RESEARCH ON CLASSIFICATION METHODS OF BARLEY PLANTS BASED ON TRANSFER LEARNING
/
基于迁移学习的大麦植株分类方法研究

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ABSTRACT
Classification of barley plants plays a crucial role in understanding barley varietal diversity and breeding. Traditional classification methods rely on expert experience and require significant manual effort. With the rise of deep learning based on machine vision technologies, particularly the emergence of transfer learning, the issue of model overfitting on small datasets has been mitigated, leading to enhanced generalization capabilities. This study employs a self-constructed barley plant image dataset to compare five state-of-the-art deep learning models, while analyzing the impacts of various factors - including image resolution and training-test split ratio - on classification accuracy. The results indicate that the DenseNet model achieves the best classification performance at an input resolution of 512×512 pixels, with an accuracy of 96.02%. Increasing the proportion of training data further improved performance, with the 80%:20% training-test split ratio yielding optimal results across all five models. Transfer learning models outperform training from scratch, with EfficientNet-v2 achieving the highest accuracy of 98.86%. Additionally, gradient-weighted class activation mapping (Grad-CAM) was utilized to generate heatmap visualizations of the decision-making processes in each transfer learning model. By applying deep learning for barley plant classification and selecting the optimal model, this research provides a reliable technical solution for barley variety identification and classification.

摘要
大麦植株分类对于理解大麦品种多样性和育种研究具有关键作用。传统分类方法依赖专家经验且需要大量人工操作。随着基于深度学习的机器视觉技术的兴起，尤其是迁移学习技术的出现，减轻了在小数据集上模型过拟合的现象，提高了模型的泛化能力。本研究采用自建的大麦植株图像数据集，对比了五种先进的深度学习模型，并分析了不同图像分辨率、不同训练集-测试集比例等因素对分类准确率的影响。研究结果表明：DenseNet 模型在 512×512 像素输入分辨率下表现最优，分类准确率达 96.02%；增加训练数据比例能提升模型性能，80%:20% 的训练-测试划分比例在五种模型中均取得最佳效果；使用迁移学习模型显著优于从头训练，其中 EfficientNet-v2 模型以 98.86%的准确率表现最佳。此外，研究还采用 Grad-CAM 技术对五种迁移学习模型的预测过程进行了热力图可视化分析。本研究通过深度学习技术实现大麦植株分类并优选最佳模型，为大麦品种鉴定与分类提供了可靠的技术方案。

INTRODUCTION
Barley is one of the world's most important cereal crops, and its cultivation plays a vital role in food security, feed supply, the brewing industry, economic development, and ecological benefits (*Ullrich, 2021*). The classification of barley plants holds significant importance for optimizing cultivation management, advancing breeding research, supporting precision agriculture, ensuring food security, and promoting industrial development (*Alahmad et al., 2022*).

The traditional methods for barley plant classification primarily rely on phenotypic data such as morphological traits, agronomic characteristics, and physiological properties. While these approaches can differentiate between varieties to some extent, they suffer from several limitations, including strong subjectivity, high labor intensity, significant environmental dependency, limited informative value, difficulties in distinguishing closely related varieties, dynamic variability, and lack of standardization (*Li et al., 2022*).

Deep learning models (e.g., Convolutional Neural Networks, CNNs) can automatically extract multi-level features from raw images, ranging from low-level edge and texture features to high-level semantic features (*Zhou et al., 2022*).

This end-to-end learning approach eliminates the laborious process of manual feature engineering required in traditional methods. Through deep network architectures and training on large-scale datasets, deep learning models can capture subtle differences in images, thereby achieving high-precision classification (*Nguyen et al., 2021*). These models autonomously learn features and patterns from data, reducing the need for human intervention and domain-specific expertise. Such automated learning capabilities make deep learning highly promising for a wide range of image classification tasks.

Deep learning has become a dominant approach for image-based classification tasks, with significant advancements in plant species identification and agricultural applications. Recent studies have explored various architectures to enhance classification accuracy and robustness. Comparative analyses of deep learning models have demonstrated the effectiveness of specific architectures for plant classification. For instance, DenseNet exhibited stable performance across multiple datasets, highlighting its robustness in feature reuse and gradient flow optimization (*Zhou et al., 2021*). Similarly, Xception outperformed InceptionV3 and VGG16 on the Plant Seeding Dataset, achieving 86.21% accuracy due to its depthwise separable convolutions (*Diaz et al., 2019*). In weed management, CNNs attained 97% accuracy in distinguishing crops (e.g., corn) from narrow- and broad-leaf weeds during early growth stages, critical for precision herbicide application (*Garibaldi-Márquez et al., 2022*). In addition, hybrid models can improve plant classification performance by combining the strengths of different architectures. Hybrid models, such as MIV-PlantNet, which integrates MobileNet, Inception, and VGG, achieved 99% accuracy on 10 Saudi Arabian plant species by leveraging complementary architectural strengths (*Amri et al., 2024*). Deep neural networks (DNNs) generally demand substantial amounts of training data to achieve optimal performance, as insufficient datasets often result in model overfitting and compromised generalization ability.

