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# AUTOMATED WHEAT RUST DISEASE CLASSIFICATION USING DEEP LEARNING TO SUPPORT SDG 1: ENHANCING AGRICULTURAL PRODUCTIVITY AND POVERTY ALLEVIATION

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**ABSTRACT**

Agricultural production is pivotal for alleviating extreme poverty and boosting economic stability in line with Sustainable Development Goal 1 (SDG 1) of eradicating poverty in all its forms everywhere. India's agricultural sector is essential to feed its growing population, projected to reach 1.6 billion by 2050. Crop diseases, particularly wheat rusts—yellow rust, leaf rust, and stem rust—are significant obstacles to agricultural productivity, causing substantial yield losses and affecting the livelihoods of millions of farmers. Therefore, developing an automated system for recognizing and classifying wheat rust diseases is crucial for ensuring food security and economic stability. This study aims to design an automated system for identifying and categorizing wheat rust diseases using advanced image processing and machine learning techniques. We collected a dataset of wheat leaf images from agricultural fields in Punjab and Haryana and applied noise filtering and segmentation methods to enhance image quality. Transfer learning and deep convolutional neural networks (CNNs) were used to develop a classifier model. The ResNet50 model achieved an accuracy of 98.5% in classifying wheat rust diseases. By addressing wheat rust diseases effectively, this system supports SDG 1 by enhancing agricultural productivity, improving food security, and contributing to the economic well-being of farmers.

**Keywords:** *Deep learning, wheat rust, transfer learning, convolutional neural networks, agricultural productivity, SDG 1, poverty alleviation.*

## 1. INTRODUCTION

Agriculture is the most important sector due to its economic influence on society, especially in developing countries [1]. Food demand is growing rapidly because of the increasing population and shortage of food ingredients. Crops like wheat, maize, and rice are the main components of food [2]. However, crop diseases are one of the biggest factors affecting the quality and quantity of crop production. These diseases cause major crop yield losses, impacting both large and small-scale farmers [3].

Small-scale cultivators in developing countries contribute up to 80% of global crop production. However, food losses are much higher in these regions due to a lack of resources and access to the latest technology [4]. According to the World Health Organization (WHO) [5], more than a hundred diseases are caused by contaminated food, affecting around 600 million people annually, with 0.4 million deaths. Farmers often lack quick and reliable methods to diagnose diseases, which hinders timely treatment and impacts crop quality and yield.

Wheat is the most important ingredient of food globally and is the most popular cereal cultivated by farmers around the world [6]. According to the Food and Agriculture Organization (FAO) of the United Nations [7], wheat accounted for nearly 28% of total global cereal production from an estimated area of 215 million hectares in 2018 and 2019.

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However, the demand for wheat is much higher than its production, especially in developing countries [2]. Diseases are a major factor contributing to low wheat production, causing 15–20% losses in global wheat production annually [8]. Common wheat diseases like leaf rust and yellow rust are widespread and can cause significant economic losses if not controlled [9]. Most farmers, particularly in developing countries, rely on agriculture experts to identify and diagnose these diseases [10].

Detecting and identifying wheat plant diseases is a challenge for farmers who need to monitor entire fields, which is time-consuming and resource-intensive due to the density of wheat crops [11]. Recent advancements in computer technology, such as human-computer interaction [12,13] and AI [14–19], have enabled the development of intelligent systems to assist farmers in identifying wheat leaf diseases through automatic methods like Computer Vision (CV) and AI-based techniques [20].

## 2. LITERATURE REVIEW

Researchers worldwide are working to provide significant guidance and insights to help farmers make better decisions and take appropriate actions. Over the past two decades, advancements in technology such as AI and computing have garnered researchers' attention. To produce an effective system for actual disease diagnosis and to categorize diseases with high accuracy, various alternative schemes with diverse combinations have been explored. These include conventional statistical and image processing techniques as well as ML-based methods for plant and leaf disease recognition, specifically for wheat disease classification. Researchers have made significant contributions to different aspects of precision agriculture [31]. Advances in digital image processing and ML methods have been used for crop leaf disease detection and recognition using leaf images [21-24]. The literature can be divided into two subsections: less intelligent methods like pure image processing or CV-based disease classification and more intelligent ones like ML-based task handling during precision agriculture.

