A Deep Learning Based Mobile Application for Wheat Disease Diagnosis

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Citation | Riaz. S, Taimour. R, Javed. M. A, Khalil. A, Afridi. Y. S, Iqbal. A, "A Deep Learning Based Mobile Application for Wheat Disease Diagnosis", IJIST, Special Issue pp 51-62, May 2024
Received | May 03, 2024, **Revised |** May 11, 2024, **Accepted |** May 16, 2024, **Published |** May 21, 2024.

Wheat is one of the major staple crops in Pakistan, playing a crucial role in ensuring food security and contributing to the country's economy. The productivity and quality of wheat crops, however, are vulnerable to several illnesses. The ability to diagnose these diseases quickly and accurately is crucial for taking the appropriate preventative actions, limiting losses, and maintaining food security. In this research paper, we build and test a wheat disease detection system adapted to the conditions in Pakistan. The suggested method uses machine learning-based techniques along with image processing algorithms to automatically detect and categorize various wheat diseases based on their symptoms. High-resolution photos of healthy wheat plants and sick plants displaying different diseases were collected from different regions of Pakistan in order to construct an accurate and robust disease detection model. The dataset has been annotated by plant pathologists who provided true labels for use in evaluation and training. To achieve the best results in wheat disease diagnosis, many cutting-edge deep-learning architectures were investigated and optimized. These included Convolutional Neural Networks (CNNs) and Transfer Learning models. Multiple models' effectiveness was evaluated using accuracy, precision, and recall, in a series of extensive trials.

Keywords: Wheat diseases, Convolutional Neural Networks (CNNs), Transfer Learning, Tensor Flow.

Introduction:

Wheat is a vital cereal crop in Pakistan, serving as a staple food for the nation's population and playing a significant role in its agricultural economy. However, the cultivation of wheat faces formidable challenges, with plant diseases being a primary concern. Various diseases, caused by fungal, bacterial, and viral pathogens, can severely affect wheat crops, leading to substantial yield losses and compromising food security in the country. Timely and accurate diagnosis of wheat diseases is crucial for implementing effective strategies for disease management [1]. Traditionally, disease identification has relied on manual visual inspection by experienced agronomists and plant pathologists. While effective, this process is time-consuming, and subjective, and may lead to misdiagnosis due to the similarity of symptoms among different diseases.

In recent years, technological advancements in the fields of machine learning, computer vision, and image processing have revolutionized the agricultural sector **Error! Reference source not found.**. These developments offer promising opportunities to automate disease detection and revolutionize the way we monitor and manage plant health. This paper aims to develop a wheat disease detection system tailored specifically to the conditions prevailing in Pakistan. By integrating cutting-edge machine learning algorithms and image processing techniques, the system will automatically identify and classify various wheat diseases based on visual symptoms exhibited by infected plants. To achieve this, a comprehensive dataset comprising high-resolution images of healthy and diseased wheat plants was collected from diverse regions in Pakistan.

In many regions of the world, the absence of infrastructure makes it difficult to quickly identify wheat infections, which pose a danger to food security. To that end, we plan to develop a mobile application for diagnosing agricultural diseases. We propose an intelligent and effective application that leverages AI computer vision and machine learning algorithms to identify agricultural diseases. Our dataset is the Plant-Village Dataset (New), which is part of the CNN family. The latest iteration of the plant-village dataset includes 10,000 photos for training and 2,500 for validation. A separate set of 33 test photos was used to evaluate the accuracy of the model.

Literature Review:

Researchers have made great strides in the field of agriculture recently. The detection of plant diseases has been accomplished using a variety of methods. Many studies reveal that they employ various algorithms; among these are Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) **Error! Reference source not found.**. Despite this, researchers are constantly on the lookout for new methods that are both more effective and more interesting to users.

