PROJECT REPORT

1. INTRODUCTION

1.1 Project Overview

The project **"GrainPalette - A Deep Learning Odyssey in Rice Type Classification through Transfer Learning"** focuses on accurately classifying different types of rice grains using deep learning techniques. A rice grain image dataset was used, containing multiple rice varieties. The dataset was preprocessed and augmented to improve model performance. A pre-trained Convolutional Neural Network (CNN) model was fine-tuned using **Transfer Learning** techniques for better accuracy with limited data. Popular architectures like **VGG16** and **ResNet50** were explored and compared. Model evaluation was done using metrics like **accuracy**, **precision**, **recall**, and **F1-score**. The final model achieved high classification accuracy, showing the effectiveness of deep learning for agricultural applications.

1.2 Purpose

- To develop an automated system for accurately classifying different types of rice grains using image data.
- To reduce manual effort, time, and human error in traditional rice grain classification methods.
- To apply **Transfer Learning** techniques for effective model training with a small dataset.
- To explore and compare the performance of popular CNN architectures like **VGG16** and **ResNet50**.
- To improve the accuracy and reliability of rice type identification for agricultural and industrial use.
- To demonstrate the power of deep learning in solving real-world classification problems in the food industry.
- To build a scalable and efficient model that can be used for future grain classification tasks.

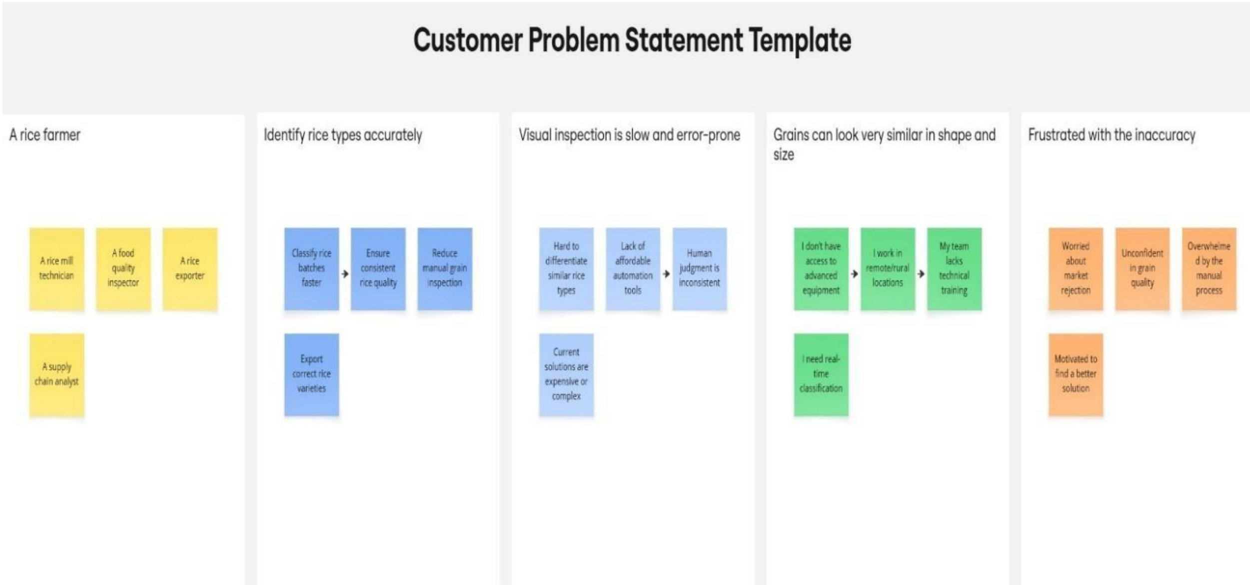
2. IDEATION PHASE

2.1 Problem Statement

Customer Problem Statement:

Create a problem statement to understand your customer's point of view. The Customer Problem Statement template helps you focus on what matters to create experiences people will love.

A well-articulated customer problem statement allows you and your team to find the ideal solution for the challenges your customers face. Throughout the process, you’ll also be able to empathize with your customers, which helps you better understand how they perceive your product or service.



Reference: https://miro.com/templates/customer-problem-statement/

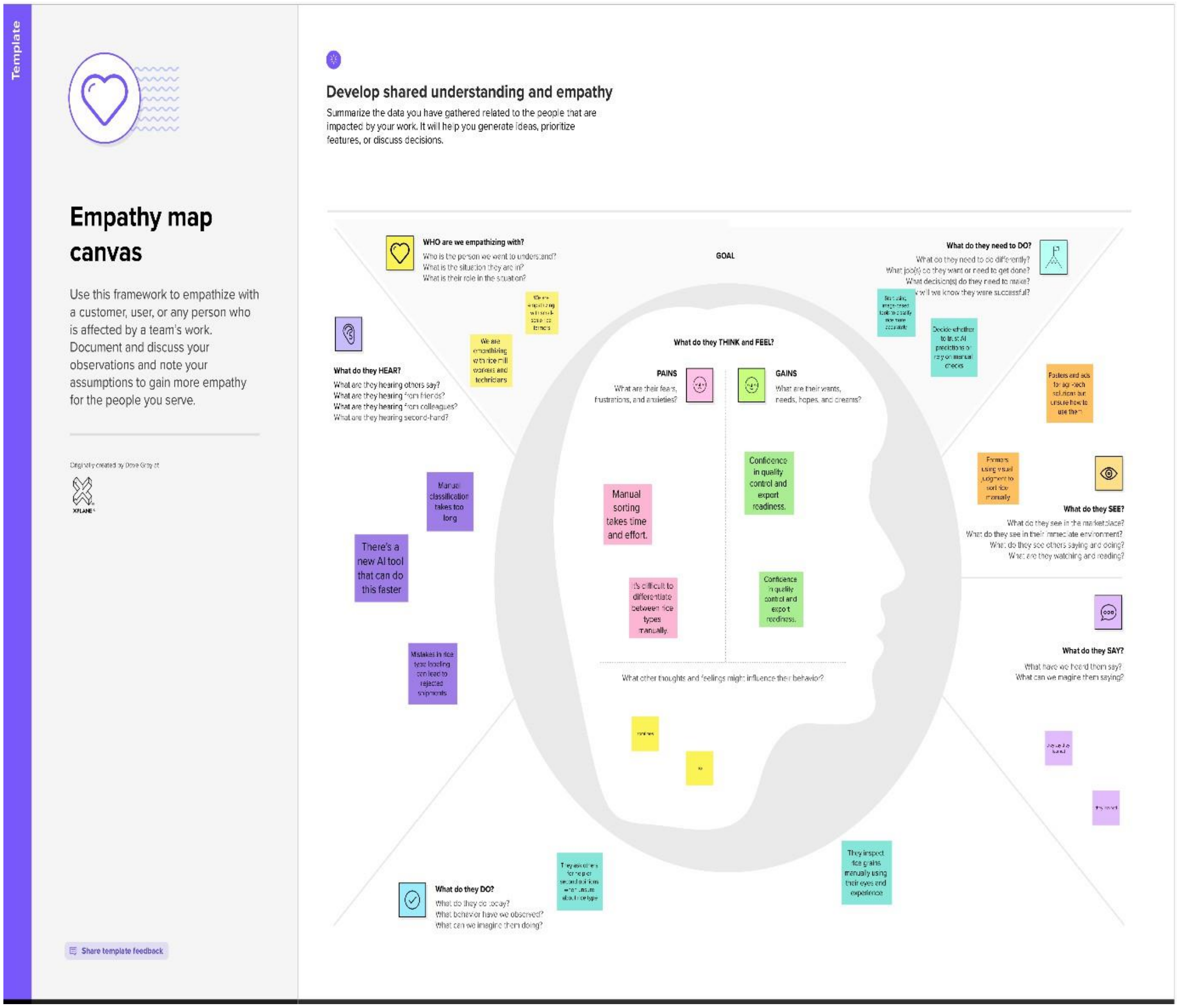
Problem Statement (PS)	I am (Customer)	I'm trying to	But	Because	Which makes me feel
PS-1	A rice farmer	Identify rice types in my harvest accurately	I rely on manual inspection	Its hard to tell types apart visually	Unsure, frustrated, and worried about selling low-quality rice
PS-2	A rice mill technician	Quickly classify rice batches during processing	I don't have time for detailed checking	Manual methods are slow and error-prone	Pressured,inefficient,and stressed

