Precision agriculture: exploration of deep learning models for farmland mapping

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ABSTRACT

Precision is required for agricultural advancements to be sustainable. Traditional farming lacks effective monitoring, resulting in resource waste and environmental problems. Farmland mapping is important for agricultural management and land-use planning. The use of deep learning techniques in farmland mapping is increasing rapidly. Excellent results have been generated from deep learning approaches in a number of applications, such as image processing and prediction. Agricultural agencies are now considering different applications of deep learning including land mapping, crop classification, and monitoring of paddy fields. This paper shall explore different deep learning models that are commonly used for image processing specifically in land mapping. The three deep learning models convolutional neural network (CNN), long short-term memory (LSTM), and recurrent neural network (RNN) were evaluated to find out which among the deep learning models is best for land mapping. It compares the classification accuracy of the models on image processing and it can be concluded that CNN algorithm normally makes better results when compared to other deep learning models. This study offers guideline and suggestions to researchers who are interested in contributing to the field of precision agriculture with the used of deep learning techniques.

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1. INTRODUCTION

More than half of the world's population relies on rice as their primary source of energy, making it one of the most significant crops in the world [1]. One of the nations that produces rice as their primary food crop and source of income for some farmers and stakeholders is the Philippines. Most of the farmers in the Philippines choose rice for their main crop [2], [3]. As technology advances, sustainable agriculture is the top issue for every nation, particularly countries where agriculture is the main source of wealth. In modern agriculture and land management, precision and efficiency are essential for sustainable and optimal resource utilization. Traditional agricultural approaches, on the other hand, frequently lack the ability to properly monitor and manage large areas of farmland, resulting in resource waste, poor output, and environmental issues. Furthermore, traditional land mapping approaches frequently fail to capture the dynamic nature of farming, limiting effective decision-making processes [4], [5].

Farmland mapping is essential to the agricultural sector because it helps farmers, stakeholders, and researchers understand and successfully manage land resources. In order to ensure sustainability and the security of food and water, farming requires effective land management. Farmland mapping used to be a labor-and time-intensive operation that needed lengthy field surveys and manual data collection to estimate the rice growing area [6]. However, recent developments in machine learning (ML) methods have completely changed this field by providing precise and effective solutions for farmland mapping. A subset of artificial intelligence known as "machine learning" enables computers to learn from data and develop over time without explicit programming. We can effectively analyze enormous amounts of satellite imagery, aerial photography, and geospatial data to automatically identify and classify various types of agricultural land by utilizing the power of ML algorithms. This technology has the potential to revolutionize farmland mapping, unlocking new insights and efficiencies that were previously unattainable through traditional methods [7].

Deep learning is a component of ML that contributed significantly in many business sectors to carry out complicated tasks that humans are unable to complete. The most often utilized applications of deep learning as a part of ML include object detection, prediction, natural language processing, and image processing. Deep learning models have performed very well when processing remote sensing data for mapping purposes [8]. Remote sensing is an advanced method that can be used to collect data about the Earth's surface without requiring direct contact. It is important in land mapping because it provides significant data for many different kinds of applications such as agriculture, urban planning, environmental monitoring, and natural resource management [9].

A number of studies on deep learning applications in precision agriculture have been undertaken. The use of remote sensing data for mapping rice crops is becoming more common in current studies [10]–[13]. Deep learning has the ability to improve the accuracy of rice crop maps, speeding the processing of large datasets, and automatically extract detailed features from remotely sensed images. In addition, methods that use deep learning allows mapping automation, minimizing the need for human intervention and enabling the timely compilation of up-to-date rice crop maps. This efficiency is particularly useful for monitoring large agricultural areas and contributes to more informed decision-making in rice crop management. Another focus of deep learning applied to remotely sensed data is on detecting crop diseases. Crop diseases are significant risks to global food security, demanding ongoing developments in detection systems to allow for early detection and prevention. Studies that applied deep learning techniques for plant and crop diseased detection [14]–[16] their main objective it to enable timely and early intervention in crop diseased management and detection, the advantage of using deep learning in crop disease detection is its ability to analyze complex patterns and features within large data sets, resulting in more accurate and efficient disease identification. Debella-Gilo and Gjertsen [17] authors reviewed the use of sentinel-2 satellite image time series (SITS) data and deep learning algorithms for mapping and tracking agricultural land use. The multilayer perception (MPL) and CNN was used on SITS data of four different temporal resolutions. The outcomes indicate that when it comes to learning time series data, CNN surpasses MLP. The study has also demonstrated that temporal CNN is acceptable and effective for Sentinel-2 images.

