Unveiling the Genetic Mosaic: A Multi-Model Exploration of Rice Varietal Diversity Through Advanced Image Classification

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***Abstract*—This study aims to unravel the genetic diversity among five prominent Turkish rice varieties—Arborio, Basmati, Ipsala, Jasmine, and Karacadag—by employing advanced image classification techniques on a substantial dataset of 75,000 rice grain images. A multi-faceted modeling approach integrating traditional machine learning classifiers like Random Forests, Support Vector Machines (SVMs), and Decision Trees, deep convolutional neural networks (CNNs), and transfer learning techniques utilizing pre-trained architectures like VGG16, InceptionV3, and MobileNetV2 was implemented. The SVM model with Principal Component Analysis (PCA) features achieved an accuracy of 98.2%, while the deep learning CNN model attained perfect 99% accuracy, showcasing deep learning's superiority in extracting genetic features tailored for rice classification. Fine-tuned transfer learning models achieved exceptional accuracies of 99.7-99.9%, demonstrating the efficacy of leveraging broad knowledge while specializing to specific agricultural applications. This synergistic approach highlights advanced image classification's power in deciphering the genetic mosaic within agricultural domains and paves the way for further exploration into deep learning applications for precise phenotypic recognition, genotype modeling, and sustainable agricultural practices.**

***Index Terms*—rice varieties, genetic diversity, image classification, machine learning, deep learning, transfer learning, convolutional neural networks, explainable AI**

I. Introduction

Rice, as a staple food and one of the most extensively cultivated grain products globally, encompasses a diverse array of genetic varieties distinguished by specific features such as texture, shape, and color. The unique characteristics inherent in each rice variety not only contribute to their individuality but also offer a basis for effective classification and assessment of seed quality. [1] [2]

In the realm of global agriculture, rice stands out as a fundamental staple, its cultivation spanning vast regions with diverse genetic varieties showcasing unique characteristics in texture, shape, and color. This extensive diversity not only defines the individuality of each rice variety but also establishes a crucial foundation for the meticulous classification and assessment of seed quality.Amidst this diversity, the intricate interplay of genetic traits not only contributes to the sensory aspects of rice but also serves as a vital determinant in shaping the adaptability, nutritional content, and resilience of these varieties, highlighting the multifaceted importance of their classification in ensuring sustainable agricultural practices worldwide. [1]

The significance of understanding and categorizing these rice varieties is particularly pronounced in regions such as Turkey, where a rich tapestry of distinct rice types flourishes. Among these, Arborio, Basmati, Ipsala, Jasmine, and Karacadag emerge as prominent players, each contributing to the intricate mosaic of rice cultivation practices. [2]

In the contemporary landscape of advanced agricultural research, the imperative to employ cutting-edge technologies for precise classification has become irrefutable. This study, therefore, embarks on a comprehensive exploration into the classification of the five noteworthy rice varieties in Turkey—Arborio, Basmati, Ipsala, Jasmine, and Karacadag. Leveraging a substantial dataset comprising 5,000 grain images, with each variety contributing 1,000 images, The images, characterized by a standardized size of 250*250 pixels, become the canvas upon which the intricate features of the rice varieties unfold. [3]

In the realm of image analysis, each pixel assumes the role of a distinct feature, contributing to the comprehensive understanding of the genetic characteristics inherent in the rice varieties under scrutiny. This pixel-level granularity enables the study to delve deeply into the nuances of texture, shape, and color, providing a nuanced perspective on the distinctive attributes that define Arborio, Basmati, Ipsala, Jasmine, and Karacadag. The marriage of cutting-edge technology, a robust dataset, and meticulous analysis lays the groundwork for unraveling the genetic intricacies of these rice varieties in the context of Turkey's agricultural landscape. [3] [4]

This research endeavors to capture the nuanced features that encapsulate their genetic diversity. Through the lens of modern technology and a wealth of data, this study aims to unravel the intricacies of these rice varieties, offering insights that transcend the traditional boundaries of agricultural understanding.The culmination of these efforts is encapsulated in comprehensive tables, providing a transparent portrayal of the models' classification prowess. [3] [4] [5]

II. LITERATURE REVEIW

This study analyzed rice leaf blast disease using various MV classifiers, including ResNet connection skipping, Inception V3, VGG 16, VGG 19, CNN, and an ensemble module KNN. The evaluation was performed on an updated rice dataset.Among the models tested, Inception V3 achieved an OA of 97.59%, a Validation Accuracy of 93.77%, an F1-score of 97.61%, an AUC of 98.44%, and a Precision of 97.30%. VGG 16 obtained an OA of 97.45%, a Validation Accuracy of 97.91%, an F1-score of 97%, an AUC of 98.01%, and a Precision of 97.66%. VGG 19 exhibited an OA of 96.49%, a Validation Accuracy of 75.76%, an F1-score of 94.17%, an AUC of 98.91%, and a Precision of 96.30%. The CNN model achieved an OA of 89.62%, a Validation Accuracy of 79.75%, an F1-score of 89.62%, an AUC of 90.01%, and a Precision of 89%. The KNN model, part of the ensemble module, attained an OA of 81%, a Validation Accuracy of 77%, an F1-score of 81%, and a K-value of 10. The ResNet model demonstrated phenomenal performance, achieving an astounding Overall Accuracy of 99.75%, Validation Accuracy of 99.16%, F1-score of 99.70%, AUC of 99.83%, and Precision of 99.50%. [3]

