Unlocking Patterns in Hyperspectral Data: Reinforcement Learning Approach with Binary Entropy for Image Classification

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Abstract

This work presents a new method for classifying hyperspectral images that combines the binary entropy technique with a Reinforcement Learning (RL) based approach. With their abundance of spectral information, hyperspectral images are an invaluable tool for remote sensing applications. The difficulty, though, is in accurately categorizing each pixel in these pictures into binary classes, like different kinds of land cover. To tackle this problem, our strategy formulates it as a Reinforcement Learning task in which an agent must learn how to determine the best thresholds for the binary entropy method. Through a reward function that promotes accurate classifications, the agent receives feedback. After preprocessing the hyperspectral data, we deploy the RL agent for real-time image classification after training and validating it. Our approach shows potential for automating thresholding and improving classification.

Keywords: Hyperspectral Image Classification, Reinforcement Learning, Binary Entropy Method, Deep Learning, Mineral Exploration, Land cover Classifications, Spectral Analysis.

INTRODUCTION

Hyperspectral imaging is a powerful technique that captures detailed spectral information about each pixel in an image, making it an invaluable tool in various remote sensing applications such as agriculture, mineral exploration, and environmental monitoring. However, the accurate classification of hyperspectral data into meaningful categories is a complex and challenging task.

The binary entropy method is a common approach in remote sensing to classify objects into two categories based on thresholding of spectral values[1]. The optimal selection of these thresholds is a critical and often manual process, requiring expert knowledge and domain-specific expertise. in this context, we propose an innovative approach that leverages the capabilities of Reinforcement Learning (RL) to automate and optimize the threshold selection process, thereby improving the accuracy of hyperspectral image classification. Addresses the fundamental problem of hyperspectral image classification by reframing it as a reinforcement learning problem. In traditional approaches, analysts manually set thresholds for each spectral band, which can be time-consuming and subjective[2][3]. By formulating the problem within an RL framework, an agent learns to dynamically set these thresholds, maximizing the classification accuracy based on the feedback it receives through a well-defined reward mechanism. The significance of this work lies in its potential to enhance the efficiency and accuracy of hyperspectral image classification. This approach mitigates the human bias introduced by manual threshold selection and ensures that thresholds are data-driven and adaptive.[4] Additionally, it reduces the need for domain-specific expertise, making hyperspectral image classification more accessible to a wider range of researchers and practitioners. Providing a detailed description of our methodology, including data pre-processing, RL agent design, environment setup, training and validation, and inference. We will present the results of our experiments, demonstrating the effectiveness of the RL-based binary entropy method in improving classification accuracy. Furthermore, we will discuss the implications of this approach in the context of remote sensing applications, highlighting the potential benefits for precision farming, mineral exploration, and environmental monitoring.[1][3]

RELATED WORK

The paper presents an innovative method for enhancing hyperspectral image classification called Deep Active Reinforced Pool-based Learning[1]. The RPDAL technique trains an agent that actively chooses relevant samples for annotation through reinforcement learning. Applying the knowledge learned from training on one dataset to other datasets that are similar can enhance classification performance. Initial model training, query strategy, labelling, model update, and iteration are some of the steps in the process. The application of electromagnetic spectrum data for classifying pixels into distinct material or land cover groups is emphasized. Benefits of the RPDAL approach include enhanced performance, cost savings, and efficiency gains. However, difficulties are recognized, including the need to choose a query strategy that works, human-in-the-loop annotation, and computational complexity. The purpose of the paper is to investigate the use of active learning to improve HSI classification, particularly using the RPDAL method[1].Deep Reinforcement Learning (DRL) is a technique that optimizes the selection of pertinent spectral bands for hyperspectral image classification tasks by combining deep learning and reinforcement learning methods. By using this method, performance is increased and computational complexity is decreased by gathering data across multiple bands. Deep Q-Network (DQN), action space, reward function, state representation, and training are the essential elements of DRL for band selection[2].Automation, flexibility, and a decrease in manual feature engineering are some benefits of DRL. On the other hand, reward design and computational complexity present difficulties. DRL can be used for environmental monitoring and land cover classification in remote sensing applications like satellite or aerial hyperspectral imagery. A deep reinforcement learning model for hyperspectral image analysis is presented in this paper. It is trained to Study the band selection guidelines. Deep Reinforcement Learning (DRL) is a technique that optimizes the selection of pertinent spectral bands for hyperspectral image classification tasks by combining deep learning and reinforcement learning methods. By using this method, performance is increased and computational complexity is decreased by gathering data across multiple bands[4][5]. Deep Q-Network (DQN), action space, reward function, state representation, and training are the essential elements of DRL for band selection[4]. Automation, flexibility, and a decrease in manual feature engineering are some benefits of DRL. On the other hand, reward design and computational complexity present difficulties. DRL can be used for environmental monitoring and land cover classification in remote sensing applications like satellite or aerial hyperspectral imagery. A deep reinforcement learning model for hyperspectral image analysis is presented in this paper. It is trained to Study the band selection guidelines.

