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RESEARCH ARTICLE

Accelerating Crop Yield: Multisensor Data Fusion and Machine Learning for Agriculture Text Classification

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ABSTRACT Sensors are now used by farmers and agronomists to help them improve their operations. They use sensor data transmitted via IoT to remotely monitor their crops. Farmers today manage crops in a controlled environment to increase yields in the name of modern farming. Crop productivity, on the other hand, is influenced by the severity of the weather and disease variations. The primary objective of this paper is to present a novel Multisensor Machine-Learning Approach (MMLA) for classifying multisensor data. The fusion strategy supports high-quality data analysis in agricultural contexts for cultivation recommendations. Based on the proposed recommendation system, eight crops were classified: cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat. Crop species were classified using three machine learning algorithms: J48 Decision Tree, Hoeffding Tree, and Random Forest. To evaluate the performance of the proposed multi-text classifier, only the top eight classes were investigated. The classifier's performance is measured in terms of precision, recall, F-measure, MCC, ROC Area, and PRC Area class, and the results are compared with the state-of-the-art classifiers. The Random forest algorithm has the lowest error measure of RMSE at 13%, RAE at 38.67%, and RRSE at 44.21%, demonstrating effectiveness in classifying the agriculture text. Thus, the use of a multisensor data fusion approach based on crop recommendation provides greater precision in prediction, resulting in a significant increase in crop yield while also creating awareness in the condition-based environmental monitoring system.

INDEX TERMS Agriculture, crop yield, cultivation recommendation, farmers, multisensor, machine learning.

I. INTRODUCTION

A large portion of Asian countries is reliant on agriculture. The expansion of agricultural-based enterprises lacks quality assurance [1]. In the name of modern farming, farmers today manage crops in a controlled atmosphere to increase yield. However, the severity of the weather and the variability in disease are impacted by crop productivity. Consequently, a novel monitoring and information technology-based application, such as the Internet of Things (IoT), is required. Decisions about irrigation, climate change, soil nutrition, etc., may be managed once the precise status of crops is understood. This significantly raises the production of crops whose quality deteriorated as a result of environmental effects [2].

Farmers and agronomists employ a sensor today, which helps them improve their operations. They remotely monitor

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their crops using sensor data that is transmitted via IoT. The machinery is controlled, and depending on its condition, the robots are given instructions to perform the necessary agricultural chores [3]. The advent of the Green Revolution has advanced agricultural methods. The usages of fertilizer and irrigation management are examples of this. The amount of agricultural produce has doubled despite the expansion of agricultural fields. Farmers' involvement in croplands has increased by 12% and there is dependable irrigation [4]. The main consumption, as mentioned before, is the use of freshwater resources. The water was taken out of the aquifers of groundwater. The need for food is growing as the world's population expands. Even stranger things are happening in arid and semi-arid areas. Although modern agricultural practices have improved food production, they have nonetheless harmed the environment. This encompasses areas including global food security, climate change, and water exchange. Concerns about finding a solution to the world's rising food demands have emerged. The food crisis is largely predicted by these economic and societal factors. There must be one billion hectares of additional croplands by the year 2050. Because of this, the growth of forests is constrained, which presents a challenge for farmers. To fit into socially approved production systems, farmers are trying [5]. Accurate monitoring and sustainable crop production are needed to meet the growing demand. Monitoring seasonal crop growth is part of monitoring vegetation dynamics [6]. However, it requires the delivery of products that promote environmental sustainability. Additionally, the developed crop inventories must be dependable and regular. To solve this problem, it is essential to gather very accurate crop status information and make reasonable decisions about how to control irrigation, change climate variables, or improve soil nutrition in agricultural settings. With the use of machine learning the current study provides an effective approach to facilitate intelligent management and decision-making in crop categorization for healthy and quality crop growing [7]. Moreover, there is increasing agricultural success with the use of machine learning as it takes advantage of the availability of varied sensors, cameras, and smartphones. The classification and mapping of agricultural plants are extremely valuable for agricultural monitoring and food security [8]. Although it has been discovered that optical data collected later in the growing season offers the best overall classification accuracy, operational crop mapping is faced with two difficulties as a result [9]. One is that cloud cover may prevent late-season optical data from being available. The other issue is that crop identification at an earlier stage of the growing season is hindered by the dependence on late-season photography. Hence it is necessary to unravel, quantify, and understand data-intensive processes in agricultural operational environments [10].

Agriculture-based data are inadequate, for this purpose it is inevitable to use the data obtained from multiple sensors to gain more knowledge of the cultivation environment. The primary objective of this paper is to present an innovative Multisensor, Machine-Learning Approach (MMLA) to classify multi-sensor data before applying the fusion strategy to support high-quality data analysis in agricultural contexts for cultivation recommendation [11]. Thus accelerating the yield of crops, more specifically crop recommender systems. The correctness of the recommendation depends on the type and the amount of data fed. The main input here is the multi-sensor data sources; the way of collecting these data sources contributes to a major theme in the proposed framework. The frameworks discussed focus on the use of different machine learning algorithms to multi-sensor data. Popular machine learning algorithms such as J48 Decision Tree, Hoeffding Tree, and Random Forest. The performances of the three algorithms are measured based on their classification accuracy. The contributions of the paper are herewith described below:

i) To investigate the combined use of multisensor data fusion with machine learning technique as a novel approach.
ii) To use popular machine learning algorithms such as the J48 Decision Tree, Hoeffding Tree, and Random Forest for classification.
iii) To analyze crop cultivation in terms of variety, season, and zone.
iv) To measure the performance of the algorithms in terms of Precision, Recall, F-measure, MCC, ROC area, and PRC area class.
v) Identification of the best classification algorithm for multisensor data. To generate classification for eight agriculture crops, namely cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat-based on the proposed recommendation system.
vi) Identifying the algorithm with the least error measure in classifying the agriculture text. A high accuracy measure can lead to a significant increase in the crop yield and avoids the wastage of seeds, time, and drastic loss in productivity, etc.
vii) Enhancing the multisensor data fusion approach by providing a recommendation of crop variety based on season and zone for cultivation.
viii) Finally, the multisensor data fusion strategy is applied for creating awareness in the condition-based environment monitoring system.

