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Microwave Remote Sensors based Image Classification and Data Analysis for Urban Areas Development

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Abstract

With various developments in satellite data, the need for image classification has extended to the highest level. Especially, optical and Synthetic Aperture Radar (SAR) data have been raised to the terabytes. Also, the study and interpretation of SAR data is very difficult due to its unique features of polarimetry, interferometry, and die-electric properties. Also, the advances in Deep Learning (DL) approaches enhanced various image processing applications such as image classification, object detection, change detection, and so on. The present work focuses on transfer learning approaches in SAR image classification to develop the urban areas. However, few changes have been made in the input size to fit the model correctly. Various classification metrics and other data analytics indicate the performance of the model outperforms traditional approaches based on image processing and machine learning.

Keywords: *Synthetic Aperture Radar, Sensors, Data Analytics, Deep Learning, Machine Learning, Image Classification, and Transfer Learning.*

Introduction

In the last few decades, we have seen a huge interest in satellite data in various image processing applications which includes coastal monitoring, smart city development, building detection, and semantic segmentation. Most of these cases use optical datasets and fewer employ their developments with radar data. But, both of these data have their advantages and limitations. There are fewer and more important reasons for using radar data in most of the sensor applications. They are (a) Firstly, the diffraction property of radar has reached to the highest limit to get the better spatial resolution of data when compared to the optical remote sensing data. (b) Secondly, all time weather monitoring is possible with SAR data. (c) Most importantly, unlike optical remote sensors, the resolution is independent of the distance of the observation.

With the recent rapid developments in the DL methods, the usage of traditional imaging approaches like wavelet analysis, transform based approaches, is limited due to the computational complexity, input quantity, feature selection, feature scaling, accuracy, and characteristics. Hence, all these works are performed with the convolutional neural network (CNN) at ease. For instance, deep learning approaches are widely used in various computer vision approaches like image recognition [1], image classification [2], image fusion [3], image segmentation [4], image matching [5], image translation [6], and so on. So, scholars, and scientists dive into deep learning for various computer vision applications. But, DL approaches are generalized to solve all the computer vision problems. This implies that there are some drawbacks that limit the application areas of DL which is explained with a simple example: if

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any deep learning model is taken to extract the image feature and analyze it for a particular class, the same model may not be useful for all the classes. Whereas, some typical image processing applications are very much generalized for all the image classes, especially, SIFT, BoW, and WA are very well used to extract the features from most of the image classes.

The remaining work of the proposed methodology is designed in the subsequent way. Section 2 explains the prior work and their limitations. Section 3 gives the comprehensive procedure of the proposed work. Whereas, the experiment details and their data analysis are elaborated in section 3. The conclusion is given in section 4 followed by the reference section.

Related Work

Traditional Approaches

In [7], the authors proposed to utilize CNN for both classification and denoising the images. However, the authors through their experimental results tried to prove the performance of CNN is reasonable. But, the imagery dataset is limited to only 600 of each class. In [8], the authors exemplified the strength of the interferometry SAR consistency in alignment of various regions exposed by desertification. The authors demonstrated the classification results, precision, recall, and so on through a confusion matrix. However, the overall classification accuracy can be upgraded up to 77% and that the results were limited only to near appropriate classes. Liu et al. in [9] proposed object-oriented features on ENVISAT ASAR data and compared them to the pixel-based approaches. However, the classification accuracy improved to 91.84% only. The histogram pattern approach was implemented at both local and global levels in [10], which is robust to the speckle noise of the TerraSAR-X dataset. But, the classification results were not satisfactory. Based on the combination of various mixture dictionary models, authors in [11] classified X band data of TerraSAR-X and COSMO-SkyMed. Further, the authors used various supervised classifiers to classify the three classes of data.

