FOREST MONITORING USING HYPERSPECTRAL IMAGERY

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***Abstract*—In many agroforestry applications, conventional imagery—provided, for instance, by RGB and/or NIR sensors—has shown to be helpful. But only hyperspectral sensors have the spectral range and accuracy needed to characterize materials and organisms. Hyperspectral imagery and the corresponding ability to conduct analysis below the pixel level have tremendous potential to aid in land cover monitoring. Performance of Hyperspectral Image classification relies heavily on both spectral and spatial data. Due to increased computational complexity, only a small number of methods have used 3-D-CNN. In this project, we use a hybrid classifier, which is a spectral–spatial 3-D CNN followed by spatial 2-D-CNN. Intensive Hyperspectral Image classification tests are run over the Indian Pines remote sensing data sets to evaluate the effectiveness of this hybrid technique and statistics on the terrain are provided.**

I. Introduction

Forests are the most widely distributed terrestrial vegetation type, and thus play an important role in providing the environmental context and shaping the dynamics of regional and global ecosystem processes. Forests are important globally for provision of fiber to meet a range of needs, from local uses to industrial utilization. Forests play a role in the lives of most people on the planet. So it is highly necessary to protect the forests and its wealth.On the other hand, In the suburban cities, there is an increase in tension because of the sudden intrusion of forest animals into residential areas. So it is highly necessary to monitor, and classify both ecosystems and protect their respective resources.

Hyperspectral images (Hyperspectral Images) contain a wealth of spectral information that can be utilized for numerous applications such as land use classification, target detection, and environmental monitoring. However, the high dimensionality and complexity of Hyperspectral Images make it challenging to extract meaningful information from them. Convolutional neural networks (CNNs) have shown promising results in Hyperspectral Image classification, but their performance is limited by the lack of sufficient labeled training data and the high dimensionality of Hyperspectral Images. A novel approach using hybrid hyperspectral image classification method that combines 3-D and 2-D CNNs to address these challenges and improve Hyperspectral Image classification performance. The classification model is used to predict the materials present in the environment using the hyperspectral data. This makes it convenient to study the environment from distance and with great accuracy.

II. Objective

The main objective of this project is to use Hyperspectral Image classification on hyperspectral images to analyze it and classify. There is a significant potential for hyperspectral images and the associated capacity to perform analysis below the pixel level to help with land cover monitoring. Both spectral and geographical data are crucial to the effectiveness of Hyperspectral Image categorization. Only a few techniques have exploited 3D-CNN because of the rise in processing complexity. In this project, we deploy a spectral-spatial 3D-CNN followed by a spatial 2D-CNN classifier which is an Hybrid Hyperspectral Image Classification method. The dataset is first loaded into the model, where the hyperspectral image is classified before being used to analyze the environment and provide statistics about the distribution of the various trees, crops such as corn,hay,oats,soybean,wheat and other forest resources such as woods,grass. It can classify buildings and towers from these forest and agricultural resources and additionally, by assessing the nearby structures and forest vegetation, it gives residents information about their safety.

III. LITERATURE SURVEY

In [1] they propose a novel RNN model that can effectively analyze hyperspectral pixels as sequential data and then determine information categories via network reasoning.RNN makes use of a newly proposed activation function, parametric rectified tanh (PRetanh), for hyperspectral sequential data analysis instead of the popular tanh or rectified linear unit. The proposed activation function makes it possible to use fairly high learning rates without the risk of divergence during the training procedure. Moreover, a modified gated recurrent unit, which uses PRetanh for hidden representation, is adopted to construct the recurrent layer in our network to efficiently process hyperspectral data and reduce the total number of parameters. Experimental results on three airborne hyperspectral images suggest competitive performance in the proposed mode.

In [2] investigates CNNs and GCNs (qualitatively and quantitatively) in terms of HS image classification. Due to the construction of the adjacency matrix on all the data, traditional GCNs usually suffer from a huge computational cost, particularly in large-scale remote sensing (RS) problems. They developed a new minibatch GCN (called miniGCN hereinafter), which allows to train large-scale GCNs in a minibatch fashion.