Zhao *et al.* [18], the authors proposed a method for accurately mapping rice paddies in complex landscape by combining (CNN) and phenological metrics with time-series and remote sensing imagery. A number of tests revealed that the suggested approach performed better than existing modern classification techniques. The proposed method shows its effectiveness by achieving high accuracy in mapping rice paddy in complex landscape. Simms *et al.* [19], the authors developed a generalized deep learning model for agricultural land classification using the latest satellite imagery. Fully convolutional network 8 (FCN-8) was selected and the U-Net type CNN architectures for the semantic segmentation of satellite image data. This approach requires fewer manual tasks from analysts and can provide timely insights into land use and changes in land use throughout the early seasons. Carranza-García *et al.* [20], the authors proposed a general deep learning framework for conducting land use and land cover classification on remote sensing images from various origins, specifically radar and hyperspectral datasets. CNN surpassed other traditional ML techniques, i.e., support vector machine, random forests, and k-nearest-neighbors. The proposed framework has shown that deep learning is a very successful method for solving the problem of classifying land use and land cover (LULC), producing promising results for every image that was analyzed. Ienco *et al.* [21] proposed a framework using the long short-term memory (LSTM) model to classify land cover via multi-temporal spatial data that are derived from SITS. The proposed model can efficiently deal with SITS based datasets: the pixel-based and object-based classification. The suggested LSTM-based classification model can be used as a feature extractor to learn a new data representation, which improves the performance of traditional classification algorithms on SITS data.

Deep learning includes a variety of neural networks and beliefs that operate based on the principles of neurons found in the human brain. For tasks involving extensive data and complex patterns, including images and speech recognition, natural language processing, and many other applications, they are very useful. Deep learning algorithms are designed to process data in a manner similar to that of the human brain [22], [23].

This comparative study aims to present the three most commonly used deep learning models for image processing, remote sensing, and land mapping. The study aims to determine the most effective deep learning model among the three for the specific task of farmland mapping. The study seeks to provide significant insights into the best deep learning approach for this specific application.

2. METHOD

This section describes the methods used to compare the three most popular deep learning models used in image processing and land mapping. The methodology for exploring deep learning models is based on three main steps: (1) acquired dataset, (2) deep learning models, and (3) application of deep learning models. The trained models' performance is then assessed to determine their effectiveness in farmland mapping tasks.

2.1. Dataset

This study compares deep learning algorithm models using sample data acquired from the internet freely and publicly accessible. Euro SAT is a dataset and deep learning standard for classifying land use and land cover. The dataset is based on sentinel-2 satellite images and were used for this study. The classification accuracy of the three models was assessed using forest images a sample data size extracted from the Euro SAT dataset.

2.2. Deep learning models

Convolutional neural network (CNN), recurrent neural network (RNN), and LSTM are three deep learning algorithm models that have been widely applied in image processing and will be used in this study. These deep learning algorithms are trained using the preprocessed data to accurately classify and categorize farmland features. Their performance in accurately identifying and describing these features is then evaluated, providing information on their efficacy for farmland mapping applications.

2.3. Application of deep learning models

The Python programming language was used to implement and test all of the deep learning models in this study. The implementation of the deep learning models applied the TensorFlow framework, an open-source library. Figure 1 shows a CNN model simulation for feature similarity, whereas Figure 2 shows an LSTM model simulation. Lastly, Figure 3 shows a simulation of the RNN model. This paper assesses the accuracy of the three models by testing them on a sample dataset consists of 2,100 forest images. These images serve as the training set used to train the model and are sourced from the Euro SAT dataset. To evaluate the model's performance, 10 images were chosen for the testing set, with the epoch, representing the number of iterations, was set to 10.

