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CONVOLUTIONAL NEURAL NETWORK FOR RAPID IDENTIFICATION OF WHEAT LEAF DISEASES: A FARMER- FRIENDLY TOOL

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Abstract
The increasing impact of wheat diseases on crop yield poses a significant challenge to farmers worldwide. This project aims to develop a user-friendly website for detecting common wheat diseases using an artificial intelligence model. By leveraging a basic Convolutional Neural Network (CNN), the website allows users to upload images of wheat plants and receive immediate feedback on the presence of any disease. This project not only serves as a practical tool for farmers but also contributes to the growing field of artificial intelligence in agriculture. The outcomes of the project include a functional prototype capable of accurately detecting and providing relevant information on multiple wheat diseases, demonstrating the potential of AI in solving real-world agricultural problems. The simplicity and accessibility of the website ensure its usability for both farmers and researchers. Overall, the project holds significant value in promoting sustainable agriculture by enabling early detection and timely response to crop diseases, ultimately improving yield and reducing losses.

INTRODUCTION

Wheat is undeniably one of the most critical staple food crops globally, forming the backbone of food security for billions and serving as a primary source of calories and protein. Its cultivation spans vast geographical regions, making it a cornerstone of agricultural economies. In countries like Pakistan, wheat is not merely a commodity but a fundamental component of the national diet and a significant contributor to the agricultural Gross Domestic Product (GDP). However, the sustained productivity of wheat is under constant threat from a myriad of biotic stresses, primarily a diverse range of diseases and pest infestations. These biological agents can severely compromise crop health, leading to substantial reductions in yield quantity and quality, thereby posing a significant challenge to farmers' livelihoods and national food security. The insidious nature of these threats often means that by the time symptoms become visually apparent to the untrained eye, Identify applicable funding agency here. If none, delete. Considerable damage may have already occurred, rendering reactive measures less effective. Therefore, the early, accurate, and rapid identification of these issues is paramount for implementing timely and effective management strategies, which are critical to safeguarding healthy crop production and mitigating severe economic losses for agricultural communities.

The advent of artificial intelligence (AI), particularly deep learning, has revolutionized various fields, and agriculture is no exception. Traditional methods of disease detection, which often rely on manual visual inspection by farmers or costly laboratory analyses, are frequently time-consuming, require specialized expertise, and are prone to human error.

Such delays in diagnosis can lead to the widespread proliferation of diseases, necessitating broader and often more aggressive interventions, including the increased use of pesticides, which can have adverse environmental impacts. Recognizing this critical need, this project embarks on the development of an intelligent wheat leaf disease detection system that leverages cutting-edge deep learning techniques. Our primary objective is to accurately detect and classify a comprehensive set of 14 distinct conditions affecting wheat leaves. This includes a broad spectrum of threats, encompassing various fungal diseases, bacterial infections, and insect-related damages, by analyzing high-resolution images of wheat leaves. The core of this system is a robust Convolutional Neural Network (CNN) model, meticulously trained on an extensive dataset comprising 20,000 RGB images, enabling it to perform this complex multi-class classification task with high efficacy.

A key innovation and driving force behind this project is the commitment to making advanced agricultural technology accessible and practical for its end-users: farmers and field workers. To this end, the system is designed with a simple, intuitive, and user-friendly web interface. This web-based platform empowers farmers to easily upload images of their wheat leaves directly from their smartphones or computers. Upon image submission, the integrated AI model swiftly analyzes the visual data to determine whether the leaf is healthy or aflicted by any of the 14 known conditions. Crucially, the system provides instant feedback, delivering not only the diagnosis but also relevant, actionable information about the detected issue, such as common symptoms, potential causes, and recommended remedial actions.

By enabling such timely and precise detection, this intelligent tool serves as a vital enabler for farmers to take prompt and appropriate actions. This could range from targeted application of treatments to prevent disease spread, to making informed decisions about switching to diseaseresistant wheat varieties for future plantings. The proposed system, therefore, transcends mere diagnostic capability; it acts as a proactive decision- support tool that significantly contributes to increased crop productivity and fosters smarter, more sustainable farming practices through the practical application of artificial intelligence in agriculture. This research not only addresses a pressing agricultural challenge but also exemplifies the transformative potential of AI in enhancing food security and promoting ecological balance in farming ecosystems.

