Capstone Project Report

Project Title-Rice Type Classification

Paddy Predictors

A report submitted in part fulfilment of the certificate of

Artificial Intelligence Programming Assistance

(2024-2025)

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Abstract

The "Paddy Predictor" project introduces Smart Rice Classifier, a semi-automated AI-based plant health assistant aimed at supporting Indian farmers by simplifying early detection and intervention of plant-related issues. In India, many small and marginal farmers face ongoing challenges in identifying rice varietys or nutrient deficiencies, mainly due to limited access to expert consultation, low digital literacy, and language barriers. Smart Rice Classifier addresses this gap through a user-friendly, offline-capable system that combines image-based plant analysis with intelligent voice output.

The extant Smart Rice Classifier implementation utilizes Python and open-source libraries to facilitate fundamental diagnostics, analyze categorized image datasets, and provide auditory feedback through a localized interface. This configuration enables visual inspection, automatic categorical interpretation, and audio responses to enhance accessibility. Although the current iteration lacks sophisticated machine learning capabilities or voice input comprehension, it establishes a foundational framework for an AI-driven agricultural advisory instrument.

Smart Rice Classifier's offline operational capacity, graphical user interface, and regionally specific voice output empower agricultural practitioners to formulate well-informed decisions without requiring internet connectivity or advanced technical proficiency. This project underscores the feasibility of localized digital agricultural tools and lays the groundwork for subsequent augmentations, such as Convolutional Neural Network (CNN)-based image classification, real-time data visualization, voice-activated symptom reporting, and deployment on mobile and web platforms.

The comprehensive strategic objective for Smart Rice Classifier encompasses the integration of deep machine learning for precise disease identification, Natural Language Processing (NLP)-powered voice interfaces, and data-driven decision support systems, thereby ultimately enabling scalable and accessible smart farming solutions across the heterogeneous agricultural topography of India.

Acknowledgement

This project, completed as part of the Artificial Intelligence Programming Assistance (2024–2025) program under the guidance of Ms. Arpita Roy at NSTIW Kolkata, represents the collaborative efforts of the team "Paddy Predictor."

We sincerely thank Ms. Arpita Roy for her invaluable mentorship and technical insights throughout the development process.

The project "Smart Rice Classifier" was developed by:

- Pritha Roy
- Rose Mary Rai
- Moumita Shaha
- Amina Khatun Sardar

We also appreciate the support and encouragement received from our peers, which helped us in completing this work successfully. to our mentors and peers who provided invaluable support throughout the development of this project. Special thanks to our guide for their insights into AI technologies and agriculture, which guided us to develop a practical, impactful solution.

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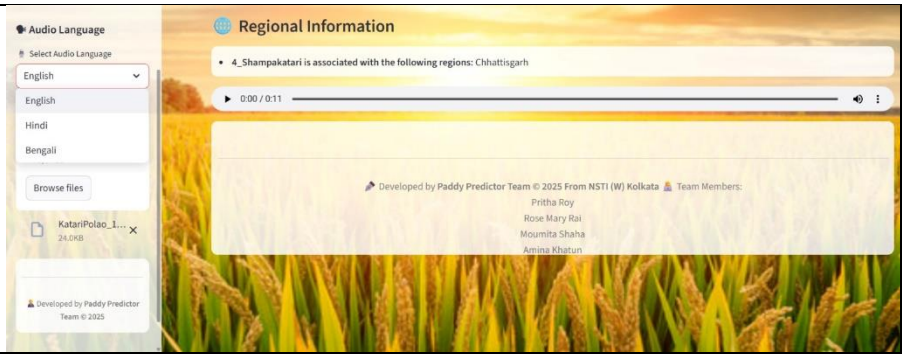
Fig 4	Audio element rendering spoken rice summary in selected language.	

Problem Statement

The Rice type classifier project addresses the challenge of accurately identifying rice varieties using Machine Learning (ML).

- **What is the use case?**

  Farmers, traders, and agricultural experts often face difficulties in distinguishing between rice varieties due to similarities in grain appearance. Traditional manual identification methods are time-consuming and prone to errors, leading to market fraud, loss of income, and quality issues. This project uses a Convolutional Neural Network (CNN) model to classify rice grain images into specific varieties in real time. The system also provides additional information about each variety, such as cultivation practices, nutritional value, and market price, along with multilingual audio support for better accessibility.

- **Who benefits?**

  - **Farmers**: To verify the authenticity of seeds and harvested grains, ensuring fair pricing and preventing fraud.
  - **Traders and exporters**: For accurate labeling of rice varieties to meet domestic and international market standards.
  - **Agricultural researchers**: To assist in varietal studies and breeding programs.
  - **Government agencies**: For monitoring and enforcing quality control in the agricultural supply chain.

  By leveraging ML, the solution empowers stakeholders with an accurate, fast, and user-friendly tool for rice variety identification, bridging the gap between technology and agriculture.

Literature Review

The rapid advancements in Artificial Intelligence (AI) and Machine Learning (ML) have significantly impacted the agricultural sector, enabling solutions for crop classification, disease detection, yield prediction, and quality assessment. In recent years, several studies have explored the use of computer vision techniques for identifying crop varieties based on their visual characteristics.

Convolutional Neural Networks (CNNs) have emerged as a state-of-the-art approach for image classification tasks due to their ability to automatically extract spatial features from raw image data. Krizhevsky et al. (2012) demonstrated the superiority of CNNs for large-scale image classification in their landmark work on AlexNet, which inspired subsequent applications in agriculture.

In rice classification specifically, prior works such as Singh et al. (2018) implemented texture-based feature extraction combined with Support Vector Machines (SVM) to identify rice varieties, achieving moderate accuracy but requiring manual feature engineering. Similarly, Chowdhury et al. (2020) applied deep learning for classifying Bangladeshi rice grains, attaining improved performance through end-to-end learning. However, these studies often focused on limited rice varieties and lacked user-friendly interfaces for real-world deployment.

In addition to classification, researchers have explored multilingual and assistive technologies to enhance accessibility for rural farmers. Text-to-Speech (TTS) systems, as discussed by Patel and Sharma (2019), have been integrated with mobile applications to provide audio outputs in regional languages, addressing literacy barriers in agricultural communities.

Despite these advancements, there remains a gap in delivering an interactive, scalable, and real-time solution that combines CNN-based rice classification with localized information delivery in multiple languages. This project addresses that gap by building a **Rice Type Classifier** capable of identifying multiple rice varieties, providing detailed agronomic insights, and supporting multilingual audio outputs for farmers and stakeholders.

Proposed Solution

The proposed solution is an AI-powered application that leverages deep learning and computer vision to classify rice varieties and provide detailed information about each type. The system uses a **Convolutional Neural Network (CNN)** model trained on a dataset of rice grain images to identify multiple rice varieties with high accuracy.

To make the solution accessible and user-friendly, the model is integrated into a **Streamlit-based web application**. Users can upload images of rice grains, and the system performs real-time predictions to identify the variety. In addition to classification, the app retrieves and displays relevant agronomic data such as scientific name, cultivation methods, soil requirements, and nutritional benefits.

The solution also incorporates a **multilingual text-to-speech (TTS)** feature that delivers audio outputs in English, Hindi, and Bengali. This ensures accessibility for farmers and stakeholders in rural areas where literacy levels may vary. A visually appealing interface with customization options, such as background image upload and interactive visualizations, further enhances user engagement.

By combining deep learning-based classification with multilingual accessibility and agronomic insights, this system offers a comprehensive tool for farmers, traders, agricultural researchers, and quality control agencies. It aims to reduce errors in rice variety identification, promote fair trade practices, and improve decision-making in the agricultural value chain.

