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Research Article

Agricultural Crop Analysis using IoT And Machine Learning

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ABSTRACT

The power of the IoT and machine learning could radically transform agriculture using precision agriculture. Sensor data in real-time is available to farmers, allowing them to select crops and management techniques in an enlightened manner. Machine learning algorithms process the information to predict which crops are best suited for a location's soil type, weather conditions, and other factors. This combination leads to increased resource use efficiency, improved crop production, proactive risk management, more responsible agriculture, and an opportunity for farmers to obtain data-driven suggestions. To maximize the benefits of these technologies, it is important to address problems like data rights and availability, as well as connectivity issues. This would allow for the continuation of R&D in the field.

Abbreviations: Internet of things(IoT), Research and Development(R&D), Machine Learning(ML), Crop suitability mapping

1. Introduction:

The predominant challenge in agriculture lies in comprehending the fluctuating climate patterns, crucial for optimal crop growth. Precision farming offers a solution, sustaining productivity and boosting yields by aligning farming practices with specific crop requirements. In India, sustaining agriculture is vital amid rising demands, where traditional methods' limitations can be mitigated through precision farming[1]. Leveraging IoT and predictive systems, precision farming aids decision-making by collecting field data for recommendations. Despite efforts to minimize losses, challenges persist in crop selection and adapting to climate shifts, exacerbated by shortcomings in current prediction methods. The proposed system aims to address these issues by enhancing yields, conducting real-time crop analysis through IoT, and optimizing parameter selection for informed decisions. Effective algorithms are pivotal for early crop prediction, utilizing ML models to generate valuable data for crop selection. The crop suggestion model's primary goal is to reduce losses by recommending suitable crops for specific fields, necessitating careful algorithm selection to ensure accuracy. Machine Learning emerges as the most promising technology for precise crop prediction and yield estimation[2].

2. Related Works

Forecasting crop yields is crucial for decision-makers at national and regional levels, expediting informed decisions. Accurate prediction models empower farmers in critical choices regarding crop selection and cultivation timing. Various methodologies, particularly machine learning (ML) techniques, have been explored for crop yield prediction. This section offers an overview of pertinent literature, excluding surveys and traditional reviews, to illuminate research trends in this area[4].
Chlingaryan and Sukkarieh (2018) conducted a thorough review on nitrogen status estimation using ML techniques, stressing the importance of sensing technologies and ML advancements in cost-effective agricultural solutions[5]. Elavarasan et al. (2018) surveyed ML models for crop yield prediction, emphasizing the significance of incorporating diverse climatic parameters for improved accuracy[6].
Liakos et al. (2018) provided a review encompassing ML applications in various agricultural domains, highlighting ML's diverse impact on agricultural practices. Li, Lecourt, and Bishop (2018) examined fruit

ripeness determination for optimal harvest timing and yield prediction, underscoring the necessity of accurate predictive models in enhancing agricultural productivity[7].

Mayuri and Priya addressed challenges and methodologies in image processing and ML for agricultural disease detection, illuminating advancements in disease management. Somvanshi and Mishra (2015) explored ML approaches in plant biology, demonstrating ML's applications in understanding and improving plant-related processes[8].

Gandhi and Armstrong (2016) reviewed data mining applications in agriculture, advocating for further research to integrate data mining techniques into complex agricultural datasets. Beulah (2019) surveyed data mining techniques in crop yield prediction, promoting their use in addressing predictive modeling challenges[9].

Our study presents the first systematic literature review (SLR) solely focusing on ML in crop yield prediction. Unlike existing surveys, which often focus on specific aspects, our SLR comprehensively reviews the literature in this field. Additionally, we analyze 30 deep learning-based studies, showcasing the effectiveness of deep learning algorithms in tackling crop yield prediction challenges.

3. Proposed Work Plan

3.1 General architecture (Figure 1)

The approach is to study the To optimize agricultural analysis through Machine Learning (ML), a methodical approach is vital. It begins with clearly defining the agricultural problem to be addressed, whether it's improving crop yield, detecting diseases, or assessing soil health. Next, comprehensive datasets are collected from various sources such as IoT sensors, satellite imagery, and historical agricultural records. These datasets undergo preprocessing steps, including data cleaning, normalization, and feature selection, to ensure they are suitable for ML modeling. Upon successful validation, the optimized ML models are deployed in agricultural settings to aid farmers in making data-driven decisions. Continuous monitoring and refinement of these models ensure their efficacy in improving productivity.

