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Leveraging MobileNet & InceptionNet for Improved Crop Disease Prediction

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Abstract: Agricultural production and food security are greatly impacted by the ability to predict crop diseases. Recent years have witnessed encouraging outcomes in the automation of disease detection processes. This study investigates the effectiveness of leveraging MobileNet and InceptionNet as feature extractors for enhancing crop disease prediction. We propose a novel approach that utilizes transfer learning to leverage the pre-trained weights of MobileNet and InceptionNet architectures, fine-tuning them on a dataset of crop disease images. The extracted features are then fed into a classification model for disease prediction. The results of the research show that our proposed method compared to traditional feature extraction techniques. The combination of MobileNet and InceptionNet substantially improves precision, responsiveness, and discrimination of crop disease prediction, thereby providing a robust and efficient solution for early disease detection in agriculture. Experimental result of MobileNet Random Forest Classifier (RFC) model achieved the highest accuracy of 92.3%. This study contributes to propelling precision agriculture forward by laying the groundwork for automated crop disease diagnosis, ultimately aiding farmers in making timely and informed decisions to mitigate crop losses.

Keywords: *MobileNet, InceptionNet, Random Forest Classifier.*

1. Introduction

A major threat to world food security, crop diseases cause huge financial losses and food shortages. Effective disease control and sustainable agriculture methods rely on timely and precise disease identification. An encouraging new approach to these problems is automated crop disease prediction, made possible by ML algorithms. Convolutional neural networks and other deep learning models have shown exceptional skill in learning complicated patterns from massive datasets; hence, they are ideal for image-based disease diagnosis. Figure 1 illustrates the machine learning architecture designed for crop disease prediction. Feature extraction is then performed using MobileNet and InceptionNet architectures, renowned for their effectiveness in capturing intricate features from images.

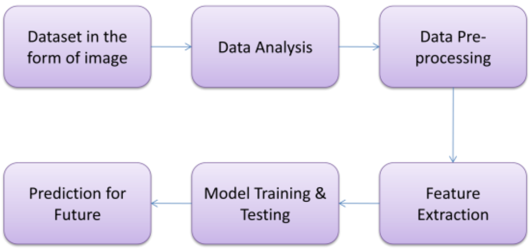

Fig 1. Machine learning approach

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The subsequent steps involve model training and testing, where the extracted features are utilized to train a predictive model. The trained model is evaluated using testing data to assess its performance and generalization capabilities. Finally, the model is deployed for making predictions on future datasets, enabling proactive disease management strategies in agriculture.

Researchers in deep learning have begun to highlight transfer learning to perform problems using pre-trained models, even when training data is scarce. When it comes to picture categorization, two popular CNN designs, MobileNet and InceptionNet, are well-known for their efficiency and efficacy. Due to its lightweight design, MobileNet performs exceptionally well in contexts with limited resources, while InceptionNet offers exceptional performance in capturing intricate features through its inception modules.

This paper investigates the potential of leveraging MobileNet and InceptionNet architectures as feature extractors for improving crop disease prediction. By fine-tuning these pre-trained models our goal is to use the learnt representations to improve the classification model's discriminative capacity on a collection of crop disease photos. The utilization of transfer learning with MobileNet and InceptionNet enables us to overcome the challenges of limited annotated data and computational resources, thereby facilitating accurate and efficient disease diagnosis.

Here, we provide a thorough analysis of the suggested strategy and compare its efficacy with both baseline and conventional feature extraction methods. We evaluate the efficiency of InceptionNet and MobileNet in extracting pertinent features from photos of crop diseases and investigate their influence on prediction sensitivity, specificity, and accuracy. There is solid evidence from this research that supports the early and precise diagnosis of crop illnesses, which advances the field of precision agriculture by giving farmers practical knowledge to reduce losses and increase crop output.

