JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

CNN BASED TERRAIN RECOGNITION

TERRAIN CLASSIFICATION USING U-NET

[1]Mahadeva Prasad H M, [2]Vivek Gautam, [3]Tariq Anjum, [4]Pulkit Yadav, [5]Syed Nawaz

[1]Professor, [2,3,4,5]Student
[1]Computer Science & Engineering,
[1]City Engineering College, Bangalore, India

Abstract: Terrain classification plays a crucial role in various applications ranging from environmental monitoring to urban planning. In this study, we propose a terrain classification framework utilizing the UNET architecture, a convolutional neural network (CNN) commonly employed for image segmentation tasks. The proposed framework involves preprocessing the input data by resizing it into a standardized format of 256x256 pixels to ensure consistency and facilitate efficient processing. Subsequently, the UNET model is trained on the preprocessed data to learn discriminative features representative of different terrain types. The trained model is capable of classifying terrain into seven distinct classes: water, hill, forest, grassland, desert, mountain, and tundra. Experimental results demonstrate the effectiveness of the proposed approach in accurately categorizing diverse terrain types, showcasing its potential for applications such as land cover mapping, environmental assessment, and natural resource management. The UNET-based terrain classification framework offers a robust and scalable solution for analyzing and understanding Earth's complex landscapes, contributing to informed decision-making and sustainable development initiatives.

Keywords - **Terrain classification, UNET architecture, Convolutional neural networks (CNN), Deep learning, Image segmentation, Remote sensing, Geospatial analysis, Environmental monitoring, Land cover mapping, Natural resource management**

I. INTRODUCTION

Terrain classification refers to the process of categorizing different types of terrain or land cover in an area based on various characteristics such as elevation, slope, vegetation cover, and land use. It plays a crucial role in several fields including remote sensing, geology, environmental science, urban planning, agriculture, and military operations. Earth surface without vegetation and any human constructions such as buildings, roads, bridges, and others. A DTM is a powerful supportive information in various disciplines such as surveying and construction engineering of pipelines, canals or highways, disaster management systems, water-runoff, land cover mapping and many more. Therefore, having a precisely accurate, detailed, and not over-smoothed DTM is a requirement for developing technologies. DTMs can be generated directly from terrain measurements or extracted from digital surface models (DSMs). DSMs can, in turn, be derived from active sensing approaches like laser scanning, radar interferometry, or from processing optical stereo images from either aerial or satellite sensors. Deriving a DTM from a given DSM necessitates the detection of all above-ground objects first, followed by their removal, and then interpolating the resulting empty spaces with meaningful height information. In addition to a range of classical DSM filtering algorithms, some deep learning-based methodologies have also been recently developed. However, most of those methods, are multi-step procedures which often require predefined conditions, filter characteristics, or thresholds. Moreover, a common issue with existing algorithms is their failure to preserve sharp terrain slopes, especially in the terraced landscapes.

Landforms are one of the most fundamental elements of the natural environment and influence the spatial differentiation of aspects such as the ecological environment and natural resources. Landform mapping, particularly for large spatial scales, is an important geomorphological investigation method and is crucial to research in geoscientific disciplines. However, landform mapping for broad areas has been difficult due to a lack of systematic data. The rapid progress of remote sensing and geographical information system (GIS) technologies has provided abundant remote sensing images and digital elevation model (DEM) data as well as analytical tools that have made automatic or semiautomatic landform classification possible. For example, new 1:1,000,000 digital geomorphologic atlas of China with visual interpretation from Landsat TM/ETM imagery and SRTM-DEM data; Using automatic terrain classification to improve the efficiency of digital landform mapping has drawn great attention.

