DEFORESTATION DETECTION USING CNN

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Abstract: Deforestation detection using convolutional neural network is a method to calculate the amount of deforestation occurred by taking input as satellite images of before deforestation and after deforestation. There are four modules in this project. First module is training. In this, we need to train the model using satellite images which are taken from the Prodes database. The features of the images are extracted by using various layers like convolution2dlayer, batch normalization layer, ReLU layer, maxpooling2dlayer. Second module is a classification module where a random satellite image is compared with a trained model from the first module to classify it into forest or deforest area. Next module is the testing module where we will get a confusion matrix to know the accuracy of the classification of images by the trained model. The last module is block division. In this a method will take satellite images of the area before deforestation and after deforestation and give the result as the amount of deforestation occurred in percentage.

Keywords: Deforestation, CNN, Convolutional layer

1. INTRODUCTION

Deforestation is the permanent destruction of forests. It can have a negative impact on the environment. The most dramatic impact is a loss of habitat for millions of species. Eighty percent of Earth's land animals live in forests and many cannot survive the deforestation. This paper aims at studying the extent of deforestation through the study of satellite images.

2. APPLICATIONS

The project is useful to the government departments in curbing deforestation and environmental protectionists in understanding the details of deforestation.

3. ARCHITECTURE

The proposed CNN convolves learned features with input data and uses 2D convolutional layers. This type of network is ideal for processing 2Dimages.Compared to other image classification algorithms, CNNs use very little preprocessing. CNNs have an input layer, and output layer, and hidden layers. The hidden layers consist of convolutional layers, ReLU layers, pooling layers, and fully connected layers.

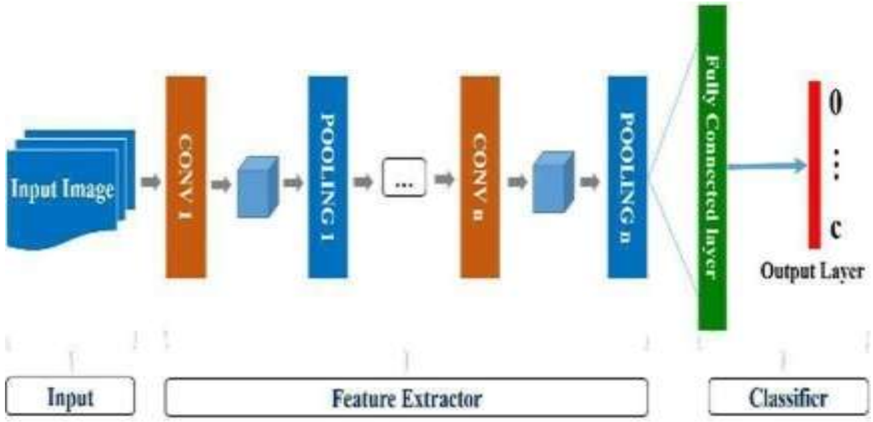

Fig .CNN Architecture.

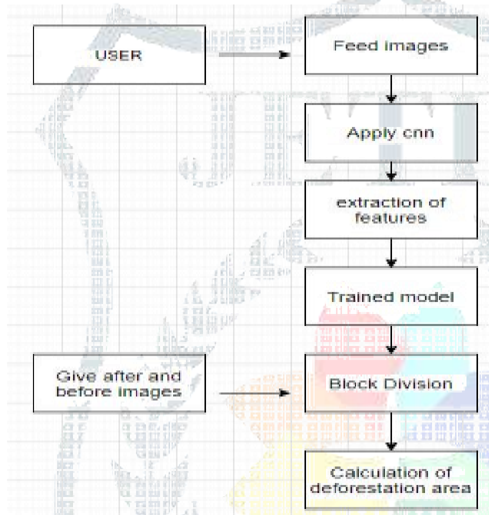

Fig . Architecture

The system will take image as input, Convolutional layers apply a convolution operation to the input. This passes the information onto the next layer. Pooling combines the outputs of clusters of neurons into a single neuron in the next layer. Fully connected layers connect every neuron in one layer to every neuron in the next layer.

