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Research Article

Enhancing Agriculture Crop Classification with Deep Learning

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ABSTRACT

To classify rice crops, the paper applies deep learning to agricultural crop images to classify rice crops. The collection includes images of wheat, rice, sugarcane, jute, and maize.
We improved variety by horizontally flipping, rotating, and shifting rice image data sets. A CNN structure classifies rice and non-rice crops.
The model has 100% accuracy on training and testing datasets; however, the classification report shows label imbalance problems for precision, recall, and F-score.
Deep learning can help classify crops as well as make decisions in agriculture based on research.
The study recommends more studies and improvements to enhance model performance and address dataset concerns. The research advances agricultural technology and emphasizes machine learning for crop management and production.

1. INTRODUCTION

Deep learning has impacted many sectors, including agriculture, in which convolutional neural network networks are used for analyzing crop images. Rice is one of the world's main crops; therefore, effective classification methods are needed for increasing production and food safety [1].

Deep learning, especially CNNs, is tested for rice crop classification in this work. The research goes further into binary classification to address real-world agricultural settings by using images of rice. Enhancement methods increase the variety of the rice image dataset's variety, improving the trained model's resilience and generalization.

Problem Statement: Deep learning-based crop classification provides promising results; however, label imbalances in the dataset make it hard to get reliable and precise results. An imbalanced label can affect model performance parameters, including accuracy, recall, and F-score, reducing the model's practicality. To guarantee the classification model's reliability and efficacy in real-world agricultural applications, this issue has to be solved. Further research is needed to identify and address dataset and model design biases and limitations.

2. RELATED WORK

2023, the paper represents A methodology for processing and classifying rice seed hyperspectral images (HSI) using deep learning and hyperspectral imaging is described. A seed-based technique uses the entire seed spectral hypercube to train a 3D-CNN to identify seed pictures from high day and night temperatures, including a control group. A deep neural network-based, pixel-based seed classification is used. The seed- and pixel-based deep learning architectures were confirmed and evaluated using hyperspectral images from five rice seed treatments with six high-temperature exposure periods during the day, night, and both. They provide a standalone GUI tool for calibrating, preprocessing, and classifying hyperspectral rice

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seed pictures. Any hyperspectral seed picture can be classified using two deep-learning architectures trained by the program. For seed-based classification using 3D-CNN, the average classification accuracy is 91.33% and 89.50% for five treatments for each exposure length and six high-temperature exposure durations for each treatment, respectively. For five treatments at each exposure time and six high-temperature exposure durations for each treatment, the DNN has an average accuracy of 94.83% and 91%, respectively. Hyperspectral rice seed image classification accuracy is greater than in the literature. The Kitaake cultivar's HSI analysis can be used to examine the temperature tolerance of different rice varieties.

2023, Vigor influences rice yield and quality. Rice production requires fast and precise vigor detection. This work used transfer learning and near-infrared hyperspectral imaging to determine rice seed vitality. They tested four artificially aged rice seeds: Yongyou12, Yongyou1540, Suxiangjing100, and Longjingyou1212. Rice seed vigor was detected using several CNN models. Both fine-tuning and MixStyle are employed to transmit vigor-detecting expertise between rice types. Using MixStyle transfer knowledge, the convolutional neural network model of Yongyou12 classified the vigor of Yongyou1540, Suxiangjing100, and Longjingyou1212, with an accuracy of 90.00%, 80.33%, and 85.00% in validation sets, respectively. This was better or close to the initial modeling performances of each variety. MixStyle statistics use probabilistic mixed instance-level profiles from cross-source domain training samples. When training examples, additional domains can be synthesized, increasing the source domain's domain variety and the trained model's generalization capacity. The findings would assist in quickly and accurately detecting several agricultural seed variations [2].

