Classification of Remote Sensing Image Scenes Using Double Feature Extraction Hybrid Deep Learning Approach

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Abstract

Over the last decade, remote sensing technology has advanced dramatically, resulting in significant improvements on image quality, data volume, and application usage. These images have essential applications since they can help with quick and easy interpretation. Many standard detection algorithms fail to accurately categorize a scene from a remote sensing image recorded from the earth. A method that uses bilinear convolution neural networks to produce a less-weighted set of models those results in better visual recognition in remote sensing images using fine-grained techniques. This proposed hybrid method is utilized to extract scene feature information in two times from remote sensing images for improved recognition. In layman's terms, these features are defined as raw, and only have a single defined frame, so they will allow basic recognition from remote sensing images. This research work has proposed a double feature extraction hybrid deep learning approach to classify remotely sensed image scenes based on feature abstraction techniques. Also, the proposed algorithm is applied to feature values in order to convert them to feature vectors that have pure black and white values after many product operations. The next stage is pooling and normalization, which occurs after the CNN feature extraction process has changed. This research work has developed a novel hybrid framework method that has a better level of accuracy and recognition rate than any prior model.

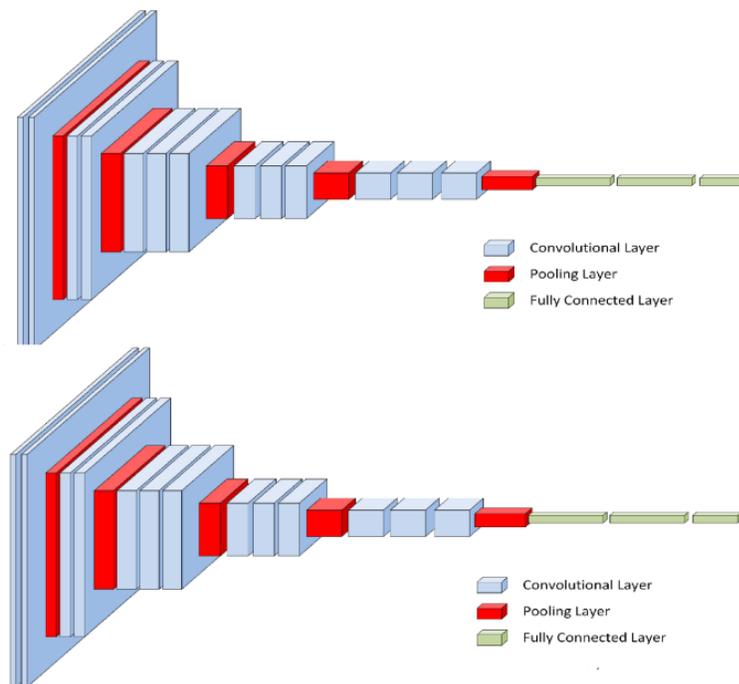**Keywords: remote sensing image, deep learning**

1. Introduction

In ancient times, photographs like the Landsat series, which used satellites to take images, had inadequate spatial resolution. As a result, the pixel sizes would be on the order of or smaller than the things of interest [1]. For the bulk of remote sensing image analysis methods, pixel-level or sub-pixel analysis has been utilized throughout the past few decades. Changes in remote sensing technologies are leading to an increase in spatial resolution [2]. This type of spatial resolution maintains the item of interest contained in the image's higher dimensions. Pixels appear as a part of a scene packed with spatial patterns, rather than separate units. In this situation, pixel-level categorization is difficult or impossible [3, 4].

