Rice Category Identification through Deep Transfer Learning Features and Machine Learning Classifiers: An Intelligent Approach

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***Abstract*—Rice category identification by image analysis is essential to ensure the quality and safety of rice production. In this study, we propose an intellectual approach to improve rice category identification using deep transfer learning features and machine learning classifiers. Specifically, we extracted features from three pre-trained models (Inception V3, VGG-19 and VGG-16) using transfer learning techniques. These were used as inputs to train MultiLayerPerceptron (MLP) and support vector machine (SVM) classifiers. The results of our experiments show that the proposed strategic results achieve high accuracy in identifying rice categories. The SVM (polynomial kernel) achieves the second-highest accuracy among all models and features, with an accuracy of 0.9948 using the VGG-19 and 0.9912 using Inception V3. The MLP classifier with (30 30) hidden layers achieve the first high accuracy, with an accuracy of 0.9972 (99.72%) using VGG-19 features. The results also show that the choice of deep transfer learning model and machine learning (ML) classifier can significantly affect the accuracy of rice category identification. Among the three pre-trained models, VGG-19 features consistently perform the best, followed by Inception V3 and VGG-16. The choice of MLP hidden layer size also affects the accuracy, with 30 HL neurons achieving the best performance. Our proposed approach using deep TL features and ML classifiers shows promising results in improving rice category identification. Our study provides valuable insights into optimizing ML models for agricultural image analysis.**

***Index Terms*—Feature extraction, Machine Learning, MLP, Rice, SVM, Transfer Learning**

I. Introduction

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RICE is a fundamental staple food consumed globally [1]. Categorizing rice based on its quality and characteristics is crucial for farmers, processors, and consumers [2]. However, manual classification of rice is time-consuming, subjective, and prone to errors. To overcome these limitations, researchers have proposed various automatic rice classification methods. Deep transfer learning refers to the transfer of knowledge from a pre-trained model to a new problem domain. Utilizing deep transfer learning, pre-trained models can be used to extract features for classification tasks [3]. This approach has shown promising results in various computer vision applications, including rice classification. The proposed methodology uses pre-trained deep transfer learning models to extract high-level features from rice images. The extracted features are inputted into ML classifiers, such as SVM and Multilayer Perceptron (MLP), to categorize rice into different classes. The proposed approach to enhancing rice category identification through deep transfer learning and ML classifiers is a promising solution for rice classification. This approach can provide accurate and efficient results while reducing the need for manual intervention.

The proposed approach has several advantages over traditional rice classification methods. It reduces the need for manual feature engineering, as pre-trained models can automatically extract relevant features from rice images. Additionally, it can handle large amounts of data with high accuracy and speed, making it suitable for industrial applications in the rice industry. The use of deep transfer learning and ML classifiers to enhance rice category identification is a promising solution. This approach can provide accurate and efficient results while reducing the need for manual intervention. The following section presents the remaining content of the paper.

- **Section 2:** the Literature Review section provides a summary of previous research in agriculture, with a focus on rice category identification. Relevant studies and methodologies used in those studies are discussed, and gaps in the existing research that the current study aims to fill are highlighted. The literature survey covers topics such as ML and DL techniques, models of feature extraction, and classification.
- **Section 3:** Methodology and Materials typically describe the methods used in the study. The data collection process and techniques have been used for feature extraction, and the classification algorithms have been used to analyze the data.

- **Section 4:** Result Analysis presents the results of the study. Tables, graphs, or other visual aids may be provided to help readers understand the data. The authors may also analyze data to support their findings and discuss any significant results they observed.
- **Section 5:** Discussions and Conclusion, which discusses the implications and findings of the study and what they mean for the field of rice identification. The authors have discussed this research's limitations and proposed ideas for future studies. Finally, the authors should summarize their findings and main points of the paper, providing a clear conclusion.

II. Literature Review

This literature survey reviews current research on the rice categorization system using extracted features from deep TLs. The performance indicators used to assess these models' efficacy are examined, and the limitations and challenges of current system approaches are discussed. Yakkundimath et al. [4] researched rice disease classification using CNN models. They found that the VGG-16 and GoogleNet CNN methodologies achieved CAs of 91.28% and 92.24%, respectively, in identifying rice disease symptoms in the field. Son et al. [5] also classified rice using DL models. Their proposed approach using CNN achieved 93.85% accuracy in recognizing and classifying whole and broken rice based on national standards. The k-NN and SVM models showed accuracies of 84.30% and 85.06%, respectively. This study demonstrates the potential of DL in automating the evaluation and classification of rice quality. Liang et al. [6] researched the recognition of rice blast disease (RBDR) using CNN models. The proposed CNN model, specifically the CNN with Softmax and SVM, exhibited superior accuracy, AUC, and ROC curves compared to LBPH+SVM and Haar-WT+SVM. The AUC and ACC (accuracy) values of CNN (0.99 and 95.83%) and CNN+SVM (0.99 and 95.82%) were noteworthy.

Kiratiratanapruk et al. [7] discussed using machine vision technology (MVT) as an alternative for fast, accurate, cost-effective, and non-destructive automated processes. The study employed MVT to classify Oryza sativa rice into 14 varieties and achieved a high accuracy rate of 95.15% using the DL model from InceptionResNetV2. Aznan et al. [8] discussed using ML with computer vision to classify rice subjects based on color and morphometric digital images extracted features obtained from smartphones. The study got the highest CA (90.7%) of the ANN's Bayesian regularization model. Deng et al. [9] developed an automatic diagnosis method for rice diseases applying DL and smartphone apps. The technique was created leveraging a huge collection of 33,026 rice diseases with 6 types. An ensemble model was employed to integrate three sub-models: SE-ResNet-50, and DenseNet-121. The Ensemble Model achieved an accuracy of 91%, reducing the misdiagnosis of diseases.

Jeyaraj et al. [10] trained and tested the system on a large dataset of over 7,000 images of 11 rice varieties. The proposed model achieved 98.2% accuracy with AlexNet. The authors compared four classifier models for a specific task, showing their accuracy, sensitivity, specificity, F1 score, and computational time. The proposed network outperforms other models with the highest accuracy (96.4%), specificity (97.4%), F1-score (97.2%), and the lowest computational time (10 seconds). The GoogleNet model also performs well, while the SVM model is the least effective, with the lowest accuracy (81.5%) and F1-score (80.2%). Koklu et al. [23] researched the quality of rice seed classification. The study used ANN, DNN, and CNN algorithms to create predictive models from 75,000 pictures containing five kinds of rice and a further collection with 106 element features. The study found that ANN achieved 99.87% accuracy, DNN achieved 99.95%, and CNN achieved 100% accuracy. These findings suggest that the models can successfully classify rice varieties. Indra et al. [12] aimed to classify excellent and damaged rice using a segmentation process with HSV color space and a GLCM for feature collection, followed by a CNN for classification. The study resulted in a prediction accuracy of 83%. Robert Singh et al. [13] presented a method to classify four types of image processing of rice grains using a cascade network (CN) classifier, considering four arrangements of elements. According to the result analysis, a CNN classifier and a BPNN were utilised for most classifications of rice types A, B, and D, achieving an accuracy range of 92% to 100%.

Shen et al. [14] proposed a method for mapping rice using optical-SAR imagery with high accuracy. The technique requires only one clear sky optical image combined with multi-temporal SAR images. They designed an algorithm to optimize object-oriented segmentation parameter classifications. The authors achieved an accuracy of 94.64% in Yangzhou City and demonstrated strong robustness to the instability of SAR image acquisition time. With an accuracy of 90.09 percent, the method consistently mapped rice in both cloudy and wet regions. Ruslan et al. [48] classified cultivated rice seeds and variants of overgrown rice seeds through the use of ML and IP techniques. The best model was achieved using RGB images and logistic regression, resulting in all 67 traits were correctly classified with 99.5% specificity, sensitivity-85.3%,accuracy-97.9%, and a median accuracy of 92.4%. Li et al. [16] proposed the EfficientNetB3DAN ML model for rice processing seed health detection. The results indicate that EfficientNet-B3-DAN outperforms other models with an overall detection accuracy of 94.17%. In a study by Hamzah et al. [17], methods for classifying the quality of white rice grain were reviewed. The authors found that the most accurate methodology was the ANN with backpropagation NN (BPNN) at 96%. They suggest exploring hybrid methods in ANN for future work.

Kaplan et al. [18] analyzed Seventy-five thousand photos were collected, with 15,000 images obtained for each rice type. These images were then used to classify five separate types of rice in Turkey. The images were classified using the k-NN and DVM models, reaching a CA of 95.5%. Arora et al. [19] proposed a method involving IP and SVM that has shown improved classification accuracy of up to 96% with minimal processing time. The three experiments used testing and training data for the classification of grains of rice. The initial two experiments, with 80-20 and 50-50 splits, achieved high sensitivity, specificity, and accuracy of 100% and 96%, respectively. However, the experiment with a 20-80 split had a reduced accuracy of 70.4% with a sensitivity (62.5%) and specificity (72%). Fatima et al. [20] proposed a framework for detecting rice grain varieties using

DL techniques. The framework employs a two-stage feature extraction and classification process using SqueezeNet and Darknet architectures. This approach achieves high accuracy in multiclass classifiers, with the proposed framework achieving 100% accuracy and a 99.2% average accuracy, outperforming previous methods. In a similar vein, He et al. [21] developed a prediction model for identifying resistant rice seeds using Raman spectroscopy, utilizing improved SVM models for the experiment. The IABC-SVM model achieved CA-100% of the test set with a running time of 13 seconds.

Sharma et al. [22] used 3000 real-time image datasets to classify fine and RLB-infected crops into two groups: infected with RLB and not infected with RLB. The study achieved high accuracy rates of 94.33% and 95.3%, respectively. Koklu et al. [23] investigated rice classification using ANN, DNN and CNN models. The dataset comprised 106 features and 75,000-grain images from five varieties commonly grown in Turkey. The models achieved high classification accuracy. The ANN accuracy was 99.87%, DNN was 99.87%, and CNN was 100%, demonstrating their successful application in rice variety classification. Díaz-Martínez et al. [24] introduced a new DL framework for classifying rice images under increased temperatures during night and day. The study also presents a user-friendly software application with a graphical interface for categorizing rice images. The application achieved an average classification accuracy of 91.33%. Zhao et al.'s [25] study demonstrates that combining CapsNets and RamanSpectroscopy can effectively identify rice GD in Heilongjiang Province, with an accuracy rate of 89% in training and 93% in testing. Saxena et al. [26] provided a technique for recognizing rice using 107 features and 75,000 samples. They used a random forest classifier to select the 20 most important features. The experimental results showed 99.85% accuracy in classifying rice samples using decision tree classification with 99.68% accuracy.

Orozco et al. [27] proposed a statistical dispersion-based ANG model for integrating spatial information with the GCN pixel spectral signature for hyperspectral image classification. This approach significantly improves classification accuracy (CA) and captures spatial and spectral characteristics with varying neighborhood pixel sizes compared to feature extraction based on fixed windows. The AN-GCN increased the classification accuracy (CA) of the data from 81.71% to 97.88% for Houston (HU) University. Kiratiratanapruk et al. [7] categorized 14 varieties of Oryza sativa rice using more than 50,000 seed samples. The study used an automated machine vision technique. The review comprises three primary cycles: pre-processing, highlight extraction, and characterization of the rice assortment. It employs four conventional AI methods and five DL methods. Cinar et al. [28] conducted a study to develop a computerized vision system (CVS) to distinguish between two exclusive rice species using 3810 images of rice grains. The AI models, including well-known ML models, identified seven features of the shape of each grain with high success rates: SVM - 92.83%, NB - 91.71%, LR - 93.02%, DT - 92.49%, RF - 92.39%, MLP - 92.86% and k-NN - 88.58%. The CVS provided high success rates for classifying rice species.

III. Model and Materials

This section presents an intelligent approach to identifying rice categories. The benchmark dataset was collected from the Kaggle repository, and pre-processing techniques were applied. Pre-trained DL models and ML classifiers were used for training and testing.