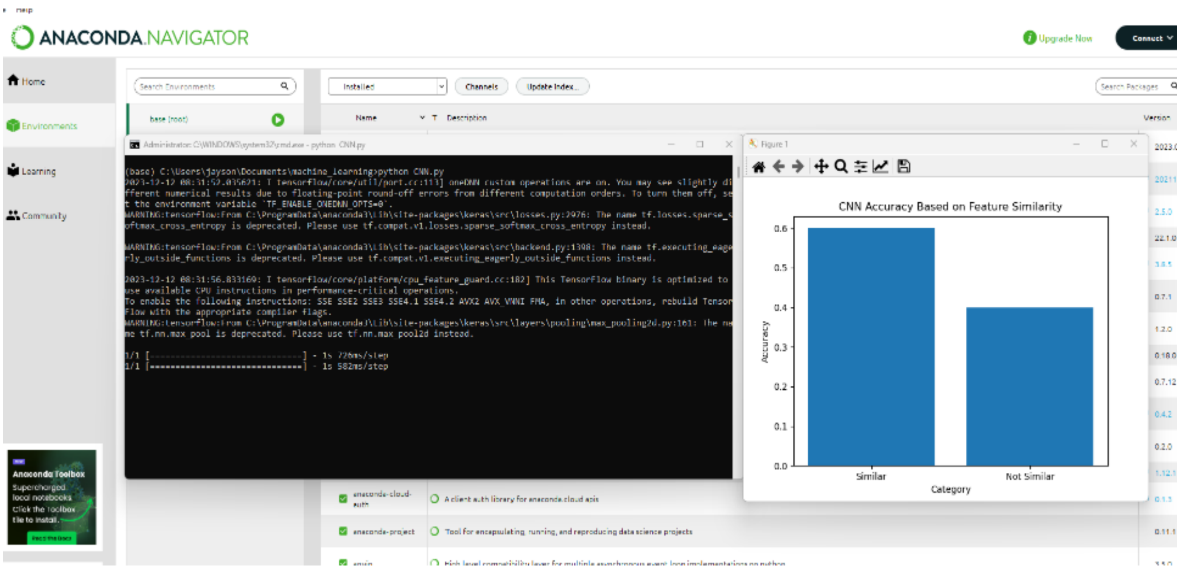


Figure 1. Simulation of the CNN algorithm model

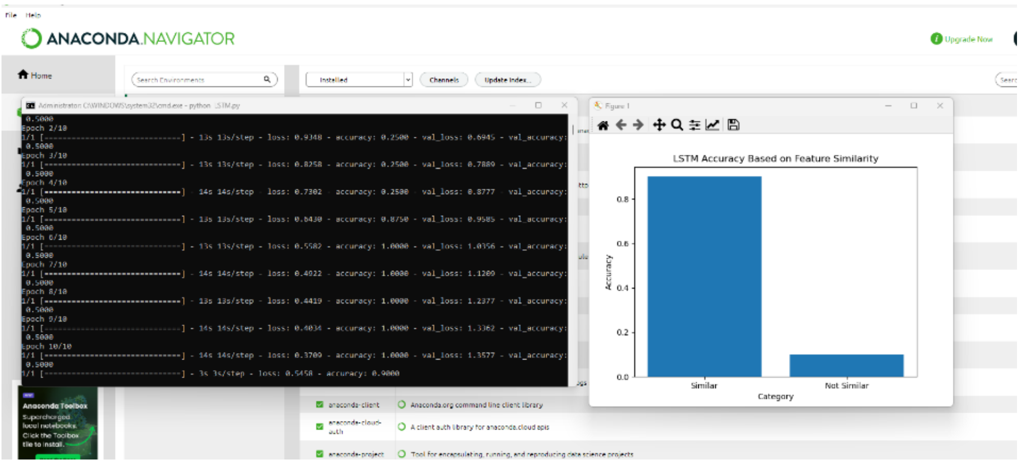


Figure 2. Simulation of the LSTM algorithm model

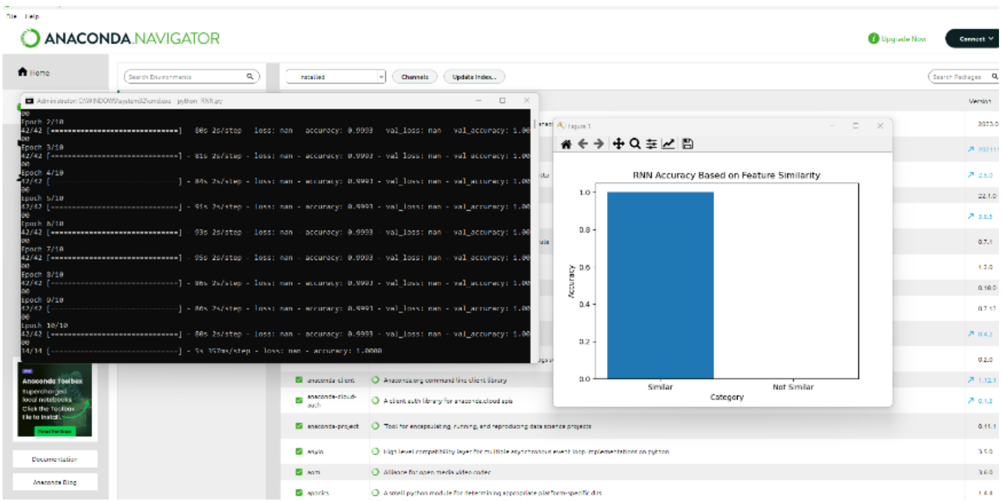


Figure 3. Simulation of the RNN algorithm model

3. RESULTS AND DISCUSSION

In this section, an exploration and comparison of the three deep learning models were presented to determine the most effective algorithm for farmland mapping. Several aspects of each model's performance and suitability for the task are evaluated and discussed. Finally, the goal is to identify the most effective algorithm model for farmland mapping.

3.1. Deep learning models

3.1.1. Convolutional neural network

CNN is a type of artificial neural network used for processing pattern grid data such as images and videos, it is a fundamental element of deep learning for image processing. CNNs can be used to categorize satellite or aerial images in order to distinguish between various land use types, including agricultural land. In general, CNN is ideal for data sets that need to be handled using a large number of nodes and parameters. With the advancement of technology, deep learning models have become a more and more popular tool for land mapping. Deep learning algorithms will be able to generate increasingly accurate and up-to-date land cover maps as more data becomes available and more efficient computational resources are produced [24].

3.1.2. Recurrent neural network

RNN an artificial neural network intended for processing sequence of data. RNNs are applicable for task involving sequential or temporal data and can be represented as input vector, because of their capacity to maintain a hidden state which is the core of the RNN that uses data from earlier time steps to analyze data at the present time step [25], [26]. As a result, they are excellent for problems like speech recognition, time series prediction, natural language processing, and tasks involving temporal aspects of land mapping.

3.1.3. Long short-term memory

LSTM a RNN architecture designed to overcome the vanishing gradient problem often encountered in traditional RNNs. LSTM is a modified version of the recurrent network that can retrieve previously stored information from a memory. This approach is applicable to both sequence and pattern recognition, as well as image processing applications [25].

3.2. Comparison of deep learning models

The classification accuracy of the three deep learning models were tested based on the feature similarity of 2,100 forest images as training set, and 10 images as test set. The accuracy of the algorithms is evaluated during three testing cycles with 10 epochs. The testing phase includes both forest and non-forest images to compare the three algorithm models as shown in Figure 4. The forest images (satellite view) provided as examples are illustrated in Figure 4(a), while the non-forest images are illustrated in Figure 4(b).

