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Foxtail Millet Growth Prediction Using Hybrid Model of Machine Learning and Deep Learning with Efficient Feature Extraction

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Abstract: Agriculture is the mainstay of the Indian economy and it is important to enhance the production with the help of technology. Crop production is a complex phenomenon that is influenced by various parameters like climatic conditions, fertilizers, production, rainfall, etc. Recent advancements in agricultural technology have embraced image annotation through Machine Learning techniques. The surge in image data has significantly fueled the interest in image annotation. Leveraging deep learning for image annotation facilitates the extraction of image features and has proven effective in analyzing vast datasets. Deep learning, drawing inspiration from the human brain's structure and relying on artificial neural networks, stands as a powerful machine learning method. This paper presents Foxtail Millet growth prediction using hybrid model of Machine Learning and Deep Learning with efficient Feature Extraction. VGG16 network used to extract features from images of the Foxtail Millet plants at different stages of growth. Decision Tree (DT), Random Forest (RF) are used machine learning models and MobileNet, SqueezeNet are used deep learning models. Hybrid model involves the combination of machine learning and deep learning models. An experimental result clears that described model is efficiently predicts the growth of Foxtail Millet in terms of Accuracy, Precision, Recall and F1-Score parameters than other classification models.

Keywords**:** *Foxtail Millet, hybrid model, DT, RF, MobileNet, SqueezeNet, VGG16.*

1. Introduction

The agricultural industry serves as a cornerstone for many nations, offering extensive employment prospects for communities and contributing significantly to the production of goods and food supply [1]. Millets are coarse grains and a repository of protein, fiber, vitamins and minerals. Millets have high nutrition and are gluten free. Millets are a must have on the list of healthy diet. There are different varieties of millets like jowar, ragi, foxtail millet, bajra, etc. Finger Millet is one such variety which is cultivated in areas with rainfall of 700-1200mm and temperature of nearly 27 degree Celsius. It does not tolerate heavy rainfall. It is grown on red soil, yellow soil and laterite soils. Foxtail millet contains a high amount of protein (11%) and fat (4%). The protein fractions are represented by albumins and globulins (13%), prolamins (39.4%), and glutelins (9.9%) [2].

Moving toward food security and sustainability, there is a pressing need for growers to optimally utilize resources to maximize the yield and quality of crops produced, thus making plant growth monitoring a cornerstone in modern precision farming. The development of a plant is the ultimate result of the complex interaction between its genotypes and the environment. Therefore, a deep understanding of a particular plant is necessary to assist in plantation management, particularly in making decisions related to fertilization, harvesting, and early pest and disease prevention plants [3]. Information collected from growth monitoring possible to know about the comparison of a plant's genes and its traits, and hence serves as a reference or indicator in plant breeding programs.

The demand for cereal production is rising globally due to the need for nutrient-focused agricultural development, green and sustainable ecosystem development, and quality development. The head of foxtail millet is an important indicator to assess the yield and quality of the grain. The detection and research of foxtail millet ear can not only help breeders to accurately evaluate germplasm resources, but also provides agriculturalists with ways to manage production costs at a reduced level [4]. Therefore, it is of great significance to study a foxtail millet ear detection method with a low arithmetic power requirement which can be applied to mobile devices for crop breeding, cultivation, yield improvement, and agricultural production.

Traditional machine learning (ML) methods such as decision trees, naïve Bayes algorithm, fuzzy logic, support vector machine, and gradient boosting algorithm usually require human involvement in feature extraction and preprocessing steps prior to model use [5]. Manual

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hand-crafted feature extraction and non-standardized preprocessing steps not only limit the model scalability but also renders the analytics work time-consuming and challenging. Deep learning is a machine learning technique that allows computers to learn by example in the same way that humans do. In deep learning, computer models learn to perform classification tasks directly from images, text, or voice. Deep learning models can achieve cutting-edge precision that can exceed humanlevel performance. The model is trained using a large amount of labeled data and neural network architecture with many layers [6]. Deep learning frameworks need a lot of information to return accurate outcomes. Data is fed in the forms of datasets. While handling the information, artificial neural networks are able to classify data with the responses received from a progression of parallel true or false inquiries including exceptionally complex numerical estimations [7].

