

Performance analysis of convolutional neural network-based image classifiers for agricultural farmland mapping

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ABSTRACT

Precise farmland mapping is essential for crop monitoring, land-use inventory, and subsidy audits. Particularly, the office of the municipality's assessor or the registry of deeds needs adequate image classifiers to categorize farmland on a large scale across different seasons and regions. The study evaluated three convolutional neural network (CNN) models, such as efficient network baseline 3 (EfficientNetB3), residual network 50 layers version 2 (ResNet50V2), and inception version 3 (InceptionV3), to identify the model that best balances accuracy and efficiency for classifying high-resolution farmland imagery. EfficientNetB3 proved to be the most suitable model, demonstrating higher accuracy, robustness, and a stronger ability to identify rice farmland patterns. While ResNet50V2 and InceptionV3 are widely used for image analysis, their performance declined when processing farmland images that exhibit substantial differences in visual characteristics. EfficientNetB3 delivered more consistent results for farmland image classification in large-scale agricultural applications. These findings highlight its potential for supporting data-driven agricultural management and policy implementation.

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1. INTRODUCTION

Precise and timely farmland mapping plays an important role in land-use inventory, crop monitoring, and agricultural subsidy validation, especially in the Philippines, where agriculture continues to contribute significantly to employment and economic activity [1]. Government offices such as municipal assessors and the registry of deeds require reliable and scalable approaches to classify agricultural lands across regions. Farmland mapping in the country remains challenging due to its archipelagic setting, fragmented land parcels, different terrain, intercropping practices, and frequent cloud cover in satellite imagery [2], [3]. Many areas still rely on manual surveying and visual photo interpretation, which require substantial time, manpower, and financial resources. These limitations highlight the need for more efficient and automated classification methods [4].

Recent advances in deep learning has proven effective in image-based land classification. Convolutional neural network (CNN) in particular, are capable of learning spatial features such as edges, textures, and shapes directly from image data without the need for manual feature engineering [5], [6]. Because of this capability, CNNs have been widely applied in remote sensing tasks. The integration of unmanned aerial vehicle (UAV) imagery with deep learning techniques has further improved the accuracy and resolution of farmland mapping [7], [8]. Comparative analyses using pre-trained CNN models further

highlight the capability of deep learning for crop monitoring from remote sensing data [9]. Nevertheless, there are still limited comparative studies focused specifically on Philippine agricultural landscapes [10]. Although international studies demonstrate the effectiveness of CNNs in crop classification and agricultural monitoring [11], [12], considering the structural complexity of local farms, it is necessary to evaluate which CNN architecture performs best under these conditions.

This study compares three CNN algorithms, such as residual network 50 layers version 2 (ResNet50V2), inception version 3 (InceptionV3), and as efficient network baseline 3 (EfficientNetB3), to determine which model provides a suitable balance between classification accuracy and computational efficiency for drone-based farmland mapping [13]–[15]. By conducting a direct performance comparison. The study aims to provide practical guidance for selecting appropriate deep learning models for agricultural land classification in the Philippines.

2. METHOD

This section outlines the methodology employed to analyze the performance of three widely used CNN algorithm models in the context of image classification. The performance evaluation is structured into three main components: i) dataset preparation, ii) selection of CNN algorithms, and iii) application of CNN models. Following the training phase, the models' performance is systematically assessed to determine their effectiveness in classifying agricultural farmland images.

2.1. Dataset preparation

This study evaluates the performance of three CNN algorithm models using aerial imagery captured by drones. The dataset consists of farmland images collected through drone-based imaging systems. These images serve as the input for training and testing the models and are used to assess the classification accuracy of each CNN model in mapping agricultural farmlands. All images were resized to the required input dimensions of the selected CNN models. Pixel values were normalized prior to training. Data augmentation techniques, including rotation and horizontal flipping, were applied to increase variability and reduce overfitting. The models were trained for a fixed number of epochs with early stopping implemented to prevent performance degradation.