(a)

(b)

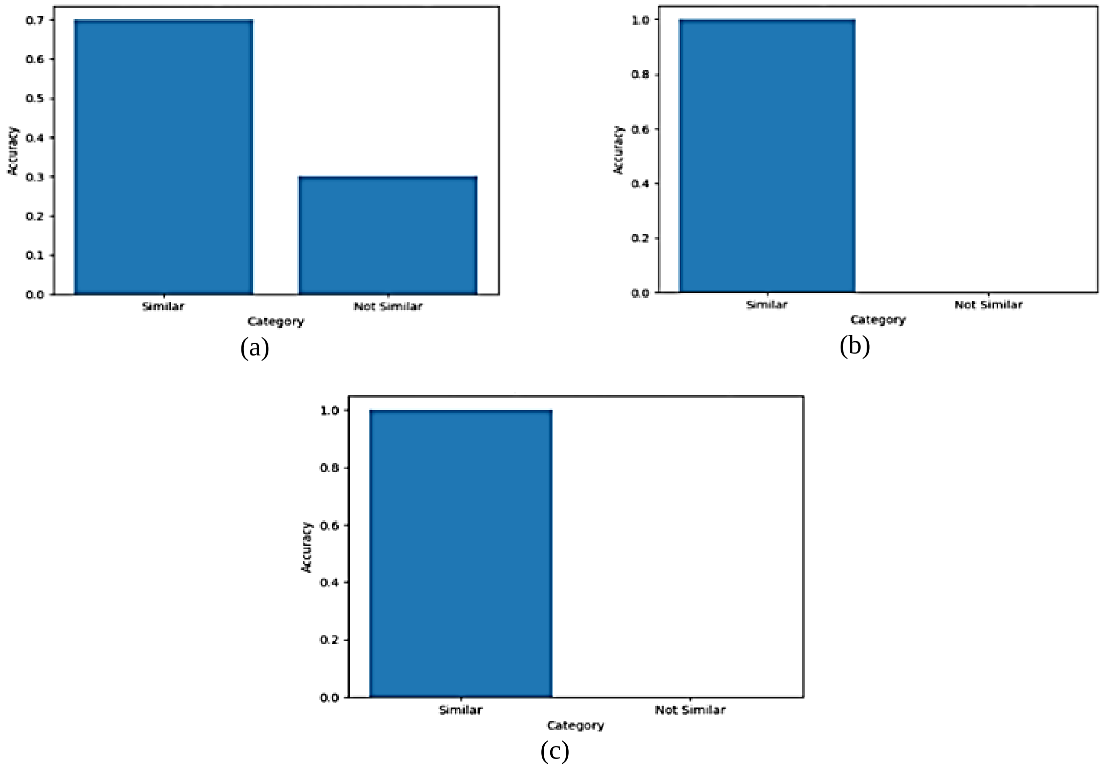
Figure 4. Sample dataset for the comparison of the three algorithm models (a) forest images and (b) non-forest images

3.2.1. Test case number 1

The first test case involves analyzing the accuracy of the three algorithms using the test set consists of 7 forest images and 3 non-forest images. The expected result is 70% match for similarity and 30% match for non-similarity. As can be seen in Figure 5 with comparison output of the classification accuracy of the three models in 70 and 30 percent feature similarity, Figure 5(a) CNN accurately classify the images based on the given output percentage of 70% match for similarity and 30% match for non-similarity. Figure 5(b) LSTM and Figure 5(c) RNN both has a result of 100% match for similarity and 0% for non-similarity classification accuracy. The results demonstrated that both RNN and LSTM have low accuracy rates in terms of image classification and had not achieved the required output percentage.

