

Wheat Leaf Disease Classification Using EfficientNet-B3 and ResNet101 with HSV Preprocessing and Transfer Learning

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ABSTRACT

Wheat is one of the most consumed grains, with 2.06 million metric tons consumed daily worldwide. Wheat leaf disease classification remains a challenging and underexplored research area. This paper proposes a deep learning framework employing EfficientNet-B3 and ResNet101 architectures with transfer learning for the automated classification of wheat leaf diseases. The Large Wheat Disease Classification Dataset (LWDCD2020), comprising approximately 4,500 images distributed across four categories — Healthy Wheat, Leaf Rust, Crown and Root Rot, and Wheat Loose Smut — is used for experimentation. HSV (Hue, Saturation, Value) preprocessing and data augmentation techniques including horizontal flipping, rotation, zoom, and width/height shift are applied to improve model generalization. Additional layers comprising batch normalization, dense layers, and dropout layers are appended to the pre-trained backbones. The modified EfficientNet-B3 achieves the highest testing accuracy of 97%, while ResNet101 achieves 95%.

Keywords: *Wheat Disease Classification, EfficientNet-B3, ResNet101, Transfer Learning, HSV Preprocessing, Deep Learning.*

INTRODUCTION

Wheat represents a major cereal crop and contributes substantially to the dietary requirements of populations in India as well as in many other parts of the world. The cultivation of wheat is closely associated with food availability, sustainable agricultural practices, and the economic well-being of farming communities. However, wheat production is frequently affected by a wide range of fungal and other pathogenic infections caused by pathogens such as Bipolarism Sorokin Iana, Puccinia trichina, and several species of Fusarium. These pathogens are associated with conditions such as crown and root rot, leaf rust, and wheat loose smut. The emergence and progression of such infections may result in considerable losses in wheat yield and can also compromise grain quality.

Wheat diseases may affect different parts of the plant during various stages of growth. Leaf infections are particularly significant because damage to the photosynthetic surface can interfere with the plant's ability to produce and transport nutrients required for normal development. Consequently, early and reliable identification of wheat diseases is an important requirement for effective crop management. Conventional diagnosis commonly involves the visual inspection of affected plants by farmers or trained plant pathologists. Although expert assessment can provide valuable information, it may require considerable time and specialized knowledge. When large numbers of plants or images need to be examined, manual inspection becomes increasingly difficult to perform efficiently.

Image-based computational methods offer an alternative means of recognizing visual characteristics associated with disease symptoms. Deep learning approaches, especially Convolutional Neural Networks (CNNs), are advantageous in this context because they can derive meaningful image representations without requiring extensive manual feature engineering. CNN-based models have demonstrated considerable potential in image classification and recognition applications, progressively learning representations ranging from low-level characteristics such as edges and textures to more complex disease-specific patterns.

Transfer learning offers a practical solution when the number of domain-specific training images is relatively limited. This strategy begins with a network whose visual features have already been learned from a large-scale image collection and subsequently adapts those learned representations to the target classification task. In the present study, EfficientNet-B3 and ResNet101 are evaluated for wheat disease classification. Efficient Net architectures aim to maintain a balance between classification performance and computational requirements through compound scaling. ResNet architectures, on the other hand, employ residual connections that facilitate the training of deeper neural networks by allowing information to pass through shortcut pathways, thereby addressing the vanishing gradient problem.

The study investigates both binary and multi-class classification settings to accurately distinguish among different wheat disease categories. Image preprocessing and data augmentation strategies are also examined to determine their influence on classification performance. Model effectiveness is quantified through accuracy, precision, recall, and F1-score to provide a comprehensive assessment.

LITERATURE REVIEW

Significant research has been conducted on automated plant disease classification using deep learning. Zhencun Jiang et al. applied CNN models including ResNet50, DenseNet121, and VGG19 using resizing, normalization, and augmentation

techniques. Their study focused on a parasitic organism lifecycle and achieved an accuracy of 93.07% with VGG16. Feraf Shaf et al. introduced a fusion approach for identifying wheat diseases by integrating additional layers — Convolution, Batch Normalization, and Leaky ReLU activation — into a Modified ResNet50 architecture, achieving 93.44% accuracy using Collaborative Generative Adversarial Network (CGAN) for data imputation.

