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Research Article

Hybrid (VGG16, ResNet50, InceptionV3 and MobileNet) Model for Wheat Leaf Diseases Detection

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ABSTRACT

Wheat is one of the most essential staple crops worldwide, and its productivity is often threatened by various diseases affecting its leaves. Early and accurate detection of these diseases is crucial to mitigate crop loss and ensure food security. This study proposes a hybrid deep learning model integrating the strengths of four well-established architectures: VGG16, ResNet50, InceptionV3, and MobileNet, for the efficient detection and classification of wheat leaf diseases.

The hybrid model leverages feature extraction capabilities from each network, combining them into a unified framework to enhance accuracy and robustness. Preprocessed images of wheat leaves from a curated dataset were used to train and validate the model. Features extracted by each architecture were concatenated and processed through a fully connected layer for final classification. The proposed system was benchmarked against standalone models, demonstrating superior performance in terms of accuracy, precision, recall, and F1-score.

By utilizing the complementary strengths of these architectures—VGG16's detailed feature capture, ResNet50's skip connections for deeper learning, InceptionV3's multi-scale analysis, and MobileNet's lightweight efficiency—the hybrid model achieves high detection accuracy while maintaining computational efficiency. This model holds significant promise for practical deployment in agricultural systems, aiding farmers and researchers in real-time disease monitoring and management.

Keywords: VGG16, ResNet50, InceptionV3, MobileNet, Wheat Disease, Hybrid model.

1. Introduction

Grain is the seed of grasses such as wheat, oats, corn, rice, millet, rye, and barley that has been harvested. Grain is important in providing human nutrient requirements. Grains supply 48% of human calories, or food energy. Grain quality is a crucial factor in market acceptance. Pricing is determined by grain quality, and quality indices differ depending on end-use needs. Physical criteria such as size, shape, kernel hardness, moisture content, and visual qualities such as the presence of damaged, infected, discolored, or foreign objects are used in grain handling units to determine quality. Acceptable grain quality also implies that the grain is free of adulterants and other potentially harmful components.[1-3] Even for trained employees or licensed traders in the grain market (anajmandi), the traditional method of grain quality evaluation, eye inspection (a manual method), is difficult in terms of speed, reliability, and precision. This quality analysis is also influenced by the mood of grain traders, which is inaccurate, resulting in the farmer not receiving the correct grain price. The quality of grain is determined by both its nutritional constituents, such as protein and glucose, as well as its physical characteristics. We are focusing on the physical components of grain analysis in this study. Thus, in this chapter, we will offer research in the area of physical feature analysis, as well as challenges to be addressed. It mostly consists of both human and machine-based procedures. Both strategies are further divided into groups. Each technique has its own set of limitations and benefits, which will be explored in the following sections. The primary focus of this study is on wheat quality analysis[4-6]. By changing a few things, this method of analysis can also be used to figure out how good other types of grain are.

Wheat Plant Diseases

In addition to causing serious damage to the field, the plant disease influences the physiological function of the plant. Furthermore, the plant diseases have the potential to spread to other Wheat plants through a variety of propagation methods. In order to determine whether or not a certain illness is present in a plant, its symptoms must be observed. These symptoms might manifest themselves in several areas of the wheat plant, including the roots, fruits, leaves, flowers, and stem. Changes in the look, size, and shape of the stem, leaves, flowers, and fruits of wheat plants can be brought about by diseases that affect wheat plants[7].

Each and every one of the challenges that come along with the never-ending pursuit of increased yields and improved quality cannot be ignored. The amount of arable acreage that is suited for wheat cultivation is decreasing as a result of a wide variety of biotic and abiotic pressures, including climate change of course[8].

Wheat genetic variety has been lost as a result of the pursuit of high-performing cultivars, which has increased the likelihood of diseases flourishing and posing a threat to the global wheat supply. This has had a significant impact on the production of wheat around the world. Common wheat diseases, such as rusts, blotches, and head blight/scabs, are mostly responsible for these losses (in significant part). A further threat to grain output is posed by diseases such as wheat blast and spot blotch, both of which have only lately been discovered or are not as prevalent as they once were. The various categories of wheat plant diseases are shown in Figure 1 [9]

Common Bunt: Affected wheat kernels have a gray-green tint and a greater diameter than normal kernels. At first, the shells of diseased kernels are undamaged,but they are readily torn during harvest, unleashing masses of black, powdery spores. The fungus releases fishy-smelling compounds.

Fusarium Head Blight: It is characterized by tan or light brown lesions that cover one or more spikelets. An orange fungal mass or dark brown discoloration may be seen on the bottom section of the glume of certain infected spikelets.

Sooty Head Molds: It is characterized by adark green or black mold that grows on the surface of mature wheat heads. Recurrent rain and a delayed harvest are the most typical causes of sooty molds on mature wheat.

Bacterial Streak: Among the most common indications of an infected streak are tiny, water-soaked spots between the veins of the leaf. Later, the streaks may join toproduce vast, uneven patches of dead tissue.

(a) (b) (c) (d)

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Research Article

(e) (f) (g) (h)

Figure 1: Wheat Disease (a) Common Bunt, (b) Fusarium Head Blight, (c) Sooty HeadMolds, (d) Bacterial Streak, (e) Barley Yellow Dwarf, (f) Leaf Rust, (g) Powdery Mildew, (h) Stem Rust.

Barley Yellow Dwarf: It is a viral disease that causes yellow orred discoloration on the wheat leaves. Near the tips of damaged leaves, the discoloration is more extreme, giving the leaves a flame-like appearance.

Leaf Rust: It produces small, round,orangish-brown lesions on the wheat leaves. These blister-like lesions are most often seen on leaves, but they may also befound on the leaf sheath.

