Image Classification for Rice varieties using Deep Learning Models

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Abstract:
Rice is the most rapidly growing crop in India, and as the population grows, demand for rice also increases. The majority of Asian countries grow rice and export it worldwide. The various rice varieties have been cultivated depending on the people's food culture. At the same time, food quality is a top priority, so we use computer vision techniques to extract rice qualitative features. The products are analyzed using image processing techniques for physical attributes such as Visual Geometry Graph (VGG16) and Vanilla CNN (also known as vanilla neural networks) to identify traits and textual features of rice grain images. VGG16 consists o f CNN architecture with 16 layers. It can train millions of datasets and achieve the highest accuracy rate. In addition, another model, namely vanilla neural networks, is an extension of the linear regression model. However, vanilla CNN has an additional hidden layer between inputs and outputs that help with extra computations. Image processing techniques are combined with neural networks to provide more accuracy in the training model rather than the manual process. Jasmine, Basmati, Arborio, Ipsala, and Karacadag rice varieties are the five types of rice image datasetsused for classification. Each of these varieties has 15000 images, for a total of 75000 images used in the training and testing process. The best image classifier is chosen based on the best accuracy score. The proposed model's outcome deliberates the better performance in determining the rice varieties.

Keywords: Convolutional Neural Network**,** Vanilla Neural Network, VGG16, Rice varieties

1. Introduction

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 pre-trained 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.

In contrast, the classification layer is upgraded from a three to two-layer fully connected layer. The ReLu function acts as an activation function. The dropout layer is increased to prevent overfitting, which reduces the number of parameters and improves the performance of the VGG16. Another model used is vanilla neural networks. It is the extension of the linear regression model. Still, both differentiates with vanilla CNN has one more hidden layer added between inputs and outputs that helps for extra computations will work in this hidden layer. We can also consider variable-length information, such as video frames and make judgments for each video frame.

A vanilla neural network's architecture is powerful enough to apply a nonlinear "activation function" comprising weights and bias to the output of each layer. The weighted sum in a vanilla neural network is calculated at each step depending on the number of layers in the network and the type of activation function used, such as the ReLu function, logic function, or hyperbolic tangent function (tanh). These models have been created by using Artificial Neural Network (ANN) and Deep Neural Network (DNN) for feature images, and for dataset images, Convolutional Neural Network (CNN) has been used. Image processing techniques are combined with neural networks, in which a neural network is trained rather than a person. The rice varieties are Basmati, Jasmine, Arborio, Ipsala, and Karacadag. These are the five types of rice image datasets taken for classification. The rice varieties contain 15000 images, and a total of 75000 images are taken for both the training and testing process [1].

The literature study, Ramesh et al. in 2022, primarily focused on recent achievements and rice quality inspection based on qualitative features. To extract textural features from rice images, they used the GLCM method. Thresholding helps determine the suitable light intensity range by removing all other pixels from a greyscale image. They concentrated on rice varieties and image processing to separate rice stalks. To identify impurities and classify rice grains to prevent damage from pests and illnesses, they used optimization approaches such as Artificial Neural Networks (ANN) and Support Vector Machine (SVM). Ilkay CINAR and Murat KOKLU used machine learning models such as Support Vector Machine (SVM), Linear

