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Research Article

Deep Learning-Based Automated Detection of Cotton Plant Diseases: A Comparative Analysis of CNN Architectures

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ABSTRACT

Deep learning methods for crop disease detection and identification of pests on leaves can significantly improve agricultural productivity and greater reliance than manual inspection on a specific road map for growing cotton. In this study, we have begin by reviewing some existing methods using Convolutional Neural Network (CNN) architectures, such as AlexNet, VGG, ResNet and DenseNet, to classify the cotton plant diseases. A comparative analysis indicating accuracy, precision, recall, and F1-score demonstrates that ResNet-152 and DenseNet-264 achieve better performance than other models in terms of maximum classification accuracy. The results of the classification show that deep learning models are accurately differentiate healthy and diseased cotton leaves, and diseased and healthy cotton plants, paving the way for early-stage diseases diagnosis.

Keywords: Cotton Plant, Disease Detection, Deep Learning, Convolutional Neural Networks, Transfer Learning, Smart Agriculture.

I. INTRODUCTION

Cotton is a vital natural fiber for the world's textile industry, which has implications for society, the environment, and the economy [1]. Cotton crops are susceptible to several different illnesses, which reduce crop output and fiber quality, which in turn costs farmers and businesses money. Accurately identifying plant diseases at the right time is vital for maintaining productivity and maintaining agricultural continuity, since it presents the cotton plant's state for future development. Traditional methods of illness detection, such as expert-performed manual visual examinations, are tedious, slow, and prone to bias [2]. Automatic, scalable, and accurate disease detection systems are essential for contemporary agriculture due to these limits. Recent years have seen deep learning, a branch of AI, acknowledged as a quickly developing technology providing reliable, scalable, and quick solutions for plant disease detection [3].

Various applications have made use of machine learning, a branch of artificial intelligence, including image recognition, NLP, and predictive analytics [4]. Here, we use a large dataset of cotton leaf photos, state-of-the-art neural network designs, and efficient training methods to improve the accuracy of disease pattern identification in cotton crops. If you're growing crops over a big region, like cotton, and physical inspection isn't an option, then deep learning based detection is the way to go [5]. It offers non-invasive, real-time large-scale disease monitoring. In the field of computer vision, CNNs have been the dominant tool for plant disease categorization. In order to automatically identify cotton plant illnesses, the research examines the efficacy of CNN architectures, particularly AlexNet, VGG, ResNet, and DenseNet. We will evaluate these models' ability to distinguish between healthy and unhealthy cotton leaves and plants using the F1-measure, recall, precision, and accuracy metrics. When compared to alternative architectures, deep models (ResNet-152 and DenseNet-264) achieve superior classification accuracy [6].

While deep learning has the potential to be a game-changer in smart agriculture, there are still drawbacks. To reach enrichment and diversity for training datasets, significant manual collection and annotation are needed under different conditions, as deep learning models are data-hungry systems which rely heavily on the quality of the training set. Furthermore, the original image-picked dataset not only have less diversity in type (elevated, CCTV, etc.) but also is sensitive to environmental factors including lighting conditions, image resolution and camera quality, which concern the generalizability of the proposed models [7]. Another hurdle is computational complexity, since training deep neural networks requires significant processing power, restricting deployment in low-resource scenarios [8].

Interdisciplinary work between agronomists, farmers, and data scientists is necessary to optimize the advantages of deep learning for plant disease diagnosis in the cotton industry [9]. The lightweight and economical models can be trained, and can be deployed in mobile/drone or other platforms, enabling disease monitoring in real-time, helping in deploying targeted measures to reduce unnecessary pesticide use, and stimulate sustainable agriculture. Moreover, integrating multi-modal data sources, such as hyperspectral imaging and environmental parameters, can improve the model accuracy as well [10]. Deep learning has the potential to revolutionize the way we detect cotton diseases, laying the groundwork for precision agriculture and enhancing the management of cotton crops. Implementing deep learning and addressing existing challenges around technology will help address gaps in accessibility of AI-powered solutions, revolutionizing disease diagnostics in the agricultural sector with benefits of enhanced productivity, economic viability, and food security.

