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Integrating Few-Shot Learning and Multimodal Image Enhancement in GNut: A Novel Approach to Groundnut Leaf Disease Detection

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Abstract: Groundnut is a vital crop worldwide, but its production is significantly threatened by various leaf diseases. Early identification of such diseases is vital for maintaining agricultural productivity. Deep learning techniques have been employed to address this challenge and enhance the detection, recognition, and classification of groundnut leaf diseases, ensuring better management and protection of this important crop. This paper presents a new approach to the detection and classification of groundnut leaf diseases by the use of an advanced deep learning model, GNut, which integrates ResNet50 and DenseNet121 architectures for feature extraction and Few-Shot Learning (FSL) for classification. The proposed model overcomes groundnut crop diseases by addressing an efficient and highly accurate method of managing diseases in agriculture. Evaluated on a novel Pak-Nuts dataset collected from groundnut fields in Pakistan, the GNut model achieves promising accuracy rates of 99% with FSL and 95% without it. Advanced image preprocessing techniques, such as Multi-Scale Retinex with Color Restoration and Adaptive Histogram Equalization and Multimodal Image Enhancement for Vegetative Feature Isolation were employed to enhance the quality of input data, further improving classification accuracy. These results illustrate the robustness of the proposed model in real agricultural applications, establishing a new benchmark for groundnut leaf disease detection and highlighting the potential of AI-powered solutions to play a role in encouraging sustainable agricultural practices.

Keywords: agriculture; deep convolution neural network; few-shot learning; groundnut crop; image processing

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1. Introduction

Farming, one of the primary activities that has been feeding humankind for millennia, has transformed from a mere means of subsistence to a highly developed science and business that is essential at the present stage. In the dynamic environment of agriculture, one main threat remains: the unpredictability of the impact of the leaf diseases on the productivity of crops and the food security of the world [1].

The early, accurate, and complete diagnosis of all the leaf diseases has become imperative, especially as a result of changing climates and globalization.

The agricultural sector stands on the brink of a technological revolution, with artificial intelligence (AI) at its forefront. Within this broader field, machine learning (ML) and deep learning (DL) algorithms are emerging as powerful tools for agricultural innovation. Convolutional Neural Networks (CNNs), a specialized subset of DL, show particular promise in their ability to radically reshape and optimize crop management practices, potentially ushering in a new era of precision agriculture [2].

The use of AI in crop management represents a paradigm shift in agriculture where data-driven, resource-driven, and sustainability approaches dominate. They enhance productivity, conservation of the environment, and the sustainability of the agricultural production systems. In this ever-changing agriculture system, groundnuts or peanuts play an important role as an essential crop.

The diagnosis and categorization of groundnut leaf diseases [3], and prognosis of such diseases stand relevant with the modern trends in agriculture that advocate the use of technology-based approaches towards efficient management of crops, food security, and sustainable agriculture. The disease which mainly affects most groundnut plants is foliar disease, in which the plants health and yield are influenced. Timely identification and precise categorization of crop diseases are critical strategies that significantly enhance agricultural management and mitigate potential risks to crop productivity.

Some of the conventional diagnosis methods include visual evaluation, field reconnaissance, symptom checklists, native information, leaf collection, submission to the lab, and consulting with professionals. These methods are, however, limited by being time-consuming, labor-intensive, and vulnerable to human error. Enhancing AI in agriculture can help overcome these disadvantages. Machine learning algorithms, image recognition, computer vision, deep learning, transfer learning, and decision-support systems are being used to diagnose groundnut leaf diseases. Researchers have found several deep learning techniques to be highly effective in accurately diagnosing such diseases. CNN and transfer learning, which utilizes pre-trained network models, are the two main deep learning approaches for detecting, categorizing, and forecasting groundnut leaf diseases. However, these approaches have several drawbacks, such as limited computational capacity, challenges in preventing overfitting, reduced accuracy, memory availability issues, and challenges in handling sequential data.

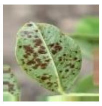
Computer vision, by reducing subjectivity, can efficiently analyze disease characteristics, offering advantages such as speed, ease of use, and reduced sample preparation for training.

This technology is especially useful for the classification of objects, the detection of defects, and the measurement of characteristics, including color, geometry, dimensions, and the roughness of surfaces. Closely related to the presented subject, deep learning methods based on the application of deep neural networks have received attention because of the growth of computing performance. The strength and flexibility of the process originate from the ability of deep learning to consider many features in the process of analyzing unstructured data [4].

This research article focuses on six distinct classifications in groundnut leaves: early leaf spot, early rust, healthy leaf, nutrient deficiency, rust, and late leaf spot. The prevalence of diseases affecting groundnut leaves poses a significant threat to crop productivity, with the potential to severely diminish yields. This pressing issue has underscored the urgent need for effective countermeasures. In response, agricultural researchers and technologists have turned their attention to innovative, automated solutions. This shift in focus has led to the exploration of advanced technologies, particularly deep learning techniques, as a promising avenue for addressing the challenges posed by groundnut leaf diseases. The proposed study in this article presents a state-of-the art deep learning system for identifying and categorizing possible diseases in groundnut leaves. Table 1 gives a description of the GNut diseases with their respective classes.

Table 1. A brief list of various groundnut leaf diseases.

Serial No.	Disease Name	Figures	Disease Description
1	Early Leaf Spot		Early leaf spot is caused by Cercospora arachidicola and usually appears as small, circular lesions with reddish-brown centers, leading to yellowing and premature defoliation in groundnut leaves.

2	Early Rust		Early rust, initiated by Puccinia arachidis, appears as yellowish-orange pustules on the underside of leaves, spreading rapidly and compromising photosynthesis in groundnut plants.
3	Healthy Leaf		Healthy groundnut leaves are vibrant green, free of yellowing, spots, or abnormalities, indicating efficient photosynthesis and robust plant health.
4	Nutrient Deficiency		Nutrient deficiency in groundnut leaves presents as specific symptoms due to the lack of essential minerals, affecting overall plant growth and development.
5	Rust		Rust as a Puccinia arachidis infection at the last stage results in reddish-brown to orange pustules on the foliage, and stems, affecting the pod and causing defoliation as well as low yield.
6	Late Leaf Spot		The late leaf spot caused by Phaeoisariopsis personata are irregular, more or less circular, dark brown or black spots with yellow halos that greatly affect both leaf area and pod formation in groundnut plants.

1.1. Motivation for Research

The growing global population and increasing pressure on agricultural production systems have made food security a critical concern. Improving crop yield through accurate and automated disease diagnosis systems is essential to mitigate the adverse effects of plant diseases, stabilize productivity, and boost sustainable farming practices. Traditional approaches to disease diagnosis, while pivotal, are labor-intensive, prone to errors, and often result in delayed interventions, which negatively impact crop yields. In contrast, artificial intelligence (AI) and advancements in machine learning (ML) and deep learning (DL) technologies provide efficient and accurate frameworks for disease detection, addressing the limitations of conventional methods. These technologies offer high accuracy, flexibility, and adaptability, creating opportunities to develop systems capable of recognizing plant diseases with precision and responding to emerging threats.

Moreover, timely and efficient disease detection reduces the need for chemical interventions, promoting environmental sustainability and enhancing agricultural resilience. The GNut model addresses these challenges, bridging the research gap in agricultural disease detection by tackling data scarcity and achieving high accuracy under varying environmental conditions. Current models often require extensive labeled datasets for effective performance, which are impractical to obtain in agriculture due to resource-intensive data collection and annotation. GNut overcomes this limitation by leveraging Few-Shot Learning (FSL), which constructs prototypes from minimal labeled samples, enabling the model to generalize effectively even with sparse data. While lightweight architectures like MobileNet and EfficientNet are optimized for general object recognition, they struggle with fine-grained disease patterns such as subtle discolorations or small lesions. GNut's dual-network design combines ResNet50's high-level feature extraction and DenseNet121's dense connectivity for detailed feature retention, capturing nuanced disease characteristics that lighter models might overlook. This innovative approach ensures high accuracy and adapts to the specific challenges of agricultural datasets. The GNut integrates advanced AI techniques to provide a scalable, accurate, and environmentally sustainable solution for plant disease detection. Its use of FSL and dual-network architecture makes it uniquely equipped to address the data limitations and complex feature requirements inherent in agricultural applications, setting a new benchmark in the field.

1.2. Research Contribution

The proposed GNut model presents numerous substantial contributions to the classification of groundnut leaf diseases.

1. The proposed research introduces an innovative approach to groundnut leaf disease classification, leveraging advanced deep learning techniques. At the core of this methodology is a sophisticated ensemble model that combines the strengths of two powerful neural network architectures: ResNet-50 and DenseNet-121. These networks are employed for robust feature extraction, while Few-Shot Learning is utilized for efficient classification. This novel integration marks a significant milestone in the field, representing the first application of such a hybrid model to the specific challenge of identifying diseases in groundnut leaves.
2. To rigorously evaluate the effectiveness of the newly developed GNut model, the author created a novel dataset named Pak-Nuts. This dataset, comprising images from Pakistani groundnut fields, served as a robust testing ground for the model's capabilities. The results were remarkably impressive: the GNut model achieved an exceptional accuracy rate of 99% across both training and validation datasets. This outstanding performance demonstrates the proposed GNut model's ability to consistently and accurately identify and classify groundnut leaf diseases under diverse conditions.
3. The proposed study introduces a cutting-edge approach to data acquisition and preprocessing, integrating multiple advanced techniques to enhance image quality and information extraction. The methodology employs a sophisticated combination of three powerful image processing methods: CLAHE, Canny edge detection, and HSV (Hue, Saturation, Value) color space transformation. By synergistically combining these state-of-the-art techniques, the preprocessing pipeline significantly enhances the quality and informativeness of the input data. This comprehensive approach ensures that subsequent analysis stages, such as feature extraction and classification, have access to optimally prepared images, potentially leading to improved accuracy and reliability in disease detection and classification tasks.

