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TRANSFER LEARNING STRATEGY FOR SATELLITE IMAGE CLASSIFICATION USING DEEP CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Machine Learning is an essential research field as it has been utilized in remotely sense image classification. In image classification, data are made up of lots of samples characterized by many datasets. Hence high level of accuracy in terms of classification and training performance is such a big challenge. Machine learning techniques have broadly employed to build a substantial and accurate classification models. This paper proposes a new classification technique for remotely sense image classification, which is called Transfer Learning-Convolutional Neural Network (TL-CNN). TL-CNN is the introduction of transfer learning Pretrained on ResNet to convolutional neural network using Aerial Image Dataset (AID) with over 10000 images within 30 classes. The remote sense image classification dataset consists of satellite images and not photographs, yet CNNs Pretrained on Remote Sense image has shown the ability to transfer to other image domains. This research work shows that, the proposed TL-CNN was able to improve the classification accuracy and returned 99.99% accuracy as against some of the existing algorithms which includes CNN with accuracy of 99.91%, SAE with accuracy of 93.98% and DBN with accuracy of 95.91%. The result also shows that, Using Pretrained CNNs as a starting point for fine-tuning on the ResNet image not only increases the training accuracy but also boosts the classification accuracy.

Keywords: Classification, Deep Learning, Satellite Image, Transfer Learning, Convolutional Neural Network, Aerial Image Dataset

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1. Introduction

Image classification plays a significant role in the interpretation of satellite imagery *(Wen et al., 2015)*. And also in many fields, such as land management, urban planning, environmental exploration and monitoring, and natural disaster detection. Over the previous decades, researchers have done a great deal of experiments in the scene classification for satellites and aerial photos, and have developed various taxonomies *(Gong et al., 2014)*. In order to make informed decisions concerning the environment, there are government ministries and agencies that are equipped to observe it. This enables us to make an effective changes around us as appropriate or desirable. This process is referred to as earth observation, and has applications in disaster response, resource management and precision farming among others.

Earth observation (EO) through remote sensing techniques is a research field where a vast variety of physical signals are measured from instruments on board space and airborne platforms. An extensive diversity of sensor characteristics is available these days, ranging from medium and very high resolution (VHR), multispectral (MS) imagery to hyper-spectral (HS) images that sample the electromagnetic spectrum with high feature. These myriads of sensors serve to particularly diverse objectives, concentrating either on obtaining quantitative measurements and estimations of geo biophysical variables or on the identification of materials by the analysis of the acquired images. Among all the different products that can be obtained from the acquired images, classification maps are perhaps the most relevant ones *(Romero et al., 2015)*.

Deep learning is a class of machine learning models that represent data at different levels of abstraction by means of multiple processing layers. It has achieved incredible success in object detection and classification by combining large neural network models, called convolutional neural networks (CNN), with powerful graphical processing units (GPUs) *(Pritt and Chern 2017)*. However, with the continuous improvement of science and technology, the spatial resolution of satellite images is getting higher and higher, and their spatial and structural patterns are becoming more and more abundant. The phenomenon of the same objects with different spectrum and the foreign ones with common spectrum are more wide spread. However, most of the classical methods are based on artificial or shallow learning algorithms, and the low middle-level semantic features extracted are limited in the description ability, which makes it difficult to improve the classification accuracy further *(Yang et al., 2018)*. Recently, deep learning (DL) has become the fastest-growing trend in big data analysis and has been widely and successfully applied to various fields of computer application successfully including sequential data, processing of natural language, speech recognition and image classification *(Abdel-Hamid et al., 2012)*. Because of its outstanding performance compared with that of traditional learning algorithms. Standing at the paradigm shift towards data-intensive science, machine learning techniques are becoming more and more important. To be specific, as a major breakthrough in the field, deep learning has proven to be a very powerful tool in many fields. Shall we embrace deep learning as the key to all? Or, should we resist a "black-box" solution? There are debatable views in the remote sensing community *(Zhu et al., 2017)*.

Remote sensing (RS) image classification problem is very challenging and ubiquitous because land-cover and land-use maps are mandatory in multi-temporal studies and constitute useful inputs to other processes. In the last decade, manual analyses of satellite imagery were feasible primarily because the volume of images available was quite low, but now that the volume of data is in high dimension, information extraction from images becomes a problem *(Romero et al., 2015)*.

