Intelligent Satellite Image Classification Using Deep Convolutional Neural Networks

Manoj Bhaskar[1], Chetan Barde[1], Prakash Ranjan[1] Nawneet Kumar[1] and Sujit Kumar[2]

[1]*Dept. of Electronics and Communication Engineering, Indian Institute of Information Technology Bhagalpur, Bhagalpur, Bihar, India*

[2]*Dept. of Electrical Engineering, Government Engineering College Banka, Bihar Engineering University, Science, Technology and Technical Education Department, Bihar, India*

Keywords: Satellite Image, Classification, Deep Learning, Batch Normalization.

Abstract: Image classification plays a key role in remote sensing, image analysis, and pattern recognition. Detecting and classifying objects in satellite images is vital for applications like marine monitoring, land use planning, ecological studies, and military operations. Satellite images, with their rich spatial and temporal information, help address many real-world challenges. However, classifying these images is challenging due to limited data availability, varying quality, and uneven distribution. Deep learning (DL) algorithms have become popular for satellite image classification because of their effectiveness in tasks such as land-use planning, disaster response, and resource management. This study introduces a deep convolutional neural network (DCNN) model combined with batch normalization (BN) for classifying satellite images. The dataset includes images from remote sensing satellites categorized into four classes: cloudy regions, deserts, water bodies, and green areas. CNNs are well-suited for image processing, as they automatically extract key features like edges and textures. Batch normalization improves training by stabilizing inputs within the network layers, making the process faster and more efficient. Our proposed model demonstrates high accuracy in classifying satellite images, achieving an overall performance of 94.50%, outperforming existing methods. This shows its potential for real-world applications.

1 INTRODUCTION

Satellite image processing involves analyzing data collected by Earth-orbiting satellites using sensors like cameras and radar. These images provide valuable insights into weather, land use, and more (Voigt, 2007) (Nguyen, 2019). A major challenge is handling the vast amount of data generated by these sensors, which is too complex for manual processing. Advanced algorithms are used to interpret the images, applying techniques like enhancement, classification, and feature extraction (Fu, 2018). These methods are widely used in fields like environmental monitoring, agriculture, and urban planning, helping track changes in crops, urban areas, and forests (Singh, 2022) (Padmanaban, 2019).

Satellite image processing involves analyzing data captured by Earth-orbiting satellites using sensors like cameras and radar. These images provide valuable insights into weather patterns, land use, and other critical aspects of Earth's surface. However, the sheer volume of data generated by satellite sensors presents a major challenge. Advanced computer algorithms are necessary to process and interpret this complex data effectively. Key techniques include image enhancement, feature extraction, and classification. Feature extraction identifies specific elements in an image, such as roads or buildings, making it useful for applications in environmental monitoring, agriculture, and urban planning. For example, satellite images are used to track crop health, urban growth, and deforestation rates. With technological advances, satellite image processing continues to play a vital role in managing Earth's resources.

Deep learning has emerged as a powerful tool for satellite image classification. Inspired by the human brain, deep learning uses neural networks with multiple layers—input, hidden, and output layers (Diker, 2022). These networks process data through interconnected neurons using weights, biases, and activation functions like ReLU, sigmoid, or tanh. This

Bhaskar, M., Barde, C., Ranjan, P., Kumar, N. and Kumar, S.
Intelligent Satellite Image Classification Using Deep Convolutional Neural Networks.
DOI: 10.5220/0013616500004664

In *Proceedings of the 3rd International Conference on Futuristic Technology (INCOFT 2025) - Volume 3*, pages 354-359
ISBN: 978-989-758-763-4