(a) Agri Land   (b) Mountain   (c) Desert

(d) Airport   (e) Beach area
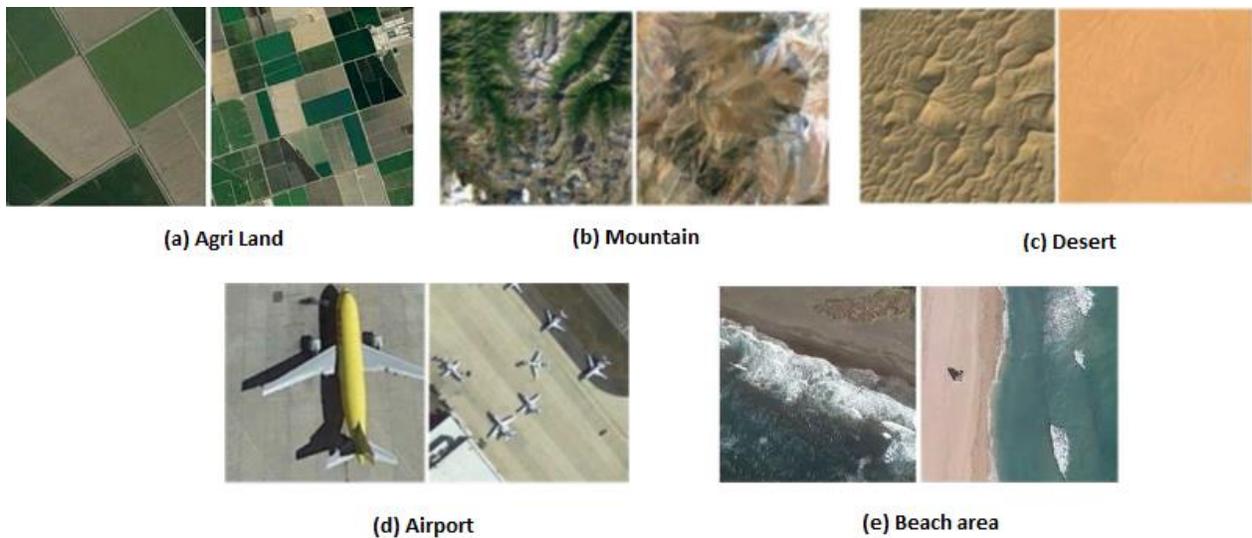
Figure 1. Sample image classification

To improve the process of monitoring dynamic processes, one approach is now viable, and by combining various data sources, parameter estimation and classification issues may be solved [5]. Changes in acquisition conditions and geometry, as well as sensor properties, all lead to variances in the resultant data images [6, 7]. Because of this, the classifier's predictions turned

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out to be inaccurate. Since, the findings may be terrible in another situation; the best classifier should only be used for a single instance. Classifiers may be used to speed up the finding of relevant situations by firstly applying them to new image data [8, 9]. Data restoration miscalculations and recalculations have decreased during the rebuilding process. Cryptograms will be equally distributed [10, 11]. By generating unusual swirls in the unknown layers, this technique recreates the feature sign by creating the data swirl feature again. A growing number of consumers are depending on the invisible coating's stimulating capabilities [12, 13]. Spinal transmission for inclines makes exercising on the network simpler. Figure 1 shows some sample image classification.

Figure 2. Dual CNN Construction for Feature Extraction

New methods for image scene classification arise from the use of deep learning (see Fig. 4). Remote sensing image scene classification and image scene classification significantly

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increased between 2014 and 2017. The incidence of this disease has increased for the two reasons mentioned below. In early 2014, deep learning techniques were used to analyze the remote sensing data. A way for deep learning-based remote sensing image scene categorization to advance is via the publication of a benchmark for large-scale remote sensing images in 2017 [14, 15]. Figure 2 shows our proposed work with dual CNN construction for feature extraction.

There has been a notable increase in the popularity of contemporary technology and gadgets in recent years with the current mobile devices and aerial cameras appearing on the market. Improvements in hardware performance increase the speed and reliability of aerial photography technology, resulting in the rapid development of imaging technology. Also, the number of ways in which imagery may be shown has grown, and the degree of clarity of how imagery is presented has increased [16]. Remote sensing imagery may be useful for identifying different land areas, urban planning, disaster relief, traffic management, and a variety of other aspects of scene classification. By categorizing enormous amounts of remote sensing image data that spans geography [17], this visualization illustrates the need to develop practical classifications for all that data.

2. Organization of the Research

Following the aforementioned discussion, here is the rest of the study paper. Section 3 includes current relevant studies in the field of remote sensing picture scene categorization. Section 4 introduced the technique for scene categorization from remote sensing pictures. Section 5 presents the research findings that were generated from the suggested paradigm. Section 6 concludes our effort and places the remaining work in the future.

3. Preliminaries

To further study the results of the prior study, which examined the possibility of conducting remote sensing image scene categorization using a three-person committee, a big margin, and posterior probability, Tuia et al. looked at, evaluated, and compared three active learning-based remote sensing image scene categorization methods: committee, large margin, and posterior probability [18]. Many studies are conducted that sought to categorize various remote sensing pictures and produced a list of the most often utilized techniques. Maulik et al. evaluated SVM-based remote sensing image scene classification techniques, which are referred to as support vector machine (SVM) systems [19]. Li et colleagues focused on classifying remote sensing images based on their spatial and contextual elements at the pixel, sub pixel, and object levels, making the point that precise geographic and environmental information is essential to picture classification [20].