Powdery Mildew: It is characterized bywhite lesions on leaves and leaf sheaths. In most cases, fungal spores may be readily removed by wiping a finger over infected regions. It has black components in addition to the white, cottony appearance during the reproductive stage.

Stem Rust: As a result, blister-like lesions appear on the stems, leaf sheaths, and leaves of the plant. The process of tearing takes place when the spores of the fungus, which are reddish-brown in color, penetrate the outer surface of plant tissues. Lesions caused by stem rust, in contrast to those caused by leaf rust, are longer and more elongated as they mature.

Various Diseases in Wheat Leaf

According to [10] the following is a list of some of the diseases that typically appear on paddy leaves. a sheath rat: Sheath rot creates sterile panicle and unfilled seeds,

Figure 2: Wheat Leaf

in addition to reducing the amount of production that occurs by preventing or reversing the occurrence of panicle emergent. As a result of this disease, the quality of the pancreas decreases, and it grows and rots, resulting in a change in the color of the pancreas. In rainy weather conditions, the prevalence of this disease is higher than in dry weather conditions.

Leaf blast:

The fungus known as Magnavorthe oryzae is responsible for the production of the Blast. Particularly affected by this disease are the parts of the rice plant that are located above the ground surface. These parts include the neck, the collar, and the parts of the pancreas, the node, and occasionally the leaf sheath and leaf. Some of the factors that contribute to increased damage include low soil moisture, low temperatures during the daytime, frequent rain

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Research Article

showers, and the presence of pollution. A representation of eat leaf that was influenced by the leaf blast may be seen in Figure 3

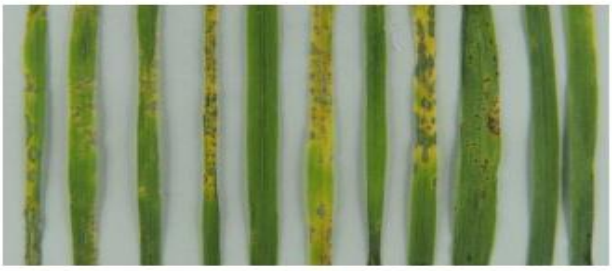

Fig 3 Wheat leaf blast

Leaf smut:

The presence of leaf smut disease could be confirmed if the leaves of the patient had the appearance of having angular patches, being minute, and having a smoky dullness. Fungi are responsible for the secretion of the leaf smut. This infectious disease has an effect on the entire leaf surface.[11] An illustration of a leaf smut that has affected wheat leaf is presented in Figure 4.

Fig. 4 leaf smut affected wheat leaf.

Brown Spot:

Brown spot is considered to be one of the most prevalent and widespread diseases that affect the reproductive system and it has a significant impact on the rate of reproduction. Spikelets, panicle branches, leaves, glumes, leaf sheath, and coleoptile are all affected by this fungal disease, which is known as a disease that affects the Heat Plant. The numerous large spots that are present in the plant leaf are evidence of the significant influence of brown spots, which have the potential to destroy the entire plant. This is illustrated in Figure 5, which depicts the brown spot that has an effect on the wheat leaf.[11]

Fig. 5 Brown Spot Affected Wheat Leaf

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Research Article

Bacterial blight:

Wheat that was planted in millions of hectares was affected by bacterial blight. Approximately 75% of the crop yield in ripe cultivation is lost due to this disease. The bacterial blight, on the other hand, will impair both the quality and the yield of the fruit. Fig. 6 depicts the heat paddy leaf that has been affected by bacterial blight.[12]

Fig. 6 Bacterial Blight Affected Paddy Leaf

There is an urgent need to deliver consistent, high yields of high quality grains. The management of diseases is an important component of successful crop management. Recognition of the disease and an understanding of the responsible pathogens are important for successful disease control.In the Indo-Gangetic plain there are several severe diseases of cereal crops (Wheat and Paddy) viz. rusts, smuts, blights, blasts, powdery mildews, downy mildews etc. Visible Pathogens responsible for these diseases severely damage cereal crops causing great decline in grain yield. It happens because of the climate condition of the region which is humid and most favorable for the growth of fungal pathogens.

As research worker of mycologist and plant pathologist, one can find and detect these diseases on the basis of external visual microscopic and macroscopic symptoms which are not 100% authentic. As a Computer Software researcher, one can detect various diseases of wheat and paddy using colour image processing, classification and object detection techniques which might prove to be more accurate in comparison to visual symptoms. In order to better understand the parameters which affect the recognition and detection of objects of varying sizes and shapes, a model needs to be designed. It is practically the real high time for the Department of Computer Science, Banasthali Vidyapith to sponsor such investigations and hence the research proposal. The problem thus demands due attention at scientific level.

At scientific and practical levels the present investigation will impart significant information on the following points:

1. It would be possible to identify the various pre and post harvest diseases of wheat and paddy on the basis of disease symptoms, etiology and disease cycles.

2. The climatic and physic-chemical factors favouring growth of fungal pathogens could be identified enabling us to formulate measures for prevention.

3. It would be possible to confirm the importance of image processing techniques in detection and analysis of plant diseases.

4. It would be possible to use image processing for measuring affected areas of disease and to determine the difference in the colour of affected areas.

5. It would be possible to adjust median filter, the thresholding method to convert filtered image into binary vision.

2. Review of Literature

k-Nearest Neighbor (KNN) Classifier, Probabilistic Neural Network (PNN), Genetic Algorithm (GA), Support Vector Machine (SVM), Principal Component Analysis (PCA), Artificial Neural Network (ANN), Fuzzy logic, and other classification techniques have been utilized in order to achieve accurate classification and to determine the

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Research Article

type of plant disease. There are also other classification techniques that have been utilized. Choosing a certain classification method is always going to be a challenging undertaking due to the fact that the classification performance might change depending on the input data and the algorithms that are taken into consideration.