II. LITERATURE REVIEW

Islam MM et al. (2023) In this work Transfer Learning (TL) fine-tuned VGG-16, VGG19, Inception-V3 and also Xception to recognize cotton leaf diseases on the basis of deep learning approach. Xception had the best accuracy with 98.70% Web Application for Real-time Cotton Disease Prediction Stage 5: Model has been created and trained on,now we can easily add validation data too. Implementation: Cotton leaf disease detection was implemented by fine tuning the top layer of pre-trained TL models (VGG-16, VGG-19, Inception-V3 and Xception) taking healthy portion data with diseased and identified normal images. Dataset: The research used 80% of public cotton leaf disease datasets to train and 20% to evaluate. While Xception has the highest accuracy (98.70%) among all TL approaches, it also provides greater precision and recall rates as well F1-score and finally their confusion matrices with respect to Ground-Truth. Drawback: The experiments were done only on cotton leaf diseases insignificant to plant disease or agriculture in general and the effectiveness of metagenomic data file stability remain to be elucidated [1].

Zhang N et al. (2023) : In this study, a method was proposed for determining the level of cotton verticillium wilt disease severity by constructing spectral data and combining SVM learning models that were optimized based on GA, GS, PSO and GWO algorithms. The best was the MSC-db3(23)-GWO-SVM model which presented accuracy of 91.2%. This method is a good classification of cotton wilt disease, and it has the potential to take early deterrent measures combined with precise agriculture. Approach: The spectral reflectance data was used to classify disease grade using Machine learning algorithms such as SVM models with different optimization techniques like GA, GS,PSO and GWO. Dataset: They used spectral data of cotton leaves naturally infected in the Shi Tuan Experimental Field, Alar City and Xinjiang. Plants were assigned to one of five disease severity levels as part of the study. Outcome: The MSC-db3(23)-GWO-SVM model attained the best performance among all models with an accuracy of 91.2% in correctly identifying cotton verticillium wilt disease, which confirms that you need to punish bad hyperparameters! Limitation: the study was performed in one cotton cultivar and one location so its generalization to other varieties or locations needs further testing [2].

Xiao Q et al. (2019): Artificial intelligence for predicting cotton pests and diseases: This study developed an LSTM-based method to predict cotton pests and related weather factors. The Apriori algorithm provided association data between weather condition and occurred pests, which also contributed to the future occurrence. An LSTM model presented an AUC of 0.97 compared to several machine-learning models. LSTM layers and fully connected layers performed for the seasonal occurrence of pests pattern. Dataset: The CPDSS Crop pest decision support system data has 15,343 weekly recorded documents of 10 insect-pests and diseases for six regions in India used interpreting data. Result: The LSTM model provided an excellent prediction for the occurrence of pests; hence the study yielded an accuracy of AUC=0.97, and the model was compared with SVM and Random forest model. Limitation; They reported their result with be biased because they set a low support and confidence threshold on the Apriori algorithm. This could have affected the interpretability and generalizability of the results [3].

Ehetisham-ul-Haq M et al. (2017) , In another study, experiments were conducted on four varieties of cotton (FH-941, FH-942 and MNH-886,, and FC 114) to develop a forecasting model for the detection of disease. The temperature, humidity and rainfall were recorded as the environmental variables; whereas population of red cotton bug (Dysdercus cingulatus) was considered for data analysis. We modeled predicted using regression analysis. For the study, environmental factors (maximum and minimum air temperature, relative humidity, rainfall) were recorded at different intervals of time alongwith red cotton bug population data from experimental fields. Results — Theoretical model indicated factors that influenced selection of envotype and expression amongst the bacterial population at different stages. The disease severity and vector population were influenced by specific temperature and humidity levels in this episode. Limitations: The research noted a poor association between vector population and disease severity, indicating the requirement for more studies to appreciate how environmental factors predict vectors populations which in turn affect the progression of diseases [4].

Kounani A et al. (2023) , Uses EfficientNet Convolutional Neural Networks (CNN) as a model pretrained for monitoring pests and diseases in cotton. Dataset: Healthy and Aphid-infested cotton plant images RESULTS: Attained 88% training accuracy and an 85% validation accuracy in distinguishing the healthy from infested plants. Weakness: Aphids are a characteristic, more pests and diseases should be added [5].

Shrivastava A (2023), Developed Convolutional Neural Networks (CNN) to recognize diseases on cotton leaves & plants. Training Dataset: Images of unhealthy and healthy cotton leaves. Outcome: It led to high performance in identification of diseases thus helping with early diagnosis. Shortcoming: the majority of research in this direction is primarily limited to image based detection and fails to capture all aspects of disease [6].