The rest of the paper is organized as follows. Section II describes the various literature review related to this study; Section III presents the description of the proposed framework Multisensor, Machine-Learning Approach (MMLA) for Agriculture Context. Section IV presents the experimental results and discussions verifying the application performance. Finally, Section V presents the conclusion and future scope of the study.

II. RELATED WORKS

The experts concentrated primarily [12] on rice agriculture monitoring. The open-access Sentinel-1 C-band data that runs for a dense time series is used in this technique. The region under consideration is southern and southeast Asia. Rice is the main food crop in these areas. And these are grown when there is a lot of cloud cover during the rainy season. The photos were taken in Myanmar, which has heavy rice cropping throughout the crop year. Land cover map images from Sentinel-1, Landsat-8 OLI, and PALSAR-2 were fused and integrated. The random forest algorithm was used to further classify the data. With kappa statistics of more than 90%, approximately 186,701 km2 of cropland was considered. Thus, a phonological time series analysis was carried out, taking into account its dynamic range, inundation, and growth stages. Although the outcome was positive for assessing and monitoring rice production, it was only on a moderate scale, and more geographic region-based forecasting of production remains a challenge for food security solutions. Due to sensor imaging limitations, Siok [13] highlighted environmental studies and the need for techniques that combine data from different platforms. The authors combined multispectral aerial and satellite imagery to create a more spectrally accurate image. The primary objective is to process the image using segmentation and classification. The study took into account environmental factors such as soil, meadows, and forests. Pen sharpening is traditionally used to indicate spectral quality values with less distortion. Obtaining a high-quality image on a cloudy day is difficult. In this case, multi-sensor data fusion integrates various sensor data to produce enhanced images. Thus, the fusion process results in a partial loss of information while improving image spectral quality. This inspired the current study, which includes a multisensor data fusion technique. The authors assessed the accuracy [14] of the agriculture information monitoring system using a big data approach. Thus, the major challenges in crop analysis are identified. The Hadoop framework was used to handle massive amounts of agricultural data. The information considered includes crop types and soil content to improve productivity. Hadoop's MapReduce programming was combined with the random forest algorithm. Agriculture datasets were initially collected and stored in the cloud. This is followed by the classification phase. It has been reported that, when compared to SVM, the random forest algorithm provides higher accuracy in agricultural data classification. This has prompted the current investigation into the random forest algorithm. Finally, the predicted results support the farmer in improving productivity. However, the authors state that forecasting agricultural productivity in terms of growth, atmospheric, and soil parameters for farmland remains a challenge. Another study used a mobile robot [15] to collect sensor data from agricultural scenes. The authors concentrated on recording repetitive, reflected, and burned images caused by sunlight and rough terrain in soybean fields. Although the recording was done for a large agricultural environment, there is a lack of texture. In addition, Han [4] concentrated on the agricultural sector's aging and decreasing skilled labor. The authors emphasized the importance of automation and mechanization to maximize efficiency and reduce costs. Sensor technology advancements have accelerated the development of self-driving agricultural vehicles. Improving performance while taking into account a wide range of operating conditions remains a challenge in the agricultural environment. Sirsat concentrated on the soil's reduced fertility [16]. Crop productivity can be predicted by evaluating the physical, chemical, and biological properties of the soil. The advancement of machine learning technologies has opened up new opportunities in agriculture and may aid in data evaluation for decision-making. The authors considered the state of Maharashtra's Marathwada region. The soil in the area is made of scarlet, blackish, and yellowish basalt rock. The primary objective was to perform soil classification. Soil classification should increase productivity, prevent soil degradation, and mitigate environmental damage. Thus, the current study was motivated by the fact that increasing crop yield is a major challenge in solving the global food security problem. However, changing temperature and rainfall trends, insufficient water and light, agricultural practices, and nutrient deficiency all have a negative impact on soil quality and crop yield. Thus, forecasting to increase production for Indian agriculture is critical. Experts proposed a novel multisensor [17], multi-temporal machine-learning approach to forecasting changes in water availability as well as the rise and fall of the Indus Civilization. The authors used a classifier algorithm to determine the region's archaeological significance. Although the study presented a machine-learning approach, it is limited to detecting archaeological mounds. Katarya used various AI techniques [18] to increase crop yield. These algorithms take into account a variety of external factors such as meteorological data, temperature, and others such as soil profile and texture to provide the best recommendations that not only result in higher yields but also the most efficient use of resources and capital. However, focusing on soil properties and nutrients, which are important factors in crop recommendation, remains difficult. López and other experts [19] concentrated on the recommendation of new crops based on changing conditions. In this sense, having reliable decision-making tools and information is critical in adapting to new agricultural productivity scenarios. The preceding assumes having enough relevant data sources to reduce uncertainty in decision-making processes. When implementing a suitable solution to support data analysis tasks in agricultural contexts, data fusion tasks have been immersed in a variety of applications and approached from various points of view. Moreover, the multisensor data fusion strategy responds appropriately to agricultural-related queries. This has inspired the current study. Moreover, the authors emphasize that there is no single evaluation metric that is appropriate for all classification problems. The current study compared different classification models on a specific dataset and different metrics. Crop diseases are a serious problem in agriculture, as stated in [25]. This affects the quality of production. Technological advancements like sensors and artificial intelligence yield promising results. For this, the wide literature on the state-of-the-art machine learning techniques utilized in agriculture is discussed in [25]. The study examined the role of data fusion in disease identification. It has been observed that a surveillance system has been developed for grape disease using temperature and humidity sensors. Similarly, environment and soil information was extracted using SVM and the random forest algorithm, achieving an accuracy of 99.6% and 99.5%, respectively. However, it seems combining multiple data sources from different sensors remains a challenge. With data fusion techniques in agriculture remaining a challenge, there is a need for advanced models. According to their review, assessing healthy and diseased crops using machine learning techniques can provide better accuracy. Another study [26] performed precision irrigation management in water-limited regions using root zone soil moisture estimation. It has been pointed out that there are no accurate spatial resolutions. The technique combined optical reflectance with physical and hydraulic soil information using automated machine learning. Thus, it is evident that machine learning algorithms are capable of identifying complex relationships. The results concerning physical and hydraulic properties yielded an RMSE value of above 0.90. However, improving crop management remains a challenge. The use of intelligent flow meters is now widely used in society [27]. Despite its convenience, the privacy of public and industry data is exposed to high-security risks. Therefore, it has introduced a multi-sensor data fusion and AI-driven flow meter. However, stability and reliability are very low in changing environmental conditions. Thus, it requires the continuous progress of new AI technologies for its integration of sensor fusion, which is highly necessary. In [28], attempted to evaluate and compare the performance of various machine learning classifiers. The multiband input datasets from multiple sensor layers were utilized. The results showed improvement in spatial resolution; the accuracy for KNN was 75% and for Nave Bayes, 64%. However, the fusion of multiple sensor values with accuracy enhancement remains a challenge. Experts [29] proposed a deep learning method to perform semantic segmentation of fused data. The method combined texture and geometrical features. Further, the imbalance class was efficiently trained using 3D segmentation. The experiments showed that an unstructured and noisy point cloud achieved an accuracy of only 86.2%. However, the investigation of feature fusion under imbalanced class conditions needs to be addressed. In [30], the agricultural vulnerability due to climate change impacts were assessed. The processing, integration, and analysis require accurate and on-time responses. To address this study, researchers introduced a data fusion technique to identify crops. Climate, soil, and water quality were investigated. Multi-label learning and classification were performed based on binary relevance and random forest application, obtaining only 67% similarity. Although the results were acceptable, the use of predicted ranking to prove crop recommendations relevant to other constraints remain a challenge. Reference [31] investigated multisensory data fusion for rice disease detection. Changes in production affect the farmers, and early detection is necessary to ensure quality and an adequate supply. The dataset of 3200 categories was collected from sensors. The proposed rice model framework provided only an accuracy of 91.25%. Thus, from this wide literature on state-of-the-art machine learning techniques, it is evident that machine learning techniques with multi-sensor data fusion have been utilized in the agriculture domain to enhance the image quality of the data collected from agricultural scenes. Most of the authors have concentrated on images of agricultural fields. However, the forecasting of agricultural productivity in terms of growth, atmospheric, and soil parameters for farmland remains a challenge. And the presented work seems to be the first work on generating the classification for crops to provide a recommendation of crop variety based on season and zone for cultivation. Few of the experts applied a multisensor machine-learning approach to forecasting changes in water availability. Moreover, past researchers have emphasized that there is no single evaluation metric that is appropriate for all classification problems. According to their review, assessing agriculture issues using machine learning techniques can provide better accuracy and more reliable decision-making in adaptation to new agricultural productivity scenarios. Thus, the current study was motivated by this fact and tries to solve the global food security problem of increasing crop yield.

