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Research Background:

- Accurate crop classification is crucial for precision agriculture, but traditional handcrafted feature methods **lack robustness** in complex environments, while standard machine learning methods require extensive **feature engineering** but struggle to exceed 55% accuracy.
- To address data scarcity and noise issues, this study established a comprehensive **data preprocessing pipeline** and employed transfer learning techniques to compare the performance of multiple algorithms.

Method :

- Data Processing:** Obtained 8 types of crop images from Kaggle, cleaned the data through blur and exposure detection, and performed data augmentation using geometric transformations and Mixup strategies.
- Machine Learning:** Conducted feature engineering using methods like PCA dimensionality reduction.
- Deep Learning:** Adopted transfer learning, using pre-trained ImageNet models MobileNetV3-Large and VGG16, and adapted them to the agricultural domain through a two-stage fine-tuning strategy.

Exploratory Data Analysis:

RGB Channel Correlation Matrix:

- RGB channel correlation coefficients for crop images: R&G=0.84, R&B=0.73, G&B=0.82;
- High correlation (>0.7) indicates high information redundancy between channels;
- Can be used for efficient data compression and dimensionality reduction.

RGB Pixel Brightness Distribution:

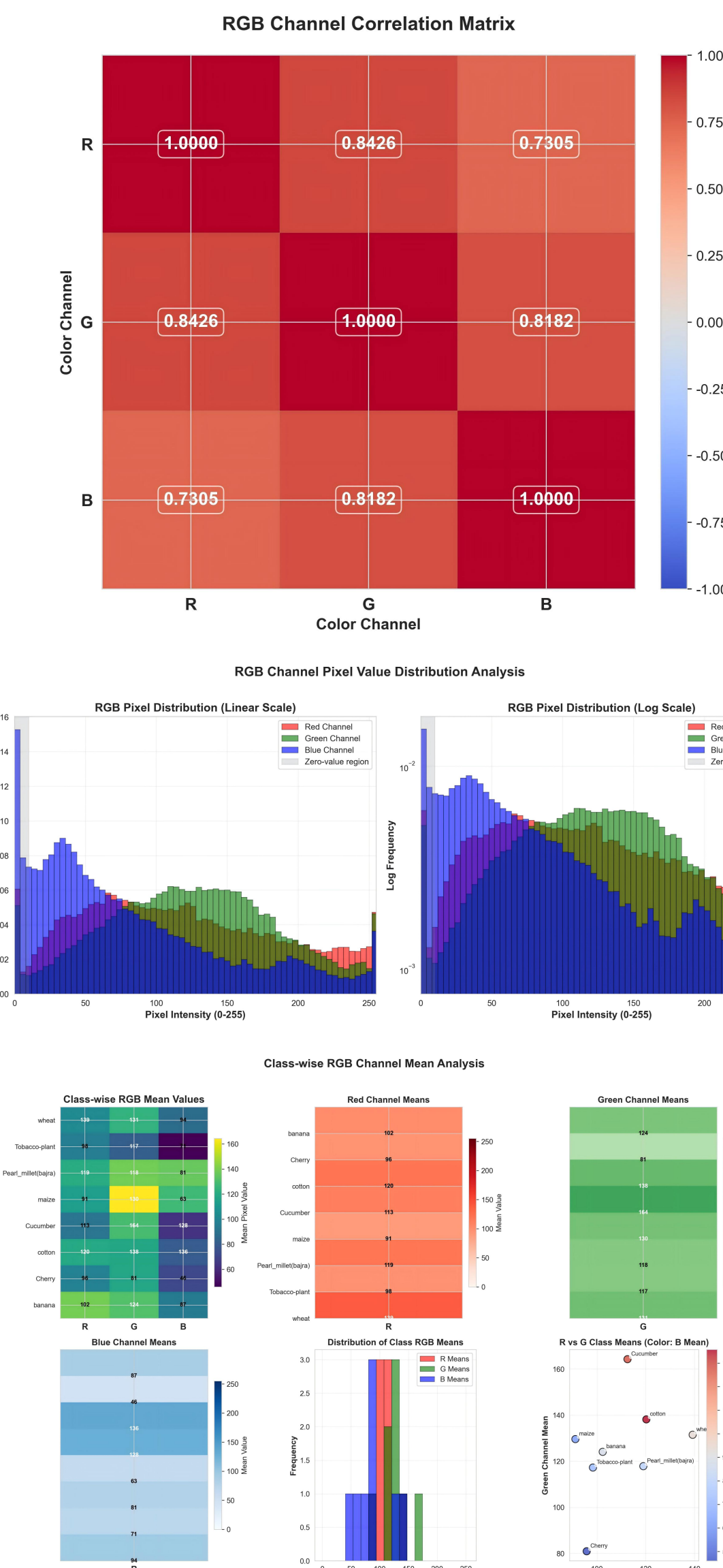
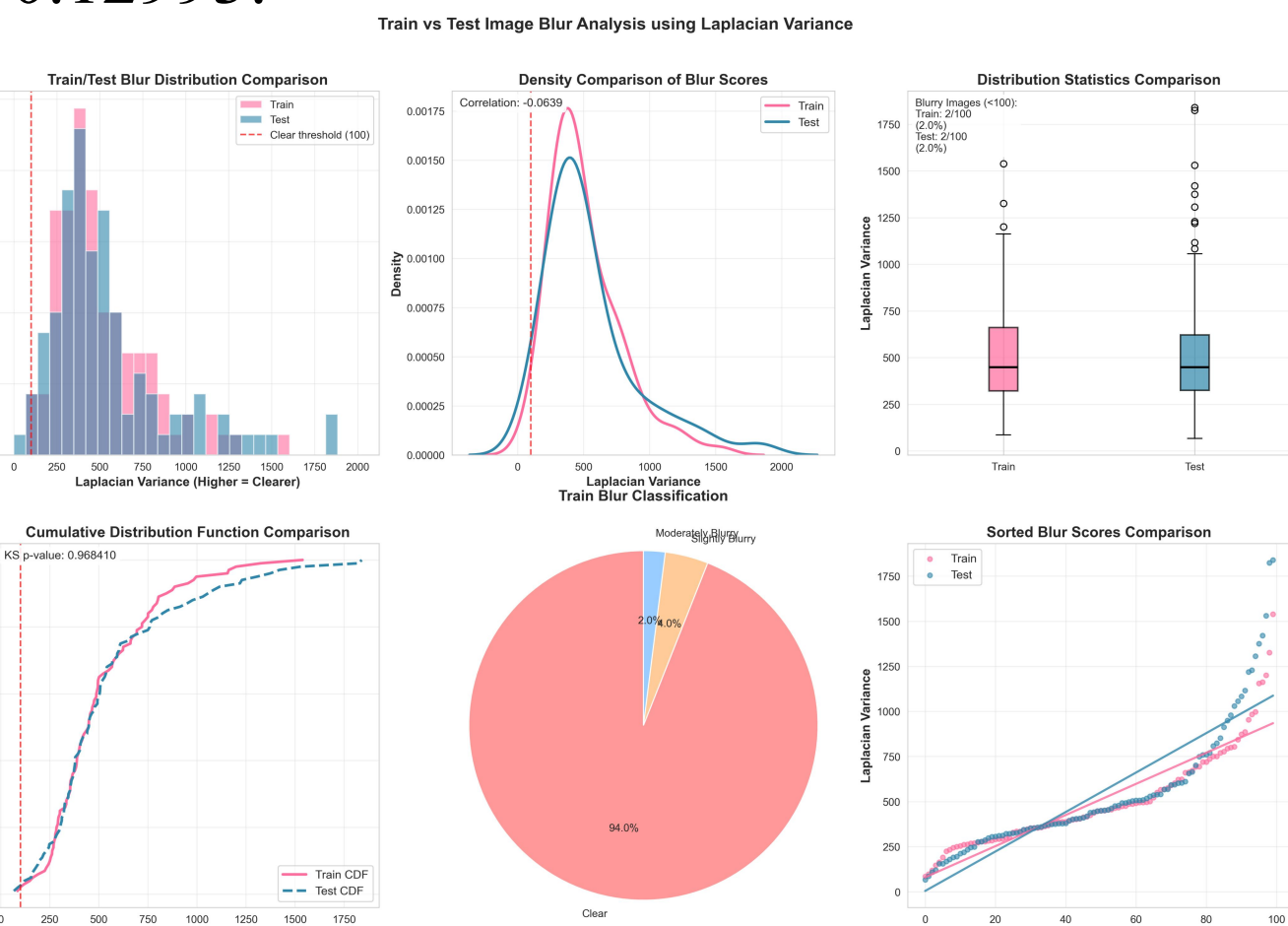
- Green channel has the highest brightness (125.86), and the overall image has a green tone
- 42.47% of pixels in the blue channel have low brightness; brightness enhancement is a key factor for improvement

Class-wise RGB Channel Mean Analysis:

- Different crops have unique mean distribution characteristics in RGB channels;
- Green channel is the primary distinguishing dimension, while red and blue channels are auxiliary distinguishing dimensions

Distribution Consistency between Training and Test Sets:

- Grayscale distribution: frequency distribution, cumulative distribution function, and statistical indicators are highly consistent;
- Blur Analysis:** Clarity distribution is consistent, with 94% of images being clear;
- Edge Strength: Distributions are highly overlapping, with a KS test p-value of 0.12993.