Transfer learning (TL) leverages pre-trained models from large-scale datasets (e.g., ImageNet) to transfer knowledge to target domains (e.g., plant classification), addressing challenges such as limited data, high training costs, and poor model generalization. In recent years, TL has achieved remarkable success in plant classification tasks, including species identification, disease detection, and leaf categorization. The most common implementation involves direct fine-tuning of pre-trained models for plant classification tasks. For instance, MobileNet pre-trained on ImageNet achieved 98.7% classification accuracy when fine-tuned on a custom medicinal plant dataset (*Duong-Trung et al., 2019*). Similarly, fine-tuned VGG16 models showed enhanced performance in agricultural disease detection, particularly for mildew classification in millet (*Coulibaly et al., 2019*). The exceptional 99.7% accuracy obtained by VGG-19 on the Swedish Leaf Dataset further validates TL's superiority in small-sample scenarios (*Siddharth et al., 2022*). Comparative studies have explored various architectures, including GoogLeNet and VGGNet with optimized TL parameters for the LifeCLEF 2015 challenge (*Ghazi et al., 2017*), while another investigation evaluated Inception V3, ResNet50 and VGG19 on 12 plant seedling categories (*Hassan et al., 2021*). Beyond direct fine-tuning, hybrid approaches combining deep learning with traditional methods have shown promising results. The integration of VGG19's deep features with handcrafted descriptors (e.g., texture and shape) achieved 93.73% accuracy using Random Forest classification (*Bansal et al., 2023*) Another study employed four pre-trained CNNs for feature extraction followed by Random Forest, significantly improving model interpretability (*Sachar et al., 2021*). These implementations demonstrate TL's dual advantage of reducing training time while enhancing classification accuracy by effectively transferring knowledge from large-scale datasets to specialized botanical applications.

As one of the world's most important crops, barley has received relatively limited research attention regarding plant classification. To address this gap, this study first systematically reviews the advantages and disadvantages of five deep learning approaches. Subsequently, comprehensive experiments are conducted on a self-constructed barley plant dataset, with evaluations focusing on: (1) input image resolution, (2) training-test split ratios, and (3) fine-tuning strategies based on transfer learning models. Finally, heatmap visualization is employed to analyze the critical regions identified by the five transfer learning models during prediction. These investigations aim to identify the optimal deep learning approach for barley plant classification and to provide technical support for the development of automated classification systems.

MATERIALS AND METHODS

Image dataset

The spike and awn morphology of different barley varieties exhibits significant differences, making them particularly suitable for computer-based classification tasks. The barley dataset used in this study was collected from the barley breeding experimental fields at Shanxi Agricultural University. Images of nine barley varieties were captured during the heading and maturation stages, photographing individual plants (including partial stems, leaves, and spikes) against a white background using a smartphone in frontal parallel shooting mode.

To enhance dataset diversity, wheat plant images were included since wheat and barley share similar spike and awn structures. The final dataset comprised 896 RGB images across nine barley varieties and one wheat variety, with the number of images per variety ranging from 52 to 233.

In this study barley varieties were labeled as Barley_0 through Barley_8 and the wheat variety was designated as Wheat. Original image resolutions included 1276×1276 pixels, 2342×2342 pixels, and 3024×3024 pixels. Due to computational constraints, all images were uniformly resized to 1024×1024 pixels.