Rafia Mumtaz et al. investigated DenseNet121, ResNet50, and VGG19 models with thresholding, morphological transformations, and foreground masking for wheat leaf disease classification, achieving up to 94.49% accuracy with ResNet50. Mohsen Azadbakht et al. examined wheat disease identification using ML methods and Spectral Vegetation Indices (SVIs) at canopy scale under different Leaf Area Index (LAI) conditions, with regression models achieving up to 94.31% accuracy.

Lakshay Goyal et al. evaluated VGG16 and ResNet50 on the LWDCD2020 dataset for classification of 10 wheat-related categories, reporting 94.88% accuracy with ResNet50. Artzai Picon et al. employed ResNet50 with artificial data augmentation and leaf mask cropping, achieving 93.0% AUC for leaf-masked images. Zendei Konn et al. applied GoogLeNet and VGG16 for wheat disease classification in North Dakota fields, with GoogLeNet achieving 93% and VGG-16 achieving 92% for leaf rust.

Mi Z et al. proposed C-DenseNet, a novel deep learning network embedding an attention mechanism for wheat stripe rust disease grading, achieving 96.99% accuracy. Wengle A et al. proposed an optimized GhostNetV2 approach with key modifications including Channel Rearrangement and Attention Mechanism-Enhancement, achieving 96.22% on the PlantVillage dataset and 95.82% on LWDCD2020.

The literature indicates that while various architectures have been explored, there remains scope for comprehensive comparisons of preprocessing techniques and compound-scaled architectures like EfficientNet-B3 combined with residual networks for wheat disease identification.

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 dataset is organized into four distinct categories representing different wheat health conditions: Leaf Rust, Crown and Root Rot, Healthy Wheat, and Wheat Loose Smut.

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. The backgrounds of images are cumbersome and complex, and the dataset demonstrates similarities among various wheat illnesses. The dataset is allocated into training, validation, and testing sets in an 80:10:10 ratio, respectively. All images are standardized to a uniform resolution of $224 \times 224 \times 3$ pixels to ensure consistency across training, validation, and testing subsets.

DATA PREPROCESSING TECHNIQUES

4.1 HSV Preprocessing

HSV stands for Hue, Saturation, and Value, which is a preprocessing technique applied to color images to influence the light intensity characteristics of visual content. 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. Transforming images into this color representation during

preprocessing facilitates the separation and analysis of relevant visual characteristics in various computer vision applications.

Hue represents the color, ranging from 0 to 360 degrees. Saturation indicates how much of the respective color must be added, where 100% saturation represents a complete pure color and 0% saturation represents no color. Value represents the brightness concerning the saturation of the color, where 0 value corresponds to total black darkness and 100 value corresponds to 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. Such enhancement methods are especially beneficial for images acquired in poor or uneven illumination, where important visual details may otherwise be difficult to distinguish.

4.2 Data Augmentation

Data augmentation is a widely adopted preprocessing strategy in computer vision 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. The following augmentation techniques were applied:

Rotation: Images can rotate within a range of angles from -20 to +20 degrees.

Height and Width Shift Range: Images can be shifted horizontally by up to 20% of their width and vertically by up to 20% of their height.

Geometric Distortion Range: The 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%.

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

Fill Mode: The 'nearest' mode is used, which fills new pixels with the value of the nearest pixel.

PROPOSED METHODOLOGY

5.1 EfficientNet-B3

EfficientNet-B3 is a convolutional model (ConvNet) that introduces a fresh scaling approach, uniformly adjusting depth, width, and resolution dimensions, boasting a straightforward yet remarkably potent compound coefficient. EfficientNet primarily uses depth-wise separable convolutions performed separately across channels and then combined, which divides the standard convolution operation into separate depth-wise and point-wise convolution operations. This lowers the number of computations while maintaining representational capacity.

The proposed modified EfficientNet-B3 architecture adapts the pre-trained backbone for wheat leaf disease classification by refining the last four layers to suit the classification problem. Four additional layers are introduced to the pre-trained EfficientNet-B3 model: Batch Normalization, a Fully Connected Dense Layer (256 units), a Dropout Layer (rate=0.45), and a Dense output layer corresponding to the number of disease classes. The dataset is randomly split into 80% for training and 20% for testing. Images are standardized to 224×224×3 dimensions.