I. LITERATURE REVIEW

Numerous studies have been conducted on wheat leaf disease detection to mitigate crop losses and improve agricultural productivity. Researchers have employed both machine learning (ML) and deep learning (DL) techniques for this purpose. While each approach has demonstrated promising results, they also present certain limitations.

Machine learning methods typically require manual preprocessing steps such as feature extraction, often relying on handcrafted features like color, texture, and shape. These methods are computationally less intensive but are frequently sensitive to variations in image quality, lighting conditions, and background noise, making their performance inconsistent in diverse real-world agricultural settings. On the other hand, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools due to their ability to automatically learn hierarchical features directly from raw image data. While CNNs have shown significantly higher accuracy and automation capabilities, they generally demand substantially larger and more diverse datasets for effective training and require significant computational resources, often necessitating specialized hardware like GPUs.

A 2023 study, for instance, explored the use of advanced deep learning models including DenseNet121, VGG19, and ResNet50 to detect yellow rust in wheat. Among these, ResNet50 achieved the highest accuracy of 96.3%, highlighting the effectiveness of deep learning in accurate and early disease identification. Conversely, another study utilized a traditional machine learning pipeline, consisting of image acquisition, preprocessing, feature extraction, and classification using Support Vector Machines (SVM) and Artificial Neural Networks (ANN). Although this method yielded reliable results under controlled conditions, it struggled with varying image conditions and required highquality inputs, showcasing the inherent challenges of feature engineering in complex agricultural imagery. Furthermore, the deployment of such models often requires careful calibration and may not generalize well to different wheat varieties or environmental contexts without re- training.

A significant observation from the existing literature is that most prior works have predominantly focused on detecting only one specific disease at a time. For instance, certain systems are specifically tailored to identify either yellow rust or brown rust alone, or perhaps a single bacterial blight. However, in real-world agricultural scenarios, wheat crops are frequently affected by multiple diseases simultaneously, or symptoms of different diseases can overlap, making a singledisease detection system insufficient and impractical for comprehensive farm management. This critical limitation highlights the urgent need for a more comprehensive detection system capable of identifying multiple diseases through a single, integrated platform, thereby providing a holistic view of crop health.

This project directly addresses that crucial gap by developing a robust CNN-based web application capable of detecting 14 distinct wheat leaf diseases, including a wide array of fungal infections, bacterial infections, and insectbased damage. The system is meticulously designed for ease of use by farmers, ensuring that the advanced underlying technology is accessible without requiring specialized technical expertise. By providing fast, reliable results along with relevant disease information, this comprehensive tool aims to support timely intervention and significantly improve crop management practices, ultimately leading to enhanced agricultural productivity and reduced losses. This project directly addresses that crucial gap by developing a robust CNNbased web application capable of detecting 14 distinct wheat leaf diseases, including a wide array of fungal infections, bacterial infections, and insect- based dam- age. The system is meticulously designed for ease of use by farmers, ensuring that the advanced underlying technology is accessible without requiring specialized technical expertise. By providing fast, reliable results along with relevant disease information, this comprehensive tool aims to support timely intervention and significantly improve crop management prac- tices, ultimately leading to enhanced agricultural productivity.

II. METHODOLOGY

The methodology for this project follows a structured and iterative approach, integrating principles of software engineering with deep learning techniques. This ensures the development of a robust, accurate, and user-centric system for wheat leaf disease detection.

The core process can be understood through the ”Block Diagram” (Figure 4.3.1), which illustrates the fundamental interactions within the system:

A. User Interaction (Input)

- The process begins with the User. This is typically a farmer or an agricultural consultant who needs to identify a potential disease on a wheat leaf.
- The User interacts with the system by initiating an ”Upload Image” action. This means they select and submit an image of a wheat leaf, usually captured with a mobile device or camera, through the system’s interface.
-

B. Image Processing and AI Model Inference

- Once the image is uploaded, it is ”Sent Image” to the ”AI Model”. Before being fed to the AI model, the image undergoes necessary preprocessing steps (like resizing and normalization) to ensure it’s in the correct format for the model.
- The ”AI Model” is the intelligent core of the system. It’s a Convolutional Neural Network (CNN) that has been trained to recognize patterns associated with various wheat leaf diseases and healthy conditions. The model processes the input image and makes a prediction about the condition of the leaf.