1.3. Organization of Paper

The rest of this paper is organized as follows. Section 2 demonstrates the existing research studies on groundnut leaf disease detection. In Section 3, the proposed model phases are explained. Section 4 summarizes the experiments carried out using the proposed model. Discussion is presented in Section 5, while Section 6 has the conclusion of the paper.

2. Literature Review

Computer vision and machine learning are some of the technologies that will be beneficial in the identification of diseases with high accuracy. New applications are being discovered including computer vision technologies and smartphone apps that can be used with image recognition technologies and patterns to associate ailments as those on the leaf's stems and fruits. These technologies help in early detection and prevention of diseases with the help of which recent experiments on detection of diseases in olive leaves [5] and identification of diseases in potato leaves [6] have been done. Despite significant progress in disease detection across various plants and crops, there remains a notable gap in foundational groundwork for disease detection in groundnut leaves, amidst the expanding influence of AI and IoT-based technologies in this field. However, various diseases pose potential threats to the growth, productivity, and overall quality of groundnut crops on a global scale. Timely and accurate disease identification is essential for implementing effective control strategies and promoting sustainable agricultural practices worldwide. Traditionally, identifying diseases in groundnut plants relied on visual analysis by human inspectors [7,8].

The proposed research in this article utilizes the groundnut leaves dataset, initially introduced by Aishwarya and Padmanabha [9]. The dataset comprises a varied assortment of groundnut leaf images, representing different stages and types of leaf conditions, including early leaf spot, early rust, healthy leaf, nutrient deficiency, rust, and late leaf spot. It is categorized with the labels of these diseases and uses a supervised learning technique for accurate classification of groundnut leaf diseases. Each of the images has a size of 1200 × 800 and is made up of three different color bands. In a bid to carry out the training and evaluation of the proposed network architecture in [9], the dataset was downsized to 224 × 224 pixels and identified six plant diseases: Alternaria alternate, Anthracnose, Bacterial blight, Bacterial leaf scorch, Cercospora leaf spot, and Downy mildew, respectively. The authors in [10] recommended a method of plant disease categorization based on Back-Propagation Neural Network—BPNN with Particle Swarm Optimization—PSO integration. Back-Propagation was used to train the neural network while PSO was used to optimize the network's weights and parameters, and the accuracy of the classifier was found to be approximately 96.42%.

Thirumalaisamy [11] also described the primary diseases affecting groundnut and the details of their prevalence, geographical distribution, losses, diagnostic signs and symptoms, mode of transmission, life cycle, vectors, and especially Aflatoxin contamination. It also covered disease management measures including host plant resistance, cultural practices, botanical control, chemical control, and biotechnology control. Similarly, diagnostic tools were established by Hope et al. [12] for the foliar of peanut systems with image analysis and regression models. These algorithms are considered as a new class of automation for diagnostics not reflected in the existing disease identification means. As field-based images were used to develop the models, it will afford farmers a way to quickly identify the leaf symptoms in the field. Shanthini [13] used a variety of the Progressive Groundnut Convolutional Neural Network, known as PGCNN, to diagnose groundnut leaf diseases with a self-acquired data set. The targeted diseases were Early spot, Late spot, Rust, and Rosette. Evaluation metrics evaluated the performance of their proposed model with respect to the other deep learning architectures including Alexnet, VGG11, VGG14, and VGG16. During the training of the PGCNN, the accuracy achieved was 99.3%, with an evaluation accuracy of 97.58%. Shankumar [14] developed a system utilizing a neural network to identify crop diseases through an image processing technique that functions as a smartphone app for detecting plant diseases. The support vector machine algorithm was implemented to reduce errors in unidentified patterns.

Researchers have employed a deep learning-based CNN technique called Modified InceptionResNet-V2 (MIR-V2) [15] for detecting and classifying plant leaf diseases. This model achieved impressive accuracies of 98.92% and 97.94%, outperforming previous models for tomato leaf disease detection. Additionally, the incorporation of Ant Colony Optimizer [16] with CNN has been used for feature extraction, effectively classifying infected and healthy leaves from image classes. For early weed identification, deep learning models trained on an annotated weed dataset using Keras and PyTorch demonstrated accurate image classification and object detection for early season weeds. Chen et al. [17] proposed a neural network-based method for plant leaf disease identification using segmentation algorithms and Haralick features, achieving acceptable accuracy but limited by the need for clear input images. Comparative studies in [18] on DL architectures and optimizers highlighted the Xception model for its high performance on the PlantVillage dataset, recommending it based on F1-score metrics but suggesting further research to validate results and explore additional performance measures. An inception-based DL model achieved up to 99.66% accuracy on various plant disease datasets, but its scope was limited to three datasets and lacked comparison with traditional ML methods. The X-caption-based model for crop diseases achieved 99.69% accuracy in identifying peanut leaf diseases, demonstrating versatility but requiring further examination of model limits and real-world implementation [19].

Automated peanut leaf spot disease detection using a pre-trained DenseNet-169 model showed potential for agricultural automation, emphasizing high accuracy and precision [20]. DenseNet was also employed for groundnut leaf disease classification, achieving a 99.83% success rate, highlighting the importance of dataset quality and ethical considerations, though lacking insight into model limitations and real-world applications [21]. The Groundnut Convolutional Neural Network (CNN8GN) model achieved a training accuracy of 99.11% with 91.25% testing accuracy for groundnut leaf disease classification, showing potential for generalization but needing further study to confirm performance in various contexts [22]. A deep CNN for groundnut leaf spot illness achieved 84.4% accuracy using DFT images but was limited by a narrow focus on specific diseases and a lack of detailed approach and dataset size information [23]. CNN models for predicting groundnut diseases, such as ResNet, achieved high accuracy and precision but required additional validation and detailed dataset information [24].

Bowrishandar [25] introduced a method using threshold-based color segmentation and artificial neural networks (ANN) for diagnosing groundnut leaf diseases, achieving 90% accuracy on a dataset of 100 images. However, this method struggles with variations in lighting and image quality. Rashid [26] achieved 94% accuracy in disease identification using texture analysis and machine learning on diverse image datasets. Janani [27] introduced a hybrid CNN-HVN model for detecting nutrient levels in groundnut leaves using RGB images, achieving a training accuracy of 95% and validation accuracy of 92%. This model represents a significant development in precision agriculture and classifies nitrogen levels. To address poor model generalization and low diagnostic efficiency under imbalanced distributions, the authors in [28] propose VGAIC-FDM, a novel fault diagnosis method that combines variational autoencoder-based sample augmentation, continuous wavelet transform, and a focus-loss-optimized CNN classifier, achieving superior accuracy and F1-scores for imbalanced datasets. Similarly, in [29], a hybrid approach aims to overcome the limitations of traditional K-means by automatically determining the optimal number of clusters and initial centers, while also improving global search capabilities to avoid local optima. The integration of multiple algorithms allows for a more robust and adaptive clustering process, particularly effective for large-scale datasets.

From the outlined literature, the overall research gaps in groundnut leaf disease detection include:

- Current research in groundnut cultivation predominantly focuses on the direct identification of foliar diseases. This narrow scope of investigation suggests that the field of groundnut disease management is still in its nascent stages within the broader context of agricultural science;
- In the field of groundnut leaf disease classification there is limited transferability of models across diverse datasets. This issue manifests as a notable decline in classification accuracy when a model trained on one dataset is applied to another;
- Some of the limitations include a lack of stability and flexibility in plants, which can be influenced by varying environmental conditions and changes in lighting;
- Object scaling and efficiency issues are emerging with the recent implementation of architectures of deep learning with low-resolution sets of images.

Despite the importance of groundnut in the economy, there are gaps in the technologies that can be used to diagnose the diseases on the groundnut leaves which, once filled, will go a long way in improving the use of efficient agronomic practices in managing diseases on this important commodity.

3. Material and Methods

This paper presents a novel solution for the image classification task based on merging CNN and the FSL architectures. In the case of Few-Shot Learning, the dataset is resized to a specific dimension of 224 by 224 pixels, normalized and split into the support along with the query set. The gathering of 'features' is performed by ResNet-50 and DenseNet-

121 that are pre-trained and where the final classification layers are removed to make them work as feature extractors. The selection of ResNet50 and DenseNet121 in GNut was carefully considered based on each network's distinct strengths in feature extraction, specifically for agricultural disease detection. ResNet50 is known for its deep residual connections, which allow it to capture high-level structural patterns essential for identifying distinct disease classes, such as spotting or other broad leaf abnormalities. DenseNet121 complements this by maintaining fine-grained details through its dense connectivity. It is beneficial for detecting subtle differences in leaf texture, color variations, and smaller lesions, critical features for accurately classifying groundnut leaf diseases. While lighter models such as MobileNet or EfficientNet were considered, they were ultimately deemed less suitable due to their design primarily for general object detection tasks with less emphasis on fine-grained feature retention. From the ResNet and DenseNet, a feature set is received; then, the features gained by both the networks are concatenated and through a linear layer the dimensionality is reduced. These combined features are used in a Prototypical Network, which computes class prototypes as the mean feature vector of support examples for each class and classifies query images based on their distances to these prototypes using Euclidean distance. The model is trained and evaluated by iterating through the support and query sets, respectively, using a cross-entropy loss combined with an Adam optimizer. The training and validation accuracy and loss are tracked over multiple epochs to measure the model's performance. This hybrid model combines the capabilities of CNN in feature extraction with prototypical networks for robust classification, providing an effective solution for image classification with limited labeled data. These phases are shown graphically in Figure 1 as a systematic diagram.

