Land Cover Classification

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Introduction:

Land-cover classification is a process of assigning land-use categories to the pixels of an image based on their spectral characteristics. The main goal of land-cover classification is to group different types of land, such as urban, agricultural, forest, water bodies, etc. This process is important for various applications, including environmental monitoring, land-use planning,resource management and mainly for sustainable development.

Land-cover classification can be performed using various methods, including supervised and unsupervised classification techniques. In supervised classification, the categories are pre-defined, and a classifier is trained using training samples for each category. The classifier is then used to classify the remaining pixels of the image. In unsupervised classification, the categories are not predefined, and the algorithm automatically groups the pixels into different categories based on their spectral characteristics. One of the main challenges in land-cover classification is to deal with the high-dimensional nature of the data.

Dataset:

The ability to automatically categorize and divide land cover is crucial for various applications such as sustainable development, self-sufficient agriculture, and urban planning. We are using the dataset from DeepGlobe Land Cover Classification Challenge to develop an algorithm that can automatically classify different types of land cover. The problem is framed as a multi-class segmentation task, with the goal of identifying and distinguishing urban, agriculture, rangeland, forest, water, barren, and unknown areas. But here for our use we will be doing Multi-label classification.

Data pre-processing:

Data preprocessing is an essential step in preparing images for machine learning tasks. Two common techniques used in data pre-processing for images are resizing and normalization.

Resizing involves changing the dimensions of an image to a specific size, which is often required when working with images of varying sizes. This is typically done using interpolation techniques, which can either enlarge or reduce the image size. Resizing images can help to reduce the computational burden of working with large images and ensure consistency in the input size of images to the model.

Normalization is another technique used to preprocess image data. It involves dividing each pixel with 255 to bring all the pixels in the range between 0 and 1. This is important because PCA is sensitive to the mean and centering the data helps to remove any biases. Normalization can also help to reduce the impact of varying lighting conditions and color intensity across different images.

Together, resizing and normalization can help to improve the accuracy and stability of machine learning models trained on image data.

Data Analysis:

The following labels are present in the data for classification namely, urban, agriculture, rangeland, forest, water, barren, and unknown.

The overall distribution of different classes or labels in our dataset is shown Figure 1:

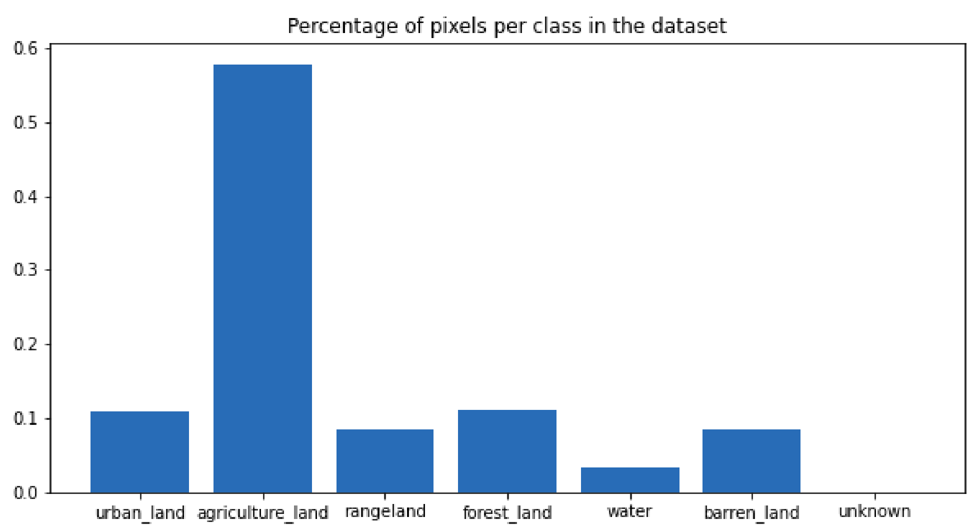

Figure 1

- The information in Figure 2.1, suggests that out of the total land area covered by the satellite image dataset, 70% of it is classified as "water". This implies that water is the dominant land cover type in the dataset, and it may be useful to further investigate the characteristics and functions of water bodies in the region covered by the dataset.

- The information in Figure 2.2, suggests that out of the total land area covered by the satellite image dataset, 60% of it is classified as "houses" or "urban land", while the remaining 40% is classified as other land cover types.