A. Proposal Model

Figure 1 displays our proposed intelligent approach for identifying rice categories using deep transfer learning features and ML classifiers. Our proposed approach includes a detailed stepwise analysis. We plan to collect rice image datasets for various rice categories and preprocess them using resizing, cropping, and augmentation techniques. Pre-trained DL models, such as VGG16, VGG19, or InceptionV3, will extract features from the images. These models will be fine-tuned on the rice images dataset to improve their ability to distinguish between different rice categories. Elements will be removed from the fine-tuned model for each image, and multiple ML classifiers, such as SVMs with different kernel types and MLPs with varying hidden layer sizes, will be trained. The proposed approach for rice category identification will be tested on a separate validation set, with the best-performing classifier chosen based on F1 score, precision, recall, and accuracy. The overall performance will be compared with other techniques, and lead removal will be investigated. This system could enhance rice sorting and grading in the food industry and aid agricultural research and development.

B. Dataset Description

Rice has many genetic variations. These variations are used worldwide to produce grain products. These variations are isolated according to characteristics, including diversity, texture, and shape. Classifying and evaluating seed quality using these characteristics that distinguish them from other rice varieties is possible. This study utilized five distinct types of rice frequently grown in Turkey: Arborio, Ipsala, Karacadag, Basmati, and Jasmine. The dataset comprises 75,000 images, with five categories of rice, each containing 15,000 images. The dataset was acquired from the Kagle ML repository. We selected 500 images for each category, for a total of 2,500 images, for the test split dataset. Figure 2 shows the randomly selected images of the rice categories.

C. Transfer Learners (TLs)

TL is a technique for reusing a previously trained model for another task [30]. The initial training step is pre-training, which teaches the general overall features of the conceptual framework. The end of the training stage notifies features particular to our data. According to experimental evidence, normal CNNs take a long time to process large image datasets. Instead of this, TL Networks are very useful[52][53]. It is important to note that this model is faster and more accurate than other custom models. The VGG network uses deeper and smaller filter sizes, such as three-by-three convolutions. The VGG-16 architecture, which includes sixteen layers of pooling (PLs), fully (FCs)

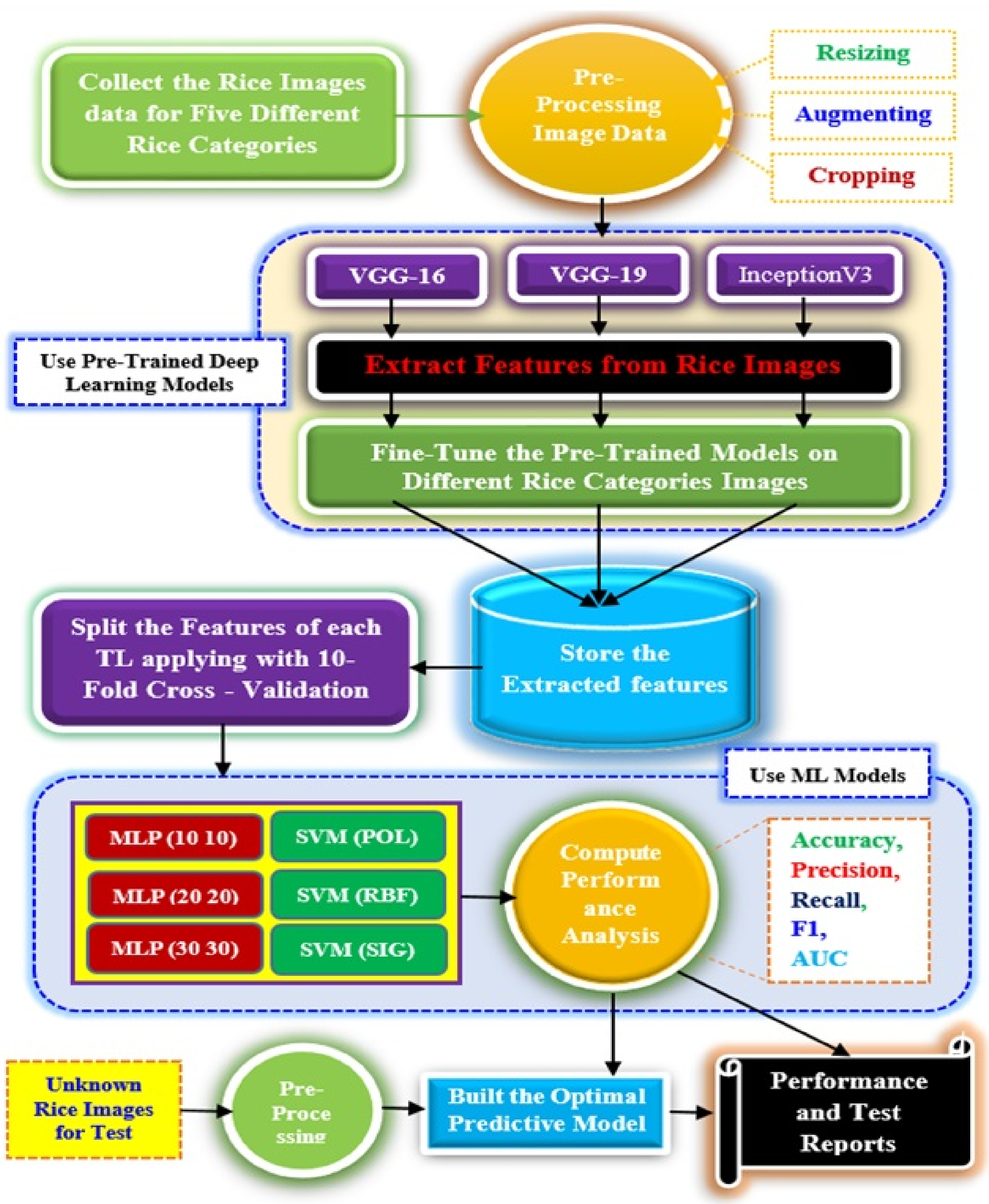

Fig. 1. Intelligent Rice Category Identification Proposal Model

connected, and convolution (CLs)layers, is a variant of VGG-Net [31][32]. Using the most straightforward convolutional filter size (3 by three conv.) allows for scanning a small portion of the surrounding pixels. Consequently, the network has discovered detailed feature representations for various images. The network accepts 224-by-224 size image input. VGG-19 is a CNN architecture developed by the VGG of Oxford University, containing 19 layers, including CLs-16 and 3-FCs. VGG-19 is a popular choice for transfer learning due to its strong performance on image classification tasks [33][34]. The pre-trained model successfully processed the large-scale ImageNet dataset, achieving high accuracy in CV tasks like image classification and object recognition by accurately tuning into the current dataset. A common approach to fine-tuning VGG-19 for transfer learning is to replace the final fully connected layers with new layers tailored to the specific task. InceptionV3 (IV3) is a CNN model developed by Google in 2015 for image classification tasks. The architecture of IV3 is designed to use multiple convolutions in parallel to capture different features in an image [35][36], allowing for more efficient use of computation resources and better feature representation. The IV3

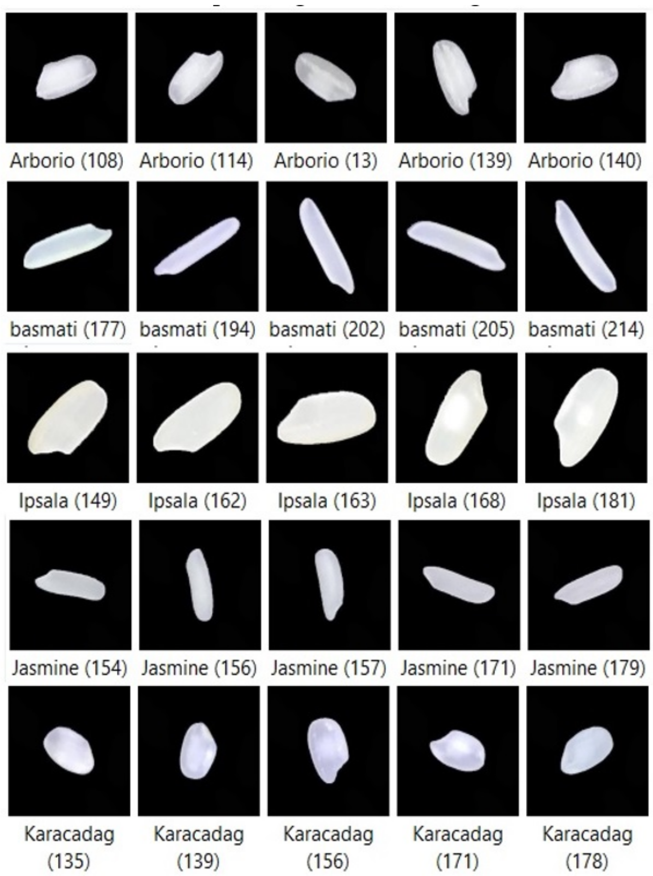

Fig. 2. Random Samples Images of Rice Categories

procedure creates a PDF over classes using CLs, PLs, and FLs. Backpropagation is used to train the PDF and reduce errors between estimated and true classes.

D. Support Vector (SVMs) Machines

SVMs are a supervised ML technique typically utilized for regression and classification applications. They function by determining the best hyperplane between two data classes. Various SVM kernels can transform the input data into a higher dimensional space, which may be more easily separable. Below is a summary of the commonly used SVM kernels: The Linear Kernel is the most basic and is suitable for linearly separable data. It maps the input data to the same dimensionality without any transformation. The Polynomial Kernel maps the input data to a higher dimensionality by raising the dot product of the feature vector to a certain degree. It works well for data with non-linear boundaries. The Gaussian (RBF) Kernel is another type of kernel[37]. In this case, the kernel maps the input data to an infinite-dimensional space, making it suitable for non-linearly separable data. The Sigmoid Kernel is a technique for mapping input data to a space of high dimensions with a sigmoid function, allowing for smooth decision-making and the capture of complicated data patterns. While it can be helpful for non-linear data, its performance can be sensitive to the choice of hyperparameters. Each kernel has its strengths and weaknesses, and the kernel is determined by the characteristics of the data and the individual situation. [38][39].

E. Performance Parameters

Accuracy is defined as an instrument's ability to measure a value accurately. The proximity of the measurement to a standard or actual value determines its accuracy [41][40]. Low readings can reduce calculation errors, and small tasks can be used to assess accuracy. Equation (1) shows the proportion of correctly classified observations.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

Precision: Based on the information its digital values convey, the precision activity demonstrates how to compare multiple measurements [40]. However, accuracy needs to be considered in its calculation. It is shown in Equation (2).

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

Recall: The recall is the proportion of accurately anticipated positives across all class inspections. It is shown in Equation (3).

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

The equation calculates the recall or sensitivity.

F1 score: The average of recall and precision combined. It is shown in Equation (4).

$$\text{F1 Score} = \frac{2 \times (\text{Recall} \times \text{Precision})}{\text{Recall} + \text{Precision}} \tag{4}$$

AUC and ROC: The ROC curve is a performance statistic used in machine learning to assess the accuracy of a binary classification model. It is computed by finding the area under the curve. The ROC curve compares the TPR against the FPR at various categorization levels. [42].

The **Lift Curve (LC)** is a crucial tool for evaluating the performance of ML models in classification problems. It provides a clear and intuitive visualization of a model's effectiveness and allows for comparing different models using the same data set. The LC displays the ratio of the TPR to the EPR at various probability thresholds predicted by the model. The EPR represents the ratio of positive instances in the entire dataset. The TPR represents the ratio of true positives among all positive samples. The LC plots the TPR/EPR ratio on the y-axis against the percentage of instances considered on the x-axis. The LC is a helpful tool for evaluating a model's performance because it shows how better it is at identifying positive samples than a baseline model randomly assigning instances to classes. The LC may be utilized to evaluate the performance of several models on a single dataset[43].

IV. Result Analysis

This section evaluates the performance of three pre-trained DL models for identifying rice categories: VGG19, IV3, and VGG16. The transfer learning features extracted from these models were input to various ML classifiers, such as SVM and MLP, for evaluation. The results analysis showed that VGG-19 outperformed VGG-16 and Inception V3, indicating its suitability for rice category identification tasks.