Regression (LR), Random Forest (RF), Decision Tree (DT), and Multi-Layer Perceptron (MLP) to classify rice varieties in 2019[1]. They achieved the highest accuracy rate of around 96 per cent classification success, but only for a small number of images (nearly 2000). Another study was about Kosba in 2016; they analyzed the chalkiness of linked rice kernels using image processing technologies and Support vector machines. Using a morphological erosion technique, they focused on splitting and detecting connected kernel chalkiness. The rice kernel's grayscale level between chalky and standard regions extracted chalkiness.
In the subsequent study, Zhencun Jiang 2021 [7] conducted image recognition research on four types of diseases using a deep learning network of migration learning. They used AlexNet to pre-train on ImageNet and reorganized a new, wholly linked layer with an average accuracy of 91.25 per cent. It was revealed that transfer learning is commonly used in less data, and the pre-trained model can greatly enhance accuracy. Multitask learning is a traditional machine learning method in which one model is used to complete multiple tasks. Another study by Phadikar et al. in 2013 [8] classified rice illnesses using characteristics extracted from affected regions of rice plant pictures. They employed a Fermi energy-based segmentation method to isolate image features using rough set theory to remove only selected features to solve the issue. The subsequent study was by Syed Jahangir Badashah in 2020 [9]; they used image processing techniques like greyscale conversion and median filtering to identify rice varieties in the field. On basmati, masoori, and brown rice varieties, the levenberg-Marquard method is employed to classify them. The properties of rice grains are recovered from collected photos using image processing methods in the subsequent investigation. To obtain an accuracy rate, Machine Learning models were applied to datasets. However, the main flaw is the lack of accurate rice analysis results. They used logistic regression, random forest, decision tree classifier, and support vector machine to get the best results. The logistic regression results are more accurate among the ML models mentioned above. Deep learning has recently gained popularity in image recognition as computer vision, and artificial intelligence technologies have advanced - Xiong et al., 2021 [10]. CNN (Convolutional Neural Network) is one of the most commonly used neural networks in deep learning. CNN has strong self-learning, adaptability, and generalization abilities. Many people have used traditional machine vision algorithms to classify rice varieties. However, most of the works in literature are implemented on smaller image datasets, whereas we used massive ones.

In this work, our main objective is to create a new model to classify the rice varieties by considering huge dataset images (i.e., 75000 images). In addition, we used some performance metrics such as cross-validation, loss, and accuracy to validate the proposed work. Furthermore, the experimental results are measured and compared between the models with accuracy rates such as rice quality, texture, colour etc.,

2. Related work

Towards an automated rice purity measuring device: a device imaginative and prescient primarily based neural network-assisted imperialist aggressive set of rules method posted with inside the year 2013 [11]. Researchers investigated image processing and imaginative and prescient abilities for wheat purity detection. The primary intention of this paper [12] is to manufacture robotic wheat purity grading devices. They have used algorithms based on artificial neural network and computational algorithms to discover pleasant accuracy; however, the proposed method does now no longer offer enough accuracy. In 2013, the paper improving deep neural networks for LVCSR [13], the usage of rectified linear gadgets and dropout turned released. Deep neural networks performed superb consequences on numerous speech reputation benchmarks. The primary difficulty of this paper is greater time complexity to get dropout will increase through schooling the humongous vocabulary speech reputation. To conquer this difficulty, they have got used ReLu rectified activation function. For this implementation, they used Bayesian optimization code and were capable of gain consequences with minimum human parameters. They analyzed the results of CNN baseline, ReLu and MBR fashions with complete series schooling; the restrictions are notice detected massive benefit from the usage of dropout with sigmoid nets. In 2012 [14], using image processing techniques and SVM classifiers, researchers investigated the creamy sweetness of Connected rice grains. An image is converted into digital form using image processing techniques.

Using a morphological erosion technique, the paper in [15] focuses on splitting and detecting connected kernel chalkiness. The author used the grayscale level among powdery and regular portions in the grains to extract chalkiness. The chalky white rice grains were classified using an SVM classifier. They discovered that employing SVM improves the accuracy of indica and japonica rice. In 2013, a study used characteristic evaluation and ruled evolutionary algorithms to classify rice diseases. The paper's primary goal in [16] is to classify rice illnesses using characteristics extracted from affected regions of rice plant pictures. They employed a Fermi energy-based segmentation method to isolate image features using rough set theory to remove only selected features to solve this problem. Compared to other classifiers, they used a rule-based classifier to control information loss and deliver the best results with less computing complexity. A review of potential computer vision applications in rice quality inspection was published in 2015[17]. They focused entirely on recent achievements and a pleasant assessment of rice's qualitative qualities. To extract textural data from rice photos, they hired the GLCM approach. Thresholding is a technique for removing all other pixels from a greyscale image and determining the suitable light depth range. They focused on rice varieties and picture processing to split rice stalks. They hired optimization strategies, neural networks, and classifier algorithms to pick out impurities and classify rice grains to lessen the harm of pests and diseases.

