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Original Article

Enhanced Classification of Rice Varieties using Cross Modality Dynamic Bidirectional Knowledge Transfer Model

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Abstract *- In recent years, rice has been the staple food for nearly half of the global population, serving as a rich source of nutrients and contributing significantly to increased crop yields. Thus, accurate rice variety classification is essential, which corresponds to distinct spot shapes and sizes. However, existing Deep Learning (DL) models have several limitations that make it difficult to distinguish among various rice varieties because of their similar characteristics. To overcome this limitation, Centered Kernel Alignment-based Cross-Domain Knowledge Transfer (CKA-CDKT) is proposed to accurately identify and classify various types of rice grains. The EfficientNet-B7 model extracts the most relevant features that have significant information on rice varieties, which helps to efficiently enhance the classification of distinct rice varieties. Rice images are acquired from benchmark datasets and are preprocessed using the hybrid filtering technique of the modified median and Wiener filters, which effectively eliminates the noise present in the rice images. In addition, the proposed rice variety classification model employs the CKA similarity metric, which helps to transfer the relevant knowledge between domains, reducing the impact of misaligned features and resulting in a more accurate variety identification. The experimental results of the proposed CKA-CDKT model display an accuracy of 99.93%, which is greater than that of existing approaches such as Lightweight ConvNeXt.*

Keywords *- Bidirectional Knowledge Transfer, Cross-modality, EfficientNet-B7, Modified Median Filter, Rice Variety Classification, Wiener Filter.*

1. Introduction

In recent years, agriculture has played an important role in India's economy, which impacts food production, increasing the challenges in population growth as well as the food demand. Rice is the staple food for nearly half of the global population and is one of the crucial sources of nutrition. The yield and quality of the rice have a significant influence on not only food security but also soil health, and the preservation of genetic diversity is also greatly impacted [1], [2]. The global importance of rice was starkly highlighted during the 2008 food crisis, when prices surged sharply, one of the steepest increases in food history, causing export prices to triple in just a few months [3-5]. This brought rice to the center of global concern, not only across Asia but in other parts of the world as well [6, 7]. During the Asian Green Revolution, the International Rice Research Institute (IRRI) played a transformative role by developing high-yielding rice varieties, which greatly boosted productivity and helped stabilize prices through effective government interventions [8-10]. Rice classification is the process of categorizing rice varieties into different groups based on unique traits such as appearance, grain size, and quality [11]. It helps in identifying and differentiating rice types for purposes such as quality control and improving the classification efficiency. However, similarities in the visual characteristics of various rice varieties make it difficult to classify rice images [12, 13]. Differentiations in lightning, environmental conditions, and natural overlap lead to misclassification, which affects the accuracy of the classification process [14, 15]. The recent rice classification method based on Machine Learning (ML) faces difficulties in accurate classification due to the extracted high morphological similarity features between the rice grain varieties. Similarly, the presence of noise in rice grain images makes the existing model capture irrelevant information that leads to misclassification. To overcome these challenges, an improved Deep Learning (DL) model has been proposed to classify rice and enhance the classification accuracy.

1.1. Problem Statement

The classification of rice varieties using image-based techniques poses a significant challenge due to the high degree of visual similarity between the different types. Variations in grain size, shape, and texture are often minimal and difficult to distinguish even with advanced imaging methods. This overlap in visual features results in frequent misclassification, thereby reducing the accuracy and effectiveness of the automated systems. Furthermore, environmental factors such as lighting and background noise can further degrade classification performance.

1.2. Objective

To enhance the accuracy of rice variety classification by employing Cross-Modality Dynamic Bidirectional Knowledge Transfer (CDKT), which effectively integrates and transfers complementary information between the visual and semantic modalities. This approach aims to improve feature discrimination and reduce the misclassification caused by visual similarities among rice varieties.

This paper is organized as follows: the literature review is presented in Section 2, and the proposed methodology is detailed in Section 3. The experimental results and discussion of the proposed Centered Kernel Alignment-based Cross-Domain Knowledge Transfer (CKA-CDKT) model are explained in Section 4. The conclusion of this research is presented in Section 5.

2. Literature Review

Some existing DL models developed for rice variety classification are analyzed and discussed as follows. Table 1 represents the taxonomy of rice variety classification literature for categorizing diverse approaches to identify existing research gaps.

Lv et al. [16] introduced an improved rice variety classification model based on the lightweight ConvNeXt technique. ConvNeXt focuses on automated identification and classification of distinct types of rice varieties. Through the feature extraction procedure, improved lightweight ConvNeXt techniques were used for rice detection and classification. However, lightweight ConvNeXt depends on the image quality for accurate feature extraction, whereas images consist of noise, uneven lighting, or distortions that minimize the classification accuracy.

Naik et al. [17] implemented an Analysis of Variance-based Support Vector Machine (ANOVA-SVM) to classify rice varieties. Initially, the rice image dataset contained 12 morphological features, four shape features, and 90 color features. An ANOVA was used for selecting high-ranking features, which were fed into an SVM for classification purposes. SVM effectively constructed an optimal hyperplane that minimized classes that were useful in texture, extracted the shape, and enhanced the classification accuracy. Nevertheless, the classification of SVM in rice grain datasets, where differences in image quality or inconsistent feature extraction produced noise, affected the model performance.

Rajeshwari et al. [18] implemented a DL-based classification model for rice varieties used in images. For the classification of rice varieties through a Convolutional Neural Network (CNN)-based architecture, RiceSeedNet was effectively utilized for the classification of rice classes. In the classification stage, rice was divided into five stages: Arborio, Basmati, Ipsala, Jasmine, and Karacadag. However, RiceSeedNet utilizes pre-extracted features rather than learning directly from raw images, which makes it struggle to learn complex spatial patterns and to differentiate similar rice varieties.

Tasci et al. [19] developed a neural model-based segmentation approach for classifying morphological characteristics and differentiating rice varieties. Initially, the spikelets per panicle were extracted for yield prediction, highlighting the advantages of using a segmentation-based method. This approach utilized the shape, color, and texture features obtained from the agro-morphological images of various rice varieties, which were manually annotated. However, the neural-based model depends on segmentation as a preprocessing step, whereas any errors in segmentation, such as inaccurate boundaries, lead to misclassification.

Razavi et al. [20] implemented Artificial Neural Network (ANN) and Deep Neural Network (DNN) methods for rice variety classification, which were performed on a feature dataset to extract the features. Processes were performed to classify rice varieties using a convolutional neural network. However, ANN and DNN utilize pre-extracted features rather than learning directly from raw images, which makes it difficult to capture complex spatial patterns, making it challenging to differentiate similar rice varieties.