III. METHODOLOGY

The farming industry is changing as a result of the Internet of Things (IoT)-based events that reduce human labor. The use of specific sensors and software retrieves real data about soil, crops, and weather. Meeting the future demands of a growing population is challenging with limited resources. The sensors in the current study collect physical parameters and transmit them to the cloud [20]. As shown in Figure 1, the most important data sources are soil information, crop type, and weather patterns. The crop's requirements vary depending on the land and weather conditions.

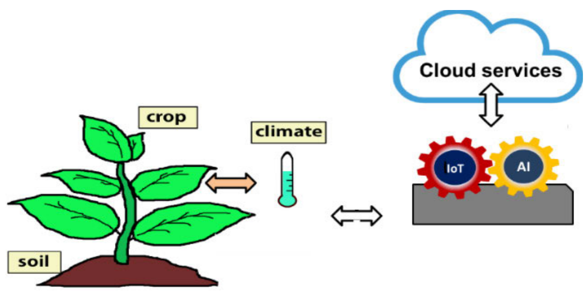

FIGURE 1. Data sources include the information collected from the air and soil.

For example, the non-contact of plant growth can be monitored using an infrared sensor. The sensor measures the plant height, width, and stem diameter for identifying growth. Further to this, the measured values are transmitted to the remote server using GSM technology. For instance, if an area space is considered, just by mapping the area to the object being detected the corresponding measurements can be calculated.

