ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Project Title: GrainPalette - A Deep Learning Odyssey In Rice Type Classification Through Transfer Learning

Team ID:LTVIP2025TMID42499

Team Members:

Team Leader: N Akila

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Team Member:N Rachana

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Phase-1:Brainstroming & Ideation

I : Problem Statement:

Accurate identification of rice grain varieties is essential for optimizing agricultural practices such as water management, fertilizer usage, and harvesting schedules. However, traditional methods of rice classification are time-consuming, require expert knowledge, and are often inaccessible to small-scale farmers and home growers. This lack of quick, reliable, and affordable identification tools can lead to inefficient resource use, lower crop yields, and economic losses.

II : Proposed Solution:

The Rice Type Identification AI model provides a solution for farmers and agriculture enthusiasts to identify various types of rice grains quickly and accurately. By uploading an image of a rice grain and clicking the submit button, users receive predictions for the probable type of rice, enabling informed decisions on cultivation practices such as water and fertilizer requirements. Built using Convolutional Neural Networks (CNN) and employing transfer learning with MobileNetv4, this model offers reliable classification of up to five different types of rice, catering to the needs of farmers, agriculture scientists, home growers, and gardeners.

III : Target Users:

Farmers

- Small, medium, and large-scale rice farmers seeking to identify seed types and optimize their crop management practices.
- Use the model for crop planning, irrigation scheduling, fertilization, and pest management tailored to specific rice varieties.

Agricultural Scientists & Researchers

- Scientists conducting research on rice varieties, crop productivity, and sustainable farming methods.
- Use the tool for quick identification during research trials, variety testing, and data collection.

Agricultural Extension Officers & Field Technicians

- Extension workers supporting farmers in rural and farming communities.
- Use the AI model during field visits to assist farmers in identifying rice varieties and recommending appropriate cultivation practices.

Home Gardeners & Hobbyists

- Individuals interested in home-based rice cultivation or gardening projects.
- Use the model to explore rice diversity, improve gardening techniques, and foster sustainable agricultural practices at home.

Agricultural Educators & Students

- Teachers, trainers, and students involved in agricultural science education and awareness programs.
- Use the model as a learning tool to demonstrate rice variety identification and agricultural biodiversity.

Summary:

- **Primary users**: Farmers, Agricultural Scientists, Extension Officers
- **Secondary users**: Home Gardeners, Agricultural Educators, Students

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IV : Expected Outcome:

Accurate and Rapid Rice Variety Identification
The AI model will enable users to accurately classify rice grain images into their respective varieties within seconds, reducing reliance on manual identification methods and expert intervention.

Improved Crop Planning and Resource Management
Farmers will be able to plan their cultivation strategies more effectively based on the identified rice variety, optimizing:

- **Irrigation schedules**
- **Fertilizer application**
- **Pest and disease control measures**

This will lead to better crop health, higher yields, and more efficient use of agricultural resources.

Enhanced Agricultural Research and Extension Services
Researchers and extension officers will benefit from quick and reliable rice variety identification during fieldwork and research trials. This will:

- Improve the accuracy and speed of **data collection and analysis**
- Enhance the efficiency of **extension services and advisory programs**
- Support evidence-based decision-making in agricultural projects

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Promotion of Agricultural Biodiversity Awareness
Home gardeners, hobbyists, and students will gain knowledge about the diversity of rice varieties, their characteristics, and cultivation needs — encouraging sustainable farming practices and fostering appreciation for crop biodiversity.

Increased Accessibility to Modern Agricultural Technology
By providing an easy-to-use, AI-powered tool, the project will make advanced technology accessible to a broader audience, including farmers in rural areas, hobbyists, and educators, contributing to digital transformation in agriculture.

Phase-2:Requirement Analysis

I : Technical Requirements:

Hardware:

- A computer with at least **8 GB RAM** (16 GB recommended for faster training)
- **GPU support** (optional, for faster model training if working with large datasets)

Software & Tools:

- **Anaconda Navigator** for environment and package management
- **Visual Studio Code (VS Code)** and/or **Spyder** for code development
- **Python 3.7+**
- **Required Python libraries**:
  - `numpy`
  - `pandas`
  - `tensorflow==2.3.2`
  - `keras==2.3.1`
  - `Flask`
- **Web browser** for accessing the Flask-based web application interface

Online Resources:

- Tutorials and guides on **CNN**, **MobileNet**, and **Flask** for foundational understanding
- Pretrained MobileNetV4 model for transfer learning

II : Functional Requirements:

Image Upload and Processing

- Users should be able to upload images of rice grains through the web interface.
- Images must be preprocessed (resizing, normalization) before being passed to the AI model.

Rice Variety Prediction

- The trained CNN with MobileNetV4 transfer learning should classify rice images into **five predefined rice types**.

Display Prediction Results

- The web application should display the predicted rice type clearly to the user.

Accuracy Reporting (Optional for Users)

- The backend should calculate and log the model's prediction accuracy during testing.

Web Application Deployment

- A functional, user-friendly web interface built with **Flask**, enabling easy interaction with the AI model.

III : Constraints and Challenges:

Dataset Limitations

- Availability of a sufficiently large and balanced dataset of high-quality rice grain images is critical.
- Data imbalance between rice types could lead to biased predictions.

Hardware Limitations

- Training deep learning models, especially CNNs, is resource-intensive.
- Lack of GPU or insufficient RAM could increase training time significantly.