Yusuke Kawasaki and Hiroyuki Uga in **Error! Reference source not found.** analyzed methods for spotting plant diseases using photographs of their leaves. They discussed several methods for removing the afflicted portion of the plant. They also looked at certain feature extraction and clustering techniques for identifying plant diseases and distinguishing between healthy and contaminated leaves. To ensure a successful harvest, accurate recognition and categorization of plant infections using image processing is essential. Methods for removing the highlights of a contaminated leaf, characterizing plant diseases, and several techniques for fragmenting the infected portion of the plant. Disease in plants can be characterized with ease using ANN methods including self-sorting highlight maps, back spread calculations, support vector machines, and so on. Based on these methods, a picture-handling strategy can be used to accurately identify and rank various plant diseases [5]. Results were evaluated using a dataset of 87k RGB photographs of healthy and defected plant leaves divided into groups of 38, out of which 25 were chosen for experimental purposes. This makes use of Al and cameras to detect objects. The proposed approach has a 93% success rate in identifying 20 distinct plant diseases across 5 different species together with back propagation neural network (BPNN) and other digital image processing techniques.

In **Error! Reference source not found.**, Monica Jhuria, Ashwani Kumar, and others discussed techniques for identifying plant illness in photographs of leaves. Two datasets are used in the implementation of support vector machine (SVM). In this case, training datasets are compared to their corresponding datasets stored photographs. After applying a filter, two photographs are compared to one another. After contrasting healthy and unhealthy regions, they arrived at a percentage fraction. An artificial neural network method has been applied for disease identification. They have a wide variety of algorithms for disease detection. Some examples of algorithms used in the artificial neural network method are backpropagation, support vector machine, and major component analysis **Error! Reference source not found.**. The proposed method has an accuracy of 91%.

With the help of deep learning and image identification, Ahmed, A. A., and Reddy, G. H. **Error! Reference source not found.** examined the technological possibility of automating disease detection. Using a publicly available dataset with 54,306 images of healthy and diseased plant leaves, a deep convolutional neural network has been trained to classify crop species based on their disease status into 38 categories, including 14 species of crops and 26 types of crop diseases. The model is accurate to within 1% on average. The average accuracy of random guessing on a dataset with 38 class labels is only 2.63%. Overall accuracy on the Plant Village dataset ranged from 85.53% (in case of Alex Net: Training from Scratch: Gray Scale: 80 – 20) to 99.34% (in case of Google Net: Transfer Learning: Color: 80 - 20), demonstrating the promising potential of the deep neural network architecture.

Methodology:

This section explains how to identify plant diseases using photographs of affected leaves. Extracting the image's attributes or valuable information from the image is the goal of image processing, a subfield of signal processing. It displays accurate results by evaluating multiple picture attributes to diagnose illnesses on plant leaves as shown in Figure 1. Crop diseases pose a significant risk to food security, yet their prompt detection continues to be challenging in numerous regions globally due to inadequate infrastructure. The aim is to develop a mobile application for diagnosing diseases that can be easily accessed by farmers. The implementation through a mobile application aims to enhance access for the average farmer. Our solution includes identifying potential causes of diseases and offering corresponding treatments. Utilizing mobile phone applications will assist farmers in improving their production levels and income.

Plant and crop diseases can be broken down into four categories: oomycetes, hyphomycetes, bacteria, and viruses. Visual examination of leaf color patterns and crown architecture remains the gold standard in conventional field scouting for crop diseases. Examining plant leaves for disease symptoms and diagnosing plant diseases based on experience requires a significant amount of time, effort, and expertise when done using the naked eye. In addition, the wide range of plants means that illnesses can manifest themselves in a wide range of ways across various crops, adding a layer of complication to the process of categorizing plant diseases. Meanwhile, a lot of research has been done using machine learning to categorize plant diseases. First, the background is removed, or the infected part is segmented using preprocessing techniques; second, distinguishing features are extracted for analysis; and third, classification or clustering algorithms are used for feature classification [9].

Most of the algorithms developed for previous machine learning techniques did not meet the needs of real-world applications, even though many novel algorithms have been established in this field. The agricultural sector that uses machine learning to improve crop yields is increasingly moving towards Deep Learning techniques and in particular CNNs. Because of its versatility in detection and classification, such as weed detection, crop pests' categorization tasks, or identification of crop illnesses, deep learning approaches are increasingly used in agriculture production. One advantage of using a Deep Learning model is that it eliminates the need for a segmentation operation when extracting features from a task. The object's retrieved features are successfully mined from the raw data.