Deep Learning Approaches

With recent developments in deep learning, authors in [12] developed various approaches like Convolutional Neural Networks (CNN), integration of CNN and transfer learning. But, the authors could not improve the classification accuracy even with seven classes. Jie Geng et al. in [13] proposed deep convolutional autoencoders on TerraSAR-X data for semantic segmentation of five labels of data. The results were compared with support vector machines (SVM), stacked autoencoders, and so on. Nevertheless, the results demonstrated an overall classification accuracy of 88.11%. In [14], the authors employed deep autoencoders on three satellite data and effectively demonstrated the results. The results were compared with prior works and the overall classification accuracy resulted at 97.15%. In [15], the authors proposed an unsupervised discriminant deep belief network and trained with weak classifiers to classify the SAR images.

From the above scenario, a few limitations drive the current work to be proposed. In most of the methodologies, road network classification, grassland classification, and water-based area classification resulted in false positives. Also, some of the pseudo labeling techniques proposed in [15] resulted in deviation. Further, the dataset used for training and testing is limited to some extent resulting in under fitting. The proposed work tries to overcome some of the limitations.

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Methodology of the Proposed Work

Network Design

With recent developments in deep learning, authors in [12] developed various approaches like Convolutional Neural Networks (CNN), integration of CNN and transfer learning. But, the authors could not improve the classification accuracy even with seven classes. Jie Geng et al. in [13] proposed deep convolutional autoencoders on TerraSAR-X data for semantic segmentation of five labels of data. The results were compared with support vector machines (SVM), stacked autoencoders, and so on. Nevertheless, the results demonstrated an overall classification accuracy of 88.11%. In [14], the authors employed deep autoencoders on three satellite data and effectively demonstrated the results. The results were compared with prior works and the overall classification accuracy resulted at 97.15%. In [15], the authors proposed an unsupervised discriminant deep belief network and trained with weak classifiers to classify the SAR images.

Resnet

Resnet is called as Residual Network introduced by Microsoft Corporation in 2015. The network blocks are called as Residual blocks in Resnet. However, there are different versions such as ResNet50, ResNet50V2, ResNet101, ResNet101V2, ResNet152, and ResNet152V2. This architecture is used in various applications of image recognition and image classification. The architecture used for the SAR image classification is given in **Figure 1**.

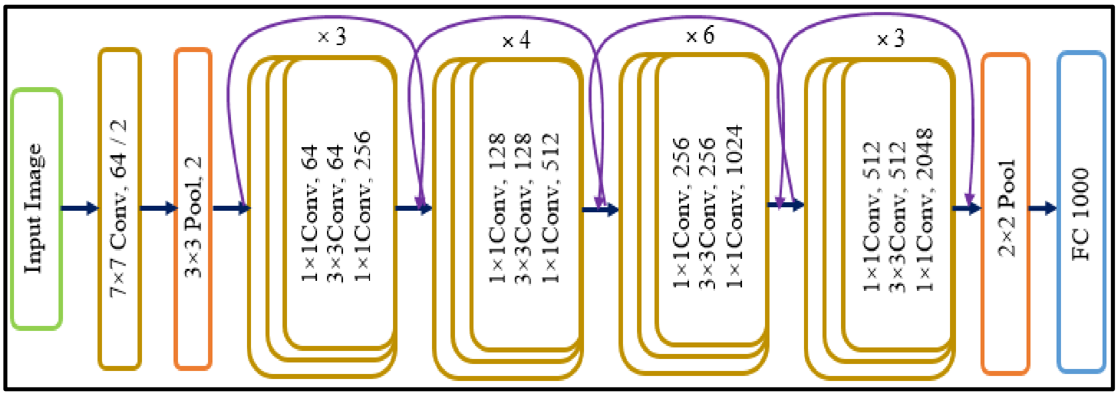

Figure 1. ResNet Architecture of the Proposed Work.

Alexnet

AlexNet is an eight layer variant of convolutional neural network as one of the deep learning model proposed by Alex Krizhevsky. This architecture was found by Alex Krizhevsky following the ImageNet model. The model became the best in the competition ILSCRC2012, popularly known as ImageNet Large Scale Visual Recognition Challenge. The model was in the top five with an error of above of 15%. AlexNet is undoubtedly the naivest and modest methods to understand neural network conceptions and techniques when compared to the state of the art deep learning architectures. The architecture flow is given in **Figure 2**.