Alsharani et al. [21] developed an automated rice variety classification based on the Quantum-Inspired Moth Flame Optimization with DL (QIMFODL) approach. A Long Short-Term Memory (LSTM) model with the QIMFO algorithm was employed to classify the rice grain efficiently according to the class labels. Here, an improved ShuffleNet model with a Squeeze and Excitation (SE) block was used for feature extraction. However, the developed QIMFODL faces challenges because of class overlap between ipsala, jasmine, and basmathi due to similar color and shape features that greatly impact the classification results.

Xudong Li et al. [22] presented an ensemble model with residual learning to improve rice grain variety classification. The presented ensemble model utilized a decision-level fusion strategy, which combined the outputs of residual learning and multi-scale kernel models by the concatenation method. Additionally, the presented ensemble model integrated a customized attention mechanism to highlight the significant characteristics of rice grains efficiently. Jintao Liu et al. [23] developed an enhanced classification model to categorize the rice grains during rice processing. The developed rice classification model, namely GMMNet, was a combination of Gaussian Matrix Self-attention Mechanism (GMSM), Multi-scale Fine Feature Extraction Module (MFFEM), and a Multi-Depth Separable Convolutional (MDSC) block. Moreover, the GMMNet model efficiently addressed the high inter-class similarity issues to enhance rice grain classification.

2.1. Research Gap

Existing traditional rice variety classification research faces challenges due to high dependence on image quality; the presence of noise and image quality affects the classification performance. Furthermore, the high similarity between certain rice varieties, such as Jasmine and Basmati, and Ipsala and Arborio, causes frequent misclassification, highlighting the need for a more robust and adaptive classification framework. Consequently, a CKA-CDKT model is proposed in this research to capture the discriminative information from the extracted features to enhance rice variety classification.

Table 1. Taxonomy of existing works with the proposed model in rice variety classification

Author	Methodology	Advantages	Limitations
Lv et al. [16]	Lightweight ConvNeXt	By effectively extracting morphological and texture features, the ConvNext model enhanced classification accuracy.	The ConvNext model was highly sensitive to noise and uneven lighting conditions that degrade the classification performance.
Naik et al. [17]	ANOVA-SVM	The ANOVA-SVM model utilized a feature ranking function to identify the significant features based on the p-values.	However, the ANOVA-SVM model suffers from inconsistent feature extraction, which reduces the model's generalizability across similar feature representations.
Rajeshwari et al. [18]	CNN-based model RiceSeedNet	The RiceSeedNet model extracts highly discriminative features that help to effectively distinguish between the different rice varieties.	The RiceSeedNet model struggles to capture the subtle spatial patterns that are crucial to differentiate visually similar rice grains.
Tasci et al. [19]	Neural network-based segmentation model	The neural network-based segmentation model effectively captures the precise shape, color, and texture of rice grains.	However, the neural network-based model depends heavily on segmentation accuracy; consequently, any errors during the segmentation phase lead to misclassification.
Razavi et al. [20]	ANN, DNN, and CNN	By integrating ANN, DNN, and CNN architectures, the model effectively extracts and identifies intricate patterns from the data.	However, the CNN model struggled to capture the fine-grained spatial differences within complex feature sets.
Alshahrani et al. [21]	QIMFODL, LSTM, and ShuffleNet-SE	The QIMFODL model performs efficient feature optimization, which enhances the ability of the LSTM model to differentiate between rice varieties.	The class overlap between visually similar varieties affects the model classification performance and leads to inaccurate results.
Xudong Li et al. [22]	Ensemble residual learning with multi-scale kernels and attention mechanism	The ensemble model utilized a decision-level fusion to fuse the rice grain features, improving the discrimination between rice varieties.	However, integrating multiple models for the classification of rice varieties results in higher computational complexity.
Jintao Liu et al. [23]	GMMNet	The developed GMMNet model effectively addresses high inter-class similarity by capturing fine-grained details across various rice grains.	Due to the presence of noise and redundant features, the developed GMMNet model failed to achieve accurate classification.
Proposed Method	CKA-CDKT	The proposed model utilizes CKA similarity to align texture, color, and shape features to effectively mitigate feature redundancy. Additionally, the CDKT model's robustness to noise and visual similarity ensures high accuracy with reduced computation time.	However, the proposed model requires careful kernel alignment tuning, which directly affects the classification accuracy.

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3. Methodology

The proposed rice variety classification framework involves four stages: dataset acquisition, preprocessing, feature extraction, and classification.

Figure 1 displays the block diagram of the proposed methodology.

3.1. Dataset Acquisition

The rice image dataset [24] comprises five different varieties of rice commonly processed in Turkey: Arborio, Basmati, Ipsala, Jasmine, and Karacadag. Table 2 depicts the description of the dataset. The sample images of the rice image dataset are given in Figure 2. Also, the Grainspace dataset [25] is considered in this research to train and validate the effectiveness of the proposed model.

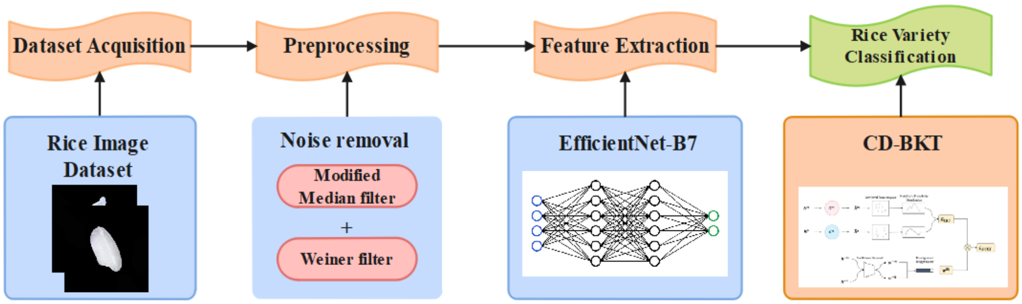

Fig. 1 Proposed framework for rice variety classification using CKA-CDKT

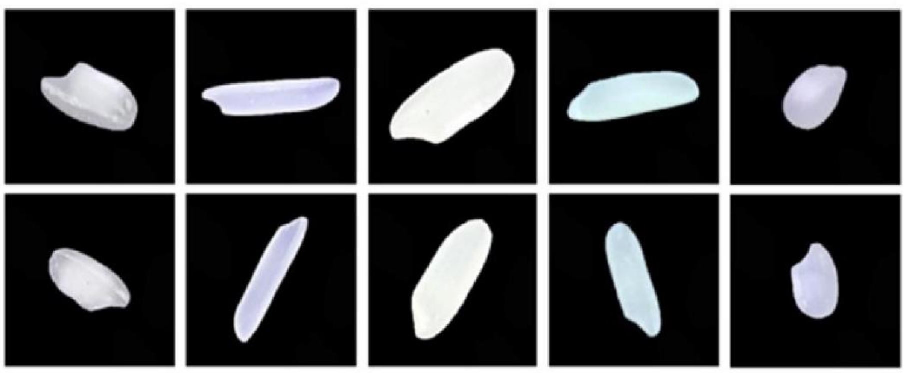

Fig. 2 Sample images of the rice image dataset

Table 2. Description of the rice image dataset utilized in rice variety classification