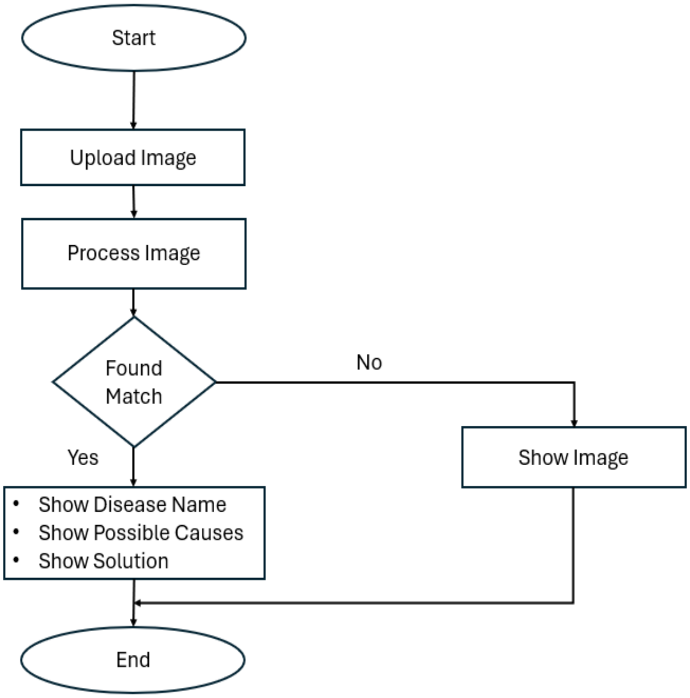

Figure 1: Flow chart of application

Convolutional Neural Network (CNN):

Major demands on CNN -based, when it comes to the classification of plant diseases, deep learning is unmatched in terms of both scale and variety of datasets **Error! Reference source not found.**. The majority of leaf disease classification systems use CNN. Other types of DL networks, such as deconvolution networks and fully convolutional networks (FCNs) are more commonly utilized for picture segmentation and medical diagnosis than for classifying diseases in plant leaves [11].

The image's local correlation is used by the convolutional layer in order to extract relevant features. The image's upper left corner is marked with a kernel. Multiplying the pixel values by their matching kernel values, summing the products, and finally adding the bias. The kernel is shifted by one pixel and the filtering process is repeated until the entire image has been processed. The pooling layer makes the model robust to translations, rotations, and scaling by randomly choosing features from the feature map of the higher layer. Maximum or average pooling is the most popular option. In maximum pooling, the input image is divided into numerous rectangular areas with the size of the filter determining which regions receive the maximum value. When regions are pooled together, the result is an average of all of them. In many implementations, convolutional layers follow a pooling layer and vice versa. For classification or detection tasks, the classifier integrates and converts multidimensional information into one-dimensional features at the fully connected layer, where each neuron is connected to the neuron above it **Error! Reference source not found.**.

VGG19:

VGG stands for Visual Geometry Group. The VGG network is specially crafted for tasks related to image classification. VGG19, a part of this network, is comprised of 19 layers, with 16 being convolutional layers and 3 fully connected layers. The convolutional layers are tasked with extracting features from input images, whereas the fully connected layers handle the classification of these features into various categories or classes.

Table 1: Dataset

Dataset	Images
Leaf rust	2000
Loose Smut	1800
Crown and Root Rot	1700
Healthy	2200

MobileNetV2:

MobileNetV2 is an attempt to design a convolutional neural network that can function well on mobile devices. It is predicated on a backward residual structure, with the bottleneck levels connecting via residual nodes. Lightweight depth-wise convolutions are used in the intermediate expansion layer to filter features and introduce non-linearity. MobileNetV2's overall architecture consists of a 32-filter fully convolutional first layer, followed by 19-filt]er residual bottleneck layers **Error! Reference source not found.**.