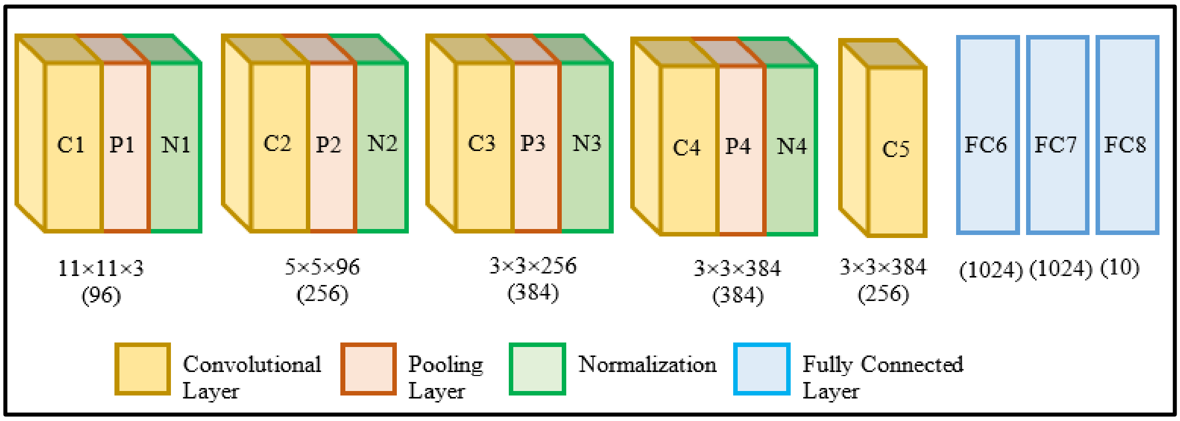

Figure 2. Alexnet Architecture used for the Proposed Work.

VGG

Alexnet was followed by Visual Geometry Group known popularly as VGG in 2014 introduced by by Karen Simonyan and Andrew Zisserman. This architecture won the competition of Classification of objects in LSVRC-2014. The architecture is given in **Figure 3**.

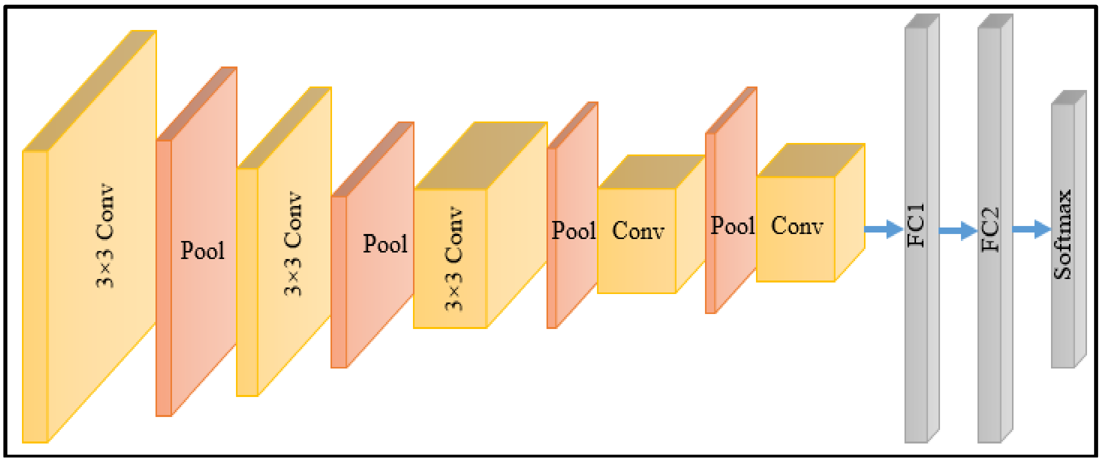

Figure 3. VGG Architecture used for the Proposed Work.