3.2.2. Test case number 2

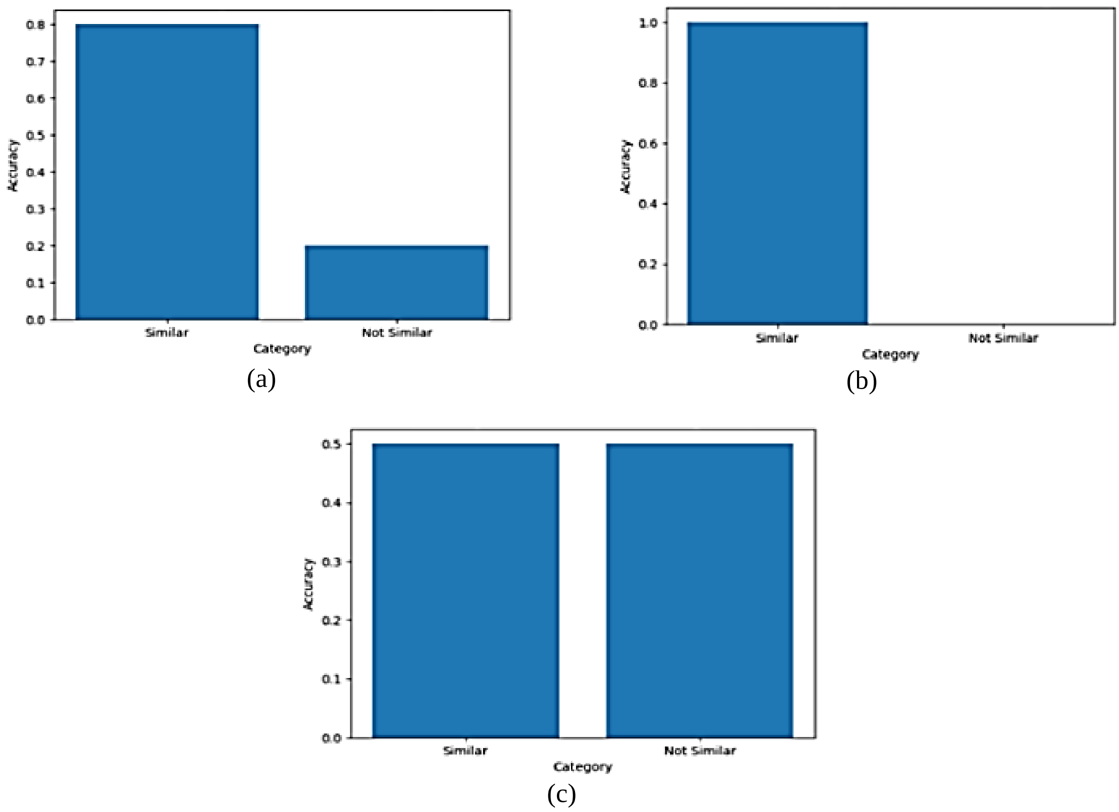
The second test case for classification accuracy of the three deep learning algorithms were consists of 8 forest images and 2 non-forest images sample test set. The expected result is 80% match for similarity and 20% match for non-similarity. As can be seen in Figure 6 the comparison output of the classification accuracy of the three models in 80 and 20 percent feature similarity, Figure 6(a) CNN accurately classify the images based on the given output percentage of 80% match for similarity and 20% match for non-similarity. Figure 6(b) LSTM has a result of 100% match for similarity and 0% for non-similarity, while Figure 6(c) RNN has a result of 50% match for similarity and 50% match for non-similarity classification accuracy. The results showed that both RNN and LSTM have low accuracy rates in terms of image classification and had not achieved the required output percentage.



(a) (b)

(c)

Figure 5. Classification accuracy test results for three algorithm models; (a) CNN, (b) LSTM, and (c) RNN based on feature similarity of 70% similarity match and 30% non-similarity match



(a) (b)

(c)

Figure 6. Classification accuracy test results for three algorithm models; (a) CNN, (b) LSTM, and (c) RNN based on feature similarity of 80% similarity match and 20% non-similarity match

3.2.3. Test case number 3

The third test case for classification accuracy of the three deep learning algorithms were consists of 6 forest images and 4 non-forest images sample test set. The expected result is 60% match for similarity and 40% match for non-similarity. As can be seen in Figure 7 the comparison output of the classification accuracy of the three models in 60 and 40 percent feature similarity, Figure 7(a) CNN accurately classify the images based on the given output percentage of 60% match for similarity and 40% match for non-similarity. Figure 7(b) LSTM has a result of 80% match for similarity and 20% for non-similarity, while Figure 7(c) RNN has a result of 90% match for similarity and 10% match for non-similarity classification accuracy. The results showed that both RNN and LSTM have low accuracy rates in terms of image classification and had not achieved the required output percentage.