2.2 Empathy Map Canvas

An empathy map is a simple, easy-to-digest visual that captures knowledge about a user's behaviours and attitudes.

It is a useful tool to helps teams better understand their users.
Creating an effective solution requires understanding the true problem and the person who is experiencing it. The exercise of creating the map helps participants consider things from the user's perspective along with his or her goals and challenges.

Reference: https://www.mural.co/templates/empathy-map-canvas



2.3 Brainstorming

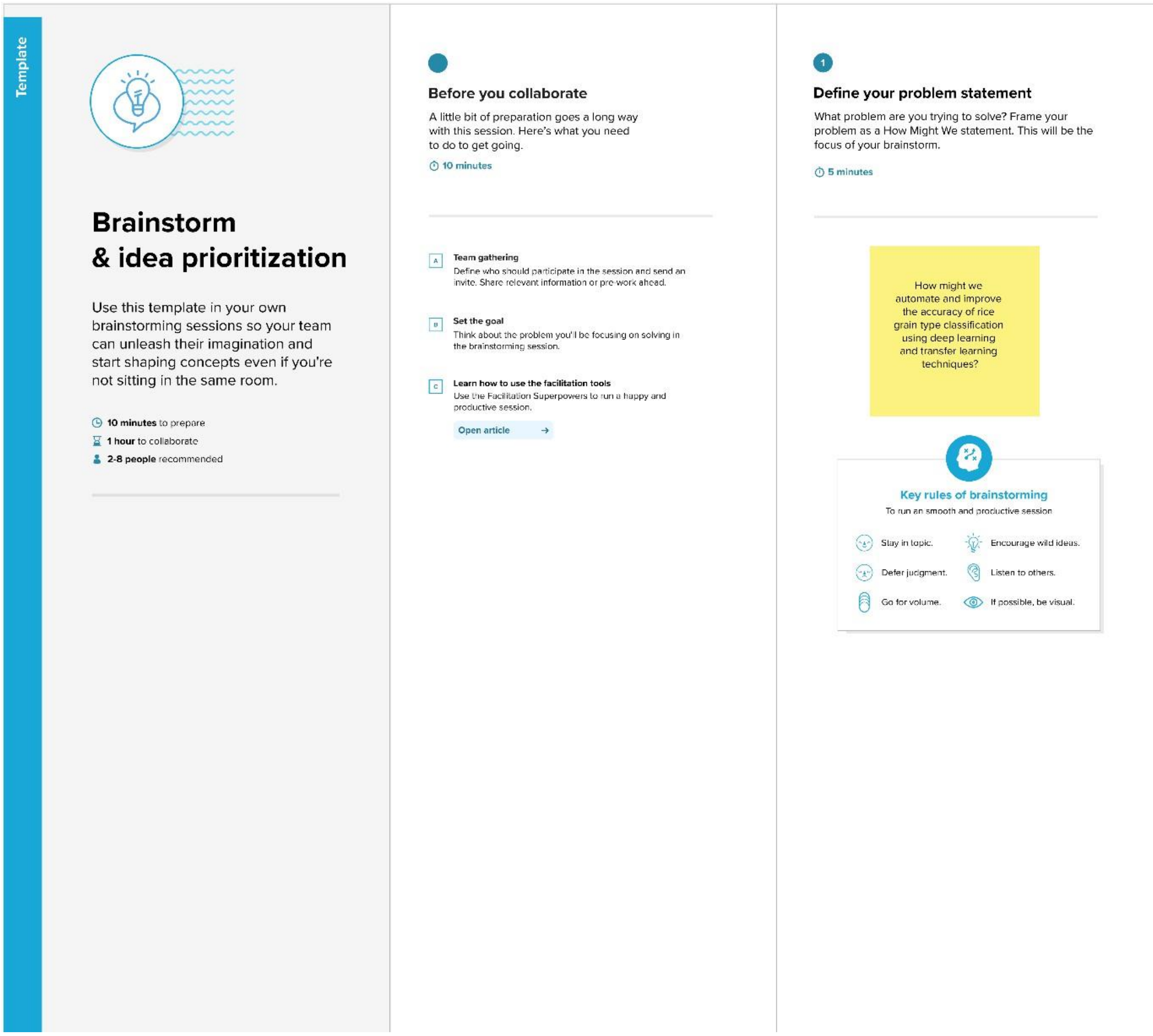
Brainstorm & Idea Prioritization:

Brainstorming provides a free and open environment that encourages everyone within a team to participate in the creative thinking process that leads to problem solving. Prioritizing volume over value, out-of-the-box ideas are welcome and built upon, and all participants are encouraged to collaborate, helping each other develop a rich amount of creative solutions.