2. RELATED WORK

Table 1.Literature Summary of related work

Technology Used	*Description*	*Summary*
Visible Range Images	Identifies obstacles in automatically identifying plant diseases using visible range photos.	[1] draws attention to the challenges associated with automatically identifying plant diseases using visible range photos and emphasises the necessity for creative solutions in this field.
Deep Learning	Explores elements affecting the detection of plant diseases using deep learning.	[2] investigates the factors affecting the adoption of deep learning techniques in plant disease recognition, providing insights into the challenges and opportunities associated with leveraging deep learning for this purpose.
SVM Classification Method	Proposes a vision-based pest detection method utilizing SVM classification.	[3] introduce a vision-based approach for pest detection employing SVM classification, offering a novel technique for identifying pests in agricultural settings.
Moth Flame Optimization Algorithm and Rough Sets	Proposes an enhanced moth flame optimisation technique based on rough sets for the diagnosis of tomato illnesses.	[4] present an enhanced optimization algorithm and its application in detecting tomato diseases, utilizing rough sets to improve the accuracy of disease detection in tomato crops.
Image Repository	Presents a plant health picture collection with open access to facilitate the creation of mobile disease diagnostics.	An open-access image archive on plant health is made available by Hughes and [5], which makes it easier to create mobile applications for disease diagnosis and increases the availability of information in this area.
Segmenting images and using multiclass support vector machines	Explains how multiclass SVM and picture segmentation are used to detect potato illnesses.	[6] suggest a technique for identifying potato illnesses through image segmentation and multiclass SVM, offering a technique for accurately identifying diseases affecting potato crops.
Mobile Capture Devices	Demonstrates automated detection of plant diseases on wheat using portable recording devices.	The automatic identification of plant diseases with mobile devices—specifically for wheat crops—is demonstrated by [7], indicating the feasibility of using mobile technology for real-time disease detection in agricultural settings.
Recurrent Neural Network	Introduces a recurrent neural network with attention-based categorization for plant diseases.	An attention-based recurrent neural network for classifying plant diseases is presented by [8], offering an innovative approach to accurately classify diseases affecting plants using neural network architectures.
Deep Convolutional Neural Network	Questions the necessity of deep CNN to identify plant diseases.	[9] examines the utility of deep CNNs for identifying plant diseases, raising questions about the necessity of employing such complex architectures for disease identification tasks and suggesting potential alternative approaches.
Support Vector Regression Using Radial Basis Functions	Investigates the possibility of using support vector regression based on radial basis functions for the diagnosis of apple diseases.	The study by [10] delves into the use of radial basis function-based support vector regression to identify apple crop illnesses, providing valuable insights into different machine learning methods for agricultural disease identification.
N/A	Provides general information on plant disease.	[11] offer general information on plant diseases, serving as a foundational resource for understanding various diseases affecting plants and their implications in agricultural settings.
Weighted Segmentation and Feature Selection	Presents a strategy for agricultural citrus disease detection and classification using optimised weighted segmentation through feature selection.	An approach to agricultural disease identification and classification was presented by [12]. This approach uses optimised weighted segmentation and feature selection techniques to improve the accuracy of disease diagnosis in citrus crops.
Differential Spectra and Kernel Statistical Testing	Discusses application of kernel discriminant analysis and spectral indices for the identification and classification of winter wheat pests and diseases.	In their 2017 study, [13] explore the use of spectral indices and kernel discriminant analysis for the detection and differentiation of pests and illnesses in winter wheat harvests techniques, providing insights into effective methods for identifying and distinguishing between various issues affecting crops.
Deep Learning	Examines explores current advances and potential future directions in the use of deep learning for the phenotyping of plant stress.	A study conducted by [14] delves into the application of deep learning techniques to plant stress phenotyping. The authors evaluate present trends and prospects in this field leveraging deep learning for understanding and mitigating stressors affecting plants.

