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Procedia Computer Science 235 (2024) 2269–2278

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Machine Learning and Data Engineering (ICMLDE 2023)

Smart Agriculture using Ensemble Machine Learning Techniques in IoT Environment

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Abstract

Crop yield is a serious concern for farmers due to irregular irrigation, soil erosion, uncontrolled seed planting, severe weather conditions, peasants, and unpredicted locust infestations. The lack of current data and the intricacy of traditional agriculture leads to inefficiency and excessive operation costs. Smart farming with Artificial Intelligence techniques and the Internet of Things (IoT) in agriculture overcome these challenges by connecting all the accessible data sources into a single, fully effective functional unit. Smart agriculture helps in the sustainability of food production by using minimum resources such as water, fertilizer, and seeds. It provides a better understanding of the soil, crop, and changing weather. Furthermore, the sensors in the system assist in monitoring and controlling the resources. In this research, we present ensemble-based machine learning approaches in the IoT environment to predict crop yields and enable sustainable farming by guiding the farmers to grow the correct crop during the correct season to increase their yields. The proposed method uses a novel ensemble-based machine learning classification approach with two levels of predictions-level-0 prediction includes (Logistic Regression (LR), Classification and Regression Trees (CART), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN)) classifiers are input as features to the level-1 meta classifier (Random Forest) to detect the distinct categories of different crops. Its predictions can be extremely close to the ground truth, which accurately predicts 22 categories of crops with 99% accuracy. Hence, the proposed Smart agriculture system can assist farmers in improved yield production and remote monitoring at low cost.

Keywords: Crop Yield; Ensemble Machine Learning; IoT; Sensors; Smart Agriculture.

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10.1016/j.procs.2024.04.215

1. Introduction

Agriculture development is an indicator of a nation's growth in economy. Based on the analysis by the World Bank in 2016, it is found that more than 65% of the working population relies on agriculture for their living. However, various reasons like drastic climate change, decline in farmland, global warming, reduction in yield, urbanization, and poor knowledge about the environmental factors that affect the yield of the crop have led to a significant setback in the field of agriculture and have become the most prominent issue for governments all over the world. People are migrating from villages to cities seeking livelihood, and the lack of farmers in the villages is a threat to society. Urban farming is generating a lot of interest and investment. This will alter the appearance of future cities and improve life expectancy. The use of Artificial Intelligence and other technological innovations are driving smart agriculture systems. Agriculturists employ smart agriculture, utilizing IoT, sensors, and Artificial Intelligence approaches in agriculture. It is a farming strategy that employs cutting-edge technology to increase the quality and quantity of crop products sustainably. To put it another way, data and IoT sensor-based smart farming facilitate the future of agriculture.

Smart farming is an innovative approach to agriculture. Governments and city councils are collaborating to establish new strategies for implementing smart city solutions to benefit businesses and citizens [1]. The challenge is to produce enough food long-term to meet the fundamental needs of an ever-growing population while preserving natural resources and biodiversity. As a result, it encourages the use of technology and machinery that is based on knowledge and conserves resources for long-term agricultural production. According to estimates, IoT sensors can potentially enhance agricultural production by 70% by 2050 [2]. According to a survey, global food production would need to expand by 60% by 2050, owing to a population expansion of approximately 900 million people [3]. The significant benefits of using IoT sensors and Artificial Intelligence techniques are increased crop yields and lower costs. It is predicted that the utilization of IoT devices in smart agriculture will reach $15.3 billion by 2025 [4]. Agriculturalists are currently receiving useful information via remote monitoring systems. Wireless sensor networks and the IoT are critical in this setting. Using mobile devices, smart agriculture enables farmers to monitor field conditions remotely. When compared to the conventional approach, IoT-based smart farming is incredibly effective because it increases farming's profitability and accuracy [1].

The demand for agricultural products is increasing each day as the global population increases. Smart technologies, such as IoT and artificial intelligence (AI), are being increasingly adopted in agriculture to efficiently develop organic crops in restricted land areas whilst overcoming the conventional obstacles that farmers face. Smart agriculture is changing people's perspectives on farming globally and is considered the key to achieving maximum agricultural yields.