2.2. Selection of convolutional neural network algorithm models

This study utilizes three widely recognized CNN algorithm models for image classification: EfficientNetB3, ResNet50V2, and InceptionV3. These models were selected due to their proven accuracy in prior studies and their distinct structural designs, which provide a varied perspective in evaluating model performance [16]. Their robustness and ability to process high-resolution image data make them well-suited for the classification of farmland imagery. This demonstrates strong feature extraction capabilities while maintaining low memory usage and processing time. In addition, the compact design is suitable for deployment on resource-constrained devices such as drones and edge devices used in agricultural monitoring [17].

ResNet50V2 builds upon the original ResNet by integrating identity shortcut connections, which support stable gradient propagation during the training of deep neural networks. The depth and structure enable effective learning of hierarchical representations, making it highly suitable for large-scale image classification. Through its robustness, scalability, and strong transfer learning capabilities, this model is widely applied in practical computer vision tasks [18]. InceptionV3 introduces Inception modules that utilize parallel convolutional layers to capture features at multiple scales. It is designed for efficiency, enabling the processing of large image datasets without significantly increasing computational demand. Its balance of accuracy and efficiency makes it a practical choice for farmland mapping tasks where multi-scale feature extraction and resource efficiency are required [17], [19]. These three architectures were implemented and compared under the same experimental conditions to determine the most effective CNN model for farmland mapping.

2.3. Application of convolutional neural network models

The CNN models used in this study were EfficientNetB3, ResNet50V2, and InceptionV3, were implemented using the Python programming language and the TensorFlow deep learning framework. The farmland image dataset was first prepared and preprocessed to ensure that the images were suitable for model training and analysis. The experimental setup followed the sequence shown below to evaluate the performance of the CNN models for farmland mapping.

Farmland image dataset → preprocessing → CNN models → training → testing → performance evaluation → best model selection

The models were trained and evaluated using a dataset of drone-captured farmland images. Each model was trained for 10 epochs under identical training conditions to ensure a fair performance comparison. A total of 20 farmland images were used as the testing dataset for model evaluation. Figures 1 to 3 present the simulation results of EfficientNetB3, ResNet50V2, and InceptionV3, respectively, illustrating their classification performance based on feature similarity. The classification outputs of the three CNN architectures were compared based on their feature similarity and classification performance to determine the most effective model for farmland mapping.

