Rice Type Classification using CNN

INTRODUCTION: -

- ### Project Overviews: -

The Rice Type Classification project leverages Convolutional Neural Networks (CNNs) to accurately classify different rice types, including Arborio, Ipsala, Basmati, Jasmine, and Karacadag. Utilizing a dataset comprising images of these rice varieties, the project involves training a CNN model to discern and categorize each type based on their unique visual features. The process begins with data pre-processing, including image augmentation to enhance the model's robustness. The CNN architecture is designed to extract hierarchical features through multiple convolutional and pooling layers, followed by fully connected layers that perform the final classification. By optimizing the model with techniques such as dropout and batch normalization, the project aims to achieve high accuracy and generalization. This system could significantly benefit agricultural industries by providing an automated, reliable method for rice type identification, thereby improving quality control and aiding in inventory management.

- ### Objectives: -

  - **Create a Comprehensive Dataset**: Assemble and preprocess a diverse and balanced dataset containing high-quality images of Arborio, Ipsala, Basmati, Jasmine, and Karacadag rice types.
  - **Design and Implement CNN Model:** Develop a Convolutional Neural Network (CNN) tailored to effectively identify and classify the distinct visual characteristics of each rice type.
  - **Apply Data Augmentation Techniques**: Enhance the dataset through image augmentation methods such as rotation, flipping, scaling, and cropping to improve model robustness and generalization.
  - **Achieve High Classification Accuracy**: Aim for a classification accuracy of at least 90% by optimizing the CNN model through parameter tuning and the use of advanced techniques like dropout and batch normalization.
  - **Develop a User-Friendly Interface**: Create an intuitive

application or web interface that utilizes the trained CNN model to allow users to upload images and receive real-time rice type classifications.

- **Evaluate Model Performance**: Conduct thorough evaluation using validation and test datasets to ensure the model's accuracy, precision, recall, and F1-score meet predefined standards.

Milestone 1: Project Initialization and Planning Phase

The "Project Initialization and Planning Phase" marks the project's outset, defining goals, scope, and stakeholders. This crucial phase establishes project parameters, identifies key team members, allocates resources, and outlines a realistic timeline. It also involves risk assessment and mitigation planning.

Activity 1: Define Problem Statement

Problem Statement: The current method of classifying rice types based on physical appearance alone is troublesome because it often leads to errors and inconsistencies. This can result in mislabeled products, customer dissatisfaction, and challenges in meeting market demands effectively. Our solution involves developing a model that accurately classify different rice types such as Basmati, Jasmine, Arborio, Karacadag, and Ipsala. This approach ensures precise labelling, better quality control, and enhanced customer satisfaction. Ultimately, our solution aims to streamline the classification process, reduce errors, and provide farmers, distributors, and consumers with reliable information about the rice they are dealing with, thereby improving overall efficiency and market competitiveness in the rice industry.

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Activity 2: Project Proposal (Proposed Solution)

This project aims to develop a Convolutional Neural Network (CNN) model for accurately classifying various rice types based on their physical and chemical properties. By leveraging deep learning techniques, the proposed solution seeks to improve labeling precision, enhance quality control measures, and streamline operational workflows within the rice industry. The project will focus on data collection, model development, rigorous evaluation, and deployment of the CNN model to provide a robust tool for efficient rice type classification.

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Activity 3: Initial Project Planning

The project will begin with a kickoff meeting to define goals, scope, and assign team roles. Following this, we will collect and preprocess a diverse dataset of rice grain images. Next, we will experiment with different CNN architectures and select the best-performing model. After training and fine-tuning the model, we will rigorously evaluate its performance. Finally, we will deploy the model and integrate it into existing workflows for efficient rice type classification.

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Milestone 2: Data Collection and Preprocessing Phase

The Data Collection and Preprocessing Phase involves executing a plan to gather relevant data from Kaggle, ensuring data quality through verification and addressing missing values. Preprocessing tasks include resizing, normalizing, augmenting, denoising, adjusting contrast, detecting edges, converting color space, cropping, batch normalizing, and whitening data.

Activity 1: Data Collection Plan, Raw Data Sources Identified, Data Quality Report

Elevate your data strategy with the Data Collection plan and the Raw Data Sources report, ensuring meticulous data curation and integrity for informed decision-making in every analysis and decision-making endeavour.