Smart agriculture is a cutting-edge crop management technique that incorporates monitoring, analyzing, and addressing inter-and-intra field crop variability, such as plant health, soil condition, fertilizer, irrigation, pesticide effect, and crop yield [5]. It supports management choices by using cutting-edge sensor and data analysis capabilities to increase crop yields and maximize returns on inputs like water and fertilizer. It employs technology to boost crop output, assure efficient fertilizer and irrigation management, and lower labor costs [6]. To increase productivity, crop quality, and the utilization of agricultural resources, a vast amount of data and information regarding crop conditions and health is collected during the growing season [7]. Smart sensors, IoT, and AI techniques have made smart agriculture possible for small family farms and farming cooperatives [8]. The main goal of smart agriculture is to assist farmers with managing their business whilst decreasing the necessary resources, hence supporting them with improved yields and reduced costs. The substantial contributions of this study are summarized below:

- A novel ensemble-based machine learning technique is proposed to predict crop yields based on the field data for environmental characteristics.
- In order to understand how various features work together to get the best result for categorizing different crops, we focused on identifying the correlation between each feature.
- Pearson Correlation technique was applied to find the correlation between the features.
- To extract correlated features that impact the classifier's performance, level-0 classifiers such as SVM, CART, LR, and KNN were input as features to the level-1 Random Forest as a meta-classifier.
- Various metrics were applied to validate the performance of the classifiers, such as smart, F1-Score, recall, accuracy, and confusion matrix.

Artificial Intelligence is rapidly increasing in smart agriculture, in which smart sensors and devices are connected via the internet [32]. Smart sensors are utilized to acquire data and monitor soil nutrients and moisture, and Machine learning techniques are applied to predict the environmental factors and how much fertilizer needs to be provided on the soil before the planting of crops.

Regarding the following sections. Section 2 includes a literature overview on smart agriculture using machine learning, IoT, and relevant techniques. Section 3 discusses the problem formulation of the proposed work, and Section 4 presents the method that will be implemented. Section 5 delves into the results of the experimentation and discussion, while Section 6 provides a conclusion to the research work.

2. Related Work

Several studies have recently been initiated with the goal of monitoring climate-related fluctuations in the atmosphere and soil utilizing sensors and machine-learning algorithms in applications that use real-time data. Old agricultural practices have many flaws due to their dependency on climate change, government policies, and recommendations from previous experiences. Table 1 presents the comparative analysis of related studies. A recommendation system for smart farming is elaborated, where heterogeneous data are obtained from different sources. Further data analysis is performed, and machine learning techniques are applied to predict upcoming risks and recommend the time required to implement the practice [10].

A system utilizing IoT sensors and machine learning techniques was developed to assess soil in real time for crop suggestion, considering its numerous properties, such as soil moisture, temperature, humidity, and pH[11]. The authors have reported that the system suggests a suitable crop to the farmers as a precise crop to be sown in the provided environment and soil conditions.

A smart crop prediction system based on Machine learning and IoT techniques is proposed for smart management of crop cultivation by predicting the most suitable crop to grow in the given environment [12]. Agricultural datasets from three different data sources, including IoT sensors with heterogeneous information, are exploited using machine-learning applications for smart farm enhancement. Three different tasks were performed: the first task was to forecast the total pear and apple crops on the Istat statistical dataset, where a neural network model showed promising results. The polynomial predictive and regression models performed better for the National Research Council (CNR) scientific data in the second task, whereas the decision tree model performed well on the IoT sensor dataset in the third and fourth tasks. The system also suggests the suitable fertilizers for the recommended crop. The information regarding the humidity, temperature, crop pH, and rainfall parameters is used to train the models.

Smart farming systems that are based on sensor technology were presented in [13]. Three machine-learning models were employed: SVM, KNN, and decision trees. The decision tree achieved the highest accuracy. Their system collects historical and real-time data for specific locations from government websites and Google Weather interface for recording humidity, temperature, and rainfall. The drawback of the proposed system is that it requires the farmers to enter the soil characteristics. It is advised to use pH, soil moisture, and environment sensors to increase accuracy for crop suggestions.

The authors in [14] described a deep learning-based system incorporating IoT. Wireless sensor networks were utilized to track and collect soil parameters such as ambient temperature, humidity, and the temperature of the soil from the field. Furthermore, the technology advises farmers on the the best techniques for irrigation by predicting the crop that is to be sown in the following crop cycle. This information was conveyed to farmers through notification messages.This technique shows that the effectiveness can be improved further by anticipating the best time to apply the pesticides, fertilizers, and manure. An IoT-enabled soil moisture monitoring system was proposed in [15] to predict the future harvest. This technology detects the amount of moisture in the soil to ensure healthy plant growth. In [16], an IoT-based information system based on fuzzy logic was developed to determine nutritional deficiency from acquired data. A set of criteria and an NPK sensor were devised to assess the measured amount and determine the type of fertilizer in the soil.

