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Deep Learning Architectures Performance in Plant Leaf Diseases

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Abstract **–** Developing artificial intelligence applications continue to make our lives easier. Image processing technology has been developed for field-useful studies in medical science, education, finance, agriculture, industry, security, and many other sectors. For agricultural products, good works are done with artificial intelligence to detect plant diseases and take precautions accordingly. In our study, a comparison was made with deep learning methods on the images of the sugar cane plant in different categories. The VGG-19 architecture, which was classified separately from the 5 pre-trained architectures AlexNet, DarkNet-53, GoogLeNet, ResNet-50, and VGG-19, reached the highest accuracy with 92.2%.

Keywords – Artificial Neural Network, Deep Learning, Image Processing, Artificial Intelligence, Deep Learning, Crop, Agriculture, Sugar Can

I. INTRODUCTION

Thanks to advent of artificial intelligence, the machine learning and deep learning techniques, crucial studies have been produced for the fields of medicine, education, finance, agriculture, industry, security, and many others [1]. In conclusion, the system works as follows: using the accumulated training, machines learn using human-created algorithms, and then search for the best answers. Machine intelligence imitates human intelligence to solve problems [2]. When the human brain first discovers an object, it gains an idea by observing it visually. That is, by looking at the object's outline, color, and size, what happened can be defined. Similarly, algorithms in image processing technology, one of the deep learning methods, were formed this way. It is the state of manipulating the image by the computer, which processes the numerical representation of an object through a series of processes to obtain the desired result through image processing [3].

Among the most widely used deep learning network models in the world are, Convolutional Neural Network (CNN) [4], proposed by LeCun et al., Recurrent Neural Network (RNN) proposed by Hihi and Bengio [5] , and Hinton's Deep Belief Networks (DBN) [6] models. CNNs are a common deep web model type. They are feedforward neural networks with a convolutional computation function and a deep structure. They can represent learned features and can classify input information without shifting according to their hierarchical structure. Convolution and pooling techniques automatically enable CNNs to pick up on various image characteristics. Before learning more complex information and structures like texture and geometry, they first learn color and brightness, then local details like edges, vertices, and lines. They can eventually create the concept of all objects from these different properties. The hierarchical abstraction process in this learning process parallels how people perceive images [7].

The classification of plant diseases from digital images is a complex process. In recent years, tools for identifying, detecting, and diagnosing plant diseases have been developed using machine learning, deep learning, and plant image classification [8]. When we look at why this situation is essential, the increase in profit in agriculture; can be achieved by spending less money and increasing productivity and food quality. Fruits and vegetables are actual agricultural products. Product quality control is required to get more valuable products. Numerous studies demonstrate that plant diseases may cause a decline in the quality of agricultural products [9]. The normal state of the plant is disturbed by diseases, which change or stop vital processes like photosynthesis, transpiration, pollination, fertilization, germination, etc. Therefore, it is crucial to make an early diagnosis of plant diseases [10]. Farmers require constant monitoring and follow-up of experts to detect this situation, which can be costly and time-consuming. Therefore, it is of great realistic importance to seek a faster, cheaper, and more accurate method to automatically detect diseases from the symptoms that occur in the plant leaf [11]. An image-based automatic inspection enables machine vision, which provides process control and robot guidance. In this study, this issue is focused on the detection of plant leaf disease based on sugarcane tissue.

For disease management, forecasting yield loss, and ensuring food safety, automatic and accurate plant disease prediction in agriculture is essential. The most recent advancement in computer vision, deep learning, holds promise for identifying and classifying diseased plants. Therefore, when some studies conducted in this context are examined, it is essential to find successful results in both the agricultural sector and computer science. The performance of deep models that have been refined by transfer learning and the performance of external networks that have been trained from scratch are both systematically evaluated by Wang et al. [12]. The deep VGG16 model with transfer learning training is the best one; it offers an overall accuracy of 90.4% on the extension test set. [12]. The proposed deep learning model may have great potential in disease control for modern agriculture. Wan et al. [9] proposed a convenient and accurate method for detecting agricultural diseases. It was studied on a relatively large dataset and achieved approximately 87% accuracy. Barbedo [13] examines a brand-new automated system that can categorize disease symptoms in plant leaves and is intended to be adaptable in a variety of settings in his study. In comparison to many automated methods, the suggested technique tries a simpler and more reliable model. Tests on a sizable data set containing images of 77 diseases belonging to 11 plant species were conducted to demonstrate the model's efficacy. The benefits of the suggested approach are further strengthened by comparison with manual partitioning. The algorithm's primary flaw, which was that it could not deal with reflections or leaf veins that were noticeably different in color from other healthy parts of the leaf, was, however, also addressed. LeNet, a deep CNN architecture, is being developed by Gayathri et al. [14] to identify tea plant diseases from the leaf image set. LeNet is cited as a successful CNN model that will be applied to enhance tea leaf and other plant leaf diagnostic measurements.

