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A Survey on the Identification of Salt Segments in Earth Surface

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ABSTRACT

The method of determining whether a subsurface target is salt or not is known as salt segmentation. There are various locations on Earth that have abundant supplies of salt, gas, and oil. It's essential for businesses involved in oil and gas extraction to locate the precise locations of substantial salt deposits. Additionally, salt-affected ground is not suitable for agriculture. The existence of salts in the soil solutions lowers the plant's ability to absorb nutrients, which in turn slows growth. Salt segmentation is thus being carried out in order to determine whether a land region contains salt or not. A specific pixel's seismic picture is examined to determine if it is salt or sediment. The dataset used is the TGS Salt Identification Challenge dataset that has 4,000 seismic image patches with a size of (101x101x3) and associated segmentation masks with a size of (101x101x1) in the training set. In the test set, which is used to assess the model, there are 18,000 seismic image patches. For locating the salt zone in the seismic pictures, two models are used. The main model is a fusion of ResNet-18 and ResNet-34 with UNET. The secondary model combines UNET with ResNet- 34, VGG16, and Inceptionv3 to provide segmentation results. With the help of these models, it is possible to identify the salt area from the seismic data and show its worth as a whole. IoU is employed as a performance indicator to assess the model.

Keywords: ResNet34, Inceptionv3, UNet, VGG16, Seismic images, segmentation.

1. Introduction

The depiction of subsurface structures is made possible by seismic imaging, which is also used to find hydrocarbon fuel sources. The seismic imaging process uses sound waves that are emitted and reflected off subsurface materials that are detected on the surface by receivers known as geophones. The sound signal that is being reflected is collected to create a 3D image of the subsurface rock structure in later stages of processing. The borders of several rock species are visible in seismic pictures. According to theory, the strength of the rejected signal is thought to be significantly correlated with the physical differences between the rocks at the area of contact.This effectively implies that, while seismic pictures provide nothing about the actual rocks, they do provide information about the borders between rocky deposits. Identification of salt deposits is crucial because seismic pictures are utilized in the search for hydrocarbon fuel sources by assisting in the discovery of possible reservoir rocks.

Agriculture and oil drilling requires the automated and precise determination of whether a subsurface target is salt. Unfortunately, it may be quite challenging to determine the exact location of significant salt deposits. Expert interpretation of salt bodies is still required for professional seismic imaging. So, identifying the exact location of salt deposits is necessary for semantic segmentation.

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In this paper, two models are used for identifying salt deposits. One of them is a traditional model and the other is ensemble model. In the first model, the images from the dataset are taken and preprocessed using the data augmentation technique. To enhance the quality of the data used to train artificial neural networks, a deep learning technique called data augmentation is used. By introducing variations to current data samples, the training dataset is artificially enlarged. The preprocessed images are then given to a deep learning model called U-Net which uses ResNet-18 and ResNet-34 as encoders. Dice loss function is then used to improve the IoU score. It is also used to figure out how closely the predicted image resmebles the original image. In second model, the normalized data is given to UNet. The UNet then employs ResNet-34, VGG16, Inceptionv3 as backbones which are pre-trained on ImageNet. These networks are then combined using weighted average ensemble technique. A publicly available dataset called as TGS dataset is used to train these two models. At last, IoU is calculated to analyze the performance of the two models.

2. Related Work

[1]. In this paper, an enhanced UNet deep network is used for the identification of faults and salt domes. Further the encoders of VGG19 and ResNet34 is used for transfer learning to improve the performance of UNet and before employing the fused UNet on seismic data, the networks are initially trained on real-world images (ImageNet). At last, ResNet skip connections are used to create a model which is unaffected by

similarity between seismic data noise discontinuities. LANDMASS, Netherlands offshore F3 block, and TGS datasets are used for the evaluation of the model performance by using the performance metrics such as F1-score, Precision, Recall and IoU. The pre-trained ResNet34 fails to detect salt boundaries in zoomed regions.

[2]. TL-DenseUNet is used for the semantic segmentation of satellite images. There are two subnetworks in the proposed TL- DenseUNet. In order to obtain multilevel semantic information, the encoder subnetwork employs a transferring DenseNet while the decoder sub-network uses dense connections to combine the information in each of the layer. Various metrics like F1 score, recall, precision, overall accuracy (OA), IoU, MIoU and kappa coefficient are used to assess the performance of TL-DenseUNet. TL-DenseUNet kappa coefficient is enhanced by more than 0.0752 when compared with a number of other cutting-edge models. The model lacks in the identification of ground features with comparable spectra that were liable to classification errors.