In 2022, crop phenology will affect crop yield and display crop growth. By observing phenological phases, agricultural production losses can be decreased, and systems and plans adaptable to their changes can guide agricultural output. Manual processing of UAV remote sensing data to detect agricultural phenological phases is time-consuming and laborious and may result in losing data. To solve this challenge, this work presents deep-learning-based rice phenological stage identification. They first gather rice life cycle images from a weather station with RGB cameras to create a dataset. Second, they clear and partition the dataset into six subgroups using object detection. In conclusion, they employ ResNet-50 as the backbone network to extract spatial feature information from picture data and accurately recognize six rice phenological stages: seedling, tillering, booting jointing, heading blooming, grain filling, and maturity. Our system provides long-term, continuous, and accurate phenology monitoring compared to other alternatives. Our technique has an accuracy of 87.33%, opening up new crop phenological stage recognition study avenues [3].

3. THE PROPOSED METHOD

The block diagram in Figure 1 includes these steps:

1. Load images: Read and load the rice images from the folder.
2. Data Preprocessing: Resize and transform loaded images into arrays.
3. Divide data into training and testing sets for model assessment.
4. Define CNN: Establishing and configuring the CNN model architecture.
5. Compile and Train CNN: Apply the specified optimization and loss function to train the model on the training dataset.
6. Assess the efficacy of the trained CNN model utilizing the test dataset.
7. Save Model and Metrics: Record the CNN model along with evaluation metrics including accuracy, loss, and training histories.
8. Generate Predictions: Use the trained model on the testing dataset.
9. Assess Model Performance: Calculate classification metrics such as accuracy, recall, F1-score, and confusion matrix.
10. Save the data-produced metrics and create visualizations (e.g., accuracy and loss plots) for future studies.
11. End: End execution of code.

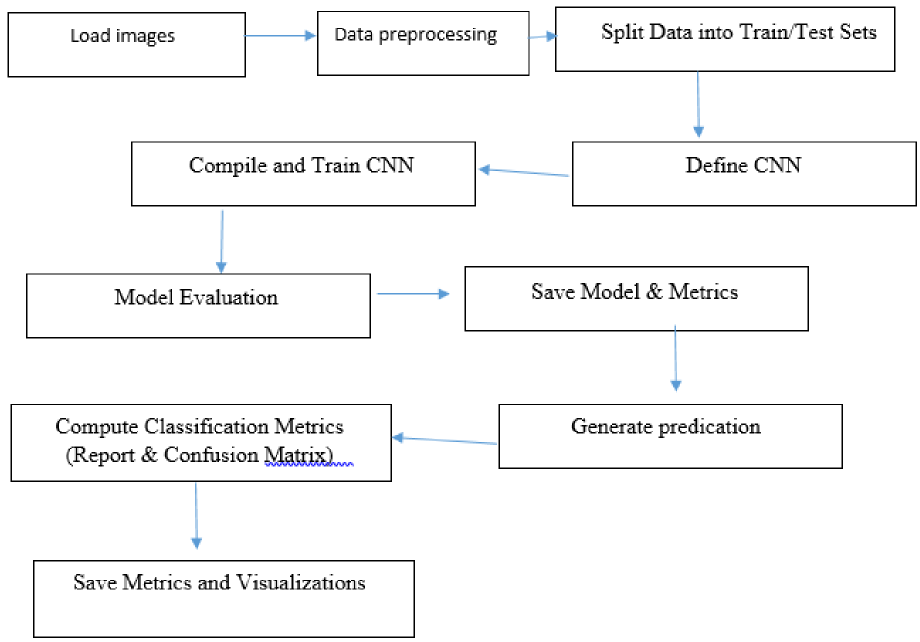

Fig.1. Is the block diagram of the proposed method.

This proposed method uses the following software as shown in Table 1 :

TABLE I. THE PYTHON LIBRARIES USED IN THE PROPOSED SYSTEM

Software	Description
Python	Widely used programming language for machine learning and deep learning tasks, known for its simplicity and extensive libraries.
NumPy	Fundamental package for scientific computing in Python, facilitating numerical operations and array data management.
Pandas	Powerful data manipulation and analysis library in Python, facilitating the creation of data frames and writing data to Excel files.
Matplotlib	Plotting library for creating static, animated, and interactive visualizations in Python, utilized here to plot training history curves for accuracy and loss.
scikit-learn	Python machine learning library provides simple and efficient tools for data mining and analysis; used for computing classification metrics like reports and matrices.
TensorFlow	Open-source machine learning framework developed by Google, employed for building, training, and evaluating deep learning models, particularly convolutional neural networks (CNNs).
TensorBoard	Visualization tool provided by TensorFlow for monitoring and debugging deep learning models; utilized here as a callback to log training metrics and visualize them in real-time.
Keras	Open-source neural network library written in Python, serving as a high-level API for TensorFlow to build and configure CNN model architectures.

