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Semantic Segmentation and Augmentation of salt in seismic images using Deep Learning

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Abstract

Salt segmentation refers to the process of separating salt from an image or a video stream. This process is often used in computer vision which is a python library application to extract specific features or objects from an image or video and can be used for various purposes, such as object recognition, tracking, and classification. The salt segmentation process typically involves segmenting the image into regions based on colour, texture, or other visual features, and then applying a threshold to separate the salt regions from the rest of the image. This can be done with various deep learning techniques like Unet, ResNet-18 and ResNet-34, VGG16 and InceptionV3, and DeeplabV3Plus. Through the ensemble approach of these models, we can achieve an accurate prediction of the model.For locating the salt zone in the seismic pictures, two models are used. The main model is an amalgam of ResNet-18 and ResNet-34 with UNET. By combining Ensemble UNET with ResNet-34, VGG16, Inceptionv3, and DeeplabV3Plus, the secondary model produces segmentation results. Besides, Data augmentation is performed to generate new training data from existing data by applying a set of transactions or modifications to the original data. This technique is commonly used to increase the size and diversity of the training data which can improve the accuracy and robustness of the trained models.

Keywords: UNET,ResNet-18, ResNet-34, VGG16, InceptionV3 and DeeplabV3Plus, TensorFlow, Albumentations, Keras.

Introduction

Seismic image processing refers to the set of techniques and algorithms used to extract useful information from seismic data acquired during oil and gas exploration [5]. Seismic data is collected using specialized sensors and equipment that generate sound waves and record the reflections of these waves as they travel through earth's subsurface**.** Seismic image processing involves the following steps:

Data acquisition: Seismic data is collected using specialized sensors and equipment and is typically recorded in digital format.

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Data pre-processing: The raw seismic data is preprocessed to remove noise and correct for various sources of error, such as variations in the speed of sound in the subsurface. Waves are sent and reflections are thrown back from the ground which is useful for seismic data.
Data imaging: The pre-processed seismic data is then used to create 2D or 3D images of the subsurface, which can be used to identify potential oil and gas reservoirs.
Data interpretation: The seismic images are interpreted by geophysicists and other experts to identify geological features and structures that may indicate the presence of oil and gas. Seismic imaging, which is also used to locate hydrocarbon fuel sources, allows for the representation of underlying structures. Using receivers called geophones, sound waves that are emitted by and reflected off subsurface materials are used in the seismic imaging process. At further steps of processing, the sound signal that is being reflected is gathered to produce a 3D image of the subsurface rock structure. Overall, seismic image processing is a complex and specialized field that plays a critical role in the oil and gas industry by enabling the exploration and discovery of new oil and gas reserves. Salt segmentation has applications in various fields, including medical imaging, remote sensing, and robotics. For example, in medical imaging, salt segmentation can be used to extract specific structures or regions of interest from medical images, such as tumours or blood vessels, to aid in diagnosis and treatment planning. The dataset contains 4000 images of 101*101 pixels. Our main goal is to predict the model with good accuracy. In this paper, enhanced deep-learning techniques are used for salt segmentation. Finally, a user interface has been deployed for the prediction of the loaded image using the ensemble approach of the trained model using python. Data augmentation can be applied to salt images (images of subsurface geological structures that contain salt deposits) to increase the diversity and size of the training dataset and improve the performance of machine learning models that are trained on this data. The ensemble model is built on convolution neural network techniques models like Unet, ResNet, VGG16, InceptionV3, and DeeplabV3Plus.Image segmentation is the process of breaking a picture into various parts or segments, each of which correlates to a distinct attribute of an item, making the image representation simpler to analyse. This paper come across semantic segmentation which involves assigning a label or category to each pixel in the image based on its semantic meaning. This can be done using techniques such as deep learning, where convolution neural networks are trained to segment images based on visual features and semantic information.

