RESEARCH ON VARIETY IDENTIFICATION OF RICE SEEDS BASED ON MACHINE VISION COMBINED WITH DEEP LEARNING
/
基于机器视觉结合深度学习的水稻种子品种鉴别研究

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ABSTRACT
As a vital food crop, rice plays a crucial role in the global food supply. Accurate seed sorting is critical for planting and sales, but traditional variety identification methods are time-consuming, inefficient, and prone to causing physical damage to seeds. To enhance identification efficiency and classification accuracy, this study employed an image acquisition system to capture images of eight locally grown rice seed varieties. After preprocessing and segmenting the original images to improve data quality, multi-dimensional features were extracted and analyzed to construct a deep learning model for rice seed identification. The results showed that the Rice-Transformer model, based on the Transformer architecture, achieved a classification accuracy of 97.71%, demonstrating excellent identification capabilities. Additionally, this study developed a user interface based on PyQT5 to visualize the identification results. It can provide a feasible solution for the efficient and non-destructive identification of rice seed varieties and has the potential to be applied in consumer markets and the food industry.

摘要
水稻作为重要的粮食作物，在全球粮食供应中占据关键地位。种子的精准分选对其种植与销售环节至关重要，然而传统的品种鉴别方法存在耗时、低效且易对种子造成物理损伤的问题。为提高鉴别效率和分类准确性，本研究通过图像采集系统获取了八种本地主要种植的水稻种子图像。在对原始图像进行预处理与分割以提升数据质量的基础上，提取其多维度特征进行分析，构建了用于水稻种子鉴别的深度学习模型。结果表明，基于 Transformer 架构的 Rice-Transformer 模型分类准确率高达 97.71%，表现出优异的鉴别能力。此外，本研究基于 PYQT5 开发了用户交互界面，实现了鉴别结果的可视化展示。该研究可为水稻种子品种的高效、无损鉴别提供可行方案，具备应用于消费市场与食品工业的潜力。

INTRODUCTION
The quality of rice seeds directly determines grain yield and production efficiency, where premium varieties exhibit both high nutritional and economic significance *(Jin B. et al., 2022)*. With advancements in breeding technologies, an increasing number of rice varieties have entered the market, making seed purity a critical concern for both cultivators and consumers (*Kumar et al., 2021)*. There are limitations to traditional manual inspection methods, including high subjectivity, high labor intensity, and low accuracy *(Din et al., 2024)*. Modern detection technologies each have their own characteristics, and SSR marker technology is regarded as the "gold standard" due to its high reproducibility and rich genetic information *(Śliwińska-Bartel et al., 2021)*. Chemical detection methods (GC-MS/LC-MS/GC-IMS) require complex sample pretreatment, which is relatively costly *(Kang et al., 2024)*. Among non-destructive testing technologies, nuclear magnetic resonance (NMR) equipment is expensive *(Agafonov & Prudnikov, 2024)*, X-ray imaging requires strict protection measures *(*Medeiros *et al., 2020)*, laser speckle is susceptible to environmental influences *(Bouzaouia et al., 2024)*, and conductivity measurement has poor reproducibility *(Mat Su & Adamchuk, 2023*). Due to low efficiency and operational complexity, these methods have yet to achieve widespread application *(Wang et al., 2025)*.

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In terms of spectroscopic techniques, near-infrared (NIR) spectroscopy has limited ability to distinguish similar varieties *(Todorova et al., 2024)*, mid-infrared (MIR) spectroscopy has low resolution *(Ng et al., 2022)*, and fluorescence spectroscopy has poor signal stability *(Zhang et al., 2023).*

To summarize, traditional methods, chemical methods, and spectroscopic techniques all have unavoidable drawbacks, while machine vision offers the advantages of non-destructiveness, high efficiency, and low cost in crop identification. Therefore, machine learning methods have been widely applied to crop classification *(Verma et al., 2025)*. By comparing the identification performance of two Convolutional Neural Network (CNN) models on 13 chickpea varieties, the practical value of deep learning in the field of smart agriculture was verified *(Ulu et al., 2025)*. Large-scale datasets from multiple studies show that the identification accuracy of Support Vector Machines (SVM) is approximately 98.50%, while that of Logistic Regression (LR) reaches 93.02%. These results suggest that machine learning and deep learning techniques have significant potential for variety identification, particularly in food crops such as rice and soybean *(Verma et al., 2025)*.

Despite numerous machine learning studies in grain identification, precise identification of rice seeds still requires further innovation. The key challenges include the scarcity of open datasets, class imbalance, a limited number of training samples, and insufficient accuracy of existing methods. To address these issues, this study developed a novel deep learning model, "Rice-Transformer", and conducted systematic comparative experiments using mainstream machine learning algorithms such as Support Vector Machine (SVM), Random Forest, and Convolutional Neural Network (CNN) for benchmark testing. Finally, it developed an integrated user interface system based on the PyQt5 framework. The method can effectively identify rice seed varieties and provide a systematic solution for the practical needs of variety management and quality inspection in modern agriculture.

MATERIALS AND METHODS

Samples

This study primarily selected eight locally cultivated rice varieties from Jiangxi Province, namely, Yongyou 12 (YY12), Taiyou 871 (TY871), Wanxiangyou Huazhan (WXYHZ), Taiyou 398 (TY398), Yexiangyou Xing 1573 (YXYH1571), H Liangyou 30 (HLY30), Changtianyou 405 (CTY405), and WuGufeng 286 (WGF286). The experiment selected approximately 4,000 grains from each of the eight rice seed varieties as research subjects. The individual seeds were placed at intervals on a black background platform during sample preparation (Fig. 1).

