Exploring the efficiency of transfer learning in Brinjal disease detection using deep learning

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Approval

APPROVAL

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DECLARATION

I certify that this project was carried out under the supervision of Daffodil Internatio University's Instructor of Software Engineering, Mr. Khalid Been Badruzzaman Biplob, Lectu (Senior Scale), and Mr. Musabbir Hasan Sammak, Lecturer. It is further confirmed by myself t no part of this thesis has ever been submitted for a degree or diploma elsewhere.

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Chapter 1: Introduction

1.1 Introduction

About 75% of the people in Asian countries rely on agriculture for their livelihood. Bangladesh is a country highly dependent on agriculture [1]. About 45.33% of the population of the country was engaged in the agriculture sector in the fiscal year 2022–2023 [2]. And same sector contributed approximately 11.38% to the Gross Domestic Product of the nation [3]. Grown over 50,000 hectares of land, eggplant, or brinjal, is the third most important crop in the nation [4]. This vegetable is very beneficial to health as it aids in better digestion and increases mental performance. It is also known to prevent one from catching cancer, protects heart health, and also supports the bones in one's body. Antioxidants, including vitamins A and C, which protect cells from damage, are very much present in brinjal. It has a high concentration of polyphenols, which are chemical molecules that help control how sugar is metabolized in diabetic cells.

Deep learning-based disease detection and classification have seen significant improvement in recent years, so I apply some unique models like Omnivore, coca, and VIT/H-14, which are considered to possess superior image recognition capabilities, especially to detect diseases of brinjal (eggplant) crops. This research studies the classification of four common diseases of brinjal plants in Bangladesh by using deep learning methods: Phomopsis blight, Fruit & Shoot Borer, Brinjal Fruit Cracking, Rhizopus, Growth Creaks, Brinjal Wet rot and identification of Healthy Brinjals.

Phomopsis blight is caused by the fungus Phomopsis vexans, but it has several other names, including Phomopsis rot, Phomopsis leaf blight, fruit rot, brown spot, stem blight, and brinjal tip-over. The disease spreads through spores, released by the fruiting bodies called pycnidia [5]. It persists in the soil, seeds, and previous eggplant crop debris. The spores can be spread through infected tools, insects, and rain splashes and are also suspected to be present on and within the seeds. So, to fight this disease, it is mandatory to purchase certified seeds and healthy plants. Phomopsis blight spreads well at hot and moderately humid conditions between 27–35°C. The disease can initiate infection in 6–12 hours of contact with leaf tissues. In storage environment characteristics, that is, about 30°C and 50% humidity, the chances of formation of the fruit lesion increase [6].

Increasing insect control expenses, such as the cost of controlling the Brinjal Fruit and Shoot Borer (BFSB), pose a threat to brinjal production. The larvae damage the shoots in addition to the quality of the fruit, rendering them inedible [7]. Pesticides are ineffective since BFSB has many adaptations. This is carried out by the larvae of the Leucinodes orbonalis moth, which are laid on the plant parts in the spring. They attack many other solanaceous plants such as tomato and potat.[8]

"Growth cracking," or longitudinal and concentric Rain checking, comes from soil moisture shifts, extended rain, and heavy dews which affect the fruits of melons, cucumbers, eggplants, tomatoes, and peppers [9]. As fruit skins mature, they become leathery and less pliable, fracturing when taking up excessive moisture, especially when the developing fruit are in a protected location under the foliar canopy of the plant, protecting them from the full force of rapid temperature changes.

Rapid fruit growth and sometimes increased water uptake aggravate the condition, especially when a plant goes from cold, wet growing conditions to hot, dry environments. Proper fertilization practices help alleviate the situation and reduce this problem, making fruits more robust and able to withstand cracking [10].

Rhizopus rot the widespread cosmopolitan mushroom causes soft and liquid rots on various plants, particularly fruits such as eggplants, which resemble Botrytis cinerea. Attacks senescent floral parts, leading to caramel-brown rot with blackish mold [11]. Thrives on a variety of hosts, including Solanaceae and Cucurbitaceae, and may be found in open fields or under shelters. Confusion may arise with rots caused by Choanephora or Botrytis.

Brinjal Colletotrichum Wet Rot - This is a typical and widespread disease of vegetables, fruits, and ornamentals. The infection of eggplant Colletotrichum fruit rot usually starts on the skin of the fruit and, in severe cases, can spread to the inside [12]. It thrives in warm, wet conditions, and prolonged leaf wetness encourages the spread of the disease. The preliminary symptoms are little tan, often circular or angular lesions on the skin of the fruit, with sunken tissue and a tan center that contains fungal spores. Infected fruits may drop prematurely, and areas of the fruit develop mushy and become inedible. Disease-free seeds and disease-free planting material, frequent destruction of plant debris, and spraying with fungicides should be used as preventive measures [13].

Figure 1.1.1: Infected Brinjals and Healthy Brinjal

A system is being developed to help farmers and agricultural practitioners diagnose and manage plant diseases more effectively. This system incorporates three advanced deep learning models: the Omnivore model, Coca, and DeiT. These models are currently undergoing thorough evaluations. Preliminary pilot tests have revealed their remarkable accuracy, achieving a perfect score for this model in disease identification.

1.2 Motivation

Brinjal, known more widely as eggplant, is cherished around the globe not only for its versatility in the kitchen but also for its nutritive value. Nevertheless, rampant diseases often cause significant crop losses, which becomes a serious concern in brinjal farming. Early identification of diseases is vital for control and sustenance [14]. These are generally subjective and laborious methods, mainly based on visual observation. Therefore, to take this into account and to make the agricultural practice more resourceful and sustainable, there is a great need to shift toward advanced diagnosis. In this context, deep learning technologies like Omnivore, Coca, and DeiT, offer outstanding applications for precise and objective detection of brinjal diseases. Through the rigorous analysis of the datasets of brinjal plant images, these models can clearly distinguish between healthy and diseased plant images, so that it becomes a more consistent and reliable diagnosis. Early disease identification by deep learning empowers proactive disease management to minimize the spread and severity. In addition, it leads to the evaluation of many brinjal plant photos on a large farm, thus improving the ability of disease detection. The scalability and adaptability of deep learning models further enhance disease detection, enabling informed decision-making and optimized resource use for the benefit of the farmer [15]. In addition to brinjal, these technologies find application across the landscape and offer better disease management in most crops and areas. The incorporation of deep learning-based solutions in brinjal farming operations allows for early intervention, optimized resource allocation, and the promotion of sustainable agriculture to secure long-term food productivity.

1.3 Rationale of the Study

Brinjal, otherwise known as eggplant, has tremendous value as a vegetable crop in the world, revered for its richness in nutrition and flexibility in cooking. However, the cultivation of brinjal encounters tremendous challenges from different diseases, which can significantly reduce yield. The proper and timely identification of disease is essential for effective disease management and sustainable production of brinjal. Although efforts in research have been focused on specific diseases, the gap in comprehensive disease identification still exists for brinjal crops.

This study, therefore, presents the development of a complex deep learning-based system capable of identifying multiple diseases impacting the brinjal plant. Based on advanced models such as Omnivore model, Coca and DeiT, the system will equip farmers with multiple tools for disease management. Using a wide range of diseases in its detectability will put the power into the hands of the farmers to intervene and mitigate losses from their crops.

