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Sensor signal processing

A Deforestation Detection Network Using Deep Learning-Based Semantic Segmentation

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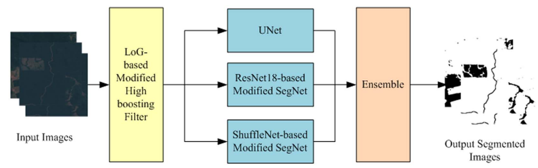

Abstract—Semantic segmentation is an important task in which the class label of each pixel is predicted. Thus, it is quite tough compared with classification and classical segmentation. Recently, deforestation has been a serious environmental issue, as it causes numerous environmental concerns: climate change and ecological loss. Hence, it is essential to recognize deforestation to save the environment. In this work, an efficient convolution neural network (CNN) model is proposed to identify deforestation in the Amazon Rainforest more precisely. At first, two modified SegNet methods are presented to make the semantic segmentation more effective. More importantly, an efficient semantic segmentation framework is proposed by integrating the merits of ResNet18-based modified SegNet, ShuffleNet-based modified SegNet, and UNet to yield more effective segmentation. Moreover, the employment of computationally faster ResNet18 or ShuffleNet in modified SegNet leads to improvement of computational efficiency and semantic segmentation performance. Thus, the proposed framework also retains advantages such as residual learning, skip connection, pointwise group convolution, and channel shuffling, which are responsible for making the optimization easier and the network efficient and faster. In addition, a Laplacian-of-Gaussian-based modified high boosting filter (LoGMHF) is employed for deblurring, edge enhancement, and denoising. The experimental analysis also shows that the proposed framework outperforms others.

Index Terms—Sensor signal processing, Amazon rainforest, deep learning, deforestation, semantic segmentation, sensor signal processing.

I. INTRODUCTION

Semantic segmentation is used very widely for the detection of deforestation, which is quite different from instance segmentation [1], [2]. In classical segmentation, the aim is to segment an image to different desired segments or regions [3], [4], [5], [6]. Semantic segmentation is the method of predicting class labels of each pixels of an image [6], [7]. Thus, it is also known as pixelwise classification technique [8]. In contrast, in classification, the motive to predict the whole image's class belongingness [9], [10], [11]. Since semantic segmentation is associated with pixel-level classification, it needs a spatial context understanding and finer details. In addition, it becomes more challenging as it needs to deal with a lack of well-defined boundary issues. Thus, semantic segmentation is quite tough compared with classification and classical segmentation works.

The Amazon rainforest is the largest rainforest on Earth. It spreads across many countries in South America, especially Brazil, Peru, Columbia, Bolivia, and Ecuador. It is filled with many different vegetation and rivers [2], [12]. The Amazon rainforest alone supplies 20% of the entire oxygen supply in this world. The influence of the Amazon rainforest on humankind and for other living beings is very vast. So protection and preservation of the Amazon rainforest is so vital for the survival of life in this planet, but it faces many issues these days. The major issue it faces is deforestation. Deforestation is the process of clearing of forest areas and vegetation for different purposes, such as farming, construction, and manufacturing, for wood [2], [13]. The effects of deforestation are very severe. It causes climate change, global warming, increase in greenhouse gases, soil erosion, and floods [2]. It is very vital to identify deforestation and take measures against it. Deforestation can be controlled and reduced by many methods, such as reforestation, afforestation, reducing the use of paper and other products made from wood, Government rules and regulations, and proper awareness and education.

Protection of the Amazon rainforest is vital. In this article, we focus on preserving its diversity by identifying the amount of deforestation in the Amazon rainforest. Here, we use the standard Amazon rainforest satellite imagery dataset [12]. By analyzing this dataset, we are finding the forest and nonforest areas in the Amazon rainforest, so that measures can be taken to stop and counter it.

Semantic segmentation can be achieved using convolution neural network (CNN) models [6], [7]. There are different CNN models for semantic segmentation, such as fully convolutional network (FCN) [6], SegNet [7], DeepLabV3+ [14], and UNet [15]. Using these deep learning architectures, we can achieve semantic segmentation.

Rakshit et al. [2] suggested a VGG16-based deep learning technique for identifying the different types of land patterns in the Amazon

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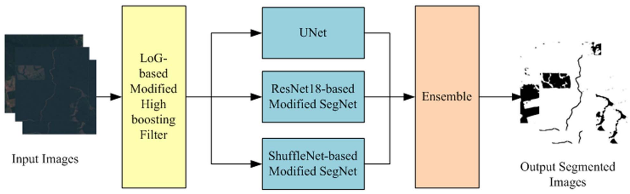

Fig. 1. Proposed semantic segmentation framework.

rainforest. In [16], a fully automatic deep learning technique is recommended to identify the deforestation. In [17], a UNet-based semantic segmentation model is suggested for identifying the amount of deforestation in the Amazon rainforest based on the satellite images. John and Zhang [13] proposed an Attention UNet-based deep network for semantic segmentation to identify deforestation. It inspires us to develop more effective semantic segmentation model for deforestation detection in the Amazon rainforest.

