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Wheat Leaf Disease Detection: A Hybrid CNN Based Approach with Multisource Data

Rajendra Prasad Pandey[1]*, Rakesh Kumar Dwivedi[2]
[1]Research Scholar and Assistant Professor, Teerthanker Mahaveer University (TMU), Moradabad, Uttar Pradesh, India.
[2]Professor, Teerthanker Mahaveer University (TMU), Moradabad, Uttar Pradesh, India.
***Corresponding author:** rajendra.004@gmail.com

Abstract
Healthy crop plays significant role for quality and good quantity productions of crops. Due to the population growth and limited farming land, it increases the demand of crop production. Wheat crop is one of the major crop of all over the world because it's huge uses. Crop disease are one of the reasons for less production and bad quality of crop production. In early days when we not used machine learning and deep learning based methods to detect the crop disease, its time taken process, with the help of machine learning based methods we can detect the crop disease timely. Timely detection of crop disease help the farmers to remedy it on early stage. For timely and finest detection of disease in wheat leaf needed because lots of machine leaning based algorithm used for detection wheat leaf disease. So to take the advantages of various machine and deep learning techniques we can used the Hybrid based approach for detection the wheat leaf disease. Hybrid approach gives the flexibility to use more than one neural network architecture according to their strength and limitations. In this paper we propose CNN based hybrid approach that works on multisource data. Here we hybridize the CNN with some customization so that our model can give finest accuracy with multi source data. The multi-source data set will help to train our model that will give finest accuracy on light weight and real time data. The result suggest the most CNN performs better when we use original plus pre-process images and with the help of data augmentation we can enhance the efficiency from all models. ***Key words:*** *Machine Learning (ML), Convolutional Neural Network (CNN), Deep Neural Network (DNN), Artifical Neural Network (ANN), Rectified Linear Unit (Relu).*

INTRODUCTION:

Wheat crop is one of the crop that number of farmers across the world and India produce in their farms. Due to its huge demand and used this become the prominent crop cultivated by farmers. Due to the wheat crop disease and not detection by in early stage wheat crops are degraded and some farmers faces the losses. Computer vision and deep learning based technique having the ability to detect the crop disease in early stage, so quality product can be produce by the farmers. In our research we not only investigate the best deep learning based techniques that works on image classification but also having the advantage of working on light weight multisource data, so that it can easily works on real time image data.. Wheat crop is one of the most prominent crop in India as well as world**. In** this context, segmentation aims to isolate the diseased areas of the wheat leaf from the healthy background tissue.

By effectively segmenting the diseased regions, the proposed approach facilitates the subsequent classification of wheat leaves as healthy or diseased. This paves the way for the implementation of automated disease monitoring systems it can deployed in precision agriculture practices. These systems can continuously monitor wheat fields for the presence of diseases, enabling farmers to take prompt action and minimize crop losses. The approach of Convolution Neural Network for detecting the leaf disease of various crops is used because CNN having the methods for complex data analysis and image analysis. To improve the more accuracy here we apply the best fit approach for different phases, means here we apply the hybrid approach of CNN based. For instance, Lee et al.'s research showcases CNN's ability to automatically identify plants based on leaf images.

But adding the inception structure also makes it take longer.

Jin et al. [14] converted wheat head spectral data into two dimensions and fed it into a hybrid neural network, concentrating first on the model's capacity for generalization. which, on the validation dataset, obtained an accuracy of 84.6%. Large-scale crop disease detection was pushed forward by this. Deng et al. [15] segmented the stripe rust disease images using the Segformer algorithm in order to overcome the low accuracy of conventional methods. The model's performance significantly improved once the data were improved. However, this approach is limited to fall wheat diseases.