Xu et al. [25] designed an image recognition-based embedded technique for wheat leaf rust disease identification, achieving 92.3% accuracy. However, their method is not robust under changing field conditions. Similarly, Islam et al. [26] combined image processing and ML to identify potato diseases, achieving 95% accuracy using only 300 images. Alehegn et al. [27] proposed a hybrid ML approach for maize leaf disease classification, achieving 95.63% accuracy. Hossain et al. [28] developed an automated SVM-based model for tea leaf disease recognition with 93% accuracy but faced limitations such as a small dataset and reliance on statistical features.

ML techniques are widely used in various domains, including agriculture. Akmal et al. [29] used plant village datasets and feature extractors like LTP, HOG, and SFTA, achieving 92.8% to 98.7% accuracy. Jerome Treboux et al. [30] used a decision tree ensemble approach, improving accuracy from 89.6% to 94.27% for vineyard discrimination. Rump et al. [31] used SVM and spectral vegetation indices for sugar beet disease detection, achieving up to 97% accuracy. However, differentiating between multiple diseases remained a challenge. Ramesh et al. [32] used RFC for papaya leaf disease identification but achieved only 70% accuracy due to a small dataset.

Phadikar et al. [33] used Bayes' theorem and SVM classifiers for rice leaf disease classification, achieving 68.1% and 79.5% accuracy, respectively. Prajapati et al. [34] used SVM for rice plant disease identification, achieving up to 93.33% accuracy. Ahmed et al. [35] compared four ML techniques for rice leaf disease detection, finding decision tree to be the most accurate at 97.91%. Panigrahi et al. [36] used various ML algorithms for maize crop disease detection, with RFC achieving 79.23% accuracy. Waghmare et al. [37] used multi-class SVM for grape plant disease identification, achieving 96.6% accuracy. Zhao et al. [38] used SVM for wheat powdery mildew detection, achieving 93.33% accuracy. GuanLin et al. [39] used SVM for wheat rust recognition, achieving 96.67% accuracy. Azadbakht et al. [40] used support vector regression for wheat leaf rust severity detection, achieving up to 99% accuracy. Researchers use ML and computer vision for plant disease detection[41,42.43].

In Table 1, we summarize the discussed related work. Various techniques have been proposed for crop leaf disease recognition in the ML domain, including maize, rice, tea, vineyard, and wheat. Different methods have been used for preprocessing, feature extraction, and recognition. However, deficiencies exist in wheat leaf disease

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recognition using ML methods, such as the unavailability of diverse datasets and robust preprocessing techniques. Our proposed framework aims to bridge this gap by achieving high accuracy in wheat disease recognition using a fine-tuned RFC framework and robust preprocessing techniques.

*Table 1: Summary Table.*

| Author | Crop | Methodology | Accuracy | Limitations |
|---|---|---|---|---|
| Xu et al. [25] | Wheat | Image processing-based embedded technique | 92.30 % | Not robust under changing field conditions |
| Islam et al. [26] | Potato | Image processing and ML, color-based segmentation | 95% | Small dataset, used statistical features |
| Alehegn et al. [27] | Maize | Hybrid ML approach | 95.63 % | None mentioned |
| Hossain et al. [28] | Tea | Automated SVM-based ML model | 93% | Small dataset, reliance on statistical features |
| Akmal et al. [29] | Corn, Potato | LTP, HOG, SFTA with multi-class SVM | 92.8-98.7% | None mentioned |
| Treboux et al. [30] | Vineyard | Decision tree ensemble | 94.27 % | Initial low accuracy, improved with DTE |
| Rump et al. [31] | Sugar Beet | SVM and spectral vegetation indices | 97% | Low accuracy for multiple disease differentiation |
| Ramesh et al. [32] | Papaya | RFC with HOG | 70% | Small dataset |
| Phadikar et al. [33] | Rice | Bayes' theorem, SVM | 68.1-79.5% | Limited dataset |
| Prajapati et al. [34] | Rice | SVM | 93.33 % | Dataset lacks variations |
| Ahmed et al. [35] | Rice | Decision tree, logistic regression, KNN, Naïve Bayes | 97.91 % | Used statistical features |
| Panigrahi et al. [36] | Maize | SVM, RFC, DT, KNN | 79.23 % | Poorly captured images |
| Waghmare et al. [37] | Grape | Multi-class SVM | 96.60 % | None mentioned |
| Zhao et al. [38] | Wheat | SVM | 93.33 % | Low accuracy |
| GuanLin et al. [39] | Wheat | SVM with RBF | 96.67 % | Invariant dataset |
| Azadbakht et al. [40] | Wheat | -support vector regression | 99% | Focused on one disease severity |