Artificial intelligence has become an important part of our daily lives by broadening our senses and allowing us to transform our environment [17].

Table 1. Comparative Study of Related Work.

Ref	Dataset	Sensors	Methodology	Parameters	Limitation
[10]	Self-captured heterogeneous data	Raspberry pi3, DHT11	Sensor and IoT Hadoop with spark machine learning	Weather forecast, atmospheric conditions, soil conditions, cropping pattern information, fertilizers doses.	Partial data implemented.
[11]	Open-source websites	Soil moisture sensor, LM35, DHT22, Ph meter	IoT sensors and Deep Neural Network	land type, soil moisture, soil type, humidity, temperature, NKP, rainfall, Ph.	Fertilizer suggestion
[12]	Istat, CNR Scientific, IoT Sensors dataset	IoT sensors	Linear and polynomial regression, neural network, decision tree, KNN	Rainfall, crop type, location, organic fertilizers, and phosphate	Data Analytic not performed and Accuracy of Classifiers not recorded
[13]	IoT sensors, government website, google weather API	DHT22 linked through Arduino UNO with ESP8266	Decision tree, KNN, SVM	Humidity, Temperature, farm location, soil type, rainfall	Low accuracy
[14]	open-source websites	humidity sensor DHT22, soil moisture sensor,Ph meter, temperature sensor LM35	Backpropagation by Gradient Descent	Humidity, Ph, NPK for soil fertility	Fertilizer suggestion not provided.
[15]	University of Agricultural Sciences website	soil moisture sensor	Neural Networks	moisture content, pH content, and salinity content	Accuracy not provided
[16]	Self-captured data	NPK sensor	Fuzzy Logic	NPK deficiency	Accuracy not provided.

3. Problem Formulation

The main problem that farmers face regarding the selection of proper crops is due to the changes in climatic conditions. These problems can be resolved through smart farming using advanced technologies, such as sensors, IoT, and machine-learning techniques. Although these techniques are available and effective, there is a need for an optimal solution for crop recommendation. Inadequate analysis, selection of relevant features, and deployment of effective algorithms are some of the limitations that are noted in the existing system. All these parameters affect crop production.

The proposed technique can address the shortcomings of existing systems. Smart agriculture system aims to suggest precise crops for a particular field area for increased yield using ensemble-based machine-learning techniques. Machine-learning algorithms have been proven to be most efficient at predicting suitable crops for increased yield by selecting the correct parameters, such as the humidity, temperature, rainfall, pH, and the pertinent number of fertilizers, such as potassium (K), phosphorous (P) and nitrogen (N). Smart sensors could provide insightful information for investigation, assisting farmers by recommending the best crop to plant. Relevant characteristics with appropriate machine-learning algorithms must be chosen, as crop suggestion performance varies depending on the type of method deployed. Crop loss can be minimized by choosing suitable crops [18].

4. Proposed Methodology

Smart agriculture is concerned with the management of geographical, temporal, and environmental parameters to improve yield, thereby increasing the agriculturist's productivity and profitability. All environmental parameters, such as soil characteristics, weather conditions, water availability, fertilizers, humidity, and temperature, differ from one

