"Enhancing Rice Quality Assessment through Integrated Neural Networks: A Synergistic Approach with CAEs and CNN"

by

A. Megharshini
Roll No. 204G1A0557

S. Anees Fathima
Roll No. 204G1A0512

V. Girivardhan
Roll No. 204G1A0532

M. Anitha
Roll No. 214G5A0503

Under the guidance of

Mr. P. Veera Prakash M.Tech, (Ph.D)
Assistant Professor

SRIT
Empowering Knowledge

Department of Computer Science and Engineering
Srinivasa Ramanujan Institute of Technology
(Autonomous)

2023 - 2024

Contents

Abstract

In the realm of food crops, rice stands as a pivotal staple, and ensuring its quality holds utmost importance for human health. The effective and precise evaluation of rice quality plays a critical role in maintaining consistent product standards within the rice industry. While the need for on-going assessment persists, traditional methods of quality detection lack the required precision and efficiency. This deficiency underscores the necessity of harnessing the power of adept machine learning techniques.

In this context, the application of neural networks such as CNN (Convolutional Neural Networks) and MobileNet emerges as a promising avenue to enhance accuracy and automation in classifying rice grain quality. By capitalizing on CNN's prowess in image classification, coupled with the feature learning capabilities of CAEs (Convolutional Autoencoders), we endeavour to address the intricate task of identifying nuanced variations indicative of rice quality. Through the harmonious integration of these methodologies, we aim to establish a robust framework for determining rice quality that not only surpasses individual techniques but also yields optimized and unparalleled outcomes.

Keywords: Rice quality, Neural networks, CNN (Convolutional Neural Networks), MobileNet, Convolutional Autoencoders (CAEs), Accuracy, Automation, Classifying, Robust framework.

Introduction

- In the landscape of food production, the significance of rice as a primary staple necessitates a keen focus on maintaining and enhancing its quality standards. The traditional methods employed for evaluating rice quality often fall short in terms of precision and efficiency, prompting the exploration of more advanced and nuanced approaches. In response to this, our project introduces a novel methodology that harnesses the capabilities of Convolutional Autoencoders (CAEs) and Convolutional Neural Networks (CNN) for the detection and classification of rice quality.

- The pivotal role of CNN lies in its adeptness at object identification, specifically tailored to discern and classify various characteristics associated with rice grains. Simultaneously, the integration of Convolutional Autoencoders contributes to the project's depth by facilitating the extraction of intricate features and patterns relevant to rice quality. This combination of CNN and CAEs creates a robust and comprehensive framework for the precise identification of subtle variations in rice quality.

Introduction

- Our project seeks not only to address the shortcomings of conventional methods but also to set a new standard for accuracy and efficiency in rice quality assessment. By capitalizing on the synergies between CAEs and CNN, MobileNet model we aim to surpass the limitations of individual techniques, offering a sophisticated and automated solution for the rice industry. This endeavor aligns with our broader goal of ensuring the consistency of high-quality rice products, thereby contributing to improved standards in the food sector and, ultimately, to the well-being of consumers.

Literature survey

s.no	Publisher/Journal	Title	Authors Name	Year of Publication	Summary of the paper
[1]	International Journal of Scientific and Research Publications.	ANALYSIS OF FEATURE EXTRACTION AND CLASSIFICTAION OF RICE KERNELS FOR MYANMAR RICE USING IMAGE PROCESSING TECHNIQUES.	1. Thae Nu Wah 2. Pann Ei San 3. Thander Hlaing	2018	In this paper, an **image processing algorithm is proposed for rice grading and it performance is tested** of Paw-San rice. KNN classifier is used for classification. Global Thresholding method is used in this work for image segmentation .From this we get accuracy in their range of 83-100%.
[2]	IEEE International Conference on Artificial Intelligence and Computer Applications	CLASSIFICATION MODEL OF WHEAT GRAIN BASED ON AUTOENCODER	S. Wentao	2020	In this study, **Deep learning has been used in speech recognition, image search, image recognition. Deep learning(DL) model such as autoencoders, uses this model to classify and identify diseased wheat images in the wheat particle database.**

Additional Summary

Additional Summary

Literature survey

s.no	Publisher/Journal	Title	Authors Name	Year of Publication	Summary of the paper
[3]	3C TIC. Cuadernos de desarrollo aplicados a las TIC	RICE QUALITY ANALYSIS USING IMAGE PROCESSING AND MACHINE LEARNING	1.R. C. Dharmik 2.Sushilkumar Chavhan 3.Shashank Gotarkar 4.Arjun Pasoriya	2022	In this work, machine learning and image processing techniques **to recognise and measure rice quality**. **The method was used to detect the edges** and Greedy filter method to extract features. **The model's accuracy is 92.36%.** The final two stages are to calculate the grain size and classify them.
[4]	International Conference on Advanced Computing and Applications(ACOMP) IEEE	DEEP LEARNING FOR RICE QUALITY CLASSIFICATION	1.Nguyen Hong Son . 2.Nguyen Thai-Nghe.	2019	In this work, **image processing algorithms and machine learning methods were to recognize 2 categories of rice**(whole rice and broken rice) using CNN with 96.16% accuracy and KNN with 85.06% accuracy.

Additional Summary

Additional Summary

Literature survey

s.no	Publisher/Journal	Title	Authors Name	Year of Publication	Summary of the paper
[5]	ResearchGate	AN AUTOMATED INSPECTION SYSTEM FOR RICE SEED QUALITY BASED ON DEEP LEARNING	1. Gao, Y. 2. Wang, W. 3. Zhang, W. 4. Gao, X.	2021	This presents an automated inspection system for rice seed quality based on deep learning techniques. The proposed system uses deep learning algorithms to automatically classify rice seeds based on their appearance features. The authors collected a dataset of 18,000 rice seed images from different varieties and manually labelled them with their corresponding quality levels.
[6]	IEEE	IDENTIFICATION AND CLASSIFICATION OF RICE SEEDS USING DEEP COVOLUTIONAL NEURALNETWORKS	1.Wang 2.R., Jiang 3.Y.Cao, F.	2020	In this , study aims to overcome **the limitations of traditional rice seed identification methods,** which rely on manual inspection and are prone to errors and subjectivity.

Additional Summary

Additional Summary

Literature survey

s.no	Publisher/Journal	Title	Authors Name	Year of Publication	Summary of the paper
[7]	IEEE	MACHINE VISION BASED QUALITY ANALYSIS OF RICE GRAINS	1. T. GAYATHRI DEVI 2. DR. P. NEELAMEGAM 3. S. SUDHA	2017	In this study, this algorithm used simple morphological **images processing methods and it can be used to perform various images based analysis**. **Majority of the operations used in this algorithm are based on Matlab commands. This algorithm is suitable to grade large number of grains** efficiently and results were compared with manual work which provided the percentage of accuracy greater or much equally to the manual work.
[8]	Easychair publications	RICE QUALITY ANALYSIS USING MACHINE LEARNING	1. K. Jaisharma 2. P. Annadasu	2020	In this paper, it is used to develop an effective model which helps in grading rice grains without labor intensifying work. **Segmentation is acquired by many techniques like region based segmentation, segmentation by clustering.** From the results obtained we can conclude that this system is efficient and cost effective.

Additional Summary

Additional Summary

Literature survey

s.no	Publisher/Journal	Title	Authors Name	Year of Publication	Summary of the paper
[9]	IEEE	RICE QUALITY ANALYSIS USING DEEP LEARNING TECHNIQUES : A REVIEW	1. Latha, M. N 2. Nandhini, R	2018	In this, discusses the importance of rice quality analysis in the food industry and the limitations of traditional methods . **It then provides an overview of deep learning techniques, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs),** and their applications in rice quality analysis.
[10]	KeAi	COMPARISON OF CNN-BASED DEEP LEARNING ARCHITECTURES FOR RICE DISEASES CLASSIFICATION	1. Md Taimur Ahad 2. Yan Li 3. Bo Song 4. Touhid Bhuiyan	2023	This study focuses on the performance comparison of **convolutional neural network (CNN) architectures in detecting and localizing rice diseases. The researchers conducted a rice disease classification comparison of six CNN-based deep-learning architectures** using a database of nine of the most epidemic rice diseases in Bangladesh. They applied a transfer learning approach to DenseNet121, MobileNetV2, Resnet152V.

Additional Summary

Additional Summary

Literature survey

s.no	Publisher/Journal	Title	Authors Name	Year of Publication	Summary of the paper
[11]	I.J. Intelligent Systems and Applications	Rice Leaf Disease Recognition using Local Threshold Based Segmentation and Deep CNN	1. Anam Islam 2. Redoun Islam 3. S. M. Rafizul Haque 4. S.M. Mohidul Islam 5. Mohammad Ashik Iqbal Khan	2021	The method uses local threshold-based **segmentation and the Convolutional Neural Network (CNN) to segment disease-affected regions of rice leaves**. The proposed method has been applied on three different datasets, including the one created by the authors, which consists of rice leaf images. They used various image augmentation techniques on these collected images and managed to get test **accuracy of 91.23%.**
[12]	ResearchGate	Convolutional neural network with transfer learning for rice type classification	1. Patel 2. Vaibhav	2019	Two methods are proposed: **one uses a deep convolutional neural network (CNN) trained on segmented rice images, and the other uses a combination of a pretrained VGG16 network and the proposed method**, using transfer learning for improved accuracy. our proposed network with pretrained weights of **VGG16 perform better than the other approaches.**

Additional Summary

Additional Summary

Literature survey

s.no	Publisher/Journal	Title	Authors Name	Year of Publication	Summary of the paper
[13]	ScienceDirect	CNN and Convolutional Autoencoder (CAE) based real-time sensor fault detection, localization, and correction	1. Jana, Debasish 2.Patil, Jayant 3. Herkal, Sudheendra 4. Nagarajaiah, Satish	2021	In order to detect, classify, and reconstruct faults in sensor data, the study introduces a novel deep learning framework for linear systems with time-invariant parameters. **The Convolutional Neural Network (CNN) in the framework is used to identify the type and existence of faults. For reconstruction, a set of separately trained Convolutional Autoencoder (CAE) networks is used for each type of fault.**
[14]	KeAi	Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network.	1. Bedi 2. Punam 3. Pushkar Gole	2021	**CNNs and CAEs are two Deep Learning methods. CNNs are utilized for input image classification into their appropriate classes, whereas CAEs are employed for effectively reducing an image's dimensionality. As compared to other Deep Learning techniques, CNN deals with images most efficiently.**

Additional Summary

Additional Summary

Existing System

EXISTING SYSTEM

In existing system uses a deep CNN to analyse rice quality based on its appearance, including colour, shape, and texture. The system was trained on a large dataset of rice images and achieved high accuracy in identifying rice quality. In existing system demonstrate the potential of deep learning CNNs for rice quality analysis, and they could have significant applications in the food industry for quality control and assurance.

Disadvantages:

- Time consuming.
- Dependence on technology.
- Lack of flexibility

Proposed System

- In this project, we propose a novel approach that combines Convolutional Neural Networks (CNN) and Autoencoders to address the task of rice quality detection.