In a wide variety of sectors, including agriculture, biological research, and others, classifications of plant diseases have a wide range of applications. An overwhelming majority of plant illnesses are brought on by fungus, bacteria, and viruses.Bacteria are thought to be significantly more primitive than fungi, and their life cycles are typically more straightforward [13]. Fungi belonging to the Puccinia triticina Eriks species are responsible for the virus that causes wheat leaf rust. It is predominantly the Puccinia triticina fungus that is responsible for the reduction in the number of kernels per head and the smaller kernel masses that crop production experiences. Additionally, the disease known as leaf rust causes the wheat leaf to become dry, which hinders the process of photosynthesis. Based on the findings of the study [14], it was estimated that the Wheat leaf rust caused a loss of approximately 350 million United States dollars in the United States of America (USA) between the years 2000 and 2004. A similar situation occurred in Australia in 2009, when the Puccinia triticina fungus, often known as leaf rust, was responsible for a loss of twelve million Australian dollars [15]. Changing from one disease control policy to another is a challenging endeavor for farmers because of the lack of information and inadequate management that they face. For the purpose of illness detection and classification, relying solely on observation with the naked eye can be quite costly. Numerous plant diseases offer a significant risk to the agricultural industry because they shorten the amount of time that plants can reach maturity. First and foremost, the morphology of the microorganisms described above can be used to identify them, with particular attention paid to the reproductive organs of these organisms.

For the purpose of accurate categorization and the identification of wheat harvests that have been impacted, the selection of features is exceedingly important. The majority of the representation of the image is dependent on superficial characteristics. Color, shape, and texture represent the low-level properties of the object. HSV-histogram, color moments, color histogram, CCV [16], moment of invariants, Zernike moments, circularity, area, and other techniques are examples of diverse form features. These are some of the several ways for feature extraction. First-order features, Grey level coherence (GLCM), SIFT, SURF, DWT, and other texture characteristics are examples of the various types of texture features.

Using color conversion for takeout HSI parameters and then performing back propagation using NN, the fundamental model for disease detection in the domain of plant and leaves has been provided in work [17]. This model employs to accomplish back propagation. Attempts to identify crop problems and diseases were made in the beginning stages of this endeavor. Wheat canopies that had varying degrees of Fusarium Head Blight (FHB) severity were used in the study[65] to collect hyperspectral data straight from the field. The purpose of this work was to construct a multispectral red-edge index model for the purpose of monitoring FHB infection. Using differential and ratio combinations of Sentinel-2 bands and digital mapping images at a regional scale, the primary objective of this work is to determine the various levels of FHB infection that exists in winter wheat. The results of this experiment generated an accuracy of 84% for REHBI, OSAVI, and RDVI, an accuracy of 74% for the contained accuracy, and an accuracy of 89% for the user's accuracy. When it comes to the automatic diagnosis of wheat plant diseases through the use of computer vision, another study [18] introduced a revolutionary approach that was named hot spot detection with statistical inference. In addition to that, the author developed a dataset of digital images of plant illnesses. During the course of the research [67], morphological analysis and a watershed segmentation strategy were utilized in order to count the spores of wheat strip rust. For this purpose, microscopic digital images were utilized. Ninety-five percent accuracy is achieved by this method. [19] The other ontological technique is utilized in the work that is done in the agriculture profession. This research makes use of the linked data method in order to implement actions that are performed in close proximity to real time by utilizing the semantic web. A smartphone application that uses an image dataset to automatically detect and localize plant diseases was proposed by [20], which is another significant addition (WDD2017). An accuracy of 95.12% and 97.95%, respectively, was reached by the author through the utilization of the VGG-FCN-VD16 and VGG-FCN-S deep learning techniques. An additional strategy that was implemented in [21] was quite similar to this one, and it utilized a combination of CNN and AleXNet models to automatically diagnose wheat leaf illnesses. In terms of accurately guessing the correct class, the proposed technique had an accuracy of 84.54%.

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Research Article

3. Methodology

The methodology used in the project involves several stages, including data preparation, feature extraction, model training, evaluation, and prediction. Initially, the dataset, which includes images of wheat and rice diseases, is collected and pre-processed. Pre-processing involves resizing the images to a consistent format, converting them into grayscale, and performing normalization or scaling, which ensures that the pixel values lie within a standardized range. The next step is feature extraction, where various features such as mean standard deviation, Grey Level Co-occurrence Matrix (GLCM), and texture features are extracted from the images. These features help in distinguishing between different disease types or healthy crops.[22]

Following feature extraction, the dataset is split into training and test sets, which are then used for training and validating the models. Training involves using deep learning architectures like Convolutional Neural Networks (CNN-2D), VGG16, ResNet50, InceptionV3, MobileNet, and a Hybrid model. In this process, the model learns patterns and representations from the data. The CNN-2D model uses basic convolutional layers with pooling, followed by fully connected layers for classification. VGG16, ResNet50, InceptionV3, and MobileNet are all pre-trained models that are fine-tuned for the specific task. These models are based on different architectures, where VGG16 focuses on deep convolutional layers, ResNet50 uses residual connections for better gradient flow, InceptionV3 incorporates multi-scale filters, and MobileNet leverages depthwise separable convolutions for efficiency. In the Hybrid model, a combination of these pre-trained models is used to leverage their individual strengths, such as improved feature extraction and reduced computational overhead.