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X. et al. [18] “In the paper authors propose a model that will classify the wheat leaf diseases and detect the major diseases occurs in the wheat leaf”.
R. and S [19] “the comparison shown the SVM algorithm and neural network based AI and machine learning algorithm to identify the diseases on wheat leaf .The accuracy of different classification based algorithm also compared”.
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Sabouri, Atefeh [21].” proposes RGB image input model for enhancement disease detection algorithm”
Mokhtar et al. [20 “in this paper author detect the tomato leaf disease like powdery mildew and early blight diseases. Image pre-processing technique for noisy removal, image resizing and background cleaning methods uses for image enhancement”

1.1 Advantage of using Hybrid Model for Multisource Data

Due to technological advancements, mobile devices are rapidly maturing. Computer vision technology can be used by mobile devices to intelligently detect and diagnose crop diseases from leaves, determine the type and severity of the diseases, and provide farmers with quick recommendations for control and prevention. Therefore, lightweight networks offer significant advantages and promising results in detecting agricultural diseases. Lightweight network models can be used in environments with limited computing resources, such as embedded systems and mobile devices, and they offer benefits like high accuracy, fewer parameters, and lower computational costs. For example, portable devices can be used for testing, appropriate suggestions can be provided based on test results, and by accessing additional data sources, agricultural productivity and control effectiveness can be improved without the need for experts or laboratory equipment.

2. MATERIALS AND METHODS USED

2.1 Image Data Set

The wheat leaf data sets used for this paper have three classes healthy leaf and two diseased leaf. The two wheat leaf diseased explored here are septoria and leaf _rust. These wheat leaf diseased data set collected from Kaggle and some primary data sets from mawana ,Uttar Pradesh, India. In our data set we maintain 5000 images. With the help of augmentation we increase it about total 7000 images.

Figure 1: Wheat Leaf Image Data

2.2 Preprocessing the Data Set

In this study, contrast enhancement was used to reduce the effects of uneven lighting in the images. Data augmentation is a method to expand the training set, aimed at improving the robustness and generalization capability of deep learning. Since there are not enough images of wheat diseases available, neural networks may become overly specialized (overfit) to the training set, which can cause problems in the CNN during testing. Therefore, techniques such as rotation, symmetrical flipping, and contrast enhancement were applied to augment the wheat disease data.

Table 1. Wheat leaf dataset after image enhancement.

Wheat Types	Images	Training Images	Testing Images
healthy	1250	950	300
leaf rust	1100	900	200
septoria	1380	1104	276

2.3 Proposed approach
LeNet was the first convolutional neural model to successfully recognize handwritten digits. In recent years, convolutional neural networks have made significant progress in various fields. Due to continuous advancements in deep learning theory and computer hardware, there are limitless possibilities for the development of convolutional neural networks. In this paper, we have integrated attention mechanisms into residual structures and combined inception and residual modules. To detect and classify the types of wheat diseases, as well as to evaluate their effectiveness, we propose a lightweight hybrid CNN model.

2.3.1 Inception Model
One of the prominent model for complex data calculation proposed by Google is Inception Model. It works as the deeper subnetwork models that works efficient for image based data. The various version of Inception model (Inception v1 to v4 and Xception) shows the continues incremental growth of this model. The Inception module can automatically select appropriate convolution kernels and pooling operations, enhancing the network's performance and efficiency. The main advantage of the Inception module is its ability to extract features at multiple scales.

2.3.2 ResNet
ResNet is a deep convolutional neural network architecture that has skip connections and residual units which can be used to build very deep architectures (18, 34, 50, 101, and 152 layers deep). ResNet potentially has the ability to tackle the degradation of deep networks that is the performance is either unchanged or even worse, with depth. It is easier for the network to learn to identify mappings or residual functions because the residual structure is meant to facilitate learning and help gradient propagation.