- The envisioned system relies on a fusion of the CNN Model, MobileNet and Convolutional Autoencoder (CAE). The implementation of the Autoencoder architecture is facilitated through the utilization of established neural network frameworks such as TensorFlow or PyTorch. These frameworks provide the essential tools and infrastructure to construct, train, and deploy the Convolutional Autoencoder, enabling efficient feature extraction and representation learning. This combined approach aims to capitalize on the strengths of both CNN and CAE, fostering accurate classification and intricate feature understanding, ultimately enhancing the system's capability for robust rice quality assessment.

Proposed System

Advantages of Proposed System:

1. Performs detection of real-time images uploaded by users in our application based on trained data.
2. Classification of Rice grain quality (three classes high, low, and medium).
3. Image pre-processing is performed in a generalized manner.
4. The difference between the manual division of classes of rice grain images and the results given by the Model is so low which indicates the model performance is accurate.

Planning Objectives

Objectives of Planning:

- **Scope:** This project is applicable for the Quality detection of Arborio, Basmati, Ipsala, and Jasmine Rice images and analyzing their Features. It is used by agricultural practitioners or farmers or anyone user can access our application.

- **Performance:** To acquire an accuracy greater than 96% by using Convolutional Neural Networks(CNN), by increasing the training data of model and by giving more images until the line of overfit.

- **Cost :**
  - Mode = Organic
  - Effort = 16 Person-Month Development
  - Time = 4 Months
  - Average Staff Required = 4 Persons

Planning Objectives

- **Time:** On a whole this project takes about 4 months (16 person-months) of time period for development and testing.

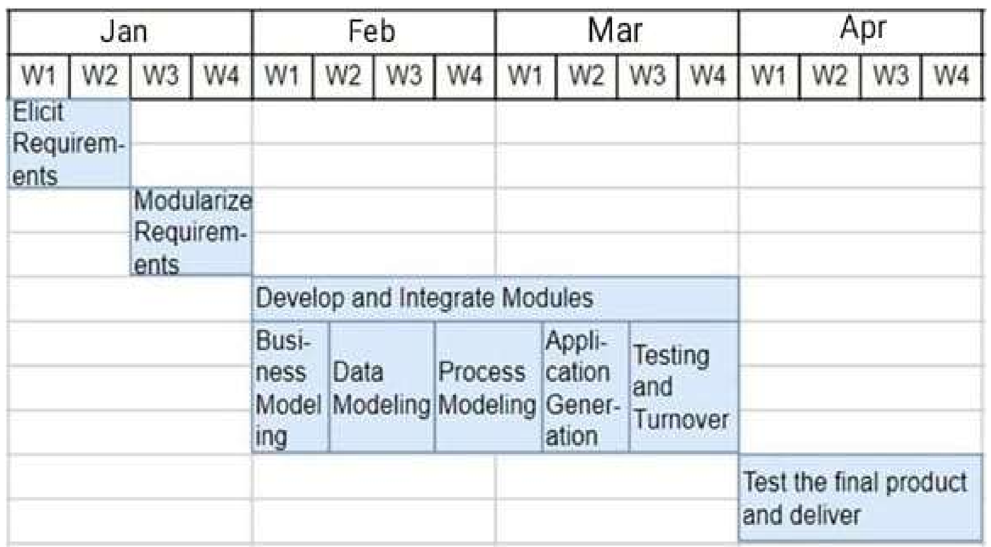


Fig 1: Modeling steps in each module

Planning Modules

Modules:

- Data Pre-processing
- Building CNN model
- Classification

Planning Functional and Non – Functional Requirements

Functional Requirements:

- Scan an image to give input to the system.
- Process and take input of the image, classify the Quality type.
- Display the type quality of the Rice image.
- Show the percentage accuracy of classified images.

Non-Functional Requirements:

- **Usability:** The application is easy to use with very less complexity of interface.
- **Availability:** Available within the device.
- **Scalability:** This model can be trained for other Rice images.
- **Performance:** Performs well with no sort of failures.

Planning System Requirements

Software Requirements:

- Google Colaboratory
- Visual Studio App

Hardware Requirements:

- **Processor:** Minimum Intel Core I5
- **RAM:** Minimum 8 GB
- **Hard Disk:** Minimum 250 GB
- **Operating System:** Windows10

Planning Testcase

Input:

Fig 2: Input Image

Output:

```
Result:  Quality is: High
1/1 [==============================] - 0s 23ms/step
Score: 0.9999977350234985
```

Fig 3: output Image

Design

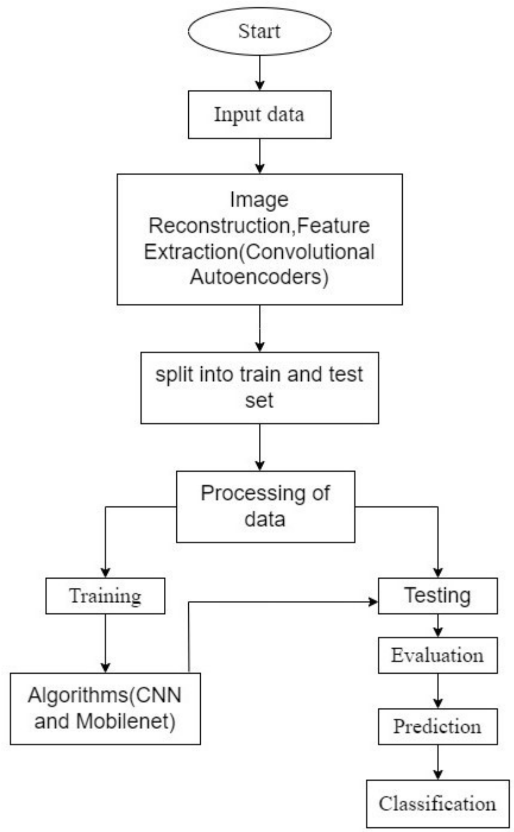


Fig 4:Architecture of proposed method

Design

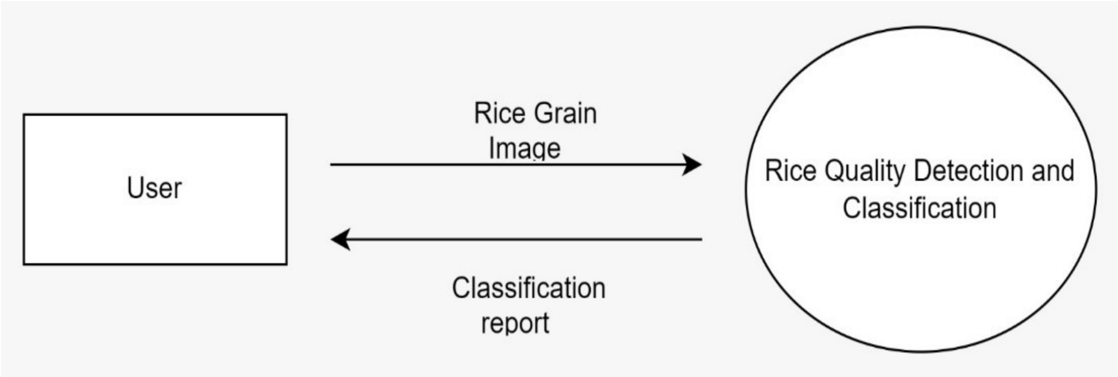


Fig 5: DFD - 0

Design

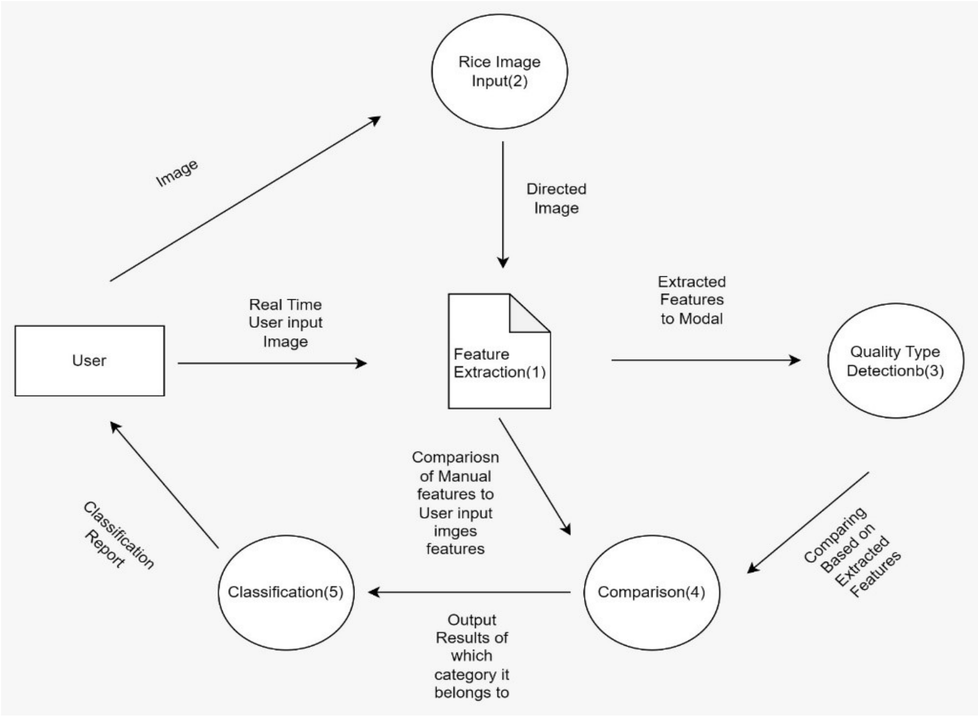


Fig 6: DFD - 1

Design

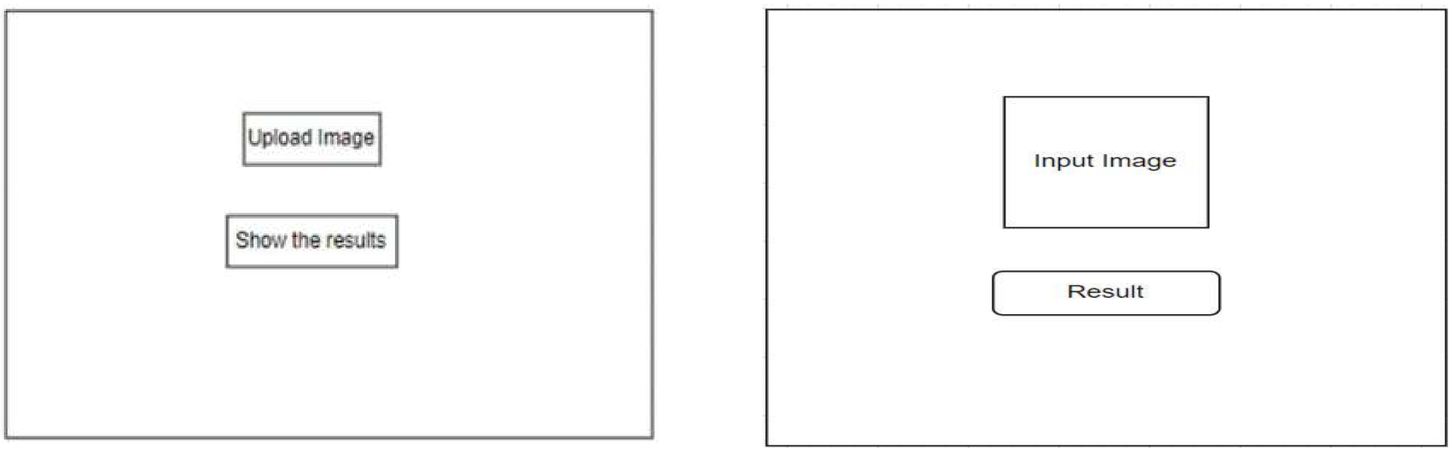


Fig 7: User interface diagrams

Implementation

Image Loading and Preprocessing:

The code imports necessary libraries such as PIL (Python Imaging Library) for image manipulation then images are loaded using the Image.open() function from PIL. After that image dimensions are retrieved to understand the size and channels of the images. A list of image filenames is generated from the folder path. Images are loaded, and basic information about their dimensions is printed. Images are displayed using Matplotlib.