Description of various modules of the system.

A. Data Collection

Historical data on many important factors is important for analyzing crop impacts. Climate models covering temperature changes, precipitation, humidity and wind dynamics form an important part of this analysis. Tracking these patterns over time can help you understand how different climates affect crop growth and production. Soil quality is another important consideration and requires careful analysis of historical data on soil composition, pH, nutrient content and organic matter[16]. It provides information about the health conditions of the soil and the ability of the soil to support healthy crops. Satellite images help monitor soil moisture over large agricultural areas. Stakeholders can influence actions by combining information from historical events with dynamic data provided by remote sensing data, satellite imagery, and ground sensors. It can be determined that farms will increase productivity and ensure food security. This collaboration reflects the evolution of technology and data-driven approaches in agriculture today[11].

B. Data Pre-processing

After collecting data on various factors affecting the crop, the next important step is to clean the data and prepare it for analysis. Data cleaning involves identifying and resolving discrepancies, and missing values that may affect analysis[12]. This process ensures the reliability and accuracy of the data set and creates a solid foundation for subsequent analysis. Standardization scales the importance of different variables into a standard range (usually between 0 and 1) and makes it easier to compare variables with different scales and units. Standardization changes the data so that the mean is 0 and the standard deviation is 1; This reduces the impact of outliers and brings the distribution of the data closer to a Gaussian distribution[13]. These techniques help control the training process of machine learning models and improve their convergence and efficiency. Structure and relationship. Similarly, precipitation classification can be made by collecting precipitation data for a certain time or region. Soil nutrient levels can be expressed as a combination or ratio derived from soil data[14][14]. By extracting and analyzing these important features, the forecast model becomes more powerful and accurate, allowing for better predictions of agricultural yields and interruptions. Through careful data management, standardization and feature engineering, the data set is improved and enriched, thus providing the basis for in-depth analysis and effective prediction of crop yield.

C. Model Analysis

Choosing an appropriate machine learning method for crop forecasting requires careful consideration of many factors, including model complexity[19], interpretability, and prediction performance. Regression models such as linear regression or polynomial regression are often used to predict crop yield when there is a relationship between input and target variables[20]. This model is simple and easy to understand; It makes it easier to understand how each input affects the estimated yield. However, they may not capture the nonsocial relationships present in the data, which may limit their effectiveness. Decision trees and random forests are popular for product yield because they can capture non-linear relationships and interactions between inputs.

Deep learning models, in particular, provide the flexibility to learn complex patterns and relationships from data, making them powerful for crop prediction. Deep neural networks, such as convolutional neural networks (CNN) or recurrent neural networks (RNN), enable more complex analysis and predictions[21] by extracting features from raw data. However, reporting these models often requires extensive data and budget, and their black status can hinder interpretation compared to simple models. On the other hand, when the data show no correlations and present complex patterns that simple models cannot capture, more complex models such as random forests or neural networks[22] would be expected to say yes. Finally, algorithm selection should be guided by the overall goal of accurate yield prediction while balancing model complexity and interpretation assumptions.