Plant-Village Dataset:

- The dataset as shown in Table 1 has been acquired from Hazara University Mansehra, KPK, Pakistan. It has 10k total images.
- It has 4 classes having diseased and healthy leaves.
- The dataset is divided into 80/20 ratio (8000/2000) for training and validation respectively.

Data Augmentation:

It's common knowledge that deep learning works best with a lot of information. Little data may not be sufficient for model training. For this purpose, data augmentation to create new examples for the training phase. Common methods of data enhancement include geometric modifications including mirroring, cropping, rotation, and translation as shown in Figure 2.

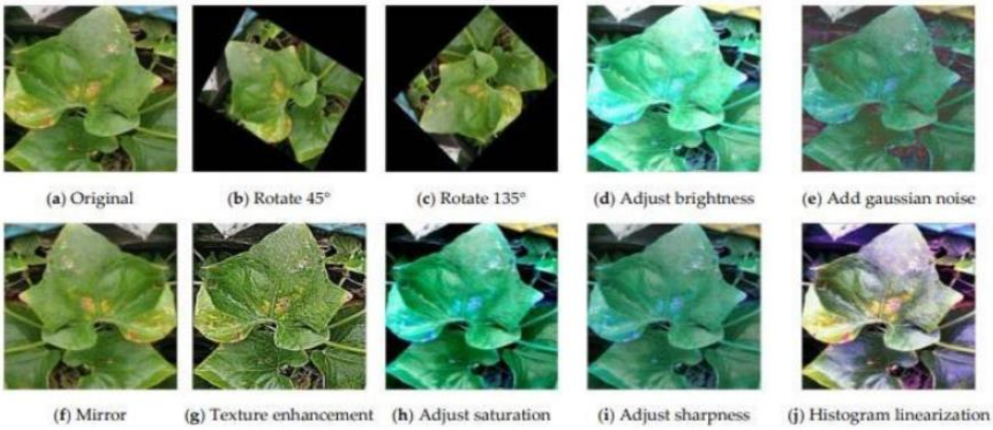

Figure 2: Data Augmentation

Data Generation:

In some cases, access to reliable information is limited. In this scenario, fake data for used in the training detection model. The usage of synthetic data creation has grown in the field of machine learning because of its inexpensive cost. Generative Adversarial Networks (GANs) methods can be used to generate fake data. To construct fictional instances from a dataset with the same properties as the original set, GAN uses a generative modeling technique called generative adversarial networks [12].

Model Selection:

Alex Net, VGG Net, GoogLe Net, Res Net, Mobile Net, and Efficient Net are only a few of the CNN-based classification models produced in DL-related research for use in classification tasks **Error! Reference source not found.**. After placing first in the ImageNet competition in 2015, Microsoft Lab unveiled the ResNet network. Using shortcut connections and residual blocks, the network was able to address the problem of gradient reduction. In 2016, Res Net networks gained more attention in the field of Deep Learning.

In 2017, Google's engineering teams unveiled the Mobile Net network for use in mobile gadgets and embedded software. In 2019, those same Google groups unveiled the Efficient Net network. The network used an easy compound coefficient to implement the strategy of scaling the depth, resolution, or width. When it comes to plant and crop diseases, Deep networks are not required for classification but are the ideal solution because of their high performance. Alex Net and VGG16 are thought to be suitable for the actual accuracy performance needed in agricultural production, in addition to Deep networks **Error! Reference source not found.**. This process of training and deployment can be divided into the following three steps. The first step is data preprocessing and preparation. The second step is Model building, training, and evaluation and the final step is model inference and deployment as shown in Figure 3.

Preparing the Data and Preprocessing

Deep Learning models prioritize data preparation and preprocessing data. Strong accurate and trained input data bounds to precise results. Original datasets require training, validation, and testing set processes, the general statistical percentages for such are 70:20:10, 80:10:10, and 60:20:20 [15]. In our model system, the model has been fed with public plant datasets by using the Kaggle platform, as it contains 87k images.