Image Down sampling:

These images are given to CAE for image reconstruction. It consists of convolutional layers for encoding the input image into a latent representation and then decoding it back to the original image shape. The resolution of the reconstructed images is 256x256.The images were used for training and testing a Convolutional Neural Network model to assess the quality of rice.

Implementation

CAE Model:

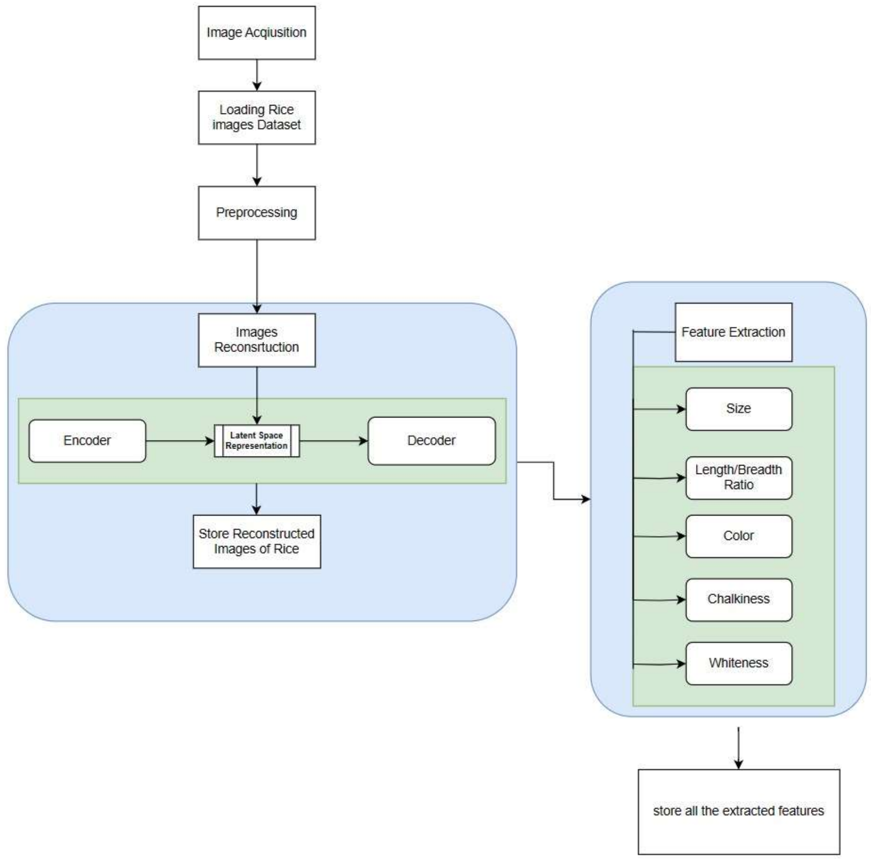


Fig 8: CAE model

Implementation

```python
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.preprocessing import image
import matplotlib.pyplot as plt
import os

# Define the path to the folder containing your images
folder_path = '/content/Rice_Image_Dataset/Basmati'

# Get a list of all image filenames in the folder
image_filenames = [filename for filename in os.listdir(folder_path) if filename.endswith('.jpg')]

# Define a directory to save the reconstructed images
output_dir = '/content/reconstructed_images1/'

# Create the output directory if it doesn't exist
os.makedirs(output_dir, exist_ok=True)  # This line creates the directory

# Define the CAE model
input_img = keras.Input(shape=(128, 128, 3))
x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(input_img)
x = layers.MaxPooling2D((2, 2), padding='same')(x)
x = layers.Conv2D(64, (3, 3), activation='relu', padding='same')(x)
x = layers.MaxPooling2D((2, 2), padding='same')(x)
encoded = layers.Conv2D(128, (3, 3), activation='relu', padding='same')(x)

x = layers.Conv2D(128, (3, 3), activation='relu', padding='same')(encoded)
x = layers.UpSampling2D((2, 2))(x)
x = layers.Conv2D(64, (3, 3), activation='relu', padding='same')(x)
x = layers.UpSampling2D((2, 2))(x)
decoded = layers.Conv2D(3, (3, 3), activation='sigmoid', padding='same')(x)
autoencoder = keras.Model(input_img, decoded)
autoencoder.compile(optimizer='adam', loss='mse')

# Loop through each image filename
for image_filename in image_filenames:
    # Combine the folder path and filename to get the complete image path
    image_path = os.path.join(folder_path, image_filename)
```

```python
# Load and preprocess the image
img = image.load_img(image_path, target_size=(128, 128))
img = image.img_to_array(img)
img = img / 255.0  # Normalize the image data

# Train the CAE on the input image
autoencoder.fit(np.expand_dims(img, axis=0), np.expand_dims(img, axis=0), epochs=50, batch_size=1)

# Reconstruct the image using the trained CAE
reconstructed_img = autoencoder.predict(np.expand_dims(img, axis=0))[0]

# Save the reconstructed image
reconstructed_filename = os.path.join(output_dir, f'reconstructed_{image_filename}')
plt.imsave(reconstructed_filename, reconstructed_img)
```

Fig 9: CAE code

Implementation

```python
def rcnn(image):
    region_proposals = selective_search(image)
    cnn = load_pretrained_cnn()  # This could be a model like VGG16, AlexNet, etc.
    features = [cnn(extract_region(image, proposal)) for proposal in region_proposals]
    svm_classifiers = load_svm_classifiers()  # Load pre-trained SVM classifiers for each class.
    bbox_regressors = load_bbox_regressors()  # Load pre-trained bounding box regressors.
    detections = []
    for feature in features:
        class_label = classify(svm_classifiers, feature)
        refined_bbox = refine_bbox(bbox_regressors, feature)
        detections.append((class_label, refined_bbox))
    final_detections = non_maximum_suppression(detections)

    return final_detections
```

Fig 10: Defining CNN Model

```python
model = Sequential()

model.add(Conv2D(filters = 32, kernel_size = (5,5),padding = 'Same',
                 activation ='relu', input_shape = (img_height,img_width,3)))
model.add(Conv2D(filters = 32, kernel_size = (5,5),padding = 'Same',
                 activation ='relu'))
model.add(MaxPool2D(pool_size=(2,2)))


model.add(Conv2D(filters = 64, kernel_size = (3,3),padding = 'Same',
                 activation ='relu'))
model.add(Conv2D(filters = 64, kernel_size = (3,3),padding = 'Same',
                 activation ='relu'))
model.add(MaxPool2D(pool_size=(2,2), strides=(2,2)))

model.add(Flatten())
model.add(Dense(256, activation = "relu"))

model.add(Dense(3, activation = "softmax"))

model.summary()
```

Fig 11: CNN Sequential Main Model

Implementation

```
model.compile(optimizer="adam",loss="categorical_crossentropy",metrics=['accuracy',precision,recall])
hist=model.fit(train_generator,epochs=10,validation_data=test_generator)
```

Fig 12: CNN Compilation Model

```
fig, ax = plt.subplots(2,1)
ax[0].plot(hist.history['accuracy'], color='b', label="Training accuracy")
ax[0].plot(hist.history['val_accuracy'], color='r',label="Validation accuracy")
legend = ax[0].legend(loc='best', shadow=True)

ax[1].plot(hist.history['loss'], color='b', label="Training loss")
ax[1].plot(hist.history['val_loss'], color='r', label="validation loss")
legend = ax[1].legend(loc='best', shadow=True)
```

Fig 13: CNN graph between Training and Validation accuracy

Implementation

```
fig, ax = plt.subplots(2,1)
ax[0].plot(hist.history['precision'], color='b', label="Training precision")
ax[0].plot(hist.history['val_precision'], color='r',label="Validation precision")
legend = ax[0].legend(loc='best', shadow=True)

ax[1].plot(hist.history['loss'], color='b', label="Training loss")
ax[1].plot(hist.history['val_loss'], color='r', label="validation loss")
legend = ax[1].legend(loc='best', shadow=True)
```

Fig 14: CNN graph between Training and Validation Precision

```
fig, ax = plt.subplots(2,1)
ax[0].plot(hist.history['recall'], color='b', label="Training recall")
ax[0].plot(hist.history['val_recall'], color='r',label="Validation recall")
legend = ax[0].legend(loc='best', shadow=True)

ax[1].plot(hist.history['loss'], color='b', label="Training loss")
ax[1].plot(hist.history['val_loss'], color='r', label="validation loss")
legend = ax[1].legend(loc='best', shadow=True)
```

Fig 15: CNN graph between Training and Validation recall

Implementation

```
base_model = tf.keras.applications.MobileNet(input_shape=(img_height,img_width, 3), include_top=False,
                          weights='imagenet')
model8 = Sequential()
model8.add(base_model)
model8.add(GlobalAveragePooling2D())
model8.add(Dense(1024, activation='relu'))
model8.add(Dense(512, activation='relu'))
model8.add(Dense(256, activation='relu'))
model8.add(Dense(128, activation='relu'))
model8.add(Dense(64, activation='relu'))
model8.add(BatchNormalization())
model8.add(Dropout(0.2))
model8.add(Dense(3, activation='sigmoid'))
model8.summary()
```

Fig 16: MobileNet Sequential Main Model

Implementation

```
model8.compile(optimizer="adam",loss="categorical_crossentropy",metrics=['accuracy',precision,recall])
hist8=model8.fit(train_generator,epochs=50,validation_data=test_generator)
```

Fig 17: MobileNet Compilation Model

```
fig, ax = plt.subplots(2,1)
ax[0].plot(hist8.history['accuracy'], color='b', label="Training accuracy")
ax[0].plot(hist8.history['val_accuracy'], color='r',label="Validation accuracy")
legend = ax[0].legend(loc='best', shadow=True)

ax[1].plot(hist8.history['loss'], color='b', label="Training loss")
ax[1].plot(hist8.history['val_loss'], color='r', label="validation loss",axes =ax[1])
legend = ax[1].legend(loc='best', shadow=True)
```

Fig 18: MobileNet graph between Training and Validation accuracy

Implementation

```
fig, ax = plt.subplots(2,1)
ax[0].plot(hist8.history['precision'], color='b', label="Training precision")
ax[0].plot(hist8.history['val_precision'], color='r',label="Validation precision")
legend = ax[0].legend(loc='best', shadow=True)

ax[1].plot(hist8.history['loss'], color='b', label="Training loss")
ax[1].plot(hist8.history['val_loss'], color='r', label="validation loss",axes =ax[1])
legend = ax[1].legend(loc='best', shadow=True)
```

Fig 19: MobileNet graph between Training and Validation Precision

```
fig, ax = plt.subplots(2,1)
ax[0].plot(hist8.history['recall'], color='b', label="Training recall")
ax[0].plot(hist8.history['val_recall'], color='r',label="Validation recall")
legend = ax[0].legend(loc='best', shadow=True)

ax[1].plot(hist8.history['loss'], color='b', label="Training loss")
ax[1].plot(hist8.history['val_loss'], color='r', label="validation loss",axes =ax[1])
legend = ax[1].legend(loc='best', shadow=True)
```

