

**CCS431-18 THESIS 1**

**THESIS 1 PROPOSAL FORM**

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| **Proposed Title** | Enhancing Agricultural Sustainability: Leaf Disease Diagnosis with Treatment Recommendations using DenseNet-121-based CNN Model |
| **Field of Study** | Deep Learning |
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| **Introduction** | |
| **Background of the Study** | Agriculture plays a vital role in the world’s economy as it serves as the primary source of food, income, and employment opportunities. According to the National Economic and Development Authority (NEDA) and the Department of Finance (DOF), the Philippines, being an agricultural country, is in the best position to have an agriculture-driven economy, which can greatly contribute to rebooting the Philippine economy. However, plant diseases and pest infections present a significant threat to agricultural productivity. Early identification and accurate diagnosis of plant diseases is essential for effective disease management and minimizing economic losses (Dawod & Dobre, 2022).  Traditional methods of disease identification rely on manual examination by experts, which can be subjective, time-consuming, and prone to errors (Dawod & Dobre, 2022). Recent advancements in computer vision and artificial intelligence have enabled significant progress in automatic plant disease detection and classification. Deep learning techniques, particularly convolutional neural networks (CNNs), have shown promising results in image recognition tasks (Sujatha et al., 2021). Transfer learning, which utilizes pre-trained models like DenseNet-121, trained on large-scale datasets like ImageNet, enhances recognition accuracy and efficiency (Tan et al., 2018; Too et al., 2019).  The availability of diverse and well-annotated datasets is crucial for training accurate deep learning models. The PlantVillage dataset, developed by Pennsylvania State University, contains a large collection of high-quality images representing 38 classes of plant diseases, making it a valuable resource for plant disease identification studies (*PlantVillage*, n.d.).  The main objective in this study is to enhance agricultural sustainability by developing a leaf disease diagnosis application using a DenseNet-121-based CNN model. The researchers aim to achieve high accuracy, sensitivity, and specificity in diagnosing leaf diseases by fine-tuning the DenseNet-121 model on the PlantVillage dataset. They will create a user-friendly web-based application that allows users to upload leaf images for diagnosis. The trained DenseNet-121-based CNN model will analyze the uploaded images and provide accurate disease identification results. To further assist them, the researchers will integrate a recommendation system into the application, suggesting appropriate treatment strategies based on the diagnosed disease information. These recommendations may include specific products, cultural practices, or preventive measures to effectively manage and mitigate identified leaf diseases. By combining leaf disease diagnosis with treatment recommendations, this study aims to contribute in enhancing agricultural sustainability. |
| **Main Objective** | The main objective of this study is to enhance agricultural sustainability by developing a leaf disease diagnosis application using a DenseNet-121-based CNN model, and providing treatment recommendations for effective disease management. |
| **Specific Objectives** | The specific objectives of this study are as follows:   1. To collect and organize a diverse and extensive dataset comprising high quality images of healthy leaves, as well as leaves affected by various diseases, to train and validate the DenseNet-121-based CNN model. 2. To implement a convolutional neural network model based on DenseNet-121 architecture to accurately classify leaf diseases from input images, achieving high accuracy, sensitivity, and specificity in disease diagnosis. 3. To create a user-friendly web-based application that utilizes the trained DenseNet-121-based CNN model to diagnose leaf diseases based on images uploaded by farmers or agricultural workers. 4. To integrate a recommendation system into the leaf disease diagnosis application, imposing the diagnosed disease information to suggest appropriate treatment strategies, including specific products, cultural practices, or other preventive measures to manage and mitigate the identified leaf diseases effectively. |
| **Significance of the Study** | The researchers have identified the beneficiaries of the proposed study as follows:   1. **Farmers and Agricultural Workers.** They will benefit from this study as this will help them identify and diagnose diseases affecting their crops more accurately and quickly. With the treatment recommendations provided, they can effectively manage and mitigate the identified leaf diseases, leading to improved crop yield and reduced economic losses. 2. **Consumers.** They will benefit from this study as this will help them in ensuring the production of healthier crops. By accurately diagnosing and managing leaf diseases, the quality of the harvested produce can be enhanced, resulting in safer and higher-quality food for consumers in the Philippines. 3. **Plant Health Authorities and Agencies.** They will benefit from this study as the research outcomes can be utilized by plant health authorities and agencies, such as the Department of Agriculture (DA) and the Bureau of Plant Industry (BPI). The deep learning-based approach developed in this study will enhance their capabilities in detecting and controlling plant leaf diseases effectively, thereby improving their disease surveillance and management programs. 4. **Future Researchers.** They will benefit from this study as it contributes to the development of advanced techniques for disease diagnosis and management. The DenseNet-121-based CNN model and the application developed in this study can serve as a valuable reference for further research and innovation in the field of agricultural sustainability and crop protection. |