structured approach enables deep learning models to extract meaningful features and classify satellite images efficiently. Several studies demonstrate the advancements in satellite image processing using deep learning. (Tripodi, 2022) developed an automated pipeline for 3D reconstruction of landscapes from high-resolution satellite images. This method used convolutional neural networks (CNNs) to extract semantic features and classify data into 16 categories, producing detailed 3D maps. Similarly, (Anggiratih, 2019) combined the ZFNet CNN architecture with the Random Forest algorithm to enhance feature extraction and classification. While the model achieved 87.5% accuracy for large vessel detection, it struggled with smaller vessels, achieving less than 50% accuracy. (Munirah Alkhelaiwi, 2021) introduced privacy-preserving deep learning (PPDL) to safeguard sensitive satellite image data. Their approach allowed CNN models to train directly on encrypted data without significant computational overhead. Testing on a dataset from Saudi Arabia demonstrated that the method effectively balanced data utility and privacy. (Ghazaleh Serati, 2022) applied a conditional generative adversarial network (CGAN) to extract building footprints in Yangon City, Myanmar, using optical satellite images. Their model achieved 71% completeness, 81% correctness, and an F1 score of 69% for building footprint extraction, demonstrating the potential of CGANs for urban mapping tasks. (Ashwini, 2023) developed an ensemble method for classifying satellite images into categories such as Cloudy, Desert, Water, and Green areas. The approach combined confidence scores from four classifiers—Decision Tree, Random Forest, Gaussian Naïve Bayes, and Support Vector Classifier—achieving an overall accuracy of 92%. (T. Yogesh, 2024) used a dataset of 5,631 satellite images to classify cloud-covered areas, deserts, green landscapes, and water bodies. They employed the VGG-16 CNN architecture, achieving high validation accuracy and showcasing the potential of deep learning for satellite image classification.

These advancements highlight the importance of deep learning in improving the accuracy and efficiency of satellite image processing. Techniques like CNNs, ensemble classifiers, and generative networks are continuously pushing the boundaries of what can be achieved, making satellite image analysis a crucial tool for addressing real-world challenges.

This research focuses on improving satellite image classification using a DCNN combined with batch normalization (BN). DCNN have emerged as a pivotal tool in modern machine learning, particularly for tasks involving image and signal processing. Their ability to automatically extract and learn hierarchical features from raw input data makes them highly effective for complex pattern recognition problems. DCNN leverage multiple convolutional layers to capture intricate spatial and temporal relationships in the data. BN enhances this process by keeping the feature distributions stable, which helps the model train faster and more effectively. Together, DCNN and BN enable the model to handle large and complex datasets while ensuring accurate results. The model is designed to classify satellite images into four categories: water bodies, green areas, cloudy regions, and deserts. Experimental results show that the proposed model achieves high accuracy in classification. The study also compares its performance with other deep learning methods, demonstrating that the proposed approach is more effective.

The study presents a DCNN model combined with batch BN to enhance the classification of satellite images. CNNs are effective for image classification as they automatically extract important features from images and classify them accurately. Batch normalization improves the learning process by ensuring the features maintain consistent distributions, which stabilizes and speeds up the training. This combination helps the model learn strong and reliable features, enabling accurate classification of large and complex image datasets. The model successfully categorizes satellite images into four types: water bodies, green areas, cloudy areas, and deserts. The proposed model achieves high accuracy, which is validated by experimental results. The model is also compared with other deep learning methods to demonstrate its effectiveness. The paper is organized as follows: Section 1 provides an introduction to various satellite image classification approaches. Section 2 outlines the proposed methodology for satellite image classification. Section 3 presents the results and discussion of the classification model, and Section 4 concludes the work.

2 DATA DESCRIPTION

This study used the RSI-CB256 dataset for satellite image classification. The dataset is publicly available online and referenced in (Available online, 2022). Fig. 1. shows sample images from the dataset, which contains 2,000 satellite images evenly divided into four categories: 500 images each for cloudy regions, desert areas, green areas, and water bodies. These categories are labeled as follows: cloudy regions are Class 1, desert areas are Class 2, green areas are Class 3, and water bodies are Class 4.