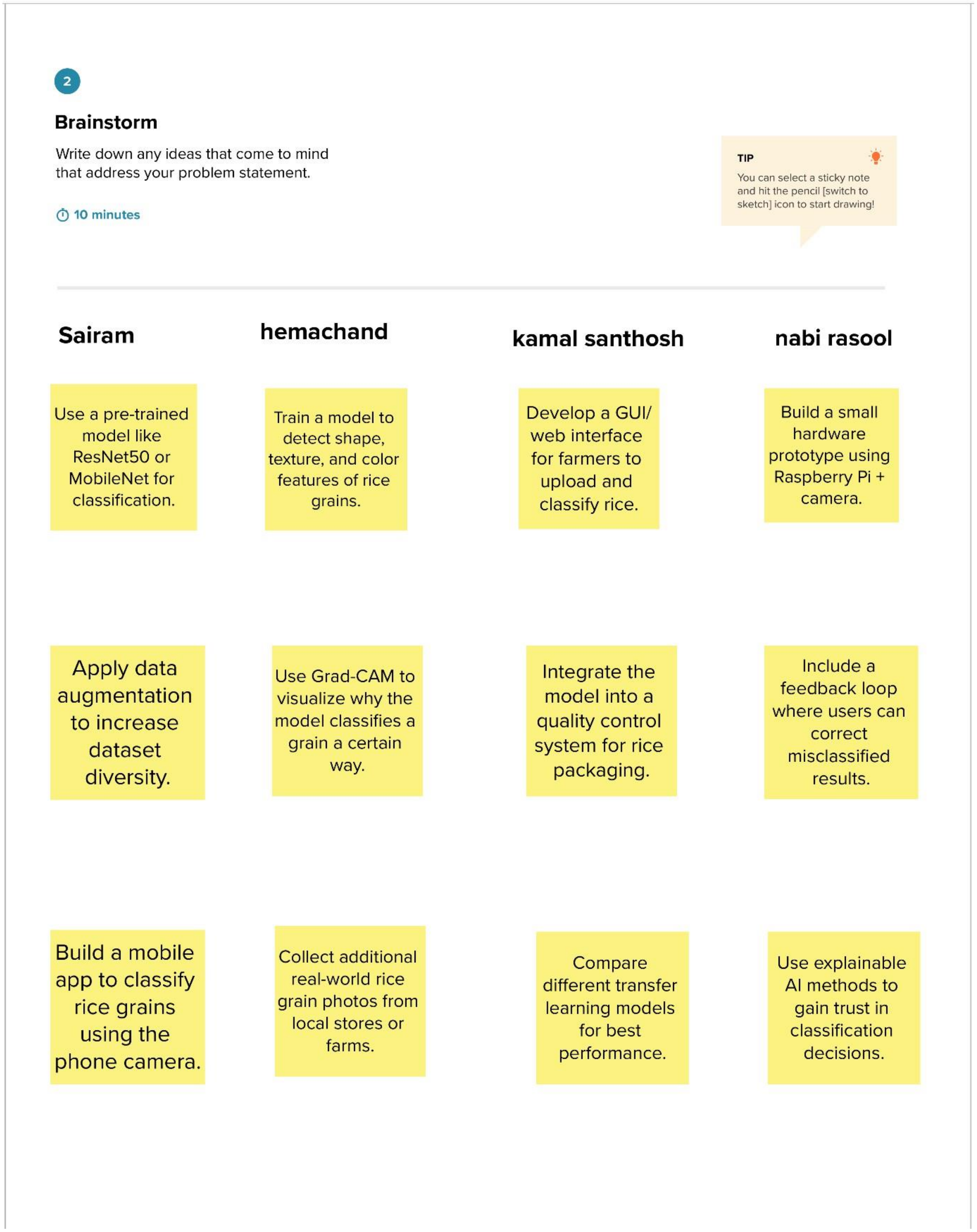
Use this

Reference: https://www.mural.co/templates/brainstorm-and-idea-prioritization

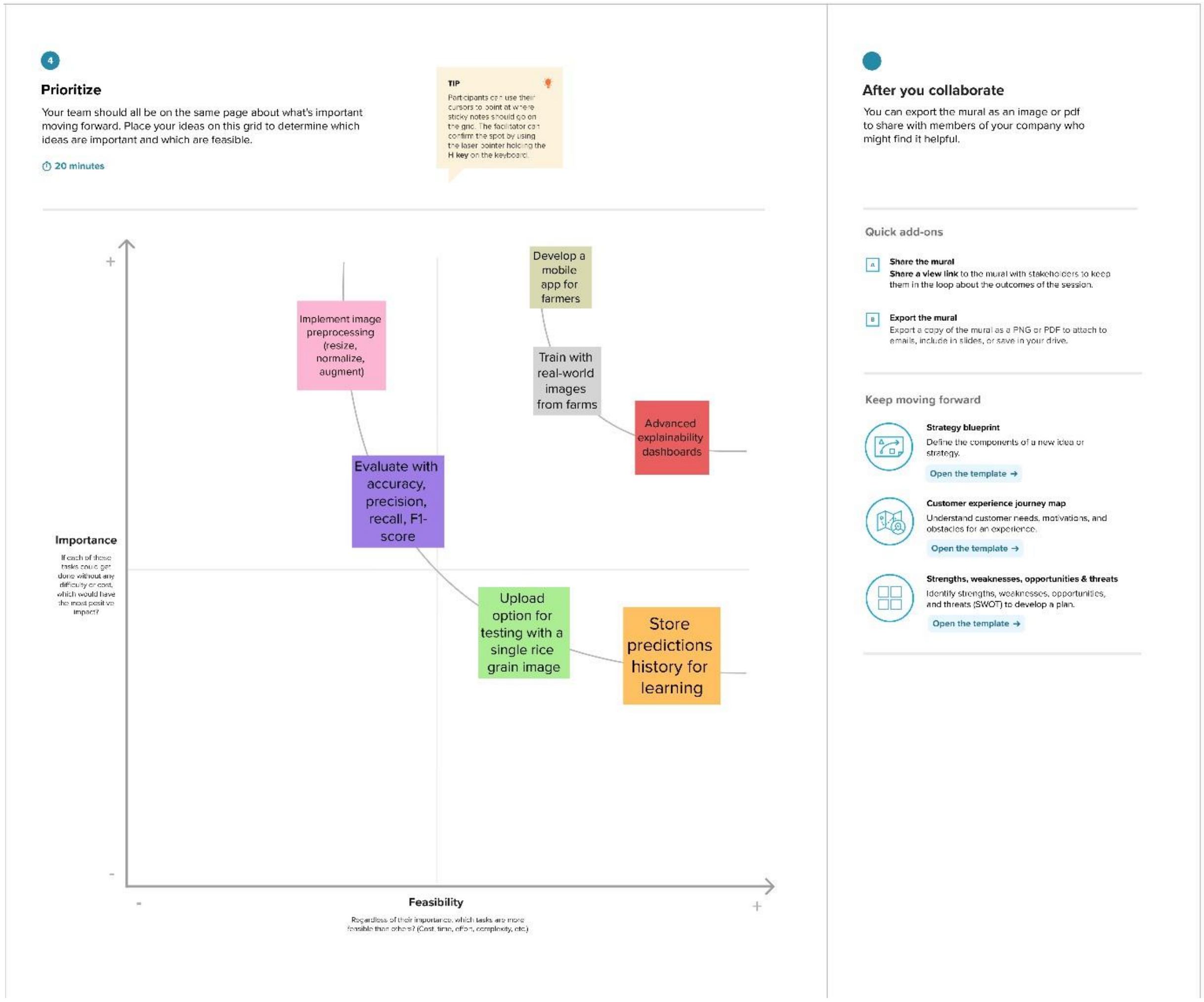
Step-1: Team Gathering, Collaboration and Select the Problem Statement