| **Scope and Limitations** | **Scope**  This study aims to develop a leaf disease diagnosis application by utilizing a DenseNet-121-based CNN model. To achieve this, a diverse dataset containing high-quality images of healthy leaves and leaves affected by various diseases will be collected and organized. The focus will be on implementing a convolutional neural network model based on the DenseNet-121 architecture, ensuring accurate classification of leaf diseases. Additionally, a user-friendly web-based application will be created to allow farmers and agricultural workers to upload leaf images for accurate disease diagnosis. Furthermore, the application will integrate a recommendation system to suggest suitable treatment strategies for managing and mitigating identified leaf diseases. The study will cover eight (8) crop species, including apple, corn, grape, mango, pepper, potato, strawberry, and tomato. The dataset used in the study will consist of 8 healthy leaf classes and 27 diseased leaf classes, totaling 35 classes.  **Limitations**  This study has certain limitations that should be acknowledged. Primarily, it focuses on leaf disease diagnosis and treatment recommendations using a DenseNet-121-based CNN model, overlooking other important aspects of agricultural sustainability. The findings may not directly apply to crop species beyond the seven species examined. The accuracy of the diagnosis may be affected by factors like image quality and user errors since the application relies on user-uploaded leaf images. It is worth noting that the study does not involve developing physical treatment products or cultural practices; it simply provides recommendations based on diagnosed diseases. The economic feasibility and cost-effectiveness of the recommended treatment strategies are not addressed. Additionally, it is important to mention that this study only focuses on detecting plant diseases on single leaves and does not extend to detecting diseases on groups of leaves. |
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| **Review of Related Literature** | |
| This chapter presents a review of the relevant literature essential for establishing the foundational knowledge required to build and develop the proposed study. The researchers gathered and utilized a range of literature pertaining to Leaf Disease Classification and DenseNet-121.  **Leaf Disease Classification**  Leaf diseases present a significant threat to agricultural sustainability, as they can cause substantial losses in crop production and reduce the quality and quantity of food (Alston & Pardey, 2014). Identifying and diagnosing leaf diseases accurately and early on is crucial for effective management and treatment. Traditional methods of disease identification rely on manual examination by experts, which can be subjective, time-consuming, and prone to errors (Dawod & Dobre, 2022). In recent years, researchers have turned to computer vision and deep learning techniques to automate the detection and classification of leaf diseases.  Computer vision techniques leverage image processing and machine learning algorithms to analyze visual information from leaf images and identify disease symptoms. Various approaches have been proposed, including hand-crafted feature extraction and segmentation combined with machine learning algorithms (Scientist et al., 2020; Dubey & Jalal, 2013; Li et al., 2012). These methods have shown promising results but often require extensive manual feature engineering and lack scalability.  Deep learning, specifically convolutional neural networks (CNNs), has revolutionized the field of image classification and object detection (Sujatha et al., 2021). CNNs can automatically learn and extract complex features from images, making them well-suited for leaf disease classification. One popular CNN model used in leaf disease diagnosis is DenseNet-121 (Barbedo, 2018). DenseNet-121 is a deep CNN model that utilizes dense connections between layers, allowing information to flow more efficiently and improving the model's ability to capture fine-grained details (Huang et al., 2017). This architecture has been shown to achieve high accuracy in plant disease recognition tasks (Mohanty et al., 2016).  The classification and diagnosis of leaf diseases in agriculture have been significantly improved with the adoption of computer vision and deep learning techniques. Traditional methods have limitations in terms of subjectivity and time-consuming manual processes (Dawod & Dobre, 2022). Deep learning models like DenseNet-121 offer promising solutions by automating the feature extraction and classification tasks (Barbedo, 2018; Huang et al., 2017). These advancements in technology enable early classification and accurate diagnosis, leading to more effective management and treatment of leaf diseases, thus enhancing agricultural sustainability.  **DenseNet-121**  DenseNet-121, also known as Densely Connected Convolutional Network, is a deep convolutional neural network architecture that has gained popularity in various image classification tasks, including leaf disease classification in agriculture. The key innovation of DenseNet-121 lies in its dense connections, which allow for direct connections between all layers within the network (Huang et al., 2017). Unlike traditional CNNs, where information flows sequentially from one layer to the next, DenseNet-121 enables direct access to the feature maps of all preceding layers. This dense connectivity enhances gradient flow, encourages feature reuse, and enables the model to capture more intricate patterns and details.  