

Project Report on

Rice Leaf Disease Prediction

Submitted in partial fulfillment of the requirements

of the degree of

BACHELOR OF ENGINEERING (Third Year)

in

COMPUTER ENGINEERING

by

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Under the guidance of

Dr. Rashmi Thakur

Associate Professor & Dean



Name of Department

Thakur College of Engineering & Technology

Thakur Village, Kandivali (East), Mumbai-400101

(Academic Year 2023-24)

CERTIFICATE

This is to certify that the project entitled "**Rice Leaf Disease Prediction**" is a bonafide work of **Rashmita Mhatre (16), Sailee Mulik (27), Khushii Nikhade (29)** submitted to the Thakur College of Engineering and Technology, Mumbai (An Autonomous College affiliated to University of Mumbai) in partial fulfillment of the requirement for the award of the degree of "**Bachelor of Engineering**" in "**Computer Engineering**".

Signature with Date:

Name of Guide: Dr. Rashmi
Thakur
Designation: Associate
Professor & Dean

Signature with Date:

Name of HOD: Dr.Harshali Patil
Name of Department:Computer
Engineering

ABSTRACT

The project endeavors to develop a predictive model for rice leaf diseases with the aim of enabling early intervention and enhancing crop management practices. By harnessing the power of machine learning algorithms, geospatial data analysis, and historical disease patterns, the proposed model will forecast outbreaks of rice leaf diseases, thereby providing invaluable support to farmers in disease prevention and improving agricultural sustainability. Rice leaf diseases pose significant challenges to farmers worldwide, leading to substantial yield losses and economic repercussions. Early detection and timely intervention are crucial for mitigating these losses and ensuring food security. However, traditional methods of disease detection often rely on visual inspection and can be subjective and time-consuming. The proposed predictive model seeks to revolutionize disease management in rice crops by leveraging advanced technologies to provide accurate and timely predictions of disease outbreaks. By analyzing a combination of environmental factors, historical disease data, and geospatial information, the model will identify patterns and trends associated with the onset and spread of rice leaf diseases. Empowering local communities is a core objective of the project, as the model's insights will enable farmers to adopt proactive measures to prevent disease outbreaks and optimize crop management strategies. By providing timely alerts and recommendations based on the forecasted disease risk, farmers can implement targeted interventions such as pesticide application, crop rotation, and irrigation management, thereby reducing yield losses and minimizing the need for chemical inputs. Furthermore, the project aims to contribute to agricultural sustainability by promoting more efficient and environmentally friendly practices. By reducing the reliance on chemical pesticides and optimizing resource allocation, the model will help mitigate the environmental impact of rice cultivation while improving overall crop health and productivity.

ACKNOWLEDGEMENT

We sincerely thank our guide Dr. Rashmi Thakur for her guidance and support for carrying out our project work. We extend our heartfelt gratitude to our esteemed guide for her invaluable guidance and unwavering support throughout the duration of our project. Her expertise, encouragement, and dedication have been instrumental in shaping our work and guiding us through challenges with clarity and patience. We are truly grateful for her mentorship, which has enriched our learning experience and contributed significantly to the success of our endeavor.

1.Rashmita Mhatre (16)

2. Sailee Mulik (27)

3.Khushii Nikhade (29)

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Chapter 1: LinkedIn Profile and Blog Writing

1.1 LinkedIn Profile Screenshots

Sailee Mulik (She/Her)
 TCET 25 || Computer Science Engineer || Web Developer
 Mumbai, Maharashtra, India · [Contact info](#)
 22 followers · 16 connections

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Activity
 22 followers

[Posts](#) [Videos](#) [Images](#)

Sailee Mulik posted this • 3mo I'm happy to share that I've obtained a new certification: Perform Foundational Data, ML, and AI Tasks in Google Cloud from Google!

Sailee Mulik posted this • 3mo I'm happy to share that I've obtained a new certification: Level 3: GenAI from [Google!](#)

Sailee Mulik posted this • 3mo Excited to share that I've successfully completed my internship at [CodSoft](#)! 🎉 Grateful for the incredible learning experience and the opportunity to work on projects. A big thank you to the amazing team at Codsoft for their guidance and support throughout the journey. Ready for the next chapter in my career! ...show more

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Experience

Web Developer
 CodSoft · Internship
 Dec 2023 - Present · 5 mos

Intern at CodSoft

⚡ React.js



Licenses & certifications

CodSoft Internship Certificate
 CodSoft
 Issued Jan 2024

[Show credential ↗](#)

Build and Secure Networks in Google Cloud
 Google
 Issued Sep 2023
 Credential ID 5367973

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Rashmita Mhatre
TCET 25 | Computer Science Engineer | Web Developer
Mumbai, Maharashtra, India - [Contact info](#)
24 connections

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Rashmita Mhatre posted this • 3mo



Exciting Project Announcement: Job Board Website @CodSoft(LLevel-2 task2)
I am thrilled to share my latest project – a comprehensive Job Board Website built from the ground up using React, Node.js, and MongoDB. ...[show more](#)

5

Rashmita Mhatre posted this • 3mo



Web Development Project: Tribute Page Level 2 task 1 @ CodSoft
I recently created a personal webpage using HTML and CSS as part of a coding project. This webpage is dedicated to someone I admire, showcasing their admirable qualities through text, images, and i ...[show more](#)

9

Rashmita Mhatre posted this • 4mo

Exciting News! Thrilled to announce that I've accepted an offer from CodSoft as a Web Developer! Ready to embark on a new journey of coding excellence and innovation. Grateful for the opportunity and looking forward ...[show more](#)



Offer letter

1 page

8

1 comment

Experience

+

Web Developer
CodSoft · Internship
Dec 2023 - Jan 2024 · 2 mos

Education

+

Skills

+

React.js

Python

Khushii Nikhade
 3rd Year Computer Engineering student
 #OPENTOWORK

Khushii Nikhade (She/Her)

TCET 25 | Front-end Development | Secretary at CSI - TCET

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Web Developer

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Khushii Nikhade posted this · 16h



I'm happy to share that I've obtained a new certification: Certificate of Participation in Online Quiz of Flipkart Runway: Season 4 from Unstop!

11

2 comments

Khushii Nikhade posted this · 1mo



In the first week of March, I had the privilege of attending the JICA networking fair, graciously hosted by the Japan International Cooperation Agency. This enriching experience provided me with the opportunity to connect with professionals and o ...show more

47

Khushii Nikhade posted this · 6mo



Back-to-back wins in the Saturday coding contest! 🎉🎉 It's an honor to secure 1st place once more, and I'm grateful for the opportunities to learn and grow through these competitions. Thanks to all who've supported me on this journey. 🚀 #CodingChampion #Consistency #backtoback

31

[Create a post](#)



Licenses & certifications



Certificate of Participation in Online Quiz of Flipkart Runway: Season 4

Unstop

Issued Apr 2024

Credential ID 0edd7b13-2442-4068-98a1-c305cab08595

[Show credential](#)



CSS

HackerRank

Issued Aug 2023

[Show credential](#)

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1.2 Blog Screenshots

M-HEALTH CARE

Home

January 16, 2024
 saileemulk
 Uncategorized
 ai, health, healthcare, technology, telemedicine
 2 comments

M-health healthcare on mobile devices

Introduction:

In the era of digital transformation, healthcare is undergoing a paradigm shift with the integration of mobile technology. Mobile health, commonly known as m-health, has emerged as a transformative force in the healthcare industry, leveraging the common use and power of mobile devices to revolutionize patient care and wellness management. This blog delves into the various ways mobile technology is changing the way we approach healthcare.

- Most of the doctors want to monitor their patients' critical statistics at home.
- Almost half of the patients are more comfortable in the video consultations program with their doctors rather than to visit in person.

1. Remote Patient Monitoring (RPM):

RPM helps in real-time monitoring of patients' health which facilitates remote management of the chronic illness with improved and appropriate outcomes.

2. Wearable Technology Integration:

There are many health and fitness wearable devices which are integrated with mobile applications. These devices enable the user to track and analyze their health and help them to take proper precautions on time. It includes tracking from tracking heart rate to monitoring the sleep patterns of the user. Example: Smart Watches.