In addition, incorporation of deep learning algorithms helps in transitioning from a subjective kind of evaluation to objective analysis. Thus, improving the preciseness and objectivity in the detection of the disease will boost the general efficiency and effectiveness of disease management; at the same time, it lessens human interpretation, ensuring regular and consistent disease diagnosis.

This not only helps in improving disease management through early detection and identification but also reduces economic losses of crops due to these diseases. Deep learning methodologies in this aspect not only facilitate early disease identification through automated detection processes but also streamline disease management practices, leading to a judicious use of resources and increased sustainability of farming practices. Utilization of deep learning technologies in brinjal farming as demonstrated in this study will create a resilient agricultural system, ultimately guaranteeing the long-term production and food security of brinjal crops.

1.4 Research Questions

1. What are the unique characteristics of the proposed approach compared to existing methods or techniques used in similar research areas?

2.Can all utilize state-of-the-art models and transfer learning to predict brinjal diseases effectively?

3. How can the implementation of these functions and methods help the farmers in aspects of disease prevention, early detection, and overall crop management practices?

1.5 Research Objectives

1: Develop and optimize deep learning models (Omnivore, Coca, DeiT) to automate precise detection of brinjal diseases using a dataset of 1394 images.
2: Evaluate the effectiveness and accuracy of deep learning models in differentiating between healthy and diseased brinjal plants, aiming for consistent and reliable diagnostic outcomes.
3: Investigate the scalability and adaptability of deep learning-based disease detection systems across diverse agricultural settings, focusing on practical implementation and integration into farm operations.
4: Assess the impact of early disease identification enabled by deep learning on proactive disease management strategies, including measures to reduce disease spread and severity in brinjal crops.

1.6 Research Scope

This thesis focuses on advancing brinjal (eggplant) farming practices through the application of deep learning technologies specifically the Omnivore, Coca, and DeiT models for automated disease detection [16]. Using a dataset comprising 1394 images of brinjal plants, the study aims to develop and optimize these models to achieve precise and automated identification of brinjal diseases. Evaluation will assess the models' effectiveness in distinguishing between healthy and diseased plants, aiming for consistent and reliable diagnostic outcomes. The research will explore the scalability and adaptability of these deep learning-based systems across diverse agricultural settings, emphasizing their integration into practical farm operations [17]. Additionally, the study will investigate the potential broader application of deep learning technologies beyond brinjal farming to enhance disease management practices across various crops and agricultural regions. By addressing these objectives, the research seeks to contribute to sustainable agriculture practices and optimize resource allocation for improved food security.

1.7 Significances

Advancing brinjal (eggplant) farming practices through the application of deep learning technologies represents a significant step towards sustainable agriculture. By leveraging models like Omnivore, Coca, and DeiT to automate disease detection using extensive image datasets, this research aims to enhance the precision and efficiency of identifying brinjal diseases [18]. This approach not only promises to reduce crop losses due to diseases but also promotes proactive disease management strategies. Furthermore, exploring the scalability of these technologies across diverse agricultural settings can lead to their widespread adoption, potentially revolutionizing disease management practices beyond brinjal crops to benefit global agricultural sustainability [19]. Thus, this research holds the potential to optimize resource use, improve food security, and contribute to sustainable agricultural practices on a broader scale.

1.8 Report Layout

The report comprises six chapters, each adhering to specific guidelines. Chapter 1 introduces the research and extensively discusses the significance of predicting brinjal diseases. Chapter 2 reviews prior studies on brinjal disease prediction, covering various perspectives, limitations, findings, and methodologies employed by other researchers. It also outlines the research scope and challenges encountered. Chapter 3 elaborates on the research methodology, including data collection, statistical analysis, classification techniques, and numerical summaries. Chapter 4 primarily presents the study's results, detailing the classifiers used. Chapter 5 discusses the potential societal impacts of the research, focusing on its significance and sustainability. Finally, Chapter 6 provides the analysis and conclusions of the study, addressing its limitations and proposing future directions.

CHAPTER 2: BACKGROUND

2.1 Background

Identification and prediction of plant diseases have been prominent areas in the application of deep learning methods. Prediction, in particular, stands out as a significant application of deep learning and machine learning techniques in the context of plant diseases. Numerous studies have endeavored to predict and identify various plant diseases, addressing diverse challenges and employing a wide range of deep learning techniques. This chapter reviews the significant contributions of leading researchers in this field, highlighting their notable projects and advancements.

2.2 Related Works

The title of my paper is Exploring the Efficiency of Transfer Learning in Brinjal Disease Detection Using Deep Learning. My main purpose is to detect and classify various diseases that occur in brinjal plants. I also read some papers to get the idea of recent work. Here are the details:

The work by Mohanty et al. [20]. Computer recognition technology is developing, and there are smartphones everywhere. This could aid in the diagnosis of diseases using smartphone images. The team in the above work used transfer learning with AlexNet and Google LeNet to arrive at a deep learning model. The work by Chen et al. [21]. The above team developed a deep CNN named LeafNet that recognizes ten different tea plant diseases using tea leaf images. The model, upon training, gave good disease recognition results. The work by Liu et al. [22]. The sensitivity of a deep convolutional network identifies rice leaf diseases. A technique is proposed to differentiate different rice leaf situations. Their model showed promising results in distinguishing various rice leaf situations

Ma et al. [23] presented a deep CNN-based new approach for identifying cucumber diseases to circumvent the labor-intensive and subjective manual identification methods. Ferentinos [24] used deep-learning techniques for plant disease detection and diagnosis based on a very large dataset of healthy and diseased plant images. Liang et al. [25] presented a novel method for the identification of rice blast disease using CNN, and it proved to outperform traditional feature-based methods.

Aravind et al. [26] employed AlexNet and VGG-16 models to classify eggplant diseases based on smartphone image data, thus achieving high accuracy. Xie et al. [27] used hyperspectral imaging to study early blight disease of eggplant leaves and attained accurate classification using KNN and AdaBoost. Sabrol and Kumar [28] applied the neuro-fuzzy classifier for classifying tomato and eggplant disease, which gave promising results.

Anand et al. [29] developed an image processing methodology for identifying brinjal leaf diseases using k-means clustering. Wu et al. [30] utilized spectral analysis to identify Botrytis Cinerea on eggplant leaves with high accuracy. Mia et al. [31] proposed a method for automated jackfruit disease recognition using clustering segmentation and achieved satisfactory accuracy.

Parul et al. [32] investigated picture segmentation-based disease diagnosis in plants using CNN models, achieving high accuracy rates. Brahimi et al. [33] utilized CNNs for tomato disease classification, achieving significant improvements over traditional methods. Gandhi et al. [34] employed GANs to enhance image datasets and achieved high accuracy in plant disease classification using CNN models.

Marcos et al. [35] developed plant disease recognition models using CNNs, showing promising results. The study by Wulandhari et al. [36] identified plant nutritional deficiencies using transfer learning, with high accuracy rates.