Feature Engineering:

Engineering Methods:

- Extracted features from color (12D), texture (33D), and shape structure (8D)
- Implemented using OpenCV, forming a 53D feature system

Engineering Value:

- Bridges raw data and models, extracting discriminative features
- Optimizes model training efficiency, accuracy, and generalization capability

Intelligent Crop Image Classification: A Comparative Study of Traditional Machine Learning and Deep Learning

Machine learning:

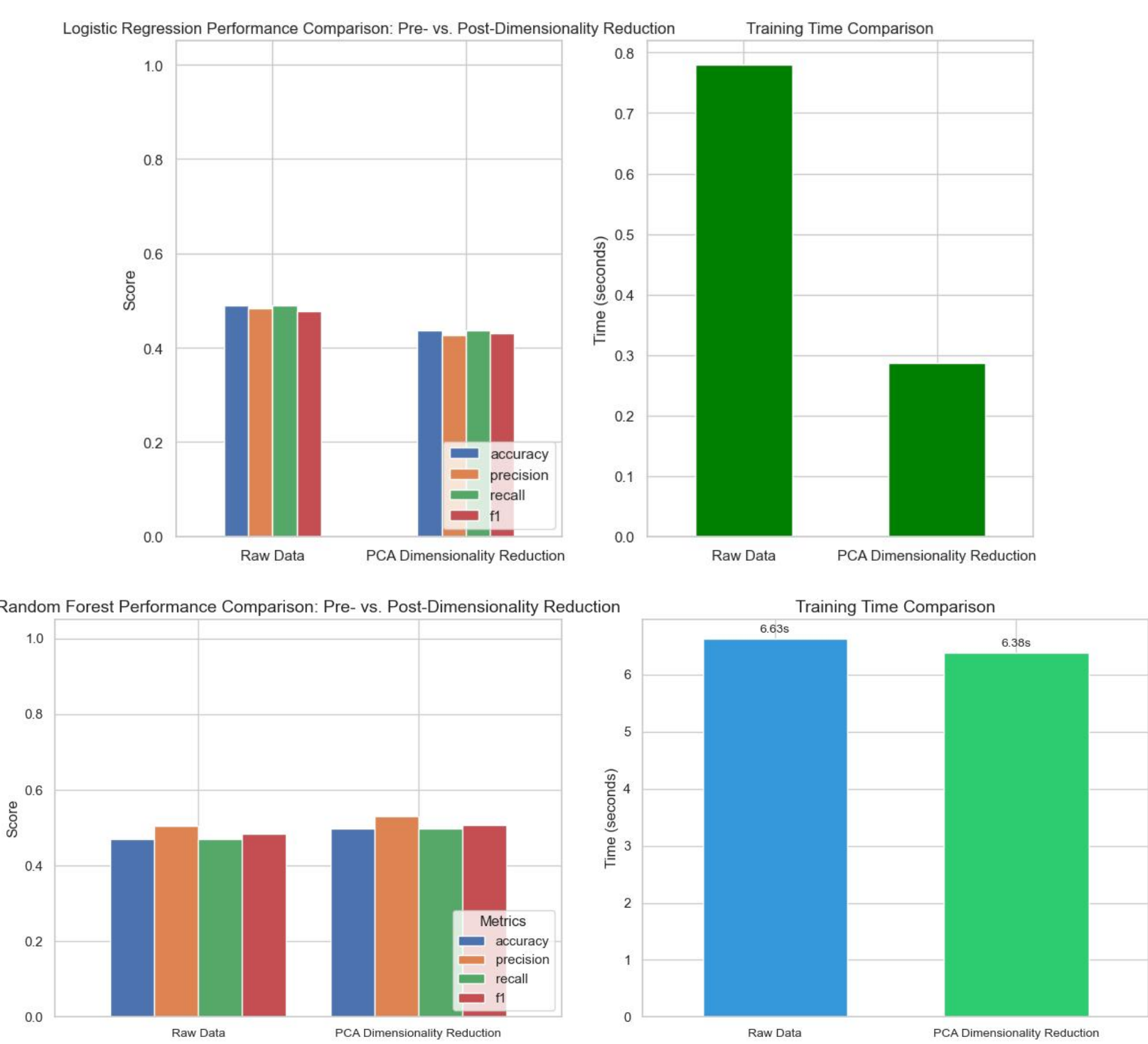
Machine learning models automatically discover patterns from data without explicit rules. This study evaluates Logistic Regression, Random Forest, and LightGBM on datasets with different dimensions (original, PCA-95%, PCA-50%).

- Logistic Regression:** Uses Sigmoid function to map linear regression outputs to probabilities.
- Random Forest:** Builds multiple decision trees using Bootstrap Aggregating (Bagging) and feature randomness to enhance stability and accuracy.
- LightGBM:** Employs histogram algorithms and Exclusive Feature Bundling for high efficiency, fast training, and support for parallel computing.