C. Result Presentation (Output)

- After the AI Model processes the image and makes a prediction, it ”Sends Result” to the ”Display Result”
component.
- The ”Display Result” block is responsible for presenting the AI model’s prediction to the User in a clear and understandable format. This includes not only the name of the detected disease (or ”Healthy”) but also additional relevant information such as

common symptoms, potential causes, and suggested remedial actions.

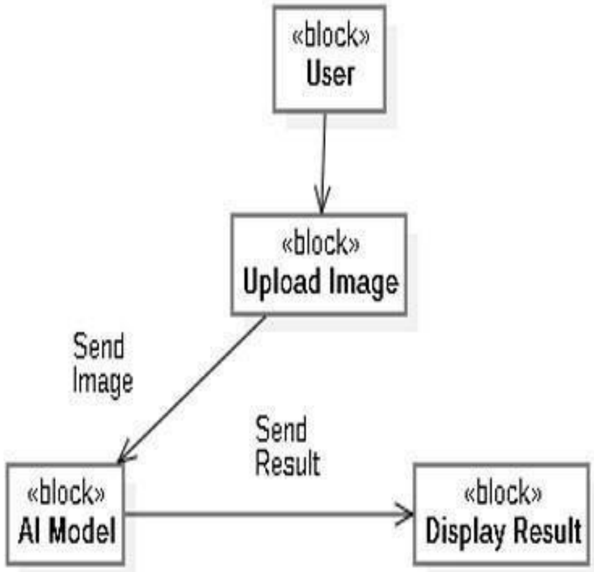

Fig. 1. Block Diagram

III. REQUIREMENTS ANALYSIS

Defines the stakeholders and their respective responsibility modules.

A. Requirements Elicitation

1) Elicitation Methods: Two primary methods were employed for requirements elicitation:

- Observation: Direct observation of farmers in their fields was conducted to gain first-hand insights into their current practices for disease identification, crop monitoring workflows, and the pain points associated with traditional methods. This provided valuable context regarding environmental conditions, typical image capture scenarios, and the practical challenges faced by farmers.
- Interviews: Structured and semi-structured interviews were conducted with a diverse group of stakeholders, including active farmers, agricultural experts, and domain specialists in plant pathology. These interviews aimed to comprehensively understand their specific needs, current challenges in disease management, desired functionalities for a digital tool, and expectations regarding accuracy, speed, and usability.

TABLE I PROJECT STAKEHOLDERS

Stakeholders	Responsibility Modules
The University Of Faisalabad	Project Sponsor
Ms. Aasma Khalid	Project Supervisor
Khizra Shahzad	Interface Model Training Model Evaluation
Khadija Nadeem	Model Training Model Evaluation
Maryam Waqas	Dataset collection Model Training Model Evaluation
Farmers	They will be the users of the system
Agricultural Consultants	They will be the users of the system
Agricultural Research Institutes	They will be the users of the system

2) Key Requirements Identified: Based on the elicitation process, the following key requirements were identified as critical for the system's success:

- Accurate Disease Detection: The paramount functional requirement is the system's ability to accurately identify and classify the type of wheat leaf disease. This includes distinguishing between visually similar conditions such as Yellow Rust and Brown Rust, as well as other fungal, bacterial, and pest-related issues among the 14 target classes.

- User-Friendly Interface: Given the target audience, a simple, intuitive, and easy-to-navigate user interface is essential. The system must provide clear instructions for image upload and interpretation of results, minimizing the need for specialized technical expertise.
- Rapid Feedback: Farmers require immediate diagnostic feedback to enable timely intervention. The system must process uploaded images and return predictions quickly to support prompt decision-making in the field.
- Relevant Information Provision: Beyond mere classification, the system must provide actionable information related to the detected disease, including common symptoms, potential causes, and suggested remedial actions, to empower farmers with practical guidance.
- Target Audience Focus: The system's design and features must be tailored specifically for its primary target audience, which includes individual farmers and agricultural consultants operating in diverse agricultural settings.