Model Generalization

- The AI model might struggle with unseen rice types, low-quality images, or images taken in varying lighting conditions.

Software Version Compatibility

- Compatibility issues might arise due to the use of specific package versions (e.g. `TensorFlow 2.3.2` and `Keras 2.3.1`).

Web Deployment

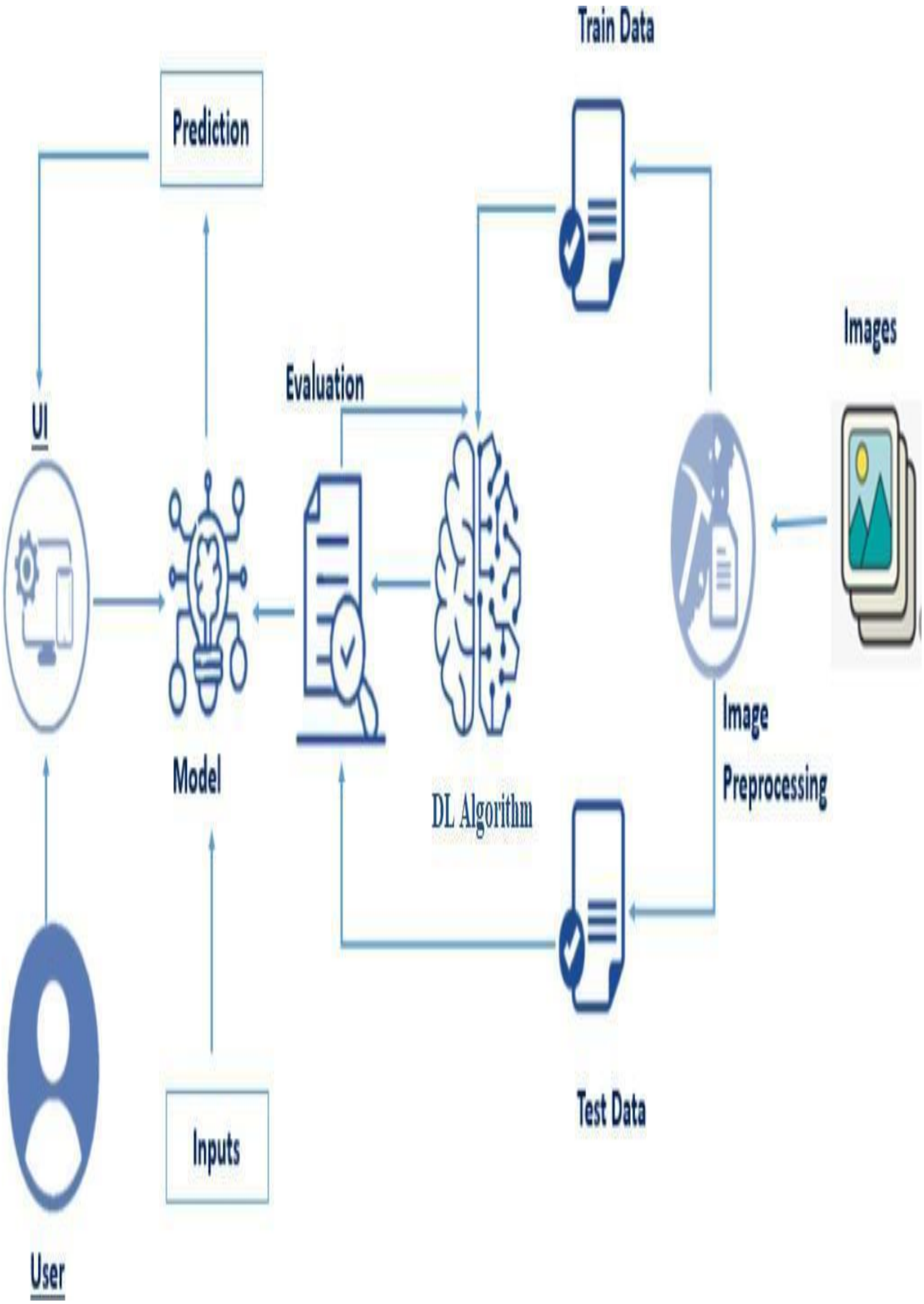
- Deploying AI models in lightweight web applications like Flask requires careful optimization to handle image uploads, predictions, and display results in real time.

