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Use of RESNET-50 Neural Network in Diagnosing Diseases Mango Leaves

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ABSTRACT

Using a state-of-the-art convolutional neural network, specifically RESNET-50, for disease diagnosis on mango leaves is the focus of this research. The end goal is to develop a trustworthy method of mango plant disease detection using leaf image analysis. The approach used comprised gathering a sizable dataset encompassing a range of mango leaf diseases. Afterward, a classification system was developed by training the RESNET-50 model on image data. The system is able to learn extraordinarily intricate and profound visual patterns in pictures of mango leaves thanks to RESNET-50's deep and complicated architecture, which improves feature extraction. With a Test Accuracy of 99.16% and a Test Loss of only 0.4332, the results demonstrate a very reliable system. This impressive level of precision verifies that the system is capable of correctly distinguishing and categorizing mango leaf diseases. Consequently, this case demonstrates promising agricultural applications of the RESNET-50 model and offers a dependable and effective means of disease detection in mango plants. This study adds to the growing body of knowledge that can aid agricultural professionals and farmers in the early detection of disease symptoms on mango leaves, allowing for the prompt implementation of preventative measures. These findings also have broader implications, such as the potential for better agricultural productivity and management brought about by the use of comparable technologies for disease analysis in different crops.

Keywords: Agricultural Application; Convolutional Neural Network; Disease Mango Leaves; RestNet-50; Feature Extraction;

INTRODUCTION

The mango tree, or Mangifera indica, is an essential crop for many tropical farmers because it produces a fruit that sells well and provides a steady income. A number of diseases, however, pose a constant danger to this plant, reducing its economic attractiveness. Mango leaf diseases like anthracnose, powdery mildew, and bacterial spot can severely diminish yield and crop quality. The leaves of a mango tree serve as a site for photosynthesis and also serve as a critical marker of the plant's overall health. When a plant starts to show signs of illness on its leaves, it's usually a sign that something is wrong with the plant overall. To effectively prevent diseases in agriculture, it is essential to be able to detect them on leaves in a short amount of time. Systems with high-precision disease-symptom detection on leaves are necessary for efficient agricultural practices. Visual observation-based conventional methods are notoriously laborious, open to misunderstanding, and skill-intensive. Consequently, it is crucial to create an automated system that can detect diseases on mango leaves. Convolutional neural networks (CNN) (Hindarto, 2023) and other technology-based approaches provide new hope for this endeavour by offering solutions that could be fast, reliable, and accurate in diagnosing diseases in mango crops.

Disease identification on mango leaves is typically a labour-intensive process that calls for seasoned farmers and agriculturalists. In this method, symptoms like spots, discoloration, or unusual texture on the leaves are carefully observed visually. Manual interpretation and recognition might be biased or incorrect because of the involvement of humans. Careful identification can take a long time, even for specialists, particularly when distinguishing between symptoms of diseases with a high degree of visual similarity. Disease identification on mango leaves requires more dependable and automated solutions due to the limitations of manual recognition. In order to diagnose different plant diseases more quickly, accurately, and consistently, systems will need to be able to overcome these obstacles. Recent advances in technology, like CNN (Suherman, Hindarto, et al., 2023), have the potential to solve this issue by improving our ability to recognize and categorize leaf images. Early disease detection and management in mango crops can be significantly enhanced with the help of automated and dependable solutions. This will allow for timely intervention to improve overall plant health and reduce losses caused by disease attacks.

This research is primarily focused on using the latest technological approaches to tackle the challenge of disease

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identification on mango leaves. The author uses a groundbreaking approach to visual pattern recognition and image processing—one that relies on convolutional neural networks. It zeroed in on the RESNET-50 (Mirza et al., 2023), (Suherman, Rahman, et al., 2023) model, in particular, because it is among the best architectures for picture classification. This model's strength is in its deep feature extraction capabilities; these enable the model to grasp and capture important details that would be challenging for a human to interpret manually. Recognizing complex patterns, such as those indicative of disease symptoms on mango leaves, can be a challenge, but RESNET-50 (Tian et al., 2022)deep and intricate structure allows it to acquire a more abstract picture. The use of CNN RESNET-50 for the categorization of mango leaf diseases has shown remarkable capabilities in accurately identifying diseases. Because many diseases affecting mango leaves have similar symptoms or are hard to tell apart visually, this skill is crucial for identifying and treating these conditions. It is believed that this state-of-the-art technology can help improve agricultural disease prevention and management by providing a dependable and efficient method for identifying and categorizing diseases in mango plants.

