

Original Article

Machine Learning Models in Precision Agriculture for Classification of Diseases

Sagar Patil^{1*,2}, Satyanarayan Reddy¹, Sandeep Sutar^{1,3}, Suchita Patil⁴

¹Department of Computer Science & Engineering, Srinivas University, Mukka, Mangaluru, Karnataka, India.

²Department of Computer Science & Engineering, Bharati Vidyapeeth's College of Engineering, Kolhapur, Maharashtra, India.

³Department of Computer Science & Engineering, ADCET, Kolhapur, Maharashtra, India.

⁴Department of Computer Science & Engineering, KITCOE, Kolhapur, Maharashtra, India.

^{1*}Corresponding Author: someone.sagar@gmail.com

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Abstract - The bond between machine learning models and the agriculture field is becoming stronger with each passing day. The pre-trained AlexNet, ResNet, VggNet, and GoogleNet models commonly support various tasks in the precision agriculture field, such as disease detection, nitrogen status estimation, leaf area index identification, nutrient status measuring, finding pesticide requirements, measuring growth, etc. These tasks involve a huge amount of data, such as simple cell phone images, satellite imagery data, vegetation index data, images from UAVs, and sensor data from various soil and water sensors. Analyzing and finding insight from such data is a complex task. In this article, a framework is proposed using the transfer learning method for disease classification using manual CNN model along with the pre-trained AlexNet, ResNet, and GoogleNet. The 5450-image dataset, is considered that includes four wheat disease labels and a healthy wheat label, is used, which was constructed from publicly available datasets. The fine-tuned models are compared for the disease prediction task using the parameters such as accuracy, F1 score, recall and precision. Transfer learning ResNet50 gives promising results once fine-tuned, having the accuracy of 93% compared with other transfer learning models, which ranges from 61 % to 78%. The framework proposed can identify diseases for various crops in agriculture field.

Keywords - Crop disease, Machine learning, Precision agriculture, ResNet50, Transfer learning.

1. Introduction

Agriculture plays a fundamental role in sustaining human civilization by ensuring the availability of food and other essential resources. Revolution in farming is not new; as the years pass, technology is becoming an everyday practice in this sector. With the advent of technology, the production quality and quantity are improving. Still, there are a lot of inherent problems in this sector, such as agricultural diseases that harm the production, uneven water supply due to uneven rainfall, lack of or more fertilizers that are being used for the production, and many other factors that adversely affect the field, because of which the quality and the quantity of the produce are diseased.

Even though technology can be used to overcome some of these challenges, it is not the ultimate solution to the problem, as it does not guarantee a hundred percent result, but it improves the benefits for the farmer and makes farming an affordable and income-generating instrument rather than just a way to survive. Machine learning technologies are being used in farming to address the many such issues arising to

facilitate the farmer in the process of cultivation. Deep learning techniques are getting employed from pre-harvesting till post-harvesting and beyond for selling the produce. Various algorithms, models, tools, and techniques from machine learning/deep learning are getting used nowadays in the name of precision farming. It is just the word coined for technology being used in farming, which involves sensors for data collection purposes, servers for data analysis, machine learning tools for creating the models, models for analyzing the data from the field, and prediction mechanisms from these models developed will be given on an output device or given to the output hardware. Robots may be used to work on the farm, UAVs can be used to monitor the status of the crop, and even satellite-captured images used to predict crop behaviour.

Research gaps from recent studies which used pre-trained models modified for disease prediction are described in detail next. The ResNet50 model is used in healthy and diseased images using the Plant Village dataset and CNN [1]. Model accuracy changes drastically when the combination of two or more datasets is employed. As the data in precision agriculture



is tremendous, smartly handling the data is the main concern. The Normalized Difference Vegetation Index (NDVI) and sensor data face the challenge of accuracy [2]. Climate conditions affect the crop disease [3]; also, a lot of diseases are having similar symptoms [4]. Different crops have similar kinds of diseases. To handle such a scenario, a model is needed which handles multiple crops with better accuracy, and the time required to apply such algorithms is again a concern [5]. Image quality decides the output for classification, as light reflection and the time of the day the image is taken affect the process [6].

Is it really affordable to the end user? One of the major questions is [7], at what stage is the disease progressed, and how to deal with it? This means detecting a disease at an early stage so that it can be controlled using fewer resources [8]. Along with the above-mentioned research challenges, a few more challenges in this field are: to increase disease-related features to enhance model performance, new algorithms could be developed to identify crop traits that signify various growth stages, research is needed to create an optimized model utilizing evolutionary learning techniques, variable rate application of pesticides, the relationship between disease class and crop varieties, newer segmentation methods for disease identification.

