Electrical and Automation Engineering

Vol: 2(1), 2023

REST Publisher; ISBN: 978-81-956353-5-1

Website: http://restpublisher.com/book-series/eae/

DOI: https://doi.org/10.46632/eae/2/1/12

Development Of Deep Learning Model for Wheat Disease Identification and Classification

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Abstract. *Plants play an essential role in climate change, agriculture industry and a country's economy. There by taking care of plants is very crucial. Just like humans, plants are affected by several disease caused by bacteria, fungi and virus. Identification of these disease timely and curing them is essential to prevent whole plant from destruction. Identification of the plant leaf diseases is the key to preventing the losses in the yield and quantity of the agricultural product. Most of the countries depend upon agriculture. Due to the factors like diseases, pest attacks and sudden change in whether condition, the productivity of crop decreases. The studies of the plant diseases mean the studies of visually observable patterns seen on the plants. It takes long time and difficult to detect a disease in a plant manually. Hence, Deep Learning is used for detection of plant diseases. For this approach, Convolution neural networks will be used for classification based on learning with some training samples of Plant leaves like wheat. The algorithm and method that are used here is convolution neural network (CNN) by using EfficientnetB3 architecture using the Python programming. Overall, the approach of training deep learning models on increasingly large and publicly available image datasets presents a clear path towards crop disease diagnosis on a massive global scale. Finally, the simulated result shows the disease of the plant and how much area it is affected.*

Keywords; *Deep Learning; convolution neural network (CNN); EfficientnetB3.*

1. INTRODUCTION

Wheat is one of the most important staple crops in the world, providing food for billions of people. However, wheat crops are vulnerable to various diseases caused by pathogens such as fungi, bacteria, and viruses. These diseases can cause significant yield losses, reduce crop quality, and increase the use of chemicals to control them, which can be harmful to the environment and human health Early detection and accurate classification of wheat diseases can help farmers to implement timely and effective disease management strategies, such as selecting disease- resistant cultivars, adjusting planting dates, and applying appropriate fungicides. This can help to minimize yield losses, reduce the use of chemicals, and improve the quality and safety of wheat products. Furthermore, with the increasing global demand for wheat and the need to ensure food security, there is a growing interest in the development of precision agriculture technologies that can improve the efficiency and sustainability of wheat production. Disease detection and classification using machine learning algorithms and computer vision techniques can contribute to the development of such technologies. In summary, the motivation for wheat disease detection and classification is to improve crop productivity, reduce the use of chemicals, and ensure the sustainability and safety of wheat production. Wheat disease detection is an important problem in agriculture, as it can help identify and prevent the spread of diseases that can cause significant damage to crops and result in reduced yields. The goal of wheat disease detection is to accurately and efficiently identify the presence of diseases in wheat crops, such as rust, powdery mildew, and Septoria leaf blotch. The problem involves analyzing images of wheat leaves and identifying any visual abnormalities or signs of disease. This can be a challenging task, as the appearance of healthy and diseased leaves can be similar, and there may be variations in lighting, camera angle, and other factors that can affect image quality.

Types of diseases: We have identified different types of diseases in the wheat crop in that there are some main diseases which reduces the yield they are:

1.Septoria tritici blotch
2.Stripe rust

Septoria tritici blotch: This fungal disease causes tan, elongated lesions on wheat leaves. Lesions may have a yellow margin, but the degree of yellowing varies among varieties. The dark, reproductive structures produced by the fungus are key diagnostic features and can often be seen without magnification. This disease is also known as speckled leaf blotch Management: Genetic resistance, foliar fungicides, crop rotation