Attributes	Description
Total number of images	75,000
Rice Varieties	5 classes [Arborio, Basmati, Ipsala, Jasmine, Karacadag]
Images in each class	15,000
Resolution	256×256
Dataset split up	80:20
Training and testing images	60,000 images and 15,000 images

3.2. Preprocessing

After data acquisition, the images are preprocessed using a filtering technique to remove noise from the rice images. The aim of the preprocessing phase is to improve the quality of the rice image by eliminating noise in the background area to improve the classification of rice varieties.

In this study, a hybrid filtering technique is utilized for noise removal and to preserve the edges of rice in the image. First, a modified median filter is used to eliminate the noise present in the background area, and then a Wiener filter is used to preserve the edges of the rice present in the image. According to the Wiener filter, the modified median replaces the pixel value of the mask matrix with a median value that minimizes the noise from the degraded images. The average value of the Wiener filter is replaced by the median value, which is mathematically formulated in Equation (1).

$$b_{mwf}(n,m) = \tilde{\mu} + \frac{\sigma^2 - v^2}{\sigma^2}\,(a(n,m) - \tilde{\mu}) \tag{1}$$

Where $b_{mwf}(n,m)$ indicates the denoised value at the position of the pixels, $a(n,m)$ represents the observed noisy pixel value, $\tilde{\mu}$ denotes the local pixel intensities in the same neighborhood, σ^2 and denotes the local variance of the pixel intensities in the same neighborhood. v^2 refers to noise variance. The MMWF offers significant advantages in enhancing the quality of degraded images. Unlike conventional MF and classical Wiener filters, the MMWF method is more effective at preserving edge details by reducing the drop-off effects commonly observed in other filters. It not only removes background noise efficiently but also maintains the integrity of important edge signals. Consequently, MMWF outperforms conventional filtering techniques in terms of both noise reduction and edge preservation, leading to superior denoising performance.

3.3. Feature Extraction

After preprocessing, a pre-trained model is used for feature extraction, namely EfficientNet-B7 in this study. The EfficientNet-B7 model is part of the EfficientNet family, which uniformly scales the depth, width, and resolution of network dimensions by utilizing a compound scaling method that achieves superior performance with fewer parameters than traditional architectures. EfficientNet-B7 serves as a powerful feature extractor for rice-variety classification. It effectively captures fine-grained visual features such as texture, shape, and edge patterns, which are essential for distinguishing visually similar rice varieties. Despite its high performance, it uses fewer parameters and requires less computational power, making it ideal for large-scale image-analysis tasks. Its ability to generalize across complex datasets further enhances its reliability in agricultural image classification tasks. EfficientNet-B7 extracts a 2560-dimensional feature vector from each preprocessed rice image to capture the deep semantic and structural information. These features include texture patterns, shape descriptors, color variations, edge details, and fine-grained visual cues. Such rich representations enable accurate classification of visually similar rice varieties.

3.4. Proposed Classification Model

A Knowledge Transfer (KT) is an ML model that is developed to transfer the information learned from one modality/domain to another effectively to enhance the target task. Specifically, this KT model is utilized when labelled data is limited, making the model efficient to learn from previously acquired knowledge, and is combined to improve the performance of the classification model. In the traditional KT model, this transfer process usually occurs within the same domain/modality, such as training a DL model on a large rice dataset and fine-tuning it on another dataset with similar characteristics. This process results in misclassification because the rice varieties have similar characteristics, and transferring the same leads to inaccurate results.

Hence, in this research, a Cross-Domain Knowledge Transfer (CDKT) extends this concept by transferring knowledge across different domains and feature distributions to address the challenges of domain shift that arise from variations in imaging modalities. Figure 3 represents the architecture of the CKA-CDKT model utilized for rice variety classification. In rice variety classification, the proposed CDKT model is especially effective due to the fact that datasets considered in this research differ in size, quality, and feature composition. Moreover, the dataset with only five classes, such as Arborio, Basmati, Ipsala, Jasmine, and Karacadag, does not fully represent all varieties under various environmental conditions. Hence, by leveraging the extracted features, such as shape, color, and texture of rice varieties as separate domains, the proposed CDKT model aligns and fuses these heterogeneous feature representations to improve the robustness and accuracy of classification models.

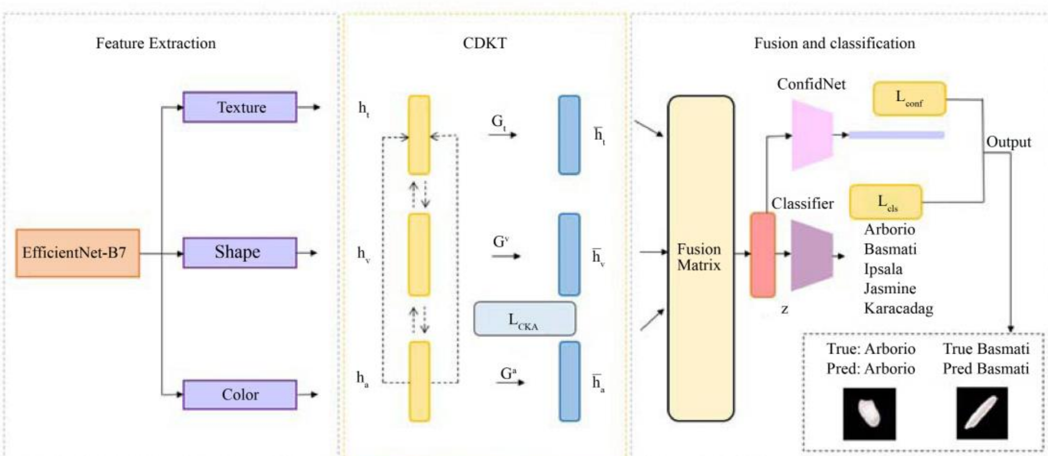

Fig. 3 represents the architecture of the CKA-CDKT model utilized for rice variety classification. In the feature extraction block, the EfficientNet-B7 model is used for extracting low-level features such as texture, color, and shape, respectively. In the CDKT block, the extracted feature types are considered as domains/modalities, and knowledge is transferred between these domains. The transferred knowledge is fused into a single vector and classified as per the rice labels in the fusion and classification block.