Hybrid model is developed in this paper which includes the combination of machine learning and deep learning classifications. Decision Tree (DT), Random Forest (RF) are used machine learning models and MobileNet, SqueezeNet are used deep learning models. The remaining paper is organized as follows, Section II explains the Literature survey, Section III explains the described methodology of Foxtail Millet growth prediction using hybrid model with efficient Feature Extraction, Section IV evaluates the experimental result analysis and finally paper concludes with Section V.

2. Literature Survey

Yang, F.; Lei, X.; Liu, Z.; Fan, P.; Yan, B. et al. [8] proposed a fast multi-apple target detection method based on the CenterNet model without anchor boxes, using the lightweight Tiny Hourglass-24 as the backbone network of the model and optimizing the residual module to achieve fast multi-apple targets in dense scenes detection. The light weight of the model structure, however, may reduce target detection accuracy and make it difficult to detect occlusion, adhesion and small-size targets in complex environments. The problem has been addressed in numerous studies by introducing attention mechanisms and multi-scale detection.

Li, X.; Pan, J.; Xie, F.; Zeng, J.; Li, Q.; Huang, X.; Liu, D.; Wang, X. et al. [9] proposed a Yolov4-tiny model for the fast and accurate detection of green peppers. Using technologies such as attention mechanism and adaptive feature fusion of multi-scale detection, the improved model ensures the detection speed of lightweight models and improves the detection performance. Patil, B. V., &Patil, P. S. et al. [10] developed a deep CNN model to detect diseases in cotton plants. Augmentation, fine tuning and image processing was performed on the leaves and different test cases gave an efficient outcome for detecting diseases in cotton plants. These methods can help farmers detect diseases as early as possible and prevent their crops from being damaged.

Dos Santos Ferreira, A.; Freitas, D.M.; da Silva, G.G.; Pistori, H.; Folhes, M.T. et. al. [11] Utilizing an unsupervised deep clustering technique, we applied unsupervised learning to two authentic weed datasets. The outcomes from these used datasets indicate a promising pathway for employing unsupervised learning and clustering in agricultural contexts. The proposed familiar unsupervised clustering accuracy serves as a reliable and more interpretable evaluation measure, particularly in scenarios with varying cluster and class numbers. Furthermore, showcasing the potential, data augmentation, and transfer learning noticeably enhance the efficacy of unsupervised learning methodologies.

Onishi, Y.; Yoshida, T.; Kurita, H.; Fukao, T.; Arihara, H.; Iwai, A. et al. [12] Suggested an efficient and precise technique for identifying fruit positions and implementing automated harvesting through a robotic arm. Employing a single deep neural network based on the Convolutional Neural Network (CNN) method called the shot multibox detector (SSD), the authors detected objects within images. This SSD approach generates multiscale predictions from multiscale feature maps and categorizes predictions based on ratio aspect was evaluated, ensuring a high level of recognition accuracy. Despite occlusion by other fruits and leaves, the method successfully detects apples. The study revealed a 90% accuracy in fruit detection using the SSD methods.

S. Das Choudhury, A. Samal, and T. Awada, [13] presented a taxonomy to divide plant phenotypes into three primary types, namely structural, physiological, and temporal properties. The authors further categorized the plant structural and physiological phenotypes: (1) holistic, which describes the properties derived from whole-plant geometrics; and (2) component, which describes the properties derived from the measurement of individual parts and organs to address the spatial scale in phenotypes. For time-related phenotypes, trajectory-based measures that reflect the quantifiable changes over time were used in techniques to address the temporal properties in plant growth alongside the event-based phenotypes that indicate the distinct salient stages in a plant’s life cycle.

