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A DATASET OF FIELD PLANT IMAGES FOR PLANT DISEASE DETECTION AND CLASSIFICATION WITH DEEP LEARNING

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***Abstract* - The United Nations Food and Agriculture Organization proposes a 70% increase in food production by 2050 to meet global population demands, recognizing that one-third of all food is lost due to plant diseases. To address this challenge, researchers have developed deep learning models to aid farmers in detecting crop illnesses. While these models are typically trained on databases like Plant Village or Plant Doc, which contain laboratory photos with consistent backgrounds, they perform poorly when applied to field images with complex backgrounds and multiple leaves per image. To remedy this, a new dataset called Field Plant has been introduced, comprising 5,170 plant disease images collected directly from plantations and manually annotated by pathologists. This dataset focuses on diseases affecting crops like corn, cassava, and tomato in tropical regions. Evaluation of state-of-the-art models on Field Plant shows superior performance compared to other datasets. Additionally, recommendations on crop cultivation are made based on factors such as soil quality, weather conditions, humidity, and rainfall, aimed at increasing agricultural output. This system benefits farmers, nations, and helps to stabilize food costs.**

Keywords - ***Boosting food production,Deep learning models,Plant diseases,Field Plant dataset,Soil, weather, humidity, rainfall,Agricultural output.***

I. INTRODUCTION

The global population is expected to reach 10 billion people by 2050. Therefore, food production must absorb this population growth, althrough the amount of available arable land is limited. The Food and Agriculture Organization of the United Nations (FAO) suggests increasing the food supply by 70% to feed the future population by 2050, while about one third of all grown food is wasted because of plant diseases or disorders. In terms of economic value, plant diseases alone cost approximately US$ 220 billion annually. Loss of crop yield is a major research concern. Plants die if their leaves cannot produce chlorophyll via photosynthesis because of diseases or disorders. Artificial Intelligence (AI) has been extensively considered to solve the problem of crop yield loss, particularly in the areas of Computer Vision and Machine Learning. Therefore, many deep Convolutional Neural Networks (CNN) have been proposed by researchers for plant disease identification and classification. The purpose of these solutions is to provide farmers with a way to identify diseases that attack plants as soon as possible and suggest countermeasures to avoid crop losses.

In order to identify and categorize plant diseases, numerous deep Convolutional Neural Networks (CNN) have been proposed by researchers; Adi et al. highlights some of the most well-known CNN. With the help of these solutions, farmers will be able to quickly identify plant diseases and recommend preventative measures to minimize crop losses.

Our research suggests a new dataset called FieldPlant1 for the identification and categorization Of plant disease from filed photos taken in various lighting scenaro.

II. LITERATURE SURVEY

This approach suggested diagnosing banana plant leaf diseases automatically. Convolution Neural Networks

This approach suggested diagnosing banana plant leaf diseases automatically. Convolution Neural Networks (CNN) have been effectively used to study plant disease detection and classification; however, because of the intrinsic limitations of the max pooling layer in CNN, CNN is unable to accurately capture the posture and orientation of objects. They employed a novel paradigm named Capsule Network (CapsNet) in light of these shortcomings. The developed model identified black sigatoka, healthy leaves, and banana bacterial wilt with a 95% test accuracy.It outperformed three other CNN architectures in terms of rotation invariance: ResNet50, LeNet5, and installing a trained CNN model from scratch. However, the test dataset with no rotation utilizing the ResNet50 architecture performs better than the recommended model. However, the suggested model performs better when rotated.

1. Survey article summarizes contemporary Capsule Network designs, addressing CNN limitations, aiming for stronger machine vision algorithms.
2. SE-AlexCapsNet enhances leaf disease identification, achieving 92.1% accuracy, suitable for low-cost smartphone applications for farmers.
3. Caps Net outperforms CNNs in plant disease identification, leveraging orientation and spatial connections for higher accuracy.
4. Tomato plant disease classification utilizes ELM model with HSV color space and Haralick textures, outperforming SVMs and decision trees.
5. Caps Net-SVM model combines Caps Net feature extraction with SVM classification, achieving 93.41% accuracy automatically.
6. InceptionV3, InceptionResnetV2, MobileNetV2, and EfficientNetB0 outperform standard CNN models in plant leaf problem diagnosis.
7. Capsule Network overcomes CNN drawbacks in image processing, offering perspective invariance; BLEU1 score of 0.536.
8. Capsule Net outperforms traditional CNNs in plant disease identification, demonstrating superior performance in crop-disease pair prediction.
9. Gabor Capsule Network detects plant diseases under varied conditions, achieving high accuracy and robustness compared to other models.
10. Multi-channel capsule network ensemble combines five independent data sources for higher accuracy in plant disease diagnosis, albeit with longer inference time.
11. Computer vision advancements broaden plant disease diagnosis beyond traditional methods, leveraging neural networks for timely and accurate assessments.

