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Leveraging CIELAB Segmentation and CNN for Wheat Fungi Disease Classification

Usman Islam*, Wakeel Ahmad, S. M. Adnan Shah
Department of Computer Science, University of Engineering and Technology Taxila, Pakistan
***Correspondence:** usmanislam937@gmail.com

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Wheat is the third most harvested and consumed grain globally, but a significant portion of its production is wasted due to diseases. Fungal infections caused by pathogenic fungi are particularly harmful, greatly reducing crop yields. Manual visual inspection of large fields is slow, exhausting, and requires specialized expertise. This research introduces a novel combination of image augmentation, CIELAB segmentation, and a fine-tuned pre-trained CNN, achieving an unprecedented 98.43% accuracy in wheat fungal disease classification, addressing gaps in current detection methods and promoting sustainable agriculture. To conduct this research, datasets from Kaggle were merged and meticulously validated to create a comprehensive set with five classes: healthy wheat and four fungal diseases. Preprocessing steps included resizing, contrast enhancement and noise removal to ensure uniform and high-quality images followed by rigorous image augmentation techniques to expand and diversify the dataset ultimately enhancing the deep learning model's robustness and accuracy. The CNN model, trained over 80 epochs achieved an impressive 98.43% accuracy in classifying wheat fungal diseases. With a precision of 98.47% and an F1 score of 98.43% the model demonstrated strong positive classification accuracy. Additionally, a recall of 98.43% and specificity of 98.47% indicated its effectiveness in identifying true positive cases and accurately detecting disease presence or absence.

Keywords: CNN; Wheat Fungi Diseases; Deep Learning; CIELAB Segmentation and Smart Farming.

Introduction:

Wheat is essential for global food security, serving as a primary food source for much of the world's population. However, wheat production is perpetually threatened by a range of fungal diseases that significantly reduce crop yield and grain quality [1]. Diseases such as stripe rust, septoria, brown rust, stem rust, powdery mildew, and fusarium head blight not only lower wheat yields but also compromise its safety and nutritional value, posing severe challenges to farmers and consumers alike [2].

Among these brown rust, yellow rust, septoria and stem rust are particularly notorious. Brown rust also known as leaf rust is caused by the fungus Puccinia triticina. It is characterized by small, round, orange-brown pustules scattered on the leaves. These pustules primarily affect the upper leaf surface, reducing the photosynthetic area and thereby decreasing the grain yield and quality [3]. Yellow rust, caused by Puccinia striiformis, is another significant wheat disease. It manifests as yellow pustules arranged in linear rows on the leaves. This disease thrives in cool moist environments and can lead to substantial yield losses if not managed properly [4]. Septoria caused by Zymoseptoria tritici, leads to the disease known as Septoria tritici blotch. It is characterized by necrotic lesions with pycnidia which are small black fruiting bodies. This disease can significantly reduce the green leaf area adversely affecting photosynthesis and grain filling [5]. Stem rust caused by Puccinia graminis f. sp. tritici, is perhaps the most devastating of all wheat rusts. It forms elongated, reddish-brown pustules on stems, leaves, and spikes. Stem rust can cause severe yield losses particularly in susceptible wheat varieties [6]. These diseases can lead to significant financial losses for farmers, increased costs for fungicide applications and broader economic consequences for countries that rely heavily on wheat production and export.

The economic impact of wheat fungal diseases is multifaceted. Direct yield losses are the most immediate and visible effect. For instance, brown rust can reduce wheat yields by up to 20% in severely affected areas directly translating to millions of dollars in lost revenue for farmers [7]. Yellow rust, thriving in cooler climates has caused yield losses exceeding 70% in some regions leading to severe economic distress [8]. Moreover, septoria, which reduces the green leaf area and thus the photosynthetic capacity of wheat plants necessitates increased fungicide use. The cost of these chemical treatments along with the labor and machinery needed for application adds to the economic burden on farmers [9]. This increased expenditure can be particularly challenging for smallholder farmers in developing countries where access to fungicides and modern agricultural practices is limited.

Stem rust poses an even more dire economic threat. The resurgence of virulent strains like Ug99 has raised alarms globally. Countries like Ethiopia and Kenya, where agriculture is a significant part of the economy, have faced severe outbreaks leading to multi-million dollar losses in wheat production [6]. The fear of such outbreaks also leads to increased investment in breeding resistant varieties and monitoring systems further straining agricultural budgets. On a broader scale, these diseases impact global wheat markets. Significant yield reductions in major wheat-producing countries can lead to increased global wheat prices affecting food security and increasing the cost of wheat-based products worldwide [10]. This price volatility can have ripple effects impacting not just farmers but also consumers and food industries globally. Farmers facing consistent losses are less likely to invest in new technologies or expand their operations potentially stunting agricultural development in affected regions [11].

