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The Effectiveness of Deep Learning Methods on Groundnut Disease Detection

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***Abstract*— Early detection of plant diseases in the agricultural sector is considered an important goal to increase productivity and minimize damage. This study deals with the use of deep learning methods to realize the automatic detection of leaf diseases in peanut plants and the explicability of the model with heatmap visualizations formed during the detection of diseases. In the study, a dataset containing 3058 images with 5 classes enriched with diseased and healthy samples of peanut leaves was used. The explainability property has also been studied to understand why the models detect a particular disease. The decision processes of deep learning models, which are usually described as the "magic box", were visualized with the heatmap method in this study. By highlighting the pixels that are effective in detecting diseased leaves with heatmap visualization, the decision-making process of the model has been tried to be made understandable. The results show that deep learning models have high performance in detecting peanut leaf diseases, and the explainability obtained by heatmap visualization is a reliable tool for agricultural specialists and producers. Thanks to the visual explanations provided by the model, the level of confidence in the detection of diseases has been increased and confidence in the decision processes of the model has been provided. This study constitutes an important step towards increasing efficiency in agricultural applications and providing a more efficient approach to disease management by investigating the impact and explicability of deep learning methods in the field of disease detection in peanut plants.**

***Keywords*— Heatmap, Explainability AI, Groundnut disease, deep learning, AlexNet**

I. INTRODUCTION

Artificial Intelligence (AI) provides improved methodologies to plant pathology experts and researchers in various sectors, encompassing disease prediction and diagnosis among others. However, the lack of transparency within AI models poses challenges for their acceptance and utilization based on results obtained in laboratory settings. The primary impediment arises from the untraceable nature of AI model operations and the absence of comprehensive visibility into the intricacies of program functioning [1].

However, people's sense of curiosity is driven by specific reasons to make the best choice. In the selection of artificial intelligence models, models that enhance human comprehension and decision-making confidence by providing impartial and equitable outcomes are favored. Therefore, for transparency and assurance, a model must be capable of offering an explanation and feasible solution in order to respond to the need for confidence [2].

In this context, this study introduces a different perspective on the "hidden boxes" within the deep learning model, referred to as latent representations, aiming to elucidate the results obtained from deep learning models utilized for the classification of plant diseases. Supporting sustainable agriculture is imperative to meet the escalating global food demand due to the increasing world population. Ensuring the utmost preservation of crop plants and produce is vital to match production with demand. Diseases observed in crops and plants significantly impact both product quality and yield, potentially impeding the achievement of this goal [3, 4].

The diagnosis of diseases to be identified in a laboratory setting demands an extensive period of time and expert knowledge. Disease symptoms, when observed directly, necessitate chemical procedures. However, most farmers attempt to visually identify diseases with inaccurate information and accumulated knowledge, often leading to incorrect treatments. Consequently, this ultimately exacerbates the condition of the plant and produce, rather than facilitating recovery [5, 6].

Groundnuts, besides being a significant food source, are cultivated as both a sustenance and income generator in numerous African countries. Rich in fats, proteins, minerals, and vitamins, groundnuts serve as a livelihood source for many producing nations. Consequently, the necessity for a technical system capable of identifying and classifying peanut crop diseases, which would enhance both yield and quality, is progressively growing [7, 8].

The groundnut dataset employed in this study comprises both raw and extracted images, with the latter further augmented through data augmentation techniques. Initially, the study employed raw images to assess the disease classification performance of the AlexNet model, a deep learning architecture. To achieve this, the Grad-CAM method was employed to compute the influence of gradients originating from the classification output in the final layer, aiming to elucidate the model's decision-making process by visualizing the specific regions that played a role in the calculation. Subsequently, exclusively diseased leaves were extracted from the raw images, and the dataset was augmented using data augmentation techniques, which led to successful disease classification using the AlexNet model once again. In this phase as well, the Grad-CAM method was utilized to highlight the image regions on which the model focused.

II. Related Works

Drawing attention to cercospora, a common leaf disease that occurs in the early stages of peanut leaves, the research presents an optimized processing approach using the backpropagation algorithm for color improvement, plane separation, removal of color characteristics and disease detection [9].

Groundnut, also known as Arachis hypogaea, is a food source with a high fat and protein content. However, diseases such as fungi, viruses and bacteria can negatively affect plant yield. This study aims to detect peanut leaf diseases using the deep convolutional neural network (DCNN). DCNN method, 6. it has achieved successful results by providing 99.88% accuracy in its combined layer [10].

