Agricultural Land-Use Classification on Satellite Data Using Machine Learning

Thao-Ngan Nguyen, Van-Ho Nguyen
University of Economics and Law, Ho Chi Minh City, Vietnam and Vietnam National University, Ho Chi Minh City, Vietnam

Abstract

Background: The utilization of satellite images has become increasingly popular for detecting land usage, focusing on agricultural land classification in recent years, due to the significant decline in bees. **Objectives:** This paper seeks to address these challenges by applying several machine learning algorithms on multi-spectral satellite data from Sentinel-2 to derive accurate land classification models. **Methods/Approach:** Specifically, we use five bands: Red, Green, Blue, NIR, and NDVI to build three models, namely Random Forest (RF), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). **Results:** Our results show that the CNN model outperforms the other algorithms on collected satellite data, with an accuracy score of 0.82, F1-score of 0.72, and AUC score of 0.94, followed by the RF and LSTM models. **Conclusions:** This highlights the importance of utilizing advanced machine learning techniques, particularly CNNs, in accurately classifying agricultural land use changes.

Keywords: satellite data; land usage; classification models; machine learning; Sentinel-2

JEL classification: C61; C63; C67
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Introduction

As the global population grows, food security has become a major concern for policymakers and researchers alike. Ensuring a reliable and sustainable food supply requires a multifaceted approach encompassing various factors, including agricultural practices, supply chain management, policy frameworks, and economic factors. In the farming sector, pollination is a crucial component that underpins crop production.

Pollination is a biological process by which pollen grains are transferred from the male reproductive organs to the female reproductive organs of a plant, enabling fertilization and seed production (Khalifa et al., 2021). This process is essential for the survival of many plant species, including those used for food production. Pollination is a fundamental pillar of crop production, and the quality and quantity of food we produce depend heavily on it. Plants rely on various vectors to transport pollen, including water, wind, and animal pollinators. Animal pollination, in particular, is critical for pollinating many crop plants. Various animals are known to be effective pollinators, including bats, moths, hoverflies, birds, bees, butterflies, wasps, thrips, and beetles. In cultivated environments, it is typically animal pollinators that serve as the primary means of pollen transport.

Pollinators play an essential role in the ecology of our planet, providing critical ecosystem services vital for human well-being. The global economic value of pollination services has been estimated to be over three trillion dollars (U.S. Forest Service, 2021), underscoring pollinators' critical role in our food systems. Moreover, of the 1,400 crop plants grown worldwide, approximately 80% require animal pollination (U.S. Forest Service, 2021). This includes many crops that provide the world's food and plant-based industrial products. Bees are particularly noteworthy among animal pollinators due to their effectiveness and widespread availability. Bee-pollinated crops, such as almonds, apples, blueberries, and cherries, contribute significantly to the human dietary supply, accounting for approximately one-third of the total (Khalifa et al., 2021). In the United States alone, the economic value of honeybee pollination has been estimated to be around 15 billion dollars annually.

Pollination is a critical ecological function crucial to crop production and global food security. The significance of animal pollinators, especially bees, cannot be overstated. Protecting and promoting pollinator health and diversity is essential to ensuring the resilience and sustainability of our food systems for future generations.

The objectives of this paper were to collect geolocated data on agricultural practices and land use. As well as the distribution and abundance of different varieties of native bees and honeybees. Based on this data, develop Machine Learning models that help improve the automatic classification of agricultural practices and land use through satellite images. In addition, it explores the relationships between land use and the welfare of managed and wild bees and promotes more sustainable agricultural and land management practices that benefit bees.

The scope of the paper is to propose and benchmark the best solution for classifying agricultural practices and land use using satellite images. In the first stages, we focus on finding the classification solution. In the next phase, we will process data from satellites with many complex images and parameters to improve the quality of the processed data input.

The paper is structured into five discernible sections. Section 1 describes the necessity of the research. The theoretical bases related to the research are presented in Section 2. In Section 3, the author delineates the research methodology and experimental designs. The research results are detailed in Section 4, and comments about the model and results are presented in Section 5. Lastly, conclusions and future Research is presented in Section 6.

Background and related work

This section focuses on the fundamental concepts, theories, and algorithms that underpin the paper and provides a review of the existing literature and research relevant to its topic.

Sentinel-2

Sentinel-2 is a European wide-swath, high-resolution, multi-spectral imaging mission. The complete mission specifications of the paired satellites, which fly in the same orbit but are phased at 180°, are intended to provide a frequent revisit rate of 5 days at the Equator (European Space Agency, 2020). Sentinel-2 carries an optical instrument payload that samples 13 spectral bands. The orbital swath width is 290 km (European Space Agency, 2020).