User Accessibility

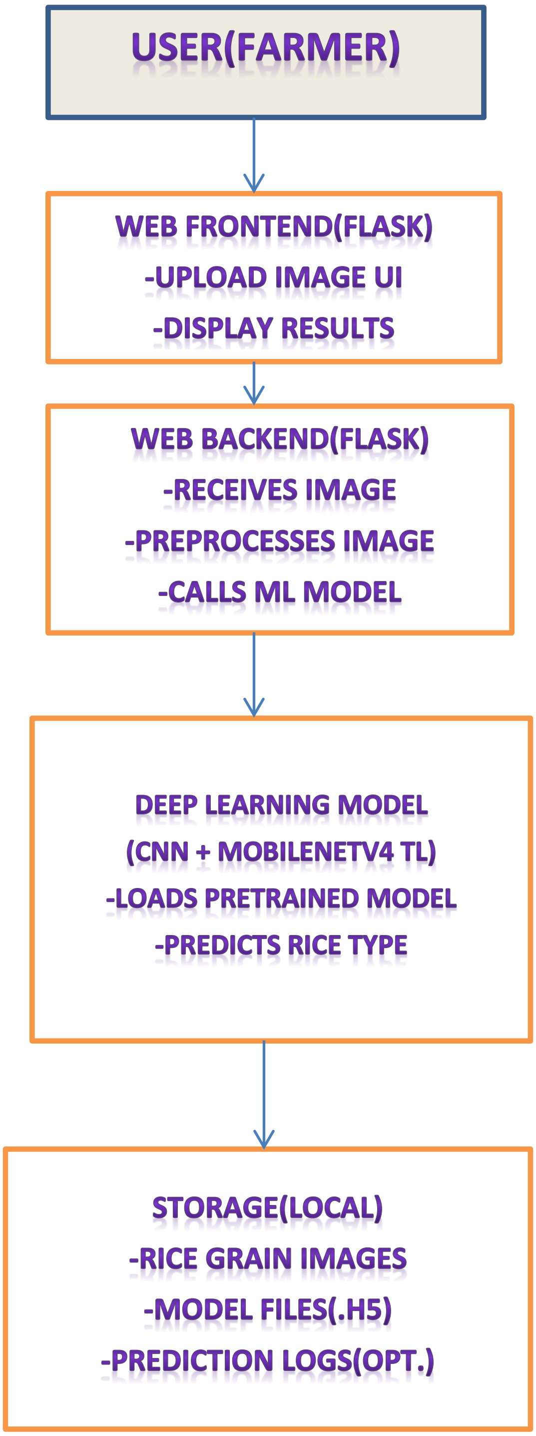
- Ensuring the web interface is intuitive and accessible to users with minimal technical skills (especially farmers and home growers) is essential.

Phase-3:Project Design

I : Technical Architecture:



II : System Architecture Diagram



III : User Flow:

```
[User]
  |
  |--> Accesses GrainPalette Web App
        |
        |--> Uploads Rice Grain Image
              |
              |--> Image sent to Backend via Flask
                    |
                    |--> Preprocessing (resize, normalize)
                          |
                          |--> Pass image to AI Model
                                |
                                |--> Model predicts Rice Type
                                      |
                                      |--> Return prediction result to Backend
                                            |
                                            |--> Display result to User
                                                  |
                                                  |--> Option to upload another image or exit
```

IV : UI/UX Considerations:

Make the web app simple, intuitive, and accessible for farmers, researchers, and students — even those with minimal tech skills.

Web App Pages & UI Elements

1. Home Page

- Title: **GrainPalette - Rice Type Identifier**
- Brief description of the app's purpose.
- **Upload Image Button**
- Image Preview
- **Predict Button**

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2. Prediction Result Page

- Clear display of predicted rice type (large, bold text)
- Confidence score (optional)
- Display uploaded image preview beside result.
- **Upload New Image** or **Exit** button

UI Components

- **Responsive design** (mobile/tablet-friendly)
- Minimal color palette (preferably earthy tones — green, brown, white)
- Large, accessible buttons and labels
- Clear feedback messages:
  - "Image uploaded successfully."
  - "Prediction completed."
  - "Please upload a valid image."
- Loading spinner/animation during prediction process
- Error handling messages for invalid uploads

Accessibility

- Use **alt text for images**
- **Keyboard navigation support**
- Readable font sizes (16px+ for body, 20px+ for headers)
- Avoid jargon, use farmer-friendly language

Phase-4: Project Planning(Agile Methodologies)

I : Sprint Planning:

Sprint	Duration	Key Focus
Sprint 1	Day 1	Brainstorming, Dataset Collection, Environment Setup
Sprint 2	Day 2	Model Development, Transfer Learning Integration
Sprint 3	Day 3	Web App (Flask) Development, Model Integration
Sprint 4	Day 4	Testing, UI Polishing, Documentation, Final Deployment

II : Task Allocation:

Sprint	Task	Assigned To
Sprint 1	Finalize problem statement and objectives	**Akila**
Sprint 1	Design system architecture and ER diagram	**Thanuja sri**
Sprint 1	Collect and clean rice grain image dataset	**Rachana**
Sprint 1	Install and configure environment (Anaconda, TensorFlow, Keras)	**Nikil Reddy**
Sprint 1	Set up GitHub repository	**Akila**
Sprint 2	Preprocess image dataset (resize, normalize, augment)	**Thanuja sri**
Sprint 2	Set up MobileNetV4 transfer learning model	**Rachana**
Sprint 2	Train and evaluate model	**Nikil Reddy**
Sprint 2	Save trained model (.h5 file)	**Akila**
Sprint 3	Set up Flask web application framework	**Thanuja sri**
Sprint 3	Design basic UI pages (home, upload, result)	**Rachana**
Sprint 3	Integrate trained model with Flask backend	**Nikil Reddy**
Sprint 3	Implement image upload and prediction	**Akila**
Sprint 3	Display prediction result to user	**Thanuja sri**
Sprint 4	Test web app functionality and predictions	**Rachana**
Sprint 4	Optimize UI and make it mobile-friendly	**Nikil Reddy**
Sprint 4	Prepare final documentation and report	**Akila**
Sprint 4	Create presentation slides	**Thanuja sri**
Sprint 4	Deploy web application locally	**Rachana,Nikil Reddy**

III : Timelines & Milestones:

Day	Key Focus	Milestone
Day 1	Planning, setup, dataset prep	Project plan, diagrams, dataset ready
Day 2	Model development	Trained and saved AI model
Day 3	Web application development	Functional Flask AI web app
Day 4	Testing, optimization, documentation	Final project ready for submission