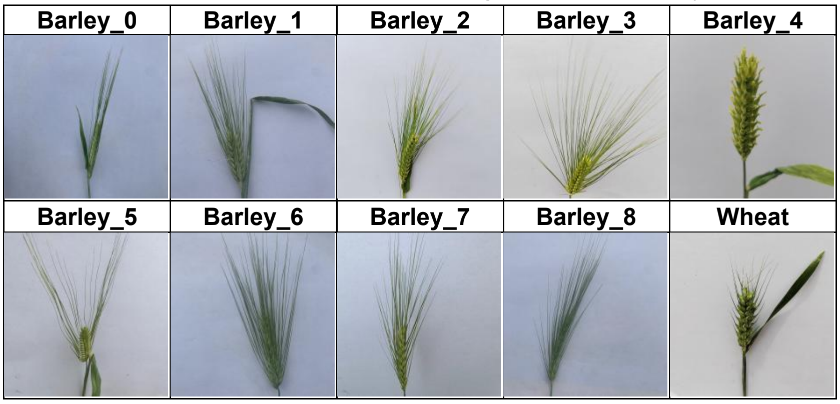


Fig. 1 - Characteristic specimens of all barley varieties and wheat

Figure 1 illustrates distinct phenotypic variations between different barley and wheat cultivars, primarily manifested in awn and spike characteristics. Awn morphology analysis demonstrates that the barley cultivar Barley_4 is classified as awn less, while the wheat cultivar Wheat exhibits short-awned characteristics, with all other barley cultivars displaying long-awned morphology. Regarding awn spatial distribution patterns, barley cultivars Barley_3 and Barley_5 show a scattered arrangement, whereas Barley_0, Barley_7, and Barley_8 present clustered awns. The intermediate awn distribution type is observed in barley cultivars Barley_1, Barley_2, and Barley_6. Spike architecture analysis indicates that barley cultivar Barley_5 possesses a distinctive two-rowed spike structure, contrasting with the six-rowed configuration of wheat. The remaining barley cultivars exhibit an intermediate four-rowed spike morphology.

Deep learning approaches for barley plant image classification

ResNet (Residual Network) was proposed by *He et al., (2016*), and achieved breakthrough performance in the ImageNet image classification competition. The core innovation of ResNet lies in its introduction of residual learning, which addresses the issues of gradient vanishing and network degradation in deep neural networks through residual connections (also known as skip connections). This architectural advancement enables the training of substantially deeper networks while enhancing their feature extraction capabilities. Due to hardware considerations, the ResNet-50 model with 50 layers was chosen as our baseline network.

DenseNet (Densely Connected Network) is a deep learning model proposed by *Huang et al., (2017*). The core innovation of DenseNet lies in its dense connection mechanism, where each layer's output is directly connected to all subsequent layers. This unique architecture significantly enhances feature propagation and reuse throughout the network while substantially reducing parameter redundancy and effectively alleviating vanishing gradient problems. DenseNet has demonstrated exceptional performance across various image classification tasks, showing particular advantages in scenarios with limited training data where its efficient feature utilization capability excels.

MobileNet-v2, developed by Google Research (*Sandler et al., 2018*), represents an optimized lightweight convolutional neural network specifically engineered for mobile and embedded devices. As an enhanced iteration of MobileNet-v1, this architecture incorporates two key innovations: inverted residual blocks and linear bottleneck layers, which collectively improve both computational efficiency and model performance.

ShuffleNet-v2, developed by Megvii Research (*Ma et al., 2018*), represents an optimized efficient convolutional neural network specifically designed for mobile and embedded devices. As an enhanced version of ShuffleNet, this architecture introduces two key improvements: an optimized network structure and a novel channel shuffle operation that reorganizes feature channels to enhance cross-group information exchange.

EfficientNet-v2, developed by Google Research (*Tan et al., 2021*), is an enhanced convolutional neural network that builds upon the EfficientNet series. This next-generation architecture achieves significant improvements through an integrated approach combining compound scaling and progressive learning strategies, which work synergistically to boost both training efficiency and model accuracy.

Evaluation metrics

This study evaluates the classification performance of the five deep learning methods using Top-1 accuracy, defined as the proportion of samples where the model's highest-probability prediction matches the true class label. To address class imbalance in the dataset, confusion matrix analysis was employed as a complementary evaluation metric. The confusion matrix provides a detailed breakdown of classification results, with rows representing actual classes, columns indicating predicted classes, diagonal entries showing correct classifications, and off-diagonal elements revealing specific misclassification patterns between classes. Additionally, this study uses the size of the model weight file as an indicator to determine the model size and employs inference speed to measure the computational efficiency of the model, excluding data loading time, with the unit in frames per second (FPS). Together, these metrics offer both quantitative performance measurement and qualitative insight into each model's classification behavior across all categories.

Training model

The experiments in this study were conducted on a Windows 10 system equipped with an Intel Core i7-12700F CPU (12 cores, 20 threads), 32GB RAM, and an ASUS TUF-GAMING RTX 3060 GPU with 12GB VRAM. For the experimental framework, OpenMMLab's MMPretrain (v1.0.0) was utilized, an open-source computer vision research platform that provides comprehensive transfer learning models and tools. As one of OpenMMLab's core libraries, MMPretrain specializes in image classification and feature extraction tasks while supporting various state-of-the-art deep learning models (*MMPretrain Contributors, 2023*).