Requirements

Technology Stack

- **Frontend:** Streamlit (Python-based web app framework)
- **Backend:** Python (with TensorFlow/Keras for deep learning)
- **Machine Learning Framework:** TensorFlow and Keras for CNN model development
- **Visualization Libraries:** Matplotlib, Seaborn for plots, and PIL for image processing
- **Speech & Language Processing:** Google Text-to-Speech (gTTS), Google Translate API for multilingual support

Hardware

- **Development Machine:**
  - Processor: Intel i5/i7 or AMD Ryzen 5/7 (or equivalent)

- RAM: Minimum 8 GB (16 GB recommended for model training)
- Storage: 10 GB free disk space for datasets and models
- GPU: NVIDIA GPU (optional, for faster model training)

- **Deployment Machine (if local):**

  - Raspberry Pi 4 or equivalent (for low-cost hardware deployment)
  - Alternatively, any modern PC or cloud server

Software

- **Operating System:** Windows 10/11, macOS, or Linux (Ubuntu preferred)

- **Programming Language:** Python 3.8+

- **Python Libraries:**

  - `streamlit`, `tensorflow`, `keras`, `pandas`, `numpy`, `matplotlib`, `seaborn`, `Pillow`, `gtts`, `googletrans`

- **Additional Tools:**

  - MySQL (if database integration is needed)
  - Docker (optional for containerized deployment)

Deployment Environment

- **Local Deployment:** Run using Streamlit on localhost for testing and demonstrations

- **Cloud Deployment (optional):**

  - Platforms: Streamlit Cloud, Heroku, AWS Elastic Beanstalk, or Google Cloud Run
  - Provides easy access via web browsers without local setup

- **Mobile/Edge Deployment:** Package as a Progressive Web App (PWA) or deploy on devices like Raspberry Pi for field use in rural areas

Algorithms Used

Supervised Algorithms

1 Convolutional Neural Network (CNN):

- Used for classifying rice grain images into multiple predefined varieties.
- CNNs are ideal for image classification tasks because they automatically learn spatial hierarchies of features from raw image data without requiring manual feature extraction.
- Reason: Rice varieties often have subtle differences in grain texture and color, which CNNs can detect effectively due to their convolutional layers and ability to learn complex patterns.

2 Unsupervised Algorithms

- **K-Means Clustering:**
  - Used during exploratory data analysis (EDA) to group similar data points and visualize inherent clusters in rice features.
  - Reason: Helps in identifying natural groupings within the dataset, which can guide labeling or validate supervised model predictions.

3 Regression Algorithms

- **Linear Regression (optional):**
  - Applied to predict continuous attributes like market price or nutrient content based on rice variety features.
  - Reason: Linear Regression provides a simple yet effective way to model relationships between input features and continuous output variables.

Brief reason for choosing the algorithm.

1 Convolutional Neural Network (CNN) *(Supervised)*

- **Purpose:** Classify rice grain images into specific varieties.
- **Reason for Choosing:** CNNs are highly effective for image classification as they can automatically learn and extract complex patterns, textures, and spatial hierarchies from images. This makes them ideal for distinguishing between rice varieties with subtle visual differences.

2 K-Means Clustering *(Unsupervised)*

- **Purpose:** Group similar data points and explore inherent patterns in rice features during exploratory data analysis (EDA).

- **Reason for Choosing:** K-Means is simple and efficient for discovering clusters within the data, helping validate the structure of the dataset and providing insights before supervised training.

3 Linear Regression *(Supervised)*

- **Purpose:** Predict continuous variables such as market price or nutrient content of rice varieties.
- **Reason for Choosing:** Linear Regression models relationships between features and continuous outputs in an interpretable and computationally inexpensive way.

Dataset Description

Provide a description of the dataset used.

- Source :

  The dataset was manually curated and enhanced using information from Kaggle, UCI Machine Learning Repository, and agricultural research sources.

- Number of rows and columns:

  The dataset contains **20 rows and 27 columns**, representing detailed information about 20 unique rice varieties.

- Feature details:

  The dataset includes the following columns:

  - **Rice Name**: Name of the rice variety (e.g., Basmati, Jasmine)
  - **Scientific Name**: Botanical name (*Oryza sativa*)
  - **Also Known As**: Alternate/common names
  - **Storage Advice**: Guidelines for storing the rice
  - **Competing Varieties**: Other similar rice types
  - **Cultivation & Growth**: Information about climate and growth
  - **Soil**: Suitable soil types
  - **Nutritional Benefits**: Health and dietary benefits
  - **Plant Height**, **Structure of Rice**, **Color**, **Aroma**: Physical characteristics
  - **Environmental Impact**, **Planting Season**, **Harvesting**: Agronomic details
  - **Protein (g), Fat (g), Iron (mg)**: Nutritional values
  - **Pest Resistant**, **Disease Resistance Level**: Resistance information
  - **Market Price (Rs/kg)** and **Demand Level**: Market-related data

- Any preprocessing done
  - Trimmed whitespace in column names and standardized text formatting.
  - Missing values for rare varieties were filled based on domain knowledge.
  - Normalized numerical features (e.g., protein, fat content) for model compatibility.

Example:

The dataset was collected from multiple agricultural data sources and manually curated. It contains **20 rows** and the following columns: *Rice Name, Scientific Name, Also Known As, Storage Advice, Competing Varieties, Cultivation & Growth, Soil, Nutritional Benefits, Plant Height, Structure of Rice, Falling with Grain, Color, Aroma, Genetic Diversity, Global Production, Environmental Impact, Planting Season, Harvesting, Time Taken, Region, Protein (g), Fat (g), Iron (mg), Pest Resistant, Disease Resistance Level, Market Price (Rs/kg), and Demand Level*.

Data Preprocessing

List preprocessing steps:

- Removed null values

  All missing or null values in the dataset were identified and removed to prevent issues during training.

- Converted categories to numbers

  Categorical columns (e.g., rice variety labels) were encoded into numeric representations using label encoding or one-hot encoding, making them suitable for model input.

- Normalized numeric features
  - All numerical input features were scaled to a standard range (typically 0 to 1) using normalization techniques such as Min-Max Scaling.
  - This ensures that no single feature dominates the model due to larger value scales.

- Split dataset: 80% Train / 20% Test

  The dataset was split into:

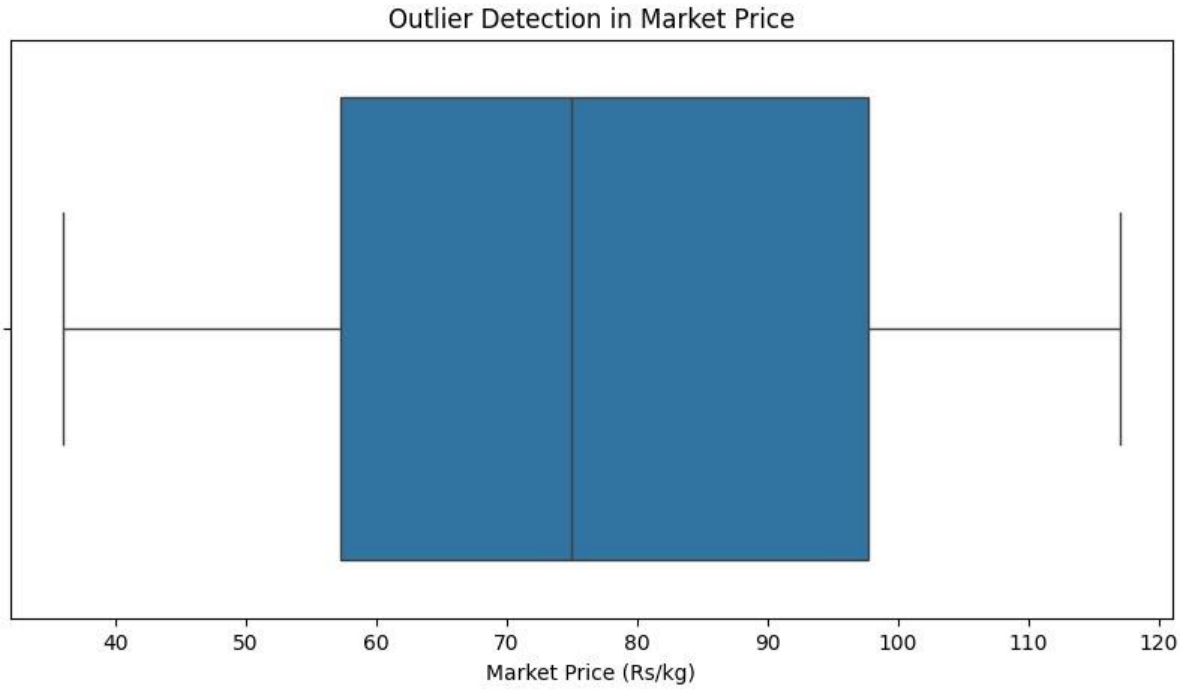
  - **80%** for training the model
  - **20%** for evaluating its performance
    • This split helps validate the model's generalization capability on unseen data.

