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Wheat Disease Identification: A Multi-Modal Approach using Deep Learning

By

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A Thesis Submitted to the School of Graduate Studies of Jimma University in Partial Fulfillment for The Degree of Master of Science in Artificial Intelligence.

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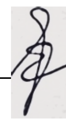
Getachew Mamo (PhD)		June 7, 2024
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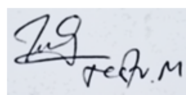
Tesfu Mekonen (MSc)		June 7, 2024
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CERTIFICATION SHEET

We, the thesis research advisors, certify that we have thoroughly reviewed and assessed the thesis titled "**Wheat Disease Identification: A Multi-Modal Approach using Deep Learning**" prepared by **Abdurezak Yisihak Tesfaye** under our guidance. Based on our evaluation, we recommend that the thesis be submitted to fulfill the thesis requirement.

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As members of the board of examiners for the MSc program, we have thoroughly examined **Abdurezak Yisihak Tesfaye's** thesis and evaluated the candidate. Based on our assessment, we certify that the thesis meets the requirements for the degree of Masters of Science in Artificial Intelligence. Therefore, we recommend that the thesis be accepted as fulfilling the thesis requirements for the degree.

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Declaration

I hereby certify that I have submitted my thesis titled " **Wheat Disease Identification: A Multi-Modal Approach using Deep Learning** " to the School of Post-Graduate Studies, Faculty of Computing and Informatics, Jimma Institute of Technology at Jimma University. This thesis is submitted for a partial fulfillment of the requirements for obtaining a Master of Science degree in Artificial Intelligence. I confirm that this work is my original creation and has not been submitted to any other institution for grading or certification.

Abdurezak Yisihak Tesfaye	____________	June 7, 2024
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Abstract

Wheat, as a global staple crop, is vital for food security, yet it remains highly susceptible to various diseases that threaten its yield. Traditional methods of disease identification, which largely rely on visual inspection, are inadequate and often result in misdiagnosis and delayed intervention. This research aims to transform wheat disease detection by developing and implementing an innovative deep learning system that integrates multi-modal data. Our study focuses on four prevalent wheat diseases: Brown Rust, Yellow Rust, Powdery Mildew, and Septoria. By making a hybrid model combining Convolutional Neural Networks (CNNs) for image-based features and Feedforward Neural Networks (FNNs) for environmental variables, we aim to enhance the accuracy of disease identification.

Data collection encompasses RGB images of both healthy and diseased wheat parts alongside crucial environmental data—altitude, temperature, humidity, and precipitation—collected from diverse Ethiopian regions: Holeta (highland), Jimma (midland), and Kemissie (lowland). A Total of 5012 data have been collected, around 3000 of them are different diseased data and the rest healthy and invalid classes data has been collected. This comprehensive dataset allows us to evaluate the hypothesis that "only RGB images are not sufficient for disease identification in AI systems, and that considering environmental factors significantly improves accuracy." Utilizing the Keras Functional API, we integrate these diverse inputs to generate a unified output, showcasing the model's capability to handle complex, multi-modal data. The experimental design breaks down into three main experiments Unimodal with Environmental Data, With Image Data only and Multi-modal data, the results show 98% for Test Accuracy which is better than the unimodal frameworks accuracy, 85.82 % for FNN (Multi-Layer Perceptron) and 94.41 % for CNN architecture.

The Experimental results analysis demonstrates the validation of this hypothesis and the establishment of a robust, adaptive model capable of accurately diagnosing wheat diseases across varied environmental conditions. The findings have the potential to transform current practices in crop disease management, emphasizing the importance of integrating multi-modal data for more reliable and timely interventions. Future works should focus on expanding the dataset to include more diverse environmental conditions and wheat varieties by integrating with IoT. This will enhance the model's generalizability and ensure its applicability across different regions and climates.

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Acronym

ADAM	Adaptive Moment Estimation
AI	Artificial Intelligence
ANN	Artificial Neural Networks
BCE	Binary Cross Entropy
CCE	Categorical Cross Entropy
CNN	Convolutional Neural Network
FAO	Food and Agriculture Organization
FNN	Feed Forward Neural Network
GPU	Graphical Processing Unit
IDE	Integrated Development Environment
JPEG	Joint Photographers Expert Groups
MIL	Multiple instance learning
MLP	Multi-Layer Perceptron
PCR	Polymerase Chain Reaction
ReLu	Rectified Linear Unit
RGB	Red, Green, Blue
RNN	Recurrent Neural Network
SCCE	Sparse Categorical Cross Entropy
UHD	Ultra High Definition
VGG	Visual Geometry Group
WSMV	Wheat streak mosaic virus

1. Introduction

1.1 Background

Agriculture is crucial due to its significant economic impact, especially in developing nations. The rising population and decreasing food supplies have caused an exponential increase in food demand. Staples like wheat, maize, and rice are essential, but crop diseases severely affect their quality and yield. These diseases are a primary cause of crop loss, impacting both large and small-scale farmers. Notably, small-scale farmers in developing countries contribute up to 80% of global crop yields, yet they suffer from higher food losses due to limited access to resources and modern technology, making early disease detection and control challenging[1]. The World Health Organization (WHO) reports that over a hundred diseases stem from contaminated food, resulting in about 600 million illnesses and 0.4 million deaths annually. Additionally, farmers lack efficient methods for timely disease diagnosis. Therefore, implementing precision agriculture can enhance crop quality and yield [1]. Often referred to as the foundation of global food security, agriculture is essential to maintaining a steady supply of food to fulfil the rising demands of a world population that is only becoming bigger. The yield and health of the crops—where even small disruptions can have significant effects—are crucial to this endeavor.

Similar to humans, plants are vulnerable to various diseases during different phenophases. As a result, overall crop yield and farmers' net profit can be significantly impacted. To mitigate this issue, early detection of plant diseases is essential. Traditionally, manual disease detection is performed by farmers or agricultural scientists [2].However, the traditional approaches used to diagnose and treat wheat illnesses have long been burdened by intrinsic shortcomings. The most important of these is the use of human visual examination, which is a labor-intensive, erroneous, and inherently subjective method. Because many illnesses share similar visual traits and nuanced details, visual analysis of wheat leaves for disease symptoms is typically inadequate. Due to this innate complexity, it is still difficult to accurately identify diseases and to intervene in a timely manner, and there is still a significant risk of significant crop output losses. It is absolutely necessary to develop a more accurate and efficient method of disease identification.

One crucial element that has frequently been ignored in the effort to solve these issues is the impact of environmental factors on the onset of disease. Wheat diseases grow in an ecosystem that is dynamically shaped by temperature, humidity, altitude, and weather patterns. These factors, which are frequently disregarded or undervalued, are crucial to the onset of disease. The fate of wheat harvests is determined by the intricate interactions between various environmental variables. Therefore, the development of a comprehensive system for detecting wheat diseases must hinge on the incorporation of these parameters in addition to conventional visual data. By doing this, we open the door to a deeper comprehension of disease dynamics and the development of a more precise, comprehensive, and robust strategy for the control of wheat diseases.

The advent of computer vision has revolutionized various fields, including agriculture, where it is increasingly used for plant disease detection. Computer vision improves algorithms and models to interpret and understand visual information from the world, enabling machines to identify, classify, and respond to objects within their environment. This technology has been particularly transformative in precision agriculture, where it aids in monitoring crop health, detecting diseases early, and optimizing resource use.

AI holds great significance for its ability to potentially transform our daily lives, professional endeavors, and recreational activities. It has proven to be highly beneficial in the business sector by automating various human tasks such as customer service operations, lead generation, fraud detection, and quality assurance. In numerous domains, AI has demonstrated superior performance compared to humans in task execution [3]. Agricultural AI is one of the crucial Application for better production of crops and it supports farmers to get a better yield on their farmland.

Plant disease detection using computer vision involves the application of image processing and machine learning techniques to analyze images of plants and identify symptoms of diseases. Traditional methods of plant disease detection rely heavily on visual inspection by experts, which can be time-consuming, labor-intensive, and subjective. With computer vision, large-scale and real-time monitoring of crop health becomes feasible, providing a more efficient and accurate alternative [4].

Recent advancements in deep learning, a subset of machine learning, have further enhanced the capabilities of computer vision in plant disease detection. CNNs, in particular, have shown remarkable success in image classification tasks. By training on large datasets of plant images, CNNs can learn to recognize complex patterns associated with different diseases, achieving high accuracy in diagnosis. Studies have demonstrated the effectiveness of CNN-based models in identifying various plant diseases, such as leaf blight, rust, and mildew, with significant accuracy [5].

In addition to CNNs, integrating multi-modal data, which includes not only visual information but also environmental data such as temperature, humidity, and soil conditions, has been shown to improve the robustness and accuracy of plant disease detection systems. This multi-modal approach can provide a more comprehensive understanding of the factors affecting plant health and disease proliferation [6].

As the global population continues to grow, the demand for food production increases, making efficient and effective plant disease management more critical than ever. Computer vision and deep learning technologies offer promising solutions to meet these challenges by enabling early disease detection, reducing crop losses, and ensuring food security. This research aims to develop and implement an innovative and comprehensive wheat disease detection system utilizing deep learning techniques and the integration of multi-modal data, contributing to the advancement of precision agriculture.

1.2 Motivation

This study is motivated by the critical need to address the difficulties encountered in identifying and managing wheat diseases in agricultural systems. Wheat is a fundamental agricultural crop that is grown and consumed extensively around the globe, serving as a crucial component in ensuring global food security. Nevertheless, the high occurrence of diseases poses a significant danger to wheat production, resulting in considerable reductions in crop output and economic consequences. Conventional approaches to illness detection, which heavily rely on human visual examination, are often insufficient and susceptible to mistakes [4]. Furthermore, these approaches fail to consider the substantial impact of environmental variables on the incidence of diseases, hence impeding the development of effective strategies for illness management [5].

Recent research has investigated the use of artificial intelligence (AI) and machine learning techniques to identify and diagnose plant diseases. As an example, [4] examined the capability of digital image processing methods in identifying and measuring plant illnesses [4]. Similarly, [5] showed the use of deep neural networks for the categorization of plant diseases using leaf pictures [5]. Nevertheless, these studies often concentrate only on imaging data and neglect to include environmental elements, which are crucial for precise illness diagnosis and prediction [6]. This constraint is noteworthy because environmental factors, such as temperature, humidity, and precipitation, have a crucial impact on the growth and transmission of plant diseases [7].

The emergence of AI and machine learning provides a significant chance to completely change the way we diagnose and control wheat diseases. By leveraging the power of modern computational approaches, it is feasible to design creative solutions that solve the limits of existing methods. Integrating multi-modal data, including RGB photographs and environmental factors, gives a comprehensive approach to illness identification. This technique not only boosts the accuracy and reliability of illness detection but also allows the construction of prediction models that reflect the intricate interaction between visual symptoms and environmental factors [8].

Furthermore, the potential effect of this discovery goes beyond agricultural output to larger social advantages. By strengthening wheat disease management procedures, we contribute to global food security initiatives, providing a stable and adequate food supply for communities globally. Additionally, the development of AI-based solutions for crop health monitoring establishes a precedent for harnessing technology to solve important concerns in agriculture. Through this study, we strive to enhance scientific knowledge, empower agricultural communities with new tools, and pave the road for sustainable and resilient agricultural systems in the face of growing environmental and social demands.

1.3 Statement of the Problem

Examining the drawbacks of depending just on RGB images of wheat leaves makes the shortcomings of traditional methods for diagnosing wheat diseases quite clear. These techniques, which are based on human visual inspection, have a variety of issues that make them less successful. The possibility of misdiagnosis is one of the main problems because many wheat disorders have subtle symptoms that are simple to miss with the naked eye. Such incorrect diagnoses have serious consequences, including delaying disease intervention and giving diseases more time to establish a stronger hold on crops. As a result, the delay may cause significant crop damage, lowering production and affecting food security.

In a country like Ethiopia, with different climate zone and altitudinal topography a number of different diseases have great chance to spread around the farm lands. And it is difficult to identify some disease with visual inspection or image-based identification. In this case there is a great probability to misclassify and negatively identify diseases correctly. As the diseases happen in different environmental conditions diseases that happen in high altitude will not have the chance to happen in low altitude so just simply taking a picture of these diseases or trying to inspect them visually will lead to erroneous predictions. It will be a good practice to identify the location of farm lard from altitude perspective and considering other environmental factors will have a potential to identify the disease correctly. We try to analyze the effect of including this Environmental Factors in this research. This is a great gap in the disease identification system and research to miss including environmental factors.

Most of the current studies on plant disease detection depend mainly on unimodal data, specifically utilizing CNN to analyze plant leaf images. While these methods have demonstrated impressive precision under controlled conditions, they sometimes ignore the unpredictable nature of real-world situations and the complex relationship between plant health and environmental elements.

Recent reviews have emphasized the efficiency of CNN models such as AlexNet, VGG, ResNet, and DenseNet in accurately identifying plant diseases solely by analyzing plant images. These models have shown amazing results, sometimes surpassing 98% accuracy under specific situations. However, they typically require large, high-quality datasets and may struggle with generalization to new environments or different disease symptoms that were not well-represented in the training data [28][29].

Despite these advancements, there remains a significant research gap in integrating multimodal data to enhance the robustness and accuracy of plant disease diagnosis systems. Current methodologies often overlook environmental factors such as temperature, humidity, and precipitation, which can significantly influence disease manifestation and progression. Integrating these factors with visual data can provide a more holistic understanding of plant health and improve disease detection accuracy in diverse agricultural settings [28][29].

This gap indicates the need for comprehensive research that combines both image-based analysis and environmental data to develop more reliable and applicable plant disease detection systems. By addressing this gap, our research can contribute to more resilient agricultural practices and better support for farmers in managing crop health.