To ensure the reliability of experimental results and achieve optimal classification performance, all five deep learning models were configured with the following unified parameter settings. The image input size was set to 1024×1024 pixels, and the batch size was set to 8. The Stochastic Gradient Descent (SGD) optimizer was selected, loss function was Cross-entropy Loss, and the training epochs were set to 100. The initial learning rate was 0.025, and the momentum parameter and the weight decay parameter were set to 0.9 and 0.0001, respectively.

The models process input images in RGB format with batch normalization applied during training. The training protocol consisted of 100 epochs with MultiStepLR learning rate scheduling, where the learning rate was reduced by a factor of 0.1 at epoch milestones 30, 60, and 90. This configuration maintains comparability across models while implementing established best practices for deep learning optimization.

RESULTS

The impact of image resolution on classification accuracy

Each image in the dataset contains only a single barley plant with a white background, and the plant occupies only a small portion of the image. Higher-resolution images can capture key structural features of barley, such as the spikes and awns. Three different input resolutions were examined: 128×128 pixels, 256×256 pixels, and 512×512 pixels, with an 80:20 train-test split ratios and models trained from scratch. The classification results are shown in Table 1.

Table 1

Classification performance of five models across different input resolutions with 80:20 training-test split

Resolution\Model	ResNet-50	DenseNet	MobileNet-v2	ShuffleNet-v2	EfficientNet-v2
128×128	82.39	94.32	92.05	81.25	94.32
256×256	85.23	95.45	93.19	84.1	92.61
512×512	93.75	96.02	92.61	90.91	95.45

The results showed that MobileNet-v2 achieved its best classification performance (93.19% accuracy) at 256×256 pixels resolution, while the other four models (ResNet-50, DenseNet, ShuffleNet-v2, and EfficientNet-v2) all performed best at the highest 512×512 pixels resolution, with classification accuracy generally improving as resolution increased. Specifically, ResNet-50 showed an 11.36% accuracy improvement, DenseNet improved by 1.7%, ShuffleNet-v2 by 9.66%, and EfficientNet-v2 by 1.13% when comparing the lowest and highest resolutions. At 512×512 pixels resolution, DenseNet delivered the strongest overall performance with 96.02% accuracy.

These findings demonstrate that higher resolutions generally enhance classification accuracy by preserving finer structural details, though the optimal resolution depends on model architecture. While most models benefited from increased resolution, MobileNet-v2's peak performance at 256×256 pixels suggests potential limitations in handling higher-resolution inputs. DenseNet's superior performance at the highest resolution indicates its effectiveness in leveraging detailed features for accurate classification.

For further error analysis, this study computed confusion matrices for all five classification models (as shown in Figure 2) at 512×512 pixels resolution. In the test set containing 176 images, ResNet-50 misclassified 11 images, DenseNet misclassified 7, MobileNet-v2 misclassified 13, ShuffleNet-v2 misclassified 16, and EfficientNet-v2 misclassified 8.

