CNN Based Automated Land Use Classification from Remotely Sensed Images

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Abstract— **A land use classification from a remotely sensed satellite images is one of the important applications which provides information on changes in land cover and land use over a period of time. It may also facilitate the assessment of environmental impacts on and potential or alternative uses of land. In the ever-changing environment, the land use change has been occurring every day. For the continuous land use changes, there is a need for creating the current land use data. Therefore, a Convolutional Neural Network (CNN) architecture is proposed to classify the remotely sensed image. The proposed architecture contains two convolutional layers followed by a fully connected layer. The fully connected layer contains three hidden layers with a single neuron in the output layer. In order to train the network, the dataset has been created manually by collecting images from Google Earth. The dataset contains 201 images for two classes, namely, building and non- building areas. Out of 201 images 157 images are used for training the network and 44 images are used for testing the network. Binary Cross Entropy (BCE) loss is used for measuring the performance of the network. The network parameters are randomly initialized and updated with Gradient descent with momentum optimization algorithm. The proposed architecture achieves 99% training accuracy and 93% testing accuracy.**

*Keywords— **Land use classification, CNN, Binary cross entropy.***

I. INTRODUCTION

In today's changing environment, the need for land changes drastically. Dramatic land use changes have been occurring every day. For this continuous land use changes and the lack of existing land map, there is a need for creating current land use information data. This helps in predict the future trends. Better we can predict, the more we can prepare for negative impacts. In order to assess the change in land use, we have manually created a dataset from Google Earth. For the land use classification, we have chosen the places which were changed from agricultural land to buildings over the decade of time or less. For the classification purpose, we have taken the images which is in present condition and also the same images which is there before 5 to 10 years gap.

Convolutional Neural Networks (CNN) are well suitable for image based applications such as image classification, segmentation, object detection, and so on. Therefore, we have proposed a custom convolution neural network architecture tailored for this application. However, we also considered an existing CNN architecture for the performance comparison. The sections of the paper are organized as follows, various literatures in the related works are discussed in section 2, and then the details of the proposed architecture and the corresponding block diagram are discussed in section 3 and 4, respectively. Followed by, the dataset generation process and a few sample images are presented in section 5 and the implementation and result analysis of the proposed method and existing methods are discussed in the section 6.

II. LITERATURE REVIEW

Juliane Huth, Claudia Kuenze et.al., in their paper [1],[7] proposed about a novel and innovative of automated process of environment for the derivation of land cover and land use information. The TWOPAC (Twinned Object and Pixel based Automated classification Chain) method provides a structured, autonomous, user-friendly, and comparable derivation of Land cover and Land use information with less manual classification. TWOPAC not only allows pixel-based classification, but it also allows classification based on object-based characteristics. It will be carried out using the Tree method (DT), for which the well-known C5.0 code has been applied, and the data will be gathered using a tree-based definition approach.

Manuel Carranza, Garcia Jorge, Garcia-Gutierre in their paper [2,4,5] proposed about environmental and social application is essential for analyzing the land use and land cover using remote sensing imagery. Because of the introduction of new techniques for digital pattern classification, the availability of RS data is increasing. Most problems in machine learning (ML) are now approached by deep learning (DL) models, which have recently emerged as a strong solution. For several image classification tasks, convolutional neural networks (CNNs) are the current state of the art. The results show that the CNN outperforms the other methods, achieving high levels of performance in all datasets analysed, regardless of their differences in characteristics.

Patrick helber, Benjamin Bischke et.al., in their paper [3,6,8,10] list out the challenges of land use and land cover classification which is done using Sentinel-2 satellite images. They present a new dataset based on Sentinel-2 satellite images that covers 13 separate spectral bands and has 10 groups with a total of 27,000 classified images in this paper. On this novel dataset with its various spectral bands, we test state-of-the-art deep Convolutional Neural Networks (CNNs). They also compare the effects of deep CNN evaluations on current remote sensing datasets. They obtained an overall classification accuracy of 98.57 percent using the proposed novel dataset. The dataset is chosen in a way that it is associated with the cities which is present in the European urban.

