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Flood Monitoring and Deduction from Satellite Images using Modified Deep Learning Techniques

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Abstract: Flood are the most common type of natural disaster, and causes thousands of casualities every year in the world. Flood causes approximately 30% loss in total disaster. In this article, We have shown to save lives, where a Novel Image Classification techniques for Satellite images using Modified CNN – Capsnet to improve the accuracy of the output. It provides faster information supply to the user, collect accurate flood event and in cost – effective manner, The proposed work helps to classify the inundates areas efficiently in order to estimate and plain relief work rapidly.

Keywords: Deep learning, Capsule Network, Image classification, Object detection, Satellite images.

I. INTRODUCTION

The proposed work is carried out to deduct flood from the acquired satellite image and then classify them using Modified Fast CapsNet classifier, Flood deduction algorithm given a abbreviated view of the range of flooding in both urban and rural areas [1]. In this Project, the accuracy of classifying inundated areas is compared by using different classifier algorithms. The proposed classification techniques that yield lower reconstruction error and higher classification accuracy.

Automatic Flood identification based on different deep learning techniques works for identifying flooded areas based on trained images on maps the output of high accuracy. These algorithms makes thousands of data and forms pattern and image regognition. Thus The performance comparison of these deep learning classificstion techniques are more beneficial for flood estimation than other existing algorithms. This proposed project considering the monitored and management of flooded area rapidly and accurately to provide an overall view of the flood event in order to plan relief work efficiently, especially in urban districts. The proposed classification technique yields lower reconstruction error and higer classification accuracy. Using the satellite image it would help in large coverage and also its easy to georectify, with high spatial resolution. The satellite image will be easy process in integrated with software.This images will be clear and stable for the monitoring and also it makes repeated observation to particular area which we are selecting. Using the satellite image, the cost effective when an limited area coverage is worked on.

A.Literature survey

The existing system is performed with Convolutional neural network, CNNs have demonstrated excellent performance on various tasks including image classification,feature extraction, and segmentation. CNNs can learn features automatically from large data sets through the organization of multi-layers of neurons and have the ability to implement nonlinear decision functions. Since it performs with only close to data sets and also images when its rotational or tilt the function couldn't be performe well, and hence we move to Capsnet technology [2], [3].

The organization of paper is as follows: Section II presents the capsule network and its working. Section III discusses the novel capsule network architecture. Section IV shows the evaluated results and Section V concludes the paper.

II. CAPSULE NETWORK

The capsule network (CapsNet) is a novel network architecture that uses a group of neurons as a capsule or vector to replace the neuron in the traditional neural network and can encode the properties and spatial information of features in an image to achieve equivariance. The CapsNet algorithm is built with multiple numbers of layers, similar to conventional neural networks. Each one of the low-level capsules, also known as primary capsules, receives a small region of the image as input and tries to detect the presence [4]. In CapsNet, the output of each capsule is a vector. In contrast, the non-linear "squashing" function is introduced to ensure that short vectors gets almost zero length, and long vectors get to a length slightly below.

This concept is called routing by agreement. In this process, the information from capsules in the primary layer is only

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supplied to the upper capsules layer if the detected item has is handled by those two capsules in the past. Sabour. Routing-by-agreement is far more effective than the primitive form of routing implemented by max-pooling. CapsNet exploits the length of the instantiation vector to represent the probability that a capsule's entity exists. Routing capsules on the top level will see a long instantiation vector only if the object is present on the image. A separate margin loss was proposed to allow for multiple categories.

A.Working with Capsnet

An efficient deep learning technique is proposed to classify features efficiently from the satellite data to detect inundated areas under complex urban landscape. This is carried out to detect flood from the acquired satellite image and then classifying them using a Modified Fast CapsNet classifier, This introduces the CapsNet architecture is called Dynamic Routing Between Capsules. Anovel type of neural network model for image classification is provided. The main advantage is that this model preserve hierarchical spatial relationships; theoretically, this architecture may learn faster and use fewer samples per class.

Automatic flood identification based on different deep learning techniques works for identifying flooded areas based on trained images and maps the output of high accuracy. Loading and processing of data, it It supports to identify the flooded area using image segmentation technique. Image optimization It helps to store and analyze the data collected by Satellite in remote places. Monitoring The damage by the flood will be estimated by Depth estimation algorithm. The length of the output vector of a capsule to represent the probability that the entity represented by the capsule is present in the current input. Its therefore use a non-linear "squashing" function.

The discriminative learning is used for the non-linearity.

$$V_j = \frac{||sj||2}{1+||sj||2} \; \frac{sj}{||sj||} \qquad (1)$$

Based on Eq(1) $\mathbf{v}_j$ is the vector output ofcapsule j and $\mathbf{s}_j$ is its total input.