An investigation into the capabilities of the RESNET-50 neural network model (Hindarto, n.d.), (Wang & Wu, 2023) for automatically detecting disease symptoms on mango leaves. The primary emphasis lies in the system's precision in categorizing diverse forms of pathological disorders frequently observed in plants. This research aims to evaluate the reliability and effectiveness of using image analysis as a tool for efficiently and accurately detecting and distinguishing disease symptoms on mango leaves. This research aims to determine the efficacy of the RESNET-50 neural network model in accurately identifying disease symptoms in mango leaves. The focus is on evaluating its accuracy and ability to classify different types of pathological disorders. Here are two research inquiries pertaining to the RestNet-50 technique: What is the proficiency of the RESNET-50 model (Kumar et al., 2022) in identifying and categorizing different diseases on mango leaves using image analysis? Additionally, how accurate is it in recognizing various symptoms? What is the performance of the RESNET-50-based classification system in identifying disease variations on mango leaves, and what is the precision and recall in differentiating between different pathological conditions?

The primary objective of this research is to investigate the feasibility of implementing a system that utilizes the CNN RESNET-50 model to detect diseases on mango leaves. The primary aim is to develop an automated solution that can offer accurate and dependable analysis of pathological conditions in mango plants. The anticipation is that the outcomes of this investigation can yield a substantial impact on agricultural methodology, particularly for farmers and agricultural specialists. The objective of this project is to develop a system that can accurately detect disease symptoms on mango leaves at an early stage. This solution is expected to serve as a practical and efficient tool for agricultural practitioners in effectively managing and resolving plant disease issues that impact crop production and quality. The aim is that the effectiveness of this method will facilitate farmers in promptly detecting issues in their mango crops, thus allowing them to take timely and more effective preventive measures. Hence, it is anticipated that the outcomes of this study will not only offer cutting-edge technological remedies but also make a direct impact on enhancing productivity and sustainability in the agricultural sector, particularly in the domain of mango cultivation.

LITERATURE REVIEW

Leaf-Net, a CNN-based method that analyzes images of leaves in Bangladesh (Ahmed et al., 2023), detects seven prevalent mango diseases—succeeding state-of-the-art models such as GGG16 and Alex-Net in terms of accuracy, precision, recall, F-score, and specificity in its evaluation. This contributes to the national economy and increases mango production by facilitating the early detection of disease symptoms. In a 5-fold cross-validation, the performance of Leaf-Net is assessed using the following metrics: average accuracy, precision, recall, F-score, and specificity: 98.55%, 99.508%, 99.45%, 99.47%, and 99.878%, respectively. These values surpass those of the most recent and cutting-edge models, such as Alex-Net and VGG16. A specialized PDICNet model for plant leaf disease detection and categorization is detailed in this article. A classifier model based on deep learning convolutional neural networks (DLCNNs) and ResNet-50, as well as a modified Red Deer optimization algorithm (MRDOA), are utilized. The model demonstrates exceptional performance, attaining F1-scores of 99.73% and 99.78% for the Plant Village and Rice Plant datasets, respectively (Reddy et al., 2023). Kimchi cabbage is an essential agricultural product in Korea, and this study uses hyperspectral imaging and a UAV to find downy mildew. Overall, the system gets 0.876, and for diseased classes, it gets 0.873 (Wiku et al., 2023). Both quantity and quality are affected by apple leaf diseases. With classification accuracies of 97.2% and 95.2%, respectively, ResNet18-RC and ResNet18-CBAM provide a theoretical foundation for disease control and prevention (Ding et al., 2022) . An adapted PDICNet model for the detection and categorization of plant leaf diseases is detailed in this article. The Black Gram Plant Leaf Disease (BPLD) dataset, which is referred