The proposed algorithms

Algorithm: Rice Crop Classification using Deep Learning

The purpose of the rice crop classification algorithm is to accurately classify rice crops from non-rice crops using deep learning techniques. The algorithm involves loading images of rice and non-rice crops, preprocessing the images, splitting the data into training and testing sets, designing a convolutional neural network (CNN) model, compiling and training the model, evaluating the model, saving the model and metrics, generating predictions, computing classification metrics, and saving metrics and visualizations. In precision agriculture and crop monitoring, the algorithm can enhance crop management, yield prediction, disease detection, and decision-making for farmers, regulatory agencies, policymakers, and rice mills. The method benefits from recent deep learning and computer vision research, allowing for tuning to specific use situations.

1. **Load Images:**
   - Read and load rice and non-rice crop photos from the folder provided.
2. **Data Preprocessing:**
   - Preprocess the loaded images:

- Resize images to a uniform size (e.g., 100x100 pixels).
- Convert images to arrays to prepare for model input.

3. **Split Data into Train/Test Sets:**
   - Divide the dataset into training and testing sets:
   - Use train_test_split function to split images and labels into X_train, X_test, y_train, y_test.
4. **Define CNN Model:**
   - Design the architecture of the convolutional neural network (CNN):
   - Create a Sequential model.
   - Add Conv2D layers with ReLU activation.
   - Add MaxPooling2D layers.
   - Add Flatten layer to flatten the input.
   - Add Dense layers with ReLU activation.
   - Add output Dense layer with sigmoid activation for binary classification.
5. **Compile and Train CNN Model:**
   - Compile the CNN model:
   - Specify optimizer (e.g., Adam) and loss function (e.g., binary_crossentropy).
   - Choose evaluation metrics (e.g., accuracy).
   - Train the CNN model:
   - Fit the model to the training data.
   - Specify number of epochs and batch size.
   - Provide validation data for monitoring performance during training.
   - Optionally, use callbacks such as TensorBoard for visualization.
6. **Model Evaluation:**
   - Evaluate the trained CNN model:
   - Use evaluate method to compute loss and accuracy on the testing data.
   - Print or display the test accuracy.
7. **Save Model & Metrics:**
   - Save the trained CNN model to a file (e.g., "rice_classification_model.h5").
   - Save evaluation metrics (e.g., accuracy) to a log file.4
8. **Generate Predictions:**
   - Use the trained model to generate predictions on the testing dataset:
   - Use predict method to obtain probability scores for each class.
   - Convert probabilities to binary predictions using a threshold (e.g., 0.5).
9. **Compute Classification Metrics:**
   - Compute classification metrics such as precision, recall, F1-score, and confusion matrix:
   - Use classification_report and confusion_matrix functions from scikit-learn.

10. Save Metrics and Visualizations:

- Save the computed classification metrics to a file (e.g., "classification_report.xlsx" and "confusion_matrix.xlsx").
- Plot and save visualizations such as accuracy and loss curves using Matplotlib.

