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Remote Sensing Based Classification with Feature Fusion Using Machine Learning Techniques

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Abstract

There are several uses for remote sensing image scene categorization, which tries to assign semantic categories to remote sensing images based on their contents. The Pass over (POEP) network proposed in this research is a hybrid feature learning as well as end-to-end learning method for remote sensing picture scene interpretation (RSISU). In order to classify scenes using remote sensing, this research suggests integrating feature fusion as well as extraction with classification methods. The newly designed (POEP) has two benefits. First, multi-resolution feature maps created by CNN are integrated using Pass over connections, which has significant advantages for addressing the existence of large-scale variance in RSISU data sets. Here we use UCI dataset with 21 classes of images as database. Initially the image has been pre-processed and by RESNET-50 with Alex net integration of architectures, the features has been extracted. Then by performance analysis and comparative analysis the optimal results are obtained.
Keywords: Remote sensing, image scene classification, RSISU, DL, RESNET-50, Alex net, Random Forest and Decision Tree.

1. Introduction:

We may measure and examine specific structures on Earth's surface with aid of remote sensing photographs, a useful data source for earth observation. The amount of remote sensing photographs is rapidly expanding as a result of advancements in earth observation technologies [1].The search for the best way to utilise the growing number of remote sensing photos for insightful earth observation has thus gained particular significance [2].Since a few decades ago, considerable studies on remote sensing picture scene categorization have been conducted, motivated by its practical applications in urban planning [3], the identification of natural hazards, environmental monitoring, vegetation mapping, and the detection of geographical objects. In land-use scene categorization, an image is given a semantic label, such as "urban" or "forest," based on what is depicted in it.

2. Related works:

DCNN has shown promising results in classification of natural picture scenes, and it is also quite comparable to the classification of image scenes from remote sensing. According to [4], the authors used the conservative SVM in addition to pre-trained CNN network method based on ImageNet, which excels on scene-level datasets like University of California, Merced (UC Merced) Land-use and Brazilian Coffee Scenes.On the scene-level dataset, the hypothesis in [5,6] additionally employed pre-trained CNN methods as well as domain-specifically enhanced, pre-trained CNN methods, which served as universal feature extractors to extract richer high-level representation features. Authors of [7,8] uses two feature extraction algorithms.In [9,10], a Discriminative CNN (D-CNN) method is put forth that, in addition to reducing classification errors, optimises discriminant objective function as well as adds a metric learning regularisation term to features of current CNN model.

3. Research methodology:

Suggested network falls under this category, which includes end-to-end learning method learning methods and hybrid feature learning. This is a significant new feature since our suggested approach's very low parameter requirements are more likely to prevent overfitting issue when training a deep CNN method on a modestly sized data set.This section discuss about the proposed methodology. The overall architecture has been given in figure 1.

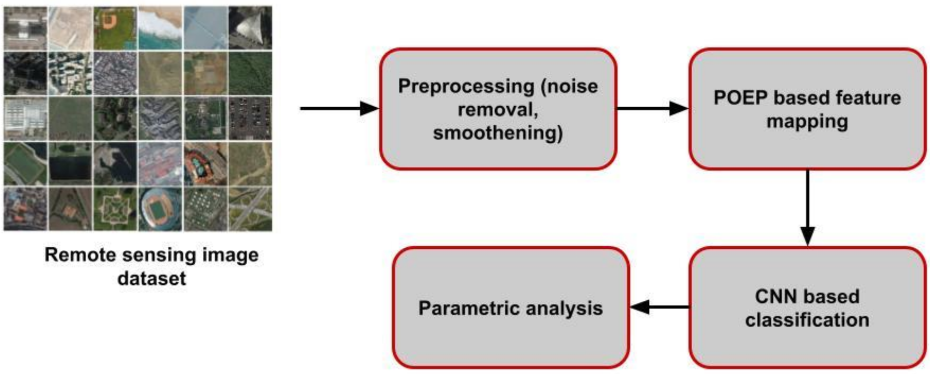


Figure-1 Overall Research architecture

3.1 Data pre-processing using Dimensionality Reduction (DR):

The pre-processing technique for DR might include a variety of strategies. The DR is taken into account for the following benefits it provides:

1) The available memory to store information degrades as the number of dimensions increases.

2) For fewer dimensions, shorter training or computation periods are required.