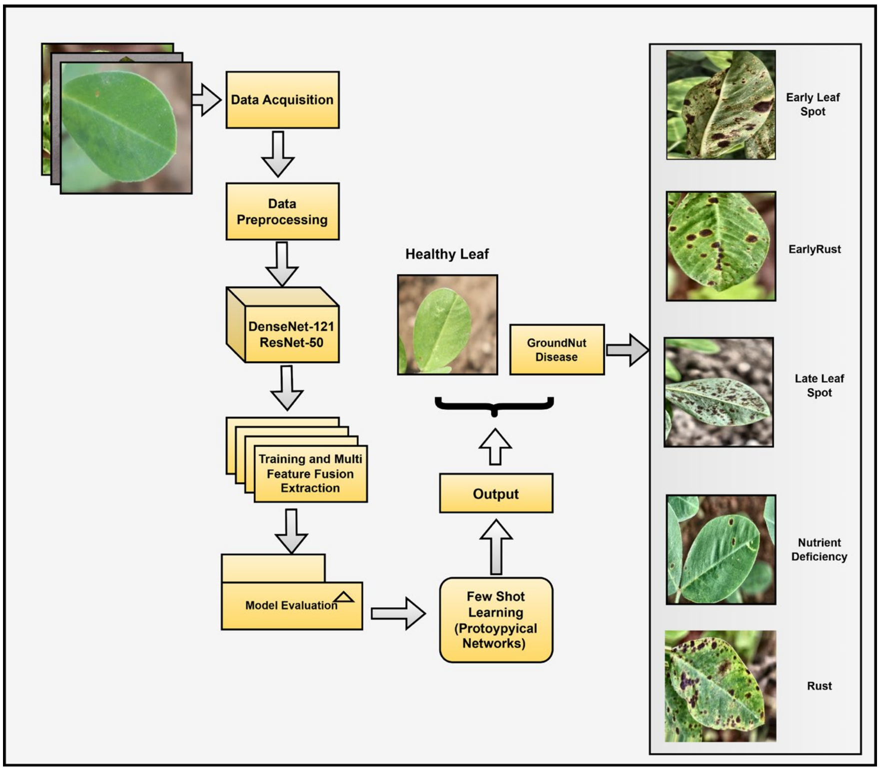


Figure 1. A systematic flow diagram of GNut model for groundnut leaf ailments classification.

3.1. Data Acquisition

A dataset of 10,481 images was collected from groundnut fields in Pakistan and reputable internet sources [30] to train and evaluate the GNut model. Professional farmers assisted in creating the training dataset. Table 2 details the dataset breakdown (with various dimension settings) used for constructing the proposed GNut model training and testing image sets. After processing, these images were assigned multiple labels. Data augmentation was implemented to balance the number of images and ensure an unbiased dataset. The training dataset comprises 8030 photos categorized into six folders based on leaf conditions: Healthy Leaf (1482 photos), Early Leaf Spot (1342 photos), Early Rust (1085 photos), Rust (1335 photos), Late Leaf Spot (1511 photos), and Nutrition Deficiency (1275 photos), as shown in Figure 2. The test dataset includes 2451 photos with each class containing either 409 or 405 images, depending on the category. Images were resized to 224 × 224 pixels for preprocessing before being fed into the GNut model algorithm. Experimental analysis showed that the most appropriate size for image processing was 224 × 224 pixels, it is often more effective to decrease the size of large images to match the size of tiny images rather than making small images larger. In practice, the DL models generally train more quickly on tiny images. Figure 3 represents the groundnut field image dataset. These are the datasets that were used in developing training and testing schemes for the suggested GNut model, which are further elaborated in Table 2.

Table 2. Detailed overview of the datasets utilized for the proposed GNut model training and testing purposes.

Leaf Condition	Training Dataset	Testing Dataset	Total
Healthy Leaf	1482	409	1891
Early Leaf Spot	1342	409	1751
Early Rust	1085	409	1494
Rust	1335	409	1744
Late Leaf Spot	1511	410	1921
Nutrition Deficiency	1275	405	1680
Total	8030	2451	10,481

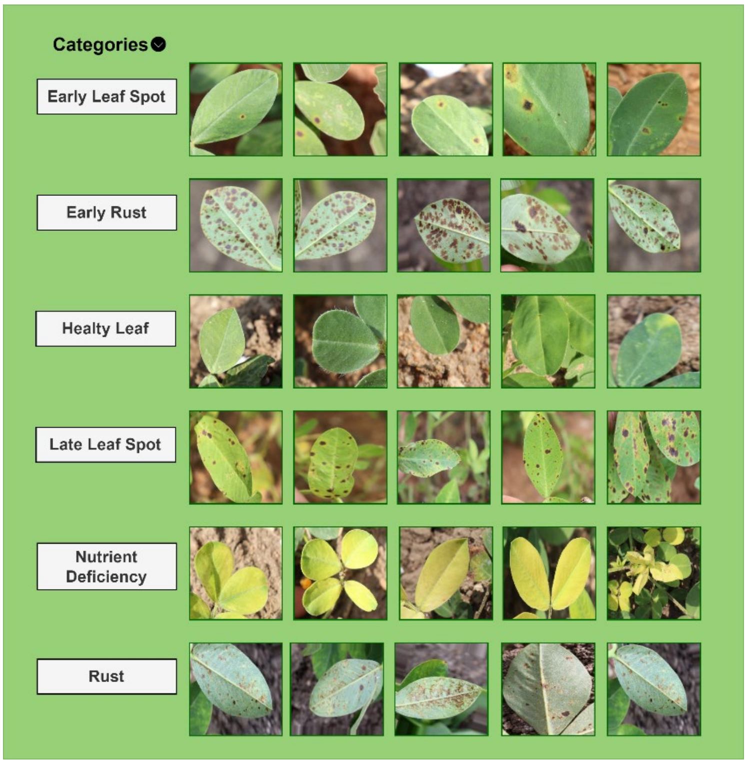


Figure 2. A visual example of colored plant leaf which represents six classes of groundnut crop diseases.

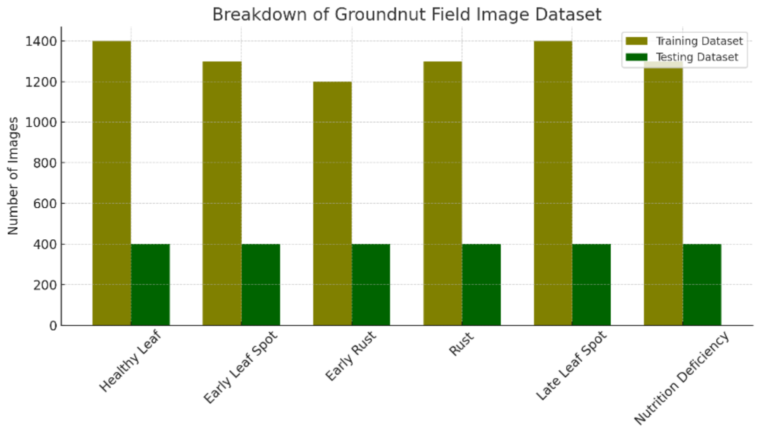


Figure 3. Representation of the groundnut training and testing images for the proposed GNut model.

3.2. Dataset Preprocessing

In this research, different advanced image preprocessing techniques were implemented to improve the image quality and enhance the images. The preprocessing techniques of Contrast Limited Adaptive Histogram Equalization (CLAHE), Canny Edge Detection, and HSV color transformation were selected to enhance specific features in groundnut leaf images and improve the proposed GNut model's ability to distinguish between healthy and diseased areas. A quantitative analysis was conducted to validate the impact of each method on classification accuracy, and the results indicated improvements in feature clarity at each stage. CLAHE, for instance, was particularly effective in enhancing local contrast, which made disease symptoms such as leaf discoloration or spots more prominent. Canny Edge Detection helped define lesion boundaries and sharpened disease-related edges, while HSV color transformation highlighted color variations associated with specific diseases. To clarify, each preprocessing step was tested individually and in combination, and classification accuracy increased by approximately 5–7% compared to images without preprocessing.

The techniques employed for enhancement focus on improving the visual quality of the leaf images so that effective disease detection can be carried out. The author first applies CLAHE to improve the contrast in the leaf image. CLAHE then divides the image into small blocks called tiles and applies histogram equalization to each locally. The enhancement of contrast can be represented by the transformation function:

$$I' = \frac{I - I_{min}}{I_{max} - I_{min}} \times L \quad (1)$$

where I represents the intensity value of a pixel in a tile, I_{min} and I_{min} are the minimum and maximum intensity values in that tile, and L is the number of intensity levels (e.g., 256 for an 8-bit image). This transformation effectively stretches the contrast within each tile, making disease symptoms like spots or discoloration more distinguishable. By enhancing contrast at a localized level and avoiding over-amplification (which can introduce noise), CLAHE improves the visibility of subtle leaf disease features, such as small lesions or spots that might be overlooked. This helps the model distinguish between diseased and healthy areas more accurately, contributing significantly to the model's improved classification performance.