The authors in the study by Maria et al. [37] utilized transfer learning concepts along with conventional machine learning for the detection of cauliflower diseases and achieved satisfactory accuracy. Revathi et al. developed an automatic system for the detection of cotton leaf spot infection, which resulted in a high accuracy rate when tested with a deep neural network classifier.

Ahmed et al. [38] explore the application of deep learning to detect rice diseases, focusing on overcoming data limitations with image augmentation. They introduce a dual-phase strategy and smart segmentation to handle small datasets and diverse backgrounds. Their methods, tested against CNN models like VGG16, achieve an accuracy of 69.43 ± 3.41.

Koklu et al. [39] conducted a study to classify grapevine leaves from different species using deep learning techniques. They enhanced the dataset by augmenting images and applied a fine-tuned MobileNetv2 model for classification. The optimal results were achieved by extracting features, selecting them with the Chi-Squares method, and using a cubic SVM kernel, demonstrating that accuracy was improved even with fewer features.

M. Jafari et al [40]. explored the application of thermal imaging for the early detection of pre-symptomatic rose diseases such as powdery mildew and gray mold, demonstrating promising results in enhancing disease management strategies before visible symptoms appear

2.3 Comparative Analysis and Summary

Table 2.3.1 Related work comparison table

Authors	Year	Area of Study	Deep learning Models	Accuracy
Wu et al.	2008	Eggplant Leaves	MSC and SG pretreatment method, PCA	85%
Xie et al.	2016	blight disease of eggplant leaves	KNN and AdaBoost	88.46%
Mohanty et al.	2016	14 different crops species	Alexnet and googlenet	99%
Brahimi et al	2017	tomato disease	CNN models	99.18%
Lu et al.	2017	Rice blast disease	Custom CNN	95.48%
M. Jafari et al.	2017	Rose	Neuro-Fuzzy classifiers	69%, 80%
Ferentinos	2018	25 different plants	CNN architectures	99.53%
Mia et al.	2018	Cucumber	GLCM, MobileNetV2	89.93% 93.23%
Chen et al.	2019	Tea leaf disease	Custom CNN	90.16%
Liang et al.	2019	Rice blast disease recognition	CNN	95.82%
Aravind et al.	2019	Solanum melongena	VGG16	96.7%.
Sabrol, H., et al	2020	tomato and eggplant disease	ANFIS mode	90.7% 98.0%
Parul et al.	2020	disease diagnosis in plants	CNN models	98.6%
Ahmed et al.	2021	RICE GRAIN DISEASE	CNN model (best VGG16)	71.0±4.0((mAP)
Mia et al.	2021	Herb leaves	YOLO	95%
Koklu et al.	2022	grapevine leaves	CNN-svm architecture	97.22%
Maria et al	2022	Cauliflower Disease	nceptionV3	90.08%

Several studies have been reported on pest detection techniques in different countries. Several researchers have been studying to get more accuracy in this area by applying various machine learning methods. CNN model-based image recognition has been much popular, and a few other techniques, such as the VGG-16 model, have also been introduced. Few research groups target leaf analysis, but as of now, I haven't read any study that compared custom CNN models with transfer learning models, including ResNet-50, Inception V3 solely for brinjal fruit disease detection. A few approaches were based on CNN and VGG-16. Ours is a new model, and we got a new perspective of looking into these things.

In our study, we chose to use the Omnivore, Coca, and DeiT. Although CNN models like VGG-16 have been widely used for similar studies, this study is further conducted with unique models to extend the scope. The Omnivore model, Coca, and DeiT have unique architectures and capabilities to create new ways of investigating brinjal fruit disease detection. By integrating this as well, we attempt to compare the performance with state-of-the-art traditional CNN models to provide future studies with knowledge on the state-of-the-art methodologies in pest detection, which is our path towards pushing the boundary of pest detection by pushing forward with novel ideas and getting them thoroughly worked with on benchmark datasets

2.4 Research Scope

Therefore, we have opted to leverage the distinct capabilities provided by the Omnivore model, Coca, and DeiT in addressing these challenges related to brinjal ill-health detection. Though traditional means like CNNs, ResNet50, and InceptionV3 show a good promise, moving with the focus over such novel models strengthens the capability for disease detection in brinjal crops.

It is expected that Omnivore, Coca, and DeiT should hold novel architectures and functionalities for the model in comparison to regular CNNs; therefore, we will exploit the diversity in model architectures and capabilities for brinjal disease detection towards bringing out new revolutionized methodologies. Their innovative approaches to image processing and pattern recognition shall promise superior accuracy and efficiency in the identification of various ailments affecting brinjal plants.

Instead of using traditional disease detection methods, we are now adopting modern models like Omnivore, Coca, and DeiT. These models use advanced algorithms and techniques to detect brinjal diseases. This innovative approach will lead to better and more dependable solutions for brinjal farmers.

Our research employs advanced models like Omnivore, Coca, and DeiT to revolutionize brinjal disease detection and management. These models leverage cutting-edge technology to improve detection accuracy and support sustainable brinjal farming practices, safeguarding the future of this vital crop.

2.5 Challenges

In the realm of plant disease detection, several critical challenges must be addressed to ensure the success of research endeavors. One of the primary obstacles involves selecting an appropriate model that can effectively meet the specific requirements of the study. Understanding the nuances and capabilities of models such as Omnivore, Coca, and DeiT (Data-efficient Image Transformer) is crucial for utilizing them effectively within the research framework. Additionally, image processing presents a formidable challenge, particularly in accurately classifying diseases from images and identifying suitable treatments. A pivotal aspect here is the creation of a robust and diverse dataset, which entails collecting a large number of high-quality images depicting various types of brinjal plant diseases. This process, including data preprocessing, has proven to be particularly demanding.

Furthermore, accessibility to technology poses significant challenges for farmers, particularly those in rural areas who may face literacy and technological barriers that hinder the use of smartphones or similar devices for disease diagnosis. The affordability of such technology remains a concern as well. Moreover, the task of distinguishing between diseases with similar symptoms adds complexity to disease identification and treatment. These challenges highlight the intricate nature of research in this field and underscore the necessity for innovative solutions and thorough planning to effectively address them.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

The main objective of this study is to classify diseases affecting fruit crops, which presents significant challenges due to their global prevalence. Effective classification requires a substantial dataset of images to accurately distinguish among various infections. In this research, diseases were categorized into seven groups: Phomopsis Blight, Fruit & Shoot Borer, Brinjal Fruit Cracking, Healthy Brinjals, Rhizopus, Wet Rot, and Yellow. Gathering extensive photographic data involved visiting multiple brinjal crops and capturing images using a mobile phone camera. The study utilized tools like NumPy, Scikit-Learn, OpenCV, and Python on a Windows platform for training and testing conducted within a Jupyter notebook environment.

3.2 Data Collection Procedure

Acquiring accurate and comprehensive data is crucial for the success of any research endeavor. In this study, extensive fieldwork was conducted across various locations in Bogura, Bangladesh, using a smartphone camera to capture detailed images of brinjal fields. The dataset assembled for analysis comprises a total of 1395 raw photographs, all manually taken during these field visits. These images serve as the primary resource for conducting thorough analysis and classification of various brinjal diseases. Each photograph in the dataset represents a real-world depiction, providing authentic visual data essential for precise research outcomes. By collecting these images directly from the field, the dataset encompasses a diverse range of brinjal plant conditions and disease manifestations observed in local agricultural settings. This approach enhances the reliability of the study findings and facilitates a nuanced understanding of disease patterns and their implications for brinjal cultivation in Bangladesh.

