International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
DOI: https://doi.org/10.17762/ijritcc.v11i9.8318
***Article Received:** 12 July 2023 **Revised:** 28 August 2023 **Accepted:** 20 September 2023*

Perception of Groundnuts Leaf Disease by Neural Network with Progressive Re-Sizing

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Abstract: India is the world's second-largest groundnut producer after Brazil. An major crop of oilseeds is groundnuts. Because of this, the crop's quality and yield have declined, which has had a detrimental effect on the agricultural economy. This is partly because the crop is more susceptible to various diseases. It is required to create more precise and reliable automated approaches to address this problem and improve the identification of groundnut leaf diseases. This article proposes a deep learning-driven approach based on a progressive scaling technique for the accurate classification and identification of groundnut leaf diseases. The five main groundnut leaf diseases that are the subject of this study are leaf spot, armyworm effect, wilts, yellow leaf, and healthy leaf. The proposed model is trained using both progressive resizing and conventional techniques, and its performance is assessed using cross-entropy loss. A fresh dataset is meticulously curated in Gujarat state, India's Saurashtra region, for training and validation. Due to the dataset's uneven sample distribution across disease categories, an extended focus loss function was used to correct this class imbalance. In order to evaluate the performance of the suggested model, a number of performance metrics are utilized, including accuracy, sensitivity, F1-score, precision, and sensitivity. Notably, the suggested model has a 96.12% success rate, which signifies a considerable increase in the disease identification accuracy. It's important to note that the model incorporating progressive resizing beats the basic neural network-based model based on cross-entropy loss, highlighting the potency of the recommended approach.

Index Terms: Plant Disease, Peanut, Image classification, CNN, Image Resizing, Ground nut, Leaf classification.

I. Introduction

Around 70% of the workforce in developed India works in agriculture. From a large selection of eligible crops, farmers may choose the best pesticides for their plants. The economy would be impacted if crop destruction caused a large loss in production. The most delicate part of the plant that is the leaf the place that sickness signs first manifest. At the beginning of their lifespan until the time they're ready to harvest, crops need to be checked for diseases. There have been a variety of methods used recently to develop semi-automatic and automated plants disease detection systems but the automatic detection of disease simply by observing symptoms in the leaves of plants can be made simpler and cost-effective. The methods are already proven that they're more effective affordable, cost-effective, as well as more accurate than observation by hand that is the standard practice.

Plant diseases cause roughly 30% of the world's agricultural harvests to be lost each year, with direct economic losses of more than $40 billion. In the previous five years, food insecurity affected more than 821 million people. Numerous illnesses are to blame for a string of losses, with leaf spot being one of the most prevalent ones that often affects crops including rice, maize, and peanuts. As a result, rapid diagnosis and correct identification of plant diseases are crucial for plant protection. The difficulty of disease identification in agriculture is further increased by professional who are able to charge high wages and a deficiency in continuous monitoring, or mistaken identification, all of which result in unstable and abrupt declines in yields as well as issues with food security. Thus, a challenge for the area of precision agriculture is the intelligent and precise diagnosis of plant diseases without depending on human labor[1]. In India's economy of edible oilseeds and agricultural export commodities, the groundnut harvest is significant. The loss of yield, quality, and early leaf mortality are all mostly caused by disease attack[2]. In order to sustainably boost output, measures must be taken toward the development of a quick and precise system for diagnosing groundnut leaf disease.

Visual investigation is the conventional method for gathering information on agricultural diseases in the field. This strategy has the drawbacks of being very subjective, ineffective, and lagging and requires the required experience of plant protection workers. Deep learning is now possible because to recent developments in computer technology for picture categorization, object recognition, and natural language processing [3]. For the purpose of extracting visual characteristics, a number deep neural network (DNN) models were built of deep neural network (DNN) models based on CNN characteristics. These models include AlexNet, VGG, ResNet, and DenseNet, which identify diseases in peanut crops.

The proposed approach makes use of deep learning and machine learning using featured datasets of peanut leaves. The trained model initially classifies the sick leaves from the plants based on the characteristics of the plants. The model's accuracy is calculated. The remainder of the essay is divided into four chapters: chapter 2, methodology; chapter 3, experiments; and chapter 4, conclusion.