From the literature review the following research gaps has been identified.

1. Many studies rely on small or invariant datasets, which restricts the generalizability and robustness of their models, particularly in real-world applications where environmental conditions vary significantly.
2. Several studies depend on conventional machine learning techniques and statistical features, which may not fully capture the complexity of plant diseases, especially under changing field conditions. There is a need for more advanced approaches like deep learning to improve model accuracy and adaptability.

## 3. METHODOLOGY

### 3.1 Research Design

In this study, the authors have selected the design science research (DSR) methodology to uncover and identify opportunities and challenges in wheat production within the agricultural sector. This approach has been chosen for the following reasons: it enables the creation of new artifacts to address productivity issues effectively.

### 3.2 Proposed Architecture

Recent academic literature has consistently highlighted the significance of Convolutional Neural Networks (CNNs) as a groundbreaking technology. In our research, we aim to leverage

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CNNs to revolutionize agricultural practices, specifically focusing on wheat production and the classification of leaf diseases using leaf images as our primary input data.

To achieve this, we explored two distinct methodologies: firstly, constructing a custom multi-layer convolutional neural network (MCNN) from scratch tailored to our specific needs, and secondly, employing transfer learning with pre-trained networks. Our objective was to devise an optimal classifier capable of accurately detecting and categorizing various wheat leaf issues. We subsequently conducted a thorough comparative analysis to evaluate the efficacy of both approaches.

### 3.3 Transfer Learning

Transfer learning has emerged as a highly effective strategy in deep learning, especially in addressing intricate challenges. By leveraging pre-trained models, where the network's layers are frozen and transferred from previously trained datasets, we mitigate the need for extensive new data collection and training. This approach proves particularly advantageous in developing robust classification networks even with limited datasets. Table 2 provides an overview of the key attributes of the pre-trained models utilized in our study, underscoring their applicability and effectiveness.This strategic use of transfer learning not only enhances computational efficiency but also accelerates model development, making it a pivotal component in our quest to advance agricultural productivity through cutting-edge technology.

*Table 2: CNN model property of VGG19 and RESN50*

| CNN Architectures | Parameters (M) | Layers | Accuracy |
|---|---|---|---|
| VGG19 | 138 | 19 | 92.70% |
| RESN50 | 25 | 50 | 94.11% |

### 3.4 MCNN

This research propose a Multilayer CNN built entirely from scratch for this task. This architecture consists of five convolutional layers, each followed by ReLU activation and max-pooling layers. Dropout layers are incorporated to prevent overfitting, followed by a Flatten operation and a fully connected layer with softmax activation for classification. Throughout training, we employ Keras to dynamically adjust the learning rate, a crucial metric for halting training when improvements cease. This model architecture is specifically designed to classify wheat leaf diseases, encompassing the entire process from input data, through processing, to the final output. Data from various sources are utilized as inputs to train and validate the model. The architecture diagram for the wheat leaf disease classification model is depicted in figure 1.