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to as Vigna Mungo in India, is introduced in this article. In order to identify and categorize diseases impacting black gram production at an early stage, this dataset was created using image processing and computer vision algorithms. There are a thousand photos in the collection that are actual crop fields in Krishna, Andhra Pradesh's Nagayalanka district. This dataset could be helpful for researchers working on early disease diagnosis and classification using image processing, machine learning, and deep learning algorithms (Talasila et al., 2022). In order to invert two-dimensional magneto telluric data, the study introduces a deep learning algorithm that addresses problems such as computational inefficiency and over-segmentation. The issue was successfully resolved by the ResNet-50 model, which was trained using a dice loss function. It was then validated using MT data from a geothermal field prospect (Xie et al., 2023). Automated manipulation of massive budding yeast cells for replicative aging studies has been made possible by microfluidic platforms. Efficient processing of large datasets of microscopy images was achieved by combining a dedicated algorithm with computer vision and residual neural network (ResNet). The program identified cell dynamic events, segmented micrographs taken with multiple traps, labeled eight characteristics of yeast budding, trained an 18-layer ResNet, translated predictions into digital signals, calculated the replicative lifespan and budding time interval of the yeast, and so on. Achieving high F1 scores with the ResNet algorithm implies that comparable deep learning algorithms could be utilized for microfluidic single-cell analysis (Xiao et al., 2024). Heart disease is dangerous, so real-time electrocardiogram monitoring and diagnosis are essential. This paper presents a ResNet-based intelligent diagnosis method that converts MITBIH Database ECG signals into 2-dimensional matrices using the Markov Transition Field. ResNet extracts abstract disease features and intelligently identifies five heartbeat types: Normal Beat, Left Bundle Branch Block Beat, Right Bundle Branch Block Beat, Premature Ventricular Contraction Beat, and Atrial Premature Contraction Beat. The model then identifies Normal Beat and Atrial Fibrillation using the PAF Prediction Challenge Database. On the MIT-BIH Database, the experiment had a high F1-score of 97.7%, accuracy of 99.2%, and mean sensitivity and specificity of 97.42% and 99.54%. The PAFPC Database generalization ability verification experiment results in 94.57%. The method has good applicability and generalization (Ji et al., 2023).

METHOD

The ResNet-50 methodology has proven to be a highly dependable approach in image analysis, particularly when it comes to classifying diseases that affect mango leaves. The success of this system can be attributed to its exceptional capacity to handle the intricacy of visual data in leaf images. ResNet-50 demonstrates its excellent capabilities in classifying diseases in mango plants by effectively utilizing a substantial and representative dataset. ResNet-50 (Durga & Rajesh, 2022) is a convolutional neural network architecture with a deep and intricate structure, allowing it to comprehend and extract intricate visual patterns from images. The model's deep layers enable it to effectively capture complicated features, making it crucial for discerning subtle distinctions among different diseases on mango leaves. The utilization of an extensive and inclusive dataset is a critical factor for the triumph of ResNet-50 in accurately categorizing diseases found on mango leaves. Comprehensive datasets containing diverse diseases, varying levels of severity, and different lighting conditions facilitate the model's ability to learn and identify a wide range of disease symptoms. The data collected from this dataset establishes a solid basis for the model to extrapolate and detect previously unseen diseases on mango leaves. The performance of ResNet-50 in classifying diseases on mango leaves using a substantial dataset demonstrated remarkable efficacy. The reliability of its ability to identify diverse symptoms of different diseases and its capacity to distinguish between similar symptoms demonstrates significant utility in agricultural applications. Through the implementation of this approach, advancements in the timely identification, assessment, and control of ailments in mango plantations can be made, which will significantly increase the overall output of agriculture.

The following is a research method for classifying mango leaf diseases using ResNet-50, as in Fig 1.

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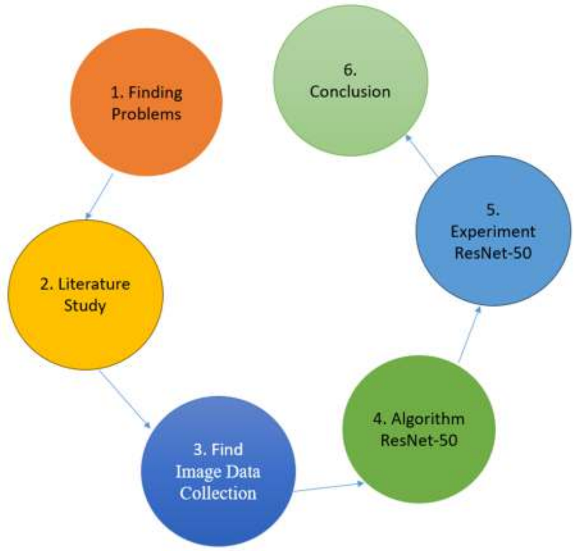

Fig 1. Research methodology for research on mango leaf diseases
Source: Researcher properties

Fig 1, The first stage of this research method is problem identification, during which the researchers look at issues with disease detection on mango leaves (1. Finding Problems). In order to comprehend the history, present state of the art, and theoretical foundation of disease classification in mango plants, the following step is to conduct a thorough literature review (2. Literature Study). Once you have a firm grasp of the theory, the next step is to gather a set of images that depict different mango leaf diseases (3. Find Image Data Collection). Several diseases, lighting conditions, and degrees of severity are considered as they gather leaf images for this process. Stage two of the research involved classifying diseases on mango leaves using images, and the ResNet-50 algorithm was the primary tool for this task (4. ResNet-50 Algorithm). ResNet-50's deep feature extraction capabilities and capacity to recognize complex visual patterns made it the ideal candidate for disease identification tasks. Applying ResNet-50 to the previously acquired image dataset (5. Experiment ResNet-50) constitutes the experimental stage, which follows the algorithm determination. The steps involved in this process include training the model, testing it, and finally evaluating how well it classifies different mango leaf diseases. Lastly, in the sixth and final stage, "Conclusion," the experimental results are described, the ResNet-50 algorithm's performance in identifying diseases on mango leaves is evaluated, and the research's contribution and implications in the agricultural context are outlined. Recommendations for future research or practical uses of this study to aid in disease management in mango plants may also be included in this conclusion. These procedures, when put together, provide a thorough methodology for analyzing mango leaves for disease classification using the ResNet-50 algorithm.