A good DL model architecture is required prior to training. Better accuracy and faster classification can be achieved with a well-designed model. CNNs, RNNs, and GANs are the three most common forms of DL networks nowadays. When it comes to the task of detecting and classifying plant diseases, CNN is by far the most used feature extraction network.

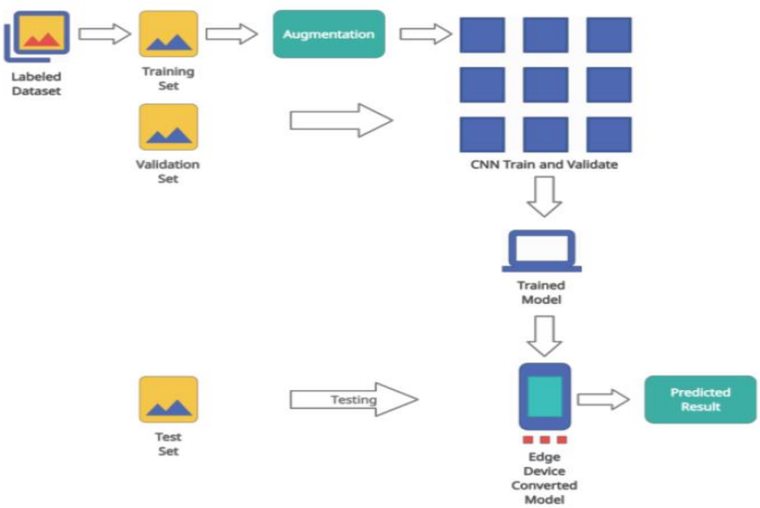

Figure 3: Steps in model training

Once the framework of the model has been built, hyperparameters can be adjusted for use in training and testing. The grid search technique can be used to iteratively explore several parameter configurations in pursuit of the optimal one. During neural networks, training data are stored in the first layer, and back-propagation is used to adjust the weight of each neuron based on whether the output matches the label. This cycle is repeated until a new skill can be taught using the available data. The model's efficacy was measured with metrics like accuracy, precision, recall, and F l score. These indexes can't be discussed in isolation; rather, they need to be introduced alongside the more general concept of a confusion matrix. In binary classification, the confusion matrix displays the expected yes/no answers **Error! Reference source not found.**.

Evaluation Measures

The classification models, involving both the detection and classification of plant diseases, were implemented with deep learning. The statistical evaluation classified the samples of images into the following statuses: True-Positive (TP), which determines the perfectly-identified image samples being infected, False-Positive (FP), which determines the wrong classified image samples being infected, True-Negative (TN), which determines the correct classified image samples being healthy and False-Positive (FP), which determines the wrong identified image samples being healthy.

$$\text{Accuracy} = TP+TN/TP+TN+FP+FN \qquad (1)$$

In plant disease evaluation, classification and accuracy are considered essential for the purpose. From equation 1 High value of accuracy and precision tends to be regarded as better for the performance. When the value of F1 is less, the trained model tends to perform much better. The capability of the trained model is applied to new data when the training and evaluation processes are finished.