[3]. U-Net plus Se-ResNet based deep learning method is used for the identification of salt segments in seismic images. After that, the model is trained using Lovasz Loss after initially employing a combination of dice loss and binary cross entropy(BCE). TGS dataset is used for the evaluation of the model which contains images of 101X101 pixels. k-fold cross validation was used for the evaluation of the model. IOU was used as the evaluation metric for this segmentation issue. An average IOU metric score of 0.9037, 0.84201, 0.866771, and 0.819871 is achieved on Lovasz-Train, Lovasz-Valid, BCE- Train and BCE-Valid respectively.

[4]. A deep-supervised network architecture called UNet with an encoder and decoder that combine feature maps with associated resolutions via jump connections is used for salt segmentation. The training is done in two-stages in which the binary cross-entropy loss is used in first 10 epochs to improve learning rate and Lovasz loss function for next 100 epochs to optimize IoU metric. The proposed method has achieved 87.39% mean Average Precision(mAP) on TGS dataset which is higher than other state-of-the-art methods. Due to lack of data, the encoder uses ImageNet pretrained weights to achieve better results and to reduce training time.

[5]. A deep CNN-based model that is combined with the human interactions is proposed for the interactive salt segmentation of seismic images. Negative and positive points are converted into two EDMs which are then paired with the seismic images to train the CNN model and included the interaction points into the proposed technique. A combination of U-net and PPM make up the model which was developed using the data from TGS dataset. The likelihood maps generated by the CNN model are then improved using a graph cut technique, which causes to update the salt boundaries. The saltISCG technique provides two mean average precisions(mAPs) of 91.59% and 86.94% on the 9:1 and 2:8 training/testing ratios respectively.

[6]. In this paper, the author develops a highly generalized fully convolutional Dense Net with the help of self –attention mechanism for automatic salt segmentation. This framework's robustness is measured by testing the proposed framework with the data set. The author uses TGS salt segmentation data set and 3-D SEAM dataset. The author suggested network architecture and used architectures of convolutional blocks, denser blocks, squeeze and excitation blocks, and transition down blocks. To evaluate the performance of the model performance metrics like F1-score, recall, Accuracy, Precision, and IoU are taken into consideration.

[7]. In order to describe the intricate distinctions between the true and modelled multiples in a nonlinear relationship, the author of this study introduces U-net, a well-known deep learning technique. This framework's robustness is measured by testing the proposed framework with Sigsbee2B data set. Architecture of the U-Net is described and the traditional LR method is reviewed. In order to compare the results of various adaptive subtraction strategies objectively, they define the signal-to- noise ratio (SNR).

[8]. In this, the author offers a thorough analysis of the recent literature visual attention models, recurrent networks, and generative models in conflictual circumstances. The architecture of the deep neural network and dl-based image segmentation models are described. The data sets are divided into 3 types for DL-based picture segmentation: 2D (pixel) images, 2.5D RGB-D (colour + depth) images, and 3D (voxel) images. The datasets KITTI and Cam Vid are among the most widely used in computer vision, together with PASCAL Visual Object Classes (VOC). Pixel accuracy, Mean Pixel Accuracy (MPA), Intersection over Union (IoU), and Dice coefficient are the measures for the image segmentation models.

[9]. The approach described in this research is based on author's involvement and uses semantic segmentation to train a deep CNN. The U-Net concept, together with ResNet and DenseNet topologies, served as the inspiration for the design of the proposed network. A total of 18,000 seismic picture patches, each measuring 101 by 101 pixels, were included in the test set. 4000 seismic image patches and related segmentation masks make up the training set. Accuracy and intersection over union (IoU) are taken into account while assessing the performance of the suggested model.

[10]. In this study, a unique U-shaped fully convolutional network (U-Net) is developed for automatically interpreting seismic stratigraphy. The author uses a Netherlands F3 seismic dataset for assessment of the model's performance on various data. For segmenting seismic strata, the suggested U-Net model beats the Bayesian neural network (BNN) model in terms of segmentation prediction speed, training time and accuracy. To evaluate the proposed model's performance, performance indicators like segmentation accuracy, prediction speed, and training time are taken into account.

[11]. This paper provides an application of DCNN for fault recognition from seismic data. The dataset provided aids in evaluating the effectiveness of various methods, and there is also a mechanism for converting geological project files into data formats appropriate for deep learning. Edge detection networks for defect recognition were first introduced. Instead of line segments, the edge detection networks can forecast more continuous problems. Optimal workflows can be created by using image processing techniques by applying a numerical evaluation method to automatically get objective and through test set performance. The U-Net model performs better because it is built for tiny data quantities.