Convolutional Neural Network

Classifying diseases on mango leaves using a Convolutional Neural Network requires a number of detailed procedures for identifying and differentiating pathological symptoms in images of the leaves. Convolutional neural networks begin by incorporating a layer that seeks to extract visual features from images of leaves (1. Feature Extraction). Essential features and patterns, such as lines, textures, and more complicated patterns that might indicate disease on mango leaves, are captured at different levels of detail by this layer. Following that, pooling layers like max-pooling combine the outputs of the convolution layers; this process attempts to decrease the data's dimensions while preserving important information. This method keeps crucial visual aspects of the leaf image while lowering the network's complexity and parameter count. Classification is performed using the information gathered from the previously extracted features in the fully connected layer, which follows a series of convolution and pooling layers (3. Fully Connected Layer). In this central layer of the classification process, different pathological conditions in mango leaves are distinguished using information that has been abstracted. Keep in mind that the CNN is training itself to optimize the network parameters at this stage (4. Training Process). A dataset of images depicting various mango leaf

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diseases was used for this purpose. In order to improve its classification accuracy, CNN learns from this dataset to identify patterns linked to each disease type. After completing the training phase, CNN is prepared to test or infer on previously unseen images (5. Testing/Inference). To do this, we feed pictures of mango leaves into a network that can identify potential diseases based on their classification. Feature extraction, data combination, classification, training, and testing are the overall steps in convolutional neural network disease classification on mango leaves. This lays a solid foundation for using AI to efficiently and accurately diagnose plant diseases.

Continuous iteration is an advanced step in the Convolutional Neural Network process for disease classification on mango leaves. This helps the network to recognize pathological symptoms more accurately. Evaluating the performance of the network is a crucial part of carrying on with this process (6. Evaluation). During the evaluation phase, the CNN is put to the test using an entirely new dataset in order to gauge the network's ability to generalize its knowledge from the training data. When evaluating the effectiveness of a classification system, metrics like F1-score, recall, accuracy, and precision are employed. In order to enhance the performance of the network, this sophisticated process also makes use of optimization techniques (7. Optimization Techniques). To improve the network's generalizability to different visual conditions, optimization can involve adjusting parameters, using adaptive learning rates, regularization techniques, or even data augmentation to increase dataset variety.

Furthermore, the model is fine-tuned at this stage (8. Fine-Tuning Model) to enhance the network's symptom recognition capabilities for more intricate or uncommon diseases. A convolutional neural network can be trained to detect symptoms that weren't in the original dataset by changing a few layers or parameters of an existing model. Improving CNN's capacity to handle the complexity and diversity of disease symptoms on mango leaves is a critical component of the ongoing development and iteration process. Further evaluation, optimization, and fine-tuning of CNN will make it a more dependable, accurate, and trustworthy solution for mango plant disease identification. Despite the significance of these phases in CNN development, the method is dynamic and subject to change as a result of new knowledge and technology that improve the processes used to optimize network performance in plant disease detection.

Residual Network 50

ResNet-50, also known as Residual Network 50 (Suherman, Rahman, et al., 2023), is a groundbreaking and robust convolutional neural network (CNN) structure specifically designed for performing image recognition tasks. ResNet-50 is a refined version of the Residual Network (ResNet) model that was initially proposed by Kaiming He and his research team in 2015. The primary distinguishing feature of ResNet-50 lies in its utilization of residual blocks, enabling the network to achieve greater depth without encountering issues of performance deterioration. The key distinctive feature of ResNet-50 compared to earlier convolutional networks lies in its utilization of residual blocks. The residual blocks incorporate shortcut connections or paths that enable direct flow between consecutive layers in the network. Performance degradation or vanishing gradient problems frequently arise when information traverses multiple layers within a highly complex network. Shortcut connections within residual blocks facilitate the transmission of gradient information to deeper layers, effectively addressing the issue of vanishing gradients.