To consider these limitations, the model needed to be developed. The article outlines a novel method using transfer learning and pre-trained models using the dataset of wheat for disease classification. Transfer learning will help in learning from the experiences of previous data, where the frozen layers are used, and then come the trainable layers, where the model differs from the previous layers, which leads to better classification of disease. The application of image augmentation to the dataset helps mitigate the effects of variations in illumination, light reflection, and other image-related inconsistencies, thereby improving the robustness. AlexNet, GoogleNet, and ResNet are used as input to the model constructed. Also, the model takes input as the wheat dataset constructed from considering various publicly available datasets for better training of the model. Extensive pre-processing is done to normalize the images and remove irrelevant data.

Major contributions of the proposed approach, particularly in comparison with existing methods, are outlined below:

- Existing models consider a single publically available dataset, in this research, a dataset is prepared using various wheat benchmark datasets.
- Research presents a novel technique with the machine learning model using transfer learning, considering three fine-tuned models.
- The results obtained from pre-trained AlexNet, ResNet, and GoogleNet were compared with a basic CNN constructed from scratch.

- Comparison against previously reported state-of-the-art approaches, demonstrating a measurable improvement over available models.

The article is organized as follows. Section 2 gives a survey of methods in area of crop disease prediction. Section 3 provides the description of the methodology and role of transfer learning in building of the models. Section 4 shows the results of the experiments along with their analysis, which includes the comparative assessment of the four selected models in terms of the required criteria. Section 5 concludes the paper and summarizes the most important results obtained.

2. Literature Survey

The productivity of agriculture in the modern age is under threat due to various aspects, including climatic changes, weed infestation, pest damage, and crop diseases. Farming ensures the availability of food to humankind [9]. It is only through the proper use of fertilizers and pesticides that crop production can be increased without compromising on the quality of the soil. Farmers use chemicals such as pesticides and herbicides on crops to protect from diseases. These pesticides puts extra cost burden on farmers as old methods needs more of such chemicals [10]. Correct use of fertilizers and pesticides depends to a great extent on the ability to properly identify crops from weeds, and progress in image analysis and ML provides interesting solutions to this problem. To manage of soil and water needs for farm precision farming tools are getting used for precise calculation of resources needed [11].

There are many factors that can affect agricultural productivity. Some of them include plant diseases and pest attack, uneven rainfall patterns, floods, and sudden changes in climate conditions. Along with these challenges, uneven fertilizer application, rules and regulations from industry, transportation from farm to market challenges, and getting right price for the produce are few more hurdles in agriculture [12]. Such difficulties pose a great deal of economic and psychological strain on the farmers, leading to debt and even in some cases, to suicide of farmers. Usage of new technologies such as CNN, image analysis methods, sensors, and UAVs can be used effectively in order to overcome these problems in agriculture.

Soil analysis in pre-harvesting, crop growth management in harvesting and quality checking at the stage of post-harvesting are the tasks done using smart farming [13, 14]. Machine learning methods can help increase agricultural productivity through prompt and affordable decision-making to improve crop yields by allocating optimal resources.

Computational models that include image analysis, fuzzy systems, recommendation systems, and object detection is useful in many application areas. ML models are used in social media analytics, review and recommendation systems, the

banking sector, automobile manufacturing process analysis, drug testing and smart city projects [15]. In a country like India, agriculture is one of the sectors which is important in the growth of the economy and sustains the livelihood of a huge number of rural populations. With the use of technology in rural areas, there have emerged many opportunities in embedding technology in agriculture.

Farmers use machine learning techniques that have been utilized to predict nutrient content, analyze and interpret this data to determine the amount of water that has been added to the soil [13]. Ripeness of avocados is checked, quality is determined, and finally grading is done using the different sizes of avocados with help of a handheld portable device such as a cell phone [16].

Applications of ML are spread across harvest activities, including pre and post-harvest tasks, such as Soil analysis in pre-harvesting, crop growth management in harvesting and quality checking at the stage of post-harvesting [17]. CNN, SVM is used in a number of important areas of farming practices, such as meteorology. Also, clustering, KNN is employed at crop and animal health tracking [13, 15, 17].

You Only Look Once algorithm predicts exact amount of chemicals applied for crop and saves the costs for farmer [18]. Mobile applications are developed for agricultural data analysis. Pictures of soils and crop are used for quality checking, nutrient requirement analysis, weed and pest identification [19].

