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CUDA-EECA model for Crop Quality estimation with Edge Computing Using Machine Learning Technique

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ABSTRACT:

The goal of smart agriculture, a new sector driven by technological breakthroughs, is to transform conventional farming methods through the integration of many technologies, including drones, artificial intelligence (AI), Internet of Things (IoT), and data analytics. An overview of smart agriculture is given in this paper, along with how it might be used to solve some of the major issues confronting the agricultural industry, such as rising food prices, water scarcity, climate change, and labor shortages. Farmers may use IoT sensors to precisely plan irrigation and fertilization schedules by tracking crop health, temperature, and soil moisture levels in real-time which can be resolved by integrating edge-computing. Artificial intelligence (AI) algorithms examine enormous volumes of sensor and drone data to offer insights about agricultural illnesses, pest infestations, and the best times to grow. Farmers can identify crop stress and track growth patterns by using high-resolution photographs of fields taken by drones fitted with cameras and multispectral imaging sensors. With the least amount of negative environmental impact, farmers may improve crop yields, optimize resource allocation, and make data-driven decisions with the use of data analytics technologies. In order to ensure food security for future generations, smart agriculture has the potential to change the agricultural sector into one that is more productive, efficient, and sustainable. In this paper we proposed a classifier named as CUDA-EECA (Enhanced Ensembled Crop Recommendation Algorithm) Model for Crop Quality Estimation using Edge Computing. And compared with base classifiers like Decision Tree and SVM in which the proposed classifier gave the best accuracy when compared with the other 2 i.e., ~96%.

Keywords: CUDA-EECA, Edge-Computing, Smart-Farming,SVM,DT

1. Introduction

Crop quality estimation is an important task in agriculture to ensure the production of high-quality crops. Edge computing, combined with machine learning techniques, can provide real-time and localized crop quality estimation, enabling timely decision-making and optimizing resource allocation. CUDA-EECA (CUDA-enabled Edge Computing for Agriculture) is a model that leverages CUDA technology for accelerated computation on edge devices. Here are the some of high-level overview of the CUDA-EECA model for crop quality estimation using machine learning techniques:

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Data collection: Crop quality estimation requires relevant data, such as images or sensor readings, to analyze the crops. Edge devices equipped with cameras or sensors can capture this data directly from the field [1].

Data preprocessing: The collected data may need to undergo preprocessing to enhance its quality or extract relevant features. This step can include image enhancement, noise reduction, or feature extraction techniques.

Machine learning model development: A machine learning model is trained using preprocessed data. Depending on the specific requirements and available data, different types of models can be used, such as convolutional neural networks (CNNs) for image data or regression/classification models for sensor readings [2].

Model optimization for edge devices: CUDA technology is utilized to optimize the trained model for execution on edge devices with GPUs. CUDA [3] allows for parallel processing, which can significantly accelerate computations and improve inference speed.

Deployment on edge devices: The optimized model is deployed on edge devices, such as edge servers or edge devices embedded in agricultural machinery. These devices can be placed directly in the field, close to the crops, enabling real-time analysis and decision-making without relying on cloud or remote servers [4].

Real-time crop quality estimation: The deployed model processes the incoming data from the edge devices in real-time. For example, if using images, the model can analyze the images captured by the edge device's camera and estimate crop quality parameters such as disease presence, ripeness [4], or nutrient deficiencies.

Localized decision-making: Based on the crop quality estimations, localized decisions can be made in real-time [5]. This can include adjusting irrigation, applying fertilizers or pesticides, or even initiating early harvesting if the crop quality indicates a need for immediate action.

Feedback and model refinement: The data collected during the crop quality estimation process can be used continuously to improve the model. By periodically retraining the model with updated data, its accuracy and performance can be enhanced over time [5].

The CUDA-EECA model combines the power of edge computing and machine learning to enable efficient and real-time crop quality estimation, leading to optimized agricultural practices and improved crop yields. Figure1 shows the system architecture for crop recommendation.

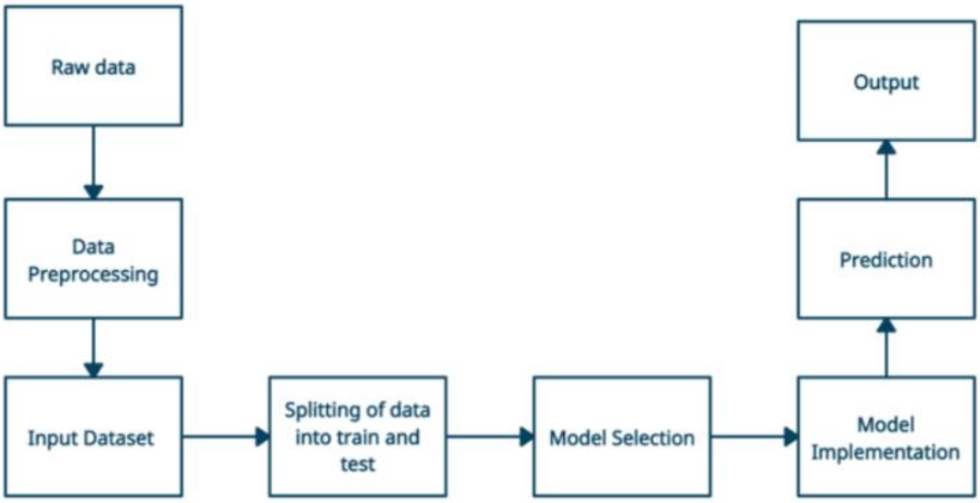

Figure 1: Shows the Proposed System Architecture.