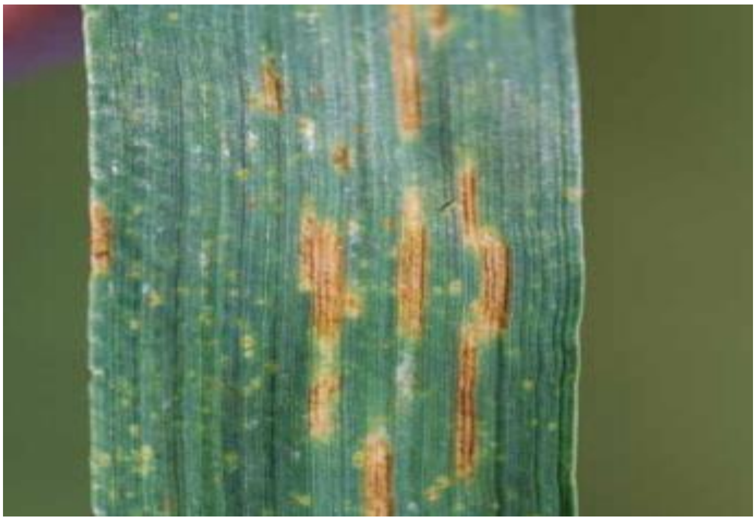

FIGURE 1. Septoria tritici blotch

Stripe Rust

Stripe rust causes yellow, blister-like lesions that are arranged in stripes. The disease is most common on leaves, but head tissue also can develop symptoms when disease is severe. Outside the United States, this disease is sometimes referred to as yellow rust. Management: Genetic resistance, foliar fungicides

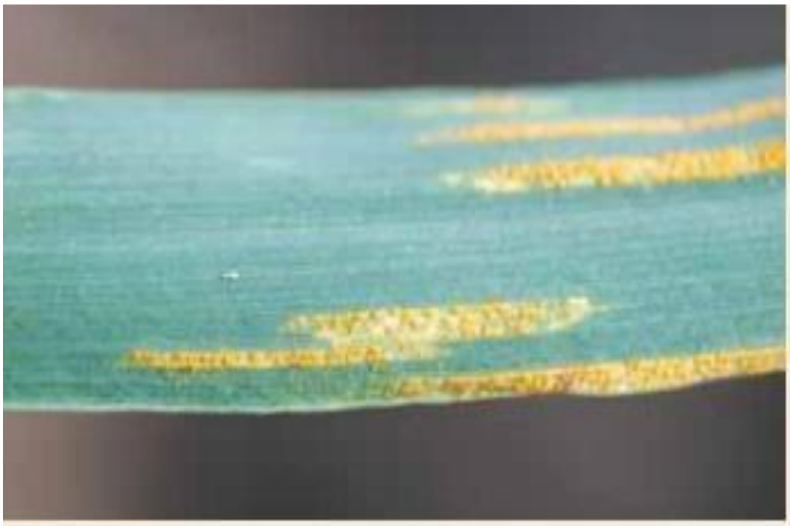

FIGURE 2. Stripe Rust

To address this problem, various machine learning and computer vision techniques can be used to develop a wheat disease detection system. This involves training a model on a dataset of labeled images of healthy and diseased wheat leaves, and using the trained model to predict the presence of disease in new images. The accuracy of the model can be improved by using techniques such as data augmentation, transfer learning, and ensemble methods. The ultimate goal is to create a reliable and efficient system that can help farmers detect and manage wheat diseases, ultimately improving crop yields and food security. Efficient Net is an image classification model family. It was first described in Efficient Net: Rethinking Model Scaling for Convolutional Neural Networks. This notebook allows youto load and test the EfficientNet-B0, EfficientNet-B4, EfficientNet-WideSE-B0 and, EfficientNet-WideSE-B4 models. Efficient Net-Wide SE models use Squeeze-and-Excitation layers wider than original Efficient Net models, the width of SE module is proportional to the width of Depth wise Separable Convolutions instead of block width. Wide SE models are slightly more accurate than original models. This model is trained with mixed precision using Tensor Cores on