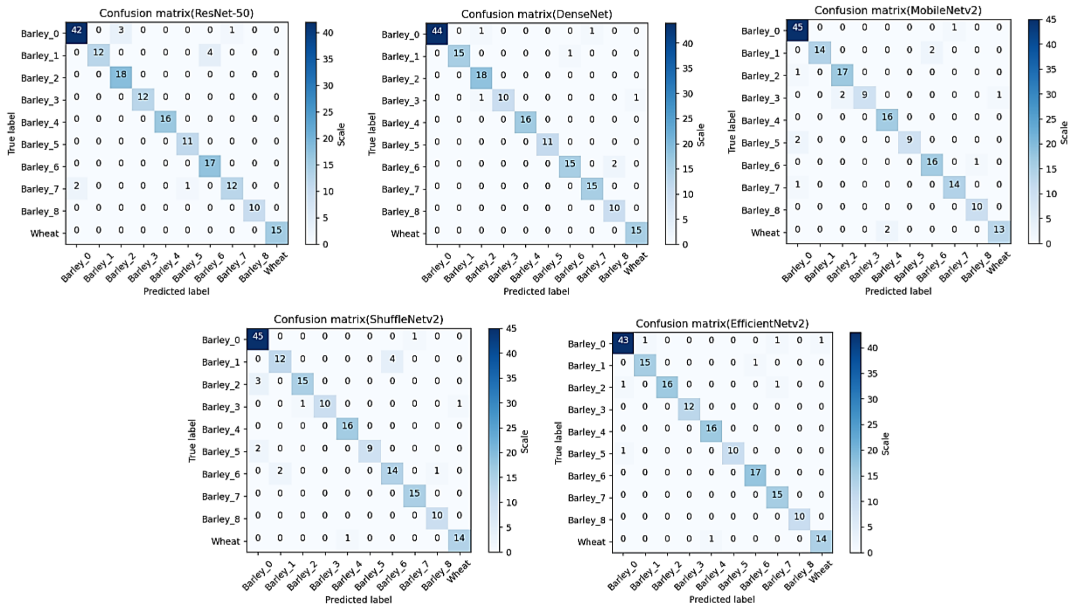


Fig. 2 - Confusion matrices of five models with 512×512 input resolution and 80:20 training-test split

A particularly notable error pattern was observed where both ResNet-50 and ShuffleNet-v2 models consistently misclassified 4 Barley_1 samples as Barley_6. This classification confusion likely stems from the morphological similarity between these two varieties, as both Barley_1 and Barley_6 possess characteristically long, spreading awns that create visual ambiguity in their distinguishing features.

The impact of different training-test split ratios on classification accuracy

The partitioning method of the training and test sets significantly influences the performance evaluation and generalization capability of the barley plant image classification model. Due to imbalanced sample sizes across different varieties in the dataset, this study employed stratified sampling to ensure that each category maintained a fixed proportion in both the training and test sets. Three different training-test split ratios were examined: 80%:20%, 70%:30%, and 60%:40%, using an input image resolution of 512×512 pixels and training the models from scratch. The classification results are presented in Table 2.

Table 2

Classification performance of five models with different training-test split ratios and 512×512 input resolution

Training-test split\Model	ResNet-50	DenseNet	MobileNet-v2	ShuffleNet-v2	EfficientNet-v2
70% : 30%	89.06	92.45	91.7	77.0	93.58
60% : 40%	87.08	90.45	91.57	78.93	90.73

Combined with Table 1, the analysis of the classification results revealed that when the training-test split ratio was 80%:20%, all five models achieved their optimal classification performance. Additionally, except for ShuffleNet-v2, the other models exhibited a trend where higher proportions of training data led to increased classification accuracy. Figure 3 presents the confusion matrices for all five classification models when the training-test split ratio was set to 70%:30%.

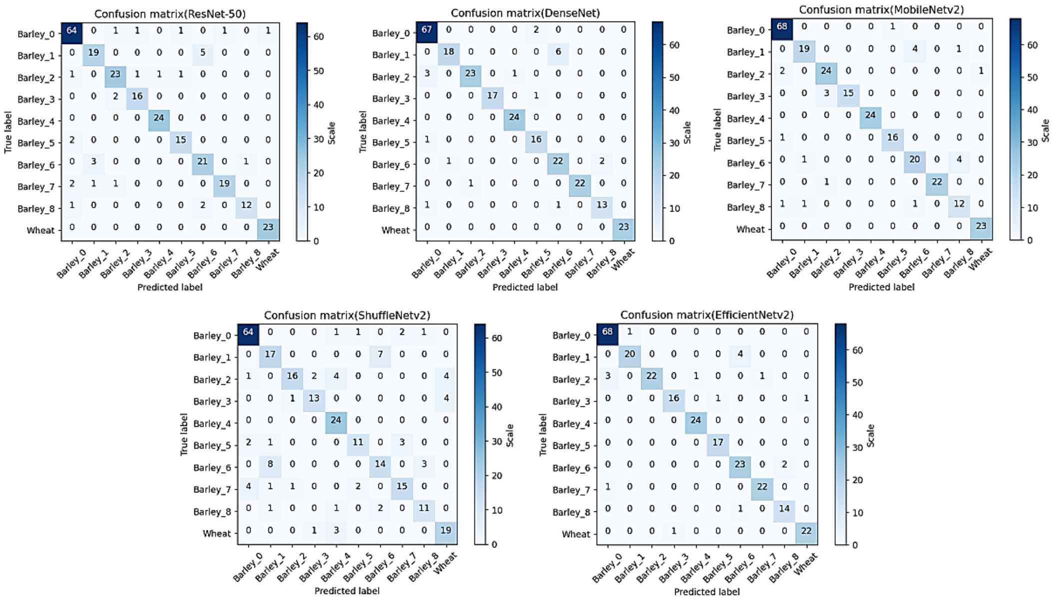


Fig. 3 - Confusion matrices of five models with 512×512 input resolution and 70:30 training-test split

When employing a 60% training and 40% testing data partition, the classification confusion matrices for all five models are illustrated in Figure 4.