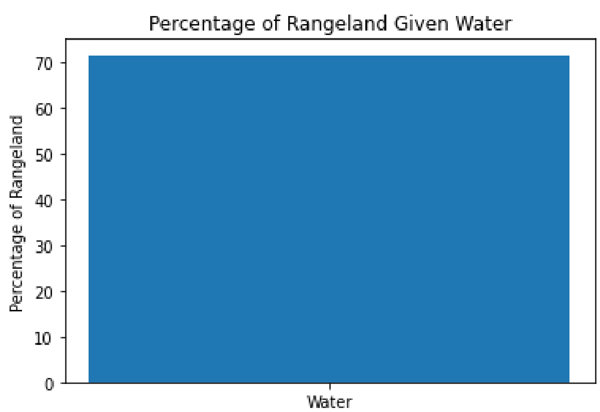

Figure 2.1

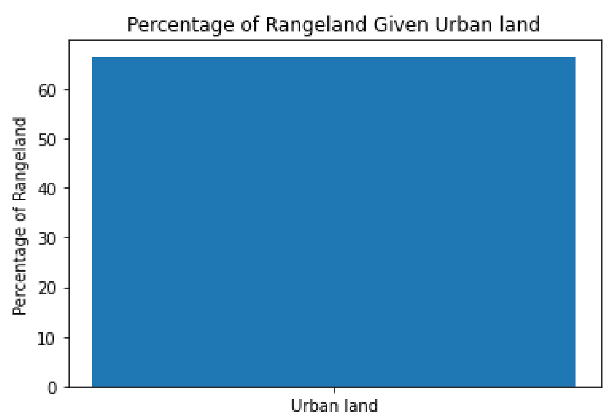

Figure 2.2

The distribution of compatible land cover types can provide insights into the ecological characteristics and functions of the area covered by the dataset. For instance, a high proportion of "rangeland" may indicate the presence of grazing lands and ecosystems that support livestock, while a high proportion of "water" may suggest the presence of water bodies such as rivers, lakes, and wetlands. These insights can be used to inform land management decisions and support conservation efforts.

Principal component analysis:

Principal Component Analysis (PCA) is a dimensionality reduction technique, which can be particularly useful for extracting the most relevant features from high-dimensional datasets, such as satellite imagery. With a large number of input variables, it is difficult to analyze or visualize the data. PCA can address this issue by identifying the most important features in the data and projecting the data onto a lower-dimensional subspace that preserves the majority of the original variance.

PCA is a method that involves transforming original variables into a new set of variables known as principal components. The first component captures the highest amount of variance, with subsequent components capturing decreasing amounts of variance. The number of principal components to keep depends on the desired level of accuracy and the amount of variance explained.

In satellite imagery, PCA can be used to identify the most essential features in the data, such as land cover types, vegetation indices, and atmospheric conditions. By projecting the data onto a lower-dimensional subspace, the complexity of the data can be reduced, making it simpler to analyze and visualize.

Visualizing the data using the principal components that is reconstruction of images can help in understanding the effectiveness of PCA in reducing the dimensionality of the data and improving the classification accuracy.

Figure 3 shows the scree plot which can be used to optimally choose the Number of Principal Components to capture and represent the most important information from Land-Cover data.

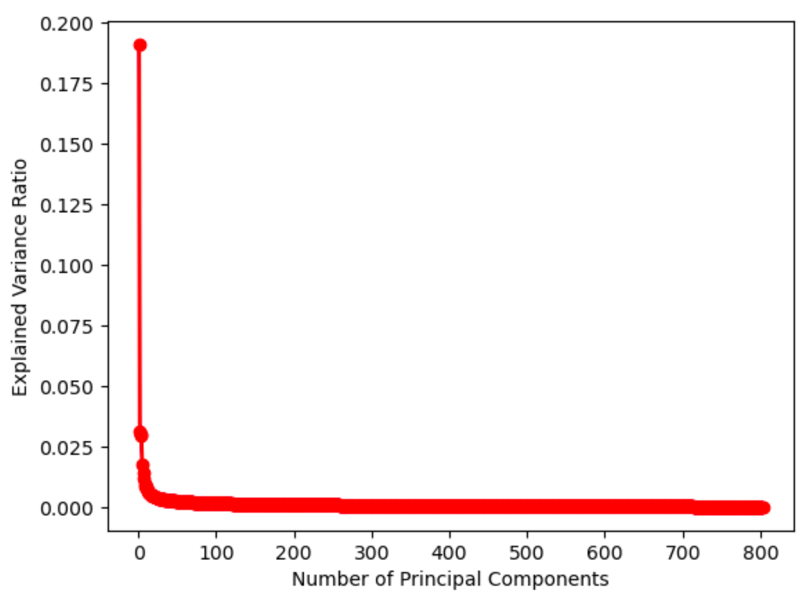

Figure 3

As observed from the above plot , 100 principal components seems to be the optimal number as above 100 principal components there isn't much information learned from images.