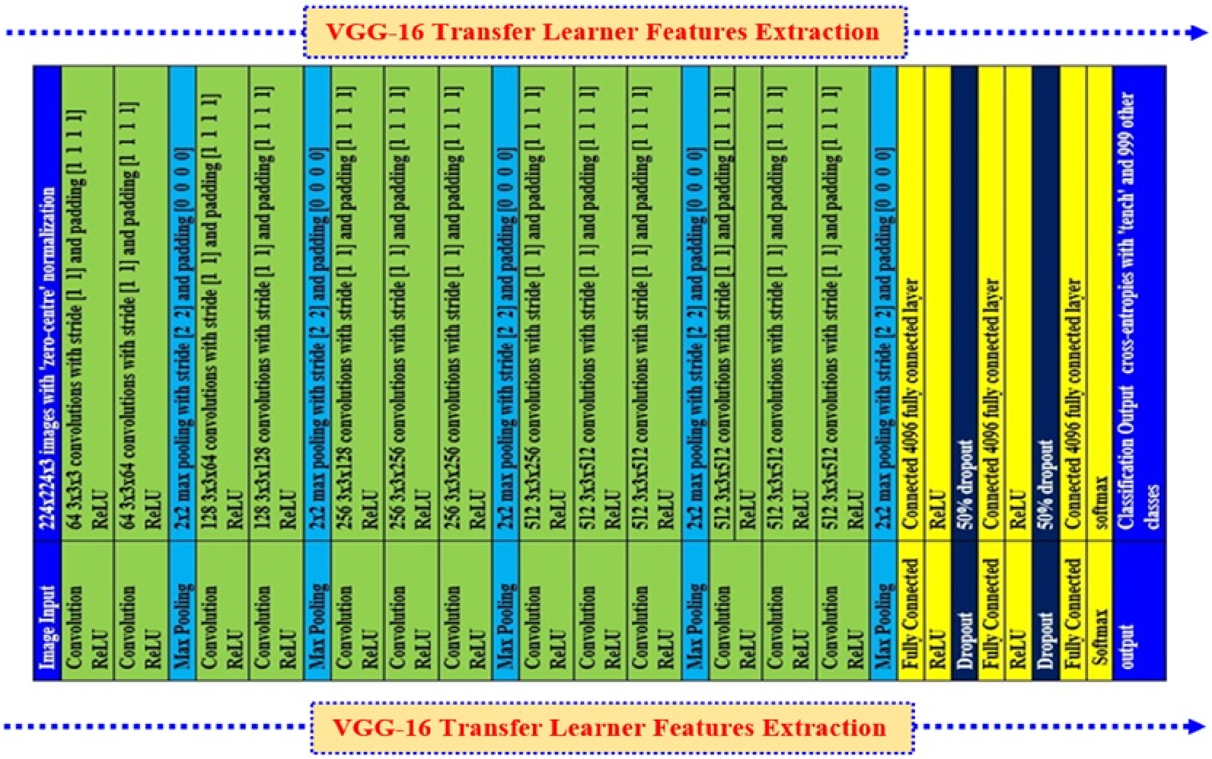

Fig. 3. VGG-16 TL Model Structure and Working Process

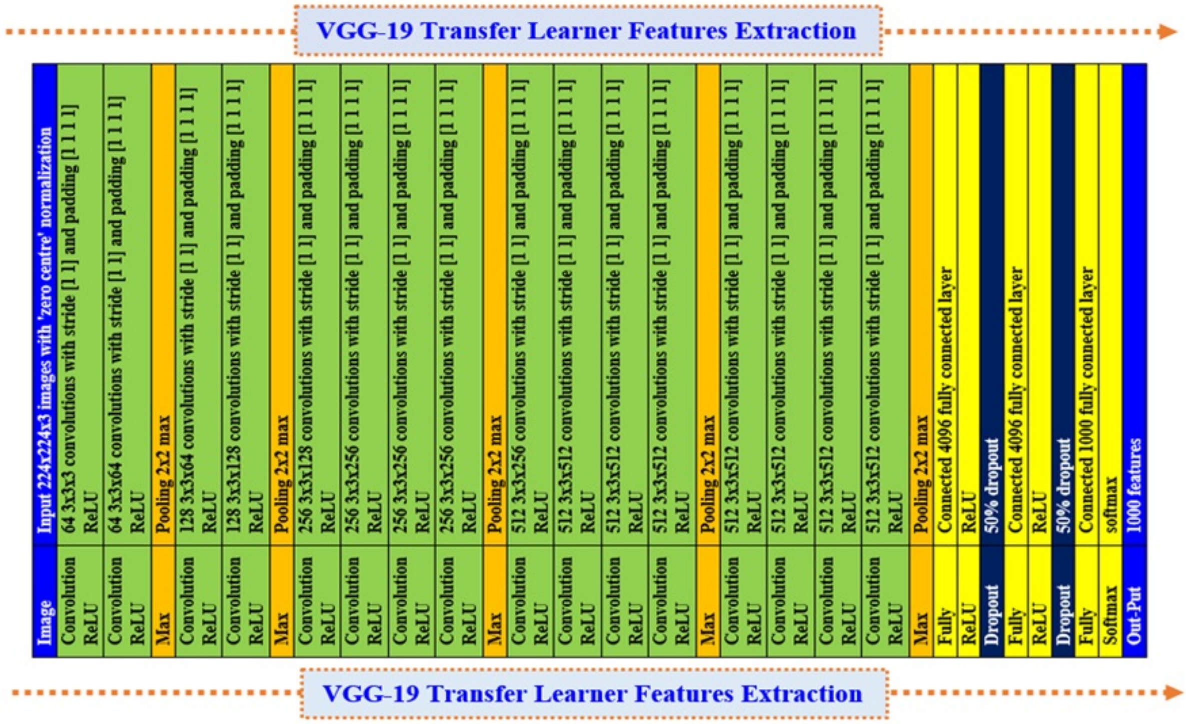

Fig. 4. VGG-19 TL Model Structure and Working Process

A. Inception V3 TL Analysis

Figure 6 shows the confusion matrix (CM) for the Inception v3 transfer learning model with MLP and SVM models.

Figure 6 (A) describes the 2 HL MLP with neurons (10 10) classifier on a 5-class classification problem. The model achieves a high accuracy of 99.28%, correctly classifying 2482 out of 2500 samples. The model performed well for most classes, except for Jas, where it misclassified three samples as Bas and two samples as Arb, resulting in a misclassification rate of 1.0% (5 out of 500 samples). For Arb, the model correctly classified 490 out of 500 samples (98.0%), misclassifying only three samples as Jas and seven as Kar. Similarly, the model correctly classified 494 out of 500 samples (98.8%) for Bas, misclassifying six samples as Jas. The model accurately classified 498 out of 500 Ips samples (99.6%), with only two misclassifications as Arb.

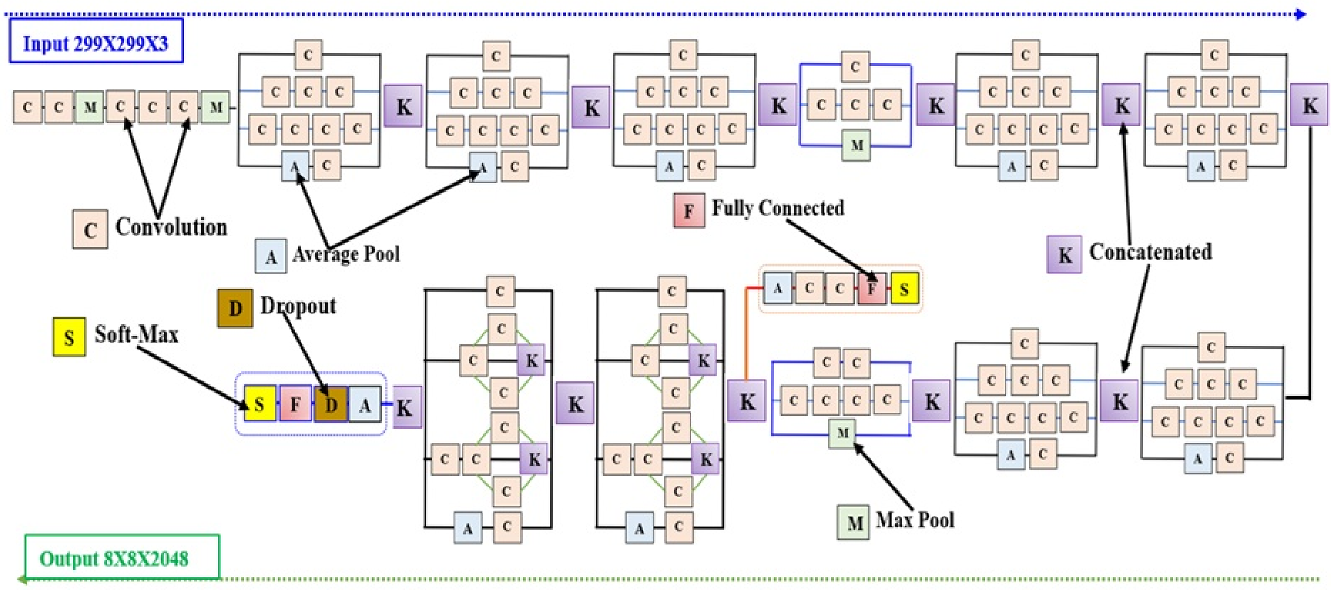

Fig. 5. InceptionV3 (IV3) TL Model Structure and Working Process

Similarly, for Kar, the model correctly ranked 495 out of 500 pieces (99.0%), with only five misclassifications as Arb.

Figure 6 (B) CM shows the performance of an MLP model with two hidden layers of 20 neurons each, trained on a multi-class classification task with five classes. The model's accuracy can be computed which is approximately 98.6%. However, upon examining the confusion matrix, it is evident that the model exhibits relatively higher confusion between the classes 'Arb' and 'Kar', as well as between 'Bas' and 'Ips'. Figure 6 (C) CM represents the performance of an MLP model with two hidden layers of 30 neurons each, trained on a multi-class classification task with five classes. The accuracy of the model can be approximately 98.8%. Figure 6 (D) displays the SVM (SIG) model, which achieved excellent performance with a high classification accuracy of 0.9824 and equally high F1, precision, and recall scores of 0.9824. The class 'Ips' is classified as highly nearer to 100% (499 out of 500 samples). Figure 6 (E) shows the SVM (POLY) methodology, which performs excellently in all metrics with a CA of 0.9912, F1 of 0.9912, prec. of 0.9912, and rec. of 0.9912 compared to other SVM kernel models. As with all models, it also demonstrates the highly performing class 'Ips' with 100% accuracy. Figure 6 (F) displays the SVM (RBF) methodology, which performs exceptionally well in all metrics with a CA of 0.9908. The Intellectual Rice Category Identification System utilized the Inception V3 (IV3) model to extract features from deep transfer learning. The rice categories were classified by SVM and MLP classifiers, with evaluation metrics including AUC, CA, F1, precision, and recall. Table I presents the experimental results. The SVM (POLY) model achieved an AUC score of 0.9999, demonstrating its ability to differentiate between positive and negative rice categories.

The model's classification accuracy (CA) of 0.9912 indicates correctly identifying the rice category in 99.12% of cases. The F1 score of 0.9912 suggests a good balance between recall and precision. The precision score 0.9912 indicates that the model made a high percentage of accurate optimistic predictions. In contrast, the recall score of 0.9912 suggests that the model correctly identified the most positive rice categories. When comparing the SVM (POLY) model with the MLP models, it was found that the MLP (10 10) achieved the highest AUC score of 0.9997. However, the other models slightly outperformed it regarding CA, F1, precision, and recall. Figure 7 displays the comparative values of CA and AUC's vital performance attributes for the experimental ML models. Additionally, Figure 8 shows the analysis of the ROC curves of MLP and SVM for all categories of models. This ROC analysis evaluates the performance of different ML models by measuring their Area under the Curve (AUC) values. The AUC value indicates the degree of separability between the model's predicted probabilities for the positive and negative classes.