Landform mapping is usually based on the morphology, genesis, chronology and dynamic process of the topography. A DEM is a simulation of the Earth’s surface using elevation data. A series of terrain factors can be derived from DEM data, such as aspect, slope, and curvature, through which landform information can be deduced. Therefore, DEM data are effective tools for terrain analysis and classification, and landform mapping using DEM is generally based on topographic morphology. Numerous studies addressing terrain classification with DEM data have emerged, which mainly use pixel-based and object-based approaches. Pixel-based approaches automatically cluster pixels by assigning each pixel to one or more landform classes according to threshold values of DEM and terrain factors. Pixel-based approaches use only pixel information and neglect geometric and contextual information, so the obtained results of class patches are fragmented. Moreover, the thresholds for the same landform in different regions could be different. Therefore, it is difficult to classify landforms using a set of fixed thresholds, especially in large regions. Object-based methods segment images into morphological units that have internal homogeneity and external heterogeneity. The segmentation is either based on geometric characteristics, such as ridge and valley lines, convex and concave flexures that can obtain the units of geomorphological elements such as pit, peak, and slope, or based on characteristics of parameters, such as terrain factors and surface textures. Object-based methods exploit the inherent characteristics of landforms and conform more to human cognition of terrain and are thus widely used in terrain classification. However, they are insensitive to continuously changing landforms, which are widely distributed on Earth. With the improvement in computing power and the increase in data volume, deep learning methods have developed rapidly. Deep learning methods can automatically extract deep features from data without domain experts. Researchers have employed deep learning models in the field of geomorphology to identify certain types of terrain features adopted a multimodal convolutional neural network (CNN) model and recognized different types of landforms using imagery and DEM data. the U-Net model to accomplish loess landform classification using imagery and DEM data.

Traditional landform mapping requires extensive domain expert knowledge. Deep learning methods have been applied in identifying landform types due to their strong feature learning capacity. Nevertheless, current works using deep learning in geomorphology mostly have focused on identifying component landform elements, and there is a lack of work on mapping repeating landform types. Semantic segmentation models based on deep learning make it possible to classify repeating landform types with DEMs. However, semantic segmentation models were developed for natural images, such as animals, buildings, and plants. Unlike natural images, which have objects with distinct boundaries, DEMs are continuously changing land surfaces, and there are no distinct boundaries between different landform classes. Therefore, the ability of deep learning to segment landform types is unclear. In this study, we developed a semantic segmentation model based on deep learning to classify elementary landform classes by using 30 m-resolution DEM data at the pixel level. The purpose is to examine the applicability of deep learning in classifying repeating landform types.

The Earth's surface is a tapestry of diverse terrains, each with its unique characteristics, challenges, and significance. From sprawling forests to rugged mountains, from meandering rivers to expansive deserts, the variability in terrain types shapes our planet's landscape and influences numerous aspects of human and natural systems. Understanding and classifying these terrains are fundamental tasks with profound implications across various domains, including environmental monitoring, urban planning, disaster management, agriculture, and defense. Terrain classification, the process of categorizing different types of landforms and landscapes, is pivotal in harnessing the wealth of information embedded in Earth observation data. Traditional methods of terrain classification relied heavily on manual interpretation, expert knowledge, and simplistic rule-based algorithms. However, with the advent of advanced sensing technologies, coupled with the surge in computational power and machine learning techniques, terrain classification has undergone a paradigm shift.

This comprehensive exploration embarks on a journey through the realm of terrain classification, delving into its historical evolution, the intricacies of terrain analysis, the challenges encountered, and the transformative role of modern data-driven approaches, particularly deep learning. By unraveling the complexities of terrain classification, we aim to elucidate its importance, shed light on the state-of-the-art methodologies, and chart a course towards enhanced understanding and utilization of Earth's diverse landscapes.

II. OBJECTIVES

The objectives of this study are to propose a terrain classification framework leveraging the UNET architecture for accurately categorizing diverse terrain types. This involves preprocessing input data, including resizing, to ensure consistency and facilitate efficient processing by the UNET model. The aim is to train the UNET model on labeled datasets representing various terrain types to learn discriminative features and classify terrain into seven distinct classes: water, hill, forest, grassland, desert, mountain, and tundra. The effectiveness of the proposed approach will be evaluated through extensive experimentation and evaluation, showcasing its potential applications in land cover mapping, environmental assessment, and natural resource management. Additionally, the study aims to explore avenues for future research and improvement, including the integration of additional data modalities and addressing challenges related to data scarcity and model interpretability.