Convolutional neural networks for image classification are well established, including GoogleNet, AlexNet, and ResNet, have shown great efficiency in diverse image recognition applications. AlexNet is one of the first CNN's. This network proved itself to be one of the fastest in image recognition on arrival and also uses the ReLU activation function, which allows training the neural network faster and more efficiently [20].

"Residual learning framework" introduced by ResNet allows resolves vanishing gradient, while a higher classification accuracy was achieved compared to the original GoogleNet model, though it increases rate of training and test errors.

GoogleNet incorporated "inception modules" with fewer parameters than AlexNet. This makes it more efficient in terms of computation. Because of the reduced number of fully connected layers, it requires less memory and storage.

In addition, GoogleNet has a lower classification error rate but has a relatively wide architecture, which reduces much of the computational power [21-23]. Various machine learning techniques have been utilized to predict nutrient

content, soil classification, and PH status. There are various types of soils with varying fertility rates depending on the nutrients content in it [24]. The analysis obtained helps take timely advice on the quantity of fertilizer to utilize. Nutrients in excess quantities are waste and costly, so the decision on the amount of fertilizer is crucial for farmers [25].

In an automated irrigation system, sensors can be used to continually provide information about the soil to the main processor. By using data mining techniques, the processor can analyze and interpret this data to determine the amount of water that has been added to the soil. Internet-based applications are used to control farming decisions and predict crop output [26].

Having access to vast datasets is crucial in deep learning models. The wide variety of crop species and diseases can create challenges in obtaining sufficient data for training models in agriculture. This problem is addressed by transfer learning, which is especially helpful when the dataset is small [27].

Table 1 shows a comparison between pre-trained models. Advantages and disadvantages are discussed in the table for the respective model used for classification with unique strengths [28, 29]. In precision agriculture, these models help in the identification of diseases and save the farmer from the burden of misclassification [30]. GoogleNets Inception module and ResNets Residual connections are the breakthrough techniques developed in recent history in this field [31, 32].

Lightweight CNN is one approach used for faster identification; one such approach using a pre-trained model gets an accuracy of 91.2 % using tomato images [33]. The dataset size and quality affects the performance, limited or non-representative image datasets severely reduce real-world model accuracy to 84% even with transfer learning [34]. Image-based machine learning methods used for rice disease classification with 172 color features from a limited image dataset of 600 images produce an accuracy of 91.4 % [35].

This review of literature gives insight into machine learning models used for the disease classification task, along with their advantages and disadvantages. Precision agriculture using machine learning provides a promising approach for forecasting the optimal amount of fertilizers and pesticides needed for maximum growth by identifying disease at an early stage.

Analyzing and finding insights from data is a complex task. This research developed a methodology using three pre-trained models and one basic CNN. These models are analyzed using various evaluation metrics for performance measure.

Table 1. Comparison of pre-trained classification models

Sr. No.	Machine learning pre-trained model	Advantages	Disadvantages
1	AlexNet	It is one of the first CNNs. This network proved itself to be one of the fastest in image recognition on arrival. It also uses the ReLU activation function, which allows training the neural network faster and more efficiently.	Excessive training data conformity by the model, i.e. overfitting.
2	VggNet	Simple architecture with small filter sizes.	The model requires significant computational resources because of its extensive parameter count.
3	GoogleNet	It has fewer parameters than AlexNet. This makes it more efficient in terms of computation. Because of the reduced number of full connected layers, it requires less memory and storage. In addition, GoogleNet has a lower classification error rate.	GoogleNet has a relatively wide architecture with a limited number of layers. As a result, there was a reduction in the network's computational power due to inefficient utilization of parameters.
4	ResNet	The challenges of Vanishing Gradient were resolved, while a higher classification accuracy was achieved compared to the original GoogleNet model.	Increases rate of training and test errors.
5	DenseNet	Layers are densely connected, resulting in fewer parameters while enhancing accuracy.	Requires a large amount of memory due to computationally complex connections
6	MobileNet	Fewer parameters are used, which increases speed. Accuracy near to VggNet and GoogleNet	Less accuracy on complex datasets. Suitable for specific applications only.

3. Materials and Methods

The model workflow is presented using system architecture along with input and output parameters. Also explains the data collection and preparation with a detailed description of the wheat crop and associated diseases, followed by data preprocessing and data augmentation for preparing robust data for the training and testing phase.

