1. INTRODUCTION

In agriculture, good crop management is essential to ensure food security and sustainability. Among various crops, rice is the staple food for the majority of people around the world, especially in Asia and Africa. Cultivation involves many stages, each of which must be carried out in detail, and inspection and inspection of rice is an important factor affecting yield and quality. The traditional rice prospecting process is done by hand; This is a time-consuming, labor-intensive and error-prone process. There is increasing interest in designing electronic systems that use advanced technologies such as computer vision and learning machine to solve these problems and increase agricultural productivity [1].

This report describes the development and use of an automatic rice grain detection that aims to revolutionize the way cultivation is managed. The system combines high technology with machine learning algorithms to improve the grain detection, classification and analysis process. By harnessing the power of technology, the system provides farmers with powerful tools to improve crop management, increase yields and increase food security and also these technologies are being used in different stages of production of agricultural and industrial foods [2]. The importance of grain analysis cannot be overemphasized, especially in the context of modern agriculture facing increasing challenges such as climate change, labor shortages and the need for sustainable practices.

The rice inspection method is not only ineffective, it also hinders farmers' ability to make informed decisions about crop management. By automating this important aspect of cultivation, the strategic system provides farmers with timely and accurate information, allowing them to take proactive steps to increase productivity and reduce risk. The development of automatic grain inspection is based on advances in computer vision and machine learning. Computer technology allows the system to analyze digital images of rice grains, eliminate disturbing features and identify patterns that indicate the health and quality of the rice [3].

Machine learning algorithms, including deep learning such as support vector machine (SVM), random forests, and convolutional neural networks (CNN), play an important role in training models to separate rice grains into different groups such as broken, immature, and immature. Eat healthy rice. Using this technology, the system can achieve high levels of grain accuracy and efficiency beyond the capabilities of the manual method [4].

Compared with the existing grain detection method, this system has many advantages. First, it reduces dependence on manual labor, thus saving farm time and labor costs. Secondly, it increases the accuracy and consistency of wheat search, reduces error and guarantees results. Third, it gives farmers a better view of healthy and good crops, allowing them to implement intervention plans to increase profitability and reduce costs. In addition, the automatic rice detection machine is designed to be flexible and adaptable to different rice types and cultivation. Its versatility enables it to be used in different agricultural environments, meeting the needs of small farms and large-scale commercial operations. But when it comes to the concept of getting most accurate results CNN proved to be good and efficient in many ways [4],[5]. Many others used different models like Artificial Neura netwroks and many more [6](hasanmd megedi) but CNN turned out to be the mose commonly used and effective method [7]

The presented project utilized CNN model and along with it integration of other models using transfer learning tends to provide easy analysis and increase in efficiency. Various machine learning pre-trained models were used in this project,like Resnet, MobileNetV3, VGG16 [8]. In the end the most efficient and highly accurate models were taken into account and presented as our project's base models. Detection and classification using image processing and machine learning techniques turned out to be more efficient in this aspect [9].

2. LITERATURE SURVEY

Xu and Weixing [1] investigated the responses of rice grain yield and quality to elevated carbon dioxide (CO_2) levels combined with soil warming in a rice paddy environment in 2020. Their study focused on understanding the complex interactions between climate change factors and rice production, providing insights into potential adaptation strategies for maintaining rice yield and quality under future climate scenarios.

Kaur and Kiranpreet [2] proposed an automated system for rice grain detection and classification using image processing and machine learning techniques in 2020. The study focused on developing algorithms to preprocess digital images of rice grains, extract relevant features, and train machine learning models for classification tasks. Through experimental validation, the authors demonstrated the effectiveness of their approach in accurately identifying and classifying rice grains into categories such as healthy, broken, and discolored grains. Their research provided insights into the integration of image processing and machine learning techniques for improving the efficiency and accuracy of rice grain detection in agricultural applications.

Huang and Chun-Wei [3] proposed a robust rice grain recognition system based on convolutional neural networks (CNNs) for smart agriculture applications in 2019. The study focused on developing a deep learning model capable of accurately identifying and classifying rice grains from digital images captured under varying environmental conditions. By utilizing CNNs, the authors achieved high levels of accuracy and robustness in rice grain recognition, even in the presence of factors such as occlusion, uneven illumination, and background clutter. Their research highlighted the potential of deep learning techniques in addressing challenges associated with automated rice grain detection and classification, paving the way for advanced agricultural technologies.

Kumar and Arvind [4] provided a comprehensive review of machine learning approaches for crop yield prediction and classification, including techniques such as support vector machines, random forests, and artificial neural networks in 2020. Their review summarized key methodologies, challenges, and applications in crop yield prediction, offering insights into the potential of machine learning for improving agricultural productivity.

Liu and Zhijie [5] reviewed recent advancements in research on rice grain size regulation, focusing on the molecular mechanisms underlying grain size determination in 2019. Their review highlighted key genes and regulatory pathways involved in controlling grain size, offering valuable insights into the genetic basis of rice yield potential and informing breeding efforts aimed at improving grain size and yield.

Hasan and Md. Mehedi [6] proposed an artificial neural network (ANN)-based approach for rice grain detection and classification in 2018. The study focused on training ANN models to analyze digital images of rice grains and classify them into different categories based on features such as shape, texture, and color. Through experimental evaluation, the authors demonstrated the efficacy of their approach in accurately detecting and classifying rice grains, achieving competitive performance compared to traditional machine learning techniques.

Zhang and Lei [7] proposed a deep learning-based approach for detecting and classifying rice diseases using convolutional neural networks (CNNs) in 2018. Their study focused on leveraging CNNs to automatically identify and classify common rice diseases from digital images, offering a promising solution for early disease detection and management in rice cultivation.

Li and Zhi [8] conducted functional analysis of rice grain weight genes using RNA interference (RNAi)-mediated gene silencing techniques in 2017. Their study aimed to elucidate the roles of specific genes in controlling grain weight and yield in rice, providing valuable insights into the genetic basis of grain development and potential targets for crop improvement through genetic manipulation.

Wang and Yu [9] investigated the responses of rice grain yield and quality to elevated CO2 concentration and high temperature stress in 2016. Their study examined the physiological and biochemical mechanisms underlying the impact of climate change factors on rice production, highlighting the need for adaptive strategies to mitigate the negative effects on grain yield and quality.

Kim and Soo-Hyung [10] developed an automated system for measuring rice grain length and width based on machine vision and neural network techniques. Their study focused on designing image processing algorithms and training neural network models to accurately measure rice grain dimensions from digital images, offering a non-destructive and efficient solution for assessing grain quality in rice cultivation.

3. PROBLEM STATEMENT

Traditional grain detection methods face difficulties in accurately identifying and classifying grains due to differences in grain size, shape, and environment. The manual process is laborious, error prone and may not work well on large farms. It can also be a useful resource to have a large collection of notes that show strong patterns.

The combination of transformative learning and CNN holds great promise against these challenges by leveraging existing knowledge from big data and advancing for the specific nuances of rice research. However, the optimal combination and optimization of transformation learning with CNN architecture to achieve effective and accurate rice grain identification is still an area of research. This work aims to solve these problems and provide insight into how to use transfer learning and CNN to improve rice detection in various agricultural fields

4. METHODOLOGY

The following is the architectural design for the rice grain detection using advanced image processing techniques and transfer learning for Feature Extraction.