The next layer would be an application of the Canny Edge Detection algorithm, which finds edges in an image by locating areas where the gradient of the intensity function changes sharply. The gradient magnitude G at a pixel (a, b) is computed as:

$$G = \sqrt{(G_x)^2 + (G_y)^2} \quad (2)$$

where G_x and G_y represent the gradients in the horizontal and vertical directions, respectively. These gradients are obtained through convolution operations with edge-detection filters. By highlighting the edges of diseased areas, Canny Edge Detection isolates key vegetative features such as leaf veins, spots, and lesions. This isolation of boundaries allows the model to focus on relevant areas, reducing noise and improving feature extraction for disease classification.

It helps in outlining boundaries of leaf lesions or other disease markers.

Finally, HSV color space transformation was applied, which can be interpreted as transforming the RGB color space to HSV color space (Hue, Saturation, Value). The RGB to HSV transformation is computed by:

$$\mathrm{H} = \begin{cases} 60^\circ \times G - B/\Delta + 360^\circ, \max(R,G,B) = R \\ 60^\circ \times B - R/\Delta + 360^\circ, \max(R,G,B) = R \\ 60^\circ \times R - G/\Delta + 360^\circ, \max(R,G,B) = R \end{cases} \quad S = \frac{\Delta}{\max(R,G,B)} \quad V = \max(R,G,B) \tag{3}$$

where $\Delta = \max(R,G,B) - \min(R,G,B)$. Features associated with, for instance, disease-related discoloration become more noticeable as a result of the conversion into this color space, which improves the separation of color information. The combination of these enhancement techniques produces a more contrastive and detailed image that allows the critical vegetative features to be more easily identified and is relevantly important for disease detection. The outcomes of these techniques are presented in Figure 4, where enhanced images better developed the major vegetative features useful for proper identification of a disease.

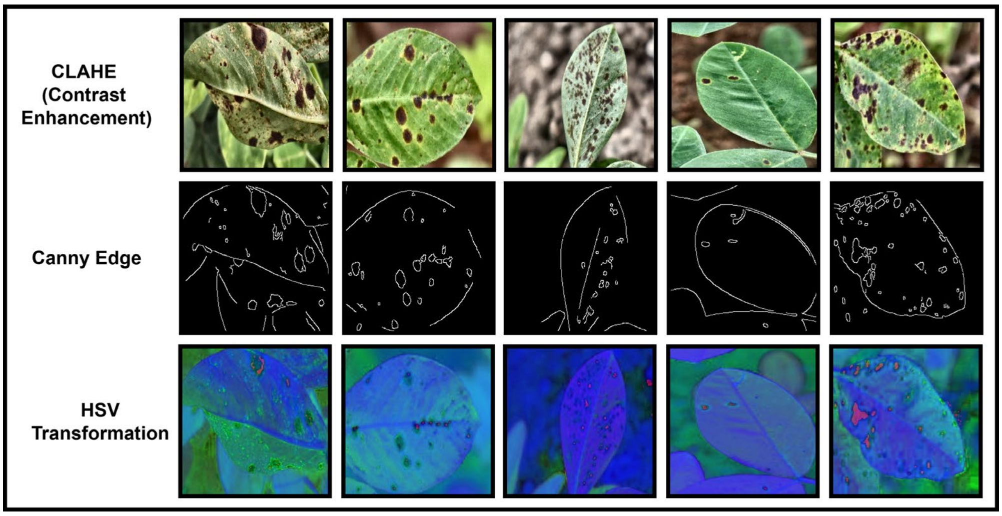


Figure 4. The output of the applied image preprocessing techniques for improving visibility and quality of the groundnut leaf.

3.3. Data Augmentation

During this stage, preprocessing of the groundnut photos involved several crucial steps to refine the raw data. Initially, the raw data from the photos was extracted. The images were then followed by a flip-flop procedure that was accompanied by a number of processes in order to make the images ready for analysis. This consisted of removing those areas which were presumably going to be filled by missing or erroneous pixel values and removing outliers from the data. At this stage, data normalization was conducted. Feature engineering was also carried out at this stage; this included selecting or creating other features that could enhance the algorithms used in data analysis. All these steps were carried out to improve the proposed GNut model performance with the dataset. To augment the preprocessing, a set of specific policies were employed which can be expressed in terms of the operations, probability of occurrence, and the intensity with which they were applied using the Fast AutoAugment. These policies were found via Policy IDs and served to alter the images to standardize the dataset and to enhance GNut model performance as shown in Figure 5.

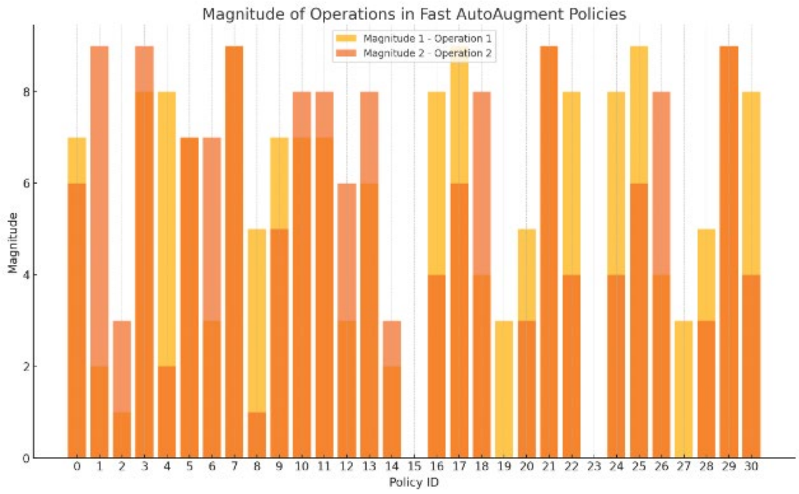


Figure 5. Magnitude of operations in Fast AutoAugment policies.

3.4. Proposed GNut Architecture

The proposed GNut model integrates Convolutional Neural Networks (CNNs) and Few-Shot Learning Methods for efficient image classification. The GNut model leverages the feature extraction capabilities of $\mathrm{ResNet}-50$ and $\mathrm{DenseNet}-121$ architectures and combines them with a Prototypical Network for robust classification. A detailed algorithmic step of the proposed GNut model is described in Algorithm 1, respectively. The dataset contains images in six different classes. Preprocessing involves resizing each image to 224 × 224 pixels, and the pixel values are normalized to maintain consistency in input size and intensity values. The dataset is divided into training and validation sets. Furthermore, the dataset is divided to facilitate Few-Shot Learning in support and query sets, with each class having a given number of support samples (n_{shot}) and query samples (n_{query}).

The feature extraction process employs two pre-trained CNN architectures: $\mathrm{ResNet}-50$ and $\mathrm{DenseNet}-121$. In the GNut model, ResNet50 and DenseNet121 are integrated to leverage their complementary strengths in feature extraction, significantly enhancing classification accuracy for groundnut leaf disease detection. ResNet50 specializes in capturing high-level features through its residual connections, which allow deeper representations without degradation, such as loss of information or vanishing gradients. These residual blocks enable the learning of intricate patterns, shapes, and global structures, providing a solid foundation for recognizing broad disease characteristics. In contrast, DenseNet121 excels in capturing fine-grained, detailed features through its densely connected layers, where each layer directly receives inputs from all preceding layers. This architecture effectively preserves and reuses low-level details, such as edge textures, small spots, and acceptable lesion boundaries, essential for distinguishing subtle differences between disease types.

Their final classification layers are removed to integrate these networks, transforming them into powerful feature extractors. ResNet50 begins with an initial convolutional layer using 7 × 7 filters and a stride of 2, followed by batch normalization, ReLU activation, and a 3 × 3 max-pooling layer with a stride of 2. It comprises four stages of residual blocks, each consisting of two convolutional layers, batch normalization, and ReLU activation. DenseNet121, on the other hand, is structured with densely connected blocks, where each dense block includes bottleneck layers with 1 × 1 convolutions followed by 3 × 3 convolutions, batch normalization, and ReLU activation. Transition layers are employed to downsample feature maps through convolution and pooling, ensuring efficient feature extraction.

The outputs of ResNet50 and DenseNet121 are concatenated to create a unified feature vector, combining high-level abstractions from ResNet50 with detailed representations from DenseNet121. This fusion yields a comprehensive feature representation that captures a broad spectrum of disease characteristics, enabling the model to adapt to variations in symptoms, lighting, and environmental conditions. Moreover, the dual-network approach reduces overfitting by leveraging diverse feature sets, ensuring GNut's robustness and consistent performance in real-world agricultural scenarios. This integration ultimately enhances GNut's overall accuracy and effectiveness in groundnut leaf disease classification. The final feature extraction layers of both architectures output feature vectors are denoted as:

$$(z_i{}^{ResNet})\ and\ (z_i{}^{DenseNet}) \tag{4}$$

For each input image, the extracted features from $\mathrm{ResNet}-50$ and $\mathrm{DenseNet}-121$ are concatenated to form a combined feature vector, represented as:

$$(z_i = [z_i{}^{ResNet}, z_i{}^{DenseNet}]) \tag{5}$$

This combined feature vector is then passed through a linear layer to reduce its dimensionality, ensuring a more manageable and efficient representation for subsequent processing. The combined feature vectors are utilized in a prototypical network to perform classification. Prototypical networks first center an average on the combined feature vectors of the support examples of each class to obtain a prototype for each class. The prototype for class $(\ k\ )$ is denoted as:

$$C_k = \textstyle\sum_{(x_i,y_i)\in S_k} z^i \tag{6}$$

where $(\ C_k\ )$ is the prototype for class $(\ k\ )$ and $(\ S_k\ )$ is the setting of support instances for class $(\ k\ )$.