It's becoming evident that taking into account a wider range of data than just RGB images can greatly increase the breadth of disease diagnosis. Although there is no denying the importance of visual signs, their capacity to convey the more specific details of disease symptoms is naturally restricted. Our study emphasizes the importance of incorporating additional data sources, especially environmental factors, in order to overcome this constraint. Through the integration of standard RGB images with data on altitude, temperature, humidity, and weather patterns, we might potentially achieve a more thorough understanding of the complex network of elements impacting the development of disease.

Research questions that would be answered at the end of the research are:

- Which deep learning architecture, a Multi-modal architecture with image and environmental data or Uni-modal nature of architecture with image proves most effective for the identification of wheat disease data?
- To what extent does the integration of environmental factors enhance the accuracy and efficiency of wheat disease detection compared to models using only images?
- What are the key differences in terms of technique between the proposed multi-modal data integration approach and traditional methods that rely solely on RGB images?

1.4 Objectives

1.4.1 General Objectives

The general objective of this research is to develop a multi-modal wheat disease detection system using deep learning techniques.

1.4.2 Specific Objectives

- To develop a Mobile App for the systematic collection of multi-modal data
- To curate a diverse and representative dataset for training and validating the deep learning model
- To explore and select an optimal deep learning architecture for disease detection
- To train a deep learning model for wheat disease identification
- To evaluate the impact of multi-modal data integration on disease detection accuracy

1.5 Scope and Limitation

The scope of the proposed study, delineates the boundaries and parameters within which the research will be conducted. This scope encompasses the geographical, temporal, and thematic dimensions of the study, providing a clear framework for the research endeavors:

The study will primarily focus on wheat crops in specific regions of Ethiopia, including but not limited to Holeta, Jimma, and Wollo. These regions have been selected for their diverse altitudes, representing highland, midland, and lowland areas, respectively. This geographical diversity ensures a comprehensive exploration of the impact of environmental factors on wheat disease occurrence across varied ecological conditions. While the initial focus is on these regions, the research methodology and insights gained may be adaptable to other geographical contexts, thereby enhancing the potential for broader applicability.

The research will unfold over a specified timeframe, including the development and implementation of the custom-developed Mobile App, dataset curation, model training and validation, and the evaluation of the wheat disease detection system in real-world conditions. The temporal scope is designed to ensure a systematic and thorough investigation while adhering to the practical constraints of the research timeline. The study aims for efficiency without compromising the depth of analysis, contributing to timely advancements in the field of wheat disease detection.

The thematic scope encompasses the integration of multi-modal data for wheat disease detection, with a specific focus on RGB images and environmental factors such as altitude, temperature, humidity, and weather patterns. The study explores various deep learning architectures, emphasizing the combination of CNN with FNN. The overarching theme revolves around addressing the limitations of traditional methods by developing a comprehensive wheat disease detection system. The study will not only strive for advancements in technology but also consider the practical implications, user experience, and potential scalability of the developed system.

1.5.1 Limitations

While the study aspires to be comprehensive, certain limitations exist within the scope. The geographical focus is initially confined to specific regions in Ethiopia, and extrapolation to other global contexts will require further validation. For this research It is only focused to work on wheat disease especially different rust types. Additionally, the study acknowledges the dynamic nature of environmental factors and aims to capture their influence within the selected timeframe, recognizing that on site sensor-based data collection long-term ecological trends may necessitate ongoing research.

1.6 Significance of the study

The study is a major advancement in the field of agriculture. With the introduction of a novel system that combines RGB images with important environmental variables, the study aims to replace traditional methods to wheat disease identification. The innovation offers a more advanced and precise toolkit to handle the complexity of disease monitoring and control, which has great potential for farmers and agricultural practitioners.Since wheat is an essential staple crop, every advancement in the diagnosis of diseases has an immediate effect on the stability of global food supplies. More accurate crop management is a result of the comprehensive wheat disease detection system's higher accuracy. With accurate disease detection, farmers may now carry out focused interventions that improve resource allocation and support estimates of total crop output. Thus, these developments contribute to global food security by guaranteeing a consistent and dependable supply of wheat. Beyond its immediate applications, the research advances our knowledge of wheat disease and their complex relationships with environmental variables. Plant pathology, agricultural technology, and sustainable agricultural practices will all benefit from the research's dual emphasis on scientific contribution and practical application. The study's methodology's potential adaptability to other crops and geographical areas emphasizes how important it is in influencing the development of contemporary agriculture.

1.7 Thesis organization

This research comprises five chapters. Chapter one includes the introduction, motivation, statement of the problem, objective of the study, scope, and limitation of the study, and significance of the study. Chapter two covers Crop Diseases, an introduction to Wheat Diseases, digital image processing, a deep learning approach discussion. Chapter three summery of and related works, Chapter four details the material and methods, including research design, proposed system architecture, data collection and corpus preparation, developmental tools, feature extraction, classification, model training, and evaluation metrics. Chapter five analyzes the results and discussion of our experiment with an overview of the chapter, dataset and experimental design, and a comprehensive discussion of the experiments. Chapter six concludes our research with a summary of our findings and recommendations for future studies.

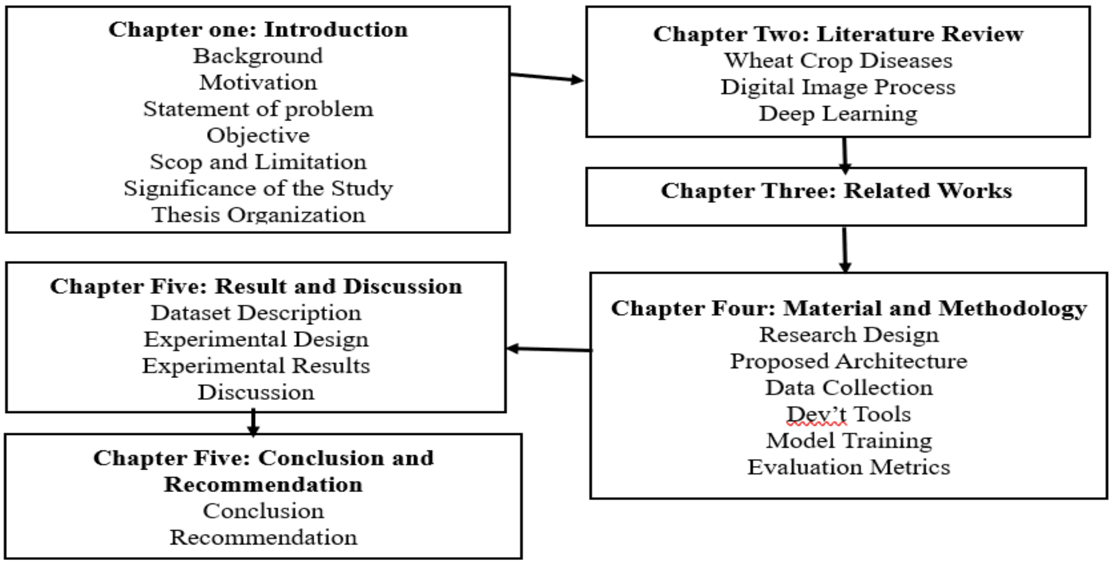


Figure 1: Organization of the thesis

2. Literature Review

2.1 Overview

Wheat is a crucial staple grain globally, serving as the leading source of calories and plant-derived protein in human food. The document highlights the substantial production of 735 million tons in 2015/2016, emphasizing wheat's economic significance and the urgent need for increased production to meet future demands due to population growth and dietary changes [9]. However, wheat is susceptible to numerous diseases that can severely impact yield and quality. Understanding these diseases, their causes, and how to diagnose them is essential for effective management and control [9].

Wheat diseases can be broadly classified into fungal, bacterial, and viral types. Common fungal diseases include Brown Rust (Leaf Rust), caused by *Puccinia triticina*, which manifests as orange-brown pustules on leaves. Another significant fungal disease is Stripe Rust (Yellow Rust), caused by *Puccinia striiformis*, recognizable by yellow pustules arranged in stripes on leaves. Septoria tritici blotch, caused by *Zymoseptoria tritici*, presents as necrotic lesions with black pycnidia. Powdery mildew, caused by *Blumeria graminis*, shows as white, powdery fungal growth on the leaf surface [9].

Bacterial diseases, though less common, can also affect wheat. Bacterial leaf streak, caused by *Xanthomonas translucens*, presents as water-soaked streaks that turn brown. Viral diseases like Wheat streak mosaic, caused by the Wheat streak mosaic virus (WSMV), exhibit symptoms of yellow streaks and mottling on leaves, leading to stunted growth [10].

Diagnosis of these diseases involves visual inspection, molecular techniques, and advancements in digital imaging. Visual inspection remains the first step, identifying symptoms like color changes and lesion patterns. Molecular techniques such as Polymerase Chain Reaction (PCR) can detect specific pathogens at the DNA level, providing accurate identification. Digital imaging and artificial intelligence (AI) are emerging as powerful tools for disease diagnosis, allowing for the analysis of leaf images to identify disease presence and type with high accuracy [11].

According to [9] the wheat disease related to this research are summarized with table below.

Table 1: Causes, symptoms and Impact on Yield of different wheat disease

Disease	Causes	Symptoms	Occurrence	Impact on Yield
Brown Rust (Leaf Rust)	*Puccinia triticina*	Small, circular to oval orange-brown pustules on leaves	Temperate wheat-growing regions	Moderate to severe, depending on resistance
Stripe Rust (Yellow Rust)	*Puccinia striiformis*	Yellow to orange-yellow pustules in stripes on leaves	Cooler regions, higher altitudes	Severe in susceptible varieties
Septoria	*Zymoseptoria tritici*	Chlorotic lesions with black pycnidia, necrotic streaks	Worldwide, especially in wet climates	Can be severe, causing up to 50% yield loss
Powdery Mildew	*Blumeria graminis*	White powdery spots on leaves, stems, and heads	Worldwide, particularly in dry climates	Moderate to severe
Healthy Wheat	N/A	Healthy green leaves and stems	N/A	Optimal yield

The relationship of each disease with the common environmental conditions according to [9] also summarized as follow

Table 2:Environmental Factors Related to different diseases

Disease	Altitude	Temperature	Humidity	Precipitation
Brown Rust (Leaf Rust)	Low to High	10-25°C	Moderate to High	200-500 mm
Stripe Rust (Yellow Rust)	High	0-15°C	High	300-600 mm
Septoria	Low to High	10-25°C	High	400-700 mm
Powdery Mildew	Low to High	15-20°C	Low to Moderate	100-300 mm
Healthy Wheat	Low to High	10-25°C	Moderate	200-500 mm

2.1 Techniques for Identifying Wheat Diseases

A vital staple crop in every country, wheat is susceptible to a number of illnesses that reduce agricultural production. In the past, diagnosing diseases was primarily done by visual inspection, which is a laborious, subjective, and error-prone approach. With automated and precise methods, recent developments in computer vision and machine learning have completely changed the area [9].

Visual Inspection and Symptom Identification

Traditional methods for identifying wheat diseases primarily rely on visual inspection and symptom identification. This involves observing the characteristic signs of diseases, such as rust pustules, mildew patches, and blight lesions, on different parts of the wheat plant. While this method is cost-effective and straightforward, it can be subjective and dependent on the expertise of the observer. For instance, Brown Rust is identified by small, orange-brown pustules on the leaves, while Powdery Mildew appears as white, powdery growth on leaf surfaces and stems [9][12].

Microscopic Examination

Microscopic examination is another traditional technique that involves studying fungal structures and spores to diagnose wheat diseases. This method provides more accuracy compared to visual inspection. For example, identifying the pycnidia of Septoria Leaf Blotch or the conidia of Powdery Mildew under a microscope can confirm the presence of these pathogens. However, this approach requires specialized equipment and technical expertise, which may not always be available in field conditions [12][13].

Remote Sensing and Imaging Technologies

Recent advancements in remote sensing and imaging technologies have introduced new methods for large-scale monitoring of wheat diseases. Multispectral and hyperspectral imaging, often conducted using drones or satellites, can detect disease symptoms and stress conditions from aerial images. These technologies analyze the reflectance patterns of wheat plants in different spectral bands to identify diseases such as Yellow Rust and Septoria Leaf Blotch. Remote sensing allows for comprehensive and real-time monitoring of vast agricultural areas, enhancing early detection and management of diseases [14][15].

Machine Learning and Artificial Intelligence

Machine learning and artificial intelligence (AI) are increasingly being integrated into disease detection systems. These technologies analyze large datasets of images and environmental data to identify patterns and predict disease outbreaks. For example, deep learning models trained on annotated images of diseased wheat can automatically classify different diseases with high accuracy. AI-powered systems can also integrate environmental factors, such as humidity and temperature, to improve the robustness of disease predictions. This approach is promising for developing scalable and automated disease management solutions [15][16].

2.2 AI in Agriculture

With its potential to improve crop management, disease detection, and yield prediction, artificial intelligence (AI) is becoming a disruptive force in the field. AI, especially machine learning algorithms, is essential to automating the diagnosis of plant diseases. To find trends in disease, these algorithms examine huge datasets that include environmental data and imaging data.

Machine learning methods were used to detect wheat rust illnesses early in the work of S. Gupta et al. (2020). The study demonstrated how AI can be used to identify diseases early and proactively, leading to proactive disease management approaches.

AI has played a key role in the development of precision agriculture, which uses sensors and drones to gather data for in-the-moment monitoring. This data-driven strategy improves overall agricultural efficiency and allocates resources optimally.

A study was presented by R. Zhang and colleagues (2018), who showed how to incorporate AI-based technology for precision farming. Their research demonstrated the advantages of using data to inform decisions while trying to maximize crop productivity and resource use.

Because wheat diseases are caused by a complicated combination of factors, researchers are focusing more and more on integrating multi-modal data, such as visual and environmental characteristics. Combining spectral and visual data offers a thorough understanding of plant health.