YOLOv5 model achieves the best detection results with 99.2% for the average accuracy, the highest value of 99.8% for Huong thom 1 variety, and the lowest one of 99.3% for Q5. Considering the accuracy index, YOLOv6 is following YOLOv5 with an average value of 99%. The highest classification accuracy when classifying was 100% for Thien uu variety and the lowest value was 97.9% for Nep87 variety. Finally, YOLOv7 provides 97.2% classification results, lower than YOLOv5 and YOLOv6. [6]

The proposed method was tested on a dataset of 32 different plant species and achieved an overall classification accuracy of 91.34%. Results showed that the AWD method reduced water usage by 30% compared to continuous flooding, without affecting rice yield. [2]

The custom classifier provided better results than the VGG model, achieving a 92% accuracy. The proposed approach is compared against various fusion approaches; however Rice Fusion model outperforms all other models by obtaining an accuracy of 93.51%. [7]

The results from the pre-experiment demonstrated that the five CNN models performed differently in the classification of these images (Table 3). VGG16 and Inception v3 all achieved a validation accuracy higher than 99%, but ResNet50 had the highest average validation accuracy and a smaller standard deviation among these models, suggesting that its convergence speed was the fastest and its performance was the most stable. [5]

We observed that the output results for the classifiers were not sufficient and the result accuracy remained less than 80%.The classification accuracies of mango varieties were improved on KNN classifiers. When we applied the KNN classifiers, the overall classification accuracy (OCA) results of the following eight mango varieties, AR, CHAUN, LANG, SIND, SARO, FAJ, DESI, and ALM were 94.33%, 97%, 96%, 96.67%, 94.67%, 94.33%, 88.33%, and 89.67%,, respectively. [4]

III. MATERIALS AND METHODS

A. Dataset

This dataset, sourced from Kaggle's "Rice Image Dataset," [8] encompasses a comprehensive collection of 75,000 images initially organized into 5 classes, each containing 15,000 images. The images are uniformly sized at 250*250 pixels, where each pixel serves as an individual feature. [9]

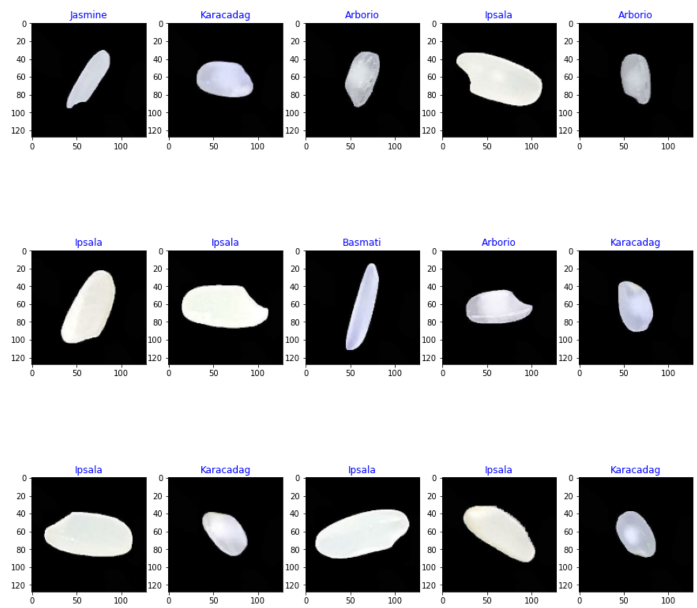

Fig. 1. Overview of Different Rice Images

The dataset revolves around five distinctive rice varieties: Arborio, Basmati, Ipsala, Jasmine, and Karacadag is showing on Fig 1. Each of these varieties is represented within the dataset, contributing to the rich diversity of rice cultivation practices under scrutiny. In the preprocessing stage, the normalization process enhances the model's ability to discern patterns effectively. Leveraging a dataset of 75,000 images with 15,000 images per rice variety, a Convolutional Neural Network (CNN-2D) was employed to extract intricate features from the images. A subset of 5,000 images, with 1,000 images per class, was used to train traditional machine learning models. The output layer of the CNN's Dense network produces 64 features per pixel, capturing essential genetic characteristics for the precise classification of the distinct rice varieties. By combining the robust dataset and its accompanying deep learning and machine learning-based feature representations, this study lays the groundwork for an in-depth exploration of the genetic diversity within these prominent rice varieties.