More significantly, this miniGCN is capable of inferring out-of-sample data without retraining networks and improving classification performance. Furthermore, as CNNs and GCNs can extract different types of HS features, an intuitive solution to break the performance bottleneck of a single model is to fuse them. Since miniGCNs can perform batch wise network training (enabling the combination of CNNs and GCNs), Three fusion strategies: additive fusion, elementwise multiplicative fusion, and concatenation fusion to measure the obtained performance gain. Extensive experiments, conducted on three HS data sets, demonstrate the advantages of miniGCNs over GCNs and the superiority of the tested fusion strategies with regard to the single CNN or GCN models.

[3] involved observation that Hyperspectral Image classification can be implemented via human vision. Compared with SVM-based classifier and conventional DNN-based classifier, the proposed method could achieve higher accuracy using all the experimental data sets, even with a small number of training samples. The classifier contains five layers with weights which are the input layer, the convolutional layer, the max pooling layer, the full connection layer, and the output layer. These five layers are implemented on each spectral signature to discriminate against others.

[4] introduces three new contributions to image classification and image search challenges. We begin by proposing a novel picture patch quantization approach. Other competing techniques need a huge code book and sampling from numerous local locations for good picture description, at the price of prohibitively long processing times. Extremely Randomized Clustering Forests are collections of randomly generated clustering trees that are more accurate, quicker to train and test, and more resistant to background clutter than existing approaches. Second, we present an effective image classification approach that closely integrates ERC-Forests and saliency maps with picture information sampling. A classifier creates an online saliency map for a given picture.

In [5], a novel is based on a deep forest algorithm for Hyperspectral Image classification. They designed the deep forest (gcForest) for spectral-based Hyperspectral Image classification, analyzed the hyperparameters of gcForest on the classification performance. A deep multigrained scanning cascade forest for spatial-based Hyperspectral Image classification is made and to enhance the performance of multigrained scanning the cascade forest is used to substitute the random forest and the complete-random tree forest; Comparing the algorithm with the state-of-the-art deep learning methods, it demonstrated that our algorithm is useful for spatial-based Hyperspectral Image classification and that it saves much time. The features generated by multigrained scanning are large and redundant, and can be used to sparse representation to solve it. Then there are many hyperparameters in dgcForest that need adjustment, and we can optimize these hyperparameters along with the structure of dgcForest simultaneously via some evolutionary algorithms. Finally, dgcForest has a good performance in image processing, and we will try it for feature extraction on the original Hyperspectral Image directly.

[6] reviews RF and SVM concepts relevant to remote sensing image classification and applies a meta-analysis of 251 peer-reviewed journal papers. A database with more than 40 quantitative and qualitative fields was constructed from these reviewed papers. The meta-analysis mainly focuses on: the analysis regarding the general characteristics of the studies, such as geographical distribution, frequency of the papers considering time, journals, application domains, and remote sensing software packages used in the case studies, and a comparative analysis regarding the performances of RF and SVM classification against various parameters, such as data type, RS applications, spatial resolution, and the number of extracted features in the feature engineering step. The challenges, recommendations, and potential directions for future research are also discussed in detail. Moreover, a summary of the results is provided to aid researchers to customize their efforts in order to achieve the most accurate results based on their thematic applications.

[7] proposes a novel approach for image classification that combines graph convolutional networks (GCNs) with convolutional neural networks (CNNs) and transfer learning. The proposed hybrid spectral-CNN (HSCNN) framework employs CNNs to learn high-level features and GCNs to extract both local and global structural information from the picture. In order to increase the model's accuracy, the authors also use transfer learning by pre-training the CNNs on a sizable dataset and then optimising them on the target dataset. Specifically on datasets with high-dimensional and complicated data, like ImageNet, the experimental results demonstrate that the HSCNN surpasses other methods in terms of accuracy. Overall, the work provides a promising method for classifying images that combines the advantages of GCNs and CNNs and uses transfer learning to boost performance.