Although the HED approach has the largest volume needs for training data, it can nevertheless outperform the HaralickFFT method in 4 of the 5 criteria by applying data augmentation techniques.

[12]. This paper introduces the usage of MH UNet for segmentation of medical images that gets beyond the challenges of uneven organ segmentation. In the proposed MH UNet, densely related blocks are used to lower training parameters and enhance gradient flow. Between the encoder and decoder, a hierarchical block is added for the purpose of gathering and combining features in order to retrieve multi-scale data. On the suggested architecture, four difficult MICCAI datasets are built and evaluated. With regard to the enhancing tumour, the suggested architecture has the highest mean dice scores.

[13]. In this study, deep learning techniques are used to partition water and land using data from Landsat-8 OLI. The process architecture consists of two parts: features for getting sea-land segmentation using state-of-the-art DCNN methods, and a dataset with bands 4, 3, 2, and 5, 6, 4 combinations that can be fed into DCNNs using Landsat-8 OLI images. Red-Green- Blue (4, 3, 2) band imaging is more accurate than images for the 5, 6, and 4 band combinations of data. The mean IoU is above 92%, and test accuracy is over 99%. These results show that the FC-DenseNet outperforms existing state-of-the-art approaches in sea-land segmentation. Sea-land segmentation is performed more effectively by DeeplabV3+.

[14]. In order to use building items from high-resolution aerial data, a new deep neural network methodology called Seg-Unet method which combines Segnet and Unet techniques is used in this paper. The Massachusetts building dataset is used to apply the suggested model. Four accuracy criteria were used to evaluate the effectiveness of the suggested strategy in building extraction following training and validation. This resulted in an average OA accuracy of 92.73%. To further demonstrate its effectiveness, this SegUnet model is contrasted with the quantitative and visual outcomes of other deep learning techniques, including the Segnet, FCN, and Unet models. The results indicated that the suggested approach beat existing DCNNs in the extraction of buildings from high-resolution aerial imagery, both quantitatively and visually.

[15]. CNN-based techniques for EM image segmentation have been proposed and have made significant advancements. UNet, one of those CNN-based techniques, is thought to be the most cutting-edge approach. The authors introduced a novel weighted loss EM picture segmentation algorithm based on encoder-decoder architecture. Without any further post- processing or pre-training, the proposed method delivered competitive segmentation results when compared to the modified encoder-decoder architecture on the ISBI 2012 EM dataset. The proposed DenseUNet is a lightweight network construction that may prevent unnecessary parameters. Thus, segmentation photos with artefacts and weighted loss will be avoided. This method for 3D EM picture segmentation will be expanded in the future.

[16]. The authors provide a process that uses a semantic segmentation method based on CNN to understand faults. This used convolution layers in preference to completely related layers at the quit of the community to put into effect the quit-to-quit class of seismic images, and followed dilation convolution to boom the receptive subject and hybrid dilation convolution to keep away from problems in it. They additionally implemented the atrous spatial pyramid pooling (ASPP) module to in addition beautify the outcomes of segmentation. The outcomes of interpretation whilst implemented to different amplitude photos had been correct and correctly recognized the fault locations. This method introduced promising outcomes in phrases of deciphering a hard and fast of actual seismic data.

[17]. This paper introduces a processing workflow to recognize geologic leads in seismic photos that lodges to encoder- decoder architectures of a convolutional neural network (CNN) followed through segmentation maps and post-processing operations. They used seismic photographs accumulated at offshore websites of the Sergipe-Alagoas Basin (northeast of Brazil) as input. After acting a patch-primarily based totally information augmentation, a complete of 29600 patches had been achieved. Out of these, 24000 had been used for training, 5000 for validation, and 600 for testing. By the use of the cube loss function, intersection-over-union index, and relative areal residual computed after severe cross-validation schooling rounds, this proved that the accuracy of the community to discover leads was better than 80%. Furthermore, the validation mistakes limits have been discovered solid inside 5% - 10% in all validation rounds, thereby ensuing in a reasonably correct prediction of the pre-labelled hydrocarbon spot.