ResNet-50 is composed of 50 layers that are made up of different residual blocks. A residual block is comprised of multiple convolutional layers that are equipped with a Rectified Linear Unit (ReLU) activation function placed between them. The ResNet-50 architecture consists of three primary types of residual blocks: basic blocks, bottleneck blocks, and dilated bottleneck blocks. The base block is composed of two 3x3 convolution layers, whereas the bottleneck block employs a combination of 1x1, 3x3, and 1x1 layers to decrease the computational burden while maintaining performance. Meanwhile, the dilation bottleneck enhances network capabilities by using dilation filters that increase spatial coverage.

An inherent benefit of ResNet-50 lies in its capacity to effectively address challenges encountered in highly complex networks. Shortcut connections enable the network to acquire more advanced representations of intricate data. The presence of residual blocks facilitates the training of deeper networks while mitigating the performance degradation problems that often arise in such networks. ResNet-50 has demonstrated remarkable efficacy in diverse image recognition tasks, encompassing image classification, object detection, and segmentation. This model serves as the foundation for numerous applications across various industries, such as medicine, agriculture, automotive, and more. Its exceptional capacity to address intricate network issues positions it as a leading option for a wide range of complex image analysis tasks. Undoubtedly, ResNet-50 has solidified its status as one of the most notable breakthroughs in the field of artificial intelligence, particularly in the realm of image processing.

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RESULT

This research investigation presents an experiment in classifying mango leaf images using the ResNet-50 model. The aim is to investigate the model's capacity to accurately detect and distinguish different diseases affecting mango leaves through detailed image analysis. The dataset utilized in this study was acquired through the Kaggle platform, comprising a compilation of mango leaf images exhibiting diverse forms of diseases. The dataset provided contains 40,000 images that encompass eight distinct categories of mango leaves. These images offer a diverse range of representations of various pathological conditions found in mango plants.

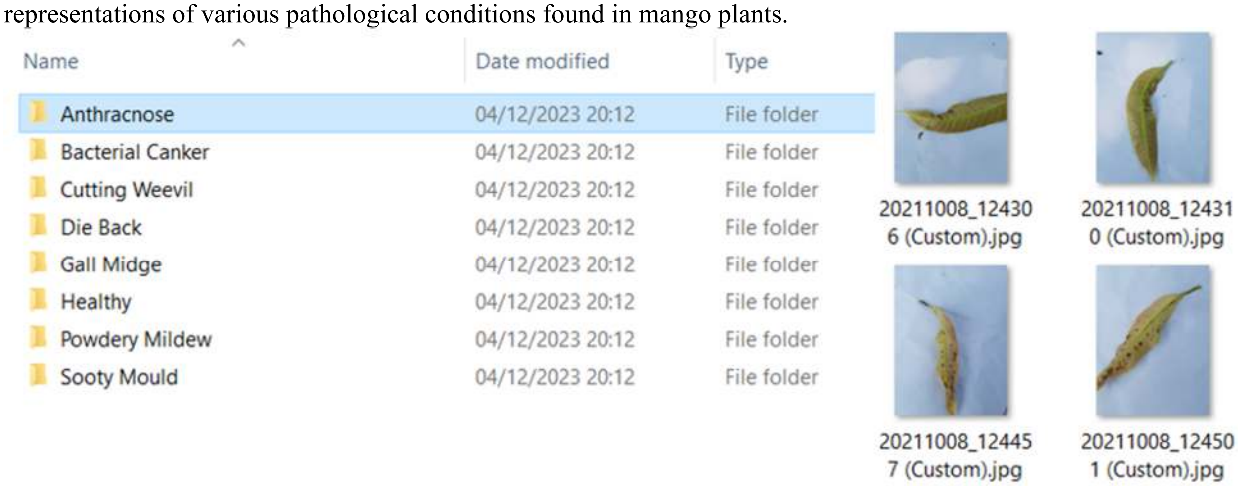

Fig 2. Dataset leaf mango
Source: Kaggle.com

The mango leaf dataset's Figure 2 showcases the variety of pathological conditions that manifest in mango plants. The dataset comprises eight distinct categories representing different diseases and health conditions found on mango leaves, including Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, and Sooty Mold. Every class corresponds to a distinct category of disease or health condition found on mango leaves. Anthracnose is distinguished by the presence of black or brown lesions on the leaves, which have the potential to extend across the entire leaf area. Bacterial Canker, however, is distinguished by the development of dark-hued lesions or ulcers on the leaves. The act of cutting by the Weevil results in harm to the leaf margins, whereas Die Back manifests as signs of withering and demise on the plant's leaves or stems. The dataset includes a class called Gall Midge, which refers to a tiny insect that induces bumps or swellings on leaves. The Healthy class represents the state of leaves that are devoid of any disease or pathological damage.