B. Functional Requirements

The core functionalities the system must perform are:

Functional Requirements: The core functional requirements for the system are:

- Real-time detection: The system must provide immediate diagnostic feedback upon image upload.
- Disease detection: The system must accurately identify and classify the type of wheat leaf disease.
- Symptoms of disease: The system must display relevant information regarding the symptoms of the detected disease.

C. NON FUNCTIONAL REQUIREMENTS

The nonfunctional requirements are:

- Response time should be fast: The system must provide rapid processing and prediction results to ensure a seamless and efficient user experience, critical for timely decision-making in the field.
- Highly Integrated System: The system should demonstrate robust integration between its various components (frontend, backend, and AI model) to ensure smooth data flow and reliable operation.
- User Friendly: The interface must be intuitive and easy to navigate, designed for farmers and agricultural consultants with varying levels of technical proficiency, minimizing the learning curve.
- Accessibility: The system should be accessible across different devices (e.g., smartphones, tablets, desktop computers) and potentially consider aspects like multilingual support in future iterations to cater to a broader user base.

IV. SPECIFIC REQUIREMENTS (HARDWARE AND SOFTWARE REQUIREMENTS)

Operating a wheat disease detection program there is a need of certain hardware or software requirements. It includes having mobile devices or desktop computers to access web based application or mobile applications. Whereas software requirements include Operating System that must be compatible with the system, unique and appropriate programming techniques need to be used. These inputs help in successful completion of a program.

A. Hardware Requirement

The following hardware requirements are recommended for better performance in image processing and model training:

- Processor: A high-performance CPU is essential (e.g., Intel Xeon or AMD Ryzen series) to efficiently handle the computational demands of data preprocessing and model inference.
- RAM: Sufficient Random Access Memory (RAM) is crucial for managing large datasets and model parameters during training. A minimum of 16GB or more is recommended to ensure smooth operation and prevent memory-related bottlenecks.
- System Type: The system should operate on a 64-bit operating system with an x64-based processor to fully utilize modern hardware capabilities and support the required software environments.

B. Software Requirement

The Following are the software requirements:

TABLE II SOFTWARE REQUIREMENTS

Requirements	Versions
Python	3.9
Tensorflow	2.15.1
Keras	2.15.0
Numpy	1.26.4
Pandas	2.2.2
Operating System	10

V. Software Development Life Cycle Model

We are going to use Incremental Model[6]. In the software process methodology at first it break down the project into small incremented parts, later apply the incremental methodology for development and testing. Process starts with the requirement analysis which is done by the design of system architecture. This iterative approach allows for early delivery of core functionalities and continuous incorporation of user feedback. It significantly reduces project risk by identifying and addressing potential issues at an early stage. This flexibility is crucial for projects where requirements may evolve over time, such as in AI development. The process is done incrementally, followed by homepage, uploading image functionality, AI Integration and information regarding disease is displayed. Each increment is tested before preceding to the next. At last, it finalize the development process.

VI. PROPOSED FRAMEWORK

The proposed framework is developed to offer a userfriendly, AI-powered solution specifically aimed at assisting farmers in detecting wheat leaf diseases efficiently and accurately. The system is designed to identify a total of 14 different classes of wheat leaf conditions, which include various diseases and insect-related issues. By leveraging image analysis, the system reduces the need for manual inspection or expert intervention, making disease diagnosis more accessible and practical, especially for farmers in remote or underresourced areas. At the core of this framework lies a Convolutional Neural Network (CNN), a powerful deep learning architecture particularly suited for image classification tasks. The CNN model was trained on a comprehensive dataset of 20,000 RGB images, enabling it to learn and differentiate complex visual patterns among the 14 classes. It extracts detailed visual features from uploaded images and uses them to classify whether a wheat leaf is healthy or affected by a specific condition. Users interact with the system through a clean and intuitive web interface, where they can upload images of wheat leaves directly from their smartphones or computers. Once an image is uploaded, it undergoes a series of preprocessing steps such as resizing, normalization, and noise reduction to ensure consistency and quality before being passed into the trained CNN model.