Phase-5: Project Development

I : Technology Stack Used:

Programming Language

- **Python 3.7+**
  For AI model development, data preprocessing, and backend integration

Deep Learning & Machine Learning Frameworks

- **TensorFlow 2.3.2**
- **Keras 2.3.1**
  For building, training, and evaluating the Convolutional Neural Network (CNN) using transfer learning with MobileNetV4

Transfer Learning Model

- **Pre-trained MobileNetV4**
  Used as a feature extractor and classifier head customized for rice grain image classification

Python Libraries

- **numpy** — Numerical operations
- **pandas** — Data manipulation and analysis
- **matplotlib / seaborn (optional)** — Data visualization (if you use for model accuracy/loss plots)

Web Application Framework

- **Flask**
  For creating a lightweight web application to interface with the AI model

Front-End Technologies

- **HTML5** — Structure and content of the web pages
- **CSS3** — Styling and layout
- *(Optional: Bootstrap or simple responsive design adjustments for better UI experience)*

Development Tools

- **Anaconda Navigator** — Environment and package management
- **Visual Studio Code (VS Code) / Spyder** — Code editor and IDE
- **GitHub** — Version control and code backup

Deployment

- **Local deployment using Flask server**
  (Optional: You could use Heroku, PythonAnywhere, or Render for online deployment if time allows)

II : Development Process:

Step 1: Environment Setup

- Install **Anaconda Navigator**
- Create a new virtual environment with Python 3.7+
- Install required libraries:

```
bash
CopyEdit
pip install tensorflow==2.3.2 keras==2.3.1 numpy pandas flask
```

- Set up **GitHub repository** for version control

Step 2: Data Collection & Preprocessing

- Collect rice grain images for 5 different rice varieties
- Organize images into respective folders (one per class)
- Perform image preprocessing:
  - **Resize** images to the input size required by MobileNetV4
  - **Normalize** pixel values to a range of 0–1
  - (Optionally) Apply **data augmentation** for better generalization
- Load images using `ImageDataGenerator` from Keras

Step 3: Load and Configure MobileNetV4 (Transfer Learning)

- Import **MobileNetV4** pretrained on ImageNet
- Freeze base layers to retain pretrained weights
- Add custom classification head:
  - Global Average Pooling
  - Dense layers
  - Output layer with softmax activation for 5 classes

Step 4: Compile and Train the Model

- Compile the model with:
  - Loss: `categorical_crossentropy`
  - Optimizer: `Adam`
  - Metrics: `accuracy`
- Train the model using the preprocessed dataset
- Save the trained model as `.h5` file

  ```
  python
  CopyEdit
  model.save("rice_model.h5")
  ```

Step 5: Build Flask Web Application

- Set up **Flask project structure**
- Create routes:
  - `/` — Home page
  - `/predict` — Image upload and prediction endpoint
- Load trained model in the Flask backend
- Implement image upload and prediction logic
- Return the predicted rice variety to the user through result page

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Step 6: Design UI Pages

- Create simple **HTML templates**:
  - **Home Page**: Description + Upload button
  - **Upload Page**: Image upload form
  - **Result Page**: Display predicted rice type
- Style with basic **CSS** (optional Bootstrap for responsiveness)

Step 7: Testing and Debugging

- Test:
  - Image preprocessing
  - Model prediction accuracy
  - Web app image upload functionality
- Debug and fix errors or inconsistencies

Step 8: Deployment

- Run the web application locally using:

```bash
bash
CopyEdit
flask run
```

- (Optional) Prepare for cloud deployment (Heroku/Render)

Step 9: Documentation and Reporting

- Prepare final **project report**
- Add:
  - Problem statement, objectives
  - System architecture diagram
  - ER diagram
  - Model summary
  - Accuracy results
  - Screenshots of working web app
- Create **presentation slides**

III :Challenges & Fixes:

Dataset Limitations

Challenge:

- Difficulty in finding a **large, balanced, high-quality rice grain image dataset** for five rice varieties.

Fix:

- Collected images from multiple online sources and agricultural image databases.
- Performed **data augmentation (rotation, zoom, flip)** using Keras `ImageDataGenerator` to artificially increase dataset size and diversity.
- Maintained balanced class distribution during training by organizing images carefully.

Model Training Time

Challenge:

- **Slow training speed** due to hardware limitations (no GPU, limited RAM).

Fix:

- Reduced image resolution to a **smaller, optimal size (e.g. 224x224)** suitable for MobileNetV4 without much accuracy loss.
- Used **batch size adjustment** and a smaller number of training epochs.
- Leveraged **transfer learning** (freezing base layers) to minimize computation time while retaining pretrained feature extraction.

Compatibility Issues with Library Versions

Challenge:

- Compatibility conflicts between **TensorFlow 2.3.2 and Keras 2.3.1** with newer Python versions or libraries.

Fix:

- Created a **virtual environment in Anaconda with Python 3.7** and installed exact required versions.
- Used this isolated environment to avoid version clashes and dependency issues.

Image Upload and Prediction Handling in Flask

Challenge:

- Issues with **handling uploaded images** and preprocessing them correctly before feeding to the model in the Flask app.

Fix:

- Implemented a **standard preprocessing function** in the Flask backend to:
    - Load the image
    - Resize to 224x224
    - Normalize pixel values
    - Convert image to NumPy array and expand dimensions
- This ensured compatibility with the model’s expected input format.