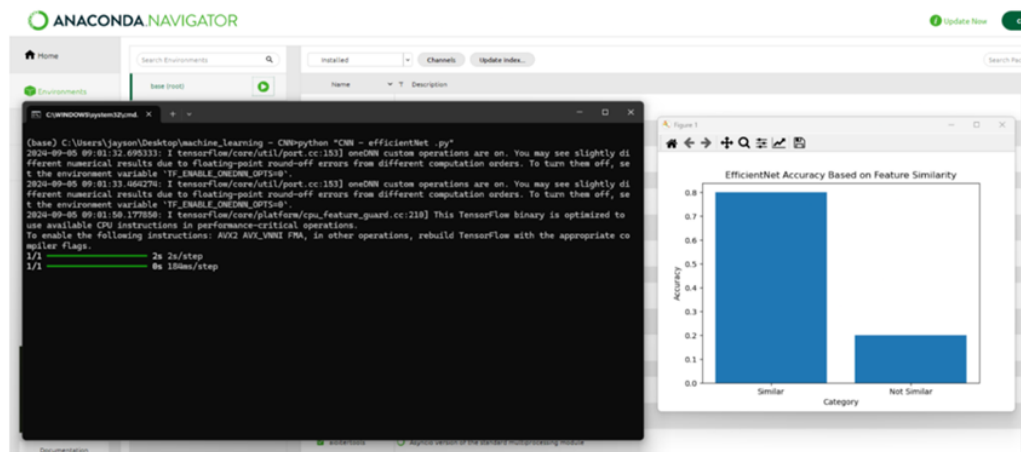


Figure 1. Simulation of EfficientNetB3

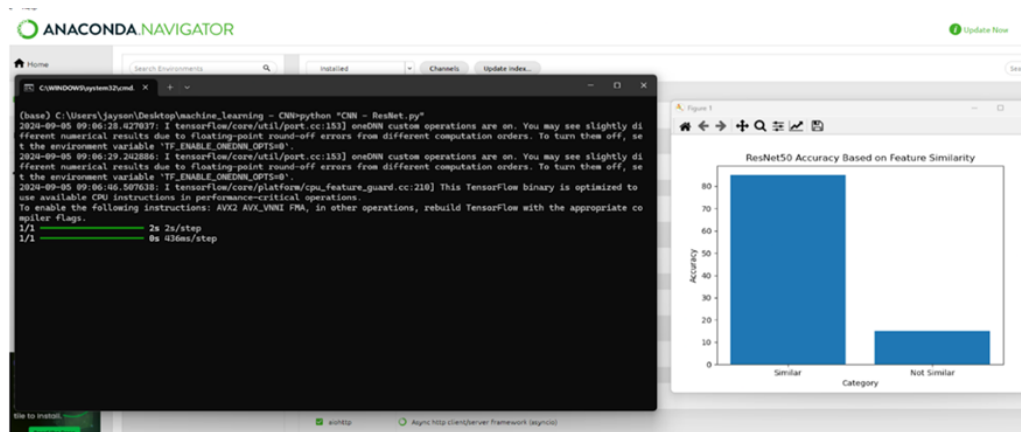


Figure 2. Simulation of ResNet50V2

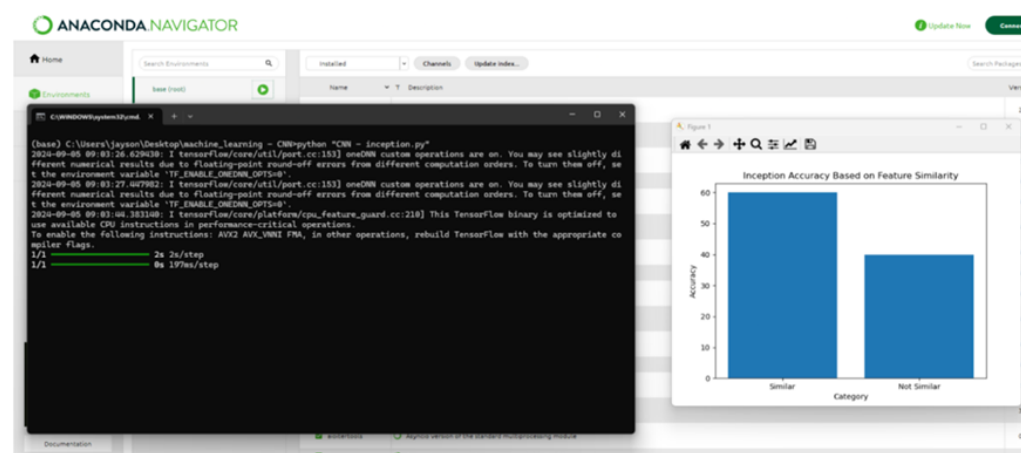


Figure 3. Simulation of InceptionV3

3. RESULTS AND DISCUSSION

This section presents an overview and performance analysis of the three CNN algorithm models used in this study: EfficientNetB3, ResNet50V2, and InceptionV3. These models were tested using a dataset of farmland images captured by drones. The evaluation focused on their accuracy, learning efficiency, and ability to classify different agricultural land features.

3.1. Performance analysis of convolutional neural network algorithm models

The classification performance of EfficientNetB3, ResNet50V2, and InceptionV3 was evaluated using a dataset of 115 drone-captured farmland images. Due to the limited availability of labeled agricultural data, transfer learning was employed, allowing the pretrained models to leverage previously learned feature representations and adapt them to the target task. The accuracy of the models is evaluated during two testing cycles with 10 iterations [20], [21]. The dataset was divided into training and testing sets to assess classification accuracy on unseen images [22]. The testing phase includes both farmland and non-farmland images to compare the three CNN models as shown in Figure 4. The farmland images taken from drones provided as examples are illustrated in Figure 4(a), while the non-farmland images are illustrated in Figure 4(b).