Remote Health Monitoring :

Managing health issues like diabetes without constant trips to the doctor. With mobile health tech, your vital signs, like blood sugar and pulse, are monitored through secure apps. Caregivers can keep an eye on you from afar, no need for frequent check-ups. It's not just about diabetes; this also works for keeping tabs on blood pressure, heart rate, and weight. Some apps even let you answer questions for your doctor remotely. It's a simple, yet powerful shift in how we take care of our health.



Industry Trends for m-Health



[1]

rapidly growing technology for the advancement in the healthcare industry, mobile application has emerged as a power technology to make significant advancements in wellness and medical health care. The ability of mobile health care applications is to produce the multiple solutions to

Current Trends in Mobile Health Solutions:



[2]

Benefits:

1. Enhanced Accessibility:

M-health on mobile devices ensures that healthcare resources and services are readily accessible to users, overcoming geographical barriers. Patients can schedule appointments, access medical information, and communicate with healthcare providers anytime, anywhere.

2. Real-time Health Monitoring:

Mobile health applications enable individuals to monitor vital health metrics in real-time, providing a continuous stream of data for proactive health management. This real-time monitoring contributes to early detection and prevention of potential health issues.

3. Remote Patient Care:

M-health facilitates remote patient care through telemedicine and remote monitoring. Patients, especially in underserved areas, can receive timely medical consultations and interventions without the need for physical presence, improving healthcare accessibility.

1.3 URL (LinkedIn Profile/ Blog)

LinkedIn Profile Link:

Rashmita Mhatre: <https://www.linkedin.com/in/rashmita-mhatre-4776b9247/>

Sailee Mulik: <https://www.linkedin.com/in/sailee-mulik-a40616271/>

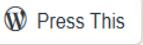
Khushii Nikhade: www.linkedin.com/in/khushii-nikhade-a6473ab7

Blog Link:

[M-health healthcare on mobile devices – M-Health Care \(wordpress.com\)](#)

1.4 Count of Likes, Shares and Comments

Share this:

 Press This  Twitter  Facebook

[Customize buttons](#)

 Reblog  Liked  7 likes

Posted by:
 saileemulik

[Previous Post](#)

2 responses to “M-health healthcare on mobile devices”

 37_COMP B_Vatsal Patel
[January 16, 2024](#) [Edit](#)

Very informative!

[Like](#)

[Reply](#)

 Pratham Mody
[January 16, 2024](#) [Edit](#)

Good and informative

[Like](#)

[Reply](#)

Count of Likes: 7

Comments: 2

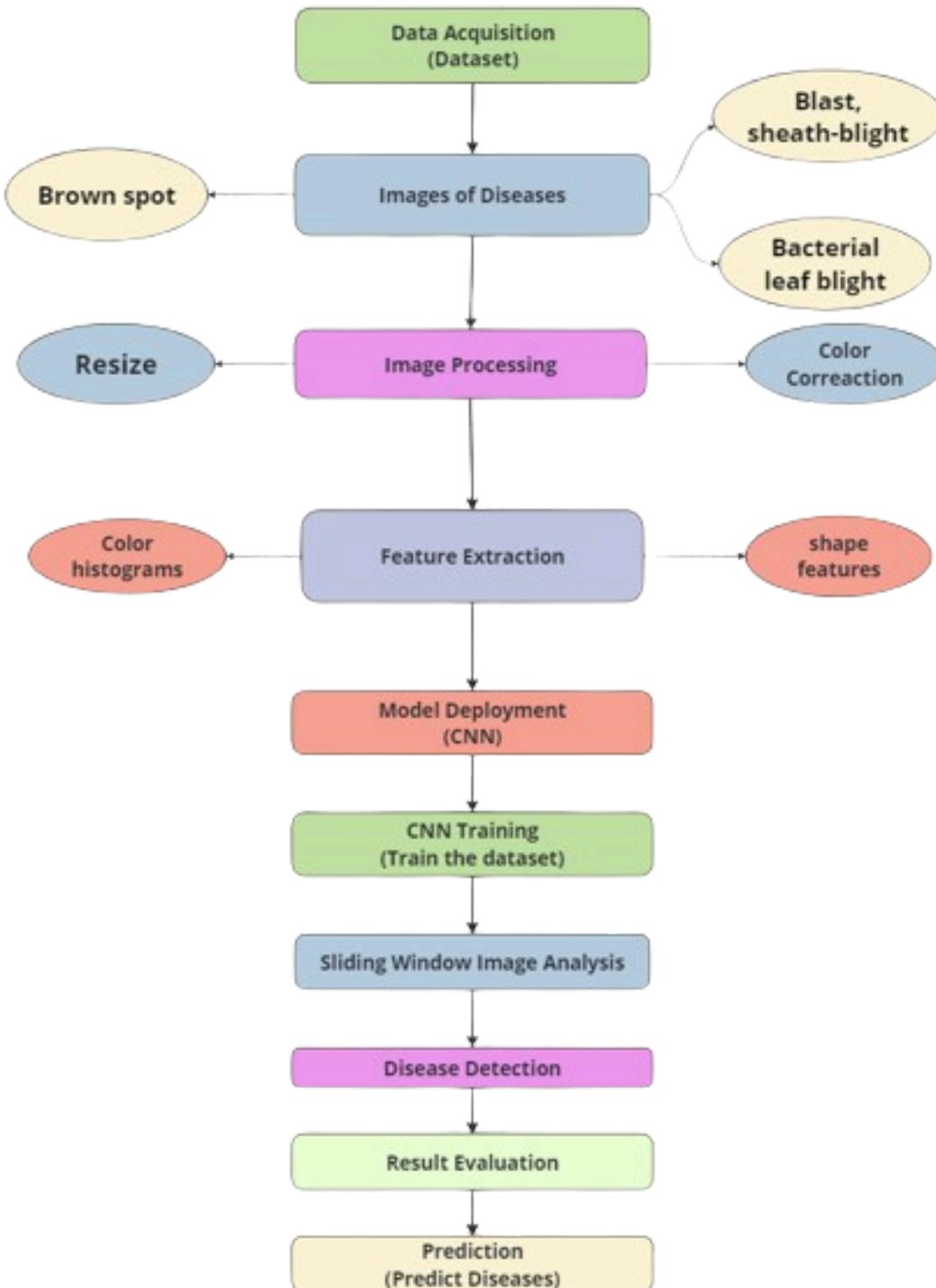
1.6 Rubrics Blog writing and LinkedIn Profile building

Parameter	Excellent	Very good	Good	Average
	20	15	10	5
Content and Creativity	Content provides comprehensive insight, understanding, and reflective thought about the topic by building a focused argument around a specific issue or asking a new related question or making an oppositional statement supported by personal experience or related research.	Content provides moderate insight, understanding and reflective thought about the topic.	Content provides minimal insight, understanding and reflective thought about the topic.	Content shows no evidence of insight, understanding or reflective thought about the topic.
Text Layout, Use of Graphics and Multimedia	Selects and includes high quality graphics and multimedia when appropriate to enhance the content's visual appeal and increase readability.	Selects and includes graphics and multimedia that are mostly high quality and enhance and clarify the content.	Selects and includes many low-quality graphics and multimedia which do not enhance the content.	Does not include any graphics, or uses only low-quality graphics and multimedia, which do not enhance the content.
Quality of Writing and Proofreading	Written content is free of grammatical, spelling or punctuation errors. The style of writing facilitates communication.	Written content is largely free of grammatical, spelling or punctuation errors. The style of writing generally facilitates communication.	Written content includes some grammatical, spelling or punctuation errors that distract the reader.	Written content contains numerous grammatical, spelling or punctuation errors. The style of writing does not facilitate effective communication.
Citations	All images, media and text created by others display appropriate copyright permissions and accurate citations.	Most images, media or text created by others display appropriate copyright permissions and accurate,	Some of the images, media or text created by others does not display appropriate copyright permissions and does not include	No images, media or text created by others display appropriate copyright permissions and do not include accurate, properly formatted citations.