11. End.

4. RESULTS AND DISCUSSIONS

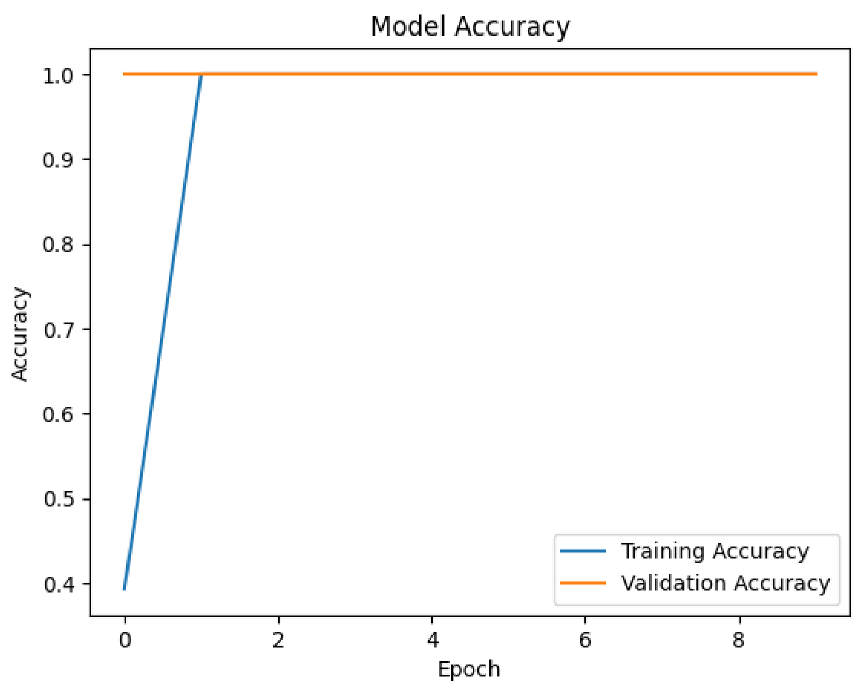

Fig.2. The model accuracy

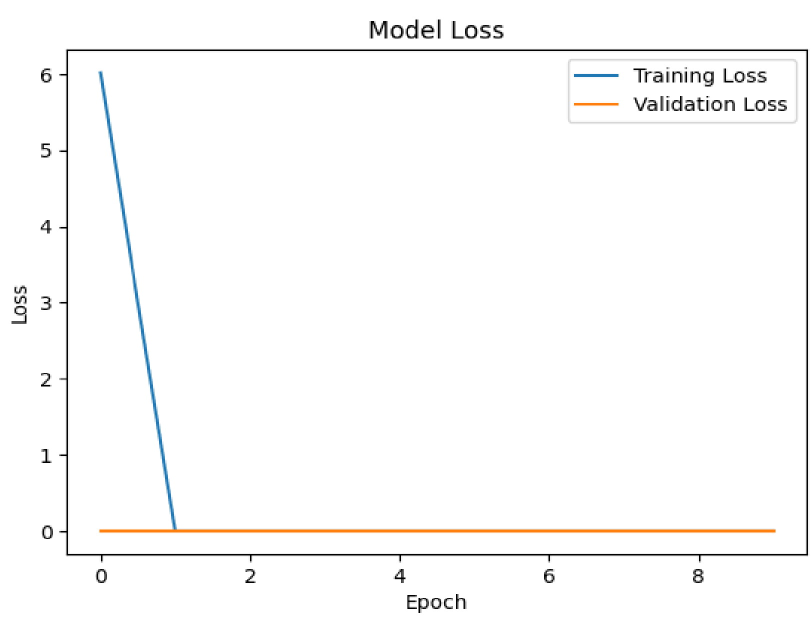

Fig.3. The model loss

TABLE II. CLASSIFICATION REPORT

	precision	recall	f1-score	support
Non-Rice	0	0	0	0
Rice	1	1	1	7
micro avg	1	1	1	7
macro avg	0.5	0.5	0.5	7
weighted avg	1	1	1	7

TABLE III. CONFUSION MATRIX

	Non-Rice	Rice
Non-Rice	0	0
Rice	0	7

Results and discussions

Based on the provided classification report and confusion matrix:

- Precision, recall, and F1-score for the class 'Non-Rice' are all 0, indicating that the model did not predict any instances of 'Non-Rice' correctly. This could indicate either a severe class imbalance or a failure of the model to learn distinguishing features for this class.
- The 'Rice' class has flawless accuracy, recall, and F1 score of 1. This shows the model identified 'Rice' successfully.
- Micro- and macro-average F1-scores indicate extraordinary performance, but class imbalance may be misleading.