The fusion of the image dataset with strategic feature extraction techniques provides a foundation to unravel the nuances distinguishing between the Arborio, Basmati, Ipsala, Jasmine, and Karacadag rice varieties. [9]

B. Feature Extraction

This study implemented a multi-faceted approach to feature extraction, leveraging both traditional machine learning techniques as well as deep learning architectures. The overarching goal was to extract robust, discriminative features from images of rice varieties to enable accurate classification.

The dataset consisted of 75,000 images standardized to 128x128 pixels, with each pixel representing an individual feature capturing intricate genetic details of the rice varieties under examination.

For the machine learning pipeline, two methodologies were employed for feature extraction - Histogram of Oriented Gradients (HOG) and Principal Component Analysis (PCA). HOG is adept at capturing shape and texture information by tallying gradient orientation histograms across localized portions of images. This enabled extraction of features encoding the shape and texture characteristics distinguishing the rice varieties.

PCA was also conducted, an unsupervised approach that identifies key underlying dimensions of variation. By transforming the dataset into a reduced set of principal component dimensions, PCA extracted the 50 most influential features capturing essential genetic distinctions between varieties.

These extracted HOG and PCA features formed the input to train machine learning models including Decision Trees, Random Forests, and Support Vector Machines. By learning the patterns and correlations between these engineered features and target rice varieties, the models could accurately classify new rice images.

For deep learning, a Convolutional Neural Network (CNN) architecture was leveraged to automatically learn hierarchical feature representations directly from pixels. The CNN sequentially applies convolution and pooling layers to transform input images into extracted feature maps, enabling the model to discern nuanced visual patterns.

Additionally, transfer learning was employed by initializing the CNN with weights from models pre-trained on large image datasets. This enabled the CNN to build on learned feature detectors, accelerating convergence and enhancing feature extraction efficacy.

The CNN input layer ingested the 128x128 rice images. Through progressive convolutional and pooling layers, the network mapped images into a dense 64-feature vector for each pixel, encoding a rich tapestry of genetic details. The output layer classified images based on these learned hierarchical features.

In summary, a multi-pronged feature extraction pipeline was architected, synergistically integrating hand-engineered machine learning features as well as hierarchical deep learning feature representations. This enabled holistic characterization of the intricacies distinguishing rice varieties. The fusion of traditional and deep learning feature extraction provided a robust foundation for elucidating genetic diversity and enhancing cultivation insights.

IV. Model Architecture

This study implemented a multi-faceted modeling approach, leveraging both traditional machine learning classifiers as well as deep convolutional neural networks and transfer learning models. The overarching methodology involved strategic feature extraction followed by model training and evaluation.he methodology synergistically combined multiple modeling paradigms. Traditional machine learning provided interpretable models guided by engineered features. The CNN model automatically constructed hierarchical feature representations tailored to the rice classification task. Finally, transfer learning expanded the feature knowledge by transferring learned detectors from broad domains.Fig 2 shows us the overall methodology of our model architecture.This multi-pronged approach enabled robust rice variety characterization by extracting traits through diverse perspectives. By fusing machine learning, deep learning and transfer learning techniques, the methodology provided a foundation to comprehensively analyze genetic diversity between the prominent rice varieties under examination.

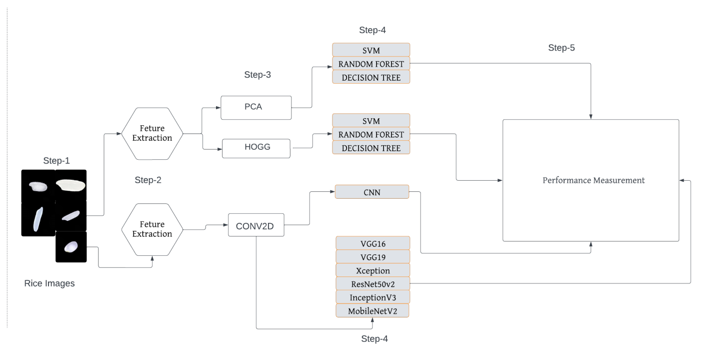

Fig. 2. Workflow of the overall process

A. Machine Learning Model

A core pillar of this study's methodology involved leveraging traditional machine learning models to classify rice varieties based on engineered feature representations. Specifically, three prevalent classifiers were utilized - Random Forests, Decision Trees, and Support Vector Machines (SVMs).