Further, it details GoogleNet, AlexNet, and ResNet and how to use their experience using transfer learning in the proposed model. Transfer learning uses freezing and unfreezing layers of convolutional neural networks. Unfrozen layers, also called as trainable layers, are used for training purposes with the newly available data into the model.

3.1. System Architecture

The framework for disease class identification is illustrated in Figure 1. The CNN classifiers were trained separately for each category of diseases. Then, based on the prediction results, a corresponding classifier was chosen to identify the disease type of a given crop, and getting such a result needs the model to be better trained.

The precision agriculture model starts with the process of data collection, and then the process of annotating and augmenting the data starts, where the images are labeled and

expanded from the available set of images. The images thus constructed are divided into training, testing, and validation phases, as 75, 15, and 10 percent respectively, i.e. 4088, 817 and 545 images respectively.

The images are fed into a customized neural network with frozen and trainable layers along with the pre-trained models, which will predict the disease on that image.

The method employed also analyzes the performance for the comparative analysis, choosing the best possible model among the models employed.

Thus, the output of the model is the detected disease class. This approach guarantees that the model learns effectively and performs consistently in practical applications, improving resource management and decision-making in agriculture.

3.2. Dataset

Curetted a dataset with 5450 images with 5 classes, one healthy and four different disease classes, namely "Crown and Root Rot, Fusarium Head Blight, Leaf Rust Brown, and Yellow Leaf Rust," from publically available datasets. Random sample images from the dataset are presented in Figure 2. Table 2 gives the details of publicly available datasets.

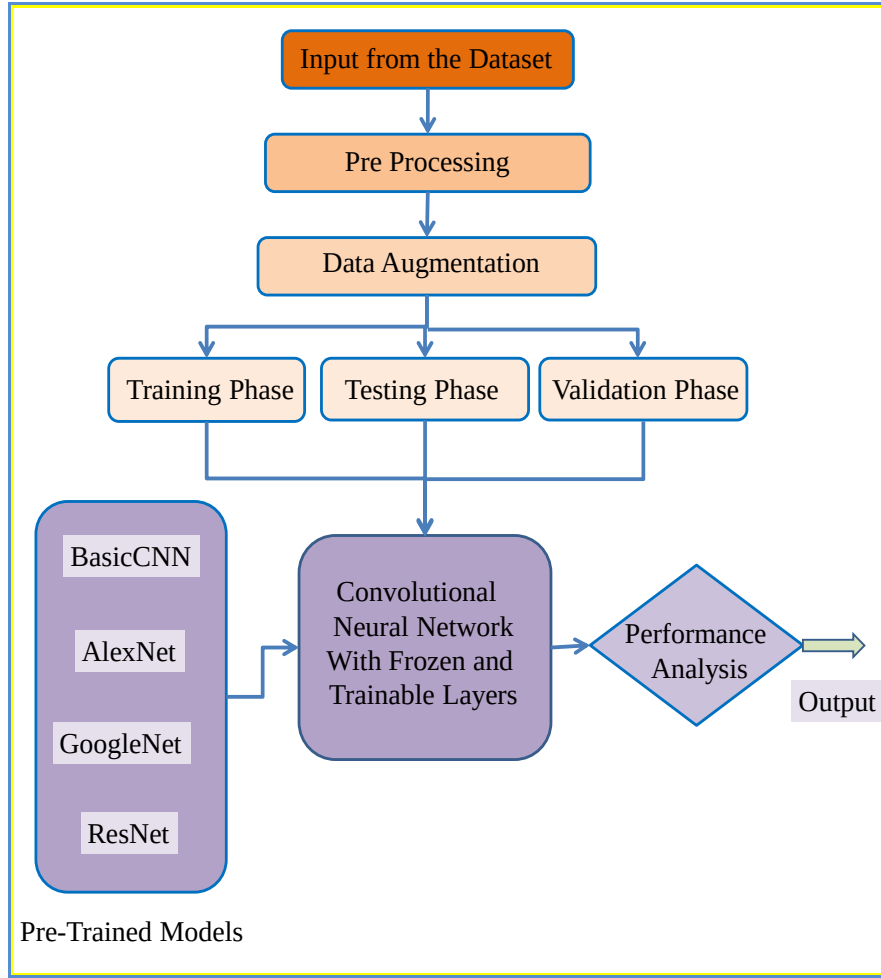


Fig. 1 System architecture and workflow of the proposed framework

Table 2. Disease prediction datasets

Name	Location
PlantVillage dataset	https://www.kaggle.com/emmarex/plantdisease
Wheat dataset LWDCD 2020	https://drive.google.com/drive/folders/1OHKtwD1UrdmhqxrppqKotxRGD
Wheat Disease Dataset - Small	https://zenodo.org/records/7307816
Wheat-Disease-Dataset	https://www.kaggle.com/datasets/amankumar2004/wheat-disease-dataset?select=Wheat-Disease-Dataset

Table 3 shows the distribution of healthy and diseased images for wheat images and the count.