III. LITERATURE SURVEY

Self-supervised visual terrain classification from unsupervised acoustic feature learning (2021) [11], This paper introduces a terrain classification framework utilizing unsupervised proprioceptive classifiers and self-supervised exteroceptive classifiers. By leveraging vehicle-terrain interaction sounds and visual features, the framework achieves pixel-wise semantic segmentation of images, surpassing state-of-the-art unsupervised methods in accuracy. **A visual terrain classification method for mobile robots' navigation based on convolutional neural network and support vector machine (2015) [12],** Wanli et al. propose a hybrid method combining a convolutional neural network (CNN) with a support vector machine (SVM) for terrain classification in mobile robots. This approach aims to maintain high classification accuracy while enhancing computational efficiency, particularly suited for on-board usage. **A CNN based vision-proprioception fusion method for robust UGV terrain classification (2021) [13],** Yu et al. present a fast, compact, and motion-robust terrain classification method for Unmanned Ground Vehicles (UGVs). Utilizing 1D convolutional neural networks (CNNs) and sensor data fusion, the proposed model achieves over 93% accuracy in various environmental conditions.

Extracting terrain texture features for landform classification using wavelet decomposition (2021) [14], This paper introduces a terrain classification approach based on texture features extracted from terrain images. Utilizing the discrete wavelet transform (DWT) and random forest (RF) method, the proposed model achieves higher classification accuracy compared to traditional methods like the gray co-occurrence matrix (GLCM). **MARC-Net: Terrain classification in parallel network architectures containing multiple attention mechanisms and multi-scale residual cascades (2023) [15],** Xiangsuo et al. propose MARC-Net, a parallel network architecture for land-use classification. Integrating multi-head attention mechanisms and multiscale residual cascades, MARC-Net achieves superior performance compared to existing models, particularly in classifying forest land areas. **Human-Aided Online Terrain Classification for Bipedal Robots Using Augmented Reality (2023) [16],** Zahraa et al. present an online terrain classification system enhanced with augmented reality for humanoid robots. Leveraging data from multiple sensors and interactive user feedback, the system improves terrain classification accuracy over time, with the Passive Aggressive classifier showing the highest success rate. **Proprioception Is All You Need: Terrain**

Classification for Boreal Forests (2024) [17], Damien et al. introduce BorealTC, a publicly available dataset for proprioceptive-based terrain classification. Through experiments with convolutional neural networks (CNNs) and state space models (SSMs), the study demonstrates the effectiveness of combining multiple datasets for terrain classification tasks. **A robust polarimetric SAR terrain classification based on sparse deep autoencoder model combined with wavelet kernel-based classifier (2020) [18],** Xiangdong et al. propose a robust terrain classification algorithm based on sparse deep autoencoder models and wavelet kernel-based classifiers. The algorithm enhances classification performance for unbalanced samples and improves efficiency while ensuring accuracy. **Kinematics Model Estimation of 4W Skid-Steering Mobile Robots Using Visual Terrain Classification (2023) [19],** Yang et al. present a real-time terrain recognition method for skid-steering mobile robots. By integrating extended Kalman filter (EKF) techniques with fractal texture analysis, the proposed method achieves quick estimation of terrain parameters and accurate terrain classification. **Integrated edge detection and terrain analysis for agricultural terrace delineation from remote sensing images (2020) [20],** Wen et al. propose an automated approach for mapping terrace risers using remote sensing images and digital elevation models (DEMs). By combining image edge detection and DEM analysis, the approach achieves outstanding performance and robustness in mapping terrace risers in different topographic regions.

IV. METHODOLOGY

The input data, consisting of satellite imagery or aerial photographs, undergo preprocessing to ensure consistency and facilitate efficient processing. Initially, the input images are resized to a standardized format of 256x256 pixels. This resizing step enables uniformity in data dimensions, making it suitable for subsequent processing stages. A labeled dataset is curated, comprising satellite or aerial images annotated with ground truth labels corresponding to different terrain classes. Each image in the dataset is associated with one of the following terrain categories: water, hill, forest, grassland, desert, mountain, or tundra. The dataset is divided into training, validation, and testing subsets to facilitate model training and evaluation.