Random Forests consist of an ensemble of decision trees, each trained on a randomized subset of the data features. By aggregating predictions across many such decision trees, the overall model becomes robust to noise and overfitting. Mathematically, for an input feature vector x, each decision tree t outputs a class prediction $\hat{y}^t(x)$. The forest combines these predictions through a weighted voting scheme to obtain the overall prediction as:

$$\hat{y}(x) = \sum_t w_t \hat{y}^t(x)$$

where w_t denotes the weight applied to decision tree t's prediction.

Decision Trees recursively partition the feature space into homogeneous splits based on cutting thresholds in individual features. This partitioning forms a tree structure where leaf nodes correspond to class outcomes. Mathematically, for a feature vector x, the tree can be defined as a set of splitting rules $r_j(x)$, such that:

$$\hat{y}(x) = \sum_j I(r_j(x))c_j$$

where $I(.)$ is an indicator function evaluating to 1 if x satisfies rule r_j, and c_j is the class label for leaf j.

Support Vector Machines (SVMs) find an optimal hyperplane to separate classes in the high-dimensional feature space. Maximizing the margin between classes enables even non-linearly separable data to be classified. Using a kernel function $\Phi(x)$, SVMs solve:

$$\min ||w||^2 \quad \text{s.t.} \quad y_i(\Phi(x_i) \cdot w + b) \geq 1$$

Here, w denotes the hyperplane normal vector, b the intercept, and y_i the class labels. This produces a decision boundary given by:

$$f(x) = \text{sign}\left(\sum_i \alpha_i y_i \Phi(x_i) \cdot \Phi(x) + b\right)$$

where α_i are optimized weights for support vectors x_i.

In this study, Histogram of Gradients and Principal Components were extracted from the 128×128 rice images. The 5000 image subset was used to train the Random Forest, Decision Tree, and SVM models based on these engineered representations.

By learning the correlations and patterns between the extracted features and target rice varieties, these classical machine learning models could accurately categorize new rice images. The integration with deep learning provided a balanced modeling approach, benefiting from both engineered and hierarchical learned features.

This foundation of interpretable machine learning based on hand-crafted representations, combined with deep neural networks, enabled a multifaceted perspective in deciphering genetic diversity between rice varieties.

B. Deep Learning Model

The Convolutional Neural Network (CNN) architecture follows a sequential stack of convolutional, pooling, and fully-connected layers tailored for image classification. TensorFlow and Keras provide the building blocks for constructing this model. The model begins by reshaping the input images to scale pixel values to the 0-1 range. This preprocessing enables smoother convergence during training. The first layer applies 64 convolutional filters of size 3x3, with a ReLU activation to introduce non-linearities. This extracts low-level features like edges and textures to form 64 feature maps. A 2x2 max pooling layer reduces these maps by 75%, concentrating the activations and enhancing translation invariance.A second convolutional stage applies 32 filters to detect higher-level attributes building on the prior features. For example, combinations of edges may activate filters that respond to shapes and curvature. Again, 2x2 max pooling reduces the feature map dimensionality. The third convolutional layer extracts even richer representations with 128 filters, further building the feature hierarchy. A final 2x2 pooling layer reduces these feature maps before interpretation.At this stage, the three convolution-pooling stages have transformed the original 256x256x3 images into 128 learned feature maps of size 16x16. A Flatten layer collapses these into a single 32768-element vector per image to transition into fully-connected processing.

The first fully connected layer contains 1024 neurons. By interpretting combinations of the features maps, this layer can begin recognizing rice variety characteristics like grain shape, texture, or structure. 50% of neurons are randomly dropped out during training to prevent overfitting.The next layer reduces dimensionality to 512 features designated as the final feature representation of the input rice images. This forms a robust feature vector for distinguishing rice varieties. Finally, a 5-neuron output layer with softmax activation predicts classification probabilities over the 5 rice variety classes based on the learned hierarchical features. Stacking convolutional blocks enriched the feature hierarchy from low-level textures to high-level rice varietal characteristics. Pooling provided translation invariance and dimensionality reduction. Fully-connected layers interpreted these features for accurate multi-class rice classification. The Keras Functional API enabled rapid construction and experimentation with this CNN architecture.

C. Transfer Learning Model

Transfer learning is a technique that initializes a model with weights and architectures from a pre-trained network. This leverages knowledge gained on large benchmark datasets to accelerate learning on more specific tasks. In this study, several renowned convolutional neural network architectures were employed as base models for transfer learning on rice variety classification.