4.1. SYSTEM ARCHITECTURE

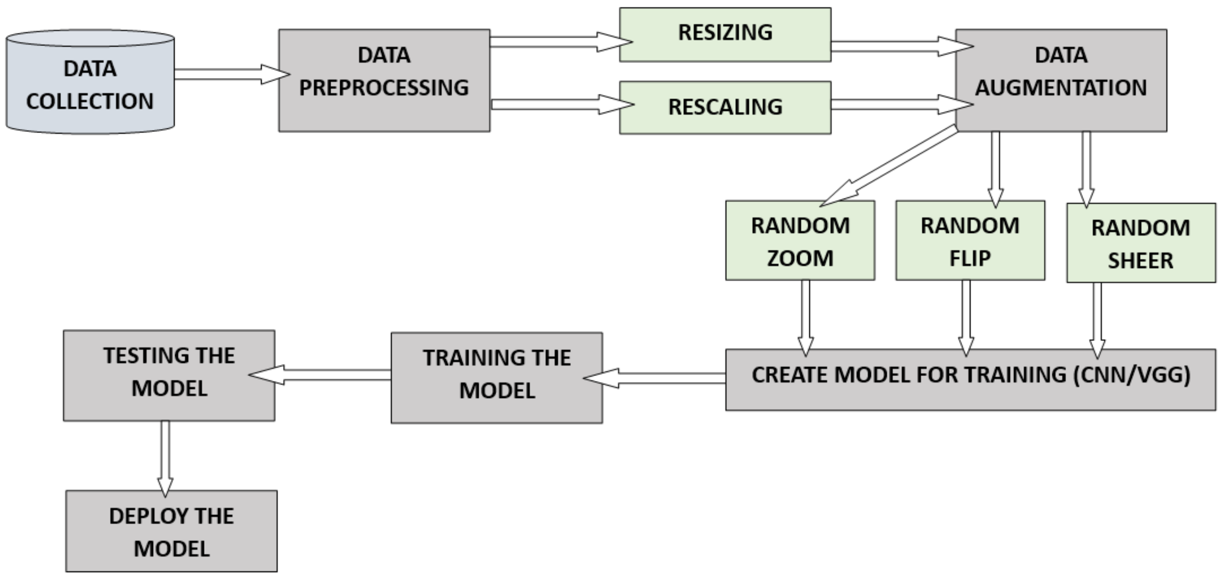


Fig 4.1: System Architecture

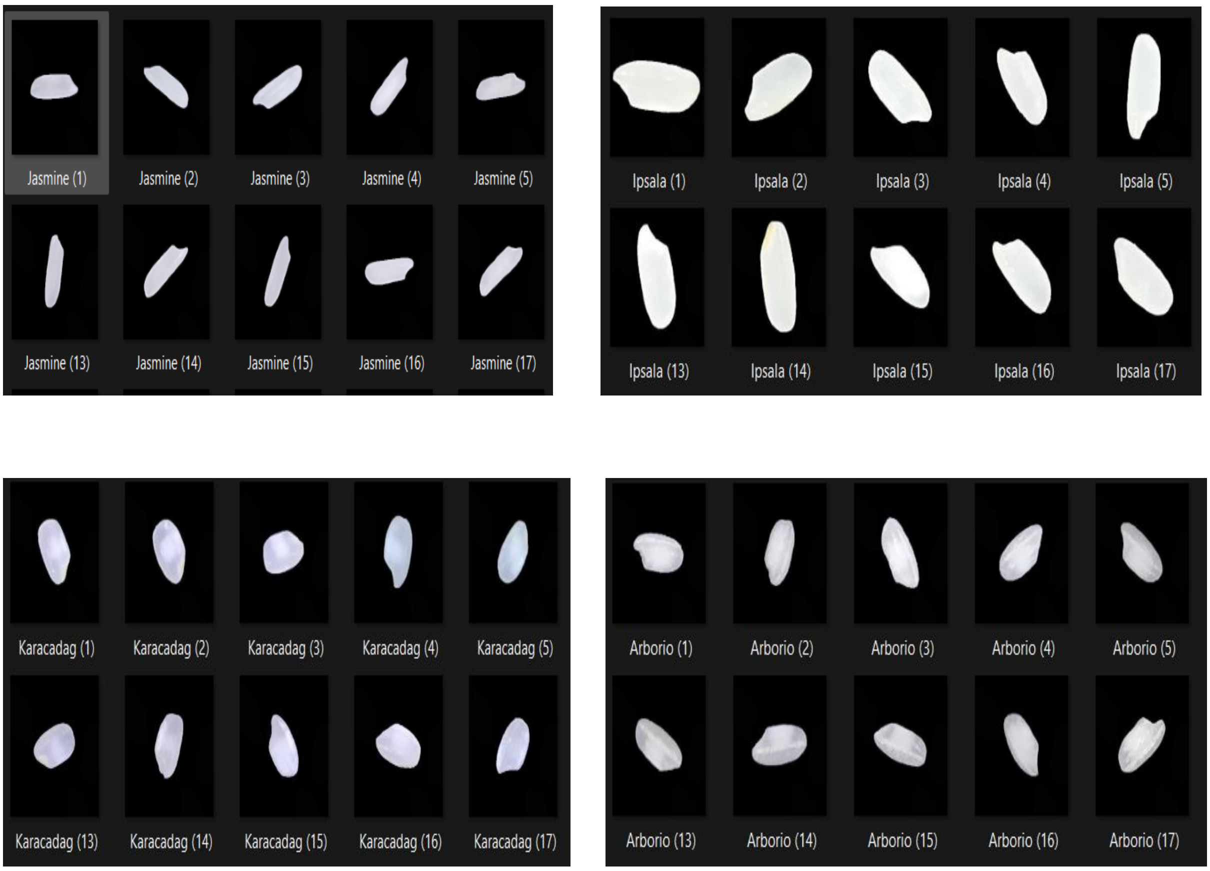
4.1.1. DATASET

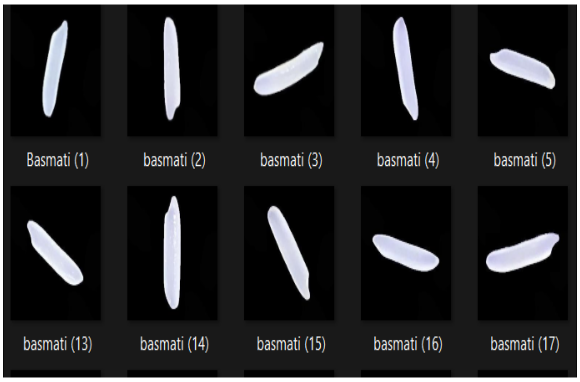
The data presented at https://www.muratkoklu.com/datasets/ contains images of rice grains classified into different types such as Arborio, Basmati, İpsala, Jasmine and Karacadağ. These images, curated and presented by Murat Köklü, are useful for research and experiments in the field of classification and analysis.

All rice species are represented by a collection of photos taken in a variety of conditions, including different lighting, backgrounds and viewing angles. These images provide diverse and comprehensive data for training machine learning models and performing deployment-related analyses. Researchers, developers and professionals interested in grain classification and analysis can use this data to introduce models for processes such as image classification, product information, especially the use of computer vision for grain analysis. This data provides a recorded image that allows supervised learning algorithms to accurately classify rice grains based on their visual characteristics. Using this information, researchers can discover and develop systems for grain classification, quality assessment, and identification. This information offers the opportunity to improve the efficiency and accuracy of agricultural processes related to crop production by facilitating experiments with machine learning algorithms and techniques.

In general, these data sets can be accessed at https://www.muratkoklu.com/datasets/. It is an important tool for projects aiming to improve rice distribution and analysis, contributing to progress in agriculture and food production.
https://www.muratkoklu.com/datasets/

Fig 4.1.1.: Images of the dataset





4.1.2. Data preprocessing

Data preprocessing is important in preparing datasets for model training and analysis. In the context of grain classification, preprocessing has many operations to model and improve image quality. This work makes the data useful for training learning models such as convolutional neural networks (CNN)

First, images can be edited to ensure consistent dimensions throughout the document. Resizing images to smaller size is important to meet the requirements of the CNN model. The image is then converted to a standard format, usually grayscale or RGB, depending on the model to be made. This change makes the image representation consistent and makes previewing easier.Normalizing pixel values is another important first step. Normalizing pixel values to a specific range (for example, [0, 1]) helps improve the training process and improves convergence during model training.

Additionally, data augmentation techniques can be used to enhance the dataset and improve its integration. Many people. The data development process often involves transforming, translating, measuring, and interpreting. These ideas introduce changes to the dataset, allowing the model to recognize strong features and improve its overall capabilities. Additionally, preprocessing may include data cleaning and quality control procedures to remove noise or irrelevant images from the dataset. This ensures that the model is trained on the correct data, allowing for better performance and generalization of unseen data. In general, data preprocessing plays an important role in the distribution of rice grains in preparing datasets for training models, improving data quality and improving the performance of learning models. CNN generally includes two steps. These are feature extraction and classification.