In 2016, the researchers developed [18] Identifying rice grains utilizing image evaluation and sparse-representation-based altogether classification. We used picture evaluation and SRC strategies to nondestructively distinguish the rice grains of 30 types for this study. The rice grains of numerous types confirmed morphological and shade differences. It caused the improvement of picture-primarily based strategies for distinguishing rice grains. According to the millimetre inside the proposed method, the rice grain photos using microscopy data was about ninety-five pixels. They observed an excessive decision allowed exceptional info about the rice grains. The grain's morphological, textural, and shade trends were quantified, and the author created an SRC classifier to expect the grain types and usage of the trends as inputs. The accuracy of the classifier, as mentioned above, was 89.1 %. The author used image processing and a support vector machine classifier to segment and classify rice samples published in 2018 [19]. This paper categorizes objects from rice samples based on feature extraction and ML techniques. They employed a dataset of five unique rice types and classification using machine learning models and single kernel-based SVM classifiers. Because of the light-weighted algorithms and feature vectors, The proposed model is more efficient in algorithmic efficiency and generates better outcomes in less time than earlier processes. The accuracy rate of segmentation and classification is 96% and 88%.

Vijayaratnam Emulse Nirmalan et al. introduced a Comparative Analysis of Different Features and Encoding Methods for Rice Image Classification in 2018 [20]. They compared the different features, namely SIFT, Multi-resolution Local Patterns, Local Color Histograms, and Random Projections. In addition, they used the feature encoding methodologies to classify rice grain images of Bag-of-visual-words, Sparse Coding, Vector of Locally Aggregated Gradients, and Fisher Vectors. They show that SIFT features with Fisher Vector encoding or Vector of Locally Aggregated Gradients generate the best results by examining the performance of a classification model with two-fold cross-validation on a dataset of 1000 photos, including ten rice categories (mean accuracy of 97%). They discovered that increasing the dictionary size increased classification performance for all feature encoding schemes.

Nguyen Hong Son and Nguyen Thai-Nghe presented Deep Learning for Rice Quality Classification in 2019[21]. In this methodology, the author used Convolutional Neural Networks and image processing techniques to distinguish and categorize two types of rice (whole rice and broken rice) based on their size in the national standard of rice quality evaluation. The accuracy of 2000 authentic images in the experiment was 93.85%. In addition, the author used Support Vector Machines with HOG features, and k-Nearest Neighbors approaches to categorize and compare the accuracy of those algorithms with results of 85.06 per cent and 84.30 per cent, respectively. These findings show that rice quality evaluation and categorization might be done automatically by utilizing a Deep Learning technique.

Ilkay CINAR, Murat KOKLUin 2019[1] introduced intercalary Classification of Rice Varieties victimization computing Methods. This study focused on cleaning, colour sorting, and rice types. For this approach, models such as providing Regression, Multilayer Perceptron(MLP), Random Forest(RF), Support Vector Machine(SVM), and call Tree were developed (DT). The author used 3810 rice grain pictures to analyze the performance indicators such as confusion matrix, accuracy, precision, and F1 score. By combining all of the models, they were able to achieve an accuracy of93.2percent (LR), 92.86 per cent (MLP), 92.83 per cent (SVM), and 92.39 per cent (RF) and 92.49 per cent (RF) (DT). Regression is the most accurate of all the models and is regarded as a good model.