Moreover, in underdeveloped countries the diagnosis of wheat fungal diseases relies on manual visual inspection, which is labor-intensive, time-consuming, and requires specialized expertise [12]. The limitations of these methods underscore the necessity for automated systems capable of providing rapid, accurate, and scalable solutions. Advances in image-based detection techniques, particularly those utilizing deep learning, have revolutionized the diagnosis and management of agricultural diseases [13]. CNNs have shown significant potential in improving classification accuracy by analyzing detailed image data. However, despite progress in applying deep learning to agricultural disease detection, there remains a gap in developing efficient, scalable, and reliable systems tailored to the diverse environments where wheat is cultivated [14] [15]. Existing methods often fall short in the early stages of infection when timely intervention is most effective [16], highlighting the need for continued research into innovative technologies that can enhance disease detection and management.

This study aims to fill this gap by developing a deep learning-based system for detecting and classifying wheat fungal diseases using leaf images. Our approach includes augmenting the dataset to enhance robustness, preprocessing the images for consistency, and employing CIELAB-based segmentation to precisely isolate diseased areas. By fine-tuning pre-trained CNN models, we optimize their performance in identifying various fungal infections in wheat leaves, thereby facilitating timely intervention and improved disease management practices. The motivation behind this research is to provide a reliable and efficient tool for early disease identification, which is crucial for mitigating crop losses and improving yield quality. By integrating deep learning techniques with traditional image processing methods, we aim to create a robust system that can support farmers in making informed decisions about disease management, ultimately contributing to the sustainability of wheat production. By addressing the limitations of traditional methods and filling the existing research gap, our study provides a promising solution for enhancing the accuracy and efficiency of disease management in wheat cultivation.

Objectives:

- To develop a deep learning system to automatically classify fungal diseases in wheat. This eliminates the need for slow and labor-intensive manual detection, improving efficiency.
- To enhance Disease Detection Accuracy: Leverage deep learning's capabilities to achieve superior accuracy in identifying specific wheat fungal diseases compared to traditional methods.
- To create an automated system that reduces reliance on specialized expertise for disease identification. This empowers farmers, even those without extensive training, to effectively monitor their crops.
- To employ image analysis techniques to potentially facilitate earlier detection of wheat fungal diseases compared to visual inspection. This allows for timely interventions to minimize crop damage.

Novelty Statement:

This study presents a novel deep learning approach for automatic wheat fungal disease classification, aiming to surpass existing methods. We employ image augmentation, preprocessing, and CIELAB segmentation to enrich the training data and extract disease-specific features. Furthermore, a pre-trained convolutional neural network (CNN) is meticulously fine-tuned for this task. This combination achieves a remarkable 98.43% classification accuracy on a dataset of 7,950 wheat leaf images, outperforming current advanced methods. This approach has the potential to significantly improve wheat disease detection and empower farmers with a tool for earlier intervention and ultimately, more sustainable wheat production.

Literature Review:

In the field of agricultural production, ignoring the early signs of plant disease can lead to the significant crop losses and ultimately the destruction of the global economy [16]. This section provides a detailed review of state-of-the-art research in the specific field of foliar diseases.

In research [17], focused on various diseases affecting wheat yield, especially leaf rust, stem rust and stripe rust. Deep learning models such as InceptionV3 and ResNet50 achieved classification accuracies of 95.65% and 81.57%, respectively, for identifying wheat diseases.

Image data were collected from the Mundi.com open-source repository and the Bishoftu Agricultural Research Institute in Ethiopia, comprising over 1,500 images of wheat diseases across three classes. Data pre-processing including standardization, formatting, and deletion and rescaling was done. In paper [18], categorized wheat diseases into four groups: healthy, leaf rust, tan spot and spot blotch. A convolution neural networks model achieved highest accuracy of 97.20%, validated by domain experts. This research employed machine learning, image processing, and knowledge-based systems, utilizing handcrafted and deep features from color and color-infrared images. Parallel feature fusion enhanced performance and compared decision tree and deep learning models like Alex Net, VGG16, ResNet101, Google Net and Xception. Expert opinions validated results and generated decision rules. The manually created dataset included 1,000 samples for each category derived from color and color-infrared images captured with RGB and near-infrared cameras. The author in [19] categorized wheat seeds into three groups; Kama, Rosa and Canadian. Various classification algorithms were assessed for prediction accuracy, with the ensemble classifier achieving the highest accuracy of 95% through hard voting decisions. This research compared the performance of algorithms such as K-Nearest Neighbors, Classification and Regression Trees, and Gaussian Naive Bayes with group approaches. The dataset from the UCI library consisted of 210 wheat grain samples from three cultivars characterized by seven physical attributes: area, girth, compaction, length, width, asymmetry coefficient, and grain furrow length.