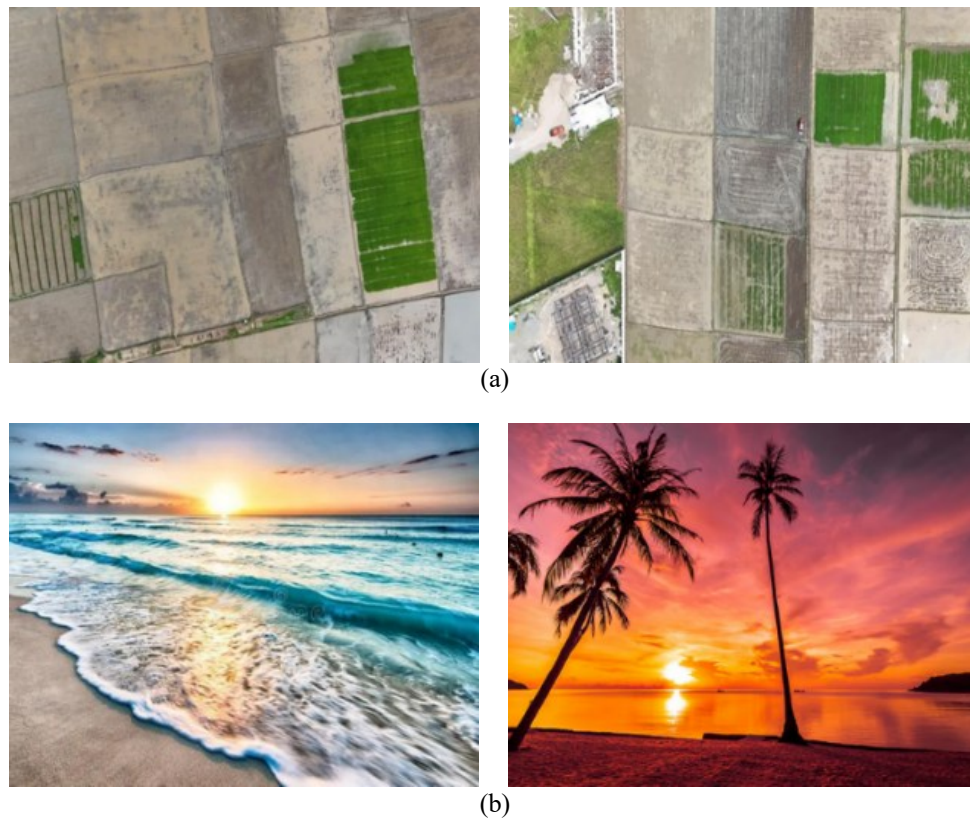


Figure 4. Sample dataset for the performance analysis of the three CNN algorithm models
(a) farmland images and (b) non-farmland images

3.2. Test cases

Three CNN models are applied to satellite imagery for farmland mapping to identify and delineate farmland areas. The study evaluates their performance based on accuracy and reliability in generating farmland maps [23]. Results are compared to determine which model performs most effectively under the given conditions.

3.2.1. Test case 1

The first test case involves analyzing the accuracy of the three algorithms using the test set consists of 18 farmland images and 2 non-farmland images. The expected result is 85% match for similarity and 15%

match for non-similarity [23]. Figure 5 presents the performance analysis of the three CNN models based on feature similarity. As shown in Figure 5(a), EfficientNetB3 achieved 85% similarity matches and 15% non-similarity matches, corresponding to a perfect classification accuracy of 100%. In Figure 5(b), ResNet50V2 recorded 80% similarity matches and 20% non-similarity matches, resulting in an overall accuracy of 80%. Meanwhile, Figure 5(c) shows that InceptionV3 attained 75% similarity matches and 25% non-similarity matches, with an accuracy rate of 75%. These results highlight EfficientNetB3's exceptional performance in image classification, while ResNet50V2 and InceptionV3 fell short of the required accuracy threshold.