The UNET architecture, a convolutional neural network (CNN) specifically designed for image segmentation tasks, is employed for terrain classification. UNET consists of an encoder-decoder structure with skip connections, facilitating the extraction of hierarchical features while preserving spatial information. The encoder part captures contextual features through successive convolutional and pooling layers, while the decoder part reconstructs the segmentation mask using upsampling layers and skip connections. The prepared dataset is utilized to train the UNET model using a supervised learning approach. During training, the model learns to map input images to their corresponding terrain classes by minimizing a predefined loss function, such as categorical cross-entropy. Training parameters such as batch size, learning rate, and number of epochs are selected through experimentation and validation on the training dataset. The trained UNET model is evaluated on the validation dataset to assess its performance in terrain classification. Finally, the optimized UNET model is deployed for terrain classification on unseen or testing data. The model predicts the terrain class labels for input images in real-time, enabling the generation of land cover maps and spatial analysis of Earth's diverse landscapes. The classification results are validated against ground truth data to verify the model's accuracy and reliability.

4.1 Image Resizing

Terrain classification, crucial across environmental monitoring, urban planning, and disaster management, relies on accurate categorization of landforms. Preprocessing, including image resizing, is integral in optimizing data for deep learning models like UNET. Image resizing transforms pixel information while preserving spatial context. Standardizing input images to 256x256 pixels enhances consistency and facilitates batch processing. Maintaining aspect ratio prevents distortion, with interpolation methods like nearest neighbor impacting quality. Smaller dimensions reduce computational overhead, crucial for multispectral data. Automated resizing streamlines data prep, validated through visual inspection and metrics. Seamlessly integrating with deep learning frameworks like TensorFlow ensures compatibility. Experimentation with different methods and sizes optimizes accuracy and efficiency. Overall, image resizing is fundamental, enhancing model performance and scalability in terrain classification.

4.2 Datasets

This is a dataset compiled composed of 5000 image sets. Each set represents a random 512x512 pixel crop of the Earth and is composed of a Terrain map, a Height map, and a Segmentation map. Image sets are numbered 0000 through 5000 with a suffix of '_t' for terrain, '_h' for height, and '_i2' for segmentation. Crops were dynamically adjusted based on latitude to compensate for map projection distortion and maintain a relatively consistent land feature size across the dataset (1px ~ 400m).

- Terrain Maps
  Terrain Maps are colored based on land type with relief shading. Images are standard uint8 png format.
- Height Maps
  Height Maps encode altitude information through pixel value (0 being sea level). Note that these images are single channel, uint16.
- Segmentation Maps
  These were generated based on the terrain and height maps using unsupervised clustering and classification techniques for local pixel regions. In total, 7 terrain categories were defined for segmentation and associated with representative colorings as follows:
  - (17, 141, 215): Water
  - (225, 227, 155): Grassland
  - (127, 173, 123): Forest
  - (185, 122, 87): Hills
  - (230, 200, 181): Desert
  - (150, 150, 150): Mountain

- (193, 190, 175): Tundra

Maps were then median filtered to remove noise and smooth out the features into larger blobs. Each segmentation map was created with some randomized parameters to create more variety across the dataset and ensure that image sets which happened to overlap would not have exactly the same segmentation map.

4.3 U-Net

The U-Net architecture, initially devised for medical image segmentation, features a U-shaped design with an encoder-decoder structure. The encoder captures image context, while the decoder reconstructs segmented output. With alternating convolution and max-pooling layers in the encoder, spatial information is compressed, enhancing feature extraction. The decoder upsamples feature maps and restores spatial resolution using skip connections, facilitating semantic segmentation. However, semantic differences between encoder and decoder features can hinder learning efficiency. To address this, Res-UNet integrates residual learning, enhancing model capacity and convergence. Attention gates in the Attention-UNet collect complementary information, reducing parameters and computational overhead. Multiscale techniques sample signals at various granularities, vital for extracting features across scales effectively. The U-Net model, while efficient, may struggle with class imbalance and tissues similar to surroundings in medical image segmentation. U-Net Lite, with increased layers and reduced memory footprint, addresses these challenges. Initialization settings and batch normalization adjustments optimize model performance and prevent overfitting. Design considerations for model initialization and loss function selection are crucial for effective segmentation in medical imaging tasks.