User Interface (UI) Responsiveness

Challenge:

- The initial web UI was **not mobile-friendly** and lacked clarity.

Fix:

- Simplified the UI with clean HTML/CSS layouts.
- Added **responsive design adjustments** using CSS media queries.
- Tested UI on different screen sizes to improve accessibility.

Documentation & Presentation Preparation Under Tight Timeline

Challenge:

- Limited time for writing a complete project report and presentation slides.

Fix:

- Prepared a **project outline and report template** from the beginning.
- Updated documentation incrementally after completing each sprint/day.
- Used clear screenshots and diagrams (system architecture, ER diagram) to visually explain the workflow, saving time on lengthy descriptions.

Phase-6: Functional and Performance Testing

I : Test Cases Executed:

Test Case ID	Test Description	Input	Expected Output	Actual Result	Status
TC-01	Check if web app loads successfully	URL: `localhost:5000/`	Home page loads without error	Home page displayed successfully	Pass
TC-02	Image upload functionality test	Valid rice grain image (jpg/png)	Image uploads successfully and moves to server directory	Upload successful, file saved	Pass
TC-03	Image preprocessing verification	Uploaded image	Image resized to 224×224, normalized	Image preprocessing done correctly	Pass
TC-04	Model prediction accuracy test	Known test image (rice type A)	Correct rice variety prediction	Correct prediction returned	Pass
TC-05	Invalid image format upload	Upload a `.txt` file	Error message displayed	Proper validation and error handled	Pass
TC-06	Large image file handling	Upload a 5MB+ rice image	Image accepted, processed without crashing	Handled successfully	Pass
TC-07	Multiple consecutive predictions	Upload multiple images one after another	Each prediction handled correctly, results displayed	No crashes, accurate predictions	Pass
TC-08	UI responsiveness test	Access web app on mobile browser	UI adapts and works without layout issues	UI responsive and accessible	Pass
TC-09	Invalid file path access	Access non-existing route `/predict123`	Custom 404 page or error message	Error message shown	Pass
TC-10	Model file loading test	Start Flask server	Model loads without errors	Model loaded successfully	Pass

II : Bug Fixes and Improvements:

Bug Fixes:

Bug Description	Cause	Fix/Resolution
Image not resizing correctly during prediction	Incorrect input shape expected by MobileNetV4	Added a dedicated image preprocessing function to resize images to **224×224** and normalize pixel values before prediction
Flask app crash on uploading unsupported file formats (.txt, .pdf)	No file type validation during upload	Added file type validation using Flask's `allowed_extensions` check to restrict uploads to **.jpg, .jpeg, .png**
Model loading error when restarting Flask app	Incorrect file path to saved `.h5` model	Fixed by using absolute/relative path properly and verifying the correct model filename in Flask backend
Web page layout breaking on mobile devices	Missing responsive CSS rules	Applied **CSS media queries** and simplified layout structure for mobile screens
Incorrect predictions on low-light or blurry images	Model overfitting to high-quality, ideal dataset images	Improved by applying **data augmentation** during training: rotation, zoom, brightness adjustments

Improvements Made:

Improvement	Reason	Benefit
Added **data augmentation** during model training	To improve model generalization on real-world images	Increased model robustness and accuracy on varied images
Implemented **simple, clean UI design with mobile responsiveness**	Original UI was cluttered and non-responsive	Improved usability for farmers, students, and mobile users
Integrated a **prediction log feature (optional)**	To track model predictions for future analysis	Helps in monitoring AI decisions and retraining needs
Optimized model by freezing **base layers in MobileNetV4**	To reduce training time on CPU-only systems	Faster model training without significant loss in accuracy
Created **incremental project documentation templates**	To avoid end-stage reporting delays	Organized and time-efficient documentation process

III : Final Validation:

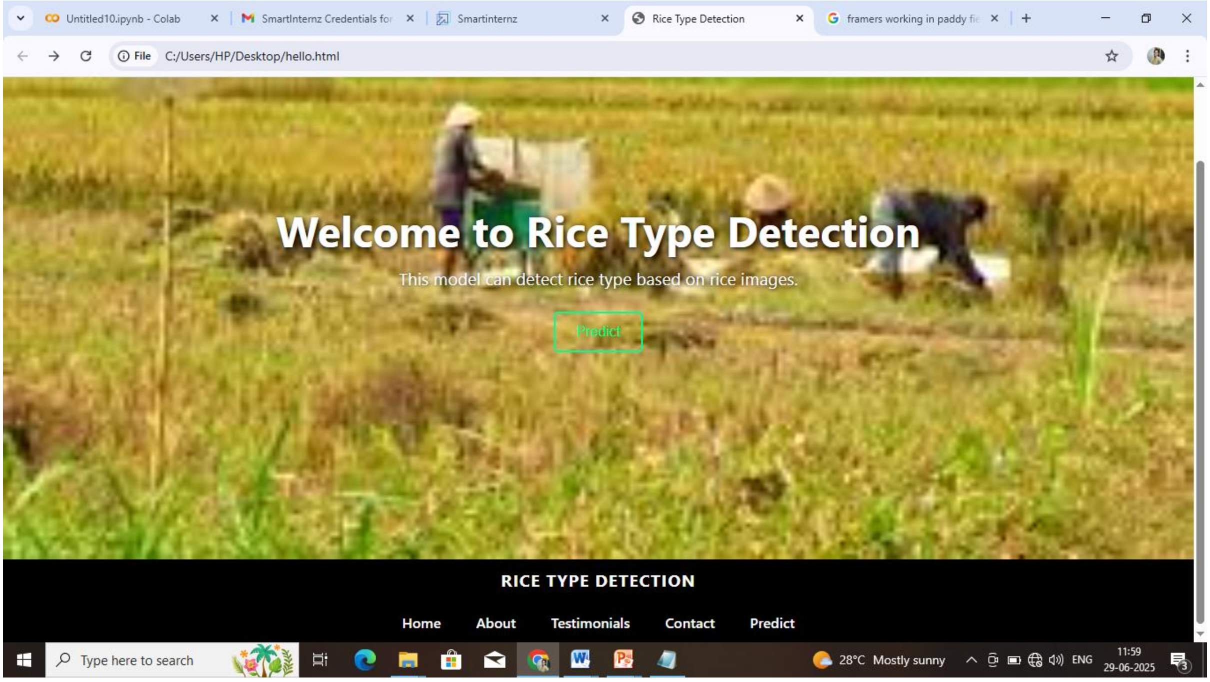
Project Successfully Meets All Initial Requirements