D. Training of Model

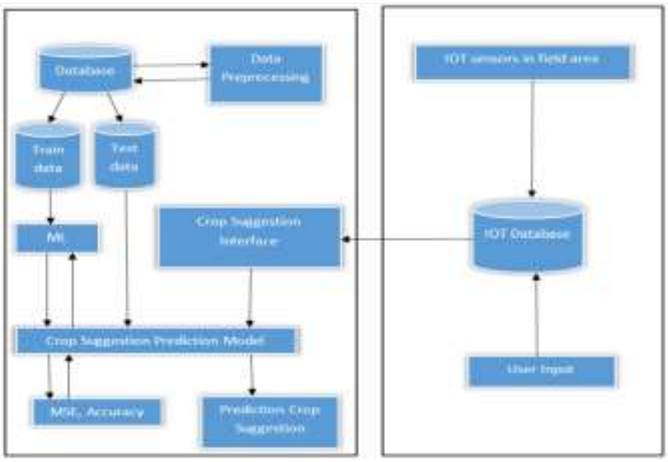
After collecting and processing the dataset for crop prediction, the subsequent stage involves categorizing the data into training and validation sets to assess the learning model's effectiveness. This partitioning enables training on a subset of the data and evaluating performance independently, offering an impartial evaluation[23]. The training set is utilized for model training, while the validation set is employed to assess performance and fine-tune hyperparameters. Cross-validation entails dividing the data into multiple subsets or folds, training the model on different folds, and evaluating performance on the remaining folds. This iterative process enhances reliability by minimizing variation introduced by training-validation splits, ensuring the model generalizes well to new data[24]. Using the validation set, the selected model is trained, hyperparameters are adjusted, and cross-validation is employed for comprehensive evaluation and optimization. This iterative training and testing approach aids in selecting suitable algorithms and metrics for accurate crop yield prediction.

E. Testing

Once you choose a machine learning model that has been trained using historical data and fine-tuned with hyperparameter tuning and cross-validation, the next step is to evaluate its performance using appropriate metrics. path. The model with the lowest MAE and RMSE value and the highest R-squared value is generally considered the best performing model. However, other factors such as computational efficiency, interpretability, and robustness should also be taken into account when choosing the final model. By evaluating and comparing the performance of different models using appropriate metrics, agriculturalists can make informed decisions and use the best models to make accurate and reliable prediction of crop fulfills the desired user requirements, and handles all exceptional cases. To test the model's accuracy, we split the labeled data into 80% of the labeled datasets as training data and 20% as data to be tested. After the application of the data that is trained and tested with the Naive Bayes algorithm, we get the precision of 85.4% in our system/study[25].

F. Architecture

The system involves real-time data collection, prediction model creation, and development of a user interface for input provision. Initially, data preprocessing occurs. Following preprocessing, a machine learning algorithm generates a prediction model. Test data is then fed into this model for prediction[26]. The model undergoes testing with random input values to assess accuracy and error during prediction. This process iterates until error reduction and accuracy enhancement are achieved. To gather inputs from both IoT sensors and users, a graphical user interface (GUI) is utilized. These inputs are then utilized by the crop prediction model to accurately forecast crops[27].



(Figure 1)

G. Feedback Loop

Creating feedback loops is important to evaluate the effectiveness of decision-making algorithms based on their impact on actual crops. This feedback involves collecting data on actual crops processed by farmers based on the algorithm's recommendations. By comparing the actual results with the predicted results and the recommendations generated by the model[28], the performance of the algorithm can be evaluated. Farmers can understand the effectiveness of the consensus model and detect discrepancies between predictions and actual results. Agricultural experts can provide specific knowledge and skills to enhance the model's understanding of complex agricultural processes and increase its accuracy. By integrating feedback from multiple stakeholders, the model continues to evolve and adapt to changes, making it effective and efficient in agricultural decision support. This positive feedback has led to collaborations for model improvements, driving continuous improvement and innovation in crop forecasting and agricultural management [35].

3. Experimental Result Analysis:

3.1 Description of the data set used.

EXPERIMENTAL RESULTS AND ANALYSIS

This paper utilized an agricultural dataset containing exclusive soil and environmental data, sourced directly from the farming community due to its unavailability publicly. The study evaluates feature selection and classification techniques employing metrics such as accuracy, specificity, recall, precision, F1 score, mean absolute error, log loss, and area under the curve. The results are tabulated in Table 1 to Table 5 [33][34].

Table 1 illustrates that the random forest algorithm achieves the highest accuracy, followed by k-nearest neighbor and bagging classifiers. Table 2 shows that random forest, when combined with sampling techniques, effectively predicts crops. Here, different sampling methods are analyzed for dataset balancing. Table 3 explores optimal feature selection techniques across various[29] classifiers using the felin dataset, considering MRFE, RFE, and Boruta methods. Table 4 evaluates MRFE's performance with RF using fold validation, while Table 5 assesses MRFE's performance with RF using data splitting validation [31][32].

Tables 4 and 5 demonstrate random forest's performance under different validation methods, showcasing the evaluation of MRFE and RF techniques. The results suggest that as the range of characteristics expands, the measured values tend to decrease.