Romero et al., 2015 also employed Unsupervised Deep Feature Extraction for satellite image classification but the accuracy is still not optimal. A number of challenges still affect the classification accuracy of the existing models which include lack of unified representation for different source images *(Shuang et al., 2018)*.

Recently, an increasing number of novel deep networks have been proposed, among which are the work of *(Ronneberger et al., 2015)* which utilized U-net to pre-trained the model which can obtain an impressive performance in image segmentation. In the same vein *Zhang, et al.*, proposed ResNet for image classification and object detection. The performance of deep learning (DL) based satellite image classification techniques has shown their effectiveness in solving real-world problems, although such performance does not reflect the full potential of DL yet. (*Yang, et al., 2018)* and (*Ahn, et al., 2019)* indicated that introducing transfer learning to RS image classification will enhance the accuracy and reduce the time consumption. However, RS data are more complex than normal image; parts of them are typically even attained by the use of different remote sensors. How to introduce transfer learning to RS image classification therefore presents a major challenge, which needs significant further research *(Zhang et al., 2018).*

Recent research shows that the convolution neural network has great advantages in feature extraction and has certain degree of invariance to the operation. Current neural network models have computational requirements and high computing resources, and deep convolution neural network models are prone to over-fitting or fall into local optimization problems, making transfer learning to be the ideal choice *(Wu et al., 2018).*

The traditional machine learning techniques for classification focus only on low-level or high-level features that uses some handcrafted features to reduce this gap and require good feature extraction and classification methods. Recent development on deep learning has shown great development and deep convolution neural networks (CNNs) have prospered in the image classification task. Deep learning is very powerful for feature representation that can depict low-level and high-level information completely and embed the phase of feature extraction and classification into self-learning but require large training dataset in general. For most of the heavy images such satellite imaging scenario, the training datasets are small, therefore, it is a challenging task to apply the deep learning and train CNN from scratch on the small dataset. Aiming this problem, we use pre-trained deep CNN model and propose a ResNet strategy based on transfer learning. Thus, in this research, we want to improve the classification accuracy of the Satellite image using a deep learning convolutional neural network (CNN) to classify satellite image by introducing transfer learning to the image classification model and fine tune it with AID dataset.

2. Related Work

This section gives the review of literatures that utilized machine learning techniques for the classification of satellite imagery.

Machine learning research stems from the idea that a computer can be given the ability to learn, as a human would do, without being explicitly programmed. Deep learning is a subset of machine learning which refers to the application of a set of algorithms called neural networks, and their variants. In such methods, one provides the network (or model) with a set of labeled examples which it learns, or trains on and labeling these examples in many ways.

Recently, deep learning (DL) has become the fastest-growing trend in big data analysis and has been widely and successfully applied to various fields of computer application successfully including sequential data, processing of natural language, speech recognition and image classification (*Abdel-Hamid et al., 2012*), because of its outstanding performance compared with that of traditional learning algorithms. Standing at the paradigm shift towards data-intensive science, machine learning techniques are becoming more and more important. To be precise, as a major breakthrough in the field, deep learning has proven as a very powerful tool in many fields.

(Praveena and Singh 2015) Proposed a hybrid clustering algorithm and feed-forward neural network classifier for land-cover mapping of trees, shade, building and road. The proposed technique performed better than all the existing algorithms taken for comparison. an effective deep neural network was also proposed by (*Shuang et al., 2018*) and compare the performance with SIFT, SURF, SAR-SIFT, PSO-SIFT, the experimental results shows that the applied transfer learning further improves the accuracy and reduces the training cost. (*Woodley et al., 2018*) employs an ensemble classifier to detect water in satellite images for flood assessment and evaluate it against MediaEval 2017, it was found that this approach is capable of creating a good classification accuracy for a seen place when bands are used and an unseen place when NDWI is used.

The performance of DL-based RS classification techniques has shown their effectiveness in solving real-world problems but the major challenge with the study was how to introduce transfer learning to RS image classification therefore, presents a major challenge. Thus, we want to improve the classification accuracy of the RS image in this research work by proposing a deep learning using convolutional neural network (CNN) architecture to classify satellite image by introducing transfer learning to the RS image.

3. Proposed Algorithms

This research work is aimed at improving the RS image classification system. This work uses different CNN architectures to classify remotely sense image using transfer learning. We used CNNs pre-trained on ResNet dataset and then fine-tuned them on the RS images. Some of these pre-trained models are available as part of Matlab exchange files, while others are provided by

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the deep learning community. The RS Image dataset consists of satellite image and not photographs, yet CNNs pre-trained on ResNet dataset have shown the ability to transfer to other image domains.