Experimental Results

Dataset Preparation

With recent developments Satellite data is mostly used for urban land use land cover mapping, understanding climate change, disaster management etc. In this context, Sentinel-1 and Sentinel-2 satellite data has been created and widely used from the url: https://mediatum.ub.tum.de/1483140. Among these, seven bands of SAR data and ten bands of optical image data are available for various applications. The various classes are water, sand, dense trees, heavy industry, bare rock, and so on. The dataset used is shortened in **Table 1.**

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Table. 1. Summary of the SAR Dataset

Image Category	**Number of Images**	**Class label**
Burial Ground	799	0
Farm Land	527	1
Lakeshore	1085	2
Mountain Road	1066	3
Mountain	964	4
Sapling	1550	5
Shrub	1451	6
Forest	1437	7
Stream	1109	8
Urban Land	914	9
Total	10902	

Results and Analysis

From **Table 2** there is clear evidence that SAR image classification works with VGG architecture.

Table. 2. Results from the Transfer Learning based Architecture

	Transfer Learning Methodology		
Metrics	**Resnet50**	**Alexnet**	**VGG**
Accuracy	76.57	90.39	96.98
Precision	82.69	90.55	97.46
F1-Score	76.23	90.43	97.45
Kappa Score	73.75	89.22	97.13
MSE	0.0742	0.01618	0.00456

The data analytics of experimental results of various architectures are given in **Figure 4, Figure 5** and **Figure 6**. The results shows that training loss is constantly varying in all the architectures, whereas there is no consistency of validation loss in Resnet. Further, the accuracy of both Alexnet and VGG are consistent with respect to the training and validation, whereas inconsistent for Resnet.

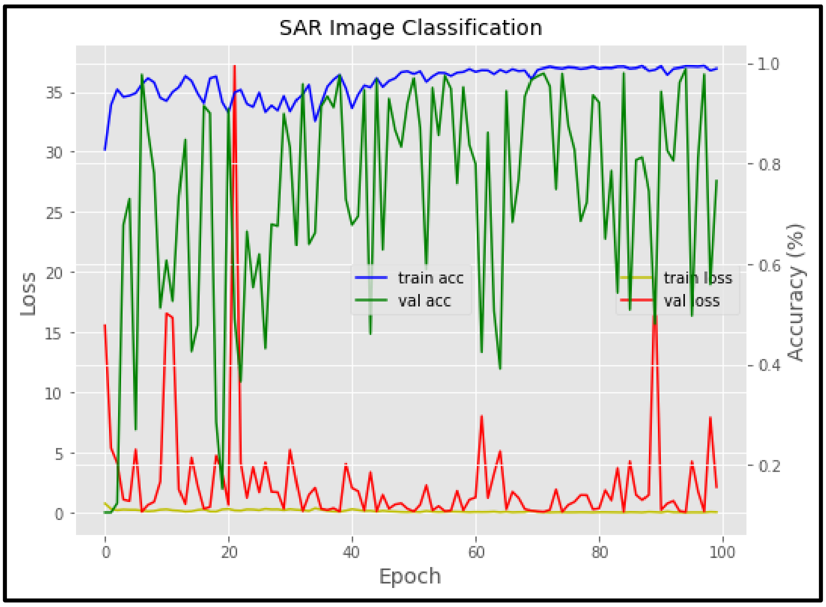

Figure 4. Metrics Evaluation for the ResNet Architecture.