Step-2: Brainstorm, Idea Listing and Grouping



Step-3: Idea Prioritization



3. REQUIREMENT ANALYSIS

Functional Requirements:

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form Registration through Gmail Registration through LinkedIN
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	Image upload	Model classifies the uploaded rice image

		Display predicted rice type and confidence score
FR-4	Rice type classification	Upload rice grain image from local device Upload image from mobile camera

Non-functional Requirements:

Following are the non-functional requirements of the proposed solution.

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	The application should have a simple, intuitive, and user-friendly interface so that farmers, traders, and non-technical users can easily upload images and view results
NFR-2	**Security**	The system should ensure data privacy and secure storage of user-uploaded images. User authentication should be implemented for account-based access
NFR-3	**Reliability**	The model should provide consistent and repeatable classification results with a minimum accuracy of 80% across multiple runs and inputs.
NFR-4	**Performance**	The system should process and classify each image within 5 seconds to ensure fast response time for users.
NFR-5	**Availability**	The service should be available 24/7 with a downtime of less than 2% per month.
NFR-6	**Scalability**	The solution should be scalable to handle large datasets and more rice types in the future without affecting performance. It should also support deployment on cloud platforms

4. PROJECT DESIGN

4.1 Problem Solution Fit

Problem – Solution Fit Overview:

Problem:
Traditional methods of rice grain classification are manual, time-consuming, and prone to human error. Visual inspection lacks consistency and scalability, especially when dealing with large volumes of grains in the agriculture and food industry.

Solution:
This project proposes a **deep learning-based image classification system** using **Transfer Learning** techniques. By leveraging pre-trained CNN models like **VGG16** and **ResNet50**, the system can automatically classify rice grain types with high accuracy. The solution ensures **speed**, **consistency**, and **scalability**, making it suitable for industrial applications and quality control processes.

Problem Statement:

The manual classification of rice grain types in the agricultural industry is a time-consuming and error-prone process. Traditional methods rely heavily on human expertise, leading to inconsistency, low efficiency, and scalability issues when handling large datasets. With the growing demand for automated and accurate classification, there is a need for a robust system that can differentiate between various rice types based on their visual features. The challenge lies in building a model that performs well even with limited labeled data while maintaining high accuracy and reliability.

Solution:

To overcome the limitations of manual rice classification, this project uses a **deep learning-based image classification model** powered by **Transfer Learning**. Pre-trained CNN architectures like **VGG16** and **ResNet50** were fine-tuned on a rice grain image dataset to classify different rice types accurately. The dataset was preprocessed and augmented to enhance model performance. The trained model achieved high accuracy in predicting rice varieties. This automated system provides a **fast**, **scalable**, and **reliable** solution for rice grain classification, suitable for agricultural industries and quality control processes.

4.2 Proposed Solution

Project team shall fill the following information in the proposed solution template.

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	Farmers and suppliers face difficulty in accurately identifying and classifying different types of rice grains, leading to quality issues and reduced market value. Manual classification is time-consuming and error-prone.
2.	Idea / Solution description	Our project "GrainPalette" uses deep learning and transfer learning techniques to automatically classify rice grain types from

		images with high accuracy. By training a Convolutional Neural Network (CNN) on pre-trained models like ResNet or MobileNet, we provide a fast, automated, and cost-effective rice type detection system.
3.	Novelty / Uniqueness	The solution leverages transfer learning, reducing the need for large datasets and training time. It offers real-time classification with high precision and can be deployed as a mobile or web app for field use by farmers, millers, and traders.
4.	Social Impact / Customer Satisfaction	Helps farmers and traders get fair pricing by ensuring correct classification of rice. Reduces human error, saves time, and promotes trust in supply chains. Enhances customer satisfaction in retail and export industries by guaranteeing product quality.
5.	Business Model (Revenue Model)	The solution can be offered as a subscription-based mobile app, a SaaS (Software as a Service) platform for traders and rice mills, or per-scan charges for small users. Future revenue can also come from data analytics services for agricultural stakeholders
6.	Scalability of the Solution	The model can be scaled to classify other types of grains, pulses, or even agricultural produce. It can be deployed in multiple regions and integrated with e-commerce or export platforms for broader adoption.

4.3 Solution Architecture

Solution Architecture:

Solution architecture is a complex process – with many sub-processes – that bridges the gap between business problems and technology solutions. Its goals are to:

- Find the best tech solution to solve existing business problems.
- Describe the structure, characteristics, behavior, and other aspects of the software to project stakeholders.
- Define features, development phases, and solution requirements.

