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Crop Health Monitoring using Machine Learning Algorithms

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I.Introduction

No life is possible without plants; although plants are essential for life, they face several challenges to grow as a variety of diseases hit them. The need for rapid recognition and diagnosis of diseases helps reduce the chances of damage to the ecosystem. High moisture and high-temperature favor disease development. The bacteria fill the water-conducting tissue of plants with slime by multiplying rapidly inside it. This results in affecting the vascular system of plants. Sick leaves may need to be pruned. Different spraying may be required for different types of diseases. Sick products and health products must be separated at the stage of collecting products.

Farmers identify the disease by examining the plant and making judgments based on their past experiences. This method does not provide accurate results as different farmers may have different experiences and the method lacks scientific rigor as well. There are chances that the farmers might miss classifying a disease and a wrong treatment may cause more damage to the plant. Likewise, domain experts' visit to the field is costly. This necessitates the need for an automated image-based disease detection and classification mechanism that can replace the domain expert. CNN's are well known for image-based classification problems. A distinguishing feature of CNN is the use of a convolution layer, which omits the need for matrix multiplication. The various layers in a typical CNN include convolution, activation, pooling, and classification. The purpose of the convolution layer is to reduce the dimension of input.

A. Motivation

The motivation behind the development and implementation of crop health detection technologies stems from a variety of factors, addressing challenges in agriculture and aiming to improve overall food production, sustainability, and economic viability.

B. Contributions

The use of ML and DL in plant disease detection has gained popularity and shown promising results in accurately identifying plant diseases from digital images. Traditional ML techniques, such as feature extraction and classification, have been widely used in the field of plant disease detection.

C. Organization of Paper

This report is divided primarily into six sections, and each component gives a thorough or succinct summary of the project. The five divisions listed are: Introduction - This section gives you an overview of the project, a description of the principal issue being addressed, the project's objectives, the methods we'll be using to carry them out, and information on the remaining sections of the report. Related Work - This section includes prior research on this issue and its drawbacks. System Requirement SRS - Information on the project's functional and non-functional needs is provided in the specification section. System Design - This provides insight into the potential results. Results- What advantages do the technique or framework being created have over the one that is currently in use, and information about. System Implementation-This section discussions about system implementation are typically found in the methodology or implementation sections. These sections provide detailed insights into how the proposed system or research work is practically carried out and put into operation. Result and analysis- Results and Analysis" section is a critical component that presents the outcomes of the research or project work. This section is where the data collected during experimentation or implementation is detailed, and the findings are analyzed and interpreted.

II. Related Work

U. Shafi, R. et al. [7] States the transformation of agriculture through IoT-based automation, particularly focusing on Precision Agriculture (PA) and Wireless Sensor Networks (WSN). PA utilizes sensors and software to optimize crop productivity by gathering real-time data on soil, crop, and weather conditions. The survey covers various aspects, including wireless communication technologies, environmental monitoring sensors, spectral imaging platforms, vegetation indices, and WSN applications in agriculture. The paper proposes an IoT-based solution for crop health monitoring, consisting of a WSN for real-time monitoring and a remote sensing platform for obtaining multi-spectral imagery. A case study demonstrates the implementation of this system, showcasing its potential. The paper concludes with insights into challenges and future directions for IoT-based agriculture automation.

R. B. Macdonald. et al. [8] address the lag in agricultural development in Northern Ontario compared to the southern regions and mitigate the limited access to information for producers, a community-based research initiative has introduced an interactive web-based information visualization and GIS decision support system. This innovative system harnesses the power of citizen science and participatory research, promoting collaboration among agricultural producers, researchers, and community stakeholders. The overarching objective is to empower northern Ontario producers with essential data, enabling them to make informed decisions regarding their crops. By tackling the information disparity and fostering collaboration, the initiative aims to cultivate mutual benefits within the community.

J. V. Stafford. et al. [9] Precision agriculture benefits from an expanding array of data resources, encompassing the proliferation of satellite constellations, the widespread utilization of unmanned aircraft systems (UAS), and the increased affordability of ground-based units. Each platform presents distinct capabilities for data collection, accompanied by varying spatial and temporal resolutions. Satellite data, despite its versatility, is susceptible to cloud cover and entails longer intervals between usable flight paths. Unmanned aircraft systems offer flexibility in sensor types and superior spatial resolution but are constrained by weather conditions and cost considerations. Ground sensors, providing ultra-high-resolution data with minimal environmental impact, necessitate labor-intensive and time-consuming data gathering Chapter 2 Related Work processes. Among these options, UAS emerges as the most versatile; however, each platform exhibits suitability for specific applications based on their respective benefits and shortcomings.

M. P. Wachowiak, et al. [10] Says dynamic agricultural sector is capitalizing on information and communication technology to enhance productivity and mitigate losses. Although current expert systems support farmers, their reliance on stored knowledge poses limitations. This paper introduces a pioneering approach that integrates the Internet of Things (IoT) into an expert system. By incorporating real-time input data, the system facilitates proactive and preventive measures, specifically in mitigating losses attributed to diseases and pests. This IoTdriven expert system strives to offer farmers timely and adaptive support, surpassing the constraints associated with conventional knowledge-based systems.