TABLE I
IV3 (+SVM AND + MLP) PERFORMANCE PARAMETER VALUES

Model	AUC	CA	F1	Precision	Recall
MLP (10 10)	0.9997	0.9892	0.9892	0.9892	0.9892
MLP (20 20)	0.9998	0.9888	0.9888	0.9888	0.9888
MLP (30 30)	0.9997	0.9884	0.9884	0.9884	0.9884
SVM(POLY)	0.9999	0.9912	0.9912	0.9912	0.9912
SVM(RBF)	0.9998	0.9908	0.9908	0.9908	0.9908
SVM(SIG)	0.9995	0.9824	0.9824	0.9824	0.9824

The MLP models with ten neurons in each of the two hidden layers (HLs) and twenty neurons in each of the two HLs demonstrated excellent performance, with AUC values of 0.9997 and 0.9998, respectively. The AUC value represents the degree of separability of the model's predicted probabilities for the positive and negative classes. Figure 9 displays the Lift curves of all the ML models. The analysis of the lift curve indicates that the SVM(POLY) model has the highest initial lift, followed by the SVM(RBF) and MLP (30 30) models. The SVM (SIG) model has the lowest lift among all the models. The lift curve analysis can assist in selecting the best model for the given problem, as it provides a clear comparison of the performance of different models.

The MLP model with 30 neurons in the two hidden layers performed well, achieving an AUC value of 0.9997. Among

MLP(10 10)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	490	0	0	3	7	500
	Bas	0	494	0	6	0	500
	Ips	2	0	498	0	0	500
	Jas	1	3	0	496	0	500
	Kar	5	0	0	0	495	500
Total		498	497	498	505	502	2500

(A)Confusion Matrix Inception V3+MLP (10, 10)

MLP(20 20)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	489	0	0	4	7	500
	Bas	1	495	0	4	0	500
	Ips	1	1	498	0	0	500
	Jas	1	3	0	496	0	500
	Kar	6	0	0	0	494	500
Total		498	499	498	504	501	2500

(B)Confusion Matrix Inception V3+MLP (20, 20)

MLP(30 30)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	488	0	0	3	9	500
	Bas	1	495	0	4	0	500
	Ips	1	0	499	0	0	500
	Jas	1	3	0	496	0	500
	Kar	7	0	0	0	493	500
Total		498	498	499	503	502	2500

(C)Confusion Matrix Inception V3+MLP (30, 30)

SVM(Sigm)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	485	0	1	1	13	500
	Bas	1	488	0	11	0	500
	Ips	0	1	499	0	0	500
	Jas	1	5	0	494	0	500
	Kar	10	0	0	0	490	500
Total		497	494	500	506	503	2500

(D)Confusion Matrix Inception V3+SVM (Sigmoidal)

SVM(Poly)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	490	0	0	1	9	500
	Bas	1	495	0	4	0	500
	Ips	0	0	500	0	0	500
	Jas	0	2	0	498	0	500
	Kar	5	0	0	0	495	500
Total		496	497	500	503	504	2500

(E)Confusion Matrix Inception V3+ SVM (Polynomial)

SVM(RBF)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	492	0	0	1	7	500
	Bas	1	493	0	6	0	500
	Ips	2	0	498	0	0	500
	Jas	0	1	0	499	0	500
	Kar	5	0	0	0	495	500
Total		500	494	498	506	502	2500

(F)Confusion Matrix Inception V3+ SVM (RBF)

Fig. 6. CM for all MLP and SVM Classifier Models for Inception V3 Features

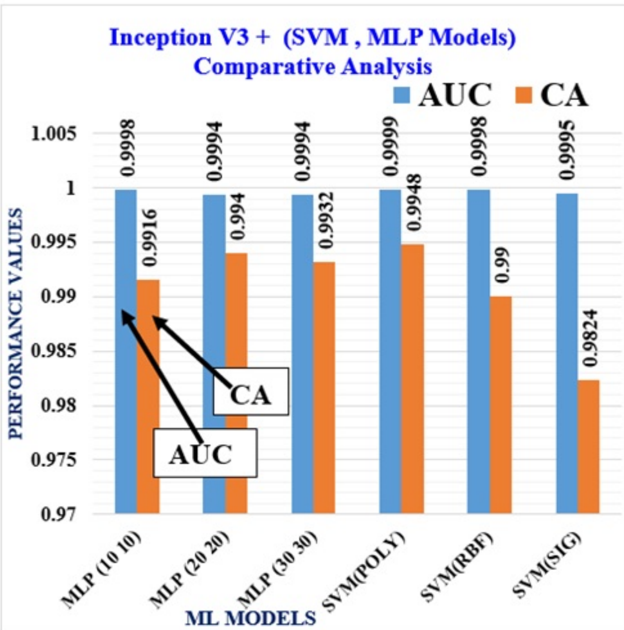

Fig. 7. Comparative Analysis ML Models of Inception V3 Features

the SVM models, the polynomial kernel SVM exhibited the best performance with an AUC value of 0.9999, represented by the light green colour. The SVM model with radial basis function (RBF) kernel also performed well, achieving an AUC value of 0.9998, represented by the gold colour. The SVM with a sigmoid kernel demonstrated slightly lower performance, with an AUC value of 0.9995, represented by the dark violet colour.

B. VGG-19 TL Analysis

Figure 10 displays the confusion matrices of the MLP and SVM models in various aspects, such as Hidden Layers and Kernels. Figure 10 (A) shows that the MLP (10 10) classifier achieved a high classification accuracy of 99.68%, with an F1 score of 99.20%, precision of 99.00%, and recall of 99.40%. The IPS class was classified more accurately than the others, with 498 out of 500 correctly classified. The MLP model with 20 hidden layers (Fig. 10 (B)) achieved a classification accuracy of 99.6% and an F1 score of 99.0%. The recall and precision values were also high at 98.8% and 99.2%, respectively, indicating good overall performance.

The class 'Jas' was classified with 100% accuracy. The MLP model with a hidden layer configuration of (30, 30) (Fig. 10 (C)) achieved a high accuracy (CA) of 0.9972 and an F1 score of 0.9930, indicating good overall performance in classification. The precision and recall values were high, with precision at 0.9940 and recall at 0.9920, indicating that the model effectively identified positive and negative instances. The SVM (SIG) model CM (Fig. 10 (D)) demonstrated high accuracy, as most diagonal values in the CM were high, indicating correct predictions for most classes. However, the model had difficulty predicting minor classes like Jas and Kar. The model has an overall classification accuracy of 0.9892, which is good. However, the F1 score and precision values are relatively lower than the recall score, indicating that the model is better at identifying true positives than avoiding false positives. In the CM (Fig. 10 (E)), the SVM (Poly) model correctly classified many samples, with only a small number of misclassifications. Fig. 10 (F) describes the CM VGG-19 features for SVM-RBF. Figure 11 displays

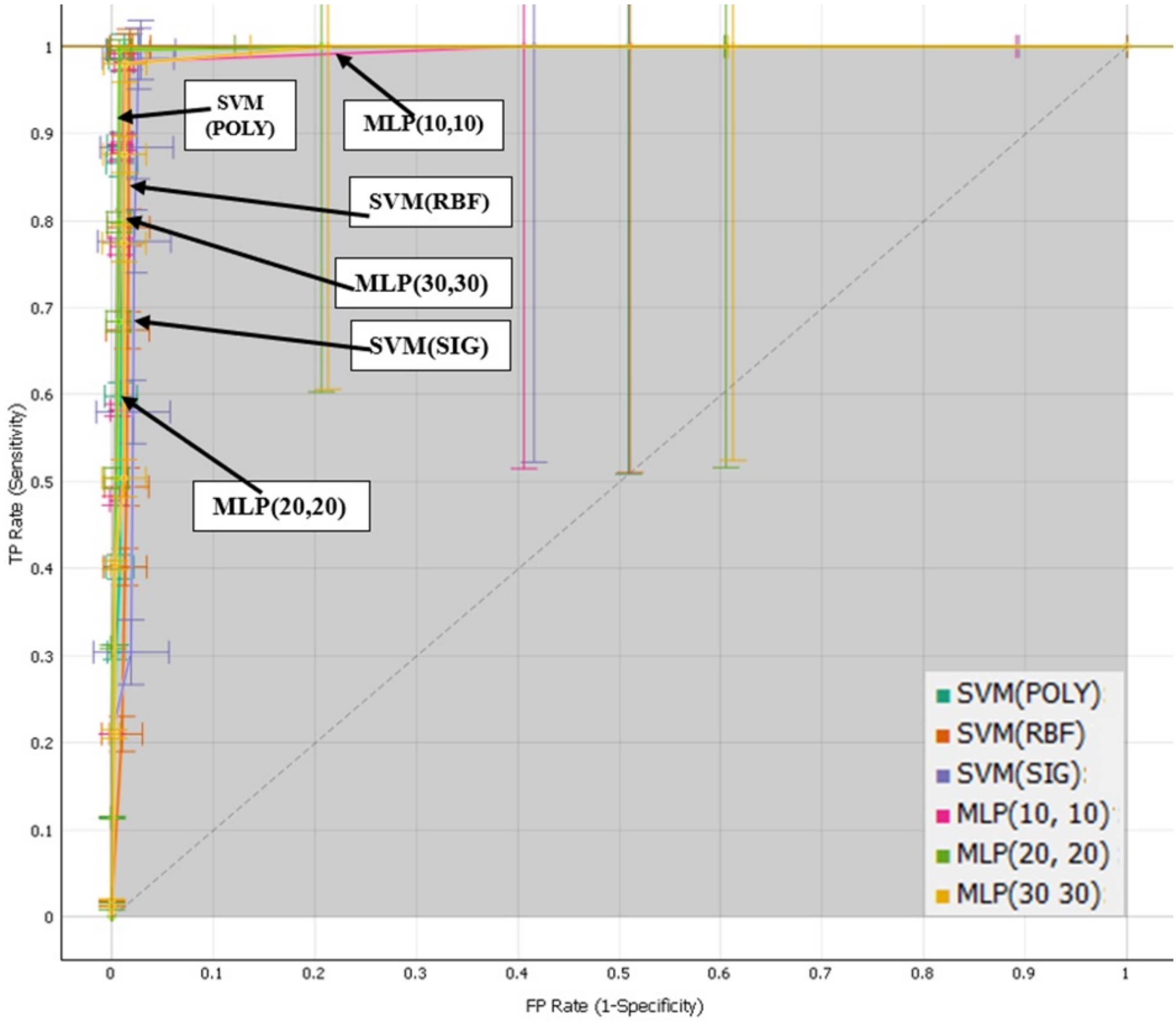

Fig. 8. ROC Curves Analysis for the Inception V3 (+SVM and + MLP)

the ROC analysis, which evaluates the performance of a binary classifier based on its TPR and FPR. The AUC is a widely used metric for assessing classifier performance. In this instance, we used the VGG-19 model to extract features and trained different classifiers (MLP and SVM) on these features. All classifiers have high AUC values, indicating good performance distinguishing between the two classes. The model MLP (20 20) achieved the highest AUC value of 1.0000, indicating perfect classification performance. These results suggest that the features of the VGG-19 model are highly effective in distinguishing between the two classes, and the SVM and MLP classifiers achieve high accuracy in image classification.

Figure 12 displays the Lift curves of all models for the VGG-19 features. The lift curve analysis indicates that the MLP (30 30) model has the highest initial lift, followed by the SVM (POLY) and MLP (10 10) and (20 20) models. The SVM (SIG) model has the lowest lift among all models. The VGG-19 model developed the Intellectual Rice Category Identification System by extracting features from deep transfer learning. SVM and MLP classifiers were then employed to classify the rice categories. The classifiers were evaluated using AUC, CA, F1, precision, and recall. Figure 13 presents a comparative analysis of the ML models MLP and SVM for VGG-19 features based on the CA and AUC parameters.

