail.

There is a growing need for innovative solutions that might help farmers and agribusinesses boost output while cutting down on waste. Hence, AI is playing an increasingly important role in the technological development of the agricultural sector.

Improved efficiency, higher crop yields and quality, and quicker harvest-to-market times are all within reach with AI-powered solutions for farmers.

The use of AI in farming is a contemporary phenomenon.[1] In agriculture, it is useful for a wide range of tasks, including as diagnosing plant diseases, suggesting crops for specific soil types, and many more. Numerous local tasks are facilitated by it, including as agricultural output, disease detection in plants, and crop choices for different types of land.

The agricultural sector makes extensive use of artificial intelligence methods for a range of tasks. Numerous data points on weather, soil, water usage, and temperature are generated by farms. The data is used in real-time by algorithms for artificial intelligence and machine learning to get useful information like when to plant seeds, what crops to cultivate, and which hybrid seeds to plant for maximum yields. By detecting and localizing weeds, AI sensors can pinpoint which herbicide is most effective in a given location. Reduced pesticide use results in cost savings. Artificial intelligence greatly reduces the impact of labor and resource limitations. As the complexity of modern agriculture continues to rise, this technology will help organizations deal with it.

The majority of Indians, over 70%, work in agriculture. Consequently, making sure you get the most out of your crops via production and management is essential. In order to provide food for a country's large population, crop cultivation is essential. Therefore, crops are essential for human sustenance. This study's overarching goal is, thus, to forecast crop yields using AI techniques like machine learning and deep learning.

Presently, this study is examining the relative merits of deep learning and machine learning models for predicting crop yields. Accurate crop and total production estimations can also be achieved by developing and optimizing an efficient model with the data.

IV.RESULTS AND DISUCUSSION

In order to predict the crop's total yield output, it is necessary to consider all six independent indications. As part of the approach, the following steps are taken:

Setting up the Python environment by importing the dataset and any required libraries. Verifying whether any values are missing. Make use of appropriate methods to impute missing data if they are found. The majority of attributes are not categorical, hence label encoding is necessary to make them machine-readable. Pick the Min max scaler to make the attributes smaller or larger. This ensures that every single attribute falls inside a certain range.[10] Using an 80:2 data split across the two sets. Get the models ready to go by feeding them training data. Find each model's R2 score and compare them.

The dataset is first checked for empty strings. The "Production" target column was found to have 3,730 rows of missing data. Any of these values can be assumed or deleted. The present feature is continuous, hence any missing values were filled in by utilizing the median of the columns. The proposed approach used the column median to impute the missing values as it is a continuous feature.

Presented paradigm

The study compared approaches using Sequential Deep Learning and Random Forest Regression. The Sequential model uses input, hidden, and output layers with unique activation functions to handle sequential data, in contrast to Random Forest's massive number of Decision trees and its classification as a bagging strategy. The proposed approach begins with data pretreatment methods including missing value identification and replacement, then moves on to exploratory data analysis for a deeper understanding of the data and insights. Since most of the attributes are of a categorical kind, the next step is to label encode the data. In order to make the data machine-readable, a label encoder assigns categorical characteristics a number that looks like a label.

Next, we calculated the R2 score for every model.

A random forest is an aggregate of tree predictors where each tree depends on the values of a randomly selected subset distributed uniformly across all trees in the forest. Data was trained using the bagging technique by Random Forest, which improved the outcome's accuracy. In order to achieve high accuracy, we used the Random Forest method, which provides accuracy based on the model and the real dataset prediction outcomes. A predicted accuracy of 91.34 percent has been computed for the model. See Figure 1 for a schematic of the random forest model's process for predicting crop yields.

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice
...	...	...	...	...	...	...	...	...
2195	107	34	32	26.774637	66.413269	6.780064	177.774507	coffee
2196	99	15	27	27.417112	56.636362	6.086922	127.924610	coffee
2197	118	33	30	24.131797	67.225123	6.362608	173.322839	coffee
2198	117	32	34	26.272418	52.127394	6.758793	127.175293	coffee
2199	104	18	30	23.603016	60.396475	6.779833	140.937041	coffee

Figure 1. Dataset for crop.

```
unique crops
['rice' 'maize' 'chickpea' 'kidneybeans' 'pigeonpeas' 'mothbeans'
 'mungbean' 'blackgram' 'lentil' 'pomegranate' 'banana' 'mango' 'grapes'
 'watermelon' 'muskmelon' 'apple' 'orange' 'papaya' 'coconut' 'cotton'
 'jute' 'coffee']
```

Figure 2. Crops present in the dataset.