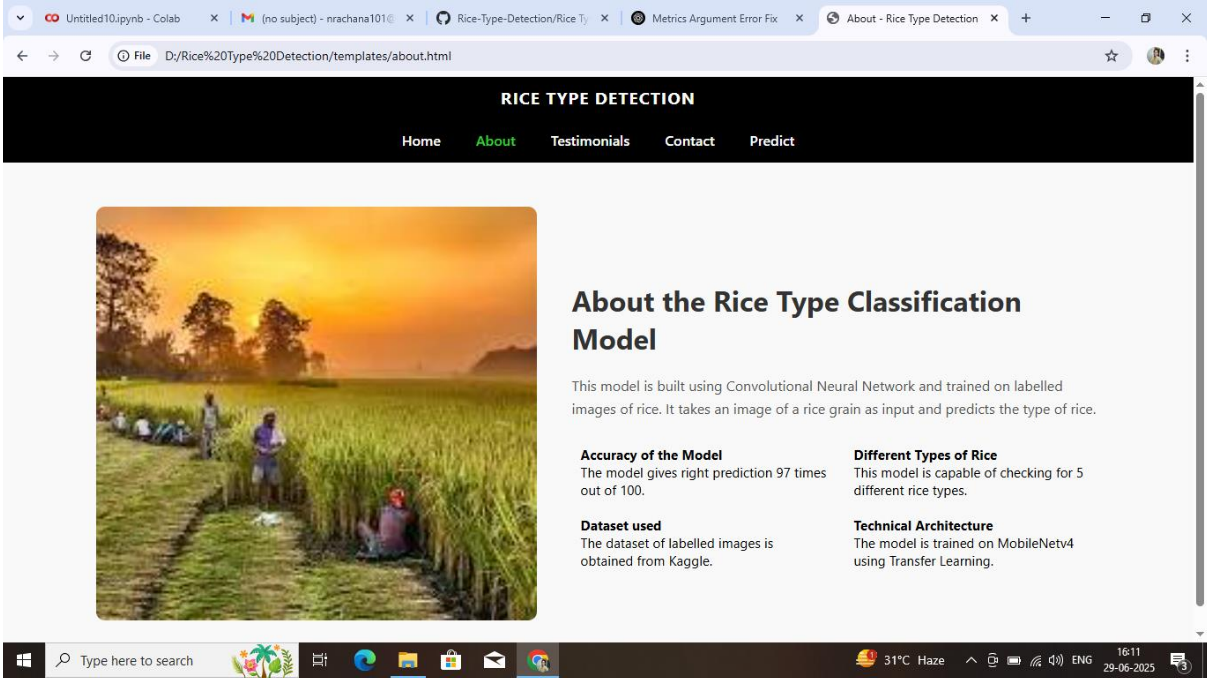
-AI-based rice variety prediction model works reliably

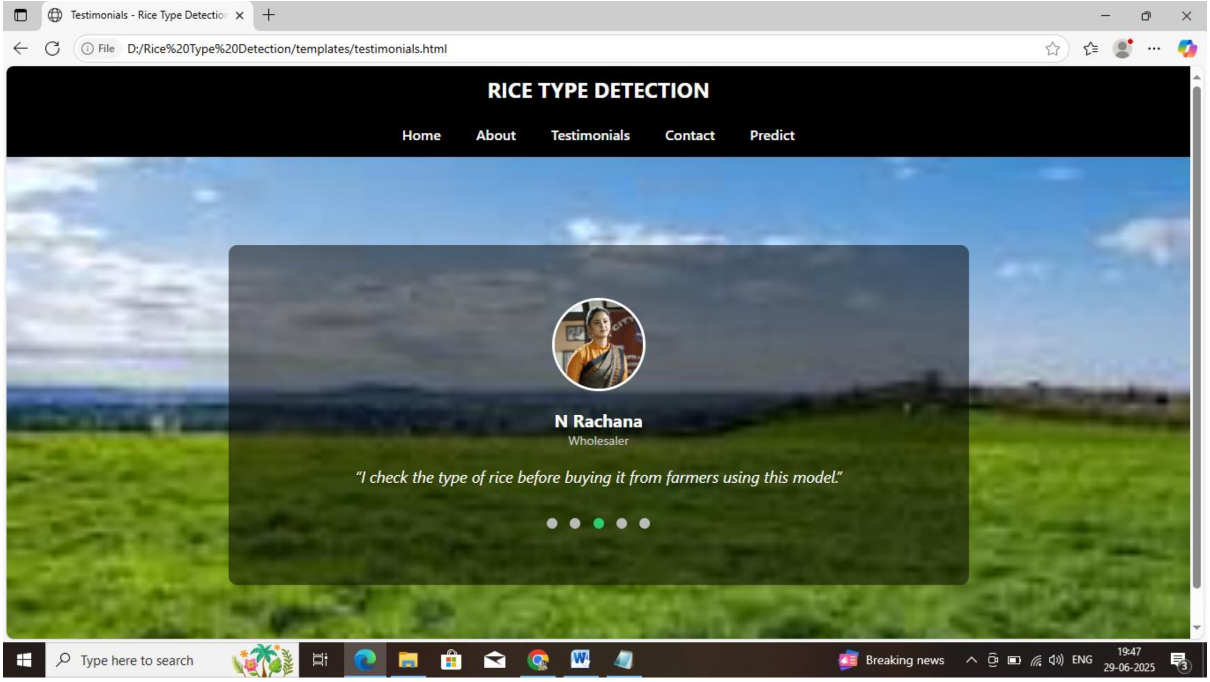
-Web application is functional, responsive, and user-friendly