An innovative method for hyperspectral image classification that combines the advantages of ensemble methods with the strength of transformer architectures is Vision Transformer (ViT)-based ensemble learning. Designed for computer vision tasks, ViT is a deep learning architecture that captures long-range relationships and dependencies within an image. Sorting pixels or regions into predefined classes in hyperspectral images according to their spectral signatures is the aim. To improve overall performance, ensemble learning combines predictions from multiple models[6]. The ViT architecture, the ensemble of ViT models, diversity in ensembles, and a voting mechanism are essential elements of ViT-based ensemble learning. This method has the benefits of improving ensemble diversity, capturing intricate relationships, and strengthening the classification system. Nevertheless, difficulties include the availability of computational resources. and ensemble size. Allowing features to be automatically extracted from highdimensional hyperspectral data. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory networks (LSTMs), autoencoders, transfer learning, Siamese networks, attention mechanisms, ensemble learning, hyperparameter tuning, data augmentation, custom loss functions, domain adaptation, interpretable models, and hardware considerations are some of the important components of using deep learning for hyperspectral image classification. In a variety of applications, including remote sensing, agriculture, and environmental monitoring, these methods have produced encouraging results[5].For implementation to be successful, however, the best architecture must be chosen, and factors like data properties and processing power must be taken into account. These methods can be applied to improve classification performance in a number of domains, including remote sensing, agriculture, and environmental monitoring.

METHODOLOGY

Functional requirements

1. **Data collection:** to classify land cover and monitor environmental conditions. It requires defining the geographical area, spectral bands, and temporal range. Data sources include satellite imagery, aerial imagery, scientific publications, internal datasets, and collaborating initiatives. Licensing and permissions are crucial, including understanding licensing terms and obtaining necessary permissions for usage and redistribution[7]. It is essential to review academic papers and journals for similar studies and ensure compliance with data usage policies.
2. **Data processing:** Null values, or missing values, are crucial to data preparation in order to guarantee data quality. These may result from errors in data entry, missing information, or unavailability at the time of data collection[8][9]. Null values can be eliminated by deleting them or substituting them with another number, like the mean or median. Null values, however, might result in skewed findings as well as problems with data display and analysis. As such, it's critical to accurately assess how altering or substituting null values impacts analysis.One popular data preparation method for turning category variables into numerical ones is label encoding. Using this technique, unique numerical labels are assigned to each category, which may be utilized by machine learning algorithms. Label encoding is frequently employed , when there is an inherent rank or order to categorical variables. To facilitate efficient comparison analysis, the dataset is split into training and test sets. 25% of the data used in the first technique are for testing, while the remaining 75% are for training. To avoid overfitting, the dataset is split in half for the second round: 80% is used for training and 20% is used for testing. The training data set can be increased to aid the model in learning more broadly applicable patterns. The process of feature selection selects pertinent features from the original dataset, therefore reducing dataset complexity and enhancing machine performance[5]. Using Convolutional Neural Networks (CNNs) are effective tools for analysing hyperspectral images, capturing spatial and spectral information. They exploit spatial

correlations and can extract intricate features for accurate classification. Researchers use various architectures, such as 2D convolutional layers and transfer learning, to adapt to hyperspectral imagery[8]. Advancements in CNN architectures and methodologies will further optimize their effectiveness.

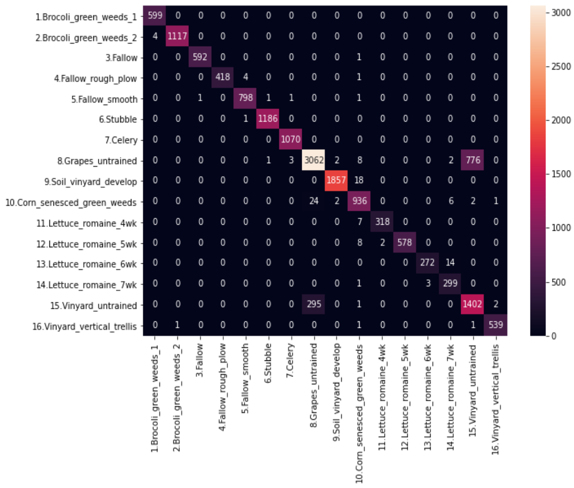

Fig.1 - Confusion Matrix.