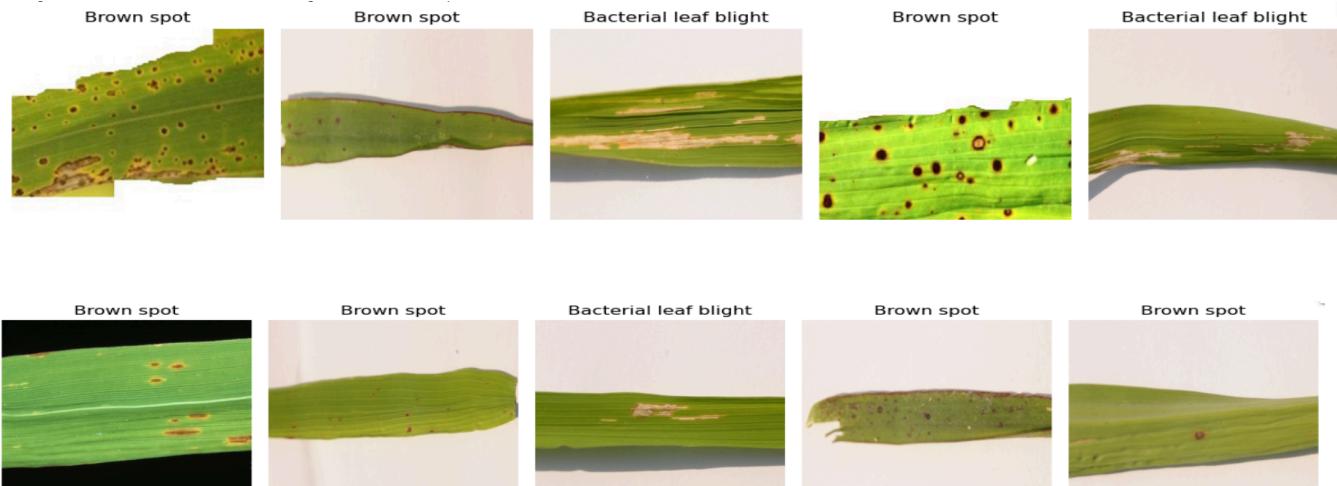
		properly formatted citations.	accurate, properly formatted citations.	
Publication of blog	The blog is posted on student's host site.	The blog is posted on free blog site.	The blog is made into a web page.	The blog is not posted.
GA12	The blog has all three of the following: Likes, shares and comments.	The blog has any two of the following: Likes, shares and comments .	The blog has received only one of the following: Likes, shares and comments.	The blog has not received either of the following: Likes, shares and comments.

Chapter 2: Prototype Development

2.1 Screenshots of Prototype Development

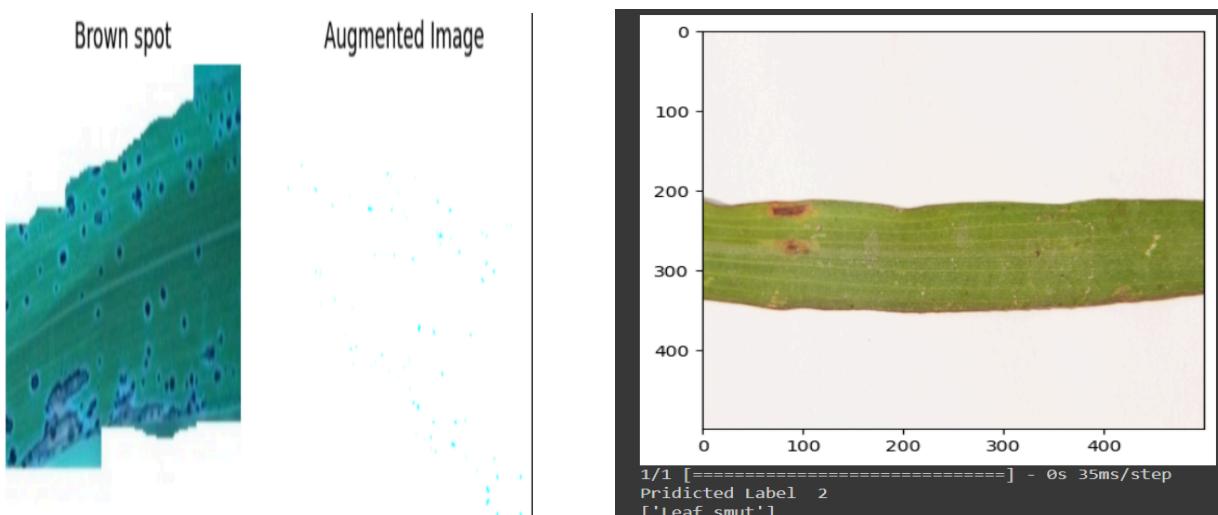


Dataset



Result:

```
1/1 [=====] - 0s 141ms/step - loss: 1.5653 - accuracy: 0.7917  
[1.5653456449508667, 0.7916666865348816]
```



2.2 Tool Description

The development of a predictive model for rice leaf diseases necessitates the utilization of various tools and technologies to collect, analyze, and interpret data effectively. The following tools are instrumental in the creation and implementation of the proposed model:

- **Machine Learning Frameworks:** Machine learning frameworks such as TensorFlow, scikit-learn, or PyTorch are essential for building the predictive model. These frameworks provide a range of algorithms and tools for training, evaluating, and deploying machine learning models. Supervised learning algorithms, such as decision trees, random forests, and support vector machines, can be employed to analyze historical disease data and identify patterns associated with disease outbreaks.
- **Geospatial Analysis Tools:** Geospatial analysis tools like QGIS or ArcGIS are utilized to process and analyze spatial data related to rice cultivation and disease incidence. Geographic Information System (GIS) techniques enable the integration of georeferenced data such as soil types, weather patterns, and land cover into the predictive model. By incorporating spatial information, the model can identify spatial patterns of disease prevalence and assess the impact of environmental factors on disease spread.
- **Data Visualization Libraries:** Data visualization libraries such as Matplotlib, Seaborn, or Plotly are employed to visualize and interpret the results of the predictive model. Visualization techniques such as heatmaps, choropleth maps, and time series plots facilitate the exploration of temporal and spatial patterns in disease incidence. Visual representations of data enable stakeholders to gain insights into disease trends and make informed decisions regarding crop management practices.
- **Cloud Computing Platforms:** Cloud computing platforms such as Google Cloud Platform (GCP) or Amazon Web Services (AWS) provide scalable infrastructure for data storage, processing, and model deployment. These platforms offer services such as cloud storage, data preprocessing, and machine learning APIs, which streamline the development and deployment of the predictive model. Cloud-based solutions enable real-time data processing and decision-making, enhancing the agility and responsiveness of the model.
- **Mobile Application Development Tools:** Mobile application development tools such as Android Studio or Flutter are utilized to create mobile applications for delivering predictive model insights to end-users, particularly farmers and agricultural stakeholders. Mobile applications enable farmers to access disease forecasts, receive alerts, and access relevant agricultural resources directly from their smartphones or tablets, enhancing the accessibility and usability of the predictive model.

2.3 Rubrics Prototype Development

Parameter	Excellent (20)	Very Good (15)	Good (10)	Average (05)
Identifying Type of Prototype (Visual prototype/Functional prototype /Presentation prototype) (GA3)	Functional Prototype	Presentation prototype	Visual Prototype with little functions	Only Visual prototype
Advantages of prototyping GA4	Identification of innovative design thinking-based approach to make a prototype which is easy to implement and cost effective Interdisciplinary knowledge is applied	Identification of innovative approach to make a prototype	Try existing methods with slight modification to make a prototype	Apply existing methods and solution as it is to make a prototype
A step-by-step break-down of prototyping GA4,GA5	Apply latest Tools and technology	Apply latest Tools and technology learned in academic s	Application of old techniques with slight modification	Application of old tools and techniques
The Spiral model GA8,GA10	Review and plan for next phase Use of own design	Develop next version of product Use of existing design	Objective determination and identify alternative solutions	Identify and resolve risks
Conclusion GA 11	(A)Clarify its purpose, function and appearance+(B)+(C)+(D) Use of project management tools and knowledge to conclude	(B) Improve user experience and marketability) +(C)+(D)	(C) Explore its manufacturability and make-up+(D)	(D) Solve problems before they occur

Chapter 3: Mathematical Model and Infographics

3.1 Description of Mathematical model used

The mathematical model used in the Rice Leaf Disease Detection research likely encompasses several components, particularly in the realm of machine learning and image processing. Here's a breakdown of potential mathematical models that could have been employed:

1. Image Preprocessing Operations: While not strictly a mathematical model in itself, image preprocessing involves mathematical operations such as resizing, noise reduction (often through filters like Gaussian blur), and color correction. These operations may involve mathematical algorithms tailored to image processing.
2. Feature Extraction: Various mathematical techniques are used for extracting features from images. These could include:
 - Color Histograms: Representing the distribution of colors in an image using mathematical histograms.
 - Texture Descriptors: Techniques like Gabor filters or Local Binary Patterns (LBPs) involve mathematical calculations to characterize the texture of different regions within an image.
 - Shape Features: Geometric properties of objects in the image, which can be described using mathematical formulas.
3. Machine Learning Models: The heart of many automated detection systems, machine learning models rely heavily on mathematical principles. Common models include:
 - Random Forests: Ensemble learning methods based on decision trees, utilizing mathematical principles for tree construction and voting mechanisms.
 - Convolutional Neural Networks (CNNs): Deep learning architectures particularly well-suited for image classification tasks, leveraging mathematical operations like convolutions and pooling.
4. Sliding Window Technique: While not a model in the traditional sense, the sliding window technique involves mathematical calculations to define the size and stride of the window as it traverses the image. This technique enables systematic analysis of different regions within the image.
5. Evaluation Metrics: In assessing the performance of the disease detection system, mathematical metrics such as accuracy, precision, recall, F1 score, and ROC curves are commonly used. These metrics quantify the performance of the model and help in its optimization.

Overall, the mathematical model used in the study likely integrates these components, leveraging mathematical principles and algorithms to process images, extract relevant features, and train machine learning models for accurate disease detection.

chat gpt vr he bhetla

3.2 Usage of Mathematical model in the project

The proposed model is a combination of regression and classification. ANN model is used for implementation. Following are the algorithmic steps of the model.

Step 1: Collect week-wise data of agro-meteorological parameters for disease forecasting.

Step 2: Load data by using the pandas library

Step 3: Perform data pre-processing on the instances of the dataset.

Step 4: Build a model based on ANN using Keras.

Step 5: Divide the dataset into two parts: training dataset and test dataset. The dataset is split into two cases (70–30%, 80–30%) and results are verified accordingly.

Step 6: Training the network by utilizing the dataset.

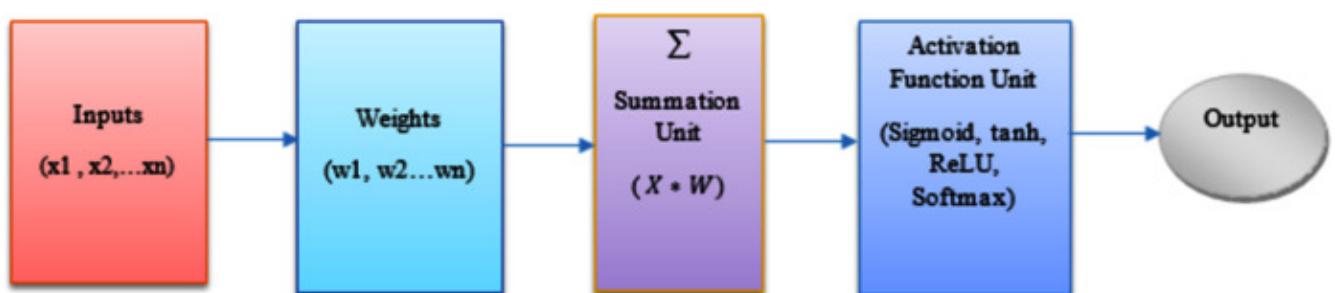
Step 7: Prediction of future values of climatic parameters.

Step 8: Evaluation of the prediction model

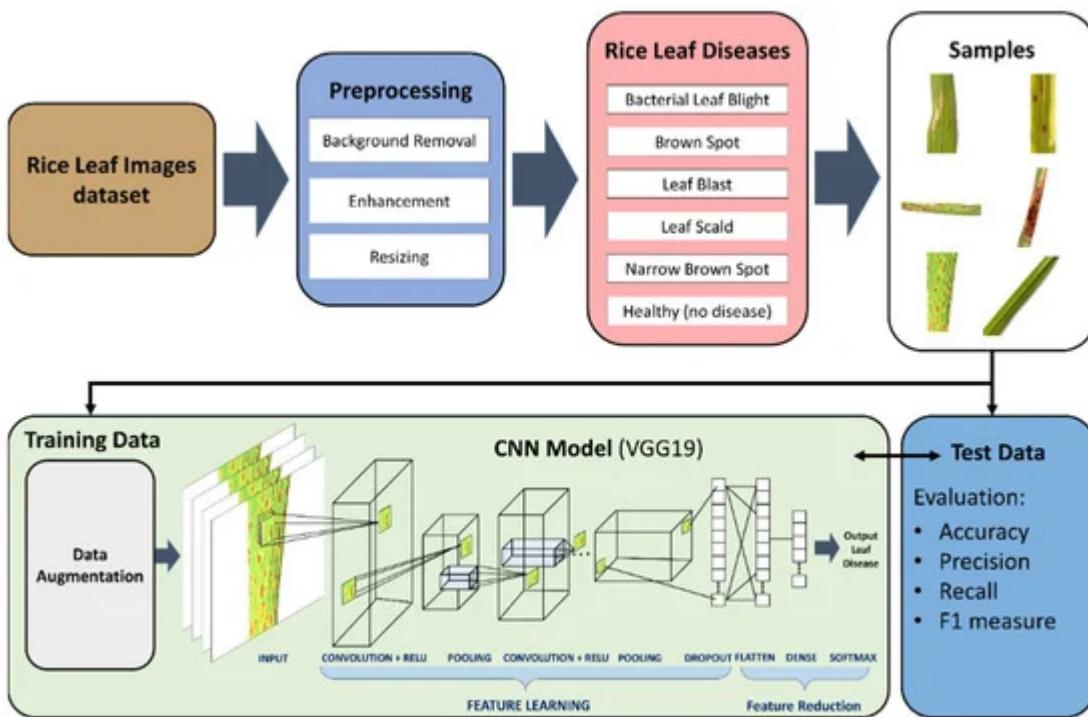
Step 9: Prediction of crop disease occurrence. The final output will be in the form of five classes namely Healthy, Rice Blast, Blight, Brown Spot, and False Smut.

Step 10: Evaluation of the classification model.

Class 1—Healthy, Class 2—Rice Blast, Class 3—Bacterial Blight, Class 4—Brown Spot, Class 5—False Smut.



3.3 Infographics



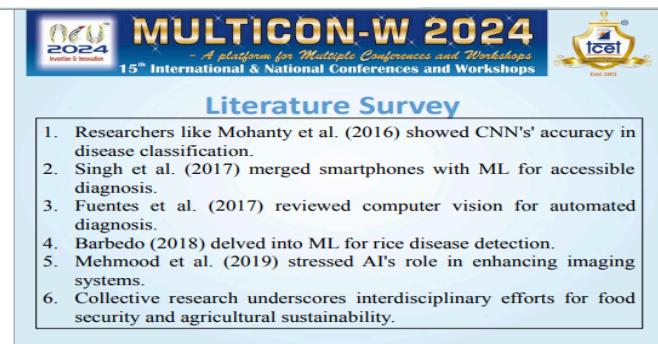
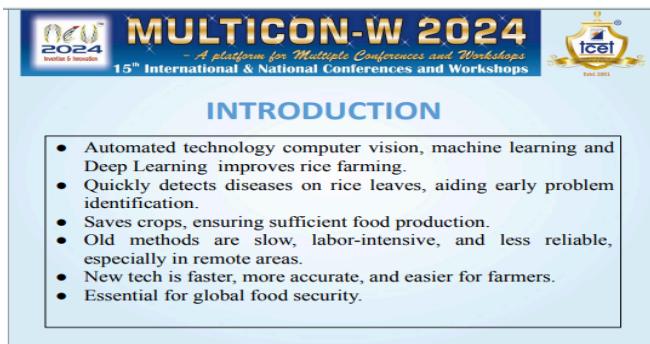
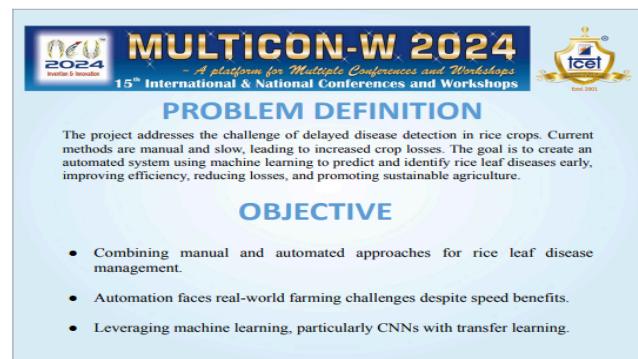
3.4 Rubrics Mathematical Model and Infographics

