International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

IMAGE CLASSIFICATION USING DEEP LEARNING MODELS FOR RICE VARIETIES

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Abstract

In India, rice is the crop that grows the fastest, and as the population increases, so does the demand for rice. Most Asian nations cultivate rice and export it to other countries. Depending on where people eat, several rice grain kinds have been cultivated. Food quality is of utmost importance, hence we extract qualitative information from rice using computer vision algorithms. Image processing techniques are used to examine the products for various physical attributes like color, texture, quality, and size.We employed deep learning techniques, such as Visual Geometry Group (VGG16) and Vanilla CNN (also known as vanilla neural networks), to recognize the characteristics and textural elements of photographs of rice grains in order to identify the different types of rice. The CNN design known as VGG16 has 16 layers. It can attain the best accuracy rate by training millions of photos from datasets. Vanilla neural networks, an expansion of the linear regression model, are another paradigm in use. To aid with additional computations, a hidden layer has been added to vanilla CNN in between the inputs and outputs. Neural networks—which train computers instead of humans—are integrated with image processing techniques. The rice varieties utilized for categorization are Basmati, Jasmine, Arborio, Ipsala, and Karacadag. There are five different types of rice picture datasets. There are fifteen thousand images in each of these kinds, for a total of seventy-five thousand images utilized in training and testing. The highest accuracy score determines which picture classification is the best.

Keywords:- Deep learning, Rice, image Classification

1. INTRODUCTION

In India, rice is the crop that is growing the fastest, and as the population grows, so does the need for rice grains. Nearly every Asian nation grows rice, which is then exported all over the world. There are numerous quality standards for rice production accessible in India. These include one's look, culinary abilities, aroma, taste, and fragrance, in addition to challenges with efficiency. It is the first tangible feature that the end user recalls from the criteria that distinguishes the many varieties of rice that are packaged and sold on store shelves. After manufacture, it is evident that technical methods are needed because rice calibration, type identification, and the separation of different quality features are labor-intensive and inefficient, especially for large-scale producers. While there are many types of rice being grown, they differ according to the different locations where people have eaten. In the process, we employ computer vision algorithms to extract the qualitative characteristics of the rice. Even now, physical and manual processes are still used. Grain classification is done by a trained human classifier, although this is susceptible to weariness and is virtually likely inaccurate due to psychological constraints in humans that might result in poor decision-making. The evaluation of cereal items is based on many physical attributes such color, texture, quality, and size, according to recent research that use machine vision systems and image processing techniques.

Utilizing photos of different rice kinds to create a non-destructive model that will improve categorization accuracy. To gather all necessary datasets and focus on developing the model through validation, testing, and training. Researching classifiers for machine learning and deep learning. Visual Geometry Graph (VGG16) Vanilla Neural Network (VNN) **Conduct** a thorough and effective analysis of each classifier. Select the approach with the highest accuracy rate.

2. IMPLEMENTATION

The inability to be spatially invariant to the input data and lots arises from the use of Vanilla CNN. The suggested system uses the Visual Geometry Graph (VGG16) and Vanilla Neural Network (VNN) for rice variety categorization. Additionally, the CNN algorithm—which can evaluate raw images without the need for pre-processing—was used to randomly distribute 75,000 rice photos from five different classes as input for the classification process. To determine which approach has the highest accuracy rate of training data, the classification achievements of four different strategies are evaluated. CNN automatically discovers the required features without human supervision and has Very High accuracy in image recognition challenges, Equitable weight distribution, The analyst is in complete control of the procedure. Big datasets are handled by this approach with ease.

Algorithm

Vanilla Neural Network

A Vanilla Neural Network works similarly to linear regression. The difference is the newly inserted layer between the inputs and outputs.

When we utilize a NN in real life, this extra layer is concealed from view because the NN handles all the extra calculations behind the scenes.

• When only one hidden layer is present, multilayer artificial neurons are usually referred to as vanilla neural networks. There are three levels of nodes in an MLP: input, hidden, and output.

• Vanilla neural networks have three layers, which are:

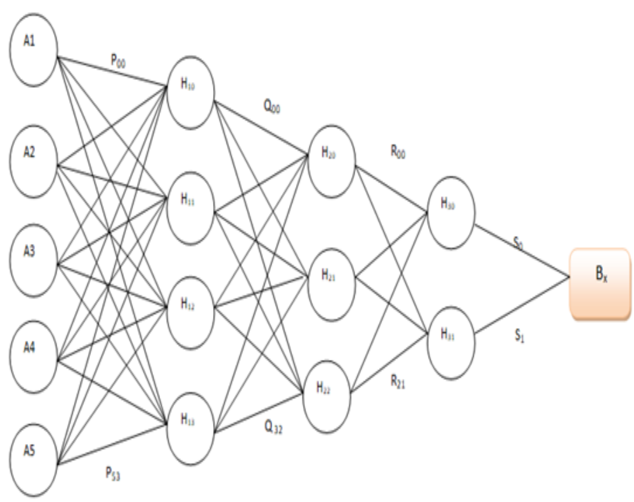

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Fig 1 3-layer VNN Architecture