Table 1
Spectral bands of Sentinel-2

Band	Resolution	Central Wavelength	Purpose
B01	60 m	443 nm	Aerosol detection
B02 (Blue)	10 m	490 nm	True-color imagery - classifying surface features, vegetation, and water bodies
B03 (Green)	10 m	560 nm	True-color imagery - classifying surface features, vegetation, and water bodies
B04 (Red)	10 m	665 nm	True-color imagery - classifying surface features, vegetation, and water bodies
B05 (Red edge)	20 m	705 nm	Classifying the vegetation
B06	20 m	740 nm	Classifying the vegetation
B07	20 m	783 nm	Classifying the vegetation
B08 – NIR (Near Infra-red)	10 m	842 nm	Near-infrared
B08A	20 m	865 nm	Classifying the vegetation
B09	60 m	940 nm	Detecting the water vapor
B10	60 m	1375 nm	Cirrus cloud detection
B11	20 m	1610 nm	Snow/ice/cloud discrimination
B12 – SWIR (Short-wave Infra-red)	20 m	2190 nm	Snow/ice/cloud discrimination

Source: Copernicus "Sentinel-2"

The Sentinel-2 twin satellites uphold the legacy of previous missions such as SPOT and LANDSAT by maintaining comparable image data and contributing to continuous multi-spectral observations (GIS Geography, n.d.). These satellites assist in providing Copernicus with an assortment of services and applications.

Algorithms

RF is a robust supervised machine learning algorithm that can be utilized for various tasks, including regression and classification. As an ensemble method, the RF model comprises many small decision trees called estimators, each generating its predictions. The RF model combines these predictions to produce a more accurate overall forecast.

A CNN was formerly meant to function only on two-dimensional data, such as photos and video, and was hence referred to as a 2D CNN. CNNs that can handle one-dimensional data in addition to two-dimensional data have recently been developed and are known as 1D CNNs. Several studies have demonstrated that 1D CNN is useful for various applications.

LSTM is a type of recurrent neural network introduced by Hochreiter and Schmid Huber in 1997 to address the issue of learning long-term dependencies in sequential data. Unlike traditional recurrent neural networks, which only propagate the output of the last time step to the current step, LSTM incorporates a memory cell that can hold information over an extended period. This allows LSTM to handle gaps in data better and retain information relevant to the task at hand.

LSTM models are particularly suited to hyperspectral data's high-dimensional and sequential nature. These models offer improved classification accuracy by identifying complex patterns in the spectral data.

The following machine learning methods were investigated: RF, support vector machine, artificial neural network, fuzzy adaptive resonance theory-supervised predictive mapping, spectral angle mapper, and Mahalanobis distance (Talukdar et al., 2020). The present study finds that the RF algorithm is the most effective for LULC classification among the six machine-learning algorithms investigated. However, it is recommended that the RF algorithm be evaluated in a range of morphoclimatic conditions to ensure its robustness and generalizability.

In a study (Minallah et al., 2015), they attempted to differentiate between 7 classes, 2 of which were different types of crops, using RF. They reported an F-score of 0.88. However, it is worth noting that this score was obtained using 10-fold cross-validation on the same dataset without an independent dataset for evaluation. (N. Laban, 2018) reported achieving an F-score of 0.89 using a deep learning CNN. Their study employed a separate evaluation dataset and prior geometric and radiometric corrections. However, their analysis involved eight classes, out of which two were crop types - sugar beet and wheat. These two classes achieved individual recall scores of 0.64 and 0.88 and precision scores of 0.03 and 0.52, respectively. Another use of CNN is presented by (Kussul et al., 2017), where an overall accuracy of 0.85 is achieved on multiple crop types. Boryan et al. (2011) used a supervised decision tree classification method, representing an early effort by the National Agricultural Statistics Service (NASS).

Several publications have employed additional expert data, specifically phenological patterns, to improve land use classification accuracy. In one study (Khaliq et al., 2018), phenological patterns were extracted from the NDVI index, and the Jeffries-Matusita Distance was used for data aggregation, followed by RF as a classifier on multi-temporal images. This method achieved an overall accuracy of 0.91 with 4 crop types. Another study by (Luciani et al., 2017) incorporated prior knowledge of the area in the form of additional expert knowledge and classified maize and two-season wheat with a decision tree approach, resulting in an overall accuracy of 0.93. In some approaches, prior knowledge of parcel boundaries has been utilized to improve pixel-based classification, as in another study (Kussul et al., 2016).