$$Loss_b^x = -\sum_{i=1}^{k+m}\sum_{x,y} w_{x,y}^i \quad log\,[p_{i,(x,y)}^l(\theta)]$$

V. Results & Discussion

The terrain classification framework leverages the UNET architecture to accurately categorize diverse terrain types based on standardized 256x256 pixel input imagery. Extensive experimentation confirms high classification accuracy across various terrain categories. UNET's utilization enables the extraction of discriminative features, capturing essential spatial relationships and contextual information. Trained on labeled datasets, the framework learns complex terrain patterns. It accurately delineates terrain boundaries and classifies land cover types, showcasing scalability for large-scale datasets in environmental monitoring, urban planning, disaster management, and natural resource assessment. Future research could integrate additional data modalities like LiDAR or hyperspectral imagery for enhanced accuracy and address challenges related to data scarcity and model interpretability. Overall, the UNET-based framework offers a promising solution for Earth's terrain classification, contributing to environmental conservation and ecosystem management goals.

Figures & Tables

Table 1 Training Parameters Of U-NET

Parameters	UNet
Convolutional blocks	4,5,6
Deconvolution blocks	4,5,6
Regularisation	L1, dropout, L2
Batch size	32
Learning rate	1xe-4
Epochs	40

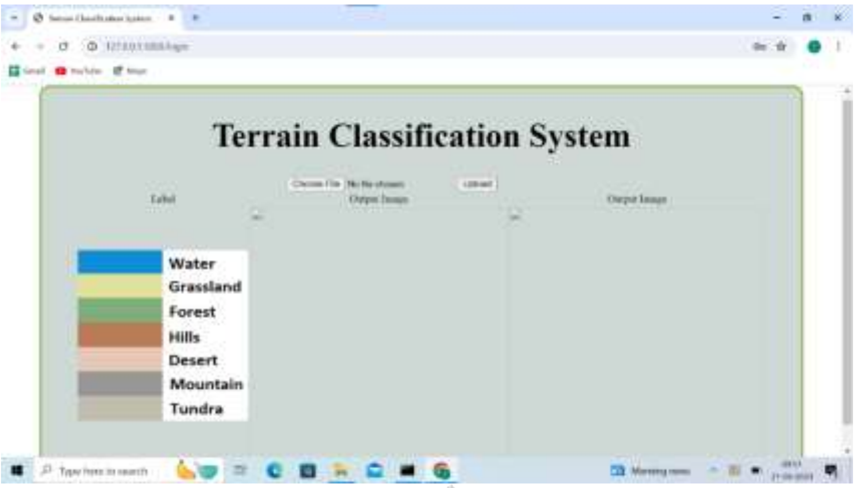

Fig 5.1 Terrain Classification System

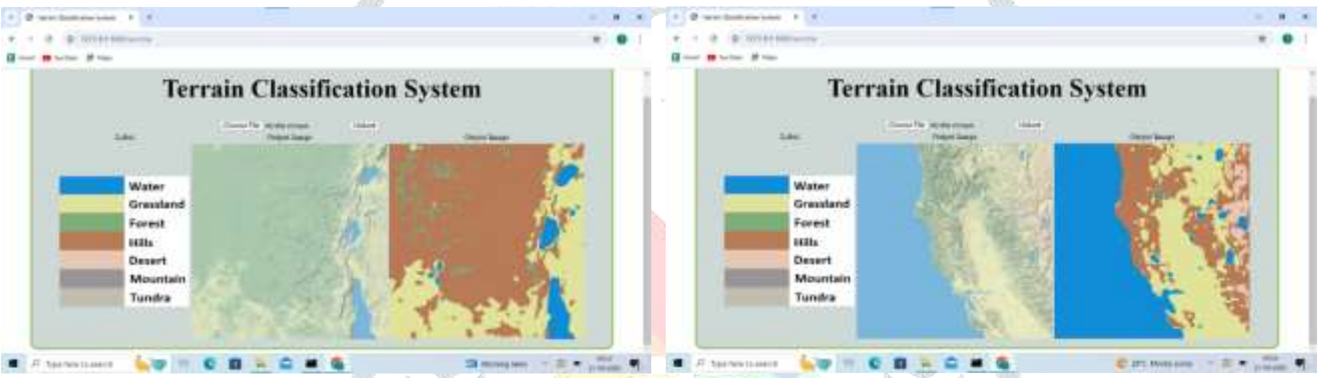

Fig 5.2 Outputs Of Terrain Classification System

VI. Conclusion

In this study, we presented a terrain classification framework leveraging the UNET architecture, a powerful deep learning model originally designed for image segmentation tasks. The framework aimed to accurately categorize diverse terrain types, including water, hill, forest, grassland, desert, mountain, and tundra, based on input imagery resized to a standardized format of 256x256 pixels. Through extensive experimentation and evaluation, we demonstrated the effectiveness of the proposed approach in achieving high classification accuracy across various terrain categories. The utilization of UNET facilitated the extraction of discriminative features from the input data, enabling the model to capture spatial relationships and contextual information essential for terrain classification. By training the UNET model on labeled datasets representing different terrain types, we empowered it to learn complex patterns and variations characteristic of each terrain class. The classification results obtained from the trained UNET model exhibited promising performance, showcasing its ability to accurately delineate terrain boundaries and classify