The models are trained using a supervised learning approach with labeled images, where the objective is to minimize the loss function (typically categorical cross-entropy for multi-class classification) through optimization techniques like Adam or SGD (Stochastic Gradient Descent). The performance of the models is evaluated based on key metrics such as accuracy, precision, recall, F1-score, and error rate. These metrics are essential for determining how well the model classifies images into the correct disease categories. Additionally, a comparison graph is created to analyze the performance of different models on two datasets, providing insights into which model offers the best performance in terms of both efficiency and accuracy

Model Descriptions

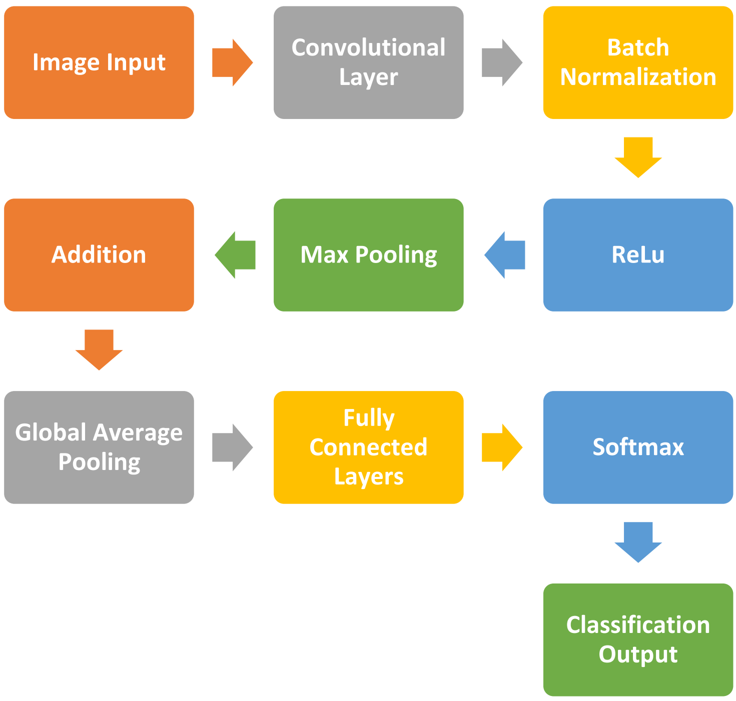

Figure 7: System Architecture

1. **Image Input**: This is the raw input to the model, typically in the form of an image (e.g., 75x75x3 for colored images). The images are passed into the deep learning network for further processing.
2. **Convolutional Layer**: The convolutional layer is responsible for extracting local features from the input image. It applies several filters (kernels) to the image, performing operations like edge detection, texture recognition, and more complex features as the network deepens. Each filter extracts a different feature of the image.
3. **Batch Normalization**: This layer normalizes the output of the previous convolutional layer. It helps in speeding up the training and improving the model's stability by reducing internal covariate shift. Essentially, it standardizes the activations within a layer so that they have a mean of 0 and a variance of 1.
4. **ReLU (Rectified Linear Unit)**: ReLU is an activation function applied after convolution and batch normalization. It introduces non-linearity by setting all negative values to zero, allowing the network to learn complex patterns. Mathematically, it's defined as:

   ReLU(x)=max(0,x)\text{ReLU}(x) = \max(0, x)ReLU(x)=max(0,x)

   ReLU helps avoid the vanishing gradient problem, making the network more efficient to train.
5. **Max Pooling**: Max pooling is a down-sampling operation applied after convolution. It reduces the spatial dimensions (height and width) of the feature maps, retaining only the most important information (the maximum value in each pooling window). This helps in reducing computation and overfitting, and it makes the model invariant to small translations in the input image.
6. **Addition (Skip Connections / Residual Connections)**: In some architectures like ResNet, skip connections are used to directly add the output of one layer to the output of another. This helps in mitigating the vanishing gradient problem by allowing gradients to flow more easily through the network during backpropagation.
7. **Global Average Pooling**: This is a pooling operation that replaces traditional fully connected layers by taking the average of each feature map produced by the convolutional layers. Instead of flattening the entire feature map, it reduces the dimensions to a single vector, one value per feature map, which can then be passed to the fully connected layers.
8. **Fully Connected Layers**: After the convolutional and pooling layers, fully connected (dense) layers are used to make predictions. These layers connect every neuron from the previous layer to each neuron in the current layer. They enable the model to learn complex representations and patterns from the feature maps produced by the convolutional layers.
9. **Softmax**: Softmax is a function applied to the output of the fully connected layer in the case of multi-class classification. It converts the raw output scores (logits) into probabilities that sum to 1, indicating the likelihood of the input belonging to each class.
10. **Classification Output**: The output layer provides the final prediction of the model. It gives the probability distribution of each class. For example, in a disease classification task, it might output the likelihood that an image belongs to each disease class.

Proposed Hybrid Model Architecture

1. Input Layer

The input image is represented as a tensor:

$$I \in R^{75\times75\times3}$$

Where 75×75 is the spatial dimension and 3 represents the RGB channels.

Feature Extraction by Pre-Trained Models

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Research Article

Let the feature extractor for each pre-trained model be represented as Fmodel(I), where the model could be VGG16, ResNet50, InceptionV3, or MobileNet. The feature maps produced are:

$$FVGG16(I) \in R^{H1 \times W1 \times C1}$$

$$ResNet50(I) \in R^{H2 \times W2 \times C2}$$

$$InceptionV3(I) \in R^{H3 \times W3 \times C3}$$

$$MobileNet(I) \in R^{H4 \times W4 \times C4}$$

Where, H,W,C are the height, width, and number of channels of the respective feature maps.

$\nabla J(\theta t)$ is the gradient of the loss with respect to the parameters.