Zhang et al. (2019) conducted a study on land cover classification using Sentinel-2A images and compared four different approaches of feature band selection. Using the support vector machine algorithm, the study aimed to classify five classes, namely crop, tree, soil, water, and road. The four approaches compared were traditional empirical indices, specific bands related to indices, specific bands after ranking by mutual information (MI), and full bands of on-board sensors. The results showed that using the selected bands after MI ranking resulted in a better classification performance than empirical indices and specific bands related to indices. However, using all 13 bands marginally improved the classification accuracy compared to the MI-based approach.

In summary, various machine learning algorithms have been used for land use and land cover classification, including RF, Support Vector Machine, Artificial Neural Networks, CNN, Decision Tree, etc. Some studies have also incorporated additional expert knowledge to improve classification accuracy, such as phenological patterns and prior knowledge of parcel boundaries. Using specific bands after mutual information ranking has improved classification performance compared to traditional empirical indices or specific bands related to indices. Back to the paper, based on the above analysis, we improved the classification accuracy and conducted a deeper analysis based on reliable data sources. We used three algorithms to find the suitable models: RF, CNN, and LSTM. Besides that, the band of satellite data we used is Red, Green, Blue, NIR, and NDVI.

Methodology

This section describes an overview of the study area. The proposed model is based on a comprehensive analysis of the existing literature and research on the study topic. A description of the dataset is presented.

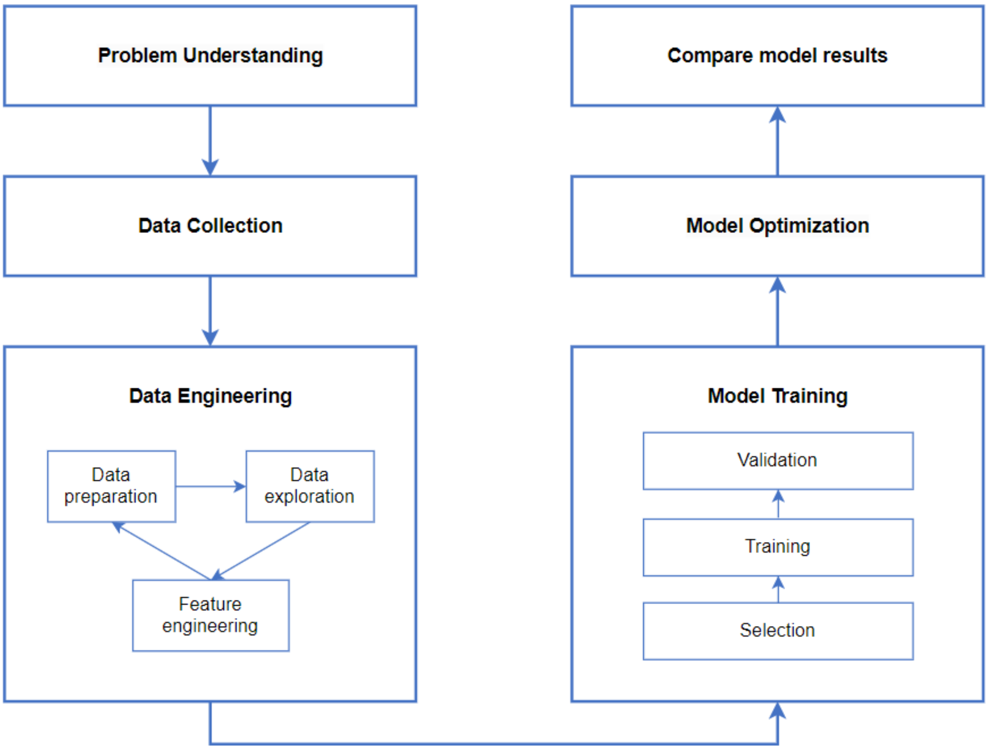
Study Area

This study analyzes data collected in the District of Guaminí. This district is located in Argentina's South-West region of the Buenos Aires Province. The economy of Guaminí is mainly based on agriculture and livestock farming, with crops such as soybean, corn, wheat, and sunflower being the main products. The study setting encompasses an area of 4824.23 square kilometers.

Proposed model

In this paper, the data used is satellite data from Sentinel-2A. This type of remote sensing data is collected by the ESA Sentinel-2A satellite. Sentinel-2A is part of the Copernicus program, a European Union-led initiative to provide accurate, timely, and free access to Earth observation data. The data is collected at several intervals to guarantee reliability and comprehensiveness. Specifically, data was collected within the time interval: 1st September 2020 to 31st May 2021. The satellites collect one image every 5 days, so there are 55 timestamps in the datasets.

Figure 1
Proposed Model



Source: Author's proposal

Problem Understanding
To begin our proposed model, we first focus on understanding the problem. Specifically, we define the agricultural land use classification problem and analyze the satellite data.