ShubhamMittal, MalayKishoreDutta, and AshishIssac in 2019 [22] projected a Non-damaging picture system based mostly wholly machine for analysis of rice pleasant connected defects for sophistication keep with inferred business value. This paper proposes a low-cost, machine-pushed image processing-primarily based machine for classifying rice samples supported by their fundamental business value. The grain barriers were regarded using a divided grayscale exposure of a rice pattern equipped with an Associate in nursing conic section. The geometrical homes derive from the oval fit. The pattern alternatives are averaged, and as well the operate vector is fed into SVM for multi-elegance categorization. The trial results reveal that the proposed machine provides 93percent, which is a significant addition to picture system-based totally rice pleasant evaluation. Future paintings could specialize within the occasion of image technique algorithms with advanced accuracy and shorter methodology instances for grading rice samples.

In 2019, an investigation of machine-learning for predicting composition was revealed: studies in yeast, rice, and Associate in Nursing wheat. This paper [23] deals with the physical characteristics of an organism that foretold the information of its genotype and surroundings in phenotype prediction. The phenotype prediction issues are easy and clean (yeast), complicated, and real-world (rice and wheat). The author utilized machine learning models to predict the phenotype gradient boosting machines compared to the bloom and random forest. Basha S et al. in 2021 [24] proposed Classification of Rice Grains using Wavelet Transformation and Neural Networks Extraction Of features. They employed image processing techniques such as grayscale image conversion and mean. In this study, the author used average filtering to produce accurate results in identifying rice types. In addition, they used Liebenberg- Marquard algorithm for classification and tested on basmati, masoori and brown rice types. The proposed model showed the highest accuracy by efficiently extracting rice images; it was published in 2020 and proposed rice grain classification using image processing and machine learning models. Image processing algorithms help get the rice grain parameters from the captured images. Supervised Learning models have been applied to datasets to obtain an accuracy rate. The main issue with the paper is rice analysis with better accuracy results. They employed a logistic regression model, Random forest model, and Support vector machine to achieve the best results., decision tree based classifier where Logistic regression outperforms all of the above Machine Learning models in terms of accuracy.

In 2021 [25], the author introduced the Rice phenology type primarily based entirely on a random wooded area set of rules for data imbalance using the Google Earth Engine. According to the proposal, It is one of the most critical industries globally, significantly contributing to its Sustainable Development Goals (SDGs). The SDG's second most important indicator, zero hunger, addresses food security (SDG 2). Rice manufacturing data is required to estimate the reputation of food security. Rice phenology is a process that involves watching the growth section of a food plant. In Lamongan Regency, the functions of an imbalance situation., minority training was sampled using an oversampling approach to correct the imbalance. Researchers in [26] introduced Multitask deep transfer learning to recognize rice and wheat leaf diseases. The problem is about rice types from many Asian countries, which affected rice and wheat's growth with various conditions. They tried to improve the VGG16 model based on multitasking transfer learning. They tested forty rice and wheat plant diseases images that yielded an accuracy rate of 97% for rice plant diseases and a 98% accuracy rate for wheat plant diseases. By improvising the method, they declared that it would be the best to identify lead diseases.

Rice plant illness detection and classification using an attention-based neural network and Bayesian optimization [27] published in 2021. The ADSNN-BO model is proposed based on a mobile Net design and enhanced attention, and it is used to classify images and detect rice leaf illnesses. They have used the Bayesian optimization method to tune hyper-parameters and cross-validation for better accuracy. The proposed plan had achieved an accuracy of 94%, excelling the other models in the classification of rice diseases. In 2022 [28], the researcher proposed a new approach for image pixel classification for rice variety identification to series data from Sentinel-2 satellite images. They focused on the farming industry, where rising demand has created confusion for producers, regulators, and officials. The author collected the data from 12 rice fields (approximately 307 acres) in 16 different geographical areas. A linear spectral un mixing model identifies particular sub-data on water, soil, and vegetative mix, then used to label each pixel for supervised learning. Our classifiers fed a 16,15 image with 15 spectral features per pixel from 16 different time occurrences as input. Each pixel is semantically classified into Basmati, IRRI, various soils, water, and other categories. According to testing data, the proposed approach has an overall accuracy of 98.6%. Basmati rice had an accuracy rate of 99%, which was compared with IRRI rice had an accuracy rate of 95.2%