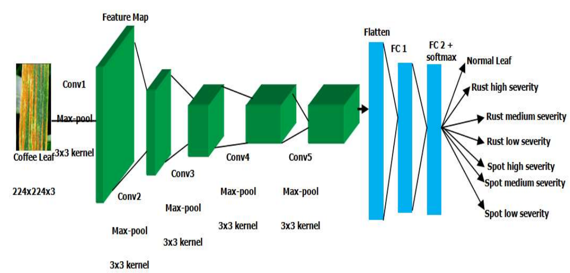


*Figure 1: The proposed model architecture*

### 3.5 Hyper-parameters

Hyperparameters are predefined parameters that significantly influence the training process of a neural network. They are adjustable settings that can be tuned to optimize the model's performance. In the context of convolutional neural networks (CNNs), experiments involve manipulating these hyperparameters to explore different configurations and enhance classification accuracy. Several key hyperparameters were selected as benchmarks for this study:

$$Loss = -\sum_{c=1}^{M} y_{o,c} \log(p_{o,c}) \quad (1)$$

**Padding**: In CNNs, padding addresses the issue of reduced output dimensions caused by convolutional layers. By adding zero layers around the input image, the study preserves the spatial dimensions of the output feature maps.

**Stride:** This parameter determines the number of pixels the filter moves across the input matrix during convolution. A stride of 1 means the filter shifts one pixel at a time, affecting the spatial resolution of the feature maps.

**Epoch:** An epoch refers to one complete pass of the entire dataset through the neural network during both forward and backward propagation. In this

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study, each epoch processes 50 images, with a batch size of 32 chosen to balance computational efficiency with memory utilization.

**Learning Rate:** Initially set at its default value, the adaptive learning rate adjusts during training. The ReduceLRonPlateau callback function dynamically decreases the learning rate by a factor of 0.5 when performance metrics stagnate, aiding model convergence.

**Optimizer:** The Adam optimizer is selected for updating network weights during training iterations. It efficiently computes adaptive learning rates for each parameter and has proven effective in optimizing convergence speed.

**Loss Function:** Categorical cross-entropy is employed as the loss function to evaluate how well the network's predictions match the true labels. It quantifies the disparity between predicted probabilities (via softmax activation) and actual class labels across the training dataset.

These hyperparameters collectively shape the training dynamics and performance of the convolutional neural network, crucial for achieving optimal classification results in this study.

where M is the number of class for this study.

Table 3: Hyperparameter values of the proposed model

| parameters | Values |
|---|---|
| Optimizer | Adam |
| Loss-Function | categorical cross-entropy |
| Epoch | 100 |
| Stride | 1 |
| Padding | 0 layer |
| Bach Size | 32 |
| Learning rate* | Initial: 0.01 |
| Momentum | 0.09 |
| Weight decay | 0.005 |

*Decreases by a factor of 1/2

### 3.6 Proposed System Framework

This research aimed to design a model for classifying Wheat leaf diseases using convolutional neural networks (CNNs) trained on image data. The CNN-based model was trained to identify images and classify them into specific disease categories. The system accepts Wheat leaf images in any digital format captured by a camera.

The process started with collecting and preparing the required Wheat leaf images. Next, pre-processing steps were implemented. Normalization adjusted the pixel intensity of each image to a standardized scale, reducing computational complexity during network training and ensuring consistent data representation. Additionally, image resizing standardized the image dimensions since images captured by cameras vary in size. This step established a uniform size for all images fed into the algorithms.

After pre-processing, a clean and standardized dataset was obtained. For classification, a deep learning approach using CNN models was employed. These models automatically extract complex features from images without manual feature engineering, enhancing their ability to classify Wheat leaf diseases accurately.

Figure 2 illustrates the architecture of the proposed CNN-based Wheat leaf disease classification system. It depicts the framework from image capture through preprocessing to the training and testing phases. The system was designed to effectively process and classify images, aligning with the research goals.

To improve classification performance, transfer learning with pre-trained CNN models was utilized. Pre-trained models were adapted by fine-tuning their learned features and adjusting output labels to match the specific disease categories studied. This approach leverages existing knowledge in neural networks to enhance feature extraction and classification accuracy for Wheat leaf disease detection.