The main objective of the proposed CDKT model is to explore and combine the various features into a uniform feature vector, which helps to enhance the classification of rice varieties. To dynamically adjust the knowledge, transfers from different feature representations are done by refining the low-level feature representation. For the mathematical representation of refined unimodal features, a transfer encoder is trained in the proposed CDKT model, which is expressed in Equation (2).

$$\widetilde{\mathrm{H}}^{\mathrm{m}} = \mathrm{E}^{\mathrm{m}}(\mathrm{H}^{\mathrm{m}}; \emptyset) \quad (2)$$

Where H^m denotes the hidden state of modality m, E^m represents the mapping function, and $\emptyset$ indicates the weights of the mapping function E^m.

3.4.1. Stages of CDAT

In this proposed KT model, there are two primary stages: 1) misaligned modality filtering and 2) KT from aligned modality, respectively. In the first stage, the irrelevant features from the extracted low-level features are filtered out by adjusting the weights of the features. After that, the knowledge from the remaining modalities is transferred to improve classification performance.

3.4.2. Proposed CKA Loss

In the first stage, the CDAT model calculates the misaligned weights, which are represented by $W^m$of a modality to leverage the degree of modality transfer dynamically. By using this misaligned weight, the low-level features are refined through the KT technique. In the existing model, this process is trained by the Kullback-Leibler (KL) divergence loss among the group of misaligned modalities. However, the KL divergence loss is asymmetric and sensitive to the chosen direction and multiple scale levels, which leads to fusing the misaligned features that greatly impact classifying the rice. Due to these limitations, the CDKT model faces challenges in classifying unseen rice images that reduce the generalization ability of the model. Therefore, in this research, a Centered Kernel Alignment (CKA)-based similarity metric is proposed and utilized instead of the KL divergence loss in the CDKT model. In rice variety classification, the inter-class differences are subtle, and cross-domain variability is high, which makes the existing conventional model difficult to classify the rice types precisely. Consequently, the proposed CKA is used as a similarity metric to ensure that the transferred knowledge in the CDKT model has more discriminative information and avoids redundant features to improve classification accuracy.

Generally, CKA is used to evaluate the degree of similarity between two kernels, but in this research, the objective is to measure the similarity between two feature domains (modalities), such as the source domain and the target domain. For the rice image dataset, $S = \{(x_1, y_1), (x_2, y_2), \dots (x_l, y_l)\}$. The features captured from the domain 1 and domain 2 (source and target) are mathematically represented by kernel matrices, which are given in Equation (3).

$$\mathrm{K}_1(\mathrm{i},\mathrm{j}) = \mathrm{k}_1(\mathrm{x_i}, \mathrm{x_j}) \text{ and } \mathrm{K}_2(\mathrm{i},\mathrm{j}) = \mathrm{k}_2(\mathrm{x_i}, \mathrm{x_j}) \quad (3)$$

Where K_1 and K_2 represent source domain and target domain-based feature sets. Firstly, the kernels are centered using an identity matrix, which is expressed in the following Equations (4) and (5).

$$\mathrm{H} = \mathrm{I} - \frac{1}{\mathrm{l}}\mathrm{ee}^{\mathrm{T}} \quad (4)$$

$$\overline{\mathrm{K}_1} = \mathrm{HKH} \text{ and } \overline{\mathrm{K}_2} = \mathrm{HK_2H} \quad (5)$$

Where H indicates centering transformations; I represents the identity matrix; $\overline{K_1}$ and $\overline{K_2}$ denotes the centered kernel matrices. After that, the CKA evaluation for cross-domain similarity is calculated using Equation (6).

$$\mathrm{CKA}\left(\mathrm{K}_1,\ \mathrm{K}_2\right) = \frac{\overline{\mathrm{K}_1} \text{ and } \overline{\mathrm{K}_2}_{\mathrm{F}}}{\sqrt{\overline{\mathrm{K}_1} \text{ and } \overline{\mathrm{K}_1}_{\mathrm{F}} . \overline{\mathrm{K}_2} \text{ and } \overline{\mathrm{K}_2}_{\mathrm{F}}}} \quad (6)$$

Where $\langle \overline{K_1}\ and\ \overline{K_2} \rangle_F$ denotes cross-domain similarity, which is represented as $\langle \overline{K_1}\ and\ \overline{K_2} \rangle_F = \sum_{i=1}^{l}\sum_{j=1}^{l} \overline{\overline{K_1}\overline{K_2}}$ refers to the Frobenius inner product; $CKA\ (K_1, K_2)$ indicates centered kernel alignment value, which ranges between [0,1]. For rice variety classification, if the CKA value is closer to one, then it is high, which represents strong alignment between the feature domains, whereas if the CKA value is close to zero, then it is low, which represents weak alignment and suggests more knowledge transfer for the domains that are less correlated. In this research, based on the extracted features, texture, color, and shape are the three primary domains considered to transfer knowledge and enhance classification. At first, the cross-domain feature similarity is evaluated from the three domains (texture, color, and shape) to identify which domain contains transferable and compatible feature representations of the five types of rice grains. The Gram matrix is a mathematical representation that encodes the pairwise similarities between the samples in a given feature space. Subsequently, the extracted features are standardized using a min-max normalization technique to generate gram matrices for each domain, center the features, and compute the pairwise CKA scores in the first stage. These evaluated pairwise scores are fed to the next stage in the CDKT model. The detailed explanations of these stages are described below:

3.4.3. Misaligned Modality Filtering

Initially, the misaligned modalities are identified and assigned to the modality confidence weights to control the cross-modal knowledge transfer in the CDKT model. In rice variety classification, modalities refer to the color, texture, size, and shape-related features, respectively. To compute the confidence score between the modalities in this research, two calibration techniques are considered in the CDKT model, which are explained as follows:

3.4.4. Cross-Entropy-Based Calibration

During the process of masking a certain modality and fusing multiple modalities, this cross-entropy technique is used to estimate the difference between predicted probability distributions and the true labels. In this KT model, the logits, which are known as the raw outputs that are not normalized, are obtained from the activation function layer of the model. To compute cross-entropy, logits are typically passed through a softmax to become probabilities, which is mathematically represented in Equation (7).

$$w^m = -\sum_{l=1}^{L} P\left(Y = \frac{yl}{z}\right) \log P\left(Y = \frac{yl}{z}^{-m}\right) \quad (7)$$

Where w^m denotes modality confidence weight; L represents the total number of class labels; l indicates the index of class label, which ranges from 1 to L; Y denotes a random variable; yl represents the l-th class label; z indicates the logit vector from the model; z^{-m} denotes logit vector when m is masked; $P\left(Y = {yl}/{z}\right)$ and $P\left(Y = {yl}/{z}^{-m}\right)$ is the predicted probability of class yl for the full set of modalities and when modality m is masked. A high cross-entropy value indicates a higher importance of modality.