The generalization abilities of pre-trained CNNs were tested in remote sensing image classification by Penatti et al. Researchers Hu, Li, and Long conducted a study in which they use Convolutional Neural Networks (CNNs) trained on the "ImageNet" data set to identify remote sensing photo scenes [21, 22].

In a research paper released in 2017, Cheng et al. introduced a large-scale scene classification benchmark called NWPURESISC45 (NWPURESISC stands for National Weather Program Enhanced Scene Classifier) and they achieved high accuracy to classify the objects. They also did a brief assessment of current advancements in remote sensing picture scene classification [23]. Xia et al. published a new standard for aerial image classification known as AID in 2017 and evaluated the methods for scene categorization that were already in use [24]. In an analysis conducted by Ma et al., deep learning was shown to be widely used in remote sensing

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image processing. As well, there have been many hyper spectral image categorization experiments [25].

But although there is a need for a detailed investigation of deep learning for scene classification, nothing has been done in this matter yet. This inspires us to examine the main challenges in remote sensing image scene classification, including deep learning-based approaches that have seen publication recently, to review leading-edge scene classification approaches, which make up the majority of those which have been published in the last five years, and to identify mainstream scene classification benchmarks, all of which are also relevant in this field.

3.1 Motivation of this Research

To categorize a remote sensing picture, you need to properly identify it using semantic classifications, such as "residential," "commercial," or "industrial." The vast majority of ground items may be found in remote sensing imagery. This is an example of how an industrial landscape may contain things like roads, trees, and buildings. While object-oriented classification may seem more straightforward than scene classification, the latter is much more difficult because of the complicated spatial distributions of ground items in scenes. For generations, detailed investigations of satellite imagery picture scene categorization have been conducted. So far, no algorithm has been able to achieve an acceptable level of classification of remote sensing picture scenes.

4. Proposed Work

The B-CNN model allowed Lin et al. to demonstrate significant performance in the detection of fine-grained visual details. Essentially, the idea is to run two CNNs simultaneously on the same image and get features, and then use a bilinear normalisation procedure to merge
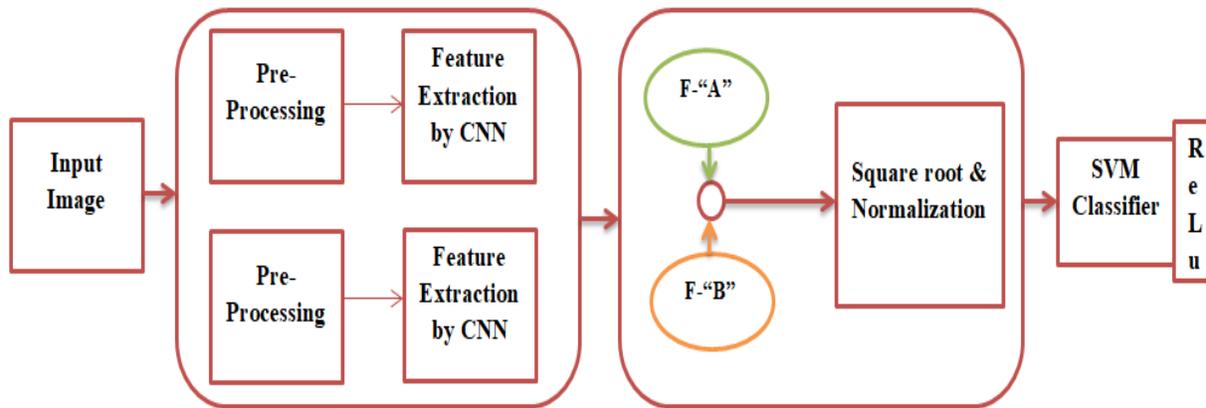
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those features and create a new feature vector [26]. Figure 3 shows the block diagram of proposed framework.

Step 1:

Connection between two nodes as the smallest number of computing units they share and the number of edges connecting them.

Two stage **CNN = (N, S)**

Where, $N = \{N_i \mid i = 1 \dots m\}$ and $S = \{S_{ij} 1 < i < j \leq m\}$

Figure 3. Proposed Framework

Step 2:

Rule 1:

The N-node set should contain the minimum amount of computing units that will participate in feature extraction.

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Rule 2:

M is the union mathematical function of I and j, where I is the minimum value of the elements and j is the maximum value of the elements.