It was discovered using a different mobile application when the literature was scanned in a different study. Ahmed et al. [15] presented the design and implementation of a machine learning-operated plant disease detector that enables farmers to diagnose the 38 most common plant diseases in 14 species. A dataset of 96,206 images, including healthy and diseased plant leaves, was used to train the CNN model. Images with busy backgrounds, low contrast, and lighting conditions were all considered. To ensure the system's usability, a mobile application has been created, giving farmers with limited resources a better opportunity to spot plant diseases in their early stages and stop using improper fertilizers that can harm plants and soil. The system's performance and classification accuracy were assessed through several sets of experiments, focusing on the classification and processing times. The proposed model can typically process a plant image using a useful mobile application in less than a second in a natural farming environment, making the system suitable for realtime inference at the network end with high prediction accuracy and response time.

This article is divided into the following sections. Following the definitions of artificial intelligence, machine learning, and deep learning, the introduction includes a section on the importance of leaf diseases and a literature review. The material and method section follows with a discussion of the dataset and methodology, followed by a discussion of the experimental findings and how the findings were assessed and added to the body of literature in the discussion section. Finally, the study's conclusion section marked the study's official completion.

II. MATERIAL AND METHOD

In this section, the material and method used in the study are explained.

A. *Dataset*

The dataset was obtained from Mendeley Data, a cloud-based shared repository where data is stored and shared [16]. The downloaded database consists of manual images of sugarcane leaf disease collected in Maharashtra, India. The dataset has five main categories; There are classes with Healthy, Mosaic, Redrot, Rust, and Jaundice. The dataset was recorded with smartphones of various configurations to preserve diversity. It contains a total of 2569 images, including all categories. The database is balanced and contains a good variety. Example images of the dataset are given in Figure 1.

Figure 1. Examples of Images from the Dataset's Categories

B. *Methodology*

Figure 2 shows the study's flowchart diagram. The dataset includes pictures of healthy plants and plants with sugarcane leaf disease in five categories. The results of training and testing these five distinct categories on five different CNN architectures, AlexNet, DarkNet-53, GoogLeNet, ResNet-50, and VGG-19, are detailed in Table 1.

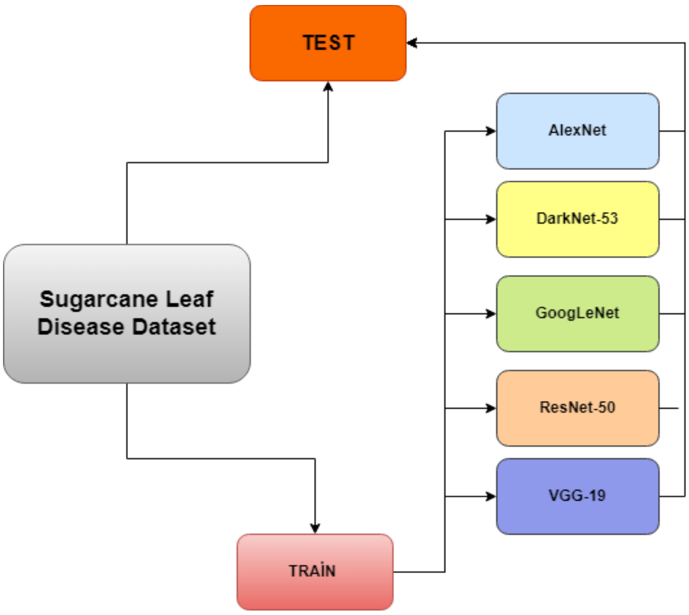


Figure 2. The Flowchart of the Proposed Model

III. RESULTS

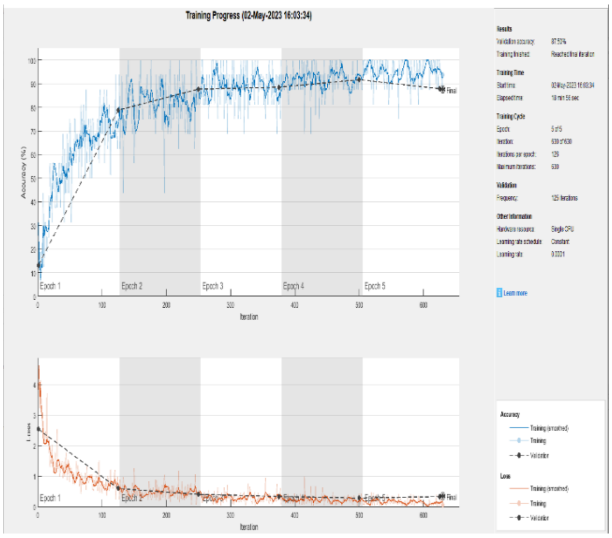
In this study, numerical computation using a variety of functions and paradigms was done using the software tool MATLAB. All experiments were carried out on a computer with 16GB RAM and an Intel Core i7 processor. The dataset consists of sugarcane plant image data with five categories, Healthy, Mosaic, Redrot, Rust, and Jaundice, obtained from the open-access site Mendeley Data, where the data is stored and shared.