Results:

Original Data (53D):

- Logistic Regression: Fast training (0.74s), low accuracy (48.96%), slow inference (7,389,124.37/s).
- Random Forest: Higher precision (0.5038) and F1-score (0.4831), slower training (6.35s).
- LightGBM: Balanced metrics (accuracy: 0.4505), fast inference (187,136.32/s).



Discussion:

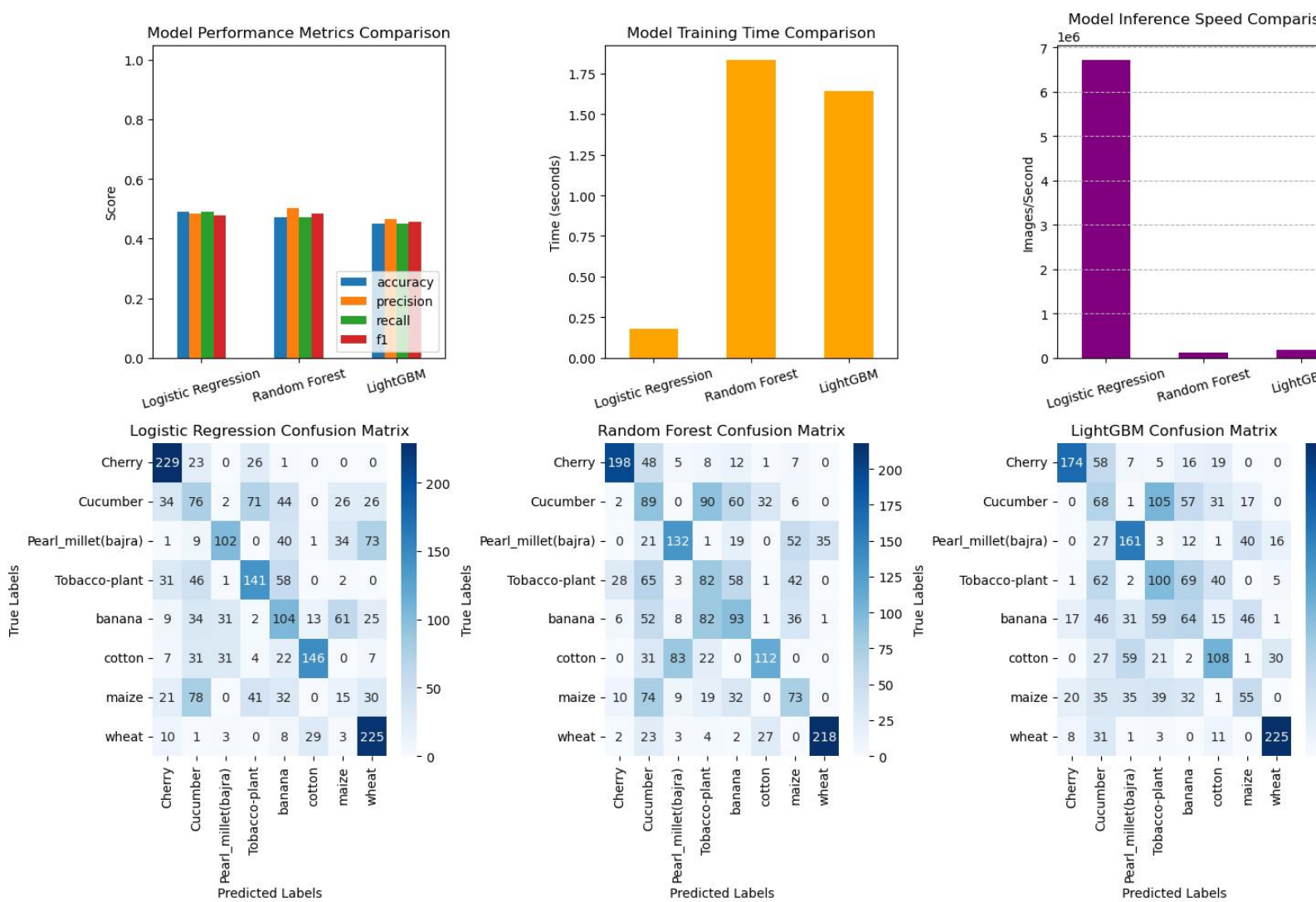
- Models **performed poorly** on original data despite feature engineering, indicating noise issues. Traditional models need enhancement for higher accuracy.
- PCA dimensionality reduction improved performance, especially LightGBM under PCA-50 settings. LightGBM showed **strong potential** with optimized PCA reduction.
- Excessive dimensionality reduction (e.g., PCA-95%) led to **feature loss** and **degraded performance**.
- Future work will **explore deep learning models** to improve pattern recognition.