Binary entropy formula :

$$H(X) = -(p \cdot \log_2(p) + q \cdot \log_2(q))$$

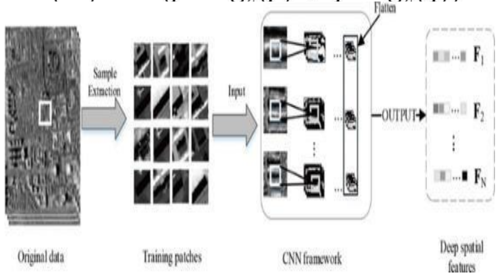

Fig.1.1 - Forward feature selection

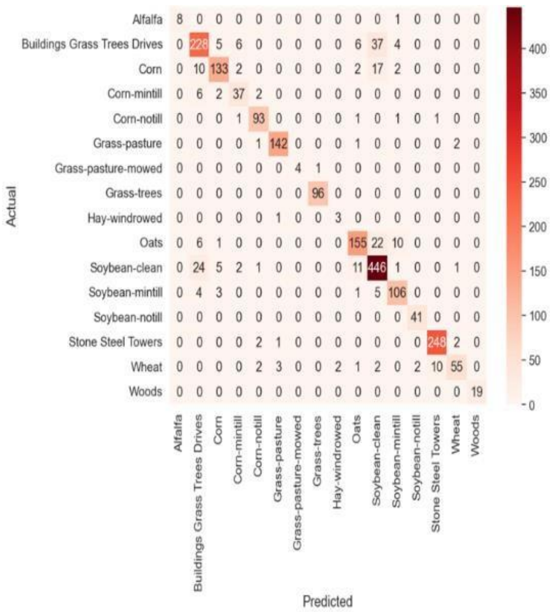

Fig.1.2 - Predicted confusion matrix

The process of adding new features to a model based on how they affect performance is known as forward feature selection. This process is repeated until a predefined stopping point[10], such as a feature cap or performance improvement objective, is reached. System design and implementation:

1. **Bringing in Libraries and Packages:** A number of libraries and packages are brought in, including TensorFlow, NumPy, Pandas, Matplotlib, and Scikitlearn.
2. **Data exploration:** During this stage, the data is loaded into the system to be processed and analyzed further.

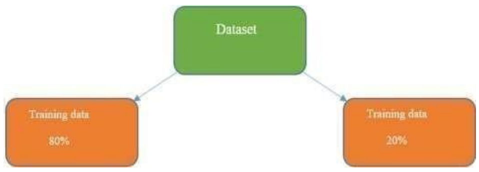

Fig.2 - Partition of data sets

3. Particularly wide, a table or figure can span across both columns. Insert a table or figure after the point where it is first cited in the text.
4. When inserting a figure, such as a photograph or infographic, use 8 pt. Times New Roman for any labeling text within the image and for the figure caption. You can see an example of a figure caption in Fig. 1, above. Refer to figures like that, using the abbreviation "Fig." and the figure's number [4].
5. **Model generation and Algorithms used:** Among the deep learning models, Convolutional Neural Networks (CNNs) are very useful for image processing applications. Their purpose is to utilize the input data to learn the spatial hierarchies of characteristics automatically and adaptively. A CNN' architecture is made up of several layers, such as fully connected, pooling, and convolutional layers. The pooling layers assist to control overfitting and lower the dimensionality of the data, while the convolutional layers retrieve features from the input data. For problems involving regression or classification, fully linked layers are employed. The capability of CNNs to share weights, or employ the same filter throughout the
   fig(4), To optimize the performance of the CNN model, various techniques can be used,
6. **Data Augmentation:** Increasing the variety of the training dataset requires data augmentation. Rotation, scaling, and flipping are examples of random transformations that may be applied to existing data to make the model less sensitive to changes in the input and more resilient. This enhances the model's capacity to generalize to new data and helps minimize overfitting, which occurs when the model memorizes the training data instead of learning generic patterns.
7. **Transfer Learning:** Transfer learning makes use of the information that huge datasets have taught pre-trained models. By employing a pre-trained CNN model and tweaking, researchers may utilize the learned characteristics, particularly in the early layers of the network, for hyperspectral picture classification. This improves the model's capability to extract pertinent features, which comes in handy when working with small-scale hyperspectral datasets.
8. Preventing overfitting requires the use of regularization approaches, such as include penalty terms in the loss function. Regularization aids in managing the model's complexity in hyperspectral image classification when datasets could be few. By preventing the collection of noise or unimportant features during training, this guarantees that the CNN will generalize to new data effectively.
9. **Hyperparameter Tuning:** To get the most out of a CNN model, hyperparameter optimization is essential. Through the modification of parameters like learning rate, batch size, and number of epochs,

