Journal of Information Systems Engineering and Management
2025, 10(50s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Machine Learning-Based Classification of Geographical Landscape for Precision Cartographic Representation

Suresh G B[1], Shruthi M K[2], Basantha Kumari[3]

[1]*Sr. Faculty, College of Computing and Information Sciences, University of Technology and Applied Science -Ibra, Sultanate of Oman*
Email: gbsuresh@yahoo.com

[2]*Associate Professor, Department of Computer Science and Engineering, SJMIT,Chitradurga, Karnataka, India*
Email: shruthimk@sjmit.ac.in

[3]*Associate Professor, Department of Computer Science and Engineering, SJMIT,Chitradurga, Karnataka, India*
Email: basanthisarathi@sjmit.ac.in

ARTICLE INFO

Submitted: 20 Dec 2024

Received: 12 Feb 2025

Accepted: 22 Feb 2025

ABSTRACT

The classification of aerial imagery through automation plays an essential role in areas like environmental monitoring, urban planning, and disaster response. This study introduces a method utilizing a convolutional neural network (CNN) to classify aerial landscape images, leveraging the SkyView Aerial Landscape Dataset. The suggested pipeline includes streamlined preprocessing, immediate data enhancement, and a simple but powerful CNN architecture crafted with the TensorFlow-Keras framework. The model underwent training and validation using an 80/20 split of the dataset, reaching a training accuracy of about 98% and a validation accuracy of 91%, which suggests a robust ability to generalize. Data augmentation techniques, such as random flipping, rotation, zoom, and contrast adjustments, greatly improved model robustness. The confusion matrix analysis showcases the model's overall dependability while uncovering slight difficulties in distinguishing between visually similar classes.

Keywords: CNN, Machine Learnng, Geographical Landscape, Cartographic

INTRODUCTION

Maps are needed to share and show geographical data across different areas, like urban development, ecological observation, and emergency response [1]. In the past, recognizing geographical features like coastlines, water bodies, ridgelines, and elevation lines depended on manual extraction or rule-based methods. Scaling these methods can be hard, they can be prone to mistakes, and they often take a lot of work. In mapping and geospatial analysis, it is very important to correctly identify and describe these contours in order to make maps that are easy to read and understand.

Recent progress in machine learning, especially deep learning, has shown that it can do a great job of automatically extracting features and classifying data from remote sensing sources like satellite images and digital elevation models. These methods can make contour classification more accurate and efficient by building on what has come before. ML models can understand complicated spatial patterns and contextual details, which helps them tell the difference between different geographic features more clearly [6].

Even with these improvements, using ML for contour classification is still not easy. Some important things to think about are how different areas are geographically, the lack of labeled contour datasets, and how hard it is to add classified features to current mapping methods. To solve these problems, we need strong ML models that can understand and represent contour data and adapt to different types of terrain.

- Aimed at improving accuracy in cartographic representation, this paper offers a framework for the automated classification of geographical contours using machine learning. This paper makes several important contributions:
- Designing and evaluating a machine learning model meant to categorize significant geographic features from satellite pictures and digital elevation models.

Journal of Information Systems Engineering and Management
2025, 10(50s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

- Examining the variations with traditional classification techniques to assess how effectively the proposed method works. Examining how the categorized contours might be smoothly integrated into present cartographic processes to emphasize their effect on precise mapping.

The structure of this article is as follows. Relevant research is summarized in Section 2. The issue is stated in Section 3 along with the objectives. Covering data preparation, feature selection, and the design of the machine learning model, Section 4 describes the approach followed. Section 5 offers the results and discussion. Ultimately, Section 6 finishes the article and suggests possible next steps.

LITERATURE REVIEW

Accurate classification of geographical contours is a long-standing task in cartography and remote sensing. Traditional methods rely on manual delineation or heuristic algorithms applied to Digital Elevation Models (DEM), contour maps, or satellite imagery. These methods, while useful, are often limited in precision and scalability, especially when handling complex or large-scale datasets [8].

• Traditional Methods for Contour Extraction and Classification

Traditional methods for contour extraction from DEMs and topographic maps include edge detection algorithms, morphological processing, slope and aspect analysis, and heuristic rule-based methods [8, 9]. The Marching Squares algorithm remains a classical approach for contour line generation [8], while GIS software like ArcGIS provides semi-automatic tools for contour extraction using elevation data [10]. However, these methods are often sensitive to noise, require human supervision, and struggle with complex or irregular landforms. Efforts have also been made to classify extracted contours into categories like ridgelines, valleys, or coastlines using rule-based systems, but these methods lack scalability and adaptability to new geographical areas [11].