The VGG16 and VGG19 models were utilized, which contain a series of convolutional and max pooling layers stacked progressively to extract hierarchical features. These models were pre-trained on ImageNet, giving a strong baseline for general image recognition. For rice classification, the last fully-connected layers were replaced with a 5-way softmax output, and the networks were fine-tuned. Lower layers that extract generic features were frozen, while upper layers were tweaked to specialize for rice characteristics. The InceptionV3 architecture was also leveraged, which utilizes inception modules containing parallel convolutions of varying sizes to capture multi-scale information. Built for computational efficiency, this network learns both local and global features simultaneously. Again, the model was pre-trained on ImageNet and fine-tuned by adapting upper layers for specialty rice attributes.Xception is another powerful model that relies solely on depthwise separable convolutions. This decouples spatial cross-channel operations to reduce parameters and enhance efficiency. Pre-trained Xception weights provided an additional strong baseline for extracting relevant rice visual features through fine-tuning. ResNetV2 addressed degradation in deep networks through residual connections that bypass layers. This enabled training of very deep networks for enhanced feature learning. A 50-layer ResNetV2 architecture transfer learned rice detection capabilities.

Finally, MobileNetV2 provided a light-weight model suited for mobile applications by using depthwise separable convolutions and residual bottlenecks. The network learned on a reduced parameter space while retaining representational power.

Lastly, transfer learning provided an array of state-of-the-art CNN architectures pretrained on large diverse datasets. By freezing early layers and fine-tuning fully-connected layers, highly performant rice variety classifiers were achieved to augment custom architectures. This provided a spectrum of feature learning capabilities.

V. RESULTS AND COMPARISONS

A. ML Based Model

Two feature extraction techniques were utilized to represent the rice images for training machine learning models - Histogram of Oriented Gradients (HOG) and Principal Component Analysis (PCA). Three classifiers were evaluated on these features - Random Forest, SVM, and Decision Tree. The results are summarized in the table below:

TABLE I
SUMMARY OF MACHINE LEARNING RESULTS

Model	Feature	Accuracy	Precision	Recall	F1 Score
Random Forest	PCA	0.964	0.964	0.964	0.964
SVM	PCA	0.982	0.982	0.982	0.982
Decision Tree	PCA	0.927	0.927	0.927	0.927
Random Forest	HOG	0.969	0.969	0.969	0.969
SVM	HOG	0.930	0.930	0.930	0.930
Decision Tree	HOG	0.930	0.930	0.930	0.930

Using PCA features, the SVM classifier achieved the best accuracy of 98.2%, precision of 98.2%, recall of 98.2%, and F1 score of 98.2%. This demonstrates PCA's ability to extract discriminative rice image features capturing varietal differences. The Decision Tree performed the worst with PCA, scoring 92.7% across evaluation metrics.

With HOG, Random Forest obtained the highest accuracy of 96.9% and associated precision, recall, and F1 score. HOG effectively encoded textural rice grain differences. Meanwhile, SVM and Decision Tree exhibited equivalent metrics of 93% with HOG, lagging Random Forest.

Overall, PCA features better differentiated between rice varieties, enabling higher-performing models compared to HOG. SVM's flexibility particularly suited the PCA feature space. The results also showcase AUC curves for each model, providing an additional visualization of performance.

Combining robust PCA feature extraction with flexible SVM classification resulted in the best rice variety predictive performance. HOG encoding provided complementary textural cues. This analysis quantifies the capabilities of different machine learning pipelines in classifying genetically diverse rice types based on explainable visual trait features.