The proposed framework employs generative AI-based data augmentation to address the imbalance within classes.

Table 3. Distribution of healthy and diseased images

Sr. No.	Name	Image Count
1.	Crown and Root Rot	1033
2.	Fusarium Head Blight	1057
3.	Healthy Wheat	1280
4.	Leaf Rust Brown	1056
5.	Yellow Leaf Rust	1024
Total		5450

3.3. Models Employed

Transfer Learning (TL) enhances task accuracy by enabling selective training of model layers [36, 37]. By keeping the earlier layers frozen, the model preserves valuable pre-trained parameters for feature extraction while fine-tuning the later layers to suit specific classification tasks [33]. This study presents convolutional neural networks and transfer learning applied to pre-trained models for improving classification accuracy.

Basic CNN: This model is a sequential CNN model [34] created from scratch for the performance comparison with the other model. The model's goal was to detect healthy or

diseased crop images. The model is created as a sequence of convolutional, pooling layers, which are 15 in count, followed by flattening and a softmax layer for the disease classification [35]. TL AlexNet: AlexNet is used for the classification of

having 8 layers of convolutional, pooling layers and then a dense layer at the end for the task of classification. As it is, the older model compared to the other two models will perform best compared with the basic CNN model.

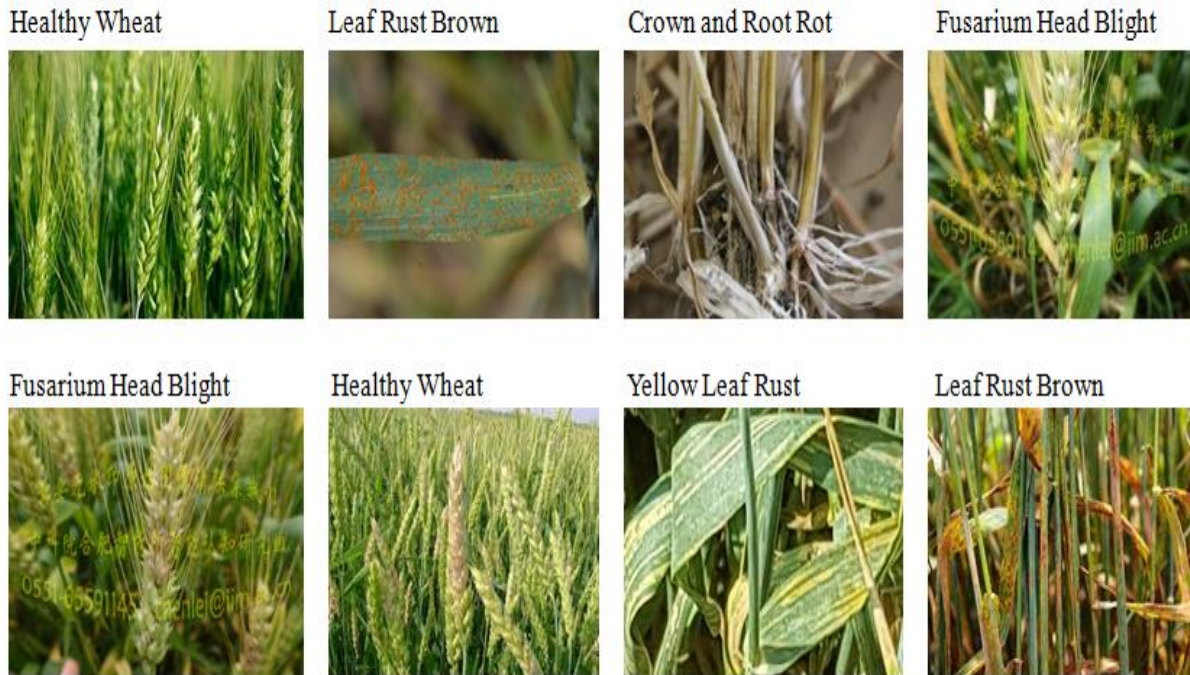


Fig. 2 Random sample images from the dataset

TL GoogleNet: GoogleNet has an inception module that is used as the basis for the dimensionality reduction. It uses the filter size of 5 x 5, and the stride used is 3, along with the ReLU activation function. GoogleNet is having 22 such convolution and max pooling layers for the classification task.