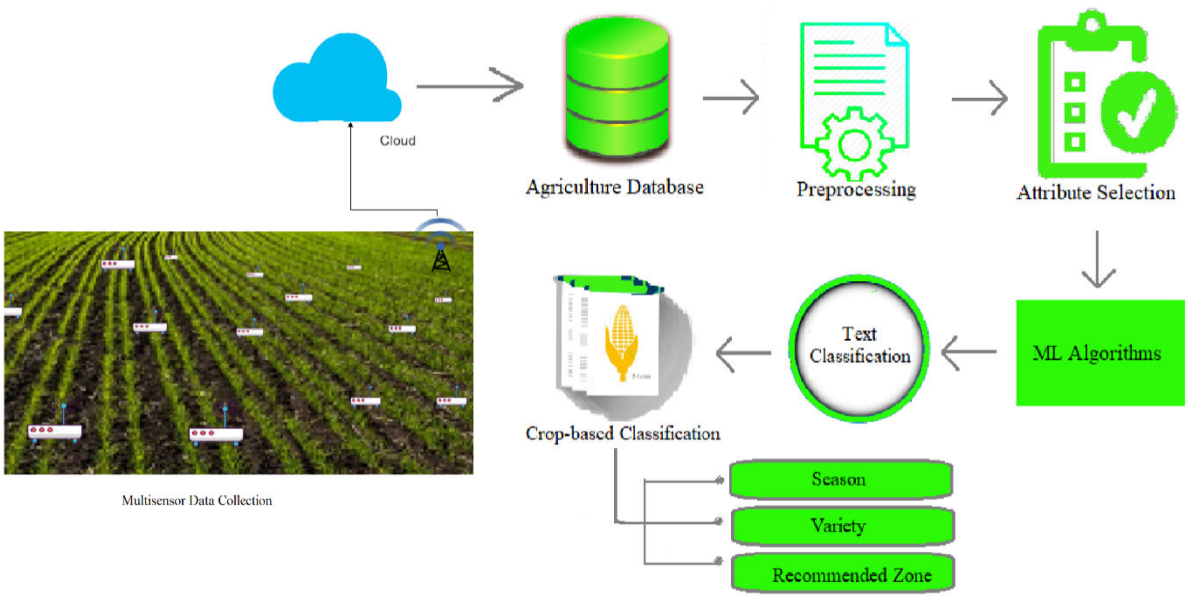

FIGURE 2. Multisensor, machine-learning approach (MMLA) framework for agriculture context.

Thus measuring the height, width, and stem diameter gets stored in the memory. In addition to this, the environmental conditions like temperature and humidity near the plant are recorded. Wireless nodes in agriculture are connected to tiny sensor devices. This node collects information from the air and soil, such as temperature, humidity, and moisture, and transmits it to the gateway node. The collected data is sent to a cloud platform for analysis. Before constructing the agricultural database, the collected data is subjected to multi-sensor fusion. Wireless nodes in agriculture are connected to tiny sensor devices. This node collects information from the air and soil, such as temperature, humidity, and moisture, and transmits it to the gateway node. Figure 2 depicts the proposed system framework. The multi-sensor data fusion technique is used here to combine information from multiple sensors to improve the accuracy of the results [21]. This technique allows for the processing of a wide range of data.

The availability of a wide range of real-time information allows for the discovery of relationships between various types of data and the recognition of useful patterns [22]. The fusion process begins in the early stages. This significantly reduces the amount of noisy and incomplete data obtained from a single sensor. The important text must be identified before classification. These serve as attributes, and the pre-processing stage includes normalization and word removal. These are special characters, conjunctions, etc. Once pre-processed, the vector components represent the associated words and their weights [23]. The number of attributes (words) in the document remains high after pre-processing, and this high number of attributes is indicative of the classification problem. However, this large number of attributes is unnecessary because most of the words in the document do not describe them. As a result, it is critical to choose a subset comprised of the most significant terms. Furthermore, the text classification is performed based on three machine learning algorithms. Decision Tree, Hoeffding Tree, and Random Forest are the three types of trees. The text classification method organizes available information into appropriate categories in a systematic manner. The classification, in this case, is based on a three-class approach. These are the seasons, the varieties, and the recommended zone.

A. DECISION TREE ALGORITHM

The most widely used data mining algorithm forecasts the target data based on the input. It allows for the classification of real-time data. The tree is then cultured and divided into subsets based on the attribute values tested. For each recursion, the process is repeated. This process is repeated until the split value no longer corresponds to the prediction [24]. It is a combination of mathematical and computational techniques. The tree used is the J48 classifier. This produces a binary tree. Once constructed, it is applied to each tuple in the database, resulting in classification. As a result, the attribute predicts the value of that item.

B. HOEFFDING TREE ALGORITHM

The algorithm is based on decision trees as well as stream data classification. The tree selects an optimal splitting attribute based on a small sample size. It is based on the Hoeffding-bound theory. For instance, suppose there are N independent observations of a random variable r with a range of R, where r is a measure of attribute selection. Here, r represents information gain, and for r to be true, it must have at least r with probability 1, which is user-specified as expressed in equation (1).

$$\epsilon = \sqrt{\frac{R^2 ln \frac{1}{\delta}}{2N}} \tag{1}$$

Algorithm:

Build (∗T)
{
d $= \emptyset$
d= Create (); //Creation of root node and label with split attribute
d =Add art t for each split predicate and label;
For each t do
T=Create splitting T to predicate
d′= Create leaf for the appropriate class
Else
d’=Td Built(T)
d=add d′ to t;
}