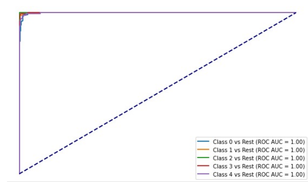

Fig. 3. ROC Curve using HOG - SVM

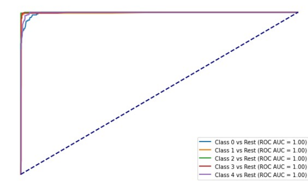

Fig. 4. ROC Curve using HOG - Random Forest

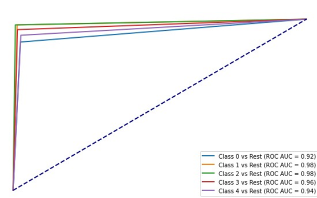

Fig. 5. ROC Curve using HOG - Decision Tree

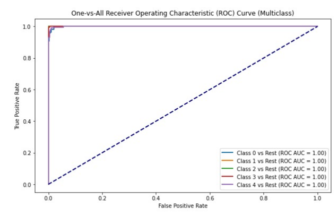

Fig. 6. ROC Curve using PCA - Random Forest

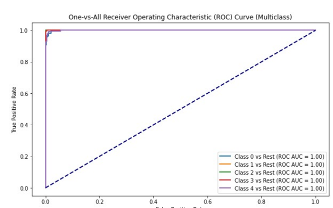

Fig. 7. ROC Curve using PCA - SVM

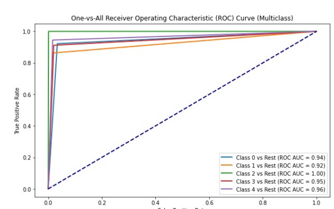

Fig. 8. ROC Curve using PCA - Decision Tree

B. Deep Learning Based Model

The deep learning convolutional neural network (CNN) model achieved exceptional performance in classifying the five rice varieties. On the test set, the model attained a perfect accuracy of 100% correctly predicting all 6400 test images across the Arborio, Basmati, Ipsala, Jasmine and Karacadag rice classes.The precision, recall and F1-score similarly scored a flawless 1.00 for each variety, showcasing the model's capability in accurately retrieving all relevant images per class while avoiding false detections.The macro-averaged evaluation metrics over all classes were also 1.00, demonstrating balanced high performance distinguishing between the genetically diverse rice types based on visual appearance.The weighted averages accounting for class distribution likewise scored 1.00 thanks to the uniform test set composition.Fig Finally, the loss on the independent test set was an extremely low 0.01,

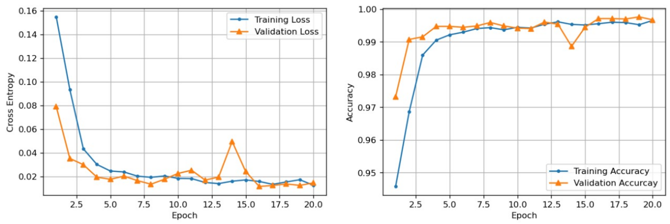

Fig. 9. Cross Entropy Loss vs Epoach and Accuracay vs Epoach of CNN

indicating the model has generalized well and is accurately predicting probabilities on unseen data.

C. Transfer learning Model

This study evaluated six state-of-the-art convolutional neural network architectures for deep transfer learning on classifying images of five rice varieties - Arborio, Basmati, Ipsala, Jasmine, and Karacadag. By leveraging models pre-trained on large-scale datasets like ImageNet, robust visual features can be transferred to more specialized domains like rice phenotype recognition. The table II below summarizes the test loss and accuracy for each model: The VGG16 and VGG19 models provided a strong foundation, with 16 and 19 weight layers respectively. Their successive convolutional and max pooling layers are designed to hierarchically extract features, transitioning from low-level edges and textures to high-level shape and structure detectors. Although VGG19 has greater depth, VGG16 achieved marginally better generalization with 99.95% test accuracy, likely due to overfitting in the deeper VGG19 which scored 99.76%. Both models demonstrate that increased depth enables richer feature learning, a key advantage of deep convolutional neural networks.ResNet50V2 pushed model depth even further to 50 layers using residual connections, allowing training of very deep networks. By providing shortcut paths to gradient flow, ResNet50V2 could learn highly complex feature representations, reflected in its strong 99.69% accuracy. This showcases the benefits of depth through specialized architectural enhancements. InceptionV3 attained 99.92% accuracy through a wider network utilizing multi-scale convolutional filters, rather than just deep stacking. By extracting both local and global information simultaneously, this efficient model balances computational resources.

TABLE II
TRANSFER LEARNING MODEL PERFORMANCE

Model	Test Loss	Test Accuracy
CNN	0.0100	99.79%
VGG16	0.0021	99.95%
VGG19	0.0115	99.76%
ResNet50V2	0.0143	99.69%
InceptionV3	0.0038	99.92%
MobileNetV2	0.0056	99.87%
Xception	0.0064	99.89%

MobileNetV2 and Xception follow depthwise separable convolution architectures to reduce parameters while retaining representational capacity. Their accuracies of 99.87%