Literature Survey:

Salt segmentation is a task in computer vision that involves identifying and delineating the boundaries of salt deposits in seismic images. Research has been done that looks at how salt segment is identified in seismic images using the most achieved technique Unet. Research gate studied the

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On segmentation issues, the U-Net design that was first put forth by(Ronneberger et al., 2015) is frequently employed [8]. Due to the usage of numerous blocks that operate at various resolutions, this design can provide features with a rich distribution of semantic meaning and resolution [2]. The mixing of low-level (high-resolution) data with semantically richer information is known to produce shortcuts that make training easier when many skip connections are used between the encoder and decoder blocks as shown in fig1. As was previously mentioned, categorization networks are increasingly being used as an encoder for the U-Net.

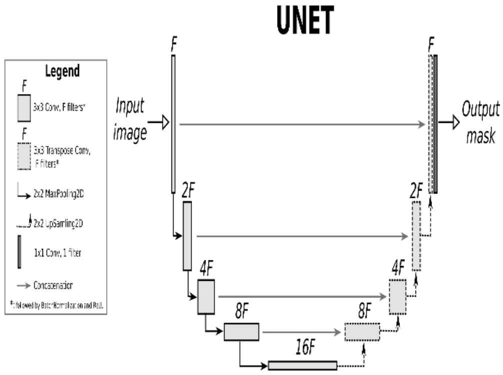

Fig1:Unet Architecture

Problem Identification:

The seismic images have a lot of particulars on the earth's surface. So, we must identify the salt coverage areas accurately. For this, we use Deep Learning techniques along with computer vision. The UNet-ResNet34 network has more IoU when compared to the.network UNet-ResNet18 [1]. Nonetheless, these two networks' IoU values are still quite low, and their segmentation performance is slow.So, We proposed this work to increase the IoU metrics by combing the models by ensemble approach. Encoders and Decoders are used in every layer of the classification. [10-18]

Methodology:

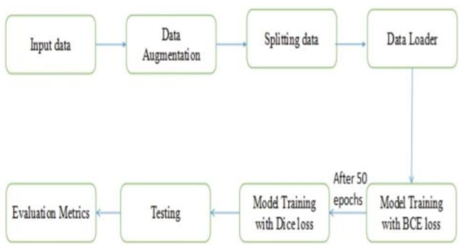

Fig:2 Model design

The seismic images in the training dataset are 101x101x3 in size, and the mask images are 101x101x1. Moreover, there are several abnormalities in the dataset where some photographs are black in colour but lack a corresponding mask. The test set includes

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18000 pictures. The training set contains a relatively little amount of data. As a result, argumentations are needed for data augmentation. The file also includes each image's depth information. 3420, 200, and 380 photos from the dataset are used for training, testing, and validation, respectively. As ResNet, VGG16, InceptionV3, and DeepLabV3Plus are added to the model, Unet uses the base models and step by step implementation is shown in Fig 2.

Implementation:

In this paper, Salt domes and faults are located using an improved UNet deep network. Before using the fused UNet on seismic data, the networks are first trained on real-world images, and the encoders of VGG19 and ResNet34 are employed for transfer learning to increase the performance of UNet (ImageNet).Resnet is used to skip some connections of noises not to disturb the data. Here, multi models are developed to increase IoU. The second model combines ResNet-34, VGG16, InceptionV3, and deepLab for segmentation. Before building the ensemble model data augmentation is performed using python library Albumentations for fast and flexible with a wide range of transformation functions on images [8]. DeeplabV3Plus is added in the model two which is a pre-trained model can be fine-tuned on a dataset of seismic images with labeled salt deposits. Fine-tuning involves training the model on the new dataset, while keeping the pre-trained weights fixed. This allows the model to learn features that are specific to salt segmentation, without requiring a large amount of labeled data.

UNet:

U-Net model beats the Bayesian neural network (BNN) model in terms of segmentation prediction speed, training time and accuracy.U-shaped architecture, which comprises of a contracting path for capturing the image's context and an expanding path for creating the segmentation map, it is known as "UNet".