Data Collection
Sentinel-2A satellite imagery is systematically collected and openly accessible for download via the Sentinel Hub, a resource developed by the European Space Agency. Besides, freely available satellite information analysis software, the Sentinel application platform, is also provided. Compared with Quantum GIS and the environment for visualizing images, this software is specially customized for the Sentinel series.

Data Engineering
Data preparation

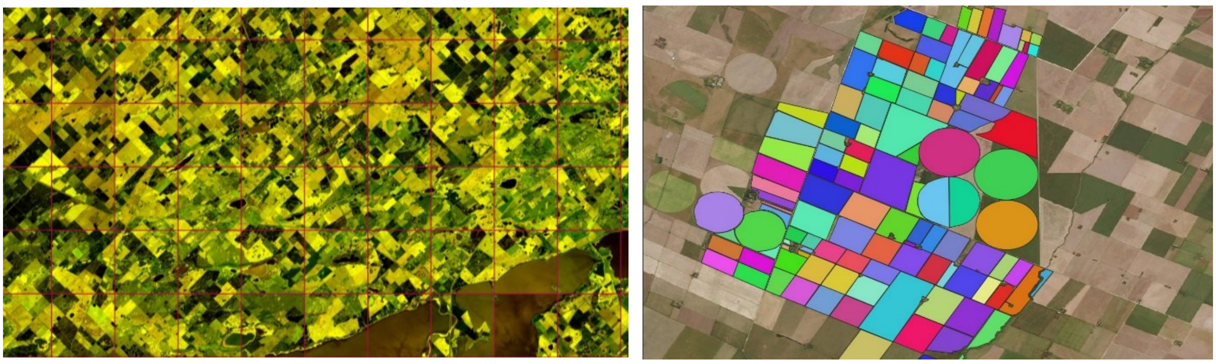
Preprocessing: As collected imagery comes collectively in very high-definition and is notoriously prone to Atmospheric noises, resampling, atmospheric correction, and subset selection are necessary for preprocessing satellite images. In particular, resampling is a necessary preprocessing step that ensures that images of each band have uniform resolution and pixel count. Subset selection allows users to select specific areas of interest for further analysis. Atmospheric correction algorithms are based on the Atmospheric/Topographic Correction for Satellite Imagery by Richter and Schläpfer (2023). This method uses the libRadtran (Emde et al., 2016) radiative transfer model to correct the atmosphere, which generates a massive look-up table for varied air conditions, solar geometries, and ground elevations. To invert the radiative transfer equation and obtain bottom-of-atmosphere reflectance, this reduced model runs significantly quicker than a complete model. As a result, the algorithm derives all gaseous and aerosol characteristics of the atmosphere, and the pictures derive aerosol optical thickness or water vapor concentration, respectively. A red, green, and blue (RGB) map of the Sentinel-2A data for the selected site after preprocessing is depicted in Figure 2.

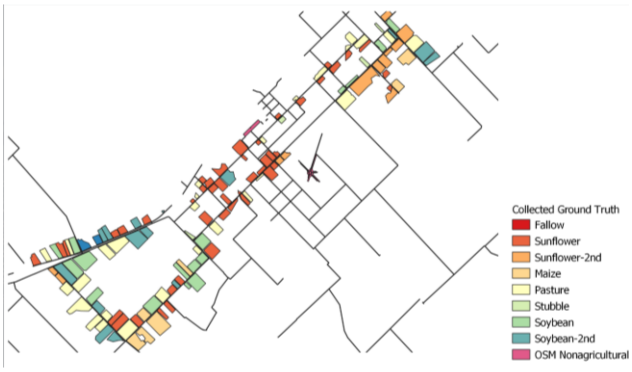
Figure 2
RGB map of the Sentinel-2A image

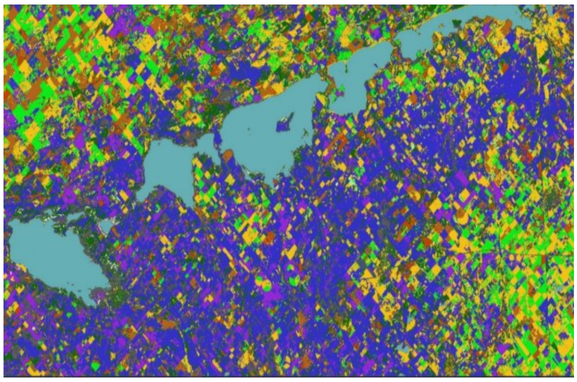
Source: Terra-Insight Hackathon "Supporting Bee-Friendly Agriculture in Argentina"

Label specific data: The resulting image from the previous step is divided into smaller areas. In each small area, different land uses are marked in different colors. Labels will be assigned to the respective areas based on the area's actual vegetation and topographical features.