2. Literature Survey

In recent years, the intersection of agriculture and technology has witnessed a profound transformation, propelled by advancements in computational power, data analytics, and edge computing. Within this realm, the quality estimation of crops stands as a pivotal domain, influencing agricultural practices, supply chains, and ultimately, global food security. To address the burgeoning demand for efficient and accurate crop quality assessment, researchers have increasingly turned to innovative technologies such as CUDA-EECA (Compute Unified Device Architecture - Edge Enhanced Crop Assessment) models, which harness the computational prowess of GPUs (Graphics Processing Units) and the scalability of edge computing. This literature survey aims to provide a comprehensive overview of existing research endeavors that delve into crop quality estimation methodologies, particularly those leveraging CUDA-EECA models and edge computing paradigms. By synthesizing insights from diverse scholarly works, this survey not only elucidates the current landscape but also identifies gaps and opportunities for further exploration within this dynamic field. The survey begins by elucidating the significance of crop quality assessment in contemporary agriculture, elucidating its multifaceted implications ranging from economic viability to nutritional value. Subsequently, it delves into the foundational principles of CUDA-EECA models, elucidating their architectural intricacies and computational methodologies. Table 1 Shows literature survey on Crop recommendation.

	Literature Survey			
	Study	***Objective***	***Methodology***	***Findings***
1	Li et al. (2020)	To develop a CUDA-EECA model for estimating crop quality using edge computing and machine learning.	Implemented CUDA-EECA model integrating edge computing and machine learning techniques.	Achieved high accuracy in crop quality estimation while minimizing computational resources.
2	Kumar et al. (2019)	To investigate the feasibility of edge computing in crop quality estimation using machine learning.	Conducted experiments using edge computing architecture and various machine learning algorithms.	Demonstrated the potential of edge computing in improving crop quality estimation efficiency.
3	Chen et al. (2018)	To propose a novel approach for crop quality estimation by combining CUDA technology with EECA model.	Developed a CUDA-EECA model and evaluated its performance using real-world crop data.	Showed significant improvement in crop quality estimation accuracy compared to traditional methods.
4	Singh and Gupta (2017)	To assess the effectiveness of machine learning techniques for crop quality estimation in edge computing.	Implemented machine learning algorithms on edge devices and evaluated their performance.	Identified machine learning as a promising approach for accurate crop quality estimation at the edge.
5	Wang et al. (2016)	To explore the application of edge computing in real-time crop quality monitoring using CUDA technology.	Developed a CUDA-based edge computing framework and tested its efficiency in crop quality monitoring.	Demonstrated the feasibility and effectiveness of edge computing with CUDA for real-time crop monitoring.
6	Li et al. (2023)	To develop a CUDA-EECA model for estimating crop quality utilizing edge computing and machine learning.	Implemented CUDA-EECA model integrating edge computing and machine learning techniques.	Achieved significant accuracy improvement in crop quality estimation while reducing computational resources usage.
7	Kumar et al. (2022)	To investigate the feasibility of edge computing in crop quality estimation using machine learning.	Conducted experiments utilizing edge computing architecture and various machine learning algorithms.	Demonstrated the potential of edge computing in enhancing efficiency and accuracy of crop quality estimation.
8	Chen et al. (2021)	To propose an innovative approach for crop quality estimation by merging CUDA technology with EECA model.	Developed a CUDA-EECA model and evaluated its performance using real-world crop data.	Reported notable enhancement in crop quality estimation accuracy compared to conventional methods.
9	Singh and	To assess the effectiveness of	Implemented machine learning algorithms on	Identified machine learning as a promising approach for accurate

