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Rice Type Detection Using Deep Learning

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ABSTRACT:

Rice is one of the staple foods. It comes in a variety of forms and has health benefits. Prediction of Rice Type has several genetic variants and is one of the most extensively produced grain products globally using deep learning. These varieties are separated from each other due to some of their features, such as texture, shape, and color. With these features that distinguish rice varieties, it is possible to classify and evaluate rice types. In this project, which includes Arborio, Basmati, Ipsala, Jasmine, and Karacadag, which are five different varieties of rice types, the goal is to train a robust model capable of categorizing rice varieties based on their visual features with high accuracy. Techniques in deep learning, along with models like MobileNet, VGG16, and InceptionV3, are employed to achieve this objective. The automated categorization of rice types has wide applications in agricultural research, crop management, and quality control. This project aims to enhance efficiency and accuracy in various rice-related processes and applications.

Key words: Rice Type, Deep Learning, Image Classification, MobileNet, VGG16, InceptionV3.

1. INTRODUCTION

Deep learning is a rapidly growing field of artificial intelligence that focuses on creating algorithms and models that can learn from vast amounts of data. It is inspired by the structure and function of the human brain, where artificial neural networks are built to perform complex tasks such as image recognition, speech recognition, and natural language processing. By utilizing massive datasets and sophisticated algorithms, deep learning has achieved unprecedented levels of accuracy and speed, allowing it to solve problems that were once considered impossible for machines. In this article, we will delve into the exciting world of deep learning, exploring its history, key concepts, and the cutting-edge applications that are transforming industries worldwide.

2. LITERATURE SURVEY

Rice is the most developing crop all over India; with the increase in population, demand for rice grains has also increased. It is cultivated in almost every Asian country and exported worldwide. In India, many quality standards for rice production are made available. These include physical appearance, cooking qualities, scent, taste, smell, and efficiency difficulties [1]. After cultivation, it is clear that technical methods such as rice calibration, type determination, and separation of various quality aspects are inefficient and time-consuming, particularly for those with large production volumes. There are different rice grain varieties cultivated. It varies based on the places of people they used to eat, while food quality is the main priority [2]. The researchers in the literature use computer vision techniques to extract rice qualitative features. However, people in several areas utilize manual and physical procedures to classify the rice grain varieties. A trained human classifier classifies grains, but this is subject to fatigue and is almost certainly incorrect due to human psychological limitations that can lead to faulty judgment [3].

Recent studies on cereal items employing machine vision systems and image processing techniques reveal that the products are evaluated based on physical characteristics such as color, texture, quality, and size [2]. We used deep learning methods like Visual Geometry Group (VGG16) [5] and Vanilla CNN [4] to identify rice grain images' traits and textural features. VGG16 works based on the CNN architecture of 16 deep layers. This network can train millions of pictures from datasets and obtain the highest accuracy rate. In addition, we have utilized the classification layer and VGG16 model to solve massive datasets into two parts. Our work consists of a new fully connected layer, loss function, and optimizer for each classification task for different classification problems involving multiple data sets. The pretrained model on ImageNet with VGG16 is used for transfer learning, and the VGG16's Convolutional layer is fixed; only the new classification layer and the fully connected layer remain stable. The feature extraction layer of the VGG16 network is retained.