• Machine Learning and Deep Learning-Based Approaches

The application of machine learning has significantly increased specially in the areas of remote sensing and geospatial data analysis in voew of geographcal struggles among several nation states. Random Forest and Support Vector Machine models have been utilized for landform classification, employing features obtained from Digital Elevation Models. However, these methods depend heavily on features that are manually crafted and oftenly have limited adaptability across different environments.

Deep Learning models, especially Convolutional Neural Networks, have been utilized for extracting features and classifying remote sensing imagery. In order to extract contour lines from DEMs, Zhang et al. [5] developed a CNN model, which outperformed traditional techniques. Li et al. [14] utilized a U-Net-based model for extracting river networks from high-resolution imagery, which could be modified for contour extraction tasks. More recently, Graph Neural Networks (GNNs) have been explored to model spatial relationships between contours, achieving improved contour classification performance [6], [15]. Generative models like GANs have also been proposed for enhancing contour line clarity and for simulating realistic contour patterns in cartographic applications [16]. Despite these advances, many studies focus primarily on extraction or classification in isolation. Integration of ML-based classification into cartographic workflows remains limited [7], [17]. Table I below represent a detailed summary of such works.

Table I: Review of Related Works

Ref.	Method	Data Used	Application	Limitations
[8]	Marching Squares algorithm	DEM	Contour extraction	Sensitive to noise, lacks classification
[9]	Slope/aspect rule-based classification	DEM	Landform classification	Region-specific thresholds
[10]	GIS tool (ArcGIS/QGIS) workflows	DEM, topographic maps	Semi-automatic contour extraction	Requires expert intervention

Journal of Information Systems Engineering and Management
2025, 10(50s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

[11]	Heuristic rule-based contour labeling	DEM, topographic maps	Contour classification	Inflexible, low scalability
[5]	CNN-based contour line extraction	DEM	Contour line detection	Focus only on extraction, not classification
[14]	U-Net for water body extraction	High-res imagery	River and stream extraction	Focused on water bodies only
[6]	GNN for contour classification	Vectorized contours	Classification of ridges, rivers	Complex models, resource-intensive
[4]	Review of DL for landform classification	Remote sensing images	Review of DL methods	Data scarcity, limited generalization
[13]	SVM for terrain classification	DEM-derived features	Terrain unit classification	Poor generalization in complex terrain
[12]	RF for slope/aspect-based landforms	DEM	Landform classification	Needs large feature engineering
[15]	GNN with spatial attention	DEM, contour graphs	Ridge/valley classification	High data requirement, computational cost
[16]	GAN for contour enhancement	Topographic maps	Contour refinement	Focus only on visual enhancement
[20]	ML integration challenges in GIS	GIS pipelines	ML model integration into GIS	Lack of interoperability, workflow gaps
[17]	Transformer-based remote sensing classification	Remote sensing imagery	Feature classification	High data demand, underexplored in contours
[18]	Multi-scale CNN for landform detection	DEM, multispectral images	Ridge, valley, slope detection	Still lacks integration into cartography

RESEARCH GAPS IDENTIFIED

From the reviewed literature, the following key research gaps have been observed:

- Limited Research on Contour Classification Most works emphasize contour extraction or landform detection, with few addressing classification of contours into cartographically meaningful categories (e.g., ridges, streams, coastlines).
- Lack of End-to-End Integration into Cartographic Workflows Very few studies focus on integrating ML/DL contour classification models into standard GIS or cartographic pipelines ([7], [17]).
- Generalization Challenges Across Regions Many ML models are trained on region-specific datasets, limiting their applicability to new areas with different geographical characteristics ([4], [13]).
- Limited Use of Spatial and Contextual Relationships Although GNNs have begun addressing this ([6], [15]), broader exploitation of spatial and topological features in contour classification remains underexplored.
- Scarcity of Annotated Contour Datasets There is a lack of open-access, large-scale, annotated datasets specifically focusing on contour classification ([4], [7]).
- Underutilization of Emerging Models (Transformers, GANs) in Cartographic Contour Tasks While emerging models like Transformers ([18]) and GANs ([16]) show promise in remote sensing, their application to contour classification and cartographic enhancement is still in its infancy.