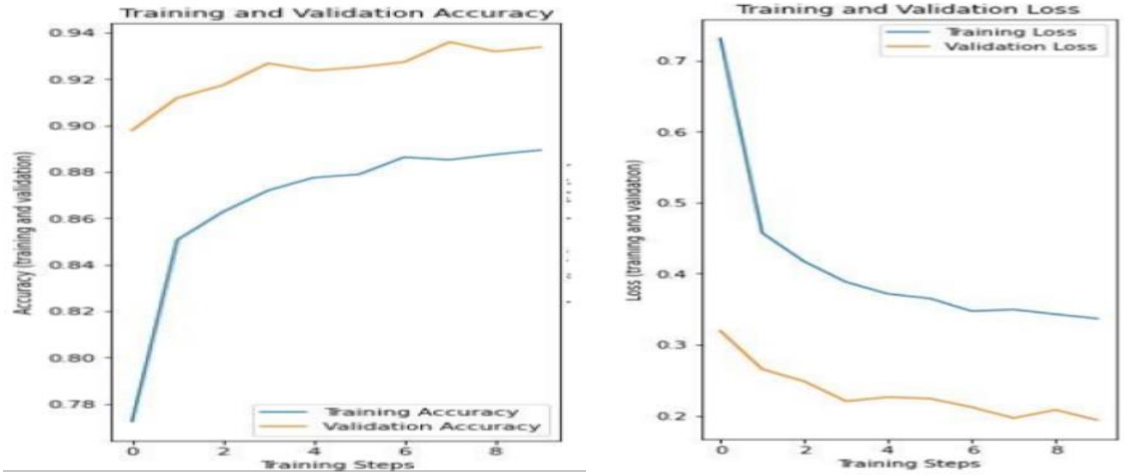

Figure 4: Model training and validation**.**

Transfer Learning:

Transfer learning comes in the classification of the machine learning technique domain. The certain technique adopts the learning capabilities from the recent tasks to the proceeding tasks **Error! Reference source not found.**. With new databases, a few layers of pre-trained networks of the model are retrained by reducing the need for masses of datasets, inclining the model towards better performance. Research by Mukti et al reports the utilization of the transfer learning model by using Res Net 50, by implementing the approach of recognizing plant diseases, as it gives satisfactory results. The report contains a dataset of 87.867 image samples where 80% of the dataset is used for the training set and the remaining 20% is used for validating the set process. The report concludes with an accuracy of 99.80% from the model implemented practically.

Tensor Flow:

TensorFlow is an open-source machine-learning framework used by researchers and developers. It offers a rich ecosystem of tools and resources for creating and deploying ML apps. Users can choose the level of abstraction they need, with the Keras API simplifying model building. Eager execution allows for fast iteration and debugging. The Distribution Strategy API enables distributed training without modifying model design, making it suitable for large ML jobs. TensorFlow also supports creating complex models efficiently with features like the Keras Functional API. Supplementary libraries like Tensor Flow Probability and BERT can be used alongside Tensor Flow for various tasks.

Results:

The proposed system results are gathered from the trained model before its deployment and after its deployment in mobile-based applications. We used a technique called cross-validation, in which we divided their data into a training set and a validation set. The model is "trained" using the training set, while its performance is "validated" using the validation set. Figure 4 depicts loss and accuracy during training and validation, respectively. The validation accuracy is higher than the training accuracy. On the training dataset, the model's loss will nearly always be smaller than on the validation dataset. Thus, a discrepancy between the train and validation loss learning curves is to be anticipated. The void between these two ideals is known as the "generalization gap." A validation loss that is smaller than the training loss may also be used to detect it. It suggests the validation dataset may be more predictable by the model than the training dataset. Accuracy is used as a measure of style in the context of typography. Accuracy refers to the proportion of correctly predicted events that our version anticipated. The formal definition of precision is as follows: the proportion of correct predictions to total forecasts is the standard by which accuracy is measured. We see convergence in our model. We obtained a validation accuracy of 93%+ in just 10 epochs as shown in Figure 4.

```
Epoch 1/50
56/56 [==============================] - 76s 1s/step - loss: 1.9670 - accuracy: 0.5963 - val_loss: 0.9167 - val_accuracy:
0.7188
Epoch 2/50
56/56 [==============================] - 47s 842ms/step - loss: 0.9288 - accuracy: 0.6926 - val_loss: 0.6480 - val_accura
cy: 0.7587
Epoch 3/50
56/56 [==============================] - 50s 895ms/step - loss: 0.7430 - accuracy: 0.7321 - val_loss: 0.6070 - val_accura
cy: 0.7743
Epoch 4/50
56/56 [==============================] - 49s 876ms/step - loss: 0.6785 - accuracy: 0.7539 - val_loss: 0.5885 - val_accura
cy: 0.7951
Epoch 5/50
56/56 [==============================] - 47s 845ms/step - loss: 0.6091 - accuracy: 0.7811 - val_loss: 0.5149 - val_accura
cy: 0.8090
Epoch 6/50
56/56 [==============================] - 50s 899ms/step - loss: 0.5869 - accuracy: 0.7794 - val_loss: 0.4834 - val_accura
cy: 0.8316
Epoch 7/50
```