Additionally, there are alternative conditions such as Powdery Mildew, which exhibits traits such as the proliferation of white powder on the leaf surface, and Sooty Mold, which manifests as a black layer resembling soot that develops on the leaves. This variation of the dataset offers a comprehensive overview of the diverse factors that can impact the well-being of mango leaves. By utilizing this dataset that contains a wide range of variations, models like ResNet-50 can be trained to identify and distinguish different visual patterns linked to various pathological conditions. This facilitates the creation of a more precise and dependable classification system for detecting diseases in mango plants.

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```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet50 (Functional)       (None, 1000)              25636712

 batch_normalization (Batch  (None, 1000)              4000
 Normalization)

 dense (Dense)               (None, 256)               256256

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 8)                 2056

=================================================================
Total params: 25899024 (98.80 MB)
Trainable params: 260312 (1016.84 KB)
Non-trainable params: 25638712 (97.80 MB)
```

Fig 3. Architecture ResNet-50
Source: Property researcher

Figure 3 provides an outline of the ResNet-50 architecture, which comprises multiple distinct layers. The central component of this architecture is the resnet-50 (Functional) layer, which has an output shape of (None, 1000) and a total of 25,636,712 parameters. Next, there is a Batch Normalization layer that has an identical output shape (None, 1000) and a parameter count of 4,000. The Dense layer has an output shape of (None, 256) and 256 parameters. Next, a Dropout layer with zero parameters (Parameter 0) is added to the model to mitigate overfitting. The dense_1 layer, also known as the dense layer, has an output shape of (None, 8) and a total of 2,056 parameters. This architecture employs diverse layers to extract features, standardize, and categorize data. The resnet-50 layer serves as the primary basis for extracting features from images. Batch Normalization is employed to expedite convergence and mitigate overfitting. The dense layer functions as a fully connected layer, enabling the network to comprehend intricate patterns in the data. Dropout is a technique that mitigates overfitting by deactivating specific units during the training process. The dense_1 layer serves as the output layer, producing an output shape of (None, 8), representing the desired number of classes for classification in the mango leaf dataset, which contains eight distinct classes. ResNet-50 is designed with this architecture to accurately classify different diseases on mango leaves using extracted image features.

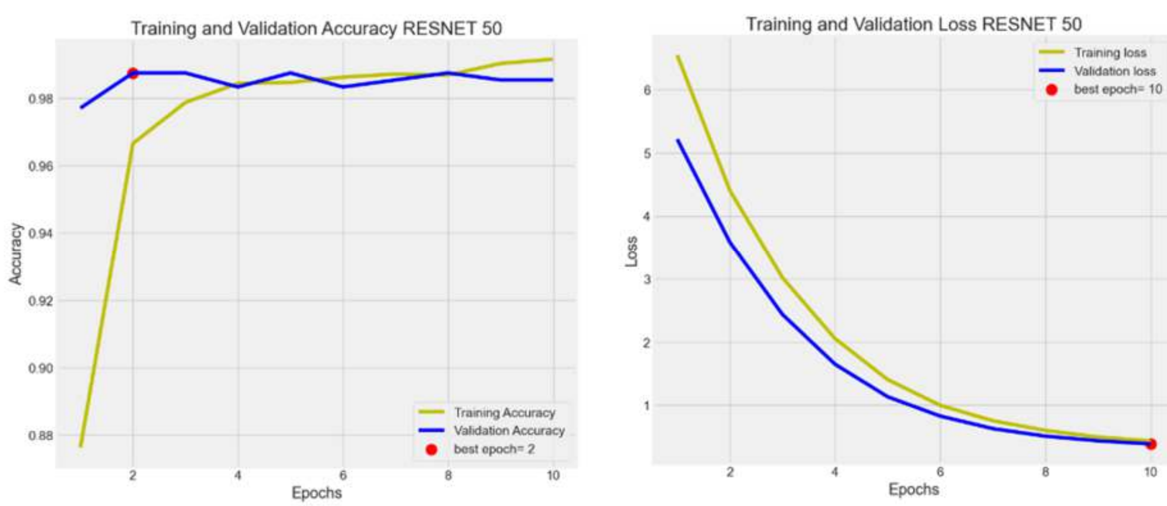

Fig 4. Performance training accuracy and loss ResNet-50
Source: Property researcher

As represented by the loss and accuracy metrics, Figure 4 illustrates the training performance of the ResNet-50 model over ten epochs. A loss value of 0.4332 and an accuracy of 99.16% are the outcomes of model training in this

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context. In contrast, at the conclusion of the tenth epoch, the validation stage (val_loss) reported an accuracy of 98.54% and a loss value of 0.3855. The ResNet-50 model correctly classifies images of mango leaves with a high degree of accuracy, as evidenced by its ability to learn complex patterns in the dataset effectively. Indicating whether the model predicts the correct target accurately or inaccurately, loss is a metric. A model's performance in discerning patterns within the training data improves as the loss value decreases.

Meanwhile, Anomaly quantifies the model's precision in data classification. A high accuracy value in this context signifies that the model demonstrates a considerable degree of proficiency in identifying and categorizing images of mango leaves. The negligible disparity in loss magnitudes between the training and validation stages indicates that the model remains unaffected by overfitting. This implies that the model not only discerns patterns within the training data but also possesses the capability to extrapolate this knowledge to unobserved data. The dependable nature of the ResNet-50 models in identifying and categorizing a wide range of pathological conditions on mango leaves is supported by its strong performance during training and validation. The model demonstrates commendable capability in handling the intricacies of image data, as evidenced by its high accuracy and minimal loss difference during both the training and validation phases. This characteristic renders it particularly promising for practical implementations, such as facilitating the timely identification and control of tropical plant diseases.

DISCUSSIONS

What is the proficiency of the RESNET-50 model in identifying and categorizing different diseases on mango leaves using image analysis?