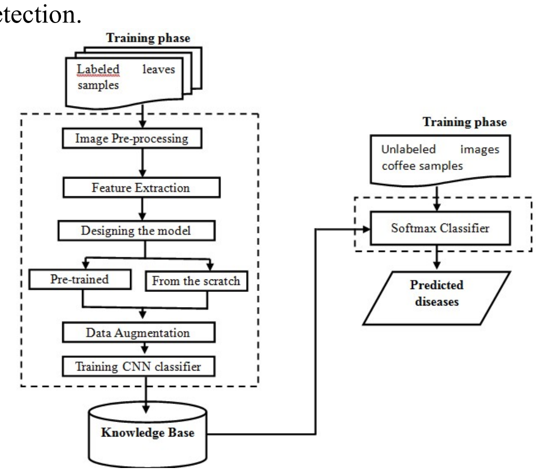


*Figure 2: Framework of the proposed model*

Furthermore, essential image features were manually extracted using Gabor filtering techniques to capture texture features. Additionally, data augmentation techniques were employed during training to present each image in various perspectives, mitigating model overfitting. Ultimately, the convolutional neural network classifier models were trained and established.

### 3.7 Dataset Preparation

Image acquisition serves as the initial phase in any computer vision system, detailing the process of obtaining and storing images from physical devices like cameras or webcams onto a computer system for subsequent processing. In developing a precise Wheat leaf disease classifier model, data were gathered from the Southern Nations, Nationalities, and Peoples' Region (SNNP) using a digital camera. Each leaf was then assigned a class label through a literature review and consultation with agricultural experts who observed the images.

### 3.8 Image Pre-processing

To ensure the classifier model meets user requirements and performs effectively, researchers meticulously assessed the quality and naturalness of collected and prepared images. This involved essential low-level image pre-processing steps.

The proposed classification model for this study adhered to six key pre-processing steps. Firstly, images were resized to match the input layer size of the CNN, typically 224x224 pixels with 3 color channels. Secondly, images were converted to binary and then grayscale. Thirdly, efforts were made to minimize degradation in image quality that may occur during acquisition.

Fourth, images were normalized to aid faster convergence of the model and enhance its ability to generalize to unseen data. Fifth, string values were converted to numeric values, and finally, one-hot encoding was applied. Additionally, given that noise is expected when capturing images, various noise filtering techniques, such as Gaussian and median filtering, were employed to effectively remove noise from the collected images.

### 3.9 Feature Extraction

The primary goal of this study is to develop a classifier model for categorizing Wheat leaf diseases using convolutional neural networks (CNNs). CNNs can either process images directly or extract essential features from them for classification purposes. In this research, both approaches were employed. To extract necessary features, researchers utilized GLCM (Gray-Level Co-occurrence Matrix) techniques, a widely used method in computer vision for texture analysis. GLCM operates by considering different frequencies and orientations within gray-scale images, and it calculates numeric features such as Entropy, Energy, Skewness, Correlation, Kurtosis, Homogeneity, and Contrast. Each Wheat leaf had these features extracted individually, showcasing various texture features in the resulting tables 4.

### 3.10 Training Methods

In this study, deep learning approaches using convolutional neural networks (CNNs) were chosen due to their specialized design for image analysis and classification. Unlike traditional machine learning algorithms that require manual feature extraction, CNNs automate this process by directly extracting relevant features from raw images using convolutional and pooling layers. This capability allows CNNs to effectively capture discriminating features that are crucial for accurate classification.

Researchers employed two main approaches: training from scratch, where all model parameters are optimized specifically for the problem at hand, and transfer learning, which utilizes pre-trained CNN models. During training, pre-trained models such as Visual Geometry Group 19 (VGG-19) and Residual Network with 50 layers were employed. These models feature up to four layers for convolutional neural network-based feature extraction, complemented by six layers of fully connected networks in the training from scratch method.