Mark s	20	15	10	5
Para meter	Excellent	Very Good	Good	Average
State ment of Probl em in real world	Students are able to identify the real-world problem that can be represent in specific mathematical model	Students are able to identify the real-world problem that can be represent in general mathematical model	Students are able to identify the real-world problem that can be represent in abstract mathematical model	Students are able to identify the real-world problem that can be represent in poor mathematical model
Techn icality	Students are able to identify clear and specific mathematical variables (parameters)	Students are able to identify generalized mathematical variables (parameters) that will be directly or indirectly influenced	Students are able to identify abstract mathematical variables (parameters) that will be directly or indirectly influenced	Students are able to identify barely relevant mathematical variables (parameters)
Desig n and Form ulation of Mode l	It completely enables the construction of a mathematical model using of tools required for mathematical modelling and simulation	It enables the construction of a mathematical model use of some tools required for mathematical modelling and simulation	It enables the construction of a mathematical model use of a few tools required for mathematical modelling and simulation	It enables the construction of a mathematical model without using tools required for mathematical modelling and simulation.
Prese ntatio n and Team Work	Student demonstrates full knowledge, answering all queries with explanations through the attractive infographics.	Student demonstrates partial knowledge, answering some of queries with explanations through the very good infographics.	Student is able to answer only basic queries utilization good infographics.	Student have poor knowledge; they are able to answer only few queries utilization poor infographics.

Evaluation of the Mathematical Model	Mathematical model is able to represent exact behaviour of real world problem identified and same is reflected using infographics	Mathematical model is able to represent similar behaviour of real world problem and same is reflected using infographics	Mathematical model is able to represent relevant behaviour of real world problem and same is reflected using good infographics	Mathematical model is able to represent irrelevant behaviour of real world problem and same is reflected using poor infographics
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Chapter 4: Research Paper

4.1 Screenshot of Research Paper Presentation



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THEORY: Modeling

A convolutional neural network (CNN)

- CNNs are neural networks designed for images.
- Use convolutional and pooling layers for feature extraction.
- Effective in tasks like image recognition.
- Shares parameters for efficient learning.
- Used in image classification, object detection.
- Involves labeled data, backpropagation, and optimization.
- Applies beyond images, e.g., in language processing.
- Constant research for improved architectures.

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THEORY: Modeling

- Rice grade: A model to estimate severity of the rice disease.
- Step 1: Primary and secondary dataset collection.
- Step 2: Rice image annotations.
- Step 3: Hyper-tuned optimized faster RCNN architecture for identification of disease and location of the disease affected area.
- Step 4: Testing.
- Step 5: Identification of instances and diseased area calculation.
- Step 6: Rice disease severity quantification and determine disease grade level.

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IMPORTANT FINDINGS

Observation

- Technological Advancements
- Accuracy and Early Detection
- Impact on Agriculture

Comparative Table

Aspect	Traditional Method	Automated Method
Technological Advancements	Relies on manual observation and diagnosis.	Utilizes advanced technologies like machine learning and computer vision.
Accuracy and Early Detection	Relatively lower accuracy due to human error and subjectivity.	Offers higher accuracy through automated algorithms and data-driven analysis.
Impact on Agriculture	Limited impact due to reliance on manual methods.	Potential for significant positive impact on agriculture, and enhanced farmer livelihoods.

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RESULTS AND DISCUSSION

- CNN model started at 58% accuracy, improved to 66% with fine-tuning the learning rate.
- Data augmentation increased accuracy to 87%, reducing overfitting risks.
- MLP struggled with disease identification, highlighting CNN's superiority.
- Random search for hyperparameter optimization had limitations.
- CNN with data augmentation is most effective for disease classification, offering insights for medical diagnostics.

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SWOT ANALYSIS

S	O	W	T
Strength	Opportunities	Weakness	Threats
<ul style="list-style-type: none"> Early disease detection Precision agriculture Improved yield Cost reduction Food security 	<ul style="list-style-type: none"> Technological advancements Collaboration Data sharing Integration with farming practices 	<ul style="list-style-type: none"> Model complexity Data limitations Algorithm bias Resource-intensive 	<ul style="list-style-type: none"> Climate change Emerging diseases Regulatory challenges Privacy concerns

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CONCLUSION

- Emphasizes automated Rice Leaf Disease Detection for better agriculture.
- Uses machine learning and computer vision for accurate diagnosis.
- Aims to reduce crop losses and improve food security.
- Ethical considerations include data privacy and equitable access.
- Calls for responsible technology deployment.
- Highlights technology's transformative impact on global food production.
- Contributes to agricultural sustainability and resilience.

FUTURE SCOPE

- Integration of Deep Learning Models
- Mobile Application for Instant Monitoring

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ACKNOWLEDGEMENT

We would like to express our sincere gratitude to TCET for providing us a platform in Multicon W 2024. Special thanks to Dr. Rashmi Thakur maam for guiding us throughout, also the colleagues and supervisors who, through their guidance and support, have helped us attain the knowledge and skills associated with our current designation. Their mentorship has been invaluable in shaping our professional growth and understanding of the responsibilities associated with our role.

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REFERENCES

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- ADVANCEMENTS IN AGRICULTURAL TECHNOLOGY, SUCH AS ARTIFICIAL INTELLIGENCE (AI), ARE REVOLUTIONIZING DISEASE MANAGEMENT AND CROP PRODUCTIVITY. (ONLINE). AVAILABLE: [HTTPS://WWW.MDPLCOM/2073-4395/13/4/961](https://www.mdpl.com/2073-4395/13/4/961)
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QUESTION and ANSWER ??

4.2 Research paper

Rice Leaf Disease Prediction

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Abstract—This project aims to develop a predictive model for rice leaf diseases to enable early intervention and enhance crop management. Leveraging machine learning, geospatial data, and historical disease patterns, the model will forecast disease outbreaks, supporting farmers in disease prevention and improved agricultural sustainability. The project seeks to empower local communities, reduce yield losses, reduce economic loss and strengthen food security in the region. The implementation of a predictive model for early detection of leaf diseases in agriculture has a transformative impact, significantly reducing economic losses, optimizing resource use, and enhancing environmental sustainability. By enabling farmers to intervene proactively, the model contributes to improved crop quality, data-driven decision-making, and resilience against climate change. The reduction in chemical dependency aligns with sustainable practices, while the overall effect ensures a more secure and consistent food supply, addressing the challenges of a growing global population. This impactful approach not only safeguards agricultural livelihoods but also promotes a resilient and sustainable future for the agricultural sector.

Keywords - Rice Leaf Disease Detection, Predictive Model, Geospatial Data, Early Intervention, Crop Management

I. INTRODUCTION

Rice (*Oryza sativa*) is one of the most important staple crops in the world, feeding more than 50% of the world's population. The emergence of many diseases that adversely affect crop productivity and quality, however, poses significant obstacles to the sustainable production of rice. In recent years, applying state-of-the-art technology—particularly in the fields of computer vision and machine learning—has proven to be a successful approach to solving these problems. The creation of automated rice leaf disease detection systems has the potential to drastically alter rice farming practices, reducing crop losses and

improving food security by enabling early disease diagnosis and targeted treatments.

Rice plants are susceptible to various diseases, including brown spot, bacterial leaf blight, blast, and sheath blight. These ailments are capable of large yield losses, which endangers the world's food security in addition to the financial security of farmers. The physical visual assessment of illness by skilled agronomists is the foundation of traditional disease diagnostic techniques, which are labor-intensive, time-consuming, and frequently inaccurate. Furthermore, access to qualified staff may be restricted in isolated or underdeveloped agricultural regions. For an accurate and efficient disease evaluation in this situation, automated technologies for detecting rice leaf disease present a viable option.