Pooja, V., Das, R., &Kanchana, V. et al. [14] proposed a disease detection and classification technique with the help of machine learning mechanisms and image processing tools. To begin with, they captured the infected area of the leaf and then performed image processing. The Support Vector Machine (SVM) classifier was used for classification and it was able to provide better results than previously used techniques.

D Ramesh, B Vishnu Vardhan et. al. [15] presents Analysis of Crop Yield Prediction Using Data Mining Techniques. With the advancement in technology several methods are used to predict the crop yields with more precision. Several researchers used Data mining techniques to predict the crop yields Data mining techniques are used with agriculture data, the term is known as precision agriculture. The main aim of the work is to improve and substantiate the validity of yield prediction, which is useful for the farmers.

3. Problem Statement

The growth of Foxtail Millet is influenced by a variety of factors, including soil moisture, temperature, and nutrient availability. Traditional methods of monitoring these factors can be time-consuming and costly. Furthermore, the relationships between these factors and crop growth can be complex and non-linear, making it difficult to accurately predict growth using conventional statistical models. Therefore, there is a need for a more efficient and accurate method for predicting Foxtail Millet growth.

4. Foxtail Millet Growth Prediction Using Hybrid Model

The block diagram of Foxtail Millet growth prediction using hybrid model of Machine Learning and Deep Learning with efficient Feature Extraction is represented in below Fig. 1.

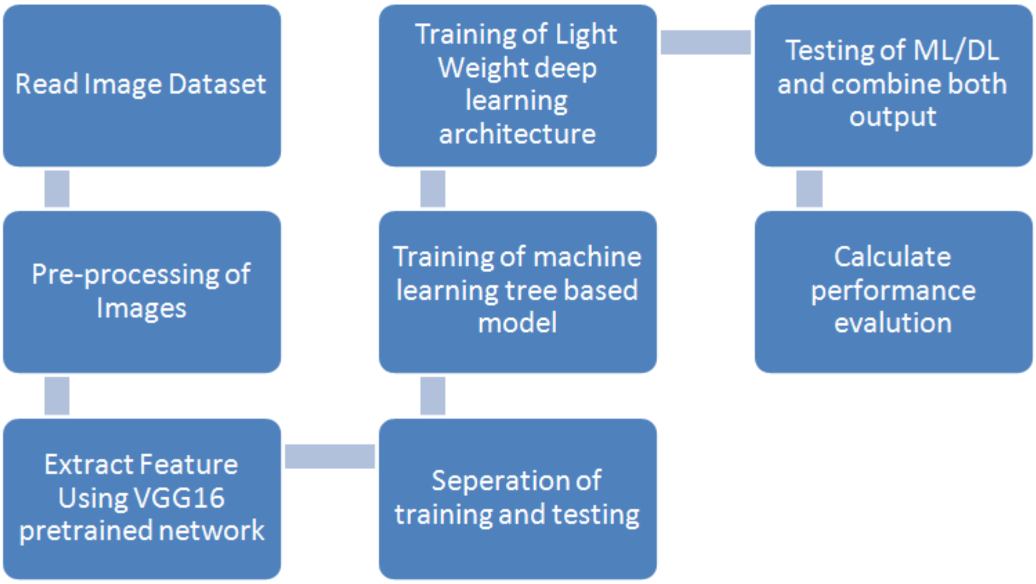

Fig. 1: block diagram of foxtail millet growth prediction

The process of Millet involves using VGG16 to extract features from images of the Foxtail Millet plants at different stages of growth. The extracted features will then be used to train tree-based machine learning algorithms, such as decision trees and random forests, to predict the growth of the crop. Additionally, to explore the use of lightweight deep learning architectures, such as MobileNet and SqueezeNet, to improve the accuracy and efficiency of the system. Finally, to combine machine learning and deep learning techniques to preprocess and transform the data before feeding it into the deep learning model, which will then extract high-level features and patterns.