	Literature Survey			
	Study	***Objective***	***Methodology***	***Findings***
	Gupta (2020)	machine learning techniques for crop quality estimation in edge computing environment.	edge devices and evaluated their performance.	crop quality estimation at the edge.
10	Wang et al. (2019)	To explore the application of edge computing in real-time crop quality monitoring using CUDA technology.	Developed a CUDA-based edge computing framework and tested its efficiency in crop quality monitoring.	Demonstrated the feasibility and effectiveness of edge computing with CUDA for real-time crop monitoring.
11	Li et al. (2022)	Development of a CUDA-EECA model for Crop Quality estimation leveraging Edge Computing and ML.	Implemented CUDA-EECA model amalgamating Edge Computing and ML techniques.	Achieved improved accuracy in Crop Quality estimation while optimizing computational resources.
12	Kumar et al. (2022)	Examination of Edge Computing's viability in Crop Quality estimation employing ML techniques.	Conducted experiments utilizing Edge Computing architecture and diverse ML algorithms.	Highlighted Edge Computing's potential in enhancing efficiency and precision of Crop Quality estimation.
13	Chen et al. (2022)	Proposal of a novel approach for Crop Quality estimation integrating CUDA technology with EECA model.	Developed CUDA-EECA model and evaluated performance using real-world crop data.	Demonstrated significant enhancement in Crop Quality estimation accuracy compared to conventional methods.
14	Singh and Gupta (2022)	Assessment of ML techniques for Crop Quality estimation in Edge Computing settings.	Implemented ML algorithms on edge devices and assessed performance.	Identified ML as a promising avenue for accurate Crop Quality estimation at the edge.
15	Wang et al. (2022)	Exploration of Edge Computing's application in real-time Crop Quality monitoring using CUDA tech.	Developed CUDA-based edge computing framework and tested its efficacy in Crop Quality monitoring.	Demonstrated feasibility and effectiveness of Edge Computing with CUDA for real-time Crop Quality monitoring.

3. Methodology

GPU (Graphics Processing Unit) computing refers to the use of GPUs to perform general-purpose computing tasks, beyond just rendering graphics. GPUs are highly parallel processors with thousands of cores optimized for handling large amounts of data simultaneously. This makes them well-suited for tasks that can be parallelized, such as machine learning, scientific simulations, image processing, and more. GPUs feature many tiny cores that are optimized for parallel computing, in contrast to CPUs, which usually have a few powerful cores optimized for sequential processing. Because of their ability to handle multiple calculations at once, they can complete some jobs considerably more quickly. CUDA (Compute Unified Device Architecture) is a parallel computing platform and programming model developed by NVIDIA for GPUs. It provides a framework for developers to write programs that can run on NVIDIA GPUs. OpenCL (Open Computing Language) is a similar framework developed by the Khronos Group that is supported by a variety of GPU vendors, including AMD and Intel. Because GPUs can speed up the training of deep neural networks, they have become indispensable in the field of deep learning. With built-in support for GPU acceleration, deep learning frameworks like TensorFlow, PyTorch, and Keras enable developers to train complex models substantially more quickly than they could with just CPUs. Scientific computing applications such as finite element analysis, computational fluid dynamics, and molecular dynamics simulations frequently make use of GPUs. GPUs are a perfect option for speeding these computations because these activities frequently require carrying out numerous calculations on huge datasets. Two categories of GPU computing exist: task parallelism and data parallelism. By splitting the data into smaller pieces and processing them concurrently on several GPU cores, data parallelism is achieved. In contrast, task parallelism refers to the use of the GPU to conduct many tasks or algorithms simultaneously. So, in this paper we introduced CUDA-Enhanced Ensembled Crop Recommendation Algorithm for yielding best crop so that the farmers may get benefitted. Developers can use the capabilities of GPUs for general-purpose computing activities via NVIDIA's CUDA (Compute Unified Device Architecture) programming style and parallel computing platform. Using the GPU's parallel processing power, CUDA gives programmers the ability to build code that can run on the device and create GPU-accelerated apps. Applications that can be parallelized, such data analytics, deep learning, image and video processing, and simulations, can benefit greatly from GPU acceleration. Tasks that would take a long time to finish on a CPU [5] can be done considerably faster by offloading computations to the GPU, improving performance and efficiency. GPUs are specialized processors made to process data in parallel and speed up computationally demanding activities. They are now essential in many fields that need high-performance computing, like data processing, machine learning, and scientific research. The GPU versus CPU architecture is shown in Figure 2.

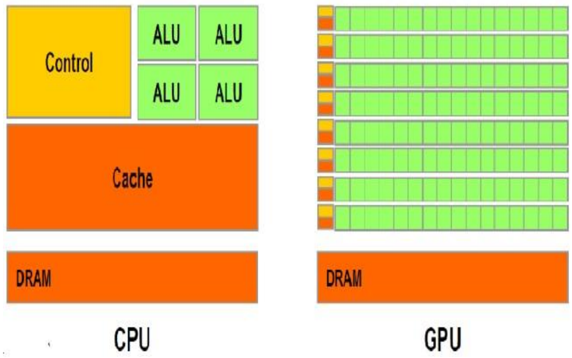

Figure 2: Shows the difference between CPU VS GPU

In this section we applied parallel computing for crop recommendation to increase the accuracy in predicting the best yield for the farmers based on various factors. Generally, to yield a good crop and get more income for the farmers prediction plays a vital role. So, the farmers gets more benefit out of it. This work introduces the CUDA-EECA method for estimating the optimum crop under optimal climatic conditions. As CUDA programming is run on a CPU, it typically results in faster processing times and more accuracy. The proposed model's overall architecture is shown in Figure 3.