III. PROPOSED CNN ARCHITECTURE

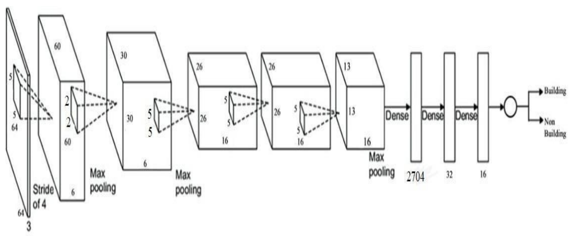

Figure.1 Proposed Architecture

The proposed architecture is shown in Figure.1. It is used for classification purpose. In this architecture we take 64x64x3 as a spatial dimension which is the input image to this architecture. In that a 5x5 filter it used and after convolution it is reduced to 60x60 with 6 layers. After that it performs max pooling function. Next step is reduced the spatial dimensionality to 30x30 with 6 layers it have 5x5 filter to get more detail of the image. Next step is spatial dimensionality reduced to 26x26 with 16 layers with 5x5 filter the process will run another one time. The next process is max pooling process, it reduce the dimension to 13x13 with 16 layer. In our architecture we use 3 dense layer to get more accuracy. Dense layer means it is the regular deeply connected neural network layer. The value of the first dense layer is 2704. It will come from 13x13x16, reducing the next dense layer from 2704 to 32. The density of the next dense layer was reduced to 32. The single neuron output is the next step, which is a binary output. It will only give output in 0 and 1 format; if the image contains a building, it will give 1 as an output; if the image does not contain a building, it will give 0 as an output. By using this architecture we have to find the whether the image have building or not.

IV. DATASET GENERATION AND DESCRIPTION

The Dataset used in this paper is taken from Google Earth. Google Earth Pro is a desktop version of Google Earth. It helps in taking the old dataset of previous years and helps in working with the dataset. The dataset is taken from different classes of land surfaces such as residential area , agricultural lands and forests .Total number of 201 images has been collected for both training and for testing.

2011 **2020**

(A) **(B)**

Figure 2 Isha yoga center

2012 **2020**

(A) **(B)**

Figure 3 Prozone mall

2014 **2020**

(A) **(B)**

Figure 3 Britannia industry

We have considered three places for the current study. Figure 2.a and Figure 2.b images are taken from the Isha yoga. It is very familiar places so that we take Isha yoga. In 2011 it is a forest area but now more number of building are developed in 2020 they developed ne The land use drastically change. We take image in google earth for current image and google earth pro for 2011 image. where Figure 3.a and Figure 3.b images are taken from Prozone Mall. In 2012 the land is used for agriculture purpose, but in 2020 same place mall was build. So that agriculture land is converted to Mall. We take image in google earth for current image and google earth pro for 2012 image. Figure 4.a and Figure 4.b images are taken from Britannia Industry Perundurai . In 2014 the land is used for agriculture purpose, but in 2020 same place Britannia Industry was build. We take image in google earth for current image and google earth pro for 2014 image.