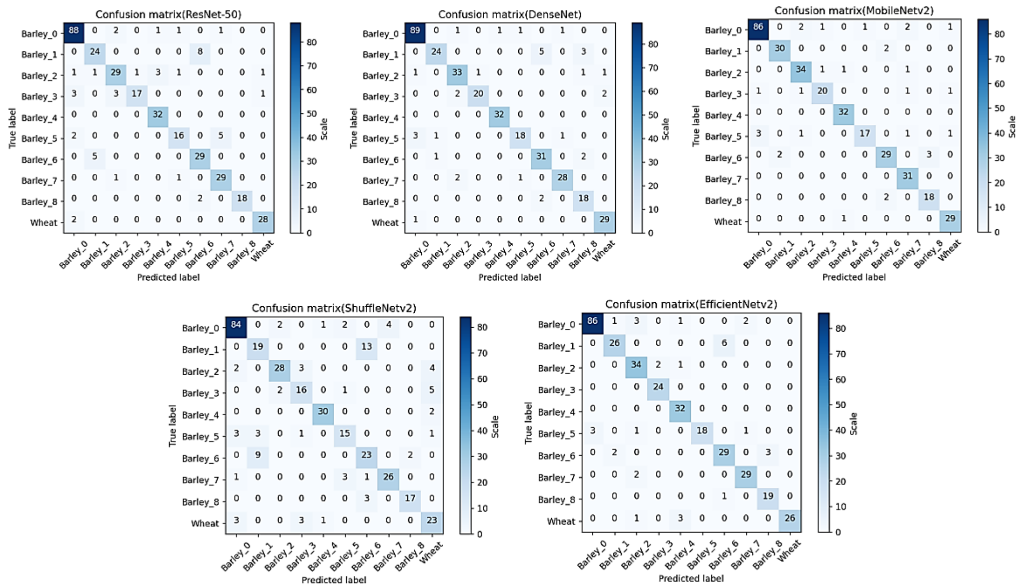


Fig. 4 - Confusion matrices of five models with 512×512 input resolution and 60:40 training-test split

The impact of transfer learning on classification accuracy

Transfer learning improves model performance by leveraging knowledge acquired from one task or domain and applying it to a related task, significantly reducing training time while enhancing accuracy (*Tan et al., 2018*). In this study, the models were initialized with weights pre-trained on the ImageNet-1k dataset and subsequently fine-tuned for barley plant image classification.

Using an 80%:20% training-test split ratio and an input resolution of 512×512 pixels, the classification results are presented in the Table 3, with corresponding confusion matrices shown in Figure 5. A comparison with Table 1 reveals that training based on ImageNet-1k transfer learning models yields better classification performance than training from scratch, with accuracy improvements of 1.70% (DenseNet), 7.39% (ShuffleNet-V2), and 3.41% (EfficientNet-V2). Among them, the transfer learning EfficientNet-V2 model achieved the highest classification accuracy at 98.86%. Its model size is moderate among the five models at 22.90 MB, while also delivering the fastest inference speed at 179 FPS. ShuffleNet-V2's classification accuracy is nearly comparable to EfficientNet-V2, yet it has the smallest model size among all five models and maintains a high inference speed (157 FPS).

Table 3

Classification performance of five pre-trained models with 80:20 training-test split and 512×512 input resolution

Evaluation metrics\Model	ResNet-50	DenseNet	MobileNet-v2	ShuffleNet-v2	EfficientNet-v2
Accuracy(%)	93.18	97.72	88.64	98.30	98.86
Size/MB	90.30	27.40	9.13	5.44	22.90
Speed/FPS	92	120	158	157	179