3.4.5. Confidence Network-Based Calibration (ConfidNet)

This calibration technique is used to estimate the model confidence for applying the model results of classification of rice types directly in the modality misalignment filtering. Here, the confidence refers to the output probabilities of rice variety classification and calculates a confidence score for every rice grain class. To obtain the confidence score C from the target value, which reflects how trustworthy the model predictions are, mathematically expressed in Equation (8).

$$C^*(z, y) = \frac{1}{L} \sum_{l=1}^{L} P(\widehat{yl} = yl/z) \quad (8)$$

Where C^* denotes the target value, y represents the true rice class label; $\widehat{yl}$ indicates the predicted class label, and z is the input feature vector generated by the fusion network. The L2 loss function of the ConfidNet model is expressed in Equation (9).

$$\mathscr{L}_{\text{conf}} = \left(\hat{C}(z; \theta^*) - C^*(z, y)\right)^2 \quad (9)$$

Where $\hat{C}$ represents the output of ConfidNet, and θ^* indicates parameters of the network. The network consists of multiple layers with the activation of the Rectified Linear Unit (ReLU); from this optimized network, the misaligned weight value is obtained by Equation (10).

$$Cw^m = \hat{C}(z^{-m}; \theta^*) \quad (10)$$

Finally, the confidence weights Cw^m are applied to filter and adjust cross-modal knowledge transfer by the proposed CKA metric, which gives higher importance to the well-aligned modalities and reduces the negative impact of poorly predictive output.

To address modality misalignment, the CDKT framework employs a more reliable data source to guide the instance-level refinement of lower-level feature representations. Through this knowledge transfer process, the confidence level of each modality is assessed by allowing the framework to reduce the distribution gap between the two modalities.

Consequently, the less confident feature representation h_m is updated to a more accurate version h^m. The KT from modality m to modality n is quantified by utilizing the CKA metric among their respective probability distributions. This process is formally expressed as $KT(m, n)$ in Equation (11).

$$\text{CDKT}(m, n) = \text{CKA}\ (P|Q) = \int_{-\infty}^{\infty} P(h^m) \log \frac{P(h^m)}{Q(h^m)}\, dh \quad (11)$$

Where $P(h^m)$ denotes the probability distribution of the low-level feature h^m, and $Q(h^n)$ represents a conditional probability distribution h^n. Both distributions $P(h^m)$ and $Q(h^n)$ are estimated based on the element-wise pairwise cosine similarity between cross modalities, which are expressed in Equation (12).

$$\mathscr{L}_{\text{CDKT}} = \sum_{m}^{M} \sum_{n, n \neq m}^{M} \text{CDKT}(m, n) \quad (12)$$

The KT is performed bidirectionally because of the nature of the CKA loss metric. To enable adaptive correction of the misaligned modality, each loss is multiplied by w^m, which represents the confidence score of the corresponding modality.

The weight adjustment factor s was then used to compare the confidence levels of the two modalities during the masking process. This adjustment factor was computed as shown in Equation (13).

$$s(m, n) = \begin{cases} 1 & \text{if } w^m > w^n \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

The proposed CKA-CDKT model enhances rice variety classification by effectively bridging the gap between the visual features and semantic understanding. Figure 4 represents the output results of the proposed CKA-CDKT model employed for rice variety classification.

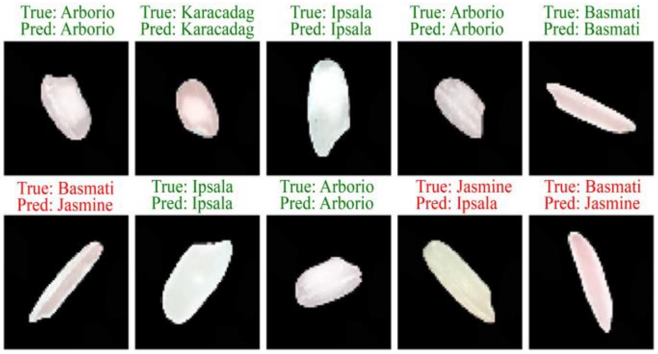

Fig. 4 Sample output images from the proposed CKA-CDKT model used in rice variety classification.

At last, the proposed CDKT model with the CKA metric learns the actual rice variety labels by cross-modal knowledge transferring dynamically by combining the two losses, which is represented in Equation (14).

$$\mathscr{L} = \mathscr{L}_{\text{cls}} + \alpha\mathscr{L}_{\text{CDKT}} \quad (14)$$

The proposed CKA metric improves feature representation by enabling mutual learning between image and textual modalities, leading to more robust and discriminative classification. Algorithm 1 represents the overall process of the proposed CKA-CDKT model in rice variety classification.

Algorithm 1:

Input: Rice dataset $D = (x_i, y_i)$, modalities m = {texture, color, shape}

Initialize: features from the EfficientNet-B7 model, transfer encoders E^m, fusion network F, classifier C, and α

for each epoch do

for each batch in D do

Extract features h^m for each modality m, and refine unimodal features: $\widetilde{H}^m = E^m(H^m)$

Fuse features: $z = F(concat(\widetilde{H}^m))$; compute logits and $p = softmax(z)$

for each modality m do

Mask m $\rightarrow z^{-m}$; compute masked P^{-m}

Compute confidence weight w^m via cross-entropy/ConfidNet.

end for

Compute centered kernels using the CKA metric $\overline{K_1}$ for each modality.

Calculate $\mathcal{L}_{CDKT} = \sum_m^M \sum_{n,n\neq m}^M CDKT(m,n)$ over modality pairs.