The study [20] focused on wheat stripe rust disease categorizing it into three classes: resistant, susceptible, and healthy. The study achieved a maximum overall accuracy of 84.10% on cropped images, using image processing techniques such as single-band and dual-band processing, VARI calculation, image segmentation, and cropping. They also employed transfer learning and various CNN architectures. In [21], the author classified wheat diseases into 10 groups including yellow rust, leaf rust and powdery mildew. The deep convolutional neural network VGG19 model achieved an impressive accuracy of 97.65% in disease classification. This study utilized image processing and deep learning techniques, extracting handcrafted and deep features from color images and incorporating parallel feature fusion for enhanced performance. Expert opinion was employed to validate classification results and generate decision rules. The manually created dataset comprised 500 samples for each category of wheat disease, derived from color images captured with an RGB camera. In another study [22], the author employed position attention blocks focusing on extracting position information from the feature map and used transfer learning to accelerate the model's training speed. Wheat leaves are categorized into four classes: healthy, rust, powdery mildew and leaf spot. The proposed model demonstrated an impressive accuracy of 96.40%, surpassing comparable models. The dataset comprised 10,000 wheat leaf images gathered from diverse regions in China, with model validation extended to the Plant Village open-source dataset.

A deep learning model [16], Cereal Conv, a Convolutional Neural Network developed in classifying images of diseased wheat leaves under varied conditions_reached an impressive 97.05% classification accuracy, outperforming the best expert pathologist by 2%. Cereal Conv utilized pre-trained networks, including VGG16, Inception V3, Mobile net, and Xception, with transfer learning followed by fine-tuning with a short classifier network. Training has been done on more than 19,000 images from UK and Ireland collected in the summer of 2019 with categories like healthy plants, yellow rust, brown rust, powdery mildew and septoria leaf blotch. In study [23] genomic prediction approaches based on machine learning algorithms including Random Forest Classification Plus Kinship (RFC_K), Support Vector Classification Plus Kinship (SVC_K) and Light Gradient Boosting Machine Plus Kinship (light GBM_K) were developed and applied. These machine-learning-based genomic prediction methodologies were widely applied to data from whole-genome association studies. The accuracies of the RFC_K, SVC_K, and light GBM_K models for Wheat Blast (WB) and Wheat Stripe Rust (WSR) reached as high as 90% and 93%, respectively.

In paper [2], the author distinguishes five classes of diseases in wheat: Powdery Mildew, Septoria Leaf Spot, Tanspot, Snow mold and one healthy class. Models such as MobileNetV2 and MobileNet demonstrated the best performance in detecting and classifying diseases on wheat leaves. The obtained accuracies for wheat leaf disease detection by the MobileNetV2 and MobileNet models were 0.9632 and 0.9628, respectively. The total dataset used in this research consisted of 100 images for each class of wheat diseases after augmentation, originally starting with 500 images in all classes but expanding to 4,000 images through augmentation for training, validation, and testing of the models. The author [24] measurements were conducted using an electronic nose device based on changes in gas composition where the sensors are exposed to it and temperature modulation by changing the sensor heater voltage. A machine learning-based model, namely the Random Forest Classification model was used to distinguish between healthy and infected samples. The classes used were healthy wheat grains and wheat grains infected by two Fusarium species with F. culmorum and F. graminearum. There are therefore three classes: healthy, infected by F. culmorum and infected by F. graminearum. The achieved classification accuracy ranged between 85% and 93% for different tested models. A performance by the best classifier was noted by recall in the range of 88% to 94%, precision ranging between 90% and 96% and accuracy in the range of 85% to 93%. Table 1 presents a summary of state-of-the-art research literature.

Material and Methods:

This section discusses the proposed methodologies for the identification and classification of diseases affecting wheat fungi plants, Figure 1 presents a step-by-step visual guide to the proposed model's operation, offering users a clear understanding of its internal processes.

Table 1. Brief summary of existing state-of-the-art.

Ref.	Year	Classes	Technique Used	Accuracy (%)
[17]	2021	3	InceptionV3	95.65
[18]	2021	4	Alex Net, VGG19, ResNet101, Google Net	97.20
[19]	2022	3	Ensemble Learning	95.00
[20]	2023	3	CNN	84.10
[21]	2023	10	VGG19	97.65
[22]	2023	4	Transfer Learning	96.40
[16]	2023	5	Cereal Conv	97.05
[23]	2024	2	RFC-K, SVC-K	93.00
[2]	2024	5	Mobile Net	96.32
[24]	2024	3	Random Forest	93.00

Dataset: To create a robust dataset for training the deep learning model to identify wheat fungal diseases, a search on Kaggle identified several datasets, each limited to one or two disease classes. Two of these datasets [25][26] were merged to create a comprehensive set with five classes: healthy wheat and four disease categories (brown rust, leaf rust, septoria, and yellow rust). Following download, the datasets were meticulously validated. This involved checking image labels for accuracy, ensuring consistent data formats, verifying image resolution, and confirming a balanced distribution of images across classes. Additionally, individual images were reviewed for blurriness, noise, or mislabeling. Any image failing these quality checks was removed. This rigorous validation ensured only high-quality, consistent data was used for merging. The final dataset contained 1,325 well-distributed, clear images suitable for model training. This transparency allows for replication of the study and maintains the research's integrity. Sample images are shown in Figure 2, and details of each class images are shown in Table 2.