C. RANDOM FOREST ALGORITHM

The random forest computes the mean decrease in classification accuracy to provide a criterion for each attribute. It is made up of a set of base classifiers. The random forest mathematical model is given as expressed in equation (2)

$$\{h(\mathrm{x}, \theta\mathrm{k}), \mathrm{k} = 1, 2, \ldots.\} \tag{2}$$

Here x is the input variable and θk is the independently distributed random vector. The primary objective is to examine crop cultivation in terms of variety, season, and recommended zone. This will enable crop management and the matching of crop supply with demand, resulting in increased productivity. As a result, labor requirements in manual harvesting and handling operations are reduced. The study predicted recommended zones to help farmers choose the right crop and avoid losses in farming. Soil properties, such as the estimation of soil drying, condition, temperature, and moisture content, aid in understanding the dynamics of ecosystems and agricultural impingement. Accurate estimation leads to accurate analysis of a region’s climate change effects and eco-environmental conditions. Furthermore, the algorithms’ performance was evaluated in terms of Precision, Recall, F-measure, MCC, ROC area, and PRC area. To obtain a higher accuracy measure and increase the crop yield the performance was evaluated in comparison to the different classification models. Recall (R) is the most widely employed machine learning metric that defines the measure of the ‘‘completeness’’ of the system as expressed in equation (3). If the recall is 100%, no prohibitions have been classified as obligations.

$$R = \frac{tp}{tp + fp} \tag{3}$$

Precision (P) is another widely used metric that provides a measure of the ‘‘soundness’’ of the system. The precision decreases if the number of obligations misclassified as prohibitions increases as expressed in equation (4).

$$P = \frac{tp}{tp + fn} \tag{4}$$

Finally, the F measure combines precision and recall to provide a single metric for algorithm comparison, as shown in equation (5).

$$F = \frac{2 * P * R}{P + R} \tag{5}$$

IV. RESULTS AND DISCUSSION

This section presents the text-based classification results. The classification was performed for eight crops, namely cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat, based on the proposed recommendation system. The species of crops were classified using three machine learning algorithms J48 Decision Tree, Hoeffding Tree, and Random Forest algorithms. The study utilized the weka tool for machine learning algorithms to perform data preparation, classification, and visualization. Thus, fulfilling the objective of the proposed study, to identify the best classification algorithm for multi-sensor data.

A. DATA COLLECTION

The dataset for the study was collected in real-time using the smart agricultural monitoring and management platform as presented in Figure 2. The sensors provided measurements on soil, crops, and weather, this includes the physical parameters such as temperature, humidity, soil nutrients, growth in days, etc. The dataset comprises 85 classes with 6789 training data and 3210 testing data. The study was conducted for only the top eight classes to evaluate the performance of the proposed multi-text classifier. The performance of the classifier is measured in terms of precision, recall, F-measure, MCC, ROC Area, and PRC Area class, and the results are compared with the state-of-the-art classifiers.

The classification results of the top eight agricultural crop classes are shown in Table 1. Precision, recall, F-measure, and MCC are all presented. In terms of precision, recall, F-measure, and MCC, the random forest algorithm outperform the other two algorithms, the J48 decision tree, and the Hoeffding tree.

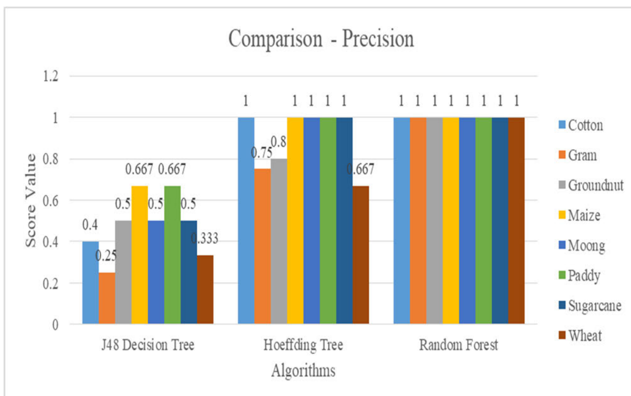

FIGURE 3. Performance comparison-based on precision.

Figure 3 compares the precision of the three algorithms, the J48 decision tree, Hoeffding tree, and Random Forest, for the eight classes. The results show that the random forest algorithm outperforms the other two classifier algorithms. Cotton,

TABLE 1. Classification results.

Agriculture Text Class	Precision			Recall			F Measure			MCC		
	J48 Decision Tree	Hoeffding Tree	Random Forest	J48 Decision Tree	Hoeffding Tree	Random Forest	J48 Decision Tree	Hoeffding Tree	Random Forest	J48 Decision Tree	Hoeffding Tree	Random Forest
Cotton	0.400	1.000	1.000	0.800	0.800	1.000	0.533	0.889	1.000	0.498	0.884	1.000
Gram	0.250	0.750	1.000	0.400	0.600	1.000	0.308	0.667	1.000	0.216	0.638	1.000
Groundnut	0.500	0.800	1.000	0.400	0.800	1.000	0.444	0.800	1.000	0.342	0.777	1.000
Maize	0.667	1.000	1.000	0.400	0.800	1.000	0.500	0.889	1.000	0.476	0.884	1.000
Moong	0.500	1.000	1.000	0.200	0.800	1.000	0.286	0.889	1.000	0.271	0.884	1.000
Paddy	0.667	1.000	1.000	0.400	0.600	1.000	0.500	0.750	1.000	0.476	0.758	1.000
Sugarcane	0.500	1.000	1.000	0.200	1.000	1.000	0.286	1.000	1.000	0.271	1.000	1.000
Wheat	0.333	0.667	1.000	0.500	1.000	1.000	0.400	0.800	1.000	0.343	0.795	1.000

gram, groundnut, maize, moong, paddy, sugarcane, and wheat have perfect precision when using the random forest algorithm. This demonstrates the effectiveness of the proposed method. For cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat, the Hoeffding tree algorithm yields 100%, 75%, 80%, 100%, 100%, 100%, 100%, 100%, and 66.7%, respectively. Similarly, the cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat values are 40%, 25%, 50%, 66.7%, 50%, 66.7%, and 50%, and 33.3 percent for the J48 decision tree. It has been discovered that the random forest algorithm works efficiently for multi-sensor data.