This study aims to investigate deep learning methods for the detection of leaf spot disease in peanut plants. Various pre-trained neural network architectures and optimization algorithms were utilized to create a model. Using a dataset of 1,000 leaf images, the study's findings reveal that the DenseNet-169 model trained with RMSProp achieved a high accuracy of 98% and precision of 98%. These outcomes hold significance for agricultural automation and disease detection systems in peanut cultivation [11].

Disease prevention techniques play a critical role in diminishing the recurrence and severity of plant diseases. In this context, the study aims to explore novel deep learning techniques by amalgamating three distinct architectures: VGG 16, Google Net, and GAN. These models aspire to forecast the likelihoods of peanut plant diseases and proficiently implement them in both centralized and decentralized agricultural domains. Furthermore, an intricate succession of deep learning applications encompasses the stages of plant disease imagery, pretreatment, segmentation, and classification. The precision values of the foremost model, encompassing peanut diseases spanning six diverse categories, were determined as follows: early leaf spot (98%), late leaf spot (96%), rust disease (95%), root root disease (98%), Alternaria (96%), anthracnose (93%), and healthy leaves (96%) [12].

Another study conducted is to develop a software approach to automatically classify and identify peanut plant diseases. Diseases such as fungi, soil-borne pathogens and viruses cause a decrease in yield. In the study, the steps of image acquisition, preprocessing, segmentation and feature extraction using the K Nearest Neighbor (KNN) method were used. The performance of the algorithm was improved by using the SVM classifier instead of KNN. As a result, the study aimed to successfully classify 4 different diseases [13].

This study aims to detect peanut leaf diseases with IoT-based automatic detection and classification methods. Disease classification was performed by determining the disease area using hybrid machine learning techniques, optimal feature selection and deep neural network based on moth optimization. The results obtained confirm that the proposed method is effective [14].

As a part of the study, the 'Customized Network' model, designed and implemented, has been employed to predict diseases in pearl millet and visualize extracted features using the Grad-CAM technique. Furthermore, the impact of transfer learning on the model's performance has been investigated. Empirical results manifest that the 'Customized Network' model attains a notable classification accuracy and significantly reduces the training time. These findings underscore the efficacy of the proposed model as a low-cost and practical tool for automating the detection of plant diseases, particularly in pearl millet cultivation [15].

Deep learning has achieved high success in the detection of plant diseases. However, these models can be difficult to explain due to their complexity. Researchers have experienced difficulties in providing classification explanations. In this study, explainable artificial intelligence (XAI) is used for plant disease detection. XAI contains algorithms that explain artificial intelligence decisions in an understandable way. In addition, important regions of disease detection have been highlighted using an XAI method called Gradient-weighted Class Activation Mapping ++ (GradCAM ++) [16].

In this study, 1D gradcam, a new visualization method for CNN models in 1D spectroscopy, was introduced. Unlike the classic gradcam, it significantly improves feature capture and correlation. Raman spectroscopy and 1D GradCAM applied to resnet effectively reflect the high accuracy of ResNet [17].

When the literature is examined, many studies have been conducted for groundnut crop and plant diseases. In this study, the explanation and evaluation of the success performances of the models were carried out using the grad-cam method in the selection of pre-trained deep learning models on a newly introduced data set. In addition, the effect of the raw and extracted images of the data set on classification success is explained. In the same way, different methods have been tried in different studies to demonstrate the reliability and explicability of the models.

III. MATERIAL AND METHODS

In this section, AlexNet, one of the deep learning models used in the study, performance metrics for the success of the model and the Grad-Cam method will be mentioned in order to present the explainability of the model. The graphical description of the study is given in Fig 1.

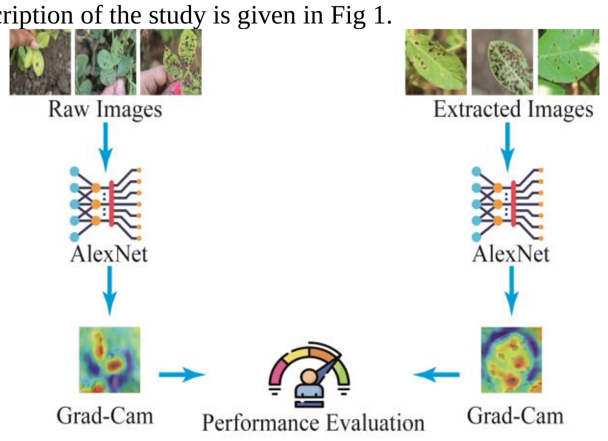

Fig. 1 Illustrator of the study

A. *Dataset*

The researchers have created a data set by obtaining images of different diseases of the groundnut plant during the Kharif and Rabi seasons from the Koppal region. The raw images consist of 5 types of diseases and 3058 images. The extracted images again consist of the same 5 diseases and 8887 images. The types of diseases used in the study and the number of images belonging to these varieties are given in Table 1. Fig. 2 shows examples of raw and extracted images obtained in the study.