2.3.3 Attentional Mechanisms
The attention mechanism is a key component of deep learning and is used extensively across many domains. It increases the model's efficiency and accuracy, helps it concentrate on important regions, and lessens the interference of irrelevant data. In order to improve the model's capacity to distinguish between wheat diseases in a complex setting, this paper adds an attention mechanism to the residual structure. Attentional mechanisms add the functionality to focus on specific region without bothering the background. Channel, spatial, and mixed attention mechanisms are the three categories into which attention mechanisms fall. CBAM is a generalpurpose, lightweight attention module. CBAM used in our model to find out the wheat leaf disease region in images, minimizing the effect of complex background on wheat leaf disease identification.

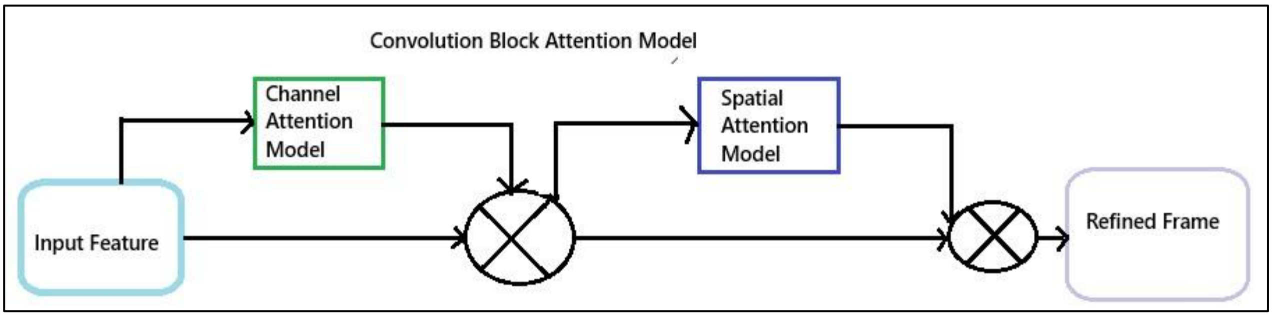

Figure 2: CBAM

3. PROPOSED MODEL
Training can be accelerated and the network width increased with the Inception module. The gradient problem and the degradation problem can both be resolved by the residual block. When these two modules are combined, network redundancy and complexity are decreased while accuracy is maintained. The efficiency and accuracy of the model are enhanced by the attention mechanism's ability to evaluate and weigh channel attention and spatial attention concurrently. Thus, the Inception-ResNet-CE (INRNCE) model, a Hybrid CNN information fusion model with multiple attention mechanisms, is proposed in this paper. This model can quickly and effectively identify wheat diseases in complex backgrounds because it is a lightweight and efficient neural network model that is appropriate for

multisource data. Three pooling layers, a fully connected layer, and two residual-CE structures make up the model framework.