[8] proposes a hybrid convolutional neural network (CNN) architecture for hyperspectral image classification that combines both spectral and spatial information. The proposed hybrid spectral and spatial CNN (HSS-CNN) architecture consists of two branches: a spectral branch and a spatial branch which are then combined through a fusion layer to generate the final classification result. According to the experiment results, the suggested HSS-CNN performs better in terms of accuracy than other approaches and is able to efficiently collect both spectral and spatial information for enhanced classification performance. The data demonstrate the value of both spectral and spatial information for classification performance and the efficiency with which the HSS-CNN model can combine the two. The study offers a promising method for classifying hyperspectral images that integrates spectral and spatial data using a hybrid CNN architecture and performs at the cutting edge on benchmark datasets.

[9] proposes a new approach for hyperspectral image classification using a hybrid spectral convolutional neural network (SCNN). The proposed model combines both spectral and spatial information to improve the accuracy of classification results.To extract combined spectral-spatial characteristics, the hybrid module includes both spectral and spatial convolutional

layers. A fully connected layer receives the retrieved features and performs classification on them. The experimental results demonstrate that, especially for complicated hyperspectral pictures, the proposed hybrid SCNN outperforms traditional approaches in terms of classification accuracy. In order to assess the significance of combined spectral-spatial properties in the suggested hybrid SCNN model, the authors also perform a sensitivity analysis. The findings indicate that the hybrid module is superior to the spectral module alone for classification. Overall, the research proposes a promising method for classifying hyperspectral images using a hybrid SCNN architecture that incorporates spectral and spatial information.

[10] identified a novel method for classifying EEG data using 3D convolutional neural networks (CNNs). The suggested method seeks to overcome the shortcomings of current EEG classification techniques, which frequently demand substantial feature engineering and have poor accuracy. The input data is preprocessed and converted into a three-dimensional (3D) tensor, with the three dimensions representing the time, frequency, and spatial positions of the scalp's EEG signal. A number of convolutional and pooling layers are present in the proposed 3D CNN architecture, which is followed by fully connected layers that output the classification result. The results of the experiments demonstrate that the proposed 3D CNN method outperforms other cutting-edge EEG classification techniques, attaining greater accuracy and robustness across various datasets. The study offers a potential method for classifying EEG data using 3D CNNs that produces cutting-edge results on benchmark datasets without a lot of feature engineering.

In [11] deep learning method for action recognition utilising depth maps is presented in this paper. The suggested technique extracts spatiotemporal information from depth maps using a 3D convolutional neural network (CNN) architecture. MSR Action3D and UTD-MHAD, two publically accessible datasets, were used to assess the suggested technique. The experimental results demonstrate that the suggested method outperforms numerous other methods for action recognition using depth maps and achieves state-of-the-art performance on both datasets. Overall, the study offers a promising deep learning method for action recognition using depth maps, which may find use in a variety of fields, such as robotics, surveillance, and human-computer interaction.

IV. COMPARATIVE ANALYSIS

The literature surveys cover a broad range of topics related to hyperspectral image classification, including various algorithms, techniques, and applications. They discuss different methods used for hyperspectral image classification, such as spectral-spatial methods, dimensionality reduction, and machine learning techniques.

In contrast, this project work specifically focuses on proposing a novel approach using a 3-D–2-D CNN feature hierarchy for hyperspectral image classification. It emphasizes the feature extraction and classification stages using CNNs and evaluates the proposed approach on the Indian Pines dataset.

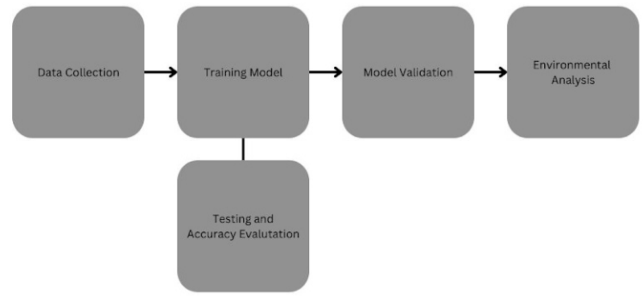

Fig. 1. Architecture Diagram

The literature surveys provide a general overview of the process and modules involved in hyperspectral image classification, including data acquisition, preprocessing, feature extraction, classification, and visualization. They discuss different datasets used for evaluation, depending on the specific studies they discuss.