Volta and the NVIDIA Ampere GPU architectures. Therefore, researchers can get results over 2x faster than training without Tensor Cores, while experiencing the benefits of mixed precision training. This model is tested against each NGC monthly container release to ensure consistent accuracy and performance over time. When convolutional neural networks are developed, they are done so at a fixed resource cost. These networks are scaled up later to achieve better accuracies when more resources are available. A ResNet 18 model can be scaled up to a Reset 200 model by adding more layers to the original model. In most situations, this scaling technique has helped provide better accuracies on most benchmarking datasets. But the conventional techniques of model scaling are very random. Some models are scaled depth-wise, and some are scaled widthwise. Some models simply take in images of a larger resolution to get better results. This technique of randomly scaling models requires manual tuning and many person-hours, often resulting in little or no improvement in performance. The authors of the Efficient Net proposed scaling up CNN models to obtain better accuracy and efficiency in a much more moral way. Efficient Net uses a technique called compound coefficient to scale up models in a simple but effective manner. Instead of randomly scaling up width, depth or resolution, compound scaling uniformly scales each dimension with a certain fixed set of scaling coefficients. Using the scaling method and Auto ML, the authors of efficient developed seven models of various dimensions, which surpassed the state-of-the-art accuracy of most convolutional neural networks, and with much better efficiency. Efficient Net is based on the baseline network developed by the neural architecture search using the Auto ML MNAS framework. The network is fine-tuned for obtaining maximum accuracy but is also penalized if the network is very computationally heavy. It is also penalized for slow inference time when the network takes a lot of time to make predictions.The architecture uses a mobile inverted bottleneck convolutionsimilar to Mobile Net V2 but is much larger due to the increasein FLOPS. This baseline model is scaled up to obtain the family of Efficient Nets.

2. LITERATURE SURVEY

Related Works:

for object detection. The paper even explains different types of object detection methods: Deep Saliency Network, Adversarial Learning, Fine grained object detection. Cong The field of agriculture [1] has been gaining attentionlately as it can be useful in genome mapping [2], another upcoming field where Artificial Intelligence [3] is playing a very crucial role. Plant phenotyping, although a subfield of agriculture, itself is an umbrella under which many sub-fields exist, like Postharvest [4], Development [5], Physiology [6], and Morphology [7].All of the before mentioned fields cover all the domains in plant phenotyping, ranging from its health detection to counting organs to fruits. With the recent advancement in computer vision and neural networks, more improved solutions have been possible. Since it is a field that requires extensive research and is upcoming hence not much has been established and is still under research. New benchmarks are being set daily with the coming of new advancements, and this paper aims to use many such advancedtechniques that were released recently to create robust models that can detect wheat heads accurately. One of the main reasons to detect wheat-heads is that it is one of the important crops that plays a pivotal role in feeding humans across the globe. Globally, wheat production was around 758.3 million tonnes in 2020.Yu Jiang et al. [8] in which there is abundant information that tells how to use CNN's for understanding stress evaluations, plant development, and post-harvest qualityassessment. There are different architectures presented thatexplain image segmentation, object detection. They even provide some SOTA solutions for certain phenotyping applications. Wu Wei et al. [9] proposed detection and enumeration of wheat grains based on a deep learning method under various scenarios and scales which gives us information about wheat grains. It states that the number of grains plays a pivotal role in determining yield. The authors use Faster R- CNN to detect wheat grains with loss less than 0.5 and mAP:0.9. The detection time is quick, under 2 seconds. It is also robust to different backgrounds and different levels of grain crowding. Zhong-Qiu Zhao et al. [10] wrote about object detection with deep learning and it is discussed about the most popular object detection architectures along with their working. This paper also explains about application domains of object detection, two of which are face detection, pedestrian detection. Some algorithms that are discussed are R-CNN, Fast R-CNN, Faster-RCNN along with different feature extractors such as FPN, Single Feature Map etc.Ajeet Ram Pathak et al. [11] in the paper proposed an explanation about deep learning techniques that are used for object detection. Some of the SOTA algorithms are discussed in this paper. It also discusses some of the benchmark datasets used.