Table III displays the performance parameter values of the VGG-16 model combined with SVM and MLP algorithms. The SVM model with a polynomial kernel achieved the highest AUC score of 0.9999 and the highest classification accuracy (CA) of 0.9948. The MLP models, each with ten neurons in their hidden layers, also performed well, achieving high scores for all performance parameters. Combining VGG-19 with SVM or MLP can lead to highly accurate image classification.

C. VGG-16 TL Analysis

The CM shows the number of predicted labels for each class (Arb, Bas, Ips, Jas and Kar) based on the actual test data labels. Figure 14 (A) shows a CM where the model correctly predicted 494 instances of the ’Arb’ class and incorrectly predicted one example of the ’Arb’ class as the ’Jas’ class. The model correctly predicted 494 instances of the ”Bas”

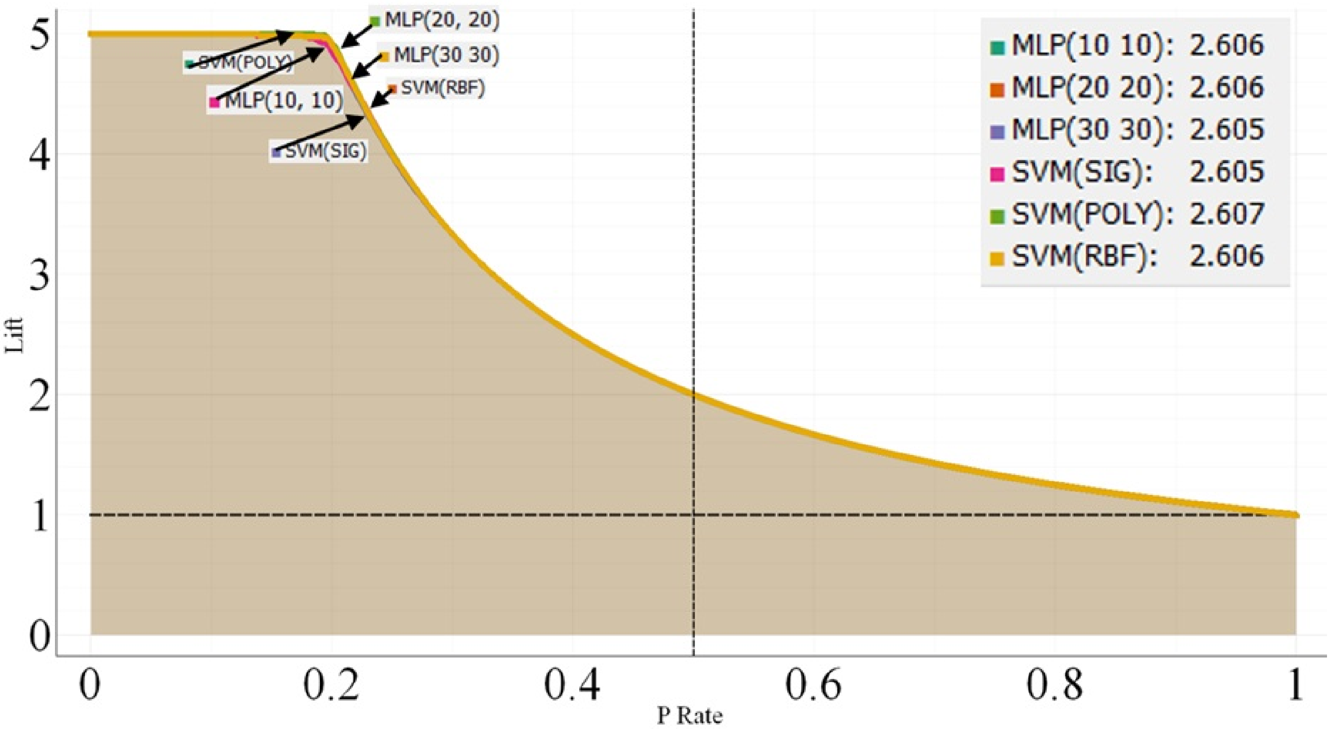

Fig. 9. Lift Curves Analysis for the Inception V3 (+SVM and + MLP)

MLP(10 10)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	493	0	0	1	6	500
	Bas	0	494	0	6	0	500
	Ips	2	0	498	0	0	500
	Jas	2	1	0	497	0	500
	Kar	3	0	0	0	497	500
Total		500	495	498	504	503	2500

(A) Confusion Matrix VGG-19 + MLP(10, 10)

MLP(20 20)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	495	0	0	1	4	500
	Bas	0	497	0	3	0	500
	Ips	1	3	496	0	0	500
	Jas	0	0	0	500	0	500
	Kar	3	0	0	0	497	500
Total		499	500	496	504	501	2500

(B) Confusion Matrix Inception V3+MLP(20, 20)

MLP(30 30)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	494	0	0	1	5	500
	Bas	0	496	0	4	0	500
	Ips	1	1	497	1	0	500
	Jas	1	1	0	498	0	500
	Kar	2	0	0	0	498	500
Total		498	498	497	504	503	2500

(C) Confusion Matrix VGG-19 + MLP(30, 30)

SVM(Sigm)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	475	0	0	2	23	500
	Bas	0	488	0	12	0	500
	Ips	3	1	496	0	0	500
	Jas	1	0	0	499	0	500
	Kar	2	0	0	0	498	500
Total		481	489	496	513	521	2500

(D) Confusion Matrix VGG-19 + SVM(SIG)

SVM(Poly)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	495	0	0	1	4	500
	Bas	0	495	0	5	0	500
	Ips	1	0	499	0	0	500
	Jas	0	0	0	500	0	500
	Kar	2	0	0	0	498	500
Total		498	495	499	506	502	2500

(E) Confusion Matrix VGG-19 + SVM(POLY)

SVM(RBF)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	488	0	3	1	8	500
	Bas	0	492	4	4	0	500
	Ips	0	0	500	0	0	500
	Jas	0	2	0	498	0	500
	Kar	2	0	1	0	497	500
Total		490	494	508	503	505	2500

(F) Confusion Matrix VGG-19 + SVM(RBF)

Fig. 10. CM for all MLP and SVM Classifier Models for VGG-19 Features

class and incorrectly predicted six instances of the ”Bas” class as the ”Jas” class. The model predicted 496 instances of the ”Ips” class correctly, three instances of the ”Ips” class incorrectly as the ”Arb” class and one instance of the ”Ips” class incorrectly as the ”Bas” class. The model predicted 500 instances of the ”Jas” class correctly. The model predicted 497 instances of the ”Kar” class correctly and three instances of the ”Kar” class incorrectly as the ”Arb” class. The CM shows that the model performed well, with high accuracy and few misclassifications. The performance values for the MLP

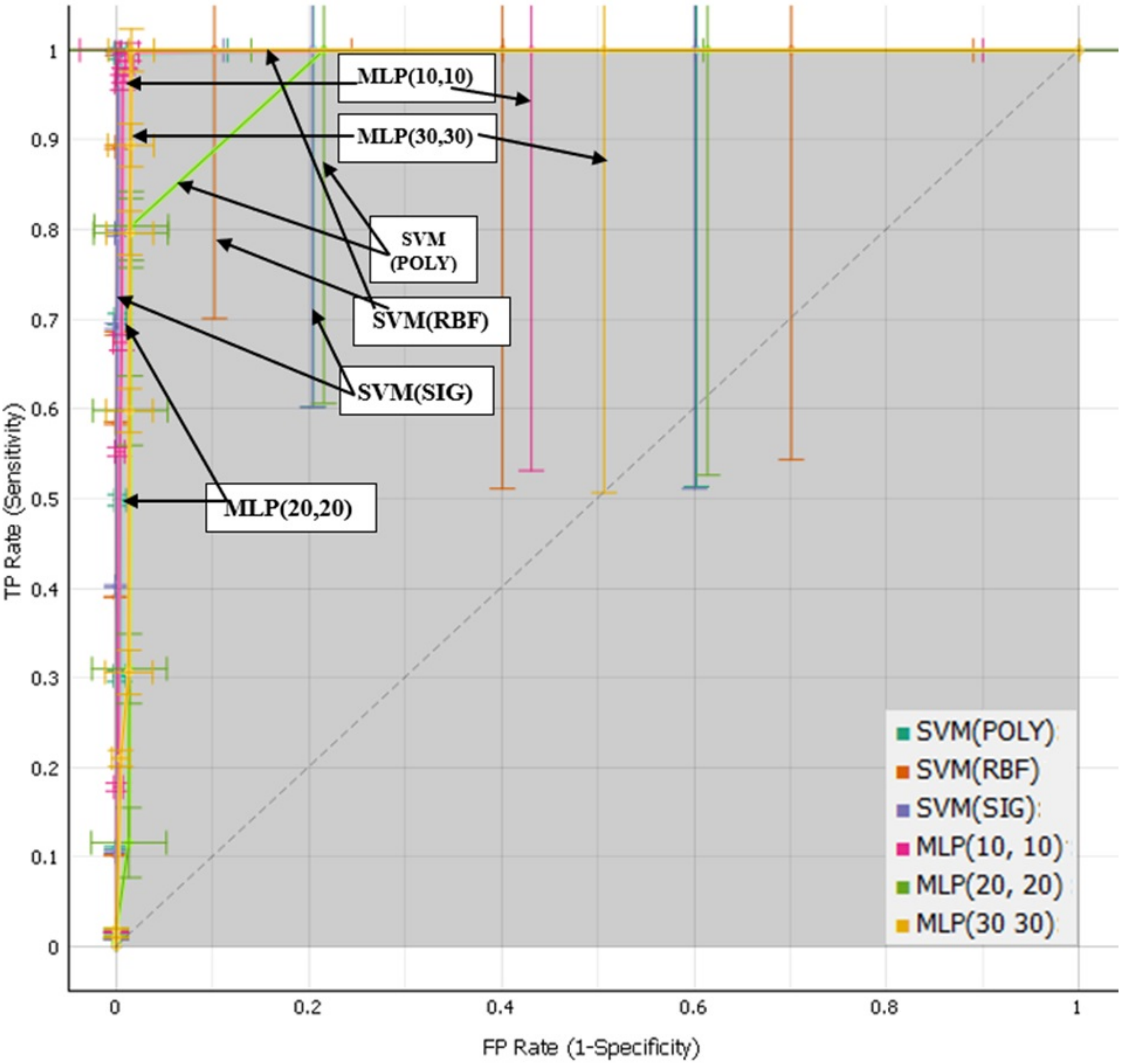

Fig. 11. ROC Curves Analysis for the VGG-19 (+SVM and + MLP)

TABLE II
VGG-19 (+SVM AND + MLP) PERFORMANCE PARAMETER VALUES

Model	AUC	CA	F1	Precision	Recall
MLP (10 10)	0.9999	0.9968	0.9920	0.9900	0.9940
MLP (20 20)	1.0000	0.9960	0.9900	0.9880	0.9920
MLP (30 30)	0.9999	0.9972	0.9930	0.9940	0.9920
SVM(POLY)	0.9998	0.9968	0.9920	0.9920	0.9920
SVM(RBF)	0.9998	0.9948	0.9870	0.9860	0.9880
SVM(SIG)	0.9995	0.9892	0.9735	0.9574	0.9900

(10 10) model based on the VGG-16 extracted features are also provided. The classification accuracy (CA) is 0.9916, indicating that the model correctly classified almost all instances. The F1 value is 0.9916, which is the weighted mean of accuracy and recall that is typically used to assess the model's performance. The CM (Fig. 14 (B)) displays the total number of accurate and wrong predictions produced by the model in each class. For instance, the model correctly predicted 493 images of the Arb class, 491 images of the Bas class, 496 images of the Ips class, 499 images of the Jas class, and 496 images of the Kar class out of a total of 500 images per class. The performance values show the accuracy and effectiveness of the model. The CA is 0.9940, meaning the model can correctly classify 99.40% of the total images. The F1 score is also 0.9940, which measures the harmonic mean of precision and recall, indicating the model's ability to balance both measures.

