Scalable Deep Learning for Categorization of Satellite Images

C. Lokanath Reddy(✉), T. Mukthananda Reddy, M. Mahendra Reddy, and M. Mohan

G. Pullaiah College of Engineering and Technology, Kurnool, Andhra Pradesh, India
chilakalalokanathreddy@gmail.com

Abstract. The analysis of satellite data has become increasingly challenging due to the vast abundance of satellite photos available in recent years. Understanding and extracting valuable insights from these images necessitates a comprehensive grasp of the underlying data they portray. The capability to identify and categorize objects within satellite photos holds significant importance across various domains, including land planning, ecology, military intelligence, and ocean monitoring. With their wealth of spatiotemporal information, satellite images serve as invaluable resources for global remote sensing applications aimed at addressing a wide spectrum of issues. This study aims to investigate the complexities associated with analyzing satellite data by developing a specialized workflow focused on mapping streets and highways to monitor urban development in cities. The study emphasizes addressing learning challenges through the configuration execution, and evaluation of deep neural network experiments. To achieve this objective, publicly accessible methods and information are utilized. The data acquisition pipeline incorporates preprocessing techniques to effectively handle inputs with varying sizes, resolutions, and spectral channels. Despite the significant potential of satellite imagery, its widespread dissemination is hindered by various challenges, including issues related to data distribution, volume, quality, and accessibility. These obstacles further complicate the study of satellite images. Additionally, satellite imagery finds application in monitoring oceanic and geographical data, highlighting its diverse utility. The proposed strategy is anchored in a scalable end-to-end approach for interpreting satellite imagery, aiming to overcome the challenges associated with analyzing large-scale satellite datasets efficiently. Through this study, we aim to contribute to ongoing efforts in harnessing the power of satellite imagery for addressing global challenges and fostering sustainable development.

Keywords: Hyperspectral remote sensing · deep neural networks · satellite images · Python · Google Collab are some of the index phrases

1 Introduction

In numerous visual tasks, such as identifying two-dimensional images, convolutional neural networks have proven to perform exceptionally well. As this paper uses deep convolutional neural networks to directly identify the spectral domain of hyperspectral

X. Cheng (Ed): BROADNETS 2024, LNICST 601, pp. 3–13, 2025.
https://doi.org/10.1007/978-3-031-81168-5_1

pictures. In particular, the design of the production process has five layers by weight, namely the production layer, the production process includes the layers of production, production, production, and production. These five layers are applied to each spectral classification than certain conventional techniques (such support vector machines and deep learning models). In line with experimental findings derived from multiple hyperspectral picture datasets. The capacity to analyze object details using distributed photos has increased with the availability of hyperspectral images; yet, this has resulted in increased data processing costs. This study looks on the priority of key point analysis in Hyperspectral image categorization. Within this work, two exceedingly subtle maps—HYDICE as well AVIRIS—are used. The content of the drawing's major content was examined after a brief introduction to the main content analysis method. The findings indicate that only the first few groups contain significant information. An accurate classification rate of roughly 70% can be achieved by using the first few essential photos. This study demonstrates the results and efficiency of using the key point analysis technique as a preliminary step in hyperspectral image classification.

1.1 Existing System

In the classification of hyperspectral images, numerous techniques have produced good results. This paper investigates three elements of the three classification methods for hyperspectral images are available: supervised, semi-supervised, and unsupervised Classification.

1.1.1 Supervised Classification

Supervised classification involves training a model using labeled data, where each pixel in the hyperspectral image is associated with a known class or category. The process typically includes selecting representative samples from each class and extracting features from the spectral signatures of these samples. Common supervised classification algorithms include Support Vector Machines (SVM), Random Forest, Maximum Likelihood Classifier (MLC), and Neural Networks.

1.1.2 Semi-supervised Classification

Semi-supervised classification techniques leverage both labeled and unlabeled data. In this approach, a portion of the hyperspectral image is manually labeled, while the rest remains unlabeled. The classifier learns from the labeled data and generalizes its knowledge to classify the unlabeled pixels.

1.1.3 Unsupervised Classification

Unsupervised classification does not require any labeled data for training. Instead, it identifies clusters or groups of pixels with similar spectral signatures in the hyperspectral image. Common unsupervised classification algorithms include K-Means Clustering, Spectral Clustering, and Gaussian Mixture Models (GMM). These algorithms partition the image into distinct regions or classes based solely on the spectral characteristics of the pixels, without any prior knowledge of the classes present in the scene.