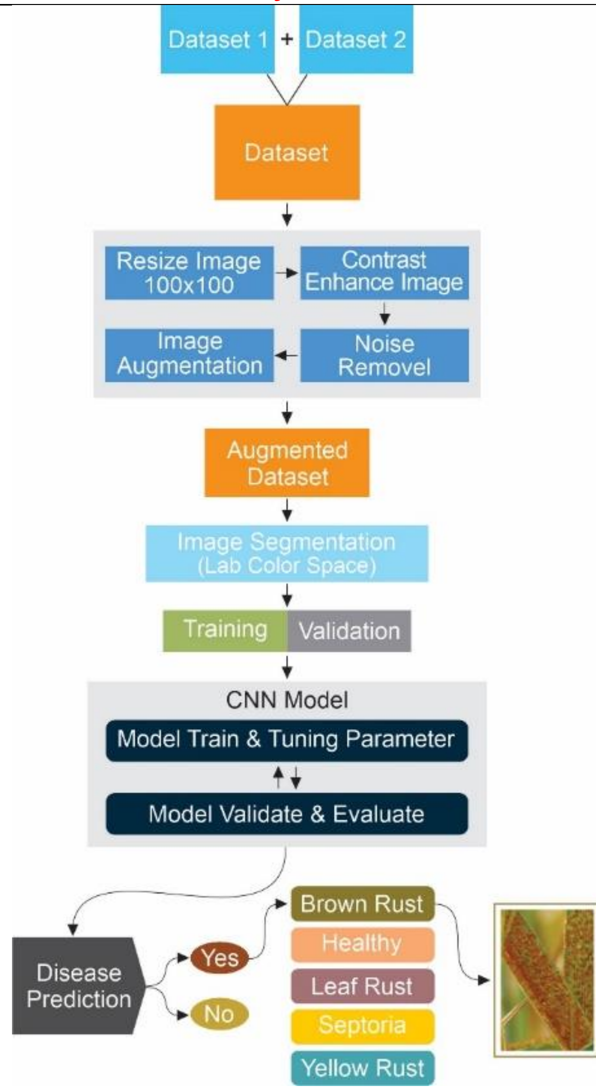

Figure 1. Workflow diagram of methodology.

Pre-Processing:

The wheat disease image dataset underwent several preprocessing steps to enhance its suitability for deep learning models. Firstly, images were resized to ensure uniformity in dimensions, facilitating model training and compatibility. Contrast enhancement techniques were applied to improve image clarity, making disease symptoms more discernible against the plant background. Additionally, noise removal procedures were implemented to eliminate abnormalities that obscure disease symptoms, enhancing image quality for effective analysis. These preprocessing steps collectively contribute to accurate disease diagnosis and support informed decision-making in crop management. Sample images are shown in Figure 3.

Table 2. Wheat Disease Merged Dataset before and after Augmentation.

S. No.	Classes	Original Dataset Images	Augmented Dataset Images
1.	Brown Rust	338	2028
2.	Healthy	435	2610
3.	Leaf Rust	249	1494
4.	Septoria	97	582
5.	Yellow Rust	206	1236
Total images		**1325**	**7950**

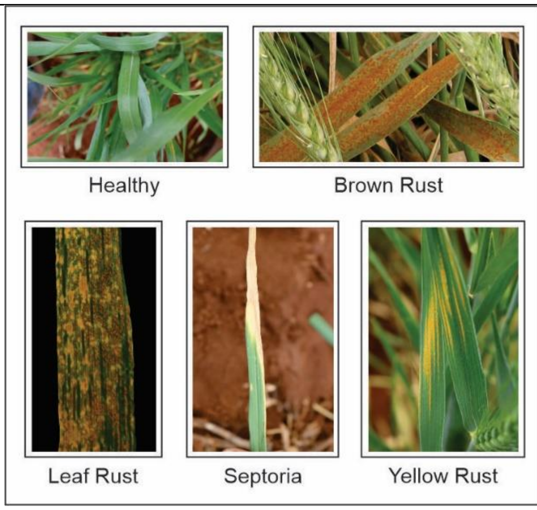

Figure 2. Sample images from datasets [25][26].

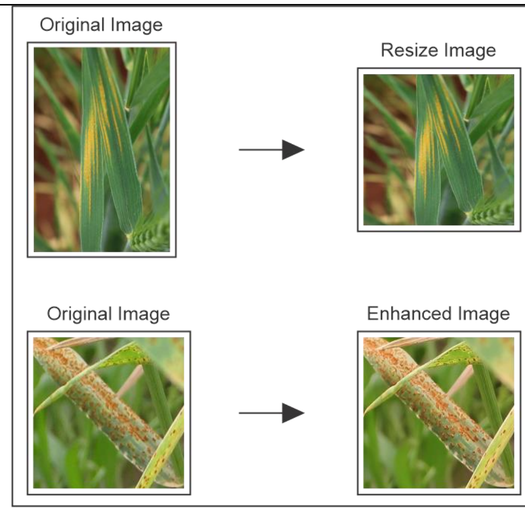

Figure 3. Sample images after pre-processing.