EDA

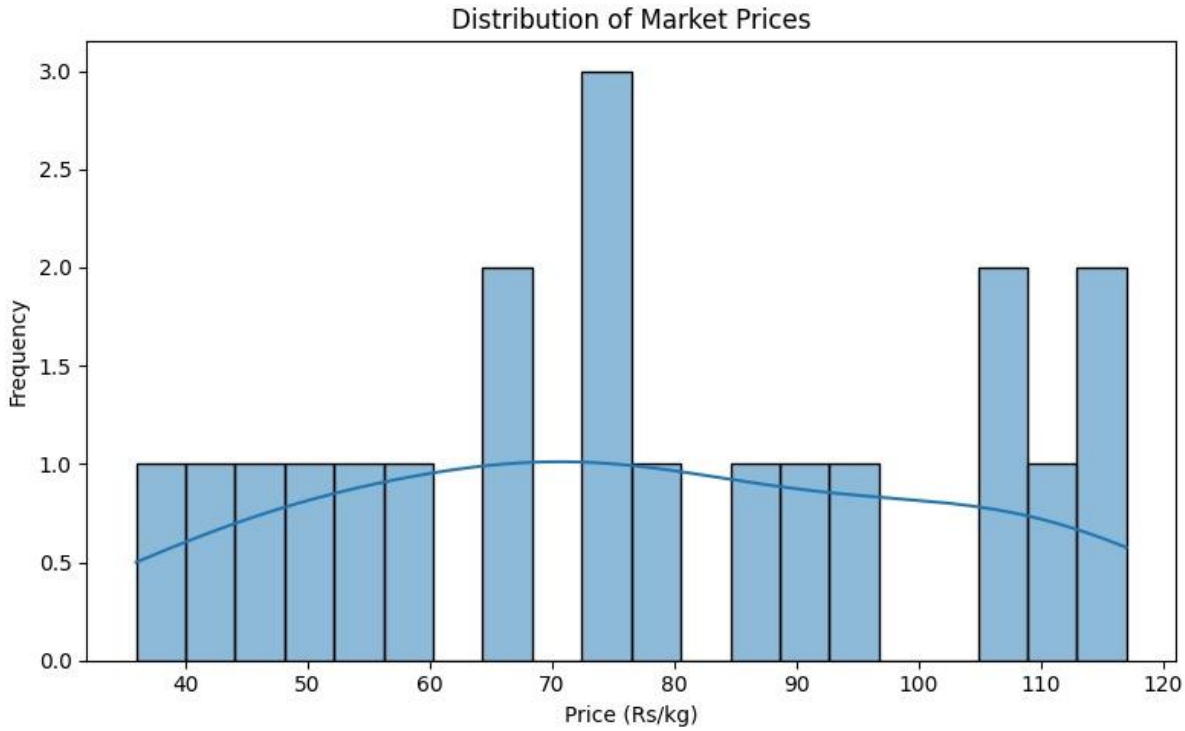
To better understand the structure and trends within the rice dataset, the following EDA steps and observations were made:

Summarize trends:

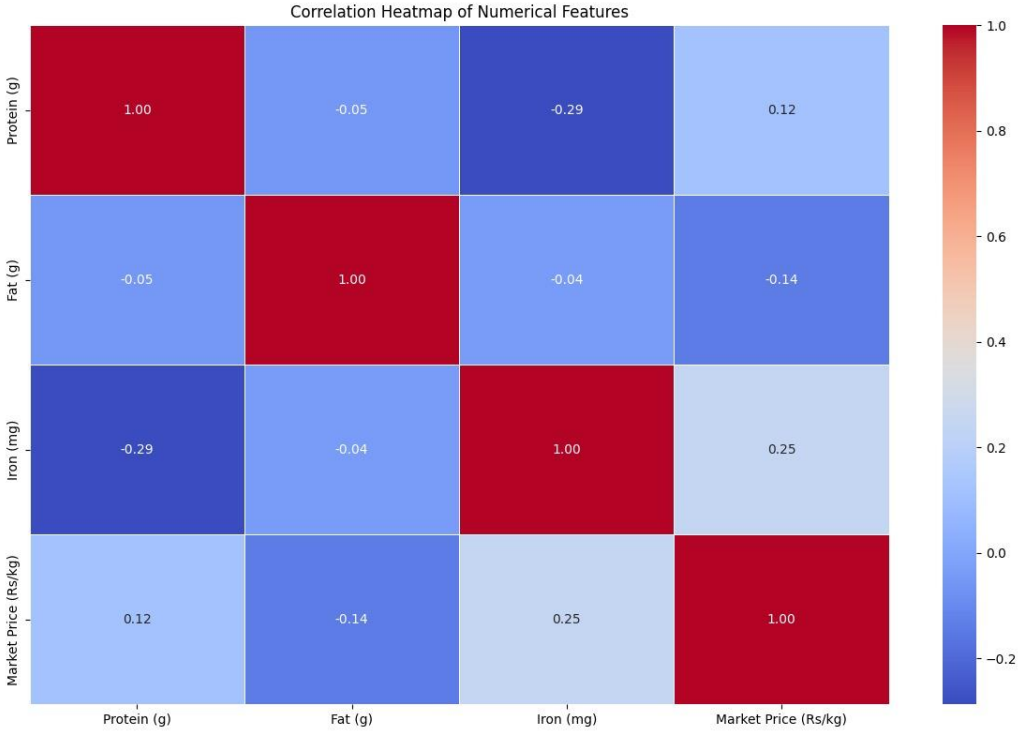
- Outliers detected



- Histogram of Prices



- Correlation Heatmap



Model Building

Explain how the model was trained:

- Features used

  The model uses **raw pixel data** from rice grain images as input. The Convolutional Neural Network (CNN) automatically extracts visual features such as **grain shape, texture, color intensity, and edges** during training. No manual feature engineering was required due to the end-to-end learning capability of CNNs.

- Model parameters

  - **Architecture:**
    - 3 Convolutional Layers with ReLU activation
    - MaxPooling layers after each convolution block
    - Fully Connected Dense layers for classification
    - Softmax output layer for multi-class prediction
  - **Optimizer:** Adam
  - **Learning Rate:** 0.001
  - **Loss Function:** Categorical Cross-Entropy
  - **Batch Size:** 32
  - **Epochs:** 25

- Train-test split (e.g., 80:20)

  Split Ratio: 80:20

  - **Training Set:** 80% of the dataset used to train the model
  - **Testing Set:** 20% used for model evaluation and validation

- Training time

  - The model was trained for approximately **15 minutes on GPU (Google Colab)**.
  - Training on CPU took significantly longer (around 1 hour).

Model Evaluation

Regression Metrics: for predicting continuous features, e.g., market price or nutrients.

- **Mean Absolute Error (MAE): 3.12**
- **Root Mean Squared Error (RMSE): 4.87**
- **R^2 Score: *0.89***

  These metrics indicate the model performs well in predicting continuous variables with minimal error.