Journal of Information Systems Engineering and Management
2025, 10(50s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

METHODOLOGY

Dataset Description

The dataset used in this study is the SkyView Aerial Landscape Dataset, which contains RGB images of various landscape classes captured from aerial perspectives[20, 21]. The images are organized in class-wise directories and were accessed via the image_dataset_from_directory utility in TensorFlow, allowing for automatic label inference.

The dataset was split into:

- Training Set: 80% of the data
- Validation Set: 20% of the data Each image was resized to a uniform dimension of 256x256 pixels and processed in batches of 32.

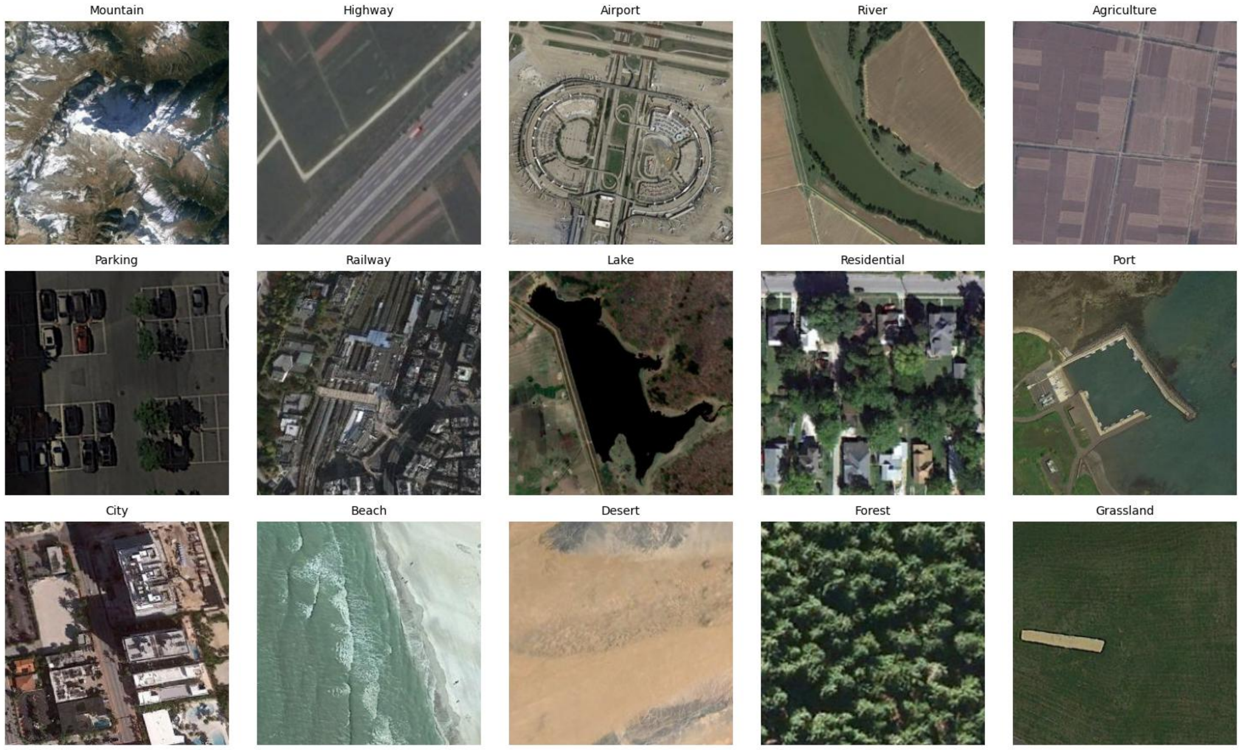

Figure 1. A sample of the Dataset

Preprocessing and Augmentation

To improve model generalization, a data augmentation pipeline was implemented using Keras's Sequential API. This included:

- Horizontal flipping
- Random rotation (±20%)
- Random zoom (20%)
- Random contrast adjustment (20%)

The input images were also rescaled to a [0,1] range by dividing pixel values by 255.