Compute total loss: $\mathcal{L} = \mathcal{L}_{cls} + \alpha\mathcal{L}_{CDKT}$ and update parameters.

end for

end for

Output: Class labels such as Arborio, Ipsala, Jasmine, Basmati, and Karacadag from the trained CKA-CDKT model

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This cross-domain dynamic knowledge transfer mechanism allows adaptive refinement using the CKA metric of shared knowledge and reduces the impact of interclass visual similarity. This model significantly boosts the classification accuracy of rice variety classification and generalization across varying conditions, contributing to a more reliable and scalable rice recognition system.

4. Results and Discussion

Experimental results of CKA-CDKT were used for rice variety classification using a rice image dataset and are presented in this section. A performance analysis of the proposed optimized DL is presented in Section 4.2, which was evaluated using the state-of-the-art methods. The comparative analysis of the proposed CKA-CDKT is evaluated with existing research work, as represented in Section 4.3. Table 3 illustrates the hyperparameter settings of the proposed CKA-CDKT model employed for rice variety classification.

Table 3. Hyperparameter Configuration of the CKA-CDKT Framework Applied to Rice Variety Classification

Hyper parameters	Values
Learning Rate	0.001
Batch Size	32
Dropout Rate	0.3
Loss function	KT loss ($\alpha = 10{,}000$)
Epochs	50
Optimizer	Adam
Classification Threshold	0.5
Activation Function	ReLU

4.1. Evaluation metrics

To estimate the proposed CKA-CDKT model's effectiveness in rice variety classification, evaluation measures like accuracy, precision, recall, and F1-score are utilized. The evaluation metrics are mathematically expressed in Equations (15)-(18).

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \times 100 \quad (15)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (16)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (17)$$

$$\text{F1} - \text{score} = 2 \times \frac{\text{precision}\times\text{recall}}{\text{precision}+\text{recall}} \quad (18)$$

Where TP, FP, TN, and FN represent the true positives, false positives, true negatives, and false negatives, respectively.

4.2. Quantitative and Qualitative Analysis

Performance of the proposed CKA-CDKT for rice variety classification was evaluated using state-of-the-art methods and is presented in this section. Table 4 presents the performance analysis of the CKA-CDKT, which is evaluated with various existing DL-based classification models, such as Convolutional Neural Networks (CNN), Residual Networks (ResNet50), MobileNet-V2 and DenseNet-169 over EfficientNet-B7 model. Table 5 presents the performance analysis of the proposed CKA-CDKT method, which is evaluated with various existing DL-based classification models, such as CNN, Transformer, Vision Transformer (ViT), KT, Knowledge Distillation (KD), and CDKT models. The proposed CDKT model allows the knowledge transfer from a more informative domain to a less informative domain, which helps to learn the morphological information efficiently.

Table 4. Evaluation of the EfficientNet-B7-based feature extraction method in rice variety classification with various pre-training models

Classifiers	Datasets	Accuracy %	Precision %	Recall %	F1-Score %
CNN	Rice image	98.45	98.50	98.60	98.45
	Grainspace	97.65	97.64	97.63	97.62
ResNet-50	Rice image	97.85	97.90	98.00	97.85
	Grainspace	97.79	97.80	97.78	97.79
MobileNet—V2	Rice image	98.56	98.54	98.51	98.52
	Grainspace	97.91	97.92	97.91	97.92
DenseNet-169	Rice image	98.15	98.25	98.35	98.15
	Grainspace	98.23	98.24	98.22	98.23
EfficientNet-B7	Rice image	99.93	99.94	99.92	99.93
	Grainspace	98.74	98.75	98.73	98.74

Table 5. Performance evaluation of the proposed classification model with existing classification approaches in rice variety classification

Classifiers	Datasets	Accuracy %	Precision %	Recall %	F1-Score %
CNN	Rice image	92.40	92.50	92.65	92.57
	Grainspace	91.63	91.64	91.62	91.63
Transformer	Rice image	94.30	94.40	94.55	94.47
	Grainspace	94.79	94.78	97.78	97.78
ViT	Rice image	96.20	96.30	96.45	96.37
	Grainspace	96.94	96.93	96.94	96.93
KT	Rice image	97.95	97.70	97.40	97.55
	Grainspace	97.15	97.14	97.12	97.13
KD	Rice image	98.78	98.75	98.72	98.73
	Grainspace	97.32	97.33	97.31	97.32
CDKT	Rice image	99.43	99.42	99.40	99.41
	Grainspace	97.56	97.55	97.54	97.53
Proposed CKA-CDKT	Rice image	99.93	99.94	99.92	99.93
	Grainspace	98.74	98.75	98.73	98.74

Table 6. Ablation study of the proposed classification model employed in rice variety classification using benchmark datasets

Configurations	Datasets	Accuracy %	Precision %	Recall %	F1-Score %
CDKT	Rice image	96.34	96.35	96.34	96.95
	Grainspace	96.87	96.88	96.86	96.87
CKA-CDKT	Rice image	97.62	97.60	97.61	97.61
	Grainspace	97.36	97.37	97.35	97.36
Weiner Filter + CKA-CDKT	Rice image	98.95	98.94	98.92	98.92
	Grainspace	97.64	97.62	97.63	97.63
EfficientNet-B7+CKA-CDKT	Rice image	99.21	99.21	99.20	99.21
	Grainspace	98.24	98.22	98.23	98.23
Weiner Filter + EfficientNet-B7 + CDKT	Rice image	99.54	99.55	99.53	99.54
	Grainspace	98.57	98.56	98.54	98.55
Proposed model (Weiner Filter + EfficientNet-B7 + CKA-CDKT)	Rice image	99.93	99.94	99.92	99.93
	Grainspace	98.74	98.75	98.73	98.74

Table 7. Statistical and computational analysis of the proposed classification model with existing approaches for the testing set of data

Classifiers	p-value	Confidence interval	Computational Time (S)	Memory size (MB)
CNN	0.0064	[0.85 – 0.92]	120	514
Transformer	0.006	[0.86 – 0.93]	110	508
ViT	0.0051	[0.87 – 0.94]	105	497
KT	0.0049	[0.88 – 0.95]	100	473
KD	0.0037	[0.89 – 0.96]	95	442
CDKT	0.0025	[0.90 – 0.97]	90	410
Proposed CKA-CDKT	0.0013	[0.92 – 0.99]	85	381

Table 8. Cross-validation of the proposed CKA-CDKT model in rice variety classification based on various k-folds

Datasets	K-folds	Accuracy %	Precision %	Recall %	F1-Score %
Rice Image dataset	k=2	97.70	97.72	97.68	97.70
	k=3	98.82	98.84	98.80	98.82
	k=5	99.93	99.94	99.92	99.93
	k=7	97.90	97.91	97.88	97.89
	k=9	99.88	99.89	99.86	99.87
Grainspace dataset	k=2	97.48	97.47	98.49	97.48
	k=3	97.56	97.55	97.54	97.55
	k=5	98.74	98.75	98.73	98.74
	k=7	97.83	97.84	97.82	97.83
	k=9	98.21	98.23	98.22	98.22

The ablation study presented in Table 6 validates the architectural choices of the proposed model to justify each component's contribution.

