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Plant Disease Identification Based on Multimodal Learning

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Abstract: Over the last ten years, multimedia learning research has progressed quickly in various fields, especially computer vision. Deep multimodal Learning is becoming more prevalent due to the growing potential of deep learning methodologies and multimodal data streams. This necessitates the development of models that can really process and analyze multidimensional data appropriately. Un-structured real-world data can naturally exist in various modalities, also known as formats, and recovered and reused mixed visual and textual data. Deep learning researchers are still prompted by the desire to extract meaningful patterns from this data. This article explores how to develop deep models that take into consideration integrating and merging heterogeneous visual data from many sensory modalities to enhance the comprehension of deep multimodal learning by the majority of computer vision researchers. Diagnosing plant diseases has become digitalized and data-driven with the rapid growth of intelligent farming, providing enhanced decision support, analysis, and planning. Meanwhile, deep Learning-based advancements in artificial intelligence and computer vision have enabled device-assisted illness detection possible, and smartphone usage is rising rapidly. This research uses a dataset of more than 54,000 controlled images of sick and standard plant leaves to identify 14 plants and associated 26 diseases, creating a deep convolutional neural network for this goal. The model outperforms a test set resistance training accuracy rate of 99.06%. Generally, device-assisted crop disease diagnosis is achieved by the ability to train deep-learning models utilizing large and expanding public image datasets.

Keywords: *Neural network, multimodal, plant diseases, Deep Learning, artificial intelligence.*

1. Introduction

This article demonstrates how to develop deep models that are capable of integrating and combining contradictory visual information from various human senses to improve the understanding of deep modal learning by the majority of machine learning researchers. However, several issues, including plant diseases, environmental issues, etc., put food security and hygiene at risk. Due to regional variances that may make proper identification impossible, researchers face their most challenging obstacle when studying diverse settings. Additionally, conventional approaches mainly rely on experts, expertise, and manuals, but most are costly, labor-intensive, and difficult to detect precisely. Therefore, developing a quick and reliable method to diagnose plant illnesses is vital for agriculture's economic and ecological benefits. There have been several efforts attempted to protect crops against diseases. Going back in time, I.P.M (Integrated Pest Management) approaches have changed how pesticides have historically been applied. The expansion of agricultural organizations, such as neighborhood clinics with ties to plantations and agriculture, has greatly aided in identifying diseases. Averaging the rise in web usage, current efforts have been focused on online information and knowledge transmission for illness prediction.

This article implements a Deep Learning CNN methodology with a transfer learning demonstration on a dataset of over 54,000 photos of 14 crops with 26 illnesses made accessible to the public by the Plant Village project.

LSVDC (Large Scale Visual Detection Challenge) and the Image Net dataset-based PAS-CAL VOC Challenge have been used as benchmarks for various visualization-related issues in computer vision, including the object identification process. In the previous three years, the top 5 errors for a deep CNN network's categorization of the images into 1000 classes has decreased from 16% to 3.57%. this article rank 26 diseases affecting 14 crops using around 54000 pictures and a transfer learning strategy based on CNN and evaluate the model's performance based on its ability to correctly predict the harvest and the disease in pairs across 38 classifications. Our results indicate advancement toward a computer-assisted plant disease prognosis system as our best-trained model achieves a mean F1 score of 0.9906.

Multimodal learning advantages:

Modes are simply information conduits. As these data come from many sources and are semantically connected to one another and occasionally offer complimentary information to one another, they represent patterns that aren't obvious when using particular modalities alone.

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Such systems combine disparate, heterogeneous data from several sensors, aiding in the creation of predictions that are more reliable.

To assess someone's present mood, for instance, we might mix data from an EEG and eye movement signals, merging two independent data sources for a single deep learning assignment. This is how an emotion detector works.