V . OVERALL BLOCK DIAGRAM

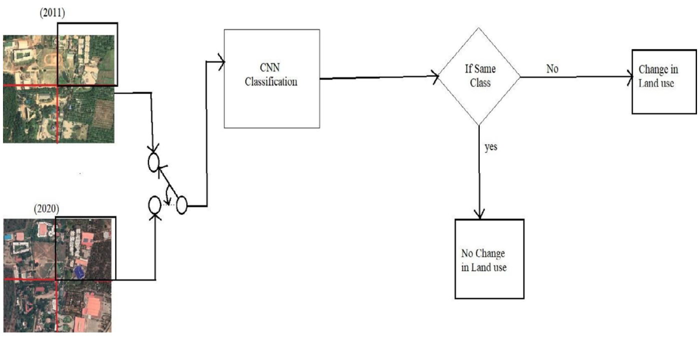

Figure 5 Block Diagram of land use classifier

In this block diagram figure 5,we considered, say , Isha yoga as a input image for illustration purpose. Here, we feed two s images of same location but captured at different timelines. For this specific example, one recent image captured in 2020 and the other image was captured in the year 2011.These are the input images to the system. The images are split into four patches of equal sizes and take one patch in each of the images. Then, they are fed into CNN classifier, we use proposed CNN architecture to get better output. This architecture checks the both images and send it to the decision condition. In this condition, it checks both images. If there is any change in both images, it gives the output as change in land use and if there is no change in the images means it will give the output as no change in land use. It is binary output so that it gives 0 or 1 only, if there is no change in land use mean it give 0 as output and if there is change in land use means it give 1 as output. The images were separate to many neurons if the neuron is in same class means it will go for Yes state and give output as no change in land use. Otherwise it will go to No condition and give output as change in land use. By splitting of image, we get more accuracy of the image. CNN classifier has binary output only so that it give more accuracy. The images are chosen from different year of the same image. So that only class will identify the changes and give accurate results. In this process, it have only one class it give output in 0 or 1 form, so that we will get better output it will find the whether the image is a building or non-building, if it is building means it will give the result as 1 and non- building means it will give the result as 0.

VI. IMPLEMENTATION AND RESULT ANALYSIS

a) TRAINING AND TESTING IMAGES

1. Total images taken - 201 images
2. Number of training images - 157 images
3. Number of testing images - 44 images

b) TRAINING PARAMETERS

1. Optimizer = Stochastic Gradient Descent (SGD)
2. Learning rate = 0.001
3. Loss function = Binary Cross entropy
4. Number of channels = 3
5. Number of classes = 2
6. Batch size = 10
7. Image scaling = 1

c) PERFORMANCE

The performance is evaluated for the dataset, it is shown as follows

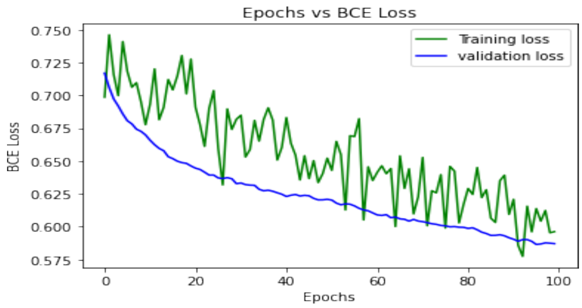

Figure 6 Epoch vs BCE loss of cnn

Figure 6 shows the epoch goes on increasing, the BCE loss is decreasing. It illustrates that when more epoch we go, the loss has been decreased.

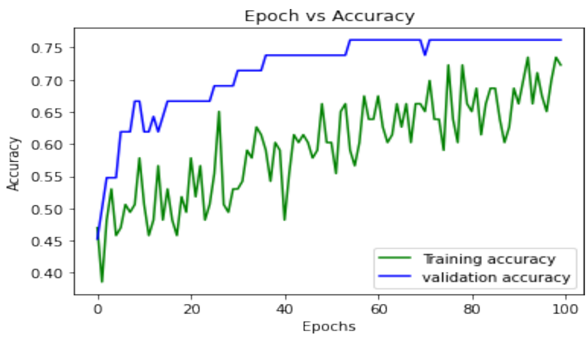

Figure 7 Epoch vs Accuracy of cnn

Figure 7 shows that as the epoch goes on increasing,accuracy has also been increased.The output measured is 74%.

d) PERFORMANCE OF PROPOSED CNN

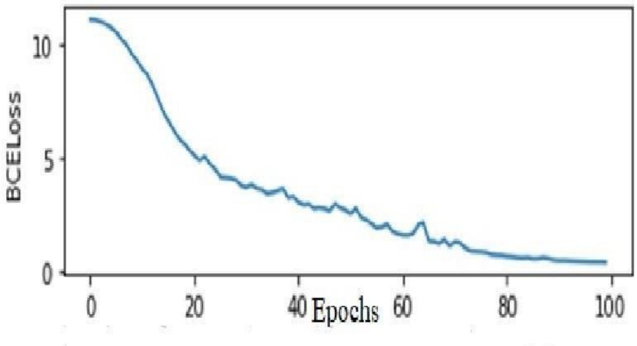

Figure 8 Epoch vs BCE Loss of proposed cnn

Figure 8 shows that graph for Epoch vs BCE Loss. As the Epoch goes on increased, the loss gets decreased.