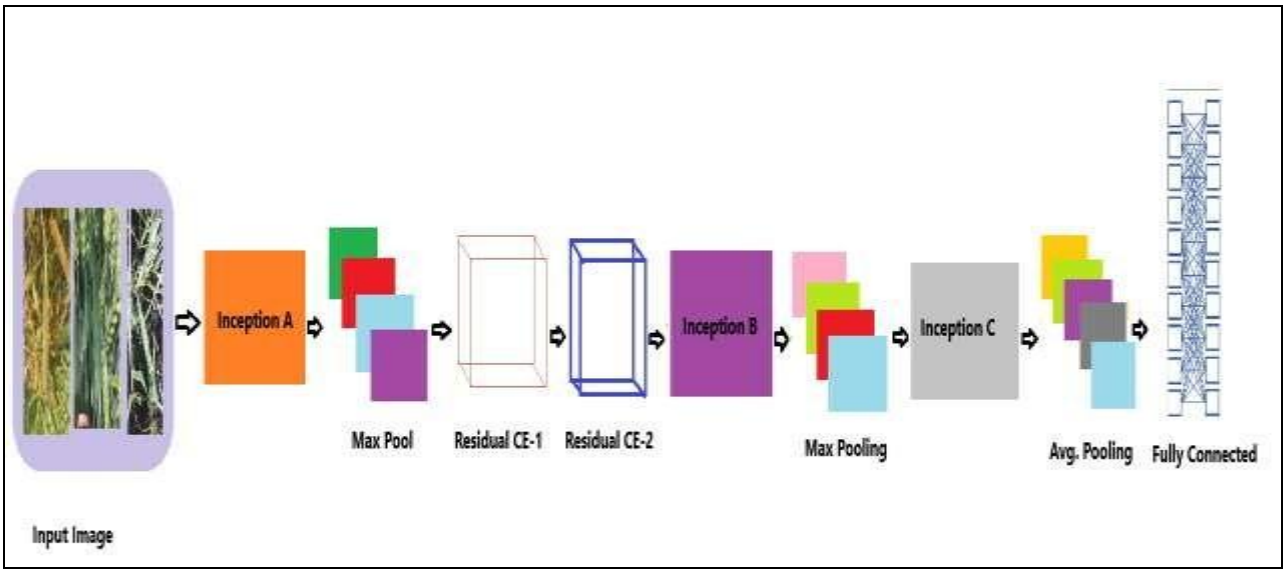

Figure 3: Proposed Hybrid Model

For the deep and detail image feature information that is needed in wheat leaf disease detection for accuracy purpose here we used three modules of inception model.

The Residual-CE module can recombine the original wheat disease image's features, which helps the model learn. Additionally, samples can be mapped from high-dimensional feature space to low-dimensional feature space using residual-CE while maintaining excellent separability. The Residual-CE-1 structure consists of an identity map, a CBAM module, an ECA module, and two 3 × 3 convolutional layers. A 1 × 1 convolution short link is added to Residual-CE-1 by Residual-CE-2.

4. RESULT

The Practical work tested and completed with some experimental setup. In our setup the hardware part include Intel ® Core i7 2.10 Ghz processor, 16 GB RAM and 4 TB Secondary storage. Our Code executed using Python 3.0, the keras 2.3.0 library with tensor flow 3.1.1.4.This paper contains three sets of experimental comparisons. The impact of the inception module on the model is examined by the first group. The impact of attentional mechanisms on the model is examined by the second group. The third group evaluates the accuracy and performance of the suggested model against the state-of-the-art algorithms. The suggested model is contrasted with the traditional lightweight CNN models in the fifth group. The INRNCE model's accuracy curve on the training dataset is displayed in Figure 4. The figure illustrates how quickly the accuracy rate rises during the initial training. The accuracy variations are more when epoch 10 to 30. After 40 epochs the accuracy rate graph shows the stability in training, overall it' shows the increasing in accuracy.