2. Literature Survey

Primary area disease leaves image segmentation and extraction of features now the center of research on plant disease detection in complicated matters. Deep learning algorithms have received increased attention in recent years from the fields of computer vision because of their superior capabilities to more conventional customized approaches. Multiple application sectors have seen a significant number of studies on the broad subject of deep Learning. These primarily consist of a number of excellent survey data of global deep learning methods, techniques, trends, and applications [4], a study of deep learning algorithms in the computer vision community, a survey that focuses on the issue of deep object detection and the best latest events, and a survey of deep learning models that contains the generative adversarial network and its list of products, applications, and issues [19], in the applications discussed in these surveys. Thus, as demonstrated, the bulk of existing machine learning systems incorporate many modalities. It is essential to gather more complex and cross-modal data from many sources, data formats, and distributions. The deeply mixed approach is useful in this situation. Deep multimodal learning approaches have shown great success in boosting academic functionality and compatibility of estimating techniques in numerous ways, from the early works of speech recognition to more current breakthroughs in language-based and picture tasks. Deep multimodal learning has made the biggest breakthrough in visual classification algorithms using the deep learning paradigm and multimodal big data computing environments. Recent years have seen the recommendation of several concurrent machine learning-based research initiatives [37]. The most recent advances in deep multimodal learning, especially for the computer vision community, have not yet been addressed by recent work. For researchers studying this issue in particular, a thorough review and synthesis of prior work in this area is essential for further advancing the deep learning field. However, there was not even a significant amount of recent work directly referencing this field of research [32–37]. Because multimodal Learning is not a novel concept, it is essential to highlight and discuss the significant overlap between this study and the surveys [32–37] between them. Recognizing emotional responses [32], human action [32], and context [33] are only a few examples of recent mixed techniques that are only relevant to particular bidirectional use cases and applications.

Additionally, specialized art facilities studies [34,36] that address the method of integrating and fusing multimodal representations inside deep learning architectures have recently been published, emphasizing the opportunities this offers the artificial intelligence field. Guo et al. [35] conducted a similar in-depth analysis of deep multimodal learning frameworks and models, highlighting multimodal representation as one of the major obstacles to bidirectional learning.

They identified the primary concerns, benefits, and drawbacks of each conceptual framework and model. Another outstanding overview study by Baltruaitis et al. [37] has just been published. It assesses recent developments in multimodal machine learning and describes them using a wide taxonomy. The five layers of combining multimodal data were also named by the researchers as presentation, translation, alignment, fusion, and co-learning. In contrast to our survey, which was largely concerned with computer vision tasks, Baltruaitis et alstudy .'s [37] was primarily targeted at the natural language processing and computer vision groups. Within the six areas of multimodal data representation, multimodal fusion, multitask learning, multimodal alignment, multimodal transfer learning, and zero-shot learning, Beyond the above infrastructure, our main focus was on state-of-the-art deep learning applications in computer vision and related widely-used datasets. A thorough analysis of multimodal technologies is also provided in this article, along with an assessment of their benefits, drawbacks, trends, and difficulties, to help users better comprehend the major possibilities for future advancement in the field.

1. Image Segmentation.

When segmenting the images, the important responsibility in a challenging situation is identifying and detecting damaged plant leaves. Separating the symptom information from the environment is the primary purpose of image segmentation. Many researchers were conducting an in-depth study on it. Ali et al. divided the disease-infected region using the Delta E color difference technique in 2021. There are generally two main approaches to picture segmentation, which are covered in more depth in the following paragraph. Several studies combine the area of interest (R.O.I) when segmenting images and other techniques. For instance, Kao et al. asserted that the convolutional autoencoder determined the R.O.I. in a picture, which also acted as a background filter. The second approach focuses solely on area segmentation. According to Pujari et al., in 2020, features could be retrieved from pictures by dividing them into several areas, each of which had a unique meaning. Akram and other scientists presented a real-time synchronous image processing paradigm. By segmenting the process into different color spaces, it can perform contrast bending, feature mapping, and significant region detection. To identify and segment images, some researchers also use deep learning techniques. Marko et al. suggested a depth-based target recognition approach and applied the two-stage method to improve the identification of plant disease images.

2. Feature Extraction

There are several issues with feature extraction for plant disease identification. The image data characteristics such as texture, shape, colors, and movement characteristics are essential prerequisites for features to extract diseases. Raza and his associates revealed a method that removes disease spots using color and textural elements. Dempster-Shafer (D-S) evidence theory and multi-feature fusion were suggested by Hu et al. for extracting features, and the findings were processed by incorporating variance to improve the D-S evidence theory's decision criteria. Additionally, Turkoglu illustrated enhanced variations of the Local Binary Patterns (LBP) approach, which analyses the R and G channels of the picture by taking into account the overall and region and converts the image into grayscale using the original LBP local quadratic value.