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Activity 2: Data Quality Report

The dataset for "Rice Type Classification using CNN" is sourced from Kaggle. Data quality is ensured through thorough verification, addressing missing values, and maintaining adherence to ethical guidelines establishing a reliable foundation for predictive modeling. The Data Quality Report will summarize data quality issues from the selected source, including severity levels and resolution plans. It will aid in systematically identifying and rectifying data discrepancies.

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Activity 3: Data Exploration and Preprocessing

The images will be preprocessed by resizing, normalizing, augmenting, denoising, adjusting contrast, detecting edges, converting colour space, cropping, batch normalizing, and whitening data. These steps will enhance data quality, promote model generalization, and improve convergence during neural network training, ensuring robust and efficient performance across various computer vision tasks.

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Milestone 3: Model Development Phase

In the Model Development Phase for loan approval, we strategically select relevant features and evaluate models such as Random Forest, Decision Tree, KNN. We initiate model training with code implementation and rigorously validate performance metrics like accuracy and recall. This phase aims to deliver a robust predictive model that enhances decision-making efficiency in the lending process.

Activity 1: Model Selection Report

In the model selection report for future deep learning and computer vision projects, various architectures, such as CNNs or RNNs, will be evaluated. Factors such as performance, complexity, and computational requirements will be considered to determine the most suitable model for the task at hand.

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Activity 2: Initial Model Training Code, Model Validation and Evaluation Report

The Initial Model Training Code employs selected algorithms on the dataset. The initial model training code will be showcased in the future through a screenshot. The model validation and evaluation report will include a summary and training and validation performance metrics for multiple models, presented through respective screenshots.

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Milestone 4: Model Optimization and Tuning Phase

The Model Optimization and Tuning Phase involves refining neural network models for peak performance. It includes optimized model code, fine-tuning hyperparameters, comparing performance metrics, and justifying the final model selection for enhanced predictive accuracy and efficiency.

Activity 1: Hyperparameter Tuning Documentation

We selected Convolutional Neural Networks (CNNs) for our rice varieties classification project due to their proven ability to handle complex image data and capture intricate visual patterns. During hyperparameter tuning, we optimized parameters like convolutional layers, filter sizes, and dropout rates to enhance model accuracy and mitigate overfitting. This process aimed to ensure robust classification of rice varieties based on image data, aligning perfectly with our project goals.

Activity 2: Performance Metrics Comparison Report

Our Performance Metrics Comparison Report highlights the significant improvements achieved through hyperparameter tuning of the CNN model. By comparing baseline and optimized metrics such as accuracy, precision, recall, and F1-score, we demonstrate the CNN's enhanced ability to accurately classify rice varieties from images. This analysis underscores the effectiveness of parameter adjustments in refining our model's predictive capabilities.

Activity 3: Final Model Selection Justification

We chose the CNN as our final model for rice variety classification based on its exceptional performance after hyperparameter tuning. Its robustness in analyzing image features and its alignment with project objectives of accurate classification make it the optimal choice. The CNN's capability to learn complex visual patterns ensures reliable predictions crucial for applications in agricultural analysis and crop management.

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Milestone 5: Project Files Submission and Documentation