5.2 ResNet101

ResNet101 is a deep CNN architecture containing 101 layers, including convolutional, pooling, and residual components. The network utilizes residual blocks that enable information to be propagated through shortcut connections while the network depth increases, addressing the vanishing gradient problem. Its architecture includes 48 convolutional layers, one max-pooling

layer, and one average-pooling layer, allowing the model to learn complex and high-level image representations.

For the modified ResNet101 model, HSV preprocessing is applied prior to feeding images into the network. Fully Connected Dense Layers and Batch Normalization are added to the baseline architecture. Data augmentation including image rotation, random cropping, and the addition of controlled noise is applied during training. The input images are processed through the ResNet101 network, which extracts discriminative features required for disease identification. These learned representations are subsequently provided to the classification stage.

RESULTS AND DISCUSSION

6.1 Experimental Settings

The suggested system runs on Google Collaboratory, utilizing a desktop equipped with an 11th Gen Intel Core i5 processor clocked at 2.40GHz and 8 GB of RAM. Python 3.7 is used as the primary programming language. OpenCV provides algorithms for visual computing applications. Matplotlib is employed for visualizing experimental data. Keras and TensorFlow facilitate model 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	1.00	0.81	0.90
Healthy Wheat	0.83	0.94	0.88
Leaf Rust	0.97	0.97	0.97
Wheat loose Smut	0.95	0.98	0.96

Table II: Classification Report — ResNet101

Name of Classes	Precision	Recall	F1-Score
Crown and Root Rot	0.97	0.89	0.93
Healthy Wheat	0.97	0.94	0.95
Leaf Rust	0.98	0.97	0.97
Wheat loose Smut	0.93	0.98	0.95

Table III: Classification Report — EfficientNet B3

Name of Classes	Precision	Recall	F1-Score
Crown and Root Rot	0.97	0.96	0.96
Healthy Wheat	0.97	0.94	0.96
Leaf Rust	0.99	0.99	0.99
Wheat loose Smut	0.95	0.98	0.96

Table IV: Classification Report — Modified EfficientNet B3

6.3 Comparison of Proposed Approaches

PROPOSED MODELS	ACCURACY
Efficient Net B3	96%
ResNet 101	95%
Modified Efficient Net B3	97%

Compared with the previously reported EfficientNet-B3 results, the proposed approach demonstrates an improvement of approximately 2% in both training and testing accuracy. The modified EfficientNet-B3 with HSV-based preprocessing achieves a training accuracy of 99.5% and a testing accuracy of 97%, surpassing the existing EfficientNet-B3 model that reported 97% training and 95% testing accuracy. ResNet101 demonstrates competitive performance at 95% accuracy, with particularly strong results in Leaf Rust and Wheat Loose Smut classification. The incorporation of HSV-based preprocessing provides a more informative representation of input images by emphasizing relevant intensity and color-related characteristics,

allowing the network to capture subtle variations associated with different disease types.

CONCLUSION

This paper presents a transfer learning-based deep learning framework employing EfficientNet-B3 and ResNet101 for automated wheat leaf disease classification using the LWDCD2020 dataset. The proposed HSV-based preprocessing technique, combined with data augmentation and architectural modifications including batch normalization, dense layers, and dropout regularization, contributes significantly to improved classification performance. The modified EfficientNet-B3 achieves the highest accuracy of 97%, while ResNet101 achieves 95% accuracy. Both models demonstrate strong per-class precision, recall, and F1-scores across all four disease categories. The results confirm that transfer learning combined with effective preprocessing and augmentation strategies can provide reliable and accurate wheat disease classification. This model will assist cultivators in spotting diseases early and protecting their crops, thereby enhancing agricultural productivity and reducing crop losses estimated at 2.06 million metric tons annually.

Future research can focus on enhancing model resilience through transfer learning with larger and more diverse datasets, integrating the developed system with IoT-enabled technologies for real-time disease monitoring in agricultural environments, and exploring explainable AI techniques to improve the interpretability of model predictions.

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