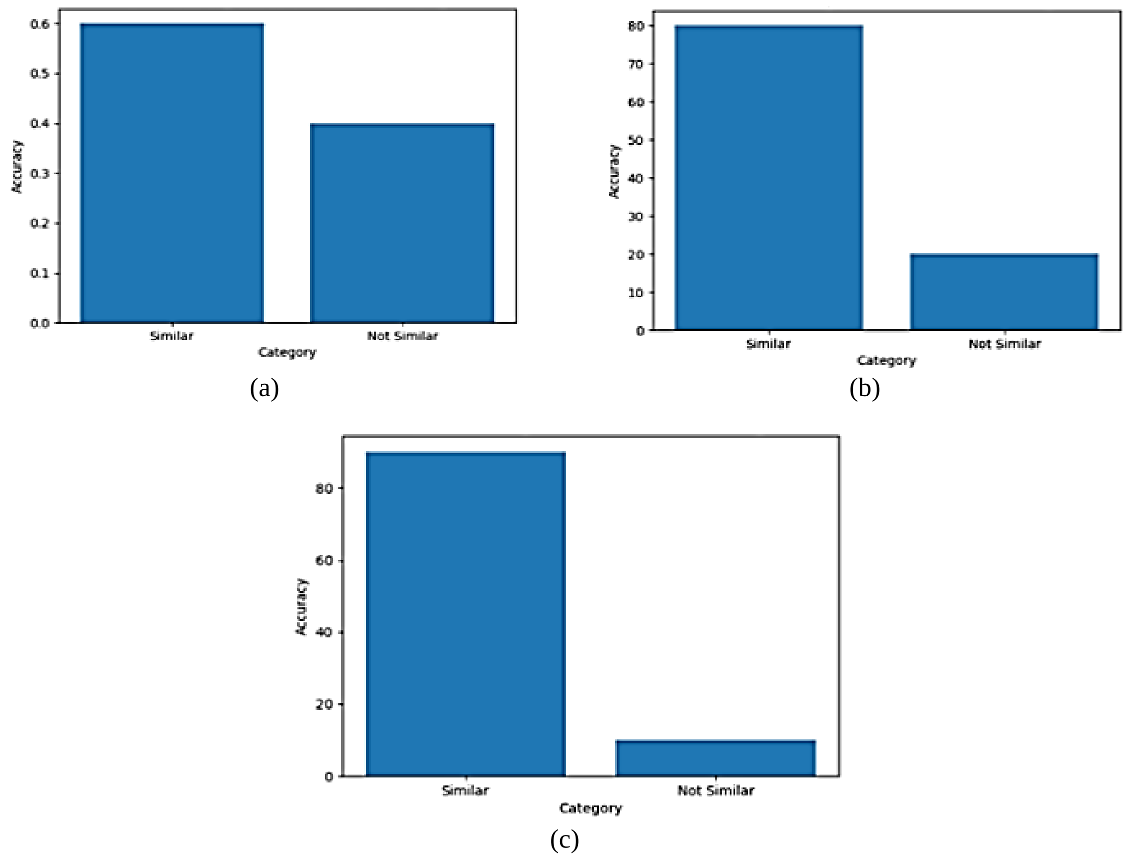


Figure 7. Classification accuracy test results for three algorithm models; (a) CNN, (b) LSTM, and (c) RNN based on feature similarity of 60% similarity match and 40% non-similarity match

Table 1 presents the results from comparing the three deep learning algorithm models. The comparison is based on the percentage of similarity and non-similarity between the predicted outputs of the models and the actual outputs for each test case. Based on the results, the CNN algorithm model performs better than the other two algorithms in terms of image classification accuracy.