II. OBJECTIVES

Reviewing the major rice leaf diseases, their symptoms, and their impact on crop health and yield. Assessing current technologies and methodologies for detecting rice leaf diseases, whether through manual or automated means, entails examining their respective strengths and weaknesses. Automated detection systems offer several advantages, such as speed and consistency, but they also face limitations in real-world agricultural settings. Recent advancements in image processing, feature extraction, and machine learning algorithms have enhanced disease detection accuracy. However, the effectiveness of these systems heavily relies on data quality, necessitating comprehensive data collection, dataset creation, and rigorous model training. Implementing automated rice leaf disease detection in broader agricultural contexts presents both challenges and opportunities. Applying transfer learning to pre-trained CNN models for automatic identification of rice leaf diseases. Improving the performance of these transfer learning

models. Evaluating and comparing the performance of various transfer learning models for rice leaf disease identification. Determining the best-performing and most effective transfer learning models for rice leaf disease identification.

III. LITERATURE SURVEY

Recent advancements in rice leaf disease prediction have sparked a wave of transformative innovation, driven by the convergence of cutting-edge technologies and interdisciplinary collaborations. Mohanty et al. (2016) catalyzed this evolution with their groundbreaking exploration of convolutional neural networks (CNNs), showcasing their unprecedented capacity to accurately discern a multitude of rice leaf diseases through robust image classification. Simultaneously, Singh et al. (2017) heralded a new era of accessibility in disease diagnosis by ingeniously integrating smartphone technology with sophisticated machine learning algorithms, empowering farmers with user-friendly tools for proactive intervention. Amidst this burgeoning landscape, Fuentes et al. (2017) embarked on a comprehensive survey, meticulously mapping the intricate terrain of computer vision methods tailored for automated disease diagnosis, including nuanced strategies tailored to the complexities of rice leaf diseases.

Complementing these efforts, Barbedo (2018) undertook a deep dive into the realm of machine learning techniques tailored specifically for rice leaf disease detection, unraveling their potential and limitations in real-world agricultural contexts. Grounded in empirical evidence, Mehmood et al. (2019) synthesized critical insights gleaned from diverse studies, emphasizing the indispensable role of artificial intelligence in propelling innovation across imaging systems, thereby charting a course towards more accurate, efficient, and sustainable solutions.[4] Through a harmonious blend of theory and practice, these seminal works collectively underscore the transformative power of interdisciplinary research and technological innovation in addressing pressing challenges in rice leaf disease prediction, ultimately advancing the cause of global food security and agricultural sustainability.

IV. WORKING OF CNN

In the realm of rice leaf disease prediction, Convolutional Neural Networks (CNNs) have emerged as a cornerstone technology, revolutionizing the automation of disease

identification and classification through leaf images. The functioning of CNNs begins with passing input images through a series of convolutional layers. These layers are composed of filters or kernels that detect specific patterns or features within the images, such as edges, textures, or shapes. Through the convolution operation, each filter scans across the input image, performing element-wise multiplication with the pixel values in its receptive field and then summing up the results to generate a feature map. This process allows the network to extract hierarchical representations of features from the input images, progressively capturing more abstract and complex patterns as information flows through the layers.

Following the convolutional layers, an activation function is applied to introduce non-linearity into the network. Rectified Linear Unit (ReLU) is a commonly used activation function that replaces negative pixel values with zero, enabling the model to learn complex relationships within the data. Subsequently, pooling layers are often incorporated to downsample the feature maps and reduce their dimensionality while retaining the most salient information. Max pooling, a prevalent pooling technique, selects the maximum value within each pooling window, effectively highlighting the presence of specific features regardless of their precise spatial location in the image. This process aids in reducing computational complexity and improving the network's efficiency by focusing on the most relevant features.

Upon completion of the convolutional and pooling layers, the resulting feature maps are flattened into a one-dimensional vector, preparing the data for input into fully connected layers.[5] These fully connected layers function akin to a traditional neural network, with each neuron connected to every neuron in the preceding layer. Through the fully connected layers, the network learns high-level features and patterns from the spatially organized features extracted by the convolutional layers. Finally, the output layer of the CNN typically consists of neurons representing different classes or categories of diseases. During the training phase, the network adjusts its parameters through backpropagation, comparing predicted outputs with actual labels and optimizing its parameters using optimization algorithms such as stochastic gradient descent (SGD) or Adam. By iteratively refining its parameters based on the training data, the CNN enhances its ability to accurately

classify rice leaf images and predict the presence of diseases. This capability enables early detection and intervention in agricultural practices, thereby contributing to improved crop management, increased yields, and sustainable agricultural practices.

V. METHODOLOGY

The research methodology for Rice Leaf Disease Detection involved acquiring a comprehensive dataset which is shown in (Fig 1.0) and employing image preprocessing, feature extraction, and machine learning model development. Additionally, the study utilized a sliding window technique to enhance the accuracy of disease detection.. Data for this study were primarily sourced through field surveys, leveraging the expertise of agricultural professionals and the collaboration of local rice farmers.[3] Additionally, a publicly available dataset of rice leaf images was utilized to augment the training dataset. In the preprocessing phase, collected images underwent a series of operations, including resizing, noise reduction, and color correction, to ensure uniformity and enhance the quality of the dataset. Furthermore, data augmentation techniques such as rotation, flipping, and brightness adjustments were applied to increase the diversity of the dataset.

The feature extraction process focused on extracting relevant attributes from rice leaf images. Color histograms, texture descriptors, and shape features were computed from each image to represent its visual characteristics. A critical component of the research was the implementation of a sliding window approach for image analysis.[10] A sliding window, with predefined size and stride, traversed the input image, partitioning it into smaller segments for individual analysis. This approach allowed for a systematic examination of different regions within the image to detect the presence of diseases.

The methodology outlined in this study serves as a comprehensive framework for the development and assessment of automated rice leaf disease detection systems. [1] It combines data collection, image preprocessing, feature extraction, machine learning, and the sliding window technique to achieve accurate and robust disease detection, thus contributing to advancements in agriculture and food security.

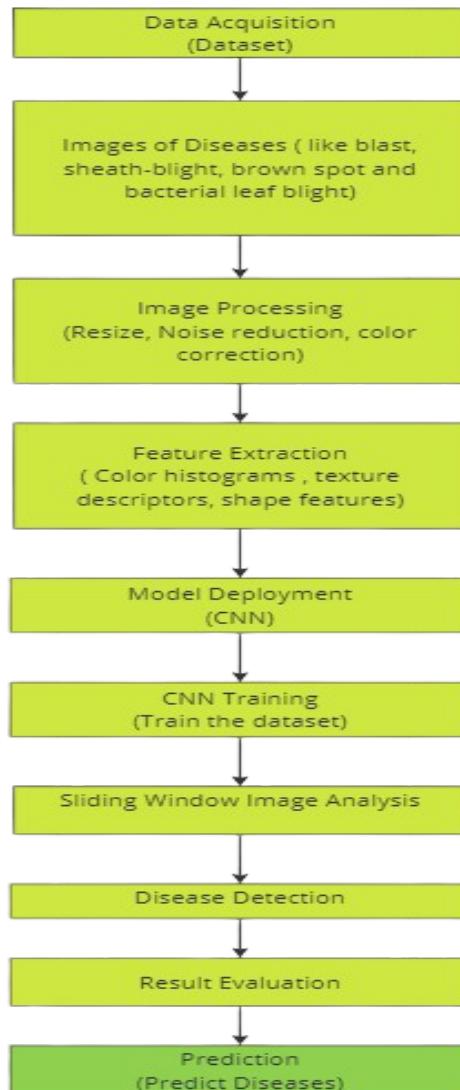


Fig 1.0 Flowchart

Datasets

In this research, we assembled a dataset by gathering publicly available rice leaf disease images from Kaggle and Mendeley data which showed in (Fig 1..1) . The dataset comprised nine diseased classes and one healthy class, which were combined to form a comprehensive collection. To enhance the diversity and size of the training dataset, data augmentation techniques were applied, resulting in a total of 10,080 images. Each class contained a specific number of images, with most classes having 1004 images, except for Leaf streak and tungro classes, which had slightly more, totaling 1022 and 1024 images, respectively. The included classes were Bacterial leaf blight, Brown spot, Hispa, Leaf blast, Leaf scald, Leaf streak, Narrow brown spot, Sheath blight, Tungro, and Healthy. [2] All images were standardized to jpg format and had a resolution of 128 × 128 pixels. Moreover, the images were captured under consistent illumination conditions and against a white background setting.

