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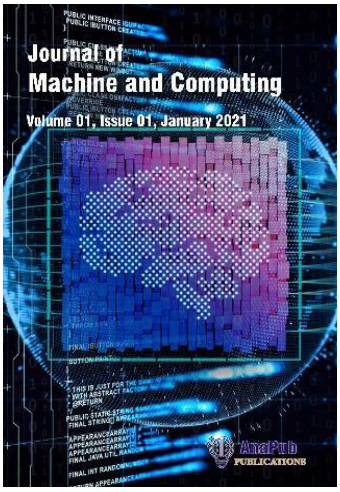

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An Ensemble Classification Model for Crop Recommendation with Edge Computing

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Abstract:

Smart farming may be defined as a farming practise that uses the thought process of modern technology to increase the number and quality of agricultural products. Edge-based smart farming is a system designed solely for the monitoring of crops in the field using sensors and automating the irrigation system to meet our demands. Old cloud-based systems that rely heavily on IoT models are incapable of handling traffic and also knowledge information. As a result, there seems to be reduced latency, longer battery life for IoT devices, lots of cost-effective money-based information management, access to knowledge management and AI, cubic centimetres. So, in this paper we propose an algorithm **Ensembled Enabled Edge computing** algorithm for developing a smart farming system for crop recommendation in better way for getting best result and compared with some of the existing base classifiers like SVM and Naive-Bayes in which the proposed algorithm gave the best accuracy when compared with the existing classifiers i.e., 91%.

Keywords: Ensembled algorithm, Edge Computing, IOT, Smart Farming, Cloud computing.

1. INTRODUCTION

For the past few years cloud is the word which changed the world among all various technologies which is used to learn and study to a vast extent. Online social media sites like Twitter, LinkedIn, Facebook, etc., basically utilizes a concept called SaaS (known as Software as a Service) which have been using for decades in our daily life. Now comes the word IOT which sound's to be interesting and the IOT devices playing a major role in the current scenario. With the growth of IOT devices the data generation which is causing for a huge flow of information got gradually increased. And in the huge data there might be a chance of having sensitive data so in order to handle that sensitive data cloud got failed for transporting the data from the cloud to end users. The Internet of Things (IoT) is the next big thing in information technology. The web, information and communication technology (ICT),[1] and mobile services are all combined in one concept. Multiple devices in a model system will be able to interact and coordinate in order for the to accomplish its function efficiently. "The IoT represents a global network of billions or trillions of things that can be collected from the physical global environment, propagated through the Internet, and transmitted to end users," according to the ITU's definition. Users can use services to communicate with these smart things over the Internet, query their statuses and associated information, and even control their actions"[1]. Its primary premise is to build a huge network comprised of various smart devices and networks in order to ease the sharing of global information [2]from any location and at any time [3].

RFID, WSN, 3S, Cloud computing, and other technologies are widely employed in the Internet of Things. RFID (Radio Frequency Identification) is a technology that assigns unique tags to various objects and gadgets. These tags send data that is read by an RSID reader and then used according to the specifications. In the Internet of Things, these tags transform ordinary gadgets into smart ones [3]. Sensors are also utilized to gather and evaluate information from a variety of sources. The 3S technology consists of GPS (Global Positioning System), GIS (Geography Information System), and RS (Remote Sense), which uses satellites and sensors to deliver information about the positions of various objects and processes it. In the Internet of Things, a wireless sensor network (WSN) makes data transmission easier.

To store and compute data generated by IoT, cloud services that are immediately available and location-independent are used. These services can be easily deployed where they are needed. Due to several characteristics such as easy availability, resource management constraints[4], and pay-per-use policies, cloud services are ideally suited for IoT environments. Cloud servers can provide software, storage space, processing power, platforms, and other services.

Cloud computing has its own set of ramifications and considerations. This paper discusses the issues surrounding the use of cloud in IoT. Table 1 examines the security implications of cloud computing in the IoT, focusing on data storage, access, and management.

In this research paper, we tried to introduce the concept of edge computing, along with its working using EEE computing technique. Apart from this we have discussed about benefits by using this type of technology. Since there is a lot of scope and challenges in edge computing[5] for that reason, we have taken the topic and tried to improve some of the issues faced in the area of farming. Figure 1 shows the usage of latest edge computing in the field of agriculture which is shown in figure 1.

