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INUNDATION MAPPING IN URBAN AREAS USING REMOTE SENSING

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Abstract— The most catastrophic and reoccurring natural disaster of all calamities is inundation. It is recognized as the foremost destructive calamity of nature which causes both economic and human losses. Mapping the inundated area is the most crucial step to identify the area that has to be focused during flood relief and rescue missions. On such events, it is impossible to do ground analysis. Thus remote sensing using Unmanned Aerial Vehicles (UAVs) plays most important role in management and inundation mapping when the event occurs. Many pieces of research on the remote sensing data are carried out using Fully Convolutional Network (FCN) model. Instead of using FCN or any other state-of art algorithms, in the proposed work convoluted neural layers was constructed based on VGG-16 with some modification for feature extraction and combines it with the Random Forest (RF) algorithm to semantically segment the flooded and non-flooded area. Rather than using a dense layer in FCN, semantic segmentation is done using fused RF method. The regions inundated were mapped efficiently by using limited dataset of hundred annotated images from Greater Houston area after Hurricane Harvey in 2017. It is observed that the proposed approach attains overall accuracy rate of 94.11% and training time of about 429.50 seconds which efficiently mapped first stage of inundation during emergency flood events.

Keywords — MANET, Multihop, MAC, Multichannel, AMNP and RBA.

I. INTRODUCTION

The extent of inundation can be mapped during major flooding events using remote sensing data present to assess the financial damages caused by the flood and to take decisions on rescue mission operations. Number of researches and services are predominantly focused on the rural regions rather than the urban areas. The inundation mapping in urban region is less considered due to its challenging nature. Even though it is vital to map the inundations it is lot difficult to monitor the hazard and map them because of the weather condition, vegetation present, land cover, terrain slope, and urban structures [17] [19]. The rescue and relief department has to map the first stage of inundation at the time when event happens. In current days remote sensing image classification has been improved significantly by using Convolutional Neural Networks (CNNs). Many CNN based segmentation [1] [11] [18]such as SegNet, U-Net, FCN [6], and traditional remote sensing methods such as thresholding [14][15], segmentation [12], change detection [2], region growing [4], probabilistic mapping [16] were used for inundation mapping. Rather than using such fully connected neural network , in present approach convoluted neural layer was constructed based on a variant of the VGG-16 state-of-art algorithm to extract the features from the dataset and then perform semantic segmentation using the Fused RF technique. Thus the methodology developed eased the process of flood mapping and aims to enhance the accuracy and decrease response time for mapping flood at the time of emergency.

II. RELATED WORK

Benoudjit A, et al. [2] proposed a novel fully automated supervised approach in which the training set is obtained from the Normalized Difference Water Index (NDWI), and thus does not need human intervention in the training phase. The classifier predominantly used pre-flood Synthetic Aperture Radar (SAR) image and Sentinel-2 optical images for extraction of the training labelled data. The water bodies are extricated from the multispectral optical images using NDWI is given by Equation (1):

$$NDWI = \frac{Green-NIR}{Green+NIR} \quad (1)$$

where, Green and NIR is band 3 and band 8 in Sentinal-2 satellite.But the major drawback of supervised type of classification is that it cannot be completely automated in the training phase and the algorithm may not perform well if there is imbalance or bias in the training set. This can be overcome using unsupervised method [3]. Shen X, et al. [14] suggested initiating multiple threshold namely high, moderate, low using multi level probability threshold from a single SAR sensor image to automate the process. Ciana F, et al. [5] performed an analysis on the statistical data analysis on time-series data of Sentinal-1 satellite. This CD approach used indices such as Normalized Difference Flood Index (NDFI), and the Normalized Difference Flood in short Vegetation Index (NDFVI) for extracting flooded areas and shallow water respectively.

Determining multiple thresholds is a critical process and inaccurate results are obtained using single threshold due to the aforementioned attributes. To overcome this challenge, change detection [7] [20] can be employed comparing the pre and post flood images. Huang M, et al. [9] proposed pixel based change detection to extract the pixel level change in the inundated region. They use backscatter variation rules to categorize the inundated regions as seriously inundated, moderately inundated, mildly inundated, and no flood. Shen X, et al. [14] suggested improved change detection (ICD) technique that uses numerous SAR images obtained pre-flood to monitor the change thus avoiding the over-detection or false positives by using multi-criteria approach. This approach effectively suppressed the noisy speckle. Chakraborty A, et al. [4] proposed iterative region growing algorithm that segments homogeneous flooded pixels starting from a seed point which is identified based on the reflective intensities indicating the inundation surrounding the seed.

