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Cloud Computing on Earthquake Dataset Using CNN Algorithm: Consequent Disaster Analysis

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Abstract: For land use planning, management/assessment, geodisaster risk mitigation, as well as post-disaster reconstructions, accurate landslip detection and mapping is crucial. The most common methods for mapping landslides up to this point have been visual interpretation and field survey. These methods are frequently criticised for being labor-intensive, time-consuming, and expensive. The deep-learning-based strategy for landslip detection and mapping has received a lot of interest due to its major benefits over the conventional techniques in light of the quick development of artificial intelligence. However, the use of a deep-learning-based approach [1] in landslip identification from satellite photos has long been limited by a lack of sufficient training samples. Studies comparing the suggested approach's viability and robustness to those of ResUNet and DeepUNet showed that it has significant potential for use in the emergency response to natural catastrophes. H5 keras model was developed and adopted. We have also considered earthquake dataset all over the world and with the help of cloud computing the impact of disaster by earthquake will be predicted.

Keywords: Cloud computing, heroku cloud, Multichannel output with cascading, H5 Convolutional Neural Network model, Convolution Neural Network (CNN) architecture, geodisaster, earthquake, landslide, ResUNet and DeepUNet.

I. INTRODUCTION

Convolutional neural networks (CNN) have made considerable strides in natural image processing during the past few years. Remote sensing photos differ from natural photographs in that they contain more intricate textures and backgrounds, making it difficult to directly apply current CNN-based algorithms. The study of CNN's potential applications in remote sensing photos has recently gained popularity. CNN has achieved significant advancements in the extraction of buildings, the detection of roads, the segmentation of water bodies, and the classification of objects using hyperspectral remote sensing. However, there are very few investigations on landslip inventory mapping with optical remote sensing pictures due to the complexity of landslip detection and the dearth of sufficient annotated data for model training. There is still much need for more research based on the few successful applications of CNN with single-temporal optical satellite pictures that have been conducted in the pertinent studies.[2-4]

II. EXISTING CNN MODELS

i. Inception V3: Szegedy et al proposed the Inception architecture in 2014. The original architecture was called GoogleLeNet. All the subsequent versions were called Inception Vn (n is the version number). Batch Normalization was added in Inception V2 as an improvement over Inception V1. In InceptionV3 model factorization methods were introduced as an improvement over V2.[4][6]

ii. ResNet50: In 2015 He et al proposed ResNet - The Residual Networks architecture. It has 50 convolutional layers with skip connections that help in improving the learning accuracy of the model. Also, it uses global averaging pooling instead of fully connected layers thereby reducing the model size.[7]

iii. MobileNet: In 2017 another CNN architecture called MobileNet was proposed by Howard et al. In this separable convolution have been arranged depth-wise and they apply the convolution operation on each color channel separately instead of taking them as a whole. The cost of computation gets reduced in this architecture.

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iv. Xception: François Chollet developed Xception in 2017. This model can be considered as an improvised version of Inception as modules of Inception have been replaced with depth wise separable convolutions. This latest and accurate model scores upon speed and accuracy.[8]

III.H5 MODEL WITH CLOUD COMPUTING

The above CNN models are less responsive and are time consuming during training. Our H5 model created using five regions of a pre-processed image as shown in figure 1. H5 mapping consists of

i. LH Upper
ii. RH Upper
iii. Central
iv. LH Lower
v. RH Lower

Figure 2 shows the imposition of keras H5 model on our assignment. Scientific symbols needs to be suppressed for clarity. An array of right shape needs to be fed into the keras model. The length or number of images you can put into the array is determined by the first position in the shape tuple. Figure 3 shows the flow diagram of our assignment.

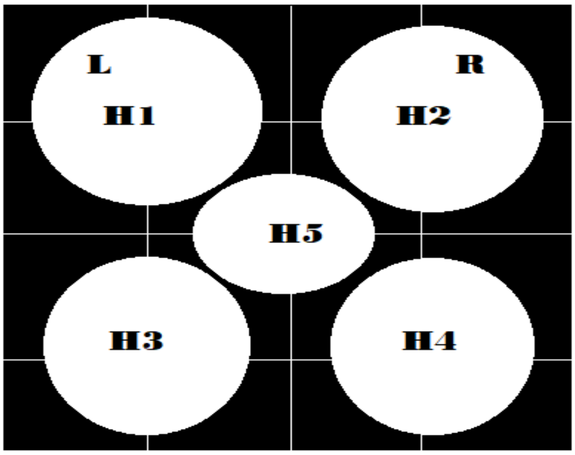

Figure 1 shows H5 region mapping scheme.