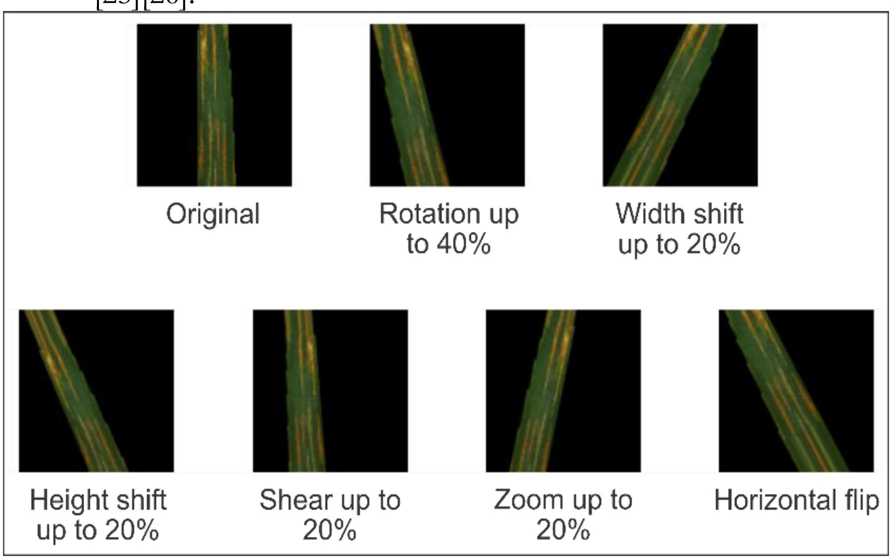

Figure 4. Augmentation strategies employed.

Image Augmentation:

Starting with 1,325 images across five wheat health categories (healthy and four disease types), a variety of image augmentation techniques were implemented to bolster the dataset and strengthen the resulting deep learning model. These techniques essentially create new, slightly altered versions of existing images, expanding the dataset to 7,950 images. Rotations up to 40 degrees, horizontal and vertical shifts up to 20%, shearing distortions, zooming, and horizontal flips were all applied. The details are given in Table 2, while sample images are shown in Figure 4. This diversification exposes the model to a broader spectrum of image variations, mimicking real-world scenarios where disease appearances might differ slightly. This augmentation process effectively enhances the dataset's robustness and the model's generalization capabilities, allowing it to perform more accurately on unseen data.

The six augmentation techniques; rotation, width shift, height shift, shear, zoom and horizontal flip, significantly enhance the model's ability to generalize by creating diverse training examples [27]. Rotation and shear introduce variations in angle and perspective, while width and height shifts adjust for positional changes. Zooming helps the model learn from different scales and horizontal flipping aids in recognizing symmetrical features. Together, these techniques improve the robustness and accuracy of the model by exposing it to a broader range of conditions.

Image Segmentation:

The Lab color space aids in segmenting wheat leaf diseases by separating color information from luminance, emphasizing the contrast between healthy and diseased tissue [28]. This approach enhances the visibility of diseases by using the real leaf color to distinguish them more clearly. The sharp contrast between black, representing healthy tissue, and white, representing diseased tissue, is illustrated in Figure 5.

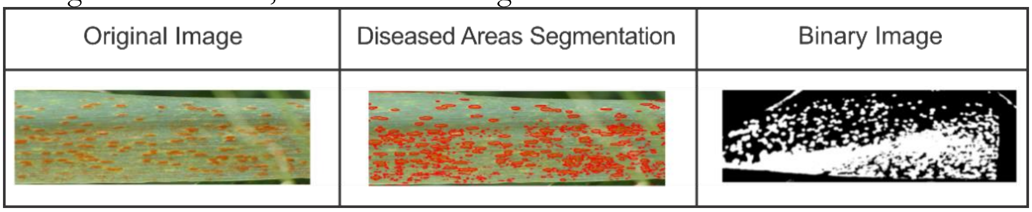

Figure 5. Lab color space segmentation results.

Data Splitting:

The wheat disease dataset was divided into two sets for model training and validation using hold out validation techniques. This ensures a variety of training samples for the model to learn the complexity of the disease. The validation set evaluates the performance of the model on unseen data and serves as an important checkpoint for generalization. This method helps to fine-tune the model, avoid overfitting, and improve reliability and accuracy for real-world scenarios.

Trained Model:

This workflow centers on training a convolutional neural network (CNN) for predicting plant diseases. Following data preparation, augmentation, and lab color space segmentation, CNN undergoes iterative training and tuning to identify disease features. Validation and evaluation then gauge the model's performance against other datasets. The objective is disease prediction, with the model classifying diseases like brown rust and leaf rust based on color labels. The architecture model begins with a convolutional layer featuring 32 filters and a 3x3 kernel size, applied to input images of 100x100 pixels with RGB color channels. ReLU activation introduces non-linearity, while 'same' padding maintains output volume size. A subsequent Max Pooling layer with a 2x2 pool size reduces spatial dimensions by half, aiding computation reduction and preventing overfitting. Additional convolutional and Max Pooling layers follow, increasing filters to 64 to capture complex features at varying abstraction levels.