Fig 20: MobileNet graph between Training and Validation recall

Results

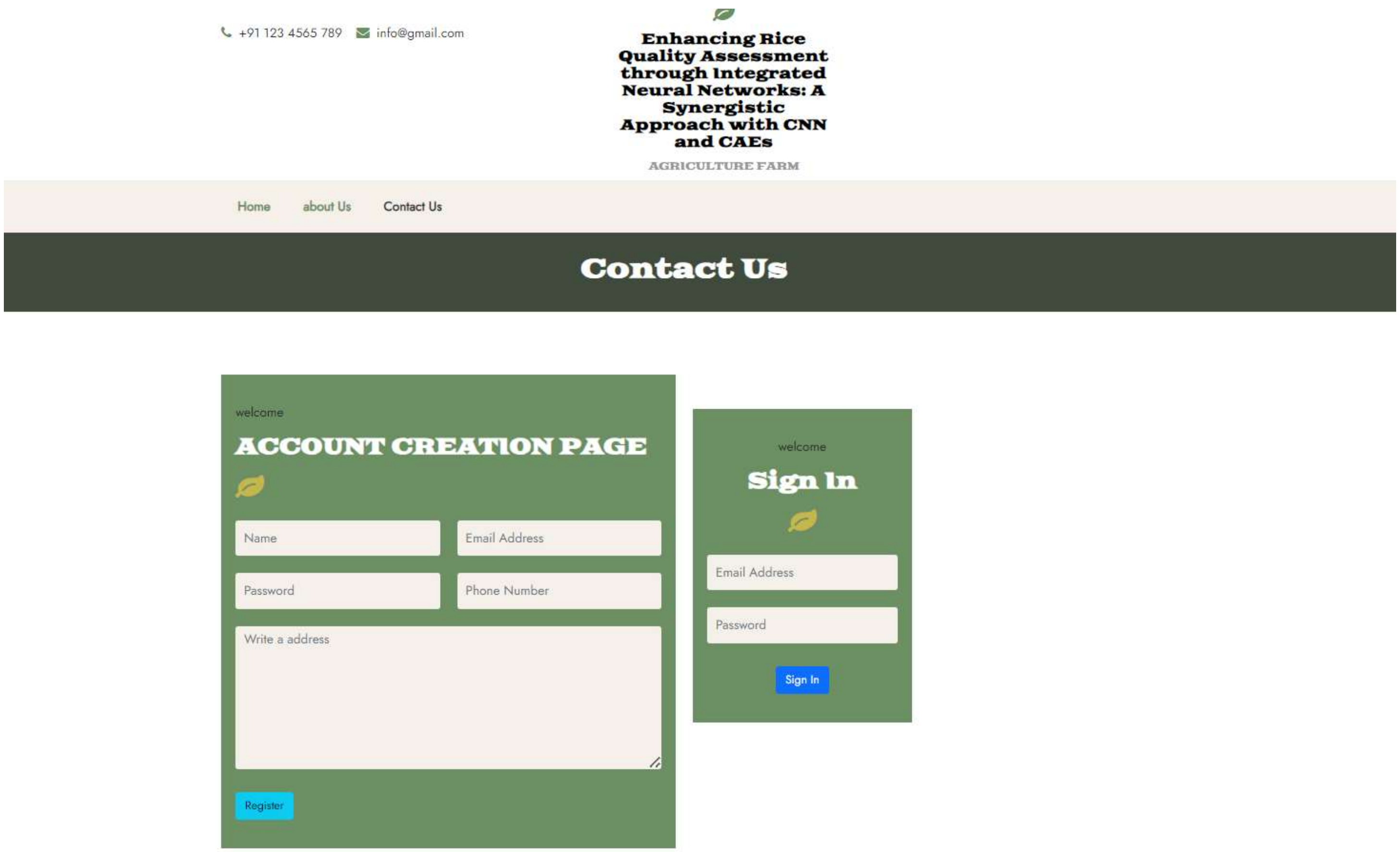


Fig 21: User Interface

Results

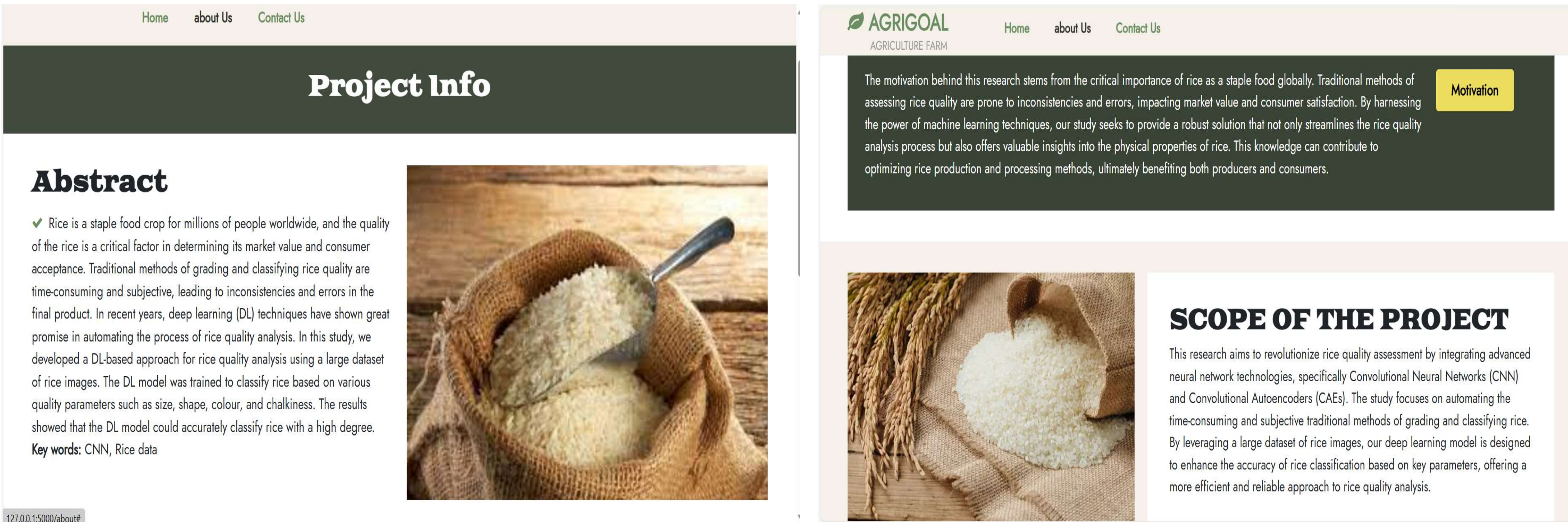


Fig 22: About us page in User Interface

Results

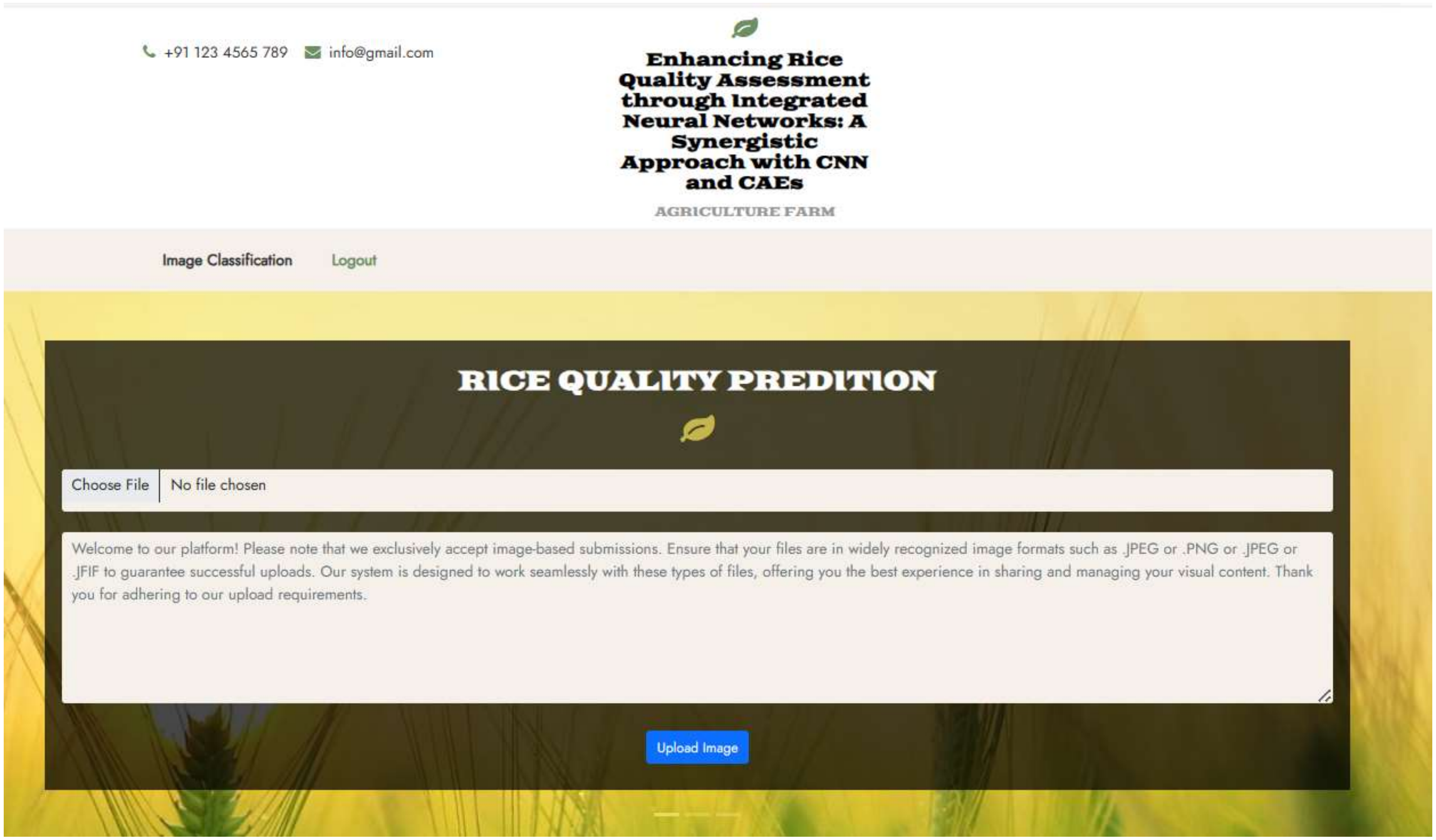


Fig 23: Upload image

Results

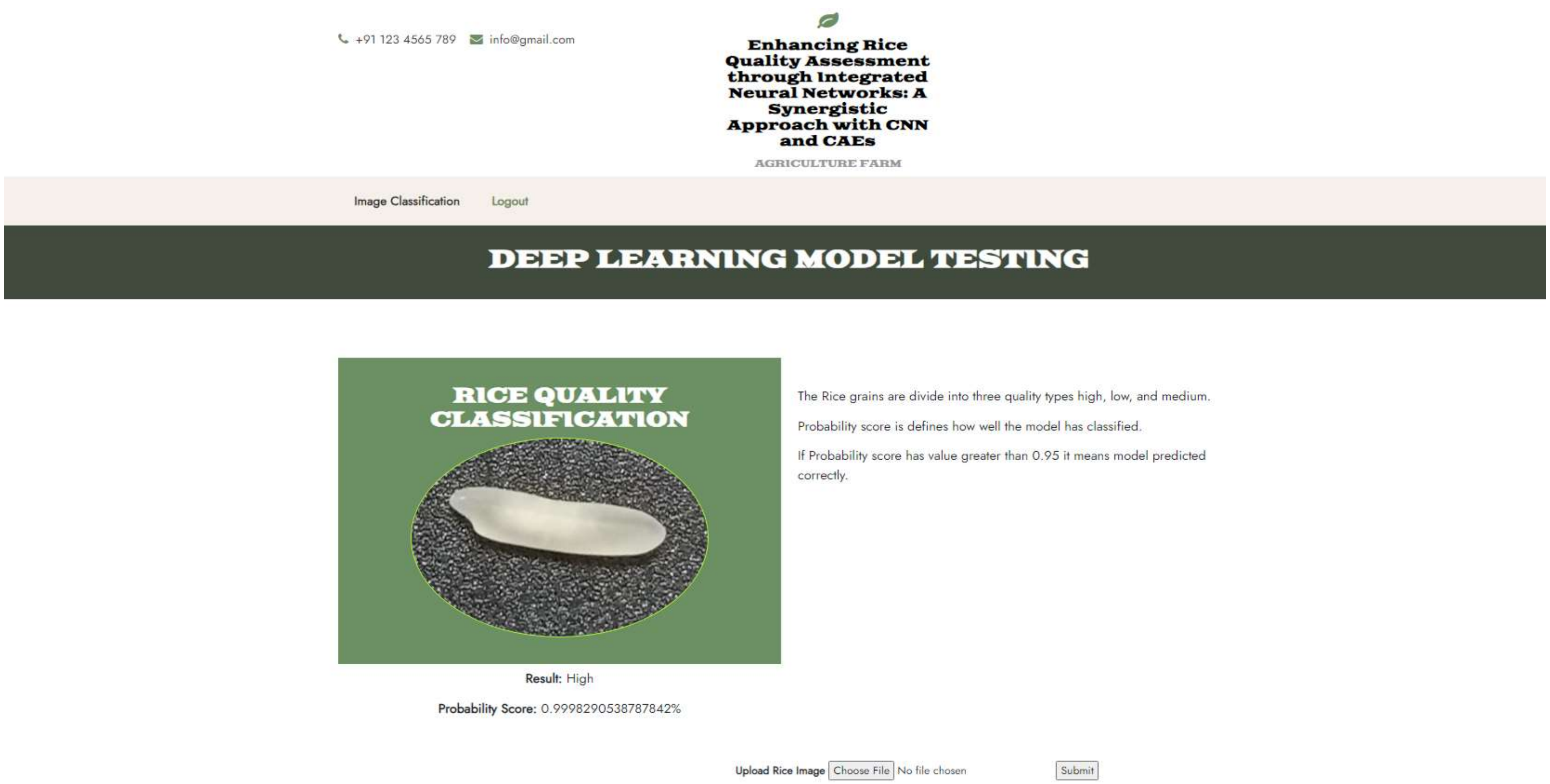


Fig 24: Result

Results

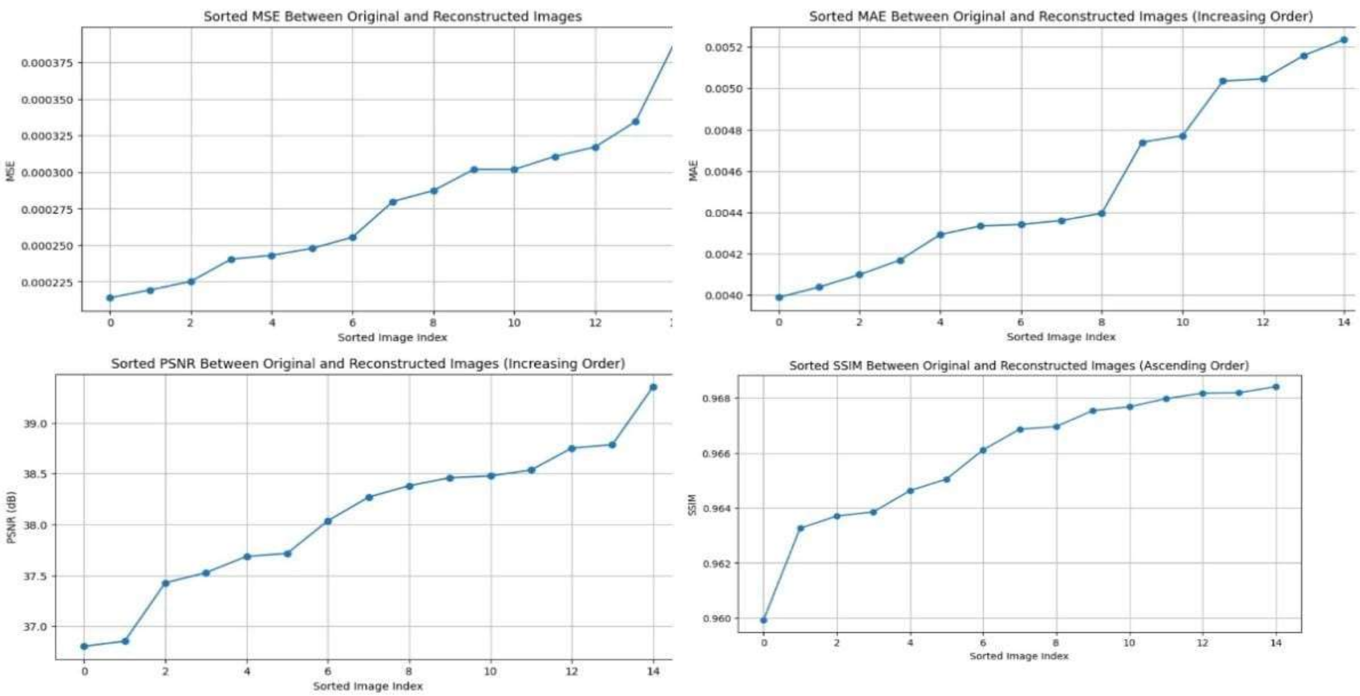


Fig 25: Difference between original and reconstructed images

Results

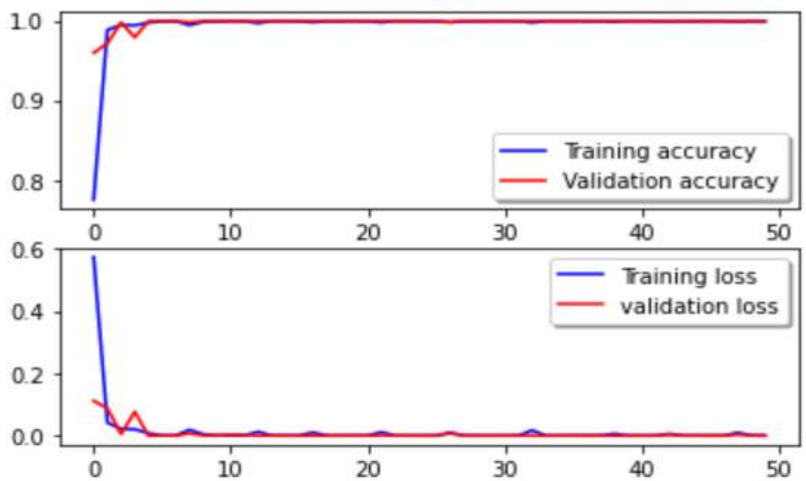


Fig 26: Comparison of CNN accuracy

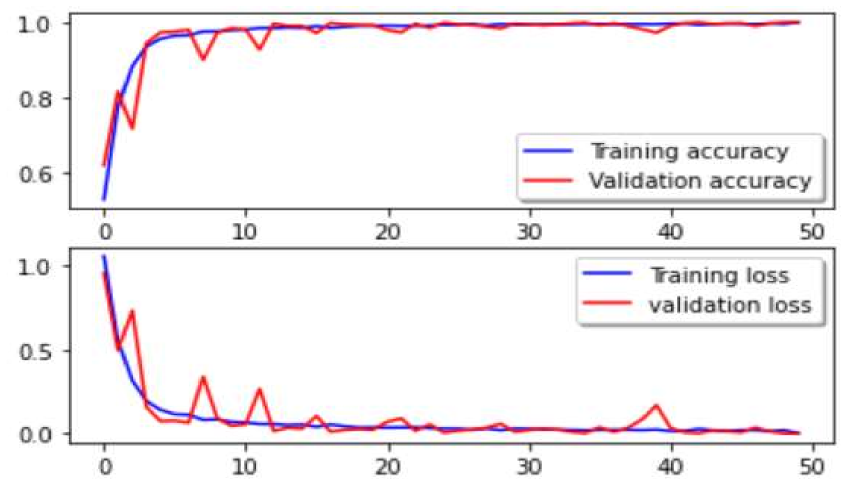


Fig 27:Comparison of MobileNet accuracy

Results

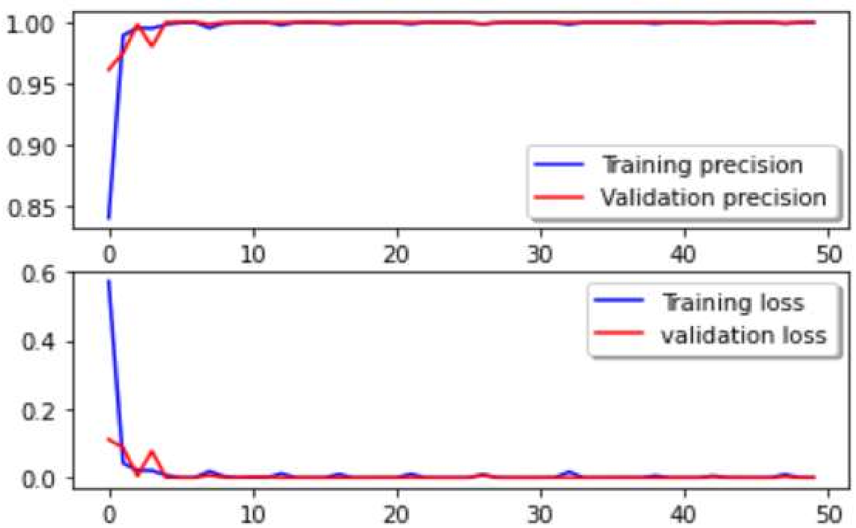


Fig 28: Comparison of CNN precision

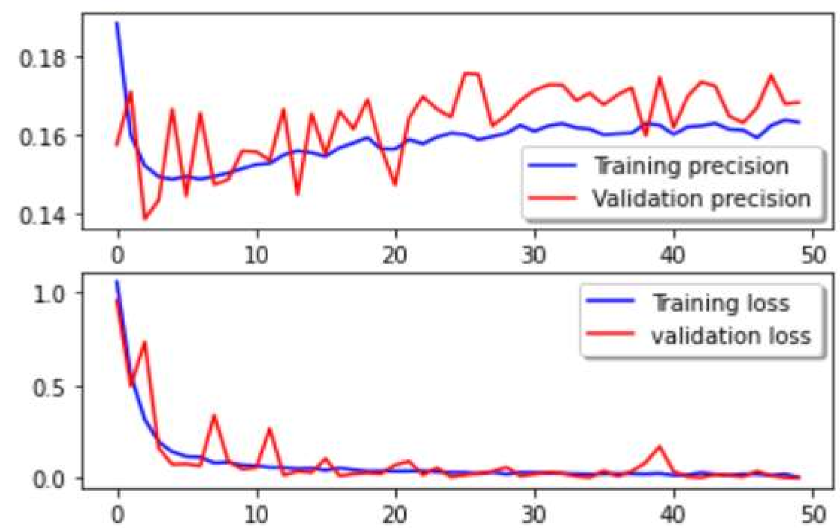


Fig 29: Comparison of MobileNet precision

Results

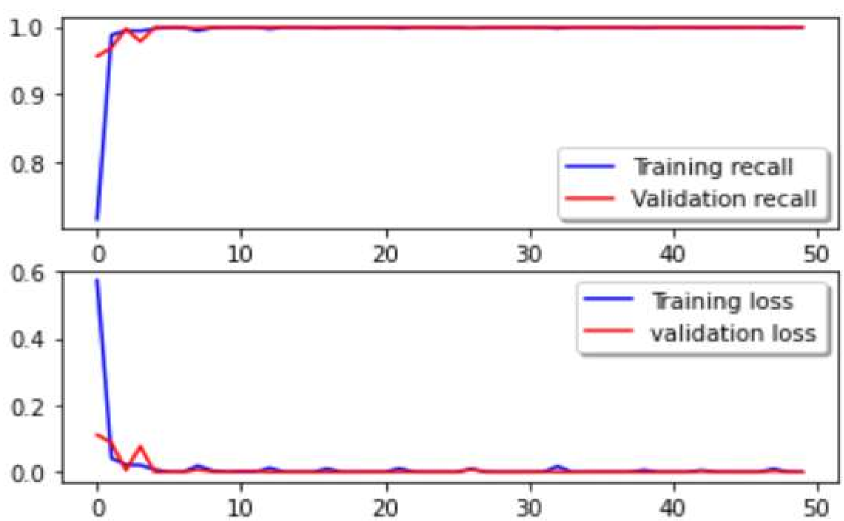


Fig 30: Comparison of CNN recall

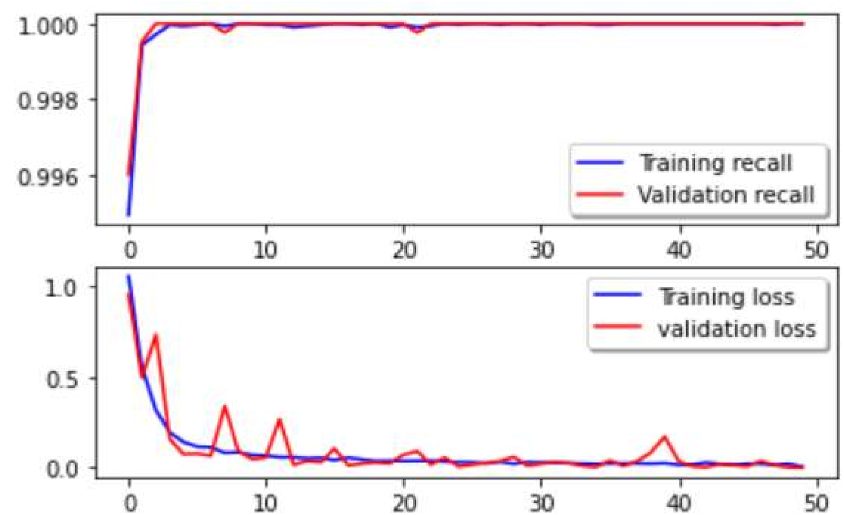


Fig 31: Comparison of MobileNet recall