[18]. In this paper MultiRes-Unet is used which utilizes the MultiRes block to assimilate the capabilities found out from the facts at diverse scales and incorporate a few more spatial details. It is also proposed to include numerous convolutional operations together with the skip connections to mitigate the variations among the encode–decoder features. The version is educated primarily based totally at the AIRS dataset containing over 220,000 homes with a spatial decision of 7.5 cm and a broad insurance of aerial images. Aerial pics for roof segmentation dataset, and the experimental effects exhibited that the proposed community can enhance the quantitative effects of Intersection Over Union to 0.78%ter including semantic edges. Brand new comparative fashions were utilized consisting of UNet, DeeplabV3, ResNet, and FractalNet networks to expose the competency of the delivered community, and the effects show the fulfillment of the delivered community for constructing item extraction from aerial imagery.

[19]. In this paper, dependable framework was recommended for performant consequences for the challenge of semantic segmentation of monotemporal very excessive decision aerial images. This framework includes a singular deep mastering architecture, ResUNet-a, and a singular loss feature primarily based totally at the Dice loss. ResUNet-a makes use of a UNet encoder/decoder backbone, in mixture with residual connections, atrous convolutions, pyramid scene parsing pooling and multi-tasking inference. ResUNet-a infers sequentially the boundary of the objects, the distance rework of the segmentation masks, the segmentation masks and a coloured reconstruction of the input. The overall performance of the modeling framework is evaluated at the ISPRS 2D Potsdam dataset. Results display brand new overall performance with a mean F1 rating of 92.9%.

[20]. A cascade model is suggested that contains two stages. One of which is detection and the other is segmentation. The detecting stage chooses potential ship-containing zones (bounding boxes). The segmentation stage receives these bounding boxes and uses them to create the ship segmentation mask. As a last boundary refinement stage, Conditional Random Field model is used which can enhance segmentation outcomes when a complete segmentation strategy is applied. With the help of publicly accessible maritime datasets, aerial ship images are used to train the detection and segmentation models. The cascade model is used to test the Airbus ship identification challenge, and the results were cutting-edge in terms of real-time performance and precise marine ship segmentation.

[21]. A modified residual recurrent Unet model is proposed which is flexible to change the filters used in the convolution units. The decoder and encoder nodes in the model are constructed on the residual blocks and recurrent convolution architecture, drawing inspiration from the Unet model. A five-level model that follows the conventional Unet is built and the nodes of the Unet topology are made up of a double unit and a recurrent convolution layer. The performance metrics like Dice, F1-Score, mIoU, Recall, and Precision are used to assess the model and the results show that the proposed mRR2 model outperforms as compared with other existing methods except for the Recall where RR32-2 achieved the best result.

[22]. A ResD-Unet architecture is proposed that helps in segmenting the images accurately. In the beginning, Residual-Dense blocks are added to the feature extraction layer made up of the original fixed-scale convolution kernel to address the issue of insufficient feature extraction in U-Net. The network is then given a BN layer to hasten the model convergence that improves the model's generalizability. At last, a hybrid loss function is suggested to enhance boundary segmentation definition by giving border pixels more weight. The experimental outcomes demonstrated the capability of the ResD-Unet network to precisely segment the images when combined with a Residual-Dense module and boundary thinning hybrid loss function.

[23]. A deep network architecture is employed for semantic segmentation that is named as Ghost-UNet which is built upon the asymmetric encoder-decoder based architecture employing U-Net and Ghost-Net. The decoder module uses the tiny feature maps to reconstruct the final map that provides the final choice and clustering after the encoder module extracts the best features from the input by reducing the resolution of the feature maps. The proposed model can also be employed with small picture sizes for GPU with poor performance and low regulation embedded devices, which is not suited for the UNet architecture and a majority of the semantic segmentation models. The Ghost-UNet model has achieved good mIoU and pixel accuracy of 74% and 97% respectively on the cityscapes dataset.

[24]. Instead of the usual layer-wise feature learning, a Res2-Unet model is proposed which uses granular level multi-scale feature learning that increases bottleneck layer receptive fields. On n-channel feature maps, it substitutes the popular 3X3 convolution arranged in the hierarchical manner with a number of minuscule groups to increase the scale variability. In addition, a function called boundary loss is suggested in order to boost the model's capability to generate building boundaries while enhancing detection performance. Res2-Unet obtained cutting-edge performances with the boundary loss and loss of BCE on all the datasets.

[25]. NAU-Net, a segmentation convolutional neural network with a layered attentional awareness network is proposed which contains four parts such as network structure, template matching, loss function, and evaluation index. With an integrated skip connection of the attention gate and a tightly supervised encoder-decoder topology, the network combines the benefits of the UNet++ and Attention Gates. The proposed model outperformed previous enhanced U-Net models in terms of accuracy and recall rates, coming up at 0.856 and 0.791 when compared to U-Net, UNet++, Attention-Unet, Dense-Unet and R2-Unet.