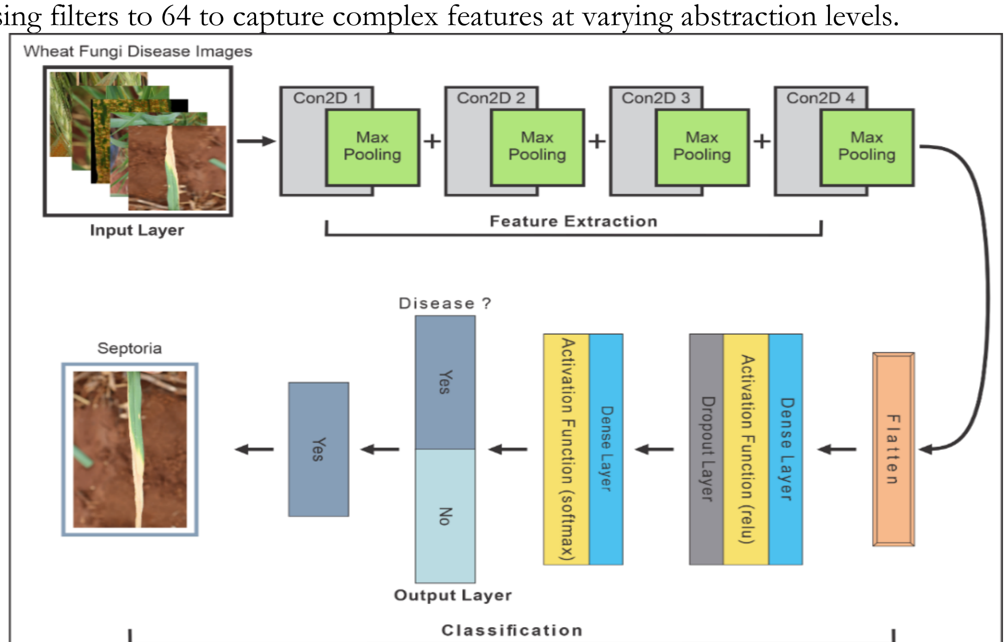

Figure 6. CNN model architecture.

Flattening transitions the 3D output model to a 1D vector, facilitating classification. A dense layer with 256 units enables learning of nonlinear feature combinations, with ReLU activation applied. Dropout, set at a rate of 0.2, prevents overfitting by randomly dropping 20% of neuron connections during training. The output layer, with units equal to the number of wheat fungal disease classes, employs 'Soft max' activation to output a probability distribution over classes. This CNN architecture, with its convolutional, pooling, and dense layers, along with activation functions, dropout, and SoftMax, is tailored to accurately identify and classify wheat diseases from affected images. The CNN model architecture is shown in Figure 6.

Result and Discussion:

This results section provides detailed insights into the experimental results obtained from the proposed deep learning CNN model. Subsequently, a comprehensive discussion of the results obtained is presented.

Performance Evaluation Measure:

When evaluating performance metrics for wheat fungi disease detection or classification using techniques such as machine learning models, several key metrics are commonly used. Accuracy is a metric that measures how often a machine learning model correctly predicts the outcome which can be calculated using Eq. (1) while precision is a metric that measures how often a machine learning model correctly predicts the positive class and is computed using Eq. (2). Recall, also known as the true positive rate (TPR) which is computed using Eq. (3) while the F1-score is computed using Eq. (4). Specificity result shows model's ability to predict a true negative of each category and is calculated using Eq. (5)

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

$$\text{F1} - \text{Score} = \frac{2\times \text{Precision} \times \text{Recall}}{\text{Precision}+\text{Recall}} \tag{4}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{5}$$

The dataset was split into 80% for training and 20% for validation to optimize training and ensure sufficient data for evaluation. The CNN model was trained for 80 epochs, balancing underfitting and overfitting while ensuring proper convergence of the loss function. The trained CNN model achieved 98.43% accuracy in identifying wheat fungal diseases as shown in Figure 7 with model loss displayed in Figure 8. Its precision was 98.47% and the F1 score balancing precision and recall also reached 98.43% demonstrating high positive classification accuracy.

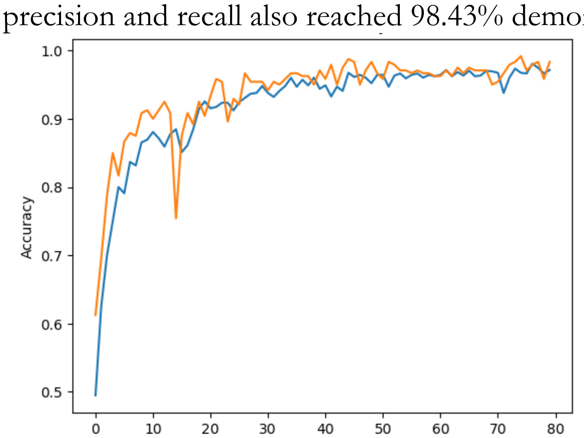

Figure 7. Training and validation accuracy.