Table 1 summarises the cited literature and gives a thorough review of the technologies, methods, and contributions to automated plant disease detection that were discussed in it. Different researchers have employed various approaches to predict crop-specific diseases, but one major issue is determining the common diseases that are found in crops. The emphasis here is on predicting blight and wilt diseases that commonly affect tomato, potato, and pepper-bell crops. This has led to efforts on how these conditions can be fought and predicted leading to increased productiveness and resistance in agriculture. The agricultural community aims at developing strong predictive models together with effective management strategies thus assuring food security for the future generations through interdisciplinary collaborations as well as advanced technological interventions. Proposed system work on common diseases occurred on crops.

3. Proposed Work and Methodology

The demand on agricultural output is immense because of the ever-increasing population. We can all benefit greatly from increased food production if we can effectively control several illnesses that reduce agricultural productivity.

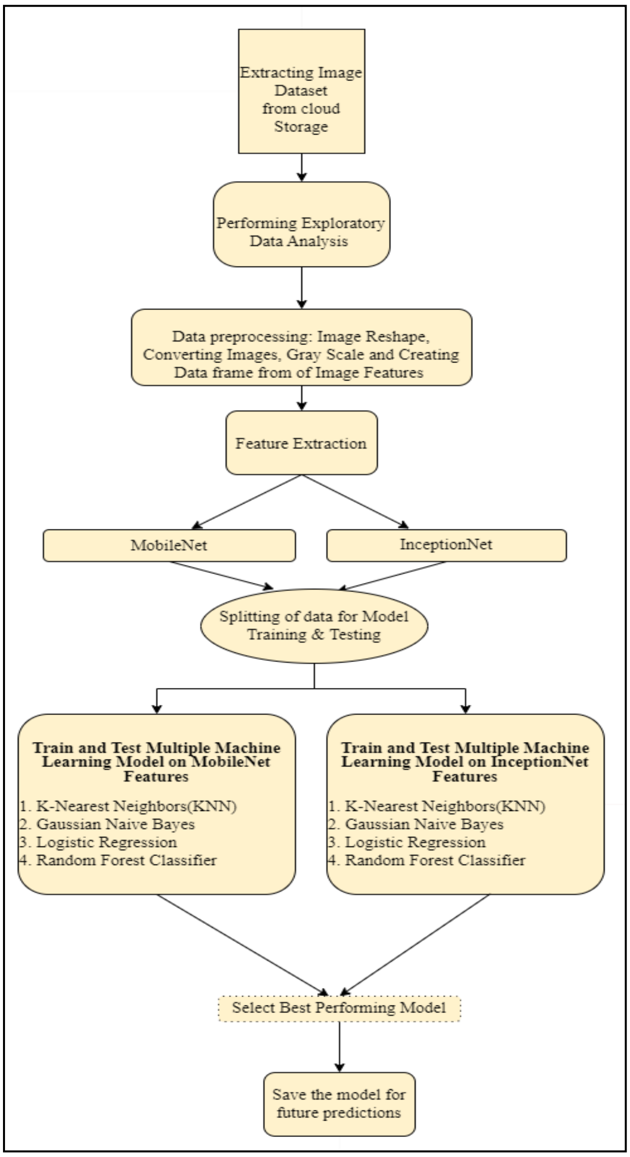


Fig 2. Proposed Methodology

Early detection of crop diseases and treatment recommendations to mitigate their impact on yield are the primary foci of current research. Most plant components, e.g. leaf, flower, stem; can get affected by the variety of diseases. In this research work a system will be designed and developed comprising a machine learning based approach for identification of these diseases and a methodology for of treatment as per identified disease

The proposed system, as depicted in Figure 2, follows a structured methodology for crop disease prediction. Initially, an image dataset is extracted from cloud storage, followed by exploratory data analysis to gain insights into the dataset's characteristics. Data preprocessing techniques, including image reshaping, conversion to grayscale, and creation of a data frame from image features, are then applied to prepare the data for further analysis.