3. Global Average Pooling

Each feature map is reduced to a single feature vector using Global Average Pooling (GAP):

$$f_{pooled} = \frac{1}{H \times W} \sum_{h=1}^{H} \sum_{w=1}^{H} F(h, w, c)$$

The output dimensions become:

$$f_{VGG16} \in R^{C1}, f_{ResNet50} \in RC^{2}, f_{Inception} \in RC_{3}, f_{MobileNet} \in RC^{4}$$

Concatenation of Feature Vectors- The pooled feature vectors is concatenated to form a single hybrid feature vector:

$$f_{hybrid} = Concat(f_{VGG16}, f_{ResNet50}, f_{InceptionV3}, f_{MobileNet})$$

Dimension:

$$f_{hybrid} \in R^{C_1 + C_2 + C_3 + C_4}$$

Dense Layer-The hybrid feature vector is passed through a dense layer with n neurons and ReLU activation**:**

$$f_{dense} = ReLU(W_{dense} \cdot f_{hybrid} + b_{dense})$$

$$f_{dense} \in R^{n}$$

Softmax Output Layer

The dense layer output is transformed into class probabilities using the softmax function:

$P(y_i|I) = \frac{exp(zj)}{\sum_{j=1}^{k} exp(zj)}$

for i=1,2,…,k

Where:

$z = W_{out} \cdot f_{dense} + b_{out}$

k=14 (number of classes)

Output:

$$P(y \mid I) \in R^{k}$$

Transfer Learning [TL]:TL is process of by before learned models on a divide but related task and then fine-tuning those models such that they are suitable for the depression classification problem at hand. This approach makes use of the information that was acquired during the first training, which has the potential to improve the models' aptitude for comprehending and categorizing material that is linked with depression. TL is process of adjusting a model that has already been trained to perform a new task. The overall objective is to minimize a combined loss function Jtotal(θ), which is a sum of the pre-trained model's loss pre-trained Jpre-trained(θ) and the task-specific loss task-specific(Jtask-specific(θ):

$$\lambda J_{pre-trained}\ (\theta)\ +(1-\lambda)\ J_{task-specific}(\theta)$$

Where:

Jtotal(θ) is the combined loss function.

Jpre−trained(θ) is the loss of the pre-trained model.

Jtask−specific(θ) is the task-specific loss.

λ is a hyperparameter controlling the balance between the two losses.

Where λ is a hyper parameter controlling the balance between the two losses.

Feature Extraction

Feature extraction is a process used in computer vision and image processing to identify and extract important information or features from an image or a set of images. The extracted features can then be used for various applications such as image classification, object detection, and image segmentation.

GLCM

Gray-Level Co-occurrence matrix (GLCM) is a texture analysis method in digital image processing. This method represents the relationship between two neighboring pixels that have gray intensity, distance, and angle. In general, we use GLCM to get texture features in images such as dissimilarity, correlation, homogeneity, contrast, and others

A GLCM uses the texture classification concept. The texture classification concept is classified using the homogeneity value. The homogeneity value is calculated for every pixel to present inside the image. After calculating the homogeneity values, a matrix of values is created. If there is a change in the homogeneity value of the particular pixel, then the GLCM value is calculated.

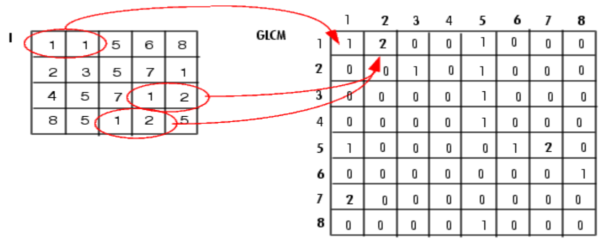

Figure 8: Gray-level co-occurrence matrix (GLCM)

Figure 8 Gray-level co-occurrence matrix (GLCM)-based artificial neural network (ANN) model using multilayer perceptron (MLP) network.

In the brain, the X-ray tumor part is different from the rest of the gray mass. The gray mass has a different texture in comparison to the tumor texture. At that point, GLCM is the best approach. If there is a sharp change in the matrix value, there is the highest chance of getting the tumor. GLCM is the best approach for classifying the pixel by pixel values.

The GLCM-based technique for image texture analysis was put forth by Haralick and group [9] way back in 1973. Each element of the GLCM matrix represents the number of co-occurrences of corresponding pixel pairs in a particular spacing (s) and direction in an image matrix, and it can be written as (Eq.)

$$\mathrm{GLCM(i,j)}_{\theta} = |\{((p_1,p_2)|I(p_1)) = i, I(p_2) = j\}|$$

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Where p_1 and p_2 represent the position of pixels in the image matrix M × N.

Construction of GLCM matrix (**a**) Image matrix (**b**) GLCM matrix The image matrix consists of a set of pixel values, which indicates the intensity of the gray level present in an image. In the image matrix, there is a co-occurrence of intensity values, viz., eight and seven two times along a 0° direction with a spacing of one (highlighted with an ellipse, Thus, value two in the GLCM matrix along the third row and the second column indicates the pixel value of eight, which occurred two times along with pixel value seven with pixel spacing is one and pixel pair direction 0°. In the GLCM matrix, i and j denote the gray level values of an image pixel. Similarly, the GLCM matrix is constructed [10]. Using the GLCM matrix, twenty-one texture features can be extracted. These features are used by many researchers [11,12,13] for different applications, and the same can be referred to for more information. where P(i, j) is (i, j)th entry in a normalized GLCM matrix, μ_x and μ_y are means of row and column of GLCM matrix further σ are the standard deviations of row and column of the GLCM matrix and G is the number of distinct grey levels in the quantized image matrix.

Training Methods

The ADAM algorithm is an example of an algorithm that helps to improve something. It could take the place of the stochastic gradient ancestor when the network value is being updated. This method is used to figure out the right learning rate for each parameter .Adam also remembers how much damage gradients have usually done in the past, which is the same thing as momentum. The Adam algorithm is used a lot in the field of deep learning because it can produce high-quality results in a short amount of time.