The dataset was trained and tested with AlexNet, DarkNet-53, GoogLeNet, ResNet-50, and VGG-19 architectures. The accuracy results of CNN architectures are given in Table 1.

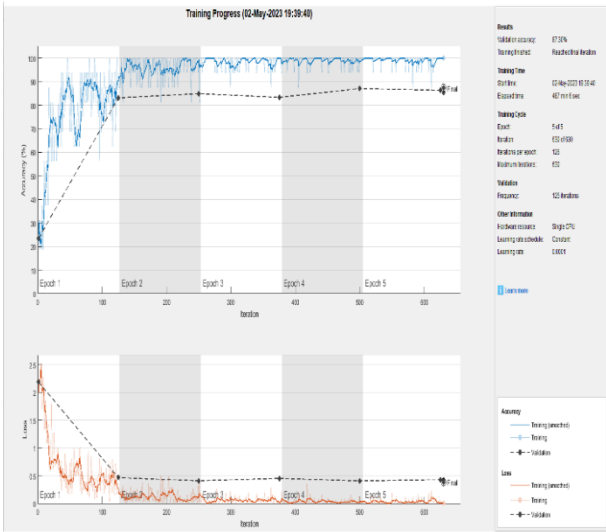
Table 1. Accuracy Performance Comparison of 5 Architectures Running the Dataset

Deep Learning Architecture	**Accuracy**
AlexNet	87,50%
DarkNet-53	87,30%
GoogLeNet	87,50%
ResNet-50	85,70%
VGG-19	92,20%

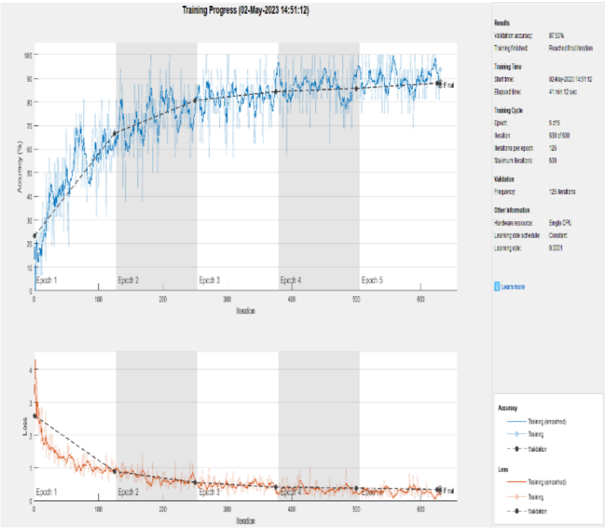
Each period of the training and testing process consists of 126 iterations and five periods, a total of 630 iterations. The training and testing process is given in Figure 3. The figure shows that although AlexNet completed the training in 18 minutes, it was the second most successful architecture among the five architectures with 87.50% accuracy. GoogLeNet, the second fastest architecture with 41 minutes in terms of time, shares second place with AlexNet with 87.50% accuracy. ResNet-50, which completed the training and testing period in approximately 102 minutes, was the architecture that completed the worst result of the study with 85.70% accuracy. The DarkNet-53 architecture, it had penultimate success with 87.30% accuracy in 487 minutes. VGG-19, which completed the training and testing process in the most extended period of approximately 723 minutes, was the most successful architecture in detecting Healthy, Mosaic, Redrot, Rust, and Yellow diseased sugarcane images with an accuracy rate of 92.20%.