3) The majority of feature extraction algorithms struggle to handle data with many dimensions.

4) DR approaches effectively handle multi-collinearity between various data features, and redundancy between features is removed.

5) The data's reduced dimensions also make it easier to visualise.

3.2 Hybrid Feature learning and end-to-end learning model:

Suggested POEP network falls within the hybrid category of an end-to-end learning system. This is an important advance since the few parameters needed by our methods increase the likelihood that the overfitting issue won't arise while training a deep CNN method on a small data set. Alexnetas well as Resnet-51 are connected via Pass Over in suggested manner.

3.3 Pass Over Connections for Multi-Layer Aggregation:

Assume that there exist three sets of feature maps, $\mathcal{X}_1 \in \mathbb{R}^{H\times W\times D_1}$,$\mathcal{X}_2 \in \mathbb{R}^{H\times W\times D_2}$, and $\mathcal{X}_3 \in \mathbb{R}^{H\times W\times D_3}$, all of which have the same spatial resolution. In this situation, a connections technique may be used to obtain aggregated multi-resolution feature map X as shown in eq. (1):

$$\mathcal{X} = [\mathcal{X}_1; \mathcal{X}_2; \mathcal{X}_3] \in \mathbb{R}^{H\times W\times (D_1+D_2+D_3)} \qquad (1)$$

Following is a full explanation of CWAvg pooling's mathematical definition. Assuming stride k and a 3-D feature map tensor of the form $\underline{Y} = [Y_1; Y_2; \dots; Y_L] \in \mathbb{R}^{H\times W\times L}, where\ Y_i \in \mathbb{R}^{H\times W}$, where Y i is a single feature map, the CWAvg pooling is carried out as eq. (2):

$$Z_j = \frac{1}{k}\sum_{i=(j-1)\times k+1}^{j\times k} Y_i, \quad j = 1,2,\dots,L/k$$

$$\frac{\partial L}{\partial U} : dU + \frac{\partial L}{\partial \Sigma} : d\Sigma = \frac{\partial L}{\partial F} : dF \qquad (2)$$

$$dF = dU\log(\Sigma)U^T + Ud(\log(\Sigma))\mathrm{U}^\mathrm{T} + \mathrm{U}\log(\Sigma)\mathrm{dU}^\mathrm{T}$$

Plugging (6) into (5), (∂ L/∂U) and (∂ L/∂) are derived as eq. (3):

$$\begin{cases} \frac{\partial L}{\partial U} = \left(\frac{\partial L}{\partial F} + \left(\frac{\partial L}{\partial F}\right)^T\right) U\log(\Sigma) \\ \frac{\partial L}{\partial \Sigma} = \Sigma^{-1} U^T \frac{\partial L}{\partial F} U. \end{cases} \qquad (3)$$

$$\frac{\partial L}{\partial C} : dC = \frac{\partial L}{\partial U} : dU + \frac{\partial L}{\partial \Sigma} : d\Sigma$$

$$dC = dU\Sigma U^T + Ud\Sigma U^T + U\Sigma dU^T$$

The partial derivatives of loss function L with respect to C can be obtained by combining (4), and utilising characteristics of matrix inner product,:, and characteristics of EIG, as follows:

$$\frac{\partial L}{\partial C} = U\left\{\left(K \circ \left(U^T \frac{\partial L}{\partial U}\right)_{\mathrm{sym}}\right) + \left(\frac{\partial L}{\partial \Sigma}\right)_{\mathrm{diag}}\right\} U^T$$

$$K(i,j) = \begin{cases} \frac{1}{\sigma_i - \sigma_j}, & \text{if } i \neq j \\ 0, & \text{if } i = j. \end{cases} \quad . \qquad (4)$$

$$\frac{\partial L}{\partial X} = \hat{I}X^T \left(\frac{\partial L}{\partial C} + \left(\frac{\partial L}{\partial C}\right)^T\right)$$