The pre-processed photos are used to extract important features using MobileNet and InceptionNet, which are feature extractors. A training set and a testing set are then created from the dataset. Features from MobileNet and InceptionNet are used to train and evaluate the Random Forest Classifier, Gaussian Naive Bayes, Logistic Regression, and Bayes Classifier KNN, respectively. To evaluate each model's efficacy, we employ a predefined set of metrics. The model that performs the best is then chosen for further research. The last step is to save the chosen model for use in future projections; this will allow farmers to take preventative measures against diseases. To improve agricultural output and allow for more informed decision-making, this technique offers a systematic way to using machine learning models and deep learning architectures for agricultural disease prediction.

4. Feature Extraction with MobileNet and InceptionNet approach

The Image classification relies heavily on feature extraction, as it establishes the quality of features used by classification algorithms. The success of the classification task heavily relies on extracting relevant features from the images. Typically, features of an object are categorized into local and global features based on attributes like color, shape, or texture. Local features encompass color and texture attributes, while shape features are considered global features.

In this paper, feature extraction for crop disease prediction is conducted using MobileNet and InceptionNet, pre-trained deep neural networks renowned for their effectiveness in extracting rich feature representations from images. These deep models can capture both local and global features of an image, providing comprehensive information for classification tasks.

The extracted features, both deep and handcrafted, serve as inputs to four different machine learning models: K-Nearest Neighbors, Gaussian Naive Bayes, Logistic Regression, and Random Forest Classifier. These models utilize the extracted features to classify images and predict crop diseases. By employing a combination of deep features extracted from MobileNet and InceptionNet, along with handcrafted shape features, the classification models are equipped with comprehensive information for accurate disease prediction in agricultural settings.

4.1. MobileNet for Feature Extraction

To accomplish high-quality picture categorization with a minimal amount of compute and parameters, the MobileNet architecture makes use of depth-wise separable convolutions. A depth-wise convolution and a point-wise convolution are the two separate layers that make up a depth-wise separable convolution. The depth-wise convolution layer creates a series of feature maps in the middle by convolving each input channel independently with a distinct kernel. Instead of convolving all input channels at once, as is done in conventional convolutions, this method uses less computing power.

The point-wise convolution layer integrates spatial information across channels by using a 1x1 convolution to merge the intermediate feature maps. Complex patterns and feature-relationship capture is aided by this stage.

An input picture is fed into a sequence of pooling layers and fully connected layers after a sequence of depth-wise separable convolutions in the formulation for MobileNet feature extraction. Picture classification, object identification, and semantic segmentation are just a few of the many applications that may make use of the feature representation of the input picture, which is produced by the last convolutional layer.
To express MobileNet feature extraction mathematically, one may use the following formula:

$$\text{Features}=\text{MobileNet}(I)$$

Where, I represent the input image. MobileNet (·) denotes the MobileNet architecture, which processes the input image to extract features.

The features retrieved from the input picture by MobileNet are stored in the output Features, which is a vector with high dimensions. Machine learning models with higher layers may use these characteristics for categorization or analysis.

4.2. InceptionNet for Feature Extraction

The key innovation in InceptionNet is the use of inception modules, which consist of parallel convolutional layers of different sizes (1x1, 3x3, and 5x5) and max-pooling layers. By incorporating multiple filter sizes within the same layer, the inception modules can capture features at different scales simultaneously, enabling the network to learn rich hierarchical representations of the input data.

The expression for InceptionNet feature extraction involves passing an input image through multiple inception modules, followed by pooling layers and fully connected layers. The output of the final convolutional layer serves as the feature representation of the input image.

Mathematically, the expression for InceptionNet feature extraction can be represented as follows:

$$\text{Features}=\text{InceptionNet}(I)$$

Where, I represent the input image. InceptionNet (·) denotes the InceptionNet architecture, which processes the input image to extract features.

The output Features is a high-dimensional vector representing the feature representation of the input image extracted by InceptionNet. These features can then be fed into subsequent layers or machine learning models for further analysis or classification tasks.