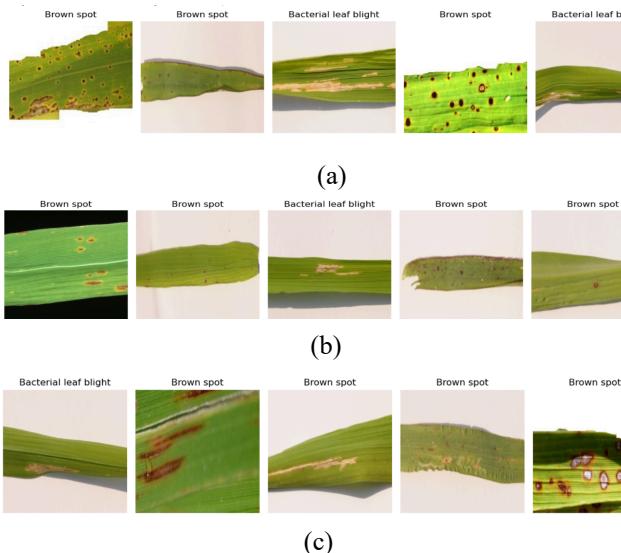


Fig 1.1 Dataset Images

VI. NEEDS

One of the most important food crops in the world, rice provides nourishment for more than half of the world's population and is an essential component of diets. Ensuring a consistent and plentiful rice crop is more important than ever as the world's population rises. Rice is cultivated extensively in many nations, especially in Asia, where it is a staple food for a huge percentage of the population and a major source of calories and important nutrients including proteins, carbs, vitamins, and minerals.

Rice crops need to be protected from pests, illnesses, and other obstacles because of their critical role in ensuring the world's food security. To increase agricultural yield, this calls for putting appropriate farming methods into place, coming up with efficient ways to manage diseases, and using cutting-edge technologies. A crucial strategy that boosts yields by leveraging cutting-edge technologies is precision agriculture.

The automated leaf disease detection system, a cutting-edge precision agriculture tool, detects plant diseases by examining photos of afflicted leaves.[2] Deep learning (DL), machine learning (ML), computer vision, and image processing methods are all combined in this system. Farmers may rapidly and precisely analyze the health of their plants thanks to automated diagnostic tools, which speed the diagnostic procedure in contrast to time-consuming and costly old human-based approaches.

This increases agricultural yields and enables more effective use of resources.[11]

The use of ML and DL models for rice plant disease diagnosis is still largely unexplored, despite the potential advantages. Increased rice crop output and reduced losses from disease outbreaks are possible with more study in this area. Convolutional neural networks (CNNs) show promise as powerful instruments for diagnosing rice plant diseases automatically. Diseases may be detected early on with the use of CNNs, reducing crop loss and preventing the spread of disease.[1]

Though DL models have many benefits, they also have drawbacks, including the need for large amounts of labeled data for training, high processing costs, overfitting vulnerability, and difficulties deciphering the predictions made by the model. One approach that shows promise for overcoming these constraints is transfer learning. Transfer learning speeds up learning and improves performance by optimizing pre-trained models on smaller datasets, especially in situations when data is scarce. This method enhances generalization performance while lowering computing requirements.

All things considered, there is a great deal of promise for transforming rice plant disease detection through the integration of cutting-edge technologies like ML, DL, and transfer learning. This will help farmers to maximize crop management techniques and will achieve a better crop yields and also increase their financial results.

VII. GLIMPSES OF OUR SURVEY

1. Are you currently involved in agriculture or farming activities?

20 responses

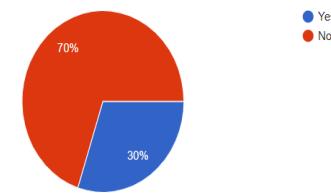


Fig 2.0 Survey Result

10. Do you think government support is essential for the widespread adoption of new technologies in agriculture?

20 responses

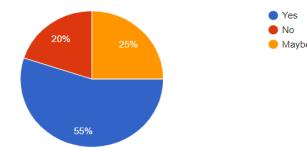


Fig 2.1 Survey Result



Fig 2.2 Survey Result

The results of the study show a significant demand for products and services that can help people and small businesses create and understand instruments for the detection of rice disease. Most respondents to the study said they think it would be helpful to improve the efficacy of diagnostic tools and automate the process of detecting rice problems with language that is easy to understand. (as shown in fig 2.0, fig 2.1, fig 2.2)

VIII. EXPERIMENTAL RESULTS

According to our research, the primary convolutional neural network (CNN) model initially attained an accuracy of 58%. However, after fine-tuning the learning rate to 0.0001, we noticed a considerable enhancement in performance, achieving an accuracy of 66%. It's important to note that increasing the learning rate beyond this threshold led to a decline in accuracy, underscoring the critical importance of selecting an optimal learning rate. Moreover, the utilization of data augmentation techniques notably improved model performance, resulting in an impressive accuracy of 87%. This underscores the effectiveness of data augmentation in bolstering the model's generalization capability and mitigating overfitting issues. On the other hand, our experiments with a multilayer perceptron (MLP) showed limitations in identifying all disease classifications accurately, suggesting that the CNN architecture is better suited for this task.[9] Furthermore, in our exploration of hyperparameter optimization using random search, we found that it was only able to identify one class effectively, indicating the need for more sophisticated optimization techniques or careful consideration of hyperparameters. Our results demonstrate that utilizing a CNN architecture with data augmentation techniques yields the most promising outcomes for disease classification tasks, providing valuable insights for improving diagnostic accuracy in medical applications.

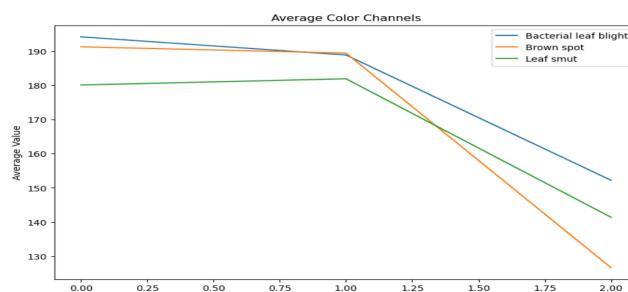


Fig 3.0 Average Color Channels

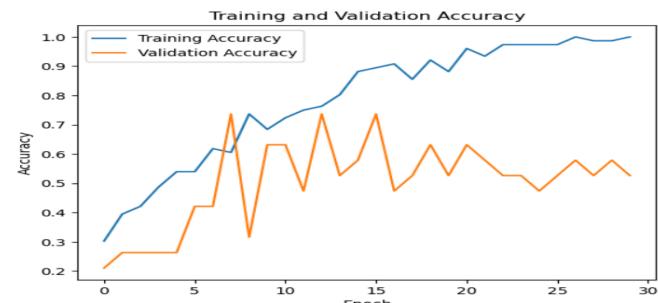


Fig 3.1 Training and Validation Accuracy

IX. DISCUSSION

The experimental results reveal a comprehensive evaluation of various methodologies for rice leaf disease prediction. Shown above (fig 3.0, fig 3.1). Initially, the primary convolutional neural network (CNN) model yielded an accuracy of 58%. However, fine-tuning the learning rate to 0.0001 resulted in a notable enhancement, elevating the accuracy to 66%. Notably, further adjustment of the learning rate led to diminished accuracy, underscoring the criticality of meticulous learning rate selection in model optimization.[7]

Integration of data augmentation techniques proved pivotal, substantially boosting the model's performance to an impressive 87% accuracy. This underscores the efficacy of data augmentation in enhancing model generalization and mitigating overfitting risks.

Contrastingly, experiments with a multilayer perceptron (MLP) underscored its limitations in accurately identifying all disease classifications.[8] This observation suggests the CNN architecture's superiority for such classification tasks. Moreover, the exploration of hyperparameter optimization via random search revealed shortcomings, with effective identification limited to a single class. This underscores the necessity for more advanced optimization methodologies or meticulous hyperparameter tuning to achieve optimal model performance.