TABLE 1. A performance evaluation of various classifiers based on the felin dataset.

Classifiers	Performance Metrics								
	Accuracy	Kappa	Precision	Recall	Specificity	F1 Score	AUC	MAE	Log Loss
Naïve Bayes	70.64	70.12	78.80	75.32	92.23	77.02	73.69	0.8	0.14
Decision Tree	73.22	72.85	80.16	77.94	92.62	79.03	75.97	0.65	0.09
Support Vector Machine	77.50	75.01	83.24	80.98	93.87	82.09	80.02	0.5	0.06
k Nearest Neighbor	83.24	80.60	87.00	85.32	94.28	86.15	87.97	0.43	0.05
Bagging	84.00	82.01	89.11	88.53	94.63	88.81	89.41	0.3	0.04
Random Forest	87.43	85.16	90.34	89.12	95.67	89.72	92.39	0.3	0.04

TABLE 2. Finding the most suitable sampling technique to balance the dataset.

Sampling Techniques	Classifiers	Performance Metrics								
		ACC	Kappa	P	R	Sp	F1	AUC	MAE	Log Loss
Without Sampling	NB	70.64	70.12	78.80	75.32	90.23	77.02	73.69	0.8	0.14
	DT	73.22	72.85	80.16	77.94	90.62	79.03	75.97	0.65	0.09
	SVM	77.50	75.01	83.24	80.98	91.87	82.09	80.02	0.5	0.06
	kNN	83.24	80.60	87.00	85.32	92.28	86.15	87.97	0.43	0.05
	Bagging	84.00	82.01	89.11	88.53	92.63	88.81	89.41	0.3	0.04
	RF	87.43	85.16	90.34	89.12	93.67	89.72	92.39	0.3	0.04
SMOTE	NB	74.76	73.63	78.93	77.18	91.41	78.04	76.93	0.6	0.09
	DT	75.65	74.97	79.37	78.64	92.36	79.001	77.42	0.5	0.07
	SVM	79.81	78.08	82.79	81.68	92.47	82.23	81.02	0.4	0.04
	kNN	85.72	83.62	86.42	84.79	94.15	85.59	87.63	0.33	0.03
	Bagging	87.39	85.71	88.58	87.95	94.71	88.26	89.23	0.2	0.03
	RF	92.42	90.00	94.47	92.80	95.17	93.62	94.94	0.2	0.02
MWMOTE	NB	75.64	75.01	80.41	79.00	92.90	79.69	77.86	0.51	0.08
	DT	76.98	75.81	80.74	79.21	93.13	79.96	78.31	0.41	0.07
	SVM	81.66	79.56	83.83	82.23	93.81	83.02	83.80	0.38	0.04
	kNN	87.13	86.88	88.81	86.83	94.39	87.80	89.38	0.3	0.03
	Bagging	89.12	87.49	90.44	89.15	95.45	89.79	91.97	0.2	0.02
	RF	93.29	91.04	95.86	94.95	96.60	95.40	95.89	0.2	0.02
ROSE	NB	73.98	72.01	77.43	76.21	90.65	76.81	75.99	0.75	0.1
	DT	75.20	73.16	77.38	76.95	91.60	77.16	77.12	0.63	0.08
	SVM	79.18	77.05	80.27	78.25	93.30	79.24	81.95	0.47	0.05
	kNN	84.00	82.63	85.05	83.16	93.51	84.09	86.00	0.4	0.05
	Bagging	85.42	83.74	87.34	86.87	94.25	87.10	87.31	0.25	0.04
	RF	90.90	88.60	93.80	91.89	94.73	92.83	92.62	0.2	0.03

TABLE 3. Identifying the best feature selection techniques with various classifiers using the felin dataset.