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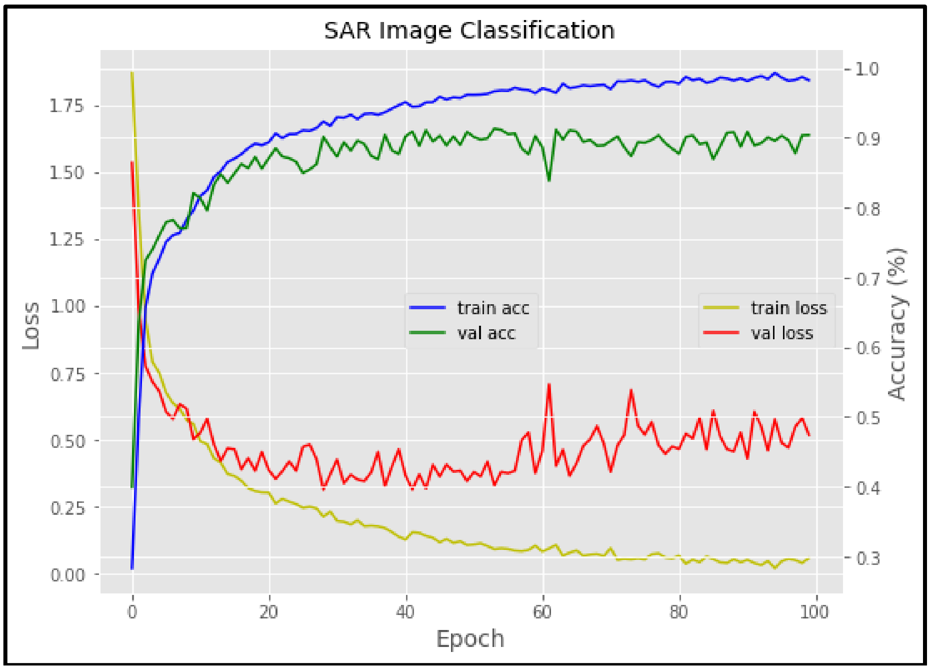

Figure 5. Metrics Evaluation for the Alexnet Architecture

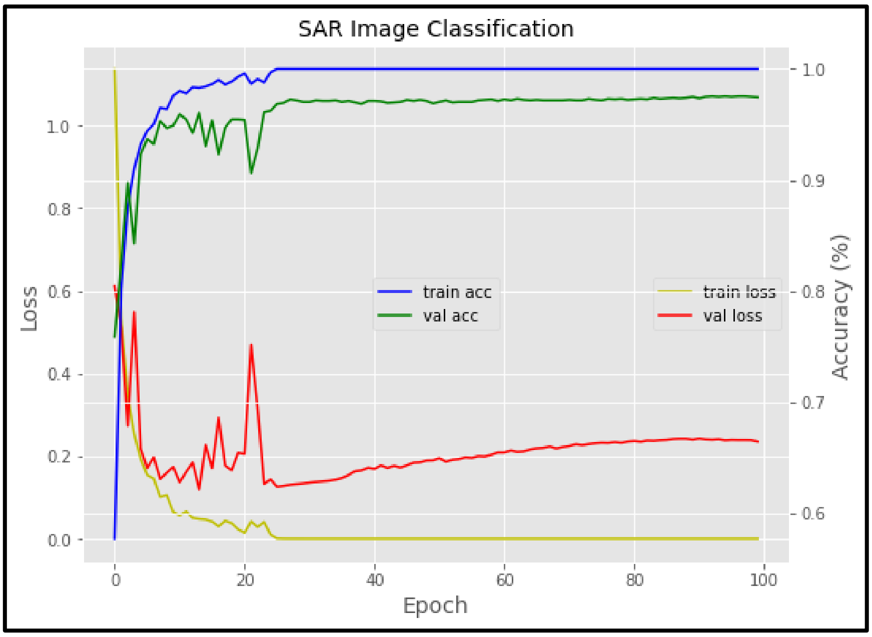

Figure 6. Metrics Evaluation for the VGG Architecture.

Conclusion and Future Work

To conclude, urban remote sensing is very important with image classification and recognition. And also, important applications like urban planning, smart cities development, and waste management can be properly controlled with remote sensing. SAR images plays an important role in this aspect. Therefore, to prove the above point image classification of different classes were implement with various transfer learning convolutional neural network approaches. Hence, the results also proves the same. Future work includes to work with various custom based architectures and compare with the TL based approaches.

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