In the confusion matrix, all 'Non-Rice' occurrences were 'Rice', suggesting a false negative. All 'Rice' occurrences were accurately detected.

The model works well detecting "Rice," but not "Non-Rice." This might be because the "Non-Rice" class isn't well represented in the training data, the classes aren't fairly distributed, or it lacks characteristics. We may need to investigate, rebalance the dataset, or redesign the model to improve "Non-Rice" outcomes.

5. CONCLUSION

Classifying rice crops is essential for crop health, production prediction, and resource management. Using satellite photos and other data, deep learning systems can reliably categorize rice harvests. These algorithms employ CNNs to extract information from photos and identify them as healthy rice crops, damaged crops, or weeds. A large collection of annotated photos is used to train the algorithm to learn category patterns and attributes.

Preprocessing satellite photos to improve vegetation health, water content, and soil conditions is a frequent deep learning rice crop categorization method. Preprocessed photos are input to a CNN model that learns rice crop varieties from these attributes. Researchers fine-tune a pre-trained CNN model for rice crop categorization via transfer learning.

Rice crop categorization using deep learning algorithms is successful because they automatically learn complicated patterns and features from raw data without feature engineering. Compared to typical machine learning, this classifies rice harvests more accurately and efficiently.

Rice crop categorization using deep learning algorithms might improve agricultural practices, crop yields, and food security.

Our model accurately identifies photos containing "Rice," receiving an F1-score of 100% for accuracy, recall, and classification.

Our next work proposals were:

Adding more "Non-Rice" photos to the dataset, or employing data augmentation methods, may address the class imbalance problem and improve the model's "Non-Rice" performance.

Adjusting pre-trained models like VGG, ResNet, or Fusion to the dataset may enhance feature extraction and classification for the "Non-Rice" class.

Adjusting hyperparameters: Planned hyperparameter adjustments, such as learning rate, batch size, and network architecture, can improve the model and make it more useful.

Cluster approaches: Ensemble learning approaches that combine models from various datasets or designs may improve classification.

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Conflicts Of Interest

The paper states that there are no personal, financial, or professional conflicts of interest.

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REFERENCES

[1] V. Manian, B. K. Dhatt, and H. Walia, "A Deep Learning Framework for Processing and Classification of Hyperspectral Rice Seed Images Grown under High Day and Night Temperatures," Sensors, vol. 23, no. 9, p. 4370, 2022. [Online]. Available: https://doi.org/10.3390/s23094370

[2] H. Qi, Z. Huang, Z. Sun, Q. Tang, G. Zhao, X. Zhu, and C. Zhang, "Rice seed vigor detection based on near-infrared hyperspectral imaging and deep transfer learning," Frontiers in Plant Science, vol. 14, 2023.

[3] J. Qin, T. Hu, J. Yuan, Q. Liu, W. Wang, J. Liu, L. Guo, and G. Song, "Deep-Learning-Based Rice Phenological Stage Recognition," Remote Sensing, vol. 15, no. 11, p. 2891, 2022. [Online]. Available: https://doi.org/10.3390/rs15112891

[4] P. K. Kumar, "Deep Learning Techniques for Plant Disease Detection: A Comprehensive Review," n.d.

[5] G. Desai and A. Gaikwad, "Deep Learning Techniques for Crop Classification Applied to SAR Imagery: A Survey," in 2021 Asian Conference on Innovation in Technology (ASIANCON), Pune, India, 2021, pp. 1-6. doi: 10.1109/ASIANCON51346.2021.9544707.

[6] L. Zhang, J. Lin, B. Liu, Z. Zhang, X. Yan, and M. Wei, "A review on deep learning applications in prognostics and health management," IEEE Access, vol. 7, pp. 162415-162438, 2019.

[7] A. Chlingaryan, S. Sukkarieh, and B. Whelan, "Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review," Computers and Electronics in Agriculture, vol. 151, pp. 61-69, 2018.

[8] N. Gandhi, O. Petkar, and L. J. Armstrong, "Rice crop yield prediction using artificial neural networks," in 2016 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR), July 2016, pp. 105-110.