1.1.4 Disadvantages

The accuracy of distinct algorithms cannot be compared. It is irrelevant and the classification is 100% accurate. Whatever the kernel type, they are all the same. A quick and cost-prohibitive procedure is needed to create a house model.

1.2 Proposed System

It is demonstrated that the suggested model eliminates every drawback of the current setup. The system will use deep learning to examine the hyperspectral PCA image and the parsing model's structure, thereby increasing the accuracy of neural network findings. It improves every distribution result's efficiency. Hyperspectral images are expected to provide higher accuracy. The objective of this research is to categorize satellite photos. Four distinct groups are created from the supplied satellite pictures by the plan. Prior to classification, feature maps are retrieved from the input image and preprocessed. Convolutional neural networks use the basic structure of images spatial information, also known as topological information like adjacency and rotation about the structures in the image, is also considered. Now we'll go over the specifics of how the neural network's various methods interacts (Fig. 1).

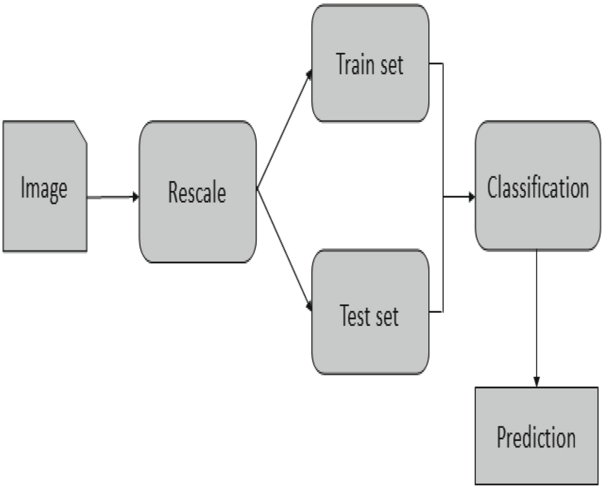

Fig. 1. Block diagram of system architecture

2 Motivation

Understanding complex global phenomena like urbanization, climate change headwinds, biodiversity research, and the social economy by stepping back and measuring overall processes at scale Images in the visible, mid-infrared, near-infrared, and ultraviolet spectrums of electromagnetic waves are captured using it. Image spectrometers can visualize a large number of pixels continuously and narrowly, so that every pixel throughout the range of wavelengths might get the entire spectrum emitted or reflected. As a result, High spectral resolution can be found in hyperspectral photos, multi-band capability, and a wealth of data. This system, also known as Global Monitoring, possesses uses in disaster relief, business control and accuracy agriculture. Earth observation information are collected using a variety of methods, which is able to broadly classified since final as well near-final (also known comparable to in situ sensing). Initially, there is that "the distance between the object and the sensor is greater than the sensor's linear size," and the second is that the distance is equal to the sensor's linear size. Image editing, noise reduction and dimensionality reduction, segmentation, and other techniques are used to process hyperspectral remote sensing images. Contains. Hyperspectral images, unlike ordinary pictures have a multitude of spectrum information that can reveal the chemical makeup and physical makeup of objects fascinating and cause image dispersion. The greatest advanced research in the hyperspectral field is hyperspectral photography analysis, in which Image categorization using computerized remote sensing is used to identify and analyze captured images of the Earth's surface and surrounding data, thereby identifying the characteristics of the image files and extracting the desired data properties.

3 Methodology

3.1 Image Quality

Interference impacts the data's quality due to noise and background obtained during hyperspectral image acquisition. The Hughes effect may be exacerbated by the small size hyperspectral picture data and the absence of domain names. People concentrated on spectral data and only used Spectral information was used in the early studies of hyperspectral image classification to carry out image classification. Support vector machines (SVM) and random forests (RF)), neural network, and so on. Manual analysis of satellite and aerial images was previously possible, owing to the scarcity of images; however, this is no longer the case. As a result, extracting relevant information from images has become a problem in today's big data environment. An important aspect of this problem is the annotated (or tagged)) process, which finds patterns and structures in satellite data images. This document explains how to interpret satellite images in order to categorize them into four different domains: water bodies, green areas, air, and desert. This translation has a wide range of applications. The proposed model has higher accuracy, which is supported by empirical results. A comparison with some deep learning models was also performed to ascertain whether component of the suggested model is optimal. This paper presents a network-based image classification algorithm that has been shown to outperform other methods. This new method not only improves classification accuracy but also lowers the model's training cost.