The architecture of DenseNet-121 consists of several dense blocks, each composed of multiple convolutional layers with batch normalization and activation functions (Huang et al., 2017). Within each dense block, the feature maps of all preceding layers are concatenated, creating a dense connectivity pattern. This design enables feature reuse and facilitates the propagation of gradients, addressing the vanishing gradient problem often encountered in deep neural networks.  DenseNet-121 has shown impressive performance in various image classification tasks, including leaf disease classification in agriculture (Barbedo, 2018; Mohanty et al., 2016). Its dense connectivity allows the model to efficiently extract and propagate features, leading to improved accuracy and robustness. Moreover, DenseNet-121 can be trained with transfer learning, leveraging pre-trained models on large-scale datasets such as ImageNet (Hussain et al., 2018). This transfer learning approach enables the model to leverage knowledge learned from a vast amount of data and generalize well to new tasks with limited training data.  DenseNet-121 is a powerful deep learning architecture for image classification tasks, including leaf disease classification in agriculture. Its dense connectivity promotes feature reuse and gradient flow, enabling the model to capture intricate patterns and achieve high accuracy. Leveraging transfer learning further enhances its performance, especially when training data is limited. DenseNet-121 has emerged as a valuable tool in enhancing agricultural sustainability by improving the diagnosis and management of leaf diseases. | |
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| **Conceptual Framework & Project Design** | |
| This chapter provides a conceptual framework essential for understanding the relationships and variables of the proposes study, and a project design essential for outlining the specific methods and procedures to be employed in conducting the study.  **Conceptual Framework**    **Figure 1: Conceptual Framework**  The collection and organization of a diverse dataset comprising healthy and diseased leaf images serve as the foundation. This dataset is used to train and optimize a DenseNet-121-based CNN model, a deep learning architecture known for its effectiveness in image classification. The trained model is integrated into a user-friendly web-based application that allows users to upload leaf images for disease diagnosis and provides treatment recommendations for effective management and mitigation of leaf diseases. This study aims to enhance agricultural sustainability by enabling accurate disease diagnosis and guiding those people who work in agriculture in implementing appropriate treatment strategies.  **Project Design**    **Figure 2: Project Design**  **Phase 1: Data Preparation –** In the first phase, it focuses on preparing the necessary data for the leaf disease diagnosis application. Data collection involves gathering relevant images and information of leaf diseases from different sources, including Kaggle and Mendeley. Once the data is collected, it undergoes preprocessing to ensure its suitability for analysis. This preprocessing includes tasks such as resizing the leaf images to a consistent size, augmenting the dataset by creating variations of the original images, and splitting the dataset into subsets for training, validation, and testing purposes. By properly preparing the data, it becomes ready for the succeeding phases of the project.  **Phase 2: Model Development and Training –** In the second phase, it focuses on developing and training the leaf disease diagnosis application model. The chosen model architecture for this project is DenseNet-121, a deep learning model known for its effectiveness in image classification tasks. This model is implemented and trained using the prepared dataset. During training, the model's internal parameters are adjusted repeatedly, allowing it to learn and improve its ability to identify leaf diseases accurately. Validation is performed alongside training to assess the model's performance and make any necessary adjustments. Once training and validation are complete, the model moves into the evaluation stage, where its performance is measured using appropriate evaluation metrics by comparing its predictions with the actual correct labels for the leaf diseases, known as the ground truth labels. This comparison allows us to assess how well the model is performing in accurately identifying the diseases.  **Phase 3: Application Development –** In the third phase, it focuses on developing the leaf disease diagnosis application. This involves creating a user interface (UI) design for a web-based application that provides an intuitive and user-friendly platform for users to interact with the system. The trained DenseNet-121 model is then integrated into the application, allowing it to receive input images and provide disease predictions using the integrated model. Additionally, a treatment recommendation system is developed within the application, utilizing the predicted leaf diseases to offer strategies, including specific products, cultural practices, or other preventive measures, for managing and mitigating the predicted disease effectively.  **Phase 4: Testing and Deployment –** In the fourth and final phase, it focuses on testing and deploying the developed application. Model testing is conducted to ensure the usability and accuracy of the integrated model within the web-based application. Various input images are used to assess the model's disease prediction and treatment recommendation capabilities, ensuring its trustworthiness and effectiveness. Once the testing phase is successfully completed, the leaf disease diagnosis application is deployed, making it available for users to access and utilize on the web. By reaching this stage, the project is ready to provide farmers and agricultural workers with a useful tool for diagnosing leaf diseases and receiving treatment recommendations, ultimately contributing to the enhancement of agricultural sustainability. | |
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