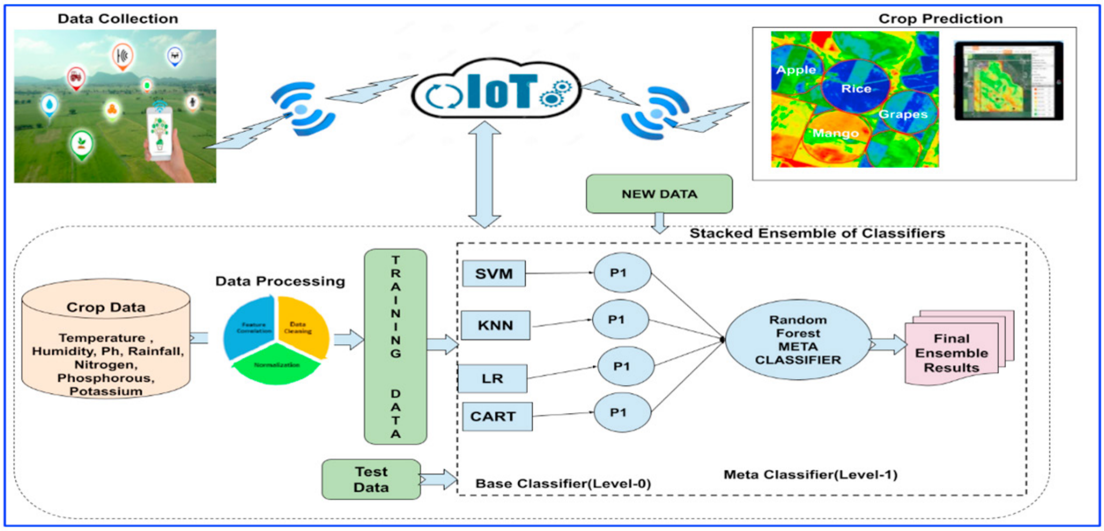

Fig. 1. Smart agriculture framework for crop recommendation

location to the next. Agriculturists encounter a huge hurdle in giving up farming due to the losses they have sustained. Smart farming effectively and efficiently uses limited inputs to produce more outputs. It is a novel approach to using digital technology to improve agricultural practices. Different technological trends are changing the parameters and shapes of smart agriculture. IoT sensors and machine-learning techniques are the major trends. The suggested method, depicted in Fig.1, intends to help farmers make informed decisions while estimating the growth of crops.

4.1. Data Acquisition using Smart Sensors

We used publicly accessible open-source datasets [36] to validate our proposed system. The open-source data for crop recommendation was collected through smart sensors using IoT devices to collect information from the environment, includes features such as temperature, humidity, pH, rainfall, potassium (K), phosphorous (P), and nitrogen (N) for appropriate crop recommendations. N, P, and K (NPK) are the three fertilizers that are used for plants.

In smart agriculture, the appropriate quantity of each fertilizer is the most significant component for plant growth. Soil temperature is measured through the LM35 temperature sensor [18][19]. The DHT22 humidity sensor detects the quantity of moisture and temperature present in the air. The pH of the soil is measured with a pH meter, and it should be constant since it impacts the availability of soil nutrients [20]. A greater quantity of N is necessary to boost leaf growth since N is primarily responsible for leaf growth. A suitable amount of P must be provided to improve the output of fruits and flowers, which is responsible for fruit, flower, and root growth. K increases the plant's overall performance [21]. As a result, by delivering the optimum quantity of NPK values, the crop's production can be increased. The NPK level in the soil can be tested using a three-in-one fertility sensor, which detects the NPK concentration in the soil and estimates the fertility of the soil, allowing for a more systematic evaluation of soil condition [22]. The data obtained from the various sensors must be transferred through IoT devices with short-range ZigBee or NFMI (near-field magnetic induction) technology [23] and further processed using the proposed ensemble-based machine learning techniques to create precise crop recommendations.

4.2. Data Processing

4.2.1. Data Pre-Processing

i. Data Cleaning: Missing values are relatively prevalent in datasets, and they might arise throughout the data gathering process using various sensors. Missing or null values are removed during the data cleaning process.

ii. Normalization: The proposed methodology uses ensemble-based classifiers, which are composed of several machine-learning techniques, such as Random Forests, LR, KNN, SVM, and CART, that are mostly affected by the range of features. To determine the similarities between the data points, these techniques use a gradient descent function and distances between them. Hence, data normalization is performed using standard scalars. Feature standardization transforms the data within the given range to fit the models by assigning each feature in the data with unit variance and a zero mean [24], as illustrated in Equation 1.

$$\acute{y} = \frac{y - \overline{y}}{\sigma} \tag{1}$$

Here, $\acute{y}$ is the average of the feature vector, and σ is the standard deviation of the feature vector.

iii. Correlation: Person correlation was used to find the correlation between the features. It captures the direction and magnitude of the features, and a linear association between two continuous features is provided [25].