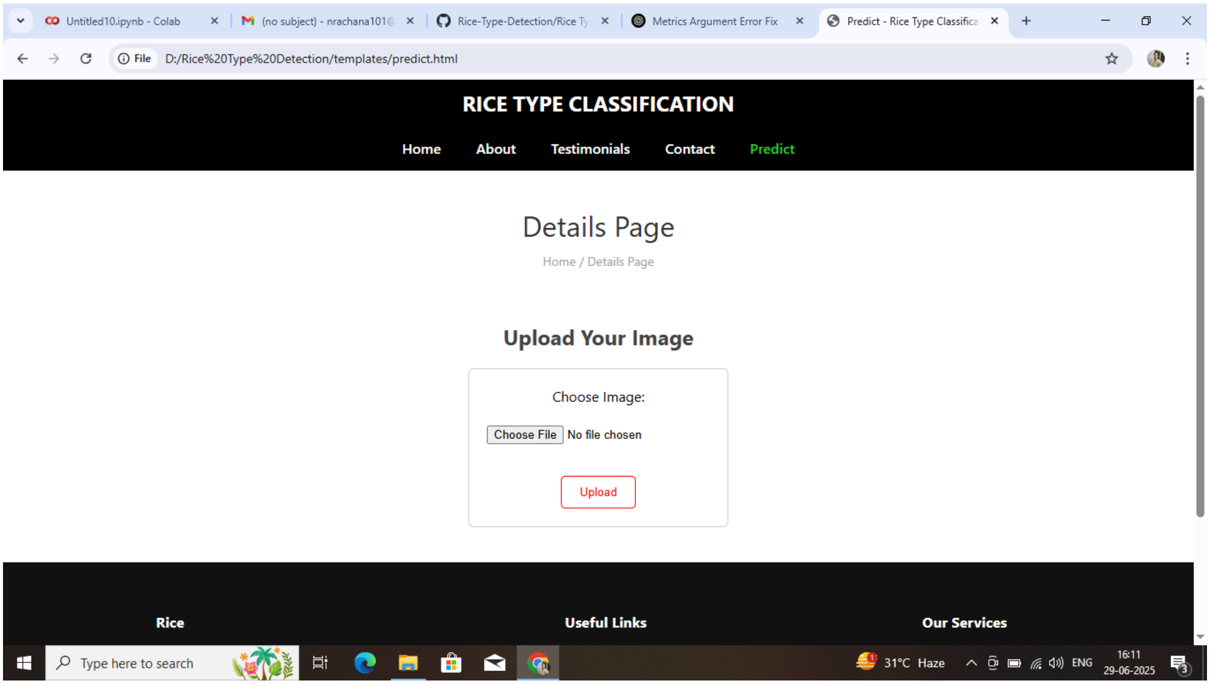
-All planned features were implemented, tested, and validated