Results

Accuracy:

The proportion of correctly classified instances among the total predictions is known as accuracy. It is calculated by dividing the number of correct predictions by the total number of predictions and is commonly used as a performance metric in classification models. Higher accuracy values indicate better model performance in terms of correct classifications.

Precision:

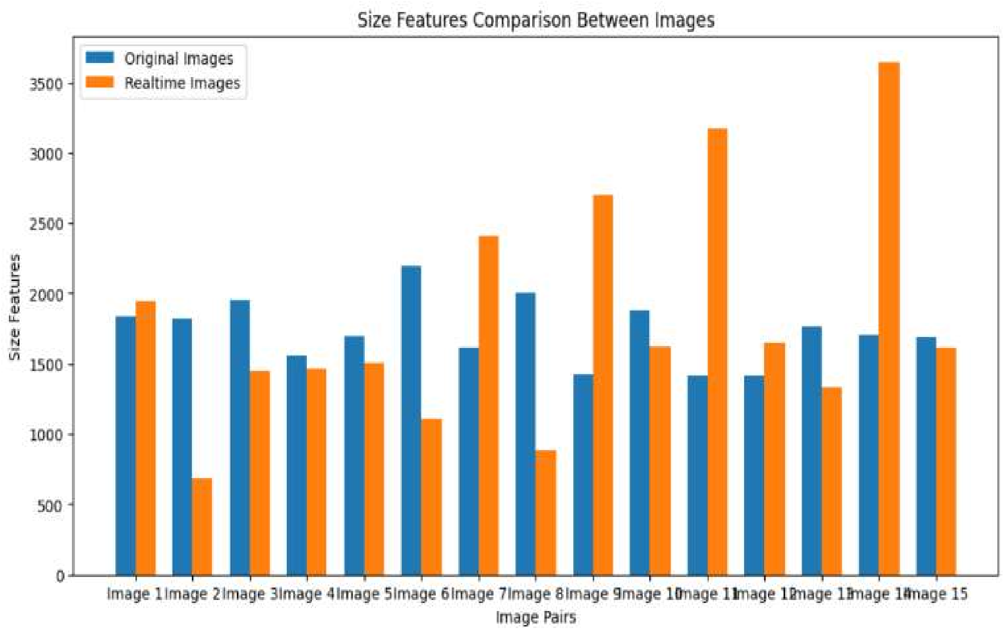
The accuracy of positive predictions is measured by precision, which represents the ratio of true positives to the sum of true positives and false positives. Precision provides insights into the reliability of positive predictions, emphasizing the ability of a model to avoid false positives and make accurate positive classifications.

Results

Recall:

The ability of a model to capture all relevant instances is assessed by recall, which represents the ratio of true positives to the sum of true positives and false negatives. High