1.1. Objective

Future research and development in this field will be fascinating as it relates to leveraging photos of plant leaves to implement machine learning models for disease identification in plants. Researchers in this field need quick access to representative datasets in order to build effective machine learning algorithms. To detect plant diseases, real-world groundnut databases are few [1-2]. There's no current standard groundnut leaf image data set in terms of dimensions and pictures. Based on our review of relevant studies. Thus, to improve research on the identification of plant diseases through computer-aided learning (ML), we believe it's essential to create and make available a database [3]. The potential benefits of this research are not fully utilized for public goods such as health and agriculture in the opinion of a lot of top researchers in machine-learning. Our goal is to build an agricultural data set that is standardized and could, in a small way, increase general public's understanding of machines learning, and their possibilities for applications.

II. Literature Survey

In a previous study [1], the Plant Village dataset's numerous plant diseases were classified using a CNN model. The numerous plant diseases will be divided into 38 separate unique classes by the AlexNet architecture. The recommended method also provides a good way to predict plant illnesses and could help with early identification. Alternative learning rates may be investigated in the future using the proposed system. [2] It focused on using photos from a given dataset (a trained dataset) in the field and historical data to apply a CNN model to forecast the pattern of plant diseases. A comprehensive inventory of all viable plant leaves will be provided, allowing farmers to choose which crop to produce while also allowing them to learn about leaves that may not have previously been domesticated. The working model of [3] uses transfer learning and convolutional neural networks to classify various plant leaf diseases. A deep learning neural network called CNN is good at classifying images. The suggested method is speedier and more precise when compared to the conventional method, which involves personally inspecting each plant leaf. Several plant diseases can be successfully predicted using the CNN model. The model is evaluated using metrics for measuring its performance, including accuracy, precision, recall, and F1 score. 4. A backward-propagating neural network A method for classifying pomegranate diseases has been proposed; it focuses on how to divide the affected area and uses textures and colours as markers.

To avoid occlusion, the photograph is often shot with a simple backdrop. The method was compared to other machine learning models for accuracy. The paper’s precise imaging recognition as well as picture display in this area deep learning has been described as a breakthrough. Convolution neural networks have demonstrated efficiency in the precise and accurate assessment of plant pathogen. VGG 16 and inception V4, ResNet with 50 101, 50, and 152 levels, as well as D nseNets that have one hundred and 121 layers are some of the models that were tested. 38 different kinds of information comprising images of damaged and healthy leaf tissue taken from 14 different plants in Plant Village were utilized in the test. 14 of the 38 plant species—healthy and diseased—taken for picture assessment were from the plant village. For the illness to be quickly eradicated and the plants to live longer, an accurate and effective result is necessary. It has been observed that DenseNets has been accurate in its assessment as the number of epochs has increased. Additionally, it takes less time and always produces speedy results. The fact that the result is 99.75% correct demonstrates the effectiveness of the method. It was necessary to use Keras with a Theano backend for the architecture's training assessment.

In this article, convolutional neural networks model Application and can be utilized in the detection and treatment of diseases in plants by comparing leaves of healthy and sickly plants using deep learning techniques. The experiment was conducted with the help of 87.848 pictures which included 25 varieties of combinations of diseased as well as healthy plants. Numerous experiments were conducted with the highest level of the accuracy of 99.535 percent success in detecting the diseases of the plant, if it has. It is possible to say that this study demonstrated the impressive performance of this method that could be utilized and used as an to detect early diseases in plants. it will certainly function in the form of a pre harvesting alert device in agriculture to ensure that farmers' harvests produce a high production.

