Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 44 (2023), No. 6, pp. 1151–1166
DOI : 10.47974/JIOS-1453

Impact analysis of convolutional neural network in classification of satellite imagery

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Abstract

The classification of satellite images is crucial for information extraction and analysis. It is a method for categorizing images based on their features. The classification process involves identifying different details along with satellite imagery patterns. Any decision made in a remote sensing study is primarily determined by how well the method of classification is performing. The process of classifying data or images is difficult. Numerous elements, such as the mixed pixel issue, can have an impact on this process. In this research paper, convolutional neural networks that are used to create remote sensing-based image classification. To determine the precision and effectiveness of the proposed deep neural network model, comparison analysis has been conducted between the proposed model and various other CNN architectures, including LeNet, AlexNet, VGGNet, and ZfNet.

Subject Classification: *68T07, 82C32.*

Keywords: *Remote sensing, Convolutional neural network, LeNet, AlexNet, VGGNet, ZfNet.*

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1. Introduction

"Using sensors mounted on aircraft or satellites, remote sensing is the process of identifying electromagnetic radiations produced from the earth's outermost layers. Many different wavelengths connected to the energy for the makeup of electromagnetic spectrum, and the different wavelengths are also referred to as wave bands or bands by other names, such as the visible, infrared, and microwave the bands. Specifically, the obvious waveband, which can only be seen by humans, makes up a very small portion of the spectrum [1, 14].

Remote sensing device [17] is made to function in one or more wavelengths depending on the specificity of the data that is needed. Many remote sensing satellites with various resolutions have been launched all over the world. These satellites offer an enormous amount of remote sensing visualization related to Earth resources. The vast amount of information provided by these satellite data is essential for the planning and development of natural resource management." The various spectrum bands are shown in the Figure 1.

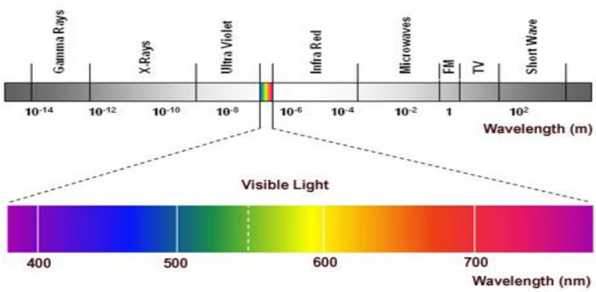


Figure 1

Spectrum bands that can be employed in remote sensing

Problems Associated with Classification

The data from remote sensing can contain both pure and mixed pixels. However, In the classification of digital data, pixel is considered as a whole unit that relates to a single class. Due to their low resolution, these pixels are typically used to represent ground-level areas, and these are formed from two or more different land cover classes. Fuzzy classification, which permits pixels to belong to a number of classes or just a few, is advised [7]. Additionally, "hard" classifications Algorithms from the past have difficulty in applications where there are quite a lot of distinct pixels. [6].

We can employ a variety of learning algorithms in this typical environment, including artificial intelligence-based neural networks, soft and sub classification techniques, and various deep learning algorithms.

Related Work

The comparison Table 1 of the classification classifiers -

Table 1
Comparative- study between classifiers for classification

Sr. No	Categories	Characteristics	Names of Classifiers	Some of the relevant References
1.	Supervised	A training stage is necessary for supervised image classification, so we must first choose some training pixels from each class.	i) Maximum likelihood, ii) Minimum distance to mean iii) Artificial neural network iv) Decision tree	[1, 6, 16, 28, 34]
2.	Unsupervised	These techniques are used to perform classification without the support of training data.	i) K-means ii) Support vector machine	[1, 16, 28, 34]
3.	Per-pixel	In these classifiers only spectral data is used which is stored in each pixel.	i) Maximun Likehood, ii) Minimum Distance, iii) Artificial neural network iv) Decision Tree	[1, 6, 14, 23]
4.	Sub-pixel	These classifiers are used to extracts meaningful information from mixed pixels on land cover classes.	i) Fuzzy-set classifiers, ii) Spectral mixture analysis, iii) Fuzzy expert system	[2, 3, 14,26]

Contd...