In 2022 [29], the researcher proposed a deep CNN-based damage classification of milled rice grains using a high-magnification image dataset. To determine market acceptance, they concentrated on rice grains' surface quality, which was time-consuming. The damage classifications are nutritious, full chalky, broken, half powdery, damaged, and damaged. Normal, individual class accuracy is 98.33 %, 96.51 %, 95.45 %, 100 %, 100 %, 99.26 %, and 98.7%. With a model size of 47 MB and a prediction time of 0.122s, the EfficientNet-B0 architecture achieves a classification accuracy of 98.37% and can further sub-classify the chalky class into three different categories: full chalky, half chalky, and chalky discoloured. This study indicates that deep CNN architectures can reliably diagnose damaged rice grains using a high-magnification image.

3. Datasets and Methods

This section has discussed datasets and the two techniques, namely Vanilla Neural Network and VGG16 models. Initially, we discussed the rice variety datasets used in this work. Further, we presented the Vanilla neural network structure and its working mechanism for image classification. Later, the VGG16 model is discussed with its working tool to accurate the result prediction.

3.1 Datasets

This work utilized the datasets with five rice varieties: Arborio, Ipsala, Basmati, Karacadag, and Jasmine harvested in Turkey. The datasets consist of 75000 images with 15000 images of rice grains type. The image in the datasets is RGB images with the size of 250×250 pixels. In addition, the datasets hold a second feature with twelve morphological, ninety colour and four shape features [1]. We presented the twelve morphological structures and four shape features in Tables 1 and 2. In table 2, the SF determines the shape factor and the equations are presented. Further, the ninety various colours are created based on the variations of RBG to HSV and YCbCr (Y-Luminance, Cb – Chroma blue, Cr – Chroma red) and XYZ colour regions.

Table 1. Twelve Morphological structure

Morphological Structures	
Minimal Axis Length	Convex Area
Perimeter	Eccentricity
Solidity	Equivalent Diameter
Extent	Aspect ratio
Roundness	. Compactness
. Area	. Major Axis Length

Table 2. Four shape structure and equations

Shapes	Equations
SF_1	$\frac{Major\ Axis\ Length}{Area}$
SF_2	$\frac{Minimal\ Axis\ Length}{Area}$
SF_3	$\frac{Area}{\left(\frac{Major\ Axis\ Length}{2}\right)^2 \times \pi}$
SF_4	$\frac{Area}{\frac{Major\ Axis\ Length \times Minimal\ Axis\ Length}{2} \times \pi}$

3.2 Vanilla Neural Network

A Vanilla Neural Network works similarly to linear regression. The difference is the newly inserted layer between the inputs and outputs. This extra layer is concealed from view when we utilize a NN in real life because the NN handles all the different calculations behind the scenes. Multi-layer artificial neurons, namely vanilla neural networks, consist of one hidden layer. There are three nodes in an MLP: input, hidden, and output. Vanilla neural networks have three layers, such as