In order to reduce noise and increase plant classification accuracy, the CNN with multi class label approach, which combines feature extraction with contour masks, has been developed in this study. Results have indicated that a number of variables, including the complexity of outdoor scenes and the diversity of plant morphology, may lower the accuracy of

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weed detection. Based on the outcomes of the trial, the CNN approach performed the best, identifying morphologically related plants with a 98.63% accuracy rate. While permitting morphological variation within each class, this strategy is especially helpful for differentiating between two classes with morphologies that are quite close to one another. Additionally, experiments have indicated that the suggested technique executes more quickly than the combined method in the earlier study. The suggested strategy therefore enhances the categorization of plants with comparable morphological characteristics. Furthermore, this method's quick processing time makes it easier to use plant detection in real time.

III. Proposed System Architecture

System architecture refers to the conceptual model that specifies a system's the structure, behaviour, and the other aspects. Architectural descriptions are a explicit description and depiction of the system created to help to study its structure as well as its actions. The components of a system and subsystems working together to build the system may be part of a system's architectural description. This section will look at the several steps that must be taken in order to create, use, and get the most probable results from different classifiers. Out of all the various results and accuracy provided by various models, we will use the model that yields the greatest results and accuracy for identifying leaf disease.

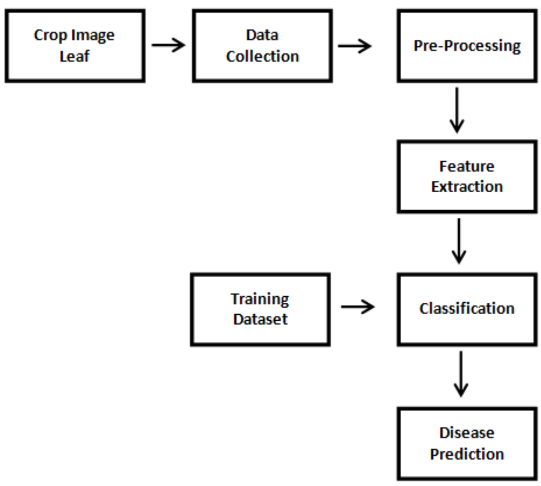

Figure 1: Proposed System Architecture

Pre-processing and data cleaning: When preparing data for analysis, it is necessary to remove or modify any information that is incomplete, erroneous, redundant, or presented improperly. As we have previously said, it is not as simple as just moving some rows about or removing some data to create way for new information. Data processing is the most common first step in the workflow of deep learning. It is used to convert raw data into a form that the network understands. Here, the input picture is first tested using the training dataset. After testing, features are retrieved from the picture. The classifier then received information about these characteristics as well as whether the picture showed a healthy or sick leaf as input. The classifier then establishes a link between the returned characteristics and the chance that a disease is present. The leaf illness is recognized in the subsequent step by comparing the input picture to the prior images in the collection.

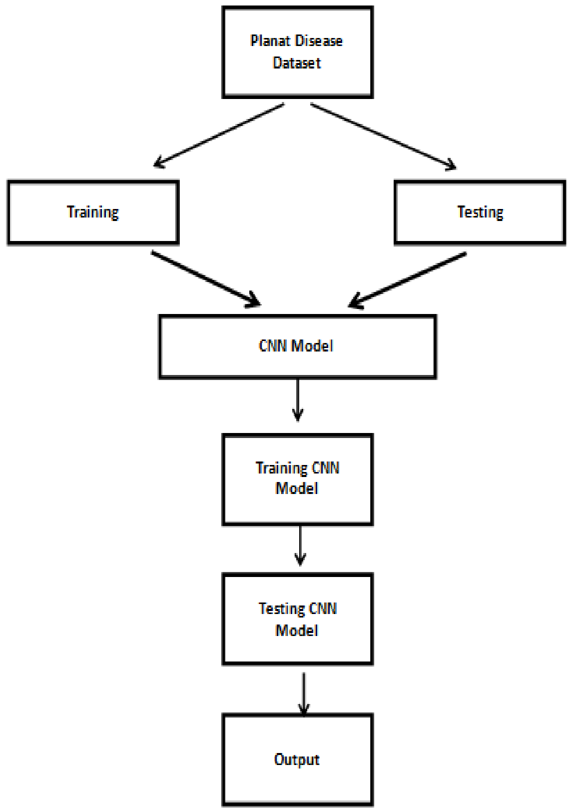

Figure 2: Classification System Architecture

3.1. Data set

3.1.1. Data Description

According to Table 1, all of the pictures are from the Koppal region. This information is taken in when it is Kharif and Rabi season. The data collection contains six different types of groups the early leaf spot the late leaf spot early signs of rust healthy leaves, as well as nutritional shortage. The time of year that groundnuts are picked and planted and harvested, it is possible to distinguish between the early and the late leaf spot. Although late leaf spot typically occurs around three months following planting early leaf spot develops in the first few months. Here is the full explanation of each disease