5.	Neural network	This classifier does not adhere to a distribution and generalizes the relationship between the input and the output.	i) Back propagation learning algorithm	[12, 18, 19, 20, 31,34]

The classifiers listed in the table above are used to classify satellite image data. In the following subsections, CNNs and their various architectures are briefly described [37-40]:

Convolutional- Neural- Network (CNN)

CNN is typically applied to image classification tasks, including satellite image classification [10, 20]. Satellite image classification involves categorizing or labeling different objects or features present in satellite images, such as buildings, roads, forests, and water bodies.

Due to their capacity to capture spatial hierarchies and learn pertinent features directly from the raw pixel data, CNNs are well suited for image classification. They are made up of several layers, such as fully connected, pooling, and convolutional layers, which combined for useful patterns and the input images features [9, 15].

Here's a general overview of how CNNs can be used for satellite image classification shown in Figure 2.

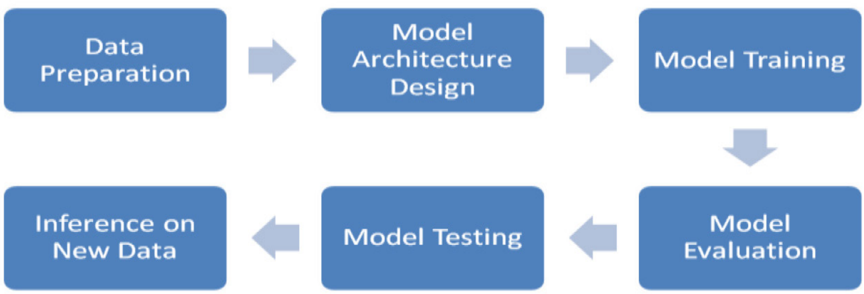


Figure 2

Steps of CNN used in satellite image classification

The typical architecture of CNN [41-44] used in satellite image classification shown in Figure 3.

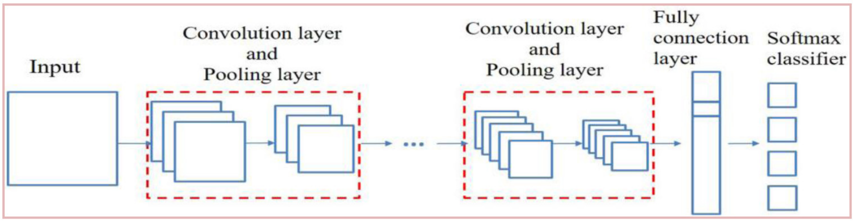


Figure 3

Architecture of Convolutional Neural Network

Here's a brief description of the typical CNN architecture used in satellite image classification mentioned in Table 2:

Table 2

Various steps involved in Convolutional Neural Network architecture

S. No.	Steps of CNN Architecture	Description
1	Convolutional Layers	These layers are used to extract features from input image with the help of filters (Kernels) after performing convolution operations on input image.
2	Activation Function	Nonlinear transformation such as Rectified Linear Unit (ReLU). Y = Activation function (Σ (weights*input + bias))
3	Pooling Layers	Used to reduce the spatial dimensions of the feature maps. Commonly used pooling is max or average pooling.
4	Fully Connected Layers	Feature maps are flattened in one dimensional vector. Every neuron of previous and current layers are connected by fully connected layers.
5	Output Layer	The output layer uses a suitable activation function (e.g., softmax) to generate class predictions.

During training, the CNN's weights and biases are learned through back propagation and gradient descent, optimizing a chosen loss function.

Loss function = true labels - predicted class probabilities,

and the network to modify its parameters for improved classification accuracy [45-50]. Several CNN architectures that are employed for satellite image classification include.

A. *LeNet :*

Yann LeCun proposed LeNet [13–14][19] as the initial CNN architecture in 1998. Without being impacted by distortions or variations, it performed well when recognizing hand digits. LeNet consists of seven layers, three of which are convolutional, two of which are sub sampling, and two of which are fully connected. LeNet draw on the essence of the image that the pixels surrounded by other pixels are all related to each other and the features are share out over the entire image. Hence it is an effective way to learn and extract the similar features from multiple location. It reduces the number of parameters and also learns from raw pixels.