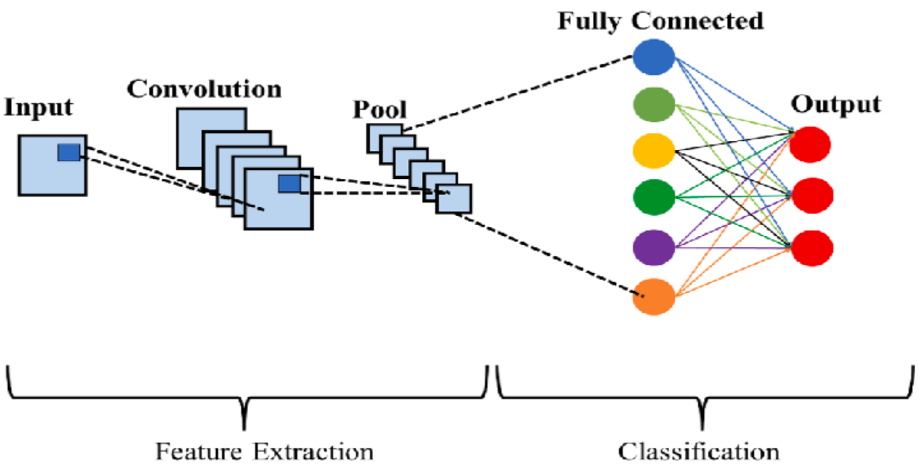


Fig.4.1.2.: Basic Block Diagram of CNN

4.1.2.1. Resizing:

Resizing is the process of changing the dimensions (width and height) of an image. This may include increasing or decreasing the size of the image. In the context of deep learning, resizing is often done to ensure that all input images of the model are the same size. Neural networks generally require fixed inputs. Resizing can be done using a variety of interpolation methods such as nearest neighbor, bilinear or bicubic interpolation. This method determines how new pixel values are calculated when the image is resized. When resizing the image for deep learning, the ratio must be preserved to avoid distorting objects or features in the image.

4.1.2.2. Rescaling:

Rescaling, also known as normalization, involves adjusting the pixel values of an image to a specific value, usually between 0 and 1 or -1 and 1. Normalizing the pixel values of a graphic helps improve the image. Convergence of optimization algorithms during model learning. It also allows the weighted model to be more evenly adjusted across different features. Rescaling the mean pixel value and dividing by the standard deviation can be done by dividing or subtracting the image pixel value by the maximum pixel value (for example, 255 for an 8-bit depth image).

Data enhancement is a technique frequently used in deep learning for image classification and can increase the diversity of training data. This difference helps improve the overall ability of the model and reduce overfitting. Random rotation, scaling, and cropping are popular enhancement techniques used for images. Editing techniques include rotation, flipping, scaling, flipping, scaling, cropping and changes in brightness or contrast.

4.1.3. Data Augmentation:

It is a process in which the dataset is expanded by applying various transformations to the existing data. This process is commonly used in machine learning tasks. There are different types of augmentation methods like random flip, random shear, and random zoom.

4.1.3.1 Random Flip

Random flip is a simple enlargement process that consists of flipping images horizontally or vertically during operation with a specific result.Horizontal flip projects the image along the vertical axis, while vertical flip projects the image along the horizontal axis.Flipping helps the model learn arbitrary features such as the orientation of objects and differentiates between training objects.

4.1.3.2. Random Shear:

Random shear applies a shear transformation to the image, skewing it along one axis by a random amount within a specific range. Shearing distorts the shape of objects in the image, which helps the model to learn features from different perspectives and orientations.

4.1.3.3. Random Zoom:

Implementation of random zoom typically involves applying an affine transformation to the image. This transformation scales the image along both the horizontal and vertical axes by different factors, introducing variability in the dataset. During training, random zoom is applied with a certain probability to generate augmented versions of the input images, thereby increasing the diversity of the training data.

Overall, random zoom augmentation helps improve the generalization ability of deep learning models by exposing them to a wider range of object scales, leading to better performance on unseen data and enhancing the model's robustness in real-world scenarios.

4.1.4. Training data:

Training data contains a dataset of rice images where each image is associated with a specific type of rice. This data is used to train the CNN model by feeding input images and labels into the model. During training, the model learns to extract features from the input image and classify it into different grain types according to the learning model.

4.1.5. Test data:

Test data is the performance of the CNN training model on some of the data collected for evaluation. It contains images of rice grains that the model was not exposed to during training. Compare the model prediction of test data to the ground truth map to evaluate its accuracy, precision, recall, and other performance metrics.

4.2. Design model:

The design model is created using a convolutional neural network (CNN) suitable for image classification. The CNN model consists of several layers, including convolution techniques for extraction, convolution techniques for minimization, and fully connected techniques for classification. This model is designed to learn and capture complex features present in grain images to ensure accurate classification.

4.3. Feature extraction:

Feature extraction is an important step in CNN modeling. Layers in the model work specifically by applying filters to the input image and controlling patterns, edges and textures. These extracted feature are then transferred to layers for classification.

4.4. Algorithms used:

The algorithm used in our project is based on the CNN model. The CNN model learns to separate rice grains into different types by matching images with corresponding labels. During training the model optimizes its parameters to minimize classification error and maximize accuracy in predicting rice type.

Algorithm:

- Import necessary libraries
- Read the dataset
- Data Preparation
- Data Preprocessing
- Model building and training (CNN)
- Evaluation
- Transfer Learning
- Visualization and Comparison

We utilized pre-trained models like ResNet50, VGG16, and MobileNetV3Small for transfer learning.

4.5. Model training:

Model training involves preprocessing images in a convolutional neural network (CNN) and correcting the model parameters (weight and neutrality) through a process called backpropagation. During training the model learns to match the input image with matching letters with a minimization function that measures the difference between predicted letters and real letters (e.g. Arborio, Basmati, İpsala, Jasmine, Karacadag). This is done using optimization algorithms such as stochastic gradient descent (SGD) or the Adam optimizer, which adjusts the parameters of the model to minimize the training process continues several times until the model converges and reaches optimal performance of the training data.

4.6. Feature Extraction:

Feature extraction involves capturing important information or patterns from images of rice grains, which are used to identify different types of rice grains. In the context of CNNs, feature extraction is usually done by the convolutional layer of the network. Layers apply filters to the input image, detecting various features such as edges, texture, and shape. As the image passes through multiple layers, the network learns to remove the complexity and abstraction necessary for accurate classification. The extracted features form the basis for distinguishing different types of rice, allowing the model to make informed predictions.

4.7. Classification:

Once the features are extracted from the rice paper, the classification process will assign labels or categories to each image based on its features. In the case of rice classification, the goal of the model is to classify each image into one of the predefined groups based on different rice types (e.g., Arborio, Basmati, İpsala, Jasmine, Karacadağ). This is usually done using a fully convolutional CNN, which performs the actual classification based on the extracted results. During training, the model learns to associate certain characteristics with each group of grains through a parameter optimization process. Thus, the model can identify rice images by type according to their learning patterns, characteristics.

In summary, feature extraction needs to capture important information from the input rice images, while classification needs to assign text to images based on the extracted features. Together, these methods allow machine learning models to accurately classify rice grains and distinguish between different types based on their visual characteristics.

4.8. Model Evaluation:

Model evaluation involves evaluating the performance of the CNN model trained on test data and analyzing its results for grain image classification. Calculate performance metrics such as accuracy, precision, recall, F1 score, and confusion matrix to evaluate the model's performance. Accuracy measures the overall accuracy of the model's predictions, while precision and recall provide information about the model's ability to identify all types of rice and prevent misclassification. The F1score is compromise between precision and recall, providing a balance between standard performance. Also, the confusion matrix shows the performance of the model by showing the number of true positives, negatives, negatives and negatives for each rice type. In general, model evaluation helps improve the effectiveness of the learned CNN model and identify areas that need improvement or optimization. We evaluate our models based on only two main measure and one unemployment and these metrics are Accuracy, Precision, and a loss function.