TL ResNet-50: The ResNet50 architecture-based model allows training deep networks, which utilize transfer learning, and the residual network with fifty layers is modified for vanishing gradient resolution and is solved using such a technique. It uses the 224 x 224 image size. The fine-tuned ResNet50 is used for improving its classification accuracy.

4. Results and Discussion

4.1. System Requirements

The four models discussed are evaluated on the system with Google Colab, utilizing Keras and TensorFlow libraries to handle deep learning tasks, having 8 gb gpu and 120 gb of memory access, having Python 3 running on it, jupyter notebook as an IDE and environment.

This platform enabled efficient use of GPU acceleration, which significantly reduced training time and facilitated experimentation with different model architectures and hyper-parameters. Parameters for the execution and evaluation are mentioned in Table 4.

Table 4. Variables configuration

Variable	Value
Dropout-rate	0.1
Activation	ReLu
Optimizer	Adam
Batch size	32
Image Size	256
Learning rate	0.001
Max epoch	30

4.2. Model Evaluation

Various approaches for crop disease recognition, including a baseline CNN and Transfer Learning (TL) variants of AlexNet, GoogleNet, and ResNet50, were assessed based on accuracy and loss. Their training and validation behavior is illustrated through accuracy and loss plots in Figures 3 to 6.

Comparison of the models employed is done to check the best model. As shown in Figure 7, the basic CNN has an accuracy of 61%, TL AlexNet is having 69%, TL GoogleNet having 78%, and overall TL ResNet50 model will perform better than the rest of the models, with an accuracy of 93%, making it highly effective for classifying the targeted classes. The better results are achieved due to the methodological advantage of considering the diverse publically available datasets for training the four models. Unlike conventional

augmentation techniques that primarily apply deterministic geometric and photometric transformations to existing samples, the proposed approach generates diverse synthetic disease images by learning the underlying distribution of disease-specific visual characteristics. The pre-trained CNN extracts hierarchical visual features, while generative

intelligence improves the diversity and balance of the training data. Thus, experimental results shown in Figures 3 to 6 on the basis of accuracy and loss plots of four models show that ResNet50 using Transfer learning having accuracy of 93 percent has superior performance than rest of the three models employed with accuracy of 61, 69 and 78 Percent.