3.2 Neural Network

Although neural networks have been around for decades, they have only gained attention from the computer vision and machine learning communities in recent years. First, an overview of neural networks is presented. The author stated that “neural networks are computational systems composed of many simple, interconnected processes that process information, from dynamic responses to external inputs.” Very roughly, one way to think of neural network algorithms as:

Based on the architecture of brain neurons Many people imagine networks as layers of neurons layered on top of one another or neurons) act as mechanisms of activation. The figure depicts a basic three-layer neural network. For a variety of vision-related tasks, the neural network can be thought of as learning models from raw data (pixel-related in our results).

The following definition of the objectives can be used for this purpose:

1. A concise examination regarding computer vision using neural network technology.
2. Create a deep neural network capable of generating semantically segmented picture maps by consuming data.
3. Compare various neural network models described in the literature. Developing and improving existing models to solve existing problems (Transformation)
4. Examine the network training on various datasets to determine its overall capabilities.
5. It analyzes existing satellite images in depth.
6. Deep learning models are used to interpret satellite images.
7. Compares the planned process with the state-of-the art technology (Fig. 2).

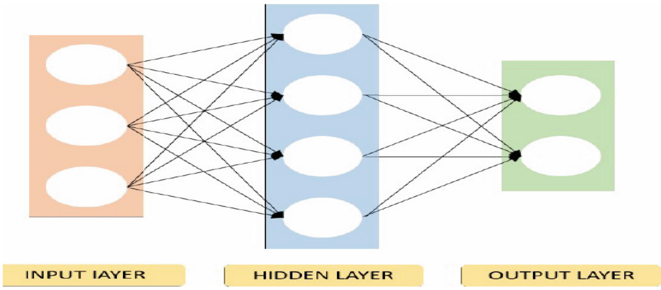

Fig. 2. Neural Network

3.3 Satellite Image Classification

In this study, dataset-RSI-CB256 was used. This is a public information collection that can be found at. This data is divided into four groups based on sensor and Google Maps snapshots. Each image is 256 $\times$ 256 pixels in size (Fig. 3).

It also distinguishes between common and distinct data t-distributed stochastic neighborhood embedding classes (T-SNE). High-dimensional data points can be mapped to two- or three-dimensional spaces using TSNE visualization. T-SNE preserves as much as possible the balance of high-dimensional data points in low-dimensional space.

Fig. 3. Shows the category distribution of the data

3.3.1 Semantic Segmentation

Over the years, features have been defined in various ways, but the basic process has remained the same: analyze images to identify objects and determine their significance. Semantic segmentation, object location and detection, instance segmentation, and image classification are the most common learning problems arising from data visualization. The process of combining the image so that each group of pixels in the image in line with the item category among the entire assembly is then defined as semantic segmentation. The object class corresponds to the path and background in the current study. The pile can also be placed on homes, lawns, garages, and other fissile surfaces. The rest of this chapter discusses recent developments in semantic segmentation solutions and data applications for satellite/aerial imagery.

4 Implementation of Modules

4.1 Dataset

Using a same dataset for training and testing also critical to comprehend how the model functions on another. This section outlines the process for creating A second, far more compact dataset that will be used to evaluate the models used in this piece. Previous research's labels pertaining to using satellite or aerial photography to learn, for example, relied on Open Street Map, a project to produce and provide open-access geospatial data (street maps included) to anybody. Rasterizing vector graphic maps extracted from Open Street Map resulted in per-pixel labels. It was observed that prediction quality was impacted by the arbitrary nature of the conversion process utilized, and therefore also in this work. A similar technique is used to generate a road map from the road maps provided in the OSM database. Data selection and loading:

- Data selection is the process of selecting hyperspectral image data, which was used in this project.
- Hyperspectral images were used in this project.

- The file contains information regarding testing, training and visual effects. 2.1.3. Previous information (Fig. 4):

Fig. 4. Datasets

The preceding data has been enhanced by the addition of randomization and jitter compensation. We can improve it by utilizing the dataset's unique features. In the case of segmentation based on satellite images, for example, the orientation of the picture is unimportant. First of all, spins and spins can only be of assistance to broaden institution without having a negative impact. Further advancements can be made, for example, by accounting for the orbital parameters of a specific satellite photographer. Randomly rotate and jitter to increase the training size by 9000 times. To eliminate redundant data, the received data is first routed through a pipeline. This includes basic training set normalization and mean centering. Before feeding into the pipeline, the standard deviation is divided by the R-G-B image mean after it has been subtracted from each training set.

4.2 Split the Dataset into Training Data Testing Data

- The process of splitting the present data into two halves is known as data splitting, and it is usually done for cross-validation purposes.
- A piece of the data is utilized for the prediction model's construction, while another portion is used to evaluate the model's effectiveness.
- Generally speaking, the majority of the data is used for training and the remaining portion is used for testing when the data set is divided into training and test sets.