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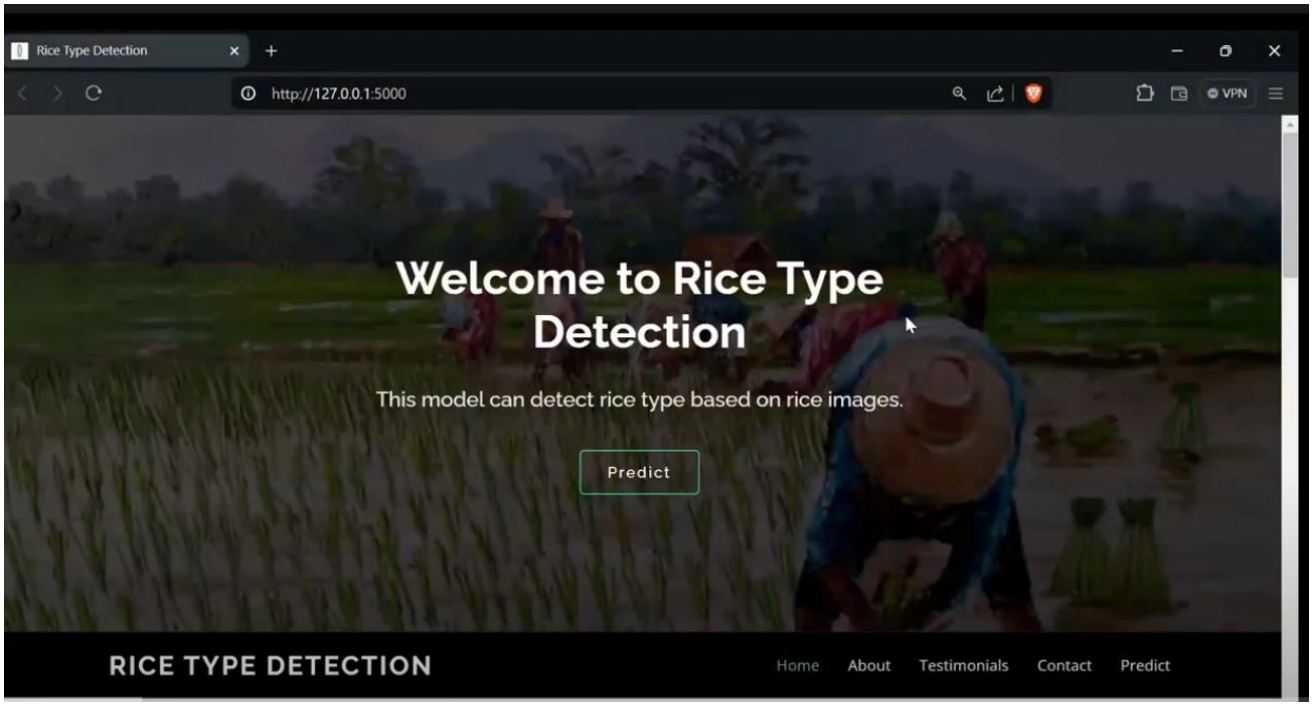
Milestone 6: Project Demonstration