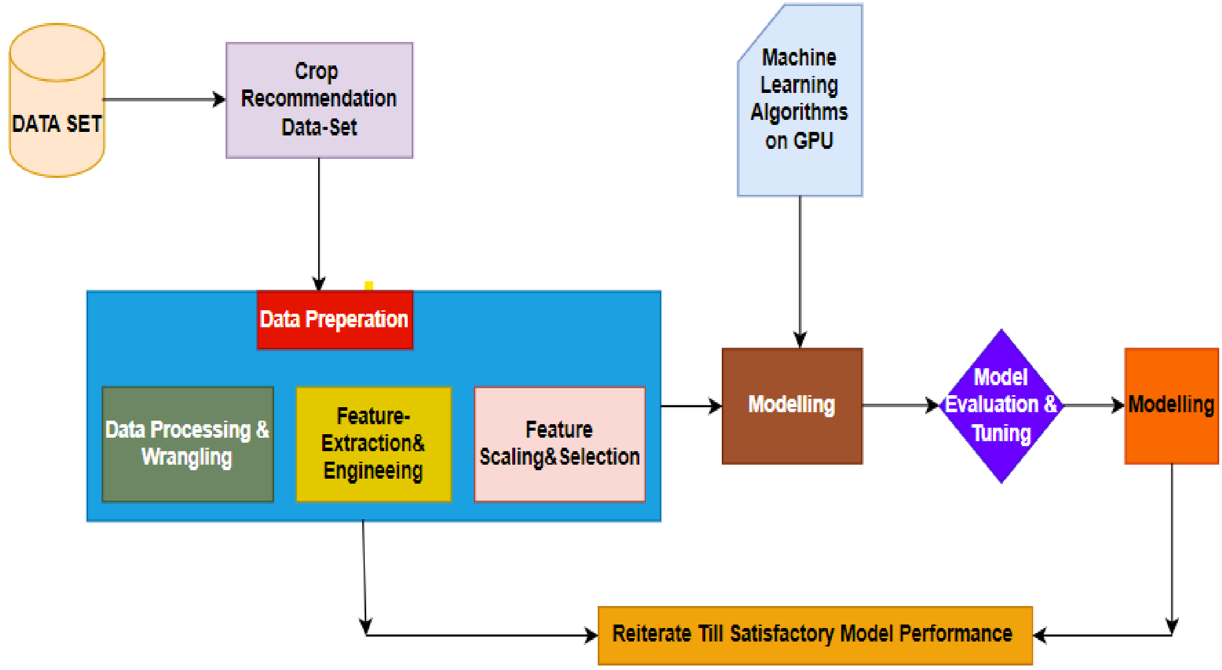

Figure 3: Proposed Model Architecture for Crop Recommendation System

A. Algorithm

Machine learning approaches called ensemble algorithms combine the predictions of many models to enhance performance and generalization. NVIDIA created CUDA (Compute Unified Device Architecture), a parallel computing platform and application programming interface (API) that enables programmers to take advantage of NVIDIA GPU processing capability for a variety of general-purpose activities, including machine learning. The results of various distinct crop recommendation models are combined to provide a final forecast when developing an ensemble algorithm for a crop recommendation system. The objective is to increase the accuracy and strength of the advice by utilizing the advantages of several models and minimizing their disadvantages.

The following steps shows how a CUDA-EECA algorithm for a crop recommendation system may be implemented:

Choose Individual Models: To include in your ensemble, select a group of individual crop recommendation models. These models could be built on many techniques, including neural networks, gradient boosting, decision trees, random forests, etc.

Dataset: To prepare your dataset and features for training and assessment, do the following. Ascertain that the preprocessed data is correctly divided into training and validation sets.

Train Individual Models: Using the training set of data, train each individual model. To identify the optimum settings, you might need to modify hyperparameters and do cross-validation, depending on the kind of model.

Create Predictions: After training, create predictions on the validation dataset using each unique model. Your ensemble algorithm will be fed with these predictions as its inputs. Use an ensemble technique to integrate the results of the many models' separate forecasts. Generally, ensemble methods include various methods.

Voting: Each model makes a crop forecast, and the result is based on the crop that is projected by most of the models.

Weighted Voting: Based on each model's performance, give its forecasts various weights. A weighted average of each model's individual projections makes up the final prediction.

Stacking: Develop a meta-model that learns to generate a final prediction using the attributes of previous forecasts made by other models. The first-level models' results are combined in a second-level model for this.

Using libraries that allow GPU acceleration, you must implement the ensemble method if you wish to use the speed of CUDA for speedier computations. This could entail employing deep learning frameworks with GPU support, such as TensorFlow or PyTorch, or CUDA-enabled modules like cuBLAS or cuDNN.