Table 1. Summary of the comparison of the three deep learning algorithm models

Deep learning model	Test case no. 1		Test case no. 2		Test case no. 3	
	Percentage of similarity (70%)	Percentage of non – similarity (30%)	Percentage of similarity (80%)	Percentage of non – similarity (20%)	Percentage of similarity (60%)	Percentage of non – similarity (40%)
CNN	70%	30%	80%	20%	60%	40%
LSTM	100%	0%	100%	0%	80%	20%
RNN	100%	0%	50%	50%	90%	10%

3.3. Discussion

The sample set is divided into two sections: Training and testing. The training set is used to train the model, while the test set is used to evaluate the model's performance and ability to complete the image classification task accurately. Based on the result, the CNN algorithm model accurately classifies all the feature similarity within the provided test set in three different test cases and with the given output percentage. Furthermore, the results showed that the remaining two deep learning models RNN and LSTM has low percentage to accurately classify the feature similarity within the provided dataset based on the required output percentage. The exploration of the three deep learning models in terms of image classification in this study showed that CNN can be widely used and effective in image-related tasks such as land mapping and remote sensing.

The result of this study also corroborates other research studies that have used the CNN algorithm model for image processing particularly in the field of agriculture. Table 2 shows research works that used the CNN algorithm model for image processing in various agricultural domains, specifically land mapping. The exploration of deep learning models in this study and the other research studies demonstrated that the CNN is the most commonly used deep learning model in terms of image classification within different fields, with a focus on agricultural applications.

Table 2. Application of deep learning model

Application (area)	DL model	Dataset	Accuracy assessment
Agriculture (land mapping) [18]	CNN	UC merced land use	93.56%
Agriculture (land mapping) [17]	CNN	Sentinel-2 satellite image time series (SITS)	94%
Agriculture (land mapping) [19]	CNN	Landsat and sentinel 2 data (images)	>95%
Agriculture land use and land cover (LULC) [20]	CNN	Hyperspectral imagery and radar	between 83.43% and 98.70%
Agriculture (crop classification) [27]	CNN – transformer (hybrid approach)	Multitemporal and multispectral dataset	Accuracy 98.97%
Weed classification (remote sensing) [28]	CNN	Images data collected by the authors	Accuracy 97%
Agriculture (crop disease classification) [29]	CNN	Data sources extracted by the author	Accuracy 98.49%
Agriculture land use and land cover (LULC) [30]	CNN	satellite image time series (SITS)	Accuracy > 93%
Agriculture (land mapping) [31]	1-D CNN	Sentinel 2 and landsat 8 temporal data	Accuracy 93.75%
Agriculture (crop classification) [32]	FCN + ConvLSTM	Sentinel 1 time series radar images	Between 86% to 88%

Future research may focus on integrating decision support systems with deep learning-based farmland mapping models to assist farmers in crop management, resource allocation, and sustainable agricultural practices. This integration could enhance the accessibility and usability of such models, empowering farmers to make informed decisions for optimizing their agricultural operations. Exploring the relationship between these tools may improve the practical utility of farmland mapping models in supporting informed and efficient agricultural decisions.

4. CONCLUSION

In this paper, we explored and compared the three most commonly used deep learning models. The findings showed that CNN accurately classify the images compared to other algorithm models used. Based on the result CNN is widely used and highly effective deep learning model in image classification. In terms of farmland management, the used of CNN algorithm model can effectively analyzed wide range of satellite imagery and geospatial data to identify different types of agricultural land. This study provides guidance for researchers interested in deep learning and its application for a wide range of agricultural challenges, such as classification and forecasting tasks. It is also useful to those working in image processing, land mapping and general data analysis. In addition, the use of this approach in agriculture has resulted in positive outcomes, contributing to more intelligent and efficient solutions targeted at improving the sustainability and effectiveness of agricultural practices.

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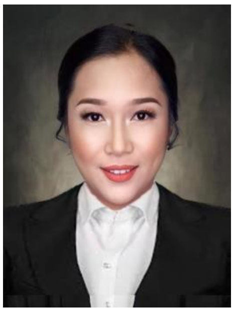
BIOGRAPHIES OF AUTHORS



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