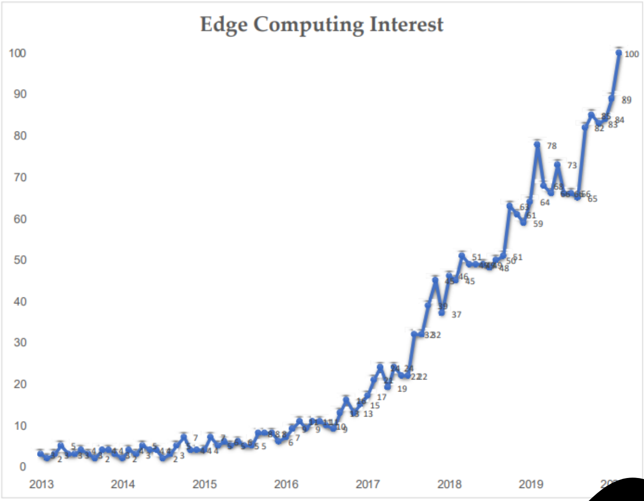


Fig1: Shows the edge computing usage

II Literature Survey

Computing is a network cloud computing model in which processing and data storage are brought directly to the data sources. This should increase response times while also conserving bandwidth. [1] "It's a popular misperception that edge and IoT are interchangeable terms. Edge computing is a decentralized system that is adaptive to topology and location, and IoT is a use case for edge computing." .Rather than referring to a single technology, the phrase refers to an architecture. [8]

The beginnings of edge computing may be traced back to content dispersed networks, which were established in the late 1990s to offer web and video content from edge servers located near to consumers. [18] In the early 2000s, these networks expanded to house applications and application components at edge servers,[6], leading to the first commercial edge computing services [6], which hosted applications including dealer tracking systems, shopping carts, reliable data brokers, and ad fixation machines. [6]

Similarly, the goal of edge computing is to relocate processing away from data centers and onto the network's edge, utilizing smart devices, mobile phones, or network gateways to execute activities and deliver services on behalf of the cloud. [23] By relocating services to the edge, it is feasible to provide content caching, service delivery, persistent data storage, and IoT management, resulting in faster response times and transfer rates. Figure2 shows how iot and edge computing is related in the field of farming Distributing the logic to multiple network nodes, on the other hand, creates additional concerns and obstacles like.

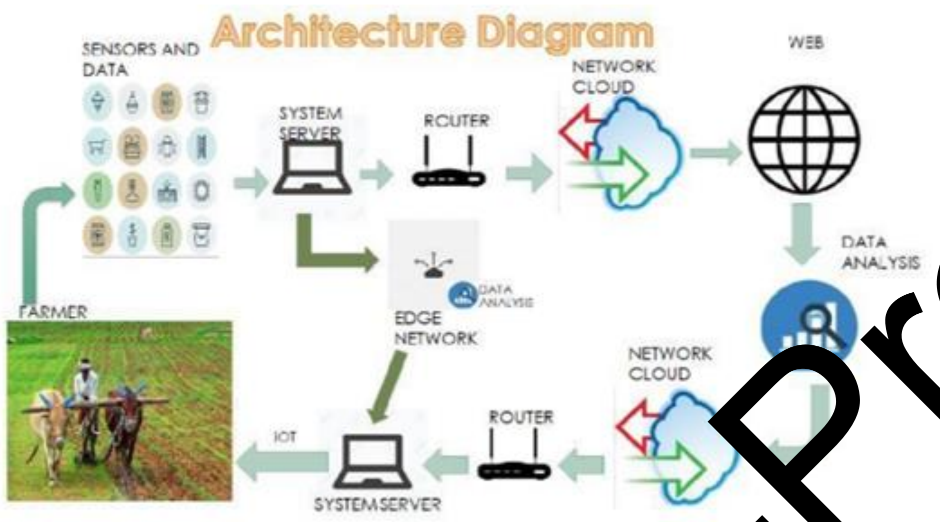
1.Privacy and security

2. Scalability

3. Reliability

4. Speed

5. Efficiency



.Fig2. Shows the architecture of Edge with IOT

In order for farmers to earn more money from the same amount of land without harming the soil, productivity needs to be increased. Indian farmers are unable to pick the suitable crop based on characteristics such as pH, N, P, and humidity[9], temperature, rainfall, and humidity. Based on the requirements of the soil, farmers frequently are unsure whether to apply regular fertilizer or organic fertilizer. Insufficient and uneven fertilization causes soil deterioration, which in turn causes nutrient mining and the emergence of second-generation nutrient management issues.Pest-related agricultural losses amount to Rs.50,000 crore, as determined by a survey carried out by the Indian Chambers of Commerce and Industry. Study [10] presented a distributed edge computing platform tailored for smart farming, aimed at enhancing crop productivity in remote agricultural areas. By leveraging a microservices architecture, the platform facilitated efficient service decomposition, enabling scalable and flexible deployment of farming applications. The integration of IoT devices allowed for real-time data collection and processing at the edge, which reduced latency and improved decision-making processes in agricultural operations. This study built a scalable edge computing platform for real-time decision-making but did not include predictive models or address specific issues such as crop selection and pest management. Other than monitoring, the proposed EEEC algorithm promises to add value by not recommending site-specific crops but relying on ensemble models and describing pest-related concerns, which makes it more actionable for farmers. In an existing study [11] a smart agriculture system utilizing fog computing is proposed to know about intrusions of animals in farmland. The system used PIR sensors, cameras, and computer vision to identify animals before they entered fields, predict future locations and promptly warn farmers. For cases of real-time applications in unserved areas with limited internet connectivity, the fog computing approach can process the data at a reasonable latency.