The process usually includes capturing images of sediment cores, preprocessing the images to enhance contrast and remove noise, and then training a UNet model to segment the layers [4]. A dataset of labelled images is used to train the UNet model, and each pixel in the dataset is assigned to either sediment or salt. The output of the UNet model can also be used to generate visualizations of the sediment layers, which can be used for further analysis and interpretation. The U-shaped architecture has an encoder and a decoder that combine feature maps with related resolutions through jump connections. The binary cross-entropy loss is utilized in the first 10 epochs of the training to increase learning rate, and the Lovasz loss function in the next 100 epochs is employed to maximize the IoU metric. For the dataset, the suggested approach produced mean Average Precision

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(mAP) of 88.02%.For the purpose of identifying salt segments in seismic images, a deep learning system based on U-Net plus Se-ResNet is applied. After initially utilizing a mix of dice loss and binary cross entropy(BCE), the model is then trained using Lovasz Loss. The model is evaluated using the TGS dataset, which includes 101X101 pixel pictures. The model was evaluated using k-fold cross-validation. The assessment metric for this segmentation problem was IOU. The backbone parameters for the ResNet and image net for loading weights, classes, and activation modes are accepted by the Unet function. An original U-shaped fully convolutional network (U-Net) is created in this study to specifically understand seismic stratigraphy [6].

ResNet: Resnet is the acronym for the residual neural network. It is also a deep learning architecture. It is made to handle the vanishing gradient issue that deep neural networks often have, which can make it difficult for the network to learn from gradients during training [2]. It has an encoder and decoder network. In the decoder, When an encoder is supplied, the U-Net will automatically construct the decoder section of the architecture. The decoder uses an encoder-generated high-dimensional feature vector to build a semantic segmentation mask. The decoder starts off by using a transpose convolution of size 2x2.ResNet uses residual connections, enabling the model to learn partial mappings as a contrast to complete mappings. By creating shortcuts across layers, these residual connections enable gradients to move freely through the network without being lost or diminishing. This allows the network to train more thoroughly and perform better than earlier deep-learning models. ResNet has performed a number of computer vision tasks, such as picture segmentation, object identification, and classification. ResNet can be trained to classify each pixel in the seismic image as either salt or sediment and can produce accurate and efficient segmentation results. It is faster to train and requires fewer computational resources. It is the backbone of the Unet which can skip some dissimilar connections in the network model. The U-encoder/down Net's sampling section can make use of a ResNet (the left half of the U). I have utilised ResNet-18 and ResNet-34 encoders in my models. ResNet-18 and ResNet-34 both have an 18-layer and 34-layer design, respectively. ResNet's 18 layer and 34 layer architectures use memory more effectively and allow for faster model training. A Res2-Unet model is developed that employs granular level multi-scale feature learning to boost bottleneck layer receptive fields rather than the customary layer-wise feature learning. In order to improve the scale variability, it replaces the well-known 3X3 convolution, which is organized in a hierarchical fashion, with a number of little groups. In order to improve the model's capacity to construct building borders while improving detection performance, a function termed boundary loss is also proposed. For all datasets, Res2-Unet achieved cutting-edge results with boundary loss and loss of BCE. ResNet has since been widely adopted in the field of computer vision and

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is often used as a backbone architecture for more complex models. This model can handle multiple layers by skipping some dissimilar layers for fast performance. Encoder and decoders plays a crucial role.

VGG16 as Backbone:

VGG16 is often used as a backbone architecture for other deep learning models, such as object detection or semantic segmentation. This is because the early layers of VGG16 have been shown to learn low-level visual features, such as edges and corners, that can be useful for a variety of computer vision tasks. Unet takes the background as a VGG16 model for pre-trained weights on large datasets[9]. The segmentation model preprocesses the VGG16 and Unet encoded weights as image net. The 16 in VGG16 refers to it has 16 layers that have weights. This network has over 138 million parameters, making it a sizable network. One of the top computer vision models to date is the CNN (Convolutional Neural Network) variant known as VGG16.

InceptionV3 as BackBone:

Inception v3 can be used for image segmentation tasks, although it was originally designed for image classification. Image segmentation is the task of dividing an image into multiple segments, or regions, with similar characteristics. Inception v3 is a versatile convolutional neural network architecture that can be applied to a wide range of computer vision tasks. Its best application depends on the specific task and the available data, but it has proven to be particularly effective in image recognition and classification tasks. The backbone to the Unet model with encoded weights as image net which can take multiple classes and activation mode. Finally, InceptionV3 has achieved state-of-the-art performance on a variety of image classification and object detection benchmarks, including the ImageNet Large Scale Visual Recognition Challenge (ILSVRC).