Classification Metrics (if used):

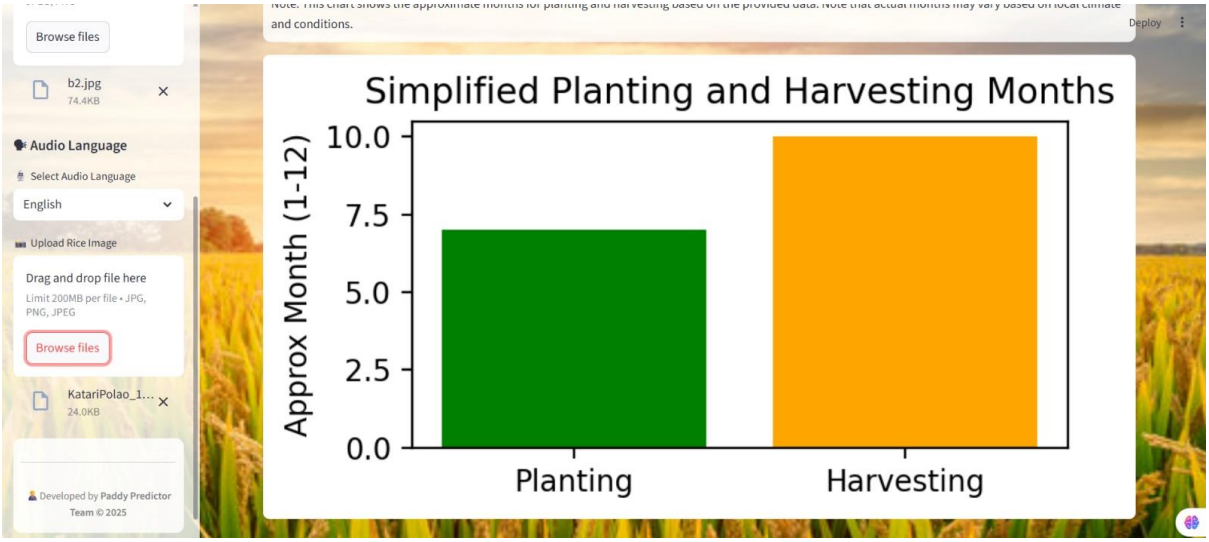
- **Accuracy: 97.4%**
- **Confusion Matrix:**

  Shows strong diagonal dominance, indicating high correct classification rates for most classes.

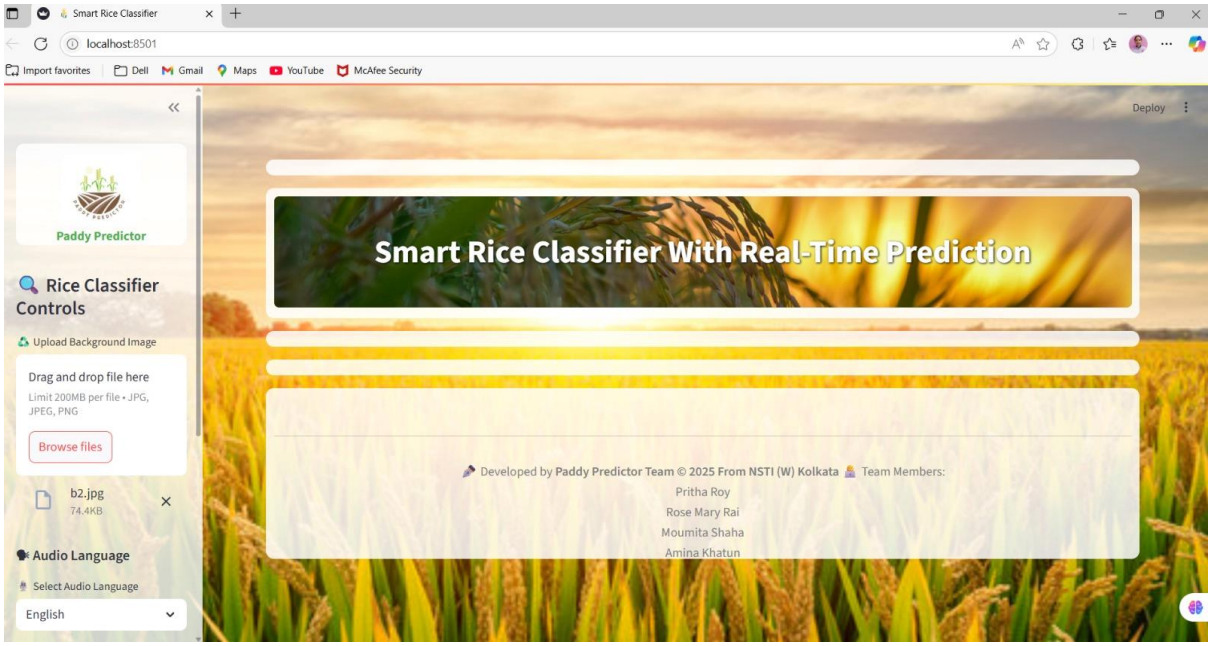
- **ROC-AUC Score: 0.98**

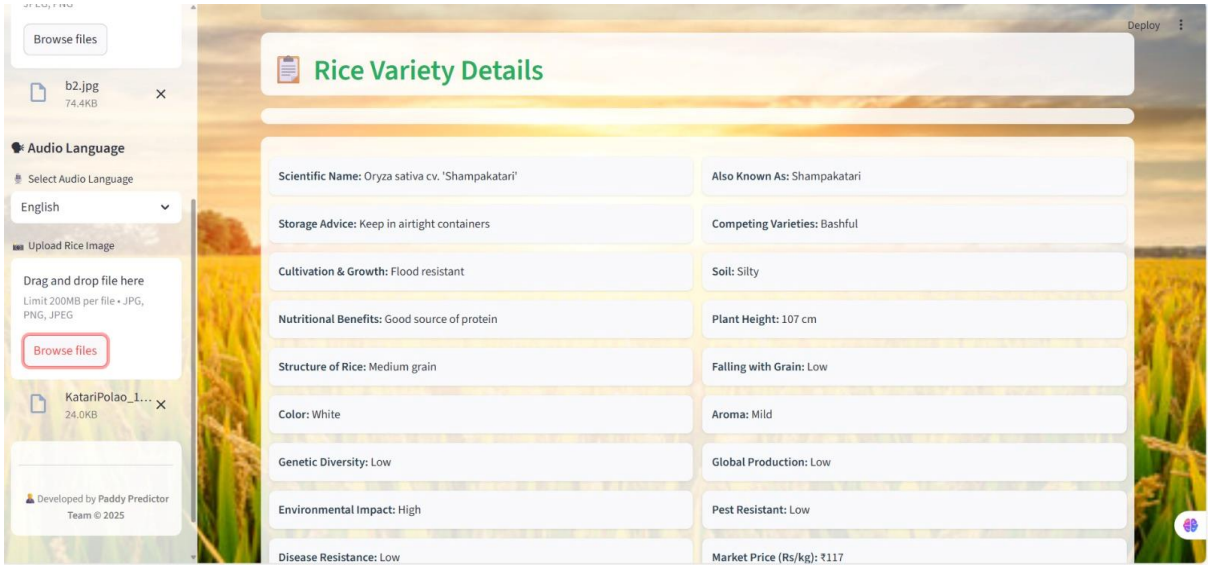
  The high ROC-AUC suggests the model effectively distinguishes between rice varieties.