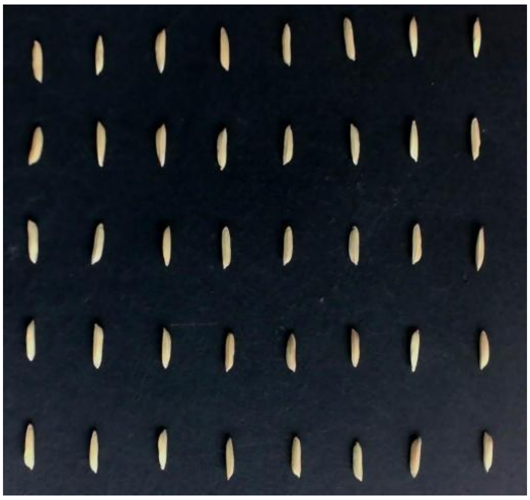


Fig. 1 - Rice seed samples

Imaging Acquisition Setup

Rice seed images were captured using a USB industrial camera (Shenzhen Zhongweiuoke Technology Co., Ltd., China) that is compatible with Windows. The camera was fixed on an adjustable stand to maintain a consistent angle of view. Its lens was located 22 cm directly above the seed sample and was in precise optical focus. Samples were placed on a black platform directly aligned with the lens to ensure image integrity and a consistent background for subsequent image processing and analysis (Fig. 2).

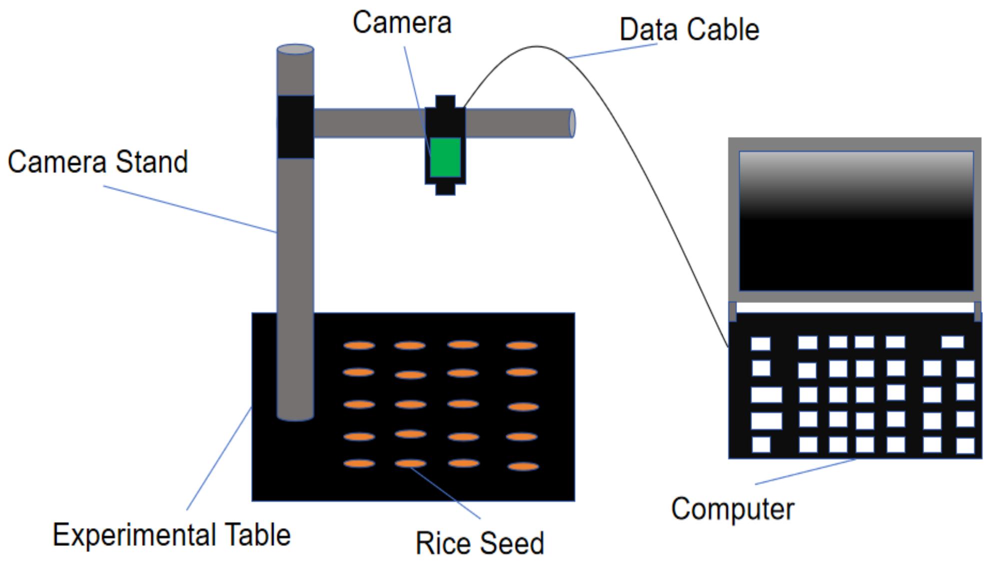


Fig. 2 - Image acquisition setup

The imaging system utilized a high-resolution industrial camera integrated with professional optical lenses. All imaging parameters, including exposure, brightness, and contrast, were precisely regulated through computer control as detailed in Table 1. This configuration ensured the acquisition of seed images with well-defined contours and sharp edges across varying illumination conditions.

Table 1

Details of imaging parameters

Brightness	Contrast	Color hue	Color saturation [%]	Gamma	White Balance [K]	Backlight Compensation
-64	1	0	69	64	4600	128

Image Acquisition

The imaging system utilizes a high-resolution camera coupled with optimized lenses to ensure clear seed image acquisition under specified illumination conditions. For the eight seed varieties, this study implemented a batch processing strategy. Upon completion of each batch, the processed samples were removed and replaced with new specimens. This approach guarantees both sample uniqueness and diversity, providing robust support for comprehensive feature extraction during model training. All acquired images were saved in high-resolution format and systematically categorized into their respective catalogs according to seed species, creating a comprehensive database for subsequent image processing and model construction.

Image Preprocessing

To accurately extract the morphological features of rice seeds, this study developed and implemented a set of image preprocessing and segmentation algorithms. First, the images were read using OpenCV, followed by a series of preprocessing operations, including the conversion of color images to grayscale maps, Gaussian fuzzy denoising, and morphological optimization. Second, the edge contours of the seeds in the image were detected, and contours corresponding to impurities or noise were removed by filtering out regions below a minimum area threshold. The remaining contours were ranked by area, and the largest 40 were retained (based on the assumption that each image contains no more than 40 seeds). Using the centroid of each contour as a reference point, image patches were uniformly cropped to a target size of 136 × 150 pixels. Finally, the extracted single-seed images were saved to the output directory.

Model Construction

This study innovatively developed the Rice-Transformer architecture, which synergistically combines convolutional feature extraction with Transformer attention mechanisms. Fig. 3 shows the schematic diagram of the Rice-Transformer architecture. Its core modules are as follows.

(1) Multi-Scale Convolution Module (MultiScaleConv): through four parallel convolutional layers with different kernel sizes (1×1, 3×3, 5×5, 7×7), it fuses and outputs multi-scale local features, capturing both fine textures and overall contours of seeds simultaneously.