Figure 3
Label specific data







Source: Terra-Insight Hackathon "Supporting Bee-Friendly Agriculture in Argentina"

Data exploration and Feature engineering: After obtaining a data set of the necessary bands for analysis and labels after being assigned, Exploratory Data Analysis (EDA) will be conducted to see an overview and details of the data. Then, outliers are excluded, and the data is used in the machine learning models.

Model Training and Model Optimization
During model training, the model is fed with input data, which was processed in the previous step, and expected output labels. The model learns to predict the correct output from the input. Optimization is adjusting the model's parameters to minimize the error between predicted and actual output.

Compare model results
Those models are contrasted on various metrics, including Accuracy, Recall, Precision, F1-Score, Receiver-operating characteristic curve (ROC), and Area under the curve (AUC); each exhibits a model's advantages from one perspective.

The formula for accuracy, precision, and recall, and F1-score are as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

Where: TP: True Positive; TN: True Negative; FP: False Positive; FN: False Negative

Results
This section presents the outcomes of data preprocessing, training, and model evaluation. It also includes visualizations of the results related to the research topic.

Training and Evaluating the Model
In the previous section, we addressed the implementation and results of three models: RF, CNN, and LSTM. In different regions or crops, the values of each band are different. Depending on the crop, the surface of that area, and so on, the corresponding band will be obtained. Data samples are randomly picked from datasets and divided into

70% for the training set and 30% for the testing set. We will summarize the results of our experiments in order to find a suitable model, and some will discuss them in this section. Firstly, we will discuss the previous results.

Table 2
Result of models

Models	RF	CNN	LSTM
Accuracy	0.81	0.82	0.77
Precision	0.79	0.80	0.79
Recall	0.69	0.72	0.64
f1-score	0.72	0.74	0.66
AUC	0.94	0.96	0.43

Source: Authors' work

For a classification task, we evaluated three models, RF, CNN, and LSTM. The results indicated that CNN achieved the highest accuracy of 0.82, outperforming RF and LSTM. Additionally, CNN exhibited superior precision (0.80) and recall (0.72) compared to RF (precision: 0.79, recall: 0.69) and LSTM (precision: 0.79, recall: 0.64). Furthermore, CNN's f1-score of 0.74 surpassed those of RF (0.72) and LSTM (0.66). Moreover, CNN demonstrated the highest discriminatory power with an AUC score of 0.96, while RF and LSTM scored 0.94 and 0.43, respectively. Overall, CNN emerged as the top-performing model, followed by RF, while LSTM showed weaker performance in recall and f1-score, suggesting potential limitations for this specific problem and dataset. Nonetheless, additional analysis and experimentation are necessary to ascertain the optimal model.

Visualization

Figure 4 shows the distribution of each label in the dataset. Soybean is the most abundant label. The reason is that the study area mainly raises bees for honey; bees are important pollinators of soybean plants. Corn is also the label with the second largest amount in the dataset. Bees help pollinate corn by visiting the male flowers, which produce the pollen, and then transferring the pollen to the female flowers, fertilizing and producing ears of corn.

Figure 5 shows that the red, green, and blue bands range from 0 to 0.3, and the NIR band has a more extended value range from 0 to 0.37. Unlike the other bands, the NDVI band has a value between -2 and 2.

Based on Figure 6, the top 3 crucial features are NIR, NDVI, and Red. These features are reportedly crucial to the result of land classification because they offer distinct insights into vegetation, soil, and water:

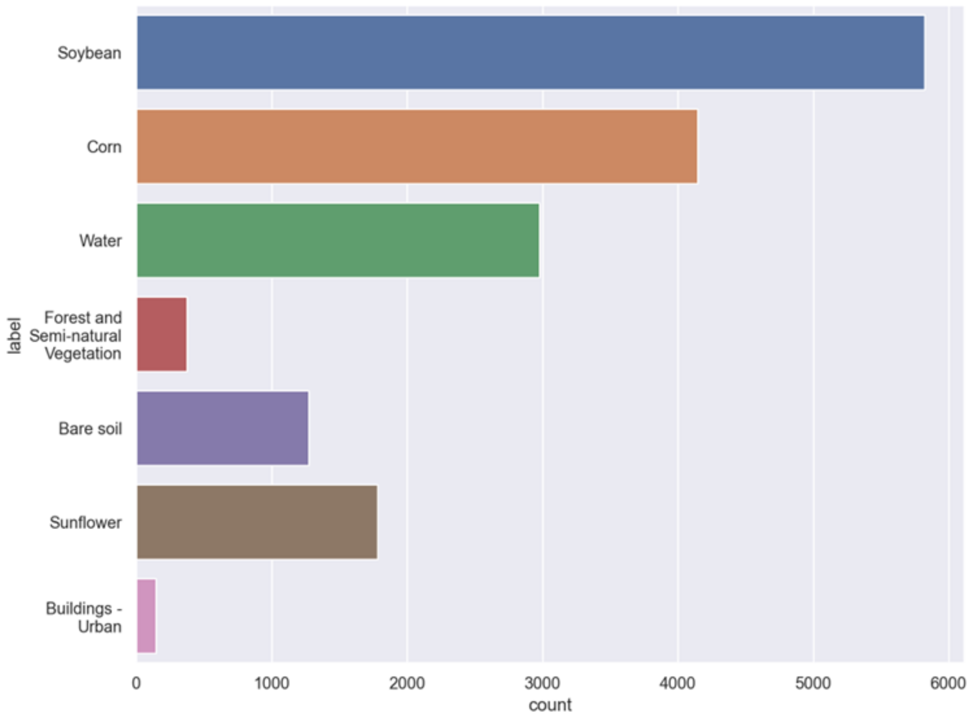
NIR plays an important role in detecting healthy vegetation, as plants effectively reflect NIR light, facilitating the differentiation of vegetation from soil and water.

NDVI evaluates vegetation health, tracks seasonal vegetation changes, and detects stress.

The red band complements NIR in NDVI calculations, as healthy plants absorb red light, further enhancing the detection of water bodies.

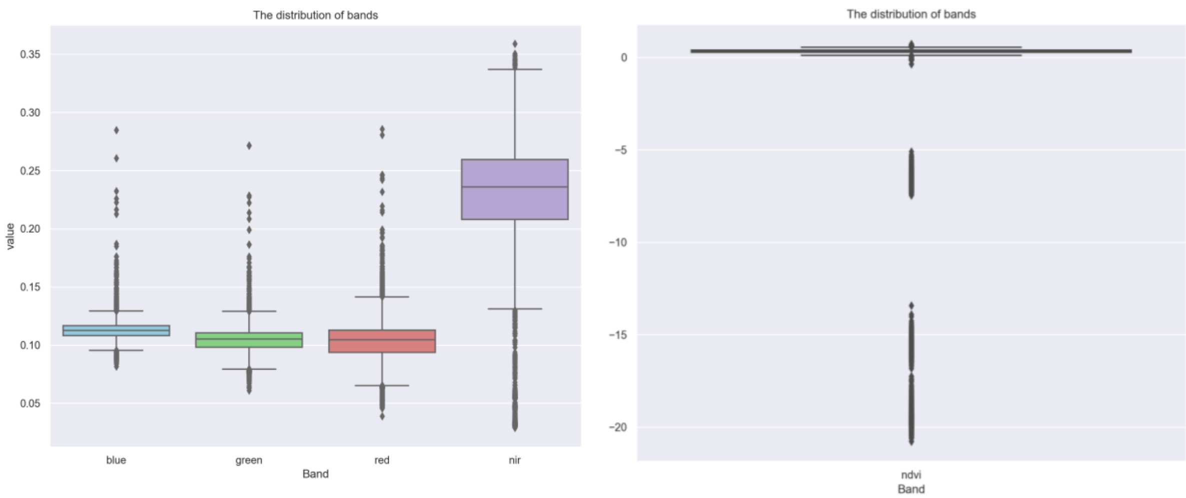
These bands enhance accuracy in distinguishing different land covers and assessing vegetation health, making them essential for land classification models.