III. METHODOLOGY

DEEP LEARNING:

Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behaviour of the human brain—albeit far from matching its ability—allowing it to “learn” from large amounts of data. While a neural network with a single layer can still make approximate predictions, additional hidden layers can help to optimize and refine for accuracy.

Deep learning drives many artificial intelligence (AI) applications and services that improve automation, performing analytical and physical tasks without human intervention. Deep learning technology lies behind everyday products and services (such as digital assistants, voice-enabled TV remotes, and credit card fraud detection) as well as emerging technologies (such as self-driving cars).

Machine learning algorithms leverage structured, labeled data to make predictions—meaning that specific features are defined from the input data for the model and organized into tables. This doesn’t necessarily mean that it doesn’t use unstructured data; it just means that if it does, it generally goes through some preprocessing to organize it into a structured format.

Deep learning eliminates some of data pre-processing that is typically involved with machine learning. These algorithms can ingest and process unstructured data, like text and images, and it automates feature extraction, removing some of the dependency on human experts. For example, let’s say that we had a set of photos of different pets, and we wanted to categorize by “cat”, “dog”, “hamster”, et cetera. Deep learning algorithms can determine which features (e.g. ears) are most important to distinguish each animal from another. In machine learning, this hierarchy of features is established manually by a human expert.

Then, through the processes of gradient descent and backpropagation, the deep learning algorithm adjusts and fits itself for accuracy, allowing it to make predictions about a new photo of an animal with increased precision.

Machine learning and deep learning models are capable of different types of learning as well, which are usually categorized as supervised learning, unsupervised learning, and reinforcement learning. Supervised learning utilizes labeled datasets to categorize or make predictions; this requires some kind of human intervention to label input data correctly. In contrast, unsupervised learning doesn't require labeled datasets, and instead, it detects patterns in the data, clustering them by any distinguishing characteristics. Reinforcement learning is a process in which a model learns to become more accurate for performing an action in an environment based on feedback in order to maximize the reward.

Convolutional neural networks (CNNs), used primarily in computer vision and image classification applications, can detect features and patterns within an image, enabling tasks, like object detection or recognition. In 2015, a CNN bested a human in an object recognition challenge for the first time.

Recurrent neural network (RNNs) are typically used in natural language and speech recognition applications as it leverages sequential or times series data.

Deep learning powers various real-world applications that often operate seamlessly in the background of our daily lives. For instance:

- Law Enforcement: Deep learning algorithms analyze transactional data to detect potential fraudulent or criminal activities, while also enhancing investigative analysis through speech and image recognition.
- Financial Services: Predictive analytics enable financial institutions to automate trading, assess risks for loan approvals, detect fraud, and manage investment portfolios efficiently.
- Customer Service: Deep learning technology is integrated into chatbots and virtual assistants, improving customer interactions by understanding natural language and providing personalized responses.
- Healthcare: Deep learning supports medical imaging specialists by analyzing and assessing medical images quickly and accurately, aiding in diagnosis and treatment decisions.

IV. SYSTEM ANALYSIS

A. EXISTING SYSTEM:

- In literature they introduced a dataset of field images called Plant Doc,it is a dataset for visual plant disease detection containing 2,598 data points across 13 plant species and up to 17 classes of diseases.
- Although it contains many laboratory images. This Plant Document data set has been used in some studies on plant disease detection, but has achieved very low performance.
- Because of the lack of extensive domain expertise, some images in this dataset may be incorrectly classified. Another researcher developed a 2-layers CNN model that extracts complementary discriminative features from citrus fruits and leaves by integrating multiple layers.
- This model differentiated healthy fruits and leaves from fruits or leaves with common citrus diseases, such as black spots, canker, scab, greening, and melanose. The dataset used in their research was contained only 213 images from the plant village

B. PROPOSED SYSTEM:

- The proposed work in the paper is the creation of a new dataset called Field Plant, which includes 5,170 plant disease images collected directly from plantations and manually annotated by plant pathologists to ensure process quality.
- The paper focuses on various diseases in three tropical cultures: corn, cassava, and tomato. diseases that attack plants as soon as possible and suggest countermeasures to The paper evaluates state-of-the-art classification and object detection models on this dataset.
- The purpose of this work is to provide farmers with a way to identify avoid crop losses.