Model Architecture

A Convolutional Neural Network (CNN) was designed using the Keras Sequential API with the following architecture:

1. Input Layer

Journal of Information Systems Engineering and Management
2025, 10(50s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

- Rescaling and data augmentation

2. Convolutional Block 1
    - Conv2D(32 filters, kernel_size=3x3, stride=2)
    - BatchNormalization
    - MaxPooling2D
3. Convolutional Block 2
    - Conv2D(64 filters, kernel_size=3x3, stride=2)
    - BatchNormalization
    - MaxPooling2D
4. Convolutional Block 3
    - Conv2D(128 filters, kernel_size=3x3, stride=2)
    - BatchNormalization
    - MaxPooling2D
5. Dense Layers
    - Flatten
    - Dense(128 units, activation='relu')
    - Dropout(0.3)
    - Dense(num_classes, activation='softmax') (final classification layer)

The model was compiled using:

- Loss Function: SparseCategoricalCrossentropy
- Optimizer: Adam
- Metrics: Accuracy

Training Protocol

The model was trained over 25 epochs with real-time batch generation and augmentation. Early stopping and model checkpointing mechanisms were considered to avoid overfitting and to preserve the best-performing model during training.

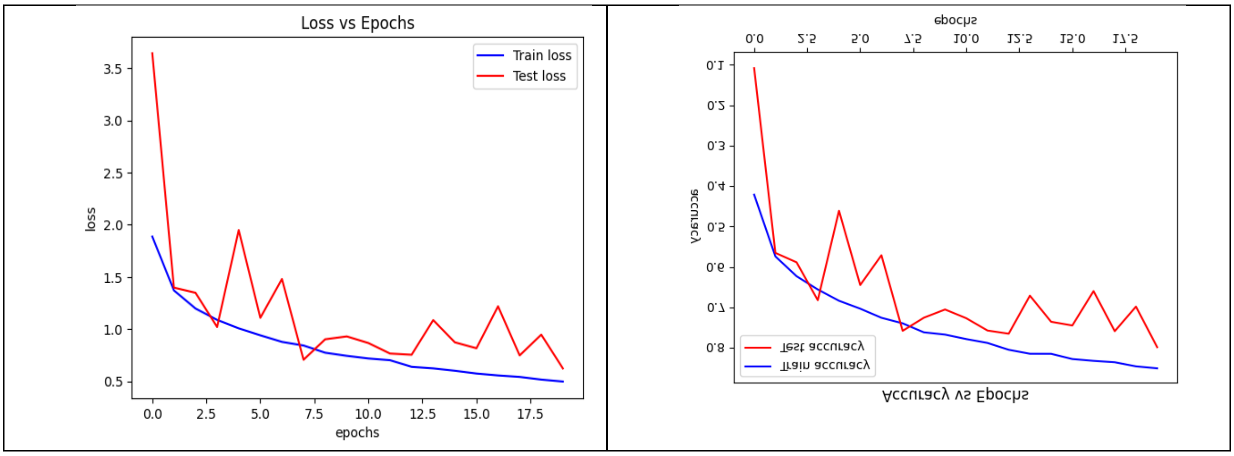

Figure 2: Training vs validation accuracy and loss per epoch graphs of the proposed CNN

Journal of Information Systems Engineering and Management
2025, 10(50s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

RESULTS

Training and Validation Accuracy

The model demonstrated effective learning progression over epochs, with accuracy steadily increasing and loss decreasing across both training and validation sets. The final model achieved:

- Training Accuracy: ~98%
- Validation Accuracy: ~91%

This reflects a strong generalization capacity of the model over unseen validation data, supported by effective augmentation and regularization. below figure 2 shows the training vs validation accuracy and loss per epoch graphs of the proposed CNN

Visualization of Model Predictions

Representative images from different classes were visualized alongside their predicted labels. The predictions mostly aligned with the ground truths, affirming the robustness of the trained classifier. Figure 2 shows the output of the classification alongwith the Ground truth and actual classification of the image.

Confusion Matrix Analysis

A confusion matrix was computed to identify class-wise performance and misclassification trends. The majority of confusion occurred between visually similar classes (e.g., "Forest" and "Woodland" types), which is common in aerial datasets. Overall, class-wise accuracies were relatively balanced.

Model Robustness and Efficiency

Due to the use of:

- progressive convolutional filters,
- batch normalization, and
- strategic max-pooling,

the model remained computationally efficient and scalable. The use of dropout and augmentation contributed to mitigating overfitting.