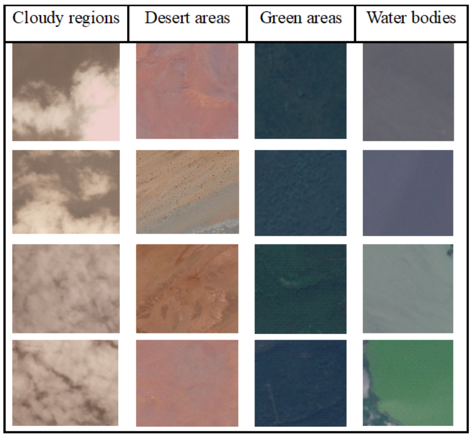

Figure 1: Samples of satellite images from Dataset-RSI-CB256.

3 METHODOLOGY

This research focuses on classifying satellite images into four types of terrain using a DCNN model combined with BN. The process starts with a satellite image as input, which is then classified into one of the four terrain categories. The methodology involves three steps: pre-processing the images, extracting feature maps, and classifying the images based on these features. Fig. 2. illustrates the basic structure of the CNN model, which includes three main layers: convolutional layers for feature extraction, pooling layers for reducing data size, and fully connected layers for final classification (Ozbay, 2023) (Onal, 2020).

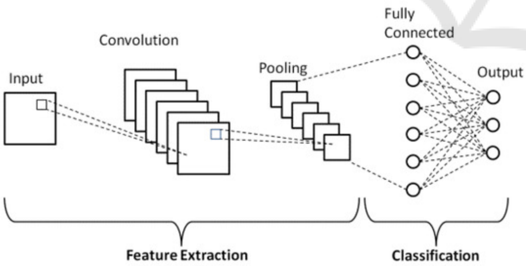

Figure 2: Basic architecture of CNN

The framework of the proposed model is depicted in Fig. 3. It begins by processing the input image as a matrix. The convolutional layer extracts features from the image by sliding filters across it, performing matrix multiplications at each position, and creating a feature map that highlights specific characteristics of the image. Next, the pooling layer reduces the size of the feature map while retaining essential information, often using max pooling to capture the most significant values. The batch normalization layer stabilizes the inputs across layers by normalizing them based on batch mean and variance (Yamashita, 2018) (Narin, 2021) This helps mitigate internal covariate shifts, speeds up convergence, allows for higher learning rates, reduces overfitting (often eliminating the need for dropout), and improves overall classification performance, particularly for satellite image classification tasks. The flattening layer then converts the matrix data from the previous layers into a single vector, making it suitable for processing in fully connected layers. The fully connected layer processes this vector by associating it with learned weights and applying an activation function, enabling the model to identify high-level features necessary for classification. Finally, the output layer classifies the input image into specific categories. It uses fully connected neurons to predict class probabilities and applies a SoftMax classifier at the end to select the category with the highest probability as the model output. The DCNN architecture, with BN, is designed for accurate classification, effectively mapping complex image data into categories.

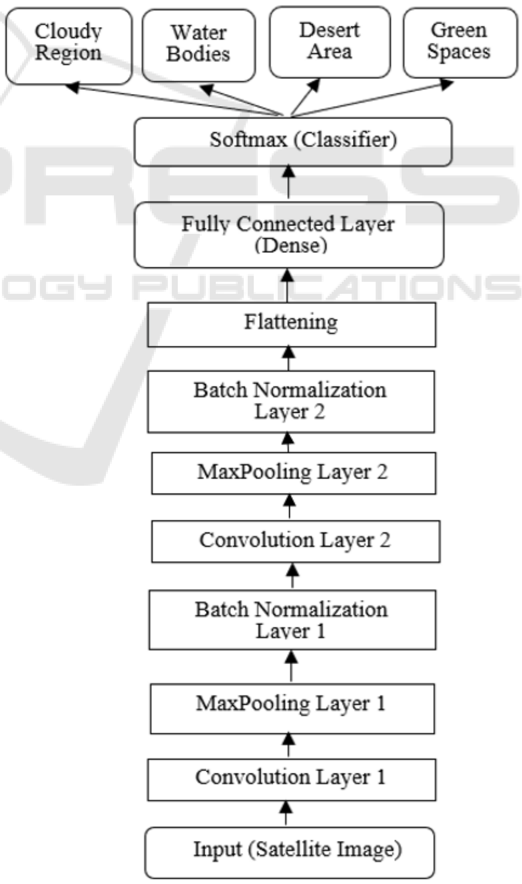

Figure 3: The framework of the proposed model.