TABLE 1
DETAILS OF THE DATASET USED IN THE STUDY

Disease	Raw Image	Extracted Image
Early Leaf Spot	885	1731
Healthy Leaf	929	1871
Late Leaf Spot	689	1896
Nutrition Deficiency	329	1665
Rust	226	1724
Total	3058	8887

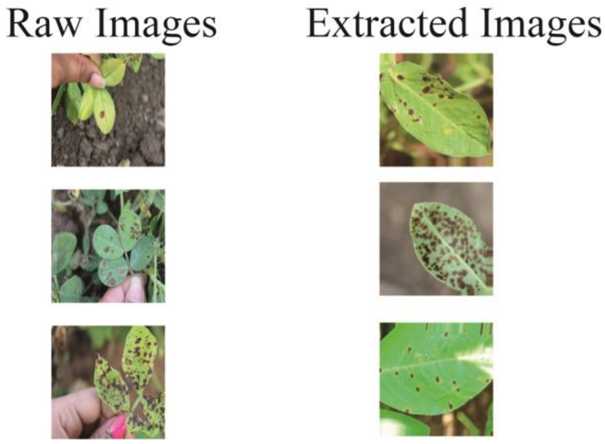

Fig. 2 Examples of images used in the study

B. *Convolutional Neural Networks (CNN)*

Convolutional Neural Network (CNN) has been one of the deep learning algorithms commonly employed for analyzing visual data. Its name originates from the mathematical linear operations among matrices, termed as convolutions. Due to its complex mathematical structure, CNN is often perceived as a black box. It processes an image through different layers, effectively separating its features. The commonly applied layers include the convolutional layer, activation layer, pooling layer (maximum, average, or global), flattening layer, and fully connected layer [18, 19]. In this study, the transfer learning method was preferred. Transfer learning is the use of knowledge learned in one task to achieve better performance in a different task. This approach is widely preferred to adapt or transfer the knowledge of a previously learned model to a new task [20].

C. *AlexNet*

AlexNet, a pioneering convolutional neural network (CNN) architecture, made a groundbreaking impact on object recognition, especially for high-resolution images. It introduced several innovative features that revolutionized the field. This architecture's significance lies in its ability to address challenges posed by high-resolution images and its success in the ImageNet competition [21-23]. AlexNet's architecture incorporated several key elements that contributed to its success. It introduced ReLU (Rectified Linear Unit) nonlinearity, which accelerated training significantly compared to traditional activation functions like tanh. Multi-GPU training in AlexNet allowed for the development of larger models and faster training times. Additionally, the use of overlapping pooling reduced errors and mitigated overfitting. The architecture of AlexNet comprises 8 layers with learnable parameters, and it's designed to process RGB images. It consists of 5 convolution layers with max-pooling and 3 fully connected layers. The activation function used in all layers is ReLU (Rectified Linear Unit), except for the output layer, which employs Softmax [24, 25].

D. *Gradcam*

Grad-CAM is a method used to visualize and explain the decisions of deep learning models [26]. This method has a name consisting of a combination of the words gradient (gradient) and class activation mapping (class activation mapping). Deep learning models, especially those used for image processing, have great features on them, especially evolutionary neural networks (Convolutional Neural Networks - CNNs) [27]. Grad-CAM is used to determine which regions are important when classifying elements of a neural network. Especially in the case of object changes or formation problems, it is extremely important to understand which features can be monitored when the neural network recognizes an object [28].

E. *Performance Metrics*

A performance metric is a measurable value that evaluates how a system, model, or process performs under a certain measure. These metrics are used to measure the success, effectiveness, accuracy, efficiency or other important qualities of something. It plays an important role in determining which areas need to be improved in decision-making processes and efforts to improve processes. Performance metrics are usually aimed at achieving certain goals or meeting a certain quality standard [29-31]. The ratio of the correct predictions of any model to the total data point is expressed as Accuracy. This is a basic assessment measure, but it may be insufficient in cases such as unbalanced class distributions [32]. The accuracy metric is calculated according to Formula 1 [33].