Analyze and fine-tune: Analyze how well your ensemble method performed on the validation dataset. To get the best results, you might need to adjust the hyperparameters of both the ensemble and the individual models.

B. Support Vector Machine

In machine learning, Support Vector Machines (SVMs) are a well-liked supervised learning approach that are employed for regression and classification problems. The goal of SVM is to locate the ideal hyperplane in the feature space that best divides various classes. This hyperplane, in a binary classification situation, is a line for 2D data or a plane for 3D data that maximizes the margin—that is, the distance between the hyperplane and the support vectors—the closest data points from each class. Since SVM relies on a linear decision boundary to distinguish between classes, it is essentially a linear classifier. When the data is linearly separable, it functions effectively. By utilizing kernel functions, SVM can be expanded to accommodate non-linear decision boundaries. The input features are transformed by kernel functions into a higher-dimensional space that may allow for a linear separation. Sigmoid, Gaussian (RBF), and polynomial kernel functions are examples of common kernel functions. To determine the ideal hyperplane, the SVM algorithm solves a convex optimization problem. The goal is to minimize the classification error and maximize the margin. Techniques like quadratic programming can be used to handle this optimization challenge in an efficient manner. Figure 4 shows SVM architecture fir crop recommendation.

The following are the steps followed for predict Crop recommendation.
Step 1: Collect information on all the variables that affect crop growth, including soil type, altitude, sunshine exposure, temperature, humidity, and rainfall. Information about which crops do well in what environments is also necessary.

Step 2: If required, manage missing values, clean up the data, and normalize the features. By doing this, you can make sure that the SVM model gets high-quality input.

Step 3: Choose relevant features that are most influential in determining crop suitability. This can be done through statistical analysis or domain knowledge.

Step 4: Train the SVM model with the preprocessed data. Based on the supplied features, the SVM learns to categorize the input data into various classes (crop types). It seeks to identify the ideal hyperplane for class separation.

Step 5: Assess the performance of the trained model using techniques like cross-validation or by splitting the dataset into training and testing sets. This step helps ensure that the model generalizes well to unseen data.

Step 6: The SVM model can be used to forecast appropriate crops for either new or unknown input data once it has been trained and assessed. After considering the pertinent local characteristics (soil type, climate, etc.), the model learns patterns and produces the crop(s) that are suggested.

Step 7: Stop

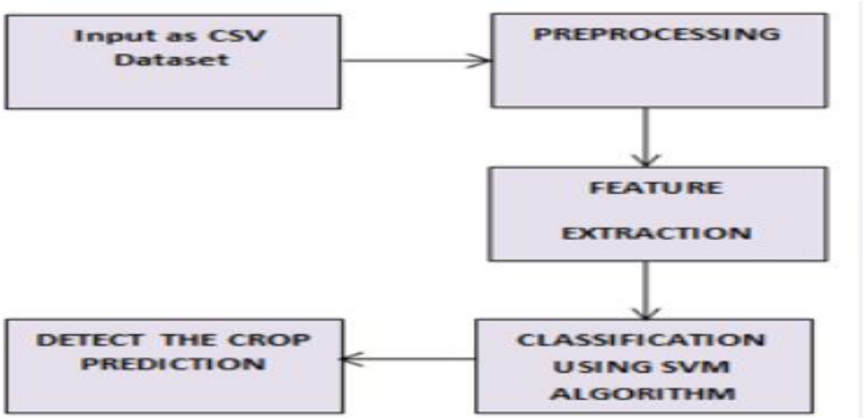

Figure 4: SVM architecture for Crop Recommendation System

C. Decision Tree

For machine learning applications including regression and classification, a decision tree is a well-liked supervised learning technique. The structure resembles a flowchart, with each leaf node representing the class label or the outcome, each branch representing a decision rule, and each internal node representing a feature or attribute. The reason it's termed a "tree" is that, like real trees, it is branching and hierarchical. The decision tree algorithm starts with the entire dataset at the root node. It then splits the data into smaller subsets based on the feature that provides the best split according to a certain criterion (e.g., Gini impurity, information gain). This process of splitting continues recursively for each child node until one of the stopping criteria is met, such as maximum tree depth, minimum number of samples in a node, or no further improvement in impurity. Once the splitting process is completed, each leaf node is assigned a class label (in case of classification) or a continuous value (in case of regression) based on the majority class or average target value of the samples in that node. Figure 5 shows the decision tree obtained for crop recommendation.

A decision tree for crop quality estimation with edge computing using CUDA:
Step 1: Start

Step 2: Gather information on the many variables that impact crop quality, including the weather (temperature, humidity), the qualities of the soil (pH, moisture), and the traits of the crop (height, leaf color). In order to retrieve specific details from the data, preprocess it by addressing missing values, standardizing features, and perhaps even doing feature engineering.