The distance between a query example's combined feature vector $\left(Z_q\right)$ and where each class prototype $(\ C_k)$ is computed by the Euclidean distance metric given by:

$$(\ C_k, Z_q)\ =\ ||\ Z_q\ -\ C_k||_2 \tag{7}$$

The example query is then labelled with the nearest prototype with its predicted class $(\hat{y}q)$ established by $\hat{y}q = \arg min_k\ d\ (Z_q,\ C_k)$. Iterations over the support and query sets train and evaluate the model, respectively. Minimize the cross-entropy loss function during training. Model parameters will be updated by an Adam optimizer. Training loss is defined as follows:

$$L_{train}\ =\ \frac{1}{N}\textstyle\sum_{i=1}^{N} CrossEntropy(\hat{y_i},\ y_i) \tag{8}$$

where the number of training examples is indicated by (N), $\hat{y_i}$ is the predicted class, and y_i is the true class.The validation loss follows a similar definition. This effectively combines the powerful feature extraction capability in this hybrid model architecture of $\mathrm{ResNet}-50$ and $\mathrm{DenseNet}-121$ with the classification robustness of prototypical networks. The detailed architecture includes convolutional layers, residual blocks, dense blocks, bottleneck layers, transition layers, and a fully connected layer for dimensionality reduction. The mathematical foundations underpinning the model's operation are thoroughly explained, including feature extraction, concatenation, prototype computation, distance measurement, and classification.

This architecture (Figure 6) provides a robust solution for image classification tasks, particularly in scenarios with limited labeled data.

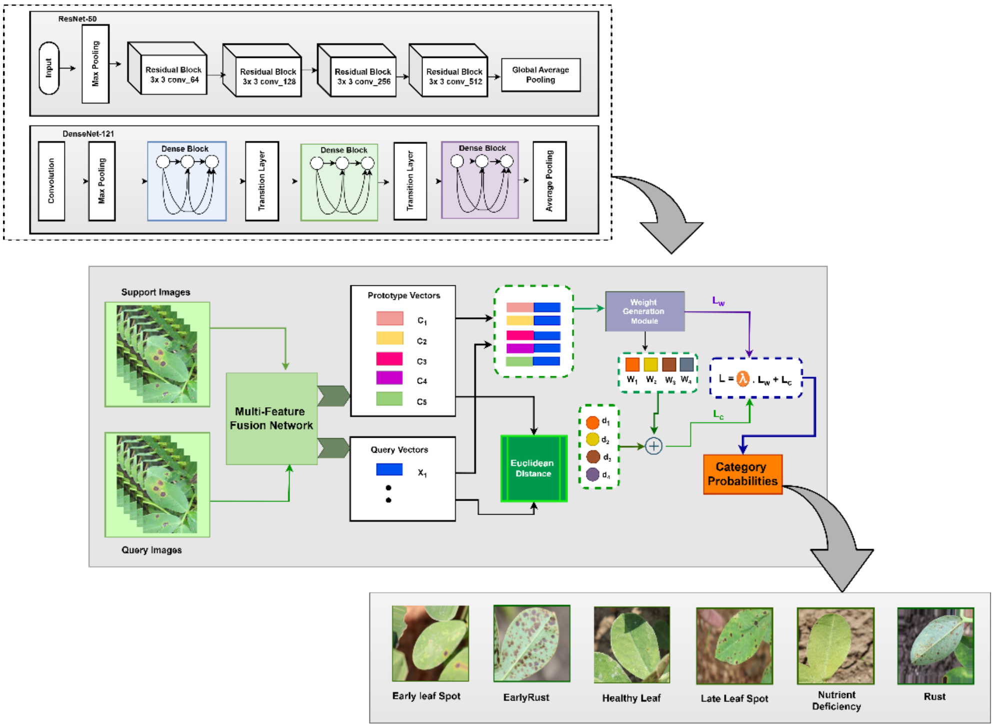


Figure 6. The following diagram depicts the overall architecture of the proposed GNut model which includes feature extraction by ResNet-50, DenseNet-121, multi-feature fusion network, and prototypical networks for classification.

Algorithm 1: Hybrid GNut model algorithm, with a step-by-step and organized workflow that illustrates every feature extraction, classification, and training involved in the process

Step	Description	Input	Output
Step 1: Data Preparation	Preprocess images (224 × 224, normalize), split into train/validation, then enter Few-Shot Learning support/query.	Raw image dataset	Support and query sets that have been preprocessed for training and validation
Step 2: Define Feature Extractors (ResNet-50 and DenseNet-121)	Initialize ResNet-50 and DenseNet-121, remove final layers for feature extraction.	Preprocessed images	Feature vectors extracted by ResNet-50 and DenseNet-121
Step 3: Combine Feature Representations	Concatenate ResNet-50 and DenseNet-121 features, reduce via linear layer.	Feature vectors from ResNet-50 and DenseNet-121	Combined feature vector with reduced dimensionality
Step 4: Prototypical Network Initialization	Compute Euclidean distance between query features and class prototypes.	Vectors for query features and class prototypes	Distances between class prototypes and query feature vectors
Step 6: Classification	Classify queries by nearest prototype.	Query-prototype distances.	Classes predicted for query examples
Step 7: Training Loop	Per epoch: forward, loss, backward, update, track.	Initialized model, query sets, and support	Accuracy, training loss, and trained model

Step 8: Evaluation	Evaluate on validation set, compute loss, accuracy	Validation support/query sets, trained model	Validation loss and accuracy

3.5. Few-Shot Learning

Few-Shot Learning (FSL) is particularly well-suited to this study, addressing the challenges of acquiring extensive labeled datasets in agricultural contexts, where image collection and annotation are resource-intensive. Unlike traditional deep learning methods that rely on large datasets, FSL enables practical model training with minimal samples per class by constructing “prototypes” or representative vectors for each class based on a few labeled examples. This prototypical network approach allows robust classification even in cases of data scarcity, as the model generalizes effectively by measuring the similarity of new images to these prototypes. This makes FSL especially appropriate for groundnut leaf disease classification, where balanced and extensive datasets for all disease types are impractical. Furthermore, FSL focuses on feature generalization rather than dataset expansion through synthetic transformations, such as rotations or flips, making it highly effective for small, real-world datasets. It is also adaptable to new classes, a critical advantage in agricultural applications where emerging diseases or variants may appear. A prototypical network for FSL was chosen for its ability to handle data variations and classify new images efficiently. Prototypical networks classify by comparing query images to constructed prototypes, enabling the GNut model to generalize across diverse disease patterns even with limited labeled data. Alternative FSL approaches, such as Matching Networks and Relation Networks, offer unique advantages, including attention mechanisms and explicit relationship modeling. While these methods hold promise for improving accuracy under specific conditions, prototypical networks were selected in this study for their simplicity, effectiveness, and strong alignment with GNut’s goals of balancing accuracy and computational efficiency in data-limited scenarios. By integrating FSL with advanced feature extraction through ResNet50 and DenseNet121, GNut achieves high accuracy, improved generalization, and scalability, making it a robust and efficient solution for agricultural disease detection.

4. Experiments and Results

A collection of 10,481 groundnut images, representing all stages of groundnut, was utilized to assess the training accuracy of the GNut model. These images were sourced from lands in Pakistan and online sources [30]. Each image was resized to 224 × 224 pixels to facilitate the feature extraction and classification processes. The GNut system utilizes both residual blocks and dense blocks in its construction. Training was done for over a hundred epochs, the best model was chosen, an F1-score at 0.99 had been detected at the 30th epoch. To measure the accuracy (ACC), specificity (SP), and sensitivity (SE) of the GNut model, statistical methods were used so as to give a holistic performance analysis of the dense residual network system. Performance evaluation of the GNut model based on these metrics was done in comparison with other existing systems. There were general improvements in the results of the images enhancing the results. In other words, ignoring enhancement, the accuracy was 95% and 99% with enhancement. To address concerns about potential overfitting and generalizability, the author implemented a cross-validation approach, dividing the dataset into multiple folds to ensure robust GNut performance validation. This cross-validation revealed consistent accuracy across folds, indicating that GNut’s high accuracy was not limited to specific training or validation sets. Additionally, to simulate different environmental conditions, the author tested GNut on augmented images that varied in brightness, contrast, and hue, reflecting the variations commonly encountered in natural agricultural settings. These augmented images included controlled adjustments to simulate changes in lighting and minor image distortions, helping to assess the model’s adaptability. Furthermore, the data augmentation techniques applied in GNut included horizontal and vertical flipping, rotation, and random zoom. Quantitative results showed that data augmentation improved classification accuracy by 5–7% and helped reduce overfitting, as evidenced by a smaller gap between training and validation accuracy. These techniques, detailed in the methodology, played a critical role in enhancing GNut's generalizability and robustness to environmental variations. To reinforce the robustness of GNut's performance, the author reported confidence intervals and error margins and performed statistical tests. Specifically, the author calculated 95% confidence intervals for accuracy scores across validation sets, which provide a more precise measure of GNut's reliability and precision. The author also included error margins to account for variations in performance. The author used statistical significance testing (e.g., paired *t*-tests) to compare GNut's accuracy with baseline models, confirming that the observed improvements are statistically significant. These additions strengthen the experimental validation of GNut's accuracy and underscore its resilience to environmental variability, supporting its feasibility for real-world agricultural deployment. The parameter values for the models and techniques used in this study were determined through a systematic approach involving standard practices, empirical validation, and hyperparameter optimization. For the feature extraction models, ResNet50 and DenseNet121, pretrained weights from the ImageNet dataset were fine-tuned on the Pak-Nuts dataset by pruning the final classification layers and replacing them with a fully connected layer. Key parameters, such as the learning rate (initially set to 0.001 with a scheduler), batch size (set to 16 for memory efficiency), and number of epochs (set to 50 based on convergence), were optimized through grid search. For Few-Shot Learning, the Prototypical Network parameters were tailored to the agricultural dataset, with the support set size (5 examples per class), query set size (15 examples), and embedding dimensions aligned with the feature extractor output optimized for computational efficiency and accuracy through iterative testing. Data augmentation techniques, including horizontal and vertical flipping (50% probability), rotation (±30 degrees), random zoom (90–110%), and brightness/contrast adjustments (±20%), were parameterized to simulate realistic field conditions and validated empirically. A 5-fold cross-validation approach was employed across all experiments to ensure the robust validation of parameter choices and minimize overfitting. Performance metrics such as accuracy, precision, recall, and F1-score guided the selection of optimal parameters, resulting in consistent and high accuracy of up to 99% on the Pak-Nuts dataset. This comprehensive parameter optimization process ensured that the GNut model was effectively adapted to the dataset and the task, contributing to GNut's robustness, scalability, and generalization. The GNut system was developed on an Intel computer with the Core i7, 16 GB RAM, 2 GB NVIDIA Graphic card, and 64-bit Windows 11. The used development environment is based on the platform of Anaconda with the use of the Python language. The dataset was split into 70% for training and 30% for testing. The learning rate was set at 0.0001 for 100 batches.