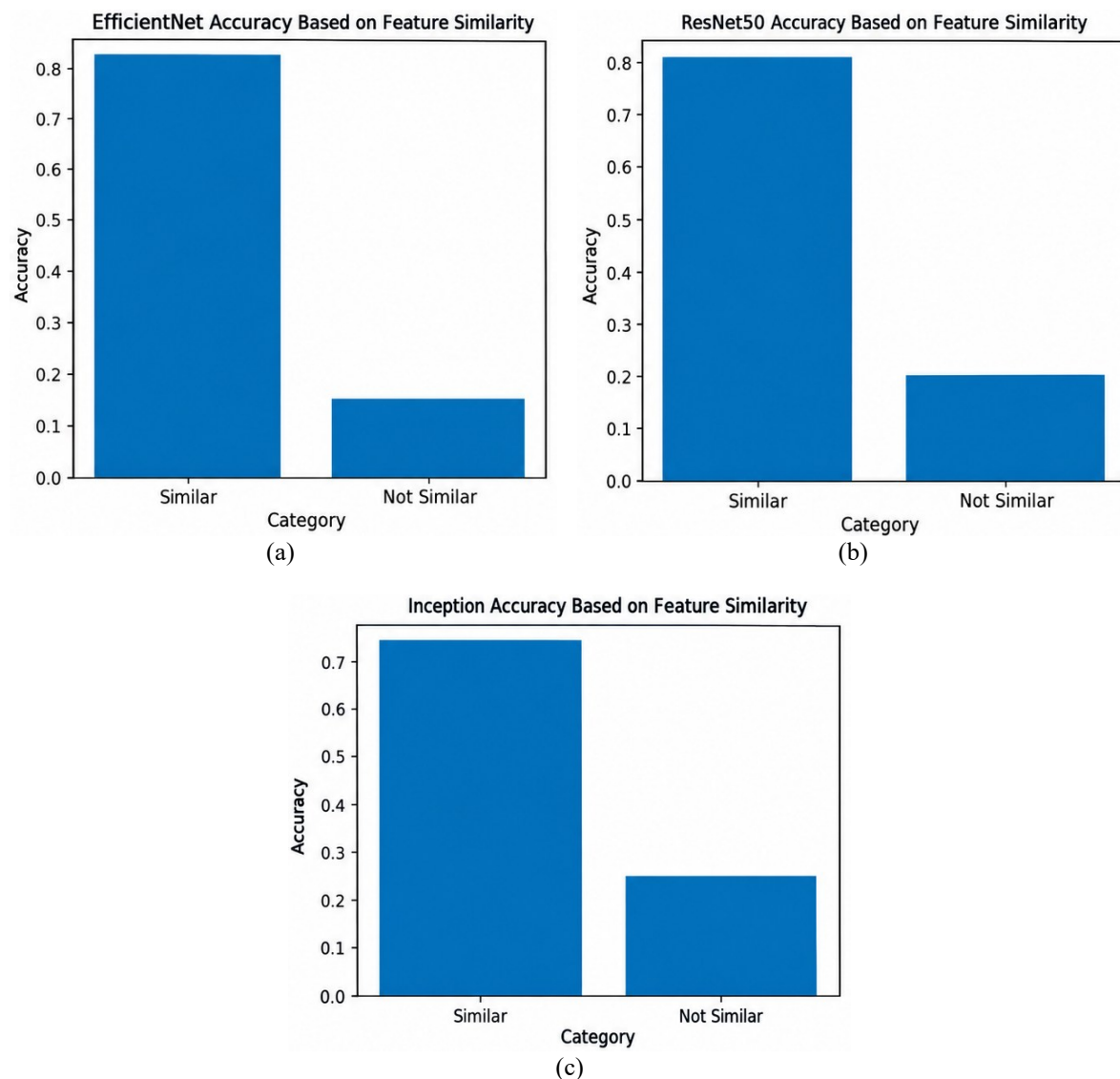


Figure 5. Classification accuracy test case 1 for the three CNN models: (a) EfficientNetB3, (b) ResNet50V2, and (c) InceptionV3

3.2.2. Test case number 2

The second test case for classification accuracy of the three deep learning algorithms consists of 16 farmland images and 4 non-farmland images sample test set. The expected result is 80% match for similarity and 20% match for non-similarity. Figure 6 presents the performance results of the three CNN models in classifying images with 80% feature similarity and 20% non-similarity. As shown in Figure 6(a) EfficientNetB3 achieved 80% similarity matches and 20% non-similarity matches, corresponding to a perfect 100% classification accuracy.

In Figure 6(b), ResNet50V2 recorded 85% similarity matches and 15% non-similarity matches, yielding a 90% accuracy rate, while Figure 6(c) InceptionV3 obtained 60% similarity matches and 40% non-similarity matches, resulting in 80% accuracy. These results highlight EfficientNetB3's exceptional performance, as both ResNet50V2 and InceptionV3 fell short of the required accuracy level. Table 1 presents the performance evaluation of the three CNN algorithm models, based on the percentage of similarity and non-similarity between the predicted outputs and the actual outputs for each test case. The results indicate that the EfficientNetB3 model achieved higher image classification accuracy compared to the other two models, demonstrating its effectiveness in this task.