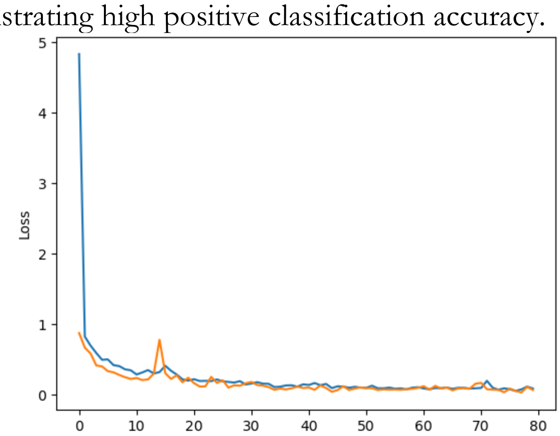

Figure 8. Training and validation loss.

The model demonstrated a recall of 98.43% effectively identifying true positive cases while its specificity of 98.47% showed its ability to accurately detect diseases or confirm their absence. The support value was set at 255 per category in the validation set to ensure sufficient data. The results are shown in Figure 9.

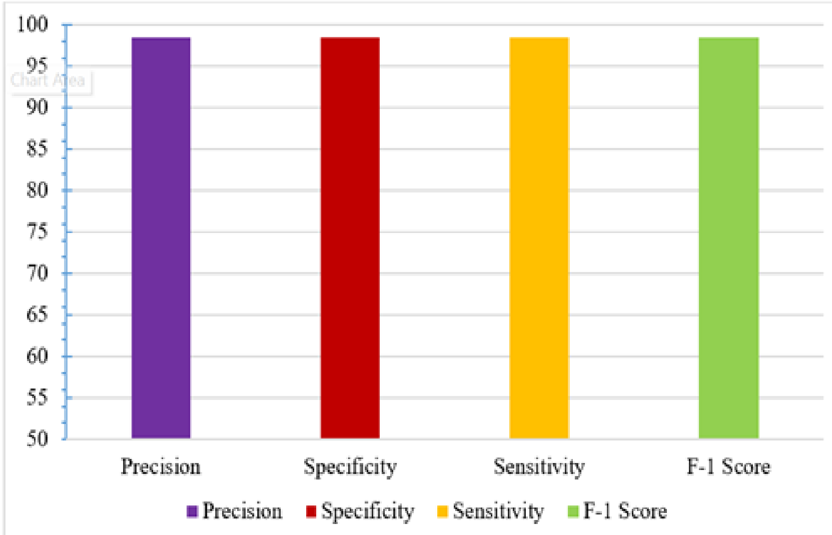

Figure 9. Results of other evaluation measure.

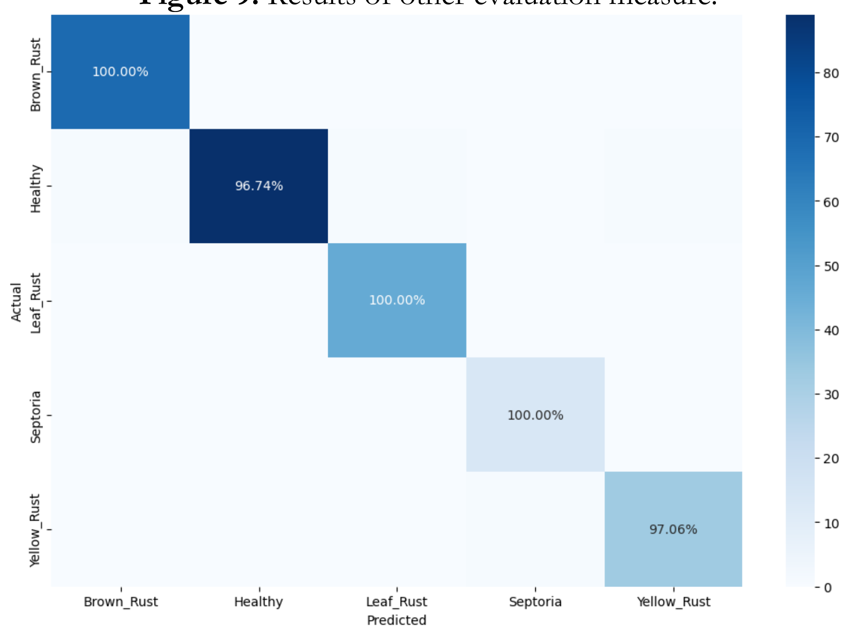

Figure 10. Confusion matrix.