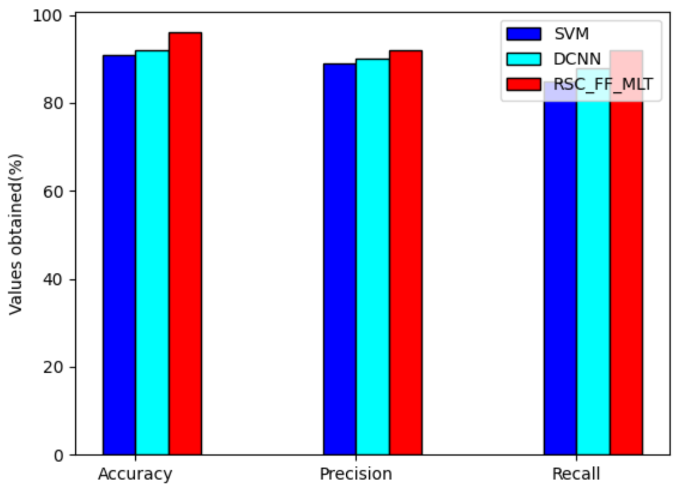
4. Experimental setup

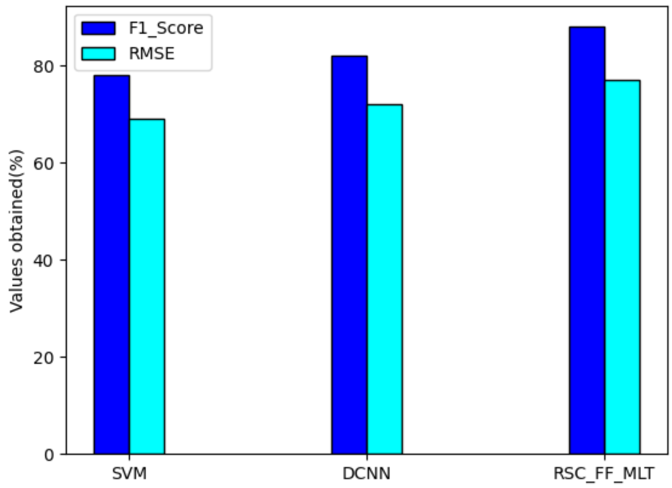
The dataset, called UC Merced Land Use dataset, has 21 scene categories, including agricultural, aircraft, baseball diamonds, beaches, buildings, chaparral, dense residential, forests, freeways, golf courses, harbours, mobile home parks, overpasses, parking lots, rivers, runways, sparse residential, storage tanks, and tennis courts. 100 256 by 256 pixel photos are included in each class.

On a computer with an Intel Core i5 GHZ processor, 8.00 GB of RAM, and nvidia, all trials are carried out. Python 3.6.5 is used to implement the suggested technique.

Table 1: Comparative analysis of proposed and existing methods

Parameters	SVM	DCNN	RSC_FF_MLT
Accuracy	91	92	96
Precision	89	90	92
Recall	85	88	92
F1 Score	78	82	88
RMSE	69	72	77





Above table-1 shows comparative analysis between proposed and existing technique for various biometric dataset based on DL methods. Parametric analysis is carried out in terms of accuracy, precision, recall, F-1 score and RMSE. Above figure- 4 (a)- (d) shows comparative analysis between proposed and existing technique for SDUMLA-HMT dataset. Here proposed technique attained accuracy 91%, precision 72%, recall 62%, F-1 score 65%. Existing technique KNN attained accuracy 82%, precision 63%, recall 55%, F-1 score 61%; while LSTM attained accuracy 88%, precision 65%, recall 58%, F-1 score 63%. One metric for measuring classification model performance is accuracy. Informally, accuracy is percentage of predictions that our method correctly predicted. Accuracy is defined as follows in formal language: Accuracy is the quantity of accurate forecasts. sum of all projections. How frequently an algorithm successfully classifies a data point can be determined, for example, by looking at the accuracy of the algorithm. The percentage of projected data points that really occurred is known as accuracy. One measure of a ML methods effectiveness is precision, or standard of a successful prediction the model makes. Ratio of overall number of true positives to total number of positive forecasts is known as precision. F1-score combines precision and recall of a classifier into one metric by computing their harmonic means. It is mostly used to evaluate the performance of two classifiers.

5. Conclusion:

This study puts forth the combination of feature fusion as well as extraction with remote sensing scene categorization approaches.Newly designed (POEP) has two benefits. First, multi-resolution feature maps created by CNN are integrated using Pass over connections, which has significant advantages for addressing the existence of large-scale variance in RSISU data sets.Our technique may be taught utilising a hybrid feature learning as well as end-to-end learning method, which enhances classification performance in comparison to manually constructed feature-based approaches or feature learning-based methods.Our POEP network, in particular, only requires 10% of the parameters required by its rivals.

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