Step 3:

The outer product operation is used when two CNNs extract features from the same image and perform bilinear pooling in position l.

$$bi - CNN\ (l, I, f_A, f_B) = f_A^T(l, I) . f_B^T(l, I)$$

Step 4:

$$\varepsilon(I) = \sum_l bi - CNN(l, I, f_A, f_B)$$

Step 5:

$$x = vec(\varepsilon(I))$$

$$y = sign(x)\sqrt{|x|}$$

$$z = {y}/{\|y\|_2}$$

Step 6:

A linear bottleneck was implemented to reduce the information loss that occurs from the use of activation functions such as "ReLU" (rectified linear unit) in CNNs.

Many CNNs use nonlinear activation functions to change the feature maps of the input, which makes the network versatile and adaptable [27]. Non-linear functions benefit from neural networks since they can theoretically approximate any arbitrary non-linear function [28, 29].

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5. Results & Discussion

The dataset was divided into training and test sets before the experiment was conducted. This research work has used a variety of training ratios in the experiments to allow for establishing comparison with other training methods. The dataset used to train and test the algorithm was generated by picking random training and test sets from the original dataset [30, 31]. Every experiment was done five times with the training set. The mean and standard deviation of the five possible outcomes were calculated. Sample dataset of remote sensing images are shown in figure 4.


Figure 4. Sample Dataset for Remote Sensing Images
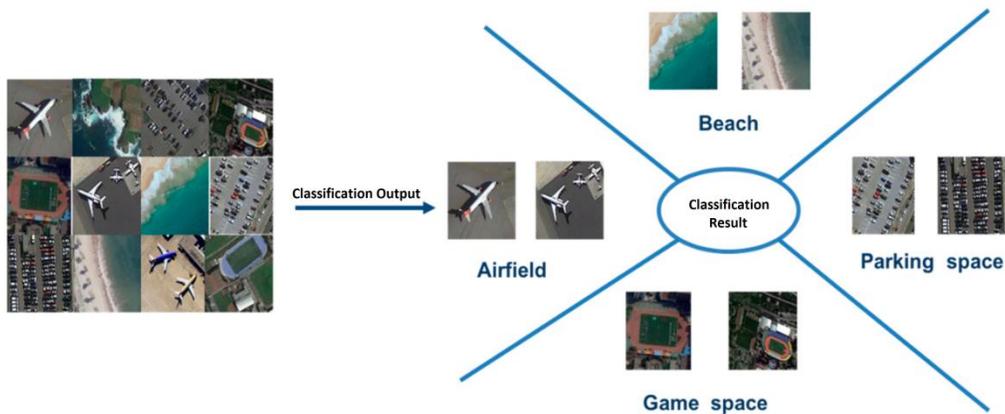
Figure 5. Categorization of Image After Classification

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The proposed research work has enhanced the training data six fold, which produce improved classification of training pictures that rotate around the machine, such as rotating them through a total of 90, 180, and 270 degrees, which is shown in the figure 4. This model-enhancing modification played a key role in the generalization of proposed dual feature extraction of CNN models [32]. Figure 5 shows the results obtained and categorized after performing proposed classification through SVM.

In general, Figure 5 shows the CNNs with many layers and parameters, such as CNNs that have many layers, layers with multiple parameters, and so on, which involve a significant amount of computation. These networks are hard to train since the quantity of training data is insufficient. This obtained result is predicated on a minor over fitting issue [33].
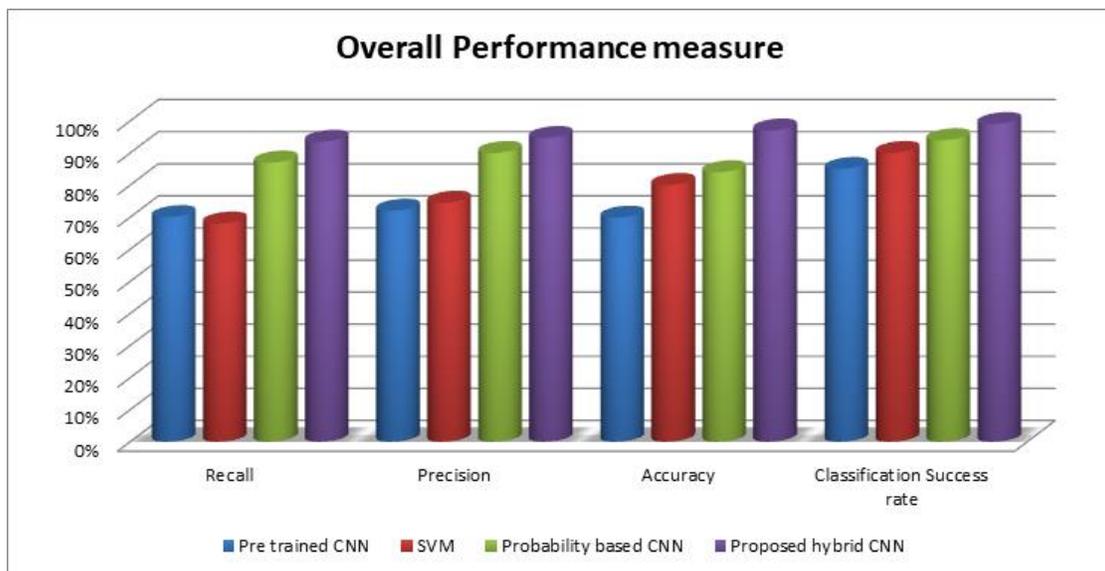
Figure 6. Overall Performance Measurement Chart