a) Convolutional layer
b) Pooling layer
c) Fully Connected layer

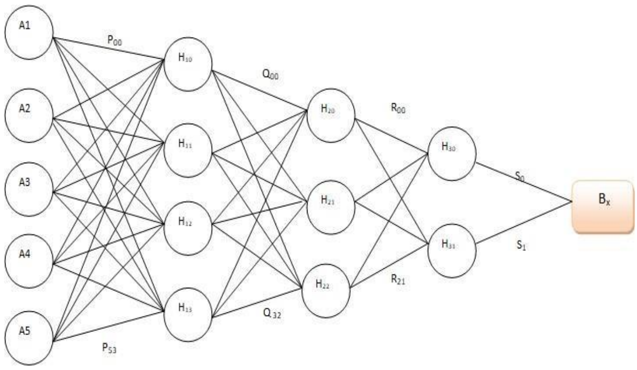

Fig: 3 Vanilla CNN layer Architecture

a) *Convolutional layer*

Convolutional neural networks (CNN) are one of the most significant components of neural networks. Convolutional Neural Networks use image recognition and classification to recognize objects, distinguish faces, and many more. They consist of neurons with weights and biases. Each neuron in the Receptive field, a portion of the visual area, responds to different stimuli. The whole visible lot is covered by these groups, which will overlap. This convolution process aims to extract high-level information from the entire image, and then high-level features are used to add the image's edges. This layer can work with high-level and low-level features, like color and gradient orientation. In addition, this architecture was processed to the next level by adding two more layers. Two layers are named valid padding and the same padding. This layer aims to reduce the dimensionality of the image contained in the original input image, enhance it, or, in some instances, keep it unchanged, depending on the desired outcome. The same padding is used when the idea must be twisted to many matrix dimensions, but valid padding is used when the matrix dimension does not need to be modified.

b) *Pooling layer*

CNN's are commonly used to classify various images, cluster them based on similarities, and identify multiple objects. These algorithms can recognize faces, signs, animals, and other items. The width and height of a standard color image are illustrated by the number of pixels in those dimensions. The most negligible levels of the three layers of colors (RGB) that CNNs understand are channels. In this layer, we remove all negative values from the filtered photos and replace them with zeros. It takes place to keep the weights from adding up to zero. When the input value surpasses a certain threshold, the Rectified Linear Unit (ReLu) transform function initiates an ode. The result will be zero if the data is less than zero, but it will increase if the information is more than a particular threshold. It has a linear relationship with the dependent variable. For each sliding window, the pooling layer offers the maximum value. Further, Pooling is divided into two categories: *Max Pooling*-The Max Pooling gives the maximum value within the Kernel's covered image, and *Average Pooling*-The Average Pooling function gives the average value inside the Kernel's hidden picture.

c) *Fully Connected layer*

A fully connected layer requires flattening. The full pooling feature map matrix is converted into a single column that is subsequently fed into the neural network. We used fully linked layers to combine these features into a model. Finally, we use an activation function like SoftMax or sigmoid to classify the output. As evidenced by the production of the Convolutional layer, adding the FC layer is usually the straightforward approach for learning nonlinear combinations of abstract level structures. Nonlinear functions can be discovered using the FC layer. As converting our image output into a specific form of Multi-layer Perceptron is completed, we must now flatten the output image into a column vector. Across several epochs, the model has essentially successfully differentiated between dominant and low-level features.

3.3 VGG16

An input layer, an output layer, and numerous hidden layers will make a Convolutional neural network. VGG16 is a CNN (Convolutional Neural Network), which is primarily considered one of the best computer vision models available today. VGG16 is a 95% accurate item classification and identification system that can classify 1000 images into 1000 categories. It is a familiar photo classification approach that uses transfer learning and is simple. The 16 in VGG16 refers to the number of weighted layers. VGG16 has twenty-one layers, including thirteen Convolutional layers, five Max Pooling layers, and three dense layers, for a total of twenty-one layers, but only sixteen weight layers or learnable parameter levels. With three RGB channels, the input tensor size for VGG16 is 224, 244.

VGG16 is notable for having 3x3 filter convolution layers with stride one and always using the same padding and max pool layer of 2x2 filter strides 2, rather than having many hyper-parameters. Throughout the architecture, the Convolutional and maximal pool layers are grouped similarly. Conv-1 has 64 filters, Conv-2 has 128 filters, Conv-3 has 256 filters, and Conv 4 and Conv 5 layers each have 512 filters. Three Fully Connected (FC) layers are added after a stack of Convolutional layers: the first two have 4096 channels each, while the third performs 1000-way ILSVRC classification and has 1000 channels (one for each class). The final layer is the soft-max layer.