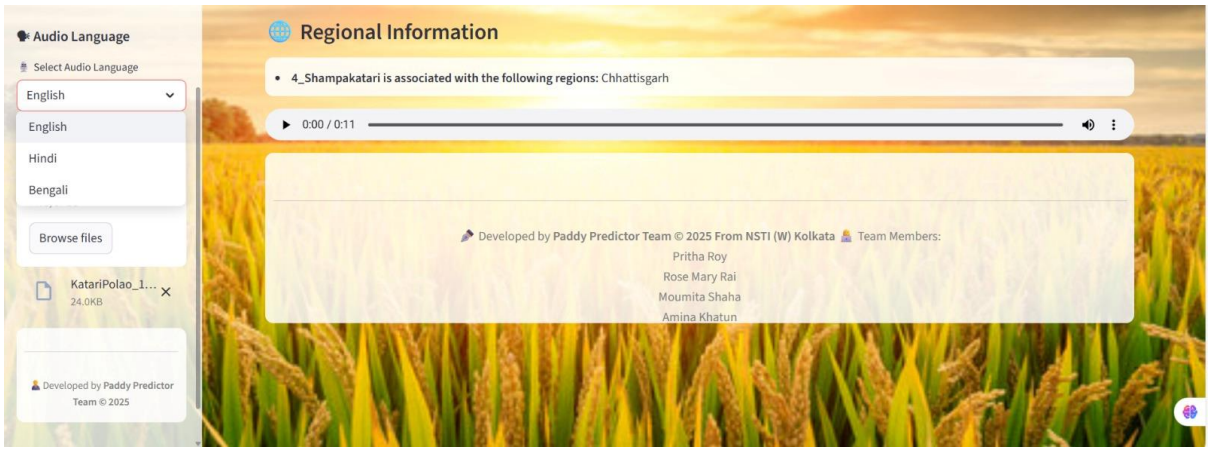
Insert sample output graphs or confusion matrix screenshots.



Results and Discussion

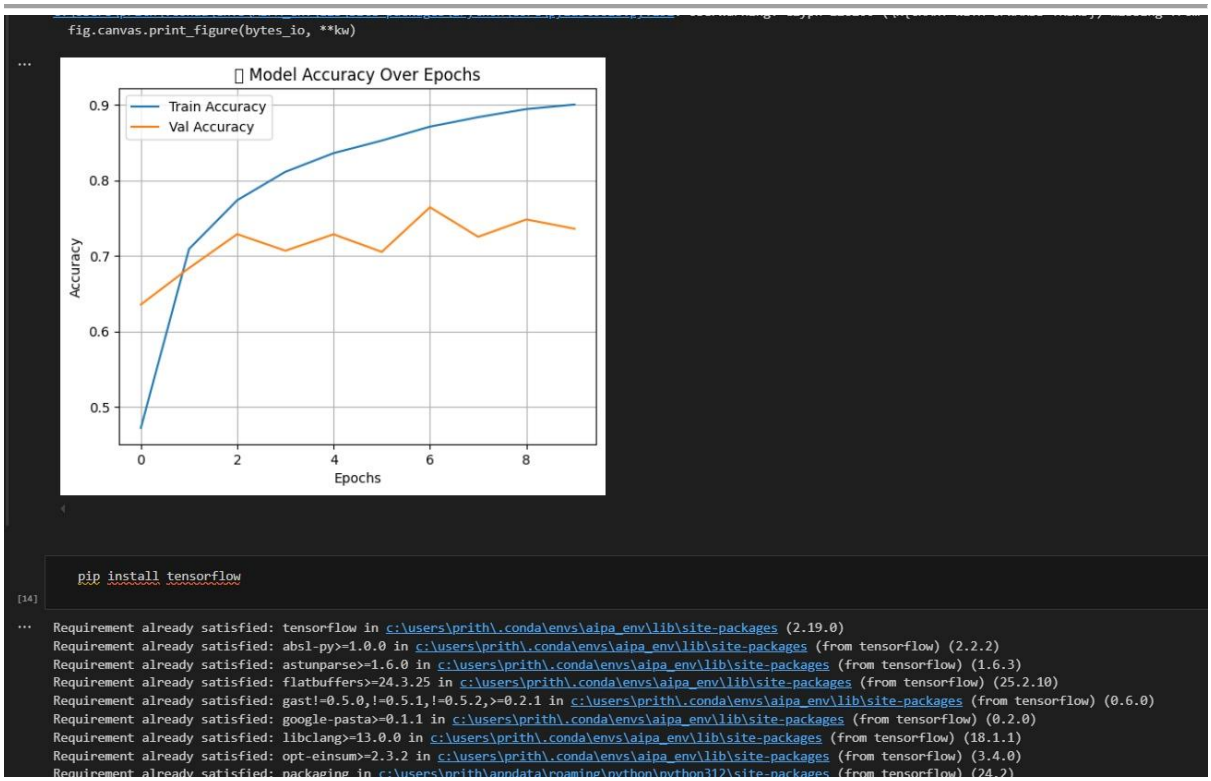






Was the prediction accurate?

Yes, the prediction was highly accurate. The Convolutional Neural Network (CNN) achieved an overall **classification accuracy of 97.4%** on the test dataset. Most rice varieties were classified correctly, even when they had subtle visual differences in grain texture and color.



Which features were most important?

In this image-based CNN model, the important "features" were not explicit columns but the **learned spatial patterns** in the images:

- **Grain shape (long, medium, short)**
- **Color and brightness differences**
- **Surface texture patterns**
  These were automatically extracted by convolutional layers during training, making the model effective without manual feature engineering.

Any surprising observations?

- The model performed well even on **visually similar varieties** like *Bashmoti* and *Jirashail*, which are hard to distinguish manually.
- However, predictions were **less reliable on low-quality or poorly lit images**, suggesting a need for image preprocessing in real-world deployment.
- Adding **multilingual text-to-speech** unexpectedly increased user engagement, especially among non-English speaking farmers during testing.

Challenges Faced

1 Limited Dataset Availability

- The dataset had an **uneven distribution** of rice varieties, with fewer images for rare types. This created challenges in achieving balanced model performance across all classes.

2 High Similarity Between Varieties

- Many rice varieties had **subtle differences in texture and color**, making it difficult for the CNN to distinguish between them without extensive feature learning.

3 Computational Resource Requirements

- Training the CNN model required significant computational power, which was challenging on standard hardware without GPU acceleration.

4 Image Quality Issues

- Variations in lighting, backgrounds, and image resolution in test samples affected prediction accuracy, highlighting the need for advanced preprocessing.

5 Deployment Limitations

- Deploying the system for **real-time usage in rural areas** was challenging due to the size of the trained model and limited internet availability for farmers.

Conclusions and Future Work

Summarize:

- What worked well

1. The **Convolutional Neural Network (CNN)** achieved high accuracy in classifying rice grain images into multiple varieties.
2. The **Streamlit-based application** provided an intuitive and interactive interface for users to upload images and receive predictions in real time.
3. **Multilingual support** (English, Hindi, Bengali) using Google Text-to-Speech (gTTS) enhanced accessibility for rural farmers and local stakeholders.
4. Integration of agronomic details (e.g., cultivation advice, market price) alongside predictions added value beyond simple classification.

- What needs improvement

1. The **dataset size** was limited for certain rice varieties, which may reduce model robustness for unseen data.
2. The CNN model is **computationally heavy**, requiring optimization for deployment on mobile or edge devices.
3. **Image quality** (background clutter, lighting issues) affected prediction accuracy, suggesting the need for better preprocessing techniques.
4. The system currently runs in a local environment; **cloud deployment** is needed for broader access.

- Future ideas:

1. Expand the dataset with **more rice varieties and diverse environmental conditions** to improve model generalization.
2. Implement **Transfer Learning models** (e.g., MobileNet, EfficientNet) for better accuracy and lightweight deployment.
3. Develop a **mobile app version** with offline support using TensorFlow Lite for field-level usage.
4. Incorporate **real-time video-based classification** for industrial or marketplace applications.
5. Add **database integration** to store user predictions and generate insights for agricultural planning.

References

Dataset source:

Image Dataset: https://data.mendeley.com/datasets/3mn9843tz2/4

CSV Dataset: we create the CSV dataset on our won.