Data Acquisition and Data Preprocessing

The PlantVillage dataset consists of 54303 healthy and unhealthy leaf images divided into 38 categories by species and disease. About 54,000 photos of diseased plants with 38 category labels are analyzed. Given only a picture of the sick plant, which combines a crop with such a disease. The dataset again for Plant Project analysis was used to analyze each crop-disease pair (figure1). The picture has been further downsized to 256X256 pixels, and several feature extraction and Deep Learning algorithms have been used for these reduced images. There were two versions: (a) colored images and (b) grayscale images. This article experiments with both grayscale and color images. This dataset is designed to help identify if the CNN model is indeed picking up on the "impression" of the plant diseases or whether it is instead detecting the dataset's "constitutional bias." Several varieties of the same plant are shown in (figure 2).

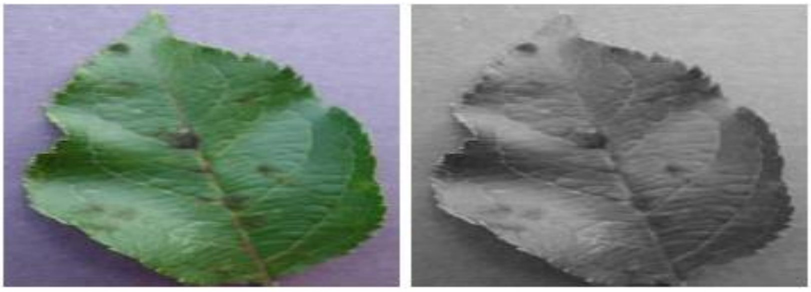


Fig 1: (a)leaf identification-colored images (b) leaf identification grayscale images

1. Performance Analysis

Most of our experiments performed are run utilizing different train-test splits, such as 7030, 8020,6040, and 5050, to evaluate how well our constructed model needs to perform and whether our methods are effective. For 40,000 of the 54,000 photographs with different angles. This article made sure that nearly all of the images with the same plant were either part of the training or testing group when performed out each of these test-train splits.

Setup of the Parameters

A. The Localization of Leaf Parameter Setup:

Tables 1 and 2 illustrate the parameter configuration for categorization neural networks and border regression neural networks, respectively. The tables &e anchors show how many candidate boxes were created.

Table 1 summarizes the neural network's parts and parameter settings.

The Network layer	Total number of kernels	kernel size	output format	various parameters
Convolution Neural Network	509	(4,8)	(18, 17, 509)	2458289
Convolution Neural Network	Anchors∗ 2	(2, 2)	-	-
SoftMax Layer	4098	--	--	--

B. The Parameter Setup of Leaf Segmentation

The Chan-Vese method's two most important settings are the initial zero level and iteration number. The starting zero level in this investigation was set as a circle with the picture's center and one-third of its diagonal length as the radius. The Chan-Vese method was set up to do 500 iterations. The image obtained via the Region Proposal Network (RPN). approach is used by the Chan-Vese algorithm, which keeps the image in the zero-level set. Every image not part of the zero-level set is rendered black to get the segmented picture outcome.

3. Proposed Methodology

the world around us can be experienced through a variety of senses, including sight, hearing, touch, smell, and scent of aromas. A modality, in general, is how something is observed. The word "modality" is typically associated with sensory modalities, essential components of modern perception and communication, such as vision and touch. Therefore, when a dataset has a number of these modalities, it is said to be multimodal. Artificial intelligence (AI) must be able to decipher and make sense of multimodal signals to advance in understanding the environment. Multimodal machine learning aims to create models that integrate and link data from several modalities.