B. *AlexNet:*

In 2012, Alex Krizhevsky proposed the "large - Deep Convolutional Neural Network" known as AlexNet [13-19]. CNN's learning capacity is increased by AlexNet thanks to its deeper and larger network, which made it possible to learn much more difficult data or objects. It was made up of 5 convolutional layers. AlexNet uses ReLU function to reduce the training time and also allows for multi-GPU training. It implements the dropout and data augmentation method to avoid the problem of over fitting. As the model is trained on GPUs, it allows faster training and also allow larger datasets.

C. *VGGNet:*

Karen Simonyan and Andrew Zisserman proposed the VGG Net [13-19] in 2014, which employs 3 by 3 the filters with motion and padding of 1, 2 by 2 layers with maximum pooling. Scale jittering is one method of data augmentation used during training. The idea of grouping multiple layers with small filter sizes is introduced. One of the most important CNN models is VGG.

D. *ZfNet:*

In 2013, Zeiler and Fergus proposed ZfNet [13-19] as a multilayer Deep Convolutional Network. By analyzing the activation of the neurons, it can visualize the network in action. It monitors the learning pattern of a model during training and used the findings in diagnosing potential problem. The size of the kernel and stride is reduced to maximize the learning of CNN. This network uses ReLU for activation and batch stochastic gradient descent is used to train. It is basically a modified version of AlexNet.

Research Methodology:

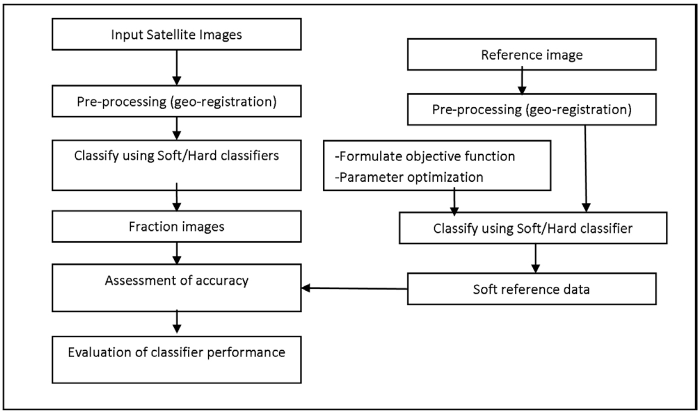


Figure 4

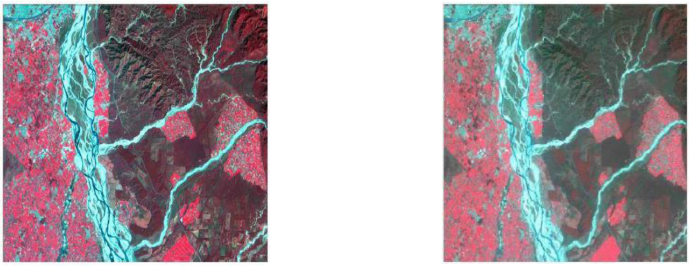
Conceptual Framework for Schematic diagram of Image Classification

Classifying digital images from remote sensing data is a difficult process that takes a variety of factors into account. Some of the key steps in image classification are used like as classification, sampling, processing and extraction of images. Decision-making in image classification is typically characterized by some degree of fuzziness or uncertainty rather than being always deterministic. Subjectivity is present in concepts like hot, cold, good, and difficult, which is similar to how we categorize imagery from remote sensors classification include. The conceptual framework for schematic diagram of image classification is illustrated in Figure 4.

Study Area & Data Used:

Haridwar, which is situated in the Indian state of Uttarakhand's hilly region. The state of Uttarakhand's boundaries is Dehradun and Pauri the Garhwal region in the north-east and east, Muzaffarnagar and Bijnor in the south, and Saharanpur in the west. The states of Uttar Pradesh's boundaries are Muzaffarnagar and Bijnor.

Due to the diversity of land cover classes and accessibility of satellite data, different land cover classes, including water, wheat, grasslands, eucalyptus, riverine sand, and dense forests, have been identified in this



(a) (b)

Figure 5

False Color Composite (FCC) using LANDSAT-8 and FORMOSAT-2 are shown in Figure 5a and Figure 5b respectively.

study. Data from the multispectral satellites Formosat-2 and Landsat-8 were used in this investigation. False color composite using Landsat and Formosat are showing in above Figure 5.

Sensor specifications of LANDSAT-8 and FORMOSAT-2 are shown in the following Table 3 and Table 4.