Adaptive Moment Estimation (ADAM): ADAM is an approach for adaptive optimization that modifies the learning rates for each parameter using a separate algorithm. Adaptive learning rates are provided, and quicker convergence is often achieved,

$$m_{t+1} = \beta_1 m_t + \mathbf{(1-\beta_1)}\ \nabla\mathbf{J}(\theta_t)$$

$$v_{t+1} = \beta_1 v_t + \mathbf{(1-\beta_1)}\ \nabla\mathbf{J}(\theta_t)$$

$$\hat{m}_{t+1} = \frac{1-\beta_1^{t+1}}{1-\beta 1} m_{t+1}$$

$$\hat{v}_{t+1} = \frac{1-\beta_1^{t+1}}{1-\beta 1} v_{t+1}$$

β1and β2 are exponential decay rates.

∇J(θt) is the gradient of the loss.

mt and vt are the first and second moment estimates respectively.

$\hat{m}_{t+1}$, $\hat{v}_{t+1}$ are bias-corrected moment estimates.

Dataset

The dataset comprises a diverse collection of images representing various rice and wheat diseases, alongside healthy crop conditions. For rice, the dataset includes 130 images of Brown Spot, 113 of Hispa, 196 of Leaf Blast, and 200 of Neck Blast, with an additional 297 images of healthy plants. For wheat, the dataset features 50 images each of Black Bust, Blast, Brown Rust, Common Root Rot, Fusarium Head Blight, Mildew, and Septoria, complemented by 245 images of healthy wheat. This dataset provides a comprehensive resource for training and validating models, enabling accurate classification and analysis of crop health and disease severity

Table 1: number of wheat disease

wheat disease	Number of images
Black Bust	50

Journal of Information Systems Engineering and Management
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Research Article

Blast	50
Brown Rust	50
Common Root Rot	50
Fusarium Head Blight	50
Healthy	245
Mildew	50
Septoria	50
Yellow Rust	226

Figure 9: Wheat Dataset

4. Result Discussion

The simulation was performed in Python using the Spyder IDE, leveraging various libraries such as TensorFlow and Keras for deep learning model development. The tensorflow.keras module was used to build and train convolutional neural networks (CNNs) for image classification, with the ImageDataGenerator facilitating data augmentation. Visualization and plotting were handled through matplotlib, enabling the display of training results and image data. The simulation also integrated cv2 for image processing tasks, such as reading and manipulating images, while tkinter.filedialog was used for file selection, allowing the user to choose input images. Together, these libraries facilitated the creation, training, and evaluation of a model to classify rice and wheat diseases from the provided image dataset.

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https://www.jisem-journal.com/

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```
Found 9164 images belonging to 14 classes.
Found 1859 images belonging to 14 classes.
Found 912 images belonging to 14 classes.
```

Figure 10: Input image and number of classes

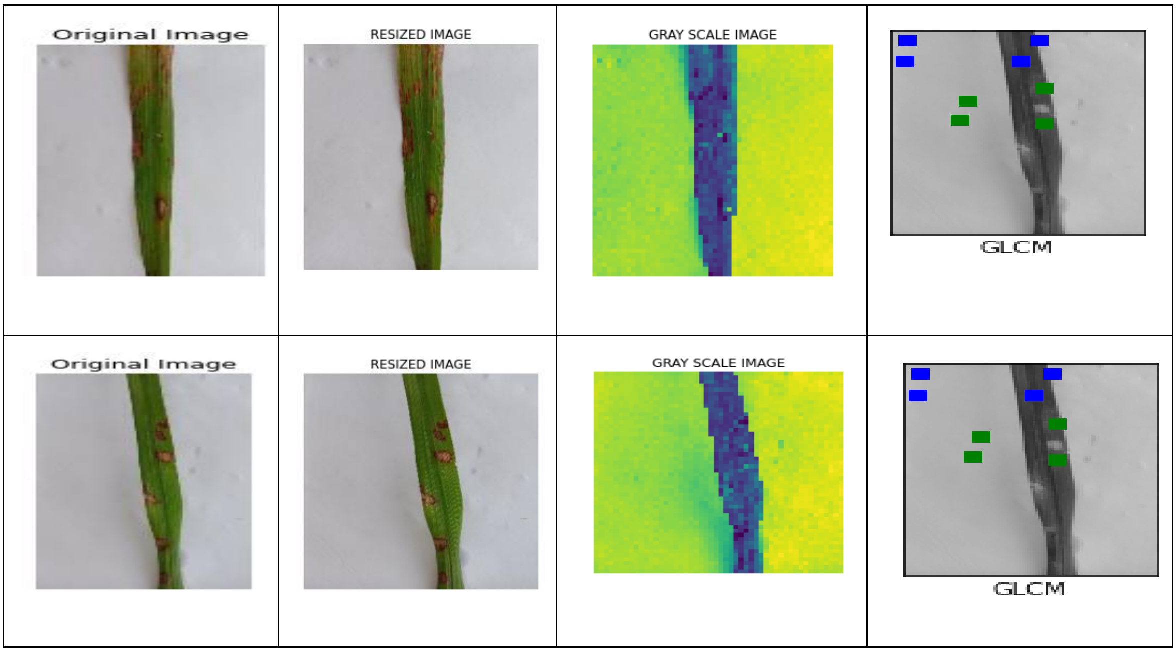
```
--------------------------------
Image Splitting
--------------------------------

