

# Wheat Leaf Disease Detection Using VGG16 and EfficientNet-B0 with HSV Color Space Preprocessing

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## ABSTRACT

**Automated detection of wheat leaf diseases from image data is essential for enabling timely agricultural intervention and reducing crop losses. This paper proposes a transfer learning-based deep learning framework employing VGG16 and EfficientNet-B0 architectures for the multi-class classification of wheat leaf diseases. The Large Wheat Disease Classification Dataset (LWDCD2020), comprising approximately 4,500 images across four categories — Healthy Wheat, Leaf Rust, Crown and Root Rot, and Wheat Loose Smut — is utilized. HSV (Hue, Saturation, Value) preprocessing along with data augmentation techniques including rotation, horizontal flipping, zoom, and width/height shifting are applied to standardize and diversify the training data. Both models are modified by appending batch normalization, dense, and dropout layers to the pre-trained backbones for improved classification performance. VGG16 achieves 92% classification accuracy, while EfficientNet-B0 achieves 93%. Evaluation is performed using accuracy, precision, recall, and F1-score metrics.**

***Keywords: Wheat Leaf Disease, VGG16, EfficientNet-B0, Transfer Learning, HSV Preprocessing, CNN, Data Augmentation.***

## INTRODUCTION

Wheat is the crucial crop consumed all around India and constitutes a major cereal crop contributing substantially to the dietary requirements of populations in India as well as in many other parts of the world. The spread of diseases such as leaf rust, crown and root rot, and wheat loose smut, caused by pathogens including *Bipolaris sorokiniana*, *Puccinia triticina*, and several species of *Fusarium*, poses a serious challenge to global food production and food security. According to studies, 2.06 million metric tons of wheat are wrecked by diseases annually. Wheat plants can experience infections across various parts, including the leaves, stems, spikes, and root systems. Therefore, reliable and precise disease diagnosis is essential for selecting appropriate treatment measures and reducing potential crop losses.

The severity and visual manifestation of a disease can differ considerably among individual plants and images. Environmental conditions, crop growth stages, disease progression, and differences in plant varieties can influence the symptoms observed in an image. This variation makes the identification process more challenging, particularly when diseases exhibit similar visual characteristics. In practical agricultural environments, disease symptoms may also be affected by factors such as illumination, background complexity, image quality, shadows, and the presence of noise. Hence, an automated and dependable disease identification

mechanism is required to facilitate early intervention and minimize production losses.

Deep learning approaches, especially Convolutional Neural Networks (CNNs), are advantageous for plant disease recognition because they can derive meaningful image representations without requiring extensive manual feature engineering. Instead of relying entirely on manually selected features, convolutional architectures progressively learn representations ranging from low-level characteristics, such as edges and textures, to more complex disease-specific patterns. Transfer learning offers another practical solution, beginning with a network whose visual features have already been learned from a large-scale image collection and subsequently adapting those learned representations to the target classification task.

In the present study, VGG16 and EfficientNet-B0 are considered for wheat disease classification. VGG-based architectures provide a comparatively straightforward convolutional design and have been widely used in image recognition applications. EfficientNet-B0, on the other hand, is specifically designed to achieve an effective balance between computational efficiency and image classification performance through compound scaling. The investigation considers multi-class classification to identify the specific disease category associated with each input image. The ultimate objective is to develop a model capable of recognizing wheat disease categories accurately from image data and providing a foundation for automated disease monitoring..

## **LITERATURE REVIEW**

Automated wheat disease detection using deep learning has attracted growing research attention in recent years. Zhencun Jiang et al. evaluated ResNet50, DenseNet121, and VGG19 for wheat disease classification, with VGG16 achieving 93.07% accuracy. Image augmentation techniques including cropping, rotation, shearing, shifting, and zooming were applied as preprocessing. This study established that VGG-family architectures demonstrate effective performance for wheat

disease classification due to their hierarchical convolutional feature extraction capabilities.

Uferah Shaf et al. proposed a fusion approach integrating additional layers — Convolution, Batch Normalization, and Leaky ReLU activation — into ResNet50 for enhanced wheat disease feature extraction, achieving 93.44% accuracy with Collaborative GAN-based data imputation. Rafia Mumtaz et al. applied thresholding, morphological transformations, and foreground masking with DenseNet121, ResNet50, and VGG19 architectures, achieving up to 94.49% with ResNet50 and 82.34% with VGG19, demonstrating the applicability of ConvNet architectures for automated feature extraction.