FS	Selected Attributes		Classifiers	Performance Metrics						
	No. of Attributes	Selected Attributes		Accuracy	Kappa	Precision	Recall	Specificity	F1 Score	AUC
MRFE	15	6	NB	85.64	83.11	87.14	86.53	93.31	86.83	87.62
			DT	87.98	85.52	88.92	87.40	94.04	88.15	89.23
			SVM	90.66	88.93	91.82	89.10	94.20	90.43	92.31
			kNN	92.13	89.25	92.60	91.32	95.40	91.95	94.99
			Bagging	95.12	93.04	96.50	95.91	96.18	96.20	97.19
			RF	97.29	95.17	98.94	97.54	98.00	98.23	99.23
RFE		8	NB	84.87	82.92	86.98	85.29	93.18	86.12	86.76
			DT	86.17	84.67	88.57	86.77	93.98	87.66	88.85
			SVM	88.83	86.78	89.81	88.37	94.14	89.08	90.93
			kNN	90.67	88.94	92.11	89.40	94.91	90.73	92.61
			Bagging	94.86	92.61	95.87	94.03	95.77	94.94	96.08
			RF	96.17	95.09	97.74	95.46	97.58	96.58	98.57
Boruta		9	NB	83.93	82.07	85.93	84.21	92.98	85.06	85.33
			DT	85.71	83.15	86.37	85.02	93.50	85.68	87.77
			SVM	86.58	84.84	87.79	87.01	94.00	87.39	88.56
			kNN	87.95	85.16	91.42	89.00	94.88	90.19	89.22
			Bagging	94.09	92.30	94.58	92.81	95.60	93.68	96.30
			RF	94.91	93.97	96.47	94.00	97.01	95.21	96.07

TABLE 4. Performance evaluation of the MRFE with the RF based on the fold validation method.

Method	Folds	Performance Metrics						
		Accuracy	Kappa	Precision	Recall	Specificity	F1 Score	AUC
MRFE with RF	10	97.29	95.17	98.94	97.54	98.00	98.23	99.23
	20	96.93	94.49	97.01	96.79	89.76	96.79	98.04
	30	94.63	92.18	94.70	94.48	87.45	94.48	96.46
	40	95.95	93.2	95.72	95.50	88.47	95.50	97.17
	50	95.43	92.68	95.20	94.98	87.95	94.98	97.10
	60	94.13	91.38	93.90	93.68	86.65	93.68	96.44
	70	94.83	91.98	94.50	94.28	87.25	94.28	96.97
	80	95.4	92.55	95.07	94.85	87.82	94.85	97.89
	90	93.93	92.22	94.74	94.52	87.49	94.52	95.79

TABLE 5. Performance evaluation of the MRFE with the RF based on the data splitting validation method.

Method	Data Splitting	Performance Metrics						
		Accuracy	Kappa	Precision	Recall	Specificity	F1 Score	AUC
MRFE with RF	25-75	84.51	81.16	84.45	88.4	87.21	86.37	86.26
	30-70	89.17	85.53	86.54	89.95	89.60	88.21	91.01
	35-65	91.81	88.67	88.74	90.14	91.36	89.43	93.21
	40-60	94.67	90.38	90.92	92.63	93.85	91.76	96.79
	45-55	96.37	91.97	92	93.21	94.04	92.60	98.04
	50-50	94.71	91.12	91.37	93.77	94.74	92.55	96.97
	55-45	96.9	93.97	93.46	95.64	96.13	94.53	98.42
	60-40	96.52	92.45	95.38	94.12	95.72	94.74	97.51
	65-35	97	94.37	97.57	96.42	97.25	96.99	98.78
	70-30	97.29	95.17	98.94	97.54	98.00	98.23	99.23
	75-25	97.11	95.55	98.56	97.02	97.98	97.78	99.00

4. Conclusion

The integration of IoT and machine learning in precision agriculture promises transformative benefits. Real-time sensor data and ML algorithms optimize crop selection and management, boosting resource efficiency and yields while managing risks sustainably. The study highlights the efficacy of the random forest algorithm, especially when coupled with feature selection methods like MRFE, for accurate crop yield prediction. It stresses the importance of thorough data preprocessing for model reliability. However, challenges like data rights and connectivity issues need resolution for widespread adoption. The feedback loop ensures continuous model enhancement through real-world data and expert input, fostering collaboration and innovation in crop management. This research lays a strong foundation for advanced precision agriculture systems, vital for addressing sustainability and food security demands. It emphasizes ongoing improvements in predictive models and collaborative efforts among stakeholders. In summary, this study [30]sets the stage for future research and practical applications driving agricultural transformation through data-driven decision-making and technological innovation.

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