Deep Learning:

Advantages of VGG16 in crop classification:

Traditional machine learning models show limited performance in complex visual tasks. Deep learning models (e.g., VGG16) have attracted attention for their ability to automatically extract features. This study compares the performance of VGG16 with traditional machine learning models in crop classification tasks and explores the advantages of deep learning in crop recognition.

- VGG16 model:** A classic 16-layer convolutional network with 13 3 × 3 convolutional layers, 3 fully connected layers, and 2 × 2 max pooling layers. It uses ReLU activation functions and Dropout to prevent overfitting.

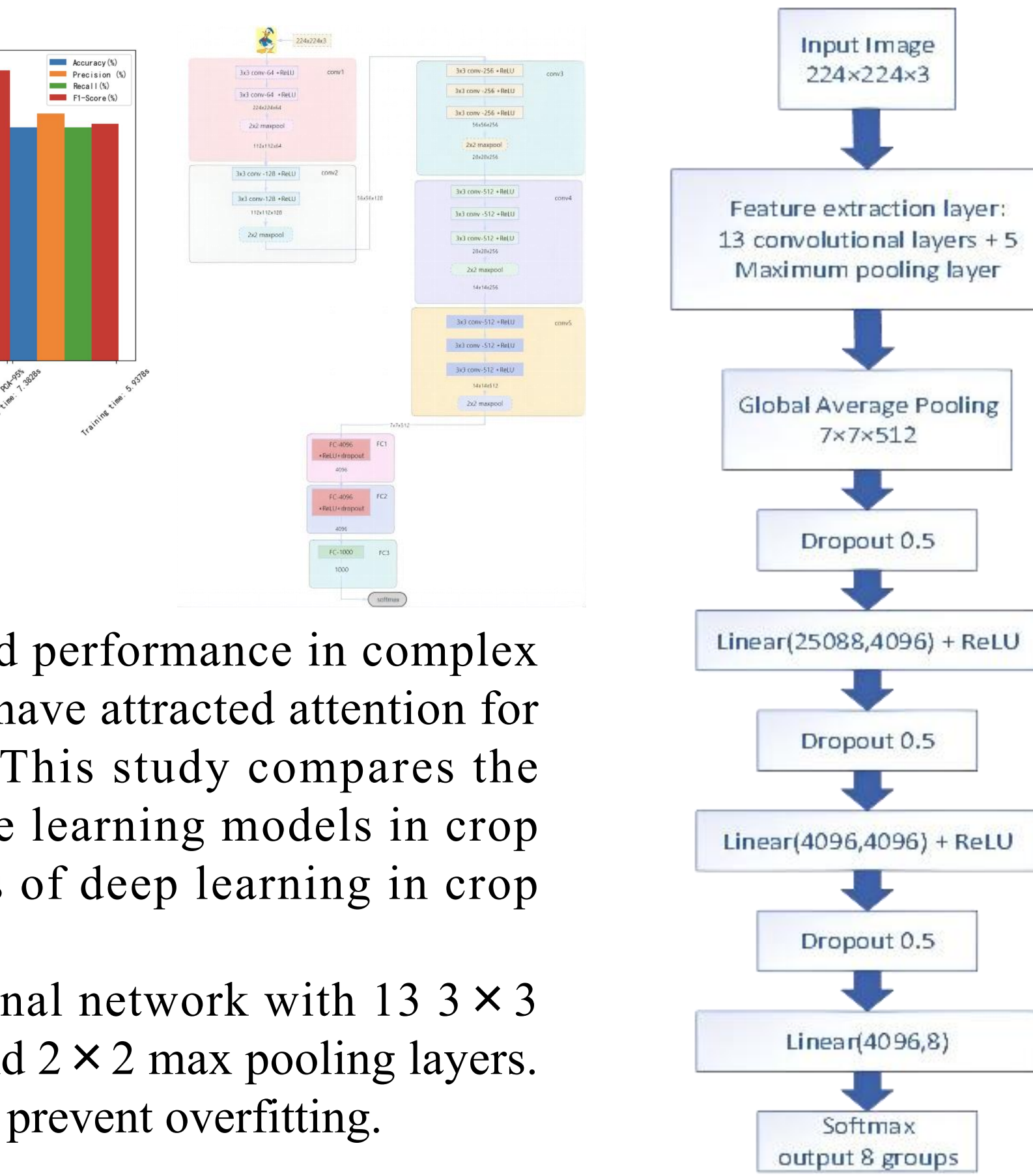


PCA-95% Data (18D):

- Logistic Regression: Fast training (0.3s), low accuracy (44.01%).
- Random Forest: Best performance (accuracy: 0.4981, F1-score >0.5).
- LightGBM: Poor accuracy (44.01%) and F1-score (44.72%).

PCA-50 Data (50D):

- LightGBM excelled (accuracy: 54.48%, precision: 55.80%).
- Random Forest: Accuracy >50%, improved metrics.
- Logistic Regression: Weak performance (metrics <50%).