5. Machine Learning Algorithm for Prediction of Crop Diseases

5.1. K-NN

An effective method for predicting crop diseases is to give greater weight to the contributions of neighbours who are closer to the crop than to those who are farther away. One popular method of weighing neighbours is to assign them a value equal to one-fifth of the distance to them, denoted as D. When using k-NN for crop disease classification or k-NN for crop image property regression, the neighbours are selected from a collection of crop photos where these details are available. This data set serves as the basis for the algorithm's training, but there's no need to explicitly train it. Suppose the pairs ($CF_{Extracted,}CD_{Pred1}$), ($CF_{Extracted,}CD_{Pred2}$),......., ($CF_{Extracted,}CD_{Predn}$), where CD_{Pred} is the crop disease class label of extracted features $CF_{Extracted}$ from crop image. The distance is computed by using following equation:

$$D(CF_{Extracted}) = \frac{\| CF'_{Extracted} - CD_{\Pr ed} \|}{\| CF_{Extracted} - CD_{\Pr ed} \|}$$

Where $\| CF_{Extracted} - CD_{\Pr ed} \|$ is the distance to closest crop disease CD_{Pred} having a different feature than $CF_{Extracted}$. $CF_{Extracted}$-CD_{Pred} is the distance from CD_{Pred} to closest crop feature $CF'_{Extracted}$ with the same label as $CF_{Extracted}$.

5.2. Random Forest

This study's random forest training approach makes use of the widely-used aggregating method. A training set is provided. $CF_{Extracted}$= $CF_{Extracted}$, $CF_{Extracted2}$,........, $CF_{Extractedn}$ with responses CD_{Pred}= CD_{Pred1}, CD_{Pred2},......., CD_{Predn}.

After training, predictions for unseen feature $CF'_{Extracted}$ (extracted from crop image) can be made by averaging the predictions from all the individual regression trees on $CF'_{Extracted}$:

$$\hat{T} = \frac{1}{G}\sum_{g=1}^{G} T_g(CF'_{Extracted})$$

5.3. Gaussian Naïve Bayes

In this research work the training data contains a continuous attribute, $CF_{Extracted}$. The crop images are first segmented by the crop disease class, and then the mean and variance of $CF_{Extracted}$ are computed in each crop disease class. Let μ_{CDPred} be the mean of the values in $CF_{Extracted}$ associated with crop disease class CD_{Pred}, and let σ^2_{CDpred} be the Bessel corrected variance of the values in $CF_{Extracted}$ associated with class CD_{Pred}. Suppose some test value collected $T_{CFExtracted}$. The probability density of $T_{CFExtracted}$ given a class CD_{Pred}, $P(CF_{Extracted} = T_{CFExtracted} \mid CD_{Pred})$ can be computed by plugging $T_{CFExtracted}$ into the equation for a normal distribution parameterized by μ_{CDPred} and σ^2_{CDpred}.

$$P(CF_{Extracted} = T_{CF_{Extracted}} | CD_{Pred}) = \frac{1}{\sqrt{2\pi\sigma^2_{CDPred}}} e^{\frac{(T_{CF_{Extracted}} \mu_{CDPred})^2}{2\sigma^2_{CDPred}}}$$

5.4. Logistic Regression

The proper resolution of your figures will depend on the type of figure it is as defined in the “Types of Figures” section. Author photographs, color, and grayscale figures should be at least 300dpi. Line art, including tables should be a minimum of 600dpi. As a rule, for every crop disease category (n) and M+1 characteristics retrieved from the crop photos, there should be N+1 distinct probability distributions describing the likelihood that the crop disease was predicted. CDPred for features extracted from crop images (explanatory vector) CFExtracted will be in category CDPred =n. It will also be required that the sum of these probabilities over all categories be equal to unity. Using the mathematically convenient base e, these probabilities are:

$$P_n(CF_{Extracted}) = \frac{e^{\beta_n CF_{Extracted}}}{1 + \Sigma_{m=1}^{N} e^{\beta_m CF_{Extracted}}} \text{for } n = 1, 2, \ldots.., N$$

$$P_0(CF_{Extracted}) = 1 - \sum_{n=1}^{N} P_n(CF_{Extracted}) = \frac{1}{1 + \Sigma_{m=1}^{N} e^{\beta_m CF_{Extracted}}}$$