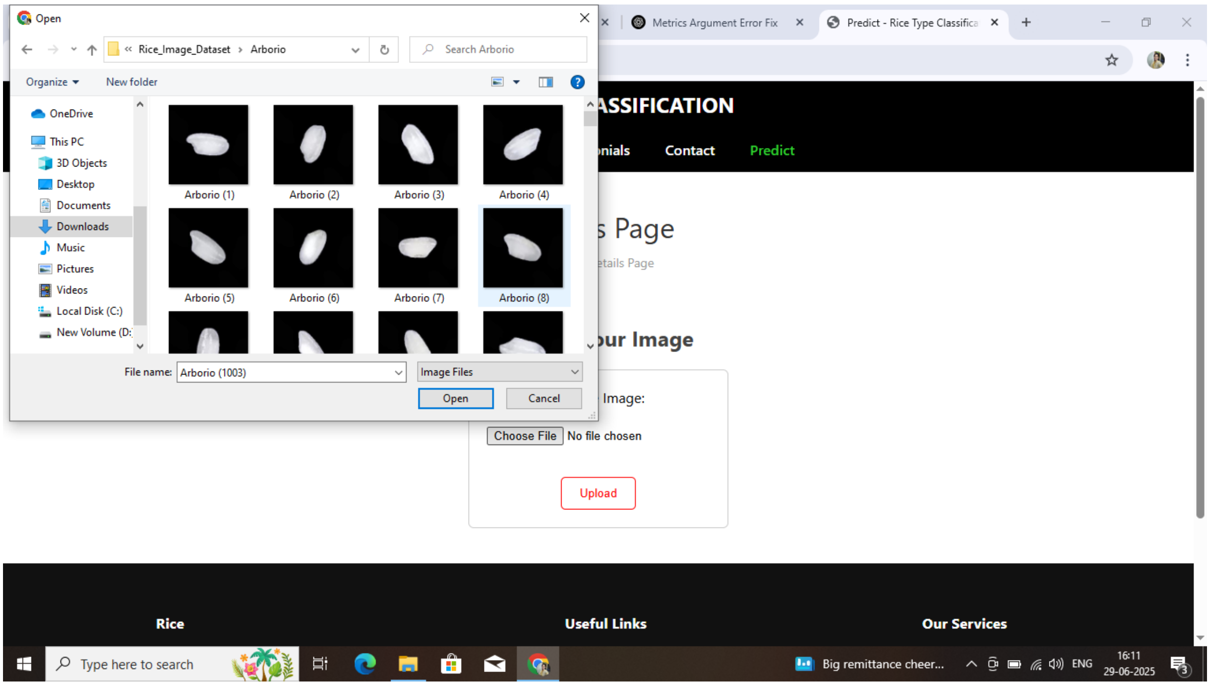
Output ScreenShots:

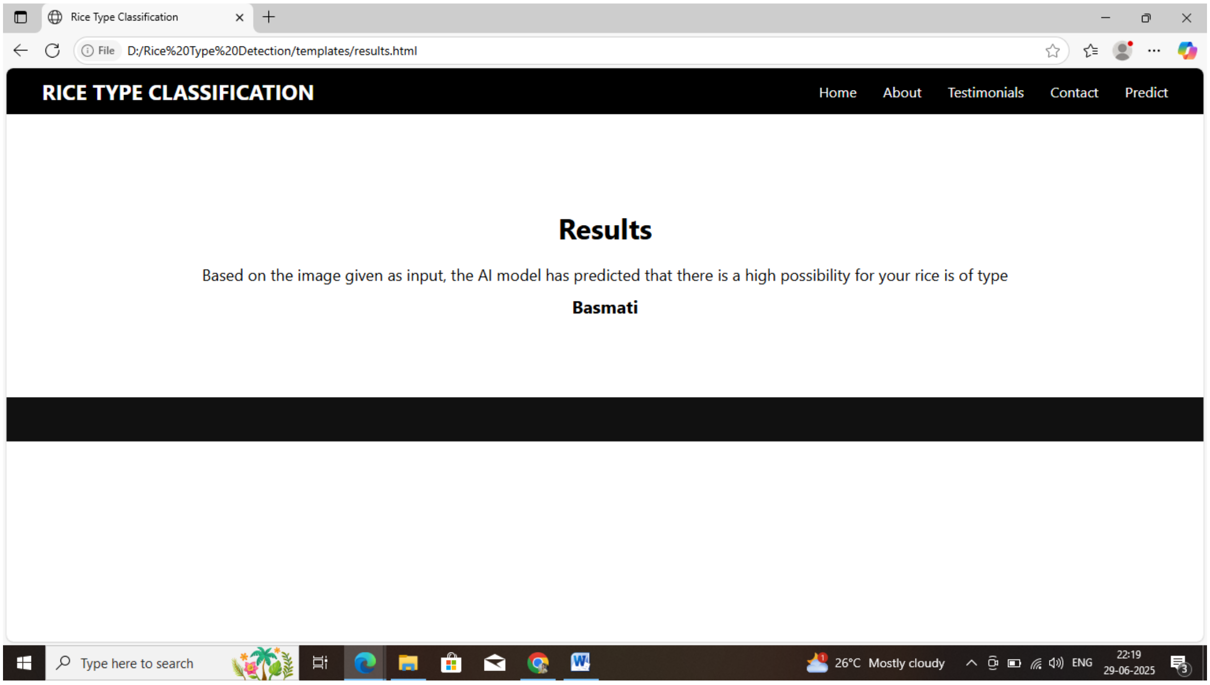





Testimonials - Rice Type Detectio
D:/Rice%20Type%20Detection/templates/testimonials.html
RICE TYPE DETECTION
Home
About
Testimonials
Contact
Predict
N Rachana
Wholesaler
"I check the type of rice before buying it from farmers using this model."
Type here to search
Breaking news
ENG
19:47
29-06-2025


Untitled10.ipynb - Colab
(no subject) - nrachana101
Rice-Type-Detection/Rice Ty
Metrics Argument Error Fix
Predict - Rice Type Classifica
D:/Rice%20Type%20Detection/templates/predict.html
RICE TYPE CLASSIFICATION
Home
About
Testimonials
Contact
Predict
Details Page
Home / Details Page
Upload Your Image
Choose Image:
Choose File
No file chosen
Upload
Rice
Useful Links
Our Services
Type here to search
31°C Haze
ENG
16:11
29-06-2025





Demo link:

https://screenapp.io/app/#/library/68617558a3a36841234dcd6f/recents/b5827540-797b-48a2-8a6c-fee7e3d69cad

GitHub link:

https://github.com/n-rachana1224/Rice-Type-Detection.git