Urban mapping has some similarities with the inundation under vegetation but the tall buildings are not as symmetric as the vegetation [10]. Ahmad S.K, et al. [1] proposed a fusion algorithm combining the advantages of the optical and SAR Images. The fusion technique was applied on each pixel to extract the flooded region in urban regions optimally. The remote sensing data of optical sensors Lansat-8 and Sentinal-2 images and SAR images of Sentinal-1 can be fused and processed to map the inundated extend. The result of the fusion algorithm produced a resilient spatial and temporal mapping rather than the individual mapping.

Therefore inundation extend mapping based on SAR data alone in regions with rough vegetation, complicated topologies and permanent cloud cover is not enough. To fill the gaps optical image sensing data can be fused to the SAR data to extract flood map accurately. Even though this approach gave reliable outputs experts were always needed to intervene the models constructed.

Deep learning approach have multi layer neural network used to learn and tune their labels themselves to classify the data better. The sub branch of neural network called convolutional neural networks (ConvNets) is best suited to learn and interpret remotely sensed visual images [8].

This type of interpreting is considered as multi-scaled approach as it can give detailed abstraction from low level to high level data in layers. Yokoya N, et al. [21] in their work proposed a framework to

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map the inundation depth and topological changes induced by the debris flow during the time of flood. The inundation and debris flow were simulated with the help of regression model (digital elevation model DEM) using LinkNet architecture. Trainning of the synthetic data to predict inundation depth and change in topology was done using Attention UNet. This technique overcame the delayed mapping limitation by combining the deep learning along with the numerical simulation. Nogueira K, et al. [11] proposed four different networks constructed on deconvolution and dilated convolutions layers alike SegNet. They also proposed combined algorithm integrating the four distinct networks thus act as complementary to each other. This combination was achieved using support vector algorithm (SVM). This fusion-SVM approach yielded considerable high results than individual networks in comparison. In our model constructed we adopt this dilated convolution layers as it provides increased receptive field while preserving resolution of the input image.

The deep learning approaches in [11] [21] addressed rapid mapping in the time major flood event. The approaches adopted either use FCN or state-of-art algorithm which is lot more time consuming to train the model. Instead the proposed approach adopts dilated CNN fused with traditional machine learning algorithm.

III. SYSTEM ARCHITECTURE

Visual Geometric Group-16 (VGG-16) has 16 layers containing trainable parameters along with the Max-pooling layers which is used to down sample the most occurring features. VGG-16 has 16 layers in which 13 layers are convolution layers and 3 dense layers that are fully connected along with 5 max-pooling layers. In our modified VGG-16 fused RF architecture the max-pooling layers are taken down as convolution layers are only used for feature extraction from the training dataset.

Convolution layers are replaced with dilated convolution or atrous convolution or hole convolution. The 3 dilated convolution layers with 3*3 dilated kernel is constructed. The three fully connected layers are chopped off and Traditional ML Random Forest is fused instead to semantically segment the features extracted by the convolutional layers and classify the remotely sensed image into a flooded and non-flooded region. This constructed model is illustrated in Figure 1.

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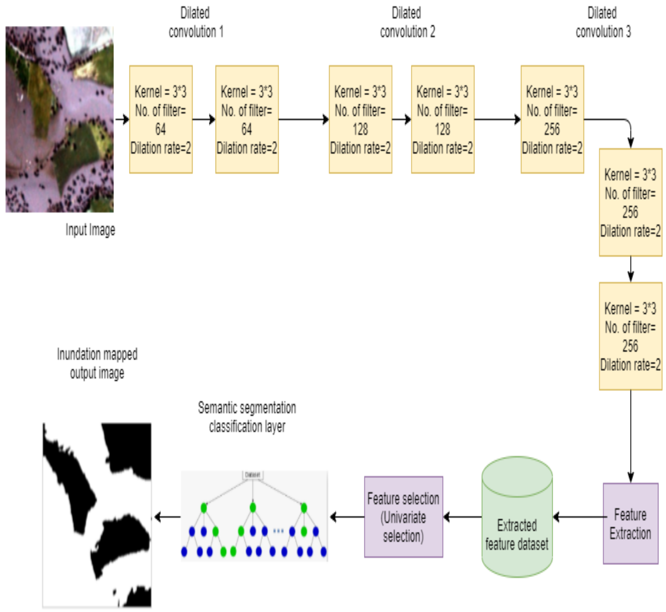