4.8.1. Metrics:

- **ACCURACY:**

  Accuracy is defined as the proportion of correct predictions in all predictions made.

$$\boxed{\textbf{Accuracy=(TP+TN)/(TP+TN+FP+FN)}}$$

- **PRECISION:**

  Precision is defined as the ratio of correctly classified positive samples (True Positive) to a total number of classified positive samples (either correctly or incorrectly).

$$\boxed{\textbf{Precision = TP/TP+FP}}$$

But for our model, we compiled a keras model directly, when you compile the model with these parameters, during training, Keras will compute both accuracy and precision metrics and in addition to minimizing the categorical cross-entropy loss while using the Adam optimizer. We achieve our required metrics with ease using the below line of code.

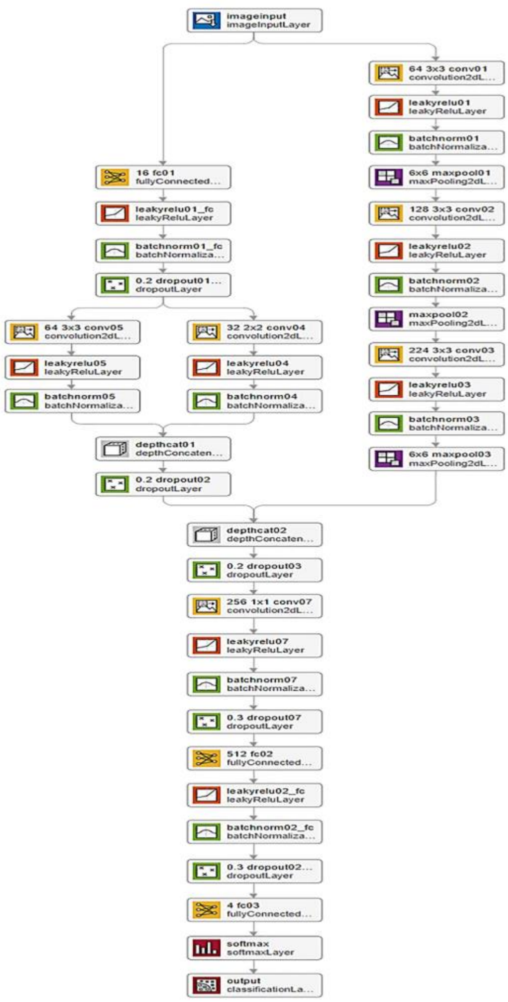
```
model.compile(loss='categorical_crossentropy', optimizer='adam',
metrics=['accuracy', tf.keras.metrics.Precision()])
```

5. IMPLEMENTATION

5.1. CNN ALGORITHM:

Convolutional neural networks, often called CNN or ConvNet, are a type of neural networks used to recognize and classify images. Some applications of CNN include object recognition, face recognition, etc.

Convolutional neural networks can learn complex objects and patterns because they have input operations, output operations, many hidden layers and millions of parameters. It uses convolution and pooling techniques to down sample the input before applying the activation function. All hidden layers are partially connected first, and the displayed layer is the last connected layer. Input image size and output image size can be compared.



Representation architecture of the proposed CNN model.

Fig.5.1: Representation architecture of proposed CNN model

5.2. Using CNN:

Performing grain classification using convolutional neural network (CNN) involves several important steps. First, grain image files are preprocessed, including conversion, normalization and enhancement and are ready for training.

Then, CNN architecture is designed, which usually has a convolutional layer for feature extraction, a pooling layer for subsampling, and all layers for classification. This model is trained using previous data where the CNN learns to extract images of rice grains and classify them into different types (such as Arborio, Basmati, Ipsala, Jasmine, Karacadag) according to the training model.

5.3. Implementation using transformation learning (VGG):

Alternatively, the use of grain separation using VGG (Visual Geometry Group) transformation learning involves the use of pre CNN models such as VGG16 or VGG19 used in the application. In this method, the pretrained VGG model is used as a subtraction method in which the layers of the VGG are frozen for the distribution of rice grains and only the outer layers are updated and corrected. The original rice images are imported into the modified VGG model and the extracted features are used as input for new methods learned to classify rice into different types. Using VGG for transformation learning allows the model to leverage information learned from ImageNet's VGG model, resulting in faster integration and better performance, especially when data on the distribution of rice grains is limited.

Overall, two transfer learning applications using CNN and VGG are suitable methods for generating food classification. The choice between the two depends on factors such as dataset size, usability, and performance evaluation.

5.4. Step by step Implementation:

- ➢ Environment Setup Instructions
- o Verify Python Installation:

```
python –version
```

- ▪ In case Python is not installed, acquire it from an official source and proceed with installation.
- o Install Python Packages:

- Utilize pip for installing Python Packages

```
pip install tensorflow flask flask_cors scikit-learn opencv-python pillow
```

- Install Front end dependencies:

```
npm i
```

- Commence front-end operation and Install front-end with

```
npm start
```

- Configure backend environment:
- Start backend server:

```
python app.py
```

5.5.Testing the model

After training, the model’s performance is evaluated on a separate dataset, called the test dataset, which contains images of rice grain that the model did not see during training Test data allows us to evaluate the overall ability of the model and evaluate its performance on unobserved data.

The training model makes predictions on testing data, and the predictions are compared to actual data to evaluate the model’s accuracy , precision, recall, and other performance metrics. This process helps detetermine the model’s ability to classify the image of rice grains by type and identify potential problems such as overfitting or underfitting. After model’s performance is evaluated on a separate dataset, called the test dataset, which contains images of rice grains.