Research has demonstrated that the accuracy of illness identification can be increased by combining spectral information, such as hyperspectral imaging, with RGB images.

In order to identify wheat diseases, M. Hasan et al. (2021) investigated the merging of RGB pictures and hyperspectral data. The research illustrated how multi-modal data might work in concert to improve the model's capacity to distinguish between various illnesses.

A number of environmental elements, such as humidity, temperature, and weather patterns, have a big impact on how often diseases develop. A more comprehensive knowledge of disease dynamics is facilitated by the incorporation of these components into disease models.

In 2019, P. Sharma et al looked into how environmental conditions affect wheat illnesses. The researchers found a relationship between disease occurrence and weather by including meteorological data in their model.

In conclusion, the literature review emphasizes the development of techniques for identifying wheat diseases, the revolutionary potential of artificial intelligence in agriculture, and the new development of multi-modal data integration. Together, these domains aid in the creation of sophisticated, all-encompassing methods for the treatment of wheat diseases. Existing research, however, suggests that more investigation is required to fully integrate a variety of environmental aspects and create generalized models that can be used in a variety of geographic contexts. In order to close these gaps, our suggested study, would investigate how environmental elements can be integrated and create a model that is adaptable to different regions.

3. Related Work

Developing efficient wheat disease detection systems is of paramount importance due to the critical role wheat plays in global food security. Effective detection and management of wheat diseases can significantly mitigate yield losses and economic impacts. With the advent of machine learning, numerous innovative approaches have been proposed to enhance the accuracy and reliability of disease diagnosis.

One notable study in this domain is the [20], which integrates visual and environmental data to diagnose rice diseases. This framework combines outputs from CNN and Multi-Layer Perceptron (MLP) architectures, achieving an impressive accuracy of 95.31%. The multimodal integration enhances the robustness and fault-tolerance of the system, making it practical for real-time field conditions. However, the model's effectiveness is highly dependent on a large and balanced dataset, and the system requires further development for full application.

In another significant contribution, researchers introduced an in-field automatic wheat disease diagnosis system using deep multiple instance learning (MIL). This system employs fully convolutional networks (FCNs) to integrate disease identification and localization using image-level annotations. With the Wheat Disease Database 2017 (WDD2017) dataset, the system achieved mean recognition accuracies of 97.95% and 95.12% for different architectures, outperforming conventional CNN frameworks. Despite its high accuracy and effective localization under variable field conditions, the system's performance is heavily reliant on the quality and quantity of training data.

A deep learning-based methodology focusing on the classification of wheat diseases in leaves and spikes [23] was proposed by another research group. Utilizing the LWDCD2020 dataset, this study employed a deep CNN architecture to achieve a high testing accuracy of 97.88%. The model demonstrated good performance across various disease categories, but faced challenges with overfitting and dependency on high-quality image data. Even though it achieves high testing accuracy it is not robust in different geographic location specially when the visual data is not strong enough to predict in real-time disease detection.

The study by [24], explored the identification of wheat fungal diseases using the EfficientNet architecture. With a dataset of 2414 labeled images, the system achieved a recognition accuracy of

94.2%. Implemented as a chatbot on the Telegram platform, this system provided a practical field tool for disease assessment. However, the need for a large volume of labeled images and the difficulty in classifying multiple diseases simultaneously were noted as challenges.

Finally, [25] focused on the spatio-temporal monitoring of wheat yellow rust using UAV multispectral imagery. By capturing time-series images, this study analyzed disease progression through various growth stages. The use of different spectral bands and indices proved effective at different stages, with the NDVI index showing high statistical dependency during disease stages. However, the study's reliance on UAV-based remote sensing may not be feasible for all agricultural settings due to cost and operational complexities.

Despite significant advancements in wheat disease detection systems, several limitations remain across the studies reviewed. Many of the proposed models, including the [20], rely heavily on large and balanced datasets for effective training. Collecting such datasets can be challenging and resource-intensive, potentially limiting the applicability of these models in diverse agricultural settings. Additionally, the issue of overfitting is prevalent in deep learning models, as seen in the CNN-based methodologies for wheat disease classification. Despite employing techniques like dropout and regularization, these models can still overfit, especially when trained on small datasets. This can affect their performance when deployed in real-world scenarios where data conditions vary significantly.

Partial automation is another common limitation. For instance, the Rice-Fusion framework requires further development to achieve full automation [20]. Fully automated systems would be more practical for widespread agricultural use, reducing the need for manual intervention and improving efficiency. Moreover, the performance of [21] and other similar models is heavily dependent on the quality and quantity of training data. High-quality, annotated images are essential for these models to achieve high accuracy, which can be a bottleneck in their development and deployment. In such cases considering environmental data will provide a realistic result by completing the missing qualities of the image data from other environmental data that will be easier for the model to make a decision.

Accurate identification of wheat diseases is essential to sustaining worldwide food security. However, existing diagnostic techniques, such as images, mostly depend on single-mode data. This particular methodology often needs to be revised to understand the complex relationship between wheat health and environmental variables, such as temperature, humidity, and precipitation. Therefore, it results in inadequate accuracy in detecting problems. The research challenge aims to develop a more advanced and reliable wheat disease detection system that combines visual information from images with essential environmental elements, to enhance its robustness and accuracy. The main focus of this proposed method is to optimize the diagnostic process by offering an extensive understanding of the factors impacting the health of wheat. The end goal is to improve prevention of diseases and maximize crop yields.

Specificity is another concern. Some models, such as [20], may need adaptation for broader applications in other crops. This specificity can limit the generalizability of the models, requiring additional research and customization to apply the techniques to different agricultural contexts. Addressing these limitations through future research and development will be crucial for creating more robust, scalable, and universally applicable systems for agricultural disease detection, thereby contributing to enhanced global food security.

4.Material and Methods

4.1 Overview

This study aims to diagnosis wheat crop disease by using deep learning algorithm that encompasses both visual (image) and environmental data (Number), specifically using both CNN and FNN using keras functional API. In order to achieve the research objectives, the following methodologies have been used for the Entire research.

4.2 Research Design

A research design is a framework used to conduct a research study. It outlines the approach and methods used to collect and analyze data to answer research questions or test hypotheses. A good research study has a clear research question, a detailed plan for data collection, and a method for analyzing and interpreting results. A well-planned research design addresses all these features. A research design includes the following elements: clear goal-directed, sampling, data collection, data analysis, methodology, timeframe, ethical considerations, and resources. For a scientifically rigorous study to produce reliable, valid, neutral, and generalizable results, a well-planned research design is essential. Nevertheless, some degree of flexibility should be allowed [17].Accordingly, this study is experimental research, which falls under the quantitative research category. The research design of this study is depicted in the following Figure

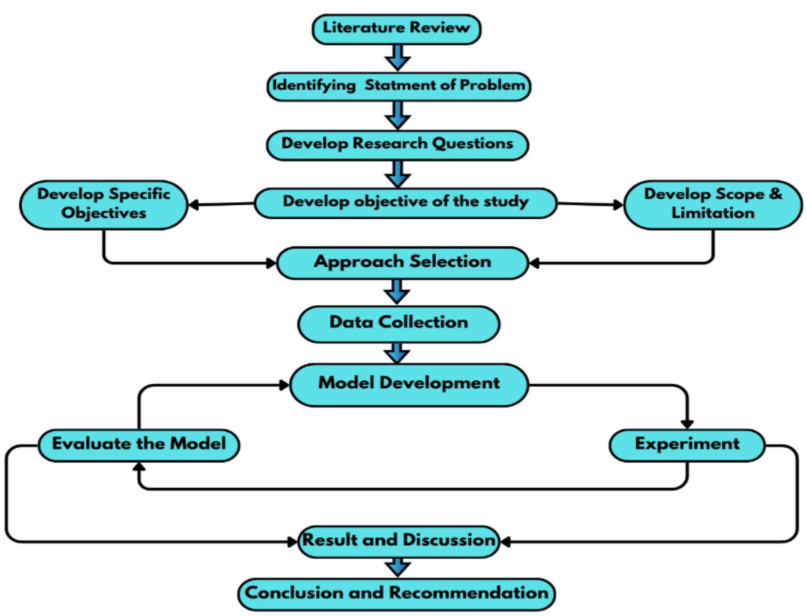


Figure 2: Research Design Diagram

To understand the area and identify the gap additional research has been conducted by the researcher. After checking different papers, it was discovered that no research has been carried out on the wheat diseases detection that encompasses on multi-modal using deep learning approaches.

As agriculture is the main revenue source and dominant for Ethiopian economy it is crucial to support with technology. Crop disease is more concerning on the production. And the production loss happened on different crop farm lands is not simple. Wheat is the basic and important crop all over the world also the crop loss is not simple. In a country like Ethiopia with different environmental condition Conducting such kinds of research is important to maximize crop production. As a researcher, the top priority problem has been considered that needs to be addressed. After analyzing the problem, the researcher has formulated research questions and established the objective and scope of the study. This study relies heavily on experimental research, making data collection crucial to its success. Before the data collection has been started, selecting an approach for feature extraction is a crucial step. Following this, the collection and preparation of the corpus has been completed, the next was selecting an approach for feature extraction.

Depending on different factors more than one deep learning approach was needed to achieve the research objective. As the research incorporates both the visual image data and additional environmental data both CNN and ANN approaches are used in this research in order to get the best result as a multi modal hybrid model data. After getting the model it has been tested with different parameters and each result were analyzed and evaluated carefully to ensure the accurate result. This research is quantitative in nature, focusing on the systematic collection and analysis of numerical data to achieve its objectives. It involves gathering images of wheat plants and detailed environmental data. These data sets are then preprocessed and used to train advanced machine learning models, such as Convolutional Neural Networks (CNNs) and Multilayer Perceptrons (MLPs). The study employs various quantitative techniques to tune hyperparameters and optimize model performance. Controlled experiments are conducted to evaluate these models using quantitative metrics like accuracy, precision, recall, F1-score, and confusion matrix analysis. The research also involves statistical analysis to validate the results, ensuring a robust, data-driven approach to improving wheat disease detection and providing actionable recommendations. The final result of these research was explained well in the discussion section. Further recommendation and result conclusions also detailed under the conclusion section.

4.3 Proposed Solution

The proposed solution a model for wheat disease detection, that uses multi-modal data. By incorporating diverse information sources such as RGB images and environmental factors including temperature, humidity, and precipitation, the holistic approach seeks to provide a more nuanced understanding of the complex interplay between wheat health and environmental conditions. This comprehensive strategy acknowledges the limitations of traditional methods that rely solely on visual cues, recognizing that environmental factors play a crucial role in influencing disease occurrence.

Moreover, the emphasis on advanced machine learning techniques reflects a commitment to harnessing the full potential of artificial intelligence in agriculture. The integration of CNN for image-based features and FNNs for environmental parameters signifies a sophisticated modeling approach. The infusion of regional adaptability acknowledges the inherent variability in environmental conditions across different wheat cultivation areas, ensuring that the proposed solution is not a one-size-fits-all model. This adaptability is crucial for the successful deployment and effectiveness of the system in diverse agricultural landscapes, ultimately contributing to more resilient and accurate wheat disease detection strategies.

4.3.1 Deep Learning Architecture

The proposed deep learning architecture for wheat disease detection adopts a pioneering approach by integrating CNN and FNNs into a hybrid model. This design is motivated by the recognition that a comprehensive understanding of wheat health requires the simultaneous consideration of both visual symptoms captured in RGB images and the nuanced environmental influences encapsulated in temperature, humidity, and precipitation data.

The CNN form the visual processing arm of the model, specializing in extracting intricate features from the RGB images. CNNs are particularly adept at discerning complex patterns and hierarchical representations within visual data, making them well-suited for identifying subtle visual symptoms indicative of various wheat diseases.

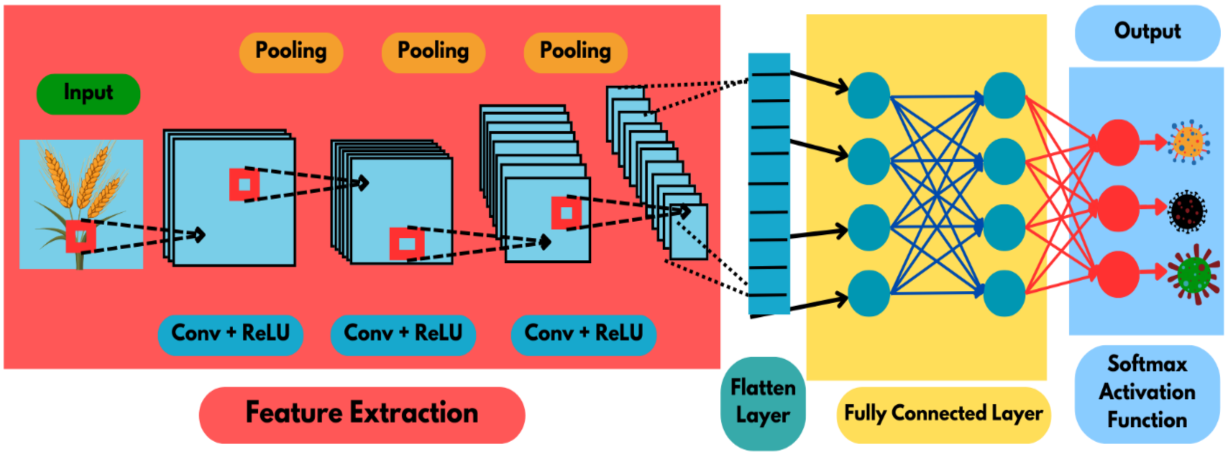


Figure 3: General Scheme of CNN Architecture

This image-based processing ensures that the model can effectively capture the diverse visual manifestations of diseases across different wheat crops.

