Image segmentation and classification of aquatic plants using convolutional neural network

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Abstract

Many advancements have been made in recent years to solve the difficulties posed by hyperspectral images. Several mathematical restrictions are used to address common problems such as regression, segmentation, spectral end-member analysis, and classification. However, the spectral domain continues to be the focus of most research. The development of new spatial-spectral techniques is necessary since high resolution remote sensing spatial pictures are now available. Nonetheless, hyperspectral imaging is still a relatively new idea in the field of computer vision. Low-level image processing, such as how to obtain and process hyperspectral images with fine spatial resolution, how to remove noise in hyperspectral images, and so forth, is the subject of very little of the current research. In the realm of hyperspectral image processing, feature extraction algorithms are either nonexistent or have very little work. Hyperspectral photography offers a greater range of applications in agriculture, industry, military detection, underwater life preservation, mineral mapping, vegetation mapping, and more because of its superior categorisation capability. However, a lack of fundamental techniques has hampered the spectral region study. Spatial dimension approaches from the field of computer vision are not considered in the current methodologies. A solid scientific basis is still required for hyperspectral imaging. It is anticipated that hyperspectral imaging will become more prevalent in the field of remote sensing in the upcoming years, and that using both spectral-spatial feature extraction techniques will have an effect on the success of hyperspectral image processing methods.

Keywords: Water bodies, Classification, CNN

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Introduction

Over the past 20 years, there have been significant advancements in aerial image processing in a number of fields, including infrastructure development and management, environmental monitoring, disaster management (including determining the severity of a disaster), agriculture development, earth's natural resources analysis, wildlife monitoring, pollution monitoring, urban planning, military surveillance, exposing land cover and land use, and more (Zhang *et al.*, 2018). When conducting resource surveys in remote locations without access to maps, aerial photos are particularly useful. Additionally, comparing aerial photos from the past and present shows how a region has changed over time. One use of remote sensing is aerial image processing, in which digital versions of the aerial photos are first saved. Information is then extracted from those digital aerial photos in accordance with the intended goals (Botha *et al.*, 2020). The many segmentation and classification techniques that can be used to aerial photographs are depicted in Figure 1. Both single-objective and multi-objective restrictions can be handled in this way (Rajendiran and Kumar, 2023; Assegid and Ketema, 2023). Classifying land cover is a multi-objective constraint since it addresses a variety of goals, such as roads, buildings, farms, barren land, and others. In contrast, a single-objective constraint will only focus on one goal, which may be any of the following: buildings, roads, and pools of water (Fisher, Flood and Danaher, 2016).

Figure 1: Samples dataset.

Because high-resolution aerial photos provide more performance accuracy, the quality of the images is crucial. It is difficult to process low-resolution aerial photos because additional steps must be taken (Sołtysiak, Blachnik and Dąbrowska, 2016). Additionally, if noise, distortions, or artefacts are present, they add to the computing complexity. In that instance, pre-processing is applied to the aerial photos prior to segmentation processing (Abid *et al.*, 2021).

Proposed Methodology

One kind of Artificial Neural Network (ANN) that has shown promise in solving classification difficulties is the convolutional neural network, also referred to as CNN or ConvNets. This is because they have unique characteristics that are similar to how people perceive patterns in visual imagery (Feng *et al.*, 2016). The input layer, convolution layer, pooling layer, activation function, fully connected layer, and output layer are the various parts that make up convolutional neural networks. Convolutional neural networks are used to classify the combined feature collection (Barclay *et al.*, 2016). After processing the input feature set, the CNN divides the images into two groups: those with water regions and those without. The convolution layer receives the retrieved features as input together with the corresponding target values. The general design of the suggested classifier model is depicted in Figure 2. Four convolution layers linked to the pooling layers make up the classifier model. There are numerous neurones in each convolution layer, and each neurone is coupled to every other neurone in the subsequent layer, making them tightly connected.

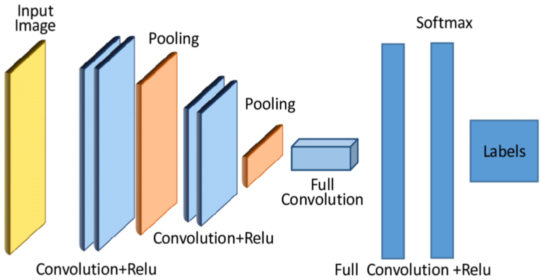


Figure 2: CNN architecture.