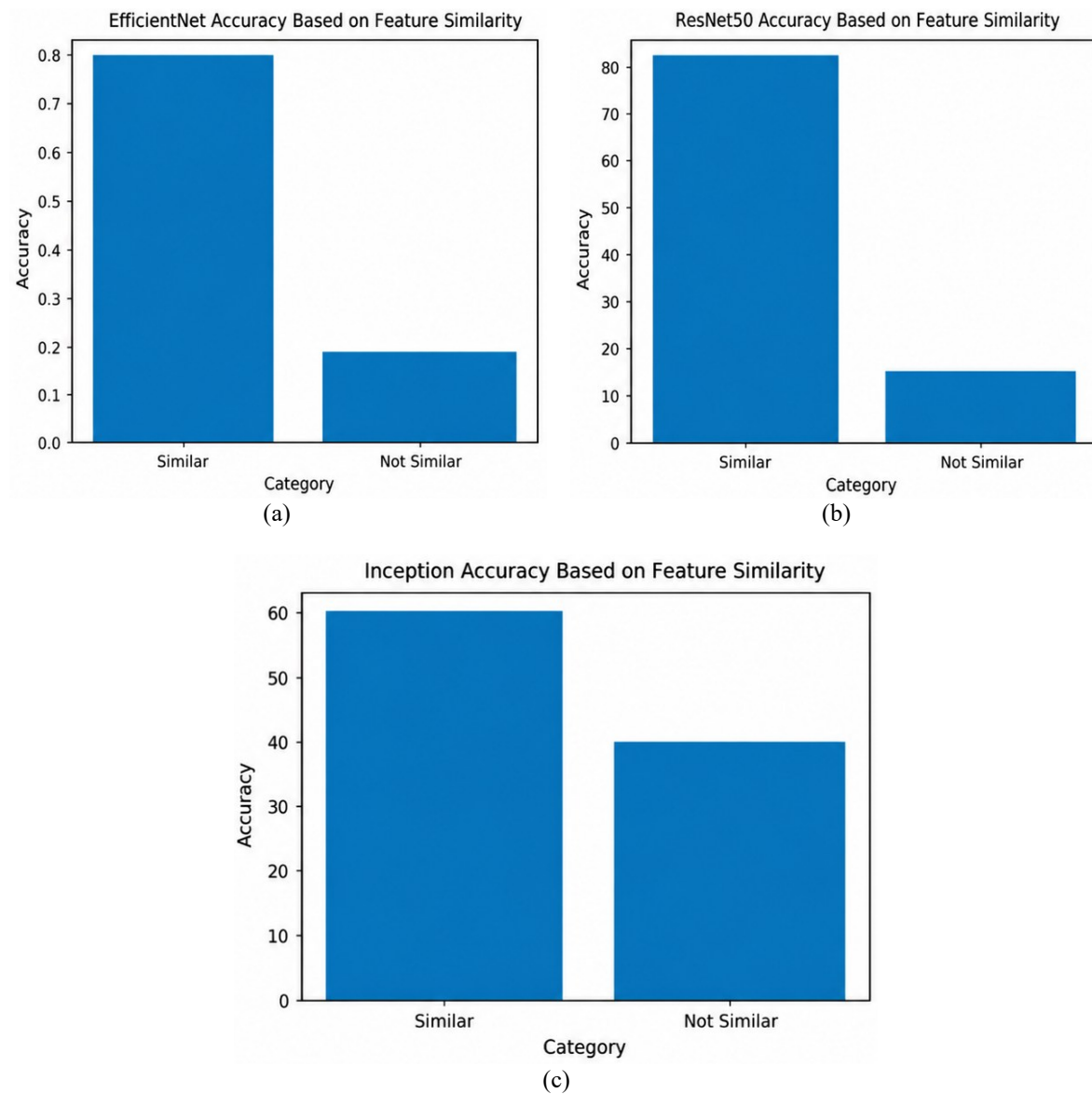


Figure 6. Classification accuracy test case 2 for the three CNN models: (a) EfficientNetB3, (b) ResNet50V2, and (c) InceptionV3