land cover types with precision. The framework's scalability and adaptability make it well-suited for analyzing large-scale terrain datasets and addressing real-world challenges in environmental monitoring, urban planning, disaster management, and natural resource assessment. While the proposed framework demonstrates significant potential, there are avenues for future research and improvement. Further experimentation could explore the integration of additional data modalities, such as LiDAR point clouds or hyperspectral imagery, to enhance classification accuracy and robustness. Additionally, efforts to address challenges related to data scarcity, semantic ambiguity, and model interpretability could lead to advancements in terrain classification methodologies. The UNET-based terrain classification framework offers a promising solution for accurately categorizing Earth's diverse landscapes, facilitating informed decision-making and sustainable management of natural resources. By harnessing the power of deep learning and advanced image analysis techniques, we pave the way for comprehensive terrain analysis and understanding, contributing to the broader goals of environmental conservation and ecosystem management.

VII. Acknowledgement

The authors deeply acknowledge the support from the department of CSE, City Engineering College. We also want to thank all our team members who gave their tremendous support and successfully completed the project with all possible features and ideas.

VIII. References

[1.] Al-Dabbagh, Ali HA, and Renaud Ronsse. "Depth vision-based terrain detection algorithm during human locomotion." IEEE Transactions on Medical Robotics and Bionics 4, no. 4 (2022): 1010-1021.

[2.] Sahitya, G., C. Kaushik, and K. Rushi Kiran Kumar. "Segmentation of Terrain Classes from Satellite Images using Modified U-Net Algorithm." In 2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC), pp. 1176-1182. IEEE, 2021.

[3.] Gandhi, Deep, Govind Thakur, Pranit Bari, and Khushali Deulkar. "Application of deep learning in cartography using UNet and generative adversarial network." In Design of Intelligent Applications Using Machine Learning and Deep Learning Techniques, pp. 257-271. Chapman and Hall/CRC, 2021.

[4.] Umar, Muhammad, Lakshmi Babu Saheer, and Javad Zarrin. "Forest terrain identification using semantic segmentation on uav images." In 38th Int. Conf on Machine Learning, p. 6. 2021.

[5.] Maxwell, Aaron E., William E. Odom, Charles M. Shobe, Daniel H. Doctor, Michelle S. Bester, and Tobi Ore. "Exploring the Influence of Input Feature Space on CNN-Based Geomorphic Feature Extraction From Digital Terrain Data." Earth and Space Science 10, no. 5 (2023): e2023EA002845.