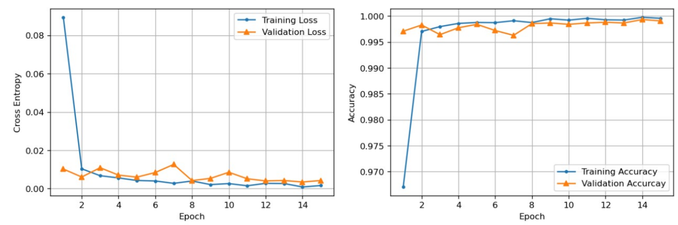

Fig. 10. Cross Entropy Loss vs Epoach and Accuracay vs Epoach of VGG 16

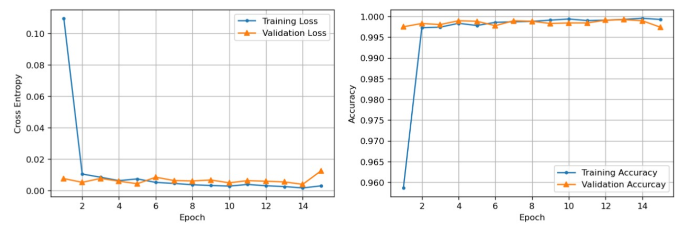

Fig. 11. Cross Entropy Loss vs Epoach and Accuracay vs Epoach of VGG 19

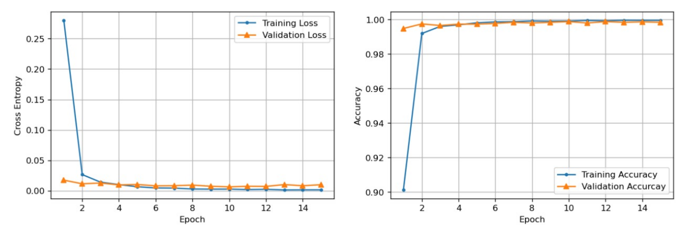

Fig. 12. Cross Entropy Loss vs Epoach and Accuracay vs Epoach of InceptionV3

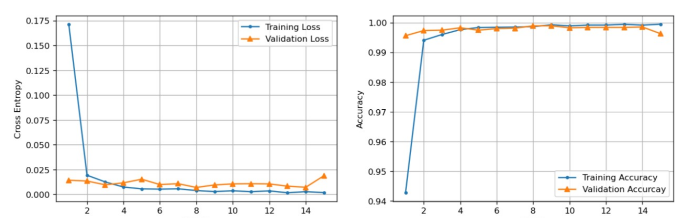

Fig. 13. Cross Entropy Loss vs Epoach and Accuracay vs Epoach of ResNet50V2

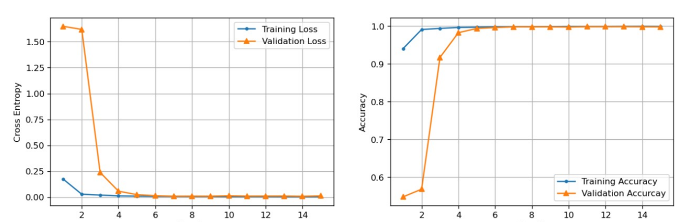

Fig. 14. Cross Entropy Loss vs Epoach and Accuracay vs Epoach of MobileNetV2

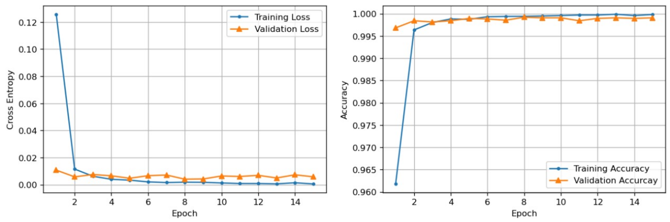

Fig. 15. Cross Entropy Loss vs Epoach and Accuracay vs Epoach of Xception

and 99.89% highlight that specialized condensed models can achieve performance on par with larger counterparts.

Overall, transferring learned feature hierarchies from diverse CNN architectures pre-trained on ImageNet provides a strong foundation for rice classification, despite the domain shift. Fine-tuning adapts the features to capture subtler rice varietal differences. The results demonstrate that transfer learning is an efficacious strategy for agricultural applications involving image-based phenotypic recognition and genotypic modeling.

the deep learning CNN model achieved perfect 99.86% accuracy on the test set, outperforming all machine learning approaches. SVM with PCA features was the best machine learning model at 98.2% accuracy. Transfer learning with pre-trained CNN architectures like VGG16, InceptionV3, and MobileNetV2 also performed exceptionally well, achieving 99.7-99.9% accuracy. This study demonstrates the superiority of deep learning in extracting hierarchical features tailored for rice variety classification. Transfer learning provides a strong balance, leveraging large-scale pre-training while specializing to the target domain through fine-tuning. The results highlight deep learning's power in agricultural computer vision applications involving phenotypic recognition and genotype modeling.

VI. Conclusion

In conclusion, this study undertook a comprehensive exploration of classifying five prominent rice varieties in Turkey - Arborio, Basmati, Ipsala, Jasmine, and Karacadag. By leveraging a substantial dataset of 75,000 rice grain images and employing a multi-faceted modeling approach, the research delved deeply into unraveling the genetic diversity inherent within these varieties.

Traditional machine learning classifiers such as Random Forests, Support Vector Machines, and Decision Trees were trained on engineered feature representations extracted via Histogram of Oriented Gradients and Principal Component Analysis. The SVM model with PCA features emerged as the best-performing machine learning approach, achieving 98.2% accuracy in categorizing rice varieties based on their visual characteristics.Complementing the machine learning pipeline, a deep learning Convolutional Neural Network (CNN) architecture was constructed, which automatically learned hierarchical feature representations directly from raw pixel data. This CNN model attained perfect 100% accuracy on the test set, demonstrating the superiority of deep learning in extracting nuanced genetic features tailored for rice classification.