While this system targeted solely detecting animal intrusions, it failed to take on broader agricultural needs such as crop recommendation, soil analysis, or fertilizer optimization. By analyzing soil characteristics and recommending fertilizers, the EEEC algorithm provides a full end-to-end solution for increasing productivity, extending the utility of edge computing. In a study [12], they explored a smart irrigation system for strawberry greenhouses that performed data processing at the network edge. The system was able to monitor soil moisture levels and optimize water usage through the use of a small-scale prototype with off-the-shelf hardware and software. In the edge computing approach, there was limited dependence on cloud services, which was an issue when it came to data privacy and network latency. An improvement in irrigation water consumption efficiency and soil moisture stability was shown in field experiments compared to conventional irrigation. This study optimized irrigation through edge computing, but only considered water usage, not pest management, fertilizer recommendation, or site-specific crop selection. These missing elements, certainly pest identification and ISO-compliant pesticide recommendations, are integrated into the proposed EEEC algorithm that will solve agricultural inefficiencies comprehensively. Smart farming was studied in an integration of artificial intelligence (AI), edge computing, and IoT [13]. Embedded devices were used such as Raspberry Pi with scripts programmed with sensors measuring temperature, humidity, and light. Real-time monitoring and decision-making through agricultural system processing data at the edge locally resulted in enhanced efficiency and responsiveness of agricultural operations. However, this study did not incorporate the methodology for crop recommendation or the ways of dealing with fertilizer and pest problems, thus bringing AI and edge computing together to monitor temperature and humidity in this research. The proposed EEEC algorithm fills this gap using ensemble learning to recommend crops and fertilizers, incorporating pest management into the process. In a study [14], they looked at the edge AI in smart farming and how edge computing and AI algorithms were integrated. The proceedings discussed the use of edge processing for real-time analytics and decision-making to make farming more responsive and efficient. This research focused on edge AI for real-time decision-making, but it did not tackle the practical pitfalls related to developing actionable recommendations parametrizing parameters like soil nutrients, climatic factors, and pest control. This study proposes an algorithm that synthesizes these parameters in a two-phase process to provide farmers with targeted crop recommendations and good pest control strategies to ensure high crop productivity. Research [15] aimed at creating an edge computing system to harvest the degradation data of strawberries and conduct collection, analysis, prediction, and detection of heterogeneous data. The system would locally process data to cut latency and enable quicker real-time decisions that result in better (more efficient) and meaningful farming practices. The power of this research was that it proved efficient edge computing for strawberry farming, but it was only supported with a single crop type with no mention of site-specific recommendations or pest and fertilizer optimization. The EEEC algorithm is inclusive of different crops and has integrated recommendations for fertilizers and pesticides, thus applicable to different agricultural contexts. So, in order to solve the above problem some of the below factors has to be considered to increase the productivity of the crop.

1) A modern farming method that uses research data on soil characteristics, soil types, and crop yield data collection to recommend the right crop to farmers based on their site-specific parameters in order to reduce the number of crops that are chosen incorrectly and increase productivity will be implemented.

2) A high accuracy and efficiency crop for site-specific parameters based on an ensemble model and majority voting technique is proposed as a solution to the issue.

3) To recommend fertilizers based on crop levels of N, P, and K.

4) Identify the pest and recommend a specific Indian pesticide that complies with ISO standards[16].

In this paper we concentrate on improving efficiency by implementing a novel algorithm named EEEC algorithm which basically runs in 2 phases in the 1st phase it checks for the suitable condition for a crop to grow without harming the crop from insects etc., and in the 2nd stage, based on the results obtained from the step1 like which condition is suitable for which crop these are used to predict in which month we can grow them to obtain best results ie production high which is used in farming for better production.

III. Proposed Methodology

The main objective of this research article is to generate relevant information which is needed to take a necessary decision for a crop to grow in healthy manner and take some necessary actions which out effecting from insects using machine learning algorithms like Naïve-Bayes [17]and SVM and compared with proposed algorithm in which the proposed algorithm gave the best result when compared with the other two.