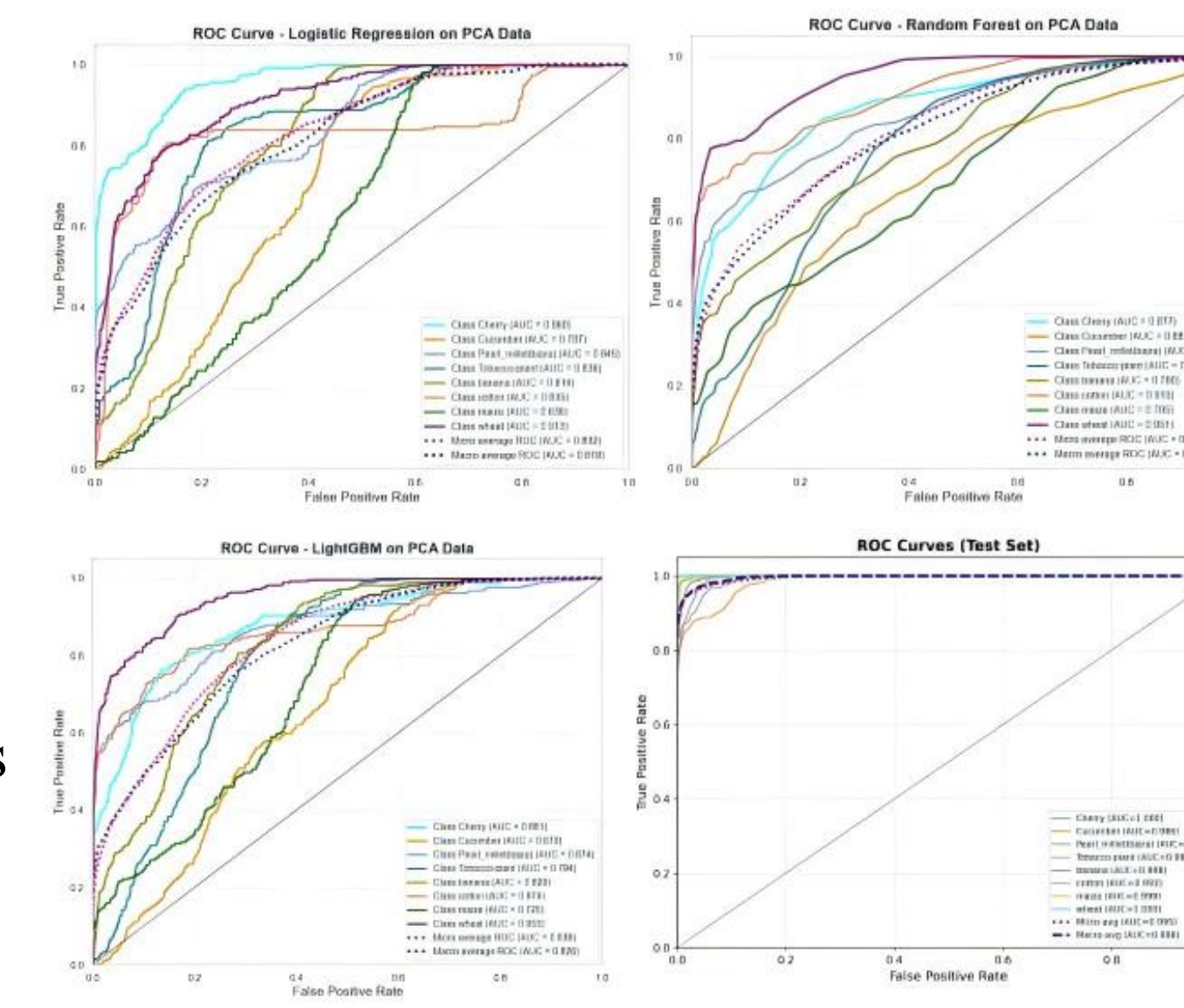
Model improvements: For the 8-class crop recognition task, the output layer was replaced with an 8-class Softmax, and additional Dropout layers were added. Training was conducted in two stages:

- First, the backbone network was frozen to quickly train the classification head (epochs=15, lr=1e-3);
- Partially unfreeze convolutional layers for fine-tuning (epochs=10, lr=1e-5).

Comparative framework: Compare with manually designed feature-based LightGBM, Random Forest, and Logistic Regression, using unified data preprocessing and augmentation strategies.