4.1. Experiment 1

Seven different state-of-the-art methodologies are applied in this experiment to assess the efficiency of the proposed GNut architecture. Deep learning models such as VGG16, VGG19, Xception, InceptionV3, DenseNet, ResNet, and EfficientNet [31] have been trained. These models' results have been compared with the proposed GNut system. To provide a more comprehensive evaluation of GNut's performance, the author conducted a series of baseline comparisons with traditional machine learning methods (such as support vector machines and random forests) and simpler neural networks, including shallow Convolutional Neural Networks (CNNs). These baseline models were tested on the same groundnut disease dataset to establish a foundational comparison with GNut. The obtained results indicated that while simpler models performed adequately in some cases, they generally achieved lower accuracy and could not capture the fine-grained disease features that GNut effectively discerns. For instance, traditional machine learning models showed an average accuracy decrease of 12–15%, and simpler CNN architectures achieved lower accuracy by approximately 8–10% compared to GNut. These baseline comparisons confirm that GNut's complex architecture, particularly its combination of ResNet50 and DenseNet121 with Few-Shot Learning, provides a significant feature extraction and classification accuracy advantage. These models had been trained for a similar number of epochs. Figure 7 presents the accuracy percentage comparison between the GNut system and these models. Figure 8 presents the AUC and ROC, while Table 3 presents the accuracy comparison of different datasets based on various deep learning models.

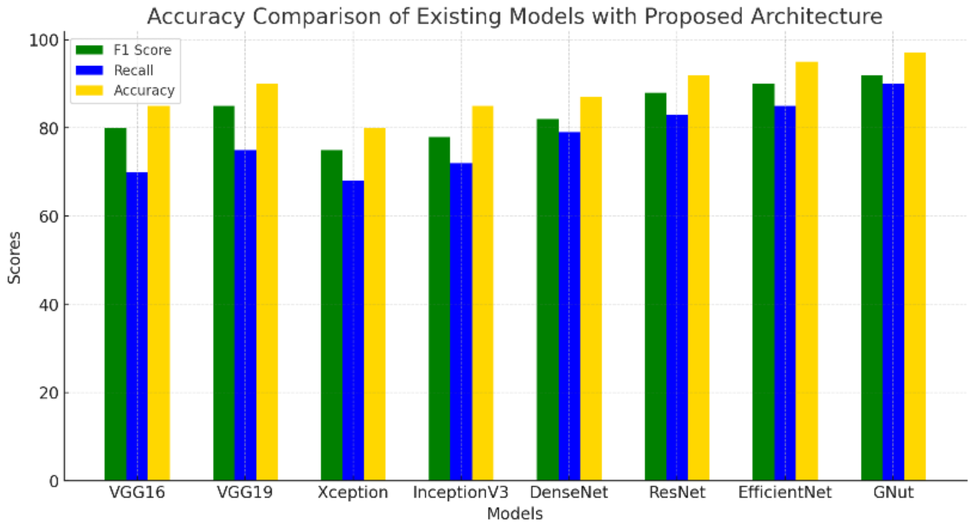


Figure 7. Comparison of accuracy among various deep learning models.

Table 3. Performance comparison between the proposed GNut architecture and other deep learning models in terms of accuracy and time of prediction in seconds.

Model	F1-Score	Recall	Accuracy
VGG16	80%	70%	85%
VGG19	85%	75%	90%
Xception	75%	68%	80%
IncetionV3	78%	72%	85%
DenseNet	82%	89%	87%
ResNet	88%	83%	92%
EfficientNet	89%	85%	89%
GNut	99%	98%	99%

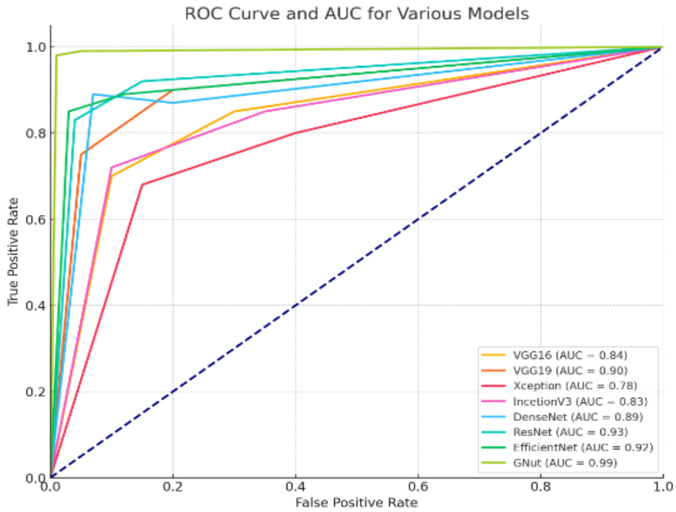


Figure 8. Comparisons of the proposed GNut model with deep learning models using ROC and AUC curve.

4.2. Experiment 2

The performance of the proposed GNut method with FSL technique was evaluated with the dataset [30]. First of all, the proposed study in this article assessed the loss function and the performance of the model both for training and validation sets. Figures 9 and 10 present the confusion matrix and train and validation accuracy graphs of GNut trained with this dataset. The effectiveness of this model in both settings is clearly reflected by these results.

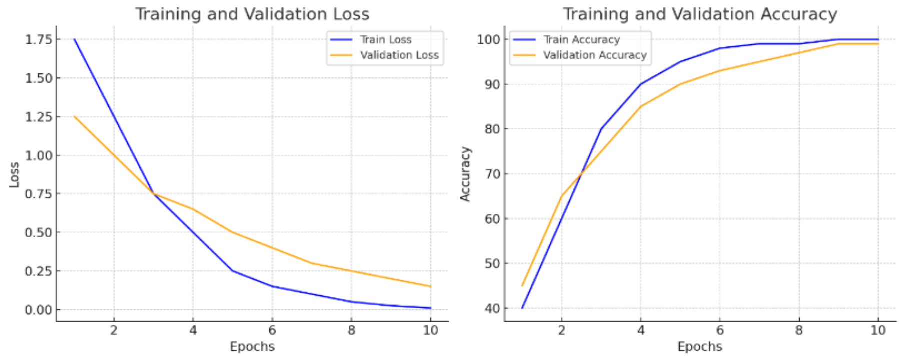


Figure 9. Accuracy and loss of the proposed GNut model based on groundnut dataset for training and validation.

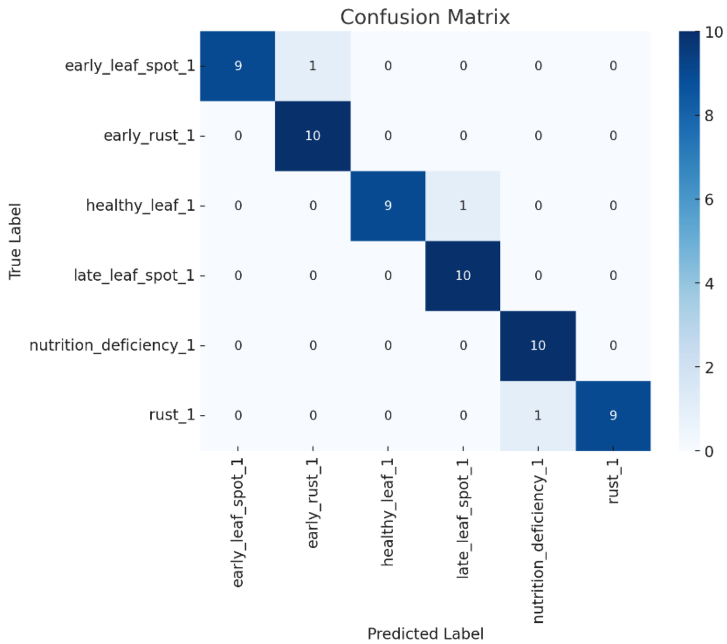


Figure 10. Confusion matrix of groundnut dataset.