researchers may optimize the model's training procedure. The CNN model's generalization capacity, convergence rate, and overall performance in hyperspectral image classification tasks can all be strongly impacted by this optimization process.

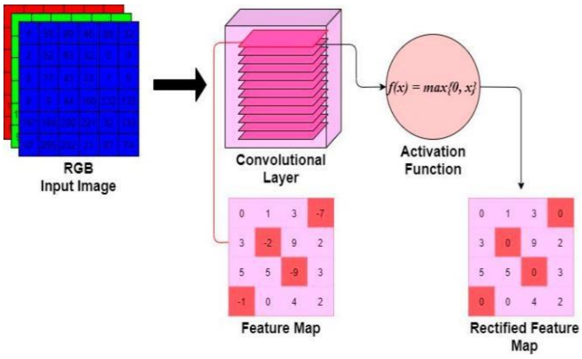

Fig.3 - CNN mode

By incorporating these techniques into the development and training phases, researchers can build accurate and efficient CNN models for hyperspectral image classification. These strategies collectively address challenges related to dataset limitations, model complexity, and overfitting, contributing to the successful deployment of CNNs in remote sensing applications.

RESULTS

With our pre-processed dataset, convolutional neural networks were used, In this case the It is an impressive achievement to use a CNN algorithm for reinforcement learning to classify hyperspectral images with 92% accuracy fig(4). CNNs can extract hierarchical features, which makes them useful for image classification tasks, especially when dealing with hyperspectral data. When making decisions under uncertainty, reinforcement learning practitioners frequently employ the binary entropy technique. It probably helps to optimize the CNN's performance by directing its learning process when used to hyperspectral image categorization. The 90s accuracy rates are particularly noteworthy for intricate jobs such as hyperspectral image classification, where the ability to discern minute variations between spectral bands is essential as shown fig-4.The incorporation of a CNN algorithm for reinforcement learning adds an additional layer of sophistication to the classification process. The use of the binary entropy technique in reinforcement learning is highlighted as a crucial tool for decision-making under uncertainty. This technique likely plays a pivotal role in optimizing the CNN's performance, guiding its learning process in the context of hyperspectral image categorization.