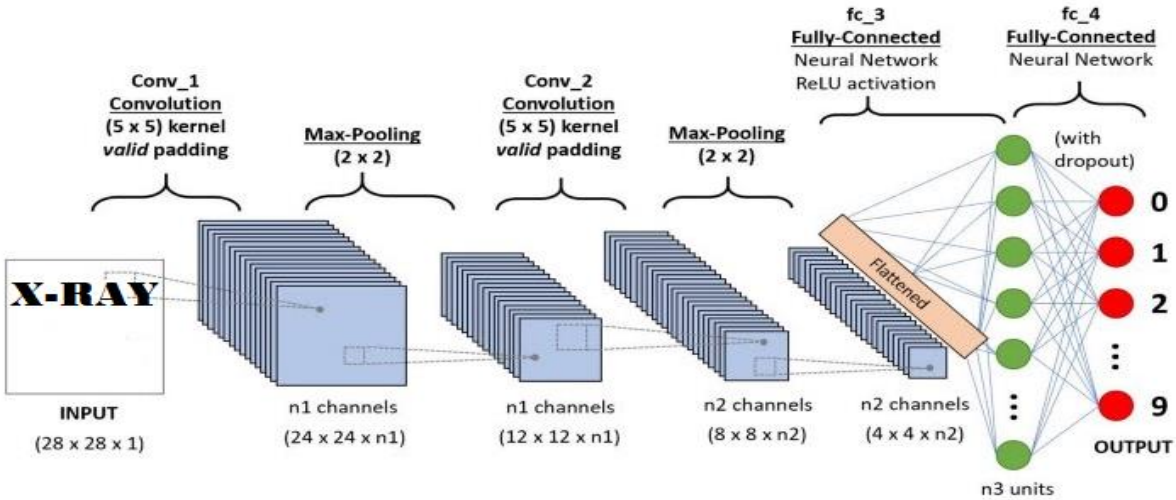

Figure 2 shows the imposition of keras H5 model

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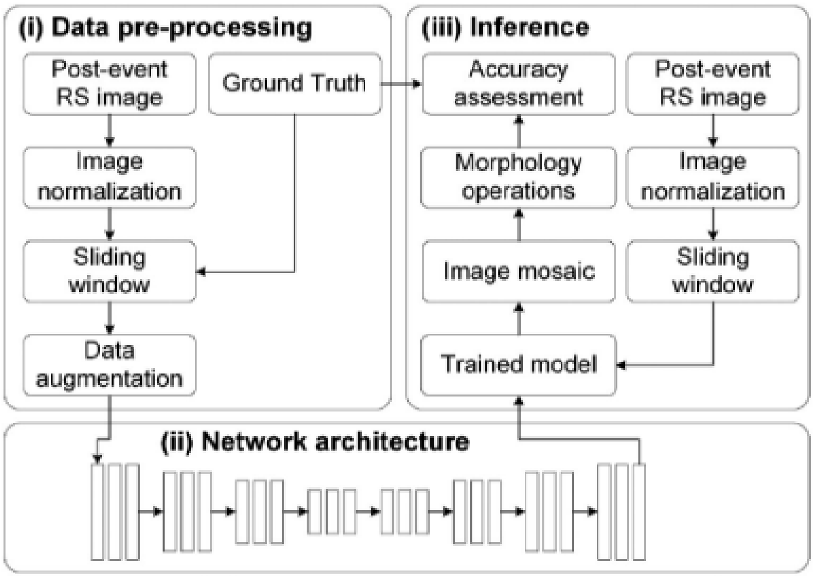

Figure 3 shows the flow diagram and architecture of our assignment.

Figure 3 displayed the architecture of the suggested method. Data preprocessing, deep network development, and inference are its three main components. Data preprocessing was primarily intended to produce training samples for deep learning model training. Technically, several data augmentation techniques were put into place to deal with the dearth of training data. A cascaded end-to-end convolutional neural network was developed to learn various features from the training samples of landslides extracted with change detection techniques and visually interpreted from high spatial resolution images.[3-4]

IV. TESTING

System testing involves the design of iterative test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs based on integrated unit tests. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application. Figure 4 shows the table containing different test cases and remarks. Verification was carried out on the system as a whole and multichannel output (channel n) with 9 test cases has proven that it’s a possibility to concatenate any number of channels to the cascade classifier. An epoch of 32 may yield better results as compared to an epoch of 10, even though it is time consuming. [9-11][13]