3.1 Convolutional Neural Network

CNNs where commonly applied in various computer application effectively including consecutive data. Convolutional Neural Networks mainly focus in learning features that are abstract; this is achieved by stacking and alternating pooling layers and convolution layers respectively. These convolutional kernels which are the convolution layers in CNN convolve raw input data with multiple local filters thus producing translation invariant local features together with the subsequent pooling layers' extract features and a fixed-length over sliding windows of the raw input data in steps of several rules including average, max and other parameters accordingly.

The CNN is composed of a series of layers, where each layer defines a specific computation as shown in figure6 these parts are: convolution layers, pooling layers, and fully connected layers. From Figure 3.1 below the convolution layers is the foremost layer in the CNN network. The input image maps are convolved with learnable kernels and are subsequently put through the activation function to form the output feature maps. The learning and working procedure of CNN can be best summarized into two phases: (a) networking training phase and (b) feature extraction and classification phase. There are two parts for the first phase: a forward part and a backward part. In the forward part, the input images are fed through the network to get an abstract representation, which is used to compute the loss cost with regard to the given ground truth labels. Based on the loss cost, the backward part computes the gradients of each parameter of the network. Then all the parameters are updated in response to the gradients in preparation for the next forward computation cycle. After sufficient iterations of training, in the second stage, the trained network can be used to extract deep features and classify unknown images. Figure 3.1 shows the Convolutional Neural Network framework used for satellite classification.

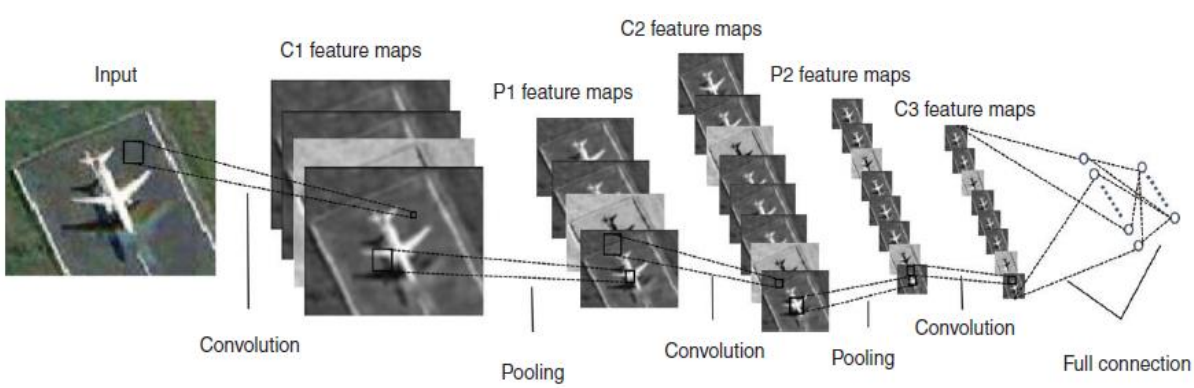

Figure 3.1 Architecture of the Convolutional Neural Networks

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3.2 Transfer learning and fine-tuning of CNN (ResNet)

Transfer learning is a deep learning application whereby a fully developed network is pre-trained with a pre-trained network which serves as a starting point to learn a new task for enhanced convergence and performance. Fine-tuning a network with transfer learning is much easier and faster than training it from a scratch. The features of the pre-trained network are transferred via transfer learning to a new task using a smaller number of training images, features and parameters. The advantage of transfer learning is that the pre-trained network has already learned many sets of features. These features are applied to a wide range of other similar tasks to reduce the training time with improved accuracy. In this research work, we introduce transfer learning using ResNet to pre-train the network.

During the training process, the weights of the CNN layers are updated after every iteration. There are 19 layers and 25.6 million trainable parameters (weights) in the ResNet architecture. For the training and optimization of such deep network, the large dataset is necessary. However, for small dataset, it is very difficult to determine the appropriate local minima for the cost function and the network will suffer from overfitting. Therefore, we initialized weights from the pre-trained ResNet model. After the weights transfer, we fine-tuned ResNet on Aerial Image dataset (AID).