Artzai Picon et al. employed ResNet50 with leaf mask cropping and superpixel-based tile extraction, improving the architecture by substituting max-pooling and  $7 \times 7$  convolutional layers with consecutive  $3 \times 3$  convolution layers, achieving 93.0% AUC with leaf masking. Zendei Konn et al. applied machine learning and deep learning techniques including VGG16 and GoogLeNet to identify wheat diseases in North Dakota fields, with VGG-16 achieving 92% accuracy and demonstrating superior performance compared with ResNet50 and neural network models.

Alaan Pbedom et al. proposed a ConvNet-based framework named Yellow-Rust-Xception for identifying different levels of yellow rust infection in wheat, achieving 91% accuracy. Wengle A et al. proposed an optimized GhostNetV2 with Channel Rearrangement, Layer Replacement, and Attention Mechanism Enhancement, achieving 95.82% accuracy on LWDCD2020. Lin Z et al. proposed a Matrix-based CNN (M-bCNN) model with a convolutional kernel matrix, achieving significant improvements over AlexNet and VGG-16, with validation and testing accuracies of 96.5% and 90.1% respectively.

The reviewed literature confirms that VGG16 and EfficientNet-B0 represent well-established and computationally relevant architectures for agricultural image classification, with

significant scope for improvement through preprocessing innovations and architectural modifications.

## DATASET DESCRIPTION

The Large Wheat Disease Classification Dataset (LWDCD2020) was utilized for this research. The dataset contains approximately 4,500 wheat leaf images distributed across four categories, comprising three disease classes and one healthy class. The four disease categories are: Leaf Rust, Crown and Root Rot, Healthy Wheat, and Wheat Loose Smut. Leaf rust is caused by *Puccinia triticina* and manifests as orange-brown pustules on leaf surfaces. Crown and Root Rot, caused by *Bipolaris sorokiniana* and *Fusarium* species, affects the root and crown systems. Wheat Loose Smut results in destruction of the grain and replacement of kernels with black spore masses.

| Wheat Disease Classes | #Images |
|-----------------------|---------|
| Healthy Wheat         | 1200    |
| Leaf Rust             | 1500    |
| Wheat Loose Slum      | 800     |
| Crown and Root Rot    | 1000    |

Table I: Distribution of Wheat Disease Classes

The dataset encompasses images captured in diverse situations, showcasing different stages of disease progression in wheat from early to late stages. Additionally, it demonstrates similarities among various wheat illnesses, making the classification task more challenging. The dataset is allocated into training, validation, and testing sets in an 80:10:10 ratio, respectively. To maintain uniformity, images are organized to have homogeneous dimensions. All images are resized to  $224 \times 224 \times 3$  pixels for model input standardization.

## DATA PREPROCESSING TECHNIQUES

### 4.1 HSV Preprocessing

HSV stands for Hue, Saturation, and Value, a preprocessing technique used on color images to influence the light intensity of an object. The HSV color model describes an image through

three components: hue, which defines the basic color; saturation, which indicates its intensity; and value, which corresponds to brightness.

Hue represents the color angle ranging from 0 to 360 degrees. Saturation indicates how much of the respective color is present, where 100% saturation represents complete pure color and 0% saturation represents no color. Value represents the brightness concerning the saturation, where 0 value represents total black darkness and 100 value represents full brightness.

The preprocessing procedure incorporates contrast stretching to improve the visual quality of input images. The existing pixel intensity values are redistributed through linear scaling so that they utilize a wider portion of the available intensity range. This expansion produces greater separation between darker and brighter regions, resulting in improved image contrast. A nonlinear transformation can also be applied to regulate brightness and contrast according to the characteristics of each image. Such enhancement methods are especially beneficial for images acquired in poor or uneven illumination conditions, which are common in agricultural field settings.