Results:

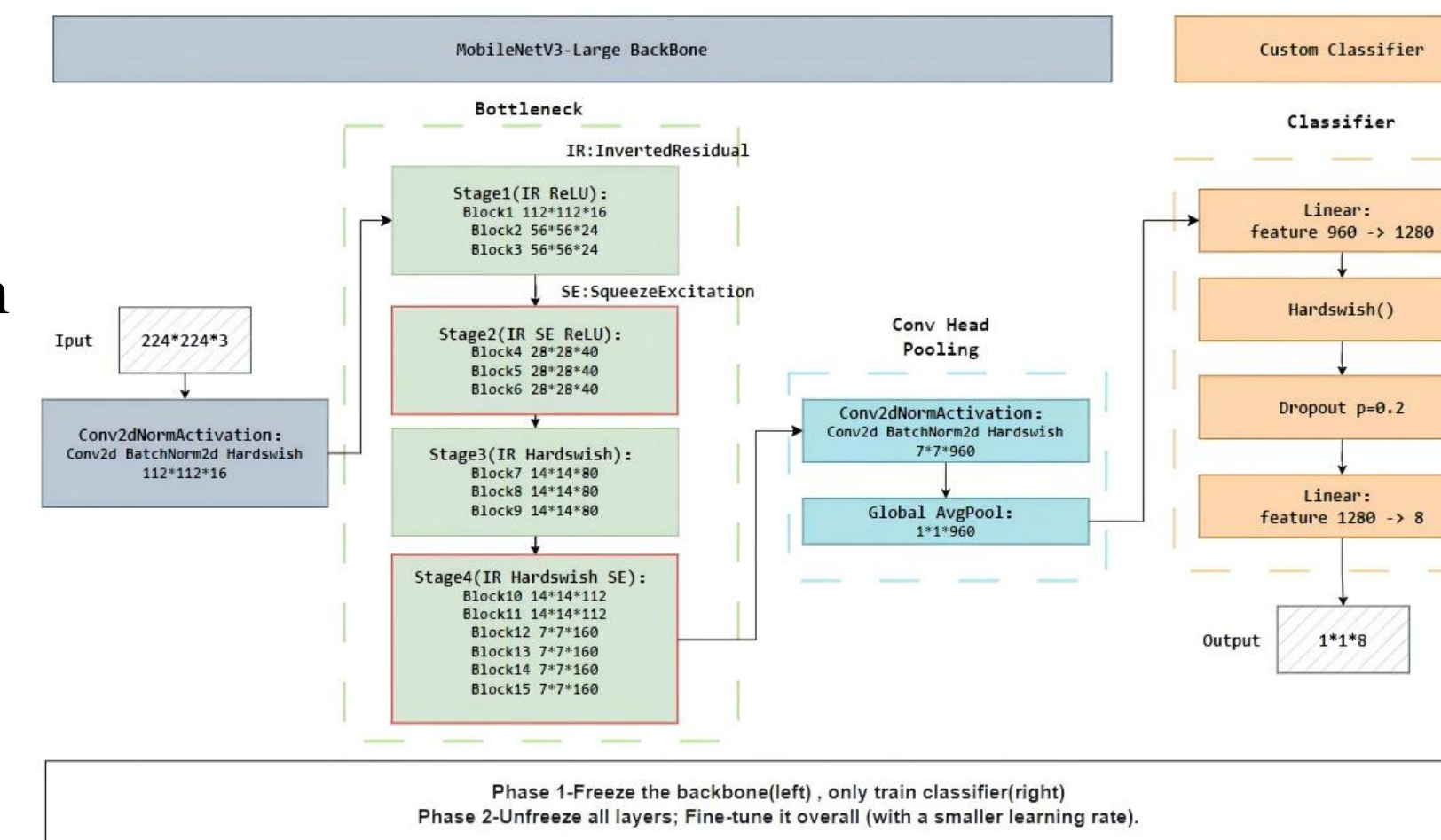
- Overall performance: VGG16 achieves 91.91% accuracy and 91.89% F1 score, which is about 40% higher than the best machine learning model (LightGBM).
- Computational efficiency: Machine learning models train in seconds and have fast inference speeds , but with low accuracy; VGG16 has high accuracy, but its parameter count (138M) and model size (>500 MB) are much larger than machine learning models.
- AUC comparison: VGG16's AUC for all crop categories is >0.98, with ROC curves close to the top-left corner; machine learning models' AUC is mostly between 0.7-0.8, with micro- and macro-averaged ROC values of only 0.8, indicating weak classification ability.