Tang et al. [12] analyses object detection based on deep learning in the paper. It explains in-depth about real-time object detection. It also challenges present in the current circumstances and proposes solutions on how to improve techniques. Steven C.H. Hoi et al.[13] elaborates about recent advances in deep learning for object detection about a general introduction given to the object detection. Then the authors dwell into 3 major parts which are detection components, learning strategies, applications with benchmarks. Some of thecomponents are feature learning, proposal generation, sampling strategies etc. At the end, the authors provide future directions on what more can be improved. Roman Solovyevet al. [14] proposed weighted box fusion for object detection models. The paper introduces a novel technique discussed known as weighted box fusion. Weighted box fusion has a better performance than NMS (nonmax suppression) and NMS-soft. It works better when using ensemble methods. Barret Zoph et al. [15] discusses about data augmentation. Augmentations play a crucial in object detection. There were many experiments with and without augmentations to show accuracies of different detectors. Iteven explains why the model regularizes and ends with explanations of many different augmentations. Guotai Wanget al. [16] explains why using augmentations at test time helps in improving the robustness and accuracies of the models. There was an experiment conducted with MRI scans of fetal brains and brain tumors which provided better model-based uncertainty. Yukang Chen et al. [17] explains mosaic data augmentation. It is explained that mosaic augmentation works very well with small objects. It also helps in exploiting the loss in statistics and helps in scale balancing large and small objects.Alexey Bochkovsky et al. [18] dwells deep on YOLOv4. The authors discuss how it is improved over YOLO v3 significantly over speed, accuracy and newer technology used. Much architecture was used in this paper which had different combinations of backbone, neck, and detector. Few of the backbones that were considered in this paper were CSPResNeXt50, CSPDarknet53, EfficientNetB3.Uponexperimentation of all these backbones, CSPDarknet53 showed the best results. Upon this the SPP block (Spatial Pyramid Pooling) was used to separate out the most significantcontext features while maintaining the same inference speed. Instead of FPN, which is extremely popular the authors prefer PANet (Path Aggregation Network) [19] and the head used was YOLO v3.

3. WHEAT DISEASE IDENTIFICATION & CLASSIFICATION

EfficientB3 is a deep learning architecture that is based on the Efficient Net architecture. It is designed to be computationally efficient while still achieving state-of-the-art performance on a variety of computer vision tasks, including image classification. Here's a possible steps that are required for using EfficientB3 to identify and classify wheat diseases: Data preprocessing: Collect a dataset of images of wheat plants with various diseases. Preprocess the images by resizingthem to a uniform size and normalizing the pixel values. Model architecture: Use the EfficientB3 architecture as the backbone of your model. The architecture consists of a series of convolutional layers, followed by pooling layers, and finally a set of fully connected layers. Transfer learning: Initialize the weights of the EfficientB3 architecture with pre-trained weights on a large dataset, such as ImageNet. Fine-tuning: Train the model on your wheat disease dataset using a fine-tuning approach. In fine-tuning, you freeze the weights of the earlier layers of the model (which are already good at recognizing basic features) and only update the weights of the later layers, which are specialized for the specific task of wheat disease identification and classification. Evaluation: Evaluate the model's performance on a holdout setof images that were not used for training. Use metrics such as accuracy, precision, and recall to assess the model's performance. Deployment: Deploy the trained model in a production environment, such as a mobile app or a web service, so that it can be used to identify and classify wheat diseases in real- world scenarios. Note that this is just a high-level block diagram, and there are many details and choices that would need to be made in each step. However, this should give you a general idea of how you could use EfficientB3 for wheat disease identification and classification.