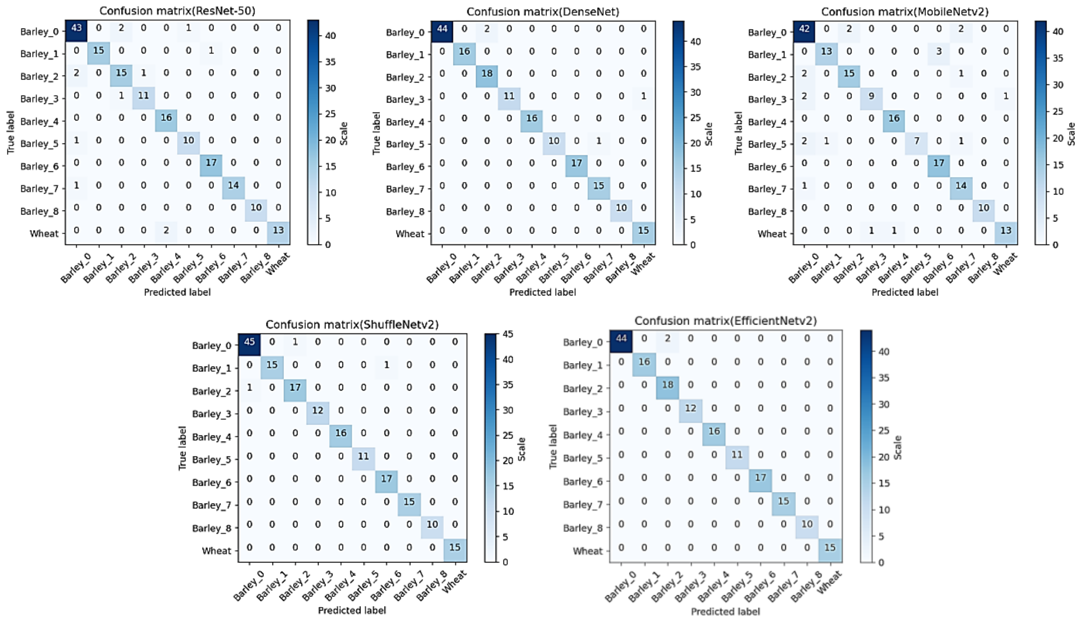
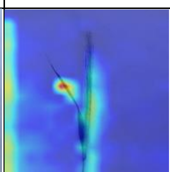
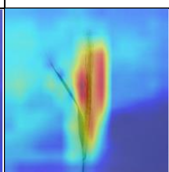
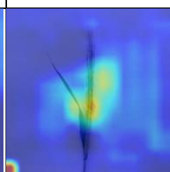
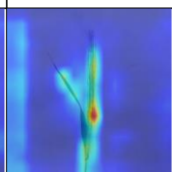
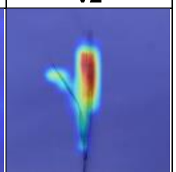
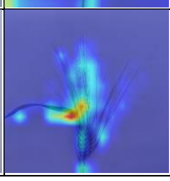
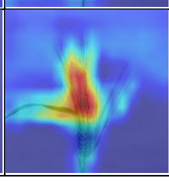
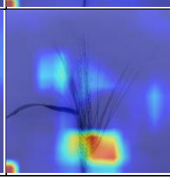
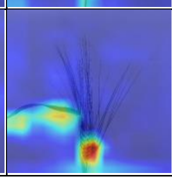
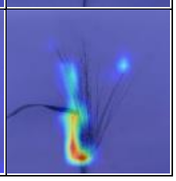


Fig. 5 - Confusion matrices of five pre-trained models with 512×512 input resolution and 80:20 training-test split

Comparative analysis of gradient-based heatmap visualization

Deep learning models demonstrate excellent performance in barley plant classification, yet their decision-making process remains opaque to end users. Gradient-based interpretation techniques, as attribution methods, utilize heatmaps to explain deep learning decisions. Grad-CAM (Gradient-weighted Class Activation Mapping) is a visualization technique that generates heatmaps to highlight image regions most influential to the model's predictions, thereby enhancing interpretability of the decision process (*Selvaraju et al., 2017*).

This study employs Grad-CAM to generate heatmaps for five transfer learning models, as shown in Figure 6. Overall, the heatmaps generated by the EfficientNet-v2 model exhibit higher response values in key structural features such as wheat spikes and awns, which aligns with the critical regions experts typically focus on during practical evaluations. This observation is consistent with the superior classification performance of EfficientNet-v2 demonstrated in earlier experiments. In contrast, some heatmaps from the DenseNet model (including varieties Barley_0, Barley_2, Barley_4, Barley_7, and Barley_8) predominantly highlight background regions. This phenomenon may stem from the gradient's inability to accurately reflect feature importance, leading to attention dispersion toward non-relevant background areas.