The first layer of capsules, the total input to a capsule $\mathbf{s}_j$ is a weighted sum over all "prediction vectors" $\hat{\mathbf{u}}_{j\,i}$ from the capsules in the layer below and is produced by multiplying the output $\mathbf{u}_i$ of a capsule in the layer below by a weight matrix

$$\mathbf{W}_{ij}. \quad \mathbf{sj} = \sum_{\mathbf{i}} c_{ij}\,\hat{\mathbf{u}}_{j|i}\,, \qquad \hat{\mathbf{u}}_{j|i} = \mathbf{W}_{ij}\,\mathbf{u}_i \qquad (2)$$

Where the c_{ij} are coupling coefficients that are determined by the iterative dynamic routing process as shown in Eq(2). The coupling coefficients between capsule i and all the capsules in the layer above sum to 1 and are determined by a "routing softmax" whose initial logits b_{ij} are the log prior probabilities that capsule i should be coupled to capsule j.

III. ARCHITECHTURE OF CAPSULE NETWORK

The Encoder takes the image input and learns to represent in which it contains all the information needed to essentially render the image. Primary(Lower) Capsule Layer, which is the lower level capsule layer. It contains 32 different capsules as shown in the Fig. 1 and each capsule applies eighth 9x9x256 convolutional kernels to the output of the previous convolutional layer, Digit(Higher) Capsule layer which is the higher level capsule layer which the Primary Capsules would route to (using dynamic routing) that contain all the instantiation parameters required for rebuilding the object [5].

The decoder takes the 16D vector from the Digit Capsule and shows us how to decode the parameters given into an image of the object it is detecting as shown in the Figure 2 with 3 layers. Fully converted layer 1, 2 and 3 of simple feed – feed forward neutral network.

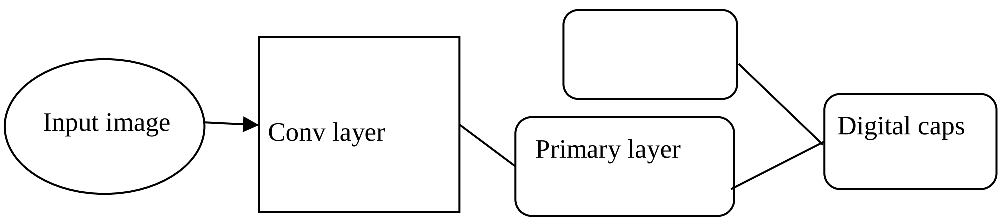

Fig. 1. Encoder of the data

The decoder is used with a Euclidean distance loss function to determine how similar the reconstructed feature is compared to the actual feature that it is being trained from as shown in Fig. 2. This makes sure that the Capsules only keep information

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that will benefit in recognizing digits inside its vectors. A capsule is an abstract idea of having a group of neurons with an activity vector that contains more information about the object. One of the main advantages of a capsule network is that it preserves the object location within an image. This feature is called "equivariance" and also the major advantages of Convolutional neural networks is their **invariance** to translation.

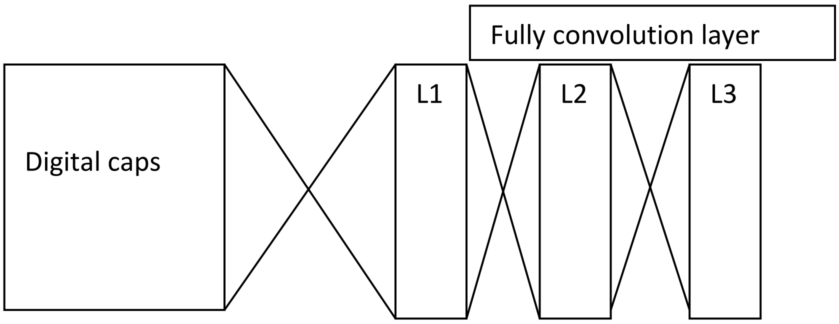

Fig. 2. Decoder of the capsnet

IV.EVALUATION RESULT

The experimental result shows the image of classification with flood affected area in different color to differentiate the accuracy. The first image of satellite shows the normal input image in Fig. 3. The number of input sets are used in the calculation for the accuracy as the experiment is about to go through in real time. This experiment brings out the clear image of flood affected area the novel deep architecture, for semantic pixel wise image labeling.