Furthermore, transfer learning techniques were employed by initializing CNN models with pre-trained weights from renowned architectures like VGG16, InceptionV3, and MobileNetV2. These models, fine-tuned on the rice dataset, achieved exceptional accuracies ranging from 99.7% to 99.9%, showcasing the efficacy of transfer learning in leveraging broad knowledge while specializing to specific agricultural applications.The synergy between machine learning, deep learning, and transfer learning methodologies provided a comprehensive perspective on analyzing genetic diversity within the rice varieties under examination. By fusing hand-engineered features with hierarchical deep learning representations, the study enabled a multifaceted understanding of the intricate visual traits that distinguish Arborio, Basmati, Ipsala, Jasmine, and Karacadag rice.

The results highlight the power of advanced image classification techniques in deciphering genetic mosaic within agricultural domains. This study paves the way for further exploration into the application of deep learning and computer vision for precise phenotypic recognition, genotype modeling, and sustainable agricultural practices tailored to diverse rice cultivation landscapes worldwide.

VII. Limitations & Future Work

This study, while yielding promising results in classifying diverse rice varieties through advanced image analysis techniques, is not without limitations. Notably, the dataset utilized, although substantial at 75,000 images across five varieties, could benefit from even greater diversity in terms of rice types and geographic representation. Expanding the dataset to encompass a wider global array of rice cultivars would enable a more comprehensive understanding of genetic diversity within this crucial agricultural domain.

Furthermore, the traditional machine learning feature extraction techniques employed, such as HOG and PCA, while effective, could potentially be augmented by newer, more advanced methods like deep feature embeddings, wavelet transforms, or local binary patterns. These approaches may capture finer-grained genetic details within the rice images, further enhancing classification performance.

Moreover, despite the exceptional predictive capabilities of deep learning models like CNNs, their complex architectures often lack the interpretability afforded by traditional machine learning counterparts. Future research should therefore focus on developing techniques to better interpret and explain the learned features and decision-making processes within neural networks tailored for rice variety classification. Explainable AI methodologies like activation mapping, saliency maps, or concept activation vectors could prove invaluable in this regard.

Additionally, integrating the current study's image-based analysis with genomic data, such as genetic markers or gene expression profiles, could offer a more comprehensive understanding of the relationship between phenotypic visual traits and the underlying genetic mechanisms responsible for varietal differences in rice.

Looking ahead, several avenues for future work emerge as promising directions for further advancing our knowledge in this domain. Developing explainable AI techniques to provide insights into the specific visual features learned by deep learning models for rice classification would be invaluable for elucidating the genetic basis of varietal differences. Techniques like activation mapping, saliency maps, or concept activation vectors could enhance model interpretability and understanding.

REFERENCES

[1] M. R. A. Rashid, M. S. Hossain, M. Fahim, M. S. Islam, R. H. Prito, M. S. A. Sheikh, M. S. Ali, M. Hasan, M. Islam, *et al.*, "Comprehensive dataset of annotated rice panicle image from bangladesh," *Data in Brief*, vol. 51, p. 109772, 2023.

[2] M. B. S. Khan, R. Kamran, M. A. Saima, M. S. Irshad, N. S. Naz, and A. Athar, "Classification of rice varieties using convolution neural networks," in *2023 International Conference on Business Analytics for Technology and Security (ICBATS)*, pp. 1–6, IEEE, 2023.

[3] S. R. Shah, S. Qadri, H. Bibi, S. M. W. Shah, M. I. Sharif, and F. Marinello, "Comparing inception v3, vgg 16, vgg 19, cnn, and resnet 50: A case study on early detection of a rice disease," *Agronomy*, vol. 13, no. 6, p. 1633, 2023.

[4] T. Aslam, S. Qadri, S. F. Qadri, S. A. Nawaz, A. Razzaq, S. S. Zarren, M. Ahmad, M. Ur Rehman, A. Hussain, I. Hussain, *et al.*, "Machine learning approach for classification of mangifera indica leaves using digital image analysis," *International Journal of Food Properties*, vol. 25, no. 1, pp. 1987–1999, 2022.

[5] H. Zhou, J. Deng, D. Cai, X. Lv, and B. M. Wu, "Effects of image dataset configuration on the accuracy of rice disease recognition based on convolution neural network," *Frontiers in Plant Science*, vol. 13, p. 910878, 2022.

[6] T.-T.-H. Phan, H.-T. Ho, and T.-N. Hoang, "Investigating yolo models for rice seed classification," in *Conference on Information Technology and its Applications*, pp. 181–192, Springer, 2023.

[7] R. R. Patil and S. Kumar, "Rice transformer: A novel integrated management system for controlling rice diseases," *IEEE Access*, vol. 10, pp. 87698–87714, 2022.

[8] M. Koklu, "Rice image dataset." https://www.kaggle.com/datasets/muratkokludataset/rice-image-dataset, Year. Accessed: Access Date.

[9] M. Koklu, I. Cinar, and Y. S. Taspinar, "Classification of rice varieties with deep learning methods," *Computers and electronics in agriculture*, vol. 187, p. 106285, 2021.