To predict the growth of Foxtail Millet, we propose a three-stage approach that combines feature extraction using the VGG16 architecture, training of tree-based machine learning models, and lightweight deep learning architectures. First, we will use VGG16 to extract relevant features from images of Foxtail Millet at different stages of growth. This will allow us to capture complex features and patterns that are important for predicting growth.

The original image of the foxtail millet ear was collected at the experimental base in Shen Feng Village, Shanxi Agricultural University. The shape of the ear of the foxtail millet is cylindrical or nearly spinning, and it is mainly in a pendulous state. A total of 300 original images were collected, and stored in JPG format, including 25 images of the heading stage (Class I), 230 images of the filling stage (Class II), and 45 images of the maturing stage (Class III).

Preprocessing, such as image enhancement, color transformation, and segmentation is a prerequisite before efficiently extracting features. The next step was to normalize (the pixels' value was reduced to a value between 0 and 1) and standardize the cropped images. In order to simulate a bigger dataset, the image augmentation technique was applied. By data augmentation, a series of images transformations, such as rotation, zooming, vertical and horizontal flipping, brightening, and shearing are applied on the images. Modified versions of the images from the dataset are generated, therefore simulating a bigger dataset and avoiding overfitting.

We will use VGG16 to extract relevant features from images of Foxtail Millet at different stages of growth. VGG16 and tree-based machine learning algorithms are both widely used for different tasks in the field of machine learning. VGG16 is a popular choice for image classification and feature extraction tasks due to its high accuracy and deep architecture, as well as its availability as a pre-trained network. On the other hand, tree-based models are commonly used for prediction tasks because they offer interpretability, can capture non-linear relationships, handle missing data and outliers, and improve accuracy through ensemble methods like random forests and gradient boosting. While VGG16 is often used for image-based applications, tree-based models are a reliable choice for many other types of prediction tasks where interpretability and robustness are important. VGG16 (Visual Geometry Group-16) refers to the VGG model, also called VGGNet. It is a convolution neural network (CNN) model supporting 16 layers. A VGG network consists of small convolution filters. VGG16 has three fully connected layers and 13 convolutional layers.

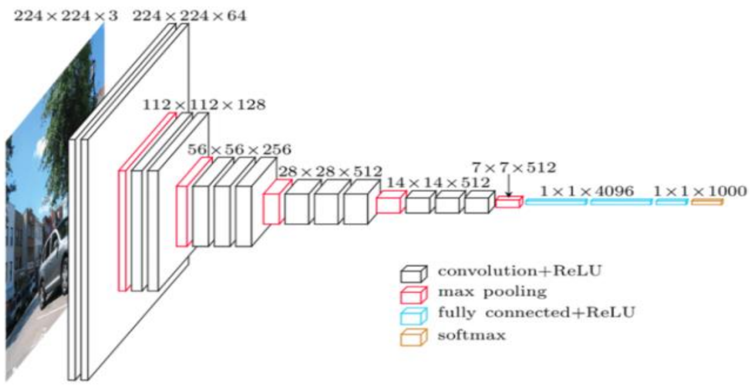

Fig. 2: VGGNET Architecture

In the next stage, dataset is divided into two parts as Testing and Training. 75% of the collected data is used as training dataset and 25% of the collected data is used as test set. First dataset is trained with machine learning model classification techniques Finally, we will incorporate lightweight deep learning architectures, which require less computational resources and are easier to interpret. Decision Tree (DT), Random Forest (RF) are used machine learning models and MobileNet, SqueezeNet are used deep learning models.

Random forest consists of several individual decision trees that operate as an ensemble. Each tree in the random forest predicts a class, and the class with the most votes is model's prediction.