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3.1.2. Early Leaf Spot

The fungus that causes early leaf spot, cercospora arachidicola, appears as the name implies very early in the growth of the crop after sowing. Most lesions found that appear on the leaf's surface tend to be lighter shades of brown. They are also surrounded with a yellow-colored halo3. The disease tends to multiply quickly in dry seasons. The injured leaves are photographed using a digital camera. One of the 1731 photos was able to catch an early leaf spot, as seen in Fig. 3.

Figure 3: Early leaf spot.

3.1.3. Late Leaf Spot

The causative late leaf spot agents, Cercospora personata, were widely observed throughout the farmer fields that were established. Infections start at 7-8 weeks after planting. On the leaves, lesions show up like tiny, elliptical darker brown spots with no yellow halo. The upper and lower surfaces have a carbon black color [33]. A digital camera can record an entire 1896 images to further analyze. See Fig. 4 to see an illustration of a leaf spot.

Figure 4: Late leaf spot.

3.1.4. Nutrition Deficiency

Nutritional deficits are greatly impacted by low iron and sulfur levels. If there's a shortage in sulfur, the yellowing starts on the middle leaf and then progresses to the upper leaves however, when there is nitrogen deficiency, it is evident with the lower leaves, then increases to young leaves. The leaves of young plants will be the first ones to show iron deficiency. Leaves turn an eerie white hue when there's insufficient chlorophyll. All 1665 photos were captured with a digital camera. Fig. 5 shows leaf yellowing brought on by a shortage of nutrition.

Figure 5: Nutrition deficiency

3.1.5. Rust

Due to the fact that it decreases the productivity of businesses due to a decrease in fodder and pod yields and also deteriorating the quality of oil the peanut rust disease is an important biotic stressor. This illness is caused by the fungus Puccinia arachidis. Rust-causing fungal parasites need live plants to reproduce. Humid, moderate conditions often support the growth of rust infections. Spores are how rust spreads from sick plants to healthy ones. The rust-related diseases, such as which can be spread via the winds or water, are able to quickly spread when they are irrigated. It is only the surfaces that are moist that can be utilized to transmit the infection. In Fig. 4. 3198 digital photos were captured which included shots of the plant's earliest corrosion signs, as well as its severances. Figure 6 displays an image of rust.

Figure 6: Rust

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IV. Experimental Methods

4.1. Data Acquisition

Photographs were made using an excellent digital camera that has an 18mm-55mm lens that was sourced from the peanut farm zone. Utilizing the assistance of an expert pathologist, photos of diseased leaves were taken to aid in diagnosing the disease [5]. Five distinct sick pictures were taken in all which included early leaf spot as well as late leaf spot early symptoms of rust.

4.2. Data Pre-Processing

4.2.1. Cropping and Resizing

To isolate the desired area of a leaf picture, a crop tool might be useful for those involved in machine learning and deep learning. After cropping, photos are downsized to 256*256 since the majority of deep learning model architectures need consistency in input image size.

4.2.2. Data Augmentation

Images captured in the field using a digital camera undergo processing. The data augmentation method, as illustrated in Fig. 7, is effective for increasing the quantity of data by adding copies of the information that have undergone minimum modification from their initial condition [4]. The images were rotated at the angle of 360° The shear range as well as the magnification both were set to 0.2 The images were vertically flipped as a an aspect of the enhancement process.