Kumar MR et al. (2023) , In this study, an automatic technique for the recognition of cotton leaf diseases has been proposed using Improved Grey Wolf Optimization (IGWO) and Bi-attention mechanism. Method: The IGWO algorithm is used to implement the optimal feature selection in leaf classification and a Bi-attention mechanism on these selected features. Dataset: It is collection of cotton leaf data containing 2384 images which are further divided into different disease class. The images were made under different lighting conditions and post-processed to enhance traits which are important for detecting disease. Results: The proposed model obtained a high accuracy rate of 97.45% in the Cotton Dataset for disease identification, which proves its efficiency. Restrictions: The study is subject to patient data restriction as the relevant diseases and leaf conditions are specific for this research [7].

Gülmez B (2023) , In the current study, a novel deep learning model was developed using GWO for detecting diseases in cotton. GWO was used to find the most efficient model architecture. Data set: The data was divided into four classes diseased cotton leaf, diseased cotton plant, fresh cotton leaf and fresh cotto plan The training and test images were organized by class, with a fixed number of samples per image. Results: The proposed model boasted an accuracy, precision and recall equal to 1.0 respectively, however the F1-score was not perfectly predicted in this approach. Its accuracy was better than ResNet50, VGG19 and InceptionV3 etc.train an image predicting capability model in TensorFlow.keras. Disadvantages: This study is highly regional and conditions regarding the disease being primarily localized, so it cannot be applied to all possible cases. In addition, the study has not been tested in different environmental situations and other cotton varieties. It also could not be ruled out that the model was only accurate because it had actually been trained on data and hyperparameters that were already known to give high accuracy, in sample [8].

Jiang P et al. (2023) This article developed a model for predicting cotton aphid infestations using deep learning, vegetation indices, and multispectral pictures captured by unmanned aerial vehicles (UAVs). We used the XGBoost method for feature selection, GWO for optimization, and the Support Vector Regression norm for prediction. Information gathered from a 63-acre cotton crop using multispectral photos captured by a UAV is included in the collection. We used the XGBoost algorithm to analyze and minimize the initial characteristics of vegetative indicators that are vulnerable to cotton aphids. Results This model of (XGBoost-GWO-SVR) were significantly better performing than all models. This achieved the best result in estimating cotton aphid infestation with a mean squared error (MSE) and mean absolute error (MAE), decreasing >90%, R2 of 0.980, respectively Disadvantages: This study only focused on cotton aphids so the result may not be acquired for other pests or diseases. Additionally, the dependency on a certain UAV multispectral data could decrease the model's flexibility in different agricultural environments or with various hardware. UAV data do not have short-wave infrared bands, which prevents the identification of certain plant stress signals as well [9].

Naeem AB et al. (2023) , This research work is all about the detection of diseases in cotton leaves using deep learning models and particularly focussed on VGG-16. In this paper, we investigate the effectiveness of several deep learning architectures like CNN, ResNet-50 and VGG-16 to cope with that. Dataset: The dataset consists of pictures of cotton leaf healthy and diseased. The images were captured from different cotton fields and preprocessing steps taken before inputs are fed to deep learning models. Results: It was seen that is the VGG-16 model performed best in disease detection with an testing accuracy of 98%. This was achieved after tuning model parameters using Adam and RMSProp optimizers. Limitation The main limitation of the study is that it focused on a specific deep learning model (VGG-16 architecture), and accordingly its findings are not necessarily generalizable to other models. Furthermore, as the data is generated for cotton leaf diseases at a particular type and stage or compatibility issues with other crops in this work are not considered [10].

Huang C et al. (2023) , This study presents a novel VFNet-Improved based intelligent vision system to monitor the dynamic change of cotton Verticillium wilt. The 3-coordinate motion platform can help to achieve automatic image capture, and the deep learning-based disease recognition system is developed for this purpose. Dataset: iNat2009-Cotton Leaves dataset collected over a period of 22 days from October (04) – November (13), which had about more than thousands images taken based on scenarios captured during sunrise time at field capacity around21 m x30m/63 acres. Seventy images including different disease manifestations were used to train and test the model. Results: The VFNet-Improved model improved with deformation convolution and soft nms reached 0.950 mAP which achieved the state-of-the-art performance on UA-Detrac dataset against other models. The system performed with high accuracy and repeatability in relation to hand measured diseased cotton leaves. The limitation of this study are that other than Verticillium wilt was not covered. Improvement of the system for use in different environmental conditions or with other host and non-host cotton diseases was not investigated. No statement concerning translation system or imaging quality [11].