### 4.2 Data Augmentation

Data augmentation is a widely adopted preprocessing strategy that increases the diversity of training samples by introducing controlled variations in input images. This approach can improve the generalization capability and robustness of machine learning models, making it particularly valuable for image classification applications. The following parameters were applied:

Rotation: Images can rotate within a range of angles from -20 to +20 degrees, introducing rotational invariance into the training process.

Height and Width Shift Range: Images can be shifted horizontally by up to 20% of their width and vertically with a maximum displacement equivalent to 20% of the image height.

**Geometric Distortion Range:** Transformation is applied within a range of -20% to +20%, generating varied image orientations and shapes.

**Zoom Range:** Images are subjected to zoom transformations allowing their scale to be increased or decreased by as much as 20% to introduce additional variation.

**Horizontal Flip:** Each image has a 50% chance of being horizontally flipped during training.

**Fill Mode:** The 'nearest' mode is used, filling new pixels with the value of the nearest pixel following any geometric transformation.

These augmentation parameters collectively increase the distinctiveness of the training dataset, assisting the models in performing effectively on previously unseen samples while improving robustness to variations in input image characteristics.

## **PROPOSED METHODOLOGY**

### **5.1 EfficientNet-B0**

EfficientNet-B0 is a convolutional neural network developed using the ImageNet dataset, which contains more than one million training images. The architecture comprises 237 layers and is designed to achieve an effective balance between computational efficiency and image classification performance. It employs a compound scaling technique that uniformly scales the network depth, width, and resolution, allowing EfficientNet to achieve better accuracy and efficiency trade-offs across various resource constraints.

**Data Preprocessing for EfficientNet-B0:** All images whose labels do not belong to the predefined set of target classes are filtered out. The images are converted to RGB from the default BGR color format, followed by resizing to a fixed dimension of 224×224 pixels. This preprocessing standardizes the input images, ensuring uniformity in size and color representation, which plays a crucial role in enabling the model to learn effectively.

**Data Augmentation for EfficientNet-B0:** Augmentation parameters including rotation, zooming, shifting, shearing, and horizontal flipping are applied for training images to enhance model robustness and performance.

**EfficientNet-B0 Architecture:** This CNN model emphasizes computational efficiency by maintaining a compact network structure while still providing strong predictive capabilities. Its architecture is optimized to reduce both the number of learnable parameters and the processing requirements, offering a more resource-efficient alternative to deeper models such as ResNet and Inception. The modified model includes Global Average Pooling, Batch Normalization, and additional fully connected layers to enhance disease-specific feature extraction.

### **5.2 VGG16**

VGG16, short for Visual Geometry Group 16, is a widely used deep convolutional architecture consisting of multiple convolutional and fully connected layers. It employs small 3×3 convolutional kernels to extract hierarchical features from input images, while ReLU activation functions are used to introduce non-linearity. Max-pooling operations are incorporated between convolutional stages to progressively reduce the spatial resolution of feature maps and retain the most significant features.

**Architecture:** VGG16's architecture emphasizes simplicity and consistency, comprising 16 learnable layers that include a series of convolutional layers and a smaller number of fully connected layers, with the final predictions generated through softmax activation. The use of small 3×3 convolutional filters with a stride of 1 and max-pooling layers contributes to its ability to grasp intricate attributes from dataset images.

**Image Classification and Transfer Learning:** VGG16 is primarily used for image classification tasks. Transfer learning using VGG16 involves taking the pre-trained network, initially trained on the ImageNet dataset, then fine-tuning it for the wheat disease classification task. The modified VGG16 model incorporates zeroPadding, Batch Normalization, and additional

convolutional base layers to improve feature extraction for agricultural image classification. Despite its relatively simple architecture compared to later models like ResNet and Inception, VGG16's performance demonstrates the effectiveness of deeper convolutional networks for image recognition tasks.

## RESULTS AND DISCUSSION

### 6.1 Experimental Settings

The experiments are conducted on Google Collaboratory using a desktop equipped with an 11th Gen Intel Core i5 processor clocked at 2.40GHz and 8 GB of RAM. Python 3.7 is the primary programming language. OpenCV provides algorithms for visual computing applications including automated object recognition and localization. Matplotlib is employed for visualizing experimental data through graphs and charts. Keras and TensorFlow facilitate neural network construction and training. The neural network training process, spanning 40 epochs, consumed approximately 4 hours to complete.