[26]. Improved UNet-based designs are proposed for the automated segmentation of brain tumours from MRI images. The MRI image's dark slices were first removed using a two-step pre-processing procedure. The image of the brain tumour was then segmented using the suggested models that are created by supplementing the UNet framework with two-pathway-residual (TPR) blocks. In addition to improving assessment criteria like DSC and sensitivity, TPR blocks in the UNet structure have also helped to minimise the number of parameters in the suggested models. The suggested models' benefits include lower computing costs, faster segmentation, and a lack of post-processing. TPRE-UNet, TPRD-UNet, and TPRED-Unet atchitectures are used for segmentation. The results show that performance is superior for the TPRE-UNet and TPRD-UNet designs.

[27]. A Dilated MultiResUNet network is used which enhance the performance of image segmentation on U-Net, Res2Net, MultiResUNet, Dilated Residual Networks, and Squeeze-and-Excitation Networks in order to minimize the loss of significant features. To replace the standard convolutional procedure, Improved Multi Block, Res Block, and Dilated Multi Block techniques are applied. In addition, two unique Dilated MultiResUNet networks are created with different block combinations to enhance U-upsampling Net's and concatenation functionality. The experimental findings shows that the two Dilated MultiResUNet networks only require 59.7% and 63.3% of the total parameters of the U-Net model, respectively, to obtain improved accuracy and better generalisation performance.

[28]. By using adaptive activation functions, the customisation is carried out using the well-known U-Net architecture, which has demonstrated its efficacy in the segmentation sector. Three changes are made to the network to improve the performance of U-Net model that includes reducing network size, using adaptive activation functions and using a threshold layer. Utilizing linear combinations of 16 well-known fundamental functions as adaptive activation functions, each convolution layer learns its own data-adaptive activation function. The proposed customised U-Net was tested on five well-known retinal imaging datasets, including DRIVE, STARE, CHASE, HRF, and ARIA, and it segmented blood vessels with 96%, 97%, 96%, 97%, and 95% accuracy, respectively. On the ISIC skin lesion dataset, the suggested network also achieved 98% accuracy for segmenting the lesion area.

[29]. Res2-UNeXt, a multi-scale deep architecture with improved performance for segmenting medical images is adopted. Encoder-decoder network

with Res2XBlocks makes up the architecture. A quick and effective approach of data augmentation is proposed to work with Res2-UNeXt.The data augmentation technique, which is based on the motion and deformation of cells, has biological repercussions. Res2-UNeXt is compared against UNet++, CE-Net, LadderNet, and other contemporary U-Net versions as well as an approach that differs from UNet design using four separate cell pictures from the ISBI cell tracking challenge dataset, FCN and DFANet. The experiments established the efficiency of Res2-UNeXt and showed the usefulness of data augmentation strategy.

[30]. To perform medical image segmentation for various tasks accurately and effectively, an improved U-Net with residual connections called HDA-ResUNet is included that adds a plug-and-play, highly portable channel attention (CA) block and a hybrid dilated attention convolutional (HDAC) layer. To combine data from various sized receptive fields, a hybrid dilated attention convolutional (HDAC) layer is used in place of the convolutional layer at the bottom of the "U"-shaped network. The 2D network used by HDA-ResUNet lost some inter-slice information. However, the suggested network was assisted by the intended CA block and HDAC layer to some extent in using the intra-slice information, leading to improved segmentation outcomes.

3. Conclusion

In this paper, two models have been suggested for identification of salt region in seismic images. We have used UNet architecture by making ResNet-18 and ResNet-34 as encoders in first model. These networks are then trained and BCE loss function is applied for first 50 epochs and then Dice loss function is employed for next 50 epochs. The UNet-ResNet34 network achieves higher IoU when compared to UNet-ResNet18 network. But the IoU value of these two networks is still very less and the segmentation performance is poor. So, we have proposed another model to enhance the performance and detection rate of salt region in the input image. The second model is an ensemble model which uses ResNet-34, VGG16 and Inceptionv3 as encoders for UNet architecture that have already been trained on Imagenet. These three networks are trained individually and the IoU value of each network is calculated. Then the results are combined by using weighted average ensemble technique. The proposed models are evaluated by using TGS salt identification challenge dataset. Out of these two models the ensemble method achieves better segmentation results on the TGS salt dataset. The ensemble method performs quite well and provides good segmentation results.

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