Decision Tree (DT) is a supervised Machine Learning (ML) method used for classification and regression analysis. Decision tree is based on the divide and conquers methodology. It divides the partition by two methods: Numerical partitions: Typically, partitions are formed on the basis of discrete values with some conditions and Nominal partition: The partitions are formed on the basis of nominal attributes. It leads splitting of the tree depending on attributes values.

MobileNet is a streamlined architecture that uses depthwise separable convolutions to construct lightweight deep convolutional neural networks and provides an efficient model for mobile and embedded vision applications.

SqueezeNet is a convolutional neural network that is 18 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database.

This will improve the efficiency and generalizability of the overall system, allowing us to scale up to larger datasets and improve our ability to predict growth accurately. By combining machine learning with deep learning, we can take advantage of the strengths of both approaches to improve the efficiency of Foxtail Millet growth prediction. By using performance parameters as accuracy, precision, recall and F1-score, described model performance is calculated.

5. Result Analysis

In this section, we present the implementation of our model and respective result analysis. A total of 300 original images were collected, and stored in JPG format. 75% of the collected data is used as training dataset and

25% of the collected data is used as test set. By using performance parameters as accuracy, precision, recall and F1-score, described model performance is calculated. The performance metrics are calculated by the equations.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \dots (1)$$

$$Recall = \frac{TP}{TP + FN} \dots (2)$$

$$Precision = \frac{TP}{TP + FP} \dots (3)$$

$$F1 - Score = 2 * \frac{(Recall * Precision)}{(Recall + Precision)} \dots (4)$$

The performance metrics are classified by using performance measure as True positive (TP)-It is the condition when a test result is positive and individual can predicted growth of foxtail millet. True negative (TN)- It is the condition when the result is negative and individual is not predicted growth of foxtail millet. False positive (FP)- It is the case when a test result is positive but individual is not predicted growth of foxtail millet. False negative (FN)-It is the case when a test result is negative but individual can predicted growth of foxtail millet.

The comparative performance analysis of described hybrid model of Machine Learning and Deep Learning with efficient Feature Extraction (ML+DL+FE), and other models as YOLOv5-Shufflenetv2, YOLOv5-Mobilenetv3small , YOLOv3-tiny and Improved YOLOv5s is represented in below Table 1.

Table 1: COMPARATIVE PERFORMANCE ANALYSIS

Classifications	Accuracy	Precision	Recall	F1-Score
YOLOv5-Shufflenetv2	91.3	90.4	90.6	88.64
YOLOv5-Mobilenetv3small	88.4	89.1	87.8	86.36
YOLOv3-tiny	79.5	78.3	78.6	77.17
Improved YOLOv5s	93.5	96.6	94.1	95.81
ML+DL+FE	97.91	98.21	97.91	97.98

Fig. 3 and Fig. 4 are shows the graphical representation of comparative analysis in terms of accuracy, recall and precision, F-Score parameters respectively.

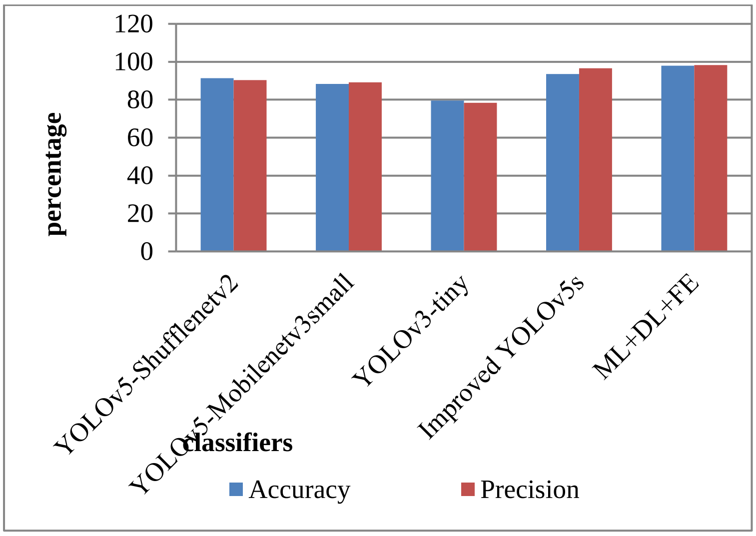

Fig. 3: comparative analysis of different models accuracy and precision parameters