Lu Z et al. (2023), This work suggested a new method to diagnose cotton Verticillium wilt by using the spectral and imaging feature. Hyper-spectral image processing and feature extraction using EfficientNet Then spectral information was preprocessed using Savitzky-Golay smoothing, and feature bands were extracted by principal component analysis (PCA)and successive projections technique. EfficientNet is a deep learning model that provides extracted image features. Dataset: a collection of 997 hyperspectral imaged cotton leaf samples in which each sample is labeled as being healthy (499) or sick (498). Conclusion: The accuracy of cotton Verticillium wilt identification was up to 98.99% by fusing spectral and image characteristics. Categorization performance was significantly better than by spectral or image features alone. These findings are fairly robust to our manipulation of verticillium wilt outcomes but should not be extended beyond that system or the varieties used in this study. It also employs a novel hyperspectral imaging technology and deep learning model, which could limit its generalization to other agricultural scenarios or solu-tions [12].

Hussain S et al. (2023) , This work examined whether temperature and relative humidity could be used to predict in-field infestation levels by the pink bollworm (Pectinophora gossypiella) of cotton using multiple regression models. The model projected predicted future climate conditions for 2040. Dataset- Data were collected from field visits in 17 districts of Punjab, India during eight years (2012–19) In order to analyze the infestation level of Pink bollworm and evaluate its future climatic conditions, levels were monitored and data was processed in Arc GIS. Results: The model indicated a general increase in the pink bollworm infestation by 2040, with greatest improvement expected to be in five districts. Our study showed that the growth capacity of P. gossypiella increased at 28 °C, which means temperature differences have a great effect on infestation rates. Drawback: The climatic based model developed in the study may be able to predict only for Temperature & Relative Humidity and not all other possible factors that affect pink bollworm infestation. Further, the prediction is Punjab specific and may be different for other areas or cotton pests [13].

Saeed H et al. (2018) , In this research cotton leaf curl virus disease was predicted and managed by resistant germplasm and bioproducts. These applications include the screening of cotton types for resistance as well an examination two bio-products in opposition to whiteflies. Data: Fifteen cotton lines were screened for reaction to disease They were making predictions on number of cases using weather, humidity and the level or rainfall. Biogenic Datura stramonium & homoeopathic Aviara In general, the 15 were not very disease-resistant. High ambient temperature and relative humidity are the most conducive to disease and whitefly buildup. Performance of Datura stramonium over Aviara in whitefly control Cons The restriction: the main constraint is that the illness and area focus of this research. It has not been tested whether these results hold for other types of cotton diseases or environmental conditions. All of which the study also applies for insect management uses a couple bio-products [14].

Shao M et al. (2022) , Dataset: 8 categories of cotton leaf diseases and one category with position natural healthy samples dataset was collected over three years on the Langfang Scientific Research Pilot Base by Chinese Academy of Agricultural Sciences. Total number of images in this dataset are 5903. Approach: The model obtains the features of ResNet34 as feature extraction. Moreover, to further improve the feature fusion and focus on diseased information it utilizes a Bilinear Coordinate Attention Mechanism{ BCAM} in this model. This also includes the attention-guided data augmentation for better learning of discriminative features. Performance It achieved an identification success rate of 96.61 percent without a noticeably large extension in parameter sizes, and the figure represents progress from existing models. Traditional CNNs: The traditional Convolutional Neural Networks (CNN) due to the closeness in diseases tend to perform poorer than usual and are not able filter out noise-out irrelevant features casually available at natural settings. Those difficulties are overcome by using bilinear coordinate attention that attends on important disease features and increases localization precision. Complex Disease Symptoms: A few cotton disease have same leaf symptoms causing difficulty in proper diagnosis. Environmental variables: Different lighting, background in the natural context can impact performance of models. The model being tested on a particular dataset gathered in controlled circumstances, and no assurance is made regarding its potential for transferability to another crop or under different conditions [15].