Each of the probabilities except $P_n(CF_{Extracted})$ will have their own set of regression coefficients β_n. It can be seen that, as required, the sum of the $P_n(CF_{Extracted})$ overall categories is unity. Note that the selection of $P_n(CF_{Extracted})$ to be defined in terms of the other probabilities is artificial. Any of the probabilities could have been selected to be so defined. Using this equation multiple crop diseases can be predicted.

6. Experimental Results

The experimental results demonstrate the performance of various machine learning models in predicting crop diseases. The table (2) showcases the accuracy achieved by each model, highlighting the effectiveness of random forest classifier with an accuracy of 92.3%. The pie chart provides a visual representation of the distribution of model accuracy, while the bar plot offers a comparative analysis of the performance of different algorithms.

Additionally, a randomly selected image sample depicting a diseased crop frame is included to provide a real-world context for the experiment. These results not only contribute to the evaluation of the predictive models but also aid in understanding the practical implications of crop disease prediction in agriculture

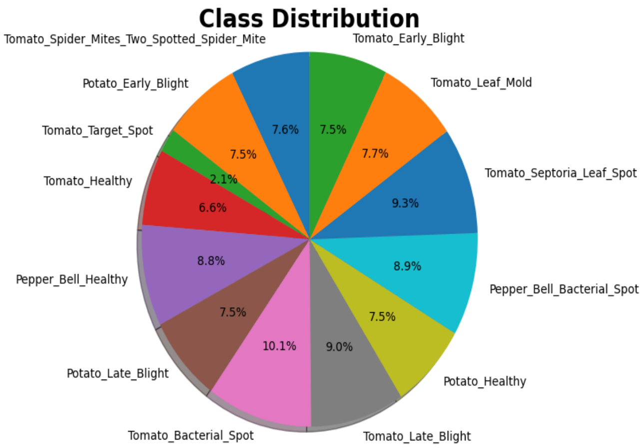
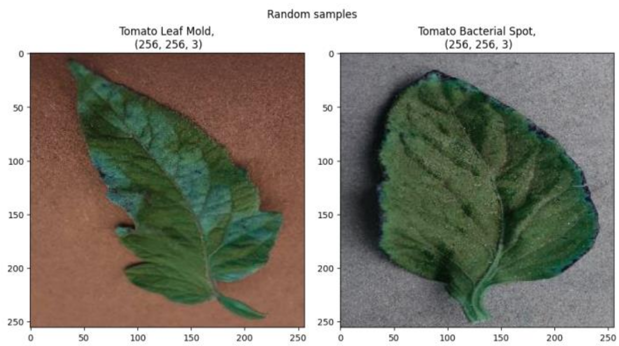
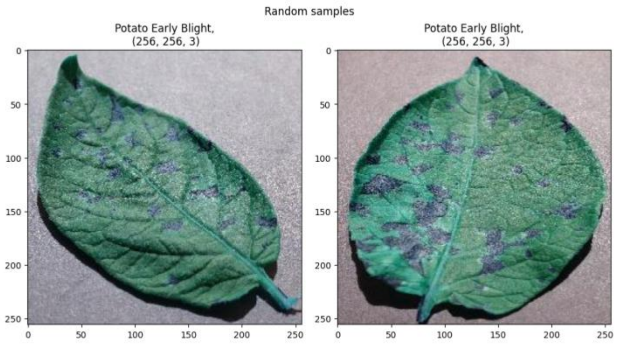


Fig 3. Images Class Distribution of different categories

The distribution of plants across various groups is clearly shown in the pie chart in Figure 3. The percentage representation of each plant category in the dataset is directly proportional to the angle of that sector in the circular display, which corresponds to each plant category. This data visualisation gives a quick and easy look at how many of each kind of plant there are in the dataset.