As indicated for the above scree plot we have used 100 principal components for our Land-Cover dataset

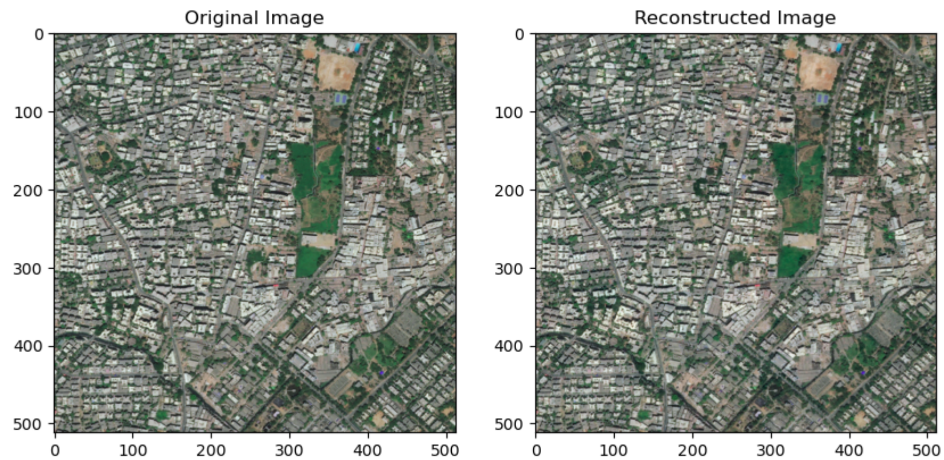

Figure 4.1

Figure 4.1 shows the best reconstruction of the image from 100 components which has an error of 0.0005. As we can see most of the features of the images were well captured within the 100 feature vector which made the best reconstruction possible.

Figure 4.2 shows the worst reconstruction image from our data for 100 components which has an error of 0.01.

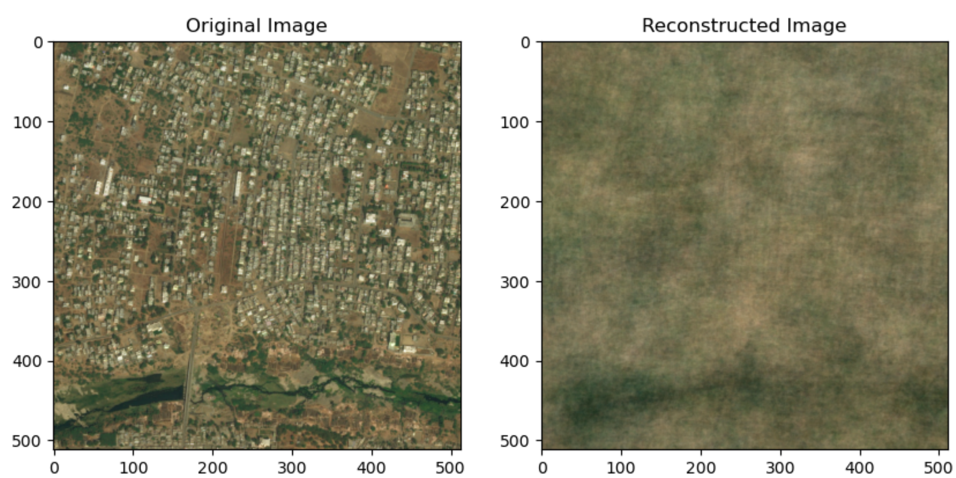

Figure 4.2

Convolutional AutoEncoder:

A Convolutional Autoencoder, a type of neural network, that is frequently used for unsupervised representation learning. In our current task, we employed a convolutional autoencoder to learn a compressed representation of input image data. The network is composed of two main components: an encoder and a decoder. The encoder is responsible for learning how to compress an input image into a lower-dimensional representation, and the decoder is responsible for learning how to reconstruct the original image from the compressed representation.

The architecture of the Convolutional Autoencoder consisted of three convolutional layers in the encoder, followed by three deconvolutional layers in the decoder. The number of filters in each convolutional layer was gradually increased, while the number of filters in each deconvolutional layer was gradually decreased, resulting in a bottleneck layer that learned the compressed representation of the input image. We evaluated the performance of the Convolutional Autoencoder on the validation set by computing the MSE loss between the original image and its reconstructed image. The lower the MSE loss, the better the performance of the Convolutional Autoencoder. In conclusion, Convolutional Autoencoder is an effective method for unsupervised representation learning of image data, and can be used as a preprocessing step for downstream tasks such as classification.