Fig. 1. System architecture

IV. Methodology

Convolutional Neural Network (CNN) is a branch of machine learning which works with artificial neural networks. It uses multiple layers to extract features from input image. The low layers detect basic shapes such as edges and corners while the higher layers detects more complex structures faces, digits etc. CNN can be used to solve computer vision problems like object detection, video processing face recognition and disaster management. Thus CNN is used to extract the features accurately and then fused with traditional machine learning algorithm for semantic segmentation. The proposed methodology can be partitioned into four modules: A) preprocessing; B) feature extraction using CNN model; C) feature selection using univariate selection; D) inundation mapping using semantic segmentation.

A. Preprocessing

Supervised machine learning algorithms learn to identify recurring patterns training on the annotated data. Therefore annotation becomes the most important step in pre-processing. While annotating the raw data, metadata is added to the dataset. Satellite images from the Greater Houston area after Hurricane Harvey in 2017 available in the Kaggle dataset. Hundred images with high pixel quality were selected and annotation of the dataset was done manually using online annotation website Apeer.com and exported.

B. Feature extraction

The convoluted neural layers are constructed based on VGG-16 with its convolution layer replaced with dilated convolution. The convolution filter is expanded by dilation rate based on which the weights are placed at the given interval. This helps to increase the kernel size which in turn increases the receptive field but preserves the resolution of the input image. This eliminates the need for down-sampling of input images. The constructed modified VGG-16 model shown in Figure 2 extracts the features from the annotated dataset.

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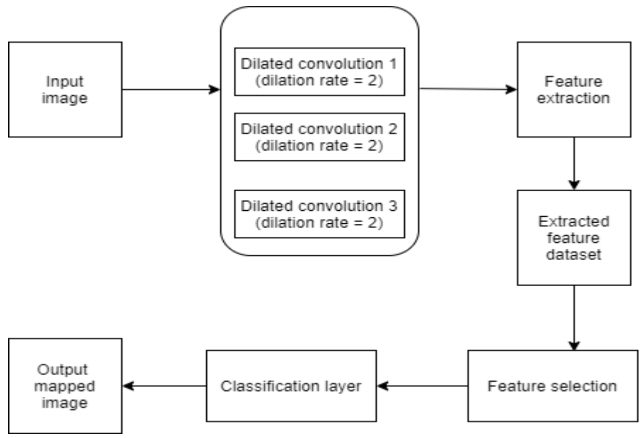

Fig. 2. Modified VGG block diagram

Pseudocode

Procedure: Feature Extraction

Input: X_train ← train_images, y_train ← train_masks

Output: Feature dataset

Start

Read source ← dataset_directory

Load train_image directory

Load annotated train_mask directory

Assign X_train ← train_images

Assign y_train ← train_masks

Model construction by modifying Vgg-16 architecture //Model constrution

Dilated convolution layer construction //Dilation rate is 2 for increased receptive field.

Save model1← model1.h5

Now features ← model1.pred(X_train) //Feature extraction

Concat the target Y ← "labels" along with the extracted features

Export the extracted dataset in csv format //features.csv

End.

C. Feature selection

The best features are selected based on the univariate statistical tests. The target variables are compared with each feature to determine significant correlation between them. This type of feature selection is also known as analysis of variance (ANOVA). The relationship between each features and target variable is only considered and thus known as "univariate". Chi-square test score is considered and best 50 scores are selected.

Pseudocode

Procedure: Feature Selection

Input: Read source ← feature dataset_path

Output: Selected feature dataset

Start

Read source ← feature dataset_path

Apply univariate selection on the feature dataset //feature selection

    df_X ← dataset features

    df_y ← labels

    features ← SelectKBest(chi2)

    fit ← features.fit(df_X, df_y)

Print n_largest features

Export the extracted dataset in csv format //features_ds.csv

End.