(2) Feature Sequence Transformation Module: efficiently converts 2D feature maps into 1D sequences, solving the input adaptation problem of the Transformer while achieving seamless transition of feature representations.

(3) Hybrid Attention Mechanism (HybridAttention): integrates channel and spatial attention, dynamically fusing their weights through a gating mechanism, which enables the model to focus accurately on key features in complex scenes.

(4) Adaptive Token Reduction Module: Prunes tokens at specific layers of the Transformer, retaining key feature tokens while discarding secondary information, thus reducing computational complexity.

(5) Transformer Encoder Block: Adopts a dual-tower structure (Hybrid Attention Layer + MLP Layer), combined with residual connections and layer normalization to stabilize the training process.

(6) Identification Head Module: Performs global average pooling on sequence features, outputs category probability distributions through fully connected layers, with the number of categories automatically adapting to the training set.

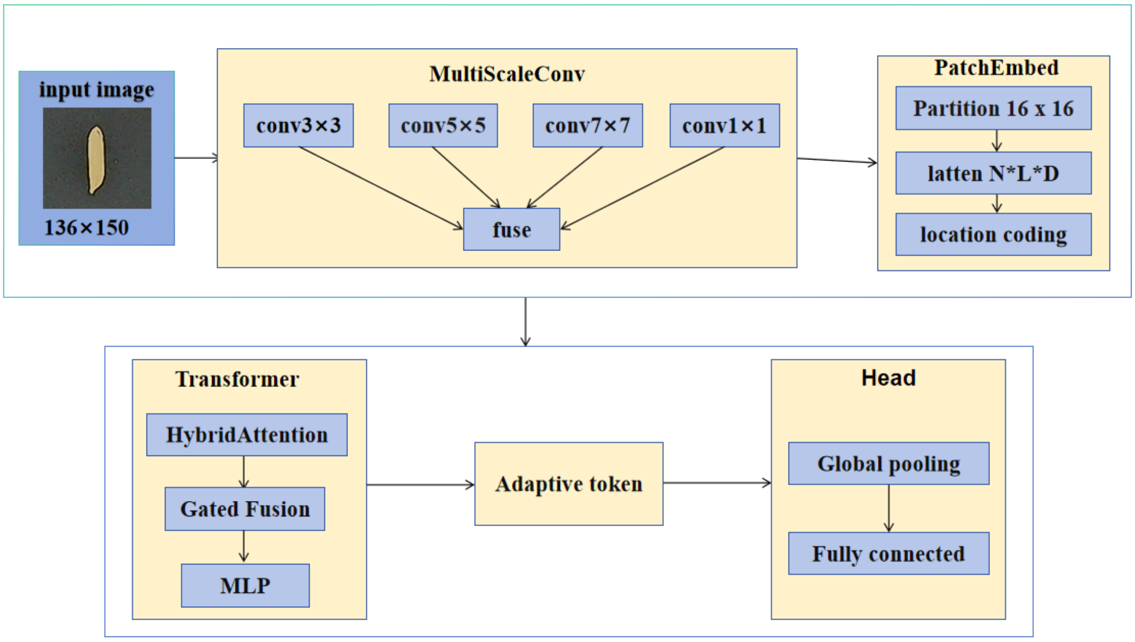


Fig. 3 – Rice-Transformer architecture

Model Training Environment

To ensure stable progression of the training processes for models, including Rice-Transformer, SVM, and Inception v1, this study preconfigured the training environment by establishing an optimized operational framework tailored to the specific requirements of each model. Detailed configuration specifications are provided in Table 2.

Table 2

Model training and testing environment configuration

Name	Parameter
CPU	AMD Ryzen 7 7735H
GPU	NVIDIA GeForce RTX 4060
Graphics Memory	8 GB
Operating System	Windows 11
Deployment Platform	Python 3.9
Deep Learning Framework	PyTorch 2.3.1
CUDA	CUDA 11.8

Model Deployment

In the deployment phase, the complete model and key training parameters were preserved to ensure rapid loading and execution within the target environment. The finalized model was then integrated into a comprehensive user interface workflow developed using PyQt5. This lightweight deployment strategy not only improves the practical applicability of the model but also enables fully automated processing for seed identification tasks.

Visual Interface Development and Design

Based on the PyQt5 framework, this study developed a modular intelligent rice seed analysis system employing a three-tier architecture (presentation layer/logic layer/data layer) that integrates six algorithmic models, including Rice-Transformer. The system enables end-to-end processing from input image, image preprocessing, image segmentation (136×150 pixels), feature extraction, and variety recognition. As shown in Fig. 4, the system interface adopts a four-zone layout comprising: a functional toolbar, a dual-view comparison area (supporting adaptive image scaling), a feature parameter panel (displaying multiple morphological indicators in real-time), and an operation log region. Furthermore, OpenCV's findContours algorithm is used to achieve seed contour detection and color labeling. Through algorithm scheduling via the strategy pattern and persistence management using Joblib, the system features: one-click switching between multiple models, automatic calculation of seed size and area, visual annotation of variety information (in dark red font), and real-time error prompts. Its modular design not only ensures functional decoupling and rapid fault localization but also maintains system stability through refined UI parameter configuration, providing an efficient and reliable intelligent solution for rice seed analysis.