Complementing the CNNs, the FNN or Multi-Layer Perceptron (MLP) constitute the environmental processing component. FNNs are employed to handle the environmental variables such as temperature, humidity, and precipitation, recognizing their importance in influencing disease occurrence. FNNs are well-suited for handling structured data and can effectively capture the intricate relationships and dependencies within the environmental factors. The integration of FNNs ensures that the model not only identifies visual symptoms but also comprehensively considers the broader context of the wheat crop's environmental conditions.

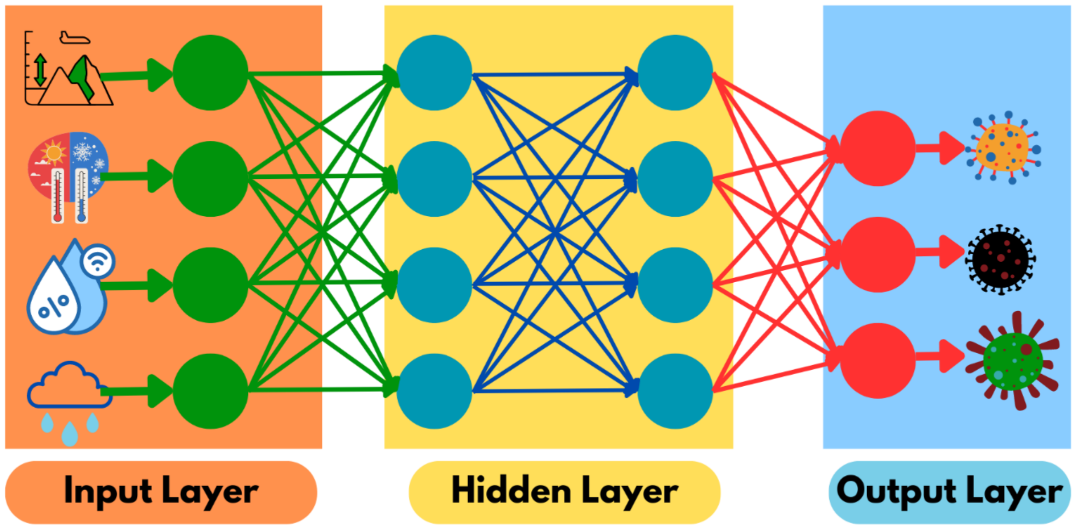


Figure 4: General Scheme FNN Architecture

The synergy achieved through the hybridization of CNNs and FNNs is pivotal for creating a model that transcends the limitations of unimodal approaches. This architecture aims to provide a holistic understanding of wheat diseases by seamlessly blending information from diverse sources, ultimately leading to a more accurate and robust wheat disease detection system with the potential to revolutionize crop management strategies in agriculture.

4.3.2 Regional Adaptability

The concept of regional adaptability in this research involves tailoring the wheat disease detection model to effectively respond to the unique environmental conditions present in different geographical areas. Geospatial analysis forms a foundational aspect of this adaptation strategy. By integrating geospatial information, the model gains insights into the specific environmental characteristics of various regions. This includes factors such as altitude, topography, and climate variations, which significantly impact the prevalence of wheat diseases. Geospatial analysis allows the model to discern region-specific patterns, creating a more nuanced understanding of the environmental context in which the crops are cultivated.

To facilitate this adaptability, the research emphasizes the collection and incorporation of localized training data. This means gathering information from a diverse range of geographical settings and encompassing various climates. The model learns from this varied dataset, enabling it to adapt to the distinct challenges posed by different regions. For instance, wheat crops in high-altitude areas might face different disease risks compared to those in lowland regions. By incorporating data from diverse locations, the model becomes more adept at recognizing region-specific disease symptoms and understanding how environmental conditions influence the overall health of the crops. This localized approach enhances the model's versatility, ensuring its effectiveness across a broad spectrum of agricultural landscapes.

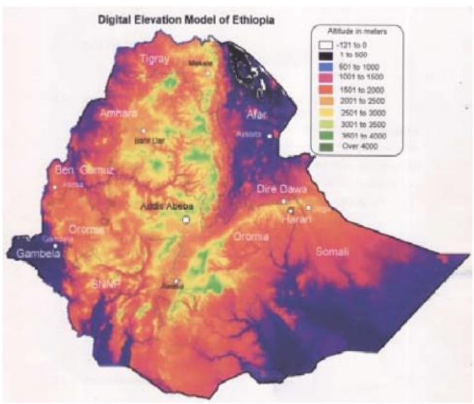
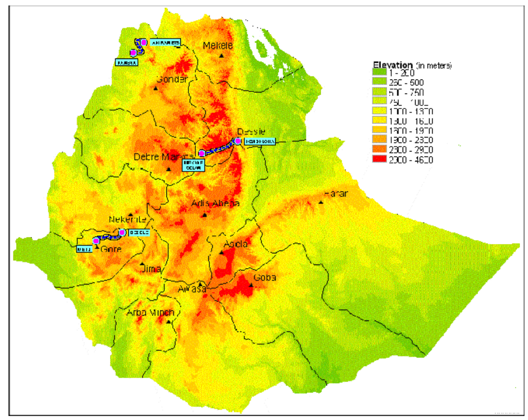


Figure 5: Different Elevation Maps of Ethiopia



4.4 Data Collection

Data collection is the most prominent step to achieve the objective of the research. For the achievement of this research work images of the wheat crop were the main requirement for wheat disease identification. As the research is experimental research data set is highly required to work on the experiments and analyze results.

The image has been collected by capturing images of a wheat leaf and stem which are affected by different wheat diseases, from different agricultural sectors and also other important images from online. To collect this data three different elevation regions were selected as Highland, Middle land, and low land Crop Cultivation Areas.

The total of 5012 images has been collected from different location of Ethiopia, More from Amhara and Oromia regions. Specifically, the highland wheat data from Holeta, The Middle land data from Jimma Zone, and Low land from Wollo Area near the border of Afar Regions. The distribution of the data set based on the location are 1100 from highland, 1129 middle land, 1220 lowland. 1563 data for not wheat (invalid) class is from online datasets. The makes the data more reliable in terms of the environmental differences. After collecting the data sets, the data has been reviewed with the help of pathologist to classify and differentiate in to different disease classes as Brown Rust, Yellow Rust, Mildew, Septoria, and Healthy. The information about the collected classes of diseases is as shown below in the table 3.

Table 3: Size of Different Disease Class Dataset

No	Class	Collected image	Format
1	Brown Rust	902	JPG
2	Yellow Rust	1132	JPG
3	Septoria	97	JPG
4	Powdery Mildew	100	JPG
5	Healthy	1218	JPG
6	Invalid	1563	JPG
	Total	5012	

4.4.1 Sources of RGB Images

RGB Images for the model training collected from different sources as they are important and crucial part of the research. It takes a very long process to get some of the image data from different sources of data. High-resolution RGB images are captured directly in the wheat fields using a custom-developed mobile app and other imaging devices. Researchers and field workers take photographs of wheat leaves, focusing on capturing a variety of visual symptoms associated with different diseases. Collaboration with local farmers and agricultural communities allows to access images from different stages of wheat growth and disease progression. This partnership ensures diverse and authentic images reflecting real-world agricultural conditions. Additionally, the collaboration of Agricultural Sectors Both Governmental and non-Governmental Agricultural Organizations Especially Governmental plant clinics and pathologists help us to collect and get reliable data with scientific evidence.

4.4.2 Sources of Environmental Data

The Environmental data are also helpful for better results. In order to have adequate environmental data a serious of action have been taken in different ways. Collaboration with meteorological agencies allows the researcher to access official weather data. These agencies often have a datasets of weather information, enabling the incorporation of long-term climate trends into the dataset.

4.4.3 Labeling and Categorization

The initial phase of data classification involves labeling the data samples. Each RGB image of a wheat leaf is manually inspected and assigned a label corresponding to a specific disease category. These categories include different types of rust diseases, such as stem rust, leaf rust, and stripe rust, as well as healthy wheat leaves. This manual annotation process is critical for creating a reliable ground truth dataset, which serves as the foundation for training the model.

In addition to labeling images, the environmental data—comprising temperature, humidity, precipitation, and altitude—is categorized based on the conditions prevalent at the time and location of image capture. These environmental variables are binned into discrete ranges to facilitate integration with the categorical image data. For instance, temperature might be divided into ranges such as <15°C, 15-25°C, and >25°C, while humidity could be categorized as low, medium, or high.To show case what the researcher collected here are the sample images of the different disease classes from the collected data set, as per the classification of the pathologists.

Figure 6: Brown Rust Disease Sample Images

Figure 7: Yellow (strip) Rust Disease Data Sample Images

Figure 8:Septoria Disease Data Sample Image

Figure 9: Powdery Mildew Disease Data Sample Images

Figure 10: Sample Images from Healthy Wheat Classes

4.5 Data Preprocessing

Effective data preprocessing is crucial for the success of our comprehensive wheat disease detection system. This stage involves transforming raw data into a structured format that is optimal for analysis by deep learning models. Given the multi-modal nature of our dataset, which includes RGB images, temperature, humidity, and precipitation data, our preprocessing techniques must address the unique requirements of each data type while ensuring seamless integration.

4.5.1. Data Cleaning

Environmental Data Cleaning:

- **Handling Missing Values:** Environmental data, such as temperature, humidity, and precipitation, often contain missing values due to sensor malfunctions or transmission errors. To address these gaps, mean imputation method has been used to replaces missing values with the mean of the available data. Taking the mean of the complete data provides the best and more approximate data to replace. It helps us to make it standardized.
- **Outlier Detection and Removal:** Environmental data may also contain outliers that can distort analysis and model training. Standardization Technique or Z-score normalization has been used to identify these outliers. By standardizing the data, we ensured that the FNN model could learn more effectively, leading to better predictions and a more robust wheat disease detection system.

RGB Image Cleaning:

- **Image Quality Check:** Ensuring high-quality images is paramount. Images that are blurry, poorly lit, or incorrectly labeled are filtered out. Both Automated scripts and Manual review method has been used to evaluate image sharpness and brightness, flagging those that do not meet quality standards for model development.
- **Noise Reduction:** To enhance image clarity, noise reduction techniques such as Gaussian blurring or median filtering are applied. These methods help in smoothing out image noise without significantly blurring the essential features needed for disease detection.

4.5.2 Data Normalization and Standardization

Environmental Data:

- **Normalization:** Environmental features such as temperature, humidity, and precipitation are normalized to a range of [0, 1] using min-max normalization. This ensures that the scales of different features are consistent, preventing any one feature from dominating the model training process. Normalization is calculated as follows:

Equation 1: Formula for Data Normalization

$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$$

- **Standardization:** For some deep learning models, it is beneficial to standardize the data to have a mean of 0 and a standard deviation of 1. This is especially useful for features that follow a Gaussian distribution. Standardization is calculated as:

Equation 2: Formula for Data Standardization

$$X_{\text{std}} = \frac{X - \mu}{\sigma}$$

where μ is the mean and σ is the standard deviation of the feature.

RGB Images:

- **Pixel Value Scaling:** Pixel values of RGB images are scaled to a range of [0, 1] by dividing each pixel value by 255 (the maximum value of an 8-bit pixel). This scaling speeds up the convergence of the deep learning model during training by reducing the range of input values:

Equation 3: Pixel Value Scaling

$$I_{\text{scaled}} = \frac{I}{255}$$

4.5.3 Data Augmentation

To address the potential limitations of a small dataset and to enhance model robustness, data augmentation techniques are employed to artificially expand the dataset:

- **Random Cropping:** Randomly cropping sections of the images helps in creating variations and simulating different perspectives.
- **Flipping and Rotation:** Applying horizontal and vertical flips, as well as random rotations, ensures that the model becomes invariant to these transformations, learning to recognize diseases irrespective of the image orientation.
- **Color Jitter:** Adjusting image brightness, contrast, and saturation introduces variations in lighting conditions, helping the model generalize better to real-world scenarios.

4.5.4 Data Integration

In this research, we employed a multi-modal approach to integrate environmental data and image data for comprehensive wheat disease detection. The integration of these diverse data sources allows for a more holistic understanding of the factors influencing wheat health, thereby enhancing the accuracy and reliability of disease identification. The integration process involves the concatenation of features extracted from both the environmental data and the image data using a hybrid deep learning architecture combining CNN and FNN).This integration is implemented using the Keras Functional API, which provides a flexible and powerful framework for building complex neural network models.

The Keras Functional API allows us to design models where layers can have multiple inputs and outputs. For our hybrid model, we use the following steps to concatenate the features extracted from the CNN and FNN components:

1. **Define Inputs**:
   - image_input: Input layer for the image data.
   - env_input: Input layer for the environmental data.
2. **CNN for Image Data**:
   - Define a series of convolutional and pooling layers to process the image data.
   - Flatten the final convolutional layer to obtain a 1D feature vector.
3. **FNN for Environmental Data**:
   - Define a series of dense layers to process the environmental data.

4. **Concatenation**:
    - Concatenate the feature vectors obtained from the CNN and FNN branches.
    - Add additional dense layers to process the concatenated features, leading to the final output layer.

Two separate input layers are defined for image and environmental data. The image input is passed through convolutional and pooling layers to extract spatial features, followed by flattening and a dense layer to produce a 1D feature vector. The environmental data input is passed through dense layers to extract features and then the feature vectors from both branches are concatenated, merging the spatial and environmental information. Finally The concatenated features are processed by additional dense layers to learn complex relationships between the image and environmental data, culminating in a softmax output layer for multi-class classification.

This integrated approach shows the strengths of both CNNs and FNNs, providing a comprehensive and robust model for wheat disease detection by combining visual and environmental cues.