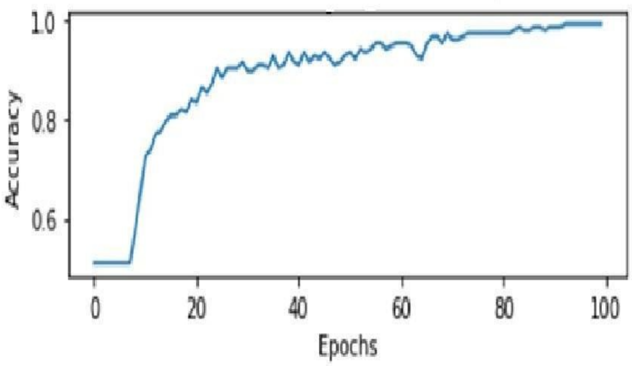

Figure 9 Epoch vs Accuracy of proposed cnn

Figure 9 shows that graph for Epoch vs Accuracy. As Epoch goes on increasing ,the accuracy also gets increased. The output measured is 93%.

Architecture	Accuracy	Loss
Existing CNN	0.74	0.69
Proposed CNN	0.93	0.40

Table 1 Accuracy and loss of architecture

Table 1 shows the accuracy and the loss of existing CNN and pro proposed CNN architecture. The accuracy and the loss function of CNN is calculated as 0.74 and 0.69 respectively. The accuracy and loss function of proposed CNN is calculated 0.93 and 0.40 respectively.

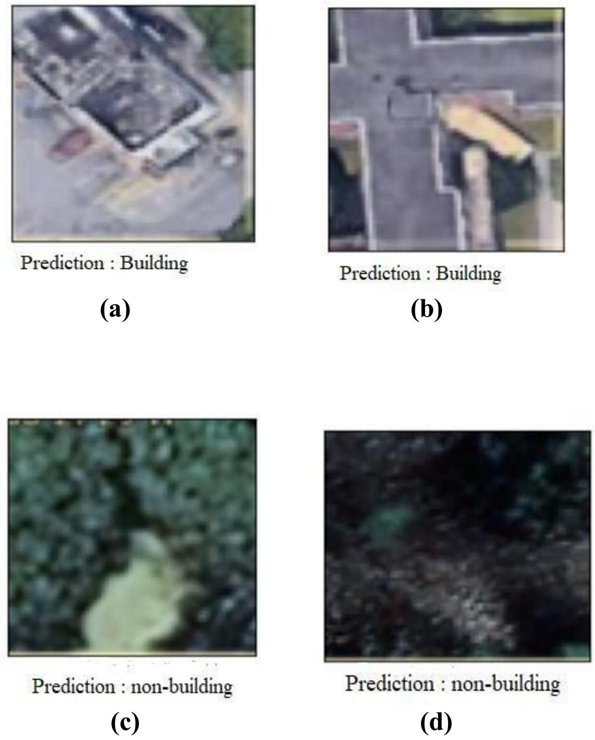

Figure 10 Prediction of Building and Non-building

Figure 10.a and Figure 10.b represent building and figure 10.c and figure 10.d represent the non- building. These are the output from the proposed convolutional neural network. The two classes are Building and non-Building. The output from proposed CNN classifies and produces the output with the accuracy of 93%.

VII . LAND USE ANALYSIS

Figure 11 Land use analysis in 2011

Figure 12 Land use analysis in 2020

Figure 11 and Figure 12 shows the land use analysis in the year 2011 and 2020.The images are made to separate into smaller blocks. If the block contains building, it is kept as 1 and if the block contains Non-Building, it is kept as 0. By counting the 1's and 0's, about 44% of land area in 2011 is converted into buildings. Comparing to 2011 to 2020, the building area is increased by 285%.

VIII . CONCLUSION

Land use information provides more information of the land surface which is helpful for analyzing current land cover scenario and for the future trends. The land use information is analyzed in two different architectures: Convolutional Neural Network and Proposed Convolutional Neural Network. The training image of 157 and the testing image of 44 are given to the architecture, the Building or Non-building information is analyzed using CNN classifiers. The accuracy of 0.93 is from proposed CNN and 0.74 accuracy from CNN architecture. The land change analysis is made for the image which is taken in 2 timelines,2011 and 2020. The land area changes of 285% is analyzed between the year of 2011 to 2020.

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