4.3 CNN

- Using appropriate filters, Convolutional Networks can effectively capture spatial and temporal dependencies in images. The design can be optimized for the image dataset by reducing the number of parameters and reusing weights.
- This is the process of forecasting based on hyperspectral images.
- Through enhancing the accuracy of each prediction result, this project will efficiently forecast data stored in the database (Fig. 5).

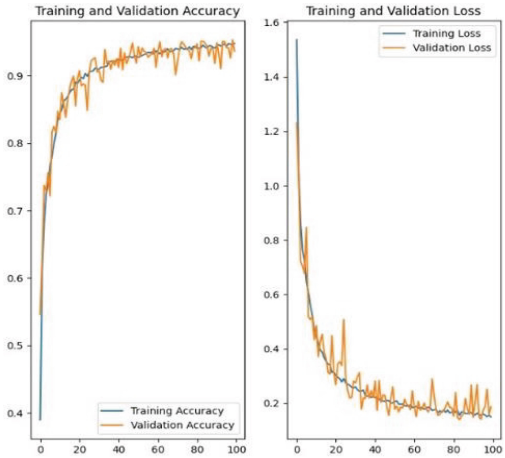

Fig. 5. Training and Validation Accuracy

4.4 Result Generation

Based on the entire distribution and result generation, the final result will be estimated. To assess the effectiveness of this method, use metrics such as;

- Accuracy
- Precision
- Recall
- F-Measure
- Confusion Matrix (Fig. 6)

4.5 Advantages

- High performance;
- Hyperspectral images improve accuracy;
- Time is reduced

```
 Modified Deep CNN-BiLSTM with attention mechanism   Acuracy is : 95.8 %
classification_report:
              precision    recall  f1-score   support

           0       0.93      1.00      0.96       516
           1       1.00      0.92      0.95       484

    accuracy                           0.96      1000
   macro avg       0.96      0.96      0.96      1000
weighted avg       0.96      0.96      0.96      1000

[[515   1]
 [ 41 443]]
```