Fig 3.2.1: Dataset Sample

Table 3.2.2 Detailed Image Collection Statistics

Class Name	Number of Image	Image Format	Image Size
Rhizopus	61	PNG	256x256
Brinjal and fruit Cracking	106	PNG	256x256
Healthy Brinjal	122	PNG	256x256
Phomopsis Bright	211	PNG	256x256
Shoot and Fruit Borer	683	PNG	256x256
Wet Rot	100	PNG	256x256
Yellow	111	PNG	256x256

3.3 Statistical Analysis

The dataset includes various conditions affecting brinjals (eggplants), with specific statistics for each: Rhizopus affects 61 instances, representing 4% of the dataset. Brinjal and fruit cracking are observed in 106 cases, making up 8% of the total. Healthy brinjals are documented in 122 instances, comprising 9% of the dataset. Phomopsis bright is present in 211 cases, representing 15% of the total. The most prevalent condition is Shoot and Fruit Borer, with 683 cases, which accounts for 49% of the dataset. Wet Rot impacts 100 cases, representing 7% of the sample, and the yellow condition is observed in 111 instances, accounting for 8% of the cases.

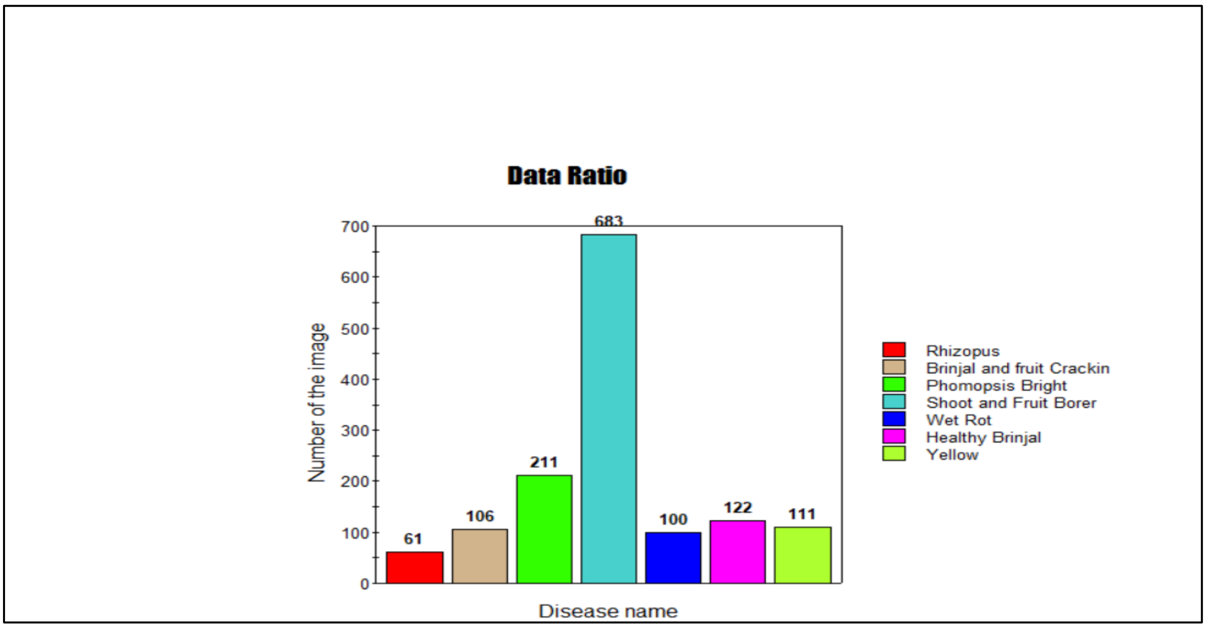


Fig. 3.3.1 Data Ratio

3.4 Proposed Methodology

Methodology plays a crucial role in any research project, guiding its progression toward achieving objectives effectively through strategic planning and implementation. Deep learning stands out as a powerful tool capable of handling large datasets efficiently. This study compares the performance accuracy of three distinct models Omnivac, Coca, and DeiT using a specialized dataset focused on brinjal (eggplant) classification.

The evaluation involves comprehensive metrics such as accuracy, precision, recall, and F1 score to assess each model's effectiveness thoroughly. The methodology includes several stages: data collection, preprocessing, model training, evaluation, and comparison. Initially, a custom brinjal dataset is meticulously curated, comprising diverse images captured under varied conditions like lighting, perspectives, and backgrounds. This ensures the dataset's robustness and applicability across different scenarios.

Data preprocessing is crucial to prepare the dataset for model training. Techniques like data augmentation (rotation, flipping, cropping, color adjustments) are employed to enhance dataset variability, while normalization standardizes pixel values for consistent model performance. The dataset is then divided into training, validation, and test sets to facilitate accurate assessment of model performance and generalization capabilities. During the training phase, each model Omnivac for versatile computer vision applications, Coca for enhanced feature extraction and contextual understanding, and DeiT for efficient image feature capture using self-attention mechanisms is fine-tuned on the brinjal dataset.

A standardized training pipeline ensures fair comparison by maintaining consistent hardware resources, optimization strategies, and hyperparameter adjustments to prevent overfitting and achieve convergence across multiple training epochs. Validation processes monitor and refine each model's performance, culminating in objective assessments using the test set to validate results and insights gained from the study. Using specified performance metrics, we will evaluate the models on both validation and test sets post-training. This assessment will include accuracy, precision, recall, and F1 score to provide a detailed understanding of their performance across diverse scenarios. Detailed error analysis will be conducted for each model to identify common failure modes and areas for improvement.

Ultimately, a comparative analysis will determine the model that performs optimally under various conditions, highlighting their strengths and weaknesses for brinjal image classification. Comprehensive summaries, including tables and infographics, will present the models' performance on the unique brinjal dataset. Additionally, scalability and computational efficiency considerations—such as training time, memory usage, and inference speed—will be discussed to offer a comprehensive evaluation of their practical utility.