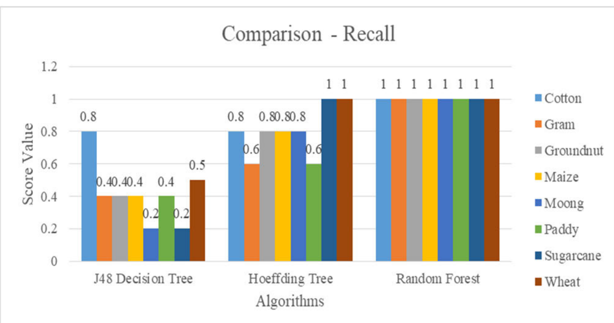

FIGURE 4. Performance comparison-based on recall.

Figure 4 shows the recall comparison for the eight classes using the three algorithms J48 decision tree, Hoeffding tree, and Random Forest algorithms. The result shows that the random forest algorithm performs better than the other two classifier algorithms. The precision for cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat using the random forest algorithm is 100%. This demonstrates the efficiency of the proposed approach. For the Hoeffding tree algorithm, it is 80%, 60%, 100%, and 100% for cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat, respectively. Similarly, for the J48 decision tree, the values for cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat are 80%, 40%, 40%, 20%, and 40%, 20%, and 50%, respectively. It is observed that the random forest algorithm works efficiently for multi-sensor data.

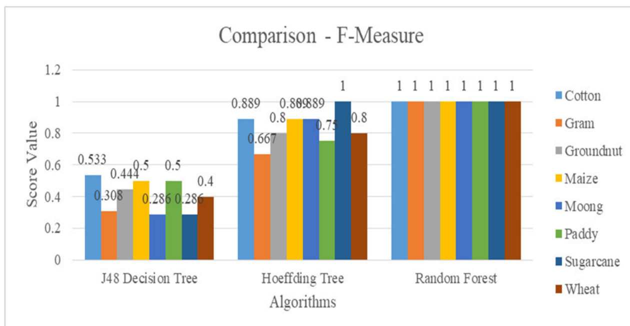

FIGURE 5. Performance comparison-based on F-measure.

Figure 5 shows the F-measure comparison for the eight classes using the three algorithms as the J48 decision tree, Hoeffding tree, and Random Forest algorithms. The result shows that the random forest algorithm performs better than the other two classifier algorithms. The precision for cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat using the random forest algorithm is 100%. This demonstrates the efficiency of the proposed approach. For the Hoeffding tree algorithm, it is 88.9%, 66.7%, 80%, 88.9%, 88.9%, 75%, 100%, and 80% for cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat respectively. Similarly, for the J48 decision tree, the values for gram, groundnut, maize, moong, paddy, sugarcane, and wheat are 30.8%, 44.4%, 50%, 28.6%, 50%, 28.6%, and 40%. It is observed that the random forest algorithm works efficiently for multi-sensor data.

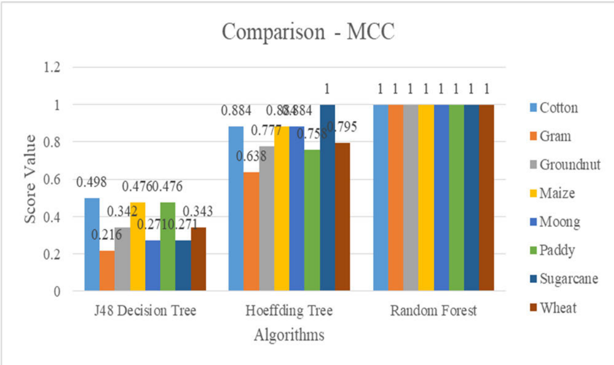

FIGURE 6. Performance comparison-based on MCC.

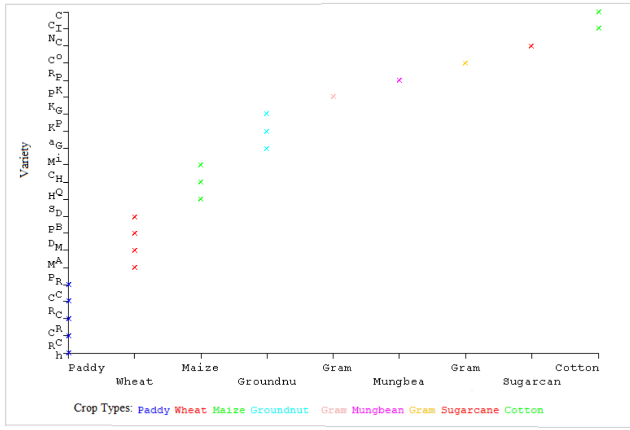

FIGURE 7. Classifications – variety.