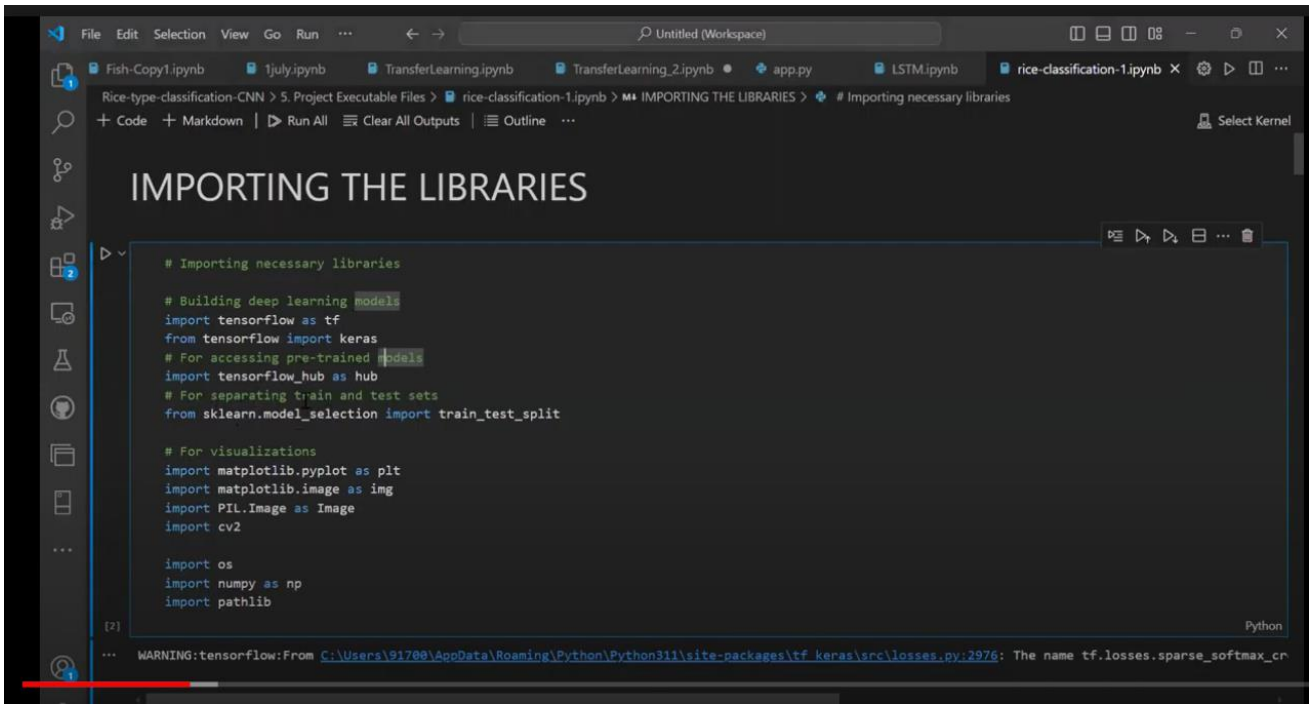
Video Presentation-

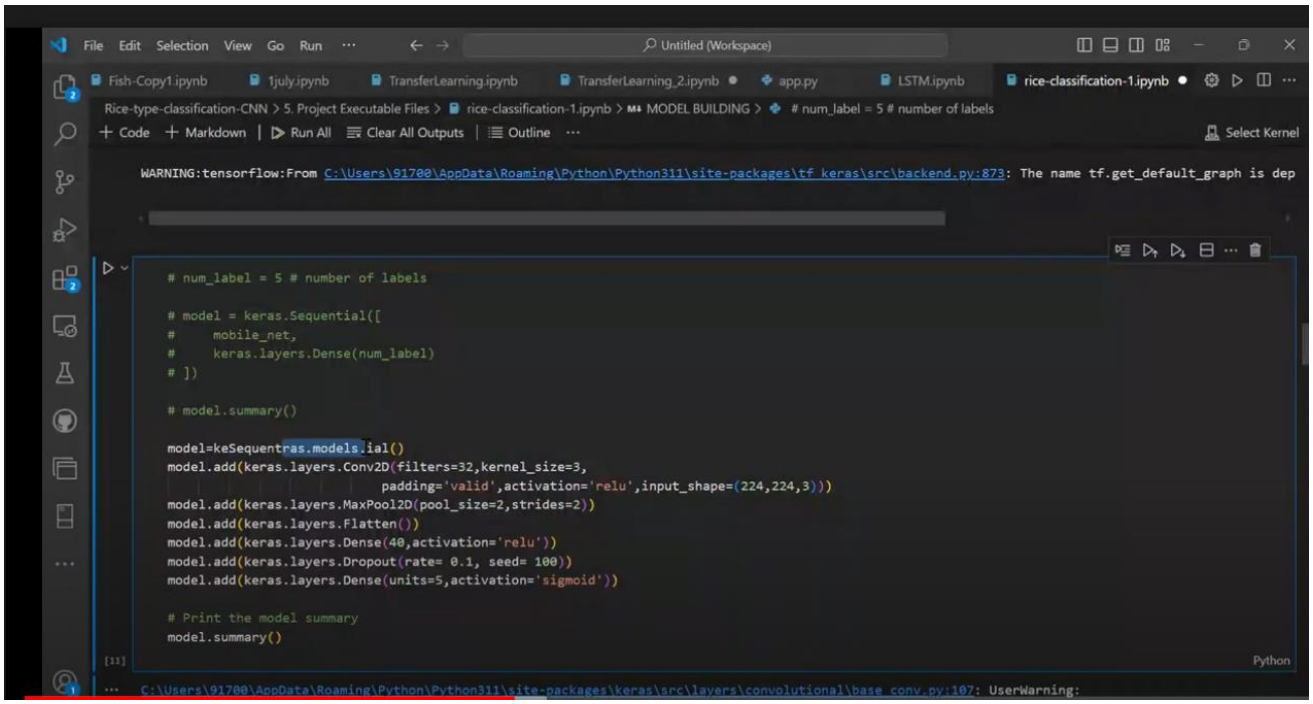
Video link: Click Here

RESULTS: -

OUTPUT SCREENSHOTS: -



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1july.ipynb
TransferLearning.ipynb
TransferLearning_2.ipynb
app.py
LSTM.ipynb
rice-classification-1.ipynb
Rice-type-classification-CNN > 5. Project Executable Files > rice-classification-1.ipynb > MODEL BUILDING > # num_label = 5 # number of labels
Code Markdown Run All Clear All Outputs Outline
Select Kernel
WARNING:tensorflow:From C:\Users\91700\AppData\Roaming\Python\Python311\site-packages\tf_keras\src\backend.py:873: The name tf.get_default_graph is dep
num_label = 5 # number of labels