3.3 Working Principle of the Proposed System

This research intends to enhance the accuracy of satellite Image classification using pre-trained ResNet and CNN algorithms. The pre-trained network with additional modification of the traditional CNN architecture as discussed in the work of *(Zhang et al., 2018)* were adopted to improve the performance of the system. The working of the proposed system is described below: The satellite Data set is resized and preprocessed. They dataset is divided into three (3) main groups which is the train, test and validate set. The train set was given 70% of the dataset while the validation and test set were given 15% each. The train set pass through different stages before a model is built, after the model was built which is tested on the test set and finally the developed model is validated. The training data set is fed to the ResNet pre-trained unit for transfer learning. The network is pre-trained via transfer learning whereby the features of the data set pattern are learnt. The output of the unit is fed as input to the network which has multiple convolution layers, Convolution layers, Rectified Linear Unit (ReLU) layer, Max Pool Layer, Fully Connected layer, Softmax layer and Classification layers. The proposed CNN network is a variant of Deep learning network that can learn dependencies between the data and extract patterns for pattern classification applications. The modification was adopted to enhance the classification accuracy in satellite images classification.

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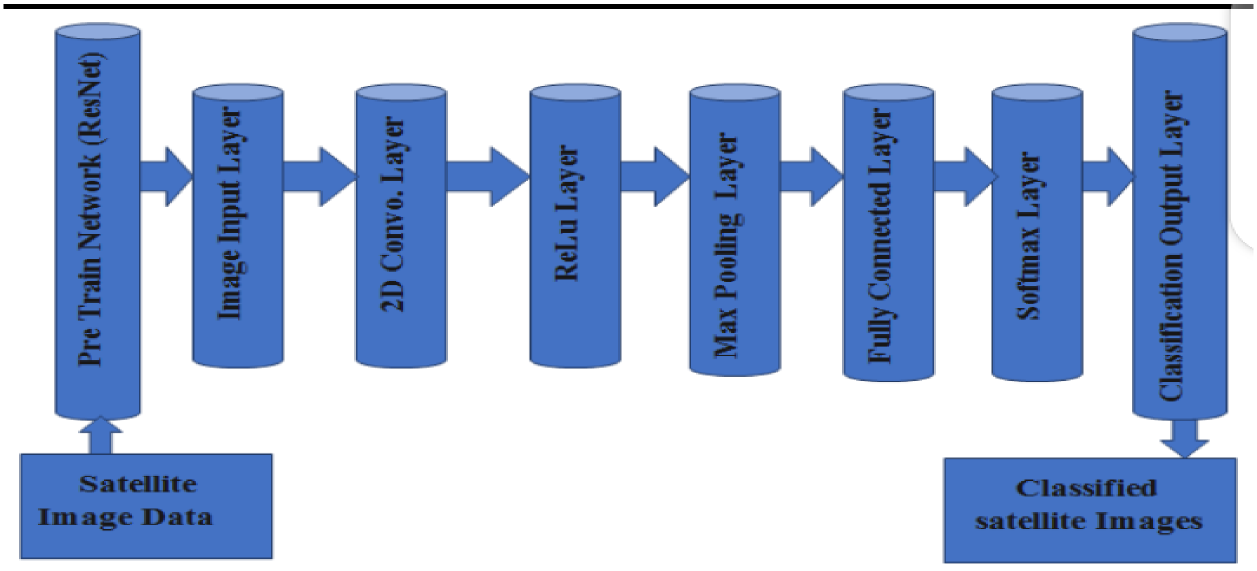

Figure 3.2 Framework for the proposed System

- **Pre-Train Network (ResNet):** Is Convolutional Neural Network that is trained on more than a million images from ImageNet database. The network is 50 layers deep and can classify images into 1000 object categories or more than that.
- **Input Layer:** Input layer in CNN should contain image data. Image data is represented by three-dimensional matrix.
- **Convolutional Layer:** Convolutional layer sometimes called feature extractor layer because features of the image are get extracted within this layer.
- **ReLu Layer:** In this layer it contains ReLu activation that makes all negative value to zero.
- **Max Pooling Layer:** Pooling layer is used to reduce the spatial volume of input image after convolutions.
- **Fully Connected Layer:** Fully connected layer involves weights, biases, and neurons. It connected neurons in one layer to neurons in another layer. It is used to classify images between different categories by training.
- **Softmax/Logistic Layer:** Softmax or Logistic layer is the last of CNN. It resides at the end of Fully Connected layer. Logistic is used for binary classification and Softmax is for multi-classification.
- **Output Layer:** Output layer contains the label which is in the form of one-hot end

4. Methodology

In this research, the standard convolutional neural network algorithm is modified to perform Satellite Image classification. We modified the algorithm using transfer learning technique.