Class name	Original Image	ResNet-50	DenseNet	MobileNet-v2	ShuffleNet-v2	EfficientNet-v2
Barley_0						
Barley_1						

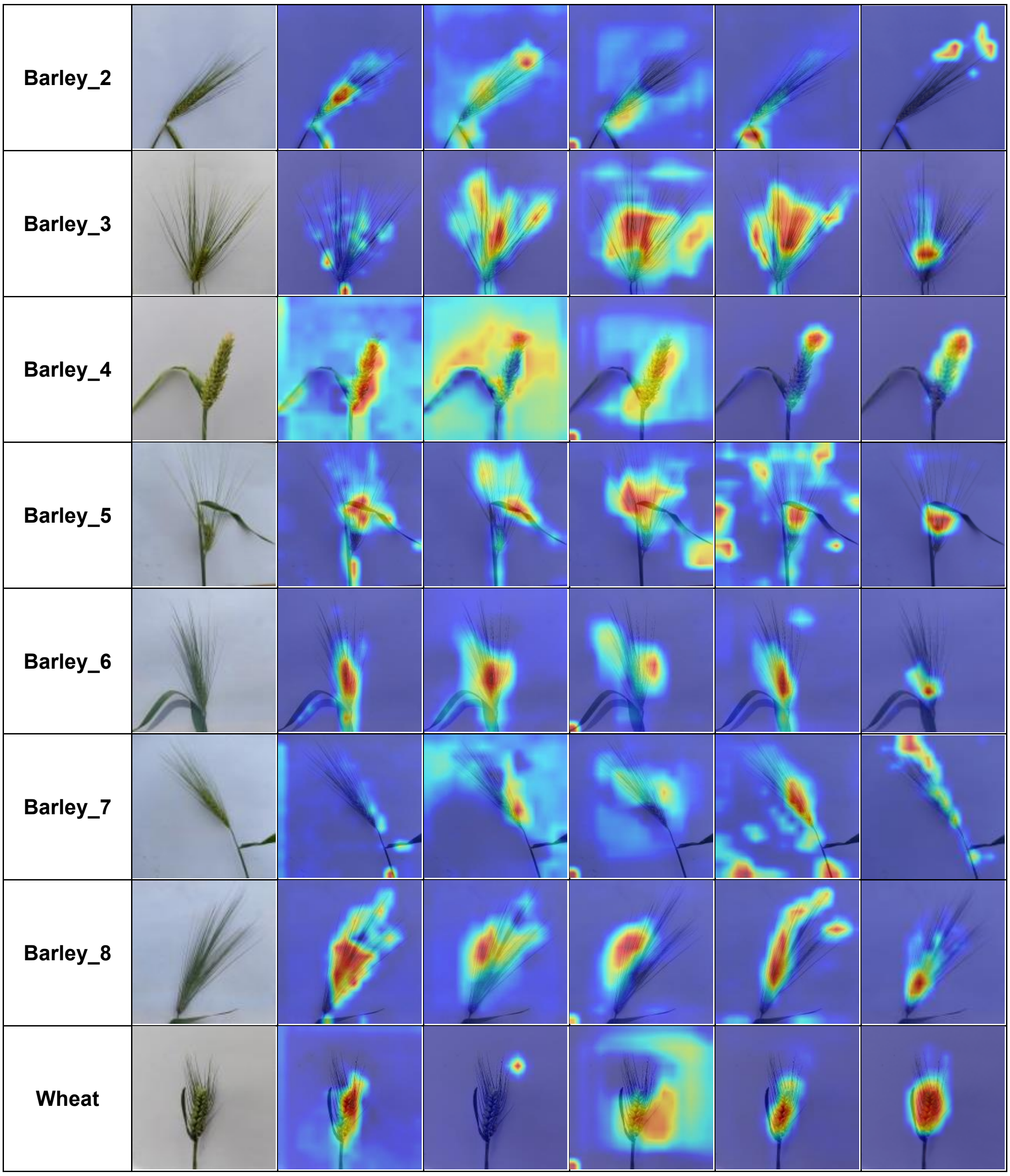


Fig. 6 - The output of the class activation maps for five transfer leaning models

CONCLUSIONS

This study reviewed recent research progress in plant classification using deep learning and evaluated the performance of five representative deep learning models. The core algorithmic concepts of these models were analyzed, along with their respective advantages and limitations. The models were then applied to a self-constructed barley plant dataset, and their classification performance was systematically assessed.

This study demonstrates that the EfficientNet-v2 model achieved the highest classification performance. Increasing the proportion of training data proved beneficial, as a larger sample size enabled the model to learn richer feature representations of barley plants. Transfer learning, through the use of knowledge acquired from large-scale datasets, not only accelerated model training but also enhanced classification accuracy. To further interpret the decision-making process, Gradient-weighted Class Activation Mapping (Grad-CAM) was employed to visualize regions of interest during prediction. The resulting heatmaps highlighted biologically significant areas, providing valuable references for plant classification analysis.

This work represents one of the few studies applying deep learning models to barley plant classification. Future research should focus on expanding the dataset with images from diverse growth stages and exploring advanced deep learning architectures to address remaining challenges in barley classification.

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