Sl. No.	Testcase	Expected Results	Actual Results	Remarks
1	Loading the images.	Successfully loaded.	Successfully loaded.	Pass
2	List the classification of images.	Displays the categories.	Displayed successfully.	Pass
3	Covert the images to Gray Scale and resize the images.	Successful.	Successful .	Pass
4	Create and save data and target data files.	Successfully saved.	Successfully saved.	Pass
5	Load the required libraries.	Successful.	Successful.	Pass
6	Create the model.	Created successfully.	Created successfully.	Pass
7	Train and validate the model.	Displays the training and validation results..	Displayed successfully.	Pass
8	Evaluate the model.	Displays the accuracy.	Successful.	Pass
9	Test the model using real time images.	Displays the results.	Successfully displayed.	Pass

Figure 4 shows the table containing different test cases and remarks.

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V.RESULTS

After the train-test split the train images are randomly chosen by few instruction sets with a certain random state set. Real-time images are fed to the system and now the trained system takes decisions that are based on the historical [12] image set. As shown in figure 5 training is done on 1057 samples which are obtained randomly by train test split. [9-10] Validation is carried out on 265 samples. Epoch is fixed to 10 and 1057 samples are evaluated epoch number of times and average training time noted on each step. [10] One can note from figure 5 that the average time taken for training is 90ms and the accuracy is ever increasing which is appreciable as compared to the above models and RNN. Figure 6 shows the validation losses incurred during training. It can be noted that as the epoch value increase and with the increasing sample size the validation loss decreases. The summation of the training loss and validation loss gives the effective loss of our H5 model which is around 2% which can also be reduced by adopting innovative pre-processing techniques. Figure 7 shows the evaluation of the model or real time testing using images captured by the camera or camcorder. Figure 8 shows the array of the image being processed after normalization. Figure 9 shows the UI screen deployed on the cloud to select image for prediction of earthquake. Figure 10 shows the result of a realime test performed to check for earthquake.

```
Epoch 1/10
1057/1057 [==============================] - 115s 109ms/step
y: 0.8642
Epoch 2/10
1057/1057 [==============================] - 99s 94ms/step -
0.9170
Epoch 3/10
1057/1057 [==============================] - 95s 90ms/step -
0.9170
Epoch 4/10
1057/1057 [==============================] - 94s 89ms/step -
0.8717
Epoch 5/10
1057/1057 [==============================] - 94s 89ms/step -
0.8868
Epoch 6/10
1057/1057 [==============================] - 94s 89ms/step -
0.9547
Epoch 7/10
1057/1057 [==============================] - 95s 90ms/step -
0.9547
Epoch 8/10
1057/1057 [==============================] - 94s 89ms/step -
0.9736
```

Figure 5 shows the process of training on the samples after train test split and time consumed at each step of training.

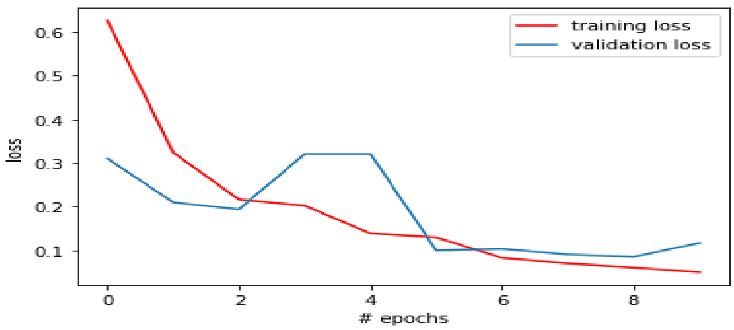

Figure 6 shows the validation losses incurred during training.

```
print(model.evaluate(test_data,test_target))

147/147 [==============================] - 3s 21ms/step
[0.07489856195693113, 0.9727891087532043]
```

Figure 7 shows the evaluation of the model or real time testing using images captured by the camera or camcorder.