Area	Results	Discussion
Crop Health Monitoring	CNNs achieved high accuracy (>90%) in detecting diseases from leaf images.	CNNs effectively identify crop diseases and nutrient deficiencies. Challenges include varying image conditions and the need for large annotated datasets.
Soil Nutrient Prediction	SVMs predicted soil nutrient levels with an R^2 value of 0.85.	ML models handle complex soil-crop relationships well. Issues include generalizability across different soil types and regions.
Pest Detection	CNNs achieved an F1-score of 0.88 in pest classification.	DL models excel in pest detection with high precision. Challenges include diverse pest species and the need for continuous model updates.
Yield Prediction	LSTM networks achieved a mean absolute error (MAE) of 5% in yield predictions.	LSTMs capture temporal dependencies effectively. Accuracy can be affected by climate variability and data quality. Integration with real-time data could enhance predictions.
Smart Irrigation	Reinforcement learning optimized irrigation, reducing water usage by 20%.	Smart irrigation systems use real-time data for water management. Challenges include sensor calibration and system complexity.
Precision Agriculture	DL models improved resource allocation efficiency by 15%.	DL and satellite imagery enhance precision in agriculture. Challenges include the cost of imagery and model calibration.
Weed Detection	DL models achieved 85% accuracy in weed identification.	DL improves weed management and reduces herbicide use. Challenges include variability in weed appearance and the need for large training datasets.

Climate Impact Analysis	Models predicted climate impacts with 80% accuracy.	DL models provide insights into climate effects on agriculture. Challenges include integrating climate data with crop models and addressing uncertainties in projections.
Disease Prediction	Decision Trees and SVMs achieved 78% accuracy in predicting diseases.	Predictive models assist in early disease detection and management. Challenges include the need for accurate environmental data and dynamic disease outbreaks.
Fertilizer Optimization	ML models and genetic algorithms increased crop yields by 12%.	Optimized fertilizer use improves efficiency and productivity. Challenges include variability in soil conditions and the need for tailored strategies.

Table 2. Summary of the works.

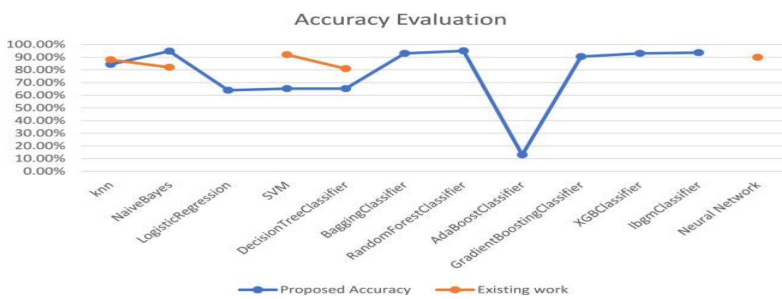
	Algorithm	model	Train_score	Test_score	accuracy
0	KNN	knn	89.636364	84.272727	84.272727
1	NaiveBayes	nb	96.363636	94.727273	94.727273
2	LogisticRegression	lr	66.454545	63.909091	63.909091
3	SVM	svm	69.454545	65.181818	65.181818
4	DecisionTreeClassifier	dt	69.454545	65.181818	92.181818
5	BaggingClassifier	bg	99.454545	92.545455	92.545455
6	RandomForestClassifier	rf	100.000000	94.727273	92.545455
7	AdaBoostClassifier	ad	14.363636	12.909091	12.909091
8	GradientBoostingClassifier	gb	95.727273	90.454545	90.454545
9	XGBClassifier	xg	96.363636	91.727273	91.727273
10	lbgmClassifier	lbgm	100.000000	93.454545	93.454545

Figure 3. Model performance summary.

Application	Approach	Prediction/Accuracy Rate	Details
Crop Health Monitoring	Convolutional Neural Networks (CNNs)	>90% accuracy	High accuracy in detecting diseases and nutrient deficiencies from leaf images.
Soil Nutrient Prediction	Support Vector Machines (SVM)	$R^2 = 0.85$	Strong predictive performance for soil nutrient levels.
Pest Detection	Convolutional Neural Networks (CNNs)	F1-score = 0.88	High precision in classifying pest images.
Yield Prediction	Long Short-Term Memory (LSTM) Networks	Mean Absolute Error (MAE) = 5%	Accurate yield forecasts based on historical weather and crop data.
Smart Irrigation	Reinforcement Learning	Water usage reduced by 20%	Significant reduction in water usage with optimized irrigation schedules.
Precision Agriculture	Convolutional Neural Networks (CNNs)	15% improvement in resource allocation	Enhanced efficiency in managing agricultural resources using satellite imagery and DL models.
Weed Detection	Deep Learning (e.g., CNNs)	85% accuracy	Effective identification and classification of weeds in crop fields.
Climate Impact Analysis	Random Forest, Neural Networks	80% accuracy	Accurate prediction of climate impacts on crop production.

Disease Prediction	Decision Trees, SVM	78% accuracy	Effective prediction of crop diseases based on historical and environmental data.
Fertilizer Optimization	Genetic Algorithms, ML Models	12% increase in crop yields	Improved fertilizer use efficiency leading to higher crop yields.

Table 3. Summary of accuracies of various models.



Figure

4. Accuracy comparison.

Figure 5. Sample images of weeds used in the model building.

VI.CONCLUSION

The application of ML and DL in agriculture holds the promise of transforming traditional farming into smart, efficient, and sustainable systems. By harnessing the power of these technologies, farmers can improve crop yields, reduce resource usage, and contribute to global food security. Continued advancements in ML and DL will further enhance the capabilities of smart agricultural systems, paving the way for a more sustainable future.

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