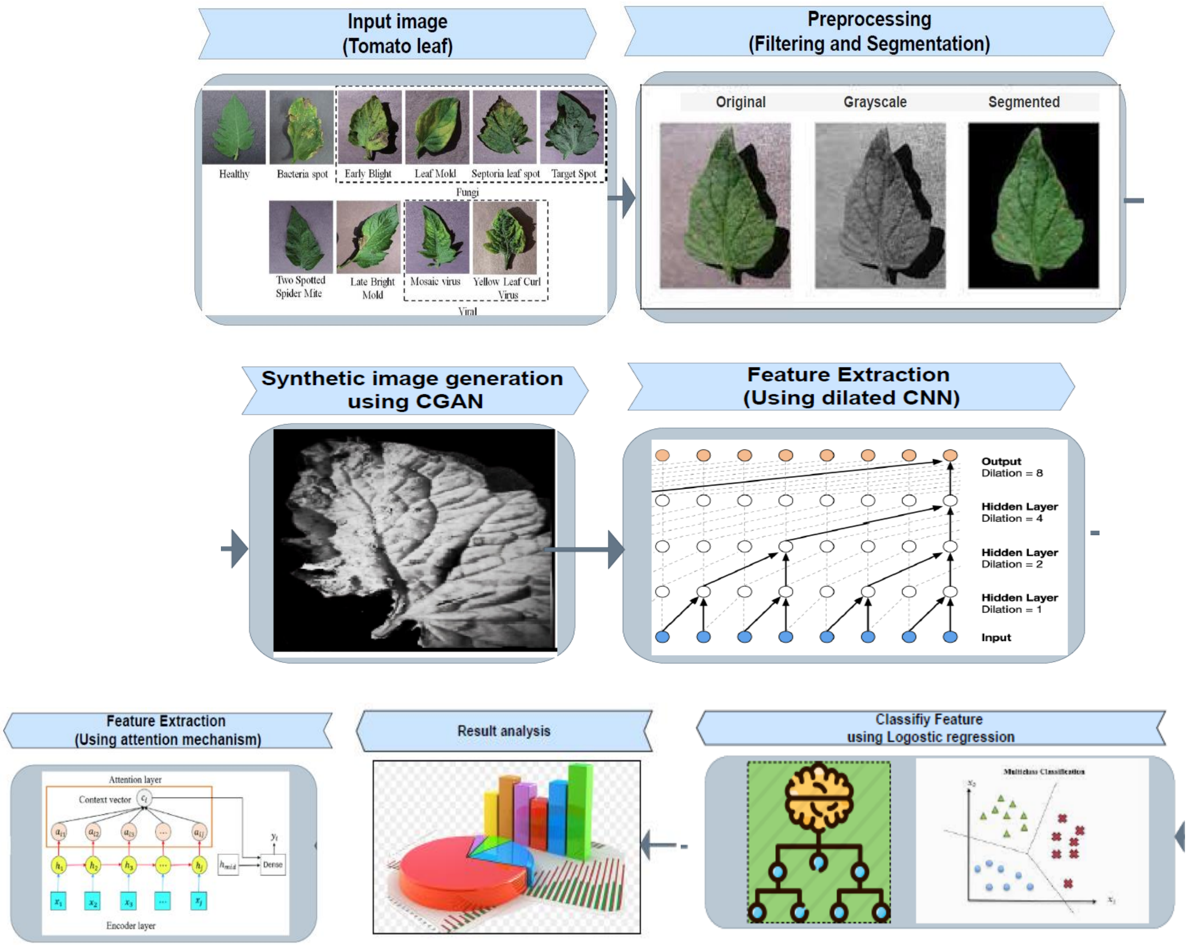


Fig 2: Multimodal learning architecture

The study of multimodal machine learning has significantly advanced recently. The main difficulties include representation, which tries to learn models of data sets that are computer interpretable from various sources; the method of translating data from one modality to another, known as translation; Discovering connections between components from two or more different approaches is the goal of alignment. Fusion, which describes the procedure of merging data from two resources to carry out such a prediction task, and co-learning, which seeks to uncover connections between elements from two or more various methodologies

Application of Deep CNN networks to the job of classification. This article concentrate on two popular designs, ResNet(50) and GoogLeNet, created for the ImageNet dataset in the ILSVRC. Kaiming He et al. Residual's Neural Network (ResNet) built an architecture with "skip conditions" that significantly included normalization. Individual thing are referred to as gated or gated recurrent units, which are appealing to R.N.N proposed design. VGG-19, a state-of-the-art method employed in the 2014 Large Scale Visual Recognition Challenge, lies at the bottom of the ResNet architecture and has a top-5 error rate of 3.57. A 34-layer plain network, which is considered to be the deeper network of the VGG-19 and has more convolution layers, then is shown, followed by a final 34-layer residual network, which is plain with skip connections at the top.