The rest of this letter is organized as follows. Section II presents the proposed method. Section III deals with results and discussion. Finally, Section IV concludes this letter.

II. PROPOSED METHOD

In this work, an efficient deep learning-based semantic segmentation framework is proposed for deforestation detection, as illustrated in Fig. 1. The contributions of the proposed framework are as follows.

1) In this letter, an efficient semantic segmentation-based deforestation detection framework is proposed by integrating the merits of ResNet18-based modified SegNet, ShuffleNet-based modified SegNet, and UNet to yield improved outcomes and more effective segmentation.
2) Moreover, two modified SegNet methods are presented in which the employment of computationally faster ResNet18 or ShuffleNet improves computational efficiency and semantic segmentation performance.
3) In addition, the advantages due to salient features, i.e., encoder–decoder network and max pooling indices of SegNet, upsampling operator, and symmetric architecture of U-Net, are integrated to deliver improved semantic segmentation performance.
4) Furthermore, residual learning and skip connection in ResNet18-based modified SegNet, whereas pointwise group convolution and channel shuffling in ShuffleNet-based modified SegNet are responsible for making the modified SegNet models quite faster and more efficient than the conventional SegNet, which makes the overall system faster and accurate.

In this framework, three efficient CNNs, i.e., ReseNet 18-based modified SegNet, ShuffleNet 18-based modified SegNet, and UNet, are ensembled by integrating the advantages of these three models to predict the output class. This improves the overall accuracy and robustness of predictions, which is typically more accurate and reliable than base models. Here, the final predicted output is based on pixelwise majority voting. Hence, a brief analysis of these models is presented for better clarity of the proposed framework.

A. Preprocessing

Satellite images usually suffer from undesired noise and blur that causes performance degradation [3]. Hence, it is essential to suppress these effects and boost the image quality. Deblurring and edge enhancement are performed by the Laplacian filter. Since it is noise sensitive, to mitigate the noise issue, a 2-D Gaussian filter is enforced before the Laplacian filter, resulting in an Laplacian-of-Gaussian (LoG) [3]. In this letter, a LoG-based modified high boosting filter is utilized that leverages the merits of LoG (deblurring, edge-enhancement, and denoising) with merits of high boosting filter (deblurring and edge-enhancement), as displayed in the following:

$$P_I(i, j) = I_I(i, j) + \alpha L_G(i, j) \tag{1}$$

where $P_I(x, y)$ is the input image, and $I_I(i, j)$ is the enhanced image. α is a weight term ($\alpha > 1$). α is taken as 1.5. $L_G(i, j)$ presents LoG on $I_I(i, j)$

$$L_G(i, j) = \frac{-1}{\pi\sigma^4}\left(1 - \frac{i^2 + j^2}{2\sigma^2}\right)\exp\left(-\frac{i^2 + j^2}{2\sigma^2}\right) \tag{2}$$

where σ denotes standard deviation, which has key role in image quality enhancement. Here, a 7×7 LoG filter with $\sigma = 1$ is considered.

B. ReseNet 18-Based Modified SegNet

In ReseNet-18 [18] based modified SegNet, instead of using the VGG16 [19] network as base classifier, an efficient pretrained network ResNet-18 is employed in encoder and decoder sections. ResNet-18 [18] has 18 layers and is composed of several convolutional layers, max pooling layers, and fully connected layers [18]. It uses skip connection, which allows for the flow of information through an alternative path to solve the diminishing gradient problem. It also uses residual learning to make the network faster that allows the network to learn easily. Skip connections are those in which some layers are skipped between input and output layers to solve the diminishing gradient problem [9], [18], [20], [21]. Residual learning and skip connection are responsible for making the optimization easier and the network efficient and faster. In the encoder section, the ResNet-18 architecture starts with a convolutional layer with 64 numbers of 7×7 filters and stride 2. It is followed by a max pool layer of size 3×3 and stride 2. Then, there are two convolutional layers each of 64 number of 3×3 filters. Similarly, there are two sets of convolutional layers with 128, 256, and 512 3×3 filters [18]. The encoder part of this model will downsample the input image, and the decoder section will upsample with the same factor as in the encoder. ResNet-based SegNet model converges faster compared with SegNet model. The encoder has a corresponding decoder in the decoder network. The decoder section primarily performs feature projection from the encoder section to the pixel space for classification. The decoder section contains upsampling layer, convolution layer, and softmax layer. Upsampling layers upsample non linearly max pooled layers in the encoder section, whereas softmax layer is used for prediction and classification.