4 EVALUATION OF THE PROPOSED MODEL

The performance of the proposed model is measured using metrics like Accuracy, Precision, Recall, and F1 score, all derived from a multi-class confusion matrix (Musali, 2024). The confusion matrix provides a detailed evaluation of the model performance by comparing predicted labels (shown in rows) with true labels (shown in columns). It highlights correct predictions on its diagonal and is essential for calculating the key performance metrics. Figure 4 presents the confusion matrix for the proposed CNN model, showing an accuracy of 94.50%. Table 1. summarizes the performance metrics, including the precision, recall, and F1 score, demonstrating the effectiveness of the model in classifying satellite images accurately.

Table 1: Performance score of the proposed model

	Precision	Recall	F1-score
Cloudy regions (Class 1)	1.00	O.97	0.98
Desert areas (Class 2)	0.97	1.00	0.99
Green areas (Class 3)	0.85	0.99	0.91
Water bodies (Class 4)	0.99	0.82	0.90

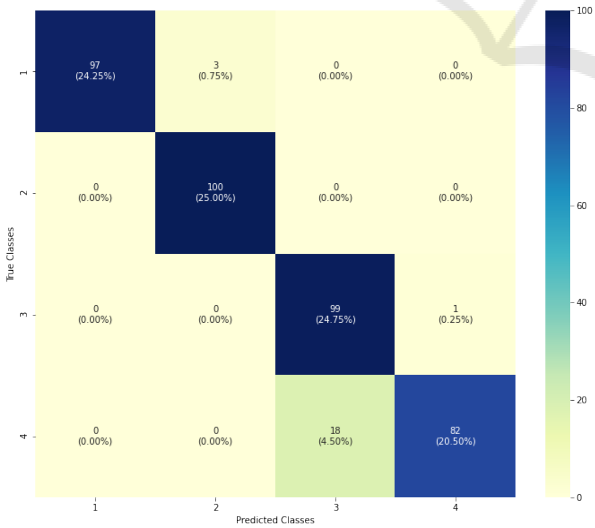

Figure 4: Confusion matrix of the proposed model.

Fig. 5. shows the accuracy of the developed CNN model, with the best training and validation accuracy achieved at 150 epochs. This plot illustrates how the model's accuracy improves as it trains, reaching 92.80%. Fig. 6. presents the model's loss, which shows the decrease in the error between the model's predictions and the actual target values on the training data. The loss stabilizes at around 150 epochs, reaching 84.75%, indicating that the model is learning effectively. Together, these figures reflect the model's learning process and how it improves over time. Fig. 7. shows the Learning Rate vs. Epoch plot, which tracks how the learning rate changes during training. The learning rate controls the size of adjustments the model makes to its weights based on errors. If the learning rate is too high, the model can make large, unstable changes, while a low rate can slow down progress. Adjusting the learning rate throughout training, using methods like learning rate decay, helps the model find a balance between fast learning and stability, ultimately improving performance and accuracy

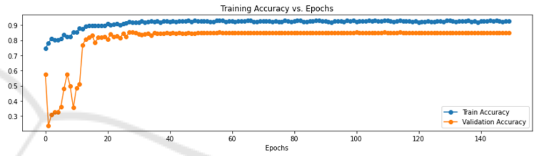

Figure 5: Model accuracy of the proposed model.

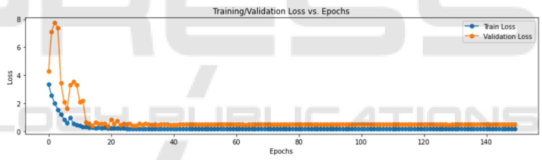

Figure 6: Model loss of the proposed model.

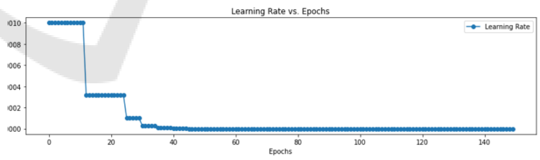

Figure 7: Model learning rate of the proposed model.