Simply down-sampling the features requires pooling, which means that each feature map's volume is continuously reduced by the pooling layer. Additionally, the output layer is reached by a single, fully connected layer. All of the convolution layers' combined information is stored in the fully connected layer, a feature vector that makes classification predictions. A neuron's operational status is determined by its activation function, which also aids in normalising the output of each active neurone. The classifier uses the Rectified Linear Unit, or ReLU, as its activation function.

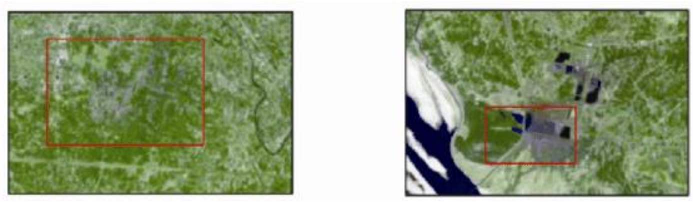
Experimental Results

There is a severe worry because it can be difficult to distinguish between the water and shadow regions in an aerial image. Water regions can sometimes become confused with the colour differentiation of buildings, trees, and other objects. Due to the water region's limited width (in terms of size), segmenting it from an aerial image might occasionally become a laborious task.

Wet Lands

Food plain lakes **Oxbows and scrolls** **Marshes/swamps**

Water Logging



Natural **Anthropogenic**

Other Water Bodies

Tanks/reservoir **Rivers** **drainage**

Figure 1: Sample aerial images with water bodies.

Finding water regions in some aerial photos might be a laborious process due to tainted or polluted water (partially or completely affected algae). Additionally, attempting to get the precise border of the anticipated water region from a low-resolution aerial photograph may not be successful.

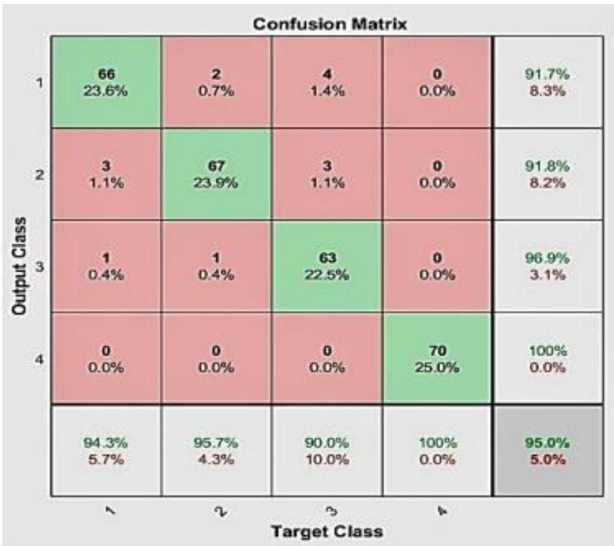


Figure 3: Confusion matrix.

Many automated image analysis algorithms seek to identify and segment particular objects of interest, such as buildings, roads, farmland, and water bodies, among the many different features included in an aerial image.

However, there are a number of difficulties that arise throughout the procedure. Moreover, reliable identification and segmentation procedures are hampered by the items of interest's resemblance to other objects in the aerial photos. Because the success or failure of one phase greatly affects the success or failure of the subsequent step, developing a water-body segmentation and classification system is a difficult undertaking at every stage.

Conclusions

One use of remote sensing is aerial image processing, in which digital versions of the aerial photos are first saved. Information is then extracted from those digital aerial photos in accordance with the intended goals. Both single-objective and multi-objective restrictions can be handled in this way. Classifying land cover is a multi-objective constraint since it addresses a variety of goals, such as farms, buildings, roads, and barren land, among others. In contrast, a single-objective constraint will only focus on one goal, which may be any of these: buildings, roads, or water bodies. Because high-resolution aerial photos provide more performance accuracy, the quality of the images is crucial. This study suggested a novel CNN-based classifier model to distinguish between photos with and without water regions. The input data for classification was the combined feature set, which included 16 texture characteristics and 5 morphological features. It is evident from experimental study that the suggested classifier model performs well when it comes to performance metrics like classification accuracy, precision, recall, and F-score. The precision, recall, and F-score of the suggested classifier model were 94.81%, 97.35%, and 96.13%, respectively. The suggested classifier model's classification accuracy was 97.86%.

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