D. Semantic segmentation

The semantic segmentation is basically annotating each pixel of the image. Due to its intense prediction it is known as dense prediction. The instances of same class are not segmented but different objects of same class can be segmented. The model trained using Random Forest algorithm semantically segments the test image to map the inundated regions. The Figure 3 illustrates how the extracted features are used by the RF semantic segment classifier to set the inundated pixels to ON (white) condition whereas the non-inundated pixels are set to OFF (black).

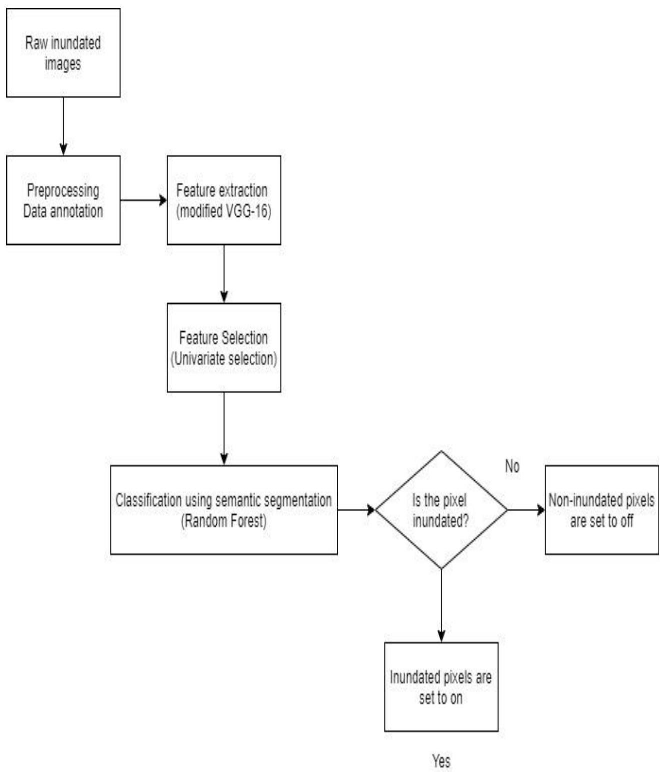

Fig. 3. Semantic segmentation workflow

Pseudocode

Procedure: Semantic Segmentation

Input: Read source ← Selected feature dataset

Output: Semantic segmented image

Start

Read source ← Selected feature dataset

Train the Random forest model using selected features

model.fit(X_train, y_train)

pred ← model.pred(X_test)

Save the RF model "RF_model.sav"

Classify the test_images using saved model //semantic segmentation.

When the region is inundated the pixel is lit (white)

Else

The region is off (black)

End

IV. EXPERIMENTAL SETUP

A. Dataset and study area

Hurricane Harvey is considered as the most catastrophic hurricane the resulted in severe inundation on regions such as Louisiana and Texas in 2017. High quality images of Hurricane Harvey in 2017 available in the Kaggle dataset [13] is selected and manually annotated with the help of Apeer.com an online annotation tool.

B. Implementation specification environment

Python programming and OpenCV library is used for implementation purpose. It is designed to solve computer vision real time problems. The model configuration is trained in google Colab since GPU is required. Google Colab is used to implement the first stage inundation mapping. Keras and TF backend libraries are used to construct modified VGG-16 model to extract features, processor above 23 GHz and above 2 cores, GPU above 1300 cudacores and above 4GB memory and windows 8.1 operating system are required for the above implementation.

Inundations in the urban areas are mapped using OpenCV python in Google Colab. Google Colab provides free RAM up to 12GB of resources. Construction of model requires is efficiently possible only with GPU and requires backend libraries such as Keras and Tensorflow. NVIDIA Tesla T4 GPU is provided for model construction and Feature extraction.

V. RESULTS AND DISCUSSION

The constructed modified VGG-16 model is used to extract the features efficiently. The fused RF classifier is used to semantically segment the inundated regions with a good overall accuracy and minimum execution time. The inundated mapped output image is shown in Figure 4.