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```
array([[-1.        , -1.        , -1.        , ...,
        -1.        , -1.        ],
       [-0.29921257, -0.29133856, -0.28346455, ...,
        -1.        , -1.        ],
       [ 1.007874  ,  1.007874  ,  1.007874  , ...,
        -1.        , -1.        ],
       ...,
       [-0.39370078, -0.11023623,  0.07086611, ...,
        -1.        , -0.992126  ],
       [-0.36220473, -0.04724407, -0.00787401, ...,
        -1.        , -1.        ],
       [-0.79527557, -0.79527557, -0.86614174, ...,
        -1.        , -1.        ]], dtype=float32)
```

Figure 8 shows the array of the image being processed after normalization.

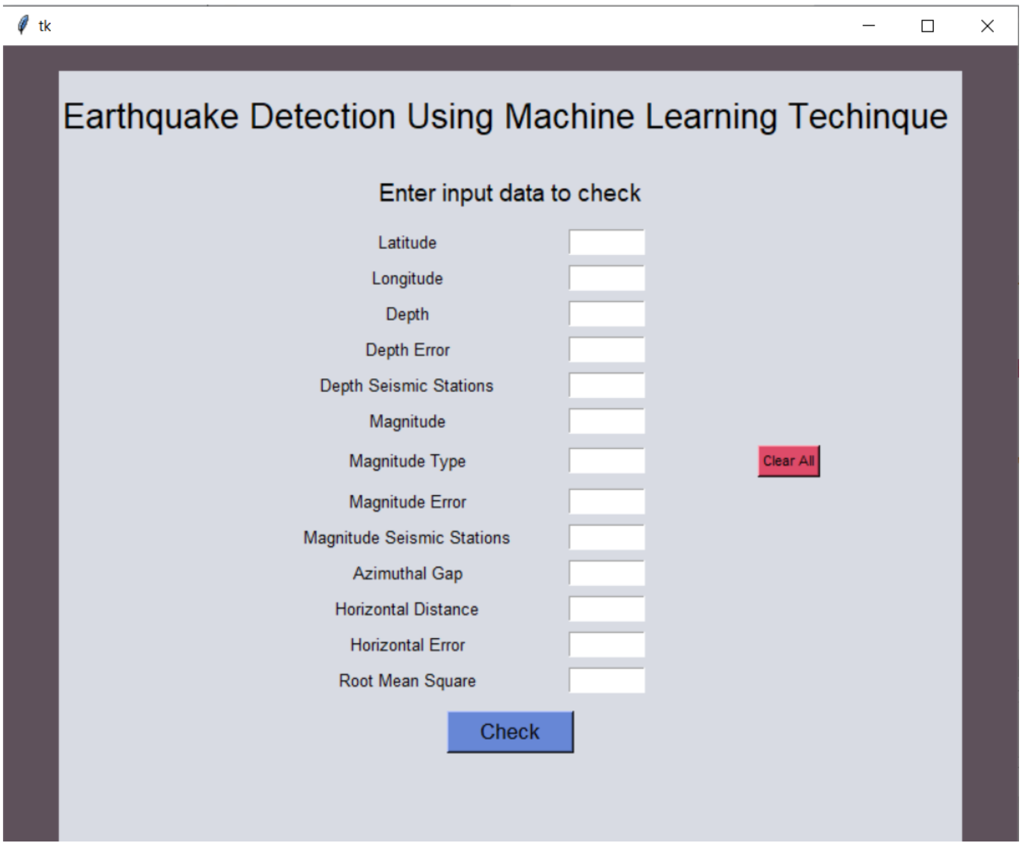

Figure 9 shows the UI screen deployed on the cloud to select image for prediction of pneumonia.

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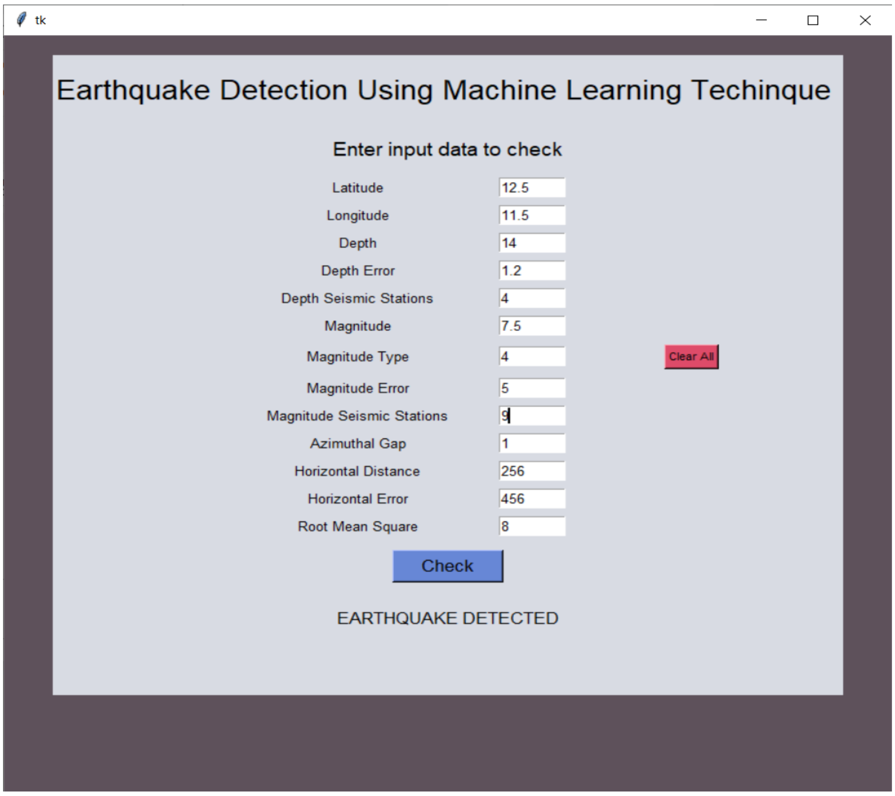

Figure 10 shows the result of earthquake predicted on the cloud

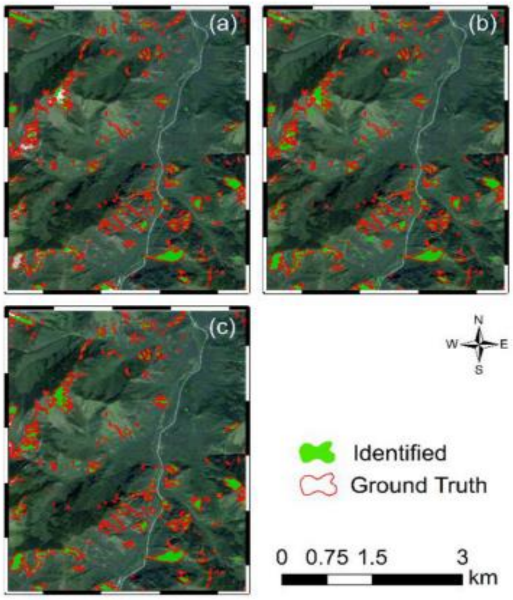

Figure 11 shows the related disaster i.e. landslide being detected.

VI.CONCLUSIONS

In this paper, in order to identify earthquake-triggered landslides from singletemporal RapidEye imageries, a novel deep-learning-based method has been presented. A novel deep learning network, called h5 keras, was then developed to learn different properties of earthquake-triggered landslides from single-temporal optical pictures. More specifically, a data preprocessing workflow was designed to generate training samples initially. Finally, morphological operations were implemented to eradicate mistakes and boost model's functionality. Two spatially distinct earthquake-affected

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regions were chosen as experiment sites to test the effectiveness of the suggested approach, and comparisons between two cutting-edge deep networks, ResUNet and DeepUNet,[11] were made. Our model fared better than ResUNet and DeepUNet with less over- and incomplete-detection findings. The model developed was then deployed on to the cloud (heroku).