1. Total Number of images = 11484

2. Total Number of Test  = 2297

3. Total Number of Train = 9187
```

Figure 11: Input image and number of classes

Layer (type)	Output Shape	Param #	Connected to
input_layer_13 (InputLayer)	(None, 75, 75, 3)	0	-
vgg16 (Functional)	(None, 2, 2, 512)	14,714,688	input_layer_13[0…
resnet50 (Functional)	(None, 3, 3, 2048)	23,587,712	input_layer_13[0…
inception_v3 (Functional)	(None, 1, 1, 2048)	21,802,784	input_layer_13[0…
mobilenet_1.00_224 (Functional)	(None, 2, 2, 1024)	3,228,864	input_layer_13[0…
global_average_poo… (GlobalAveragePool…	(None, 512)	0	vgg16[0][0]
global_average_poo… (GlobalAveragePool…	(None, 2048)	0	resnet50[0][0]
global_average_poo…	(None, 2048)	0	inception_v3[0][…

Figure 12: Hybrid Model

Wheat Simulation Result



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Research Article

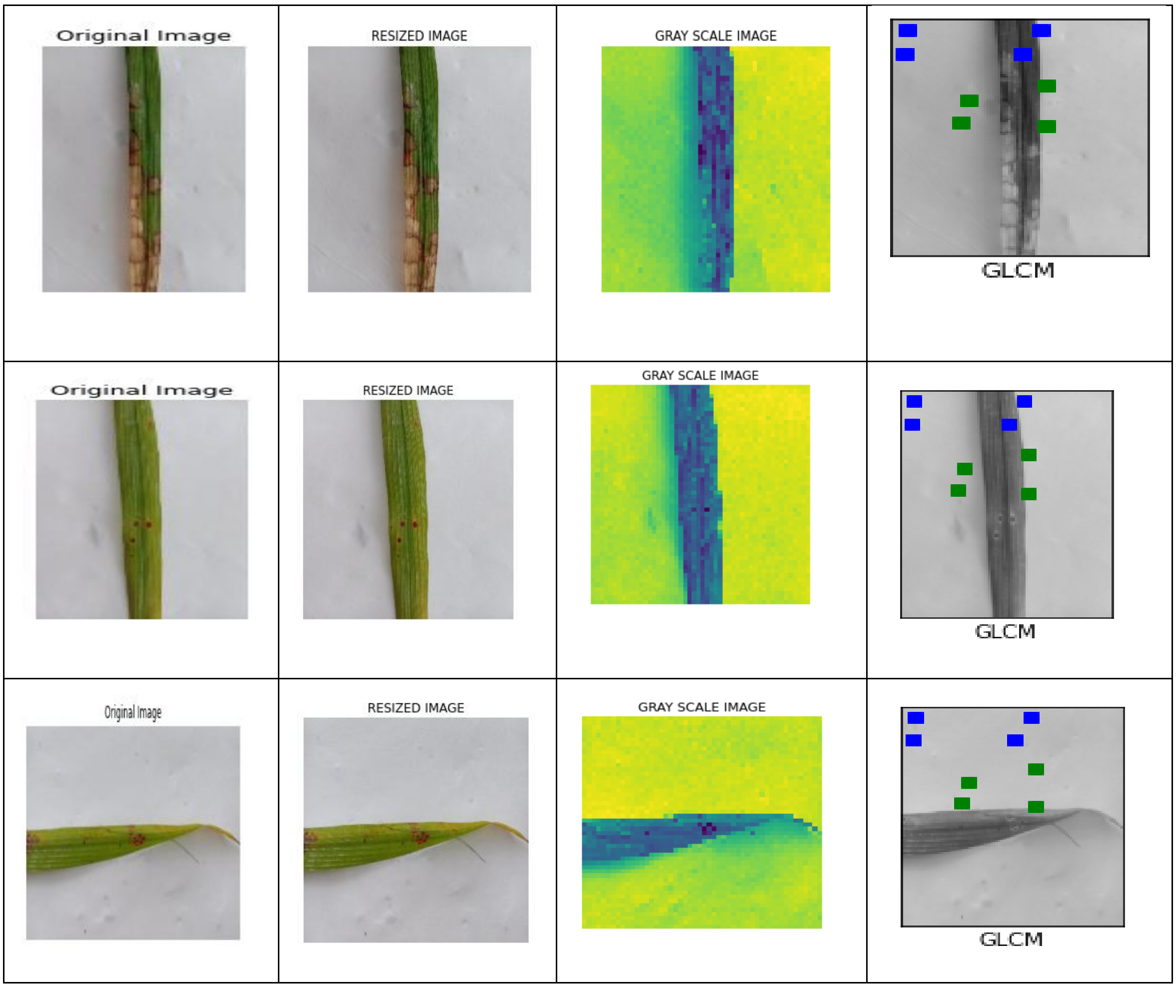

Figure 13: Processed Dataset Images

Table 2: Wheat Disease Performances for Hybrid proposed model

Disease	Accuracy	Precision	Recall	F-Score	Error Rate
Wheat_Black_Bust	98.5%	97.4%	96.8%	97.1%	1.5%
Wheat_Blast	97.8%	96.2%	95.5%	95.8%	2.2%
Wheat_Brown_Rust	99.1%	98.5%	97.7%	98.1%	0.9%
Wheat_Common_Root_Rot	98.0%	96.5%	94.9%	95.7%	2.0%
Wheat_Fusarium_Head_Blight	97.6%	95.8%	93.2%	94.5%	2.4%
Wheat_Healthy	99.5%	99.2%	99.6%	99.4%	0.5%
Wheat_Mildew	98.9%	97.9%	97.0%	97.4%	1.1%
Wheat_Septoria	98.3%	96.8%	95.2%	96.0%	1.7%
Wheat_Yellow_Rust	99.2%	98.4%	98.0%	98.2%	0.8%

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2025, 10(36s)
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Research Article

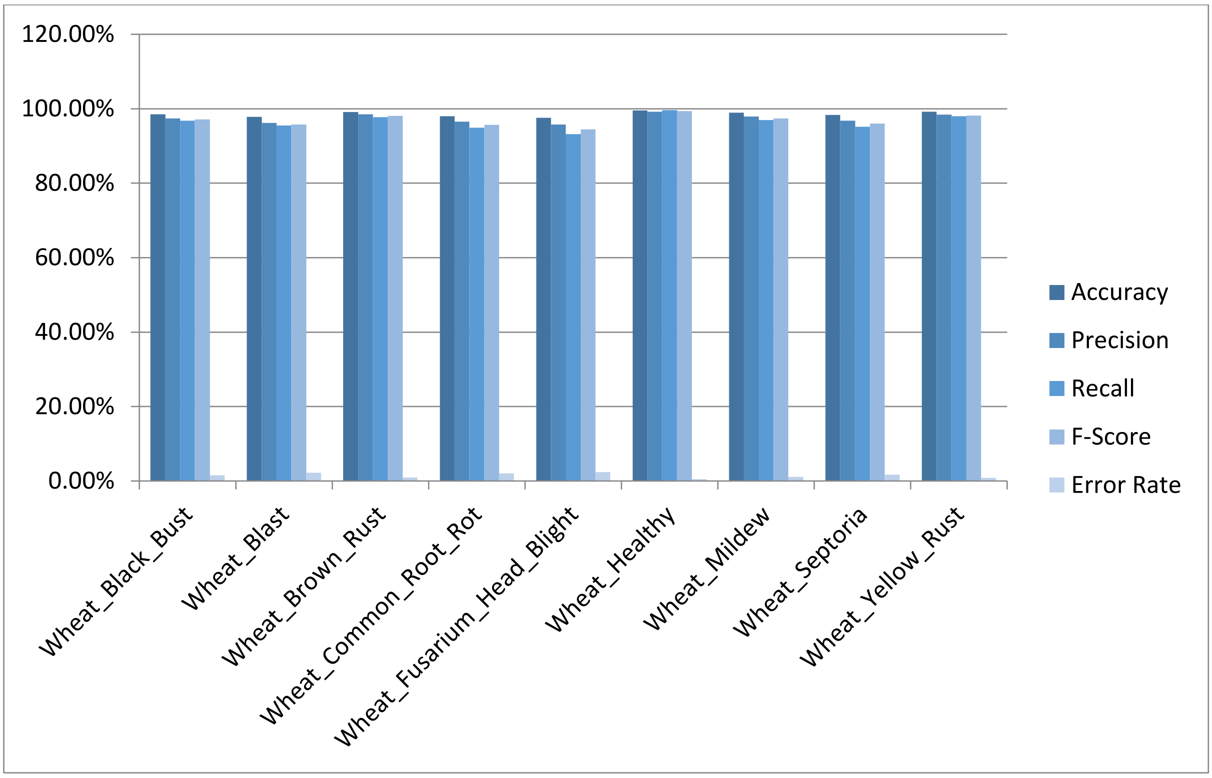

Figure 14: Wheat Disease Performance of Hybrid

The table 2 evaluates the performance of a classification model for detecting various wheat diseases and healthy wheat samples using metrics such as Accuracy, Precision, Recall, F1-Score, and Error Rate. The highest-performing category is "Wheat Healthy," with an outstanding accuracy of 99.5%, near-perfect precision (99.2%) and recall (99.6%), and the lowest error rate of 0.5%. Similarly, "Wheat_Yellow_Rust" and "Wheat_Brown_Rust" exhibit excellent performance, with accuracies of 99.2% and 99.1%, and low error rates of 0.8% and 0.9%, respectively."Wheat_Mildew" achieves a high accuracy of 98.9% and an error rate of 1.1%, reflecting robust detection capabilities. Categories such as "Wheat_Black_Bust," "Wheat_Septoria," and "Wheat_Common_Root_Rot" show reliable performance, with accuracies ranging from 98.0% to 98.5% and error rates between 1.5% and 2.0%. However, "Wheat Blast" and "Wheat_Fusarium_Head_Blight" have slightly lower recall values, which contribute to their overall accuracies of 97.8% and 97.6%, and slightly higher error rates of 2.2% and 2.4%, respectively. Overall, the model demonstrates excellent classification performance across all categories, with particularly strong results for healthy wheat, yellow rust, and brown rust, highlighting its reliability and precision in detecting wheat conditions.