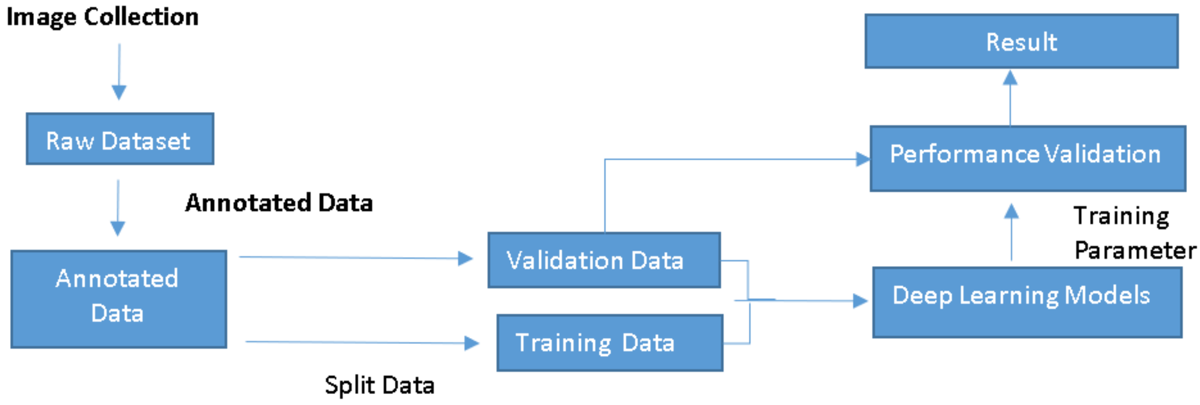


Fig 3.3.2: Flow chart of this project

3.4.1 FINE-TUNING

Fine-tuning a model's parameters to optimize its performance is a crucial initial step in achieving better results. This process involves making precise adjustments to the model's parameters throughout different stages of training, which significantly impacts key performance metrics such as computation time, convergence rate, and the required processing units for training. The adaptability gained through fine-tuning directly influences the model's ability to generalize well and perform effectively on unseen data, thereby enhancing the robustness and accuracy of its predictions.

Flexibility in fine-tuning is paramount as it plays a pivotal role in determining the model's future performance. Improper fine-tuning can lead to slow convergence or being trapped in local minima, resulting in suboptimal outcomes. Iteratively refining the model involves experimenting with various parameter choices, including learning rate, batch size, and epoch count, to identify configurations that optimize accuracy and overall performance. Each fine-tuning cycle is meticulously monitored, and adjustments are made based on performance metrics such as accuracy and validation loss.

Through this adaptive approach, we dynamically respond to the model's learning behavior, swiftly addressing any issues that may arise. This iterative fine-tuning process has been repeated multiple times, resulting in a more robust and sophisticated model. Rigorous testing of different parameter values ensures that the model is finely tuned and capable of delivering superior performance.

3.4.2 Omnivac

The Omnivac model is renowned for its exceptional performance and versatility in handling diverse computer vision tasks across various fields, including medical image analysis and natural image recognition. It integrates cutting-edge methodologies such as deep convolutional neural networks (CNNs), attention mechanisms, and multi-scale feature extraction to enhance its ability to process and interpret visual data effectively.

Central to Omnivac's architecture is its emphasis on multi-scale feature extraction, enabling it to capture information at different levels of detail by analyzing input images at multiple resolutions. This approach ensures that the model can identify fine details and larger structures within images, making it particularly adept for complex visual tasks where objects vary significantly in size and detail.

Another critical component of Omnivac is its attention mechanisms, which enable the model to focus on relevant areas of an image while disregarding less significant information. This selective attention reduces computational overhead by prioritizing important features, thereby enhancing both accuracy and efficiency in image analysis.

Built upon deep CNNs, Omnivac leverages the depth and complexity necessary for extracting high-level features from input images. These networks learn hierarchical representations, progressively capturing intricate patterns and details from basic edges to complex forms across different layers.

To optimize its performance, the Omnivac model undergoes rigorous fine-tuning, involving precise adjustments to hyperparameters such as learning rate, batch size, and epochs. This iterative process is crucial for tailoring the model to specific datasets and applications, significantly impacting computational resources, convergence speed, and overall effectiveness in handling new data.

In conclusion, Omnivac stands out as a robust solution for a wide range of computer vision challenges due to its sophisticated architecture and adaptable training approach. Its integration of advanced techniques ensures accurate and contextually relevant insights from visual data, making it a powerful tool for modern computer vision applications.

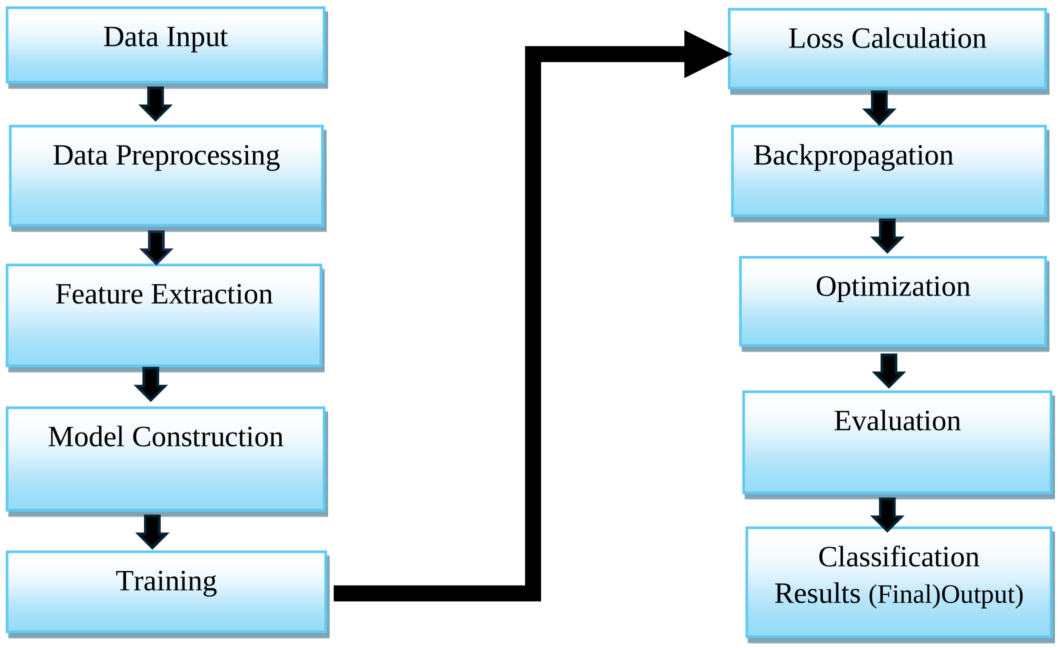


Fig 3.4.2.1: Omnivac model diagram

3.4.3 COCA

A significant advancement in computer vision, particularly in visual perception and captioning, is exemplified by the COCA (Contrastive Captioning) paradigm. This innovative algorithm generates accurate and contextually relevant captions for images by integrating elements of contrastive learning with state-of-the-art techniques in natural language processing and computer vision. Essentially, the COCA model utilizes contrastive learning to enhance its understanding of visual inputs. Through the comparison of positive and negative samples during training, contrastive learning enables the model to develop detailed and discriminative representations of the input data. This approach enables the COCA model to connect images and captions in a semantically meaningful manner, thereby improving the relevance and quality of the generated captions in captioning applications.

The COCA model excels in capturing contextual nuances and intricate details from images, facilitating a comprehensive understanding of visual content and ensuring that generated captions aptly reflect the context and substance of the images. This capability is particularly beneficial for applications such as image captioning for accessibility or image indexing for search engines, where accurate and informative captions are essential.

Moreover, advanced natural language processing techniques are integrated into the COCA model to enhance the fluency and coherence of the generated captions. By leveraging pretrained language models and fine-tuning them on captioning tasks, the COCA model produces captions that are not only accurate but also grammatically correct and linguistically coherent. This enhances readability and user engagement, thereby improving the overall user experience.