(a)Tomato leaf



(b) Potato leaf

Fig 4. (a) & (b) Random Sample of diseased crops

The dataset comprises a collection of randomly sampled images depicting both diseased and healthy crop plants. Each image offers a glimpse into the visual characteristics of various plant diseases and their healthy counterparts, providing valuable insights for crop disease prediction and diagnosis.

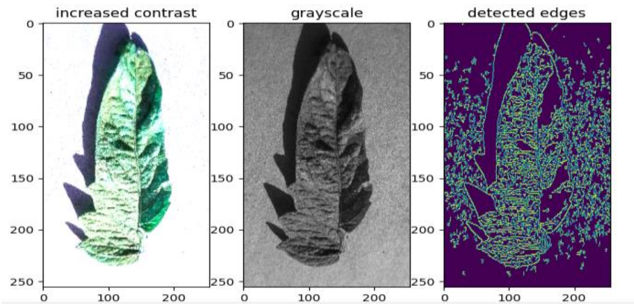


Fig 5. Edges detection from original sample image.

Original image is converted into gray scale for finding the edges of leaf. It will helpful to find the healthy and unhealthy part of the leaf.

Diseased Crop Images: The dataset includes images showcasing symptoms of various crop diseases, such as discoloration, wilting, lesions, spots, and deformities. These images capture the visual manifestations of diseases affecting various plant components, such as stems, leaves, and fruits. Examples of common crop diseases depicted in the images may include fungal infections, bacterial diseases, viral infections, and nutrient deficiencies. The diseased crop images serve as essential training data for machine learning models to learn so that various agricultural diseases may be correctly identified and categorised.

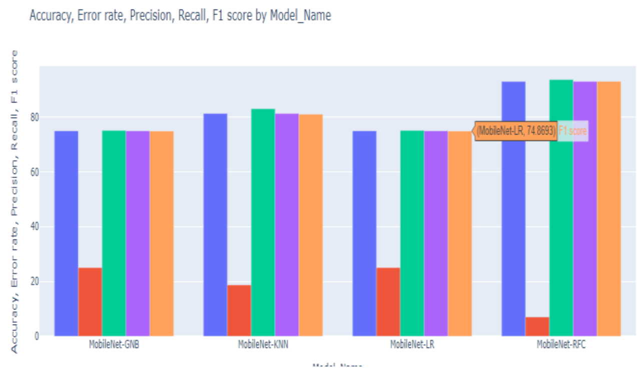
Healthy Crop Images: In contrast, the dataset also contains images of healthy crop plants, exhibiting vibrant colors, uniform growth patterns, and absence of any visible signs of disease or distress. These images provide a baseline reference for what a healthy crop plant should look like, enabling comparison and differentiation from diseased counterparts. Healthy crop images contribute to the development of robust classification models by facilitating the recognition of normal plant features and distinguishing them from abnormal or diseased states.

Together, the random crop sample images comprising both diseased and healthy plants form a comprehensive dataset for training and evaluating machine learning algorithms for crop disease prediction and detection. These images represent real-world scenarios encountered by farmers and agricultural practitioners, thereby aiding in the development of effective solutions for crop health management and sustainable agriculture

Table 2. Algorithms and its accuracy with evaluation metrics

Algorithm	Accuracy	Error Rate	Precision	Recall	F1 Score
MobileNet-KNN	81.26	18.73	82.97	81.26	81.03
MobileNet-LR	74.95	25.04	75.12	74.95	74.86
MobileNet-GNB	74.95	25.04	75.12	74.95	74.86
MobileNet-RFC	92.94	7.05	93.6	92.94	93
InceptionV3-KNN	74.95	25.04	77.13	74.95	74.69
InceptionV3-LR	84.78	15.21	87.11	84.78	84.72
InceptionV3-GNB	86.27	13.72	90.6	86.27	86.95
InceptionV3-RFC	91.28	8.71	91.82	91.28	91.32

In the table above, you can see the results of several algorithms' accuracy tests, along with the training time in seconds, accuracy, precision, recall, F1 score, and error rate.