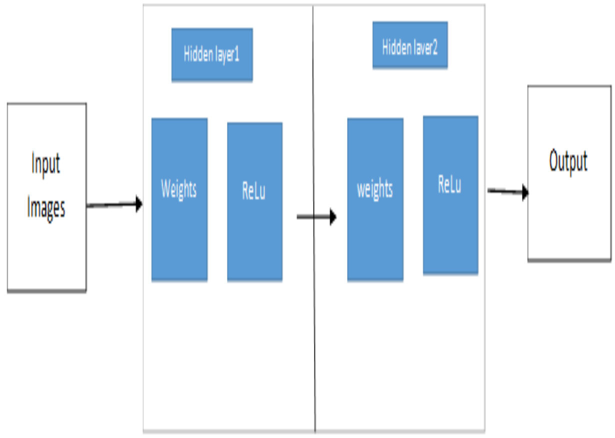

Fig 2: VNN Process

CNNs are typically used to classify images, cluster them according to similarities, and subsequently identify different objects. Many CNN-based algorithms can recognise faces, signs, animals, and other objects. A standard colour image is viewed as a rectangular box with width and height determined by the number of pixels in those dimensions. Channels are the depth layers in the three layers of colours (RGB) that CNNs understand.

VGG16

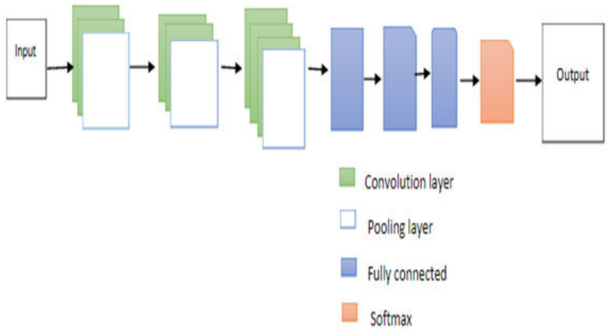

Fig 3: VGG16 architecture

A Convolutional neural network is made up of an input layer, an output layer, and many hidden layers. VGG16 is a CNN (Convolutional Neural Network), which is widely regarded as one of the best computer vision models currently available. VGG16 is a 95% accurate item classification and identification system that can categorize 1000 pictures into 1000 different categories. It's a popular photo classification method that's straightforward to use using transfer learning. The 16 in VGG16 stands for 16 weighted layers. VGG16 comprises thirteen Convolutional layers, five Max Pooling layers, and three dense layers, totaling 21 layers, but only sixteen weight layers, or learnable parameters levels. The input tensor size for VGG16 is 224, 244 with three RGB channels. The most distinctive feature of VGG16 is that, rather than having a huge number of hyper-parameters, they focused on having 3x3 filter convolution layers with stride 1 and always used the same padding and maxpool layer of 2x2 filter strides 2. The convolution and maximum pool layers are organized similarly throughout the architecture. Conv-1 Layer has 64 filters, Conv-2

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Layer has 128 filters, Conv-3 Layer has 256 filters, Conv 4 and Conv 5 Layers have 512 filters. Following a stack of Convolutional layers, three Fully Connected (FC) layers are added: the first two have 4096 channels apiece, while the third performs 1000-way ILSVRC classification and so has 1000 channels (one for each class). The soft-max layer is the last layer.