3. METHODOLOGY

3.1. METHODOLOGY OF THE WORK

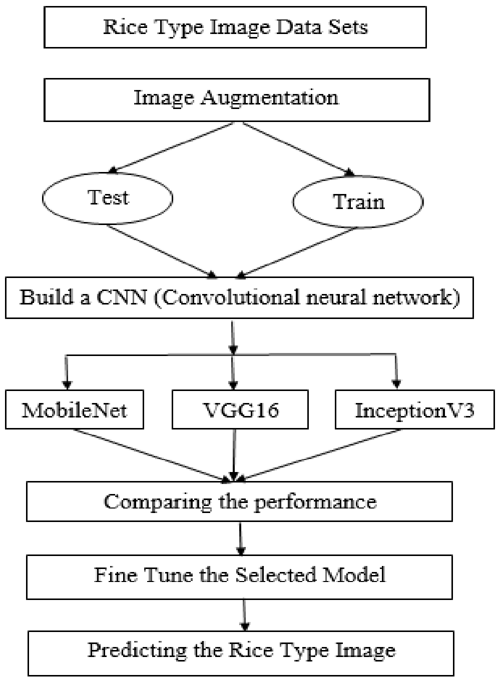

Figure. 1: Methodology

3.2. DATASET

The Type of Rice Image dataset is taken from Kaggle, which contains various rice images differentiated by five categories: Arborio, Basmati, Ipsala, Jasmine, and Karacadag. The dataset is split into training 80% and testing 20%. The train set is split into Arborio, Basmati, Ipsala, Jasmine, and Karacadag. The test set is also split into Arborio, Basmati, Ipsala, Jasmine, and Karacadag.

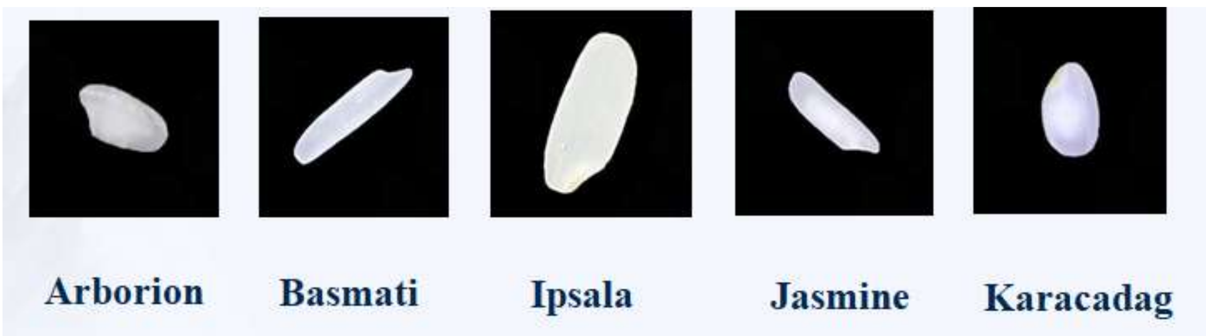

Figure. 2: Types of Rice Images

3.3. IMAGE AGUMEBTATION

Image augmentation is a technique used in convolutional neural networks (CNNs) to artificially increase the size of the training dataset by applying various transformations to the original images. It is primarily used to prevent overfitting and improve the generalization capability of CNN models. By applying these transformations, the augmented images have variations in their appearance, while still retaining the essential features of the original images. This helps the model generalize better to unseen data and reduces the risk of overfitting.

3.4. EXPLORATORY DATA ANALYSIS (EDA)

3.4.1. DISTRIBUTION OF CLASS LABEL

To identify if the dataset suffers from class imbalance, where the number of instances in different classes is significantly different. Class imbalance can lead to biased learning and poor performance, especially for the minority class.

3.4.2. IMAGE SAMPLES

"Train image data from Data Augmentation 1" refers to the images generated through data augmentation techniques applied to the original training dataset. These augmented images are created by applying various transformations to the original images, such as rotation, shifting, flipping, zooming, and changing brightness, among others.

3.5. BUILD A CNN (CONVOLUTION NEURAL NETWORK)

The CNN (Convolutional Neural Network) model is a type of deep learning model commonly used for processing and analyzing visual data, such as images. It is particularly effective in tasks such as image classification, object detection, and image segmentation. They consist of multiple interconnected layers that learn to extract and represent hierarchical patterns and features from input images.

3.6. CNN ARCHITECTURES MODEL

3.6. 1. VGG16

The VGG16 (Visual Geometry Group) architecture consists of 16 convolutional layers with small 3x3 filters, followed by max pooling layers. It is a very simple, effective CNN model for image classification tasks. It is a widely used baseline for comparison bench marking in various image classification tasks. The VGG16 architecture contains 13 convolutional and 3 fully connected layers, with 3×3 kernels for the convolutional layers and 2×2 parameters for the pooling layers.