4.2.2. *Ensemble Machine Learning*

Stacking is an ensemble-learning strategy that involves training a meta-classifier with the predictions generated by numerous classifiers [26]. Random Forest is regarded as the meta-classifier in the suggested technique. Figure 1 demonstrates the training of five different classifiers: SVM, LR, KNN, CART (level-0 classifier), and Random Forest (meta classifier). The predictions of level-0 classifiers are piled up and used as features in the level-1 meta-classifier, which provides the final prediction. This approach improves machine-learning accuracy and provides better predictive performance than a single classifier [27]. Brief descriptions of all the algorithms utilized are provided below.

- KNN: This is a non-parametric learning technique with the k nearest training samples from the dataset as the input and a class membership as the output, with an object that is categorized by the majority vote of its neighbors [28]. The KNN method predicts a new data point's class or continuous value using the K closest data points, assuming that comparable objects exist nearby [29].
- SVM: This produces an N-dimensional hyperplane that distinguishes between two classes of data points by providing the most significant possible distance between the data points from both classes. It searches the search space for separators that best separate the various
- LR: This predicts the probability of a categorical dependent or target variable being classified into two or more classes. One is known as binary classification, and the other is multi-class classification. In the binary class, LR provides probabilistic values that fall between zero and one rather than an exact number, such as zero or one [31].
- CART: This forecasts a class label based on a finite set of values for the target variable, such as whether it will rain tomorrow [32].
- Random Forest: This is a series of decision trees that have been applied to distinct subsets of a dataset and averaged in order to enhance prediction performance. Instead of relying on a single decision tree, the Random Forest determines the result using predictions from all of the trees using the majority of votes. [33].

4.2.3. *Model Training*

The training dataset contains features such as humidity, temperature, soil pH value, rainfall, and NPK values. Corresponding to these parameters are five different kinds of machine-learning techniques, including an ensemble of classifiers, KNN, SVM, LR, and CART, and they are compared with their accuracy, recall, precision, and F1-score values.

4.2.4. *Model Prediction*

The new data for the field area and its corresponding parameters are tested on the trained model. By comparing the accuracy, F1-score, precision, and recall produced by the ensemble of machine learning classifiers, the trained crop prediction model then performs the required procedures and proposes the best crop. The most accurate result that is obtained through the proposed ensemble of classifiers can be adapted to recommend the best crop yield to the farmers.

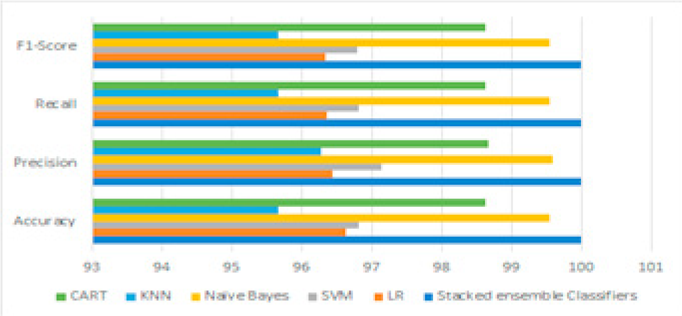

Fig. 2. Results of Classifiers Accuracies

4.2.5. Model Evaluation

Four assessment criteria were used to analyze the performance of the model: recall, precision, F1-score, and accuracy [34,35].

4.3. Experimental Results and Discussion

The experiments show the importance of the predicted values based on the comparative study (Table 2). It also contains a comparison with some recent studies, emphasizing the significance of the suggested technique. Evaluating the prediction metrics of the trained models is a significant process phase. Cross-validation (CV) is the standard technique for separating data into training and test data. The 10-fold cross-validation technique was utilized to evaluate the ensemble machine learning technique that was trained on the smart agriculture dataset. Cross-validation avoids overfitting of the models. The proposed ensemble-based machine learning classification was implemented utilizing an open-source dataset [36]. The smart agriculture dataset consists of seven features (temperature, humidity, pH, rainfall, and NPK) with 22 different categories of crop yields [36].

Table 2. Comparative Study of Related Work.

Methodology	Accuracy	Precision	Recall	F1-Score
Proposed Ensemble Machine Learning	99.7	99.68	99.66	99.68
LR	96.7	96.44	96.36	96.35
SVM	97.7	96.15	96.81	96.80
KNN	97.4	96.28	95.68	95.67
CART	98.63	98.68	98.63	98.63
DNN [11]	96.89	—-	—-	—-
KNN, SVM, and Decision Trees [13]	84.90,88.91,91.03	—-	—-	—-

Several experiments were conducted to assess the ensemble classifier's recognition performance using various evaluation metrics, including F1 score, precision, accuracy, and recall. Table 2 and Fig. 2 illustrate the performance evaluation results obtained from an ensemble machine learning technique and compared with the individual classifiers such as SVM, LR, CART, and KNN machine learning models trained on the smart agriculture dataset. The best results were obtained using the proposed ensemble machine learning technique, which was 99.7%, compared to the other machine-learning algorithms.