C. ShuffleNet-Based Modified SegNet

In this modified SegNet framework, ShuffleNet [22] is used as a base classifier to make the framework more efficient. Group convolution and channel shuffle are two vital direction of ShuffleNet network [22], [23], [24]. The main idea behind ShuffleNet is to reduce the computational cost of convolutions by factorizing them into smaller, less expensive operations. To achieve this, ShuffleNet uses a group convolutional operation followed by a channel shuffling operation that mixes feature maps across groups [22], [23], [24]. By using group convolutions and channel shuffling, ShuffleNet is able to reduce the number of parameters and floating-point operations required for convolutions, while still maintaining high accuracy on image classification tasks. It also has a decoder system that contains upsampling layer, convolution layer, and softmax layer to improve the performance.

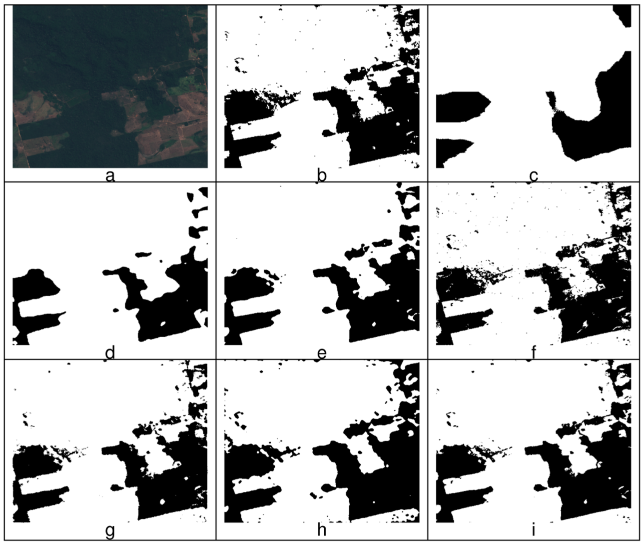

Fig. 2. Qualitative performance comparison-1. (a) Original image. (b) Groundtruth image. (c) FCN. (d) DeepLabV3+. (e) SegNet. (f) UNet. (g) ResNet18-based modified SegNet. (h) ShuffleNet-based modified SegNet. (i) Proposed method.

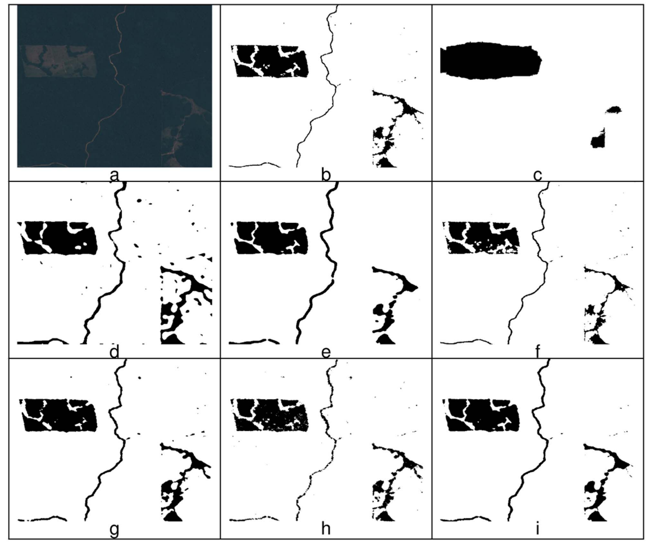

Fig. 3. Qualitative performance comparison-2. (a) Original image. (b) Groundtruth image. (c) FCN. (d) DeepLabV3+. (e) SegNet. (f) UNet. (g) ResNet18-based modified SegNet. (h) ShuffleNet-based modified SegNet. (i) Proposed method.

D. UNet

UNet [15] is one of the most widely used model for semantic segmentation as it gives precise outputs even with very less training images [25]. UNet does not have any fully connected layers. In UNet [15], instead of pooling, upsampling operators are used in order to increase output resolution. It has symmetric architecture and in shape of U. This CNN model consists of two major parts. The first part is the contracting part, which is used to get the context and details from the image. The second part is the expanding part, which is used for enable precise localization.

III. RESULT AND DISCUSSION

This section comprises a detailed analysis of the overall performance to present the superiority of the proposed framework. The proposed model is compared with FCN [6], SegNet [7], DeepLabV3+ [14], UNet [15], ResNet18-based modified SegNet, and ShuffleNet-based modified SegNet. The experimental works are carried out using the Amazon Rainforest dataset [12].

To provide a precise and equitable comparison, the entire experimental project is carried out on the same platform. The simulation is executed on a device with the following specifications: an Intel Core i7-11700 CPU running at 2.50 GHz, 16 GB of RAM, and an NVIDIA T400 8 GB GPU. The programming language is MATLAB R2020b. To ensure a fair comparison, the fivefold cross-validation is done, and the mean performance is presented here.