6. RESULT ANALYSIS

6.1. Dataframe creation with labels and images and visualization:

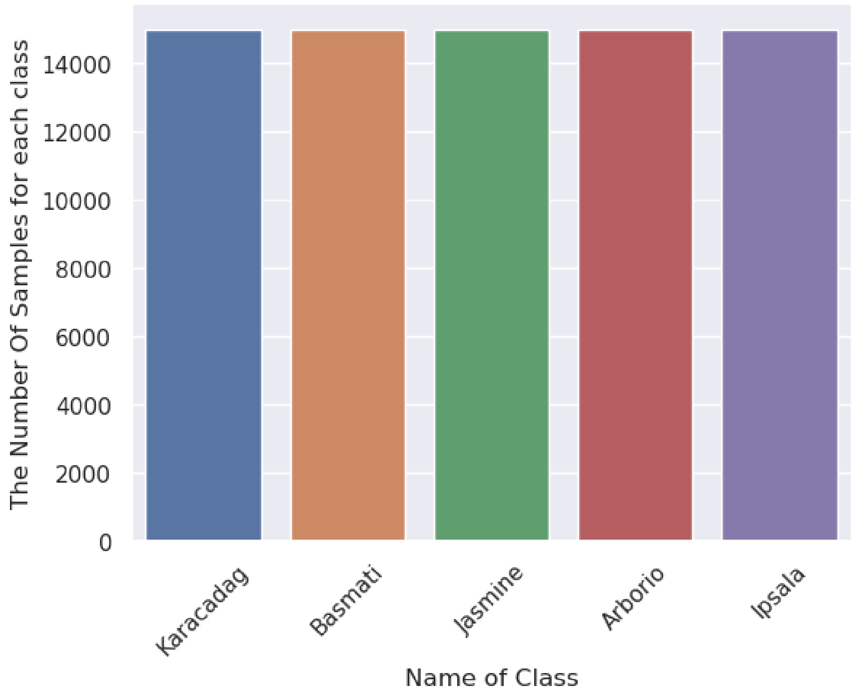


Fig 6.1.1: Countplot to plot the classes

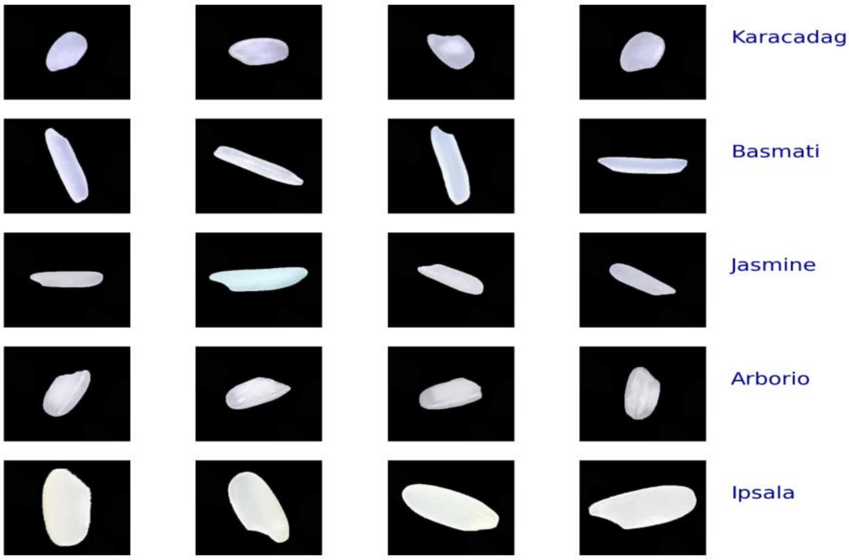


Fig 6.1.2: figure and grid of subplots

6.2. Metrics comparision Graphs

6.2.1: Accuracy, Precision , Loss graphs for our models

CNN Model

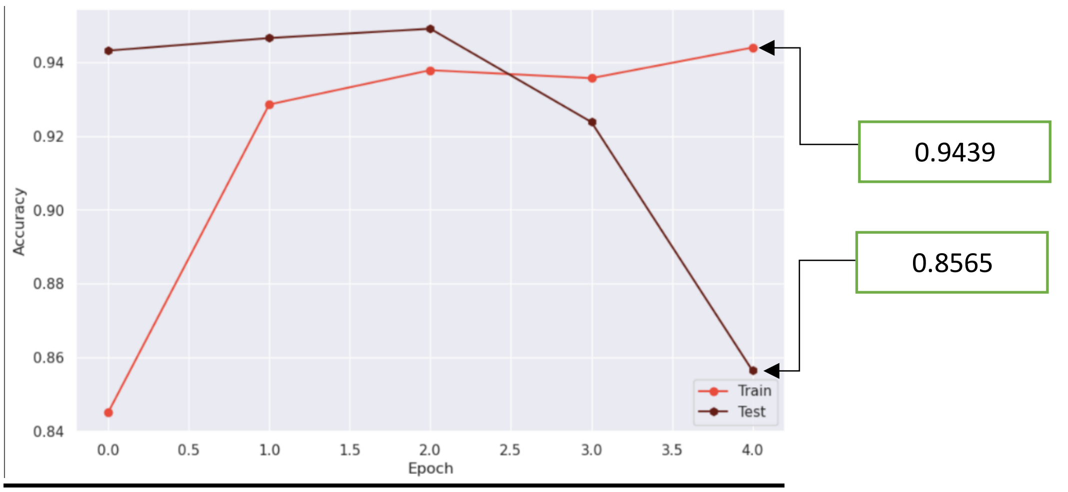


Fig 6.2.1.1: Accuracy comparision between Validation and Train Dataset

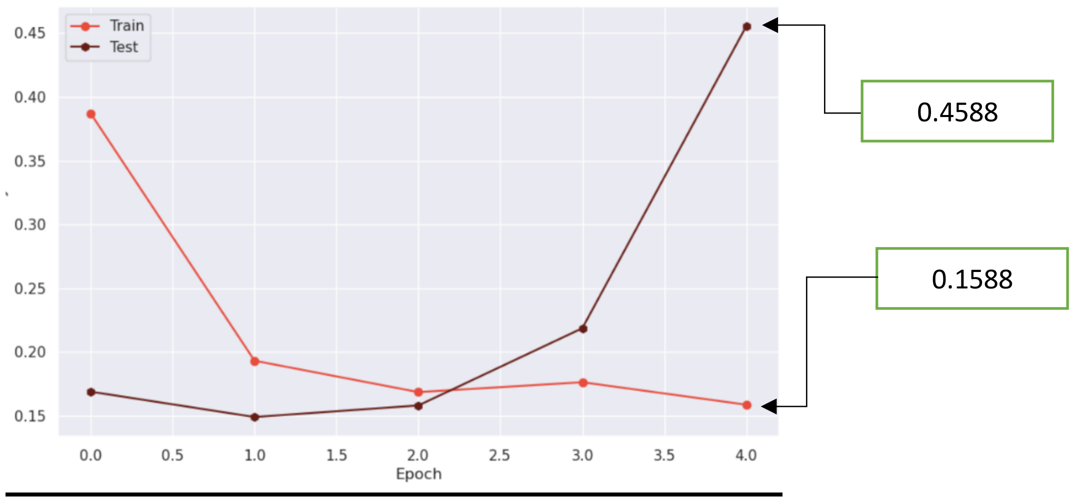


Fig 6.2.1.2: Loss comparision between Validation and Train Dataset

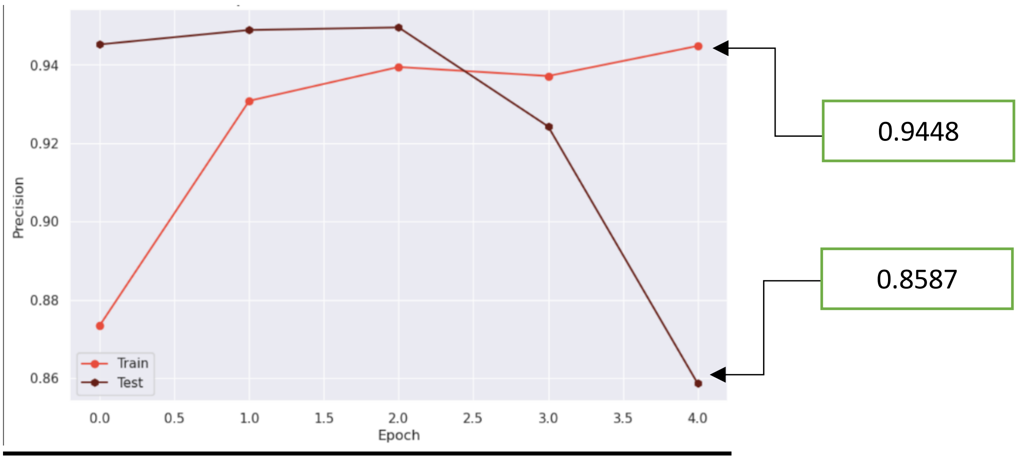


Fig 6.2.1.3: Precision comparision between Validation and Train Dataset

VGG16

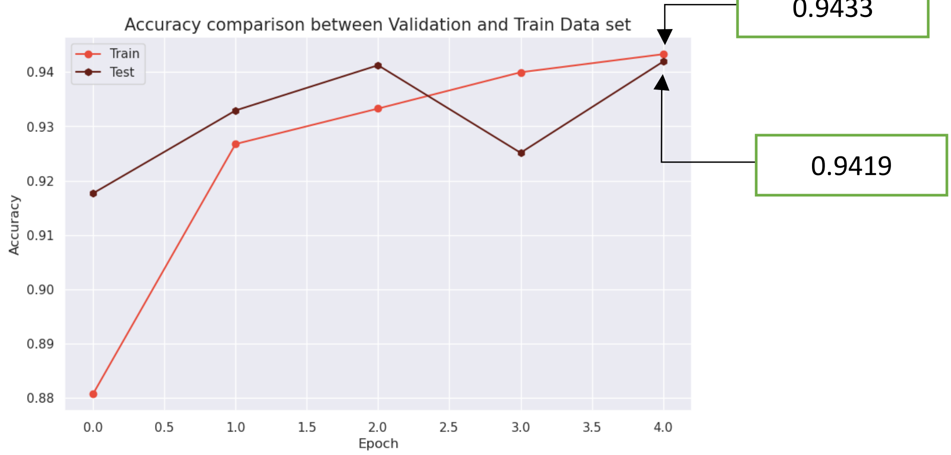


Fig 6.2.1.4: Accuracy comparision between Validation and Train Dataset

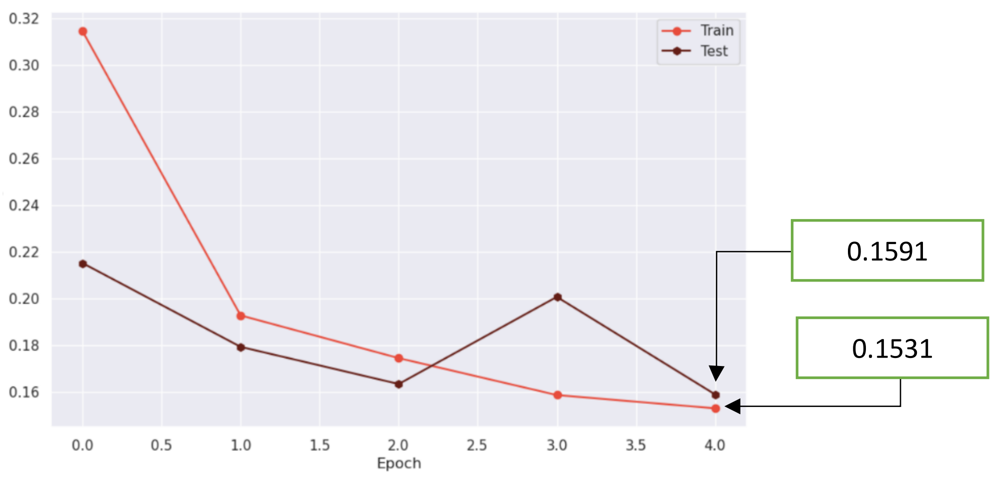


Fig 6.2.1.5: Loss comparision between Validation and Train Dataset

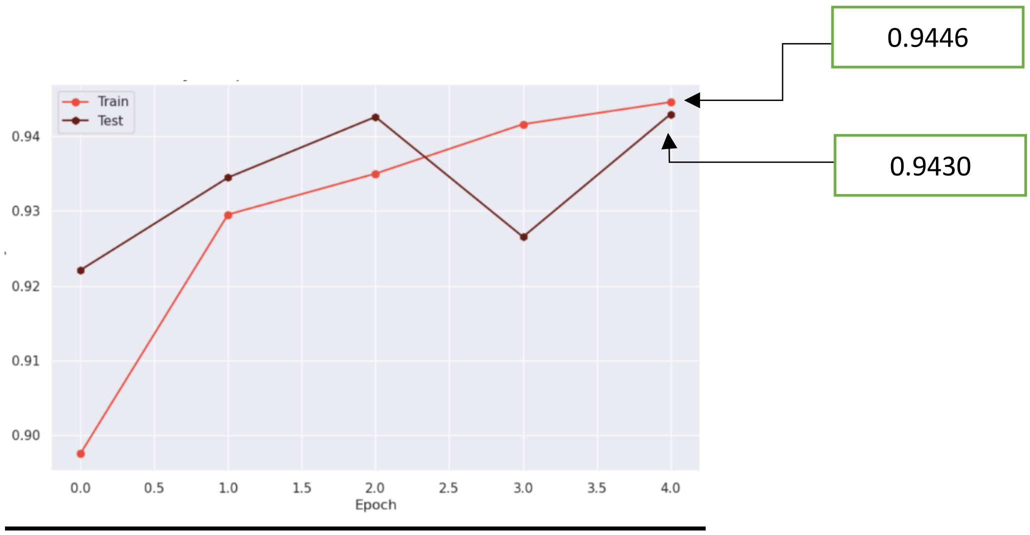


Fig 6.2.1.6: Precision comparision between Validation and Train Dataset

6.2.2. Metrics comparision between our model and other models:

for better understanding of the differences between the metrics, our models and other models have been compared using plot and they are given in the below analysis graphs.

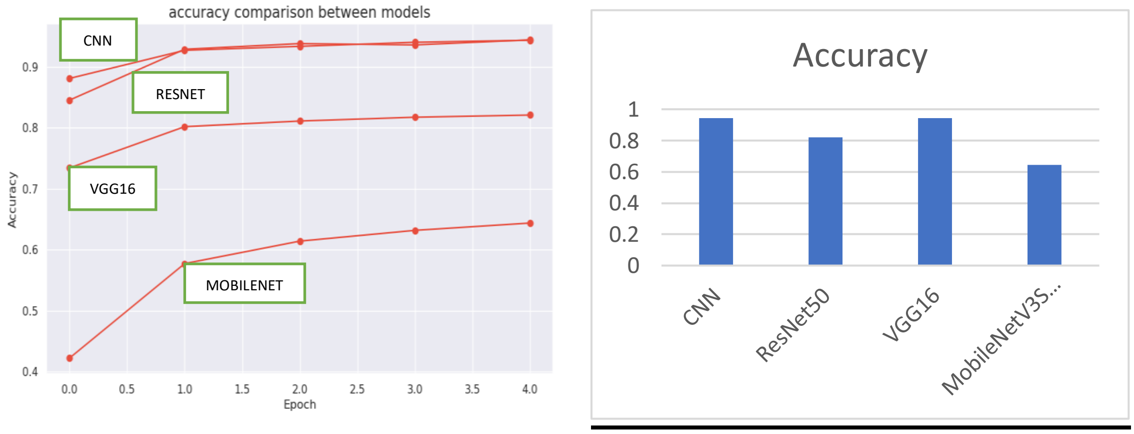


Fig 6.2.2.1: Accuracy comparision between models

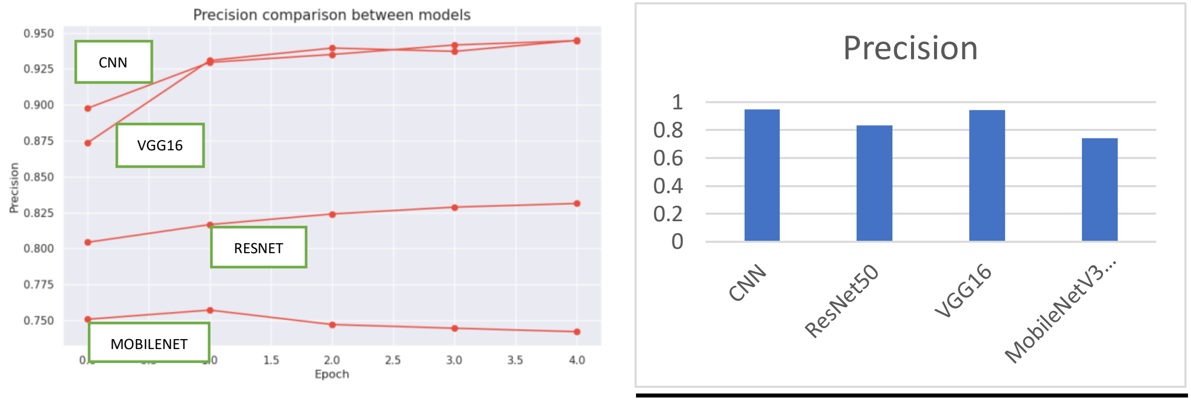


Fig 6.2.2.2.: Precision comparision between models

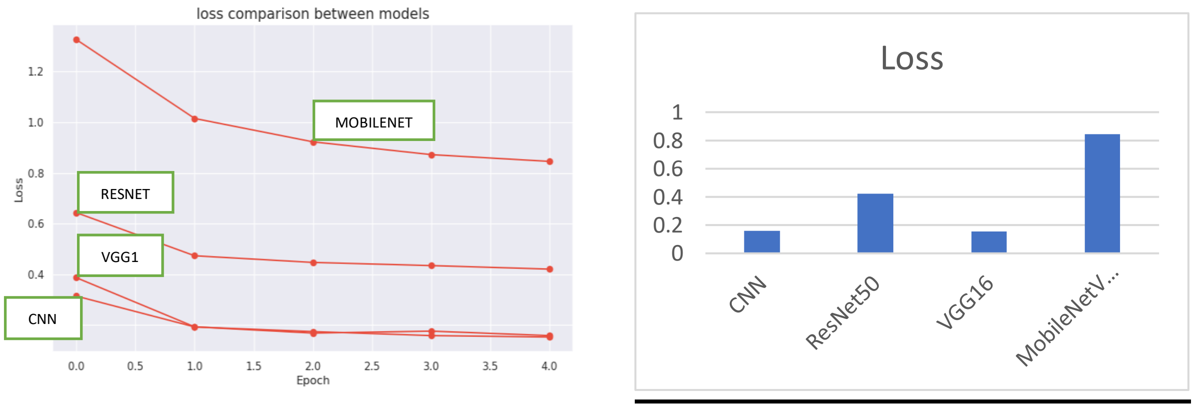


Fig 6.2.2.3.: loss comparision between models

6.3. Performance metrics of various models:

6.3.1. CNN model metric values:

```
Epoch 1/5

1875/1875 [==============================] - 436s 232ms/step - loss: 0.3870 - accuracy: 0.8451 - precision: 0.8734 - val_loss: 0.1690 - val_accuracy: 0.9431 - val_precision: 0.9452

Epoch 2/5

1875/1875 [==============================] - 155s 83ms/step - loss: 0.1932 - accuracy: 0.9285 - precision: 0.9308 - val_loss: 0.1491 - val_accuracy: 0.9465 - val_precision: 0.9489

Epoch 3/5

1875/1875 [==============================] - 162s 86ms/step - loss: 0.1686 - accuracy: 0.9378 - precision: 0.9395 - val_loss: 0.1582 - val_accuracy: 0.9490 - val_precision: 0.9496
```