Anwar S et al. (2023) , The research work employed transfer learning with Convolutional Neural Networks (CNNs) to detect cotton diseases using pre-trained models on new datasets. Compilation: The corpus consisted of 2654 unique photographs, with a total of 1362 available from local farm sites; and 1292 were downloaded through the Internet. There was new cotton leaf (left); curl virus leaves; and bacterial blight. Image Augmentation: Performed Image augmentation to increased the types and size of data in datasets. Machine Learning Model TuningPerformance of our model is measured using accuracy, precision recall,F1 Score and forecast time. For 256×256 pixel images, the DenseNet169 and ResNet50V2 models reached maximum accuracy up to 96%. Among the models, MobileNetV2 with 32x32 pictures had worst (52% accuracy) Based on confusion matrix analysis, the percentage of true positive predictions for fresh leaves were higher than 91% and bacteria blight was around 87%, while it dropped to about76% when dealing with curl virus detection in models trained with using image size at resolution of128x128 pixels. Local data from 2 Pakistani locations was used in the studyRestrictions. This limitation could restrict the generalizability of models to different environments and climates. Hardware limitations: CPU-based execution restricts the scope of models that may be utilized. Some future implementations, including those running on smartphones and embedded devices might be easier to use or accessible [16].

Hussain S et al. (2023) , The present study was through in the cotton genotypes; carried out during 2022-23 using Randomized Complete Block Design with ten treatment combinations. Plant height, net photosynthetic rate (μmol CO2 -m-1s-l), hydrogen peroxide content by bioassay method, total phenols contents using Folineciocalteau reagent and ascorbic acid were measured at the full flowering stage after 4 consecutive years performance of some selected traits including yield contributing plant characters and finally seed cotton yield g ha-‘ Data Recording and Measurement: Measurements for biochemical parameters are made with help of infrared gas analyzer 'IRGA CI-320+spectrophotometer. Results: Genotypes differed significantly in all the plant traits as indicated by Analysis of Variance (ANOVA). Plant height, transpiration rate, ascorbic acid content number of bolls and peroxidase had a positive correlation with seed cotton yield. There are also significant correlations between some other traits, which reflects the complex and diversity of cotton germplasm. Conclusion: We identified genotypes BH-247 and BH-606 as high performers based on principal component and cluster analyses. These genotypes are suggested for core-cotton belt and multi-locations testing is under process [17].

III. RESEARCH GAP

1. **Limited Dataset Diversity**:
    - Current datasets might not cover all the varieties of plants or the full spectrum of diseases.
    - Many datasets are collected under controlled conditions. There's a need for datasets capturing real-world conditions, including various lighting, angles, and backgrounds.
2. **Scalability and Real-time Detection**:
    - While deep learning models are effective, they can also be computationally intensive. Lightweight models that can operate in real-time, especially on mobile devices or in remote locations with limited resources, are crucial.
3. **Generalization across Different Geographies**:

- Plants may exhibit disease symptoms differently in varied geographical and climatic conditions. Models trained in one region might not generalize well to others.

4. **Integration with Other Data Sources**:
    - Combining image data with other sources, like soil health data, weather data, or historical disease spread patterns, has not been extensively explored.
5. **Early Disease Prediction**:
    - Detecting diseases before visible symptoms manifest can prevent widespread outbreaks. More research is needed on predicting diseases based on subtle, early-stage indicators.
6. **Handling of Rare Diseases**:
    - Some diseases are rare but devastating. Due to their rarity, datasets might not have adequate samples, making model training for these diseases challenging.

IV. MAIN APPROACH IN DEEP LEARNING

4.1 Approach in Deep Learning

1. **Data Collection**:
    - Gather a large dataset of plant images. These images should encompass a variety of diseases across different stages of progression.
    - The data might used from public datasets.
2. **Data Preprocessing**:
    - Images are often resized to a uniform dimension suitable for deep learning models.
    - Augmentation techniques, such as rotations, translations, and zooming, are applied to increase the dataset's size and robustness. This helps in improving model generalization.
3. **Model Selection**:
    - Convolutional Neural Networks (CNNs) are the most common choice for image-based classification tasks.
    - Popular architectures like AlexNet, VGG-16, 19, ResNet-50,101,152, and DenseNet-169,201,264 can be employed.
4. **Model Training**:
    - The neural network is trained using the training dataset. During this phase, the model learns to identify features from the images that are indicative of specific diseases.
    - Cross-entropy loss is typically used as the loss function for classification tasks.
    - Optimizers like Adam is employed to adjust the model weights based on the loss gradient.
5. **Validation and Hyperparameter Tuning**:
    - A separate validation set, not used during training, is employed to tune hyperparameters and prevent overfitting.
    - Techniques like dropout used to enhance model performance.
6. **Evaluation**:
    - Once the model is trained, its performance is assessed on a test dataset.
    - Metrics like accuracy, precision, recall, and F1-score give insight into the model's performance.