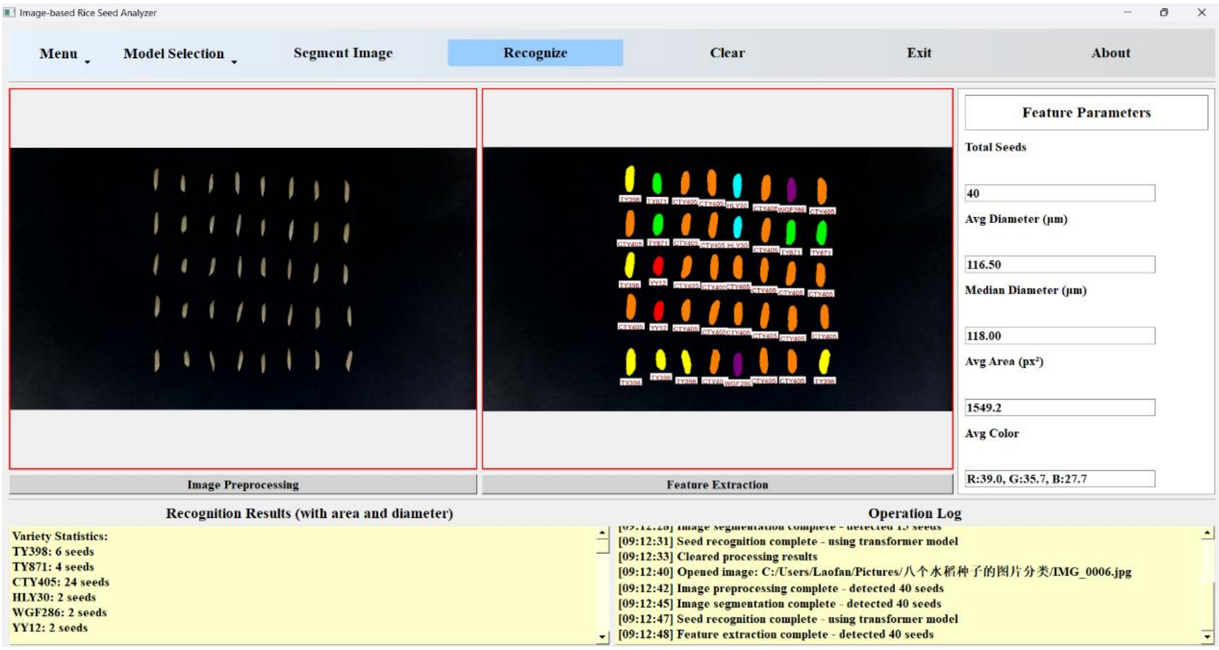


Fig. 4 - Intelligent rice seed analysis system

RESULTS

Image Preprocessing Result

All seed samples underwent surface cleaning to eliminate interference from impurities. As shown in Fig. 5, the final output single seed images are clear, with good integrity and uniform specification, and can be used for model training. After image segmentation, each category contains 4000 seed images, and a dataset of more than 33000 seed images is constructed. This dataset is divided into a training set, validation set, and test set in a ratio of 7:2:1. All images were uniformly resized to 136×150 pixels and used for model training, parameter adjustment, and performance evaluation, respectively.

(a) CTY405 (b) TY871 (c) WXYHZ (d) HLY30

(e) WGF286 (f) YXYH1573 (g) YY12 (h) TY398

Fig. 5 - Processing results after image acquisition

Model Evaluation

In the research on rice seed identification, the effectiveness of the proposed Rice-Transformer model is examined. As shown in Equations 1-4, this experiment adopted four data evaluation metrics. Accuracy, Precision, Recall, and F1-score.

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

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

where:

True Positive (TP) represents the number of correctly identified seeds belonging to the target variety, [pcs]; False Positive (FP) denotes non-target varieties erroneously classified as the target, [pcs]; False Negative (FN) refers to target variety seeds misclassified as non-target, [pcs]; True Negative (TN) indicates correctly rejected seeds of other varieties, [pcs].

Table 3

Comparison of identification results of different models

Model	Accuracy [%]	Precision [%]	Recall [%]	F1-Score [%]
SVM	93.42	93.45	93.42	93.43
KNN	88.44	88.47	88.38	88.39
Random Forest	80.89	81.30	80.89	80.95
ResNet	80.71	81.22	80.71	80.60
Inception v1	94.90	94.90	94.90	94.93
Rice-Transformer	**97.71**	**97.70**	**97.69**	**97.69**

As can be seen in Fig. 6, Rice-Transformer performs well in related tasks, with its accuracy, precision, recall rate and F1-score significantly higher than those of models such as SVM, KNN, Random Forest, ResNet, and Inception V1. Specifically, it outperforms the second-ranked model (Inception V1) by 3%, and has a more significant advantage over traditional machine learning models, showing greater recognition capability and lower error rates. The complete consistency of the four metrics reflects their excellent performance in balancing precision and recall, resulting in stable and reliable results in practical applications without fluctuations caused by metric trade-offs. It is indicated that the Rice-Transformer is more adept at capturing long-range dependencies and global features of rice seed images than traditional CNNs and machine learning models. This enables it to have stronger generalization ability in complex scenarios such as varying lighting conditions and changes in structure and morphology. Consequently, it is suitable for practical production application tasks such as grain identification and quality screening, making it the best model choice for rice seed variety identification.