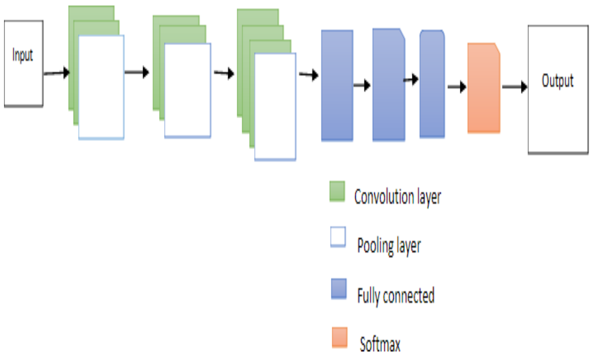

Fig 2. Architecture of VGG16

4. Experimental Results

This section contains the classification results obtained using the vanilla neural network and VGG16 algorithms. The study's data set includes characteristics extracted from 75,000 rice grain photos. This data was utilized as input in the Vanilla CNN and VGG16 algorithms. For the five rice varieties, image classification outputs were provided. The visuals in the data collection were used to give a brief overview of CNN. The performance and accuracy-based measurements of the classification algorithms utilized in the research were estimated using a confusion matrix. For both the Vanilla Convolutional neural network and VGG16 classification algorithms, the confusion matrices were produced. Based on the classification accuracy, we have utilized CNN model for better accuracy for the dataset with 75000 images obtained from rice photographs. To evaluate the performance of the proposed system, we used the metrics like sensitivity (SN), specificity (SP), Precision(P), F1-Score (F1), Accuracy (AC), and False positive (FP), False Negative (FN).

Generally, we used the confusion matrix to determine the classification accuracy in machine learning techniques. This matrix aids simply the way to decide the connectivity among the classifier's performance and test outcomes. It also helps in determining the efficacy of true and false classification of positive and negative samples [30]. The representation of the confusion matrix is presented in the reference [31]. We observed that the Vanilla CNN technique provides a classification success rate of 95.39%, and the confusion matrix of Vanilla CNN is presented in Fig. 3. This model employs 15,000 images from each rice kind as input and uses the CNN technique.

Table 3 Statistical results based on results from CNN model (%)

Metrics	**Arborio**	**Basmati**	**Ipsala**	**Jasmine**	**Karacadag**
SN	99.43	99.67	99.75	99.23	99.84
SP	99.82	99.81	99.89	99.84	99.91
P	99.41	99.72	99.84	99.21	99.64
F1	99.54	99.42	99.73	99.74	99.98
AC	99.92	99.75	99.81	99.13	99.71
FP	0.12	0.09	0.03	0.11	0.09
FN	0.38	0.39	0.08	0.52	0.37

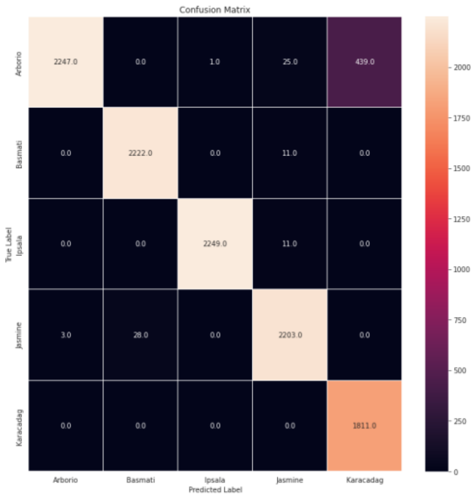

Fig 3. Vanilla CNN Confusion matrix

In addition, we utilized the weights of the VGG16 network for training the network using the transfer learning technique to gain more success in the CNN method. The confusion matrix of VGG16 is presented in Fig.4. Later, finetuning was applied in the network topology to prevent the trained CNN model from overfitting.