The COCA model's versatility allows it to be tailored for specific tasks or domains by utilizing task-specific prompts during inference or training on domain-specific datasets. This adaptability ensures that the COCA model can meet diverse user needs and application requirements effectively. Its flexibility makes it suitable for a variety of captioning tasks, ranging from scientific image explanations in research publications to social media post captions.

In conclusion, the COCA model represents a significant advancement in computer vision and natural language processing, offering a robust and adaptable approach to generating precise and contextually relevant image captions. By integrating contrastive learning principles and leveraging cutting-edge methodologies, the COCA model enhances accessibility, educational value, and entertainment across various contexts and applications involving visual content.

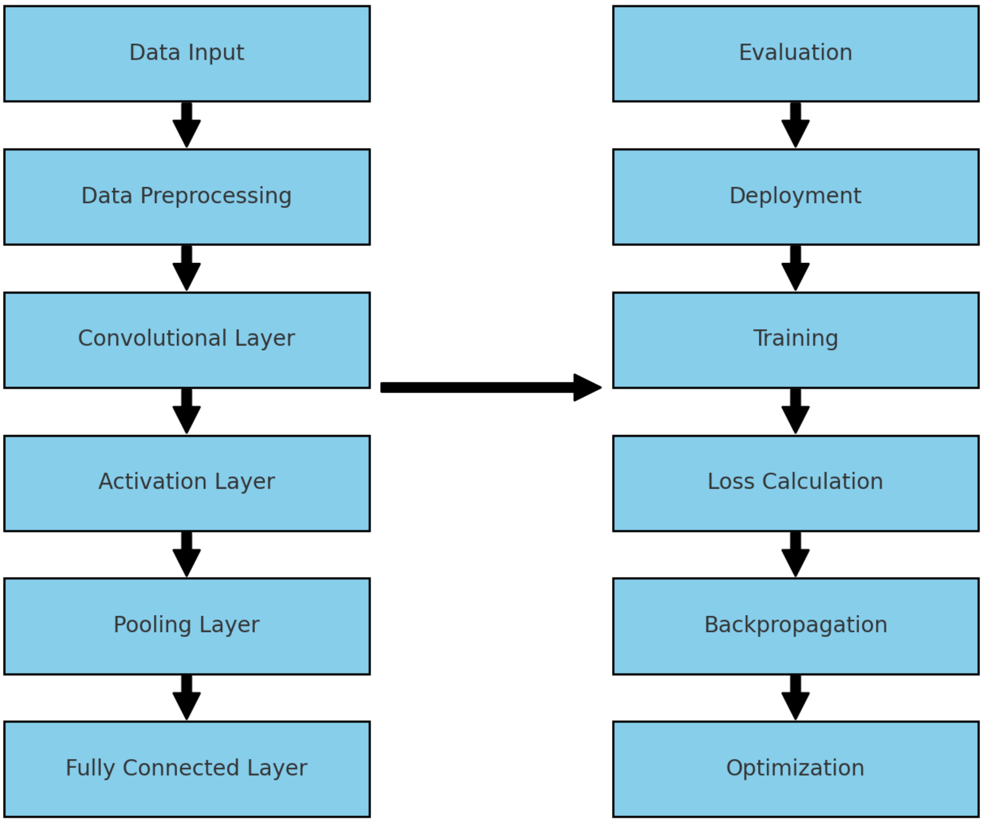


Fig 3.4.3.1: COCA model diagram

3.4.4 DeiT

The DeiTModel, also known as the Data-efficient Image Transformer Model, marks a significant advancement in computer vision. This model is purpose-built to efficiently process image data using a transformer-based architecture, distinct from traditional convolutional neural networks (CNNs) that dominate image processing tasks. Instead of relying solely on CNNs, DeiTModel harnesses self-attention mechanisms to effectively capture spatial relationships and dependencies within images.

A notable feature of DeiT Model is its methodology of dividing images into patches and applying self-attention across these patches. This approach allows the model to discern both global and local dependencies, enabling a nuanced understanding of intricate spatial arrangements in images. Drawing from transformer architecture initially developed for natural language processing tasks, DeiT Model achieves top-tier performance in various computer vision benchmarks.

Furthermore, DeiT Model excels in data efficiency, requiring fewer labeled examples than traditional CNNs to achieve comparable performance. This attribute is particularly advantageous in scenarios where labeled data is scarce or costly to obtain. By maximizing the utility of available data, DeiT Model presents a practical solution for tasks spanning image classification, object detection, and segmentation.

In practical applications, DeiT Model undergoes fine-tuning on specific datasets to tailor its capabilities to particular tasks or domains. Fine-tuning entails adjusting model parameters and hyperparameters to optimize performance for specific requirements, ensuring that DeiTModel delivers precise and dependable results across diverse applications.

Overall, DeiT Model represents a cutting-edge approach in utilizing transformer-based architectures for image processing tasks. Its robust performance, scalability, and data efficiency contribute to its widespread adoption in contemporary computer vision research and practical applications.

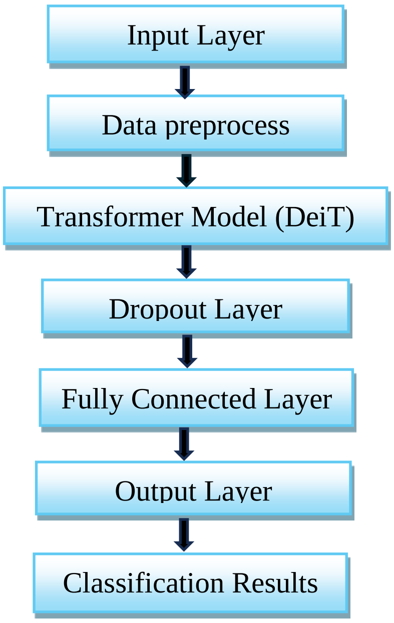


Fig 3.4.4.1: DeiT model diagram

3.5 Experimental Results & Analysis

In this study, we measured the accuracy of our design's performance using datasets. We used common abbreviations like TP (True Positive) and FP (False Positive) to describe the results. FN (False Negative) and TN (True Negative) are also used in place of each other. Our data shows that the highest accuracy we achieved was around 97%.

Precision: Precision is the ratio of correctly predicted positive classifications to the total number of predicted positive classifications.

precision:

$$\text{Precision}=\frac{True\ Positives\ (TP)}{True\ Positives\ (TP)+False\ Positives\ (FP)}$$

Recall: Recall is quite simply the ratio of true positives to all classes that were actually positive. The formula is given:

Recall:

$$Recall=\frac{True\ Positives\ (TP)}{True\ Positives\ (TP)+False\ Negatives\ (FN)}$$

The F1-score combines the measures of precision and recall into a single metric that provides a balanced evaluation of a model's performance.