The RESNET-50 model excels at utilizing image analysis to detect and classify different diseases present on mango leaves accurately. The model's capabilities are remarkable, as it demonstrates exceptional accuracy and reliability in identifying visual patterns and distinguishing substance differences in mango leaves affected by disease. The primary benefit of this model resides in its capacity to conduct thorough feature extraction from images of mango leaves. RESNET-50 possesses an intricate network architecture that allows for the detection of complex and nuanced visual characteristics. This enables him to distinguish between different diseases that impact mango leaves by analyzing distinct visible symptoms. This model possesses the capability to identify specific patterns, such as lesions, alterations in colour, or variations in texture, which are challenging to discern through manual observation. RESNET-50 has proven its capacity to accurately classify diseases through a rigorous training regimen utilizing various datasets. The accuracy of this method surpasses traditional manual identification techniques, ensuring consistent and dependable diagnosis. The model's efficacy was also demonstrated in accurately discerning nuanced distinctions between diseases that may exhibit visual resemblances, thereby ensuring accurate categorization despite the presence of overlapping observable traits.

Moreover, the dependability of RESNET-50 holds significant practical consequences in the realm of agricultural practices. The high accuracy and reliability of this technology create opportunities for early disease detection and effective management strategies for mango crops. Through prompt and precise disease identification, farmers can promptly implement suitable interventions, thereby minimizing the adverse effects of diseases on crop yields. Furthermore, the dependability of this model also serves as a valuable instrument for agricultural specialists, aiding in the creation of comprehensive disease management protocols and facilitating more knowledgeable decision-making. The RESNET-50 model demonstrates high efficiency in utilizing image analysis to identify and categorize different diseases on mango leaves. This highlights its potential as a sophisticated technology for agricultural diagnosis. The exceptional precision, dependability, and capacity to discern subtle diseases emphasize its importance in revolutionizing disease management practices in mango cultivation and other agricultural domains.

How accurate is it in recognizing various symptoms?

The RESNET-50 model demonstrates exceptional accuracy in identifying different disease symptoms on mango leaves, primarily due to its remarkable capability to differentiate intricate visual characteristics. This model demonstrates excellent capability in accurately identifying a wide range of symptoms, effectively detecting significant alterations in diseased mango leaves. This capability is facilitated by a deep neural network architecture and intricate layers, allowing it to extract detailed and nuanced features from images of leaves. RESNET-50 possesses the capability to comprehend and discriminate disease symptoms that frequently exhibit a level of visual resemblance that is challenging to discern through manual means. The strength of this model lies in its capacity to feel distinctions among different symptoms of comparable illnesses. RESNET-50 can detect even the most subtle distinctions despite the visual similarities of the symptoms. This enables the model to offer a more accurate diagnosis, even in cases where symptoms

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may be similar or overlapping. The model's capacity to discern disease symptoms with precision is a notable advantage in endeavours to detect and control disease in mango plants promptly.

Nevertheless, it is crucial to bear in mind that the precision of the model is also contingent upon the calibre of the training dataset employed. Utilizing datasets encompassing a diverse range of disease symptoms can enhance the model's capacity to identify distinct symptoms accurately. Hence, to achieve an optimal level of precision in identifying disease symptoms on mango leaves, it is crucial to focus on the quality and representation of the dataset employed in the training process of the model.

What is the performance of the RESNET-50-based classification system in identifying disease variations on mango leaves?

The RESNET-50-based classification system demonstrates remarkable efficacy in detecting disease variations on mango leaves. This model effectively addresses the intricacy of disease variations with a noteworthy level of precision, accurately identifying different disease variants on mango leaves with consistent accuracy. The primary benefit of this system is its capacity to discern nuanced visual distinctions among other pathological conditions that impact mango leaves. RESNET-50 exhibits exceptional capability in accurately categorizing a diverse range of diseases, even when the optical characteristics of these diseases are similar. The deep network architecture enables it to conduct profound feature extraction from leaf images, discerning subtle variations that may indicate signs of illness. This model demonstrates resilience in addressing the challenge of identifying analogous disease symptoms, such as spots that possess nearly identical attributes. The evaluation results show that the classification system based on RESNET-50 achieves a commendable level of accuracy in detecting different disease variations on mango leaves. Precision plays a crucial role in the prevention and management of plant diseases. This system greatly enhances the early detection and management of illness in mango plants by effectively identifying different disease variants. As a result, farmers are able to promptly and efficiently address plant health issues, leading to more effective control and prevention of diseases.

