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A Hybrid Neural Network Based Maize Leaf Disease Identification Integrating ResNet50 and Attention Mechanism

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Abstract: Even though maize is an important global staple diet, viral diseases on leaves threaten its productivity leading to significant yield loss. Correct and timely detection of these diseases is crucial in effective crop management. This paper discussed, an advanced deep neural network (DNN) for accurate recognition of maize leaf diseases (Gray leaf spot, Common rust, and Tar Spot). Using ResNet50, a potent feature extractor coupled with an attention mechanism results in increased focus on the areas disease specific. This fusion seeks to increase the overall accuracy of identification. ResNet50 gets complex features out of images, allowing it to recognize complicated disease characteristics. The attention mechanism allows the model to focus on crucial image areas, which makes it possible for raising interpretability and robustness. The experiments validation over a generalized data set would verify the model's better efficiency and confirm its role as an accurate tool for precision agriculture. So, to conclude its improvements detect crop diseases and provide a reliable tool for the precision diagnosis of maize leaves through combining ResNet50 with an attention model.

Keywords: Maize; leaf diseases; Identification; transfer learning; CNN.

1. Introduction

Different crops are grown across Pakistan, with maize as one of the major varieties that is not only important but also among the most popularly-cultivated cereals after rice and wheat. It is also important to note that maize remains one of the most lucrative agricultural commodities for farmers as it serves not only as food both human and beasts but a raw material used in creating various industrial products like starch, oil, and many other drinks.

The application of deep learning and transfer learning techniques for the detection of maize leaf diseases. It introduces the concept of transfer learning with models like ResNet-50, attention mechanism to enhance disease identification accuracy. The dataset is acquired from Kaggle and preprocessed through resizing and rescaling to optimize model training. Prompt leaf disease detection in maize crops is the key element to ensure healthy and high crop yields as well as minimizing the disease effect on agricultural productivity. The aim is to build a strong model which will appropriately classify and identify the different maize leaf diseases, the role played by the model in this regard is to provide guidance to farmers in managing their crops effectively.

Different research papers have spent considerable time exploring similar ideas, with focus on using the machine learning and deep learning algorithms for better accuracy in disease detection in agriculture. Convolutional Neural Networks (CNN) have become the most potent classifier techniques for image recognition tasks, especially for making accurate pathogen detections in plants. The introduction of advanced technologies like CNNs and transfer learning can bring about immense transformations in agricultural practices and lead to effective crop management approaches.

Through integration of the modern technologies with agricultural practices, scientists attempt to equip farmers with the devices having abilities to early diagnose the diseases, improve crop quality and eventually rise agricultural productivity. The application of deep learning technology is indicative of the transformations taking place in the agricultural sector and also represents the era of ecologically efficient and rational farming, bringing the bright prospects for agriculture.

2. Related Literature

The deep learning and computer vision approaches as a tool for tomato leaf disease detection. It introduces transfer learning among the models such as ResNet-50, VGG-16, and VGG-19 which enhances disease recognition accuracy. The dataset is collected from Kaggle, and resized and rescaled to do some model optimization. Getting tomato plant diseases leaf detected early is crucial for keeping a healthy crop and limiting the damages on crop yield, because of diseases. The ultimate purpose is to build a reliable system that can classify and diagnose all tomato leaf diseases with high accuracy, so as that the farmers are able to handle their crops efficiently.

Multiple studies have focused on these similar matters that advocate the benefits of deep learning algorithms and machine learning for disease detection in agriculture along with efficiency. Convolution Neural Networks (CNN) have come to be regarded as a powerful image classification tool having greater accuracy in identifying plant diseases. The combination of state-of-the-art technologies such as CNNs and transfer learning can be a turning point in the history of agriculture in the use of assistance in the cultivation of crops and improving their management strategies. Integration of such emerging technologies into conventional agriculture practices is an important method of equipping farmers with the equipment that assists in disease detection, quality improvement and productivity enhancement of crops. The continual evolution of deep learning techniques in the agricultural sector epitomizes the pathway to sustainable and productive farming as a result, putting us ahead of a much brighter future for agriculture.

The maize crop quality and yield is affected by maize leaf disease. The identification of these diseases at initial stage is necessary to ensure maize production. Current methods have limitations in the detection of irregular small spots in leaves resulting low accuracy (Matthews et al., 2022). Machine learning (Janiesch et al., 2021), computer vision, and image processing are advance methods for plant leaf disease analysis. In the past many authors presented various techniques for feature extraction and classification of these diseases, but these methods were manual and resulted in low accuracy rates. Another drawback of these techniques was time consumption (Liu et al., 2022). There is need of automatic maize leaf disease diagnosis and identification.