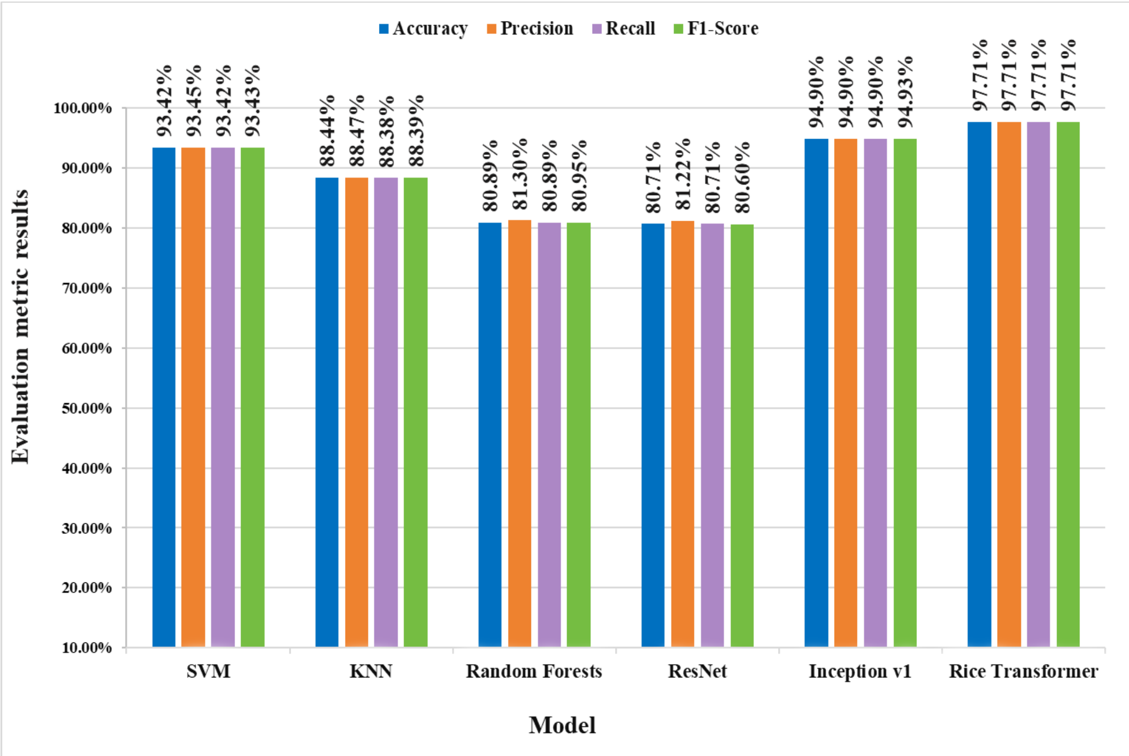
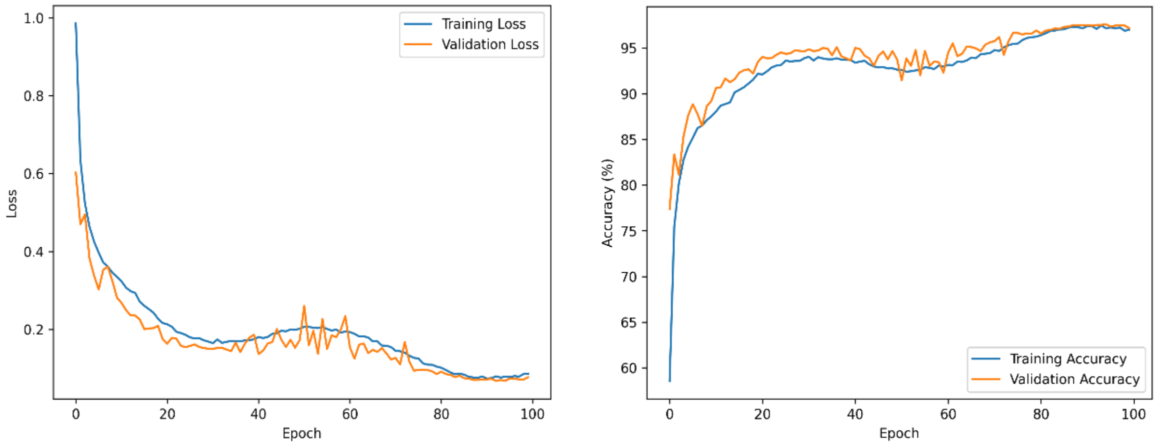


Fig. 6 - Results of rice seed variety identification

Training and Validation Loss Curves

As shown in Fig. 7a, the loss decreases with time for both the training and validation sets as the model gradually converges. Although the loss in the validation set exhibits minor fluctuations, its overall trend is consistent with the training set loss, and no overfitting occurs. For the accuracy curves (Fig. 7b), both training and validation accuracy increase sharply initially, then plateau in later stages. Despite slight fluctuations in validation accuracy, it remains close to the training accuracy, demonstrating the model's generalizability to unseen data. In conclusion, the model achieves high accuracy and robust generalization in rice seed variety identification, providing reliable support for seed identification.



(a) Training and Validation Loss (b) Training and Validation Accuracy

Fig. 7 – Loss and accuracy curves of Rice-Transformer

Confusion Matrix and ROC-AUC Curve

The confusion matrix is a key tool for evaluating model performance. By analyzing the correspondence between rows (correct labels) and columns (predicted labels), along with diagonal elements (correct classifications), it enables calculation of Precision and Recall, providing more granular insights than a single accuracy metric.

This study proposes that the Rice-Transformer model performs well in classifying eight rice seed varieties (e.g., YY12 and TY871). As can be seen from the diagonal values of the confusion matrix (Fig. 8), most of the samples were classified correctly. For example, the number of misclassified TY398 varieties was minimal. However, there were mutual misclassifications between similar varieties such as CTY405 and HLY30, which may be due to the high feature similarity between them. It suggests the need to improve the feature extraction model or extend the training data.