recall values indicate the model's effectiveness in identifying a significant portion of the actual positive instances, minimizing false negatives.

Results



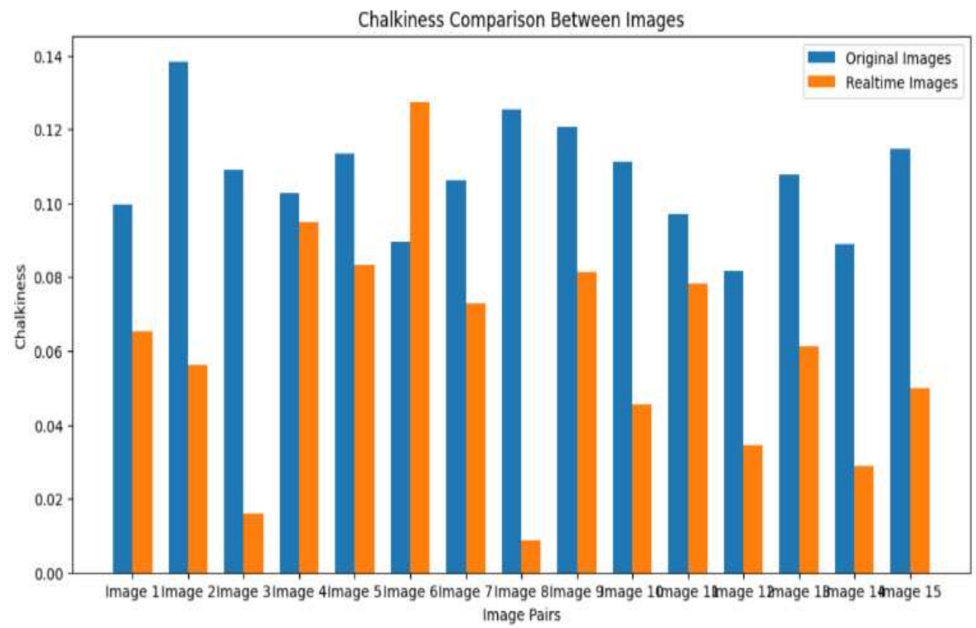
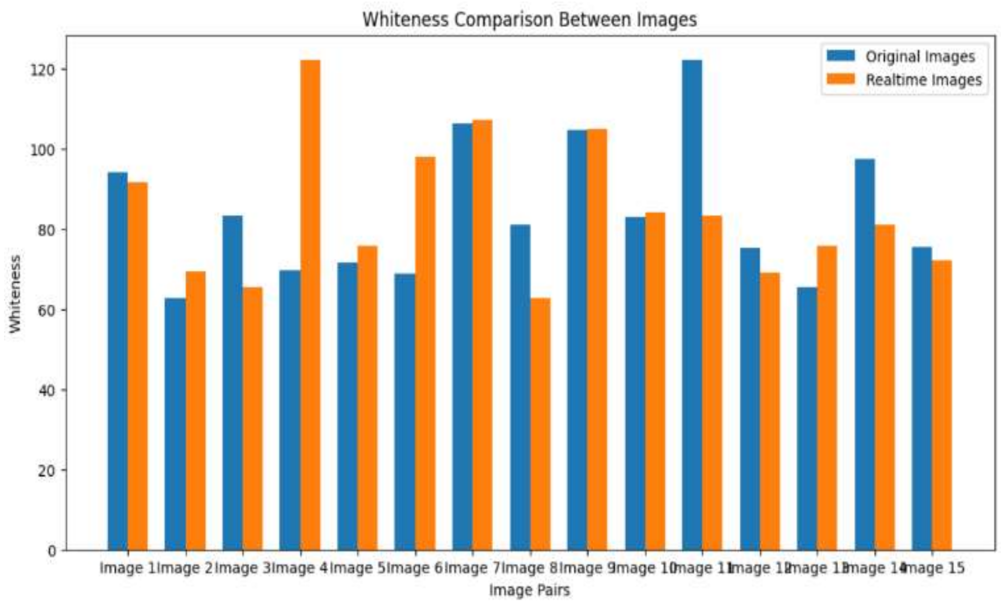


Fig 32: Size and chalkiness Feature comparison between original and real time images

Results



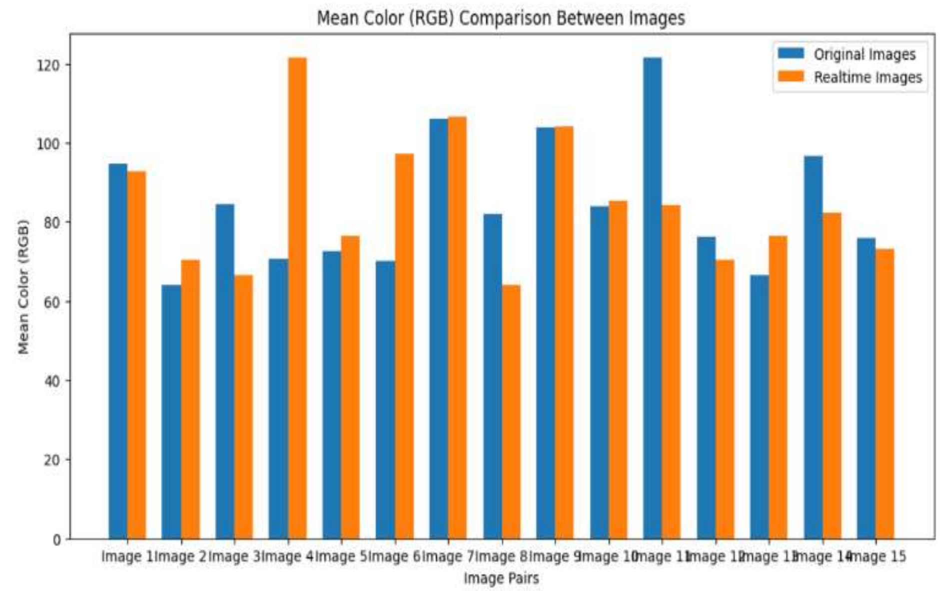


Fig 33: whiteness and color Feature comparison between original and real time images

Conclusion

In culmination, our project's fusion of Sequential Convolutional Neural Networks (CNN) and Convolutional Autoencoders (CAEs) signifies a breakthrough in precision for rice grain quality assessment. By harmonizing CNN's adept object identification with CAEs' feature learning, the resulting framework exceeds the limitations of conventional methods. The model's fine-tuning, coupled with data augmentation, ensures robust adaptability and generalization, validated by impressive evaluation metrics.