The CM (Fig. 14 (C)) and performance values of the VGG-16 extracted features with MLP (30 30) classifier show that the model achieved high accuracy with an overall classification accuracy (CA) of 0.9932. Looking at the confusion matrix, the model made a few incorrect predictions, with only three misclassifications for Class Arb, 8 for Class Bas, 2 for Class Ips, and 2 for Class Jas. The model performed

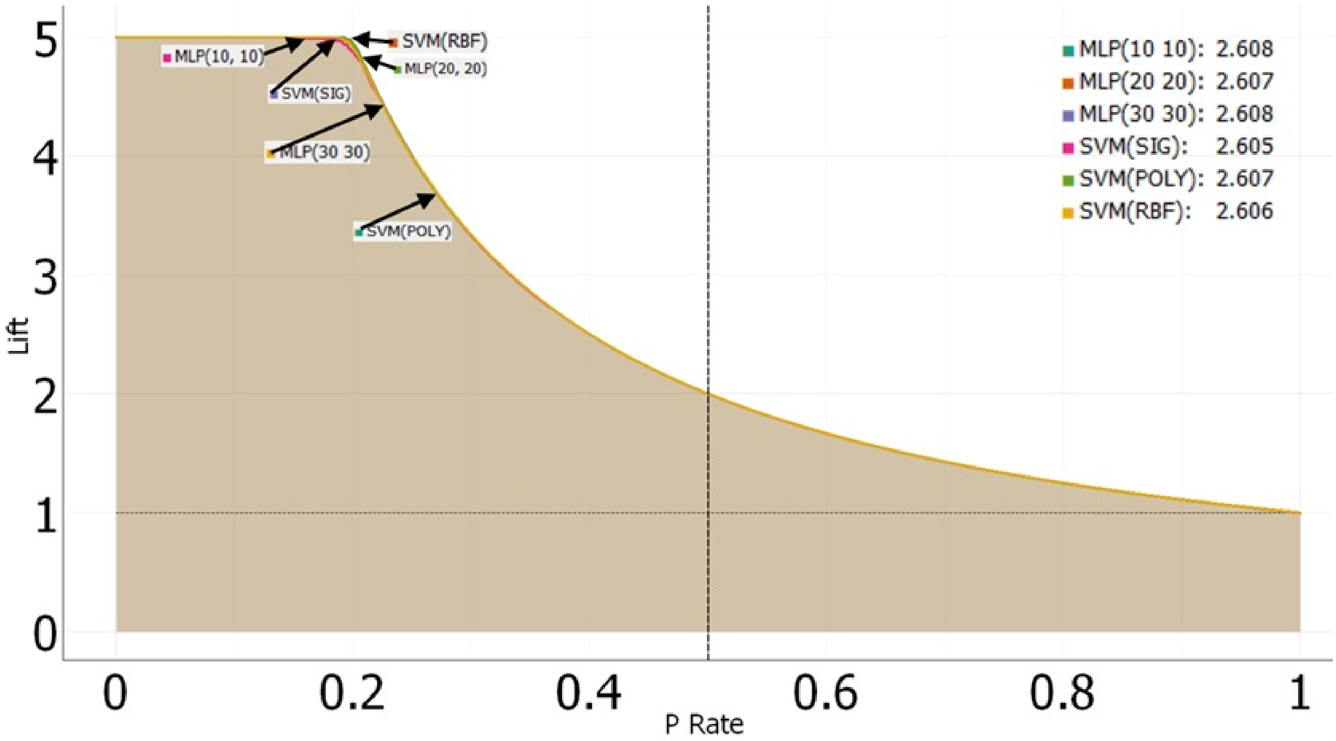

Fig. 12. Lift Curves Analysis for the VGG-19 (+SVM and + MLP)

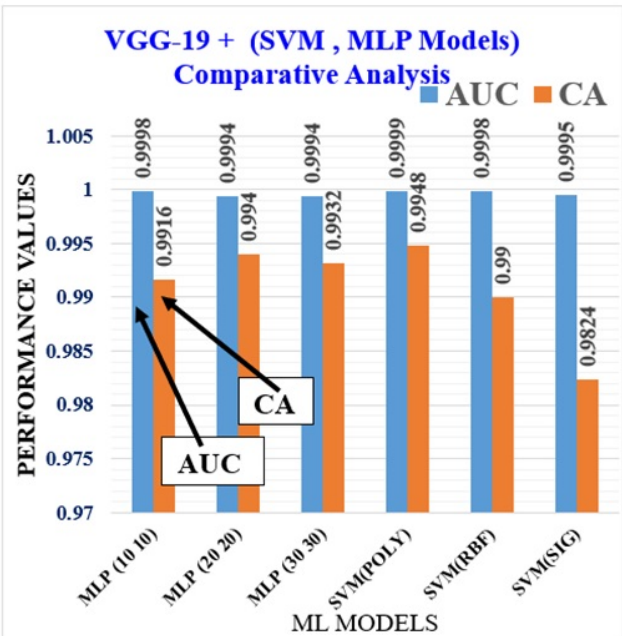

Fig. 13. Comparative CA and ROC Analysis of ML+VGG – 19 Features

exceptionally well for Class Kar, with no misclassifications. The high F1 value of 0.9932 for classes indicates that the model is robust and performs well. In overview, these results suggest that VGG-16 extracted features with MLP (30 30) classifier can be adequate for the task of rice category identification.

Based on the CM (Fig. 14 (D)) for the SVM (Sigm) classifier using VGG-16 extracted features, it can be observed that the model achieved high accuracy with an overall CA of 0.9848. However, it needs help with the Jasmin and Kar Rice categories, as evidenced by the lower number of correct predictions (497 and 495, respectively) compared to other types. The F1 score, precision, and recall are not provided for this classifier and model, so evaluating these metrics is impossible. Fig. 14 (E) shows the SVM (POLY) confusion matrix. The class ”Jas” is classified as 100% and has a total accuracy of 0.9948. Fig. 14 (F) shows the SVM (RBF) confusion matrix. The class ”Jas” classifies nearly 100% (499 out of 500) and has a total accuracy of 0.99.

Fig. 15 shows the ROC curves (MLP (10 10)-Dark green, MLP (20 20)-Brown, MLP (30 30)-Purple, SVM (POLY)-light Green, SVM (SIG) Maroon, SVM (RBF) Dark Gold). The results for the ROC curves indicate that all models have high performance, with AUC values ranging from 0.9994 to 0.9999. SVM with polynomial kernel has the highest AUC value of 0.9999, followed by MLP with ten neurons in each layer and 20 neurons in each layer, with AUC values of 0.9998 and 0.9994, respectively. SVM with RBF kernel and MLP with 30 neurons in each layer have AUC values of 0.9998 and 0.9994, respectively. SVM with a sigmoid kernel has the lowest AUC value of 0.9995.

Figure 16 shows the lift curves of all models for the features of VGG-19. The lift curve analysis indicates that the MLP (30 30) model has the highest initial lift, followed by the SVM (POLY) and MLP (10 10) and (20 20) models. The SVM (SIG) model has the lowest lift of all the models. Figure 17 shows the comparative analysis (CA and AUC parameters) of the MLP and SVM models for the VGG-16 features.

Table III shows the performance parameter values of the VGG-16 model combined with SVM and MLP algorithms. The SVM model with a polynomial kernel has the highest AUC score of 0.9999 and the highest classification accuracy (CA) of 0.9948. The MLP models with ten neurons in each

MLP(10 10)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	494	0	0	1	5	500
	Bas	0	494	0	6	0	500
	Ips	3	1	496	0	0	500
	Jas	0	0	0	500	0	500
	Kar	3	0	0	0	497	500
Total		500	495	496	507	502	2500

(A) Confusion Matrix VGG-16 + MLP(10, 10)

MLP(20 20)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	493	0	1	0	6	500
	Bas	0	491	0	9	0	500
	Ips	2	2	496	0	0	500
	Jas	0	1	0	499	0	500
	Kar	4	0	0	0	496	500
Total		499	494	497	508	502	2500

(B) Confusion Matrix VGG-16 + MLP(20, 20)

MLP(30 30)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	496	0	1	0	3	500
	Bas	0	492	0	8	0	500
	Ips	2	1	497	0	0	500
	Jas	0	2	0	498	0	500
	Kar	4	0	0	0	496	500
Total		502	495	498	506	499	2500

(C) Confusion Matrix VGG-16 + MLP(30, 30)

SVM(Sigm)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	476	0	0	2	22	500
	Bas	0	471	0	29	0	500
	Ips	3	0	497	0	0	500
	Jas	0	3	0	497	0	500
	Kar	5	0	0	0	495	500
Total		484	474	497	528	517	2500

(D) Confusion Matrix VGG-16 + SVM(SIG)

SVM(Poly)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	495	0	0	1	4	500
	Bas	0	490	0	10	0	500
	Ips	2	1	497	0	0	500
	Jas	0	0	0	500	0	500
	Kar	4	0	0	0	496	500
Total		501	491	497	511	500	2500

(E) Confusion Matrix VGG-16 + SVM(POLY)

SVM(RBF)		Predicted					Total
Class		Arb	Bas	Ips	Jas	Kar	
Actual	Arb	490	1	2	0	7	500
	Bas	0	485	5	10	0	500
	Ips	2	2	496	0	0	500
	Jas	0	1	0	499	0	500
	Kar	5	0	1	0	494	500
Total		497	489	504	509	501	2500

(F) Confusion Matrix VGG-16 + SVM(RBF)

Fig. 14. CM for all MLP and SVM Classifier Models for VGG-16 Features

hidden layer also perform well, achieving high scores for all performance parameters. Combining VGG-16 with SVM or MLP can lead to highly accurate image classification.

TABLE III
VGG-16 (+SVM AND + MLP) PERFORMANCE PARAMETER VALUES

Model	AUC	CA	F1	Precision	Recall
MLP (10 10)	0.9998	0.9916	0.9916	0.9916	0.9916
MLP (20 20)	0.9994	0.9940	0.9940	0.9940	0.9940
MLP (30 30)	0.9994	0.9932	0.9932	0.9932	0.9932
SVM(POLY)	0.9999	0.9948	0.9948	0.9948	0.9948
SVM(RBF)	0.9998	0.9900	0.9900	0.9901	0.9900
SVM(SIG)	0.9995	0.9824	0.9824	0.9828	0.9824

V. Discussions

Table IV shows that MLP and SVM models have been evaluated using three different pre-trained models: VGG19, IV3, and VGG16, and their AUC and CA values are reported. Comparing the AUC and CA values of the three pre-trained models, we observe that VGG-19 has the highest AUC and CA values for all models, followed by Inception V3 and VGG-16.

This suggests that VGG-19 is the most effective pre-trained model for the classification task. Looking at the MLP and SVM models individually, we see that MLP (30, 30) has the highest AUC value of 0.9997 and the highest CA value of 0.9972 among all the models evaluated. It uses the VGG-19 pre-trained model for transfer learning. On the other hand, MLP (20, 20) has an AUC value of 1.0 when evaluated using the VGG-19 pre-trained model, which is the highest AUC value obtained for any model. However, its CA value of 0.9960 is lower than that of the MLP (30 30) and SVM (POLY) models. This suggests that while SVM (SIG) effectively distinguishes between positive and negative samples, its predictions are less precise than those of the other models. Based on the given results, VGG-19 is the most effective pre-trained model for the classification task. MLP (30 30) has the highest AUC and CA values, while MLP (20 20) has the highest but slightly lower CA value.

SVM models have comparable AUC values to MLP models but generally have higher CA values, indicating their superior precision in predictions. 'unclassified rice images' (Fig. 18) refers to a collection of digital images of various rice grains, such as Arborio, Karacadag, Basmati, jasmine, and Ipsala. To classify the images into their respective rice types, ML models such as MLP with hidden layers like (10 10), (20 20), (30 30), and SVM models (LR, poly, or RBF) can be confidently employed. The unclassified rice images can be used to train MLP and SVM models for accurate classification. TLs can categorize unclassified rice images based on their features and attributes. TLs can categorize unclassified rice images into different categories based on their features and attributes. Trained models can organize new rice images with ease.