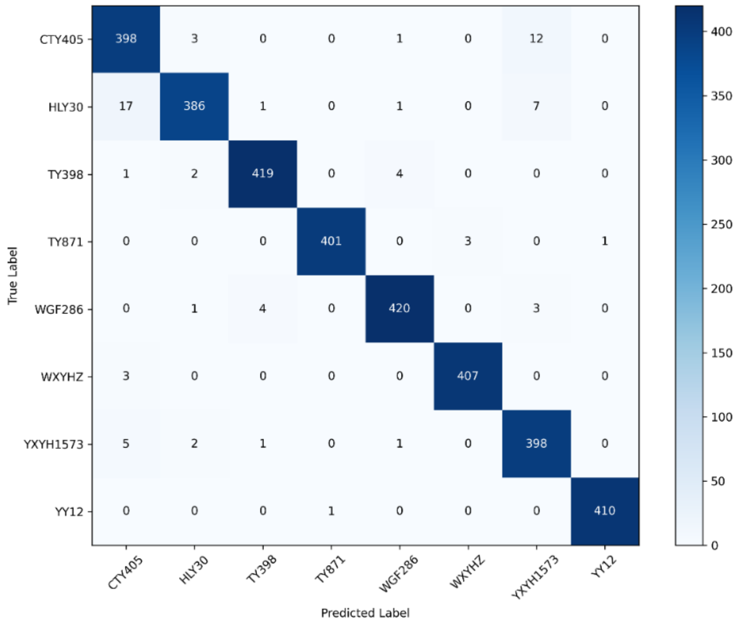


Fig. 8 – Confusion matrix of Rice-Transformer

The Rice-Transformer model utilizes the advantages of its own architecture to effectively capture detailed features of rice seeds, demonstrating great potential for variety identification. As shown in the ROC-AUC analysis in Fig. 9, the dashed line serves as a baseline for random guessing. Although further optimization is needed to distinguish highly similar varieties, the model has shown significant utility and technical advantages.

$$\mathrm{FRP} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} \tag{5}$$

$$\mathrm{TRP} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{6}$$

where: FRP (False Positive Rate) represents the misclassification rate of the non-target category, [%]; TRP (True Positive Rate) represents the correct identification rate of the target category, [%].

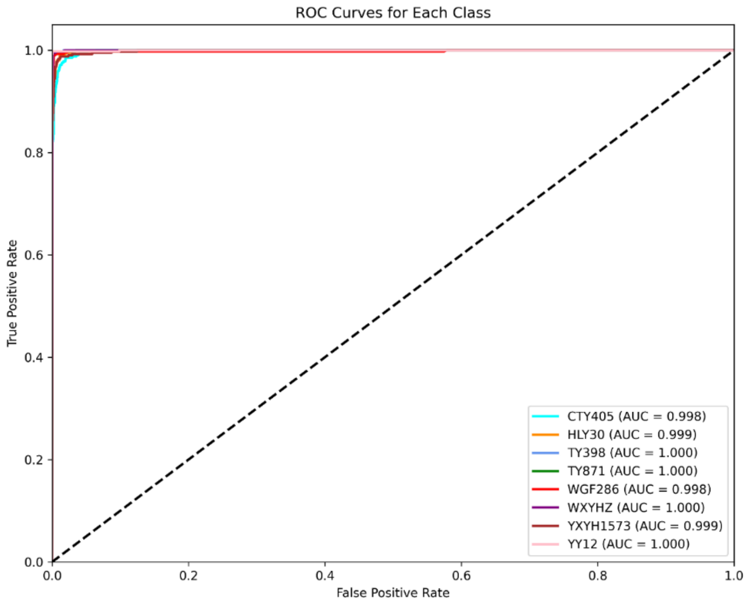


Fig. 9 - ROC curve of rice seed datasets

The results show that the Rice-Transformer model exhibits excellent performance. The ROC curves for all categories are very close to the upper left corner of Fig. 9. Among them, four varieties (such as TY 398) have an AUC value of 1.0, and the rest of the varieties have an AUC value close to 1.0. It shows a very high positive-negative sample discrimination ability. Compared to traditional machine learning models such as SVM and KNN, Rice-Transformer has a significant advantage in classification tasks that rely on its transformer architecture, which can capture complex features more effectively.

Performance of the Proposed Rice-Transformer Model on Eight Varieties

Most of the rice seeds of CTY405, HLY30, TY398, TY871, WGF286, WXYHZ, YXYH1573, and YY12 varieties have an accuracy of more than 98%, of which TY398, WXYHZ, and YY12 are close to 100%. In terms of precision, TY398, TY871, and YY12 are close to 99%, indicating that the recognition of these three varieties is highly reliable. Except for YXYH1573 and CTY405, the recall of all other varieties exceeded 98%, with TY398, WGF286, WXYHZ, and YY12 having extremely high authentic sample capture rates. For the F1-score, the values range from 94. 69% to nearly 100%, and all varieties maintain a stable and balanced performance between precision and recall, with TY398 and YY12 at the highest level of the combined recognition index. Additionally, the average loss remains at a single-digit level. It further verifies that the model features high precision, strong robustness, and excellent generalization ability, and can effectively support agricultural application scenarios such as rice seed identification.