3.1 Convolution : The main purpose of convolution is to extract features from the input image. The convolutional layer is always the first step in a CNN. It consists of an input image, a feature detector, and a feature map. The light from the flashlight is the filter and the region that sliding over is the receptive field. The light sliding across the receptive fields is the flashlight convolving. The filter is an array of numbers. The distance the light slides as it travels is called the stride. The convention is a stride of two. We need to specify parameters like number of filters, the filter size, the architecture of the network, and so on. The CNN learns the values of the filters on its own during the training process.

3.2 ReLUlayer : TheReLU (rectified linear unit) layer is another step in convolution layer. You're applying an activation function onto your feature maps to increase non-linearity in the network. It removes negative values from an activation map by setting them to zero. Convolution is a linear operation with element wise matrix multiplication and addition.The real-world data will be non-linear. We can account for that with an operation like ReLU, tanh or sigmoid. ReLU is a popular choice because it can train the network faster without any major penalty to generalization accuracy.

3.3 Pooling: Pooling progressively reduces the size of the input representation. It makes it possible to detect objects in an image. It helps to reduce the number of required parameters and the amount of computation required. It also helps control overfitting.

Flattening

We flatten the pooled feature map into a sequential column of numbers(along vector). This allows the information to become the input layer of an artificial neural network for further processing.

3.4 Fully connected layer

We add an artificial neural network to our convolutional neural network. The main purpose of the artificial neural network is to combine the features into more attributes. These will predict the classes with greater accuracy. This combines features and attributes that can predict classes better. At this step, the error is calculated and then back propagated. The weights and feature detectors are adjusted to help optimize the performance of the model. Then the process is repeated and our network trains on the data.

Once the network has been trained, you can pass in an image and the neural network will be able to determine the image class probability for that image with a great deal of certainty. The fully connected layer is a traditional Multi-Layer Perceptron. It uses a classifier in the output layer. The classifier is usually as of tmax activation function. Every neuron in the previous layer connects to every neuron in the next layer. To use the features from the output of the previous layer to classify the input image based on the training data.

Softmax function

This brings the values between 0 and 1 and makes them add up to 1 (100%). The softmax function takes a vector of scores and squashes it to a vector of values between 0 and 1 that add up to 1.

4. ALGORITHM

Input: Before and after deforestation images of a land.

Output: Display of the percentage of deforestation

i. Starts with an input image

ii. Applies many different filters to it to create a feature map

iii. Applies a ReLU function to increase non-linearity

iv. Applies a pooling layer to each feature map

v. Flattens the pooled images into one long vector.

vi. Inputs the vector into a fully connected artificial neural network.

vii. Processes the features through the network. The fully connected layer provides the "voting" of the classes.

viii. Trains through forward propagation and backpropagation for many epochs. This repeats until we have a well-defined neural network with trained weights and feature detectors.

4.1 CNN Sequence Classification

CNN is a Deep Learning algorithm which can take in an input image, assign learnable weights and biases to various aspects or objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand- engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