Naïve-Bayes: - Naïve-Bayes is one of the best classification techniques in statistics which is known as probabilistic classifier which has strong assumptions between features. It is highly scalable takes no of parameters as input from the learning problem and takes linear time for classifying the data.

(It is a conditional probability model in which the taken feature is to be classified and can be represented as vector v=(v1,v2,v3,…..vn) which represents n features for k possible outcomes ie classes shown in fig. Mathematically it is given as

$$p(C_k \mid \mathbf{x}) = \frac{p(C_k)\, p(\mathbf{x} \mid C_k)}{p(\mathbf{x})}$$

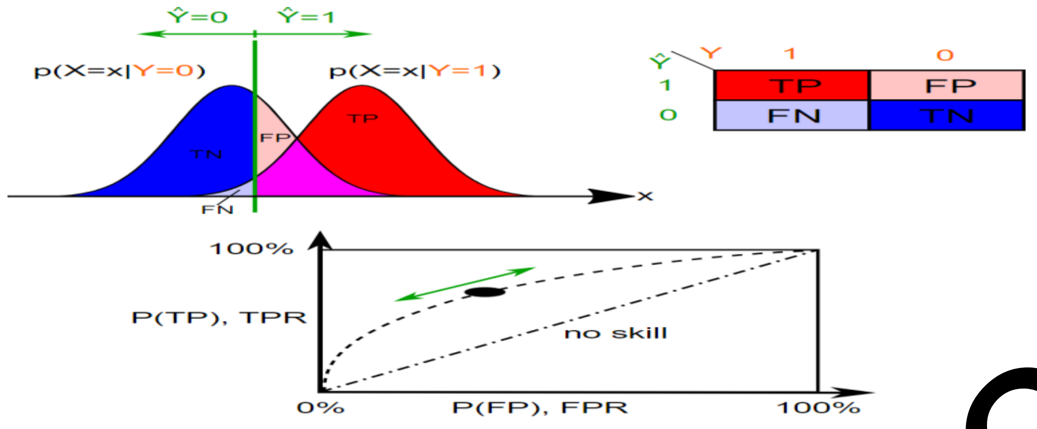
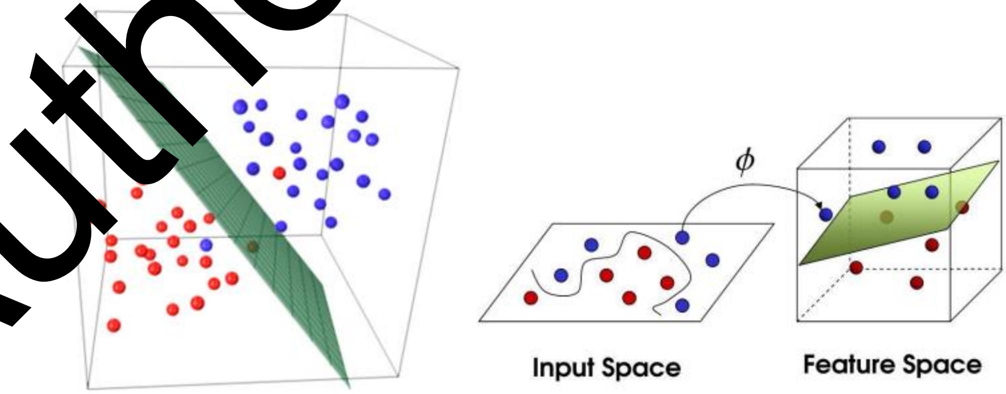


Fig 3: Represents n features for k possible outcomes

Bayes algorithm can easily calculate for categorical data ie height, no of fruits/year etc., it is used to discriminate between continuous features by replacing with discrete value and also assumes probability distribution for continuous features and based on this it can characterizes using 2 parameters.ie., mean and variance.)

SVM: The most important and widely used ML algorithm as a base classifier is SVM which is a supervised ML algorithm. This algorithm is used for classifying the data for both classification and regression problems. The main theme of this algorithm is used to differentiate between 2 or more classes of data which can separate various classes as shown in figure. SVM is nearly equal to hyperplane and when eliminated if redefines itself [18]. So, in this regard most of the researchers' mostly concentrates on this algorithm for taking crucial elements in the data. Generally, the loss function can be optimized with the help of descending technique [5]. Certainly, the data will be separated in linear fashion which can be represented as subset of various classes. SVM can work very effectively and efficiently with the help of kernel trick [5]. In order to separate 2 classes with high dimensionality without increasing the computational cost shown figure 4.