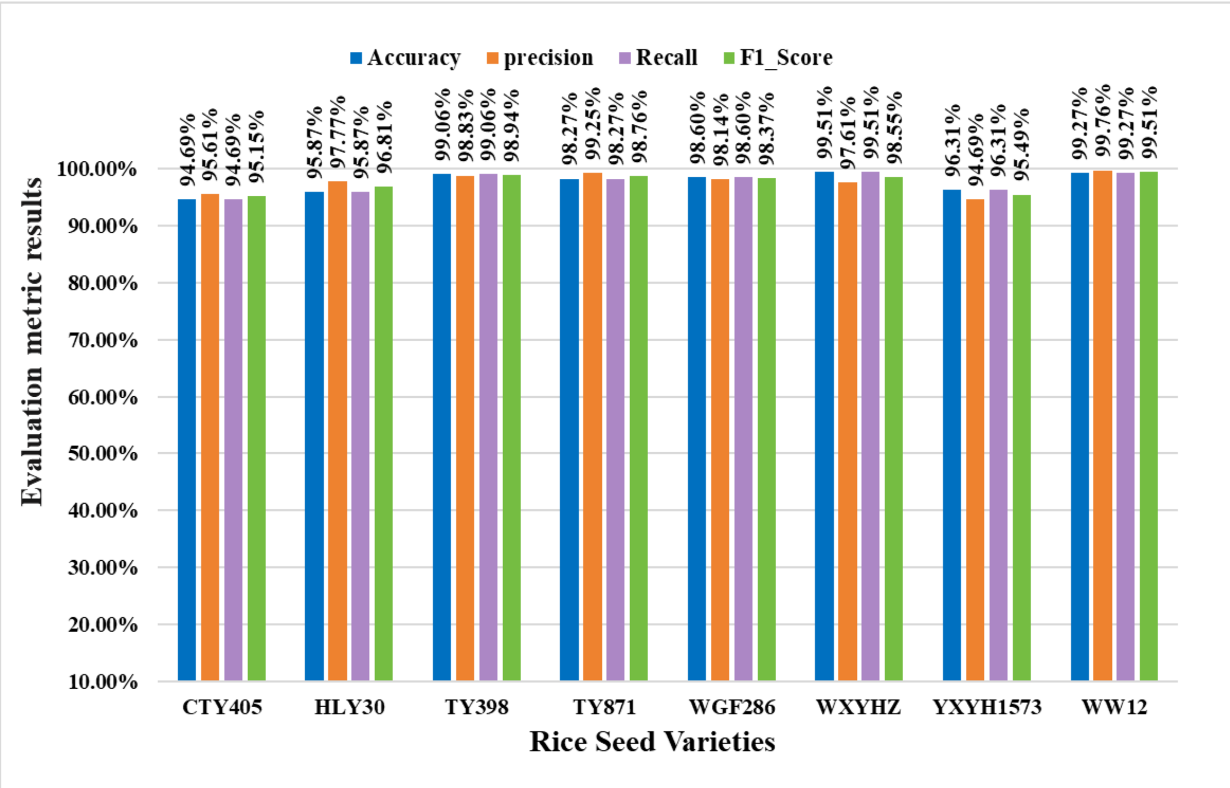


Fig. 10 - Identification performance of Rice-Transformer

Performance comparison of Rice-Transformer with existing works

To evaluate the identification effect of the proposed model in similar scenarios, performance validation was conducted through comparative experiments and related research works. Table 4 presents the comparison results, constructed across multiple dimensions, including model architecture, dataset size (total number of samples and varieties), and crop categories, with accuracy serving as the primary evaluation metric. The results show that the rice-transformer model performs well in the rice seed identification task. The model processed a dataset containing 33,074 data entries, including all rice seed categories collected in this study, with an accuracy rate of 97.71%. When compared to other recognition models designed for rice or cereal seeds, the rice-transformer model ranked among the top in terms of accuracy. It indicates that the model can accurately determine the class to which the sample belongs in rice seed variety identification, has excellent recognition performance, and is competitive in the field of crop identification.