5 TRAINING, VALIDATION AND TESTING OF THE MODEL

The dataset used in this study consists of remote sensing satellite images, which are divided into four categories: cloudy regions, desert areas, water bodies, and green spaces. To prevent overfitting, a dropout rate of 0.2 is applied in the hidden layer, which helps the model generalize better and speeds up the learning process. During training, the Adam optimizer is used to adjust the weights and biases of the model. A fully connected dense layer with a Softmax activation function is then used to classify the images into one of the four categories. The model is implemented using TensorFlow version 1.0, with 80% of the data used for training. A small portion of the training data is also set aside for validation, while the remaining 20% is reserved for testing the model's performance.

6 RESULTS AND DISCUSSION

This study introduces a DCNN architecture combined with BN for classifying satellite images. The dataset used in this study consists of images from remote sensing satellites, categorized into four classes: cloudy regions, desert areas, water bodies, and green spaces. The performance of the proposed model is compared with traditional statistical methods and other deep learning models. Table 2. shows that our CNN model achieves the highest accuracy in satellite image prediction, with an accuracy of 94.50%. In comparison, the RNN, which is often used for time series forecasting, had lower performance in this task. The other methods tested, including SVM, Random Forest, KNN, Decision Tree, PPDL, VGG16, ResNet50, and DenseNet121, achieved accuracies of 72.84%, 84.20%, 80.56%, 75.33%, 90.92%, 89.00%, 89.80%, and 90.50%, respectively.

Table 2: Comparison of results with existing methods

Methods	**Accuracy (%)**
SVM	72.84
Random Forest	84.20
KNN	80.56
Decision Tree	75.33
PPDL Techniques	90.92
VGG16	89.00%
ResNet50	89.80%
DenseNet121 [9]	90.50%
The Proposed Model	**94.50%**

7 CONCLUSIONS

In this study, a DCNN model with BN is proposed to classify satellite images into four categories: cloudy regions, desert areas, water bodies, and green spaces. Satellite images are commonly used to solve various problems in remote sensing, but classifying them can be difficult due to issues like data availability, quality, quantity, and distribution. Traditional methods often struggle to handle these challenges accurately. To improve the classification accuracy, a new approach is introduced that combines feature generation, feature selection, and model design. The proposed BN-based CNN model is effective in capturing complex patterns in satellite images, achieving better results during training and testing compared to other methods using the same dataset. The results show that this model is highly effective for satellite image classification. The study also suggests that future research should focus on reducing the model's complexity and further improving its performance, with batch normalization playing a key role in enhancing stability and speeding up training.

ACKNOWLEDGMENT

The author would like to thank Dilara Ozdemir for providing the Satellite Remote Sensing Image dataset RSI-CB256, which includes categories such as cloudy regions, desert areas, water bodies, and green areas, and is available in resources like the GitHub repository by Dilara Ozdemir.

REFERENCES

Voigt, Stefan, Thomas Kemper, Torsten Riedlinger, Ralph Kiefl, Klaas Scholte, and Harald Mehl. (2007). Satellite image analysis for disaster and crisis-management support. IEEE transactions on geoscience and remote sensing. vol. 45, no. 6 pp. 1520-1528. IEEE

Nguyen, Thi Mai, Tang-Huang Lin, and Hai-Po Chan (2019). The environmental effects of urban development in Hanoi. Vietnam from satellite and meteorological observations from 1999–2016. Sustainability. vol. 11, no. 6 pp. 1768.

Fu, Hualian, Yuan Shen, Jun Liu, Guangjun He, Jinsong Chen, Ping Liu, Jing Qian, and Jun Li. (2018). Cloud detection for FY meteorology satellite based on ensemble thresholds and random forests approach. Remote Sensing, vol. 11, no. 1, pp. 44.

Singh, Kamal Kant, Dhiraj Kumar Singh, Narinder Kumar Thakur, Sanjay Kumar Dewali, Harendra Singh Negi, Snehmani, and Varunendra Dutta Mishra. (2022). Detection and mapping of snow avalanche debris from Western Himalaya, India using remote sensing satellite images. Geocarto International. vol. 37, no. 9, pp. 2561-2579.