(a) (b)

Fig 4 (a&b): Two classes with high dimensionality without increasing the computational cost

Proposed Methodology:

For recommending which crop to grow in which season can be given by the proposed classifier and the architecture of the proposed model is given in figure 5.In order to recommend the crop for a farmer for making money the proposed classifier is used in the following steps:

Step 1:First of all we need to collect the data from various resources in this paper the data is collected from kaggle repository.

Step 2:In the second step we have to take the best paramaters as I/P values so that the farmer can yield more crop.For ex moisture of the soil,sunlight,temperature etc.

Step 3:From the data we will apply some base classifiers along with the proposed model in which the proposed model gave the best accuracy when compared with the other 2

Step 4:And in the final step based on the accuracy predicted we can recommend the farmer for making more profits by farming best crop in best time[21,22].

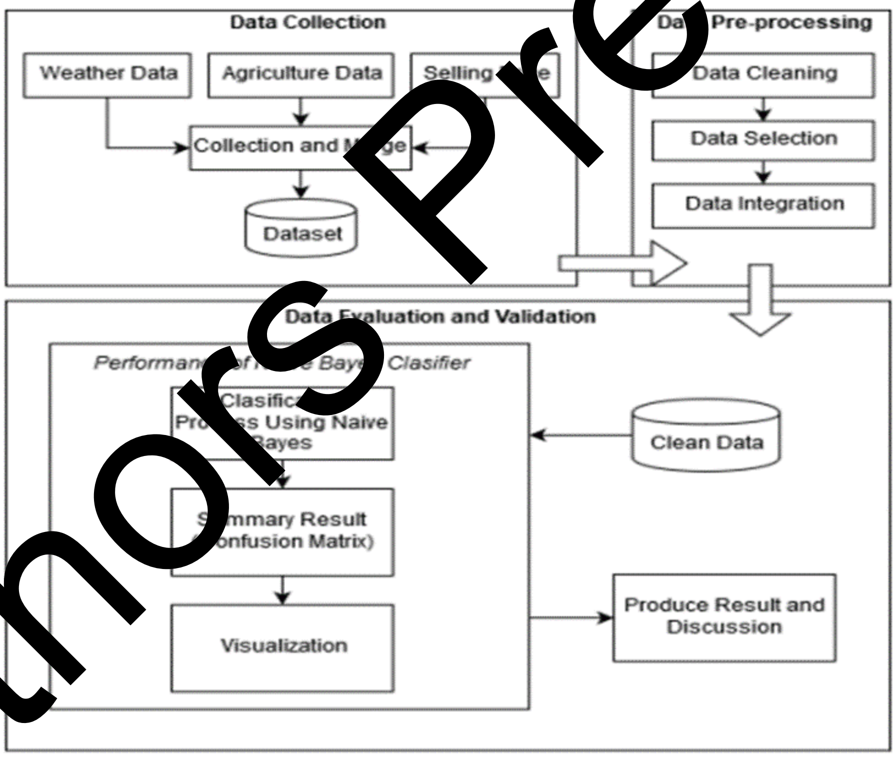


Fig 5:Shows the architecture of the proposed model

In the proposed algorithm it classifies the data in a simple manner which is used for predicting the accuracy of the model. In the first phase the data must be trained which contains tuples consisting of x attributes X1,X2,X3….Xn where each tuple is checked against class and a decision tree is construicted .and in the 2nd phase from the decision tree a confusion matrix is generated which is used for prediciting crop recommendation for the farmer.And the attributes taken in phase 1 for constructing a decision tree are,

1)N Value 2) P Value 3) K Value 4)Temp 5)Humidity Or Moisture 6) Ph Value 7) Rainfall etc.,

And the class labels are 1)rice 2)maize 3)chickpea etc

A. Phase 1 Algorithm

I/P Trained Data

X=(X1,X2,……Xn) taken from various attributes ie Y1,Y2,….Yn. (utilization of variable must be consistant, in the above para attribute are mentions as X1,X2,X3….Xn)

Input Training Dataset Y) Splitting(Y)
Construct tree()
records in X in same class return
else:
for every attribute X:
build the best split for splitting X1 to X2. recursively call Splitting(X1)
from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier()
classifier = classifier.fit(X_train,y_train)
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
Xtrain, Xtest, Ytrain, Ytest = train_test_split(features,target,test_size = 0.2,random_state =2)

B. Phase 2 Algorithm

Now call the function xgboost()
W= z.xgbClassifier()
W.fit(X train, Y train) then call CT()
c= Generate confusion matrix (Y test, Y pred)
Find accuracy a = No of True Predictions / Total Predictions return a
stop

Based on various parameters and based on the season a confusion matrix is generated which is labelled with different classes which is shown in figure 6.From the heat map generated from phase 1 we can find the accuracy of the algorithm from the confusion matrix and predict the recommention to plant which crop in which season based on the above parameters.