4.3. Specifics of the Implementation

4.3.1. CNN - Densenet

Densenet-169 is a well-known member of the Densenet family that is renowned for its effectiveness in deep learning models. With its 169 layers of intricate design, Densenet-169 is a well-known choice for image categorization applications. This model utilizes fewer training parameters because it has a shallower depth than previous Densenet variants. Densenet-169 and other models from the Densenet family offer a dependable approach to deep learning. Because of their ability to solve issues like fading gradients, enhance feature reuse, and employ powerful feature propagation techniques, these models are highly regarded. One of these reliable deep learning architectures is Densenet-169, which uses only a few trainable parameters.

Figure 8 depicts the study's utilization of Densenet-169's layered design. This design makes use of transitional layers, deep layers, convolutional layers, maxpool layers, and fully linked layers. The SoftMax activation function is applied repeatedly during the model construction. Convolutional layers are in charge of capturing picture properties, while maxpool layers assist in reducing the input size. The operations of an artificial neural network are carried out by fully connected layers, which come after the maxpool layers and receive their input from a flattened layer. The hierarchical structure is described in further detail in Table 1. This structure has been a cornerstone of the investigation for the study.

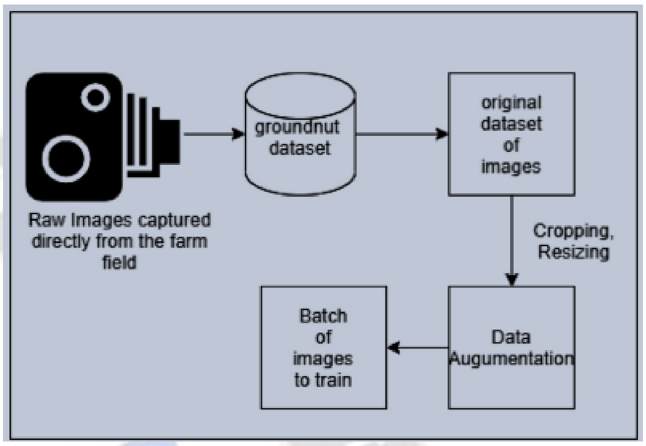

Figure 7: Data expansion on the group of image.

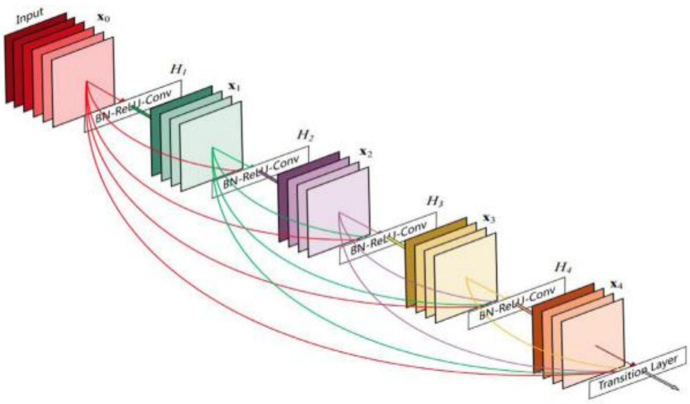

Figure 8: Proposed CNN Architecture

Table 1: Model summary

conv5_block31_1_conv (Conv2D)	None, 6, 6, 128)	204800
conv5_block31_1_bn (Batch Normalization)	(None, 6, 6, 128)	512
conv5_block31_1_relu (Activation)	(None, 6, 6, 128)	0
conv5_block31_2_conv (Conv2D)	(None, 6, 6, 32)	36864
conv5_block31_concat (Concatenate)	(None, 6, 6, 1632)	0
conv5_block32_0_bn (Batch Normalization)	(None, 6, 6, 1632)	6528
conv5_block32_0_relu (Activation)	(None, 6, 6, 1632)	0
conv5_block32_1_conv (Conv2D)	(None, 6, 6, 128)	208896
conv5_block32_1_bn (Batch Normalization)	(None, 6, 6, 128)	512
conv5_block32_1_relu (Activation)	(None, 6, 6, 128)	0
conv5_block32_2_conv (Conv2D)	(None, 6, 6, 32)	36864
conv5_block32_concat (Concatenate)	(None, 6, 6, 1664)	0
bn(Batch Normalization)	(None, 6, 6, 1664)	6656
relu (Activation)	(None, 6, 6, 1664)	0
conv2d (Conv2D)	(None, 4, 4, 1024)	15336448
max_pooling2d (MaxPooling2D)	(None, 1, 1, 1024)	0
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 256)	262400
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32896
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 5)	645
Total params: 28,275,269		
Trainable params: 28,116,869		
Non-trainable params: 158,400		