model = keras.Sequential([
mobile_net,
keras.layers.Dense(num_label)
#])
# model.summary()
model=keSequentras.models.ial()
model.add(keras.layers.Conv2D(filters=32,kernel_size=3,
padding='valid',activation='relu',input_shape=(224,224,3)))
model.add(keras.layers.MaxPool2D(pool_size=2,strides=2))
model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(40,activation='relu'))
model.add(keras.layers.Dropout(rate= 0.1, seed= 100))
model.add(keras.layers.Dense(units=5,activation='sigmoid'))
# Print the model summary
model.summary()
[11]
Python
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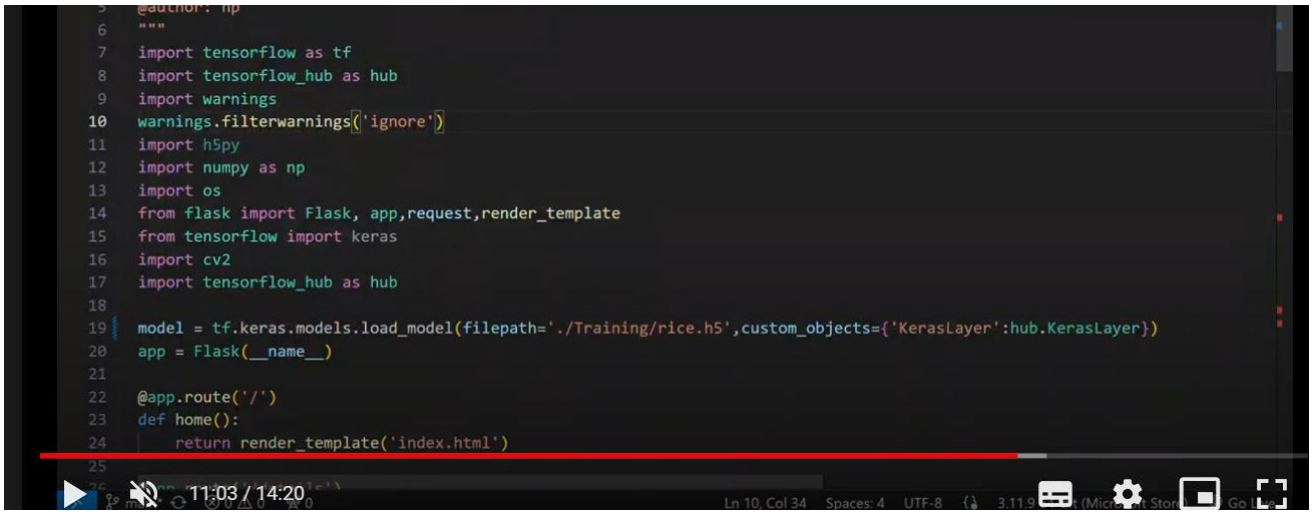
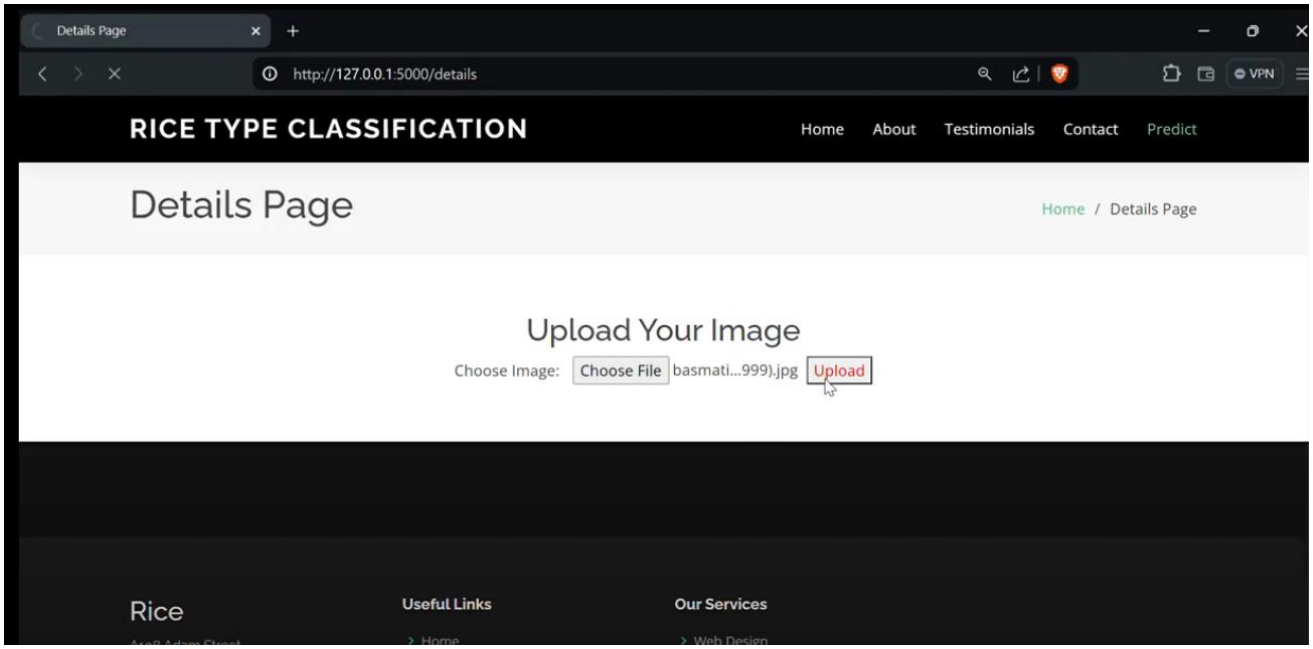