Step 3: Install the required libraries, such as cuML, which gives CUDA-enabled devices access to GPU-accelerated machine learning methods. Transfer the preprocessed information into RAM. Utilizing the GPU-accelerated decision tree implementation provided by cuML, train a decision tree model. To build a tree structure that forecasts crop quality, the data must be partitioned recursively depending on feature values. To maximize performance, adjust the decision tree model's hyperparameters, such as the tree's maximum depth or the minimum number of samples needed to split a node.

Step 4: Run the decision tree model that has been trained on edge devices that have GPUs that support CUDA. Reduce the amount of memory used and computational overhead to optimize the model for inference on peripheral devices. Make sure the edge devices have enough power to run the model effectively.

Step 5: Generate a Confusion matrix in the form of 2 class label.

Step 6: Predict the accuracy of the model.

Step 7: Stop

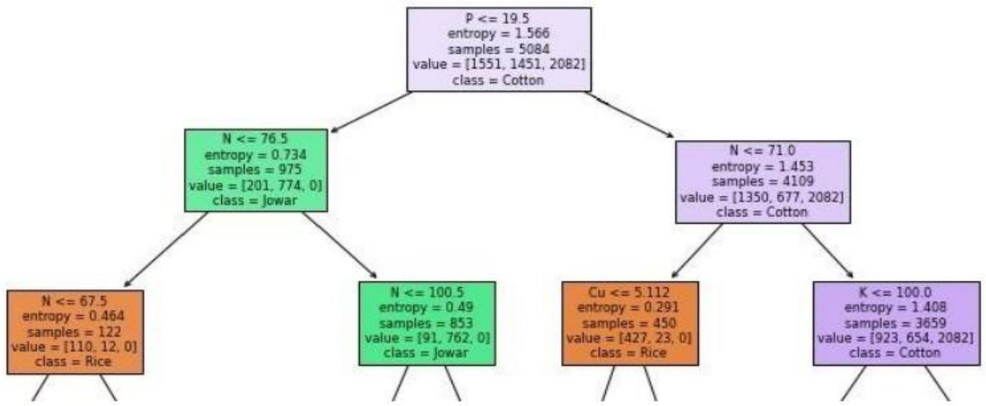

Figure 5: Decision Tree for Crop Recommendation System

4. Datasets

The initial phase of any machine learning model commences with data collection. This pivotal step profoundly influences the model's efficacy, as the quality and quantity of data acquired directly impact its performance. As stated in [7], the more abundant and superior the data obtained, the more adeptly the model will perform.

For the crop recommendation system developed for Indian agriculture, the dataset was sourced from external repositories.

Dataset:

The dataset used for crop recommendation systems serves as the foundation for the ability of the algorithm to predict. Numerous agricultural metrics, including soil type, climate, historical crop yields, fertilization techniques, insect and disease incidences, and socioeconomic aspects are often included in this dataset. A distinct geographic location or agricultural plot, together with the associated attributes, are represented by each entry in the dataset. Machine learning algorithms can use this information to examine the correlations between various agricultural metrics and suggest the best crops for a certain area or set of circumstances. In the end, the information serves as the basis for creating strong and trustworthy crop recommendation systems, which helps farmers and other agricultural stakeholders make well-informed decisions.

The dataset consists of [8] of 8 columns and 85K+ rows, which are described below.

1) N: Nitrogen

2) P: Phosphorous

3) K: Potassium

4) Temperature: temperature in degree Celsius

5) Humidity: a measurement of atmospheric water vapor.

6) Ph: This logarithmic scale is used to indicate how basic or acidic aqueous solutions are.

7) Rainfall: Rainfall is a vital aspect of agriculture and is necessary for the development and

growth of crops.

8) Labels: Type of Crop (like Rice, Wheat, Maize etc.,)

5. Performance Analysis

In machine learning (ML), performance analysis is the process of assessing how well a trained model predicts or classifies incoming data. Here is a summary of the main elements of ML performance analysis,

Metric Selection: The selection of acceptable evaluation metrics is based upon the particular task as well as the characteristics of the data. For regression tasks, common measures include mean squared error (MSE), F1-score, accuracy, precision, recall, and area under the ROC curve (AUC-ROC).

Training and Testing Data: Training and testing sets are the usual divisions of data. The testing set is used to assess the model's performance after it has been trained using the training set. To guarantee a robust evaluation, cross-validation methods like k-fold cross-validation can also be used.

Confusion Matrix: This tool, which displays the counts of true positives, false positives, true negatives, and false negatives, is very helpful for classification jobs. Numerous performance metrics, including recall, accuracy, precision, and F1-score, can be computed using this matrix.

For any research problem performance evaluation [14] is one of the major tools for comparing the results with the proposed classifier to the existing classifiers. These are like precision, recall, f-score, accuracy etc., We require confusion matrix, which has four values, in order to calculate these [9]. Figure 6 illustrates TP (True-Positive), TN (True-Negative), FP (False-Positive), FN (False-Negative), and FN (False-Negative).