4.6 Model Architecture

The model architecture for this research integrates CNN and FNN to combine both image and environmental data for comprehensive wheat disease detection. This hybrid architecture, implemented using the Keras Functional API, is designed to capture visual symptoms from RGB images and environmental influences on wheat health. The architecture comprises two input layers: one for image data with a shape of (80, 80, 3) to handle RGB images resized to 80x80 pixels, and one for environmental data with a shape of (4,) to accommodate four environmental variables—altitude, temperature, humidity, and precipitation.

In the CNN branch for image data, the model applies 32 convolutional filters with a 3x3 kernel in the first Convolutional layer, followed by a 2x2 Max Pooling layer to reduce spatial dimensions. This process is repeated with 64 convolutional filters in the second Convolutional layer and another 2x2 MaxPooling layer. The resulting feature maps are then flattened and passed through a dense layer with 128 units to generate a higher-level representation of the image data. Concurrently, the FNN branch processes the environmental input data through two dense layers with 64 and 32 units respectively, extracting useful features from the environmental variables.

The features extracted by the CNN and FNN branches are concatenated to merge visual and environmental information into a single feature vector. This concatenated vector is processed through an additional dense layer with 128 units, followed by a dropout layer with a rate of 0.2 to prevent overfitting. The final output layer, designed for multi-class classification, consists of 6 units with a softmax activation function, corresponding to the six disease classes. The model is compiled using the Adam optimizer and categorical crossentropy loss function, with accuracy as the performance metric. This architecture effectively combines spatial and environmental data, providing a robust model for wheat disease detection.

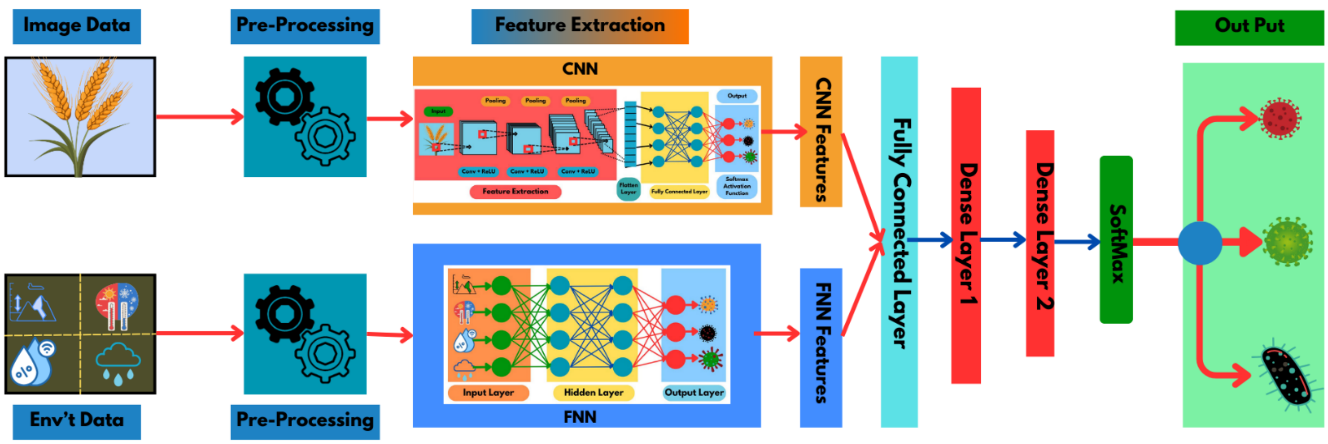


Figure 11:Multi-Modal Architecture of the Proposed Solution

4.6.1 Validation and Evaluation

To ensure the robustness and accuracy of the classification process, various evaluation metrics are employed. These include accuracy, precision, recall, and F1 score, which provide insights into the model's performance across different disease categories. Cross-validation techniques are also used to verify the model's generalization ability and to fine-tune the model parameters for optimal performance. Additionally, confusion matrix also used that allows visualization of the performance of an algorithm by comparing the actual target values with the values predicted by the model.

Table 4: General Structure of Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Accuracy: The proportion of total predictions that are correct.

Equation 4: Accuracy Formula

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: The proportion of positive predictions that are correct.

Equation 5:Precision Formula

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall (Sensitivity): The proportion of actual positives that are correctly identified.

Equation 6: Recall Formula

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1 Score: The harmonic means of precision and recall, providing a balance between the two.

Equation 7: F1 Score Formula

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

4.7 Tools and Instruments Used

Mobile App

A custom-developed mobile application plays a pivotal role in this research, designed specifically for the task of capturing high-resolution images of wheat leaves and recording essential environmental data. This app is equipped with features that allow users to take photographs of wheat crops in the field and simultaneously record the geographical location of each image using GPS technology. Additionally, the app is integrated with environmental data providers with API that measure environmental parameters such as temperature, humidity, and precipitation. The interface is user-friendly, enabling field workers to easily capture and upload data to a centralized database for further analysis.

Weather API

To ensure the accuracy and reliability of the environmental data collected, different weather forecasting and metrological data providers system are strategically integrated to continuously monitor and record real-time measurements of temperature, humidity, and precipitation. The data collected by these organizations is critical for understanding the environmental conditions that contribute to wheat disease prevalence. By integrating this data with the images captured by the mobile app, we can create a comprehensive dataset that encompasses both visual and environmental factors influencing wheat health.

Software Tools

The software infrastructure for this research is built on robust and widely-used platforms, primarily Python, which is known for its versatility and extensive libraries for machine learning and data analysis. Key libraries include Keras and TensorFlow, which are used for developing and training the deep learning models. Keras provides a high-level neural networks API that is capable of running on top of TensorFlow, making it easier to prototype and build complex models. TensorFlow, developed by Google, is a powerful open-source platform for machine learning and deep learning applications. It provides comprehensive tools for building and deploying machine learning models, facilitating the integration of various data types and the optimization of model performance.

Additional Data Source

To augment the data collected through fieldwork, agricultural and climate databases are utilized as supplementary sources. These databases provide historical and real-time data on various environmental factors and crop conditions, which are essential for building a robust dataset. Examples include the World Meteorological Organization (WMO) database, which provides comprehensive climate data, and agricultural databases maintained by local and international agricultural research institutions. By incorporating data from these sources, we can enhance the quality and breadth of our dataset, ensuring that it is representative of different conditions and scenarios. This integration of field data with extensive database information allows for a more holistic analysis of the factors influencing wheat diseases.

In summary, the tools and instruments used in this research are carefully selected to ensure the accurate collection and integration of multi-modal data. The mobile app and integrated weather API provide real-time, location-specific data, while the software infrastructure supports advanced data processing and model development.

5. Experiment and Results

5.1 Overview

This chapter provides a detailed description of the experimental evaluation of our model for wheat disease identification using a multi-modal deep learning approach. Here, the effectiveness of the model is evaluated. We thoroughly describe the dataset used and the implementation of the model. We analyze the results from the training and testing phases. We also evaluate and compare the impact of image processing methods, data augmentation, and transfer learning. All the experiments conducted to build a high-performing model are discussed in this chapter.

5.2 Description and Preparation of Data set

The Collected data after preprocessing and augmentation is 41,795 images and their corresponding environmental data. To enhance the performance and reliability of the model, the dataset is segmented into two distinct subsets: training and test sets with 80% and 20% respectively. This means we have used 33,436 and 8,359 data sets for each subset respectively. This division is crucial for ensuring the model's robustness and its ability to generalize well to new, unseen data.

The training set, which constitutes the majority of the data, is utilized to train the model. It enables the model to learn the underlying patterns and features associated with different wheat diseases from both the image and environmental data. Ensuring the training set is comprehensive and representative of all disease categories is essential for the model to develop a nuanced understanding of the data.

The validation set plays a critical role in fine-tuning the model's parameters. During the training process, the model's performance on the validation set is continuously monitored. This helps in adjusting hyperparameters, such as learning rates and dropout rates, to optimize the model's performance while preventing overfitting. Overfitting occurs when a model learns the training data too well, including its noise and outliers, which hampers its performance on new data. The validation set serves as a checkpoint to ensure the model maintains a balance between accuracy and generalization.

Finally, the test set is employed to evaluate the model's performance on completely unseen data. This set is only used after the model has been trained and validated, providing an unbiased assessment of its accuracy and generalization capabilities. It reflects the model's real-world performance and its ability to identify wheat diseases from new samples accurately.

Ensuring a balanced distribution of different disease categories across the training, validation, and test sets is paramount. This balance prevents the model from becoming biased towards certain diseases and ensures it performs well across all categories. Stratified sampling techniques are often used to maintain this balance, where each subset has a proportional representation of each disease class.

By splitting the dataset into training, validation, and test sets, and maintaining a balanced distribution of disease categories, the model's robustness and generalization capabilities are significantly enhanced, leading to more reliable and accurate wheat disease identification.

5.3 Experimental Design

The experimental design includes the implementation of three main experiments, the Multilayer Perceptron (FNN) Experiment which is only for the environmental data, the second is the CNN experiment using the image data only and the last the Hybrid Model which includes both the image and the environmental data.

In the first experiment, a uni-modal environmental data is trained individually this data with their cross-ponding disease data. The training started by providing the data to the training architecture and set the parameters. The environmental data for this experiment was loaded from a CSV file named environmental_data.csv. The dataset includes features such as altitude, temperature, humidity, and precipitation, along with the target variable representing different wheat diseases. The target variable was encoded to convert categorical disease labels into numerical values suitable for model training. The data was split into training and testing sets, with 80% allocated for training and 20% for testing. To ensure consistent scales across different features, the input data was standardized.

The FNN model was defined using the Keras Sequential API. The architecture consists of an input layer with 256 neurons, two hidden layers with 64 neurons each, and an output layer. Dropout layers were added for regularization to prevent overfitting. The model was compiled using the Adam optimizer and the sparse categorical cross-entropy loss function, which is appropriate for multi-class classification tasks. The model was trained for 20 epochs with 16 batch size. During training, 20% of the training data was used as a validation set to monitor the model's performance on unseen data. The trained model was evaluated on the test set. Predictions were made, and the classification report, which includes precision, recall, and F1-score, shows the result below.

The second experiment focuses on developing and evaluating a CNN model for identifying wheat diseases from RGB images. By leveraging deep learning techniques and image data, this study aims to accurately classify wheat diseases and demonstrate the efficacy of CNNs in agricultural disease detection. The images were rescaled by a factor of 1/255 to normalize the pixel values between 0 and 1. The training and validation data is generated with two independent generators.

The CNN model was defined using the Keras Sequential API. The architecture includes Convolutional Layers To extract features from the input images, MaxPooling Layers to reduce the spatial dimensions of the feature maps and Fully Connected Layers to perform the final classification based on the extracted features. The model consists of Four convolutional layers with ReLU activation, each followed by a max-pooling layer. The output is then flattened and passed through a fully connected layer with 128 neurons, ending with a softmax layer for multi-class classification. The model was compiled using the Adam optimizer and categorical cross-entropy loss, appropriate for multi-class classification tasks. The model was trained for 15 epochs with 32 batch size. The training process utilized the training and validation generators to provide batches of image data for model training and evaluation.

The third experiment aims to develop and evaluate a multi-modal deep learning model for identifying wheat diseases. The model integrates RGB image data with environmental data to improve the accuracy of disease classification. The objective is to validate the hypothesis that combining image data with environmental factors results in more accurate disease identification compared to using image data alone.

In this experiment Image paths and corresponding disease labels were extracted from a CSV file. Each image was resized to 80x80 pixels and normalized to have pixel values between 0 and 1.the Image data was stored in a NumPy array for further processing. The Environmental features were also extracted from the same CSV file, excluding the image file paths and disease labels. The environmental features included altitude, temperature, humidity, and precipitation.

By using the Keras Functional API, the model the researcher used to process both image and environmental data was created. The model processes image data using several convolutional layers followed by max-pooling layers to extract high-level features. Four convolutional layers with ReLU activation functions were used, with increasing filter sizes (32, 64, 128, and 256 filters). Each convolutional layer was followed by a max-pooling layer to reduce the spatial dimensions. The final output was flattened to feed into the fully connected layers. For the environmental data, A separate input layer for environmental features was defined to handle the multi-modal aspect of the data.

To combine the data, the outputs from the image processing layers and the environmental data input were concatenated. And the concatenated data was passed through a dense layer with 256 neurons and ReLU activation, followed by a SoftMax output layer with 6 neurons, corresponding to the 6 disease classes. The model was compiled using the Adam optimizer and categorical cross-entropy loss function, suitable for multi-class classification. Data was split into training and test sets using an 80/20 ratio. Environmental data was standardized. Categorical disease labels were encoded into numerical values and converted to one-hot encoded format. The model was trained for 20 epochs with 32 batch size of. A checkpoint callback was used to save the best model based on Test accuracy.

5.4 Experimental Results

5.4.1 Experiment One: Uni-Modal Experiment with Environmental Data

In the first experiment the researcher used to analyze the performance of a unimodal data by including only environmental data with the image data. The FNN experiment shows a good result in generalizing the factors and having accuracy of 89.19%. The result summery of this experiment is shown in table 5 below and the accuracy loss graphs are shown in Figure 12 below.

