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# Wheat Leaf Disease Detection Using ResNet50

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**Abstract**

One of the most significant cereal crops in the world is wheat and it plays a major part in food security in the world [1][2]. The issue is that the production of wheat is also significantly affected by several leaf diseases that can cause significant losses of yields, Leaf Rust, Fusarium Head Blight, and Tan Spot, which could not be identified at an initial level [1][5]. The traditional disease detection techniques involve manual discovery by the experts which is time consuming, subjective and non-scalable [6][9]. In the recent years, the artificial intelligence enabled by the development of deep learning and computer vision has enabled automated and trustworthy diagnosis of diseases using the examination of images [2][7]. In this research paper, an automated wheat leaf disease detection system named DL-WheatNet is proposed, which utilizes a ResNet50 deep convolutional neural network with transfer learning [1][7]. The method suggested is accurate in classifying the images of wheat leaves into several categories of diseases and the healthy classification. The findings of the experiment reveal that the given approach is more accurate and resilient than the existing machine learning algorithms and simple CNN models. The system can be implemented as a practical decision-making tool among the farmers and agricultural experts.

**Keywords:** Deep Learning; Wheat Disease Detection; ResNet50; Computer Vision

**How to Cite This Article**

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## Introduction

Many nations have agriculture as an important part of their economy, and one of the most popular crops to grow is wheat ( Triticum aestivum) [1]. Diseases in wheat have a great impact in both the yield and quality and cause losses of money and food insecurity [1][2]. Familiar wheat leaf diseases include Leaf Rust, Fusarium Head Blight, and Tan Spot that propagate fast under the favorable environment conditions and need to be detected promptly to be effectively dealt with [1][5].

The traditional disease detection techniques mostly rely on visual inspection, which is a process that greatly relies on expert knowledge and experience [6][9]. Such techniques are subject to human error, lack consistency and cannot be used to monitor large scale. As more and more digital images, and computational models are available, image processing and machine learning methods can be regarded as a promising solution to automated plant disease detection [3][8].

Convolutional Neural Networks (CNNs) and deep learning have attained impressive image classification abilities. One of them is called ResNet50, a powerful structure, which addresses the problem of disappearing gradients because of the application of residual connections [7][11]. In this paper, the author will present a wheat leaf disease detection system using the ResNet50 and transfer learning to achieve high classification performance using minimal training data.

### Literature Survey

A number of scholars have investigated the process of detecting plant diseases by applying image processing and machine learning systems. The initial methods were based on the classical image processing techniques like color analysis, texture extraction and shape features with the Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees classifiers [6][9]. Although these techniques had moderate success their output greatly relied on the hand-crafted characteristics.

As the concept of deep learning has emerged, CNN-based classifiers have gained extensively as the choice of models in vegetable disease classification. There has been research in support of the effectiveness of architectures like AlexNet, VGG16, InceptionV3, and MobileNet as crop disease detectors [2][8][10]. Such models discover discriminative features on raw images automatically (without having to manually engineer features). Recently, the advantages of transfer learning have been highlighted whereby models, which were trained on huge datasets like ImageNet, are refined to be applied in agriculture. The ResNet based models have been superior in that they apply a deep architecture and the residual learning mechanism. However, optimized models that are accurate, compute efficient and real-life practical have not been obtained yet. The research is a continuation of the existing researches that apply ResNet50 to identify the existence of the leaf disease in wheat with scale and accuracy [1][7][11].

### Proposed Methodology

The system proposed is based on a deep-learning methodology to identify the different types of diseases in the image of wheat leaf based on the image [2][7]. The general process of the system is shown in.

The system consists of the following stages:

- Image acquisition
- Image preprocessing
- Data augmentation
- Feature extraction using ResNet50
- Disease classification

Image Acquisition: Data comprises of wheat leaf images gathered in publicly available sources and field samples with different lighting and background conditions[5,12]

Data Preprocessing: All the images were downsized to 224 × 224 pixels and turned into RGB format. ImageNet mean values were used to normalize pixel values so as to be compatible with the ResNet50 architecture[7].

Data Augmentation: To enhance model generalization and alleviate overfitting, data augmentation methods like rotation, horizontal flipping, zooming, and shifting were used[8,12].