Below shows how the algorithm is organised.

4.1 CNN Training Algorithm

```
Sliding Window Process
sf ← Extract Shadow Features
Normalize sf by equation (2)
regularization feature data, size = 13×13
repeat:
  Forward Propagation:
  cd ← Convolution2D(sf);
  mp ← Max_pooling(cd);
  fc ← Fully_connected(mp);
  class label ← Soft_max(fc);
  Backward Propagation:
    conduct backward propagation with Adam;
Until w_i convergences;
  Use the trained network to predict the labels
```

4.2 Transfer Learning CNN

❖ ***Input:***

1. *Data acquisition and Importation* $X_i = \{X_i, . . . , X_n\}$
2. *Normalise data and resize sattelite image*
3. *Data splitting to 70% for training, 15% for testing and 15% for validation*
4. *Network Pretrain with ResNet*
5. *Fine Tuning with AID dataset*
6. *Learn Features and Pattern via transfer learning*
7. *Train CNN*
8. *Classify the validation images using the fine-tuned network, and*
9. *Calculate the classification accuracy.*
10. *Validate the model*

5. Experimental Setup

In this paper, the proposed (TL-CNN) algorithm is developed and tested using three different satellite image datasets. The experiment is conducted using Mathlab 2018a. We run the experiment using different parameter setting for each dataset, the average result of each experiment is recoded. We evaluate the performance of the proposed method by compering our results with another similar research conducted with the same

The developed RS image classifier uses transfer learning convolutional neural network (TL-CNN) architectures to classify remotely sense image using transfer learning pre-trained on ResNet and then fine-tuned them on the Aerial Image Dataset (AID). In order to ascertain the best performing model, the simulation result was analyzed and compare in three different phases including accuracy, training performance and computational time. The figure below was obtained from the matlab simulation environment portraying basic information including the

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parameters configuration, training progress, number of iterations and epochs and validation accuracy for the proposed transfer learning CNN and the conventional CNN.

Figure 5.1 Parameters and simulation Result window

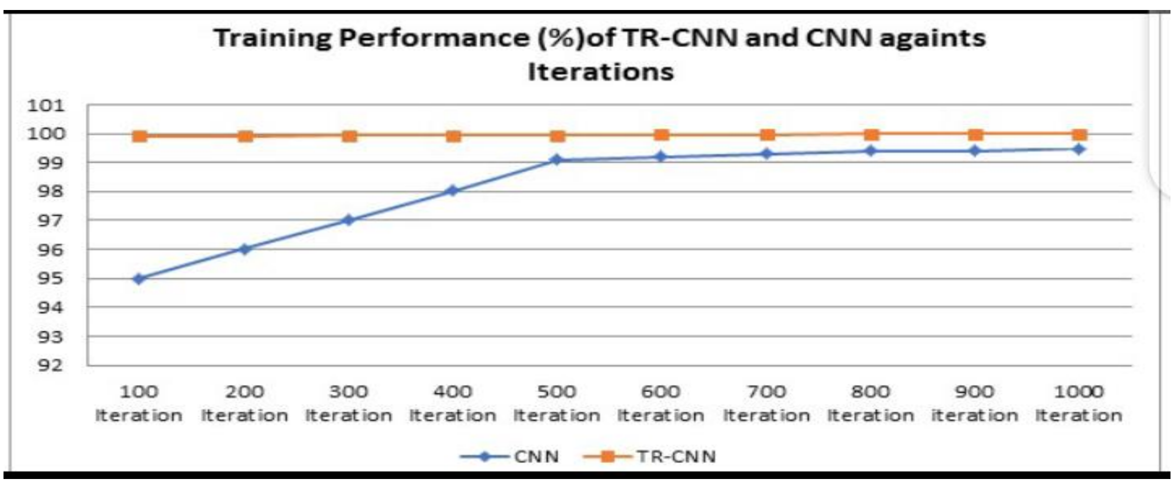

Figure 5.2 Report for the Training performance for the TR-CNN and CNN

5.1 Evaluation of Result

5.1.1 Results Evaluation in Terms of Classification Accuracy

For classification accuracy, the higher the value in percent, the better the model been built, in this research work, the result gotten was analyzed against the existing system classification accuracy of CNN, SAE and DBN. Table 2 below present the classification accuracy of the existing results obtains for the overall spectral features against the transfer learning convolutional neural network (TL-CNN).