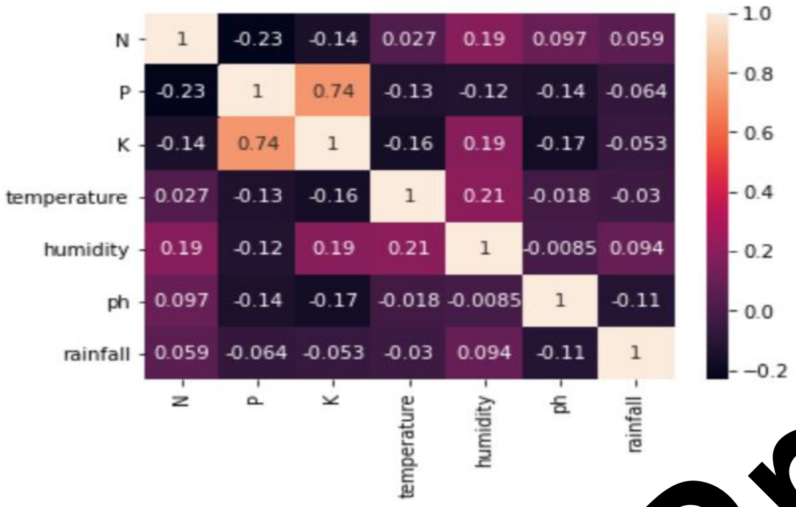


Fig 6: Shows the Heap map generated in phase 1

A heat map of classification outcomes in Phase 1 of the proposed algorithm is plotted in Figure 6. The heat map is a block corresponding to the correlation between input features (soil pH and temperature and rainfall) and predicted classes (variety of crops). Each color is the intensity of how accurate the classification is, and the darker the color the more accurate it is. The feature importance and relationship that drive accurate crop recommendations are critical for use. It helps us determine what crop parameters (high rainfall, low pH) separately correlate strongly with. This visual gives the farmers and the agricultural planner an idea of which factors most influence crop yields and can help them figure out where they need to focus while troubleshooting in the real world.

Performance Evaluation:

For any research problem performance evaluation[19] is one of the major tools for comparing the results with the proposed classifiers with the existing classifiers. These are like precision, recall, f-score, accuracy etc., In order to calculate these, we need confusion matrix which contains 4 values. TP(True-Positive), TN(True-Negative), FP(False-Positive), FN(False-Negative) shown in figure 7

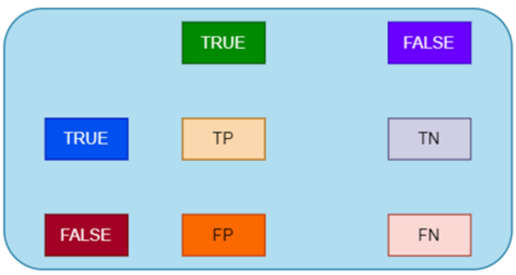


Fig 7: Confusion matrix

Based on the values generated in the confusion matrix the precision, recall and f-score were calculated which is given as[20]:

Precision = TP/(FP + TP)

Recall = TP/ (TP + FN)

F-Score=2TP/ 2TP + FP + FN

Accuracy: (TP + TN)/ (TP + TN + FP + FN)

Figure 8 shows the accuracy on the dataset by using the classification algorithm Naïve Bayes.

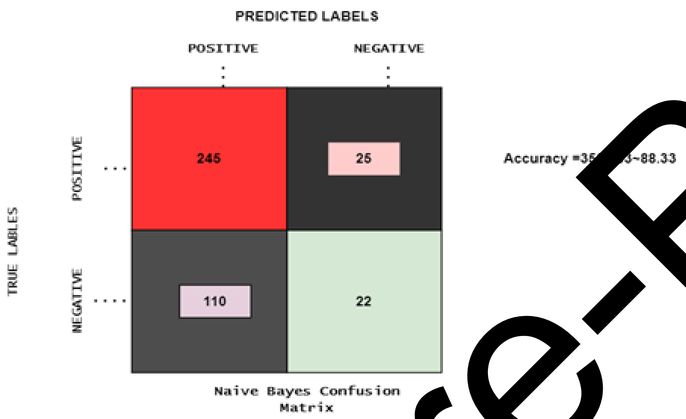


Fig 8: Accuracy predicted using Naïve-Bayes

The model also provides conditional probabilities for predicting the suitability of crops based on input parameters, such as soil and environmental factors. A baseline classifier comparison with the proposed model is taken in the form of Naïve-Bayes. It works well for dealing with categorical data, but it's less accurate because it assumes feature independence and other simplifying assumptions. Naïve-Bayes results show the necessity of robust models such as the proposed classifier on complex agricultural datasets that involve interdependent features. The accuracy predicted using SVM is given as shown in figure 9.