3.6.2. InceptionV3

The InceptionV3 architecture utilizes a combination of convolutional layers with different filter sizes to capture features at multiple scales. It includes the Inception module, which performs parallel convolutions with different filter sizes and concatenates their outputs. InceptionV3 has shown strong performance on image classification tasks, especially for complex datasets.

3.6.3. MobileNetV2

The MobileNet architecture is designed for efficient inference on mobile and embedded devices. It uses depth-wise separable convolutions to reduce the number of parameters and computations. MobileNetV2 offers a good balance between accuracy and computational efficiency.

4. EXPERIMENTAL RESULTS

Comparison of CNN Architecture Models

S.NO	Name of the Architectures Model	Accuracy
1.	InceptionV3	70.0%
2.	MobileNet	62.0%
3.	VGG16	24.0%

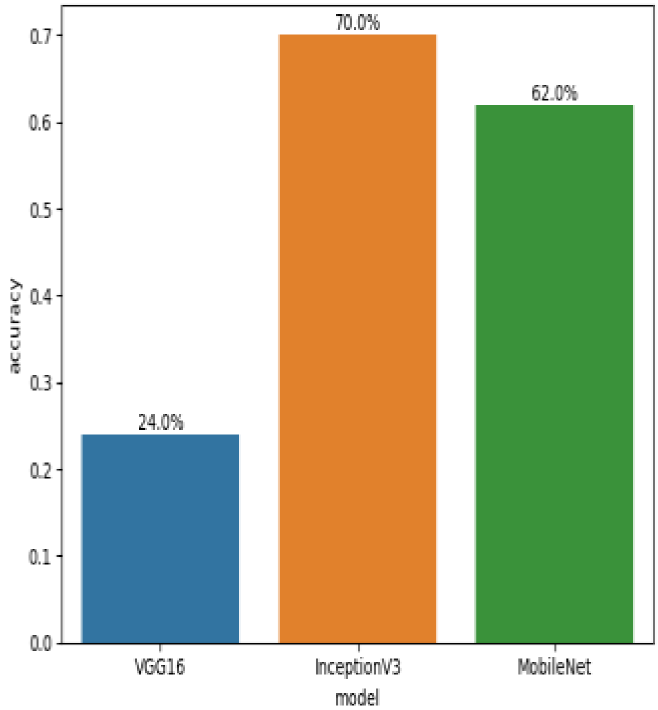

Figure. 3: Comparison of CNN Architecture Models

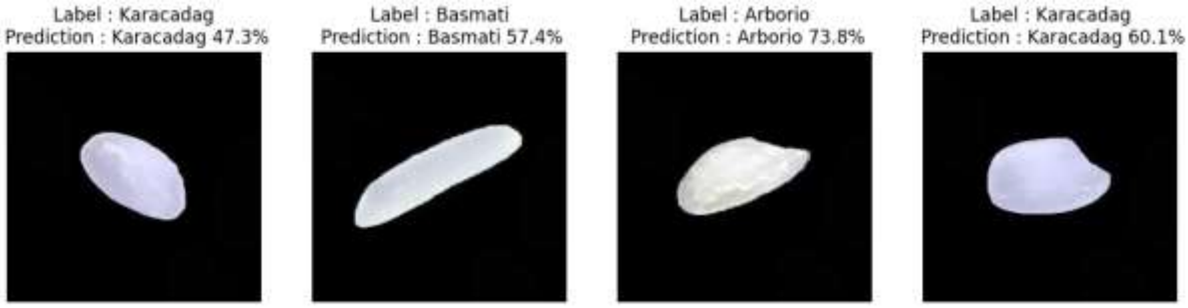

Figure. 4: Output Images of Rice Type Detection

5. CONCLUSION

Images of various rice types underwent classification utilizing deep learning models, including MobileNet, InceptionV3, and VGG16. To enhance the assessment of rice texture, shape, and color this project selected the model demonstrating high accuracy during testing. All trained on the same dataset for rice-type image classification. The VGG16 model achieved a validation accuracy of 24.0% with a loss of approximately 1.65%. In comparison, the InceptionV3 model achieved a validation accuracy of 70.0% with a loss of about 0.94%, while the MobileNet model attained a validation accuracy of 62.0% with a loss of around 1.02%.

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