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BIOGRAPHY

VISHESH S (BE(TCE), MBA(e-Business)) born on 13th June 1992 hails from Bangalore (Karnataka) and has completed B.E in Telecommunication Engineering from VTU, Belgaum, Karnataka in 2015. He also worked as an intern under Dr. Shivananju BN, former Research Scholar, Department of Instrumentation, IISc, Bangalore. His research interests include Embedded Systems, Wireless Communication, BAN and Medical Electronics. He is also the Founder and Managing Director of the corporate company Konigtronics Private Limited. He has guided over a thousand students/interns/professionals in their research work and projects. He is also the co-author of many International Research Papers. He has recently completed his MBA in e-Business and PG Diploma in International Business. Presently Konigtronics Private Limited has extended its services in the field of Software Engineering and Webpage Designing. Konigtronics also conducts technical and non-technical workshops on various topics. Real estate activities are also carried out under the guidance of Siddesh B S BE (civil). Vishesh S along with his father BS Siddesh has received various awards and applauses from the scientific and entrepreneurial society. He was appointed as the MD of Konigtronics Pvt Ltd (INC. on 9th Jan 2017) at an age of 23 years. His name is indexed in various leading newspapers, magazines, scientific journals and leading websites & entrepreneurial forums. He is also the guide for many international students pursuing their Masters.

Pramith L pursuing BE in CSE in one of the reputed college Bangalore Institute of Technology (BIT), Bangalore. He has done Intenship at Konigtronics Private Limited on Embedded system Design and Development. He is well versed in Python Programming. He is also the co-author of a research paper on Earthquake prediction. He has also actively participated in proceedings of many training programs on Embedded systems development and Python.