The qualitative performances of several methods with the Amazon Rainforest dataset are presented in Figs. 2 and 3. Similarly, Tables 1 and 2 present the quantitative performances in these experiments, respectively. From these figures and tables, it is observed that the proposed framework outperforms others due to the integrated advantages of encoder–decoder network and max pooling indices of SegNet, upsampling operator and symmetric architecture of U-Net, residual learning, skip connection, channel shuffling, and pointwise group convolution. These salient features boost the feature discrimination capability and, thus, semantic segmentation performance as well.

Table 1. Semantic Segmentation Performance for Experiment 1

Methods	Recall (%)	Precision (%)	IoU	Dice
FCN	97.00	86.61	0.8747	0.9151
DeepLab V3+	99.74	88.80	0.9106	0.9395
UNet	99.07	96.80	0.9707	0.9792
SegNet	98.36	80.28	0.7982	0.8841
Modified SegNet (ResNet18)	99.29	95.49	0.9624	0.9735
Modified SegNet (ShuffleNet)	99.56	95.43	0.9637	0.9745
Proposed Model	**98.85**	**97.81**	**0.9766**	**0.9833**

Table 2. Semantic Segmentation Performance for Experiment 2

Methods	Recall (%)	Precision (%)	IoU	Dice
FCN	94.98	97.21	0.9292	0.9608
DeepLab V3+	95.89	99.85	0.9611	0.9783
UNet	99.91	96.01	0.9609	0.9792
SegNet	99.24	96.52	0.9601	0.9786
Modified SegNet (ResNet18)	97.41	97.02	0.9756	0.9721
Modified SegNet (ShuffleNet)	98.79	99.12	0.9657	0.9895
Proposed Model	**99.33**	**99.72**	**0.9836**	**0.9952**

Residual learning, skip connection, channel shuffling, and pointwise group convolution make the modified SegNet faster than SegNet, thus making the proposed framework faster. In Experiment I, the proposed framework achieves the best 0.9833 Dice coefficient and 0.9766 Intersection over Union (IoU), whereas UNet gives the second-best performance (0.9792 Dice and 0.9707 IoU). Similarly, in Experiment 2, the proposed framework gives the best performance with 0.9952 Dice and 0.9836 IoU. On the other hand, in Experiment 2, ShuffleNet-based modified SegNet gives the second-best performance, whereas the UNet delivers the third-best performance.

Table 3 presents the mean fivefold cross-validation performances. It shows that the proposed model outperforms others in all the performance measures: 94.09% recall, 96.30% precision, 0.9040 IoU, and 0.9518 Dice score. This is due to the combined advantages of

Table 3. Mean Semantic Segmentation Performance Using Fivefold Cross-Validation

Methods	Recall (%)	Precision (%)	IoU	Dice
FCN	76.03	81.49	0.7528	0.7867
DeepLab V3+	86.71	89.46	0.8583	0.8806
UNet	92.52	94.79	0.9192	0.9364
SegNet	88.26	90.70	0.8753	0.8946
Modified SegNet (ResNet-18)	90.53	93.74	0.9029	0.9211
Modified SegNet (ShuffleNet)	92.16	95.66	0.9223	0.9388
Proposed Model	**94.09**	**96.30**	**0.9404**	**0.9518**

UNet, ResNet18-based modified SegNet, and ShuffleNet-based modified SegNet. ShuffleNet-based modified SegNet ranks second, whereas UNet delivers quite similar performance. If two models among UNet, ResNet18-based modified SegNet, and ShuffleNet-based modified SegNet yield inaccurate prediction, then the proposed semantic segmentation approach gives poor performance. Hence, there is a scope to improve the performance further. Both the quantitative and qualitative analyses of the proposed framework convey that the combined benefits of the UNet, ResNet18-based modified SegNet, and ShuffleNet-based modified SegNet improves the overall performance of the proposed framework over all the six comparing deep learning models.

IV. CONCLUSION

In this letter, an efficient deep learning-based semantic segmentation framework is proposed for the automatic identification of deforestation. The combined benefits of UNet, ResNet18-based modified SegNet, and ShuffleNet-based modified SegNet help the proposed framework in performing better than others. Furthermore, we have learning and skip connection in ResNet18-based modified SegNet, whereas pointwise group convolution and channel shuffling in ShuffleNet-based modified SegNet are responsible for making the modified SegNet models quite faster and more efficient than the conventional SegNet, which make the overall system faster and accurate. The proposed model is compared with six different deep learning models by means of seven performance metrics using a standard Amazon Rainforest dataset. The qualitative and quantitative result analyses show that the proposed framework outperforms others with a Dice score of 0.9518 and an IoU of 0.9404.

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