Figure 6 shows the overall performance measures of the proposed framework model. Classification assignments need 80% of the data by utilizing the majority of that data for training is impractical.

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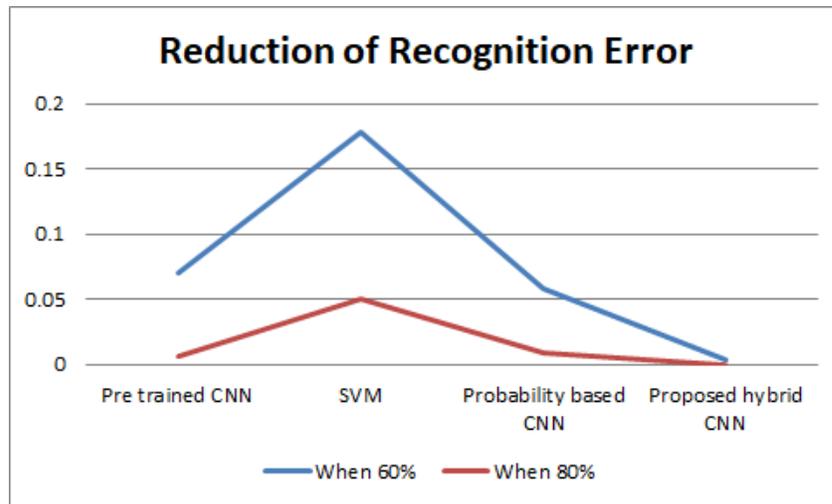
Figure 7. 60% Data for Training in the Dataset for Various Methods

Table 1. Overall Performance Metrics

S.No	Methods	Recall	Precision	Accuracy	Classification Success rate	Recognition error
1	Pre-trained CNN	70%	72%	69.83%	85%	0.934
2	Single Classifier SVM	68%	74.5%	80%	90%	0.123
3	Probability based CNN	87%	90%	84%	94%	0.022
4	Proposed hybrid CNN framework	93.5%	94.67%	97%	99%	0.0001

The proposed algorithms are evaluated by using 60% of the training data, which are split between the existing and proposed benchmarks. When compared to conventional techniques, the suggested method has shown a reduction in the recognition error during examination. This is also true since the proposed technique has decreased the misclassification error because this research work utilizes a superior classifier, which is known as SVM. For the dataset, 80% of the data and 20% of the data are being divided between training and testing. There are practically zero recognition errors, when double feature extraction via CNN is used. A manual labelling of 80%

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of the data is unrealistic due to the amount of time it would take. Table 1 contains overall performance measures.

To maximize efficiency and classification accuracy, the fewer data required the better. We tried achieved through training on just 60% of the data results in an accuracy of 90%.

6. Conclusion

Thus the hybrid proposed algorithm is achieved in more accurate classification of image scenery from the dataset compared to other existing method. One interesting thing to note about the proposed CNN model is a more filter contained model is that it outperformed the deep model in terms of fine-tuning. Randomly initialized weights and biases are also considered as a good option for training datasets. However, determining whether a dataset has grown to a substantial size might be challenging. Researchers will try to see if the data support this feature extraction or fine-tuning of well-known CNN models in future investigations. It may be possible to get acceptable results by fine-tuning the original model, which is already more complicated, but if possible, it is better to divide the original model to enhance the performance. Further, the deep models and working should be considered to reduce the model's size and complexity.

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