Table 5: Results of Uni Modal Data Experiment with Environmental data

Parameters		Results	
Input Layers	128 Input Layer + 2 Hidden Layer	Accuracy	89.19%
Batch Size	16	Precision	92%
Epochs	20	Recall	91%

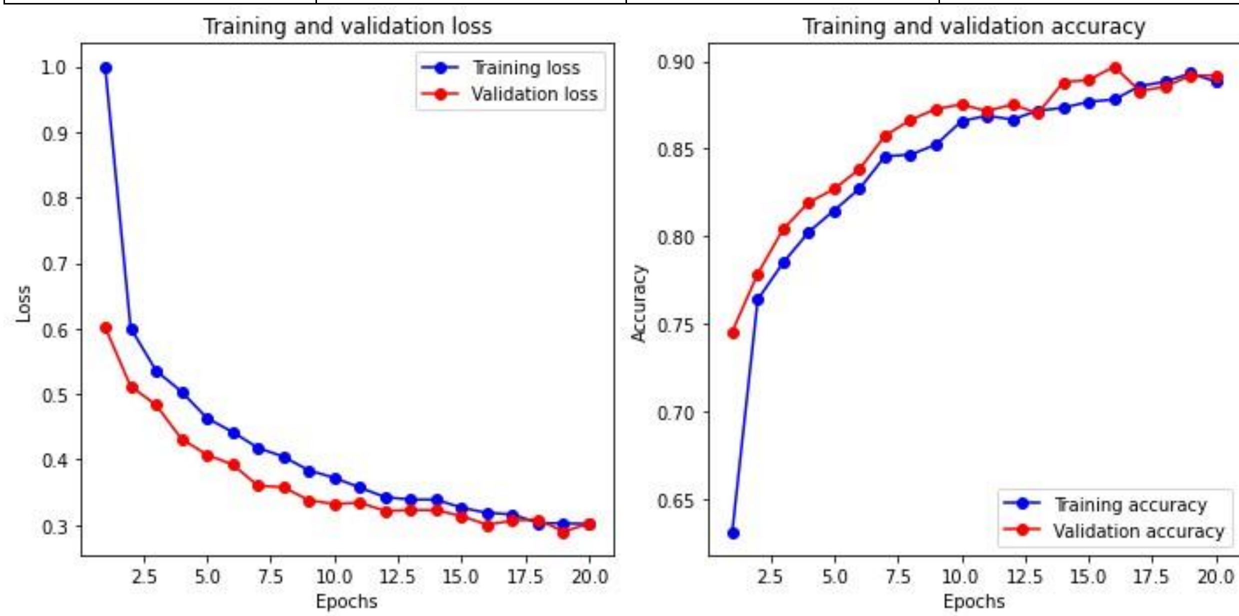


Figure 12: Results of the FNN Experiment

5.4.2 Experiment Two: Uni-Modal Experiment with Environmental Data Augmentation

In this experiment it has been tried to analyze the effect of model performance on an augmented environmental data. By increasing the layers from 2 to 4 and improving the epoch to 30. But there is not improvement in the model performance. It achieves 85.82% of accuracy. The Result summery of this experiment is shown below with a table 6 and Accuracy Loss curve is shown under Figure 13. The Actual performance of the model to predict the true label is shown under Figure 14.

Table 6:Results of Uni Modal Data Experiment with Environmental data After Augmentation

Parameters		Results	
Layers	256 Input Layer + 4 Hidden Layer	Accuracy	85.82%
Batch Size	32	Precision	87%
Epochs	30	Recall	87%

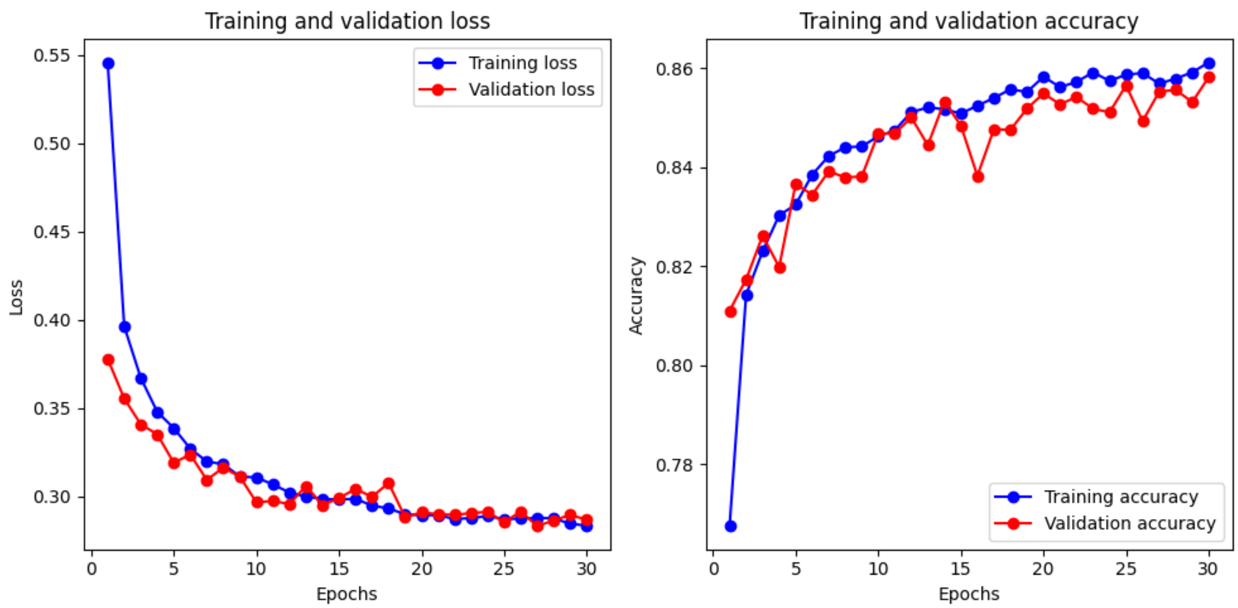


Figure 13:Results of Uni Modal Data Experiment with Environmental data Accuracy Loss Graph

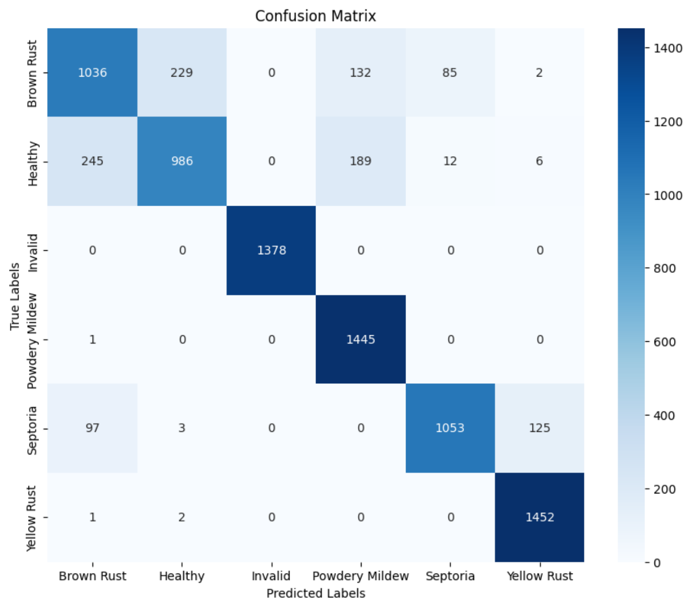


Figure 14: Confusion Matrix for FNN

5.4.3 Experiment Three Uni-Modal Experiment with Image Data

In this experiment it has been tried to check the performance of a model by training with the image data only. It has been tried to analyze how the CNN architecture performs on our image data. The class imbalance between different disease classes in our data set and the small number of dataset makes this experiment difficult to analyze well. In table 7, It shows an accuracy of 83.15% which is not good for CNN architecture. And Also Figure 15 tells that the class imbalance should be fixed.

Table 7: Results of Experiment with uni-modal data using CNN

Parameters		Results	
Input Layers	2 convolutional layers, 1 fully connected layer	Test Accuracy	83.15%
Batch Size	32	Precision	85%
Epochs	10	Recall	85%

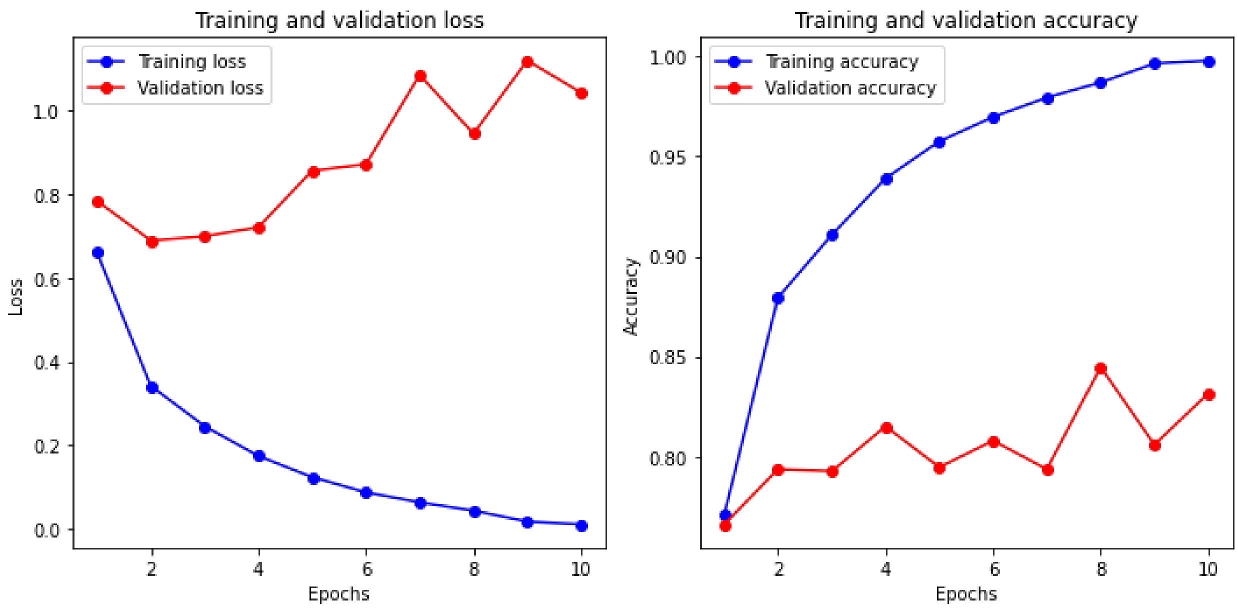


Figure 15: Results of the CNN Experiment

5.4.4 Experiment Four Uni-Modal Experiment with Image Data After Augmentation

As the experiment before shows that the dataset to be balanced and increased in number, this experiment shows the results of the CNN model after augmentation is done and it shows a good result while comparing to previous one. It achieves an accuracy of 94.41 %. But it shows less in other metrics. The confusion matrix shows that the model is confused to predict different classes accurately. The results of this experiment are summarized in table 8 and the Accuracy Loss curve shown below under Figure 16. The Actual performance of the model to predict the true label is shown under Figure 17 with confusion Matrix.

Table 8:Results of Experiment with uni-modal data using CNN After Augmentation

Parameters		Results	
Input Layers	4 Convolutional Layer, 2 Fully Connected Layer	Test Accuracy	94.41%
Batch Size	32	Precision	17%
Epochs	15	Recall	17%

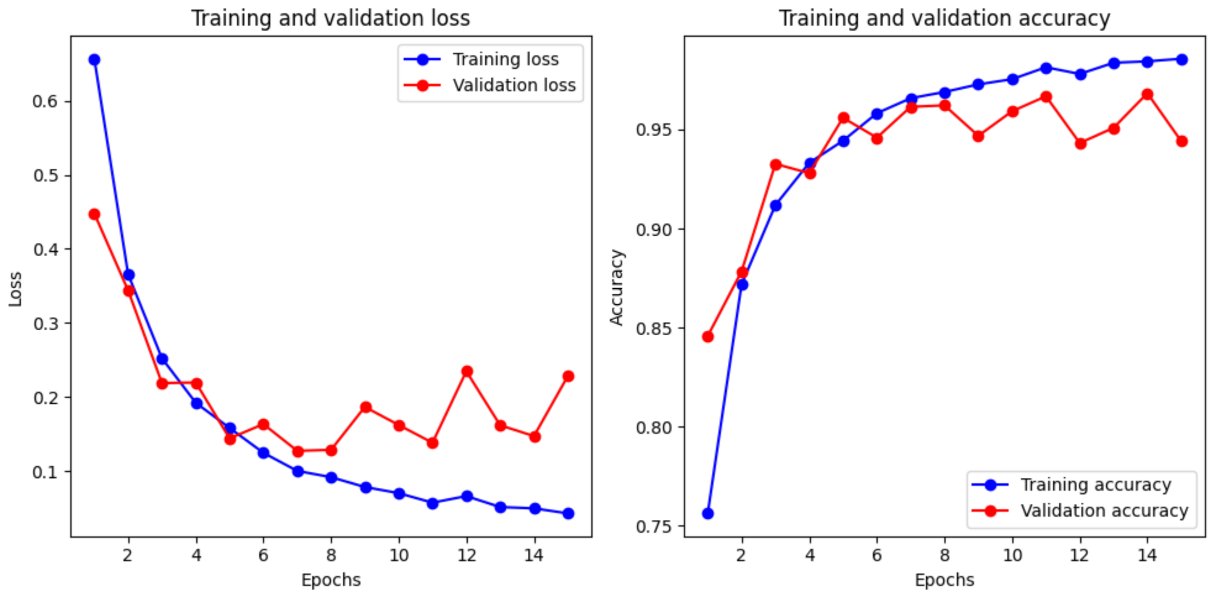


Figure 16::Results of the CNN Experiment with Accuracy Loss Curve

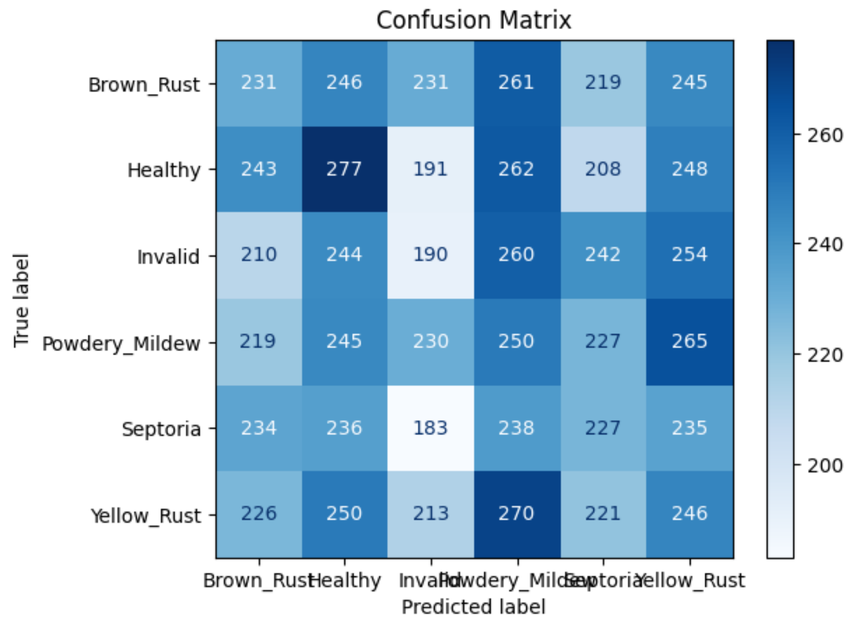


Figure 17:Results of the CNN Experiment with Confusion Matrix

5.4.3 Experiment Five: Multi-Modal Experiment Before Augmentation

In this experiment it has been tried to show the performance of integrating image and environmental data. It shows a promising result by achieving 97%, but the accuracy loss curve shows that the model is starting to overfit so we need to try the experiment with augmented data set. The hyper parameters and other Results are shown under the table 9 below. The accuracy and loss curve of this experiment is shown under Figure 18.