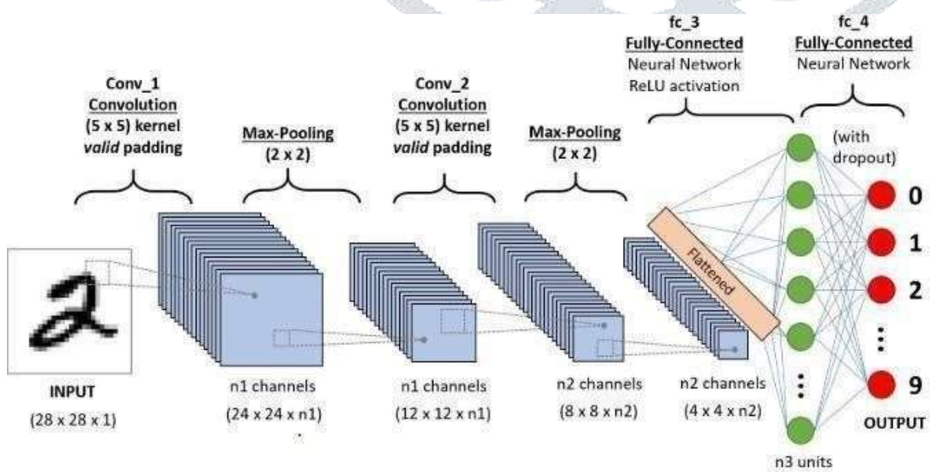

Fig. A CNN sequence to classify handwritten digits

4.2 Flattening of an image

A ConvNet is able to successfully capture the Spatial and Temporal dependencies in an image through the application of relevant filters. The architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and reusability of weights. The network can be trained to understand the sophistication of the image better.

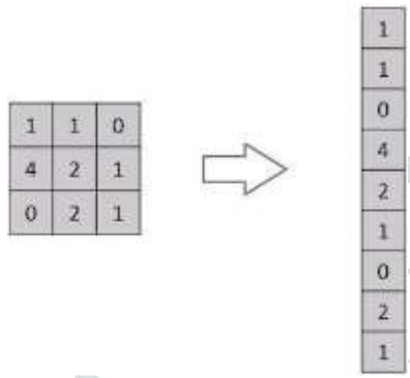

Fig. Flattening of a 3x3 image matrix into a 9x1 vector.

4.3 An image with three planes

In the figure, we have an RGB image which has been separated by its three color planes—Red, Green, and Blue.

The role of the ConvNet is to reduce the images into a form which is easier to process, without losing features which are critical for getting a good prediction. This is important to design an architecture which is not only good at learning features but also is scalable to massive data sets.

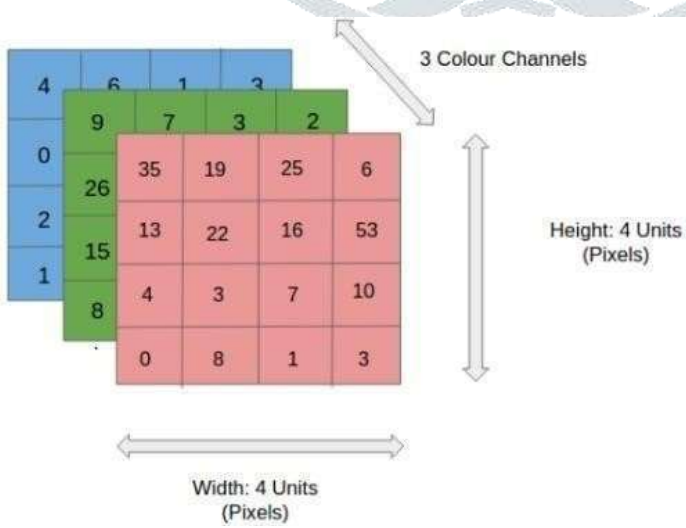

Fig. 4x4x3 RGB Image.

5. RESULTS AND DISCUSSION

First the images are taken and are trained using convolution neural networks. And a trained model is created which is used to classify the test data.

In this system, first, the images of different times are classified according to the purpose of change detection. Then by overlaying the two classified images with a proper overlay condition, we can determine the location and amount of any changes. As our goal is to determine deforestation, the only two classes considered are the forest and non-forest. The two images are classified using the Maximum-Likelihood method.

After training, the ACCN model is obtained. The classification is done, when an image is selected. As shown in the below figures the first image selected is classified as forest area and the second image selected is classified as deforest area.

Fig. Image of forest area by satellite

Fig . Image of forest after deforestation

It will compare both the images with the block division method and calculate the amount of deforestation occurred throughout the years. Final output shows the amount of deforestation as 60 percent.

Fig . Output showing Deforestation percentage

6.CONCLUSION

The proposed system "Deforestation detection using convolutional neural networks" has presented an approach to arrive at an idea about deforestation statistics. It takes forest images as input and generates the extent of deforestation using the trained CNN model. This module is efficient and calculates the extent of the deforestation. The project is useful to track the accurate amounts of deforestation happening through years and leads to environmental protection. It can be enhanced further by implementing the measures to be taken to enhance the Forest Coverage.

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