Methodology

We use two feature extraction techniques, PCA and convolutional autoencoder, to extract features from high-quality land cover images. The extracted features were then used for land cover classification using three different classifiers: decision tree, random forest, and XGBoost.

The first step was to use a convolutional autoencoder to extract features from the images which we have discussed above.Convolutional autoencoder was used to extract features, and then PCA was used to further reduce the dimensionality of the feature vectors. This process can enhance classifier performance by lowering the computational complexity of the classification problem. Finally, three different classifiers were used for land cover classification. Decision tree is a simple yet effective classifier that makes decisions based on a set of rules. An ensemble classifier called random forest combines many decision trees to increase accuracy and decrease overfitting. Another ensemble classifier that makes use of gradient boosting to enhance model performance is called XGBoost. Additionally the three classifiers were also used on extracted features using PCA and compared both the feature extraction methods. From the empirical results a combination of Autoencoder with PCA captured the features very well when compared to only using PCA on the images.The results of three different models and their accuracy on two different approaches is shown in Table 1

	PCA features	AutoEncoder+PCA features
Decision Tree	11.11	12.34
Random Forest	**25.92**	**32.98**
XGBoost	14.81	16.04

Table 1: Classifier model with their Accuracy on different approaches

Evaluation and analysis

In land cover classification, the accuracy of the model is an important evaluation metric. The percentage of correctly categorised pixels or samples is how accuracy is calculated. It is determined by dividing the total number of pixels in the dataset by the number of pixels that were properly categorised. Accuracy in multi-label classification may be calculated as the sum of the accuracy of each label.While accuracy is a commonly used metric in land cover classification, it may not always be the most appropriate metric, depending on the specific objectives and requirements of the project.

Discussion

The obtained accuracy of 33% in the land cover classification task is relatively low, indicating that the classification model needs further improvement. One possible factor contributing to the low accuracy is the limited availability of high-quality land cover images. Without sufficient training data, the model may not be able to learn the complex patterns and relationships between different land cover types, resulting in lower accuracy. The selection of feature extraction methods and classifiers may also play a role in the low accuracy. Although PCA and convolutional autoencoder are effective techniques for feature extraction, It is possible that other feature extraction techniques or classifiers may be more suitable for this dataset, and further exploration is needed to identify the best approach. Additionally, there might be other elements influencing the performance of the classification model, such as noise in the images or preprocessing operations done on the data.

Future Works

One potential approach is to use convolutional neural networks (CNNs) for feature extraction and classification. CNNs have shown impressive performance in various image classification tasks, be it LeNet or even AlexNet. By using CNNs, the model can learn more complex and discriminative features from the images, which may improve the accuracy of the classification results.

Another possible approach is to leverage pretrained models. Pretrained models, such as VGG, ResNet, and Inception, have been trained on large-scale image classification datasets and have shown to be effective in transfer learning. By using a pretrained model as a feature extractor, the model can benefit from the learned features and can potentially achieve higher accuracy with less training data.

Moreover, recent advances in computer vision, such as vision transformers, can also be explored for land cover classification. The performance of the classification model may be enhanced by the use of vision transformers, which have demonstrated promising results in a variety of computer vision applications. By using a vision transformer, the model can learn more complex and abstract features from the images, which may lead to better classification results.

Overall there are several approaches which can be used for classification and the main limitations are data and computational bottleneck as the satellite imagery tends to be rare and they are large in size.

Conclusion

In conclusion, our study focused on land cover classification using feature extraction techniques and machine learning algorithms. We utilized PCA and convolutional autoencoder to extract features from high-quality land cover images and then performed PCA on the feature arrays to reduce the dimensionality of the data. We employed decision tree, random forest, and XGBoost algorithms to classify the land cover types.

The acquired accuracy of 33% suggests that the land cover categorization model still has space for improvement. The lack of accuracy may be caused by the scarcity of high-quality photos, the available feature extraction methods and classifiers, and other variables. To enhance the model's functionality and obtain greater accuracy, more testing and research are required.

Reference links:

https://arxiv.org/abs/1805.06561

https://competitions.codalab.org/competitions/18468

https://www.kaggle.com/datasets/balraj98/deepglobe-land-cover-classification-dataset

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