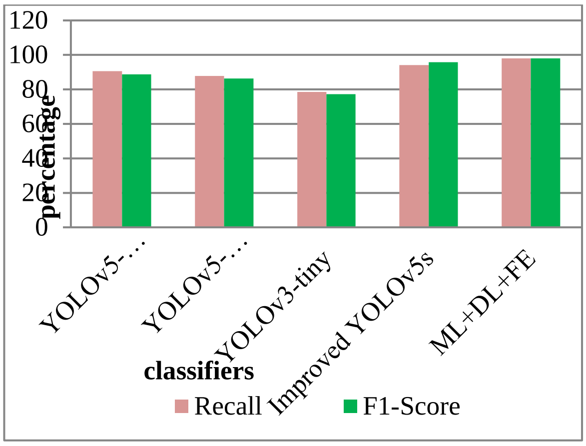

Fig. 4: comparative analysis of different models recall and f1-score parameters

Fig. 5, Fig. 6 and Fig. 7 are Histogram images, Features extracted images through VGG16 and Augmented Images of described model respectively.

Fig. 5: Histogram Image

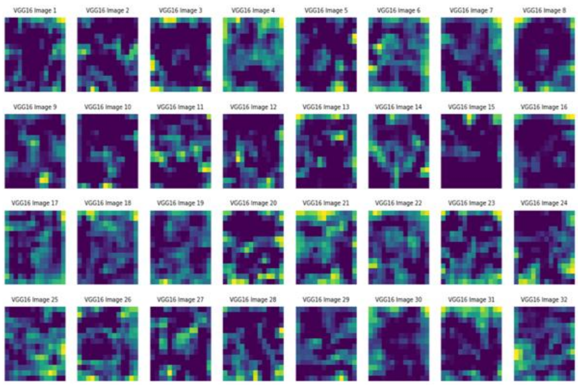

Fig. 6: Features Extracted Images

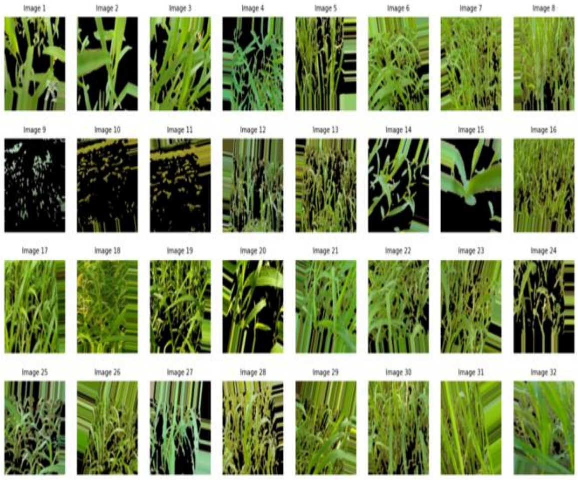

Fig. 7: augmented images

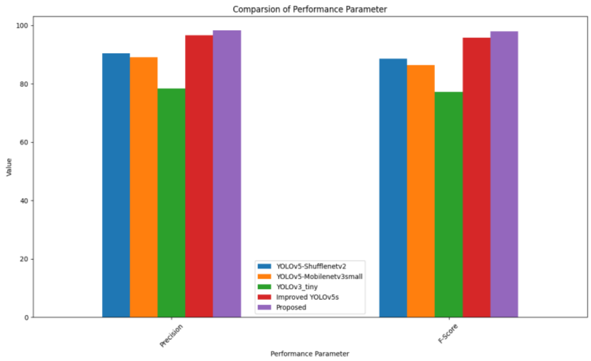

Fig. 8: Comparison of performance parameter

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              YOLOv5-Shufflenetv2  YOLOv5-Mobilenetv3small  YOLOv3_tiny  \
Precision                   90.40                    89.10        78.30
F-Score                     88.64                    86.36        77.17