V. SYSTEM DESIGN

A. SYSTEM ARCHITECTURE

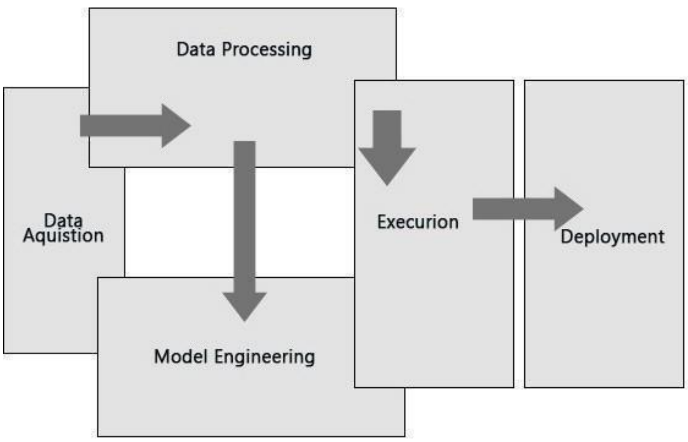

Figure 1: System Architecture

B. DATA FLOW DIAGRAM

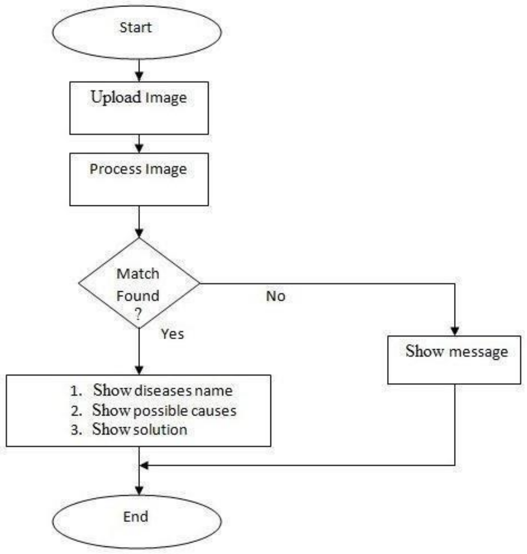

Figure 2: Data Flow Diagram

The Data Flow Diagram (DFD), also known as a bubble chart, is a graphical representation used to depict how information moves through a system and the transformations it undergoes. It consists of system processes, data inputs, outputs, and external entities. DFDs can model systems at different levels of abstraction and are crucial for understanding information flow and processing within a system.

C. UML DIAGRAMS

UML stands for Unified Modelling Language. UML is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML

D. USE CASE DIAGRAM

A use case diagram in UML is a behavioral diagram derived from use-case analysis. It provides a graphical overview of a system's functionality, showcasing actors, their goals (represented as use cases), and dependencies between them. The diagram primarily illustrates which system functions are executed for each actor, with the option to depict actor roles within the system.

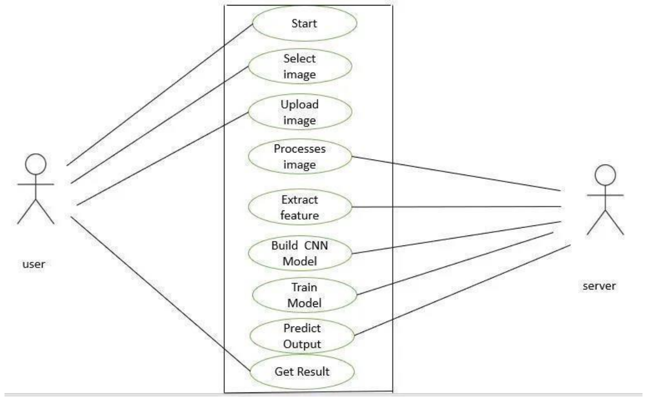

Figure 3: Use Case Diagram

E. CLASS DIAGRAM:

The class diagram refines the use case diagram, detailing the system's design by classifying actors into interrelated classes. Classes in the diagram may have "is-a" or "has-a" relationships, with each class capable of providing methods and possessing attributes.

F. Activity Diagram:

Activity diagrams capture process flows within the system, illustrating activities, actions, transitions, initial and final states, and guard conditions. They depict the flow of control and execution steps of a use case, including sequential and concurrent processing.

G. COLLABORATION DIAGRAM:

Collaboration diagrams illustrate interactions between objects, listing numbered interactions to trace their sequence. They help identify possible interactions each object has with others.

H. COMPONENT DIAGRAM:

The component diagram showcases high-level system components and their interrelationships. It depicts what components constitute the system after development or construction phases.