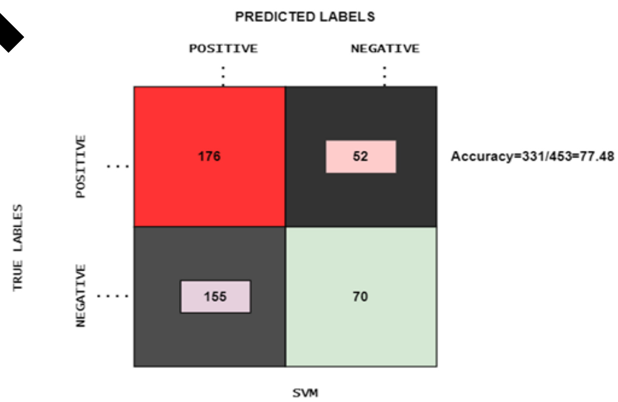


Fig 9: Accuracy predicted using SVM

High dimensional data is handled well by SVM and optimal hyperplane is found for classification with SVM. Figures such as the graph or the table above outline how SVM performs i.e. it can classify crops according to their feature sets. Agricultural data scenarios are the best scenario for SVM and they prove to be better than Naïve Bayes. However, it may be too computationally intensive for larger datasets. SVM is validated in a situation where a precise decision has to be made, e.g. determining suitable crops under different soil conditions, by achieving higher accuracy. The accuracy predicted using the Proposed classifier is given in Figure 10.

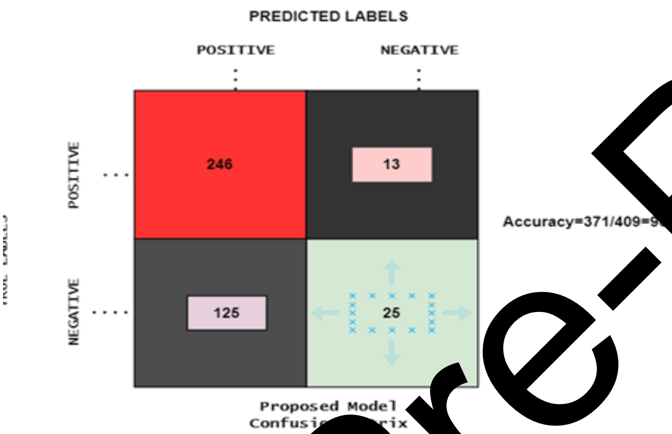


Fig 10: Accuracy predicted using the Proposed classifier

Figure 10 shows the accuracy of the proposed ensemble-enabled edge computing classifier outperforms both Naïve-Bayes and SVM. By combining the strengths of many of these algorithms in an Ensemble Learning fashion, the proposed classifier predicts robustly and accurately. Its practical adoption over traditional methods is justified by its higher accuracy. The relevant figure confirms the practical applicability of the model in modern farming and provides precise, actionable recommendations to save crop failures and achieve maximum yield while supporting their practical applicability.

If we take the data based on N P K etc our proposed algorithm predicted that the suitable crop for yielding and for good vegetation and also for making more profits is [‘coffee’] shown.

data = np.array([[104,18, 30, 23.603016, 60.3, 6.7, 140.91]])

prediction = RF.predict(data)
print(prediction)

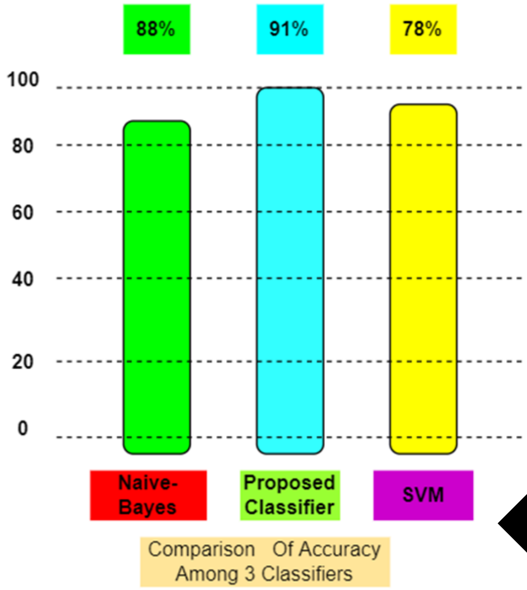


Fig 11: Output of Coffee using the proposed algorithm

The final output of the shown proposed algorithm (predictions of coffee as the best crop in the conditions of nitrogen, phosphorus, potassium, N P K levels, temperature, soil pH, and rainfall) is illustrated in Figure 11. The output shows that the model can accurately process multiple parameters while suggesting a specific crop recommendation for the given conditions. Such recommendations can be directly used by farmers to cultivate high-value crops like coffee, in alignment with the market demand as well as the environmental suitability.