Table 3

LANDSAT-8 Specifications [35]

Band # and Type	Band 1 Coastal	Band 2 Blue	Band 3 Green	Band 4 Red	Band 5 NIR	Band 6 SWIR1	Band 7 SWIR2	Band 8 Pan	Band 9 Cirrus	Band 10 TIRS1	Band 11 TIRS2
Bandwidth (in µm)	0.43 to 0.45	0.45 to 0.51	0.53 to 0.59	0.63 to 0.67	0.85 to 0.88	1.57 to 1.65	2.11 to 2.29	0.50 to 0.68	1.36 to 1.38	10.6 to 11.19	11.5 to 12.51
Resolution (in Meter)	30	30	30	30	30	30	30	15	30	30 (100)	30 (100)

Table 4

FORMOSAT-2 SPECIFICATIONS [36]

Spectral Bands	**Bands**	**Wave Lengths (in µm)**	**Resolution (in Meter)**
1 PAN (Panchromatic band)	1	0.45 - 0.90	2

4 MS (Multispectral bands)	B1(Blue)	0.45 - 0.52	8
	B2(Green)	0.52 - 0.60	
	B3(Red)	0.63 - 0.69	
	B4(NIR)	0.76 - 0.90	

LANDSAT-8 is used for classification while FORMOSAT-2 has been used as reference data.

Results & Discussions:

The evaluation of accuracy makes an effort to put a number on the accuracy of the classifier or the overall performance of the classifier. This is made possible through comparing it with referencing data, which precisely represent all classes of land cover. For evaluating classification accuracy, there are numerous different metrics available. Examples include an error matrix, a table of contingencies, and a confusion matrix, the precision error matrix tables are considered as an example. It distinguishes between user and producer accuracy as well as general accuracy [32, 33].

Kappa statistic was considered to be a crucial precision indicator that cans helps to identify the training space using confusion metrics [30]. Using the above statistics we can also evaluate the error matrix and classify the "sub pixel classified imagery" [25, 26]. Few evaluation metrics are given in Table 5.

Table 5

Evaluation metrics

S. No.	Evaluation Metric	Formula	Description
1	Precision(P)	TP/(TP+FP)	ratio of relevant output to the total number of output
2	Recall/sensitivity (R)	TP/(TP+FN)	ratio of relevant output to all the input and output queries.
3	Accuracy(Acc)	(TP+TN)/(TP+TN+FP+FN)	Calculates the ratio of correct predicted classes to the total number of samples evaluated
4	Specificity(S)	TN/(FN+TN)	ratio of correctly labeled output to the total number of negative output
5	F-measure(F)	2(PxR)/(P+R)	harmonic average between recall and precision

Table 6

Accuracy of CNN of different classes

Accuracy of Classifier	
Classes	Accuracy using CNN
Water	98.25
Wheat	91.23
Riverine sand	92.98
Grassland	96.49
Dense forest	94.74
Eucalyptus	89.47

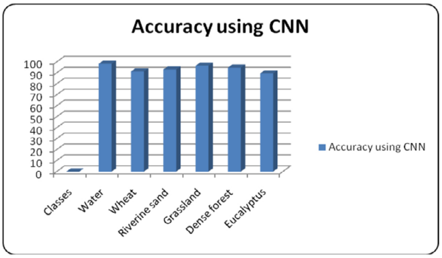


Figure 6

Accuracy of CNN of different classes

In this study, classification is carried out using a deep neural network called CNN. Comparative analysis has also been done between different CNN architectures such as LeNet, AlexNet, VGGNet and ZfNet. Landsat-8 satellite image is used and Formosat-2 satellite image is used for reference. The accuracy of all classes using CNN is categorized in the following Table 6 and Figure 6.

The overall accuracy of CNN classifier is 94% with Kappa 92.63. Comparative analysis of different architecture of CNN such as LeNet, AlexNet, VGGNet and ZfNet are shown in the following Table 7 with overall accuracy and their Kappa values, Figure 7.