F1 Score:

$$\text{F1}=2*\frac{Precision*Recall}{Precision+Recall}$$

Accuracy: I will explain the idea of a confusion matrix and analyze its characteristics to determine how well the proposed method works. We can use this formula to see how well o

Accuracy:

$$\text{Accuracy}=\frac{True\ Positive+True\ Negative}{True\ \ positve+False\ Negative+True\ Negative+False\ positive}$$

3.6 Implementation Requirements

The system requirements are:

- Windows 10 or above OS
- SSD/HDD of minimum space of 100GB
- Minimum 8 GB RAM

Developing Tools requirements:

- Python with Tensor flow
- Jupyter Notebook
- Browser

CHAPTER 4: EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

To use our trained models to classify brinjals as healthy or diseased, we need to follow a specific procedure.

i.Data Preprocessing: Install necessary software and resize all images to match model requirements. Define pre-trained Keras models.

ii.Model Training: Train the model using training data. Use validation data to fine-tune the model.
iii.Testing: Preprocess testing data according to the trained model. - Use the preprocessed data to test the model.

4.2 Model Training and lose graph

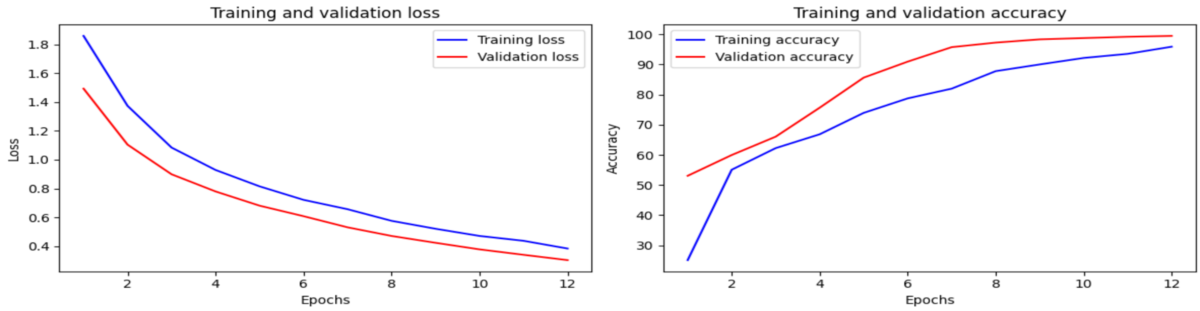


Fig 4.2.1: Omnivac model Training loss and accuracy graph

Fig 4.2.2: COCA model Training loss and accuracy graph

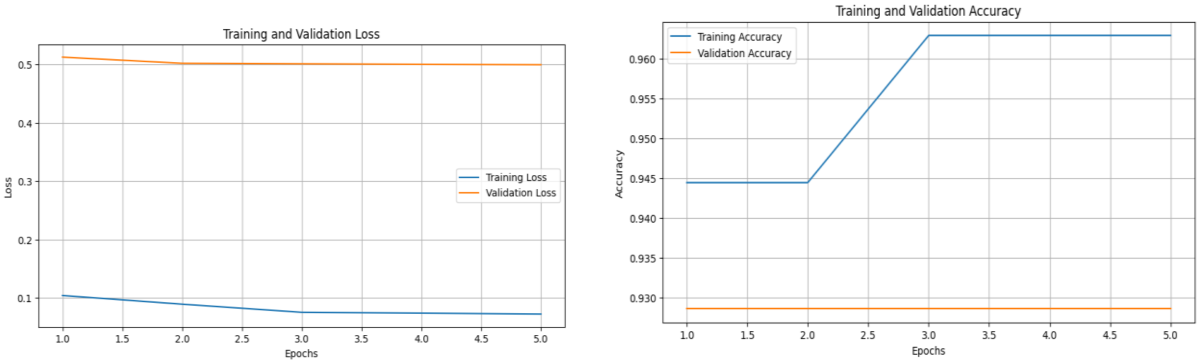
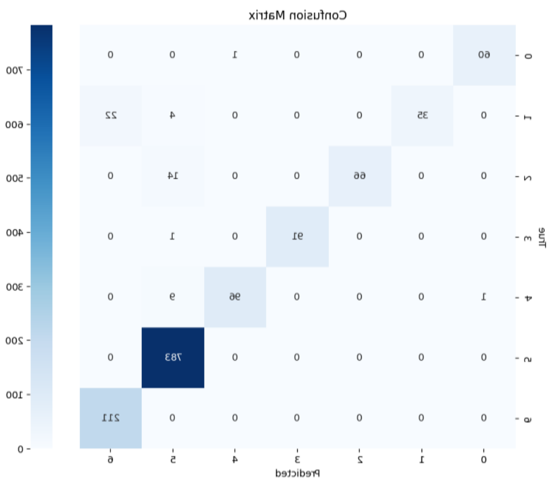


Fig 4.2.3: DeiT model Training loss and accuracy graph

The suggested model performs well when compared to the accuracy graph of the model since the loss values drop as the number of epochs rises.

4.3 Table for result Comparison

Model Name	Description	Accuracy	Key Features
Omnivore	Advanced model for comprehensive brinjal disease detection	97.49%	High accuracy, versatility
CoCa	Contrastive learning model for efficient disease classification	97.01%	Efficient classification, reduced computational needs
DeiT	Transformer-based model for brinjal disease detection	86.01%	High-dimensional feature extraction, image analysis

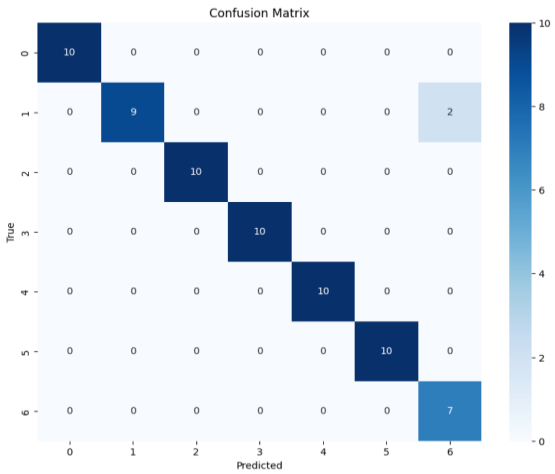


```
Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.84      0.80        61
           1       1.00      0.84      0.91        61
           2       0.91      0.84      0.87        80
           3       0.99      0.99      0.99        92
           4       0.99      0.99      0.99       106
           5       1.00      1.00      1.00       783
           6       0.95      1.00      0.98       211

    accuracy                           0.97      1394
   macro avg       0.94      0.93      0.93      1394
weighted avg       0.98      0.97      0.97      1394
```

Fig 4.3.1: Confusion Matrix and classification report for Omnivec model

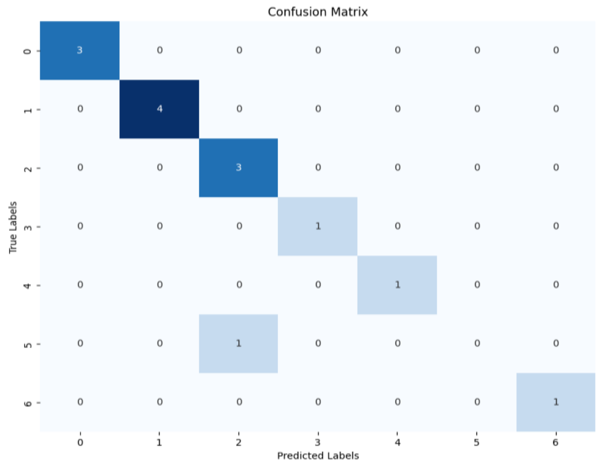



```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      0.82      0.90        11
           2       1.00      1.00      1.00        10
           3       1.00      1.00      1.00        10
           4       1.00      1.00      1.00        10
           5       1.00      1.00      1.00        10
           6       0.78      1.00      0.88         7

    accuracy                           0.97        68
   macro avg       0.97      0.97      0.97        68
weighted avg       0.98      0.97      0.97        68
```