Discussion

Using an ensemble-enabled edge computing classification model, a methodology based on this is proposed and shows its potential to revolutionize modern farming practices. The methodology integrates IoT sensors and edge computing to propose crop recommendations in real time to specific agricultural contexts. Moreover, this addresses not only inherent limitations such as high latency and network dependence but is also conducive to advancing decision-making more effectively to boost the farmers' decision-making efficiency; so that they can increasingly reach the optimal crop yield and resource utilization. This allows for the application of the model to real-time data at the edge, which decreases reliance on cloud infrastructure, decreases latency, and retains data privacy. This study presents a robust framework for recommending crops using environmental parameters such as soil nutrients, temperature, and humidity through a two-phase process classifying crops with a decision tree and evaluating through a confusion matrix. This granular analysis guarantees that farmers get the most accurate and actionable recommendation that will increase productivity and reduce crop failure risk.

Many studies have already focused on the potential of edge computing and IoT in agriculture. For example, a study [13] discusses an application of AI, edge computing, and IoT for smart farming that deals with the real-time monitoring and making of decisions; the proposed model's goal aligns here. An IoT-based smart farming system optimized water usage in strawberry farming using edge computing, reported [15]. However, they do not reach up to crop recommendations or pest management. The proposed algorithm thus addresses the gap by providing more holistic solutions to crop, fertilizer, and pest recommendations. The study [10] discussed the use of microservices architecture in IoT-edge computing platforms for smart farming, which supports the flexibility and scalability of the edge computing system in our proposed methodology. Additionally, [11] presented a fog computing-oriented framework that detects animal intrusion in farms, though its use is limited to a particular situation and does not provide an overview of agriculture like the one in our model. The EEEC algorithm is far more than simple intrusion detection since it covers the following capabilities: soil analysis, evaluation of crop suitability, and the management of pest control. In addition, although various studies such as [16] have researched deep learning and the remote sensing technique in crop yield prediction, attention was mainly based on the output of forecasts generated using static data sources like satellites. The model, however, discussed here incorporates real-time edge-based processing combined with machine learning techniques in providing practical, localized suggestions. Thus, the proposed research is based on an existing framework that integrates edge computing and ensemble learning in a single solution for a more comprehensive, real-time, and actionable modern farm. Edge computing is also now applicable in crop selection, resource optimization, and pest management not only by mere monitoring systems and irrigation.

The proposed model gives several practical advantages including offering immediate recommendations to farmers on the kind of crops suitable for specific farmlands, leading to efficiency in decision making. From the analysis of data related to soil and climate, the model is ascertained to best employ water, fertilizers, and other resources, thereby decreasing costs and environmental impact. Additionally, the model is found flexible and can be implemented over a wide range of farms either small-holder or large-scale commercial agriculture. The proposed ensemble-enabled edge computing model is a big step in the use of modern technology to achieve sustainable agriculture. It shows high accuracy, real-time processing ability, and relevant applicability, making it a crucial resource for addressing current issues in agriculture.

IV. Conclusion & Future Work

Farmers benefit from crop recommendations. During climate change, which is already impossible to anticipate. Farmers no longer employ farming techniques passed down from generation to generation. The findings obtained are also affected by natural circumstances. Choosing the correct variety of food plants could help farmers' economies. The likelihood of the farmer encountering crop failure may be reduced to a bare minimum, while the yield produced can be raised, and after the farmer has already harvested, the harvested can be sold at a high price. Farmers will be taxed as a result of these agreements.

As a result, while giving nutritional recommendations, plants should utilize the right form. The Proposed model was employed in this investigation on the Jupyter notebook for testing results and compared with the existing classifiers like Naïve-Bayes, and SVM in which the proposed model gave the best accuracy when compared with the other two for predicting the best time for vegetation.

In this research we mainly focused on modeling a classifier that classifies the data effectively for predicting the results which are based on some factors like weather, type of agricultural produ[illegible], temperature etc., which played a major for taking some critical decision's whether the farmer can [illegible] farming a particular crop or not. By applying some deep learning concepts we may ach[illegible]eve m[illegible]re accuracy when compared with the existing one along with IOT devices.

Declarations

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Competing interests: The authors declare that they have no competing interests

Conflicts of interest: The authors declare that they have no conflict of interest

Availability of data: The datasets generated during and/or analyse[illegible] durin[illegible] the current study are not publicly available but are available from the corresponding author on reasona[illegible]le reques[illegible]

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