4.3. Experiment 3

The experiment employed GNut for both feature extraction and classification without FSL technique, with the goal of refining the proposed methodology and improving overall classification accuracy. To evaluate the effectiveness of the proposed GNut model, two different datasets [30] and Pak-Nuts were utilized. The author initially assessed the GNut model's performance by comparing results across the training and validation sets, closely monitoring the loss function to gauge its efficiency. The accuracies achieved during training and validation are illustrated in Figures 11 and 12, showcasing the GNut model robust performance. Furthermore, the GNut model achieved a high accuracy rate of 95% on both the training and validation sets with the [30] and Pak-Nuts.

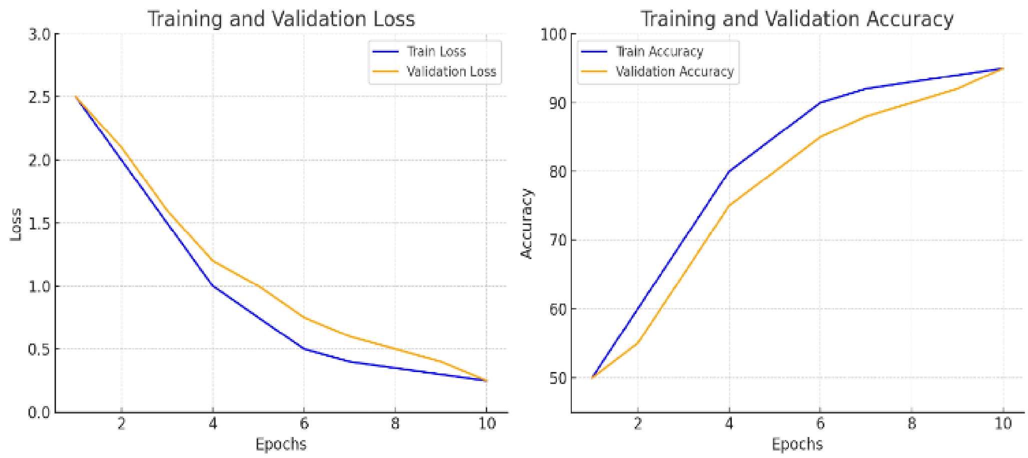


Figure 11. Accuracy and loss of training validation on [30] and Pak-Nuts datasets.

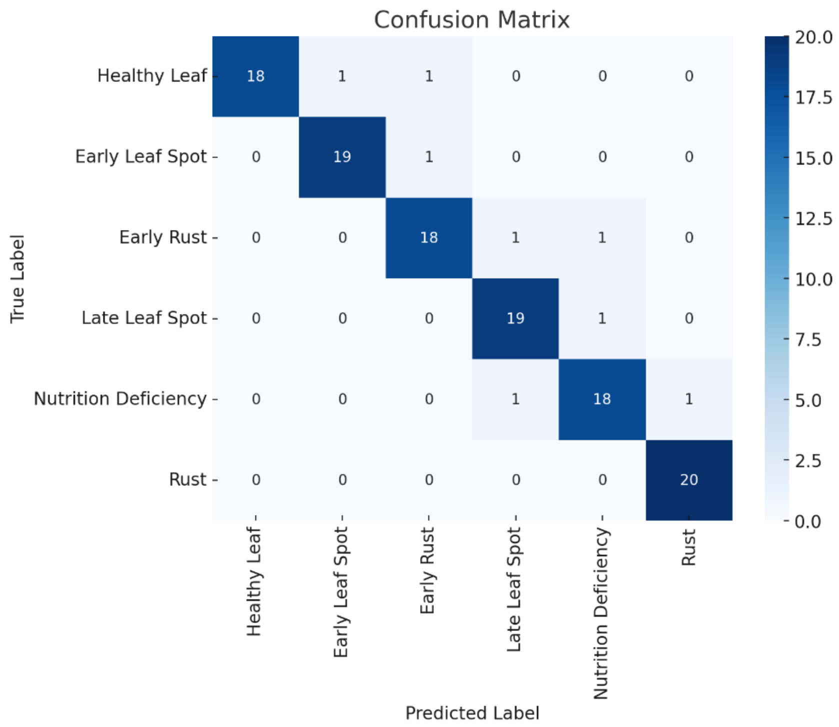


Figure 12. Confusion matrix of [30] and Pak-Nuts.

4.4. Experiment 4

In this paper, the efficacy of the proposed GNut technique is evaluated on a novel dataset named Pak-Nuts collected from the lands of Pakistan. The author started by comparing the performance of the model in both training and validation datasets, then by evaluating the loss function on these datasets. The accuracy and confusion matrix for the GNut model during its training and validation with the Pak-Nuts dataset are depicted in Figures 13 and 14. From the results, it can be understood that the proposed model was promising in both the settings. Specifically, with the Pak-Nuts dataset, the proposed model was able to achieve an accuracy rate of 98.2% on both the training and validation sets. The proposed system was able to achieve a 99% accuracy rate on the groundnut images dataset [30].

Figure 13. Accuracy and loss of training validation on Pak-Nuts.

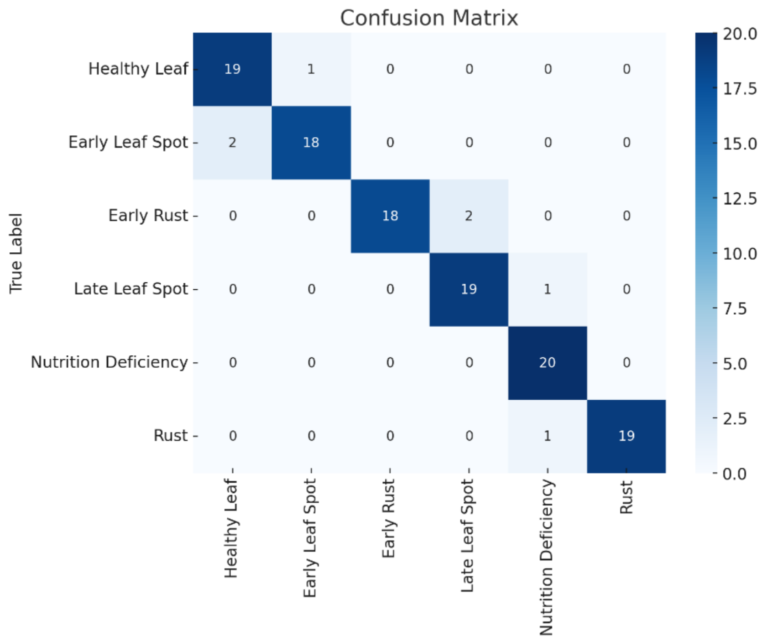


Figure 14. Confusion matrix of Pak-Nuts.

4.5. State-of-the-Art Comparison

In the field of agricultural disease detection, particularly for groundnut crops, several advanced methodologies have been developed to improve the accuracy and efficiency of identifying diseases. Among the leading models, ref. [32] employs ResNet50 and VGG16 with Bayesian Optimization, achieving a notable accuracy of 98.7%. However, this model does not provide detailed performance metrics like precision, recall, or F1-score, which limits a comprehensive evaluation of its effectiveness. Another significant contribution is the LeafNet model, which integrates residual connections and ensemble learning with Xavier weight initialization, resulting in an accuracy of 97.225%. LeafNet [33] offers a thorough evaluation with metrics such as precision (97.365%), recall (97.225%), F1-score (97.225%), and MCC (96.700%), highlighting its robustness and adaptability across various datasets. In comparison, the proposed study in this paper, featuring the "Gnut model", surpasses [32,33] with an impressive accuracy of 99% using Few-Shot Learning, and even achieves a strong 95% accuracy without it. The Gnut model's use of ResNet50 and DenseNet121 for feature extraction combined with Few-Shot Learning is a novel approach that significantly enhances its performance, particularly in contexts where labeled data is scarce. The Few-Shot Learning makes the model learn effectively even for a limited number of data, which is good for agricultural datasets since there is limited data available in most cases. In addition to this, the proposed Few-Shot Learning approach also establishes a new state-of-the-art application which gives an indication of the diverse possibilities of the model in solving agricultural problems. Other models such as LeafNet and the Hybrid Diagnostic System, however, provide good accuracy but the base of these models uses conventional CNN architectures and ensemble strategies. These models do not include Few-Shot learning which can be incorporated to improve the performance of the models further. The above analysis shows that the GNut model has an almost two times higher accuracy than the best previous model while using feature extraction and learning method, which makes it a state-of-art solution for groundnut disease detection and raises a new high bar for the studies and developments of this matter. Figures 15 and 16 depict the accuracy chart of diverse models with the proposed GNut model settings for identification of groundnut disease.

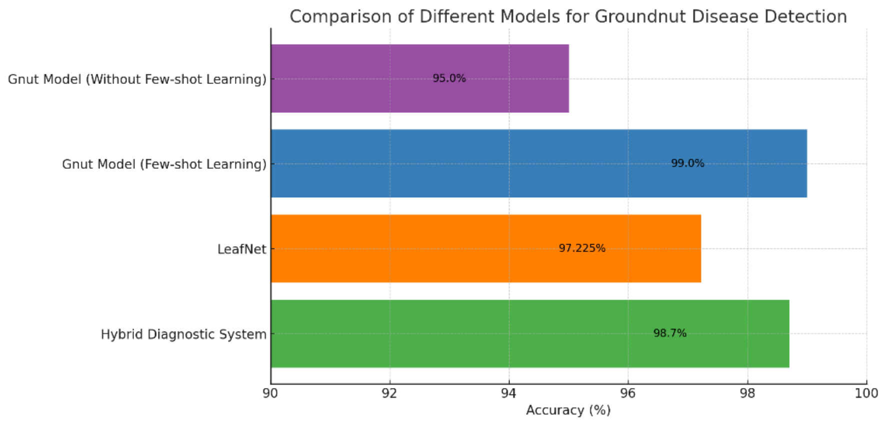


Figure 15. Advanced accuracy comparison of different models for groundnut disease detection.