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Table 2 Performance Overall Spectral Features

Models	Classification accuracy in percentage %
CNN	99.91
SAE	93.98
DBN	95.91
TL – CNN	99.99

Based on table 2 above, the proposed system outperforms the existing systems in terms of classification accuracy. By introducing transfer learning and exploring a different CNN architecture which was a major weakness of the existing system, the transfer learning convolutional neural network (TL-CNN) was able to improve the classification accuracy achieving 99.99 % as against the existing work of CNN with accuracy of 99.91%, stacked auto-encoders SAE with accuracy of 93.98% and deep belief network DBN with accuracy of 95.91%., although, among the existing system that was used to evaluate the proposed model, the existing benchmark i.e conventional CNN also obtain classification accuracy of 99.91% which was very closed to the classification accuracy of proposed system algorithms with only 0.08 difference.

In order to portray clearly the accuracy of the proposed TL-CNN, a sample of classified satellite images using the proposed TL-CNN is shown in the figure 5.3 and Figure 5.4 below showing the overall accuracy of the Transfer Learning Convolutional Neural Network after running 1000 iteration and we got 99.99% accuracy.

Figure 5.3 Performance of the classifier during training

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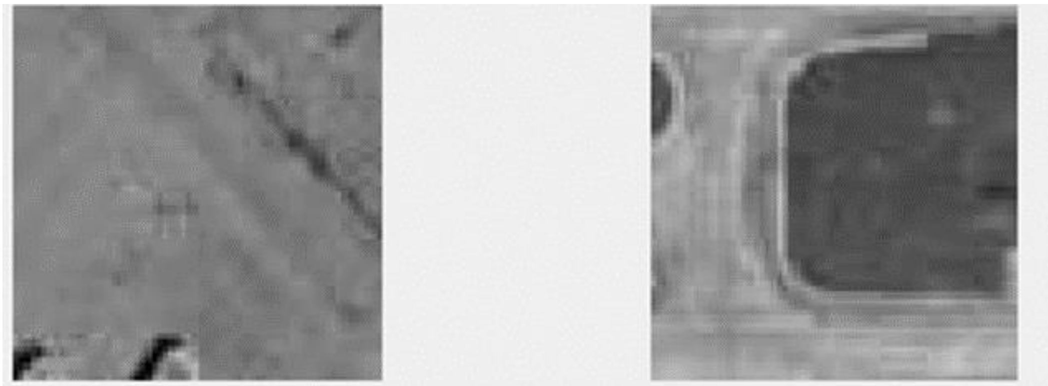

Figure 5.4 Performance of the classifier during training

Figure 5.3 and 5.4 shows four RS images in grayscale with 99.99% classification accuracy respectively. The results obtain above is further represented for evaluation in a graphical chart for more understanding by readers.

