remote sensing

Editorial

Artificial Intelligence-Based Learning Approaches for Remote Sensing

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1. Introduction

Remote sensing (RS) is a method for understanding the ground and for facilitating human–ground communications. New developments in RS have led to HR (high-resolution) monitoring of the ground on a global scale, giving a huge amount of ground observation data. Thus, AI-based deep learning approaches and its applied signal processing are required for RS. These approaches can be universal or specific AI tools, including well-known neural networks, regression methods, decision trees, etc. In this Special Issue, we aimed to describe recent developments and trends regarding topics such as advanced AI-based deep learning techniques and RS data processing. Sixteen papers were finally published in this Special Issue.

2. Overview of Contributions

The contribution by Zoubir et al. [1] yielded a dataset with 6900 images that feature three common deficiencies of concrete bridges. The deficiencies include cracks, efflorescence, and spalling. To compensate for trials with incomplete training data, transfer learning techniques were introduced and tested to categorize the three deficiencies. In addition, two gradient-based backpropagation interpretation methods were adopted to create a pixel-level heatmap and to localize deficiencies in the test data. Objective and subjective performances were compared to give reliable information on deficiency localization.

The contribution by Yang et al. [2] introduced the forward-propagation concept and then added forecast features such as weather, temperature, terrain, and land-cover-type distributions. Based on this information, the authors could assess the CCIs of over-the-horizon communications on the intercity connection. According to the paper, based on 1300 sets of created terrains and landforms, two deep learning models were adopted to predict the PL of over-the-horizon communications among venues in a land-based ducting environment. The authors used LSTM prediction to verify their PL prediction using deep learning.

The contribution by Duan et al. [3] presented and certified a novel suggestion with un-labeled, upsampled, generated data, which could be worthless for unwarranted non-graph data. The authors proved that the feature circulation can enable deep learning of imbalanced graphs. In addition, the authors experimentally controlled collaborative data synthesis via the generation of virtual samples in the central region of a minority. Their data upsampling framework was assessed by numerous real-world learning network datasets. According to this paper, their work provided varied and reliable benchmark models with a big advantage.

In the contribution by Wen et al. [4], the authors creatively presented a spatial endurance criterion to choose 1-O features with wealthier local facts for the computation of 2-O data to guarantee the efficiency of M-O features. To minimize the consequence of inevitable positive/negative sample inequity in target finding, weight-adaptive factors

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were considered to adapt to the disadvantages of the cross entropy cost. In addition, the MIoU was built to perform an anchor box regression from numerous viewpoints. In this work, the authors presented an improved Wallis shadow automatic compensation approach to pre-process aerial data, presenting a basis for the subsequent data-matching processes. The authors also provided a consumer-grade unmanned aerial vehicle, obtaining a platform to collect aerial data for investigational validation. The simulation results suggested that their framework obtained outstanding results for each numerical and subjective metric.

In the contribution by Nie et al. [5], the authors presented a frequency/spatial interaction network (SSIN) for pansharpening. The main difference from conventional work is that the authors considered the features of pansharpening as being abstract and multispectral and then interrelated them repeatedly to progressively integrate frequency/spatial information. To improve frequency/spatial information fusion, the authors presented a frequency/spatial attention module to provide more efficient frequency/spatial information transfer on the network. The simulation results were conducted on the QuickBird, WorldView-4, and WorldView-2 datasets and proved that their approach overcomes conventional methods subjectively and objectively.

In the contribution by Albu et al. [6], the authors presented a CNN for weather forecasting using radar product prediction. The authors proposed the NeXtNow model, an improved version of the ResNeXt architecture. The proposed NeXtNow has an encoder/decoder convolutional architecture and plots radar results from previous moments and from the future. The authors authenticated their method utilizing radar data that were composed from the Romanian NMA and the Norwegian MET. In addition, they experimentally determined that the presence of numerous past radar results leads to more precise forecasts in the future. According to their paper, the proposed NeXtNow presented enhanced results.

In the contribution by Shao et al. [7], the authors proposed a rotated balanced feature-aligned network (RBFA-Net). In this work, the authors proposed three networks: BAFPN, AFAN, and RDN. The first network, BAFPN, is an enhanced version of FPN that improves multi-level features; therefore, it can reduce the adverse influence of feature variances. In the second network (AFAN), the authors used an arrangement convolution layer to adaptively line up the convolution features to rotated anchor boxes to alleviate the misalignment issue. In the third network (RDN), the authors presented a TDM to regulate the feature maps to handle any struggles with regression and classification tasks. The simulation results used eight SOTA rotated detection benchmark networks; among them, the proposed method presented the best performance in terms of mean average precision metric.

In the contribution by Han et al. [8], the authors presented an approach to categorizing atmospheric duct (AD) parameters by means of AIS signals in conjunction with AI. The proposed approach comprises an AD categorizing model. The categorizing model adjudicates the type of AD, and the inversion model reverses the AD parameters, giving the type of AD. Their research results suggest that the accuracy of the AD-categorizing model based on DNN outperforms others by 97% and that the AD parameter reverse model has higher inversion precision than that of the conventional approach, therefore showing the efficiency and precision of this new approach.