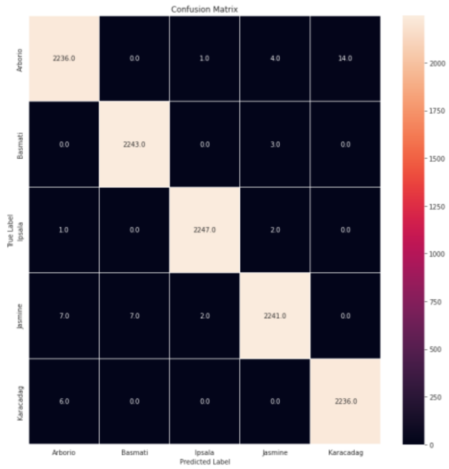

Fig: 4: VGG16 Confusion Matrix

The VGG16 model attains the classification success rate of 99.58%. The analyses of both models reveal that the VGG16 provides ~5% better accuracy than Vanilla CNN. Based on the performance analysis, we noticed that the CNN model provides better results, and the statistical results of the CNN model are shown in Table 3. The performance of the proposed model is compared with the state-of-art existing techniques, namely Support Vector Machine (SVM), Linear Regression (LR), Deep Neural Network (DNN), Convolution Neural Network (CNN) is presented in Table 4. The comparison results deliberated that the proposed model provides better results rather than existing model. The final image classification evaluation demonstrates accurate rice type prediction among five different rice varieties images.

Table 4 Comparison of proposed model with existing system

References	**Number of Images**	**Class**	**Classifier**	**Accuracy (A)**
Kaur et al. [11]	850	16	SVM	87.86%
Nazir et al. [31]	1,500	4	LR	91.54%
Aukkapinyo et al. [2]	7,500	3	CNN	98.45%
Son et al. [21]	1,700	5	DNN	99.12%
Proposed Model	75,000	5	CNN	100%

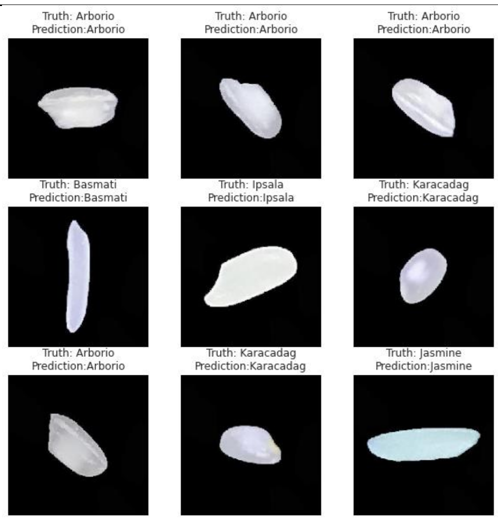

Fig 5. Final Output

The overall experimentation results of the proposed work are measured and presented in Figure 5. Fig.5 conveys the calculated texture properties of all rice kernels with 100% accuracy rate. The model deliberates the outcome with better classification and proves its efficacy in determining the variety without any deviation in the results.

5. Conclusion

Deep learning models such as Vanilla Neural Network (VNN), and VGG16 were used to classify images of rice types (Visual Geometry Graph). We developed a novel model by utilizing enormous picture datasets in this work. It is classified using roughly 75000 photographs from five rice types, each of which has15000 images in a dataset. Cross-validation is presented concerning performance metrics. We selected the model with a high accuracy rate in the testing phase to better evaluate rice quality, texture, color, and other characteristics. We selected the most effective classifier based on the efficiency and accuracy of all two techniques. VNN (95.3%), VGG16 (99.5%) accuracy. VGG16 has the highest accuracy of 99.5% among the rest of the classifiers. We used CNN with VGG16 model to achieve better classification of rice varieties. The proposed model outcome deliberates the better performance in determining the accurate rice varieties with accuracy of 100%.

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