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} * 100 \qquad (1)$$

IV. EXPERIMENTAL RESULTS

The previously trained AlexNet model was preferred in the study. It is a deep learning model that has the ability to make quick decisions in studies due to the fact that the number of parameters is small and the size is not too large. Firstly, a classification was made with the raw images of the data set and its performance was evaluated. The validation and loss graph obtained from the first stage of the study is given in Fig. 3

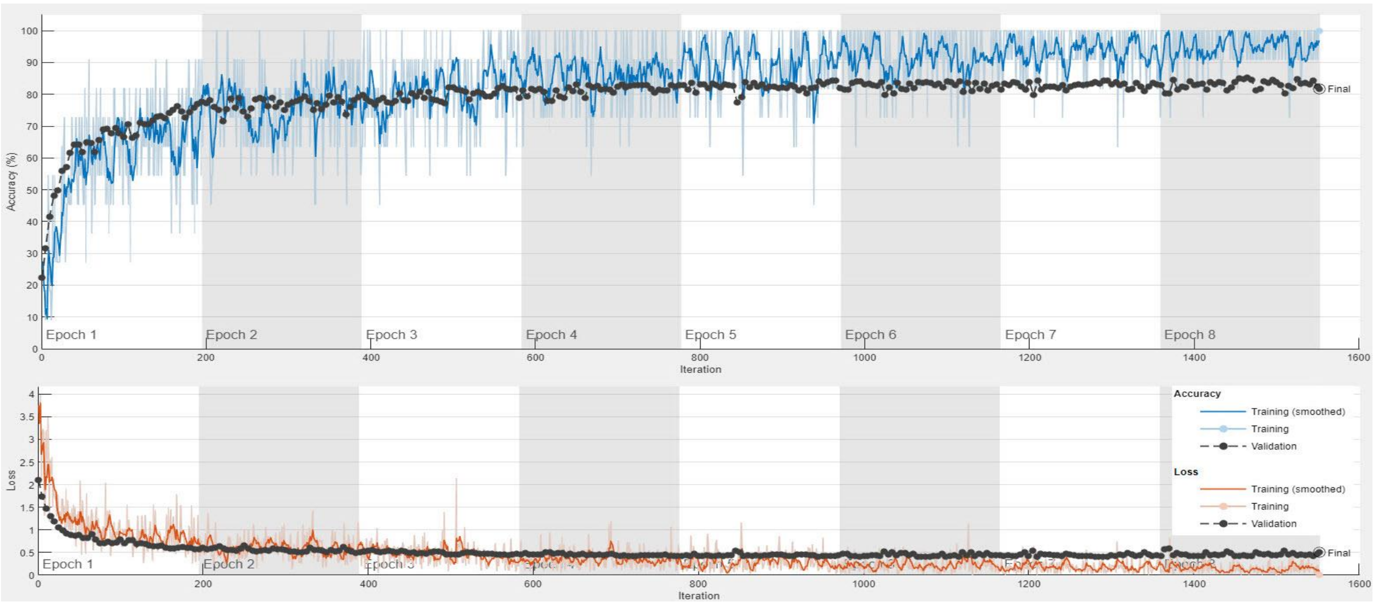

Fig. 3 Training, validation and loss graphs of the pre-trained AlexNet model with the raw images

When the graph was examined, the success of the AlexNet model in classifying raw images was calculated as 81.82%. It can be said that the success of the model did not change much after the 4th epoch, and as a result, the classification success was at an acceptable level. In the second stage, the classification of only diseased leaves obtained from raw images was carried out again with the AlexNet model. The validation and loss graph obtained as a result of this training is given in Fig. 4.