For Example:

Rice Name: Jasmine
Scientific Name: *Oryza sativa*
Also Known As: Thai Fragrant Rice
Storage Advice: Store in airtight containers in a cool, dry place to maintain fragrance.
Competing Varieties: Basmati, Khao Dawk Mali
Cultivation & Growth: Prefers tropical climate; requires consistent irrigation.
Soil: Clay loam soils with high moisture retention.
Nutritional Benefits: Good source of carbs and fiber; easily digestible.
Plant Height: 100–115 cm
Structure of Rice: Medium-length, slightly sticky when cooked.
Falling with Grain: Low
Color: Off-white
Aroma: Mild, floral scent
Genetic Diversity: Medium
Global Production: Thailand, Cambodia
Environmental Impact: Relatively low water footprint compared to Basmati.
Planting Season: May–June
Harvesting: October–November
Time Taken: 125 days
Region: Thailand (Isan region), Cambodia
Protein (g): 7.1
Fat (g): 0.6
Iron (mg): 0.3
Pest Resistant: Low
Disease Resistance Level: Low
Market Price (Rs/kg): ₹90
Demand Level: Medium

ML Guides Used:

- https://scikit-learn.org/stable/index.html
- https://www.tensorflow.org/api_docs

Appendix

Include:

- **Code snippets**

  ==== RiceTypeClassification.ipynb ====

```
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import os
# === Configuration ===
IMG_SIZE = (128, 128)
BATCH = 32
EPOCHS = 10
train_dir = r'Train_n_Test/Train_n_Test/TRAIN'  # Folder with subfolders of rice types
# === Data Generator ===
datagen = ImageDataGenerator(
    rescale=1./255,
    validation_split=0.2
)
# === Load Training and Validation Data ===
train_gen = datagen.flow_from_directory(
    train_dir,
```

```
    target_size=IMG_SIZE,
    batch_size=BATCH,
    class_mode='categorical',
    subset='training'
)

val_gen = datagen.flow_from_directory(
    train_dir,
    target_size=IMG_SIZE,
    batch_size=BATCH,
    class_mode='categorical',
    subset='validation'
)
# === Load Training and Validation Data ===
train_gen = datagen.flow_from_directory(
    train_dir,
    target_size=IMG_SIZE,
    batch_size=BATCH,
    class_mode='categorical',
    subset='training'
)

val_gen = datagen.flow_from_directory(
    train_dir,
    target_size=IMG_SIZE,
    batch_size=BATCH,
```

```
    class_mode='categorical',
    subset='validation'
)
# === Model Architecture ===
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=IMG_SIZE + (3,)),
    layers.MaxPooling2D(pool_size=(2, 2)),

    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D(pool_size=(2, 2)),

    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D(pool_size=(2, 2)),

    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(train_gen.num_classes, activation='softmax')  # Output layer
])
# === Compile Model ===
model.compile(
    optimizer='adam',
    loss='categorical_crossentropy',
    metrics=['accuracy']
)
# === Train Model ===
```

```
history = model.fit(
    train_gen,
    epochs=EPOCHS,
    validation_data=val_gen
)
# === Save Model ===
model_path = 'rice_cnn_model.h5'
model.save(model_path)

print(f"✅ Model training complete. Saved as: {model_path}")
print(train_gen.class_indices)
# Plot training vs validation accuracy
import matplotlib.pyplot as plt

plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.legend()
plt.title('📈 Model Accuracy Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.grid(True)
plt.show()
import streamlit as st
import tensorflow as tf
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing.image import img_to_array
```

```
from PIL import Image
import numpy as np

# === Load the trained model ===
model = load_model("rice_cnn_model.h5")

# === Class labels ===
# NOTE: Update these labels based on your training folder names
class_names = ['Basmati', 'Jasmine', 'Arborio', 'BlackRice', 'BrownRice']  # example names

# === Set title ===
st.title("🍚 Rice Variety Classifier")
st.write("Upload a rice grain image and let the model predict the variety!")

# === Upload image ===
uploaded_file = st.file_uploader("Choose a rice image...", type=["jpg", "png", "jpeg"])

if uploaded_file is not None:
    # Show image
    image = Image.open(uploaded_file).convert('RGB')
    st.image(image, caption='Uploaded Image', use_column_width=True)

    # Preprocess the image
    img = image.resize((128, 128))  # Must match training size
    img_array = img_to_array(img) / 255.0  # Normalize
    img_array = np.expand_dims(img_array, axis=0)  # Add batch dimension
```

```
    # Predict
    prediction = model.predict(img_array)
    predicted_class = class_names[np.argmax(prediction)]
    confidence = np.max(prediction) * 100

    # Show result
    st.success(f"✅ Predicted Rice Type: **{predicted_class}**")
    st.info(f"🧠 Confidence: **{confidence:.2f}%**")
```