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4.4. Experimental Results

The groundnut leaf dataset comprises 1031 images labelled in six classes, is used for training and evaluating the efficiency of the densenet model recognising and categorizing the disease. Images of leaves that are affected are retrieved from the data for the purpose of validating root leaf diseases in groundnut. The model is trained with information from the training set before being used to sort the data in the test collection. Utilizing RMSprop being the optimization engine, the densenet-169 model is able to achieve an overall reliability of 99.83 percent.

Table 2: Report on CNN classifier classification for the suggested dataset

	Precision	Recall	F1-score
Late leaf spot	1.0000	1.0000	1.0000
Early Rust	0.9866	1.0000	0.9893
Early Leaf Spot	0.9953	1.0000	0.9951
Rust	1.0000	0.9922	0.9911
Nutrition Deficiency	1.0000	0.9932	0.9946
Overall Accuracy			**0.9843**

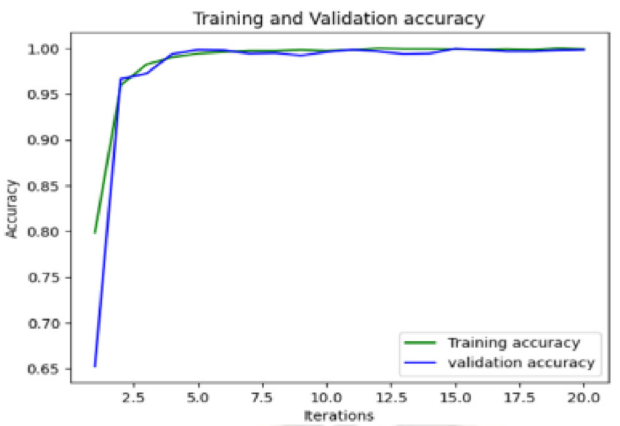

Figure 9: Accuracy of the model and accuracy of validation of the CNN-169 classification system

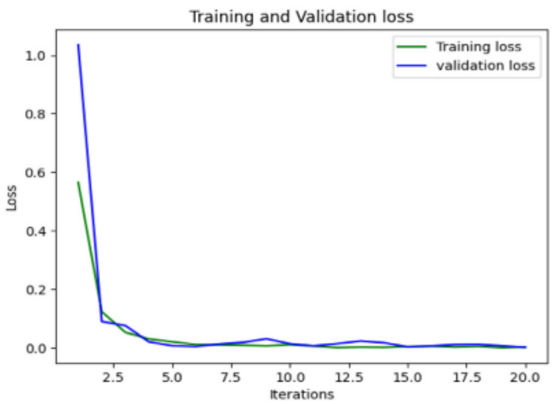

Figure 10: Loss of model and loss of validation from CNN classifier.

4.4.1. Result Analysis

Table 2 displays the accuracy, recall, and F1-score of the CNN densenet-169 model. Precise predictions may be provided for late leaf spot. Figure 7 compares the model's precision and validation accuracy according to number repetitions and also shows the graphs of accuracy with respect to the amount of iterations. The decrease in accuracy of the accuracy of the model and validation can be seen in Fig. 8.

V. Conclusion

Research on deep learning technologies is progressing swiftly. The Densenet can successfully classify and detect leaf diseases of the groundnut plant using the results from the CNN Densenet architecture (Densenet-169). The usefulness of the groundnut leaf data set is demonstrated by the model's performance during test and training utilizing the dataset. The Densenet model has a 99.83 percent success rate, while the suggested model has been shown to have greater accuracy ratings. In this article, the goal of producing standardized data on agricultural practices that aid in educating the public about machine learning and its potential applications has been achieved.

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