The analysis indicates that a considerable number of rice images remain unclassified across all categories and models of MLP and SVM algorithms for the IV3, VGG-16 and VGG-19 TL features. Specifically, the SVM model with sigmoid kernel failed to classify 23 rice samples with the Inception V3 features, while the VGG-19 and VGG-16 models could not classify 25 and 26 rice samples, respectively. These findings suggest that these models have limitations in accu-

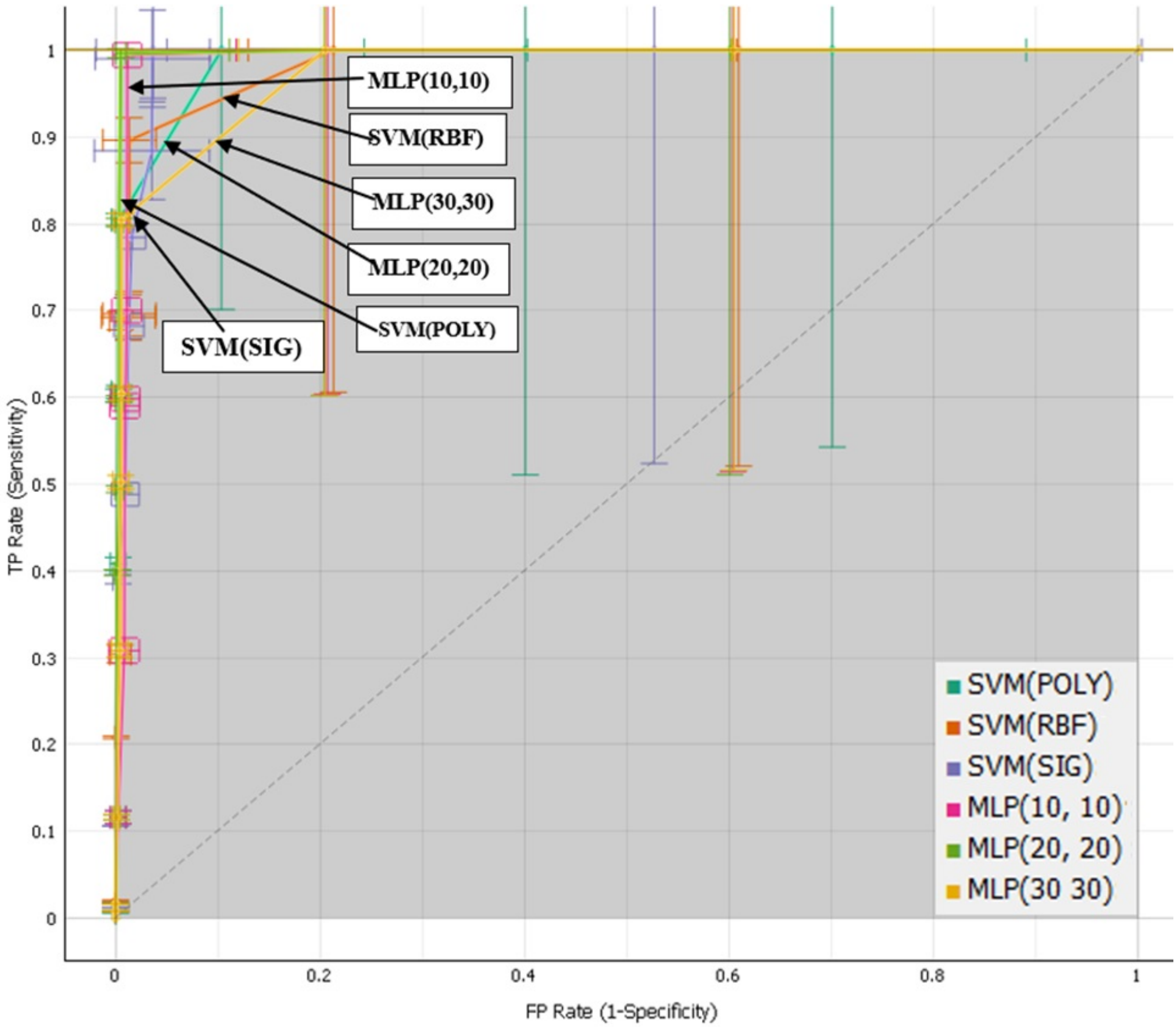

Fig. 15. ROC Curves Analysis for the VGG16 (+SVM and + MLP)

TABLE IV
INCEPTION V3, VGG-19, VGG-16 (+SVM AND + MLP) AUC AND CA ANALYSIS

Model	Inception V3		VGG-19		VGG-16	
	AUC	CA	AUC	CA	AUC	CA
MLP (10 10)	0.9997	0.9892	0.9999	0.9968	0.9998	0.9916
MLP (20 20)	0.9998	0.9888	1.0000	0.9960	0.9994	0.9940
MLP (30 30)	0.9997	0.9884	0.9999	0.9972	0.9994	0.9932
SVM(POLY)	0.9999	0.9912	0.9998	0.9968	0.9999	0.9948
SVM(RBF)	0.9998	0.9908	0.9998	0.9948	0.9998	0.9900
SVM(SIG)	0.9995	0.9824	0.9995	0.9892	0.9995	0.9824

rately identifying specific rice images. It may be necessary to conduct further investigation and refinement of the models to improve their performance on unclassified rice images. Figure 18 displays some of the frequently unclassified rice pieces (most of SVM (SIG) in all TLs), while Table V presents the CA comparative study for all TL features with all ML (SVM and MLP) models. The results indicate that the VGG-19 pre-trained model consistently outperforms the other two models across all MLP and SVM classifiers, with the highest accuracy values in almost all cases. Therefore, VGG-19 is the most effective pre-trained model for this task. Among the MLP classifiers, MLP (30 30) with the VGG-19 pre-trained model achieved the highest accuracy of 0.9972. The accuracy values of MLP models with smaller hidden layer sizes (10, 10, 20, 20) are slightly lower compared to MLP (30, 30), indicating that increasing the size of the hidden layers can improve the model's accuracy. Among the SVM classifiers, SVM (POLY) with VGG-19 pre-trained model achieved the highest accuracy of 0.9968, followed closely by SVM (RBF) with the same pre-trained model. The pre-trained SVM (SIG) model has the lowest accuracy values for this task compared to other models, suggesting its

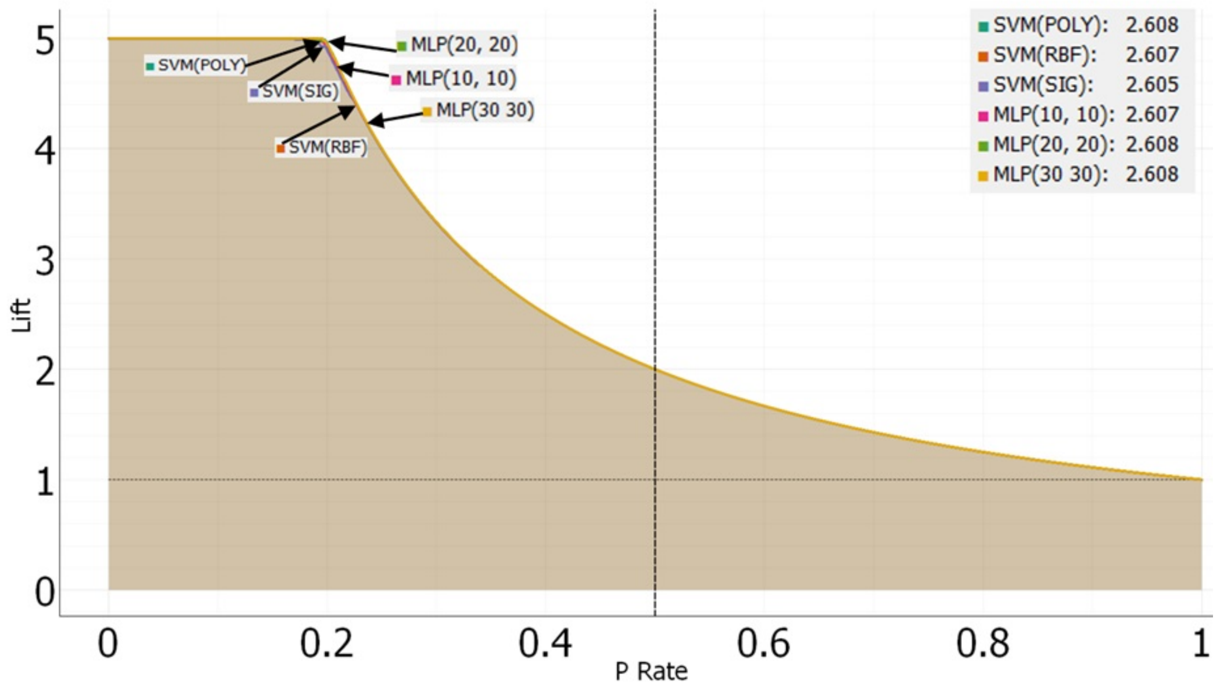

Fig. 16. Lift Curves Analysis for the VGG16 (+SVM and + MLP)

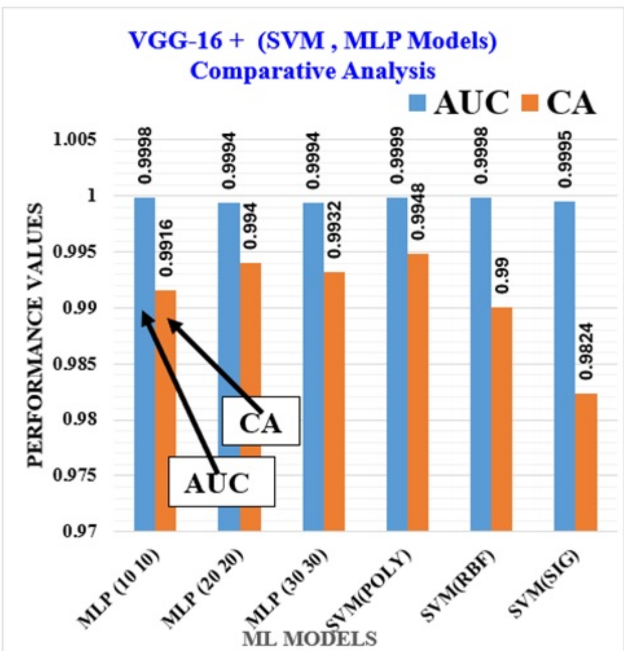

Fig. 17. Comparative CA and ROC Analysis of ML+VGG – 16 Features

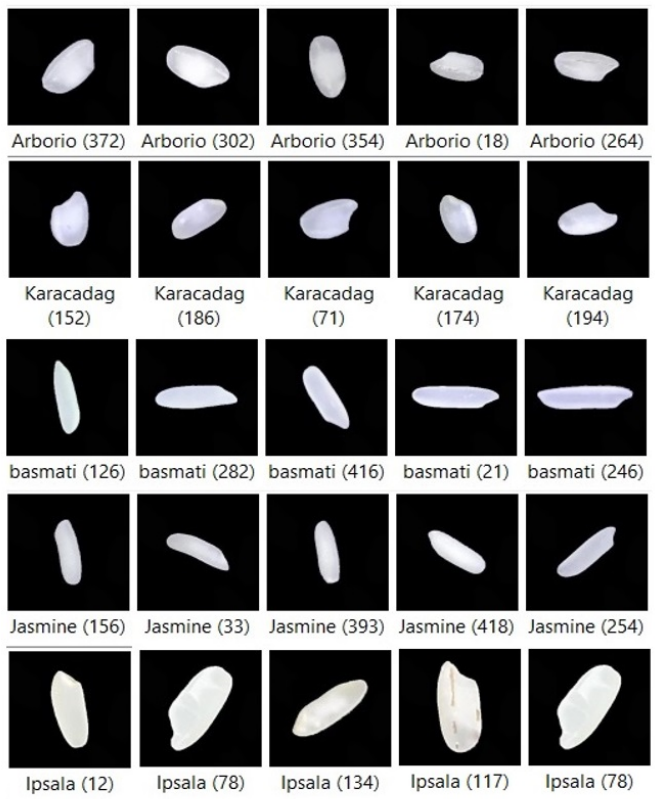

Fig. 18. Unclassified samples for all Experimental ML models

lower effectiveness.