In summary, the results underscore the efficacy of employing a CNN architecture augmented with data augmentation techniques for disease classification tasks, offering valuable insights into enhancing diagnostic accuracy in medical applications.

X. CONCLUSION

In summary, this research emphasizes the significance of automated Rice Leaf Disease Detection systems in bolstering agricultural practices, particularly in the context of rice cultivation. Leveraging advanced technologies, such as machine learning and computer vision, we have strived to develop accurate and accessible tools for early disease diagnosis. These systems have the potential to mitigate crop losses, enhance food security, and empower farmers. However, it is imperative to address ethical considerations and responsible technology deployment as we progress. This study underscores the pivotal role of technology in safeguarding global food production and supporting the well-being of rice-dependent communities. It is our hope that this research contributes to the ongoing advancement of agricultural technology and aids in addressing the pressing challenges of disease management in rice farming. As with any technological advancement, it is crucial to consider ethical implications and ensure responsible deployment. Ethical considerations in this context encompass concerns regarding data privacy, equitable access to technology, and the potential implications for traditional farming methods. Responsible deployment of technology entails addressing these issues while promoting transparency, accountability, and inclusivity throughout the development and implementation phases. This research underscores the transformative impact of technology in safeguarding global food production and supporting the welfare of rice-dependent communities. By advancing agricultural technology and addressing the challenges of disease management in rice farming, it contributes to ongoing efforts aimed at enhancing agricultural sustainability and resilience amid evolving environmental and socio-economic pressures.

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4.3 Rubrics

Sr. No		Question	Marks (20)	Marks (15)	Marks (10)	Marks (05)
			Excellent	Very Good	Good	Poor
1	Organization of Content	Do research paper is organized with proper sections and relevant content ?	If paper includes all heads including: 1) abstract, 2) introduction, 3) objectives, 4) methodology, 5) experimental plan, 6) result and discussion, 7) conclusions, 8) future scope. 9) References	If paper includes any 8 topics out of 1) If paper includes any 7 topics out of 1) abstract 2) introduction, 3) objectives, 4) methodology, 5) experimental plan, 6) result and discussion, 7) conclusions, 8) future scope. 9) References	If paper includes any 6-7 topics out of 1) 1) abstract, 2) introduction, 3) objectives, 4) methodology, 5) experimental plan, 6) result and discussion, 7) conclusions, 8) future scope. 9) References	If paper includes any 5 topics out of 1) abstract, 2) introduction, 3) objectives, 4) methodology, 5) experimental plan, 6) result and discussion, 7) conclusions, 8) future scope. 9) References
2	Correct Content with respect to Grammar and language	Do the research paper written in scientific language which clearly defines the research work done?	The writing is dull and un engaging. Some sentences are awkwardly constructed so that the reader is occasionally distracted. Word choice is merely adequate, and the range of words is limited.	The writing is generally engaging, but has some dry spots. Sentences are well phrased and there is some variety in length and structure. Word choice is generally good.	The writing is generally engaging, but has some dry spots. Sentences are well phrased and there is some variety in length and structure. Word choice is generally good.	The writing loses interest in the reader. Errors in sentence structure are frequent enough to be a major distraction to the reader. Many words are used inappropriate

			correct. Word choice is consistently precise and accurate.			
3	Design, Development and Implementation	Does research paper have proposed model, flowcharts, results of implementation and analysis?	All 4 parameters met: 1) Modern Tool Usage 2) Feasibility 3) User friendliness 4) Application	Any 3 parameters met: 1) Modern Tool Usage 2) Feasibility 3) User friendliness 4) Application	Only 2 parameters met: 1) Modern Tool Usage 2) Feasibility 3) User friendliness 4) Application	Only 1 parameter met: 1) Modern Tool Usage 2) Feasibility 3) User friendliness 4) Application
4	Presentation and Team Work	Does paper presentation team exhibit communication skill and co-operation while giving presentation?	<ul style="list-style-type: none"> Student demonstrates full knowledge, answering all queries with explanations. Movements seem smooth and help the audience visualize. Diverse talents are present in team with 	<ul style="list-style-type: none"> Student is at ease with information and answers all queries without elaboration. Made movements or gestures that enhance articulation. Team is concentrated with only one type of skill set. 	<ul style="list-style-type: none"> Student is uncomfortable with information and is able to answer only basic queries. Very little movement or descriptive gestures. Team members are not contributing much for multifaceted development of idea 	<ul style="list-style-type: none"> Student does not have grasp of Information and can't answer queries about subject. No movement or descriptive gestures. Team members are passive only one person is taking some efforts

			different skill set			
5	Qualification toward s Quality of Paper and research claims	Does the research paper have novelty, mathematical models, result and its analysis with proper conclusion consisting of project claim with proper verification, validation, and diagnostics?	Paper has novelty, mathematical models, Research claim and result analysis with some diagrammatic representation	Paper has 1) novelty, 2) mathematical models, 3) result analysis without any validation and verification	Paper has 1) novelty, 2) mathematical models, 3) result analysis and claim is not clear.	

Examiner can put ✓ (Tick) wherever applicable
 and put X (cross) if not applicable

Note:
Overall
 1
Remark

(Review Paper/Technical Paper/Poster/Case Study)

Name and Signature of Evaluator:

Chapter 5. Outside Participation certificates

5.1 Certificate(Screenshot)

NA

5.2 Rubrics

Parameter	Excellent (20 Marks) 100 %	Very Good (15 Marks) 75 %	Good (10 Marks) 50 %	Average (05 Marks) 25 %
Problem Identification GA 2	<p>Insightful and in-depth background information is provided to illuminate the issues through inclusion of:</p> <ul style="list-style-type: none"> • history relevant to the presentation, the “big picture” • a succinct description of the significance of the project 	<p>Background information is provided, including references to the work of others and an explanation of why the project was undertaken, to help put the presentation in context.</p>	<p>Little background information is presented using relevant references to help the audience understand the history and significance of the project.</p>	<p>Very little or no background information is presented to help the audience understand the history and significance of the project.</p>
Content GA 4	<ul style="list-style-type: none"> • Addresses all specified content areas. • Material abundantly supports the topic. • Use of engineering terms and jargon matches audience knowledge level. 	<ul style="list-style-type: none"> • Addresses most content areas. • Material sufficiently supports the topic. • Use of engineering terms and jargon mostly matches audience knowledge level. 	<ul style="list-style-type: none"> • Addresses some of the content areas. • Material minimally supports the topic. • Use of engineering terms and jargon minimally matches audience knowledge level. 	<ul style="list-style-type: none"> • Addresses few of the content areas. • Material does not support the topic. • Use of engineering terms and jargon does not match audience knowledge level.

Visuals GA4,GA5	<ul style="list-style-type: none"> • Use of prezi or advance tools Text is easily readable. • Graphics use constantly supports the presentation. • Slide composition has a professional look that enhances the presentation 	<ul style="list-style-type: none"> • Use of Powerpoint presentation Text is readable. • Graphics use mostly supports the presentation. • Slide composition is not visually appealing, but does not detract from the presentation 	<ul style="list-style-type: none"> Text is readable with effort. • Graphics use rarely supports the presentation. • Slide composition sometimes distracts from the presentation 	<ul style="list-style-type: none"> • Text is not readable. • Graphics use does not support the presentation. • Slide composition format is clearly distracting, obscuring the presentation
Presentation Skills GA 7	<ul style="list-style-type: none"> • Clearly heard and polished. • Attitude indicates confidence and enthusiasm. • Audience attention is constantly maintained. 	<ul style="list-style-type: none"> • Clearly heard but not polished. • Attitude indicates confidence but not enthusiasm. • Audience attention is mostly maintained. 	<ul style="list-style-type: none"> • Difficult to hear and/or moments of awkwardness. • Attitude indicates some lack of confidence and/or disinterest in subject. • Audience attention is minimally maintained 	<ul style="list-style-type: none"> • Inaudible; several awkward pauses. • Attitude indicates lack of confidence and/or disinterest in subject. • Audience attention is not maintained
Participation level GA 12	International / National	State	District / Local	Institute