What is the precision and recall in differentiating between different pathological conditions?

Precision and recall are crucial evaluation metrics for assessing the effectiveness of classification systems, particularly in distinguishing various pathological conditions in mango leaves. Precision quantifies the degree of correctness in predicting positive instances of a specific category, whereas recall assesses the system's ability to retrieve all instances of a particular category.

$$\text{Precision} = \frac{\mathit{True\ Positive}}{\text{True Positives+False Positives}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Within this particular framework, the utilization of the RESNET-50 model as a classification system exhibits a notable degree of accuracy and completeness in discerning pathological states on mango leaves. Precision pertains to the degree of exactness in accurately recognizing a specific pathological condition. Recall quantifies the system's ability to identify and acknowledge all occurrences of a pathological condition accurately.

$$\text{Recall} = \frac{\mathit{True\ Positive}}{\text{True Positives+False Negatives}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

For instance, if out of a hundred leaf samples affected by disease, the system accurately identifies 90 samples as positive (True Positives) and ten samples as incorrect (False Positives), then the precision formula can be expressed as:

$$\text{Precision} = \frac{90}{90+10} = 0{,}9 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

This indicates that the system accurately identifies 90% of the samples as positive.

Recall quantifies the system's capacity to identify all positive examples out of the entire set of positive examples. The recall formula is calculated as the ratio of true positives (90) to the sum of true positives (90) and false negatives (10) in a sample of one hundred leaves affected by disease.

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$$\text{Recall} = \frac{90}{90+10} = 0,9 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. \quad (4)$$

This indicates that the system can retrieve 90% of all truly positive instances.
The RESNET-50-based classification system demonstrates exceptional precision and recall values, indicating its robust capability to classify different pathological conditions on mango leaves accurately. This system enables precise and efficient identification of diseases in mango plants.

CONCLUSION

This research investigates the use of the ResNet-50 model to classify mango leaf images, aiming to detect and distinguish different diseases affecting mango leaves through detailed image analysis. The dataset used is a compilation of 40,000 images from the Kaggle platform, encompassing eight distinct categories of mango leaves. The ResNet-50 architecture comprises multiple layers, including the ResNet-50-layer, Batch Normalization layer, Dense layer, Dropout layer, and dense_1 layer. The model's training performance over ten epochs showed a high degree of accuracy and precision in data classification, with a loss value of 0.4332 and an accuracy of 99.16%. The model's dependable nature in identifying and categorizing a wide range of pathological conditions on mango leaves is supported by its strong performance during training and validation.

The RESNET-50 model is a highly accurate and reliable tool for identifying and categorizing diseases on mango leaves using image analysis. Its intricate network architecture allows for the detection of complex and nuanced visual characteristics, enabling it to distinguish between different diseases by analyzing distinct visible symptoms. The model's precision in recognizing various symptoms is also noteworthy, as it can detect even the most subtle distinctions despite visual similarities. The RESNET-50-based classification system demonstrates remarkable efficacy in detecting disease variations on mango leaves, even when the optical characteristics of these diseases are similar. The model's precision and recall are crucial evaluation metrics for assessing the effectiveness of classification systems, particularly in distinguishing different pathological conditions on mango leaves. The system can accurately identify 90% of the samples as positive, demonstrating its robust capability in accurately classifying other pathological conditions on mango leaves. This technology holds significant practical implications in agricultural practices, enabling early disease detection and effective management strategies for mango crops.

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