J. D. Rudd, et al. [11] This paper highlights the growing significance of Wireless Sensor and Actuator Networks (WSAN) in various domains, particularly in agriculture, focusing on crop irrigation control. The use of WSAN addresses real-time challenges and contributes to the development of autonomous systems. However, in third-world countries like Pakistan, the adoption of WSAN is hindered by the high hardware/system cost. To overcome this challenge, the paper emphasizes the need for indigenous development of sensor and actuator motes. The study not only discusses crop irrigation control but also outlines efforts in the indigenous design and development of WSAN and its protocol, aiming to make this technology more accessible and cost-effective in resource-limited regions

R. Shahzadi, et al. [12] This study introduces a low-cost IoT system for soil moisture monitoring using Watermark 200SS sensors, addressing the limited adoption of soil moisture sensing technology by farmers. The system utilizes Arduino-based microcontrollers and LoRa radios for wireless communication. Field sensor data is transmitted to a receiver connected to the Internet, allowing visualization and analysis on an open-source website (ThingSpeak.com) using MATLAB. Successfully tested in a wheat field, this system aims to overcome barriers such as high cost and difficulties in data collection and interpretation, potentially facilitating widespread adoption of affordable and user-friendly moisture sensing technologies among farmers.

III. Proposed Work

A. Problem Statement

Agriculture remains a foundational pillar of economies worldwide, and the health of crops is paramount to the sustenance and economic stability of many regions. Wheat, as one of the predominant staple crops, faces several threats from environmental factors, pests, and diseases. Among these threats, fungal diseases such as Stripe Rust and Septoria pose significant challenges to wheat production, leading to substantial yield losses and economic damage each year. In the case of Ethiopia, a country with a vast agrarian sector, these diseases represent a persistent and formidable obstacle that can compromise the food security of millions. The conventional approach to managing wheat crop health has largely relied on visual inspection by experts. This method, while valuable, is increasingly unfeasible due to its labor-intensive nature, its reliance on subjective assessments, and the sheer scale of modern agricultural operations. Moreover, the early stages of disease manifestation may be subtle and easily overlooked by even the most experienced agronomists. As a result, there is an urgent need for more efficient, objective, and scalable methods of disease detection and monitoring. Recent advances in technology present a possible solution to this challenge. With the rise of machine learning, and in particular, deep learning techniques, there is the potential to automate the process of disease detection in crops. The application of convolutional neural networks (CNNs) to image classification tasks has shown remarkable success in various domains, including medical diagnostics, facial recognition, and indeed, agricultural monitoring. However, developing a machine learning model that can accurately identify and classify wheat leaf diseases from images presents its own set of challenges

B. Dataset Descriptions:

The dataset collected was sourced from the Holeta wheat farm which is meticulously categorized into three distinct classes, including Healthy Wheat Leaves, Leaves Affected by Stripe Rust, and Leaves Affected by Septoria. The dataset contains a total of 10,000 images, with a balanced distribution across the three categories.