On the other hand, this project work provides a detailed description of specific modules involved in your approach. It includes data acquisition and preprocessing, feature extraction and concatenation using 3-D and 2-D CNNs, data analysis and classification using machine learning algorithms, and visualization and reporting of the results. It focuses on the implementation details of your proposed approach.

In terms of evaluation and performance, the literature surveys provides comparative evaluations of different methods based on performance metrics like classification accuracy, overall accuracy, kappa coefficient, or user's and producer's accuracy. However, your project evaluates the proposed approach on the Indian Pines dataset and outperforms state-of-the-art methods in terms of classification accuracy. This project uses the Indian Pines dataset for evaluation, which has a spatial dimension of 145x145 and 224 spectral bands. The dataset also provides ground truth information with 16 classes of materials.

In summary, the literature surveys provide a broader overview of hyperspectral image classification techniques and their applications. They discuss different methods, datasets, and performance evaluations. On the other hand, this project work focuses on proposing a specific approach using a 3-D–2-D CNN feature hierarchy. It emphasizes the methodology, implementation details, and evaluation of the Indian Pines dataset.

V. ARCHITECTURE DIAGRAM

A. Data Acquisition and Preprocessing

This component is responsible for acquiring and preprocessing the hyperspectral data. This may involve filtering out the noise, correcting for atmospheric effects, and aligning the data with ground control points to ensure accuracy.

B. Model Training and Visualization

This component analysis hyperspectral data and trains a model using it. This involves the use of machine learning algorithms, statistical models, and other analytical tools to detect patterns in the data. Visualization is done to present the results of the analysis in a format that is easy to understand.

C. Environment Analysis

This component uses the trained model for analyzing the given Hyperspectral Image and displaying various types of environments, terrains, and crops.

VI. PROPOSED WORK

Hyperspectral image classification has been an active research area in recent years due to its wide applications in various fields such as remote sensing, agriculture, and environmental monitoring. However, accurate classification of hyperspectral images is still a challenging task due to the high dimensionality and complex spectral signatures of hyperspectral data. In this project, we propose a novel approach that uses a 3-D–2-D CNN feature hierarchy for hyperspectral image classification.
The proposed approach consists of two stages: the feature extraction stage and the classification stage. In the feature extraction stage, a 3-D CNN is used to extract the spectral-spatial features from the hyperspectral data cube. Then, a 2-D CNN is used to further extract the spatial features from the output of the 3-D CNN. In the classification stage, a fully connected layer is used to classify the extracted features into different classes.

To evaluate the proposed approach, we conducted experiments on a hyperspectral dataset, Indian Pines. The experimental results demonstrate that the proposed model approach outperforms the state-of-the-art methods in terms of classification accuracy.

The classified output is then visualized using various methodologies to provide detailed statistics on the contents available in the map and their proportions to get a better understanding about the region.

VII. MODULES

A. Data Acquisition and Preprocessing

This module involves acquiring hyperspectral data from the remote sensing device, such as an aircraft or satellite. The data is then preprocessed to remove noise, correct for atmospheric effects, and align the data with ground control points to ensure accuracy. The preprocessing steps may include radiometric calibration, spectral calibration, and geometric correction.

B. Feature Extraction and Concatenation

This module extracts spatial-spectral features from the hyperspectral data using a 3D CNN. The 3D CNN consists of multiple convolutional layers, followed by batch normalization and rectified linear unit activation functions. The output of the 3D CNN is a feature map that captures both spatial and spectral features of the hyperspectral data.Then spatial features from the RGB images of the hyperspectral data are extracted using a 2D CNN. The 2D CNN consists of multiple convolutional layers, followed by batch normalization and ReLU activation functions. The output of the 2D CNN is a feature map that captures spatial features of the RGB images.The outputs of the 3D and 2D CNN feature extraction modules are combined by concatenating them along the feature dimension. This results in a fused feature map that captures both spatial and spectral features of the hyperspectral data.