Table 7

Analysis of different CNN architectures

Accuracy Metric	LeNet	VGG	AlexNet	ZfNet
Overall Accuracy	84.37	85.44	87.16	84.19
Kappa	67.64	69.26	71.77	65.8

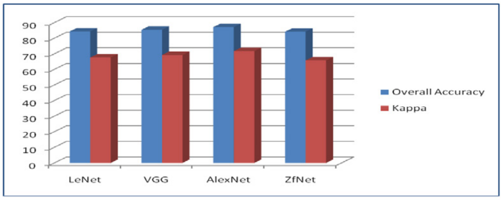


Figure 7

Accuracy of CNN of different classes

The output of satellite imagery using CNN with the help of LANDSAT-8 and FORMOSAT-2 is shown in Figure 8.

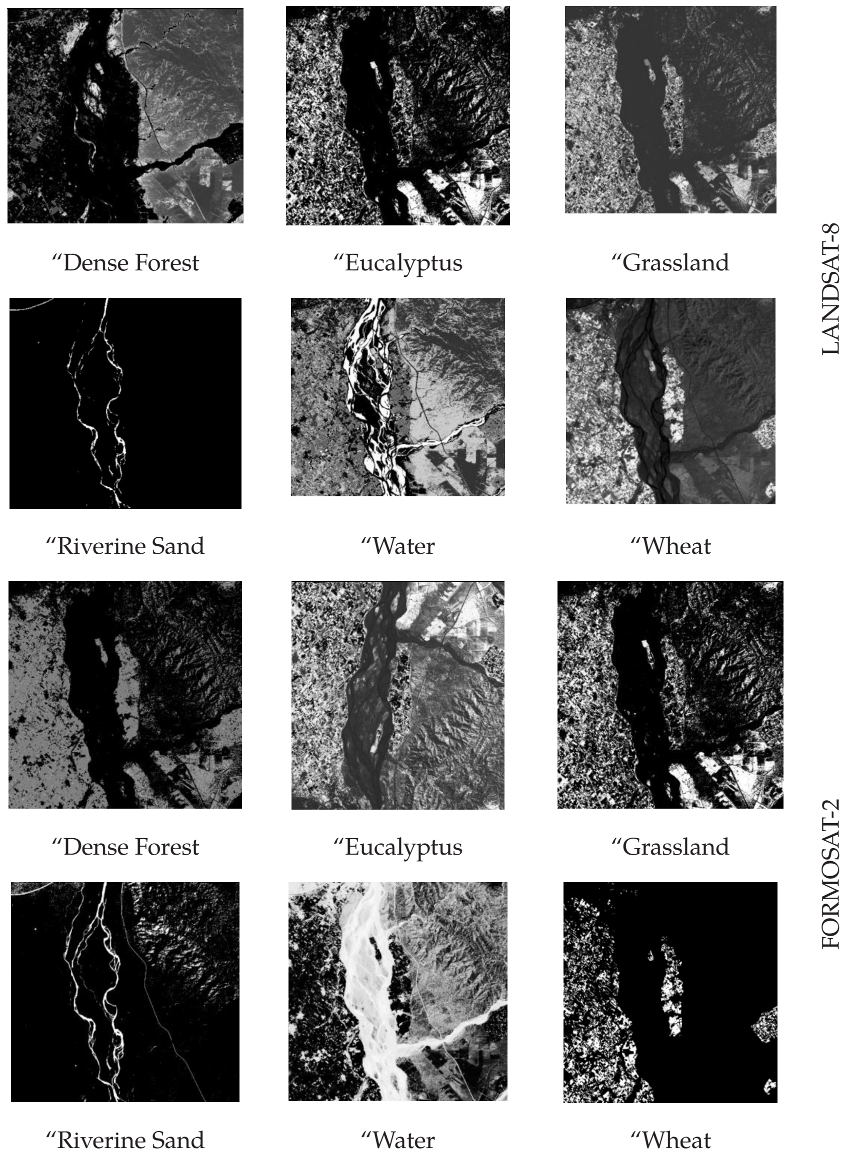


Figure 8

Classified outputs of CNN using Landsat-8 and Formosat-2

Conclusion

In this paper deep neural network CNN used to test its performance on satellite imagery. This algorithm can overcome the limitations of other architectures of convolutional neural network like LeNet, AlexNet, VGGNet and ZfNet. Overall accuracy is achieved by more than 6 % using CNN. This algorithm is also effective for handling the pixels that are noisy in behavior and comparative analysis has also been done. Overall, we can conclude that CNN algorithm perform local spatial information that perform more effectively in terms of noise sensitivity classification and than the conventional classifiers used in this work.

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