Healthy Stripe Rust Septoria

Fig 1. Healthy,stripe rust and septoria leaf

C. Proposed Architecture

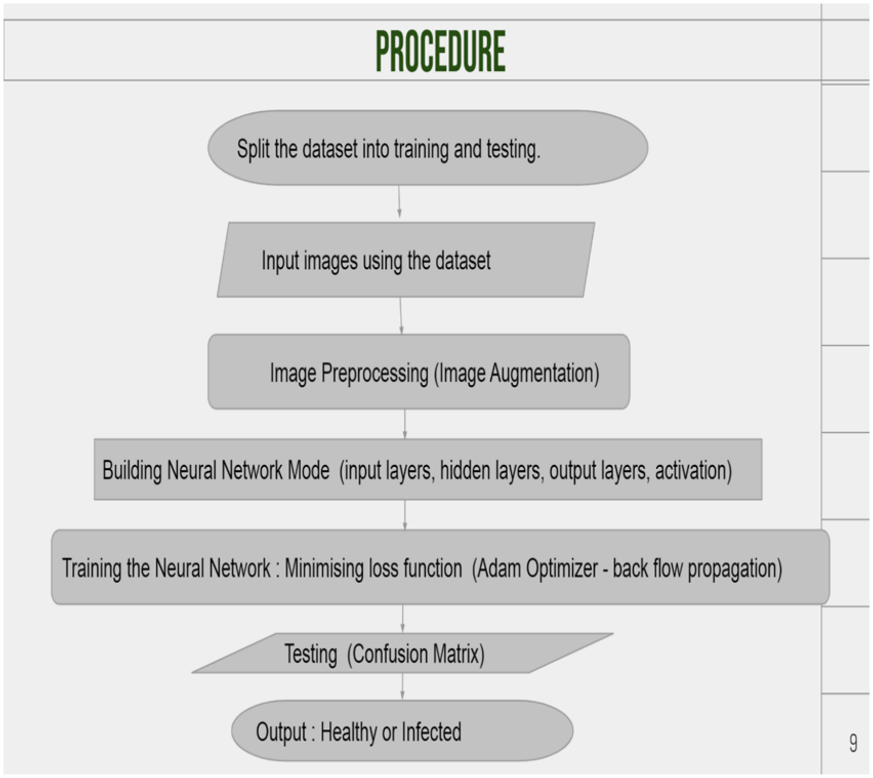

Fig 2. Proposed Architecture

1. Data Acquisition: The system collects multi-modal data from the agricultural field using ground-based IoT sensors and aerial drones equipped with high-resolution cameras. IoT sensors capture environmental parameters such as soil moisture, humidity, temperature, and light intensity, providing crucial insights into the growing conditions of the wheat crop. Simultaneously, aerial drones capture images of the crop canopy, allowing for detailed visual analysis of individual plants and leaves.
2. Data Preprocessing: Raw data collected from IoT sensors and drones undergoes preprocessing to clean, standardize, and augment it for analysis. This preprocessing step involves data cleaning to remove outliers and inconsistencies, normalization to standardize feature scales, and augmentation to enhance the diversity of the dataset. Additionally, data fusion techniques may be employed to integrate information from different sources into a unified dataset.
3. Feature Extraction: Relevant features are extracted from the preprocessed data to capture key characteristics indicative of wheat leaf health. Feature extraction techniques may include spectral analysis to analyze the reflectance properties of leaves across different wavelengths, texture analysis to quantify patterns and structures, and morphological analysis to characterize leaf shape and size. These extracted features serve as input to the machine learning models for disease detection.

4. Model Training: Supervised machine learning models, particularly deep learning models such as convolutional neural networks (CNNs), are trained on the extracted features to classify wheat leaves into different health categories. Transfer learning techniques may be employed to leverage pre-trained models and fine-tune them for the specific task of disease detection. The models are trained using labeled data, where each sample is annotated with its corresponding disease condition (e.g., healthy, Stripe Rust, Septoria).

5. Model Evaluation: The trained models are evaluated using separate test datasets to assess their performance. Performance metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) are computed to quantify the model's effectiveness in distinguishing between healthy and diseased wheat leaves. Cross-validation techniques may be employed to ensure robustness and generalization of the models.

IV.Results and Discussion

A. Experimental Setup

The experiment is done on Google Service Provider called “Google Colab”. We ustilized 45 GB RAM and 40 GB of nvidia GPU available in Google Colab. During Training, the epoch was set to 40. **Technology used:** Programming Languages is Python, Machine Learning Libraries are TensorFlow and PyTorch, Data Processing Libraries: Pandas and NumPy, Computer Vision Libraries: OpenCV, and finally Visualization Libraries: Matplotlib as well Seaborn

B. Performance Analysis

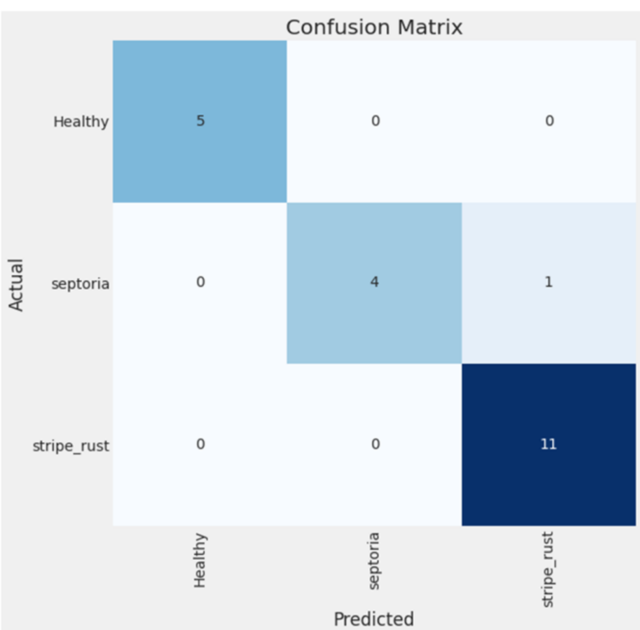

Fig 3. Performance Analysis

Classification Report:

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	precision	recall	f1-score	support
Healthy	1.00	1.00	1.00	5
septoria	1.00	0.80	0.89	5
stripe_rust	0.92	1.00	0.96	11
accuracy			0.95	21
macro avg	0.97	0.93	0.95	21
weighted avg	0.96	0.95	0.95	21

Fig 4. Classification report

V.Conclusions

The experiment demonstrates the effectiveness of the model architecture and training approach in learning from the provided dataset. The achieved performance metrics, particularly the validation accuracy, indicate the model's capability to classify unseen data accurately. These results suggest that the model has learned meaningful patterns from the data and can make reliable predictions. Further experimentation could involve testing the model on additional datasets to evaluate its generalization across different data distributions. Fine-tuning hyper parameters or exploring alternative model architectures could potentially improve performance further. It is essential to conduct thorough testing on completely separate test datasets to validate the model's realworld performance and ensure its reliability in practical applications. Continual monitoring and evaluation of the model's performance over time can provide insights into its robustness and potential areas for improvement

VI.References

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