C. Data Analysis and Classification

This module involves using machine learning analytical techniques to classify the hyperspectral data into different land cover types, such as forests, grasslands, and water bodies. The classification process may involve the use of supervised or unsupervised learning algorithms, such as decision trees, support vector machines, and artificial neural networks. The accuracy of the classification model can be evaluated using validation techniques such as cross-validation.

D. Visualization and Reporting

This module involves presenting the results of the data analysis in a visual format that is easy to understand. The visualization can be done using various techniques such as maps, graphs, and charts. The reporting module generates reports on the state of the forest ecosystem, highlighting areas where various different environments and terrains are found.

CONCLUSION

The use of hyperspectral imagery for forest monitoring has the potential to provide more detailed and accurate information on forest conditions, which can be valuable for environmental management and conservation efforts. The Hybrid Hyperspectral Image Classification approach can enhance the capabilities of existing monitoring systems by providing more accurate and reliable classification results.The experimental results demonstrated that this approach outperformed several state-of-the-art methods, achieving higher overall accuracy on the hyperspectral dataset. The approach was able to accurately distinguish between different forest types, including deciduous, coniferous, and mixed forests, as well as detect changes in forest conditions due to disturbances such as forest fires and insect infestations.

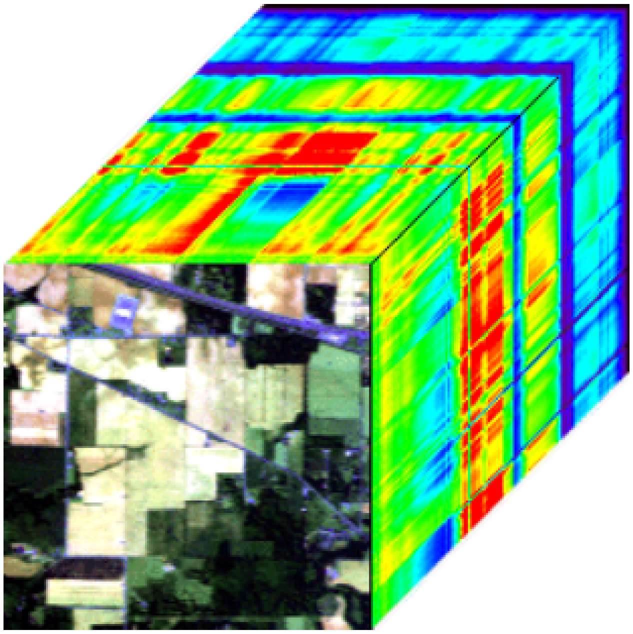

Fig. 2. Hyperspectral Image - Indian Pines

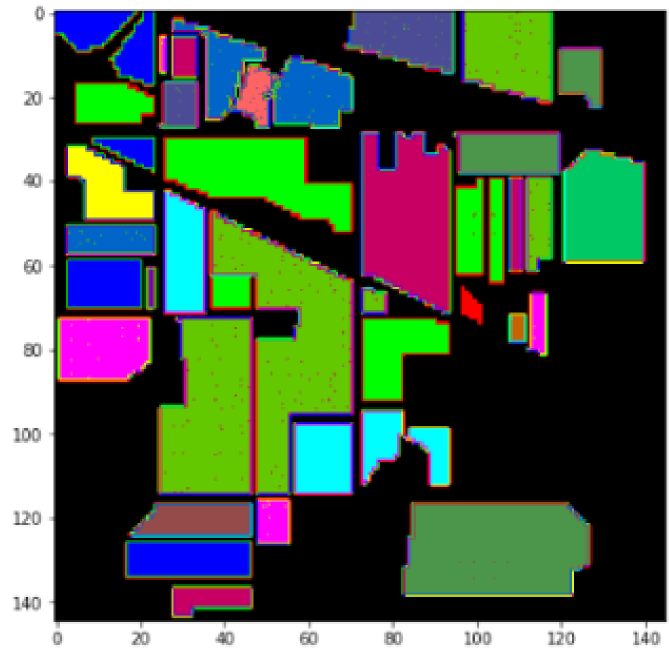

Fig. 3. Ground truth Image - Indian Pines

VIII. Resource Used

A. Data Set: Indian Pines - Hyperspectral data

The Indian Pines data set shown in figure 2 has images with 145×145 spatial dimension and 224 spectral bands in the wavelength range of 400 to 2500 nm, out of which 24 spectral bands cover the region of water absorption have been discarded.