The system then analyzes the input and provides an immediate prediction. Along with the classification result, the system displays detailed information about the identified disease or pest, including common symptoms, possible causes, and suggested remedial actions. This informative feedback helps users not only understand the issue but also take timely and appropriate measures for disease control.

The framework follows the Incremental Software Development Life Cycle (SDLC) model, which allows for stepbystep development and testing. This approach enabled the team to build a strong foundation and progressively integrate new features, such as improved UI design, accurate image classification, and interactive result display. Future enhancements like additional disease types, farmer recommendations, or multilingual support can also be integrated easily due to the modular nature of the system.

The overall system architecture is organized into three main layers:

1) The presentation layer serves as the user interface and is responsible for capturing user inputs and displaying results.
2) The application layer manages logic, system control, and coordinates interactions between the user interface and the backend processes.
3) The integration layer contains the AI model and

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handles backend processing, including image classification and data handling.

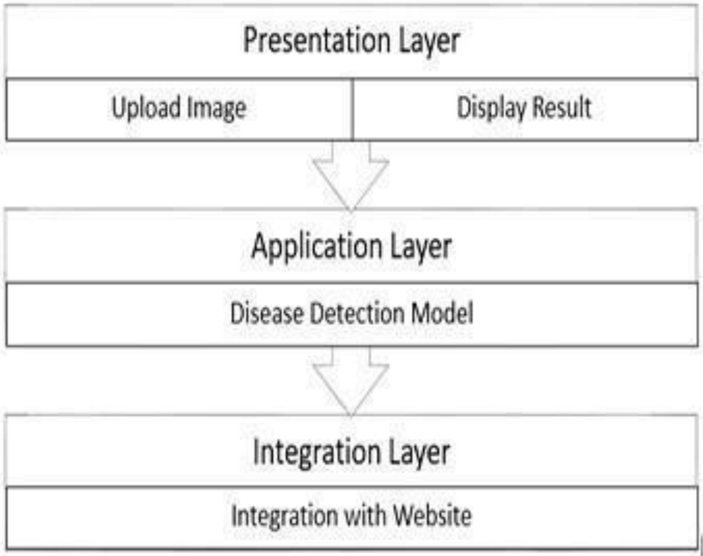

Fig. 2. Software Architecture Diagram

Its thoughtful design and flexible architecture make it a scalable and valuable asset for agricultural communities aiming to improve productivity and minimize crop losses.

VII. DATASET

A. Dataset Acquisition and Initial State

Our dataset was sourced from a publicly available repository, providing a foundational collection of wheat leaf images.

Initially, this raw dataset comprised approximately 13,084 RGB images, distributed across 15 distinct classes, which included various wheat leaf diseases and healthy conditions. A notable characteristic of this initial collection was its significant class imbalance, with certain disease categories and the healthy class having a disproportionately higher

Fig. 3. Tan Spot

Fig. 4. Brown Rust

B. Dataset Balancing and Augmentation

To mitigate the adverse effects of this class imbalance on model training and to ensure fair and robust learning, we meticulously balanced the dataset. Through a cautious application of data augmentation techniques, the dataset used for training was expanded to a total of 19,045 RGB images. This comprehensive and now balanced collection aims to facilitate the development and rigorous evaluation of our deep learning model for accurate and early disease detection in wheat crops. The strategic involvement of diverse disease and healthy samples, combined with the achieved balanced class representation, significantly enhances the generalization capabilities and real-world applicability of models trained on this refined dataset.

TABLE III: DISTRIBUTION OF IMAGES ACROSS WHEAT LEAF DISEASE CLASSES (BEFORE AND AFTER BALANCING)

Disease Class	Original Images	Balanced Images
Aphid	903	1301
Black Rust	576	1301
Blast	647	1300
Brown Rust	1271	1303
Common Root Rot	614	1303
Fusarium Head Blight	611	1303
Healthy	1000	1300
Leaf Blight	841	1300
Mildew	1071	1300
Mite	800	1300
Septoria	1141	1301
Smut	1303	1303
Stem Fly	236	1000
Tan Spot	770	1300
Yellow Rust	1301	1301
Total	13084	19045

VIII. ALGORITHM

A. Data Collection and Preprocessing

This model requires the collection of dataset that contains wheat disease images. Images will undergo different steps that include image resizing, image augmentation to improves robustness of a model.