By isolating specific components, this ablation analysis reveals that the interaction between preprocessing, feature extraction, and CKA-based CDKT is responsible for the model's performance on benchmark datasets. Performance evaluation of the proposed CKA-CDKT model in terms of statistical and computational analysis is represented in Table 7.

Also, the cross-validation of the proposed model based on the K-fold cross-validation technique for the rice image dataset and the Grainspace dataset is illustrated in Table 8. From the results, the proposed CKA-CDKT model achieves superior performance when compared to existing traditional models because it effectively aligns and transfers knowledge across different feature domains by increasing the similarity between their kernel representations.

Also, the CDKT model reduces domain discrepancy and enhances the discriminative power of learned features, which leads to improved generalization on the testing set. Since the proposed CKA metric helps to eliminate redundant and irrelevant information, it has less computational complexity and memory usage.

The proposed rice variety classification model achieved optimal performance at k=5 folds, due to the balanced trade-off between training data diversity that allows the model to learn stable, robust features without excessive variance.

4.2.1. Graphical Representation

Figure 5 a), b), and c) represent the graphical visualization results obtained by the proposed CKA-CDKT model in rice variety classification. The CKA-CDKT model achieves better results because the CKA metric effectively aligns the feature distributions from multiple domains, such as texture, color, and shape, which ensures more consistent and transferable feature representations.

This CKA alignment, proposed instead of the KL-divergence loss, minimizes the inter-domain discrepancies that lead to improved differentiation between classes, which is clear from the confusion matrix in Figure 5(a). Also, the efficiency of the CKA-CDKT that converges during training and eliminates the influence of redundant features and optimizes kernel similarity is ensured by the results in the accuracy curve in Figure 5(b). Moreover, the CKA-CDKT achieves optimal receiver operating characteristic curve values in Figure 5(c), which enhances true positive rates and reduces false positives, indicating robust generalization and results in minimizing overfitting across rice varieties.

Figure 6 represents the explainability analysis of the proposed model employed for rice variety classification. Results from the saliency maps demonstrate that warmer colors, specifically red and yellow, indicate regions where the model prioritizes feature extraction for decision-making.

This visualization confirms that the CKA-CDKT model focuses on critical morphological attributes such as grain shape and texture, thereby enhancing classification accuracy and providing interpretability.

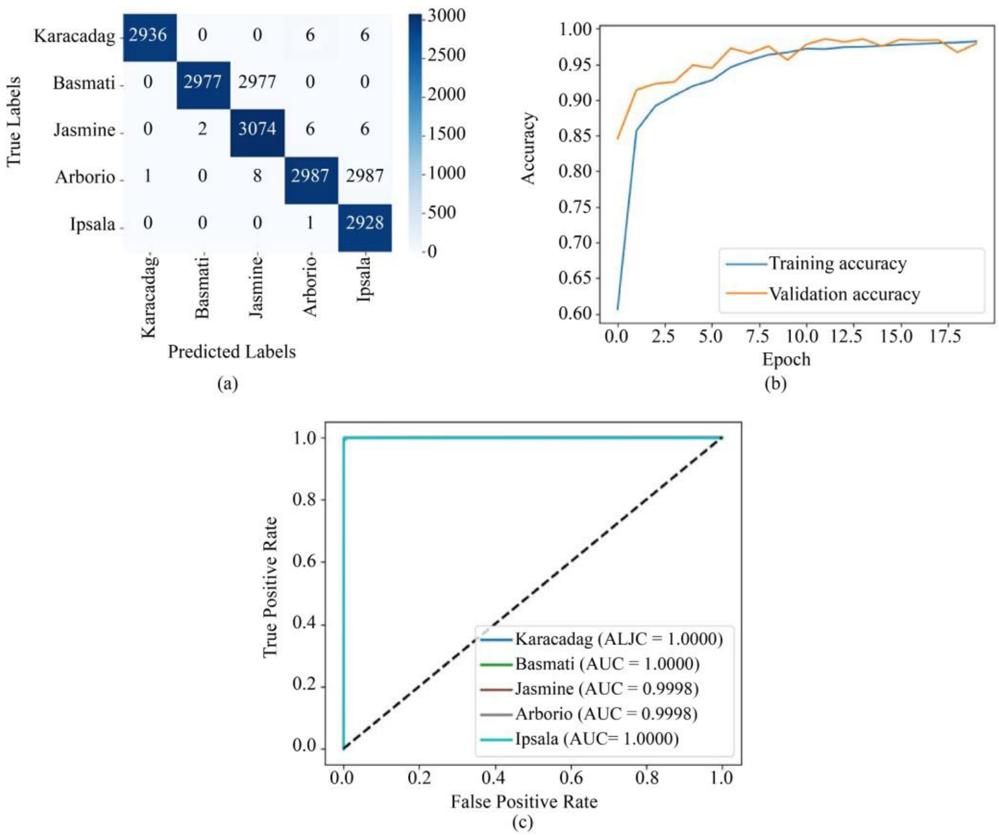

Fig. 5(a) Confusion matrix, (b) Accuracy curve, (c) ROC curve representation of the proposed CKA-CDKT model utilized in rice variety classification based on the rice image dataset