B. Indian Pines - Ground Truth

The ground truth shown in figure 3 is designated into 16 classes of materials except for the black unknown region.

In figure 4, the legend for the ground truth image of the Indian Pines data set is shown. It consists of 17 different categories like materials and plantation.

IX. Output

The output of the model is a classification map, which assigns each pixel in the input image to one of the predefined classes. This map is generated by passing the input hyperspectral image through the hybrid hyperspectral image classification model, which extracts features at different levels of abstraction using both 3D and 2D convolutions. These features are then combined and passed through fully connected layers to produce the final classification map. The resulting map shows the spatial distribution of different land cover types in the input hyperspectral image and can be used for various applications such as land use planning, environmental monitoring, and natural resource management. accuracy: 0.9940

Various terrains and their respective colors:

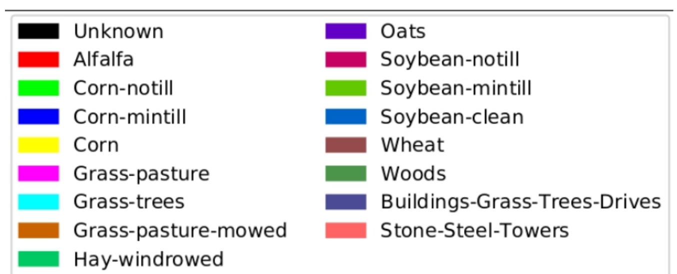

Fig. 4. Legend - ground truth image

1) Blue - Soybean(clean)
2) Indigo - Corn(mintill)
3) Dark Purple - Oats
4) Black - Unknown
5) Slate Grey - Buildings-Grass-Trees-Drives
6) Lime Green - Soybean(mintill)
7) Crimson - Alfalfa
8) Brown - Wheat
9) Magenta - Soybean
10) Olive Green - Woods
11) Coral - Stone-Steel-Towers
12) Green - Corn(nothill)
13) Sea Green - Hay(windrowed)
14) Yellow - Corn
15) Cyan - Grass,trees

The image is then distinguished by their distinct colors. The image contains 17 specific data each colored differently. This is then used to show detailed statistics on the percentage of each type of vegetation and buildings present in that area.

Fig. 5. Classification map

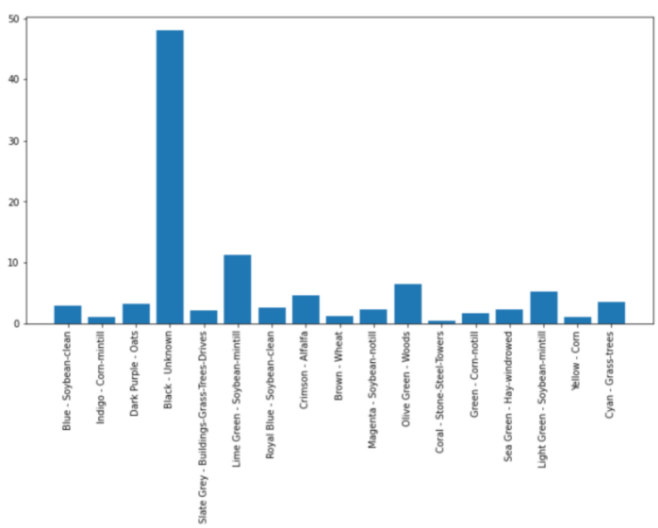

Fig. 6. Graph between Types of terrains vs Occupied percentage

In figure 6, the terrains and their percentage of space occupied in the loaded dataset is displayed. This is used to assess the area occupied by the vegetation, crops and farmland as well as the woods, driveways and buildings made of steels and stones.

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