B. Feature Extraction via CNN

- Conv2D (32 filters, 3x3, ReLU): Extracts low-level features like edges and textures from the input image.
- MaxPooling2D (2x2): Reduces spatial dimensions to lower computation and retain important features.
- Flatten: Converts the 2D feature maps into a 1D vector for input to dense layers.
- Dense (64 units, ReLU): Learns abstract feature com

C. Training Process

The model is trained using a supervised learning approach, where it minimizes a loss function specifically, categorical cross- entropy through the process of backpropagation. An optimizer such as Adam is employed to adjust the model's weights iteratively, aiming to enhance classification accuracy across all 14 disease classes. The training is performed over multiple epochs using a labeled dataset of wheat leaf images, allowing the model to generalize and correctly identify patterns associated with each disease class.

TABLE IV: CNN MODEL LAYER SPECIFICATIONS

Layer (Type)	Output Shape	Param #
Conv2D	(None, 253, 253, 32)	896
MaxPooling2D	(None, 126, 126, 32)	0
Conv2D 1	(None, 124, 124, 64)	18496
MaxPooling2D 1	(None, 62, 62, 64)	0
Flatten	(None, 246016)	0
Dense	(None, 64)	15745088
Dense 1	(None, 15)	975
Total params:		15765455
Trainable params:		15765455
Non-trainable params:		0

D. Prediction and Classification

Once trained, the model accepts a new wheat leaf image, processes it through the network, and outputs the predicted class among multiple wheat diseases such as Aphid, Black Rust, Blast, Common Root Rot, Fusarium Head Blight, Healthy, Leaf Blight, Mildew, Mite, Septoria, Smut, Stem Fly, Tan Spot, and Yellow Rust. This image, typically uploaded by a farmer or agricultural consultant via the user-friendly web interface, first undergoes the same preprocessing steps (resizing to 255x255 pixels and normalization) that were applied to the training data. This ensures consistency and optimal input format for the trained network. The preprocessed image is then fed forward through the entire CNN architecture. Each layer of the network extracts increasingly complex features, from basic edges and textures in the initial convolutional layers to highlevel patterns indicative of specific diseases in the deeper layers. The final dense layer, equipped with a softmax activation function, outputs a probability distribution across all 15 predefined classes. This distribution indicates the model's confidence that the input image belongs to each specific class.

IX. PROBLEM FACED

During the project, we faced significant challenges with data validation and dataset imbalance, as the number of images for different wheat diseases varied greatly. This unevenness made it difficult for the model to learn equally well across all disease categories, affecting the overall accuracy. Specifically, classes with fewer initial samples were prone to overfitting, while larger classes could dominate the learning process. Additionally, authenticating the model‘s predictions required careful testing to ensure reliable results, which was challenging due to the incomplete and uneven data. To overcome these issues, we applied data augmentation techniques to balance the dataset and performed thorough validation using multiple metrics. These efforts helped improve the model‘s accuracy and sturdiness, while teaching us valuable lessons about handling real-world data challenges in AI projects. This experience underscored the critical importance of robust data preprocessing and iterative validation in developing reliable AI solutions for agricultural applications.

X. RESULTS AND DISCUSSION

The comprehensive evaluation of the wheat leaf disease detection system involved multiple levels of testing to ensure its effectiveness and readiness for real-world application. The testing process included manual testing, unit testing, functional testing, integration testing, and system testing.

- Manual Testing was performed to verify the system's behavior under normal and edge-case conditions, ensuring that the user interface and prediction outputs were functioning as expected.
- Unit Testing focused on individual components such as image preprocessing, model prediction, and input validation to confirm each part was working correctly in isolation.
- Functional Testing ensured that the core functionality of the application uploading images and returning accurate disease predictions performed as intended.
- Integration Testing verified that different modules (frontend, backend, and model) worked together smoothly, identifying and resolving issues related to data flow and communication between

components.