The CART algorithm achieved a prediction accuracy of 98% compared to the other algorithms. SVM and KNN obtained similar prediction accuracy of 97.7%, and LR achieved the lowest accuracy of 96%. In general, the ensemble of machine learning classifiers outperformed the individual classifiers in predicting 22 distinct crop yields. In addition, a comparative analysis was performed with other related works proposed in [11] and [13]. Table 2 and Fig. 2 show that our proposed ensemble of machine learning classifiers outperformed the KNN, SVM, decision trees, and DNN approaches proposed in [11] and [13].

Based on the overall assessment, ensemble machine learning is the optimal solution and performs better with multiclass classifications, which involve separating each crop into individual categories. Furthermore, because the ensemble machine learning employs two levels of prediction in which the level-0 prediction is input as features to the level-1 meta-classifier to detect the distinct categories of different crops, its predictions can be extremely close to the ground truth observed data. The ensemble machine learning model outperformed SVM, CART, LR, and KNN classifiers out of the five different machine-learning techniques. Model stacking is an effective ensemble method in which predictions that are generated by several machine-learning algorithms are input into a meta-classifier. This meta-classifier algorithm is trained to integrate model predictions most efficiently to generate a final set of predictions. When modeling the suggested technique, Random Forest is employed as the meta-classifier since it assesses each tree's estimate and predicts the final result based on the majority vote of the predictions. Stacked models outperform individual models in terms of prediction accuracy and robustness when applied to agricultural crop production data.

```
N = 91
P = 94
K = 46
temperature = 29.36
humidity =76.24
ph = 6.14
rainfall = 92.82

sample = [N, P, K, temperature, humidity, ph, rainfall]
single_sample = np.array(sample).reshape(1,-1)
pred = model.predict(single_sample)
print("predcited class",pred)
```

```
predcited class ['coffee']
```

Fig. 3. Predicted Results for New Data

The results were validated for the new data. The trained model accurately predicts the type of crop to be suggested using the precise NPK values of the fertilizers for a particular field area that contains optimal humidity, temperature, rainfall, and soil pH value parameters. The predicted results presented in Fig.3 can be recommended to farmers for sustainable agriculture. The results that the model predicts would be extremely useful in determining which crops to plant in a specific field area.

The results that were obtained from the ensemble of classifiers for the prediction of 22 categories of crop yields are illustrated through the generated confusion matrix presented in Fig. 4. A confusion matrix summarizes the predictive results of a classification problem. The values of correct and incorrect predictions are summarized in the form of a table [35]. The confusion matrix presents the average accuracy that is obtained in the predictions for the 22 categories of crop yields. Through the ensemble of classifiers, out of 22 crop yields, 18 crops were accurately predicted with 100 % accuracy. There was a little confusion between Jute and rice, and it achieved an accuracy of 98%. Pigeon peas and kidney beans achieved an accuracy of 98%, and moth beans and lentils achieved 99% accuracy. This proves the efficacy of the proposed ensemble machine-learning technique for predicting crop yields. The model assists in recommending appropriate crops to farmers to achieve higher yields while utilizing fewer resources. This study demonstrated the effective use of ensemble machine-learning techniques to recognize 22 different crop yield categories. An ensemble-based classification approach can improve classification performance under specific crop conditions with appropriate parameters. The ensemble machine learning performed better regarding the overall Classification performance for the smart agriculture dataset and predicted accurate results for almost all the crop yields. Therefore, it can be used to suggest appropriate crops for smart agriculture.