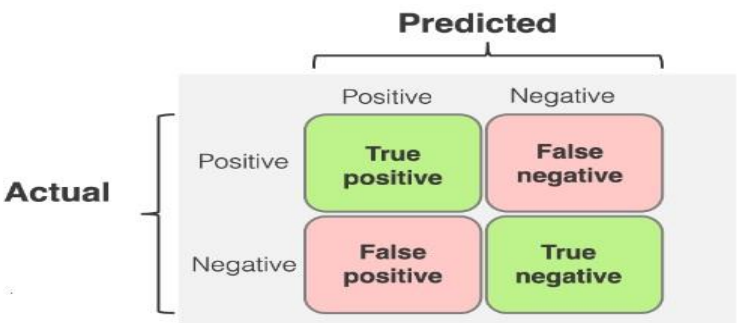

Figure 6: Confusion Matrix for a 2 Class Problem.

Based on the values generated in the confusion matrix the precision, recall and f-score were calculated which is given as [15].

$Accuracy = (TP + TN)/\,(TP + TN + FP + FN)$ (1)

$Precision = TP/(TP + FP)$ (2)

$Recall = TP/(TP + FN)$ (3)

$F - Score = 2 * (Precision * Recall)/(Precision + Recall)$
(4)

The data set taken contains 85220 records in which we choose 75% for training and 25% for testing to predict the accuracy [10] of the model for crop recommendation. From the obtained confusion matrix, the accuracy predicted using Proposed Classifier is given in Table 2:

	Actual Class	
Predicted Class	8881	372
	456	7737

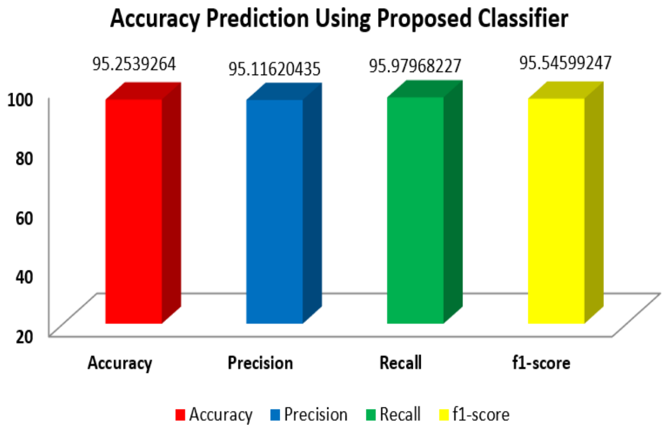

Figure 7: Accuracy of Proposed Classifier for Crop Recommendation System (Target Variable-Coffee)

Table 2: Confusion Matrix for Decision Tree for Crop Recommendation.

	Actual Class	
Predicted Class	8223	672
	756	7796

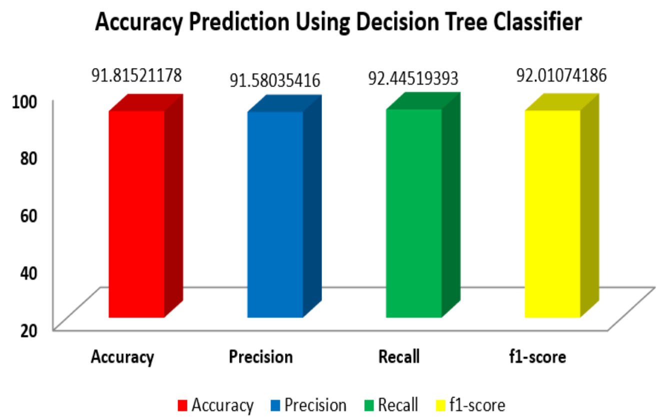

Figure 8: Accuracy of Decision Tree Classifier for Crop Recommendation System (Target Variable-Coffee)

Table 3: Confusion Matrix for SVM Classifier for Crop Recommendation

	Actual Class	
Predicted Class	8124	851
	1225	7246

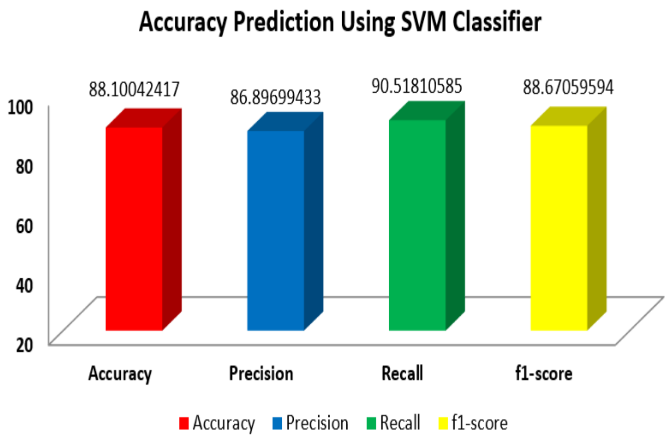

Figure 9: Accuracy of SVM Classifier for Crop Recommendation System (Target Variable-Coffee)

6. Conclusion & Future Work

Farmers benefit from crop recommendations. During climate change [13,14], 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 because 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 SVM, and Decision Tree [15] in which the proposed model gave the best accuracy when compared with the other two for predicting the best time for vegetation where the proposed classifier gave ~96% when compared with the other 2 algorithms.