### 6.2 Classification Results

| Name of Classes    | Precision | Recall | F1-Score |
|--------------------|-----------|--------|----------|
| Crown and Root Rot | 0.94      | 0.89   | 0.92     |
| Healthy Wheat      | 0.91      | 0.90   | 0.90     |
| Leaf Rust          | 0.94      | 0.98   | 0.96     |
| Wheat loose Smut   | 0.91      | 0.91   | 0.91     |

**Table II: Classification Report CNN EfficientNet-B0 Model**

| Name of Classes    | Precision | Recall | F1-Score |
|--------------------|-----------|--------|----------|
| Crown and Root Rot | 0.88      | 0.96   | 0.92     |
| Healthy Wheat      | 0.87      | 0.93   | 0.90     |
| Leaf Rust          | 0.96      | 0.91   | 0.94     |
| Wheat loose Smut   | 0.96      | 0.89   | 0.92     |

**Table III: Classification Report — VGG16**

### 6.3 Training and Testing Accuracy

The EfficientNet-B0 model achieves a training accuracy converging above 95% after 18 epochs, with testing accuracy stabilizing around 93%. The training and testing loss curves demonstrate consistent convergence with no significant overfitting, indicating that the augmentation and dropout regularization strategies effectively improve model generalization. The VGG16 model achieves training accuracy of approximately 90% and validation accuracy of approximately 89% after 10 epochs. The train and validation loss curves for VGG16 decrease smoothly and consistently, confirming that the model learns meaningful representations throughout the training process.

### 6.4 Comparison of Proposed Approaches

| PROPOSED MODELS      | ACCURACY |
|----------------------|----------|
| CNN Efficient Net B0 | 93%      |
| VGG-16               | 92%      |

EfficientNet-B0 outperforms VGG16 with a 1% advantage in overall accuracy, which can be attributed to its compound scaling mechanism that simultaneously adjusts network depth, width, and resolution. VGG16 demonstrates competitive performance, particularly for Crown and Root Rot and Wheat Loose Smut classification, where recall values of 0.96 and 0.89 respectively indicate strong disease detection capability. Both models benefit significantly from HSV preprocessing, which enhances the separation of disease-related color characteristics from illumination variations. The combination of data augmentation and HSV-based preprocessing improves the generalization of both architectures to unseen wheat leaf images.

Comparison with Existing Methods: Both models demonstrate improvements over baseline VGG19 (89.01%) and InceptionV3 (84.02%) reported in the literature, confirming the value of the proposed preprocessing and architectural modifications. The Efficient-Net B0 result of 93% also surpasses the DenseNet baseline of 87.24%, validating the

effectiveness of compound-scaled lightweight architectures for agricultural image classification.

## CONCLUSION

This paper presented a transfer learning-based classification framework employing VGG16 and EfficientNet-B0 architectures for automated wheat leaf disease detection using the LWDCD2020 dataset. The proposed methodology integrates HSV-based preprocessing with data augmentation strategies including rotation, horizontal flipping, zoom, and geometric distortion to standardize input data and improve model generalization. Architectural modifications comprising batch normalization, zero padding, and additional dense layers are applied to both pre-trained models to enhance disease-specific feature extraction.

The EfficientNet-B0 model achieves 93% classification accuracy, while VGG16 achieves 92% accuracy. Both models demonstrate strong per-class precision, recall, and F1-score values, confirming their reliability for multi-class wheat disease classification. VGG16 demonstrates particularly strong performance for Leaf Rust and Crown and Root Rot categories, while EfficientNet-B0 shows competitive and balanced performance across all four disease classes.

These results confirm that lightweight and well-established CNN architectures, when enhanced with appropriate preprocessing techniques and transfer learning, can provide reliable tools for automated agricultural disease monitoring. This model will assist cultivators in early disease spotting and the protection of crops from diseases, supporting the agriculture sector in enhancing productivity and reducing crop losses.

Future research can focus on improving model performance through transfer learning with larger and more diverse datasets, integrating the developed system with IoT-enabled technologies to facilitate real-time disease monitoring in agricultural environments, and exploring model compression techniques to enable deployment on resource-constrained edge devices for field-based agricultural applications.

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