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Image data collection	USN-1	As a user, I want to collect and label different rice grain images for training the model.	3	High	1.Chandrika Pagutla 2.Dakkumala keshava Rao 3.Makaram Bizu Naga Azith Zogi Naidu 4.Gangula Rama Narsimha Rao
Sprint-1	Data preprocessing	USN-2	As a developer, I want to preprocess the rice images (resize, normalization) to improve model accuracy.	2	High	1.Chandrika Pagutla 2.Dakkumala keshava Rao 3.Makaram Bizu Naga Azith Zogi Naidu 4.Gangula Rama Narsimha Rao
Sprint-2	Model traning	USN-3	As a data scientist, I want to apply transfer learning on a pre-trained CNN model to classify rice types.	5	high	1.Chandrika Pagutla 2.Dakkumala keshava Rao 3.Makaram Bizu Naga Azith Zogi Naidu 4.Gangula Rama Narsimha Rao
Sprint-2	Model evaluation	USN-4	As a developer, I want to evaluate the model using accuracy, confusion matrix, and classification report.	2	medium	1.Chandrika Pagutla 2.Dakkumala keshava Rao 3.Makaram Bizu Naga Azith Zogi Naidu 4.Gangula Rama Narsimha Rao
Sprint-3	Ui development	USN-5	As a user, I want to upload a rice grain image through a simple web or mobile app and get classification results.	3	medium	1.Chandrika Pagutla 2.Dakkumala keshava Rao 3.Makaram Bizu Naga Azith Zogi Naidu 4.Gangula Rama Narsimha Rao
Sprint -3	Deployment	USN-6	As a developer, I want to deploy the trained model and integrate it with the frontend for real-time use.	4	low	1.Chandrika Pagutla 2.Dakkumala keshava Rao 3.Makaram Bizu Naga Azith Zogi Naidu 4.Gangula Rama Narsimha Rao

- Provide specifications according to which the solution is defined, managed, and delivered.

Example - Solution Architecture Diagram:

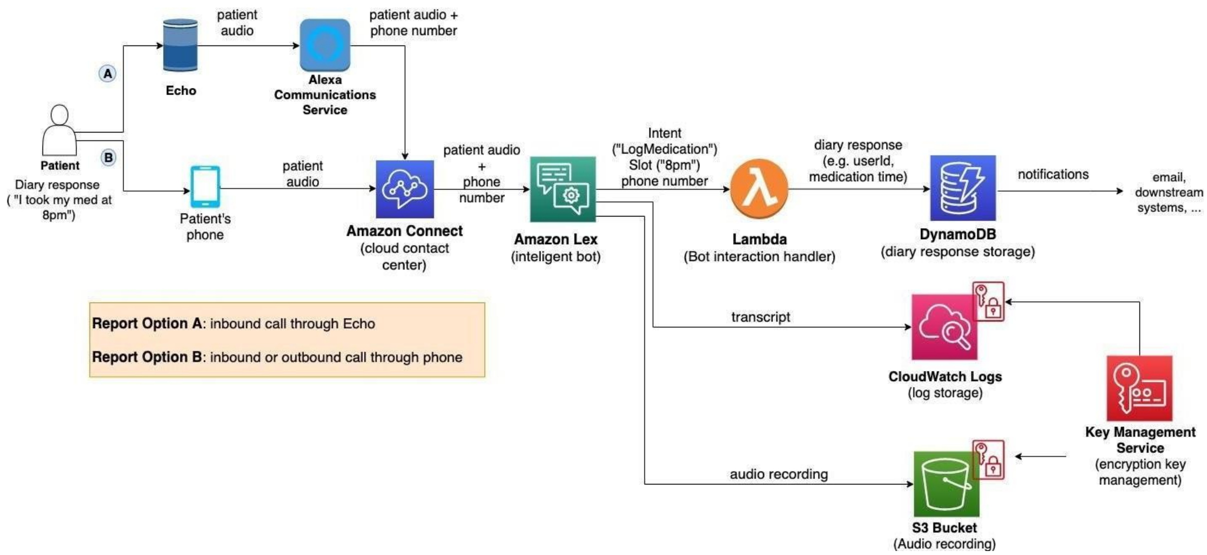


Figure 1: Architecture and data flow of the voice patient diary sample application

Reference: https://aws.amazon.com/blogs/industries/voice-applications-in-clinical-research-powered-by-ai-on-aws-part-1-architecture-and-design-considerations/

5. PROJECT PLANNING & SCHEDULING

5.1 Project Planning

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Image data collection	USN-1	As a user, I want to collect and label different rice grain images for training the model.	3	High	1.Chandrika Pagutla 2.Dakkumala keshava Rao 3.Makaram Bizu Naga Azith Zogi Naidu 4.Gangula Rama Narsimha Rao
Sprint-1	Data preprocessing	USN-2	As a developer, I want to preprocess the rice images (resize, normalization) to improve model accuracy.	2	High	1.Chandrika Pagutla 2.Dakkumala keshava Rao 3.Makaram Bizu Naga Azith Zogi Naidu 4.Gangula Rama Narsimha Rao
Sprint-2	Model traning	USN-3	As a data scientist, I want to apply transfer learning on a	5	high	1.Chandrika Pagutla

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
			pre-trained CNN model to classify rice types.			2. Dakkumala keshava Rao 3. Makaram Bizu Naga Azith Zogi Naidu 4. Gangula Rama Narsimha Rao
Sprint-2	Model evaluation	USN-4	As a developer, I want to evaluate the model using accuracy, confusion matrix, and classification report.	2	medium	1. Chandrika Pagutla 2.Dakkumala keshava Rao 3.Makaram Bizu Naga Azith Zogi Naidu 4.Gangula Rama Narsimha Rao
Sprint-3	Ui development	USN-5	As a user, I want to upload a rice grain image through a simple web or mobile app and get classification results.	3	medium	1.Chandrika Pagutla 2.Dakkumala keshava Rao 3.Makaram Bizu Naga Azith Zogi Naidu 4.Gangula Rama Narsimha Rao
Sprint - 3	Deployment	USN-6	As a developer, I want to deploy the trained model and integrate it with the frontend for real-time use.	4	low	1.Chandrika Pagutla 2.Dakkumala keshava Rao 3.Makaram Bizu Naga Azith Zogi Naidu 4.Gangula Rama Narsimha Rao