As we deploy this cutting-edge technology into practical applications, it not only addresses existing challenges but also pioneers a new era of automated and elevated rice quality standards, crucial for global food security. This success is a testament to the collaborative efforts of neural network researchers, showcasing the impactful role of machine learning in revolutionizing the production and quality control of vital food crops like rice, ensuring both agricultural sustainability and consumer well-being.

Future Scope

Future enhancements to our integrated neural network approach for rice quality assessment could involve the incorporation of advanced sensor technologies and real-time data collection during the rice cultivation and processing stages. Implementing a more dynamic system that adapts to changing environmental conditions and crop variations could further improve the model's accuracy and robustness. Additionally, exploring the integration of explainable AI techniques can enhance the interpretability of the model's decisions, providing valuable insights for stakeholders. Continuous updates to the dataset and model architecture will ensure adaptability to emerging rice varieties and quality parameters.

Reasearch Paper

Research Paper

References

[1] Thae Nu Wah, Pann Ei San, Thandar Hlaing (2018); Analysis on Feature Extraction and Classification of Rice Kernels for Myanmar Rice Using Image Processing Techniques; International Journal of Scientific and Research Publications (IJSRP) 8(8) (ISSN: 2250-3153).

[2] S. Wentao, "Classification Model of Wheat Grain based on Autoencoder" *2020* IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), Dalian, China, 2020, pp. 830-832

[3] Dharmik, R. C., Chavhan, S., Gotarkar, S., y Pasoriya, A. (2022). Rice quality analysis using image processing and machine learning. 3C TIC. Cuadernos de desarrollo aplicados a las TIC, 11(2), 158-164.

[4] N. Hong Son and N. Thai-Nghe, "Deep Learning for Rice Quality Classification," 2019 International Conference on Advanced Computing and Applications (ACOMP), Nha Trang, Vietnam, 2019, pp. 92-96.

References

[5] Gao, Y., Wang, W., Zhang, W., & Gao, X. (2020). "An automated inspection system for rice seed quality based on deep learning". Journal of Food Process Engineering, 43(6), e13396.

[6] Wang, R., Jiang, Y., & Cao, F. (2019). "Identification and classification of rice seeds using deep convolutional neural networks". Journal of Food Engineering, 263, 92-101.

[7] T. G. Devi, P. Neelamegam and S. Sudha, "Machine vision based quality analysis of rice grains" *2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI)*, Chennai, India, 2017, pp. 1052-1055.

[8] Annadasu, P. and Jaisharma, K., 2020. "Rice Quality Analysis Using Machine Learning" (No. 4761). EasyChair.

References

[9] Latha, M. N., & Nandhini, R. (2020). "Rice quality analysis using deep learning techniques: A review". Computers and Electronics in Agriculture, 174, 105404.

[10] Md Taimur Ahad, Yan Li, Bo Song, Touhid Bhuiyan, "Comparison of CNN-based deep learning architectures for rice diseases classification", Artificial Intelligence in Agriculture,Volume 9,2023, ISSN 2589-7217.

[11] Islam, Redoun Islam, S. M. Rafizul Haque, S.M. Mohidul Islam, Mohammad Ashik Iqbal Khan, "Rice Leaf Disease Recognition using Local Threshold Based Segmentation and Deep CNN", International Journal of Intelligent Systems and Applications(IJISA), Vol.13, No.5, pp.35-45, 2021.

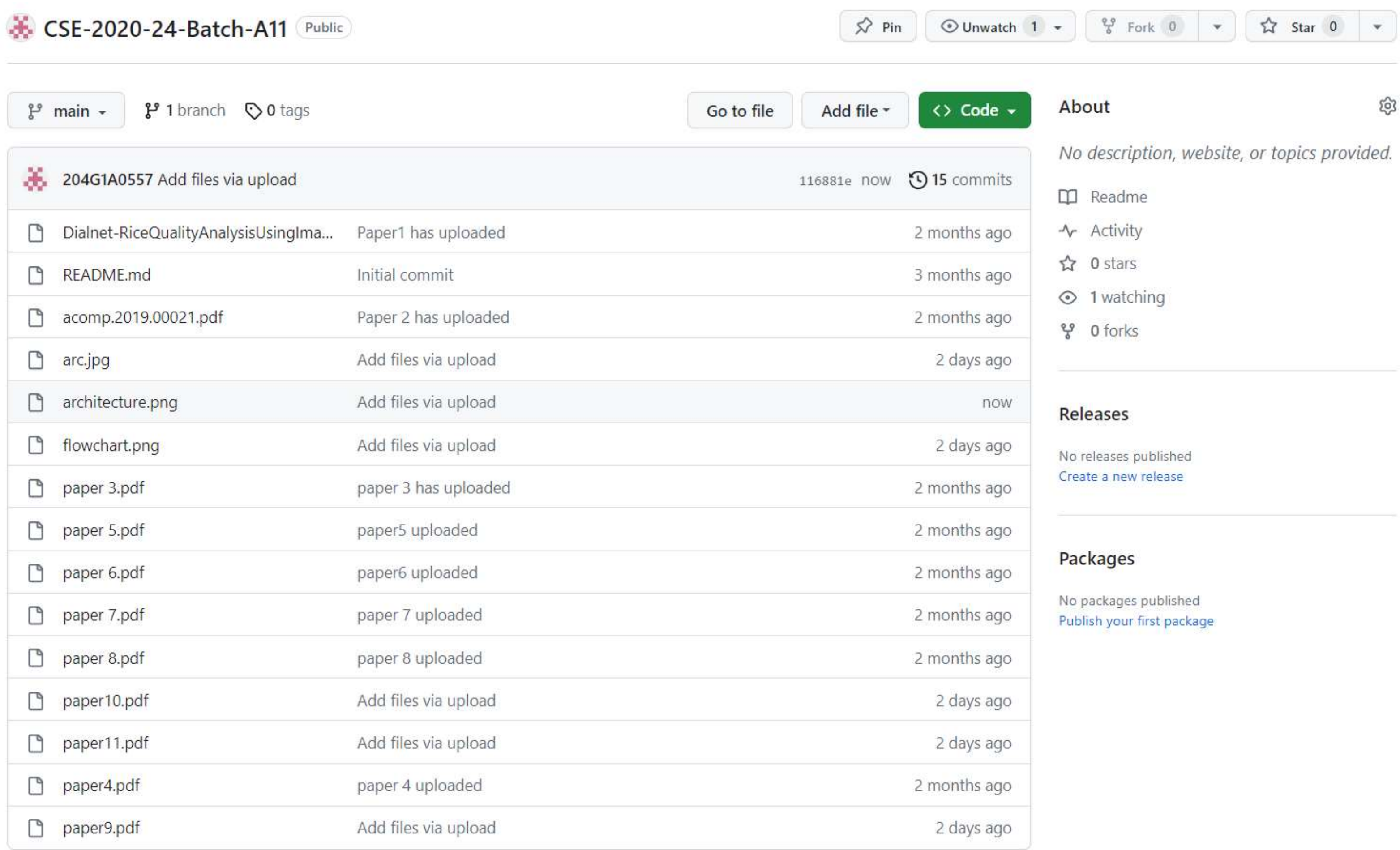
[12] Patel, Vaibhav. (2017). "Convolutional neural network with transfer learning for rice type classification".

References

[13] Jana, Debasish & Patil, Jayant & Herkal, Sudheendra & Nagarajaiah, Satish & Dueñas-Osorio, Leonardo. (2022). "CNN and Convolutional Autoencoder (CAE) based real-time sensor fault detection, localization, and correction". Mechanical Systems and Signal Processing. 169. 108723.

[14] Bedi, Punam, and Pushkar Gole. "Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network". Artificial Intelligence in Agriculture 5 (2021): 90-101.

Git Hub Dashboards of each student

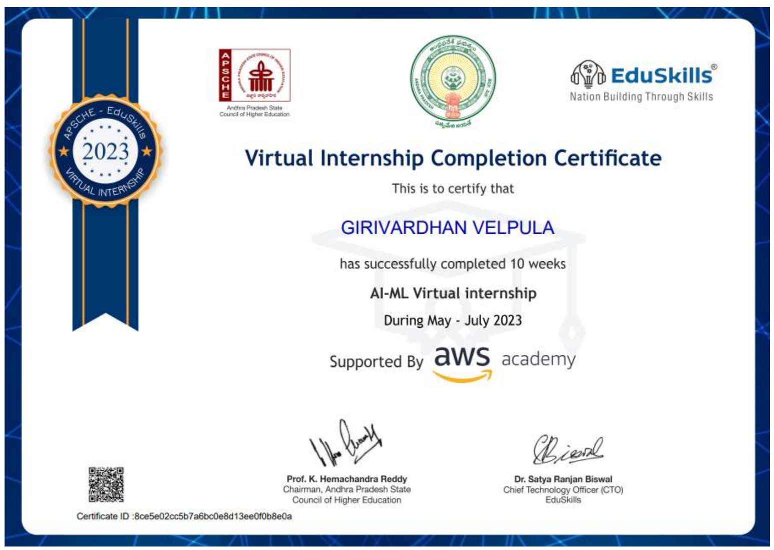


Git Hub Link

https://github.com/204G1A0557/CSE-2020-24-Batch-A11


APSCHE - EduSkills 2023 Virtual Internship
EduSkills
Nation Building Through Skills
Virtual Internship Completion Certificate
This is to certify that
MEGHARSHINI ANKE
has successfully completed 10 weeks
AI-ML Virtual internship
During May - July 2023
Supported By aws academy
Prof. K. Hemachandra Reddy
Chairman, Andhra Pradesh State Council of Higher Education
Dr. Satya Ranjan Biswal
Chief Technology Officer (CTO) EduSkills
Certificate ID :aea3a20b51e7d0e269a55e72ebf9790b