"""
import tensorflow as tf
import tensorflow_hub as hub
import warnings
warnings.filterwarnings('ignore')
import h5py
import numpy as np
import os
from flask import Flask, app,request,render_template
from tensorflow import keras
import cv2
import tensorflow_hub as hub
model = tf.keras.models.load_model(filepath='./Training/rice.h5',custom_objects={'KerasLayer':hub.KerasLayer})
app = Flask(__name__)
@app.route('/')
def home():
return render_template('index.html')
11:03 / 14:20
Ln 10, Col 34 Spaces: 4 UTF-8


Details Page
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VPN
RICE TYPE CLASSIFICATION
Home
About
Testimonials
Contact
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Upload Your Image
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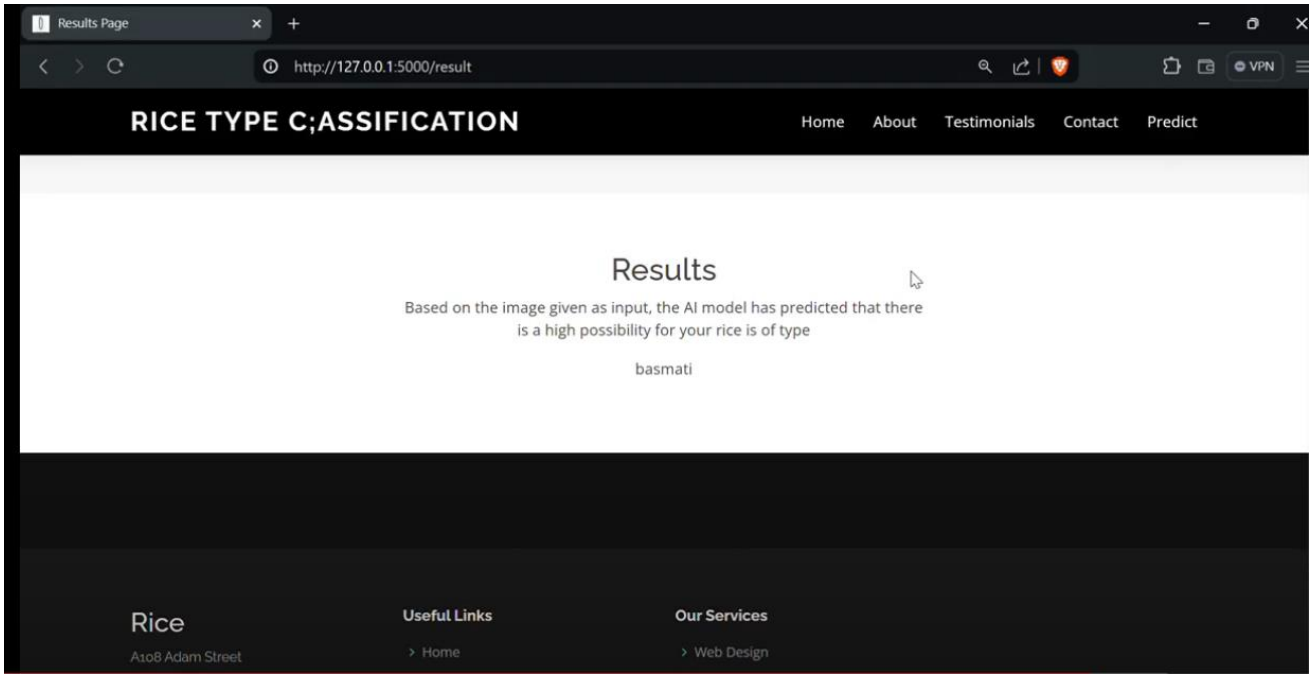
Our Services