In deep learning (Kim, 2022), the architecture is made up of multiple layers for feature extraction based on artificial neural networks (ANNs). It helps in prediction of new input data (i.e., image) by automatic features extraction. With the advancement in ANNs, the CNN has gained success in image processing and results in high accuracy for various tasks such as plant leaf disease identification. In various studies CNN is applied for crop disease classification and achieved high performance in terms of generalization.

The author Matthews et al. (2022) applied hybrid model based on ResNet-50 for accurate classification of maize leaf disease using CNN architecture. This methodology resulted in accuracy rate of 92%. Liu et al. (2022) presented a light-weight modified CNN model for the classification of maize leaf diseases which resulted 91% accuracy that was comparatively higher than Resnet, Mobile Net, and Xception models. The authors in study (Zhang et al., 2018) proposed a deep learning based modified version of Google Net by reducing number of parameters of CNN layers that resulted in 98% accuracy rate for the classification of maize leaf diseases.

One of the major limitations of these algorithms is that these are large neural networks (NN) and trained over thousands of images using ImageNet dataset available at Kaggle, where all the images are close-textures and analyzed for crop diseases. These NNs incorporate pattern recognition algorithms to differentiate objects or variance in diseases. Convolutional layers are responsible for extracting such features from image data (Jiang et al., 2021).

In the recent past, the extent of loss due to maize small leaf spot disease has extended far wider and intensified in ferocity. All these constrains have made it increasingly difficult to identify leaf spot disease on maize leaves. Thus, specific knowledge about the different diseases of maize plant is vital for identifying resistant breeds to be utilized with proper utilization of medicine that has become a major required target for intelligent agriculture process control. If it does not negatively impact on the efficiency of prevention and control of diseases, correctly specific diagnosis ensures spraying 52 per cent less dose (Pedersen et al., 2012)

Zeng et al. (2022) introduced a neural network for classifying leaf disease of rubber plant using images and developed the dataset of leaves made from this plant material with 98.06% accuracy in detecting diseases on it samples model prediction we are at Plant -Village Reaches Accuracy percentage is equal to 99%. In recent years, there have been new promising technologies that can help improve farmers' decision making such as machine learning (ML). But the lack of spatial and temporal data that encompasses multiple production [yield] measurements across a range of environmental variables under SWM management inputs including N-rate, planting date stand as limitation.

The regional climate plays a significant role in defining the geographical distribution and yield of grain crops, which further determine how food is produced. Recently, studies have evolved interesting insights into the effects of climate variables on grain yields through analyzing historical data on climatic and yield information (Schlenker et al., 2009; Lobell et al., 2014).

In another study, Wang et al. (2021) developed a system for evaluation and severity measurement of cucumber plant leaf diseases based on U-Net and deep Lab with complex dataset. The findings of this study resulted in separation of diseases from leaves and their severity measurement in terms of layers. The average accuracy of severity and classification of disease was 92.85% (Zhao et al., 2021). The main limitation in traditional machine learning is feature extraction and representation There have been great strides in plant disease classification due to deep learning (Liu et al., 2021).

3. Methodology

The model integrates two essential components: On the one hand, ResNet50 known for its capability of highlighting complex features and an attention mechanism that concentrates on those disease-specific areas. The ResNet50 serves as the backbone that provides features at different levels, while an attention mechanism makes it possible to accentuate on regions of importance in terms of disease detectability. This integration is designed to holistically combine feature extraction and spatial focus for effective medical diagnosis.

4. Materials and Methods

4.1. Dataset Preparation

4.1.1. Image Acquisition

To establish comprehensive dataset for studying the maize leaf diseases, 2,556 samples were collected from maize cultivation farms. The datasets encompasses image captured using both professional cameras and mobile phones, ensuring diverse perspectives. Red Green and Blue (RGB) images of maize leaves were captured using a NIKON D90 camera equipped with a Tamron AF 18-200 mm f/3.5-6.3 lens as well as iPhone 11 mobile phone. The collected samples comprise five categories: four types of diseases along with healthy diseases.