*Table 4: extracted texture features from the wheat dataset*

| Entropy | Energy | Skewness | Correlation | Kurtosis | Homogeneity | Contrast |
|---|---|---|---|---|---|---|
| 0.06053 | 0.126301 | 2.158967 | 0.122763 | 0.01447 | 0.99998 | 5.95581 |
| 0.04836 | 0.119847 | 1.790198 | 0.108785 | 0.0118 | 0.999975 | 9.66787 |
| 0.10914 | 0.310663 | 0.591272 | 0.171573 | 0.04119 | 0.999989 | 7.3093 |
| 0.04914 | 0.115945 | 1.576879 | 0.084204 | 0.00958 | 0.999975 | 5.89392 |
| 2.10983 | 90.112731 | 0.158712 | 0.849869 | 0.68805 | 0.972535 | 0.99999 |

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| | | | | | | |
|---|---|---|---|---|---|---|
| 0.13809 | 0.222363 | 4.08659 | 0.214823 | 0.03785 | 0.999992 | 4.7837 |
| 1.70892 | 128.58379 | 0.070822 | 0.894122 | 0.43964 | 0.973957 | 0.31066 |

*GLCM techniques

### 3.11 Experimental Setup

Our experimental setup utilized Python programming language and the Flask framework for model deployment and testing. Experiments were conducted on a desktop computer equipped with an Intel® Core™ i7 CPU @ 2.70GHz, 8.00 GB of RAM, and a 64-bit Microsoft Windows 10 operating system, providing a robust environment for training and evaluating our models.

## 4 EXPERIMENTAL RESULT AND ANALYSIS

n this study, experiments were conducted using different testing configurations: 80% of the data allocated for training and the remaining 20% for testing, as well as 70% for training and 30% for testing. The classifier was evaluated using both extracted features, obtained using Gray Level Co-occurrence Matrix (GLCM) for metrics like Entropy, Energy, Skewness, Correlation, Kurtosis, Homogeneity, and Contrast, and non-extracted features.

The performance of the developed classifier model was assessed using accuracy, precision, recall, and F-measure metrics. This comprehensive analysis aimed to evaluate the effectiveness of the classifier under varying experimental conditions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

$$Sensitivity = Recall = \frac{TP}{TP + FN} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

$$Specificity = \frac{TN}{FP + TN} \quad (5)$$

$$F_1 = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \quad (6)$$

### 4.1 ResNet-50 model performance

In the context of using this model for Wheat classification, the default parameters of the state-of-the-art model were left unchanged. However, the last layer, which consists of fully connected layers, was adjusted to fit our specific classification problem. During the experiment, different training scenarios were applied: 80% for training and 20% for testing, and 70% for training and 30% for testing. These setups yielded accuracy rates of 84% and 69% respectively. As a result, the first scenario, which performed better, was chosen for detailed analysis.

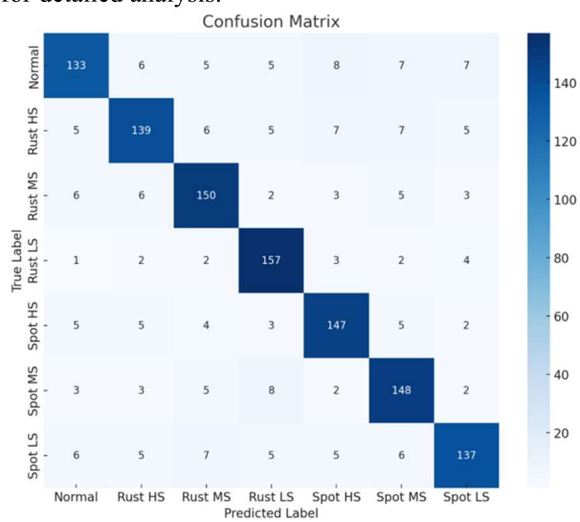


*Figure 3: ResNet-50 confusion matrix*

he confusion matrix above demonstrates how effectively the developed classifier model operates. It shows that the model achieves an accuracy of 84.1% in real-world applications. Furthermore, detailed accuracy results for the ResNet-50 state-of-the-art algorithm, broken down by each class, are presented in Table 5 below:

*Table 5: ResNet-50 Model performance analysis*

| Class | Recall | Precision | F-measure | TPR | FPR |
|---|---|---|---|---|---|
| Normal | 77.80 % | 83.70% | 80.60 % | 77.80 % | 22.20 % |
| Rust high severity | 79.90 % | 83.80% | 81.80 % | 79.90 % | 20.10 % |
| Rust Medium severity | 87.80 % | 83.80% | 85.70 % | 87.80 % | 12.20 % |
| Spot high severity | 86.00 % | 84.10% | 85.00 % | 86.00 % | 14.00 % |
| Spot Medium severity | 86.60 % | 83.70% | 85.10 % | 86.60 % | 13.40 % |

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| | | | | | |
|---|---|---|---|---|---|
| Spot Low severity | 80.20 % | 86.20% | 83.00 % | 80.20 % | 19.80 % |
| Weighted average | 84.30 % | 84.20% | 84.30 % | 84.30 % | 15.70 % |

### 4.2 VGG-19 model Performance

The architecture of this state-of-the-art model consists of 19 layers, comprising convolutional layers, pooling layers, and three fully connected layers organized into three blocks. Two of these blocks contain 4096 neurons each, followed by a layer with 1000 neurons representing class probabilities. The model's hyper-parameters and parameters such as the number of filters, filter size, stride, and padding were kept at their default values during training, except for the modification of the last layers to accommodate the number of classes in this study. In this experiment, two testing scenarios were employed: one where 80% of the dataset was used for training and 20% for testing, and another with 70% for training and 30% for testing. This approach resulted in accuracies of 90% and 87.3%, respectively, with the first scenario chosen for detailed analysis. The following confusion matrix illustrates the model's performance:

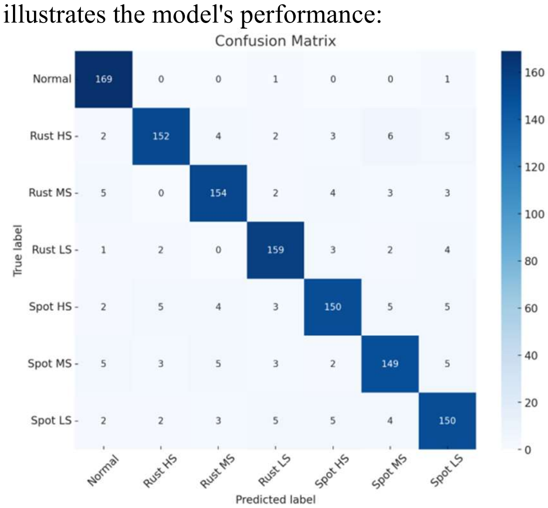


*Figure 4: VGG-19 confusion matrix*

The researcher utilized a confusion matrix to present the experimental outcomes of the developed Wheat leaf disease classification model. This experiment involved manually splitting the dataset into training and testing subsets. Out of a total of 6000 images, 4800 (80%) were allocated to the training dataset, while the remaining 1200 (20%) were assigned to the testing dataset. The VGG-19 model, a state-of-the-art algorithm used in this study, achieved an accuracy of 90% on the testing dataset, correctly classifying 1080 out of 1200 images. The remaining 120 images (10%) were classified incorrectly. Based on the results from all testing scenarios, the first test option was selected for detailed analysis, as shown in the table 6 below.

*Table 6: VGG-19 model performance analysis*

| Class | Recall | Precision | F-measure | TPR | FPR |
|---|---|---|---|---|---|
| Normal | 98.90 % | 90.90% | 94.70 % | 98.90 % | 1.10 % |
| Rust high severity | 87.40 % | 91.60% | 89.40 % | 87.40 % | 12.60 % |
| Rust Medium severity | 90.10 % | 91.70% | 90.80 % | 90.10 % | 9.90 % |
| Rust Low severity | 93.00 % | 91.40% | 92.10 % | 93.00 % | 7.00 % |
| Spot high severity | 87.80 % | 90.10% | 88.90 % | 87.80 % | 12.20 % |
| Spot Medium severity | 87.20 % | 88.10% | 87.60 % | 87.20 % | 12.80 % |
| Spot Low severity | 87.80 % | 88.10% | 87.90 % | 87.80 % | 12.20 % |
| Weighted average | 90.30 % | 90.18% | 90.20 % | 90.30 % | 9.90 % |