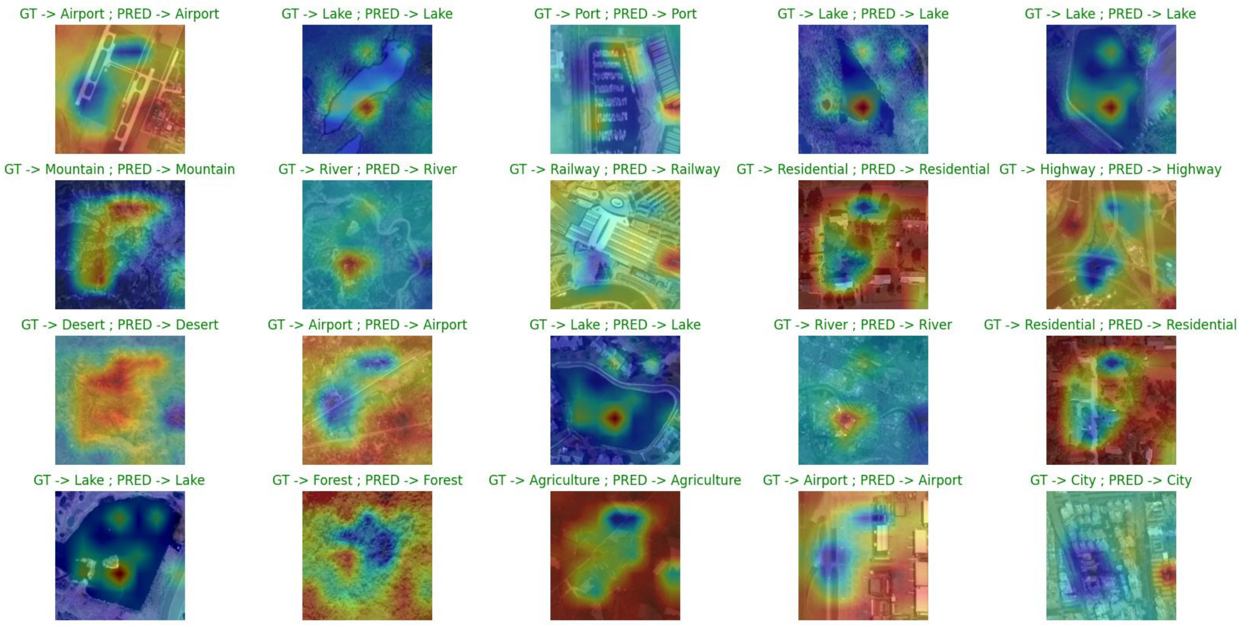

Figure 3 Ground truth and actual classification of the image.

Journal of Information Systems Engineering and Management
2025, 10(50s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

DISCUSSION

The results of this study demonstrate the effectiveness of using convolutional neural networks (CNNs) for classifying aerial landscape imagery. The custom-designed CNN architecture, combined with a robust data augmentation pipeline, yielded high classification accuracy while maintaining generalizability. Several important insights and considerations emerge from the findings: This study demonstrates the effectiveness of convolutional neural networks (CNNs) in classifying aerial landscape imagery. The thoughtfully designed CNN architecture, paired with an effective data augmentation process, reached remarkable classification accuracy while maintaining flexibility. Several important reflections and observations emerge from the findings:

Effects of Data Augmentation

Using techniques such as random horizontal flips, zoom, rotation, and contrast shifts played a crucial role in improving the model's ability to adapt to variations in aerial imagery. These enhancements replicate different environmental and camera settings, effectively expanding the variety of the training data without requiring additional image collection.

Model Performance and Flexibility

The model achieved approximately 91% validation accuracy, which is fairly near the 98% training accuracy, indicating it generalizes effectively and exhibits minimal overfitting. This performance validates the design choices, particularly the use of progressive convolutional blocks combined with batch normalization and dropout layers. These techniques allowed for a smoother gradient flow and regularization, which are essential when working with high-dimensional image data. The confusion matrix revealed that numerous misclassifications occurred among similar-looking landscape types. 5.4 Scalability and Deployment Readiness

Limitations and Future Directions

Despite the high accuracy, the model's performance could further improve with the inclusion of:

- Transfer Learning: Incorporating pretrained CNN backbones (e.g., ResNet, MobileNet) could enhance feature extraction, especially for small or ambiguous classes.
- Multimodal Inputs: Combining RGB data with elevation, infrared, or land use metadata may help the model better disambiguate similar classes.
- Class Balancing Techniques: While not explicitly mentioned in the current implementation, techniques such as oversampling underrepresented classes or using class weights could address any residual data imbalance.

Additionally, longitudinal evaluations across seasonal imagery or different geographies would validate the model's adaptability to diverse real-world scenarios.