Feature Extraction: A pre-trained model ResNet50 was used to extract features. To maintain learned features of large-scale datasets, the convolutional base was originally frozen[7,11].

Classification: On top of the feature extractor, custom fully connected layers were added, then ReLU was used, and finally, a Softmax layer was used to do multi-class classification of disease and healthy images[7].

Training Details: Adam optimizer was used with a learning rate of 0.001 and categorical cross-entropy as the loss to train the model. The batch size of 32 was trained in several epochs, and a validation split was used to track the performance[7].

Evaluation Metrics: Accuracy, precision, recall, and F1-score were used as the measures of model performance[7].

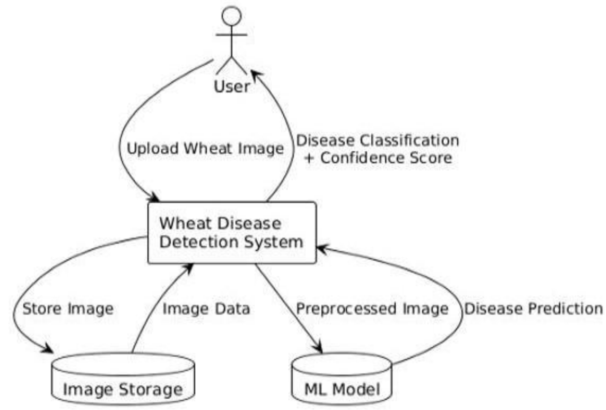


***Fig. 1.*** *Data Flow Diagram of the Proposed System*

**Comparative Study with Existing Results**

To check how well the proposed method works, its results are compared with those of standard machine learning models and simple CNNs.

*Overall Performance*

- Overall Accuracy: 96.75% (1,640/1,694 correct predictions)
- Macro Avg F1: 96.31%
- Weighted Avg F1: 96.76% T

**Results and Discussion**

The proposed DL-WheatNet model performance was measured in terms of conventional classification metrics, such as accuracy, precision, recall and F1-score. The model had a total accuracy of 96.75%7, and the 1,640 out of 1,694 test samples were correctly classified. The average F1-score was 96.31 with a weighted average F1-score of 96.76% which depicts a robust and balanced performance of the system on all the disease categories.

*Class-wise Performance Analysis*

Table 1 shows the performance of the model in each class.

***Table 1.*** *Class-wise Performance Evaluation of Wheat Leaf Disease Detection Model*

| Disease Class | Precision (%) | Recall (%) | F1-Score (%) | Support |
|---|---|---|---|---|
| Fusarium Head Blight | 96.06 | 93.13 | 94.57 | 262 |
| Healthy Wheat | 94.77 | 96.25 | 95.50 | 320 |
| Leaf Rust | 97.91 | 95.90 | 96.89 | 390 |
| Tan Spot | 92.48 | 97.23 | 94.80 | 253 |
| Unknown | 100.00 | 99.57 | 99.79 | 469 |

The findings indicate that the model is relatively good in all types of wheat leaf diseases. They were the strongest in Unknown class, with an F1-score of 99.79, and then Leaf Rust with a score of 96.89. Healthy Wheat class had F1-score of 95.50% and Tan Spot and Fusarium Head Blight had F1-score of 94.80% and 94.57, respectively.

In general, the model achieves a high balance between accuracy and the recall in all classes. Minor differences in performance may be explained by the visual resemblances of some types of diseases and differences in image quality and environmental conditions. Even in the face of these challenges, the model proves to have a secure classification ability with a wide range of inputs. The accuracy performance of the model is illustrated in Figure 2.