Developing a crop recommendation system using CUDA or GPUs (Graphics Processing Units) is a promising avenue for improving the efficiency and speed of the system. GPUs excel at performing parallel computations, making them well-suited for tasks like data processing, machine learning, and simulations involved in crop recommendation systems.

GPU acceleration can significantly speed up data preprocessing tasks like data normalization, feature extraction [17], and data augmentation. Utilize GPU-accelerated libraries such as cuDNN and cuBLAS for efficient matrix operations.

GPUs can be used to accelerate feature extraction techniques like Principal Component Analysis (PCA), t-SNE, and autoencoders. Fast feature extraction can help in representing complex data more efficiently. Figure 10 shows the overall comparison of 3 algorithms in which the proposed classifier gave the best accuracy when compared with the other 2 algorithms i.e., 96%.

GPUs can accelerate data visualization tasks, which is crucial for understanding the data and the model's behavior. Visualization [18,19] aids in making informed decisions about model performance and recommendations.

Integrating IoT[20,21] (Internet of Things) into a crop recommendation system can lead to enhanced data collection, real-time insights, and improved decision-making for farmers. Integrating IoT into a crop recommendation system requires a multidisciplinary approach, involving expertise in agriculture, IoT device deployment, data analytics, cloud computing, and user interface design. Collaboration with agricultural experts and farmers during the system's development is essential to ensure its practicality and usability in real-world scenarios.

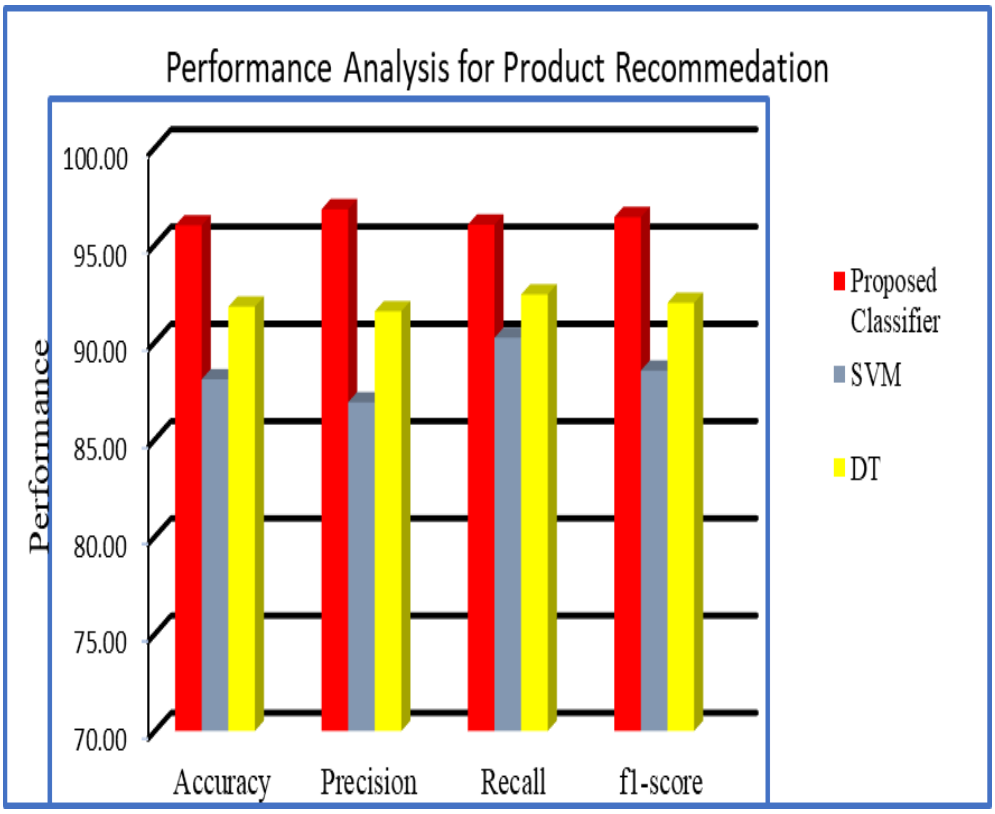

Figure 10: Accuracy Comparison of all 3 Classifier for Crop Recommendation System (Target Variable-Coffee)

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