The performance of the CNN model on specific classes like yellow rust and septoria revealed some interesting insights and challenges. When evaluating yellow rust, the model generally performed well but there were instances where it confused yellow rust with other rust diseases such as brown rust. This misclassification likely occurred due to the subtle visual similarities between the rust diseases where yellow rust and brown rust share overlapping symptom patterns like pustules on leaves making it challenging for the model to distinguish between them accurately. In the case of septoria, the model faced more significant challenges. Septoria can present with symptoms that vary widely in appearance including small, water-soaked lesions that can be confused with early stages of other diseases. Additionally, variations in image quality and environmental factors such as lighting conditions further complicated accurate identification. These issues led to some misclassifications where septoria was occasionally mistaken for yellow rust or other disease classes with similar visual features. These challenges highlight the need for augmentation and enhancing the training dataset with more diverse and representative images to improve the model's ability to differentiate between diseases with similar appearances. This would help in increasing the overall accuracy and reliability of the CNN model in identifying specific wheat fungal diseases like yellow rust and septoria.

The confusion matrix shown in Figure 10 represents the actual conditions on the y-axis and the predicted conditions on the x-axis with percentages representing the model's accuracy for each condition. The model predicted brown bell, leaf rust, and septoria conditions with 100% accuracy. One of the main observations was that the model occasionally misclassified brown rust as leaf rust and vice versa. This issue likely arose due to the visual similarities between the two diseases which can present with overlapping symptoms making them difficult to distinguish even for a trained model. Another notable challenge was with septoria, which sometimes got confused with yellow rust. The subtle differences in symptom presentation, especially in images with lower quality or varying lighting conditions contributed to this misclassification. The model also faced difficulties with accurately identifying healthy wheat, occasionally misclassifying it as one of the disease classes. This issue was more pronounced in images where the healthy wheat had some natural discoloration or minor blemishes that could be mistaken for disease symptoms. The model achieved 100% accuracy for some conditions due to the distinctiveness of their visual features like the bright yellow pustules of yellow rust which are easily recognizable. In contrast, the model struggled with diseases such as brown rust and leaf rust due to their overlapping symptoms making them hard to differentiate. Variability in symptom presentation, like with septoria and inconsistencies in image quality or quantity also contributed to reduced accuracy.

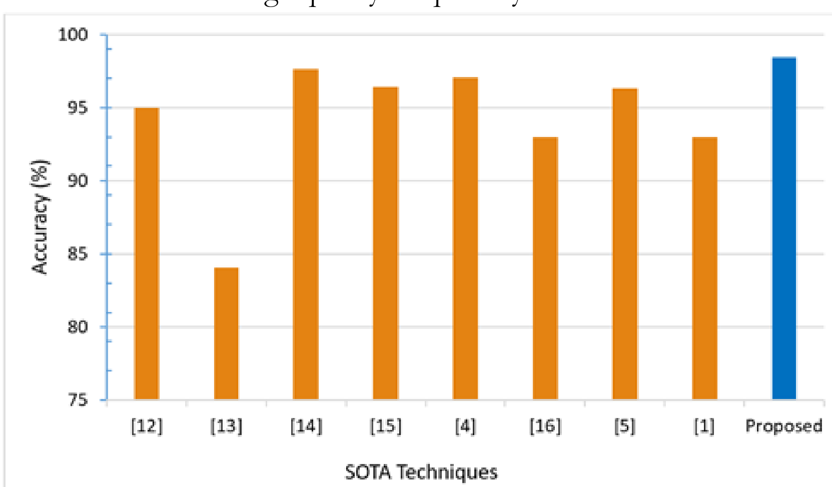

Figure 11. Comparison with existing state of the art techniques.

Figure 11 represents results of our proposed model against state-of-the-art studies that used different learning models. While comparing the results we specifically considered studies that worked with the WDD-2020 and WDD-2021 dataset on wheat plant. Our analysis revealed that our work covered more wheat fungi disease classes, and our fine-tuned, pre-trained model achieved a leading accuracy of 98.43%.

Conclusion and Future Work:

The agricultural sector is vital for high-quality food production and a strong economy. Fungal diseases in wheat can severely impact yields and species diversity leading to significant losses. Early detection through accurate automated techniques can boost production quality and reduce economic losses. Wheat, the world's third most harvested grain faces considerable waste due to disease, particularly from pathogenic fungi. Manual inspection is time-consuming and requires expertise, but automated classification can enhance crop quality and quantity. This study proposes a deep learning solution to detect and classify wheat fungal diseases aiming to improve detection, classification and accuracy. After preprocessing and augmenting dataset CIELAB-based segmentation is carried out to accurately isolate the diseased regions of the leaf. Then a pre-trained Convolutional Neural Network (CNN) was adjusted for optimal hyper-parameters and used to identify fungal diseases in wheat. We used the wheat fungi dataset containing 7,950 samples across five disease classes including healthy plants. Our experiments measured classification accuracy, precision, recall, specificity, F1 score and support comparing results with advanced studies. The CNN achieved 98.43% classification accuracy outperforming other state-of-the-art models. Future research should aim to develop a pest identification model to improve wheat health monitoring by detecting pest infestations.

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Author's Contribution: Usman Islam write code, perform experiments, and produce the results. Wakeel Ahmad and S. M. Adnan Shah help in analyzing results and writing research article.

Conflict of Interest: Authors declare that there is no conflict of interest regarding this work.

Project Details: This research work is done to fulfill MS degree requirements.

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