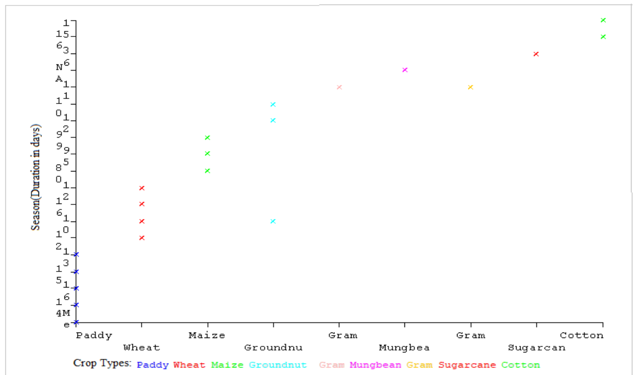

FIGURE 8. Classifications – season.

Figure 6 compares the MCC for the eight classes using three algorithms: the J48 decision tree, the Hoeffding tree, and Random Forest. The results show that the random forest algorithm outperforms the other two classifier algorithms. Cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat have perfect precision when using the random forest algorithm. This demonstrates the effectiveness of the proposed method. Cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat have 88.4 %, 63.8 %, 77.7 %, 88.4 %, 88.4 %, 75.8 %, 100 %, and 79.5 % for the Hoeffding tree algorithm, respectively. Similarly, the cotton, gram, groundnut, maize, moong, paddy, sugarcane, and wheat values are 40%, 25%, 50%, 66.7 %, 50%, 66.7 %, 50%, and 33.33% for the J48 decision tree. It has been discovered that the random forest algorithm works well with multi-sensor data. Table 2 compares the results of the ROC and the PRC Area. It has been discovered that Random Forest produces the best crop classification results.

TABLE 2. Comparative results of ROC and PRC area class.

Agriculture Text Class	ROC Area			PRC Area Class		
	J48 Decision Tree	Hoeffding Tree	Random Forest	J48 Decision Tree	Hoeffding Tree	Random Forest
Cotton	0.911	0.995	1.000	0.400	0.967	1.000
Gram	0.900	0.936	1.000	0.387	0.654	1.000
Groundnut	0.927	0.991	1.000	0.456	0.927	1.000
Maize	0.961	0.964	1.000	0.654	0.877	1.000
Moong	0.902	0.991	1.000	0.410	0.943	1.000
Paddy	0.868	0.986	1.000	0.574	0.903	1.000
Sugarcane	0.920	1.000	1.000	0.422	1.000	1.000
Wheat	0.928	0.983	1.000	0.385	0.854	1.000

Table 3 presents the proposed recommendation system's zone and variety-based results. Cotton crops of two varieties, i) CNH012, and ii) CICR-3, take 165 and 150 days, respectively, and are suitable for the zones of i) Gujarat, Maharashtra, and Madhya Pradesh, and ii) Punjab, Haryana, and Uttar Pradesh. The 110-day-long gram varieties of I PKV Kabuli-4 and ii) CRIDALATHA are suitable for i) Maharashtra, Madhya Pradesh, and ii) other rain-fed regions in South India. Karnataka, Maharashtra, Jharkhand, and Manipur are among the states. HSCI, HQPM-4, and MCH-36 with a maturity period of 80-99 days are suitable for Kharif-affected states. Paddy varieties CR Dhan-401, CR Dhan-601, CR Dhan-501, IET 20193, and IET 19140 with maturities of 150, 160, 152, and 135 days are suitable for shallow rainfed conditions. Wheat varieties such as MPO 1215, MACS 6222, PDW 314, DBW39, and VL 907 are recommended for the various zones. Thus, crop variety recommendations based on zone and season are provided to raise awareness of the condition-based environmental monitoring system. Figures 7–9 show the classification based on variety, season, and recommendation zone.

The error measure is depicted in Figure 10. The MAE, RMSE, RAE, and RRSE were used to evaluate the error measure. The MAE value for the J48 decision tree, Hoeffding tree, and Random Forest algorithm is 12%, 5%, and 7%, respectively. The RMSE values for the J48 decision tree, Hoeffding tree, and Random Forest algorithm are 25%, 17%, and 13%, respectively. The J48 decision tree, Hoeffding tree, and Random Forest algorithm RAE values are 65.78 %, 29.03 %, and 38.67 %, respectively. Likewise, the RRSE values for the J48 decision tree, Hoeffding tree, and Random Forest algorithm are 82.55 %, 58.12 %, and 44.21 %, respectively.

TABLE 3. Zones and variety-based recommendation.