I. DEPLOYMENT DIAGRAM:

Deployment diagrams represent the configuration of runtime elements of an application, particularly useful when the system is ready for deployment.

VI. SYSTEM TESTING

System testing, also referred to as system-level tests or system-integration testing, is the process in which a quality assurance (QA) team evaluates how the various components of an application interact together in the full, integrated system or application. System testing verifies that an application performs tasks as designed. This step, a kind of black box testing, focuses on the functionality of an application. System testing, for example, might check that every kind of user input produces the intended output across the application.

A. STATIC TESTING:

The early-stage testing strategy is static testing: it is performed without actually running the developing product. Basically, such desk-checking is required to detect bugs and issues that are present in the code itself. Such a check-up is important at the pre-deployment stage as it helps avoid problems caused by errors in the code and software structure deficits.

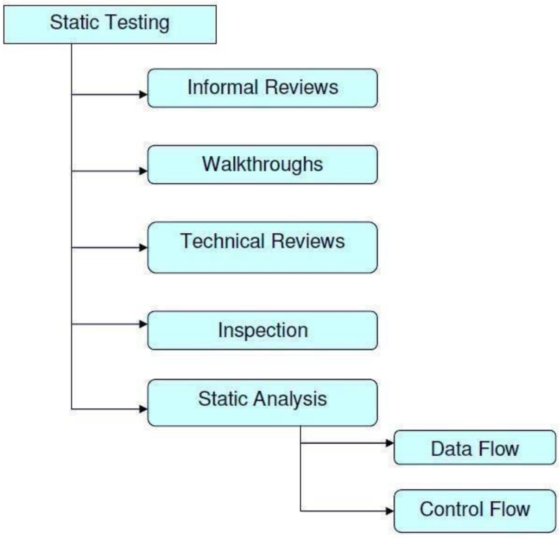

Figure 4: System testing diagram

B. Structural Testing:

Testing software effectively requires running it. Structural testing, also called white-box testing, is crucial for identifying and rectifying bugs and errors during the preproduction phase of software development. During this stage, unit testing, based on the software's structure, is conducted using regression testing. Often automated, this process operates within a test automation framework to expedite development. Developers and QA engineers have access to the software's structure and data flows, enabling them to monitor system behavior changes through mutation testing and comparing test outcomes with previous results (control flow testing).

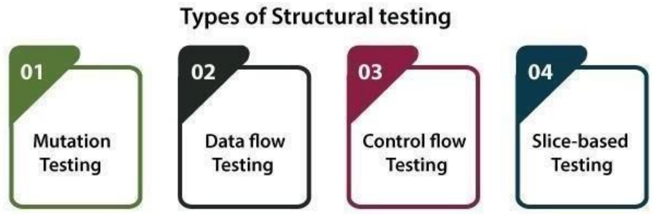

Figure 5: Types of Structural testing

C. BEHAVIOURAL TESTING:

The final testing phase, behavioral testing or black-box testing, focuses on observing how the software responds to various actions from a user's perspective. QA engineers conduct numerous tests, often manually, to assess usability and user experience. They interact with the software as typical users would, reacting to any bugs or issues encountered. Automation, particularly for repetitive tasks like regression testing, is common to reduce human error. For instance, automating the testing of filling registration forms on a website can streamline the process.

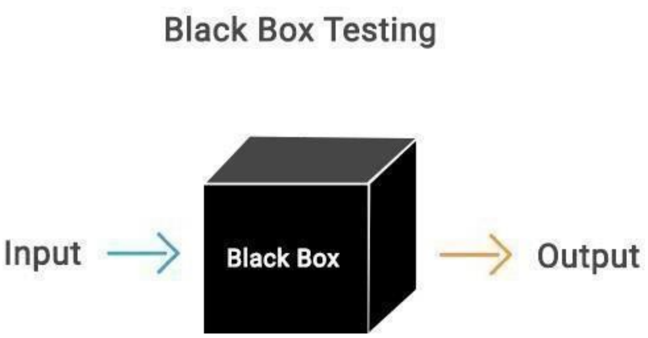

Figure 6: Black box Testing

VII. CONCLUSION

The conclusion of the paper that we have made available a dataset of 5,170 annotated plant disease images collected directly from plantations, which is composed exclusively of field images classified by plant pathologists. The dataset has the be widely used in plant disease research and management and is the first potential to plant disease dataset with annotated cassava images. The authors also suggest that the dataset can be enriched with more disease classes. The paper and finds that classification tasks on Field Plant outperformed those on other evaluates state-of heart classification and object detection models on this dataset datasets such as Plant Village and Plant Document.

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