4.2 Data Collection

Our data collected from the open-source site of kaggle. com. We will have thousands of photos for plant leaves with different class names. Illustrative image depicts cotton plant leaves on which we want to get this correct identification of the relationship with their corresponding disease. Downscaling a cotton crop/disease pair from the PlantVillage dataset to 256*256 pixels prior running Model optimization and predictions.

Source : https://www.kaggle.com/datasets/janmejaybhoi/cotton-disease-dataset

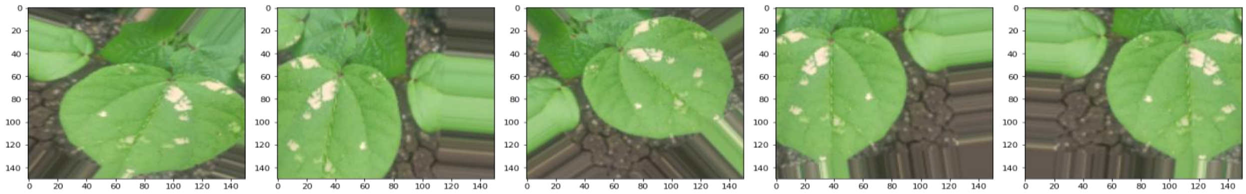

Figure 1. Dataset sample

V. RESULT ANALYSIS

5.1 Result evaluation parameters

Model performance is evaluated using the Accuracy, Precision, Recall, and F1-Score parameters; each of these metrics contributes to the efficacy of a deep learning model in its own way. As a general performance indicator, accuracy is a popular assessment metric that calculates the ratio of properly categorized examples to the total instances, indicating how well predictions were made. The percentage of correctly predicted positives to all positive forecasts is called precision. To ensure that the model catches all relevant occurrences while lowering false negatives, recall is a performance parameter that measures how many genuine positives are successfully detected by the model. An essential statistic to use when dealing with an unbalanced dataset is the F1-Score, which identifies the balance between Precision and Recall as their harmonic mean. In their combined form, these four metrics measure the precision and applicability of a model's predictions, allowing for a more complete evaluation of its categorization performance.

5.2 Result analysis

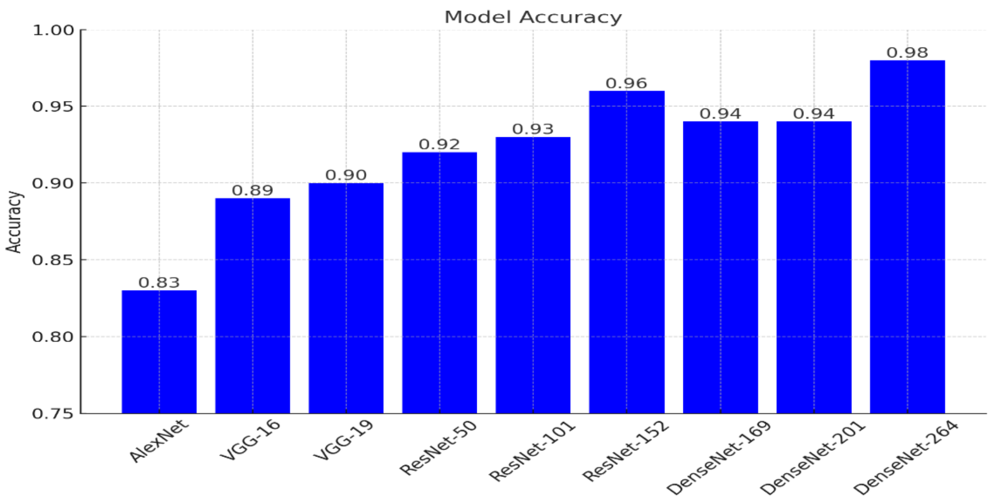

Figure 2. Dataset sample

The Accuracy figure 2 shows that the classification accuracy on different deep learning models. Accuracy gives a ratio of number of times the model predicts the labels correctly as compared to actual values. The higher the accuracy value, the better the model is. According to the chart, DenseNet-264 reaches the highest accuracy of 0.98, followed by ResNet-152 at 0.96. Among the architectures we compared, AlexNet, one of the earliest input images that primitives, has the lowest accuracy of 0.83.