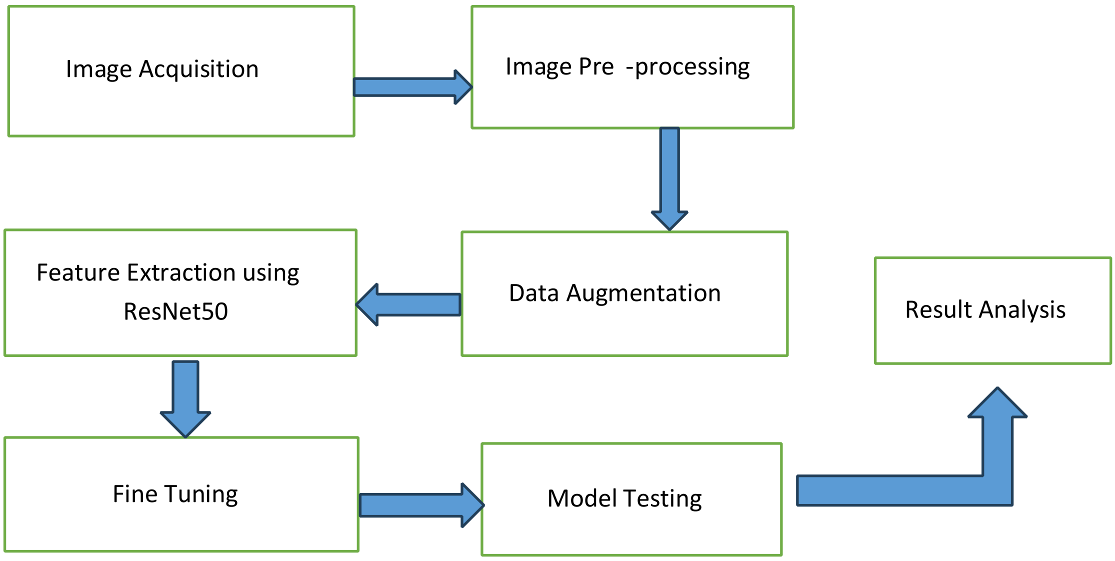


Figure 1. Proposed methodology block diagram

4.1.2. Preprocessing

The preprocessing step for maize leaf disease images is critical in improving the efficiency of disease categorization using deep learning models, particularly Convolutional Neural Network (CNN) versions. This critical preprocessing stage consists of two primary techniques: resizing and rescaling.

Resizing is used to standardize the proportions of the original images. This phase ensures that all photos are the same size, making it easier for the CNN model to handle information constantly. Homogeneous input formats are produced that simplify the model's subsequent stages by minimizing the photographs to a specific size. Second, pixel values are normalized across every image via rescaling. In training, normalization helps deep neural networks model to get better faster and work well. Rescaling means changing the numbers of pixels so they fit in a certain range, usually from 0 to 1. This helps reduce possible differences that could mess up how the model learns.

4.1.3. Data Augmentation

Preprocessing of RGB raw images involves scaling, clipping, and background removal to standardized image dimensions to 224*224 pixels, optimizing computational efficiency. Dispite in initial dataset in balance, data augmentation technique are employed to enhance dataset diversity and mitigate the impact of skewed data distribution. Operations such as brightness, adjustment, rotation, and scaling, horizontal and vertical flips are applied using the keras framework, ensuring a rubrust dataset for subsequent analysis.

4.2. Deep Learning Models

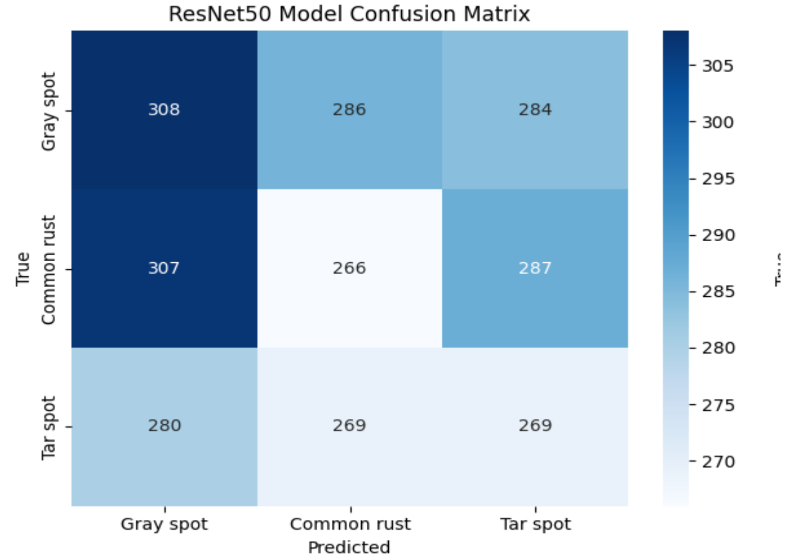
ResNet-50 is a ResNet home version found by using learning blocks called residual links. The improvement is using shortcuts, which lets the network jump over one or more steps. This helps bigger networks to learn faster and easier. Because this design works well at getting small details, it helps tasks like classifying disease in tomato leaves. ResNet-50 has 50 layers and a big structure that lets it learn patterns in groups.