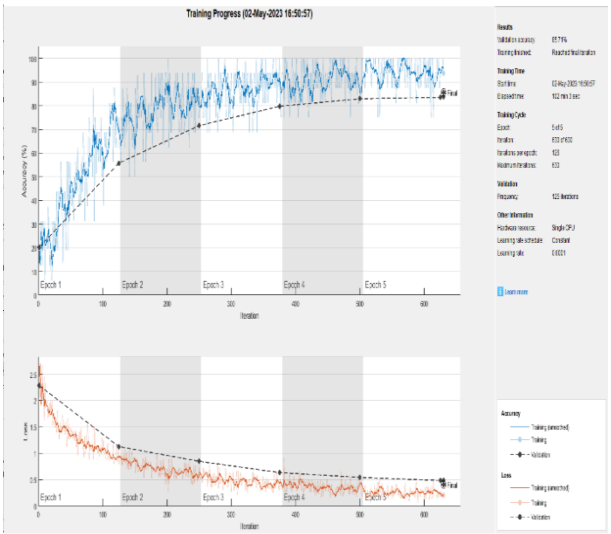
A. AlexNet



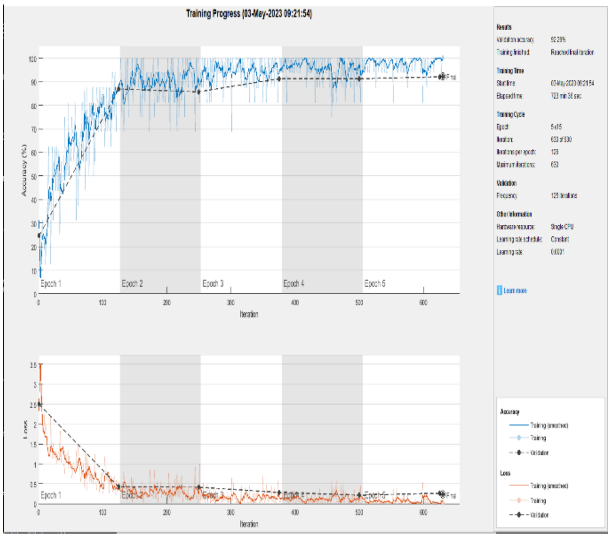
B. DarkNet-53



C. GoogLeNet



D. ResNet-50



E. VGG-19

Figure 3. The Training Progress of the Deep Architectures

After the training and testing phases of CNN architectures, the confusion matrix, also known as the error matrix, in statistical classification problems in machine learning is shown in Figure 4.

Confusion Matrix AlexNet

	Healthy	Mosaic	RedRot	Rust	Yellow
Healthy	77	20	7		
Mosaic	1	89	1		1
RedRot		2	95	1	6
Rust		2	5	89	7
Yellow	1		9		91

Confusion Matrix DarNet-53

	Healthy	Mosaic	RedRot	Rust	Yellow
Healthy	80	16	6		2
Mosaic	1	89		1	1
RedRot	4		92	1	7
Rust	1	1	5	96	
Yellow	1	1	12	4	83

Confusion Matrix GoogLeNet

	Healthy	Mosaic	RedRot	Rust	Yellow
Healthy	89	14	1		
Mosaic	4	84	1	2	1
RedRot		1	94	5	4
Rust	1	2	15	83	2
Yellow	1		7	2	91

Confusion Matrix ResNet-50

	Healthy	Mosaic	RedRot	Rust	Yellow
Healthy	79	14	11		
Mosaic	1	89	1		1
RedRot	2	6	85	1	10
Rust	2	2	6	93	
Yellow	1	2	12		86

Confusion Matrix VGG-19

	Healthy	Mosaic	RedRot	Rust	Yellow
Healthy	85	15	2		2
Mosaic	1	89	1		1
RedRot		1	100	2	1
Rust			2	100	1
Yellow			4	6	91

Figure 4. Confusion Matrix of the Deep Architectures

IV. DISCUSSION

Artificial intelligence, machine learning, and deep learning have started to be used to identify agricultural diseases due to recent advancements in AI technology.

The proposed study has achieved actual results in classifying images of sugar cane into five categories with deep learning architectures, one of the machine learning methods, a sub-branch of artificial intelligence. The VGG-19 architecture was the most successful in detecting images of Healthy, Mosaic, Redrot, Rust, and Jaundice diseased sugarcane with an accuracy of 92.20%.

While obtaining images from a single region can be considered one of the study's minuses, in future studies, the accuracy can be increased by connecting successful architectures and developing hybrid models. The study can be expanded with more original and larger data sets.

V. CONCLUSIONS

In order to increase food production and decrease agricultural losses brought on by diseases and pests due to a growing global population, advanced technologies, such as artificial intelligence, are urgently required. The ability of artificial intelligence to assist in making better and more efficient use of available resources is anticipated to have a significant positive impact on the agricultural sector. In other words, artificial intelligence can help make coexistence with other species on Earth sustainable by reducing the harm done to the planet's environmental resources. A key component of smart agriculture is image recognition for agricultural diseases.

This study used deep learning architectures to compare various deep learning techniques to images of sugar cane plants in various categories. The highest accuracy was attained by the VGG-19 architecture, which was classified separately from the five pre-trained architectures AlexNet, DarkNet-53, GoogLeNet, ResNet-50, and VGG-19. Its accuracy was 92.2%.

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