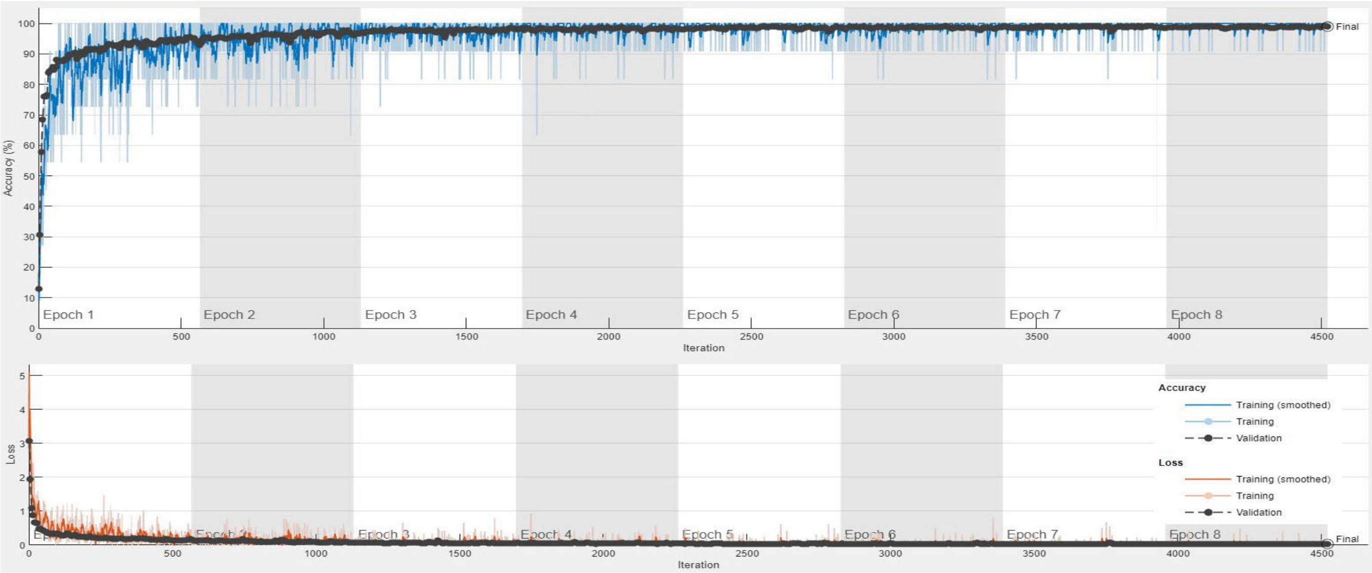

Fig. 4 Training, validation and loss graphs of the pre-trained AlexNet model with the exracted images

When the graph was examined, the success of the model in classification was obtained as 99.02%. Modell was able to achieve a high level of accuracy after the third epoch. it can be said.

When examined in both stages, classification was made primarily with 3058 raw images using the AlexNet model. Then, these raw images were extracted and 8887 images were obtained. When the results are compared, it is thought that increasing the number of data increases the classification success. However, in order to understand the accuracy of this statement, it is necessary to know where the models are focused in the image during the training phase. For this reason, the Grad-Cam method was used to interpret the models at the end of each stage. As a result of this method, the results obtained at both stages are given in Fig. 5 and Fig. 6.

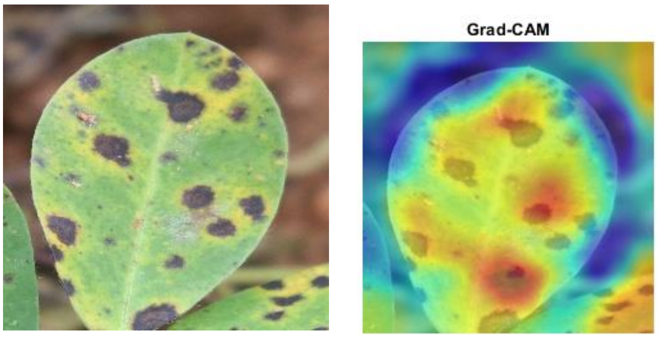

Fig. 5 The parts that the model focuses on to increase the prediction in the classification of extracted images

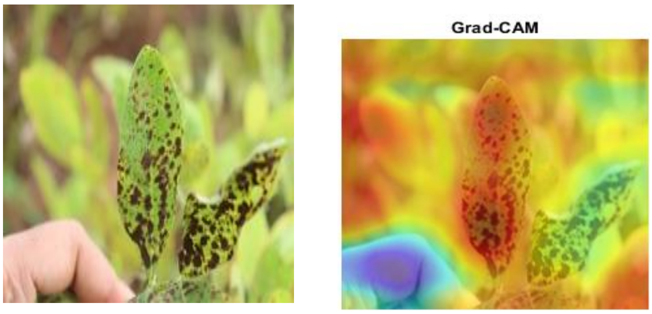

Fig. 6 The parts that the model focuses on to increase the prediction in the classification of raw images

When the given Figures 5 and Figure 6 are examined, it is seen that the AlexNet model focuses only on the leaf on the extracted images, and even focuses on diseases on the other leaf when there are other leaves next to the leaf. On the raw images, it can be said that the classification success is low due to the fact that the model focuses on other places next to the leaf and uses them as information during the training phase.

V. Conclusions

As a result, having a large number of data and clearing the images from noise increases the success of the model. In addition, the effectiveness of deep learning models using heat maps allows researchers or users to interpret the models at an understandable level.

In this study, the classification of different diseases found in peanuts with deep learning models can be presented to farmers by supporting them with mobile applications that will be developed with reference.

Another aim of this study is to detect plant diseases by deep learning method, which can increase agricultural productivity and reduce their harmful effects, thus providing a more sustainable agricultural practice.

In order to investigate the success of the models in the selection of deep learning models, the prediction abilities of the models can be explained in more detail by using different methods such as Grad-Cam. In addition, the performance of techniques such as Grad-Cam can also be evaluated.

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