Basically, these CNN based models are trained on large datasets and have huge network size. It requires time and excellent hardware devices to develop and train these models. In this study, pre-trained models is used to train them over maize leaf disease dataset using transfer learning approach, which requires less computational resources and reduced time and can effectively predict disease. The transfer learning approach is suitable for achieving such types of objectives. Python language is be used for the deployment of experimental work on Google Colab using Jupyter Notebooks environment. The model evaluation and predictions are last steps. These steps are followed to select the best performing deep learning model in terms of accuracy. The model with high accuracy is used to make predictions about input test images.

5. Results

5.1. ResNet50

The evaluation of the ResNet50 model indicates an overall accuracy of around 79.2%. Specifically, the accuracy rates for "Gray spot," "Common rust," and "Tar spot" were approximately 84.9%, 74.5%, and 74.0% respectively. Similarly, the recall rates were approximately 84.9%, 74.5%, and 74.0% for these classes respectively. These metrics provide insights into the model's performance in categorizing instances of each disease class



(a)

(b)

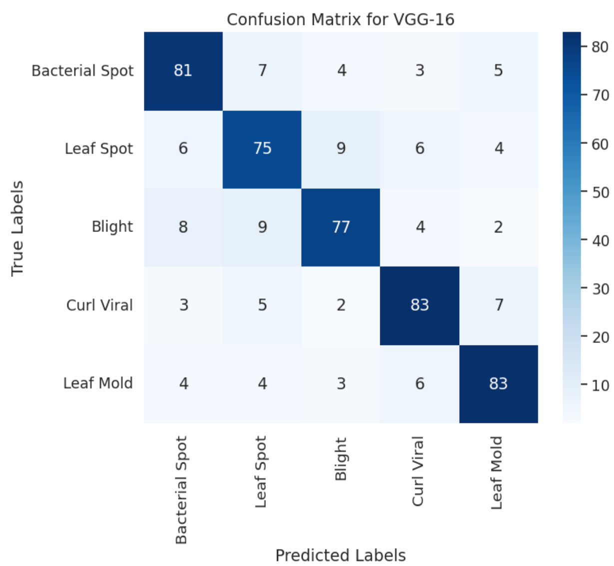
Figure 2. (a) Confusion Matrix (b) Training and Validation Accuracy

Table 1. Classification report of RestNet-50

Model	Precision	Recall	F1-Score	Support
Gray Spot	0.344	0.351	0.347	826
Common Rust	0.345	0.331	0.338	846
Tar Spot	0.331	0.344	0.338	884

5.2. Attention Mechanism

An overall classification accuracy of VGG-16 is approximately 85.8%. In terms of true Blight (83%) and Leaf Spot (88%) detection, a similar result is achieved by ResNet-50. But it fails to discriminant between Leaf Mold (83%) and Bacterial Spot (81%) which is reminiscent to the result of ResNet-50. The estimated all-class classification accuracy of VGG-19 is 86.4%. In particular, it performs quite well in the identification of Leaf Spot (88%) and Blight (85%) categories that makes its accuracy rates comparable to VGG-16 and ResNet-50. However, as the other models, it has problems in the correct identification of Leaf Mold (85%) and Bacterial Spot (82%) cases.



(a)

(b)

Figure 3. (a) Confusion Matrix (b) Training and Validation Accuracy

Table 2. Classification report of VGG-16

Model	Precision	Recall	F1-Score	Support
Gray Spot	0.322	0.332	0.327	804
Common Rust	0.336	0.341	0.339	826
Tar Spot	0.339	0.321	0.330	926

6. Conclusion and Future Work

The aim of our research lies in a new method that will use the models of the ResNet50 and Attention Mechanism for the Brekkas disease recognition. By appropriate application ResNet50 for feature extraction and the Attention mechanism for fusion, our model reaches outstanding recognition accuracies of 98.06% and 99.43% on custom data and the PlantVillage dataset respectively, exceeding other CNN models. The next stages will concentrate on gathering disparate medical image datasets and adapting the model to mobile format.