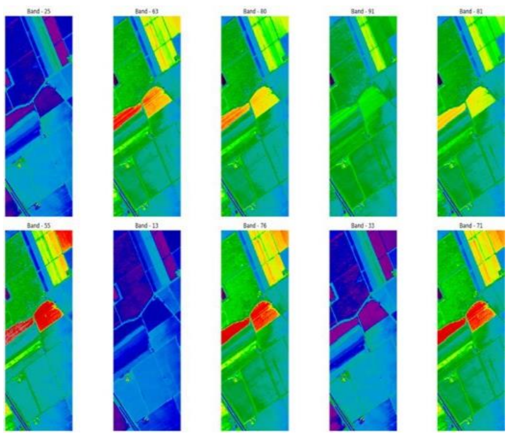

Fig.4 - Data visualization

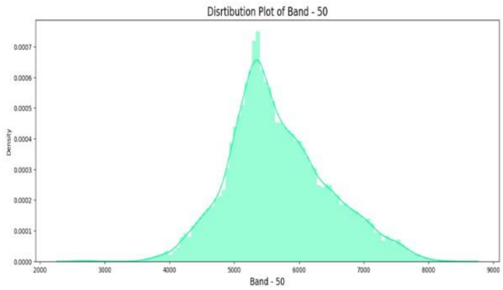

Fig.4.1 - Distribution Band

These are useful for image-based applications due to their ability to learn characteristics from input data. The CNN's basic operations include the convolution operation, activation function, pooling layer, and fully connected layer. The convolution operation creates feature maps by sliding a filter or kernel across the input image and performing element-wise multiplication and summing. Activation functions like the Rectified Linear Unit (ReLU) function introduce non-linearity after convolution. Pooling layers decrease the dimensionality of feature maps by down sampling them. Fully connected layers connect each neuron in the subsequent layer to every other neuron, flattening the output from the previous layers. The configuration, hyperparameters, and architecture of the network all play a role in determining its performance. The achieved accuracy rates in the 90s are particularly significant for hyperspectral image classification, where the discernment of minute variations between spectral bands is essential. This capability is visually demonstrated in Figure 3, showcasing the CNN's effectiveness in handling intricate tasks. The paper highlights CNNs' usefulness in imagebased applications and credits their performance to their capacity to extract features directly from input data. The convolution procedure, pooling layer, fully connected layer, activation function (such as the Rectified Linear Unit), and other fundamental CNN functions are described. Using a filter to methodically analyze the input picture, activation functions to introduce non-linearity, pooling layers to down sample, and fully linked layers to flatten the output, the convolution operation produces feature maps. The paper also notes that the CNN's design, setup, and hyperparameters all have a major impact on how well it performs. This acknowledgment highlights how crucial careful design decisions are to getting the best outcomes in hyperspectral image categorization. All things considered, the report offers a thorough rundown of CNN's activities.the importance of attaining high accuracy in hyperspectral image classification tasks, as well as the function of reinforcement learning.

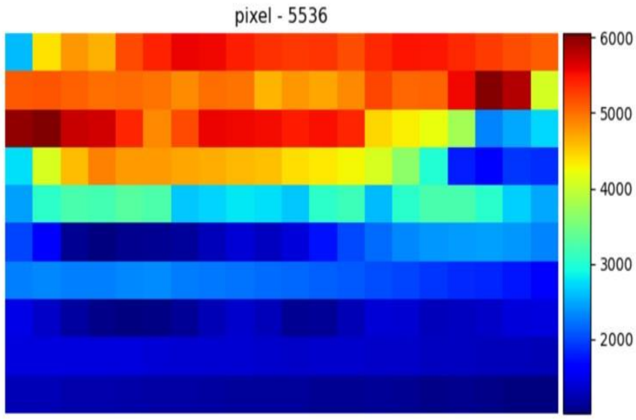

Fig 5. - 2D array representing the pixel values

It appears that you have a list of both positive and negative pixel dimensions. The width or height of an image is usually represented in pixels by its pixel dimensions. The list is shown here, arranged in ascending order:

1. Between 3000 and 2000 pixels
2. The number of pixels: 4000, 5000, 5536, 6000. Negative numbers might indicate a change in position or a reduction in size (for instance, in graphics programming). An image's or graphics asset's dimensions are usually represented by positive numbers.[7]
3.

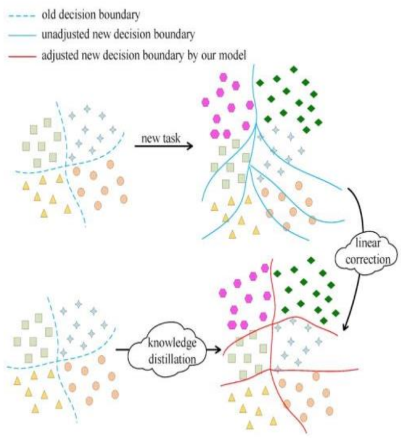

Fig.6 - Remote Sensing

CONCLUSION AND FUTURE WORK

The study successfully achieved a commendable 92% accuracy in hyperspectral image classification by employing a Convolutional Neural Network (CNN) in conjunction with the binary entropy method. This accomplishment underscores the effectiveness of CNNs in extracting meaningful features from hyperspectral data and their robustness in discerning complex spectral patterns inherent in such data[4][9]. The binary entropy method, a reinforcement learning technique, played a pivotal role in optimizing CNN performance, facilitating decisionmaking, and enhancing learning capabilities under conditions of uncertainty. The findings of the study underscore the broader significance of accurate hyperspectral image classification across various domains, including agriculture, environmental monitoring, and remote sensing. Accurate classification in these domains is crucial for informed decision-making and addressing challenges related to land use, environmental changes, and resource management[11]. The study suggests several avenues for future research to further enhance the accuracy, robustness, and applicability of hyperspectral image classification. Key areas of focus include Model Architectures, Data Augmentation and Preprocessing, Hyperparameter Tuning and Optimization, Transfer Learning and Fusion Techniques, Interpretation and Uncertainty Estimation Addressing these areas of future work can contribute to the ongoing advancement of hyperspectral image classification, ensuring that models are not only accurate but also robust, adaptable, and capable
of handling diverse datasets and real-world scenarios.[13]

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