Figure 4: Accuracy values:

To make our model communicate with App we must convert it into the Tensor Flow lite version, which is made for mobile Versions **Error! Reference source not found.**. So, you can build or create a mobile app and make the app communicate with the model. The following steps are being done:

- The saved model was converted into TFLite.

```
model.save('mobilenet.h5')
```

- Model converted to TFLite which is then used to develop a mobile application.

```
# convert the model to TFLite
import tensorflow as tf
from tensorflow import lite
from tensorflow.keras.models import load_model
converter = lite.TFLiteConverter.from_keras_model(model)
tfmodel = converter.convert()
open ("model.tflite" , "wb") .write(tfmodel)
```

The prototype application uses a camera or device media to get an image of the crop as shown in Figure 5. Preview the images and send them to API, for disease detection are shown in figure 6 and figure 7. Results page showing detected disease as given in Figures 7 and 8 for diseases such as Root Rot and Leaf Rust. The healthy wheat plant results are given in Figure 9.

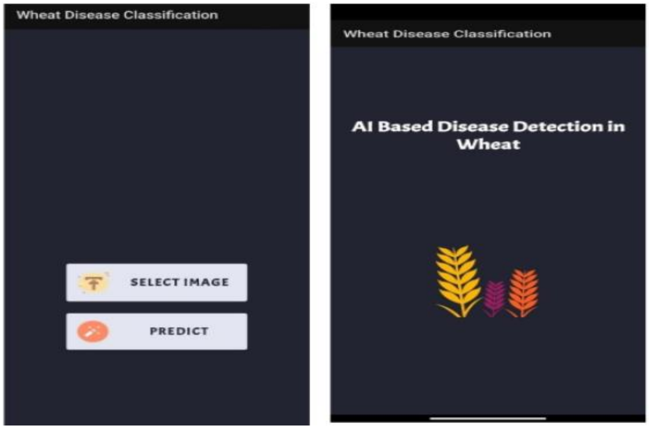

Figure 5: Prototype of mobile application

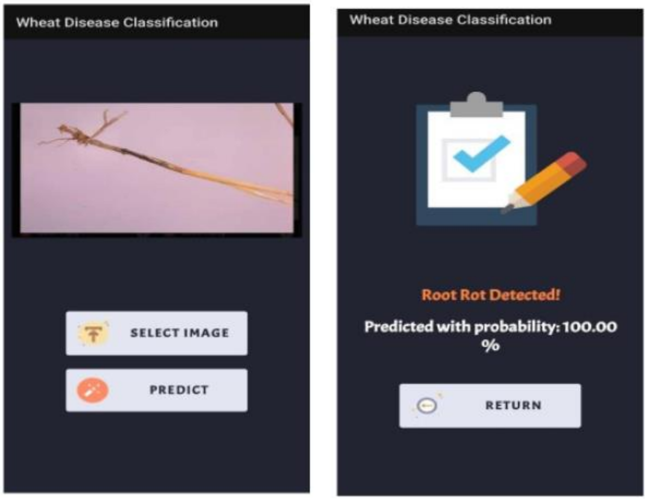

Figure 6: Root Rot disease

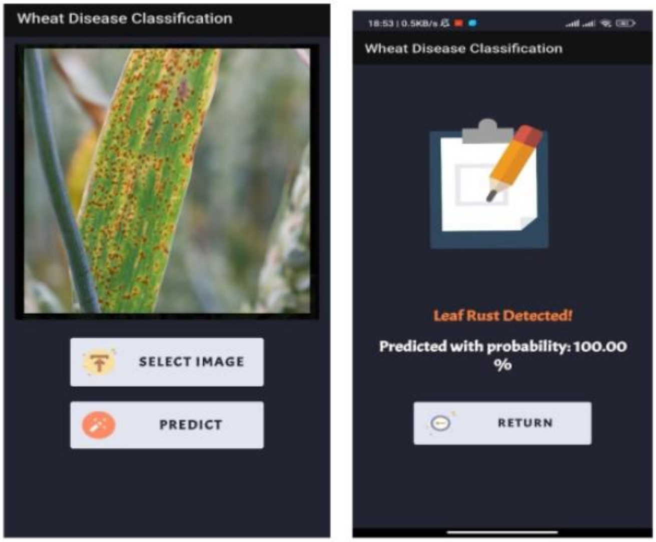

Figure 7: Leaf Rust disease

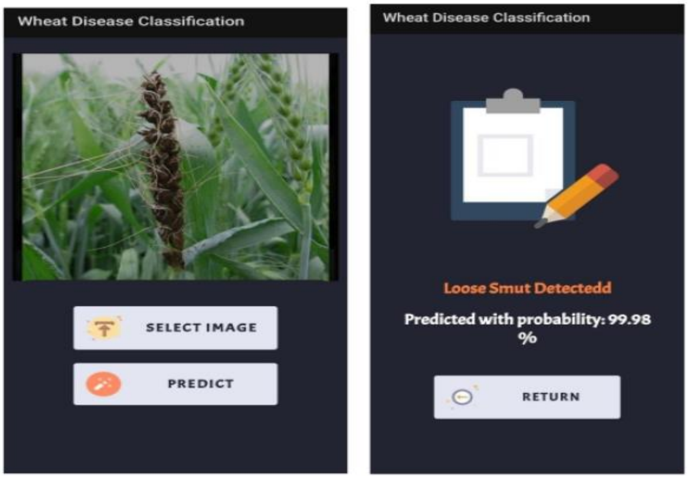

Figure 8: Loose smut disease

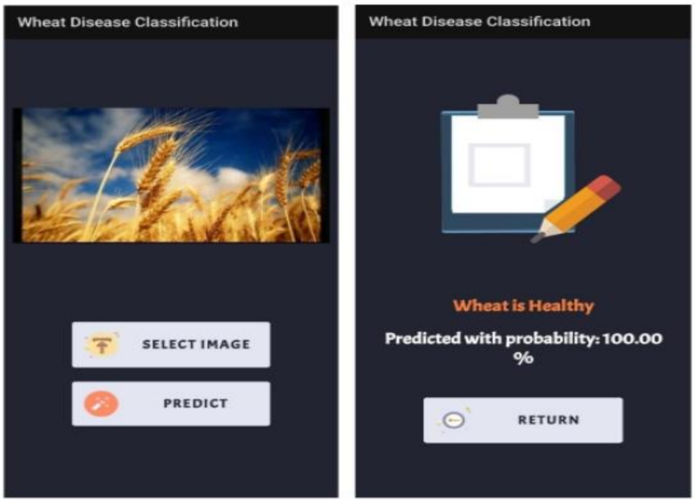

Figure 9: Healthy leaves

Conclusion:

Wheat diseases are serious hazards to food security and must be addressed immediately to prevent total crop failure. Many times, however, farmers are unable to tell the difference between diseases that present with identical symptoms. Because of this, fertilizer applications may be under- or over-applied. If diseases are misdiagnosed. Professionals in the field are required to identify wheat crop illnesses. Who can prevent the loss of the entire harvest? To mitigate this loss and better instruct farmers via video, in the proposed solution we apply Convolutional Neural Network (CNN) multi-layer ANN algorithms hereinafter referred to as Deep Learning Algorithms. The overarching goal was to enhance the efficacy of agricultural methods. Currently, machine vision-based plant disease and pest detection equipment are being widely used in agriculture, replacing the more laborious and time-consuming practice of identifying these problems by eye. We trained and validated our strategy using a transfer learning method. We also conducted an evaluation of the design using a dataset of 14 plant types and 38 class labels. We propose an intelligent and effective application software that leverages AI computer vision and machine learning algorithms to identify agricultural diseases. We have faith that this study's findings will be seen as supplementary to those already published, opening the door to important studies of transfer learning methodologies for plant and disease identification.

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