APSCHE - EduSkills 2023 Virtual Internship
EduSkills
Nation Building Through Skills
Virtual Internship Completion Certificate
This is to certify that
Anees Fathima S
has successfully completed 10 weeks
AI-ML Virtual internship
During May - July 2023
Supported By aws academy
Prof. K. Hemachandra Reddy
Chairman, Andhra Pradesh State Council of Higher Education
Dr. Satya Ranjan Biswal
Chief Technology Officer (CTO) EduSkills
Certificate ID :ed746f87d251b2ff837f39f2b70971ce


APSCHE - EduSkills 2023 Virtual Internship
EduSkills
Nation Building Through Skills
Virtual Internship Completion Certificate
This is to certify that
GIRIVARDHAN VELPULA
has successfully completed 10 weeks
AI-ML Virtual internship
During May - July 2023
Supported By aws academy
Prof. K. Hemachandra Reddy
Chairman, Andhra Pradesh State Council of Higher Education
Dr. Satya Ranjan Biswal
Chief Technology Officer (CTO) EduSkills
Certificate ID :8ce5e02cc5b7a6bc0e8d13ee0f0b8e0a


APSCHE - EduSkills 2023 Virtual Internship
EduSkills
Nation Building Through Skills
Virtual Internship Completion Certificate
This is to certify that
Anitha M
has successfully completed 10 weeks
AI-ML Virtual internship
During May - July 2023
Supported By aws academy
Prof. K. Hemachandra Reddy
Chairman, Andhra Pradesh State Council of Higher Education
Dr. Satya Ranjan Biswal
Chief Technology Officer (CTO) EduSkills
Certificate ID :349ffba7acdd5f4dd51dcab68f7d9d07


N·E·A·T National Educational Alliance for Technology
AICTE All India Council for Technical Education
EduSkills Nation Building Through Skills
2024
Certificate of Virtual Internship
This is to certify that
MEGHARSHINI ANKE
Srinivasa Ramanujan Institute of Technology
has successfully completed 10 weeks
Android Developer Virtual Internship
During January - March 2024
Supported By : India Edu Program
Google for Developers
Karthik Padmanabhan, Developer Ecosystem Lead, MENA & India, Google
Shri Buddha Chandrasekhar, Chief Coordinating Officer (CCO), NEAT Cell, AICTE
Dr. Satya Ranjan Biswal, Chief Technology Officer (CTO), EduSkills
Certificate ID :607ea762ae78f98deaf0d81bfd76ee35
Student ID :STU620d0b5b886ac1645022043
Internship Grade B


N·E·A·T National Educational Alliance for Technology
AICTE All India Council for Technical Education
EduSkills Nation Building Through Skills
2024
Certificate of Virtual Internship
This is to certify that
Anees Fathima
Srinivasa Ramanujan Institute of Technology
has successfully completed 10 weeks
Android Developer Virtual Internship
During January - March 2024
Supported By : India Edu Program
Google for Developers
Karthik Padmanabhan, Developer Ecosystem Lead, MENA & India, Google
Shri Buddha Chandrasekhar, Chief Coordinating Officer (CCO), NEAT Cell, AICTE
Dr. Satya Ranjan Biswal, Chief Technology Officer (CTO), EduSkills
Certificate ID :f2225da3a8d8bf7a5c0b97809db2c1dd
Student ID :STU61406954208d61631611220
Internship Grade B


N·E·A·T National Educational Alliance for Technology
AICTE All India Council for Technical Education
EduSkills Nation Building Through Skills
2024
Certificate of Virtual Internship
This is to certify that
GIRIVARDHAN VELPULA
Srinivasa Ramanujan Institute of Technology
has successfully completed 10 weeks
Android Developer Virtual Internship
During January - March 2024
Supported By : India Edu Program
Google for Developers
Karthik Padmanabhan, Developer Ecosystem Lead, MENA & India, Google
Shri Buddha Chandrasekhar, Chief Coordinating Officer (CCO), NEAT Cell, AICTE
Dr. Satya Ranjan Biswal, Chief Technology Officer (CTO), EduSkills
Certificate ID :983aebe339d05793c9a2d4bef9e37807
Student ID :STU620d1995460191645025685
Internship Grade E


N·E·A·T National Educational Alliance for Technology
AICTE All India Council for Technical Education
EduSkills Nation Building Through Skills
2024
Certificate of Virtual Internship
This is to certify that
Anitha M
Srinivasa Ramanujan Institute of Technology
has successfully completed 10 weeks
Android Developer Virtual Internship
During January - March 2024
Supported By : India Edu Program
Google for Developers
Karthik Padmanabhan, Developer Ecosystem Lead, MENA & India, Google
Shri Buddha Chandrasekhar, Chief Coordinating Officer (CCO), NEAT Cell, AICTE
Dr. Satya Ranjan Biswal, Chief Technology Officer (CTO), EduSkills
Certificate ID :886c22ccd273ce0829b58a38ebc24a14
Student ID :STU620d2e1e7de3611645027815
Internship Grade B

AIP Conference Proceedings

CHAITANYA BHARATHI INSTITUTE OF TECHNOLOGY
(UGC- AUTONOMOUS)
PRODDATUR
Vidya Nagar, Proddatur, YSR Kadapa (Dist.), Andhra Pradesh 516360

ICIAET-24 Proceedings

International Conference on Innovative Approaches in Engineering & Technology (ICIAET-24)
5th & 6th April 2024
Organized by Department of Electrical & Electronics Engineering

Certificate of Appreciation

This certificate is awarded to Dr./Mr./Mrs./Miss. Veera prakash pobbatti ,of SRIT - Anantapur has participated and presented a paper entitled Enchancing Rice Quality Assessment through integrated Neural networks: A synergistic Approach with CNN and CAEs with Paper ID: ICIAET-P172 in **ICIAET-2024.**

Dr V Mahesh Kumar Reddy
Convenor & Organising Chair

Dr G Sreenivasula Reddy
Principal, CBIT

turnitin
Official sponsor

"Enhancing Rice Quality Assessment through Integrated Neural Networks: A Synergistic Approach with CNN and CAEs"

AIP Conference Proceedings

CHAITANYA BHARATHI INSTITUTE OF TECHNOLOGY (UGC- AUTONOMOUS) PRODDATUR
Vidya Nagar, Proddatur, YSR Kadapa (Dist.), Andhra Pradesh 516360

ICIAET-24 Proceedings

International Conference on Innovative Approaches in Engineering & Technology (ICIAET-24)
5th & 6th April 2024
Organized by Department of Electrical & Electronics Engineering

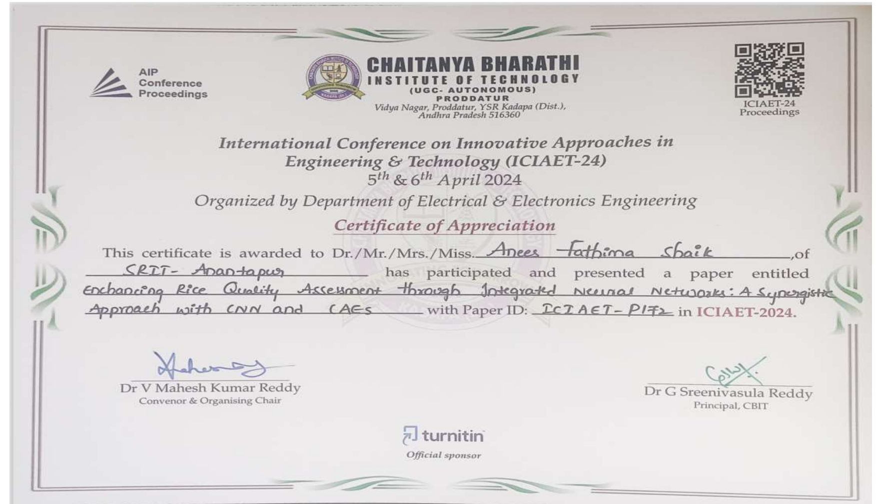
Certificate of Appreciation

This certificate is awarded to Dr./Mr./Mrs./Miss. Megharshini Anke, of SRIT - Anantapur has participated and presented a paper entitled Enchancing Rice Quality Assessment through Integrated Neural Networks : A Synergistic Approach with CNN and CAEs with Paper ID: ICIAET- P172 in ICIAET-2024.

Dr V Mahesh Kumar Reddy
Convenor & Organising Chair

Dr G Sreenivasula Reddy
Principal, CBIT

turnitin
Official sponsor



AIP Conference Proceedings

CHAITANYA BHARATHI INSTITUTE OF TECHNOLOGY (UGC- AUTONOMOUS) PRODDATUR
Vidya Nagar, Proddatur, YSR Kadapa (Dist.), Andhra Pradesh 516360

ICIAET-24 Proceedings

International Conference on Innovative Approaches in Engineering & Technology (ICIAET-24)
5th & 6th April 2024
Organized by Department of Electrical & Electronics Engineering

Certificate of Appreciation

This certificate is awarded to Dr./Mr./Mrs./Miss. Anees Fathima Shaik, of SRIT- Anantapur has participated and presented a paper entitled Enchancing Rice Quality Assessment through Integrated Neural Networks: A Synergistic Approach with CNN and CAEs with Paper ID: ICIAET- P172 in ICIAET-2024.

Dr V Mahesh Kumar Reddy
Convenor & Organising Chair

Dr G Sreenivasula Reddy
Principal, CBIT

turnitin
Official sponsor

AIP Conference Proceedings

CHAITANYA BHARATHI INSTITUTE OF TECHNOLOGY (UGC- AUTONOMOUS) PRODDATUR
Vidya Nagar, Proddatur, YSR Kadapa (Dist.), Andhra Pradesh 516360

ICIAET-24 Proceedings

International Conference on Innovative Approaches in Engineering & Technology (ICIAET-24)
5th & 6th April 2024
Organized by Department of Electrical & Electronics Engineering

Certificate of Appreciation

This certificate is awarded to Dr./Mr./Mrs./Miss. Anitha Myla, of SRIT- Anantapur has participated and presented a paper entitled Enchancing Rice Quality Assesment through Integrated Neural Networks : A Synergistics Approach with CNN and CAEs with Paper ID: ICIAET- P172 in ICIAET-2024.

Dr V Mahesh Kumar Reddy
Convenor & Organising Chair

Dr G Sreenivasula Reddy
Principal, CBIT

turnitin
Official sponsor

AIP Conference Proceedings

CHAITANYA BHARATHI INSTITUTE OF TECHNOLOGY (UGC- AUTONOMOUS) PRODDATUR
Vidya Nagar, Proddatur, YSR Kadapa (Dist.), Andhra Pradesh 516360

ICIAET-24 Proceedings

International Conference on Innovative Approaches in Engineering & Technology (ICIAET-24)
5th & 6th April 2024
Organized by Department of Electrical & Electronics Engineering

Certificate of Appreciation

This certificate is awarded to Dr./Mr./Mrs./Miss. Girivardhan Velupula, of SRIT- Anantapur has participated and presented a paper entitled Enchancing Rice Quality Assesment through Integrated Neural Networks : A Synergistics Approach with CNN and CAEs with Paper ID: ICIAET - P172 in ICIAET-2024.

Dr V Mahesh Kumar Reddy
Convenor & Organising Chair

Dr G Sreenivasula Reddy
Principal, CBIT

turnitin
Official sponsor

Thank You!!!