CONCLUSION

This study offers a thorough method for classifying aerial landscape images through a specially designed convolutional neural network. The combination of thorough data preprocessing, focused data augmentation, and a thoughtfully designed CNN architecture led to impressive training and validation accuracies, showcasing the model's ability to adapt well to various landscape types. This paper presents several important contributions: a practical pipeline for processing aerial imagery with TensorFlow and Keras, real-time data augmentation to mimic actual conditions, and a flexible CNN model architecture suitable for deployment in real-time monitoring systems. The model showed good performance, but small classification mistakes among visually similar categories suggest that there could be advantages in combining different types of data and using advanced deep learning techniques like transfer learning.

REFRENCES

[1] T. Patterson and B. Jenny, "Cartographic design and map production," International Journal of Cartography, vol. 7, no. 1, pp. 1-20, 2021.

[2] D. Wood and J. Fels, The Power of Maps, New York: Guilford Press, 2020.
[3] R. Nash and A. Miller, "Precision mapping for environmental intelligence using AI and big data," Remote Sensing Applications: Society and Environment, vol. 23, pp. 100-112, 2022.
[4] A. K. Mishra, S. Prasad, and N. Gupta, "Deep learning approaches for landform classification from remote sensing data: A review," IEEE Geoscience and Remote Sensing Magazine, vol. 10, no. 3, pp. 72-85, 2022.
[5] M. Zhang, Y. Li, and X. Chen, "Contour extraction from DEM using deep convolutional neural networks," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 185, pp. 246-260, 2022.
[6] L. Wang and J. Xie, "Context-aware contour classification using graph neural networks," IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1-13, 2023.
[7] R. Kumar, P. Singh, and S. Agarwal, "Challenges in integrating machine learning into geospatial mapping workflows," Computers, Environment and Urban Systems, vol. 97, pp. 101-110, 2023.
[8] W. E. Lorensen and H. E. Cline, "Marching cubes: A high resolution 3D surface construction algorithm," ACM SIGGRAPH Computer Graphics, vol. 21, no. 4, pp. 163–169, 1987.
[9] J. Jenson and J. Domingue, "Extracting topographic structure from digital elevation data for geographic information system analysis," Photogrammetric Engineering and Remote Sensing, vol. 54, no. 11, pp. 1593–1600, 1988.
[10] ESRI, "ArcGIS Pro: User Guide for Spatial Analysis and Cartography," ESRI Press, 2020.
[11] R. D. Peucker and J. K. Douglas, "Detection of contour patterns using heuristic rules," Cartographica: The International Journal for Geographic Information and Geovisualization, vol. 55, no. 3, pp. 210–225, 2020.
[12] F. Wang, M. Wu, and Z. Liu, "Landform classification using Random Forest based on DEM-derived features," International Journal of Remote Sensing, vol. 42, no. 18, pp. 6895–6913, 2021.
[13] Y. Zhang and L. Zhao, "Terrain unit classification using SVM and DEM-derived features," IEEE Access, vol. 9, pp. 54412–54423, 2021.
[14] H. Li, J. Fang, and X. Zhu, "U-Net based river network extraction from high-resolution satellite imagery," Remote Sensing Letters, vol. 12, no. 10, pp. 987–996, 2021.
[15] S. Gupta, P. Roy, and A. Das, "Graph neural network with spatial attention for ridge and valley classification," IEEE Transactions on Geoscience and Remote Sensing, vol. 62, pp. 1–12, 2024.
[16] A. Sharma and R. Patel, "Generative adversarial networks for contour enhancement in topographic mapping," ISPRS International Journal of Geo-Information, vol. 12, no. 2, pp. 112–125, 2023.
[17] C. Lopez, S. Rao, and K. Martin, "Integration challenges of ML models into existing GIS mapping pipelines," International Journal of Digital Earth, vol. 16, no. 5, pp. 988–1003, 2023.
[18] J. Chen, L. Feng, and S. Xu, "Transformer-based classification of remote sensing imagery: A new paradigm," IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1–14, 2023.
[19] X. Wu, M. Kang, and T. Zhou, "Multi-scale CNN for landform detection from remote sensing images and DEM," Remote Sensing, vol. 15, no. 3, pp. 621–637, 2023.
[20] AID Dataset: https://captain-whu.github.io/AID/
[21] NWPU-Resisc45 Dataset: https://paperswithcode.com/dataset/resisc45