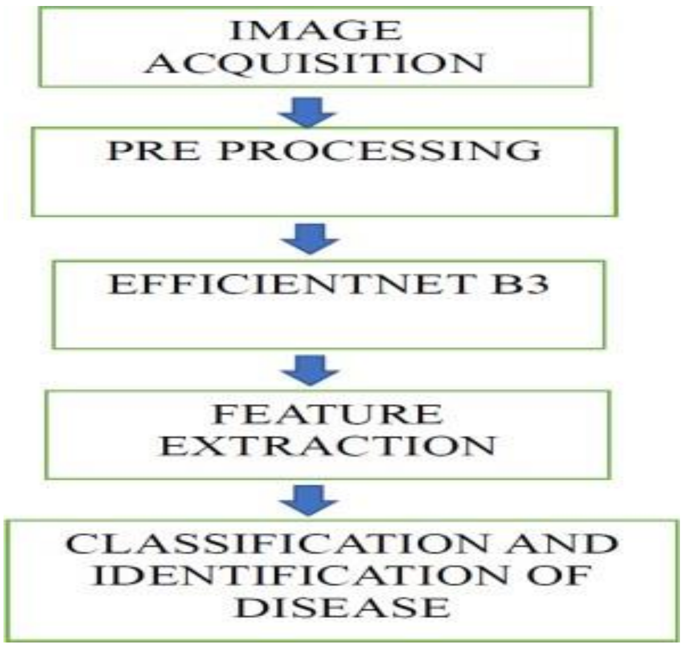

FIGURE 3. Block Diagram for Wheat Disease Identification andclassification

Algorithm :

1) Image pre-processing using the dataset that was gathered.
2) Add the necessary modules.
3) Open the dataset and load images.
4) Train the model, then it will generate the images withlabels.
5) create the model for efficientnetB3 algorithm.
6) By using the algorithm it will do width scaling resolutionscaling and depth scaling for the given dataset .
7) It will generate the confusion matrix and training andvalidation loss and accuracy.
8) It will show the probability for a single image.EfficientnetB3 Architecture :

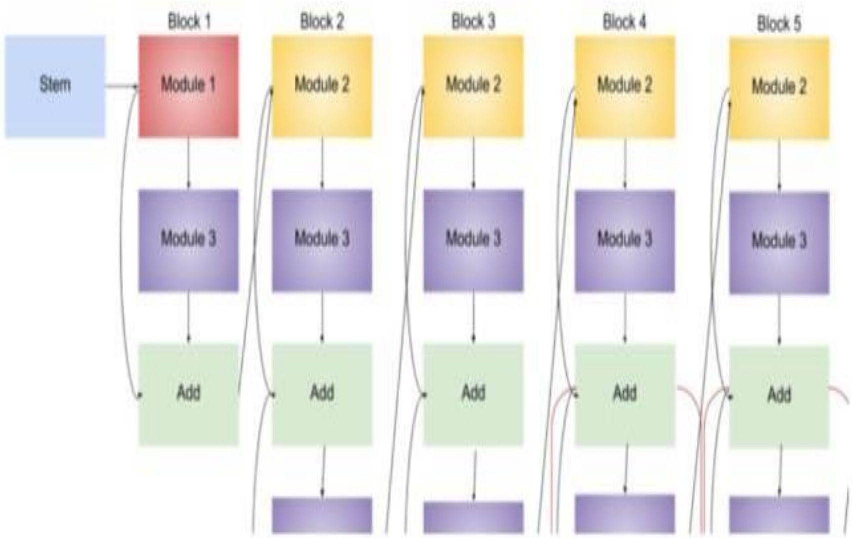

FIGURE 4. Architecture for EfficientNet-B3

4. RESULTS AND DISCUSSIONS

Experimental Setup:

The introduced wheat disease identification and classification was performed in Python 3.9and the results were carried out.

Data Set:

We have identified two diseases which reduces the yield they are Stripe Rust and Septoria tritici blotch so for the identification of diseases in wheat leaves we need a dataset foridentification and classification purpose. Hence we have acquired the dataset from Kaggle which consists of the imagesof these diseases. The name of the dataset in Kaggle is wheat_leaf which consists of 402 images.

TABLE 1. Dataset

Types of diseases	No of samples
Healthy	102
Septoria	100
Stripe rust	200

Training and Validation Loss: After loading the dataset then the dataset will be classified into 14 epochs each epoch contains certain amount of data using the pre trained model it will show the loss and accuracy during the testing and trainingof data. Here we can observe the accuracy of the testing and training data.For this model after running the 14 epochs we have obtained the maximum accuracy.