CNN algorithm model	Test case no. 1		Test case no. 2	
	Percentage of similarity (85%)	Percentage of non-similarity (15%)	Percentage of similarity (80%)	Percentage of non-similarity (20%)
EfficientNetB3	85	15	80	20
ResNet50v2	80	20	85	15
InceptionV3	75	25	60	40

The results from both similarity tests show a clear pattern—EfficientNetB3 consistently delivered the most accurate classifications, achieving a perfect 100% accuracy in both cases. This means that regardless of whether the similarity ratio was 85%–15% or 80%–20%, the model was able to correctly identify every farmland image. ResNet50V2 also performed well, with accuracy scores of 80% and 90%, but its results were less consistent. This variation might be because, while its residual learning approach is great at managing deep layers and avoiding training issues, it can sometimes struggle when the differences between image classes are subtle—something quite common in farmland mapping [24].

InceptionV3 had the lowest accuracy in this study, with 75% and 80%. Its strength lies in capturing patterns at multiple scales, which works well in many image classification problems, but in this case, the complexity of farmland textures may have limited its ability to perform as strongly as the other two models. EfficientNetB3 outperforms ResNet50v2 and InceptionV3 by employing a compound scaling strategy that optimizes depth, width, and input resolution for improved feature extraction. The architecture enhances the capture of spatial patterns in farmland imagery, crucial for accurate classification, while advanced feature recalibration mechanisms allow for better focus on relevant areas and noise reduction. As reflected in the results, EfficientNetB3 demonstrated greater consistency and stability across different similarity conditions, indicating stronger generalization capability and robustness. These characteristics make it particularly suitable for precision land mapping and agricultural monitoring applications.

This research shows how deep learning can make a real difference in agriculture [25]. By testing three well-known CNN models, we found that EfficientNetB3 stood out as the most reliable for classifying farmland images [26]. Its ability to capture fine details in drone imagery makes it especially useful for supporting tasks like crop monitoring and land management. In this way, the study not only highlights the strengths of EfficientNetB3 but also offers practical insights that can help farmers and researchers use artificial intelligence tools more effectively in precision agriculture [24].

EfficientNetB3 shows high performance in farmland image classification, but future research can improve precision land mapping systems through several avenues. Integrating multimodal data sources like satellite imagery, drone images, and ground sensor data could enhance classification accuracy by providing comprehensive spatial and environmental context. Utilizing transfer learning from extensive agricultural datasets may further optimize model generalization and performance stability across various regions and crop types. Incorporating explainability methods, such as gradient-weighted class activation mapping (Grad-CAM), is essential to build trust among stakeholders by revealing which image areas influence classification decisions. Lastly, integration with geographic information systems (GIS) will enable actionable analysis and resource planning in agriculture. Future research should focus on these four aspects to enhance both technical performance and practical application in precision agriculture. Additional evaluation metrics, including precision, recall, and F1-score, will be incorporated in future research to further strengthen performance assessment and real-world applicability.

4. CONCLUSION

The performance analysis of the three CNN algorithm models EfficientNetB3, ResNet50V2, and InceptionV3 revealed that EfficientNetB3 consistently delivered the highest classification accuracy across all test cases. Its ability to effectively capture fine-grained features in high-resolution images enabled it to outperform the other two architectures in both similarity and non-similarity classifications. While ResNet50V2 and InceptionV3 achieved respectable results, their accuracy levels fell short of the target thresholds in certain scenarios. These findings suggest that EfficientNetB3 is the most suitable algorithm model among the three for farmland image classification tasks, offering a reliable balance of precision, efficiency, and robustness in real-world applications.

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data supporting this study are available from the corresponding author, [ACT], upon request but are not publicly shared due to privacy restrictions.

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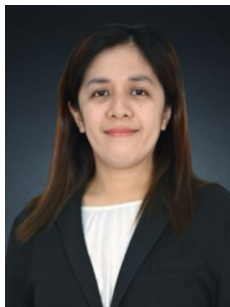
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