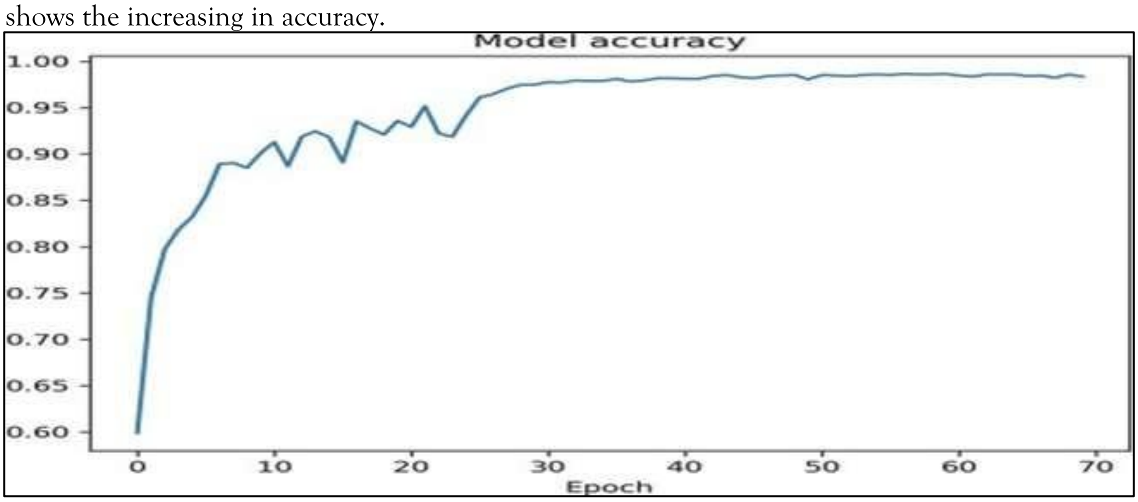

Figure 4: Accuracy in Training

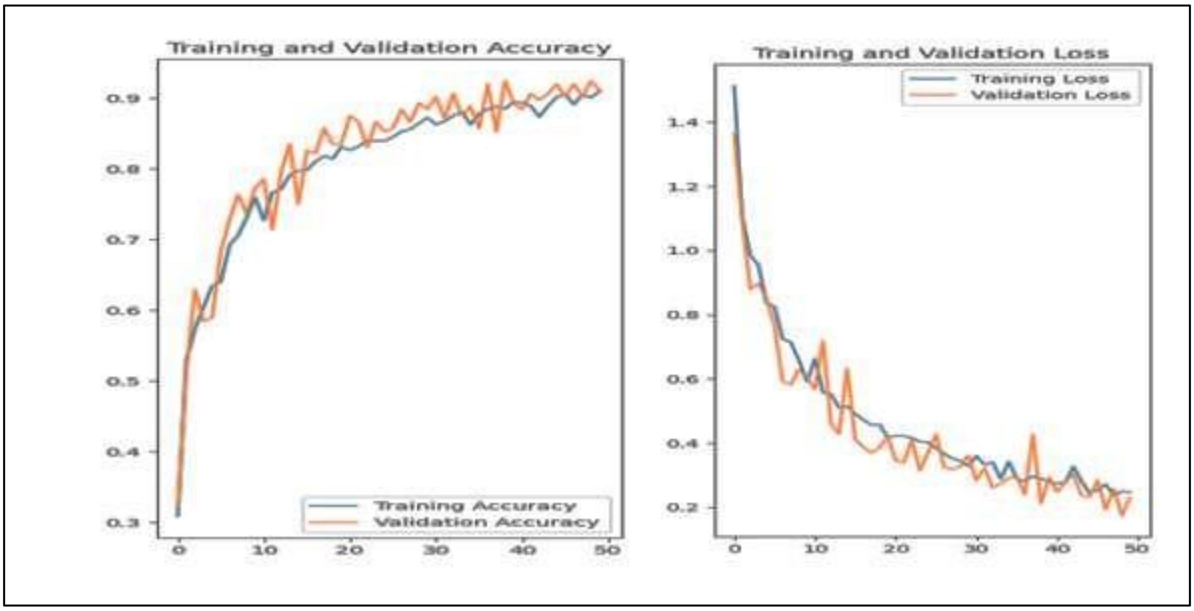

Figure 5: Training and validation accuracy with loss

4.1 Analyzing the impact of Inception Model

We tested various models with Inception modules and ran four sets of experiments using the wheat disease dataset to investigate the impact of the Inception module on the model. Table 2 displays the findings. As can be seen from the analyzing table, the model's accuracy and F1-score both are increased by 0.80%, and 0.90%, respectively, when only one Inception module(Inception-A) used in model ,the model's performance improved more than when both Inception-A and Inception-B were added. In addition to improving performance the most, we can get it when three Inception module were used.

Table 2: Analyzing the impact of three inception module

Inception -A	Inception-B	Inception-C	Accuracy (%)	F1-Score (%)
N	N	N	94.80	94.41
Y	N	N	95.60	95.31
Y	Y	N	96.10	95.40
Y	Y	Y	97.95	97.88

4.2 Effect of Attentional Mechanisms on the Model

The outcomes of incorporating various attention mechanisms into the model indicate that attention mechanism increase the model accuracy. In our model adding the attentional mechanism shows the little bit impact of when we used one attentional mechanism. The model's detection accuracy rises by more than 1% when two attention mechanisms are added, with CBAM.