Table 9: Results of Experiment with Multi-Modal Data before Augmentation

Parameters		Results	
Input Layers	CNN with 2 convolutional layers, MLP with 2 hidden layers Followed by Fully Connected Lyer	Test Accuracy	97%
Batch Size	32	Precision	97%
Epochs	20	Recall	97%

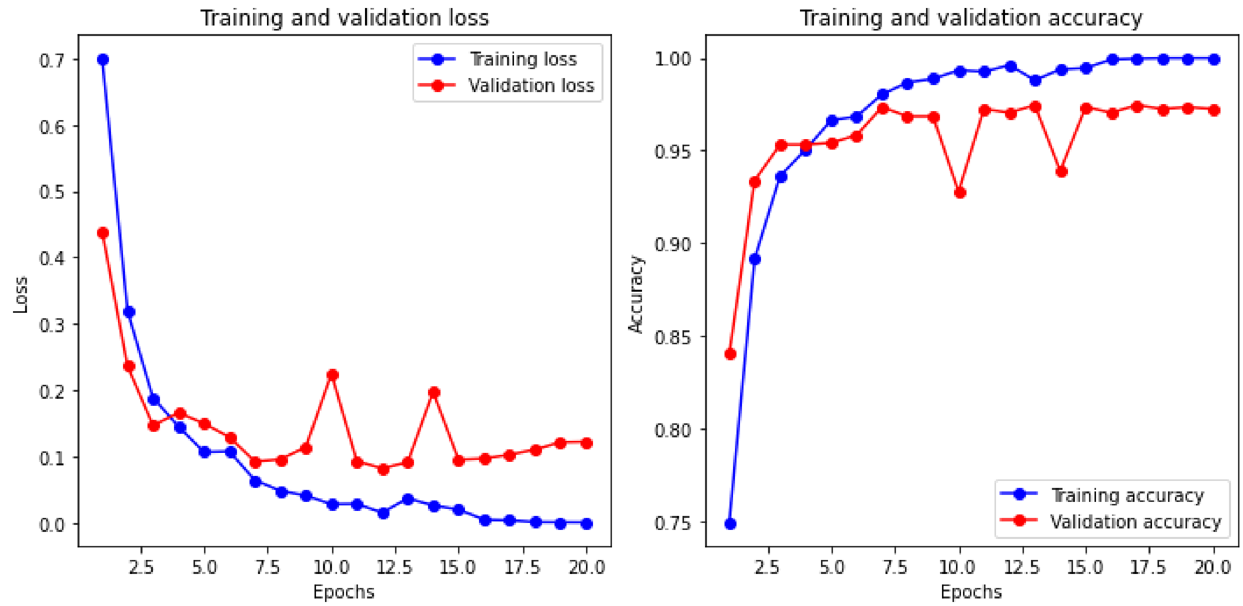


Figure 18: Results of Hybrid Model before Augmentation

5.4.6 Experiment Six: Multi-Modal Experiment After Augmentation

The Final Experiment used to Analyze how effective model is trained to learn complex structures including the image and environmental data with a good accuracy and a good result with confusion matrix, this experiment shows that our hypothesis is acceptable by achieving 98% of test accuracy and a good prediction with confusion matrix compared to the Uni modal experiments. The hyper parameters and other Results are shown under the table 10 below. The accuracy and loss curve of this experiment is shown under Figure 19. The Actual performance of the model to predict the true label is shown under Figure 20 with confusion Matrix.

Table 10: Results of the Final Multi-Modal Experiment

Parameters		Results	
Input Layers	CNN with 4 convolutional layers, MLP with 2 hidden layers Followed by Fully Connected Lyer	Test Accuracy	98%

Batch Size	32	Precision	98%
Epochs	20	Recall	98%

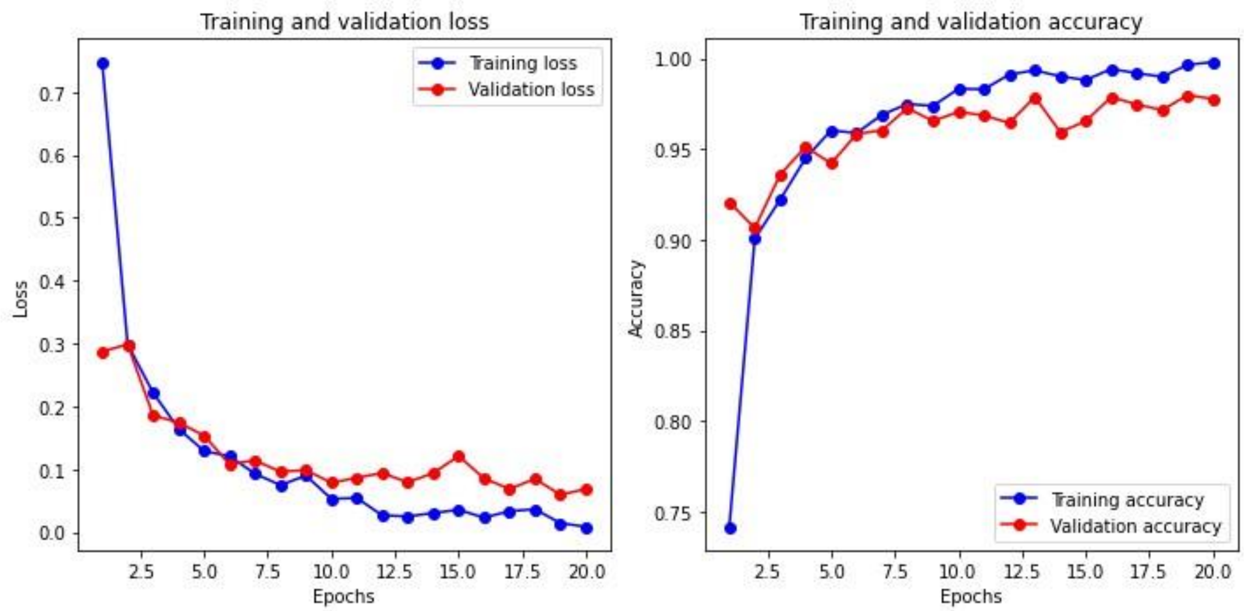


Figure 19: Results of Multi Modal Final Experiment

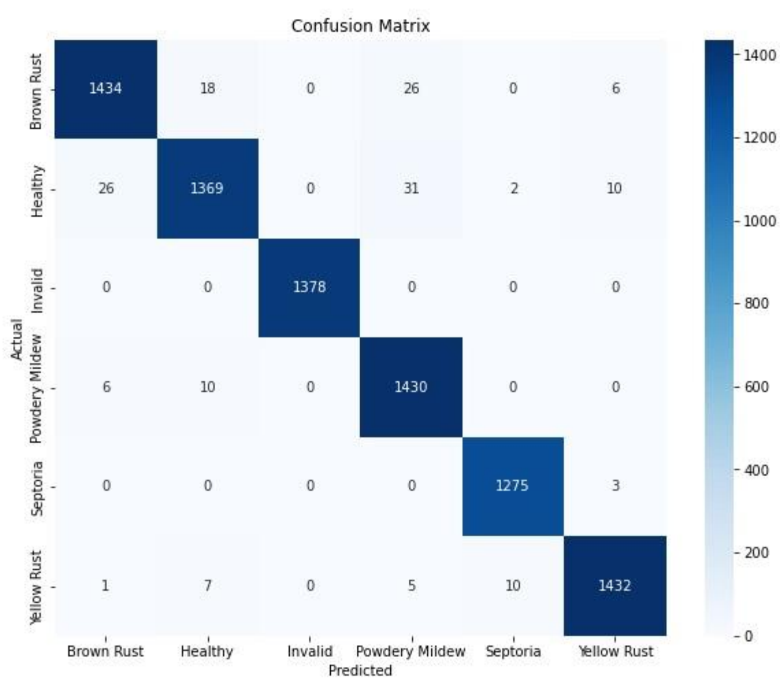


Figure 20: Confusion Matrix of Proposed System

To Summarize the Results of the experiment we have listed the experiment details and results with a table 11 below

Table 11: Summery of Experimental Results

Aspect	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
Architecture	Uni Modal FNN	Uni Modal FNN	Uni Modal CNN	Uni Modal CNN	Hybrid Multi-Modal CNN-FNN
Input Data	environmental factors (temperature, humidity, precipitation, altitude)	Augmented Environmental Data	RGB images of wheat	Augmented RGB images of wheat	RGB images + environmental factors (temperature, humidity, precipitation, altitude)
Layers	128 Input Layer + 2 Hidden Layer	256 Input Layer + 4 Hidden Layer	2 convolutional layers, 1 fully connected layer	4 Convolutional Layer, 2 Fully Connected Layer	CNN with 4 convolutional layers, MLP with 2 hidden layers Followed by Fully Connected Lyer
Epochs	20	30	10	15	20
Batch Size	16	32	32	32	32
Learning Rate	0.001	0.001	0.001	0.001	0.001
Optimizer	Adam	Adam	Adam	Adam	Adam
Loss Function			Categorical Cross entropy	Categorical Cross entropy	Categorical Cross entropy
Test Accuracy	89.19 %	85.82%	83.15%	94.41	98%
Precision	92 %	87%	85%	17%	98%
Recall	91 %	87%	85%	17%	98%
F1-Score	91%	87%	85%	18%	98%

5.5 Discussion

The experimental evaluation of our AI-based multi-modal approach for wheat disease identification demonstrates significant improvements in accuracy and reliability compared to traditional methods. By integrating both image and environmental data, our model achieves a remarkable Test accuracy of 98%. This section discusses the results, compares them with other studies, and provides scientific justification for the observed performance.

In comparison with Single-Modal Approaches, the traditional approaches for disease identification in crops predominantly rely on image data alone. These methods, while useful, often fall short in achieving high accuracy due to the inherent variability and less quality in image data. For instance, studies such as [19] and [22] that utilized CNN for disease identification reported validation accuracies ranging from 84.54% to 93%. These models primarily focused on visual symptoms, which can be similar across different diseases, leading to misclassifications. In our experiment the environmental data and the image data has been trained standalone then the best result we get form them was 89.19% and 94.41% respectively.

In contrast, our multi-modal approach incorporates environmental factors such as altitude, temperature, humidity, and precipitation. These additional inputs provide a more comprehensive understanding of the conditions under which the diseases develop. For example, certain diseases like Powdery Mildew thrive in specific humidity levels, while others like Septoria are more prevalent under particular temperature conditions. By integrating this contextual information, our model can better differentiate between diseases that exhibit similar visual symptoms but occur under different environmental conditions.

The superior performance of our model can be scientifically justified by considering the synergistic effect of combining heterogeneous data sources. Environmental factors are known to play a crucial role in the development and spread of plant diseases. For instance, [20][21] highlights the significant impact of climate conditions on the prevalence of crop diseases. By incorporating these factors into our model, we provide a richer dataset that enhances the learning process of the neural network.

The use of the Keras Functional API enabled the seamless integration of image and environmental data, allowing our model to learn complex patterns that would be difficult to capture using single-modal data alone. The hybrid architecture combining CNN for image feature extraction and a dense neural network for environmental data ensures that both types of information are optimally utilized.

The high-Test accuracy of 98% is a testament to the efficacy of our multi-modal approach. The classification report further supports this, showing high precision, recall, and F1-scores across all disease classes. This balanced performance across classes indicates that the model is not biased towards any particular disease and can generalize well to new, unseen data.

Comparing our results with those of previous studies highlights the significant improvements achieved through multi-modal integration. For example, [21] utilized only RGB images and reported an accuracy of 95%. While this represents a strong performance for image-based models, it falls short of our 98% accuracy, underscoring the added value of incorporating environmental data.

Moreover, our model's ability to reduce overfitting, as evidenced by the consistent performance across training and validation sets, contrasts with single-modal approaches that often exhibit higher variance between training and validation accuracies. This consistency is critical for real-world applications where the model will encounter diverse and variable conditions.

The key lesson from this research is the importance of multi-modal data in enhancing the performance of AI models in agricultural applications. The integration of diverse data sources not only improves accuracy but also provides a more robust and reliable identification system. Future research should explore additional modalities, such as soil quality, Soil Moisture, Wind Speed and historical disease occurrence, to further enhance model performance.