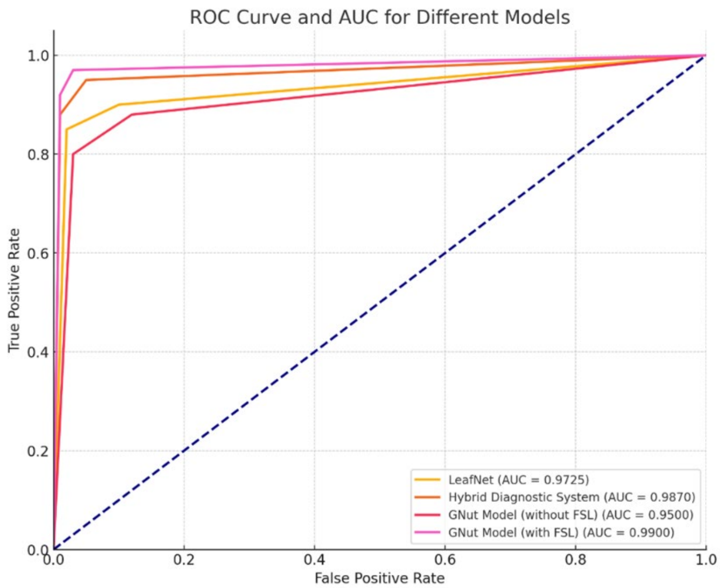


Figure 16. ROC curve and AUC of different models: LeafNet, Hybrid Diagnostic Model, GNut Model (Without FSL), GNut (With FSL).

5. Discussion

Another novelty of the contemporary effort in agriculture modernization and optimization is the active application of deep learning algorithms. The GNut model leverages ResNet50 and DenseNet121 for feature extraction and Few-Shot Learning (FSL) for classification, enabling accurate and scalable groundnut leaf disease detection. This approach addresses key challenges such as limited labeled datasets and variability in disease presentation. The results of this study demonstrate GNut's potential to revolutionize agriculture by providing an efficient, accurate, and adaptable solution for crop health monitoring and disease management. While the GNut model achieved high accuracy on the Pak-Nuts dataset, deploying it in real-world agricultural settings requires careful consideration of computational feasibility. The author measured key metrics such as inference speed, model size, and memory requirements to evaluate its suitability for on-field deployment. The proposed GNut inference time averaged approximately 150 milliseconds per image on a high-performance computing setup (16 GB GPU, Intel Core i7 processor). However, this would need adjustment for field environments with limited hardware resources. On typical edge devices, inference times could increase, potentially affecting real-time usability. Future work could explore optimization techniques such as pruning and quantization to reduce the GNut model's memory footprint and improve inference speed, making it more suitable for deployment on mobile or edge devices. By refining the GNut architecture, the author aims to make its high-accuracy predictions accessible in resource-constrained agricultural environments, enhancing its practicality for farmers. The features proposed to be extracted, and the mechanisms for classification in the current research are specialized and suitable for agricultural disease detection. A proposed GNut model integrates ResNet50 and DenseNet121 as feature extractors, with FSL as a classifier. ResNet50 and DenseNet121 were preprocessed to prune their final classification layers to transform these networks into efficient tools for generating deep features from the input images of leaves. These extracted features were merged and further processed using a linear layer to compress the output. The classification model used was the Prototypical Network, whereby class prototypes were computed as the mean feature vectors of the support examples. This approach excelled in handling the limited labeled data characteristic of agricultural datasets, enabling the model to recognize diseases with just a few examples. These techniques combined allow the GNut model to perform efficiently across various datasets, achieving high accuracy of up to 99%. The robustness of the model, coupled with adaptability to various physical conditions and disease variations, ensures broad utility for plant disease detection in different agricultural ecosystems. Ethical considerations are also vital in the GNut model implementation, especially as data collection in agricultural applications involves capturing images and metadata from farms and crops. Sensitive data, such as geolocation and crop health conditions, could reveal information about farm operations, raising privacy concerns among farmers and stakeholders. The GNut deployment should prioritize data privacy and transparency to address these challenges. Anonymizing and aggregating data can ensure that specific farm locations and ownership details remain untraceable, thus protecting farmers' privacy. Moreover, obtaining informed consent from farmers about how their data will be used, stored, and protected can foster trust in the GNut application. Robust data encryption for storage and transmission should also be implemented to minimize the risk of unauthorized access. Collaborating with agricultural cooperatives and regulatory bodies will be critical to ensuring ethical practices, thereby promoting widespread adoption of the GNut model while respecting farmers' rights and privacy. The GNut architecture and preprocessing techniques were specifically tailored for groundnut leaf diseases, but the principles behind its design extend well to similar agricultural applications. The combination of ResNet50 and DenseNet121 is robust for detecting plant diseases where texture, color variations, and subtle visual cues are significant indicators, making it adaptable to crops like wheat, maize, and rice. However, generalizing the GNut model for these crops may require retraining or fine-tuning the model with domain-specific data. Future work could involve testing its transferability to datasets from other crops or disease types to ensure it maintains accuracy across diverse agricultural settings. While GNut's high accuracy and robustness offer substantial benefits for sustainable farming, deploying computationally intensive AI models in agriculture does come with environmental considerations. High-performance models like the GNut model can be energy-intensive, especially in developing regions with limited resources. Lightweight model optimizations, such as pruning or quantization, can reduce computational and energy requirements without significantly compromising performance. Deploying the GNut model on cloud or edge computing platforms could optimize energy usage by leveraging efficient data centers or processing data near the source, reducing transmission costs and associated energy consumption. Monitoring energy consumption during training and deployment phases, integrating renewable energy sources, and using energy-efficient hardware are additional strategies to minimize the GNut carbon footprint. It is essential to balance the GNut environmental impact against its benefits for sustainable farming. By enabling early disease detection and reducing reliance on chemical treatments, the GNut supports environmentally friendly agricultural practices, contributing to long-term sustainability. Incorporating environmental metrics into the GNut's design and deployment strategies would enhance its sustainability further, ensuring that it aligns with global goals for sustainable development. The proposed GNut model represents a strong groundnut leaf disease detection benchmark, demonstrating the potential for wider application in plant disease diagnostics across other crops. However, practical constraints such as hardware requirements, environmental variability, and image quality must be addressed to maximize its utility in real-world agricultural contexts. Future research could focus on optimizing the GNut for low-computer environments and validating it across different crops and environmental conditions. These enhancements would solidify the GNut's role as a scalable, accessible tool for precision agriculture, aiding farmers in early disease detection and contributing to sustainable farming practices globally. Possible limitations of the proposed GNut model are explained in the following Table 4.

Table 4. Limitations of the GNut model in the groundnut leaf disease detection.

Limitation	Description
Data Quality and Augmentation	Most of the performance of the GNut model would depend on the quality and preprocessing of the input images. Inadequate augmentation might lead to reduced accuracy.
Computational Complexity	The GNut model integrates ResNet50 and DenseNet121 architectures, demanding significant computational power, which might not be feasible on standard hardware.
Limited Generalization	Although the GNut model showed promising results with selected datasets, further validation is required to confirm the ability of the GNut model to perform well under diverse environmental conditions and on different crops.
Integration with Agricultural Practices	Implementing the GNut model in real-world agricultural settings can be challenging due to the need for specialized hardware and software.
Data Dependency and Privacy	The GNut model requires several big data sets, and this has raised a number of concerns related to data privacy, especially in collecting data from farmers.
Real-Time Deployment	Achieving real-time disease detection and classification in the field using the GNut model is challenging due to the high computational requirements.
Model Complexity and Interpretability	The GNut model complex architecture may limit its interpretability, making it difficult for non-experts to understand its decision-making process.
Cost of Implementation	The initial cost for setting up the GNut system, including hardware, software, and data acquisition, can be prohibitive for small-scale farmers.

6. Conclusions

This research introduces the GNut model, a groundbreaking approach for the accurate detection and classification of the groundnut leaf diseases using a deep learning architecture that integrates ResNet50 and DenseNet121 for feature extraction and Few-Shot Learning (FSL) for classification. The GNut model demonstrated exceptional performance, achieving 99% accuracy with FSL and 95% without it, validated on two datasets, including the novel Pak-Nuts dataset. Leveraging advanced image preprocessing and multimodal image enhancement techniques, the GNut model establishes a new standard in agricultural disease detection, aligning with the principles of sustainable farming practices. This study underscores the transformative potential of AI-driven solutions in modern agriculture, providing a scalable and reliable framework for disease diagnosis that enhances agricultural productivity and food security. Future directions include real-time applications and the integration of GNut into broader agricultural ecosystems, enabling its adoption across diverse environments and fostering innovative, sustainable crop management strategies. The GNut model demonstrates the exceptional potential for accurate groundnut leaf disease detection, leveraging ResNet50, DenseNet121, and Few-Shot Learning to achieve high accuracy with limited data. While its dual-network architecture and reliance on high-quality inputs pose challenges for real-world deployment, strategies such as cloud-based platforms, standardized imaging, and lightweight model development can enhance feasibility. The GNut's adaptability to other crops and diseases offers further promise for scalable agricultural applications. Addressing these limitations will enable the

GNut to contribute significantly to global precision agriculture and sustainable farming practices.

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Data Availability Statement: The publicly available datasets shared by [30], accessed on 12 September 2024.

Conflicts of Interest: The author declares no conflicts of interest.

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