Figure 4
The distribution of data labels in the dataset



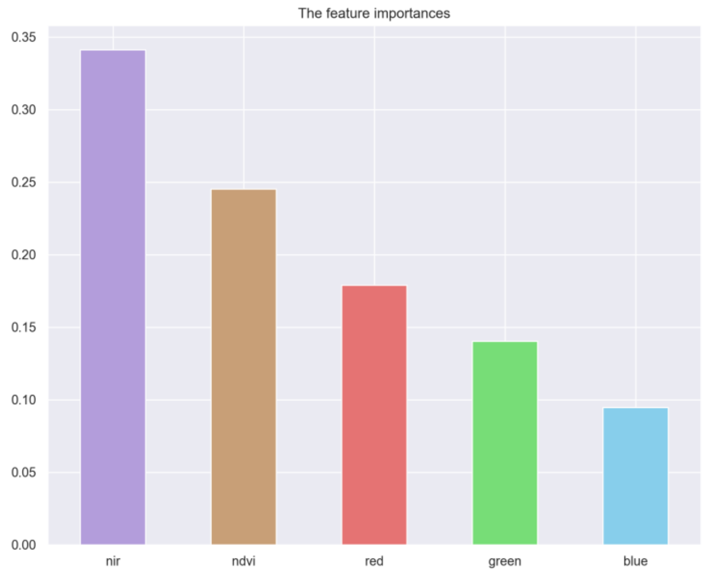
Source: Authors' work

Figure 5
The distribution of bands



Source: Authors' work

Figure 6
The features importance



Source: Authors' work

Discussion

In this paper, our research question is about machine learning models that help improve the automatic classification of agricultural practices and land use through satellite images. After reviewing the literature, we can see that the RF model is the critical player in this research question. We chose three implementation models: RF, CNN, and LSTM. In conclusion, we achieved several positive results, such as high accuracy in the model (approximately 82%).

One concern about our findings was the real-time data problem and the process data used in modeling. Some potential concerns should be considered when working with real-time data and processing data: data quality, volume, privacy, and security. In addition, modeling with real-time data and processing data can be computationally intensive, requiring significant computational resources to process the data in real-time. Therefore, efficient algorithms and hardware infrastructure must be utilized to ensure the timely processing of the data. Another drawback is that climate change affects the timing of flowering, rainfall patterns, and temperatures, which all impact the behavior of bees and the production of honey. In addition, the impact of class imbalance within the agricultural land-use categories should be considered. Agricultural landscapes are inherently diverse, and some land-use types may be underrepresented in the dataset. This imbalance can introduce bias into the model, potentially impacting its predictive performance for minority classes. To mitigate this issue, techniques such as resampling methods, class-weighted loss functions, or data augmentation should be explored. Moreover, creating more balanced and representative datasets could significantly improve the model's reliability and applicability across various agricultural scenarios.

The changing climate affects the timing of flowering, rainfall patterns, and temperatures, which impact the behavior of bees and the production of honey. To adapt to these changes, beekeepers should be proactive and flexible, using traditional knowledge and modern technology to manage their hives in the face of changing environmental conditions. This paper provides valuable insights into the potential of using remote sensing data and machine learning algorithms for land classification. The findings have important implications for future research and strategies to address the agriculture and beekeeping industry challenges.

Conclusion

This paper explored using satellite data and machine learning algorithms for land classification. The results showed that the CNN model performed the best in accuracy, precision, recall, F1-score, and AUC, followed closely by the RF model. The study also identified NIR, NDVI, and RED as the three most crucial features for achieving accurate land classification results.

This paper provides valuable insights into the potential of using remote sensing data and machine learning algorithms for land classification. The findings have important implications for future research and strategies to address the challenges of the agriculture and beekeeping industry.

In the future, we will refine models and expand data preprocessing. The following are a few of them. Firstly, the data preprocessing is built to transfer complex data about images and bands to the desired data input. It can help save time processing raw data and get the result on time. Secondly, explore the use of more advanced machine learning techniques, such as deep learning, to improve the accuracy of models. In order to learn more complex features from the input data and make more accurate predictions. Thirdly, different satellite data types should be investigated, and the research areas should be expanded to include typical land characteristics and atmospheres worldwide to improve classification accuracy. These data sources can provide more detailed and accurate information about land cover and land use, which could help improve models' performance.

References

1. Boryan, C., Yang, Z., Mueller, R., & Craig, M. (2011). Monitoring US agriculture: the US Department of Agriculture, National Agricultural Statistics Service, Cropland Data Layer Program. *Geocarto International*, 26(5), 341–358. https://doi.org/10.1080/10106049.2011.562309
2. Emde, C., Buras-Schnell, R., Kylling, A., Mayer, B., Gasteiger, J., Hamann, U., Kylling, J., Richter, B., Pause, C., Dowling, T., & Bugliaro, L. (2016). The libRadtran software package for radiative transfer calculations (version 2.0.1). *Geoscientific Model Development,* 9(5), 1647–1672. https://doi.org/10.5194/gmd-9-1647-2016
3. European Space Agency. (2020). *Sentinel-2 - Overview. Copernicus*. Retrieved from https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-2/overview
4. GIS Geography. (n.d.). *Sentinel-2 bands and combinations: Your complete guide*. Retrieved from https://gisgeography.com/sentinel-2-bands-combinations
5. Khalifa, S. a. M., Elshafiey, E. H., Shetaia, A. A., El-Wahed, A. a. A., Algethami, A. F., Musharraf, S. G., AlAjmi, M. F., Zhao, C., Masry, S. H. D., Abdel-Daim, M. M., Halabi, M. F., Kai, G., Naggar, Y. A., Bishr, M., Diab, M. a. M., & El-Seedi, H. R. (2021). Overview of Bee Pollination and Its Economic Value for Crop Production. *Insects, 12*(8), 688. https://doi.org/10.3390/insects12080688
6. Khaliq, A., Peroni, L., & Chiaberge, M. (2018). Land cover and crop classification using multitemporal Sentinel-2 images based on crops' phenological cycle. *IEEE Workshop on Environmental, Energy, and Structural Monitoring Systems (EESMS)*, 1–5. https://doi.org/10.1109/EESMS.2018.8405830
7. Kussul, N., Lavreniuk, M., Skakun, S., & Shelestov, A. (2017). Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data. *IEEE Geoscience and Remote Sensing Letters, 14*(5), 778–782. https://doi.org/10.1109/lgrs.2017.2681128
8. Kussul, N., Lemoine, G., Gallego, F. J., Skakun, S. V., Lavreniuk, M., & Shelestov, A. Y. (2016). Parcel-Based Crop Classification in Ukraine Using Landsat-8 Data and Sentinel-1A Data.

IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 9(6), 2500–2508. https://doi.org/10.1109/jstars.2016.2560141

9. Luciani, R., Laneve, G., Jahjah, M., & Collins, M. (2017). Crop species classification: A phenology based approach. *IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, 4390–4393. https://doi.org/10.1109/igarss.2017.8127974
10. Minallah, N., Rahman, H. U., Khan, R., Alkhalifah, A., & Khan, S. (2015). Land usage analysis: A random forest approach. *7th International Conference on Recent Advances in Space Technologies (RAST)*, 245–249. https://doi.org/10.1109/rast.2015.7208349
11. N. Laban, B. A. (2018). Seasonal Multi-temporal Pixel Based Crop Types and Land Cover Classification for Satellite Images using Convolutional Neural Networks. *13th International Conference on Computer Engineering and Systems (ICCES)*, 21-26. https://doi.org/10.1109/icces.2018.8639232
12. Richter, R., & Schläpfer, D. (2023). Atmospheric/Topographic Correction for Satellite Imagery (ATCOR-2/3 User Guide). https://www.rese-apps.com/pdf/atcor3_manual.pdf
13. Talukdar, S., Singha, P., Mahato, S., Shahfahad, N., Pal, S., Liou, Y., & Rahman, A. (2020). Land-Use Land-Cover Classification by Machine Learning Classifiers for Satellite Observations - *A Review*. *Remote Sensing, 12*(7), 1135. https://doi.org/10.3390/rs12071135
14. U.S. Forest Service. (2021). *Why is Pollination Important?* Retrieved from https://www.fs.usda.gov/managing-land/wildflowers/pollinators/importance
15. Zhang, T.-X., Su, J.-Y., Liu, C.-J., & Chen, W.-H. (2019). Potential Bands of Sentinel-2A Satellite for Classification Problems in Precision Agriculture. *International Journal of Automation and Computing, 16*(1), 16-26. https://doi.org/10.1007/s11633-018-1143-x

About the authors

Thao-Ngan Nguyen (B.S.) received the Honors B.S. degree in Management Information Systems (MIS) from the Faculty of Information Systems, University of Economics and Law (VNU–HCM), Vietnam, in 2023. She is a Data Engineer at an international company in Ho Chi Minh City. Her research interests include business intelligence, data analytics, and machine learning. She can be contacted at **nguyenthaongan719@gmail.com**.

Van-Ho Nguyen (M.A.) received the B.S. degree in Management Information System (MIS) from the Faculty of Information Systems, University of Economics and Law (VNU–HCM), Vietnam, in 2015 and the Master's degree in MIS from the University of Economics Ho Chi Minh City, Vietnam, in 2020. He is a Full Lecturer at the Faculty of Information Systems, UEL, VNU-HCM. His research was published in top journals including Journal of Hospitality and Tourism Insights, Journal of Hospitality and Tourism Technology, IEEE Access, Business Systems Research, Journal of Information Processing Systems, International Journal of Information Management Data Insights, and Annals of Operations Research. He also works as a reviewer for well-known Scopus/ISI-indexed journals such as Journal of Business Analytics, Journal of Marketing Analytics, Business Systems Research, Journal of Information Processing Systems, Behavior & Information Technology, Annals of Operations Research, and others. His research interests include business analytics, business intelligence, data analytics, and machine learning. He is a corresponding author and can be contacted at **honv@uel.edu.vn** and/or **nguyenvanho.uel@gmail.com**.