- System Testing was conducted to evaluate the complete and integrated system's performance, covering scenarios like handling multiple users, different image qualities, and stress testing.

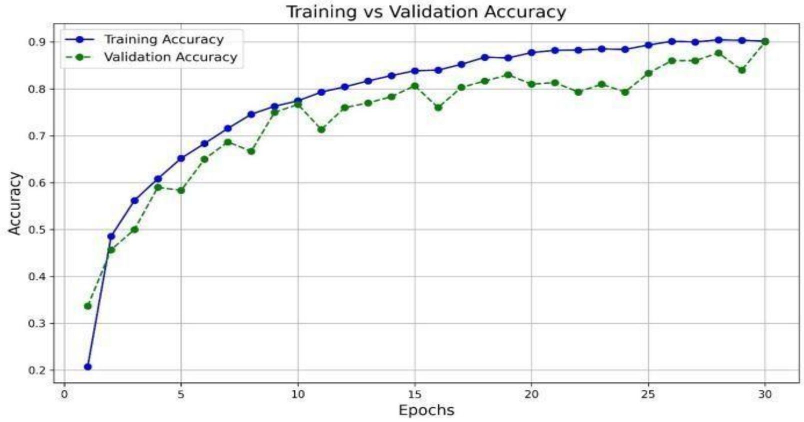

Fig. 5. Training and Validation Accuracy

Fig. 6. Training and Validation Loss

Through these layered testing methods, the system achieved 90% accuracy, proving its robustness and practical utility. The model's high precision in distinguishing between 14 classes of wheat leaf conditions including diseases and insectrelated damage demonstrates its value in supporting agricultural health monitoring. These results not only confirm the technical success of the system but also highlight its potential to aid farmers in early detection and timely treatment, ultimately contributing to improved crop productivity and food security.

XI. LIMITATIONS

The project faced certain limitations that impacted its overall performance and scope. Due to limited time and resources, the dataset used for training contained a relatively small number of images. As a result, the model may not have been exposed to all stages of wheat diseases or to variations caused by different weather conditions. This inherent data scarcity can limit the model's robustness when encountering novel environmental contexts or subtle disease manifestations not present in the training set. Additionally, the model performs best with clear, high-quality images; blurry, lowresolution, or poorly lit images can significantly reduce the accuracy of predictions. Such challenging image conditions are frequently encountered in real-world agricultural settings, posing a practical constraint on the system's immediate applicability. Furthermore, while data augmentation was applied, the initial severe class imbalance for certain diseases could still subtly influence the model's learning bias, potentially affecting its performance on less represented classes in unseen data.

XII. FUTURE WORK

Future enhancements include expanding the dataset with diverse wheat leaf images to improve model accuracy, and incorporating additional disease classes for broader detection. Integration with mobile apps or drone technology can enable real-time, large-scale monitoring. Further improvements may involve explainable AI, multilingual support, ofline functionality, and the use of environmental data for predictive analysis.

XIII. CONCLUSION

This project successfully developed an AI-based tool to detect 14 different wheat leaf conditions, encompassing 11 distinct diseases and 3 insect-related issues. Leveraging a meticulously curated dataset of 20,000 RGB images, the proposed Convolutional Neural Network (CNN) model demonstrated a robust performance, achieving a strong accuracy of 90%. This high level of accuracy showcases the model's reliability and its practical utility in real-world agricultural scenarios, where timely and precise diagnosis is paramount. Key accomplishments of this research include the design and implementation of an accurate and efficient deep learning model capable of multi-class classification for wheat leaf conditions. Furthermore, the development of a userfriendly web interface ensures accessibility, allowing farmers and field workers to easily upload images and receive immediate, actionable disease diagnoses. The system's robustness was thoroughly validated through a comprehensive evaluation process, including manual, unit, functional, integration, and system testing, confirming its ability to handle varying image qualities and multiple user accesses effectively. By enabling early and accurate detection of wheat leaf diseases and pest infestations, this intelligent system empowers farmers to take proactive and timely interventions. Such capabilities are crucial for preventing widespread crop loss, optimizing resource allocation (e.g.,
targeted pesticide application), and ultimately increasing overall wheat yield. This directly contributes to enhanced food security and promotes more sustainable agricultural practices. In conclusion, this project has successfully fulfilled its objectives by delivering a scalable, accessible, and impactful solution that significantly supports agricultural productivity and exemplifies the transformative potential of artificial intelligence in addressing critical challenges in modern farming.