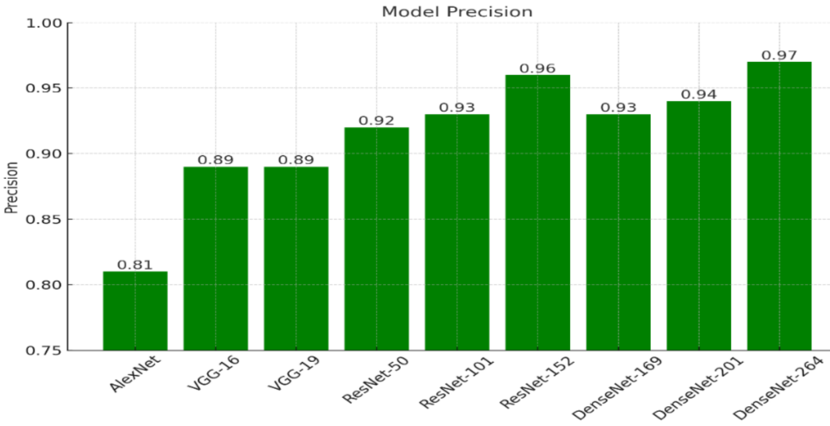

Figure 3. Dataset sample

Precision figure 3, The values of precision for each of the models The precision is the number of relevant instances retrieved over the number of instances retrieved. This means that more of the predicted positive classes are positive. As shown, DenseNet-264 had the highest precision (0.97), closely followed by ResNet-152 and ResNet-101, and AlexNet had the lowest precision (0.81). This means that deeper models and the models with more parameters perform better.

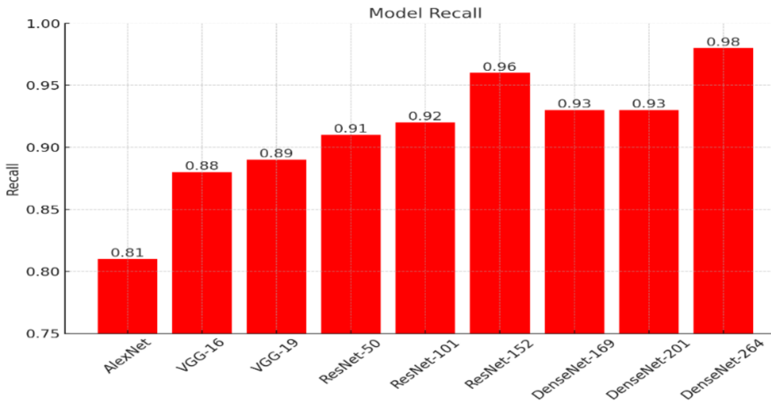

Figure 4. Dataset sample

Recall figure 4 shows the recall values of each deep learning model. Recall is the proportion of positive which were identified correctly. The recall score is inversely related to the both false positive and false negative rate. The best result is again achieved with DenseNet-264, with 0.98 recall, while AlexNet again has the worst recall score (0.81). Larger architectures (ResNet-50, ResNet-101, ResNet-152) also demonstrate good recall values