              Improved YOLOv5s  Proposed
Precision                96.60     98.21
F-Score                  95.81     97.98
```

Fig. 8: Improved proposed YOLOv5vs

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2/2 [==============================] - 0s 34ms/step - loss: 0.0869 - accuracy: 0.9792
Test Loss: 0.0869053304195404, Test Accuracy: 0.9791666865348816
2/2 [==============================] - 0s 35ms/step
Accuracy:  97.91666865348816
Precision:  98.21428571428571
Recall:  97.91666666666666
Fscore:  97.98424467099166
```

Fig. 9: performance Improvement

From results it is clear that, the efficiency of described Foxtail Millet growth prediction using hybrid model of Machine Learning and Deep Learning with efficient Feature Extraction (ML+DL+FE) is high in terms of performance parameters than other models. Obtained values of parameters are 97.91%, 98.21%, 97.91% and 97.98% for accuracy, precision, recall and F1-score respectively.

Discussions

To predict the growth of Foxtail Millet, the proposed a three-stage approach that combines feature extraction using the VGG16 architecture, training of tree-based machine learning models, and lightweight deep learning architectures. First, stage used VGG16 to extract relevant features from images of Foxtail Millet at different stages of growth. This process for to capture complex features and patterns that are important for predicting growth.

VGG16 and tree-based machine learning algorithms are both widely used for different tasks in the field of machine learning. VGG16 is a popular choice for image classification and feature extraction tasks due to its high accuracy and deep architecture, as well as its availability as a pre-trained network. On the other hand, tree-based models are commonly used for prediction tasks because they offer interpretability, can capture non-linear relationships, handle missing data and outliers, and improve accuracy through ensemble methods like random forests and gradient boosting. While VGG16 is often used for image-based applications, tree-based models are a reliable choice for many other types of prediction tasks where interpretability and robustness are important.

Next, stage train tree-based machine learning models such as decision trees, random forests, and gradient boosting machines on the extracted features. These models are robust to missing data and outliers and can capture non-linear relationships between input features and output variables. Moreover, they provide interpretability, which is important for understanding the factors that influence Foxtail Millet growth.

Finally, incorporated lightweight deep learning architectures, which require less mathematical models and algorithms are easier to interpret. This improved the efficiency and generalizability of the overall system, allowing us to scale up to larger datasets and improved ability to predict growth accurately. By considering models such as Machine learning and deep learning, obtain the improvement of the strengths of both approaches to improve the high accuracy and moderate efficiency of Foxtail Millet growth prediction models useful for farmers to optimize their agricultural practices and improve their yields..

6. Conclusion

In this Foxtail Millet growth prediction using hybrid model of Machine Learning and Deep Learning with efficient Feature Extraction is described. A total of 300 original images were collected, and stored in JPG format. VGG16 network used to extract features from images of the Foxtail Millet plants at different stages of growth. 75% of the collected data is used as training dataset and 25% of the collected data is used as test set. Decision Tree (DT), Random Forest (RF) are used machine learning models and MobileNet, SqueezeNet are used deep learning models. Hybrid model involves the combination of machine learning and deep learning models. To evaluate our system performance, we employ the Recall, Accuracy, Precision and F1-Score parameters. The comparative performance analysis the efficiency of described Foxtail Millet growth prediction using hybrid model of Machine Learning and Deep Learning with efficient Feature Extraction (ML+DL+FE) is high with performance parameters than other models. Obtained values of parameters are 97.91%, 98.21%, 97.91% and 97.98% for accuracy, precision, recall and F1-score respectively.

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