Epoch 4/5

1875/1875 [==============================] - 155s 83ms/step - loss: 0.1764 - accuracy: 0.9356 - precision: 0.9372 - val_loss: 0.2187 - val_accuracy: 0.9237 - val_precision: 0.9243

Epoch 5/5

1875/1875 [==============================] - 154s 82ms/step - loss: 0.1588 - accuracy: 0.9439 - precision: 0.9448 - val_loss: 0.4552 - val_accuracy: 0.8565 - val_precision: 0.8587

6.3.2. VGG16 model metric values:

Epoch 1/5

1875/1875 [==============================] - 154s 81ms/step - loss: 0.3145 - accuracy: 0.8807 - precision_2: 0.8975 - val_loss: 0.2152 - val_accuracy: 0.9177 - val_precision_2: 0.9221

Epoch 2/5

1875/1875 [==============================] - 151s 81ms/step - loss: 0.1928 - accuracy: 0.9268 - precision_2: 0.9295 - val_loss: 0.1794 - val_accuracy: 0.9329 - val_precision_2: 0.9345

Epoch 3/5

1875/1875 [==============================] - 155s 83ms/step - loss: 0.1746 - accuracy: 0.9333 - precision_2: 0.9350 - val_loss: 0.1635 - val_accuracy: 0.9413 - val_precision_2: 0.9426

Epoch 4/5

1875/1875 [==============================] - 158s 84ms/step - loss: 0.1587 - accuracy: 0.9400 - precision_2: 0.9416 - val_loss: 0.2008 - val_accuracy: 0.9251 - val_precision_2: 0.9265

Epoch 5/5

1875/1875 [==============================] - 157s 84ms/step - loss: 0.1531 - accuracy: 0.9433 - precision_2: 0.9446 - val_loss: 0.1591 - val_accuracy: 0.9419 - val_precision_2: 0.9430

6.3.2. other model metric values:

ResNet50 model’s performance metrics:

```
Epoch 5/5
1875/1875 [==============================] - 163s 87ms/step - loss: 0.4210 - accuracy: 0.8207 - precision 1: 0.8313 - val loss: 0.4230 - val accuracy: 0.8191 - val precision 1: 0.8305
```

MobileNetV3Small model’s performance metrics:

```
Epoch 5/5
1875/1875 [==============================] - 155s 83ms/step - loss: 0.8459 - accuracy: 0.6437 - precision 3: 0.7421 - val loss: 0.8519 - val accuracy: 0.6256 - val precision 3: 0.7065
```

7. CONCLUSION & FUTURE SCOPE

In summary, the development and application of an automatic rice detection system holds great promise in revolutionizing rice cultivation and pioneering precision agriculture. Leveraging advanced technologies such as computer vision, machine learning and deep learning, the system provides farmers with a powerful tool to optimize crop management practices, increase yields and ensure crop quality and food safety in a sustainable manner. The system addresses the key challenges of commercial agriculture through features such as improved efficiency, improved accuracy, improved crop management, scalability, adaptability and sustainability. Additionally, integration of up to date information such as forecasting, disease diagnosis and crop monitoring ensures that farmers are supported with actionable information, better able to make informed decisions and reduce risk. As technology continues to evolve, grain analysis using machines has the potential for further development and innovation, paving the way for a more profitable, productive and sustainable future of agriculture. Overall, the proposed system represents a significant step forward in using technology in global agriculture to solve the world's food security problems and improve people's health.

7.1. FUTURE SCOPE

- Further fine-tuning and optimization of both models could potentially improve their performance.
- Exploring different architectures or variations of the CNN model might yield even better results.
- Data augmentation techniques could be employed to enhance the generalization ability of the models.
- Ensemble methods, where predictions from multiple models are combined, could be explored to further boost performance.
- Transfer learning could be utilized, especially with pre-trained models, to leverage knowledge learned from similar tasks or datasets.
- Hyperparameter tuning could be conducted to find the optimal configuration for both models.
- Deployment of these models in real-world applications, possibly on edge devices or cloud platforms, could be considered after thorough testing and validation.

- Overall, the provided models have shown promising performance, and with further refinement and exploration of techniques, their accuracy and efficiency could be improved for various applications.

8. REFERENCES

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9. APPENDIX-I

SAMPLE CODE

9.1 Rice_grain_classification.ipynb   sample code

```
# import requirement libraries and tools
import os
from tensorflow import keras
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style= "darkgrid", color_codes = True)
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense, Flatten
import warnings
warnings.filterwarnings('ignore')
# Set the path to the dataset
dataset_path = '/kaggle/input/rice-image-dataset/Rice_Image_Dataset'

# Initialize empty lists for storing the images and labels
images = []
labels = []

# Loop over the subfolders in the dataset
for subfolder in os.listdir(dataset_path):

    subfolder_path = os.path.join(dataset_path, subfolder)
    if not os.path.isdir(subfolder_path):
        continue

  # Loop over the images in the subfolder
    for image_filename in os.listdir(subfolder_path):
       # Load the image and store it in the images list
```

```
        image_path = os.path.join(subfolder_path, image_filename)
        images.append(image_path)

        # Store the label for the image in the labels list
        labels.append(subfolder)

 # Create a pandas DataFrame from the images and labels
df = pd.DataFrame({'image': images, 'label': labels})
df.head()
# plot the classes
```

9.2 App.py (back- end) sample code:

```
from flask import Flask, request, jsonify
from flask_cors import CORS
from tensorflow.keras.models import load_model
import numpy as np
from PIL import Image
import io
from collections import Counter
import random
app = Flask(__name__)
CORS(app, resources={r"/predict": {"origins": "*"}})

model = load_model("krishna_model.h5", compile=False)
mapper = {
    0: {
        "name": "Arborio",
        "remedy": "Arborio is a short-grain rice variety renowned for its high
starch content, imparting a creamy texture to dishes like risotto. Originating
in Italy, it is favored for its ability to absorb flavors and create
delectably rich and velvety rice-based dishes."
    },
    1: {
        "name": "Basmati",
        "remedy": " Hailing from the Indian subcontinent, Basmati rice is
characterized by its long grains and distinctive aroma. Its fluffy texture,
fragrant scent, and nutty flavor make it a popular choice for a variety of
dishes, especially in South Asian and Middle Eastern cuisines."
    },
    2: {
        "name": "Ipsala",
        "remedy": "Ipsala is a type of Turkish rice known for its unique
flavor and texture. Grown in the Ipsala region of Turkey, this medium-grain
```

```
rice is often used in traditional Turkish cuisine, contributing to dishes with a delightful blend of taste and consistency."
    },
    3: {
        "name": "Jasmine",
        "remedy": "With its long, slender grains and floral aroma, Jasmine rice is a staple in Southeast Asian cuisine. Originating in Thailand, this fragrant rice complements a wide range of dishes, providing a light and fluffy texture that enhances the overall dining experience."
    },
    4: {
        "name": "Karacadag",
        "remedy": "Karacadag rice is a local variety grown in the Karacadag region of Turkey. With its medium grains, it adds a hearty and substantial character to Turkish dishes. This rice variety is valued for its versatility and ability to adapt to diverse culinary applications in Turkish cuisine."
    },
}
.
.

.

.

if __name__ == "__main__":
    app.run(debug=True)
```