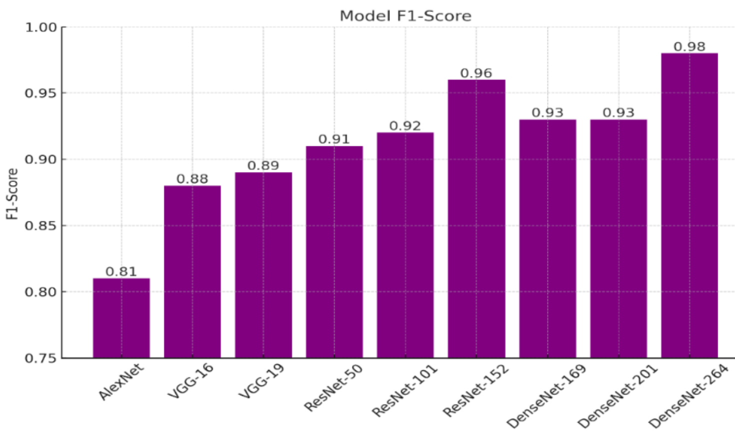

Figure 5. Dataset sample

The f1-score figure 5 is the harmonic mean between precision and recall, and provides a balance between the two metrics. This is an important metric when there is an imbalance between precision and recall. Finally, the DenseNet-264 model also achieves the highest result for F 1 -score, at 0.98, confirming its superior performance in various metrics. ResNet-152 and real-ese-ResNet-101 are the next two winning models with F1-scores of 0.96, 0.92 respectively, while AlexNet is a way off with a dull F1-score of 0.81.

5.3 Experimental analysis

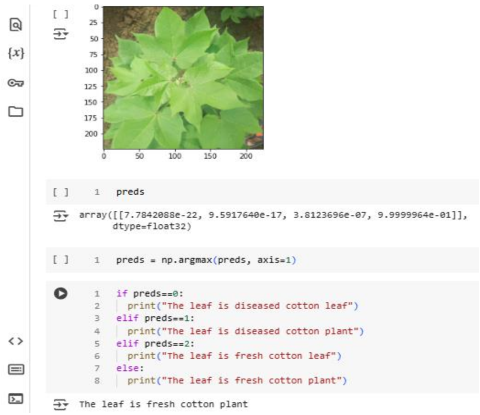

Figure 6. classification process for identifying the condition of a cotton leaf

The figure 6 depicts a classification process for identifying the condition of a cotton leaf using a deep learning model. The displayed code extracts predictions from a model and applies np.argmax(preds, axis=1) to determine the class with the highest probability. The conditional statements then map the predicted class index to corresponding labels: diseased cotton leaf, diseased cotton plant, fresh cotton leaf, or fresh cotton plant. In this instance, the model classified the input image as a fresh cotton plant, indicating that the leaf in the image appears healthy.

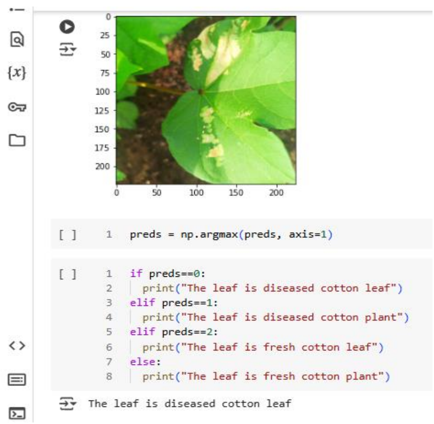

Figure 7. The deep learning model for cotton leaf disease classification

The figure 7 the deep learning model for cotton leaf disease classification. The np. argmax(preds, axis=1) gets Index of class with highest probability. Then, mapping index from the conditional statements is directed towards four categories: diseased cotton leaf, diseased cotton plant, fresh cotton leaf, and fresh cotton plant. So, here, the model recognized the input image with the following labels as a diseased cotton leaf because the visible yellow patches in the leaf might be a sign for infection/disease of the plant.

V. CONCLUSION AND FUTUREWORK

Recent advances in deep learning has shown great potential for achieving cotton plant disease detection with less reliance on manual inspection. Out of all the deep learning models that were applied for the classification task, ResNet-152 and DenseNet-264 achieved the top performance metrics of accuracy, precision, recall, and F1-score among all deep learning models which can be used for disease diagnosis task. The classification results show that we can classify the healthy and diseased leaves and plants. Small perfect datasets are required, and the approaches are complex due to the similarity between some diseases and the computational requirements of deep learning models.

We detected some misclassification risks, highlighting the necessity of diverse training data and well-annotated datasets. Future research could emphasize the development of lightweight models that can be run on low-power edge-device in order to ensure real-time disease confirmation. Integrating various multi-modal data (e.g., hyperspectral imaging, environment conditions, time sequences) can significantly improve the detection accuracy. Solving these challenges will enable scalable and practical deep learning tools in agriculture, resulting in sustainable farming, increased yield, and early detection of diseases, thereby maintaining food security globally.

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