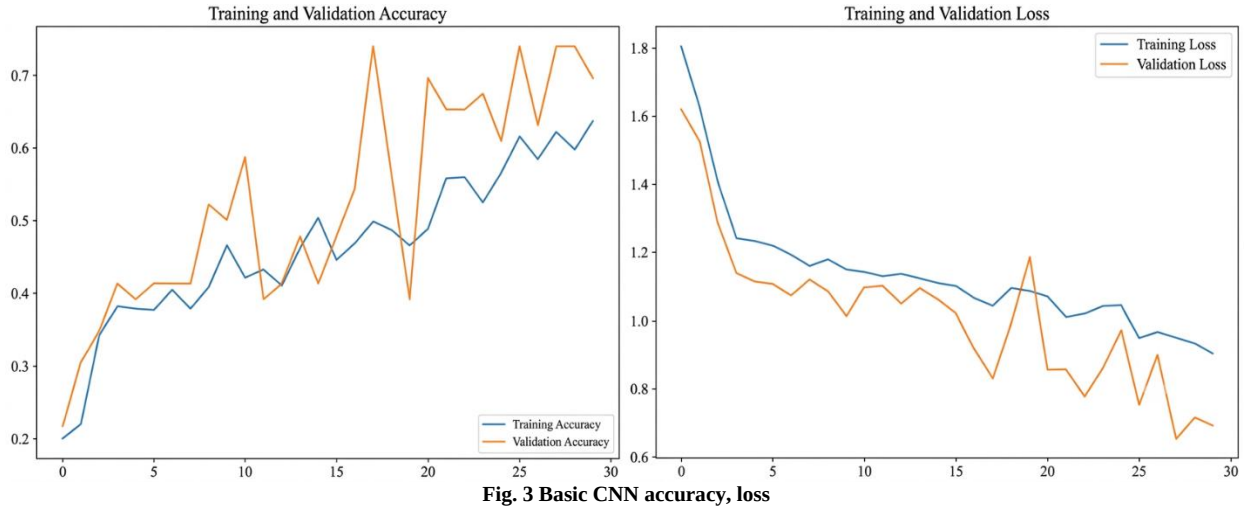


Fig. 3 Basic CNN accuracy, loss

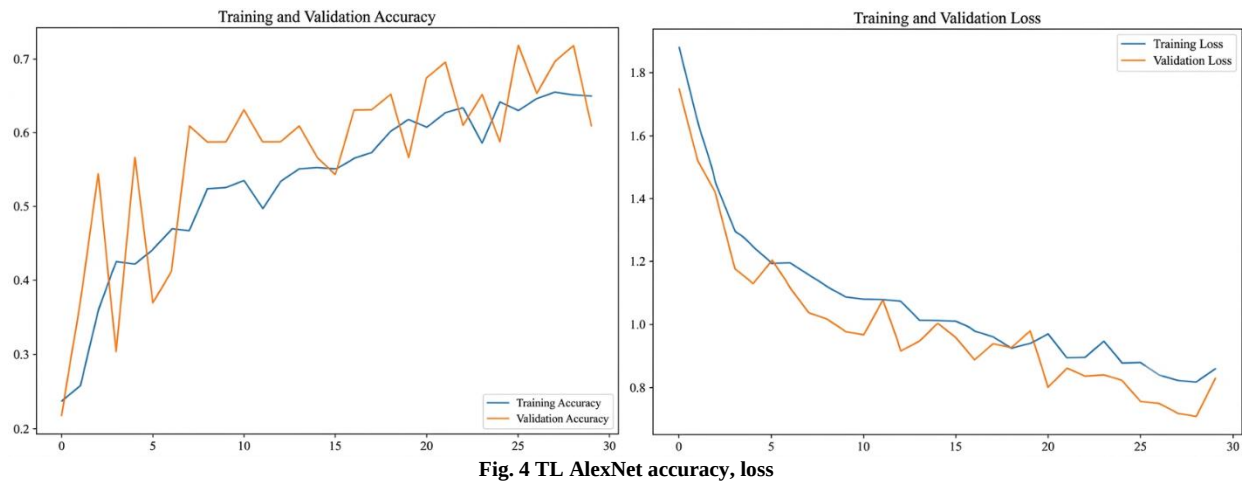


Fig. 4 TL AlexNet accuracy, loss

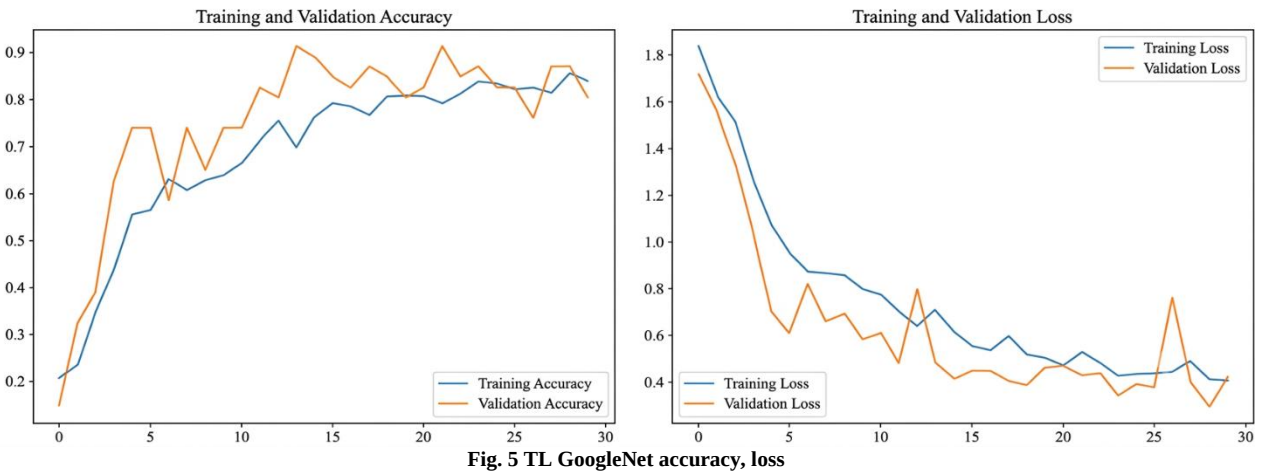


Fig. 5 TL GoogleNet accuracy, loss

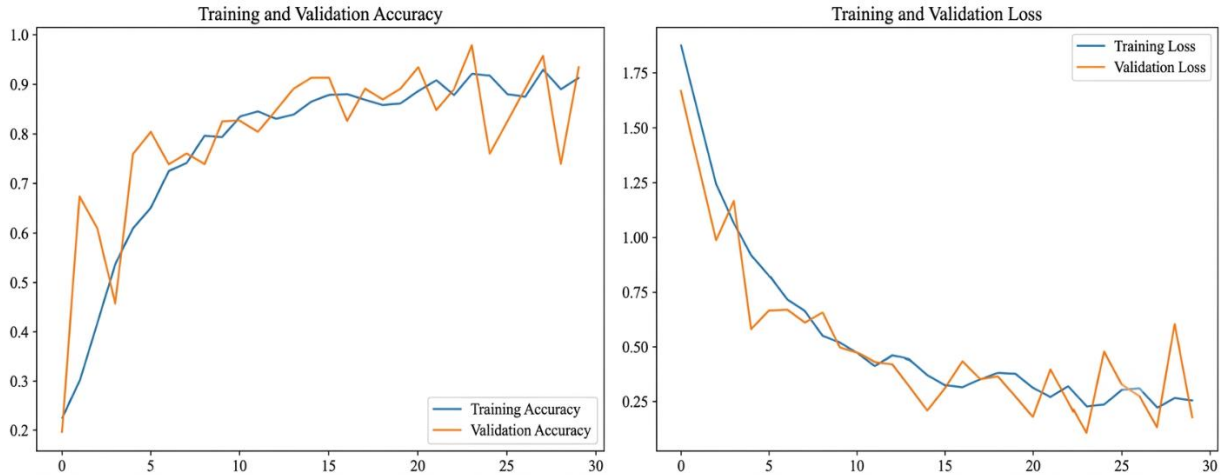


Fig. 6 TL ResNet50 accuracy, loss

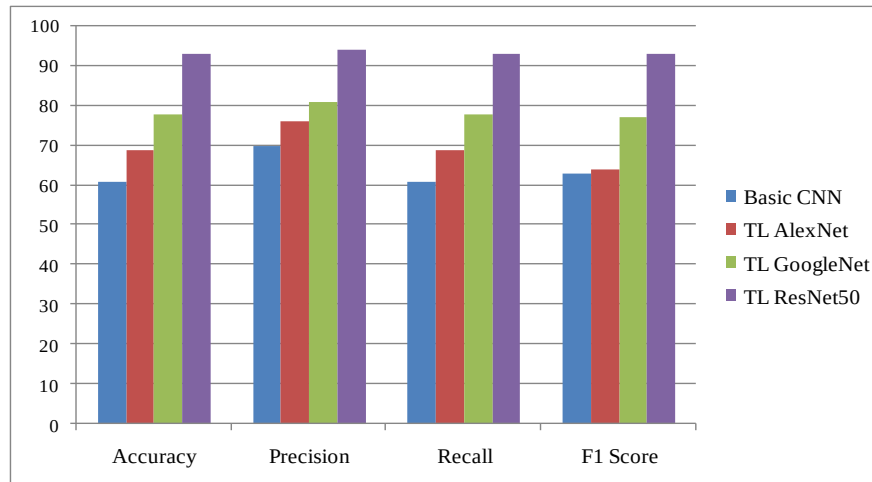


Fig. 7 Comparison of models using various evaluation metrics

5. Conclusion

The work presented here analyzes the machine learning model using a transfer learning approach to predict the disease of a crop, which will ultimately benefit the farmer using the wheat crop images with 5 classes as an input to the proposed models. We compare different approaches for disease classification, such as basic CNN, transfer learning with AlexNet, GoogleNet, and ResNet, using various machine learning model evaluation metrics, and we found that ResNet50 with transfer learning gives promising results, overall transfer learning ResNet50 model performs better than rest of the models, with an accuracy of 93%, making it highly effective for classifying the targeted wheat disease classes.

The methodology used for fine tuning the parameters can be used as the basis for other models. The machine learning models, such as AlexNet, signified the importance of using GPUs for parallel processing while deep learning happens. GoogleNet was designed in a way to make computation more efficient by using inception modules, whereas ResNet uses

residual learning to train exceedingly deep networks and address issues that arise during gradient descent.

Also, the work underscores the importance of robust dataset creation for the specific crop species, as the classification accuracy mainly depends on how well the data is curated, pre-processed, and augmented for a particular task. Precision agriculture using machine learning provides a promising approach for forecasting the optimal amount of fertilizers and pesticides needed for maximum growth by identifying disease at an early stage. In the future, the models can be analyzed using multiple crops at the same time under varying conditions. The transfer learning approach could be modified with fine-tuning of unfrozen layers for training new data from other crop categories.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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