Table 4

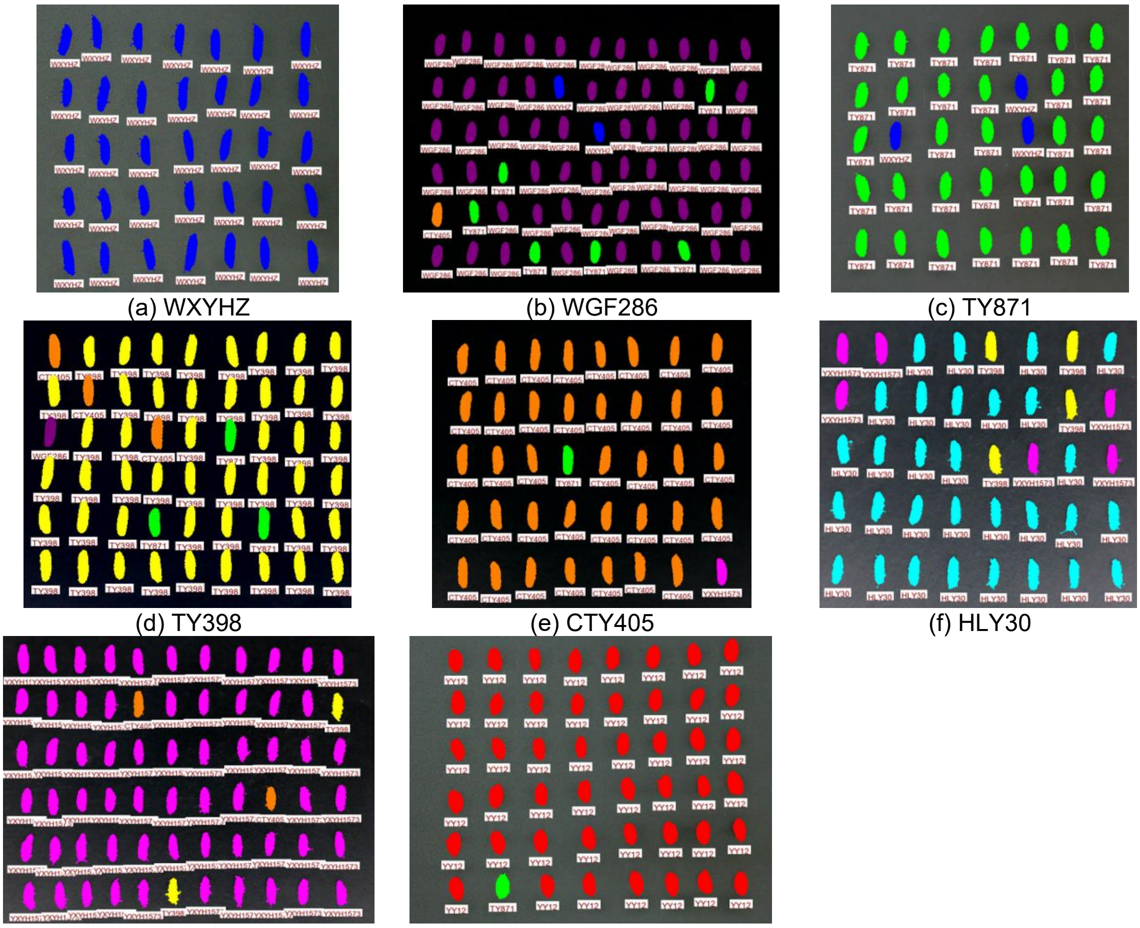
Performance comparison of the Rice-Transformer with existing works

Approaches	Dataset Length	Variety Count	Category	Accuracy [%]
RiceSeedNet *(Rajalakshmi et al., 2024)*	13,000	13	Rice Seeds	97.00
InceptionV3 *(Gilanie et al., 2021)*	50,000	14	Rice Seeds	95.15
Multi-modal Late Fusion *(He et al., 2023)*	3194	8	Rice Seeds	97.40
Random Forest *(Fabiyi et al., 2020)*	8640	90	Rice Seeds	98.33
CNN *(Komal et al., 2022)*	6000,000	22	Rice Seeds	77.50
Rice Le3 *(Anggrawisesa et al., 2024)*	27,000	20	Rice Seeds	96.78
Inception V3 *(Jaithavil et al., 2022)*	12,000	3	Rice Seeds	83.33
MFSwin Transformer *(Bi et al.,2022)*	32,500	19	Maize Seeds	96.47
Vision Transformer (*Jin X. et al., 2023)*	6,000	6	Sun flower Seeds	96.60
GoogLeNet *(Luo et al., 2023)*	47,696	140	Weed Seeds	93.11
DensNet20 *(Laabassi et al., 2021)*	31,606	4	Wheat grain	95.68
Hybrid Vision Transformer *(Dönmez et al., 2023)*	3,000	2	Maize Seeds	96.33
Rice-Transformer *(Proposed model)*	**33,074**	**8**	**Rice Seeds**	**97.71**

Identification Performance of the Interface System

To explore the actual recognition effect of the Rice-Transformer model integrated into the interface system for eight rice seed varieties, experimental samples were prepared for this study. All sample images show various arrangements of a single variety of rice seeds, and different varieties of rice seeds have distinctive appearance and color characteristics.

The experimental results are shown in Fig. 12. In the recognition task of the rice converter model, the seed region of WXYHZ was marked in blue color with 100% recognition accuracy. In addition, the model was recognized in five other rice varieties, namely YXYH1573, TY871, TY398, CTY405, and YY12, which performed well on the model, with their recognition rates remaining steadily above 90%. These results further validate that the model maintains reliable recognition performance for most target species after integration into the interface.



(a) WXYHZ (b) WGF286 (c) TY871
(d) TY398 (e) CTY405 (f) HLY30
(g) YXYH1573 (h) YY12

Fig. 11 - Identification performance of interface system

The experimental results are shown in Fig. 12. In the recognition task of the rice converter model, the seed region of WXYHZ was marked in blue color with 100% recognition accuracy. In addition, the model was recognized in five other rice varieties, namely YXYH1573, TY871, TY398, CTY405, and YY12, which performed well on the model, with their recognition rates remaining steadily above 90%. These results further validate that the model maintains reliable recognition performance for most target species after integration into the interface.

CONCLUSIONS

This research constructed an image acquisition device and established an image dataset of eight cultivated rice seed varieties in Jiangxi Province, China. Based on the image preprocessing and segmentation algorithms, a rice seed recognition model with the Transformer architecture was developed. The Rice-Transformer model performs well with an overall accuracy of 97.71%. The rest of the evaluation metrics, such as precision, recall, and F1 score, also reach 97.69%, which significantly outperforms the traditional machine learning methods and convolutional neural network (CNN) models. Furthermore, this study developed an integrated user interface system based on PyQt5. The system implements image preprocessing, feature extraction, and result visualization, which effectively support the practical application requirements. This study proposes an efficient and cost-effective method for varietal identification of rice seeds. It is suitable for large-scale seed identification tasks, which are of great practical significance for guaranteeing food security in agricultural production and promoting sustainable agricultural development.

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