Padmanaban, Rajchandar, Avit K. Bhowmik, and Pedro Cabral. (2019). Satellite image fusion to detect changing surface permeability and emerging urban heat islands in a fast-growing city. PloS one, vol. 14, no. 1, pp. e0208949.

Diker, Fadime, and İlker Erkan. (2022). Classification of satellite images with deep convolutional neural networks and its effect on architecture. Eskişehir Technical University Journal of Science and Technology A-Applied Sciences and Engineering. vol. 23, pp. 31-41.

Tripodi, S., N. Girard, G. Fonteix, L. Duan, W. Mapurisa, M. Leras, F. Trastour, Y. Tarabalka, and L. Laurore (2022). Brightearth: Pipeline for on-the-fly 3D reconstruction of urban and rural scenes from one satellite image. ISPRS Annals of the Photogrammetry. Remote Sensing and Spatial Information Sciences. vol. 3, pp. 263-270.

Anggiratih, Endang, and Agfianto Eko Putra. (2019). Ship identification on satellite image using convolutional neural network and random forest," IJCCS (Indonesian Journal of Computing and Cybernetics Systems), vol. 13, no. 2, pp. 117-126.

Alkhelaiwi, Munirah, Wadii Boulila, Jawad Ahmad, Anis Koubaa, and Maha Driss. (2021). An efficient approach based on privacy-preserving deep learning for satellite image classification. Remote Sensing. vol. 13, no. 11 pp. 2021.

Ghazaleh Serati, Amin Sedaghat, Nazila Mohammadi and Jonathan Li. (2022). Digital surface model generation from high-resolution satellite stereo imagery based on structural similarity. Geocarto International. vol. 37, no. 26, pp. 11390-11419.

Ashwini, K., R. Bhuvaneswari, and Perla Sree Neha. (2023). Remote Sensing Image Classification Based on Confidence Score of Ensemble Machine Learning Classifiers. In 2023 International Conference on Evolutionary Algorithms and Soft Computing Techniques (EASCT). pp. 1-6. IEEE.

T. Yogesh and S. V. S. Devi. (2024). Enhancing Remote Sensing Image Classification: A Strategic Integration of Deep Learning Technique and Transfer Learning Approach. Second International Conference on Data Science and Information System (ICDSIS), Hassan, India, pp. 1-5.

Available online: https://www.kaggle.com/datasets/mahmoudreda55/satellite-image-classification (accessed on 20 October 2022).

Özbay, Erdal, and Muhammed Yıldırım. . (2023). Classification of satellite images for ecology management using deep features obtained from convolutional neural network models. Iran Journal of Computer Science. vol. 6, no. 3, pp. 185-193.

Önal, Merve Kesım, Engin Avci, Fatih Özyurt, and Ayhan Orhan. (2020). Classification of minerals using machine learning methods. In 2020 28th Signal Processing and Communications Applications Conference. (SIU), pp. 1-4. IEEE.

Yamashita, Rikiya, Mizuho Nishio, Richard Kinh Gian Do, and Kaori Togashi. (2018). Convolutional neural networks: an overview and application in radiology. Insights into imaging. vol.9, pp. 611-629.

Narın, Derya, and Tuğba Özge Onur. (2021). Investigation of the effect of edge detection algorithms in the detection of covid-19 patients with convolutional neural network-based features on chest x-ray images. In 2021 29th Signal Processing and Communications Applications Conference, (SIU), pp. 1-4. IEEE.

Ioffe, Sergey. (2015). Batch normalization: Accelerating deep network training by reducing internal covariate shift. arXiv preprint arXiv:1502.03167.

Musali, Suresh Kumar, Rajeshwari Janthakal, and Nuvvusetty Rajasekhar. (2024). Holdout based blending approaches for improved satellite image classification. International Journal of Electrical and Computer Engineering (IJECE) vol. 14, no. 4 (2024): 3127-3136.