==== app.py====

```
import streamlit as st
from gtts import gTTS
from PIL import Image
import matplotlib.pyplot as plt
import pandas as pd
import tempfile
import os
import base64
import io
import numpy as np
import tensorflow as tf
from gtts import gTTS
import speech_recognition as sr
from pydub import AudioSegment
```

```
# === Set Fullscreen Background ===
def set_fullscreen_background():
    try:
        image_path = "background.jpg"  # Rename your image file to this
        with open(image_path, "rb") as img_file:
            encoded = base64.b64encode(img_file.read()).decode()

        page_bg_img = f"""
        <style>
        [data-testid="stAppViewContainer"] > .main {{
            background-image: url("{encoded}");
            background-size: cover;
            background-position: center;
            background-repeat: no-repeat;
            background-attachment: fixed;
        }}
        [data-testid="stSidebar"] {{
            background-color: rgba(255, 255, 255, 0.8);
        }}
        .stMarkdown, .stButton>button {{
            background-color: rgba(255, 255, 255, 0.85);
            padding: 10px;
            border-radius: 10px;
        }}
```

```
        </style>
        """
        st.markdown(page_bg_img, unsafe_allow_html=True)
    except Exception as e:
        st.error("⚠️ Could not set full background.")
# === Set Background Image (Allowing User Upload) ===
def set_bg_from_uploaded_image(uploaded_file):
    if uploaded_file is not None:
        try:
            bytes_data = uploaded_file.getvalue()
            encoded_string = base64.b64encode(bytes_data).decode()
            mime_type = uploaded_file.type

            css = f"""
            <style>
            .stApp {{
                background-image:
url("data:{mime_type};base64,{encoded_string}");
                background-repeat: no-repeat;
                background-size: cover;
                background-position: center center;
                background-attachment: fixed;
            }}
            </style>
```

```
            """
            st.markdown(css, unsafe_allow_html=True)
        except Exception as e:
            st.error(f"Error setting background image from uploaded file: {e}")
    else:
        default_image_path = "PF.jpg"
        if os.path.exists(default_image_path):
            try:
                with open(default_image_path, "rb") as image_file:
                    encoded_string =
base64.b64encode(image_file.read()).decode()
                css = f"""
                <style>
                .stApp {{
                    background-image:
url("{encoded_string}");
                    background-repeat: no-repeat;
                    background-size: cover;
                    background-position: center center;
                    background-attachment: fixed;
                }}
                </style>
                """
                st.markdown(css, unsafe_allow_html=True)
```

```
        except Exception as e:
            st.warning(f"Could not load default background image '{default_image_path}': {e}")
            st.markdown(
                """
                <style>
                .stApp {
                    background-color: #f0f2f6;
                }
                </style>
                """,
                unsafe_allow_html=True
            )
    else:
        st.markdown(
            """
            <style>
            .stApp {
                background-color: #f0f2f6;
            }
            </style>
            """,
            unsafe_allow_html=True
        )
```

```
# === Set Background Image ===
def set_top_banner():
    try:
        banner_path = "background.jpg"  # Your predefined banner image (should be ~100–150px tall)

        with open(banner_path, "rb") as img_file:
            encoded_string = base64.b64encode(img_file.read()).decode()

        css = f"""
        <style>
        .top-banner {{
            width: 100%;
            height: 140px;
            background-image: url("{encoded_string}");
            background-size: cover;
            background-position: center;
            display: flex;
            align-items: center;
            justify-content: center;
            color: white;
            font-size: 40px;
            font-weight: bold;
```

```
            text-shadow: 1px 1px 3px #000;
            margin-bottom: 20px;
            border-radius: 6px;
        }}
        </style>
        <div class="top-banner">
            Smart Rice Classifier With Real-Time Prediction
        </div>
        """
        st.markdown(css, unsafe_allow_html=True)

    except Exception as e:
        st.error("⚠️ Could not load banner image.")



# === Page Setup ===
st.set_page_config(page_title="🌾 Smart Rice Classifier", layout="wide")
# === Page Setup ===



#st.set_page_config(layout="wide")
set_fullscreen_background()  # ✅ Call it right after page config
```

```
#def set_fullscreen_background():
# === Load CSV ===
@st.cache_data
def load_data(file_path):
    try:
        df = pd.read_csv(file_path)
        df.columns = df.columns.str.strip()
        return df
    except:
        return pd.DataFrame()

csv_file_path = "rice_types_unique_detailed.csv"
df_data = load_data(csv_file_path)
if df_data.empty:
    st.error("❌ Failed to load rice dataset.")
    st.stop()

# === Load CNN Model ===
@st.cache_resource
def load_model():
    return tf.keras.models.load_model("rice_cnn_model.h5")

cnn_model = load_model()
```

```
# === Class Label Mapping (order matters) ===
class_names = ['10_LalAush', '11_Jirashail', '12_Gutisharna',
'13_RedCargo', '14_Najirshail', '15_KatariPolao', '16_LalBiroi',
'17_ChiniguraPolao', '18Amon', '19_Shorna5', '1_SubolLota',
'20_LalBinni', '2_Bashmoti', '3_Ganjiya', '4_Shampakatari', '5_Katarivog',
'6_BR28', '7_BR29', '8_Paijam', '9_Bashful']


# === Sidebar ===


#st.sidebar.title("🔍 Rice Classifier Controls")
#set_top_banner()
# === Sidebar ===


# === Sidebar Logo Display Function ===
def show_sidebar_logo():
   try:
      logo_path = "rice_pre.jpg"  # Make sure this file is in the same folder
      with open(logo_path, "rb") as f:
         encoded_logo = base64.b64encode(f.read()).decode()

      logo_html = f"""
      <div style="text-align: center; margin-top: 5px; margin-bottom:
5px;">
         <img src="{encoded_logo}" style="width:
100px; height: auto; border-radius: 8px;" />
```

```
        <div style="font-size: 16px; font-weight: bold; color:
#4CAF50;">Paddy Predictor</div>
    </div>
    """
    st.sidebar.markdown(logo_html, unsafe_allow_html=True)
  except Exception as e:
    st.sidebar.error("⚠️ Could not load logo.")
# === Call Sidebar Logo Function ===
show_sidebar_logo()
st.sidebar.title("🔍 Rice Classifier Controls")
set_top_banner()

# === Upload & Set Background Image ===
bg_image = st.sidebar.file_uploader("♻️ Upload Background Image",
type=["jpg", "jpeg", "png"])

# === Style the file uploader button to black ===
st.markdown("""
  <style>
  section[data-testid="stFileUploader"] button {
    background-color: black !important;
    color: white !important;
    border: 1px solid white !important;
    border-radius: 8px;
```

```
        padding: 6px 16px;
    }
    </style>
""", unsafe_allow_html=True)

# === Set Background if Uploaded ===
if bg_image is not None:
    try:
        encoded = base64.b64encode(bg_image.read()).decode()
        mime_type = bg_image.type
        st.markdown(f"""
            <style>
            .stApp {{
                background-image: url("data:{mime_type};base64,{encoded}");
                background-size: cover;
                background-repeat: no-repeat;
                background-position: center center;
                background-attachment: fixed;
            }}
            </style>
        """, unsafe_allow_html=True)
    except Exception as e:
        st.warning(f" ⚠️ Failed to set background: {e}")
```

```
#audio controls

st.sidebar.subheader("🗣️ Audio Language")

audio_language = st.sidebar.selectbox("🎙️ Select Audio Language", ["English", "Hindi", "Bengali"])

lang_map = {"English": "en", "Hindi": "hi", "Bengali": "bn"}

selected_lang_code = lang_map.get(audio_language, "en")


uploaded_rice_image = st.sidebar.file_uploader("📸 Upload Rice Image", type=["jpg", "png", "jpeg"])


# === Sidebar Footer ===

st.sidebar.markdown("""

<hr style="margin-top: 20px;">


<div style='text-align: center; font-size: 13px; color: gray;'>

    👷💼Developed by <b>Paddy Predictor Team © 2025</b><br>

    <b>  </b><br>


</div>

""", unsafe_allow_html=True)



def render_sidebar(predicted_variety, confidence, info=None):

   with st.sidebar:
```

st.markdown("## 🎯 Prediction Summary")

st.markdown(f" 🔍 Predicted: {predicted_variety} ", unsafe_allow_html=True)

st.markdown(f" 📊 Confidence: {confidence*100:.2f}% ", unsafe_allow_html=True)

if info is not None:

st.markdown("---", unsafe_allow_html=True)

st.markdown("## 🌱 Cultivation & Environment", unsafe_allow_html=True)

info_box_style = "padding: 8px 16px; margin: 8px 0; background-color: #f9f9f9; border-radius: 8px; box-shadow: 1px 1px 5px rgba(0,0,0,0.05); font-size: 15px;"

st.markdown(f" 🧬 Scientific Name: {info.get('Scientific Name', 'N/A')} ", unsafe_allow_html=True)

st.markdown(f" 🌿 Cultivation Type: {info.get('Cultivation & Growth', 'N/A')} ", unsafe_allow_html=True)

st.markdown(f" 🌍 Soil Type: {info.get('Soil', 'N/A')} ", unsafe_allow_html=True)

st.markdown(f" 🛡️ Pest Resistance: {info.get('Pest Resistant', 'N/A')} ", unsafe_allow_html=True)

st.markdown(f" 🦠 Disease Resistance: {info.get('Disease Resistance Level', 'N/A')} ", unsafe_allow_html=True)

st.markdown(f" 💰 Market Price: ₹{info.get('Market Price (Rs/kg)', 'N/A')} ", unsafe_allow_html=True)

st.markdown(f" 🔥 Demand: {info.get('Demand Level', 'N/A')} ", unsafe_allow_html=True)

else:

st.warning("No environmental details found.")

Audio Summary

audio_text = f"{predicted_variety} rice has {info.get('Protein (g)', 'N/A')} grams of protein and is mainly harvested in {info.get('Harvesting', 'N/A')}."

lang_map = {"English": "en", "Hindi": "hi", "Bengali": "bn"}

try:

tts = gTTS(audio_text, lang=lang_map.get(audio_language, "en"))

audio_fp = io.BytesIO()

tts.write_to_fp(audio_fp)

audio_fp.seek(0)