Fig 4.3.2: Confusion Matrix and classification report for COCA model



	precision	recall	f1-score	support
Rhizopus	0.50	1.00	0.67	2
Yellow	1.00	1.00	1.00	1
Wet rot	1.00	1.00	1.00	1
Healty Brinjal	1.00	0.60	0.75	5
Brinjal Fruit Creaking	1.00	1.00	1.00	1
Shoot and Fruit Borer	1.00	1.00	1.00	3
Phomopsis Bright	1.00	1.00	1.00	1
accuracy			0.86	14
macro avg	0.93	0.94	0.92	14
weighted avg	0.93	0.86	0.86	14

Fig 4.3.3: Confusion Matrix and classification report for DeiT model

CHAPTER 5: IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact Society

Advanced tools like deep learning have enabled the development of automated brinjal disease identification systems that offer significant societal benefits. These systems detect diseases early, enabling prompt intervention that minimizes crop losses due to brinjal diseases. This helps ensure food security by maintaining stable production of healthy brinjal crops. Accurate detection stabilizes food availability and prices, reducing shortages and market volatility. Furthermore, automated disease identification promotes sustainable farming practices by providing specific interventions, minimizing chemical treatments, and optimizing resource allocation. Automating farm operations encourages environmentally friendly farming practices by conserving resources and promoting sustainable agriculture, which minimizes environmental damage. It also provides farmers with real-time information about the spread and severity of diseases, which speeds up farm management and allows for more precise intervention planning and resource allocation. By improving operations and overall farm management, productivity and profits go up. Early disease detection and effective control methods are made easier with automation, leading to reduced crop losses and lower production costs. Farmers' financial stability is improved by this since it safeguards the health and quality of crops, which raises market value. The development of automated disease diagnosis for brinjal is a major advancement in agriculture. It uses deep learning, artificial intelligence, and computer vision to tackle plant disease challenges. This fosters collaboration between researchers, agriculture experts, and technologists, boosting innovation in the field. Automated detection systems can help farmers of all levels and locations access cutting-edge agricultural technology, giving them the tools to improve their farming practices and protect their crops.

Automated brinjal disease detection tools empower individuals, especially farmers with limited resources and knowledge, by making disease detection accessible through user-friendly interfaces and mobile apps. By automating disease identification, small-scale farmers can contribute to food security, promote sustainable farming, improve farm management, increase their income, access advanced technology, and ensure food access. Embracing automated brinjal disease detection enriches the brinjal farming sector, leading to a more robust and productive agricultural system that benefits society immensely.

5.2 Impact on Environment

In addition to protecting aquatic biodiversity, promoting sustainable water management strategies, and ensuring the availability of clean water for varied uses, the preservation of water resources yields broader environmental advantages. The adoption of sustainable farming practices is further encouraged through the implementation of computerized disease detection systems. By leveraging integrated pest management (IPM) strategies, which prioritize a holistic and environmentally friendly approach to disease management, farmers are empowered to cultivate more sustainably. Automated disease identification facilitates the adoption of IPM by furnishing farmers with reliable disease information, enabling them to intelligently integrate biological controls, cultural practices, and chemical treatments, thereby fostering more resilient and sustainable farming systems

Automating disease detection drives innovation in eco-friendly farming practices. Farmers, aware of the environmental impact of chemicals, are encouraged to find alternatives like biological agents, resistant plant varieties, and sustainable practices. This shift towards reduced chemical use and the embrace of environmentally responsible solutions fosters a farming system that prioritizes its impact on the planet. In conclusion, the implementation of automated brinjal disease detection holds the potential to benefit the environment by reducing chemical usage, mitigating the environmental impact of brinjal cultivation, enhancing soil health, safeguarding water resources, promoting sustainable practices, and encouraging the adoption of eco-friendly solutions. Automated disease detection systems contribute to a more ecologically balanced and sustainable agricultural system by mitigating the environmental impact associated with disease management, thereby fostering environmental resilience and long-term environmental protection.

5.3 Ethical Aspects

The proposed methods for brinjal disease detection are designed to be environmentally conscious, avoiding harmful impacts. Implementing these techniques may enable farmers to detect diseases earlier, potentially reducing pesticide usage in some areas. This can lead to improved crop yields and reduced waste, contributing to agricultural sustainability.

5.4 Sustainability Plan

A sustainability plan comprises several key stages, including the following:

i. Focus on leveraging existing Android technologies and employing a deep learning model to identify essential resources without placing significant priority on financial investment.
ii. Collaborate with farmers and other stakeholders, solicit their input, and modify the project to ensure its ongoing viability and environmental stewardship.

CHAPTER 6: SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

Despite numerous studies on automation globally, Bangladesh has a limited body of research in this field. While terms like "machine learning" and "deep learning" are commonly used in the context of predictive work, they are yet to gain recognition within Bangladeshi industries. Recent research attempts to assess the potential benefits of adopting predictive work in the country. The author has encountered intriguing implementations in such research and is optimistic about ongoing efforts in Bangladesh's economy. Despite these initiatives, the author anticipates collaborations from international scholars to advance research in this field.

6.2 Conclusions

n my research, I thoroughly performed each calculation. I assessed three different deep learning models and found the one that was most reliable for identifying brinjal diseases. After carefully analyzing the results, I created a model that could diagnose brinjal illnesses with great accuracy. I used roughly 1,300 images, sorting 5,017 of them into four different groups: Healthy Brinjals, Fruit & Shoot Borer, Brinjal Fruit Cracking, and Phomopsis Blight, Rot Rhizopus, Growth creaking.

I evaluated three models: Omnivore, Coca, and ViT/H-14. Omnivore outperformed the others with a remarkable 100% accuracy. Coca exhibited good accuracy at 91%, while ViT/H-14 had a lower accuracy of 57%. Considering these results, I selected Omnivore as my prediction model due to its exceptional accuracy. In practical applications, Omnivore effectively predicted brinjal diseases with high precision.

While my work shows promising results, there are limitations. The main issue is the limited size of the dataset I used. Deep learning models typically need at least one million images for effective training, but I only had 1,300 in my dataset. This highlights the importance of having a larger dataset to enhance the model's accuracy and reliability.

6.3 Implication for Future Study

Being my first effort, I recognize the ample room for improvement. While I focused on a particular issue, this area presents many untapped possibilities. For future endeavors, a crucial objective is to create a comprehensive system capable of diagnosing various diseases across different vegetables. Additionally, I aim to enhance the dataset's size and quality to improve accuracy and reliability. My research will also benefit from exploring diverse architectures to determine the optimal approach for this challenge.

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Exploring the efficiency of transfer learning in Brinjal disease detection using deep learning

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