Figure 19 compares CA and AUC performance across all TL models using SVM and MLP classifiers. The results indicate that VGG-19 features outperformed VGG-16 and IV3 features regarding AUC and CA. The study found that the MLP (30 30) and SVM(POLY) algorithms were the most effective for rice image classification, achieving the highest performance values for CA and AUC across all TLs. Therefore, combining VGG-19 features with either MLP (30 30) or SVM(POLY) is recommended to classify rice images accurately using transfer learning techniques.

Figure 20 compares the accuracy values of the MLP and SVM models. The comparison of accuracy values for MLP and SVM models using VGG19, IV3, and VGG16 features shows that both MLs have high accuracy values. Table VI presents a comparative analysis of other research on rice image processing and prediction systems compared to the present study. In particular, the MLP (30 30) algorithm achieves high CA values for all features, with the VGG-19

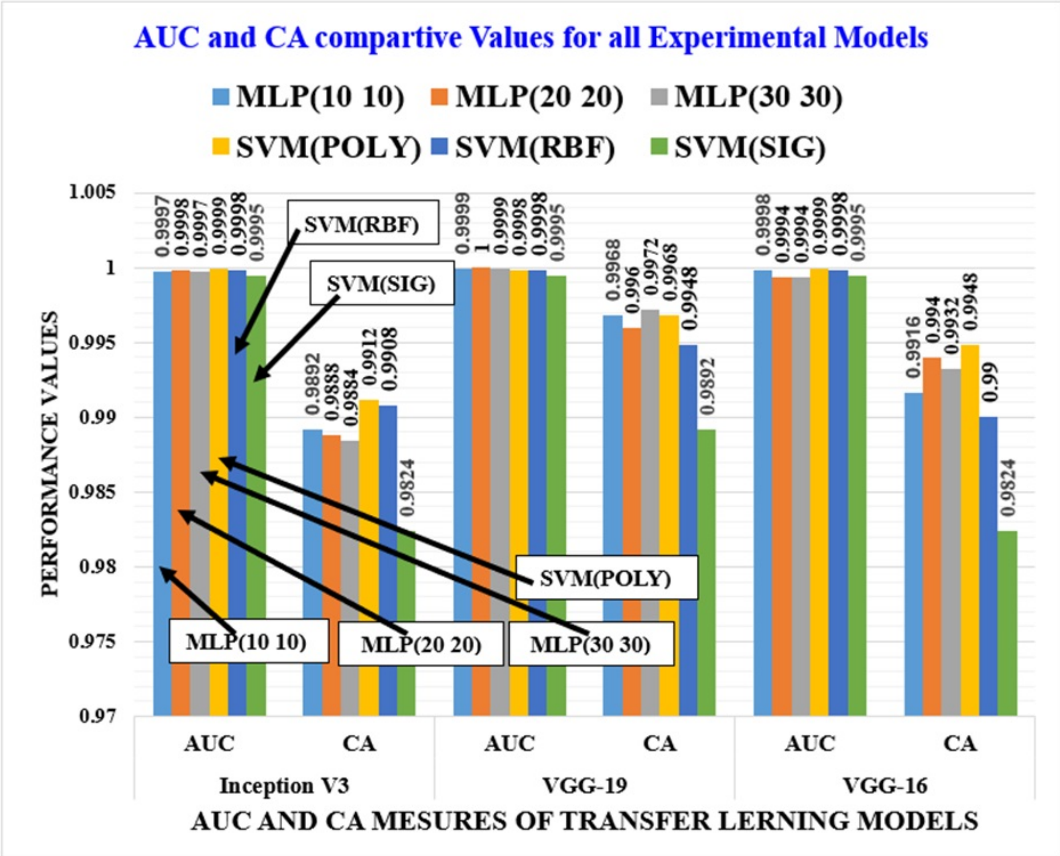

Fig. 19. AUC and CA Comparative to all classifiers for the TLs Rice features data

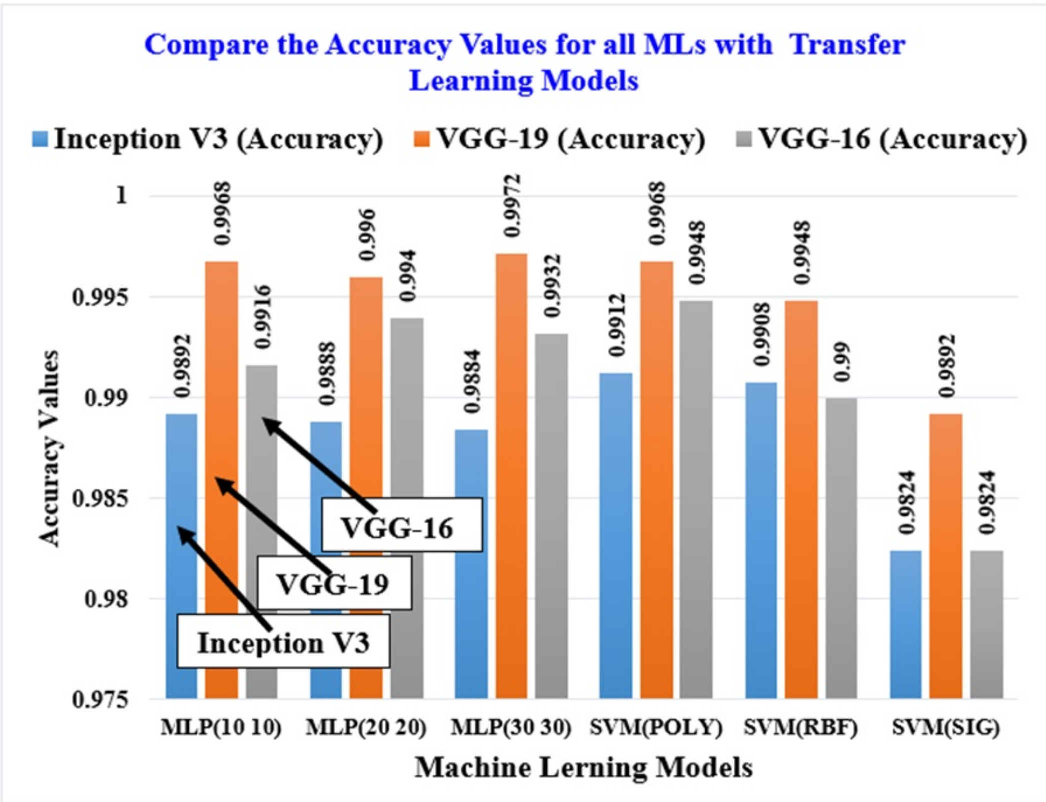

Fig. 20. Comparative Analysis for All Classifiers Accuracy with All TL Models' Features

features having the highest accuracy value of 0.9972. Similarly, the SVM (POLY) algorithm performs well, achieving

TABLE V
COMPARISON OF PROPOSED STUDIES WITH EXTERNAL RESEARCH ON RICE SEED CLASSIFICATION

Ref.No.	Author	Description and Applied Models	Results and Analysis
[44]	Fabiyi et al.	The study aims to accurately classify rice seeds based on their unique visual and spectral characteristics using a diverse dataset of 8,640 sources from 90 species.	The precision and recall of the Spatial+85LDA components from Spectral (%) were 79.64, 78.80, and 78.27 respectively.
[45]	Chatnuntawech et al.	The study employs a Spatial Spectral Deep CNN for accurate rice variety classification, utilizing spectral and spatial information for improved accuracy compared to traditional methods.	The study analyzed various ML models, including SVM (95%), ResNet-B (97.54%), VGGNet (86.41%), ResNet (88.23%), ResNet-B (91.09%), and Ensemble (93.27%).
[46]	Nguyen-Quoc et al.	The study uses classification methods on rice seed images, including the imputation and HOG descriptor, for improved accuracy.	The accuracy in % 10-NN imputation was 82.53, zero imputation was 83.85, and linear interpolation was 90%.
[7]	Kiratiratanapruk et al.	The study used MV to classify 14 types of rice after studying over 3,500 samples, focusing on texture, shape, and color.	The accuracy of VGG-19 (I/P image size) was assessed at different image sizes, with values ranging from 72.50% to 90.94%.
[47]	Kirbaş et al.	This research employs ML for rice grain classification, utilizing numerical feature extraction from rice image data.	The CA values of the ML models k-NN-0.883, SVM-0.726, SGD-0.928, RF-0.918, and NB-0.906 were analyzed.
[48]	Ruslan et al.	The study classifies weedy rice using IP and ML techniques, capturing RGB and monochrome images and extracting features for input into seven ML classifiers.	The RGB MCT and Mono MGT models have varying accuracy rates, with RGB MCT showing the highest accuracy at 97% and Mono MGT at 96.3%.
[49]	Tuğrul, B.	The study classifies five Turkish rice seed types using deep learning techniques, utilizing a new dataset and trained CNNs like VGG, ResNet, and EfficientNets.	The CNN architectures achieved an accuracy rate of 0.97 in VGG, 0.89 in ResNet, 0.82 in EfficientNet, and 0.96 in Custom.
[50]	Tran et al.	The study uses ANN and CNN models to classify 17 Vietnamese rice grain varieties using pre-trained VGG16 and ResNet50 models, using extended ILTP features and augmented images for experimentation.	The ACC (%) ANN model was enhanced by VGG16 (96.41) and ResNet50 (97.88), resulting in a final score of 92.82.
[51]	Petchsod et al.	The research introduces a unique GAN architecture for translating mobile phone images in closed environments, achieving a 90.06% accuracy in weedy rice recognition.	The percentages for M.1 and M.2 are 81.15%, 90.06%, 87.86%, and 87.79% respectively.
This std.	Current study	The study employs DL-extracted feature + ML models to accurately classify rice seeds based on their distinctive visual and spectral characteristics from a diverse dataset of 8,640 sources.	The accuracy of various ML models, including **VGG-19+MLP (30 30) (with 99.72% (Rank 1)), VGG-19 + SVM(POLY)(with 99.68% (Rank 2)), VGG-16+ Support Vector Machine (POLY)(with 99.48% of CA), and Inception V3+SVM (POLY), is 99.12%.**

high accuracy values for all features. The highest accuracy value of 0.9948 was achieved for the VGG-16 features. These results suggest that MLP and SVM models effectively classify rice images using transfer learning techniques.

VI. Conclusion

Deep transfer learning with pre-trained models and ML classifiers can effectively enhance the task of Rice Category Identification. The experiments using VGG19, IV3, and VGG16 pre-trained models show that VGG-19 consistently outperforms the other two models across all MLP and SVM classifiers, with the highest accuracy and AUC values in almost all cases.

Among the MLP classifiers, MLP (30 30) with the VGG-19 pre-trained model achieved the highest accuracy of 0.9972. Among the SVM classifiers, SVM (POLY) with the VGG-19 pre-trained model achieved the highest accuracy of 0.9968. These results suggest that increasing the size of hidden layers can improve the accuracy of MLP classifiers and that SVM classifiers are effective for this task when using a polynomial kernel function. The experiments demonstrate that the proposed approach can achieve accuracy values above 99% for all pre-trained models. Deep transfer learning with pre-trained models and ML classifiers is a promising strategy for enhancing the task of Rice Category Identification, which can be further extended to other classification tasks in agriculture and food science.

Several potential avenues exist for future work in rice category identification using deep transfer learning features and ML classifiers. One possible direction for future work is to explore other pre-trained models, such as ResNet, DenseNet, or EfficientNet, to see if they can provide even better results for this task. Investigating ensemble models that combine multiple pre-trained models for improved accuracy may also be worthwhile. Future research could focus on developing advanced feature extraction techniques that capture subtle differences between rice grain images of different categories. This could involve using complex DL architectures or incorporating additional image processing techniques.

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