9.3 App.js (front- end) sample code:

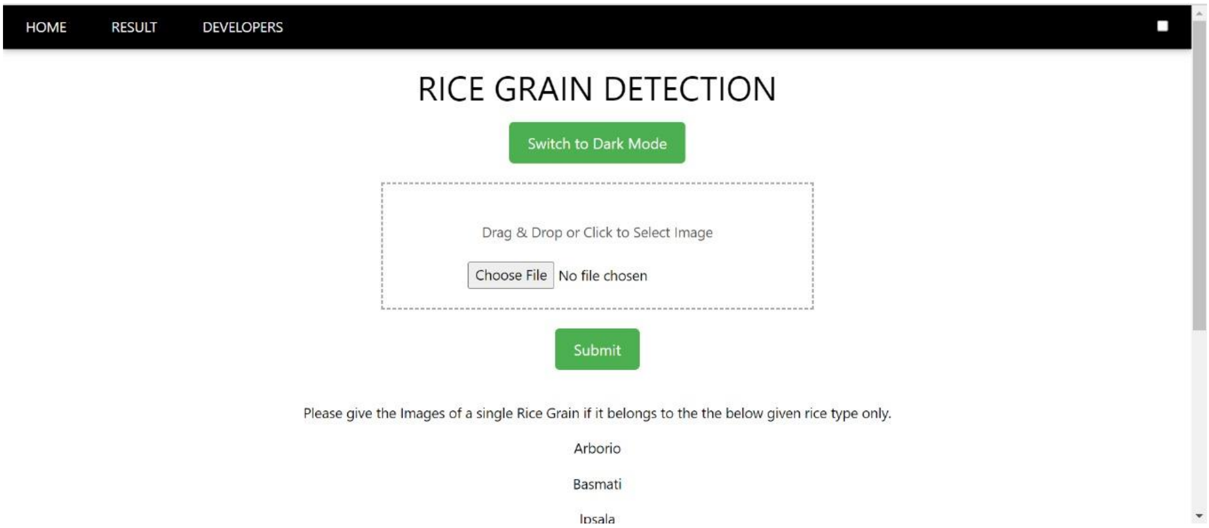
```
import React, { useRef, useState } from 'react';
import './App.css';

function App() {
    const [image, setImage] = useState(null);
    const [previewImage, setPreviewImage] = useState(null);
    const fileInputRef = useRef();
    const [results, setResults] = useState([]);
    const [darkMode, setDarkMode] = useState(false);

    const toggleDarkMode = () => {
        setDarkMode(!darkMode);
    };

    const handleSubmit = async (e) => {
        e.preventDefault();
```

```
    if (!image) {
        console.error('No image to submit');
        return;
    }

    const formData = new FormData();
    formData.append('file', image);

    try {
        const response = await fetch('http://localhost:5000/predict', {
            method: 'POST',
            body: formData
        });

        if (!response.ok) {
            throw new Error(`HTTP error! status: ${response.status}`);
        }

        const data = await response.json();
        setResults(data.result);
    } catch (error) {
        console.error('Error during image submission:', error);
    }
};

const handleImageChange = (e) => {
    const file = e.target.files[0];
    if (file) {
        setImage(file);
        const reader = new FileReader();
        reader.onloadend = () => {
            setPreviewImage(reader.result);
        };
        reader.readAsDataURL(file);
    }
};
```

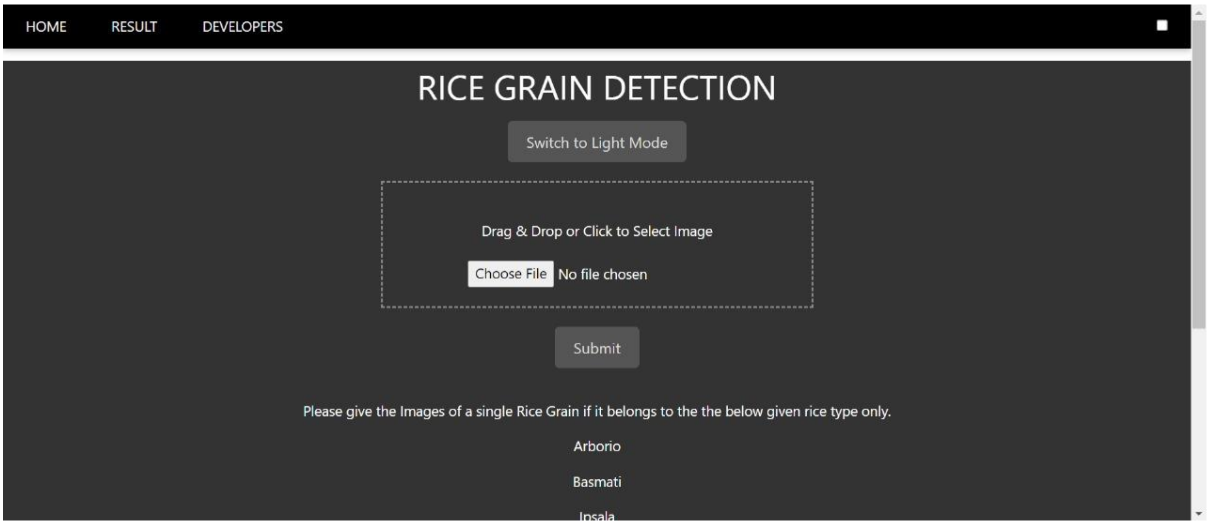
10. APPENDIX – II

SCREENSHOTS

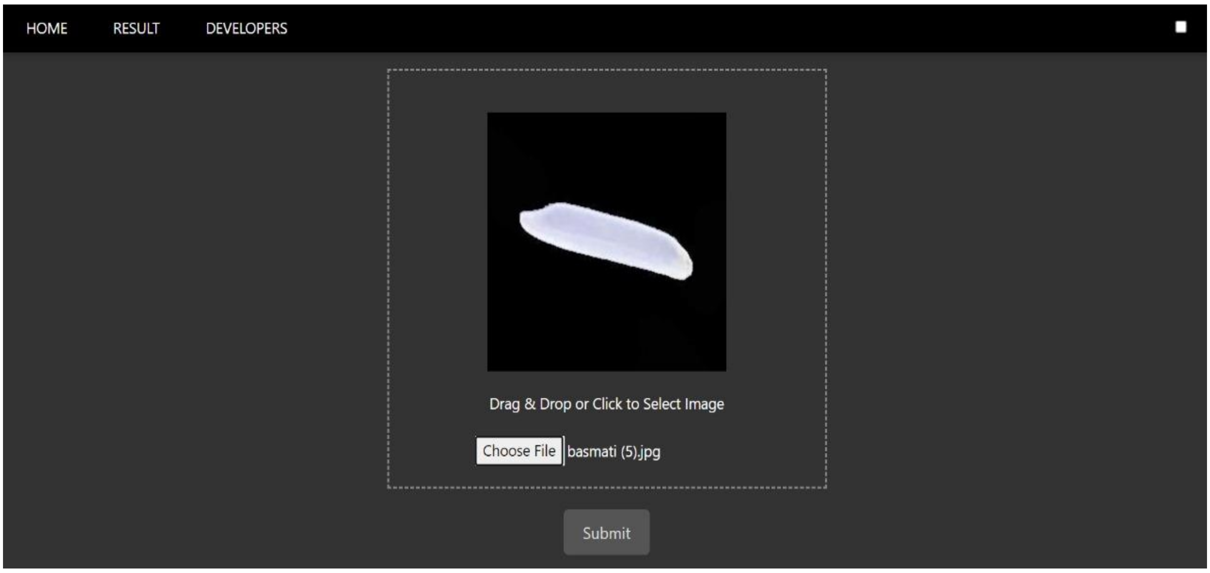
10.1. Front-end



10.2. Front-end (dark mode)



10.3. Front-end with rice grain image uploaded



•

10.4. Front-end – result displayed