4.3 Comparative Analysis of Proposed model with the classical multisource model

Comparative test analysis always shows the actual impact of research work that any one performs.

Here we shows the comparative analysis of our proposed hybrid model (INRNCE) with three model MobileNetV3 –Small, MobileNetV3-Large, EfficientNetb0 to show the effectiveness of our proposed model. In comparative table we can see the Proposed model (INRNCE) shows the height classification accuracy of wheat leaf disease detection with less training time. Although MobileNetV3-Small model also having the less training time (1.48 h), but our proposed model having best accuracy 97.96 and F1-Score 97.95 and minimum training time 1.38 h. It will clearly shows the impact of Our proposed approach that we follow in our proposed model.

Table3: Comparative Analysis of Proposed model with the classical multisource model

Model	Accuracy (%)	F1-Score (%)	**Training-Time (h)**
MobileNetV3-Small	94.74	94.83	1.48

MobileNetV3-Large	95.85	95.92	1.50
EfficientNetb0	95.92	95.97	1.75
INRNCE	97.96	97.95	1.38

5. DISCUSSION

In our proposed model we introduce inception modules in network. These three inception modules put in specific positioned or order in the model. The first Inception-A module positioned at start of the network, Inception-A module contains the basis fundamental nature, extract the feature on various scaling point. Inception-A could be worked as feature extracting on different scales. Inception-B positioned in the center of the network as a transition since it was a deduction module the use of this module to feature the map's size, increasing network's depth and and receptive field. We positioned Inception-C at the end as the network's top layer because it was a more sophisticated Inception module that could be used to extract finer-grained and graterscale features.

The residual structure is a technique used in deep learning that uses identity mapping to address the degradation issue as the number of network layers rises. To balance the network's expressiveness and computational efficiency, the number of residual structures must be chosen based on the task and dataset. This paragraph describes our three attempts to introduce the residual structure and a comparison of the outcomes.

6. CONCLUSION

Make a significant contribution to wheat disease control by correctly identifying it through multisource in intricate agri-land environments. The integration of attention module (CBAM and ECA) with residual block , that can carry refined version of feature , this optimized input feature with combination on three inception module create new optimal network with few parameters and minimal computation. Our hybrid approach shows the minimize computation with maximum accuracy. Our proposed hybrid model INRNCE shows the highest accuracy in our experiments results. In table 2 we can see the that INRNCE model get the accuracy of 97.95% and F1-score 97.88% in compare to without three inception modules that accuracy 94.80 and F1-score
94.42 respectively. Three Inception modules gives the boost in our proposed model.

Furthermore attentional mechanism also increase the performance of INRNCE model. The CBAM attentional model uses to decrease the parameter that tends to increase the computations speed on complex data. It could also use for deeper leaning that colud help to find out the classification of wheat leaf diseases. If we compare our model to other CNN based classical model the number of parameter used is lowest in our model. Furthermore, we contrasted the IRCE model with traditional lightweight models. The IRCE model takes the least amount of time to train—just 1.38 hours—and is 1.98% more accurate than the most accurate model, EfficientNetb0. This paper demonstrates the viability of the suggested model through experimental comparison. Our approach can offer accurate and dependable technical tools for identifying and detecting wheat disease. Our approach also not bound to users not to use one type of specific data, although we prepressed the input data but the input data may be multisource data. When any user like farmers want to detect the dieses they can used mobile devices like cell phone images to identify diseases and get advice on how to apply pesticides to reach the right levels and boost wheat yields.

But there are drawbacks to our approach as well. Our model uses more computing power and has a higher computational load than traditional lightweight models. This is precisely what we must do better in our upcoming work. We discovered during the experiment that the model's performance can be impacted by the image's quality. The image quality of the crop disease image databases that are currently available is subpar.

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