Fig. 3. Input image, the area is affected by flood

They have the several attractive properties first is that it only requires forward evaluation of a fully learnt function to obtain smooth label predictions and with increasing depth, a larger context is considered for pixel labeling which improves accuracy, and it is also easy to visualise the effect of feature activation in the pixel label space at any depth, this is shown in the Fig. 4 as the inputs are given.

Fig. 4. Flood affected area with accuracy of 60%

Although extremely important, floods are difficult to monitor, because they are highly dependent on several local conditions, such as precipitation, drainage network, and land cover. Though during the flood time, the satellite image gives us the input during the real time experiment and thus helps to identify the flood affected place and help the people to come out of it.

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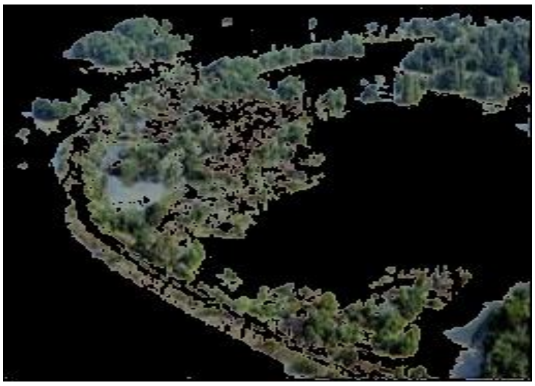

Fig. 5. Flood affected area

A first and essential step towards such monitoring is based on identifying areas most vulnerable to flooding, helping authorities to focus on such regions while monitoring inundations. From the image of Fig. 4 and Fig. 5 we can get the accurate and difference of the area affected by the classification of the image, CNN's detect features in images and learn how to recognize objects with this information. Layers near the start detecting really simple features like edges and layers that are deeper can detect more complex. It then uses all of these features which it has learned, to make a final prediction. CNN's only look for features in images, and checked on each image from the input. How capsule networks solve this problem is by implementing groups of neurons that encode spatial information as well as the probability of an object being present.

In this work, we tackled such task using distinct strategies all based on ConvNets. Specifically, its proposed novel ConvNet architectures specialized in identifying flooding areas as well as a new strategy focuses on exploiting network diversity of these ConvNets for inundation identification.

V.CONCLUSION

Main aim of this project is to detect the flood from the acquired satellite image and minimize the losses of life of human and the property from manmade. From the modified Novel Image Classification technique for Satellite Images using Modified CNN-CapsNet to improve the accuracy of the output. The proposed architecture will be evaluated using remote sensing image datasets. An efficient deep learning techniques are proposed to classify features efficiently from the satellite data to detect inundated areas under complex urban landscape.

There are still some challenges for using the deep learning method for mapping the water. These issues would be reduced by performing a 3D terrain analysis and combining the results with those of image segmentation assuming that the surface of the water (lakes and in our case, flooded areas) are flat, Where this would be helpful in making it out at real time basis that would be gaining accurate output and saves human lives.

REFERENCES

[1]. François Chollet. 2016. Xception: Deep Learning with Depthwise Separable Convolutions. CoRR abs/1610.02357 (2016). arXiv:1610.02357
[2]. Huang, X.; Wang, C.; Li, Z. A near real-time flood-mapping approach by integrating social media and post-event satellite imagery. Ann. GIS 2018, 24, 113–123.
[3]. Paoletti, M.; Haut, J.; Plaza, J.; Plaza, A. A new deep convolutional neural network for fast hyper spectral image classification. SPRS J. Photogramm. Remote Sens. 2018, 145, 120–147.
[4]. Wei Zhang, Ping Tang and Lijun Zhao, Remote Sensing Image Scene ClassificationUsing CNN –CapsNet Remote Sens.2019,11, 494; doi:10.3390/rs11050494
[5]. Rinat Mukhometzianov and Juan Carrillo, CapsNet comparative performance evaluation for image classification, 2019, 24, 167-126.
[6]. Asmamaw Gebrehiwot, Leila Hashemi-Beni, Gary Thompson, Parisa Kordjamshidi Deep Convolutional Neural Network for Flood Extent Mapping Using Unmanned Aerial Vehicles data, Sensors 2019, 19, 1486 ; doi:10.3390/s19071486.
[7]. Sergii Skakun, A Neural Network Approach To Flood Mapping Using Satellite Imagery, Computing and Informatics, Vol. 29, 2010, 1013–1024.
[8]. Leila Hashemi-Beni 1,*, Jeffery Jones 1, Gary Thompson 2, Curt Johnson 2 and Asmamaw Gebrehiwot, Challenges and Opportunities for UAV-Based Digital Elevation Model Generation for Flood-Risk Management. Sensors 2018, 18, 3843; doi:10.3390/s18113843.

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