5. Conclusion

The key hurdles in agricultural productivity are crop selection, fertilizer selection, and decision-making. Environmental factors such as temperature, rainfall, soil fertility, and humidity all impact agriculture production. Bearing in mind the importance of agriculture in a country's economy, it is crucial to monitor those factors that may affect crop yield. Smart agriculture prediction aims to enhance the quality and quantity of agricultural yield using emerging technologies. This research proposes a unique strategy that leverages IoT, smart sensors, and ensemble machine-learning

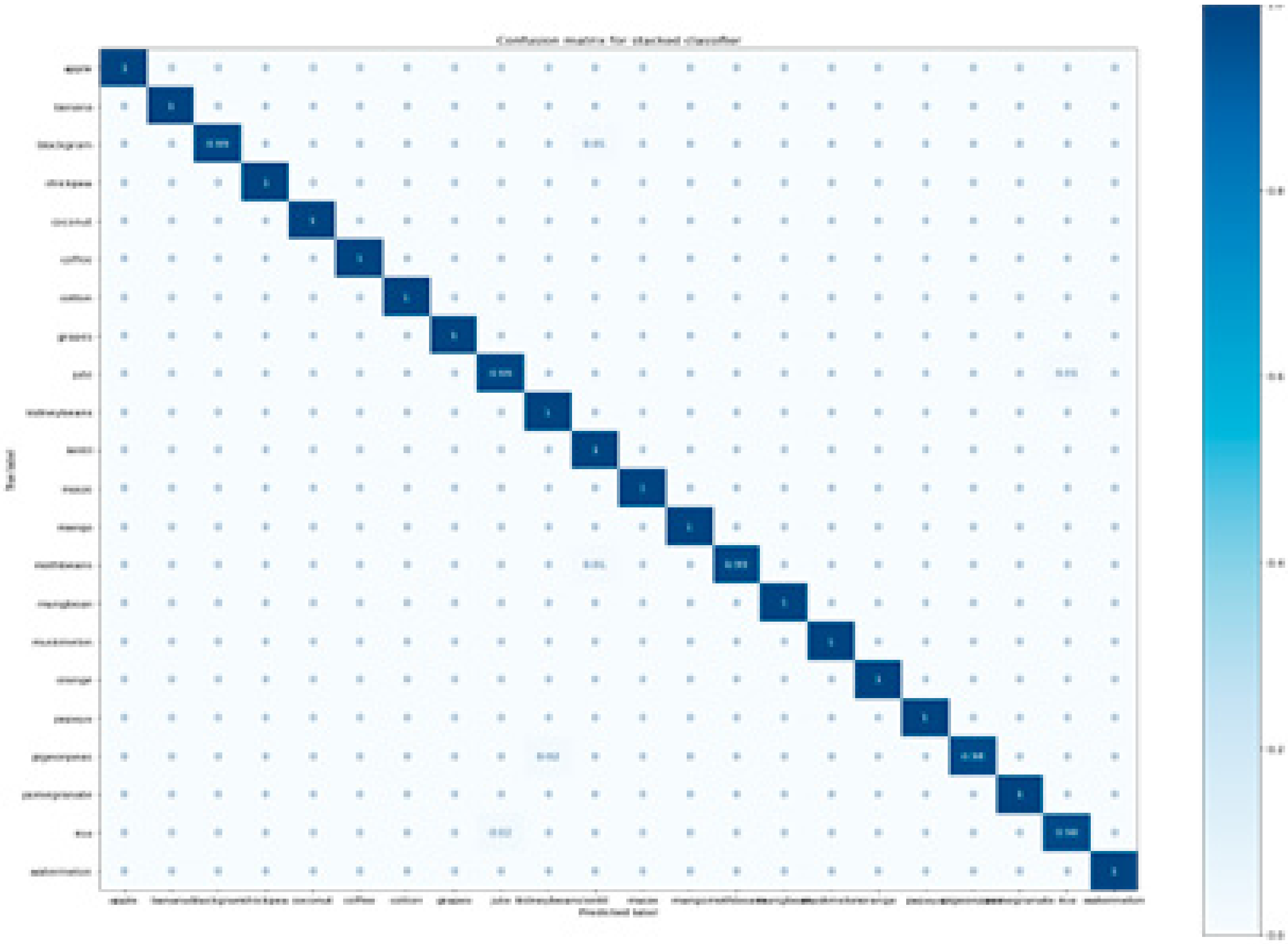

Fig. 4. Confusion Matrix

algorithms to select ideal crops based on environmental factors collected by IoT sensors. The proposed ensemble machine learning technique outperforms other machine learning algorithms and accurately predicts 22 categories of crop yields with an accuracy of 99%. The proposed technique recommends the type of crop to be produced in a certain field area based on the humidity, temperature, rainfall, soil pH, and NPK fertilizer values.

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