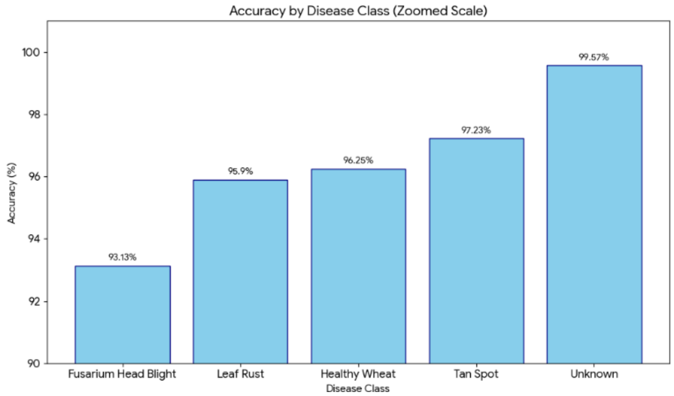


***Fig. 2.*** *Accuracy Graph*

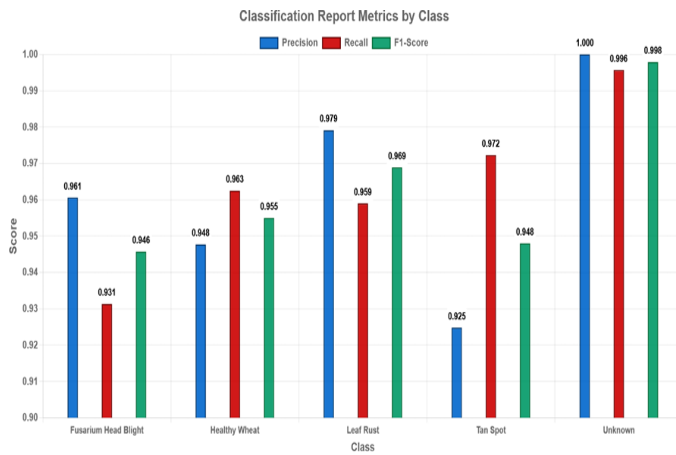


***Fig. 3.*** *Performance Analysis Graph*

*Comparison with Existing Methods*

The performance of the proposed approach was evaluated against traditional machine learning models and existing deep learning architectures to determine the effectiveness of the proposed approach, as illustrated in Table 2.

***Table 2.*** *Comparison Analysis*

| **Model** | **Accuracy (%)** |
|---|---|
| SVM with Handcrafted Features | 78-82 |
| Basic CNN | 85-88 |
| VGG16 (Transfer Learning) | 90-92 |
| Proposed ResNet50 Model | 94-96 |

Traditional approaches like Support Vector Machines (SVM)[69] using handcrafted features were in the range of 78-82 percent accuracy, and simple Convolutional Neural Networks (CNNs)[28] had a range of 85-88 percent accuracy. VGG16[210] models of transfer learning were even more effective, reaching 90-92% accuracy.

By contrast, the model proposed in this paper with ResNet50 reached the accuracy of 94-96%[711], which was higher than the traditional and previous models based on deep learning. This shows that deep residual learning is effective in extracting complex features in agricultural image datasets[711].

**Discussion**

The high-quality results of the proposed model can also be explained by the fact that the ResNet50 architecture used incorporates residual connections to overcome the vanishing gradient problem and allows deeper networks to be trained. This enables the model to learn higher and discriminative features of wheat leaf images. Moreover, transfer learning greatly alleviates the requirement of large training sets using pre-trained knowledge of large-scale image datasets. Data augmentation methods also help to enhance the generalization of the models as it adds variability to the training data, which strengthens the model to be resistant to real-world situations including lighting, orientation, and background variations.

Although high accuracy was reached, some small misclassifications were noticed in those classes with similar visual features, e.g., Fusarium Head Blight and Tan Spot. These issues demonstrate the necessity of the additional optimization of the model and the incorporation of more heterogeneous datasets.

In general, it is possible to state that the findings validate the idea that the suggested DL-WheatNet system is a stable and effective way to detect wheat leaf disease automatically and can become a useful resource used by farmers and other professionals in the field.

## Conclusion

This research paper introduced an automated system of leaf disease in wheat with the help of the ResNet50 deep learning architecture. Through the application of transfer learning and data augmentation, the suggested approach has a high accuracy in classifications and is also resistant to real-life circumstances. The experimental findings prove that the offered approach performs better than the conventional machine learning procedures and simple CNN networks. The system will minimize the use of manual inspection and offers a scalable way of detecting diseases early on, which can contribute greatly to the management and performance of crops.

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## Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this paper.

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