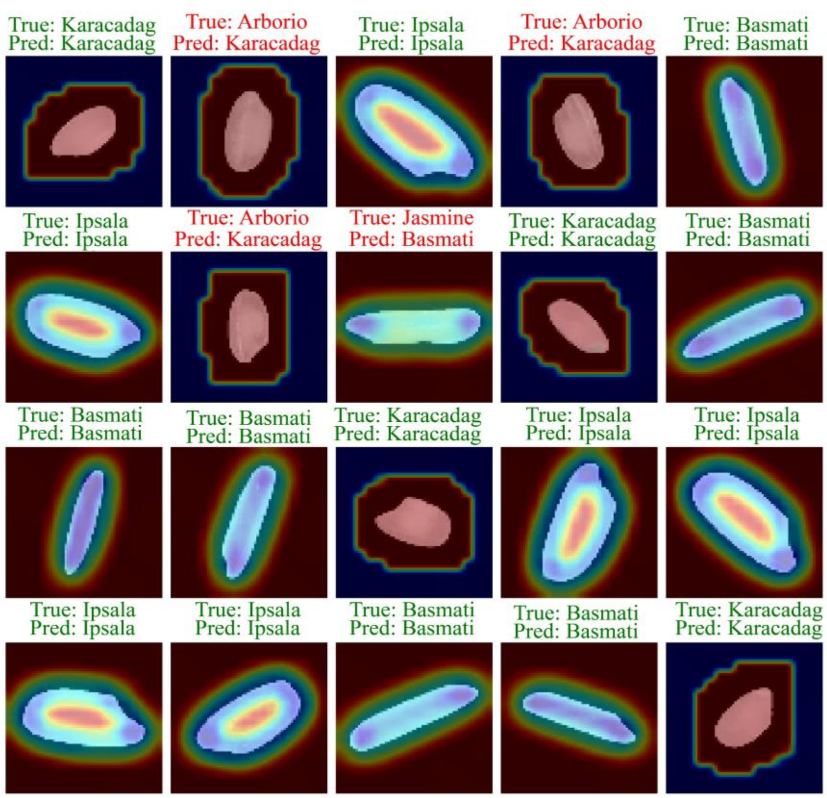

Fig. 6 Explainability analysis results (saliency maps) of output rice class varieties obtained from the proposed CKA-CDKT model

Table 9. Comparative study of CKA-CDKT with various existing rice classification models using the rice image dataset

Methods	Accuracy %	Precision %	Recall %	F1_Score %
ANOVA-SVM [17]	99.89	N/A	N/A	N/A
RiceseedNet [18]	99	99	99	99
ARVDC [21]	99.66	99.15	99.14	99.14
Ensemble Model [22]	99.51	99.76	99.64	99.76
GMMNet [23]	97.06	96.33	95.70	95.95
Proposed CKA-CDKT	99.93	99.94	99.92	99.93

Table 10. Comparative study of the CKA-CDKT with various existing rice classification models using the Grainspace dataset

Methods	Accuracy %	Precision %	Recall %	F1_Score %
CBAM-ParNeXt V2 [16]	94.81	94.81	94.84	94.80
Proposed CKA-CDKT	98.74	98.75	98.73	98.74

4.3. Comparative Analysis

A comparative analysis of the proposed CKA-CDKT is compared with an existing classifier model, which is employed for rice variety classification using only publicly available rice image datasets. Existing DL approaches, such as Lightweight ConvNeXt [16], ANOVA-SVM [17], RiceseedNet [18], ARVDC [21], the Ensemble method [22], and GMMNet [23], are used for comparison with the proposed method, which is presented in Tables 9 and 10. The proposed CKA-CDKT achieves an accuracy of 99.93% and a precision of 99.94%, which are greater than those of existing classification models. The EfficientNet-B7 model extracts multiscale features that help fine-tune the CNN with the CKA-CDKT model effectively. This method accurately classifies rice varieties by differentiating between various classes with similar characteristics.

4.4. Discussion

The proposed CKA-CDKT model achieves better results in rice variety classification than existing classification approaches. Existing classification approaches, such as the Lightweight ConvNeXt [16], ANOVA-SVM [17], RiceSeedNet [18], ARVDC [21], Ensemble method [22], and GMMNet [23] models, have limitations, such as the model failing to classify the rice varieties accurately due to data imbalance issues, and CNN-based models also extract irrelevant features that degrade the performance of the model and provide inaccurate results.

These limitations affect the detection and classification model, leading to inaccurate results. Hence, the proposed rice variety classification model transfers the relevant knowledge between domains and reduces the impact of misaligned features, which helps to improve accurate rice type classification.

The proposed CDKT model achieves better results by replacing the KL-divergence with the CKA metric that evaluates similarity between domain features and transfers the knowledge accordingly, which leads to improved classification of rice varieties.

4.4.1. Real-world applications

Experimental analysis validates that the CKA-CDKT framework achieves better results for rice variety classification. By leveraging fine-grained morphological extraction and prioritizing domain-invariant features, the proposed model effectively mitigates the impact of varying lighting conditions in field environments.

A significant contribution of this proposed framework lies in its computational efficiency, as it achieves high classification accuracy with less processing time. Furthermore, the proposed model's robustness is that it is trained on a benchmark dataset of 75000 images. This ensures that the model captures a wide variance of agricultural parameters, which allows it to maintain high performance without performance degradation. Hence, the proposed CKA-CDKT-based rice variety classification model is efficient for large-scale deployment and real-world agricultural scalability.

4.4.2. Generalizability and Transferability of the Proposed Model

The proposed CKA-CDKT model demonstrates robust generalizability through k-fold cross-validation, achieving great performance at k=5 by maintaining consistency across various data subsets.

For transferability, the proposed framework prioritizes domain-invariant features such as texture, size, and shape, which constitute fundamental morphological characteristics across multiple crop species. To address the limitations of CDKT, the CKA metric is integrated into the model to effectively minimize domain variability and eliminate redundant data. This integration enhances the model's capacity to generalize for unseen data and classify the various rice grains with high interclass similarity. Because the proposed framework utilizes domain-invariant features common to most cereal grains, it is adaptable to other crop species where experimental and environmental conditions remain consistent. Consequently, the framework demonstrates significant potential for real-world agricultural scalability across specific rice varieties.

5. Conclusion

The proposed CKA-CDKT method accurately identified and classified rice grain varieties efficiently. The EfficientNet-B7 model extracted the most relevant features that had significant information on rice varieties, which helped to efficiently enhance the classification of distinct rice varieties. Initially, the rice images were acquired from benchmark datasets and preprocessed using the hybrid filtering technique of the modified median and Wiener filters, which effectively eliminated the noise present in the rice images. In addition, the proposed rice variety classification model employed CDKT with a CKA similarity metric, which was utilized instead of the KL divergence loss function to efficiently learn subtle information about rice types to enhance classification. Experimental results of CKA-CDKT demonstrated that the model attained 99.93% and 98.74% accuracy for rice image and Grainspace datasets, which were greater than that of existing approaches such as ANOVA-SVM. In the future, an advanced DL model-based classification with a feature selection model will be used to enhance the accuracy of rice variety classification.

Conflicts of Interest

The author(s) declare that there is no conflict of interest regarding the publication of this paper.

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