Crop	Season (duration in days)	Zone	Variety
Cotton	165	Gujarat, Maharashtra, and Madhya Pradesh.	CNH012
Cotton	150	Punjab, Haryana, and Uttar Pradesh are wilt-free areas.	CICR-3 (CISA 614)
Gram	110	Maharashtra, Madhya Pradesh under irrigated conditions.	PKV KABULI-4
Gram	110	South India under rain-fed conditions.	CRIDALATHA (CRHG-4)
Groundnut	108	West Bengal, Orissa, and Manipur under Kharif rain-fed conditions.	Girnar – 3 (PBS 12160)
Groundnut	122	Karnataka and Maharashtra under timely sown irrigated condition in Rabi and Summer season.	Kadiri Harithandhra (K 1319)
Groundnut	105-110	Jharkhand and Manipur in Kharif Season.	GPBD 5
Maize	80-82	Himachal Pradesh and Uttarakhand under the Kharif season.	HSC1
Maize	95	Punjab, Haryana, Delhi, West, and Central UP, Bihar, Jharkhand, Orissa, Eastern UP, Andhra Pradesh, Karnataka, Tamilnadu, Maharashtra, Rajasthan, Madhya Pradesh, Gujarat, and Chhattisgarh under Kharif Season.	HQPM-4
Maize	99	Karnataka, Tamil Nadu, and Maharashtra in Kharif season under irrigated and rainfed conditions.	MCH 36 (Hybrid) (DKC 9099)
Moong	NA	Karnataka, Tamil Nadu, and Orissa in the Kharif season.	PKV AKM-4 (AKM-9904)
Paddy	145-150	Orissa, West Bengal, Tamil Nadu, and Andhra Pradesh under irrigated late sown conditions as well as shallow rainfed lowland.	CR Dhan 401 (REETA)
Paddy	160	Boro Area of Orissa, West Bengal, and Assam.	CR Dhan 601 (IET 18558)
Paddy	152	Semi-deep water condition of Uttar Pradesh and Assam.	CR Dhan 501 (IET 19189)
Paddy	132-135	Terraced area of Meghalaya and Manipur hills both under irrigated and rainfed conditions.	RC Maniphou 11 (IET 20193)
Paddy	NA	Andhra Pradesh, Tamil Nadu, Gujarat, Orissa, and West Bengal under irrigated conditions.	Chinsurah Rice (IET 19140)
Sugarcane	360	Tamil Nadu, Karnataka, Maharashtra, Kerala, Interior Andhra Pradesh.	Co-0218
Wheat	120	Madhya Pradesh, Chhattisgarh, Gujarat, and Rajasthan (Kota and Udaipur Division only) under timely sown irrigated conditions.	MPO(JW) 1215 (MPO 1215)
Wheat	108	Maharashtra, Karnataka, Andhra Pradesh, and Tamil Nadu under timely sown irrigated conditions.	MACS 6222
Wheat	169	Punjab, Haryana, Western Uttar Pradesh, Delhi, Rajasthan (Excluding Kota & Udaipur Divisions), Tarai Regions of Uttarakhand, Paonta Valley & Una District of Himachal Pradesh under timely sown irrigated conditions.	PDW 314
Wheat	123	Eastern Uttar Pradesh, Bihar, Jharkhand, West Bengal, Assam, and Orissa under timely sown irrigated conditions.	DBW39
Wheat	167 irrigated & 180 rainfed	Madhya Pradesh	VL Gehun 907 (VL 907)

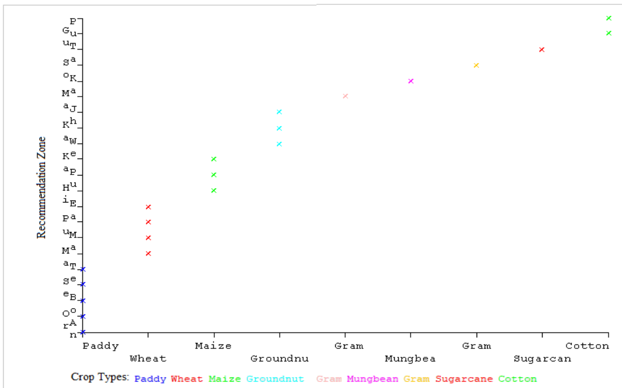

FIGURE 9. Classifications – recommendation zone.

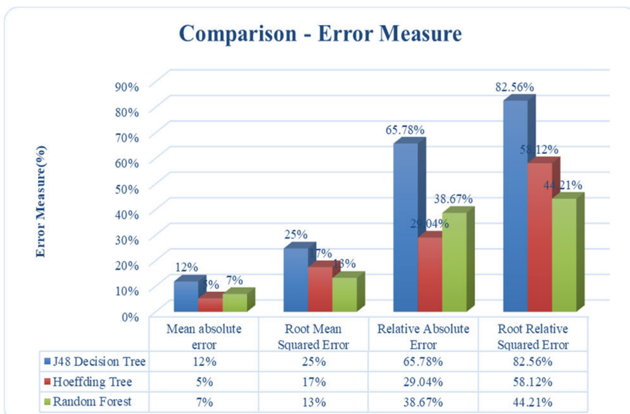

FIGURE 10. Comparison of error measure.

Random forest algorithms have the lowest error measures of 13%, 38.67%, and 44.21%, respectively. As a result, the random forest algorithm has the lowest error measure in classifying agricultural text. Thus, the use of a multisensor data fusion approach based on crop recommendation provides greater precision in prediction, resulting in a significant increase in crop yield while also raising awareness of the condition-based environment monitoring system.

V. CONCLUSION

Agriculture is a major sector of the Indian economy, and it is being impacted by changing temperature and rainfall patterns, a lack of water, and other poor agricultural practices. The current study assists farmers in making decisions about increasing crop production. Experiments on the benchmark dataset show that the random forest algorithm has the lowest error measure in classifying the agriculture text, with RMSE 13%, RAE 38.67%, and RRSE 44.21%. Thus, the use of a multisensor data fusion approach based on crop recommendation provides greater precision in prediction, resulting in a significant increase in crop yield while also raising awareness of the condition-based environment monitoring system. Future research should consider methods that take into account all parameters in the agricultural field to improve the prediction process. As a result, the random forest algorithm classifies the agricultural dataset with high accuracy and a low error rate.

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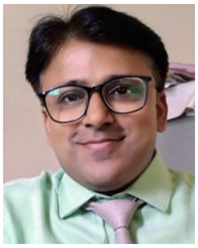

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