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REFERENCES

Aleryani, A. Y. (2016). Comparative study between data flow diagram and use case diagram. International Journal of Scientific and Research Publications, 6(3), 124–126.

Bui, T., Nguyen, T. T., Nguyen, T. S., Kawarazuka, N., Schreinemachers, P., & Liu, Y. (n.d.). Introducing an agricultural app to urban vegetable farmers: A pilot study in Hanoi.

Boehm, B., & Lane, J. A. (2007). Using the incremental commitment model to integrate system acquisition, systems engineering, and software engineering. CrossTalk, 19(10), 4–9.

Dixit, A., & Nema, S. (2018). Wheat leaf disease detection using machine learning method—a review. Int. J. Comput. Sci. Mob. Comput., 7(5), 124– 129.

Fawakherji, M., McGarvey, B., Rousseau, D., Reyns, P., & Midtiby, H. S. (2021). Wheat spike detection in RGB-D images using semantic segmentation and Hough transform. SoftwareX, 13, 100645.

Figueroa, M., Hammond-Kosack, K. E., & Solomon, P. S. (2018). A review of wheat diseases—a field perspective. Molecular Plant Pathology, 19(6), 1523–1536.

Goguen, J. A., & Linde, C. (1993). Techniques for requirements elicitation. In Proceedings of the IEEE International Symposium on Requirements Engineering (pp. 152–164). IEEE.

Hossain, M. A., & Sajib, M. S. (2019). Classification of image using convolutional neural network (CNN). Global Journal of Computer Science and Technology, 19(2), 13–14.

Reis, H. C., & Turk, V. (2023). Integrated deep learning and ensemble learning model for deep feature-based wheat disease detection. Microchemical Journal, 197, 107545.

Helms, M. M., & Nixon, J. (2010). Exploring SWOT analysis—where are we now? A review of academic research from the last decade. Journal of Strategy and Management, 3(3), 215–251.

Indolia, S., Goswami, A. K., Mishra, S. P., & Asopa, P. (2018). Conceptual understanding of convolutional neural network—a deep learning approach. Procedia Computer Science, 132, 679–688.

Kumar, N., Belhumeur, P. N., Biswas, A., Jacobs, D. W., Kress, W. J., Lopez, I. C., & Soares, J. V. (2012). Leafsnap: A computer vision system for automatic plant species identification. In ECCV 2012 (pp. 502–516). Springer.

Kim, S. H., Wang, Q. H., & Ullrich, J. B. (2012). A comparative study of cyberattacks. Communications of the ACM, 55(3), 66–73.

Mohameth, F., Bingcai, C., & Sada, K. A. (2020). Plant disease detection with deep learning and feature extraction using Plant Village. Journal of Computer and Communications, 8(6), 10–22.

Mandava, M., Vinta, S. R., Ghosh, H., & Rahat, I. S. (2024). Identification and categorization of yellow rust infection in wheat through deep learning techniques. EAI Endorsed Transactions on Internet of Things, 10.

Mensah, G. B., & Dutta, P. K. (2024). Evaluating Ghana's Health Institutions and Facilities Act 2011 for AI risks. Mesopotamian Journal of Artificial Intelligence in Healthcare, 2024, 35–41.

Pequeno, D. N., Ferreira, T. B., Fernandes, J. M., Singh, P. K., Pavan, W., et al. (2024). Production vulnerability to wheat blast disease under climate change. Nature Climate Change, 14(2), 178–183.

Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. SN Computer Science, 2(3), 160.

Sparviero, S. (2019). The case for a socially oriented business model canvas: The social enterprise model canvas. Journal of Social Entrepreneurship, 10(2), 232–251.

Zhou, W., Li, M., & Achal, V. (2024). Environmental and human health impacts of chemical pesticide usage. Emerging Contaminants, 2024(8), 100410.