Performance and efficiency of MobileNetV3-Large and VGG16 models:

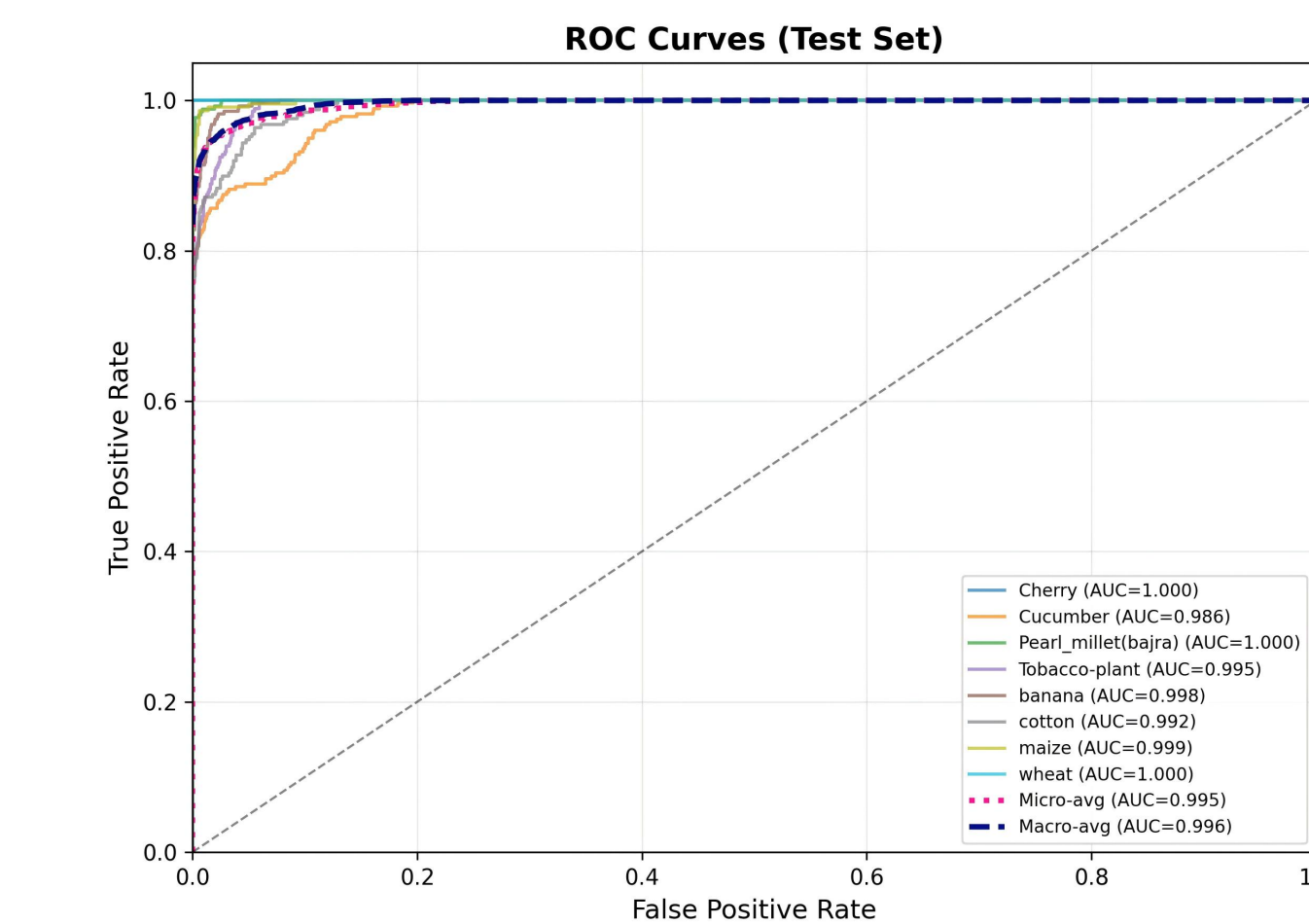
MobileNetV3-Large5

- Lightweight network optimized with hardware-aware NAS and NetAdapt for architecture.
- Innovations: Depthwise separable convolutions, Squeeze-and-Excitation modules, and hard-swish activation functions.
- Two-stage training strategy: Pre-train the classification head (10 epochs) + global fine-tuning (5 epochs).
- Final test accuracy is 93.44%, with only 5.4M parameters and an inference speed of 823 FPS, with a latency of 6.41 ms.



Results and Discussion:

- Exploratory data analysis: Displays data distribution and features.
- Hyperparameter tuning: In the PyTorch framework, using the AdamW optimizer and cross-entropy loss function, with a two-stage training strategy.



Deep learning significantly outperforms traditional machine learning in crop classification. MobileNetV3-Large provides the best balance between performance and computational cost, making it suitable for real-time agricultural monitoring.

Code:

[https://github.com/zhouzhongjie0714-lang/Intelligent-Crop-Image-Classification-A-Comparative-Study-;](https://github.com/zhouzhongjie0714-lang/Intelligent-Crop-Image-Classification-A-Comparative-Study-)

Video:

[https://www.bilibili.com/video/BV1vJibBfEtA?vd_source=8ceca89d2b163d2db4999f1450c81d73.](https://www.bilibili.com/video/BV1vJibBfEtA?vd_source=8ceca89d2b163d2db4999f1450c81d73)