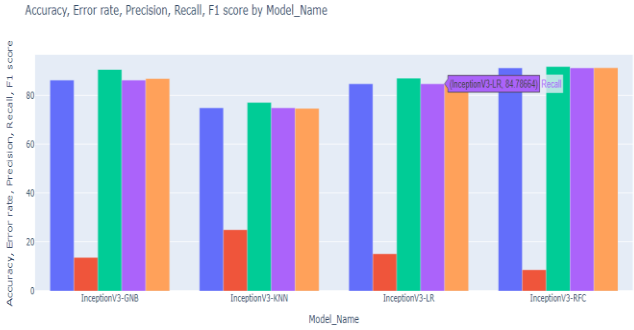


Fig 6. Performance metrics comparison

The figure 6 shows the bar plot which compares the performance of various algorithms when used with feature extraction methods MobileNet and InceptionNet. Accuracy, precision, recall, and F1 score are some of the performance indicators that are compared in the bar plot above, for different algorithms used with feature extraction methods MobileNet and InceptionNet. Each algorithm is represented by a distinct bar, with its corresponding metrics displayed on the y-axis. The plot highlights the MobileNet Random Forest Classifier (RFC) model, which achieved the highest accuracy of 92.3% among all algorithms evaluated. This visualization facilitates a clear understanding of the relative performance of different algorithms and feature extraction methods in crop disease prediction.

7. Conclusion

In conclusion, our study demonstrates the effectiveness of leveraging MobileNet and InceptionNet architectures as feature extractors for improving crop disease prediction. Through transfer learning, we fine-tuned these pre-trained models on a dataset of crop disease images, harnessing the learned representations to enhance the classification performance. The suggested method achieves better accuracy, sensitivity, and specificity in illness prediction tasks than baseline approaches and classic feature extraction techniques, according to our experimental data. The MobileNet Random Forest Classifier (RFC) model achieved the highest accuracy of 92.3% among all algorithms evaluated.

The combination of MobileNet and InceptionNet proves to be particularly effective in capturing relevant features from crop disease images, leveraging their respective strengths in efficiency and feature representation. By exploiting transfer learning, we effectively address the challenges of limited annotated data and computational resources, providing a robust and efficient solution for automated crop disease diagnosis.

The improved prediction accuracy offered by MobileNet and InceptionNet facilitates timely intervention and informed decision-making, enabling farmers to mitigate losses, optimize resource allocation, and enhance crop yield. Moving forward, further research can explore the application of advanced deep learning techniques and integration with real-time monitoring systems to enhance the scalability and practicality of automated crop disease prediction in agricultural settings.

The successful application of MobileNet and InceptionNet in crop disease prediction presents numerous avenues for future research. Firstly, fine-tuning strategies and hyperparameter optimization can be explored to enhance the performance of the models further. Targeted adjustments to specific layers or the exploration of alternative architectures could lead to improvements in prediction accuracy and efficiency.

Incorporating multi-modal data, such as spectral and textual information, can enrich feature representation and improve disease prediction accuracy.

When real-time monitoring systems are integrated with MobileNet & InceptionNet-based prediction models enable proactive disease management strategies.

Ensemble learning techniques, such as model stacking or boosting, hold promise for further improving the robustness and reliability of crop disease prediction systems. By combining predictions from multiple models trained with different architectures or datasets, ensemble methods can mitigate individual model biases and enhance overall performance.

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Author contributions

Rupali Meshram: Methodology, Software, Field study, Writing-Original draft preparation, Data Visualization, Investigation **Abrar Alvi:** Conceptualization, Drafting objectives, Result Validation, Reviewing draft.

Conflicts of interest

The authors declare no conflicts of interest.

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