Results Page
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VPN
RICE TYPE C;ASSIFICATION
Home
About
Testimonials
Contact
Predict
Results
Based on the image given as input, the AI model has predicted that there is a high possibility for your rice is of type
basmati
Rice
A108 Adam Street
Useful Links
Home
Our Services
Web Design

ADVANTAGES: -

- **High Accuracy and Efficiency**:

  CNNs can achieve high classification accuracy due to their ability to automatically learn and extract relevant features from images, reducing the reliance on manual feature engineering.

- **Scalability and Automation**:

  Once trained, CNN models can quickly and automatically classify large volumes of rice samples, significantly speeding up processes in agricultural industries and reducing human labor.

- **Consistency and Reliability:**

  Automated classification using CNNs ensures consistent and objective results, minimizing human error and variability that can occur with manual inspection and classification.

DISADVANTAGES: -

- **Requirement for Large Datasets:**

  Training CNNs effectively requires large amounts of labeled data, which can be time-consuming and expensive to collect and annotate, especially for less common rice types.

- **Computationally Intensive:**

  CNN training and inference can be computationally intensive, requiring significant hardware resources such as high-performance GPUs, which might not be accessible for all users or organizations.

- **Potential for Overfitting:**

  Without proper regularization techniques and sufficient diverse data, CNNs can overfit to the training dataset, leading to poor generalization and reduced performance on unseen data.

CONCLUSION: -

In conclusion, the development and implementation of this CNN-based rice type classification model represent a significant advancement in the rice industry. By addressing the shortcomings of traditional classification methods, this model promises to enhance accuracy, efficiency, and consistency in identifying different rice varieties. The benefits extend across the supply chain, from farmers to consumers, ensuring better product labeling, improved quality control, and higher customer satisfaction. Ultimately, this project aims to set a new standard in rice classification, driving the industry towards greater precision and reliability.

FUTURE SCOPE: -

The future scope of rice type classification using CNNs is promising, with potential advancements poised to enhance accuracy, efficiency, and applicability. With the integration of more extensive and diverse datasets, models can be trained to recognize even subtle variations among a wider range of rice types, including hybrids and regional varieties. The incorporation of advanced techniques such as transfer learning and federated learning can further improve model performance and adaptability to different environments. Additionally, the development of lightweight, mobile-friendly models can enable on-site classification using smartphones, benefiting farmers and quality control inspectors in remote areas. The system could also expand to encompass other grain types, contributing to a comprehensive agricultural management tool that leverages AI for improved crop monitoring, inventory management, and supply chain optimization.

SOURCE CODE FILES LINK(IN GITHUB): -

Click Here

GITHUB LINK:

Click Here

PROJECT DEMO LINK(RUN IN GOOGLE BROWSER): -

Click Here