With growing access to data, advances in examinations carried out in the initial step of the asset procedure are imaginable. Building extraction from raster information is a significant step, particularly for urban planning and ecological research. The key issue with the semantic segmentation tool is the partial accessibility of masks. Therefore, labelling data are not perfect for the training step. To alleviate this issue, the contribution by Glinka et al. [9] proposes a solution to the automation of data classification from cadastral data from an exposed spatial dataset utilizing CNN and classifies and obtains buildings from HR from these data. The simulation results prove that the semantic ML segmentation on this spatial dataset presents satisfactory quality regarding the results.

In general, most of the current deep learning-based approaches are merely data-driven and neglect the filtering approach; therefore, they normally require adopting big data to generate training/validation/test datasets. However, a challenge is enhancing the correctness and conducting speed. To alleviate this issue, the contribution by Wang et al. [10] presented an SMD-Net for effective and high-precision InSAR filtering by opening the sparse regularization approach to handling the filtering model with a network. Different from conventional DL-based filtering approaches, the SMD-Net generates a physical filtering process in the network and covers less parameters and layers. It is thus expected to ensure accuracy of the filtering without sacrificing speed. The simulation results proved that the presented approach enhanced numerous conventional filtering methods subjectively and objectively.

The contribution by Das et al. [11] examined the built-up expansion procedure and its probability in an area of India by utilizing multi-temporal Landsat satellite data and a combination of the ML approach and a fuzzy method. To generate the built-up expansion probability model, several indices were used, such as dominance, diversity, and connectivity for every year. This information was gathered and then combined with the fuzzy method. The simulations were conducted using data from 2001 to 2021; the built-up areas were enlarged by 21.67%, while water and vegetation bodies were reduced by 4.63% and 9.28%. This study can serve as a guide to decision-makers presenting management plans for systematic urban growth without harming the environment.

SAR is a cutting-edge microwave sensor that has been broadly adopted in remote sensing surveillance, and its process is not affected by weather or light conditions. Ship instance segmentation using SAR is able to yield not only the box-level ship location but also the pixel-level ship contour. This approach plays an significant role in remote sensing surveillance in the ocean. However, most conventional approaches have limited box-positioning abilities, therefore deterring precision enhancement in instance segmentation. To alleviate this issue, the contribution by Ke et al. [12] presented a GCBANet for enhanced SAR ship instance segmentation. This approach has two novel blocks to guarantee excellent performance: GCIM-Block and BABP-Block. The authors conducted extensive simulations to prove each block's efficiency.

Remote sensing data of the Earth are influenced by numerous factors. Based on common/known hypotheses and a generation adversarial network, the contribution by Wang et al. [13] presented the SDTGAN approach to connect spectral data and to directly create target spectral remote sensing data. Additionally, more feature map information is presented to compensate for the lack of information in the spectral data and to enhance the geographic precision. By considering features such as supervised training with a balanced dataset, cycle consistency cost, and perceptual cost, the distinctiveness of the result is ensured. The simulation results prove that the presented SDTGAN approach outperforms conventional approaches.

SAR can generate microwave remote sensing data without weather restraints. Deep learning-based SAR ship detection approaches are hard to achieve on satellite data because deep learning typically has complex models and huge computations. To alleviate this issue, the contribution by Xu et al. [14] used the YOLOv5 method and presented a lightweight on-board SAR ship detector. In this work, the authors researched three topics: how to minimize the volume of the model, how to decrease the number of floating point operations, and how to understand on-board ship detection without losing precision. To test the proposed method, an evaluation was tested on an embedded platform NVIDIA Jetson TX2. The simulation results proved that the proposed methods outperformed conventional approaches subjectively and objectively.

Current conventional SAR moving target shadow detectors have low precision due to their incomplete feature-extraction capacities between complex scenes. To alleviate this issue, the contribution by Bao et al. [15] presented a new DLN called ShadowDeNet. This network was invented for better shadow detection of moving ground targets on signal SAR data. The authors proposed five approaches to ensure its performance: (1) HESE for better shadow saliency, (2) TSAM for focusing on ROI, (3) SDAL for deep learning on a moving target, (4) SGAAL for creating adjusted anchors, and (5) OHEM for choosing distinctive hard negative data. The authors tested the simulation on public SNL signal SAR data. The simulation results were tested with the SOTA benchmarks, and the proposed ShadowDeNet outperformed conventional approaches subjectively and objectively.

Pine wilt is an overwhelming disease that kills a vast number of affected pine trees within a short time. In the contribution by You et al. [16], the authors challenged this issue by detecting pine wilt disease. The main issue in detecting this disease is that data with low resolutions are used; therefore, there is high vagueness due to poor image resolution. In this work, the authors proposed two steps: (1) gathering the disease and hard negative data utilizing a CNN and (2) adopting an object-detection method to localize the disease. The authors adopted numerous image augmentation approaches to boost performance and to avoid overfitting. The simulation results were tested with the SOTA benchmarks, and the proposed method outperformed conventional approaches subjectively and objectively.

3. Conclusions

This Special Issue collected papers that emphasis new Artificial Intelligence-Based Learning Approaches for Remote Sensing. Furthermore, this Special Issue expects to encourage more research in the field of AI-based approaches for RS.

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