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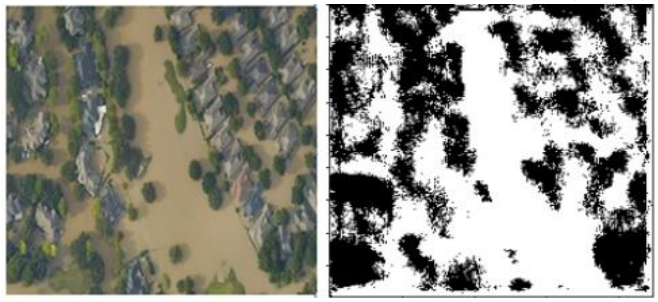

Fig. 4. Inundation mapped output

A. Overall accuracy

The overall accuracy of the model build is evaluated using this metric. The overall accuracy can be computed using Equation (2). Accuracy can be obtained dividing the correct prediction to the total predictions arrived using the constructed model. The proposed constructed model achieved overall accuracy of 94.11% which is better than state-of-art VGG-16 algorithm with accuracy rate of 92.7%.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (2)$$

B. Receiver Operating Characteristic Curve (ROC)

ROC curve is obtained by plotting true positive rate against the false positive rate as shown in Figure 5. The figure illustrates that the true positive rate equals to 0.94 on the scale of 0 to 1.

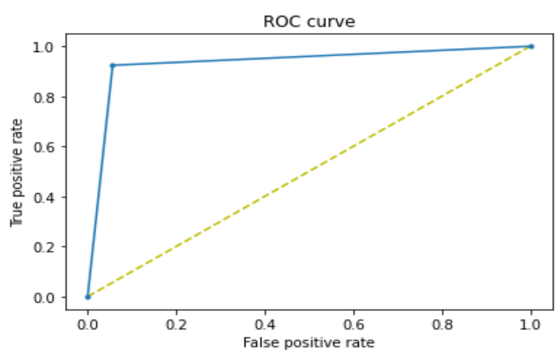

Fig. 5. ROC curve

C. Area Under Roc Curve (AUC)

It is the estimate of the whole two-dimensional area under the ROC curve. The AUC value obtained is illustrated in Figure 6. The integral sum of the area below the ROC curve is 0.9410.

```
#AUC curve
from sklearn.metrics import auc
auc_value = auc(fpr, tpr)
print("Area under curve, AUC = ", auc_value)
```

```
Area under curve, AUC =  0.9410844057620679
```

Fig. 6. Area under the ROC curve

D. Confusion matrix

Confusion matrix estimates the performance of the constructed model. It is an a×a square matrix where 'a' denotes the number of target class. Confusion matrix compares the ground truth values with the predicted values to measure the classification model performance. The confusion matrix of the proposed classification model is shown in Figure 5.3. The true negative rate is approximately equal to 2.7 e+04 and the true positive rate obtained is approximately 0.3 e+04. Of the 4 e+04 data provided more than 3 e+04 data are classified correctly.

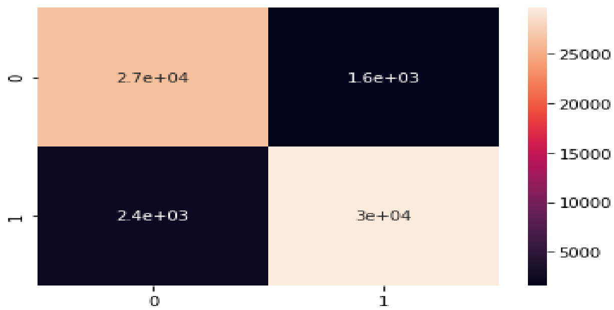

Fig. 7. Confusion matrix

VI. CONCLUSION AND FUTURE WORK

A. CONCLUSION

Instead of Fully connected neural network or any other state-of-art algorithm, this present work proposes constructing modified convoluted neural layers based on VGG-16 architecture to extract the features efficiently. The model is constructed using Keras and Tensorflow libraries. The extracted features are then semantic segmented by fused Random Forest (fused RF) classifier instead of using fully connected layers. This method gives good accuracy of 94.11% in flood extend mapping with a limited 100 image dataset which exceeds VGG-16 accuracy rate of 92.7% in classification. The VGG-16 model used resource such as NVIDIA Titan Black GPU and was trained for weeks while the proposed system uses traditional Random Forest to train the extracted features. The training time of the constructed model is 429.5 seconds. Thus it is observed that promising classification results can be achieved even though having a limited dataset by fusing the CNN model with a traditional machine learning algorithm (Random forest).

B. FUTURE WORK

Further the accuracy of proposed model can be improved by merging the semantic segmentation results with three dimensional terrain analyses of the inundated area. Still mapping of inundated areas under canopy or dense vegetation is a challenging task. This work can be extended to predict the destruction severity mapping due to flooding using Generative adversarial Network (GaN) technology.

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