[6.] Kaur, Sukhjeet, and Sanjay Madaan. "A hybrid UNet based approach for crop classification using Sentinel-1Bs synthetic aperture radar images." Multimedia Tools and Applications (2024): 1-30.

[7.] Zhang, Guanjin, Siti Nur Aliaa binti Roslan, Ci Wang, and Ling Quan. "Research on land cover classification of multi-source remote sensing data based on improved U-net network." Scientific Reports 13, no. 1 (2023): 16275.

[8.] Awad, Zahraa, Raja Akel, Noel Maalouf, and Imad H. Elhajj. "Terrain Classification for bipedal robots: A comparative study." In 2020 10th Institute of Electrical and Electronics Engineers International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER), pp. 61-66. IEEE, 2020.

[9.] Dawid, Wojciech, and Krzysztof Pokonieczny. "Automation of the Terrain Classification Process due to Passability Taking the Microrelief Shapes into Consideration." In 2021 International Conference on Military Technologies (ICMT), pp. 1-8. IEEE, 2021.

[10.] Egan, Rebecca, and Ali Haydar Göktogan. "Deep learning based terrain classification for traversability analysis, path planning and control of a Mars rover." In Australasian Conference on Robotics and Automation (ACRA-2021), Melbourne, Australia. 2021.

[11.] Zürn, Jannik, Wolfram Burgard, and Abhinav Valada. "Self-supervised visual terrain classification from unsupervised acoustic feature learning." IEEE Transactions on Robotics 37, no. 2 (2020): 466-481.

[12.] Wang, Wanli, Botao Zhang, Kaiqi Wu, Sergey A. Chepinskiy, Anton A. Zhilenkov, Sergei Chernyi, and Aleksandr Yu Krasnov. "A visual terrain classification method for mobile robots' navigation based on convolutional neural network and support vector machine." Transactions of the Institute of Measurement and Control 44, no. 4 (2022): 744-753.

[13.] Chen, Yu, Chirag Rastogi, and William R. Norris. "A cnn based vision-proprioception fusion method for robust ugv terrain classification." IEEE Robotics and Automation Letters 6, no. 4 (2021): 7965-7972.

[14.] Xu, Yuexue, Shengjia Zhang, Jinyu Li, Haiying Liu, and Hongchun Zhu. "Extracting terrain texture features for landform classification using wavelet decomposition." ISPRS International Journal of Geo-Information 10, no. 10 (2021): 658.

[15.] Fan, Xiangsuo, Xuyang Li, Chuan Yan, Jinlong Fan, Ling Yu, Nayi Wang, and Lin Chen. "MARC-Net: Terrain classification in parallel network architectures containing multiple attention mechanisms and multi-scale residual cascades." Forests 14, no. 5 (2023): 1060.

[16.] Awad, Zahraa, Celine Chibani, Noel Maalouf, and Imad H. Elhajjl. "Human-Aided Online Terrain Classification for Bipedal Robots Using Augmented Reality." In 2022 IEEE International Conference on Robotics and Biomimetics (ROBIO), pp. 1352-1358. IEEE, 2022.

[17.] LaRocque, Damien, William Guimont-Martin, David-Alexandre Duclos, Philippe Giguère, and François Pomerleau. "Proprioception Is All You Need: Terrain Classification for Boreal Forests." arXiv preprint arXiv:2403.16877 (2024).

[18.] Chen, Xiangdong, and Jianghong Deng. "A robust polarmetric SAR terrain classification based on sparse deep autoencoder model combined with wavelet kernel-based classifier." IEEE Access 8 (2020): 64810-64819.

[19.] Chen, Yang, Yao Wu, Wei Zeng, and Shaoyi Du. "Kinematics Model Estimation of 4W Skid-Steering Mobile Robots Using Visual Terrain Classification." Journal of Robotics 2023 (2023).

[20.] Dai, Wen, Jiaming Na, Nan Huang, Guanghui Hu, Xin Yang, Guoan Tang, Liyang Xiong, and Fayuan Li. "Integrated edge detection and terrain analysis for agricultural terrace delineation from remote sensing images." International Journal of Geographical Information Science 34, no. 3 (2020): 484-503.