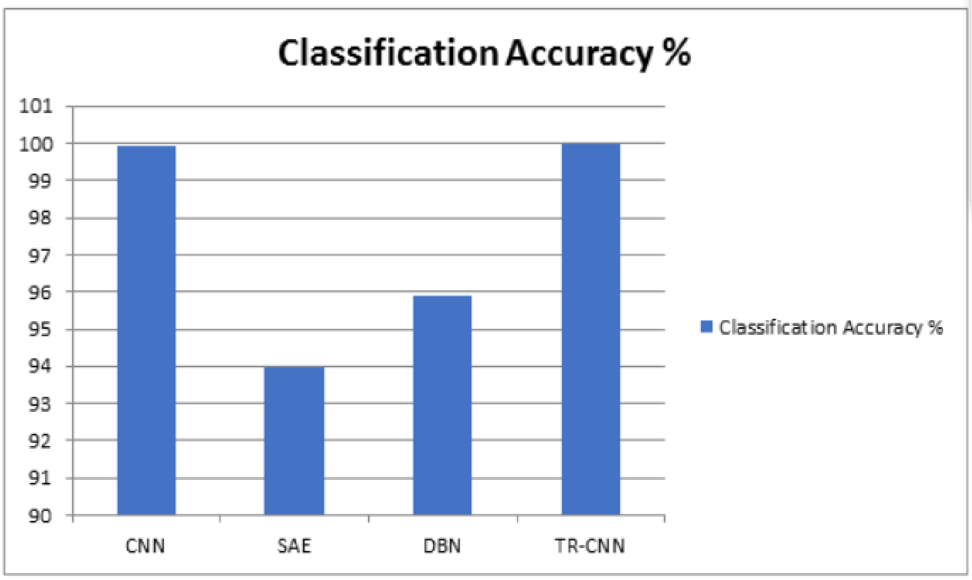

Figure 5.5: Classification accuracy of the existing results obtains in Indian Pines for the overall spectral features against the TL-CNN model.

Clearly from figure 5.5 above, the proposed TL-CNN and conventional CNN achieved the best classification accuracy as against the existing SAE and DBN. Achieving a value closer to 100%. But we further evaluate the two best performing models in terms of training and computation so as to clearly differentiate the impact of introducing transfer learning to the convolutional neural network. This details analysis the comparison is presented in the following subsections.

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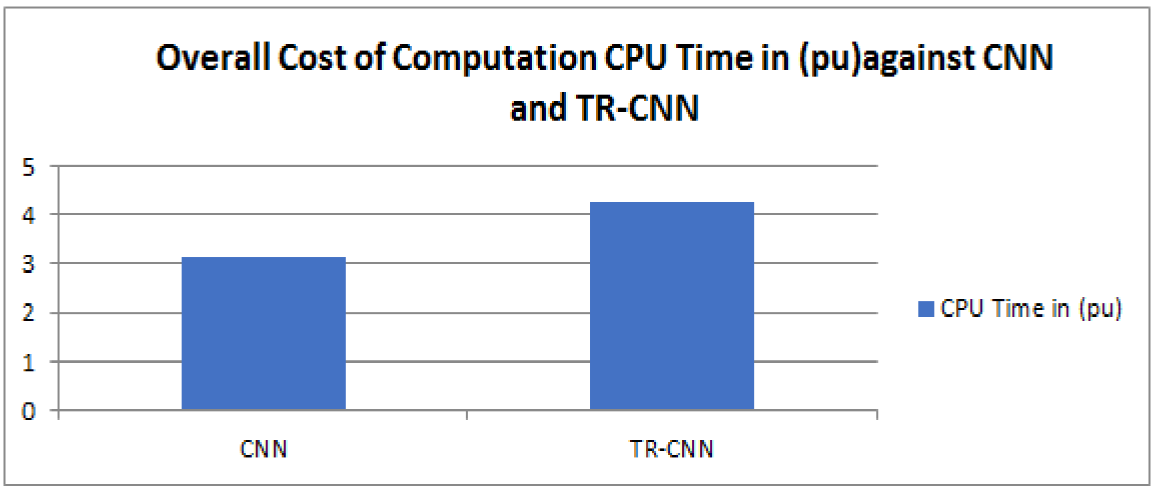
5.1.2 Results evaluation in terms of Training Performance

Similarly, for the training performance, the higher the value in percent, the better the training performance. From Figure 5.1 and figure 5.2 above, the training accuracy was evaluated after 100, 200, 300 up to 1000 iterations. The training accuracy obtained by the proposed TL-CNN after the simulation was 100% as against the conventional CNN which obtained 99.48% respectively. This is due to the introduction of a pretrain network (ResNet) which was introduce into this research work with sole aim of enhancing the training performance, validation and classification accuracy. Thus, demonstrating the suitability and applicability of transfer learning in the context of satellite image classification *(Huang et al., 2017)*.

5.1.3 Results evaluation in terms of Computational Time

One of the major drawbacks of the proposed system as against the existing system is the cost of computing, this was further proven in table 3 above, the proposed system has the highest computational time of 4.25 as against the conventional CNN which has 3.15. Thus, the proposed model has high cost of computation when compare to the existing models.

Table 3: Computational Complexity of the Proposed TL-CNN and Conventional CNN



Clearly, from the result analysis above. The proposed model in general was able to enhance the classification accuracy significantly compare to the state-of-the-art classification techniques. Although this result was achieved at the expense of significant cost of computation. Hence, the proposed model demonstrates suitability of application in the context of satellite image classification.

5. Conclusions And Contribution To Knowledge

This research work revealed an alternative technique for features selection and classification for high dimensional dataset.

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