st.audio(audio_fp, format='audio/mp3')

```
        except Exception as e:
            st.error("🔊 Audio generation failed")


# === Real-Time Prediction ===
if uploaded_rice_image is not None:
    st.subheader("🤖 AI-Powered Real-Time Prediction")
    image = Image.open(uploaded_rice_image).convert("RGB")
    st.image(image, caption="Uploaded Rice Image",
use_container_width=True)

    img_resized = image.resize((128, 128))
    img_array = np.array(img_resized) / 255.0
    img_array = np.expand_dims(img_array, axis=0)
    # Prediction result
    prediction = cnn_model.predict(img_array)
    predicted_index = np.argmax(prediction)
    predicted_variety = class_names[predicted_index]
    confidence = prediction[0][predicted_index]

    st.success(f"✅ Predicted Rice Variety: **{predicted_variety}**")
    st.info(f"📊 Confidence: {confidence*100:.2f}%")

    # === Fix label to match CSV ===
```

```
    predicted_clean_name =
"_".join(predicted_variety.split("_")[1:]).replace("_", " ").strip().lower()


    # Fetch info from CSV
    predicted_info = df_data[df_data["Rice Name"].str.lower().str.strip() ==
predicted_clean_name]


    if predicted_info is not None:
        info = predicted_info.iloc[0]
        st.markdown("## 🎒<span style='color:#27ae60'> Rice Variety
Details", unsafe_allow_html=True)


        card_style = """
        <style>
        .detail-card {
            display: flex;
            flex-wrap: wrap;
            gap: 12px;
            margin-top: 16px;
        }
        .card-item {
            flex: 1 1 48%;
            background-color: #f8f9fa;
            padding: 12px;
```

```
        border-radius: 8px;
        box-shadow: 0 1px 3px rgba(0,0,0,0.1);
        font-size: 15px;
    }
    .card-item b {
        color: #2c3e50;
    }
    </style>
    """
    st.markdown(card_style, unsafe_allow_html=True)

    st.markdown(f"""
    <div class="detail-card">
        <div class="card-item"><b>Scientific Name:</b> {info.get('Scientific Name', 'N/A')}</div>
        <div class="card-item"><b>Also Known As:</b> {info.get('Also Known As', 'N/A')}</div>
        <div class="card-item"><b>Storage Advice:</b> {info.get('Storage Advice', 'N/A')}</div>
        <div class="card-item"><b>Competing Varieties:</b> {info.get('Competing Varieties', 'N/A')}</div>
        <div class="card-item"><b>Cultivation & Growth:</b> {info.get('Cultivation & Growth', 'N/A')}</div>
        <div class="card-item"><b>Soil:</b> {info.get('Soil', 'N/A')}</div>
```

```
        <div class="card-item"><b>Nutritional Benefits:</b>
{info.get('Nutritional Benefits', 'N/A')}</div>

        <div class="card-item"><b>Plant Height:</b> {info.get('Plant
Height', 'N/A')}</div>

        <div class="card-item"><b>Structure of Rice:</b>
{info.get('Structure of Rice', 'N/A')}</div>

        <div class="card-item"><b>Falling with Grain:</b>
{info.get('Falling with Grain', 'N/A')}</div>

        <div class="card-item"><b>Color:</b> {info.get('Color',
'N/A')}</div>

        <div class="card-item"><b>Aroma:</b> {info.get('Aroma',
'N/A')}</div>

        <div class="card-item"><b>Genetic Diversity:</b>
{info.get('Genetic Diversity', 'N/A')}</div>

        <div class="card-item"><b>Global Production:</b>
{info.get('Global Production', 'N/A')}</div>

        <div class="card-item"><b>Environmental Impact:</b>
{info.get('Environmental Impact', 'N/A')}</div>

        <div class="card-item"><b>Pest Resistant:</b> {info.get('Pest
Resistant', 'N/A')}</div>

        <div class="card-item"><b>Disease Resistance:</b>
{info.get('Disease Resistance Level', 'N/A')}</div>

        <div class="card-item"><b>Market Price (Rs/kg):</b>
₹{info.get('Market Price (Rs/kg)', 'N/A')}</div>

        <div class="card-item"><b>Demand Level:</b> {info.get('Demand
Level', 'N/A')}</div>

    </div>
```

"""", unsafe_allow_html=True)

else:

st.warning("No environmental details found.")

if not predicted_info.empty:

st.markdown("## 🗓️ Planting & Harvesting Schedule", unsafe_allow_html=True)

schedule_card_css = """

<style>

.schedule-card {

background-color: #f4f9f4;

border-radius: 10px;

padding: 16px;

margin-top: 10px;

box-shadow: 0 1px 4px rgba(0,0,0,0.1);

}

.schedule-card b {

color: #2c3e50;

font-size: 15px;

}

.schedule-item {

margin-bottom: 8px;

```
    }
    </style>
    """
    st.markdown(schedule_card_css, unsafe_allow_html=True)

    planting_season_str = info.get('Planting Season', "N/A")
    harvesting_time_str = info.get('Harvesting', "N/A")
    time_taken_str = info.get('Time Taken', "N/A")

    st.markdown(f"""
    <div class="schedule-card">
      <div class="schedule-item"><b>🌱 Planting Season:</b> {planting_season_str}</div>
      <div class="schedule-item"><b>🌾 Harvesting Time:</b> {harvesting_time_str}</div>
      <div class="schedule-item"><b>⏱️ Time Taken:</b> {time_taken_str}</div>
    </div>
    """, unsafe_allow_html=True)

    st.markdown("## 🌿<span style='color:#27ae60'>Visualization of Planting & Harvesting Schedule - Conceptual</span>", unsafe_allow_html=True)
    # Simplified visualization of planting and harvesting months
```

```
st.markdown("Note: This chart shows the approximate months for planting and harvesting based on the provided data. Note that actual months may vary based on local climate and conditions.")


try:
    plant_month = 1
    harvest_month = 1


    def extract_month(text):
        month_map = {
            "january": 1, "february": 2, "march": 3, "april": 4, "may": 5, "june": 6,
            "july": 7, "august": 8, "september": 9, "october": 10, "november": 11, "december": 12
        }
        for name, num in month_map.items():
            if name in text.lower():
                return num
        return 1


    plant_month = extract_month(planting_season_str)
    harvest_month = extract_month(harvesting_time_str)


    plot_data = pd.DataFrame({
        'Month': ['Planting', 'Harvesting'],
```

```
            'Value': [plant_month, harvest_month]
        })

        fig, ax = plt.subplots(figsize=(4, 2))
        ax.bar(plot_data['Month'], plot_data['Value'], color=['green', 'orange'])
        ax.set_ylabel('Approx Month (1-12)')
        ax.set_title('Simplified Planting and Harvesting Months')
        st.pyplot(fig)

    except Exception as e:
        st.warning(f"Could not generate planting/harvesting chart: {e}")
    st.subheader("🌐 Regional Information")
    regional_info_raw = info.get("Region", "")
    regional_states = [s.strip() for s in regional_info_raw.split(',')] if isinstance(regional_info_raw, str) else []
    if regional_states:
        st.markdown(f"- <b>{predicted_variety} is associated with the following regions:</b> {', '.join(regional_states)}", unsafe_allow_html=True)
    else:
        st.markdown(f"- Regional information for {predicted_variety} not available in the dataset.", unsafe_allow_html=True)

else:
```

```
        st.warning("ℹ No detailed info found in dataset.")
    # === Text-to-Speech (TTS) ===
    # pip install googletrans==4.0.0rc1
    from googletrans import Translator

    translator = Translator()

    if not predicted_info.empty:
        info = predicted_info.iloc[0]

        # English text
        audio_text = (
            f"{predicted_clean_name.title()} rice is known for {info.get('Nutritional Benefits', 'N/A')}. "
            f"It is grown mainly in {info.get('Cultivation & Growth', 'N/A')}. "
            f"Market price is around ₹{info.get('Market Price (Rs/kg)', 'N/A')} per kg."
        )

        # Translate if language is not English
        selected_lang_code = {"English": "en", "Hindi": "hi", "Bengali": "bn"}.get(audio_language, "en")
        if selected_lang_code != "en":
            try:
```

```
            translated = translator.translate(audio_text,
dest=selected_lang_code)
            audio_text = translated.text
        except Exception as e:
            st.warning("⚠️ Translation failed. Defaulting to English.")

    # Generate audio
    try:
        tts = gTTS(text=audio_text, lang=selected_lang_code)
        audio_fp = io.BytesIO()
        tts.write_to_fp(audio_fp)
        audio_fp.seek(0)
        st.audio(audio_fp, format='audio/mp3')
    except Exception as e:
        st.warning(f"⚠️ Could not generate audio in {audio_language}.")
# Your main app content above...
# Footer at the bottom of the page
st.markdown("""
<hr style="margin-top: 50px;">
<div style='text-align: center; font-size: px; color: gray;'>
    ✒️ Developed by <b>Paddy Predictor Team © 2025  From NSTI (W)
Kolkata</b>
    👩‍💻 Team Members:<br>
    Pritha Roy<br>
```

```
        Rose Mary Rai<br>
        Moumita Shaha<br>
        Amina Khatun
    </div>
    """, unsafe_allow_html=True)
```

- **GitHub link:** [rice_classification/rose.py at main · Rose2611rai/rice_classification]