5. Conclusion

This research delves into the transformative potential of deep learning in addressing the critical challenge of wheat and rice disease detection, presenting a multifaceted approach that combines technical rigor with practical utility. By employing a diverse range of state-of-the-art deep learning models, including CNN-2D, VGG16, ResNet50, InceptionV3, and MobileNet, alongside a hybrid model, the study underscores their varying capabilities in classifying diseases with precision and reliability. The hybrid model emerged as a standout, achieving near-perfect classification accuracy across categories, demonstrating the value of combining architectural strengths for enhanced performance. Notably, the framework integrates robust preprocessing and augmentation techniques to optimize model generalization, ensuring consistent performance across diverse datasets. A key achievement lies in its application-oriented implementation—a web-based system that facilitates real-time disease detection, empowering farmers with actionable insights for timely interventions.

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Research Article

The study's emphasis on evaluating performance metrics such as accuracy, recall, precision, F1-score, and error rate provides a holistic understanding of each model's strengths and limitations, revealing nuanced patterns in disease classification, especially in challenging categories like "Rice_Bacterial_Blight" and "Wheat_Fusarium_Head_Blight." These findings have profound implications for sustainable agriculture, as early and accurate disease detection is pivotal for reducing crop losses, enhancing yield, and ensuring food security. Moreover, the methodology and results lay a foundation for future research, encouraging exploration into more complex diseases, multi-crop systems, and integration with IoT-based smart farming technologies. By bridging advanced machine learning with practical farming needs, this study exemplifies a significant stride toward revolutionizing agricultural diagnostics, emphasizing scalability, accessibility, and impact on global food production systems.

Enhance the system by integrating IoT sensors for real-time data acquisition and disease monitoring, creating a comprehensive smart farming solution.

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