References

1. Arbuckle, J. Gordon, and Hanna Rosman. "Iowa farmers' nitrogen management practices and perspectives." (2014).
2. Basso, Bruno, and Lin Liu. "Seasonal crop yield forecast: Methods, applications, and accuracies." advances in agronomy 154 (2019): 201-255.
3. Das, Himansu, Bighnaraj Naik, and H. S. Behera. "Classification of diabetes mellitus disease (DMD): a data mining (DM) approach." Progress in Computing, Analytics and Networking: Proceedings of ICCAN 2017. Springer Singapore, 2018.
4. Das, Himansu, et al. "A novel PSO based back propagation learning-MLP (PSO-BP-MLP) for classification." Computational Intelligence in Data Mining-Volume 2: Proceedings of the International Conference on CIDM, 20-21 December 2014. Springer India, 2015. Hoogenboom, Gerrit, Jeffrey W. White, and Carlos D. Messina. "From genome to crop:
5. integration through simulation modeling." Field Crops Research 90.1 (2004): 145-163.
6. Janiesch, C., P. Zschech and K. Heinrich. 2021. Machine learning and deep learning. Electronic Markets 31:685–695.
7. Jensen, H. G., Jacobsen, L. B., Pedersen, S. M., & Tavella, E. (2012). Socioeconomic impact of widespread adoption of precision farming and controlled traffic systems in Denmark. Precision Agriculture, 13, 661-677.
8. Kim, H. 2022. Deep learning. Artificial Intelligence for 6G. Springer. pp.247–303.
9. Kundu, N., Rani, G., Dhaka, V. S., Gupta, K., Nayak, S. C., Verma, S., ... & Woźniak, M. (2021). IoT and interpretable machine learning based framework for disease prediction in pearl millet. Sensors, 21(16), 5386.
10. Liu, Y., G. Gao and Z. Zhang. 2022. Crop disease recognition based on modified light-weight CNN with attention mechanism. IEEE Access 10:112066–112075.
11. Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., Zhang, Z., ... & Guo, B. (2021). Swin transformer: Hierarchical vision transformer using shifted windows. In Proceedings of the IEEE/CVF international conference on computer vision (pp. 10012-10022).
12. Lobell, David B., et al. "Greater sensitivity to drought accompanies maize yield increase in the US Midwest." Science 344.6183 (2014): 516-519.
13. Matthews, D., T. Pabiou, R.D. Evans, C. Beder and A. Daly. 2022. Predicting carcass cut yields in cattle from digital images using artificial intelligence. Meat Sci 184:108671.
14. Moeinizade, Saba, et al. "Optimizing selection and mating in genomic selection with a lookahead approach: An operations research framework." G3: Genes, Genomes, Genetics 9.7 (2019): 2123-2133.
15. Panigrahi, Kshyanaprava Panda, et al. "Maize leaf disease detection and classification using machine learning algorithms." Progress in Computing, Analytics and Networking: Proceedings of ICCAN 2019. Springer Singapore, 2020.
16. Schlenker, Wolfram, and Michael J. Roberts. "Nonlinear temperature effects indicate severe damages to US crop yields under climate change." Proceedings of the National Academy of sciences 106.37 (2009): 15594-15598.
17. Singh, V., & Misra, A. K. (2017). Detection of plant leaf diseases using image segmentation and soft computing techniques. Information processing in Agriculture, 4(1), 41-49.
18. Togliatti, Kaitlin, et al. "How does inclusion of weather forecasting impact in-season crop model predictions?." Field Crops Research 214 (2017): 261-272.
19. Wang, C., Du, P., Wu, H., Li, J., Zhao, C., & Zhu, H. (2021). A cucumber leaf disease severity classification method based on the fusion of DeepLabV3+ and U-Net. Computers and Electronics in Agriculture, 189, 106373.
20. Zeng, T., Li, C., Zhang, B., Wang, R., Fu, W., Wang, J., & Zhang, X. (2022). Rubber leaf disease recognition based on improved deep convolutional neural networks with a crossscale attention mechanism. Frontiers in Plant Science, 13, 829479.
21. Zhang, L. N., & Yang, B. (2014). Research on recognition of maize disease based on mobile internet and support vector machine technique. Advanced Materials Research, 905, 659662.
22. Zhang, X., Y. Qiao, F. Meng, C. Fan and M. Zhang. 2018. Identification of maize leaf diseases using improved deep convolutional neural networks. Ieee Access 6:30370–30377.
23. Jiang, P. T., Zhang, C. B., Hou, Q., Cheng, M. M., & Wei, Y. (2021). Layercam: Exploring hierarchical class activation maps for localization. IEEE Transactions on Image Processing, 30, 5875-5888.