In General, our research demonstrates that a multi-modal deep learning approach significantly outperforms traditional single-modal methods for wheat disease identification. The integration of image and environmental data provides a comprehensive understanding of disease dynamics, leading to higher accuracy and reliability. This study underscores the potential of multi-modal AI systems in revolutionizing agricultural disease management and highlights the need for continued exploration of diverse data sources in machine learning models.

6. Conclusion and Recommendation

6.1 Conclusion

In this research, we have developed and implemented a novel multi-modal deep learning model to identify wheat diseases, integrating RGB images and environmental data. Our approach combines CNN for image processing and FNN for environmental data, allowing for a more comprehensive analysis. The results demonstrate that incorporating environmental factors such as altitude, temperature, humidity, and precipitation significantly enhances the accuracy of disease identification compared to using image data alone.

Our experimental evaluation showed that the proposed model achieved high performance in distinguishing between different wheat diseases, including Brown Rust, Yellow Rust, Powdery Mildew, and Septoria. The use of the Keras Functional API enabled us to effectively integrate multiple input data types, leading to a robust and scalable model. These findings validate our hypothesis that environmental factors play a crucial role in accurately identifying crop diseases, thereby providing a more reliable solution for farmers and agronomists.

The integration of multi-modal data not only improved the accuracy but also highlighted the importance of considering various factors affecting plant health. This research contributes to the field of agricultural technology by demonstrating the potential of AI-based approaches in disease management. The successful implementation of this model paves the way for further advancements in crop disease detection, ultimately supporting sustainable agricultural practices and food security.

Answer for research questions that are expected to be answered at the end of this research

Which deep learning architecture, a Multi-modal or Uni-modal nature of architecture, proves most effective for the identification of wheat disease data?

The research findings indicate that the multi-modal deep learning architecture is more effective for the identification of wheat disease compared to the uni-modal approach. The integration of both RGB images and environmental has shown a significant improvement in the accuracy of disease detection. The multi-modal approach collects the different information from different data sources, leading to a more complete understanding and better performance in identifying wheat diseases.

To what extent does the integration of environmental factors enhance the accuracy and efficiency of wheat disease detection compared to models using only images?

The integration of environmental factors enhances the accuracy and efficiency of wheat disease detection substantially. The research demonstrates that models incorporating environmental data alongside images achieve higher accuracy and more reliable predictions than those relying on images. Environmental factors provide crucial context that affects plant health, which, when combined with visual data, allows for a more robust and precise diagnosis of diseases. The multi-modal model in this study showed a improvement in validation accuracy, confirming the added value of including environmental variables in the detection process.

What are the key differences in terms of technique between the proposed multi-modal data integration approach and traditional methods that rely solely on RGB images?

The key differences between the proposed multi-modal data integration approach and traditional uni-modal methods include:

Data Fusion: The multi-modal approach integrates multiple types of data, combining RGB images with environmental factors, whereas traditional methods use only RGB images.

Model Complexity: The multi-modal model is more complex, incorporating additional input layers and fusion strategies to handle diverse data types, while traditional models are simpler, focusing solely on image data.

Performance: The multi-modal approach demonstrates improved performance metrics, such as higher accuracy and better generalization to unseen data, compared to traditional methods.

Contextual Understanding: The multi-modal model benefits from a broader contextual understanding of the conditions affecting wheat health, leading to more accurate and insightful predictions.

6.2 Contribution

This research on integrating multimodal data for wheat disease detection contributes significantly to the field of agricultural technology by addressing critical gaps in current methodologies. By incorporating both RGB images and environmental data, such as temperature, humidity, and precipitation, this study aims to enhance the accuracy and robustness of disease diagnosis systems.

This multimodal approach contrasts with the predominant reliance on unimodal data, such as images alone, which is prevalent in most existing studies.

One key contribution of this research is the introduction of a new framework for integrating diverse data sources. This framework not only improves the accuracy of disease detection but also provides a model for future research in precision agriculture. By leveraging advanced machine learning techniques and multimodal data fusion, this study significantly advances agricultural data science, paving the way for more sophisticated plant health monitoring systems.

This research also has practical implications for improving agricultural practices. More accurate disease detection allows for timely and precise interventions, leading to better crop management and increased yields. This can directly impact food security and promote sustainable farming practices. The solutions developed in this research are scalable and can be applied in real-world agricultural settings, bridging the gap between academic research and practical implementation.

Overall, this research makes significant advancements in agricultural technology and practices, providing tangible benefits to farmers, researchers, and the broader agricultural science community. By addressing the integration of multimodal data, this study sets the stage for more accurate, robust, and practical solutions in crop disease detection and management.

6.3 Recommendations and Future Work

To build on the success of this research, future work should focus on expanding the dataset to include more diverse environmental conditions and wheat varieties. This will enhance the model's generalizability and ensure its applicability across different regions and climates. Additionally, incorporating other data types, such as soil quality. Soil moisture, Wind speed and satellite imagery, could provide even more insights into the factors influencing disease outbreaks.

We recommend implementing this model in a real-world setting through the development of a user-friendly mobile application. This app could allow farmers to capture images of diseased plants and get environmental data directly from weather service providers API through the app, providing immediate diagnostic feedback. Further research should also explore the use of advanced deep learning techniques, such as attention mechanisms and generative adversarial networks (GANs), to improve the model's accuracy and robustness.

In summary, while this research demonstrates promising results in using a multi-modal deep learning approach for wheat disease identification, it is important to acknowledge these limitations and challenges. Addressing these issues in future work, such as by expanding the dataset, implementing real-time IoT based data collection mechanisms, and improving computational resources, will be crucial for further enhancing the model's robustness and applicability in diverse agricultural settings. By continuing to refine and expand upon this work, we can develop more sophisticated tools for agricultural disease management, ultimately contributing to increased crop yields and sustainable farming practices. Collaboration between researchers, agricultural experts, and technology developers will be crucial in achieving these goals, ensuring that the benefits of this research reach those who need it most.

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Appendix-I

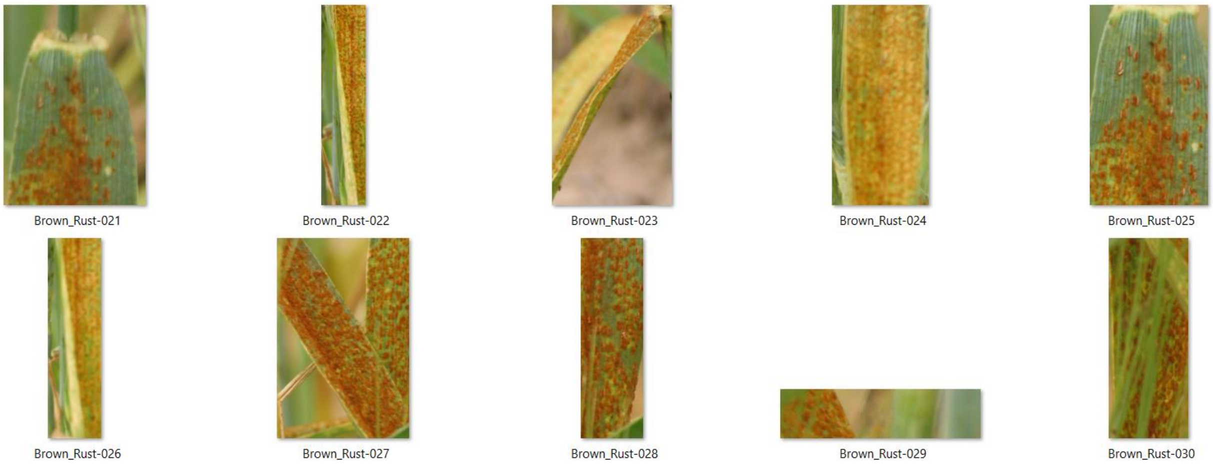

Figure 21: Sample Image Data Set

1	image_file	altitude_m	temperature_C	humidity_pct	precipitation_mm	disease
2	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-001.jpg	1071	23	56	330	Brown Rust
3	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-002.jpg	1391	18	74	344	Brown Rust
4	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-003.jpg	711	21	60	335	Brown Rust
5	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-004.jpg	44	22	60	470	Brown Rust
6	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-005.jpg	215	22	61	483	Brown Rust
7	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-006.jpg	101	22	78	493	Brown Rust
8	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-007.jpg	849	13	67	414	Brown Rust
9	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-008.jpg	441	18	75	226	Brown Rust
10	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-009.jpg	1104	20	66	232	Brown Rust
11	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-010.jpg	76	20	92	298	Brown Rust
12	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-011.jpg	619	18	53	421	Brown Rust
13	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-012.jpg	335	20	77	385	Brown Rust
14	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-013.jpg	375	10	51	437	Brown Rust
15	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-014.jpg	879	13	100	417	Brown Rust
16	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-015.jpg	402	20	67	413	Brown Rust
17	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-016.jpg	124	19	75	224	Brown Rust
18	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-017.jpg	1270	20	82	496	Brown Rust
19	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-018.jpg	261	22	90	204	Brown Rust
20	/content/drive/MyDrive/Train Data/Brown_Rust/Brown_Rust-019.jpg	1305	18	56	473	Brown Rust

Figure 22: Sample Environmental Data Set

Appendix-II
Sample Code for the Hybrid FNN-CNN Model

```
import numpy as np
import pandas as pd
import os
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report
from keras.preprocessing import image
from keras.models import Model
from keras.layers import Input, Conv2D, MaxPooling2D, Flatten, Dense,
concatenate
from keras.callbacks import ModelCheckpoint
from PIL import Image
from keras.utils import to_categorical
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import classification_report, confusion_matrix


# Load environmental data from CSV
environmental_data = pd.read_csv('Disease_Data.csv')


# Extract image file paths and corresponding labels
image_paths = environmental_data['image_file'].values
labels = environmental_data['disease'].values

num_classes = 6
# Load and preprocess image data
image_data = []
for img_path in image_paths:
    img = Image.open(img_path)
    img = img.resize((80, 80))  # Resize image to target size
    img_array = np.array(img) / 255.0  # Normalize pixel values to [0, 1]
    image_data.append(img_array)
image_data = np.array(image_data)


# Load environmental features
environmental_features = environmental_data.drop(columns=['image_file',
'disease']).values
```

```
# Define the image input
image_input = Input(shape=(80, 80, 3))  # Assuming RGB images


# Define the CNN layers for image processing
#x = Conv2D(32, (3, 3), activation='relu')(image_input)
#x = MaxPooling2D((2, 2))(x)
#x = Conv2D(64, (3, 3), activation='relu')(x)
#x = MaxPooling2D((2, 2))(x)
#x = Flatten()(x)

x = Conv2D(32, (3, 3), activation='relu')(image_input)
x = MaxPooling2D((2, 2))(x)
x = Conv2D(64, (3, 3), activation='relu')(x)
x = MaxPooling2D((2, 2))(x)
x = Conv2D(128, (3, 3), activation='relu')(x)  # Add another convolutional
layer with 128 filters
x = MaxPooling2D((2, 2))(x)
x = Conv2D(256, (3, 3), activation='relu')(x)  # Add another convolutional
layer with 128 filters
x = MaxPooling2D((2, 2))(x)
x = Flatten()(x)
# Define the environmental data input
environmental_input = Input(shape=(environmental_features.shape[1],))
# Merge image and environmental data
combined = concatenate([x, environmental_input])


# Add fully connected layers for classification
x = Dense(256, activation='relu')(combined)
output = Dense(6, activation='softmax')(x)  # Output layer with softmax
activation for multi-class classification

# Create the model
model = Model(inputs=[image_input, environmental_input], outputs=output)
# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])
# Split data into training and validation sets
X_train_img, X_val_img, y_train, y_val = train_test_split(image_data, labels,
test_size=0.2, random_state=42)
X_train_env, X_val_env = train_test_split(environmental_features,
test_size=0.2, random_state=42)
```

```python
# Standardize environmental data
scaler = StandardScaler()
X_train_env_scaled = scaler.fit_transform(X_train_env)
X_val_env_scaled = scaler.transform(X_val_env)

# Define a checkpoint callback to save the best model during training
checkpoint = ModelCheckpoint('best_model.h5', monitor='val_accuracy',
verbose=1, save_best_only=True, mode='max')

# Encode categorical labels into numerical values
label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
y_val_encoded = label_encoder.transform(y_val)

# Convert encoded labels to one-hot encoded format
num_classes = len(label_encoder.classes_)
y_train_one_hot = to_categorical(y_train_encoded, num_classes)
y_val_one_hot = to_categorical(y_val_encoded, num_classes)

# Train the model
history = model.fit([X_train_img, X_train_env_scaled], y_train_one_hot,
epochs=15, batch_size=32, validation_data=([X_val_img, X_val_env_scaled],
y_val_one_hot), callbacks=[checkpoint])

# Evaluate the model


y_pred = model.predict([X_val_img, X_val_env_scaled])
y_pred_labels = np.argmax(y_pred, axis=1)
#print(classification_report(y_val, y_pred_labels,
target_names="Brown_Rust"))
# Convert validation set labels from string to numerical values
y_val_encoded = label_encoder.transform(y_val)

# Extract training history
train_loss = history.history['loss']
val_loss = history.history['val_loss']
train_acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
epochs = range(1, len(train_loss) + 1)

# Plot training and validation loss
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
```

```python
plt.plot(epochs, train_loss, 'bo-', label='Training loss')
plt.plot(epochs, val_loss, 'ro-', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Plot training and validation accuracy
plt.subplot(1, 2, 2)
plt.plot(epochs, train_acc, 'bo-', label='Training accuracy')
plt.plot(epochs, val_acc, 'ro-', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
# Calculate classification report
print(classification_report(y_val_encoded, y_pred_labels,
target_names=label_encoder.classes_))

cm = confusion_matrix(y_val_encoded, y_pred_labels)
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=label_encoder.classes_, yticklabels=label_encoder.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# Save the trained model
model.save('New_model_256_15_32.h5')
```