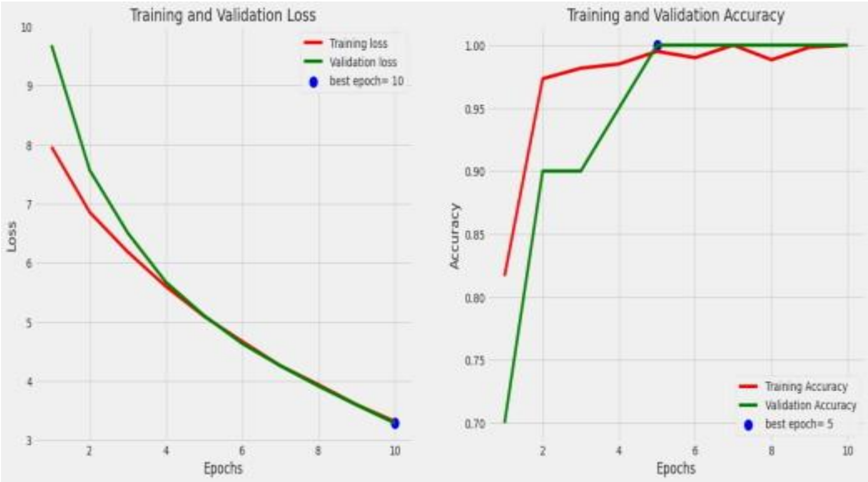

FIGURE 5. Training and Validation Loss

Classification Report:

TABLE 2. Classification Report

	precision	recall	f1-score	support
Healthy	1.00	1.00	1.00	5
septoria	1.00	1.00	1.00	5
stripe_rust	1.00	1.00	1.00	11
accuracy			1.00	21
macro avg	1.00	1.00	1.00	21
weighted avg	1.00	1.00	1.00	21

Confusion Matrix : Here we have obtained the following confusion matrix.

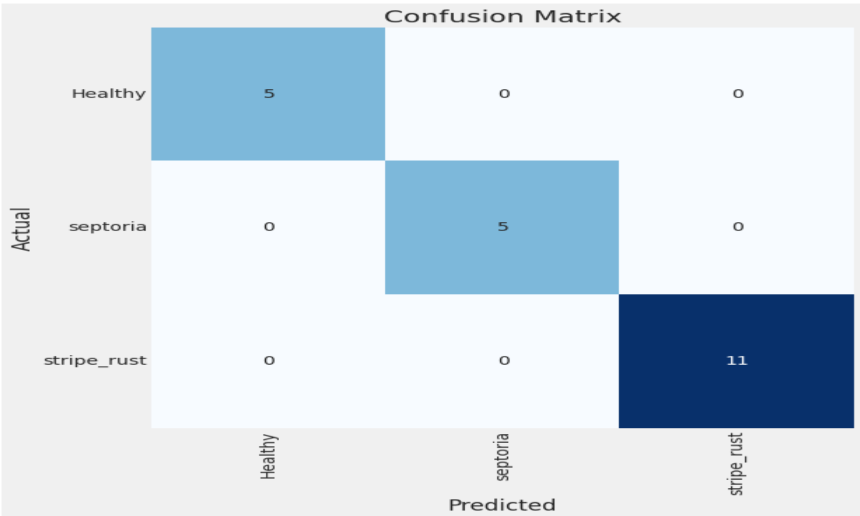

FIGURE 6. Confusion Matrix

5. CONCLUSION

In this paper, we concentrate to identify the diseases of wheat using convolution neural network algorithm. It is one of the finest and best algorithm that is there in deep learning. The architecture we have used here is effecientnetb3 for image classification purpose for various diseases we have taken. Based on the structure of leaf and the pattern identified on the leaf we have classified into two diseases. The diseases we have identified are Septoria and Sripe rust. We have obtained the results of 100% accuracy. We have used Deep learning to implement this. This method we have used provide best resultsin the less time and better than the general process of identifying the diseases.

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