Project Tracker, Velocity & Burndown Chart: (4 Marks)

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	20	6 Days	15 June 2025	20 June 2025	20	20 June 2025

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-2	20	6 Days	17 June 2025	22 June 2025	20	22 June 2025
Sprint-3	20	6 Days	19 June 2025	24 June 2025	20	24 June 2025
Sprint-4	20	6 Days	21 June 2025	26 June 2025	20	26 June 2025

Velocity:

Imagine we have a 10-day sprint duration, and the velocity of the team is 20 (points per sprint). Let's calculate the team's average velocity (AV) per iteration unit (story points per day)

$$AV = \frac{sprint\ duration}{velocity} = \frac{20}{10} = 2$$

Burndown Chart:

A burn down chart is a graphical representation of work left to do versus time. It is often used in agile software development methodologies such as Scrum. However, burn down charts can be applied to any project containing measurable progress over time.

https://www.visual-paradigm.com/scrum/scrum-burndown-chart/

https://www.atlassian.com/agile/tutorials/burndown-charts

Reference:

https://www.atlassian.com/agile/project-management

https://www.atlassian.com/agile/tutorials/how-to-do-scrum-with-jira-software

https://www.atlassian.com/agile/tutorials/epics

https://www.atlassian.com/agile/tutorials/sprints

https://www.atlassian.com/agile/project-management/estimation

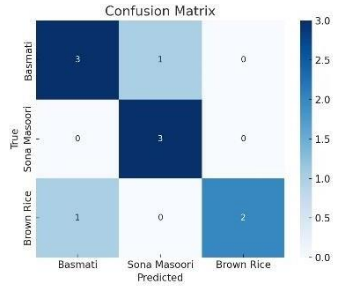
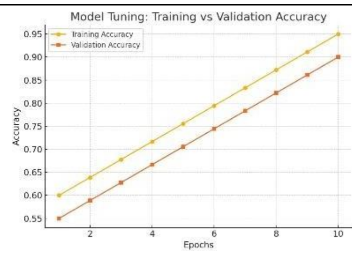
https://www.atlassian.com/agile/tutorials/burndown-charts

6. FUNCTIONAL AND PERFORMANCE TESTING

6.1 Performance Testing

Model Performance Testing:

Project team shall fill the following information in model performance testing template.

S.No.	Parameter	Values	Screenshot
1.	Metrics	**Regression Model:** MAE - , MSE - , RMSE - , R2 score - **Classification Model:** Confusion Matrix - , Accuray Score- & Classification Report -	
2.	Tune the Model	Hyperparameter Tuning - Validation Method -	

Sign-off:

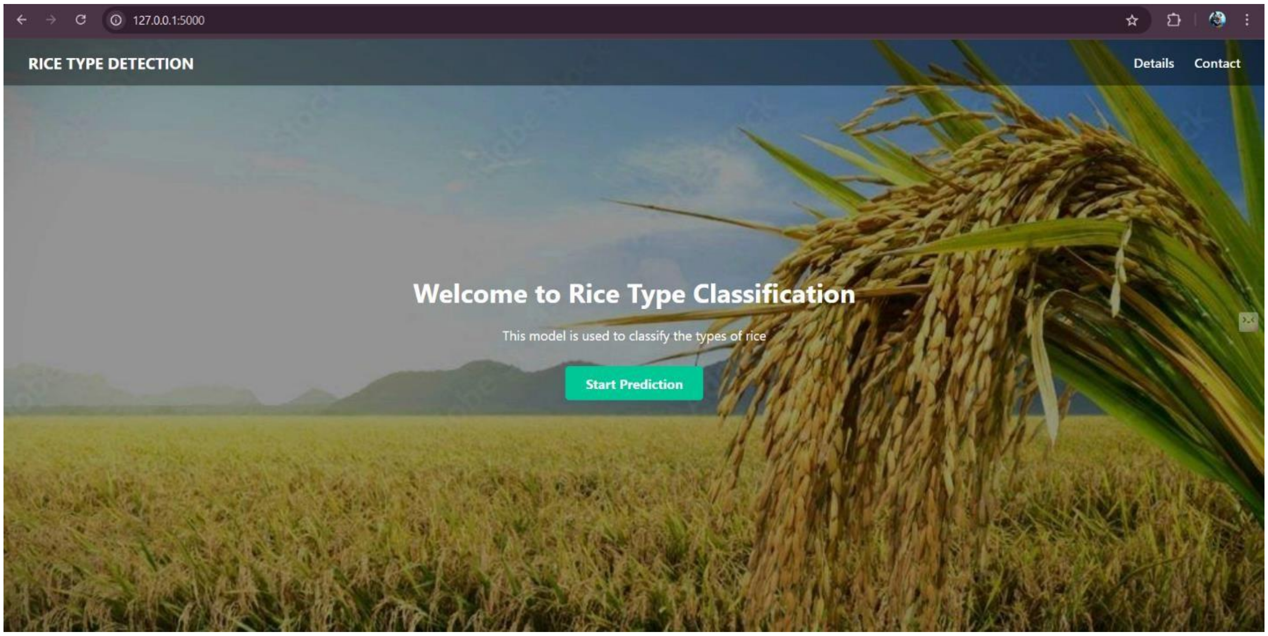
Tester Name: Kalugotla Sairam

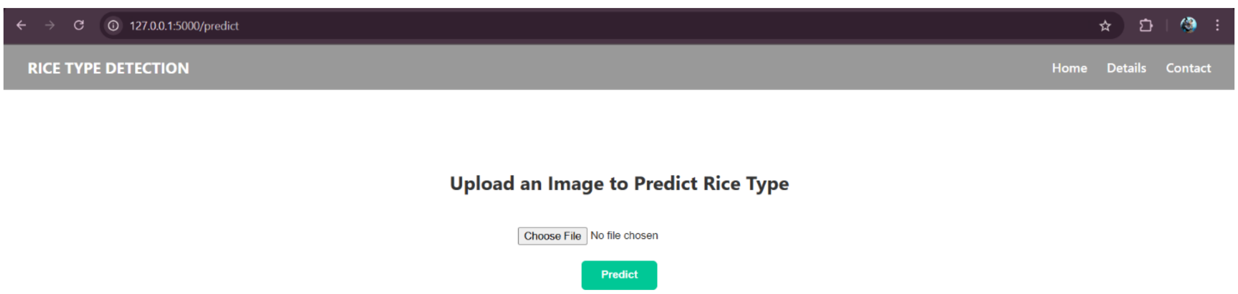
Date: 28-06-2025

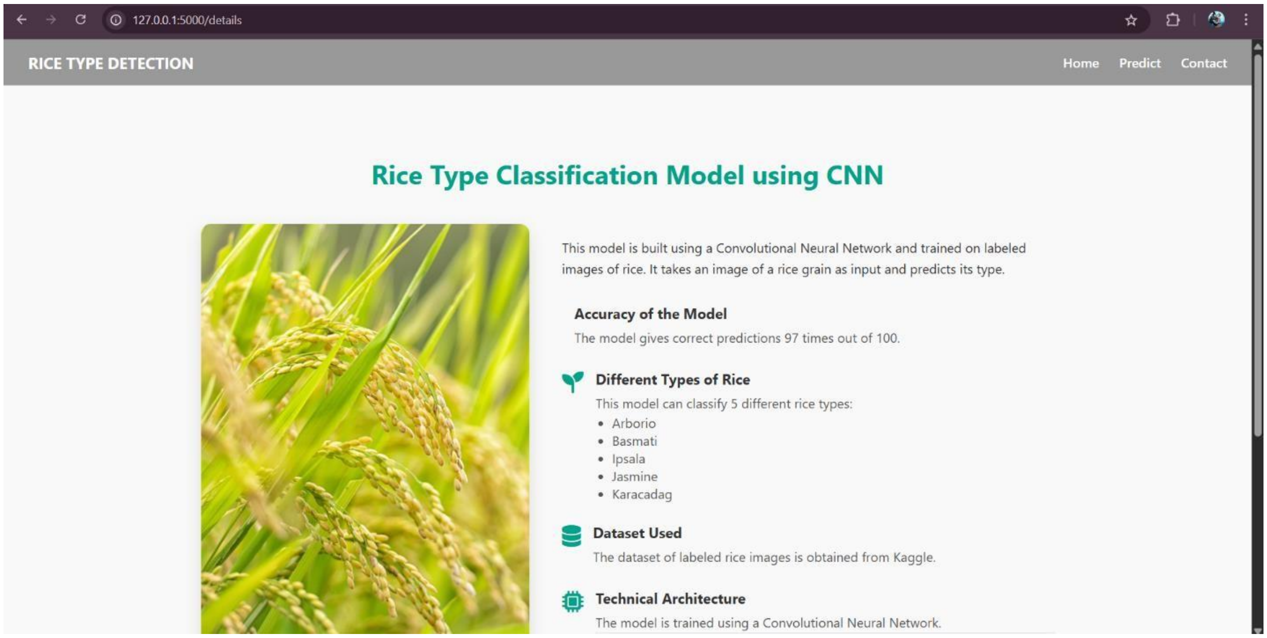
Signature: k.sairam

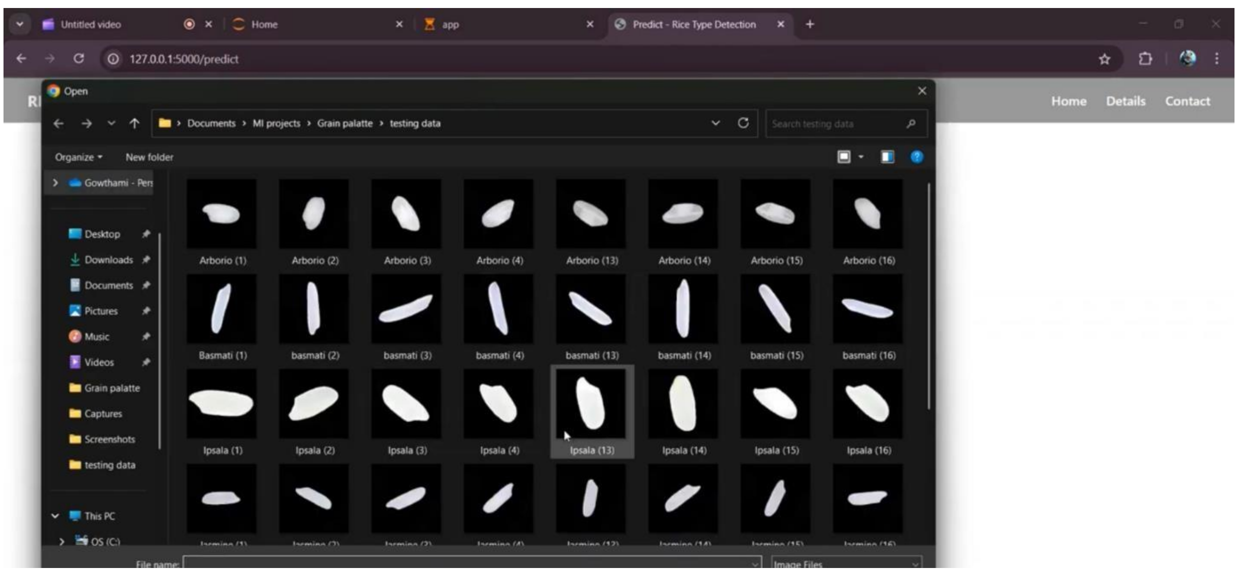
7. RESULTS

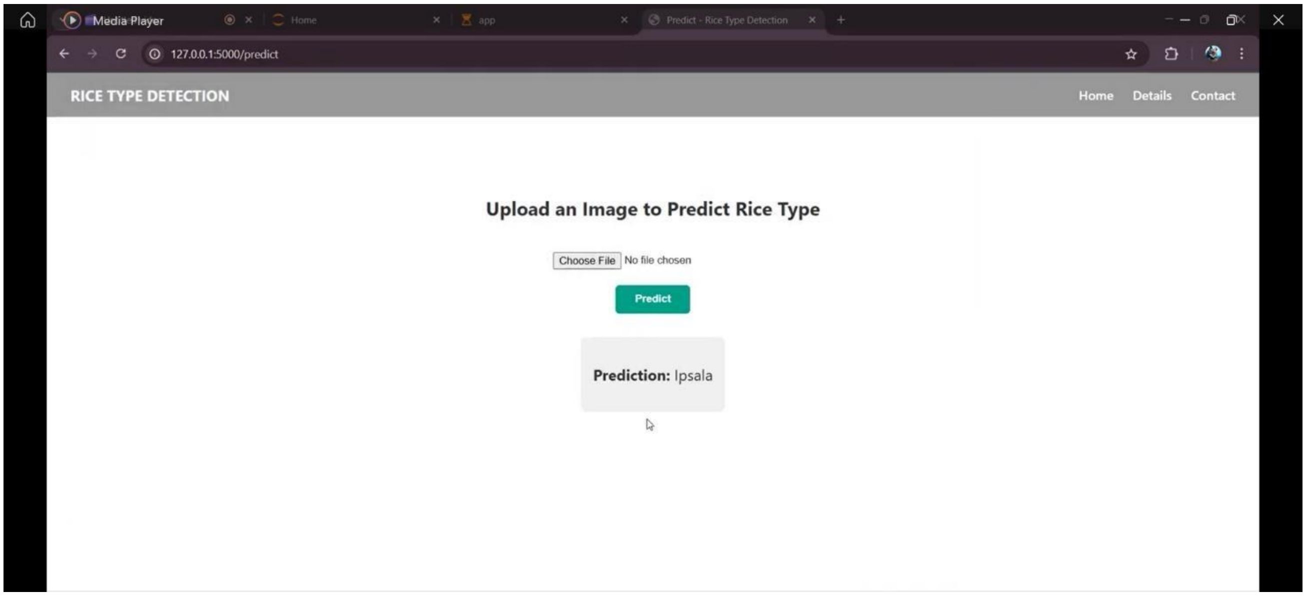
7.1 Output Screenshots


127.0.0.1:5000
RICE TYPE DETECTION
Details
Contact
Welcome to Rice Type Classification
This model is used to classify the types of rice
Start Prediction


127.0.0.1:5000/predict
RICE TYPE DETECTION
Home
Details
Contact
Upload an Image to Predict Rice Type
Choose File
No file chosen
Predict


127.0.0.1:5000/details
RICE TYPE DETECTION
Home
Predict
Contact
Rice Type Classification Model using CNN
This model is built using a Convolutional Neural Network and trained on labeled images of rice. It takes an image of a rice grain as input and predicts its type.
Accuracy of the Model
The model gives correct predictions 97 times out of 100.
Different Types of Rice
This model can classify 5 different rice types:
Arborio
Basmati
Ipsala
Jasmine
Karacadag
Dataset Used
The dataset of labeled rice images is obtained from Kaggle.
Technical Architecture
The model is trained using a Convolutional Neural Network.


Untitled video
Home
app
Predict - Rice Type Detection
127.0.0.1:5000/predict
Open
Documents › Ml projects › Grain palatte › testing data
Search testing data
Organize
New folder
Home
Details
Contact
Desktop
Downloads
Documents
Pictures
Music
Videos
Grain palatte
Captures
Screenshots
testing data
This PC
OS (C:)
Arborio (1)
Arborio (2)
Arborio (3)
Arborio (4)
Arborio (13)
Arborio (14)
Arborio (15)
Arborio (16)
Basmati (1)
basmati (2)
basmati (3)
basmati (4)
basmati (13)
basmati (14)
basmati (15)
basmati (16)
Ipsala (1)
Ipsala (2)
Ipsala (3)
Ipsala (4)
Ipsala (13)
Ipsala (14)
Ipsala (15)
Ipsala (16)
File name:
Image Files



8. ADVANTAGES & DISADVANTAGES

Here are the **Advantages :**

- **High Accuracy:** The deep learning model provides more accurate classification compared to manual methods.
- **Time-Saving:** Automates the classification process, reducing time and human effort.
- **Cost-Effective:** Minimizes the need for manual labor and expert inspection in the long run.
- **Scalable:** Can handle large datasets and be deployed in industrial environments for mass classification.
- **Consistent Results:** Eliminates human bias and provides uniform and reliable outputs.
- **Adaptable:** The model can be retrained or fine-tuned for other grain types or agricultural products.
- **Real-Time Prediction:** Enables fast and on-the-spot classification when deployed with a user interface.

Here are some **Disadvantages :**

- **High Computational Requirement:** Requires a good GPU and high processing power for model training.