In our implementation of ResNet, the final fully connected layer contains 38 outputs, which further feed the SoftMax layer. This article compares the performances on the Plant dataset by utilizing the transfer learning method to train both of these models, ResNet and GoogLeNet. The weights of the fully connected layers in ResNet and the loss (1,2,3) layers in Google Net are reset when learning is transferred. The proposed approach developed images and performed bilateral filtering (B.F) picture preprocessing. Otsu's thresholding segmentation attention-based enlarged CNN model of feature extraction's hyper-parameters are finely adjusted in logistic regression (L.R) to optimize classification performance to the most significant degree feasible. An experimental and simulation study is done to ensure the attention-based dilated CNN-LR model functions appropriately. The experimental results in Table 1 demonstrate that the ADCLR model outperforms present condition methods on a variety of parameters. In the future, sophisticated DL-based picture segmentation algorithms will be used to improve the detection efficiency of the ADCLR technique.

The methods of our next preprocessing are calculated from the initial photos of specific leaf diseases. Preprocessing assists in extracting from the images more exact features. Then, to manage imbalances incorrectly labeled data and produce strong prediction results. The reduced ambient noise of the bilateral filtering technique benefits the leaf image in our method. This strategy to feature extraction, which combines dilated CNN with hybrid attention, is suggested. To improve the Learning organization, extract features, identify, and analyze leaf, This paper provides a new hybrid model that dynamically converts its hierarchical framework into a deep convolution. The elements could utilize dilated neural networks to collect valuable data. By accurately describing the network topology, our hybrid approach, built on a paradigm that also uses hierarchical self-dilation methods and utilizes dilated CNN, simplifies training time and improves performance. The efficiency of the convolution network's dynamic routing algorithm has increased, and a new approach for convolutional network dynamic convolution improves the effectiveness of the convolutional network's efficient routing tuning algorithm.

4. Experimental Results

The overall accuracy Across all of our trials on the Plant Village Dataset, the proposed model gives results ranging from 79.9% to 99.06%, illustrative of a significant range of accuracy variation.

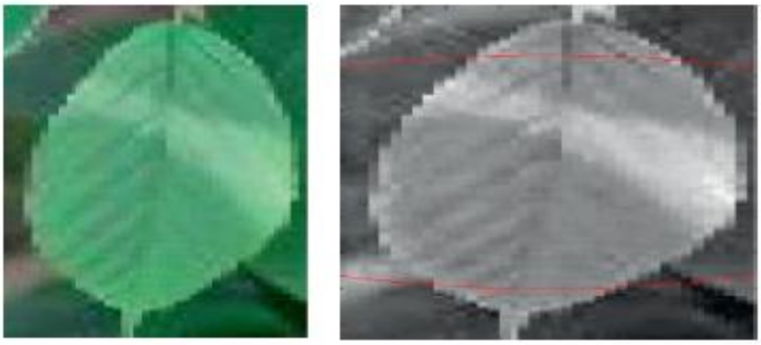


Fig 2: Healthy leaf segmented using the Chan-Vese algorithm: (a) image acquisition; (b) initial grayscale images.

This article examines the training-to-test set ratio to tackle the problem of over-testing and discovered that even in the last scene when there was only 20% training data and the remaining 80% test data, the model still obtained a good 96.7% accuracy (GoogLeNet::Color::20-80) as shown in figure3 and 4.