For this experiment, the researcher evaluated the recall, precision, and F1-measure values to gain a better understanding and analysis of the results. Precision measures the ratio of correctly predicted true classifications to all predicted true classifications, while recall measures the ratio of correctly predicted true classifications to all actual instances of the class. The experimental results indicate that the classifier model developed using the Residual Network-50 achieved 86% accuracy with 80% of the data used for training and 20% for testing. Out of 1200 records, 1032 were correctly classified, while 168 were misclassified. Additionally, the same pre-trained model was tested with a split of 70% for training and 30% for testing, achieving 78% accuracy. This corresponds to 1404 correctly classified records out of 1800, with 396 misclassified.

Furthermore, the researcher explored developing the model using all extracted features in the VGG-19 Pretrained model. In the first test

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scenario with 80% training and 20% testing, 960 records were correctly classified, resulting in 80% accuracy. In the second scenario with 70% training and 30% testing, the model achieved 75% accuracy. The experimental analysis using the pre-trained model with all features is depicted in the following figure 5.

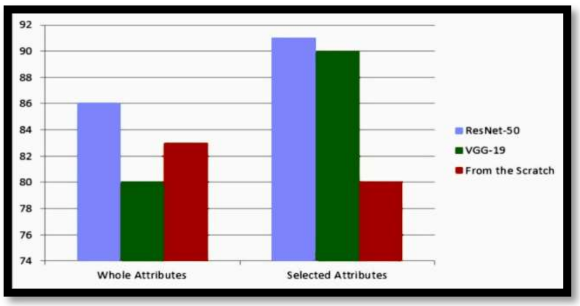


*Figure 5: Accuracy comparison of the model with all the attributes*

Figure 5 illustrates the comparative performance of the developed models using both Residual Network-50 and Visual Geometry Group (VGG-19) across different test scenarios. Notably, the Residual Network-50 pretrained model outperforms VGG-19, achieving higher accuracy with the selected attributes. The experiment also extended to develop classifier models using these pretrained models with selected attributes. Attributes were selected based on information gain ratio, where features like Energy, Skewness, Correlation, Kurtosis, and Homogeneity were chosen. The following figures 6 depict the experimental results using these selected attributes.Additionally, experiments were conducted using the selected attributes with pretrained models (ResNet-50 and VGG-19) and from scratch, where the models were trained with 80% of the data for training and 20% for testing. The results show that ResNet-50 achieved 91%, VGG-19 achieved 90%, and the model trained from scratch achieved 80% accuracy, respectively.

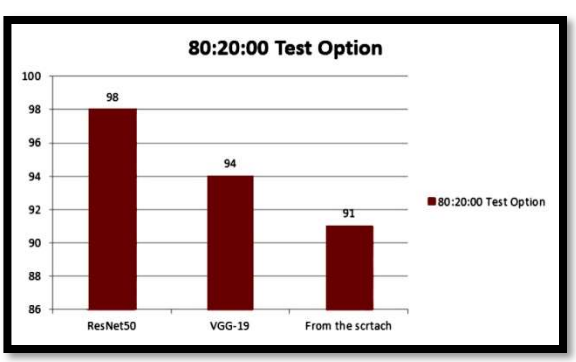


*Figure 6: Accuracy comparison of pre-trained models with extracted features.*

## 5 CONCLUSION AND FUTURE WORKS

This study focuses on developing a classifier model capable of detecting and categorizing Wheat leaf images into various classes: Healthy, Rust (with high, medium, and low severity), and Brown Spot (with high, medium, and low severity). Data collection was conducted in the south nation and nationalities of people, followed by extensive preprocessing to enhance data quality for effective classification. The approach employed convolutional neural networks (CNNs), utilizing both pretrained models and training from scratch. The default test scenario involved splitting the dataset into 80% for training and 20% for testing. Additionally, experiments were conducted by extracting necessary features from the images and using CNNs for both feature extraction and classification. The developed classifier achieved 98% accuracy using ResNet-50. Future research directions include expanding the model to recognize nutrient deficiencies and other classification labels from given images.

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