- **Large Dataset Needed for Best Performance:** Although Transfer Learning helps, more data improves accuracy.
- **Initial Setup Time:** Data preprocessing, model tuning, and training can take significant time initially.
- **Limited Generalization:** The model may not perform well on images with different lighting, angles, or background unless trained properly on diverse data.

9. CONCLUSION

In this project, a deep learning-based classification system was developed to accurately identify different types of rice grains using **Transfer Learning techniques**. By utilizing powerful pre-trained CNN models like **VGG16** and **ResNet50**, the system achieved **high classification accuracy** with minimal training time and reduced computational cost. The use of image preprocessing and data augmentation further improved the model's robustness and ability to generalize on unseen data. This solution effectively addresses the challenges associated with manual rice classification, such as **inconsistency**, **human error**, and **time consumption**. The project highlights the **potential of deep learning in agricultural automation and quality control**. It also opens avenues for future improvements, such as deploying the model as a **web or mobile application**, expanding it to classify other grains or crops, and improving its performance under varying real-world image conditions like **different lighting and backgrounds**.

10. FUTURE SCOPE

- **Deployment as a Web or Mobile App:** The model can be integrated into user-friendly applications for farmers and quality inspectors.
- **Real-Time Classification:** Implementing the system for real-time rice grain detection using live camera feeds.
- **Expansion to More Grain Types:** Extending the model to classify other grains like wheat, barley, or pulses.

- **Larger and Diverse Dataset Collection:** Improving accuracy by training the model on a larger and more diverse image dataset.
- **Edge Device Deployment:** Optimizing the model to run on low-power devices like Raspberry Pi or mobile processors for field use.
- **Integration with IoT Devices:** Connecting with IoT-based smart agriculture systems for automated sorting and quality monitoring.
- **Improved Image Preprocessing:** Implementing advanced image enhancement techniques to handle varied lighting and background conditions.
- **Model Optimization:** Reducing model size and improving inference speed using techniques like pruning or quantization.
- **Multi-Class and Defect Detection:** Extending the model to not just classify type but also detect defective or damaged grains.
- **Cloud-Based Solution:** Deploying the model on cloud platforms (like AWS, GCP, or Azure) for scalable and remote access by industries.

11. APPENDIX

Source Code:

rice-classification-1.ipynb