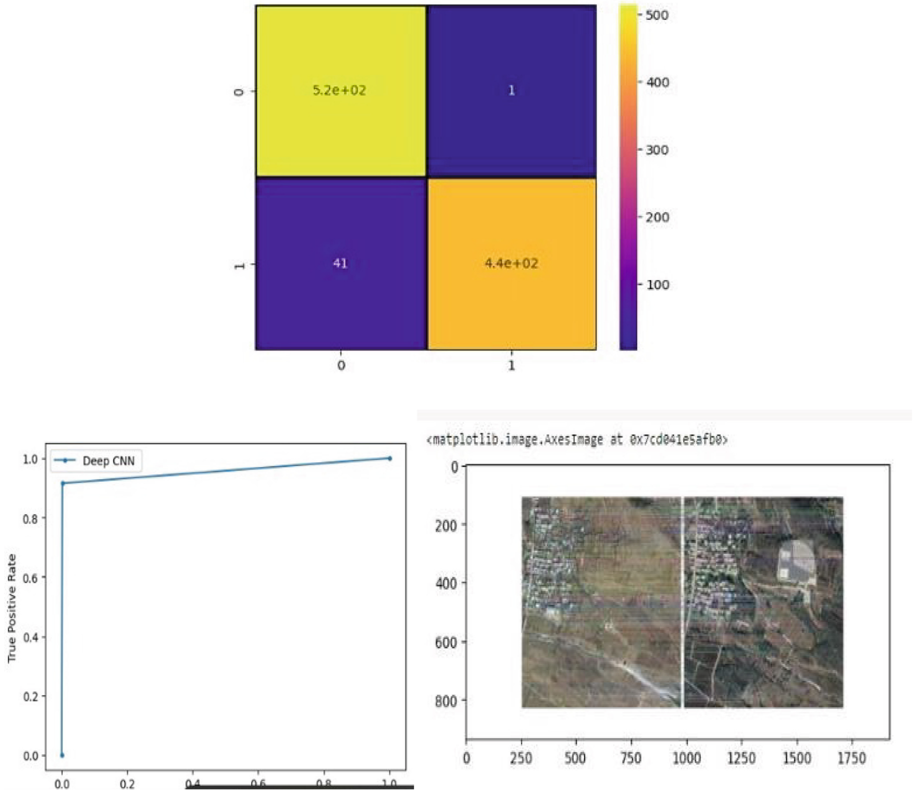

Fig. 6. Accuracy result of evaluate the effectiveness of hyperspectral images

5 Conclusion

The primary goal of this project is to use satellite image data to better understand the design, implementation, and evaluation of deep-water pipelines. The categorization and examination of hyperspectral pictures are crucial part utilizing hyperspectral image processing in our investigation. This article explains different approaches to the classification of hyperspectral images, such as supervised, unsupervised, and semi-supervised classification. Although the supervised and unsupervised classification methods discussed in this article have distinct advantages, each method's application has limitations. This research can be expanded by using different materials. It can also examine more than four satellite images at once. Other deep learning models can be defined as well. A fascinating study would be to investigate the effect of various bone structures on Efficient Nets. Image classification can also be done with multi-resolution remote sensing image models. Many data solutions are becoming increasingly expensive. Multiple problem solutions that make use of large amounts of data would be extremely beneficial. Introduction to the use of deep learning technology and the creation of deep pipelines for satellite imagery. This project started with gathering valid data and thinking about ways to improve deep learning models. A comparison of various neural network architectures listed in the literature. To understand the training network's overall capabilities, run it through various datasets. Using the standard testing method, the model was evaluated on samples from the unobserved Prague dataset as well as the Massachusetts dataset. These are compared to provide the final model evaluation.

References

1. Teng, M.Y., Mehrubeoglu, R., King, S.A., Cammarata, K., Simons, J.: Investigation of epifauna coverage on seagrass blades using spatial and spectral analysis of hyperspectral images. In: 2013 5th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS), Gainesville, FL, USA, pp. 1–4 (2013)
2. Ke, C.: Military object detection using multiple information extracted from hyperspectral imagery. In: 2017 International Conference on Progress in Informatics and Computing (PIC), Nanjing, China, pp. 124–128 (2017)
3. Notesco, G., Ben Dor, E., Brook, A.: Mineral mapping of Makhtesh Ramon in Israel using hyperspectral remote sensing day and night LWIR images. In: 2014 6th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS), Lausanne, Switzerland, pp. 1–4 (2014)
4. Pike, R., Lu, G., Wang, D., Chen, Z.G., Fei, B.: A minimum spanning forest-based method for noninvasive cancer detection with hyperspectral imaging. IEEE Trans. Biomed. Eng. **63**(3), 653–663 (2016)
5. Zhang, X., Zhang, A., Meng, X.: Automatic fusion of hyperspectral images and laser scans using feature points. J. Sens. **2015**, 9, Article ID 415361 (2015)
6. Kwon, H., Hu, X., Theiler, J., Zare, A., Gurram, P.: Algorithms for multispectral and hyperspectral image analysis. J. Electr. Comput. Eng. **2013**, 2, Article ID 908906 (2013)
7. Ma, Y., Li, R., Yang, G., Sun, L., Wang, J.: A research on the combination strategies of multiple features for hyperspectral remote sensing image classification. J. Sens. **2018**, 14, Article ID 7341973 (2018)

8. Binol, H.: Ensemble learning based multiple kernel principal component analysis for dimensionality reduction and classification of hyperspectral imagery. Math. Probl. Eng. **2018**, 14, Article ID 9632569 (2018)
9. Li, S., Song, W., Fang, L., Chen, Y., Ghamisi, P., Benediktsson, J.A.: Deep learning for hyperspectral image classification: an overview. IEEE Trans. Geosci. Remote Sens. **57**(9), 6690–6709 (2019)
10. Camps-Valls, G., Bruzzone, L.: Kernel-based methods for hyperspectral image classification. IEEE Trans. Geosci. Remote Sens. **43**(6), 1351–1362 (2005)
11. Camps-Valls, G., Bandos Marsheva, T.V., Zhou, D.: Semi supervised graph-based hyperspectral image classification. IEEE Trans. Geosci. Remote Sens. **45**(10), 3044–3054 (2007)
12. Hughes, G.: On the mean accuracy of statistical pattern recognizers. IEEE Trans. Inf. Theory **14**(1), 55–63 (1968)
13. Wang, X., Feng, Y.: New method based on support vector machine in classification for hyperspectral data. In: 2008 International Symposium on Computational Intelligence and Design, Wuhan, China, pp. 76–80 (2008)
14. Fu, A., Ma, X., Wang, H.: Classification of hyperspectral image based on hybrid neural networks. In: 2018 IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2018, Valencia, Spain, pp. 2643–2646 (2018)
15. Li, J., Bioucas-Dias, J.M., Plaza, A.: Semi supervised hyperspectral image segmentation using multinomial logistic regression with active learning. IEEE Trans. Geosci. Remote Sens.Geosci. Remote Sens. **48**(11), 4085–4098 (2010)