3. EXPERIMENTAL RESULTS

Data Exploration

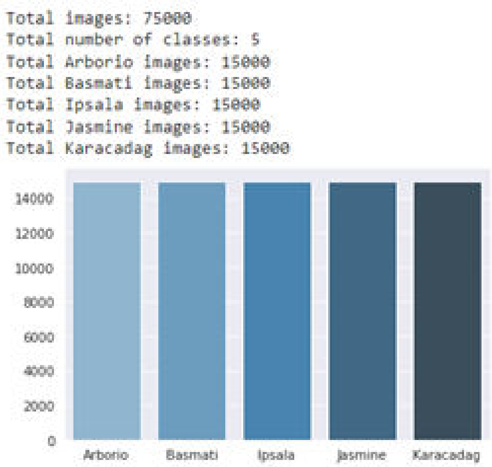

Fig 4: Data Exploration

Vanilla Neural Network

Training Model

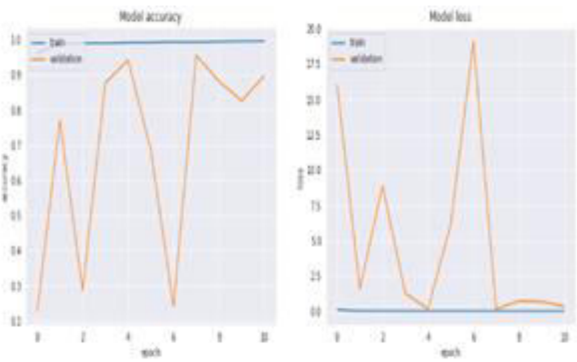

Fig 5: VNN Training Model

Model Evaluation of VNN

Confusion Matrix

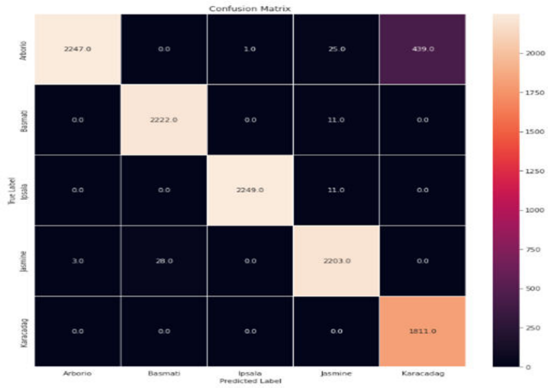

Fig 6: VNN Confusion Matrix

VGG16

Training Model

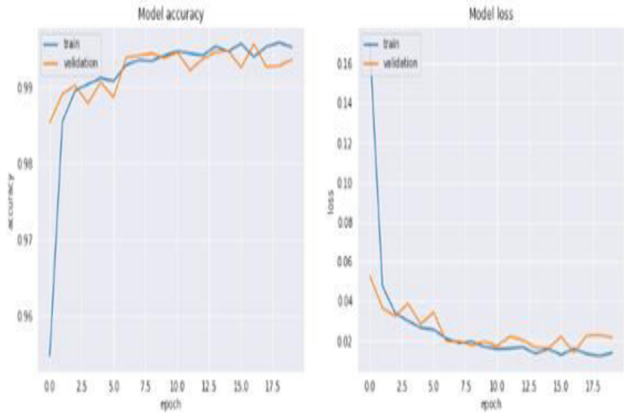

Fig 7: VGG16 Training Model

Evaluation of VGG16

Confusion Matrix

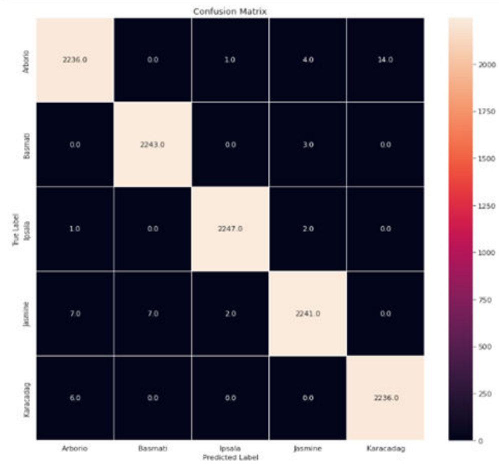

Fig 8: VGG16 Confusion Matrix

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Final Output

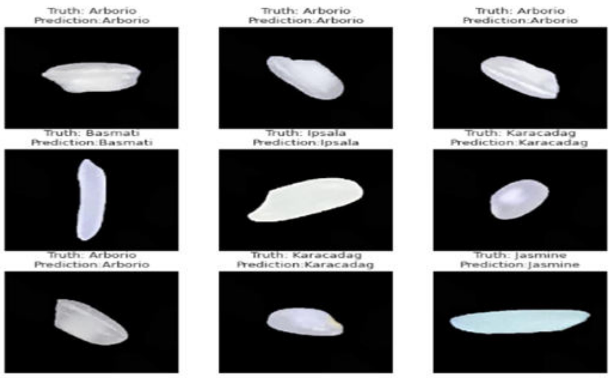

Fig 9: Final Output

CONCLUSION

Images of different types of rice were classified using deep learning models like the Vanilla Neural Network (VNN) and VGG16 (Visual Geometry Graph). Using massive image datasets, a unique model has been constructed that classifies approximately 75000 photos from five different types of rice, with each type having 15000 images in a dataset. Performance metrics were brought up in respect to cross validation. Subsequently, the testing data are evaluated, and the best model for assessing the quality, texture, color, and other attributes of rice is selected based on its highest accuracy rate. Based on the effectiveness and precision of all four methods, we choose the best classifier. Accuracy of VGG16 (99.5%) and VNN (95.3%). VGG16 is considered the best classifier because it has the highest accuracy of all of the models, at 99.5%. The second model has a 95.3 percent accuracy rate. These are the methods that were tested and yielded the most precise outcomes on schedule.

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