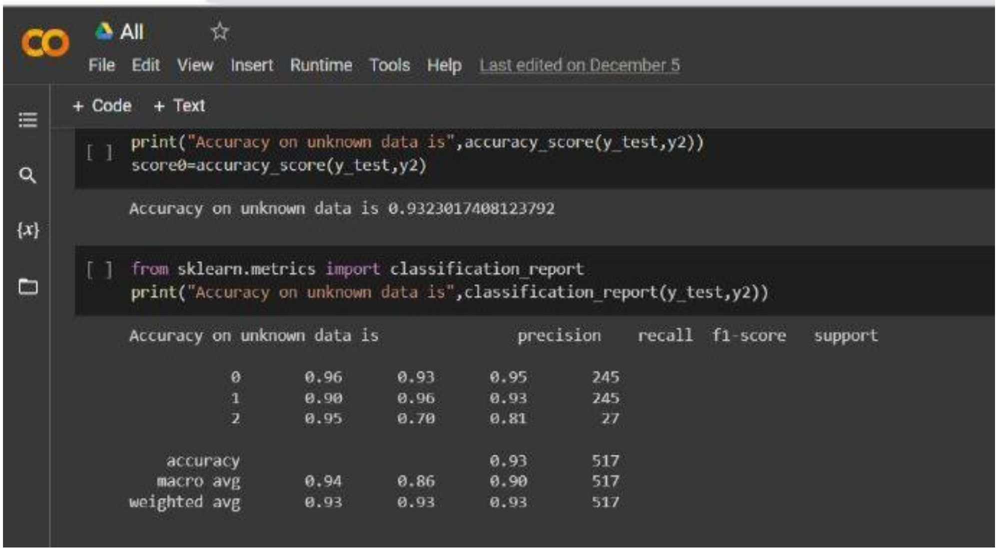


Fig 3: Evaluation of Output parameters

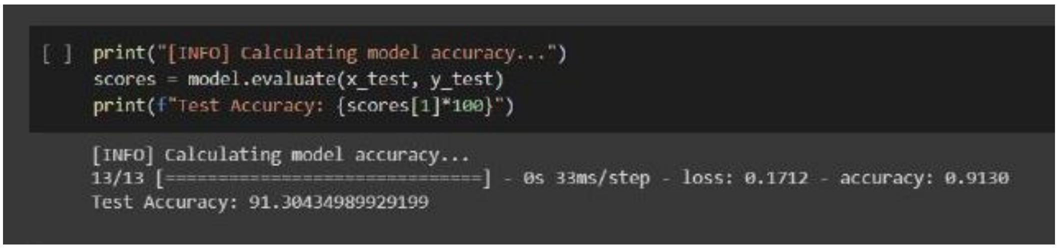


Fig 4: Accuracy after 13 epochs

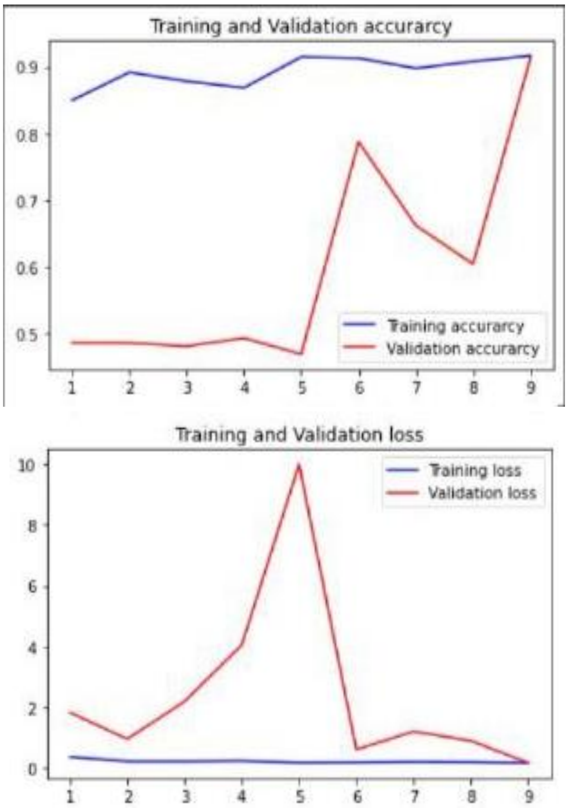


Fig: 5 Accuracy in training and validation

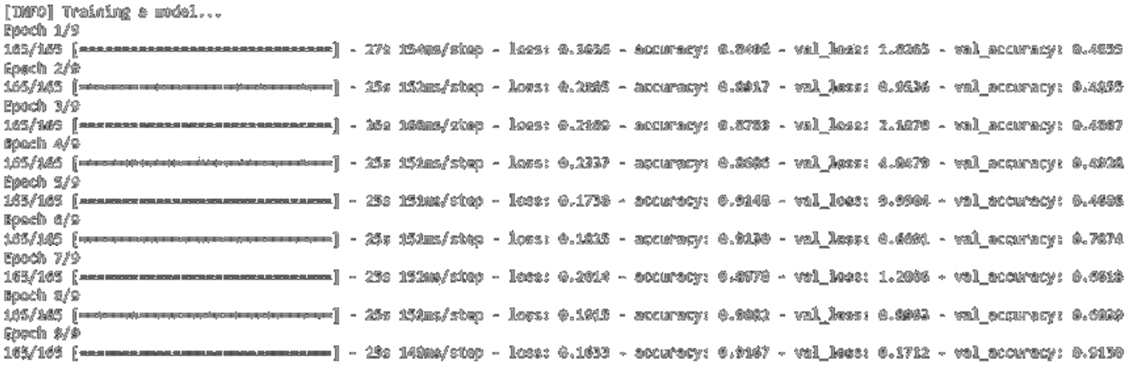
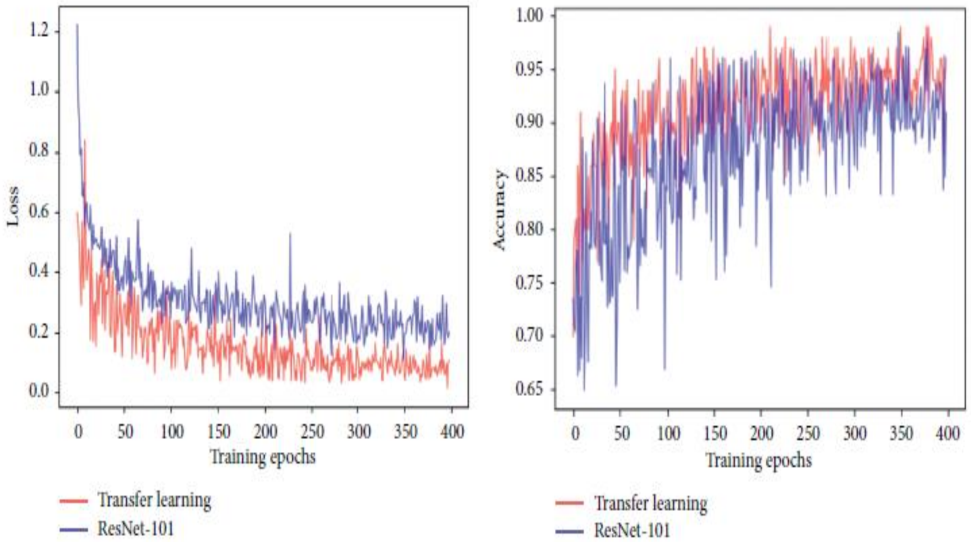


Fig 6: accuracy of a training model

Table 2: Composition and Setting of Parameters Transfer of Learning

	Reset	Google Net
Train 20% Test 80% Color Grey Scale	0.9562 0.8560	0.9775 0.9113
Train 60% Test 40% Color Grey Scale	0.9699 0.9854	0.8915 0.9347
Train 70% Test 30% Color Grey Scale	0.9534 0.9092	0.9907 0.9442

On colored datasets rather than grayscale ones, the models performed better. This article experimented using the greyscale dataset to see whether the model could differentiate between the illness and the crop without a color image, and the CNN network could recognize the biases that have been present.



(a) (b)

Fig 7: Comparison of loss values and accuracy between transfer learning and classical Learning

The performance did suffer due to the lack of color information. Even in the worst scenarios, the accuracy was still 79%, which was reasonably satisfactory. All of the findings have been presented, assuming that the model can concurrently identify both the crop and the illness. However, if the dataset could be modified to include the previously mapped product, our proposed model gives better results.

5. Conclusion

Deep Learning has significantly improved in classifying images and identifying objects in recent years. To handle the problem of plant disease detection in a complicated environment, this research offers a recognition model incorporating the multimodal algorithm, CV algorithm. In addition to adapting to complex settings, the model significantly improves identification precision. In contrast to the usual model, the model used in this research not only ensures the convolutional neural network's stability but also decreases the quantity and quality of convolutional neural networks' demand on the data set while producing effective results. When applied in real, a model that solves the problems of environmental complexity can produce accurate identification results. This study also contributes to the development of current thinking and assists in its accuracy.

Conflicts of Interest: The authors declare no conflict of interest

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