DeepLabV3Plus:

DeepLabV3plus has been successfully applied to a wide range of image segmentation tasks, including medical image segmentation, object segmentation, and semantic segmentation of outdoor scenes. To use DeepLabV3Plus for salt segmentation, a pre-trained model can be fine-tuned on a dataset of seismic images with labeled salt deposits. Fine-tuning involves training the model on the new dataset while keeping the pre-trained weights fixed. This allows the model to learn features that are specific to salt segmentation, without requiring a large amount of labeled data. To further improve the performance of DeepLabv3 on salt segmentation, dditional data augmentation techniques can be used, such as random cropping, rotation, and flipping as shown in fig3. These techniques can help the model generalize better to new seismic images. Overall, DeepLabv3 is a powerful architecture for

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salt segmentation tasks, and its performance can be further improved by fine-tuning labeled seismic images and using the latest features of the architecture.

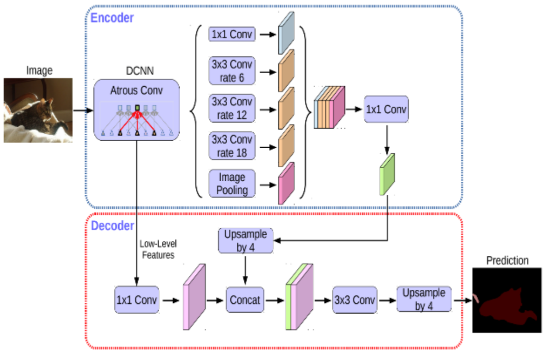

Fig3:DeepLabV3Plus model

Data Augmentation:

The training dataset contains relatively little data. A need for augmentation results from this. The practise of leveraging the photos that are already there in the current dataset to add extra data to it is known as data augmentation. This can be accomplished by applying a variety oftiny adjustments to the image, such as flipping, geometric modifications, cropping, rotating, noise injection, etc. Albumentations and Keras utils are built-in libraries for this Python version.

Building Model by combining results:

We propose evaluating three UNet variations to find which design has better detection accuracy. The three networks' decoders are comparable in that they each have layers for convolution, up-sampling, and concatenation. An ensemble approach is used for building the model with high accuracy. CNN models are rated differently depending on the problem and the model's architecture. As measuring criteria, accuracy, precision, and recall are most frequently used [6]. For the segmentation challenge, we used IOU as the assessment metric. The Unet developed backbone models ResNet-18, ResNet-34, and InceptionV3 and VGG16 and multiclass semantic segmentation DeepLabV3Plus are ensembled. The segmentation results from the ensemble method are pretty effective. The IoU value of each network is determined after each network has undergone unique training. The weighted average ensemble approach is then used to integrate the results. Graphs are plotted for IOU and validations. Testing labels are used for predicting the salt bodies in images.

Results and conclusion:

In this article, deep learning modelsare suggested for identifying salt traces in seismic images.We make ResNet as encoders and decoders in the first model then Vgg16,inceptionV3, and DeeplabV3Plus are added to the second model. While the decoder module polishes the segmentation outcomes along object boundaries, the encoder module handles multiscale contextual information by using dilated convolution at several scales.

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The BEC loss function is applied to the first 50 epochs after the CNN models have been trained [7].Dice loss function is applied for the rest of the epochs. These epochs refers to a single pass through the entire training dataset during the training process of a neural network. During an epoch, the network is presented with each example in the training set exactly once, and the weights of the network are updated based on the errors made by the network in predicting the output. The single models with Unet and ResNet-18 and Unet and ResNet-34 are developed but the segmentation performance is less. So, an ensemble method is chosen for increasing the performance metrics with Unet and ResNet and VGG16, InceptionV3, and DeepLab for combing the results with a weighted approach. Additionally, because DeepLab uses dilated convolution, we can maintain a constant stride while gaining a broader field of vision without increasing the number of parameters or the amount of processing as we travel deeper into the network. Moreover, it permits larger feature maps to be generated, which is helpful for semantic segmentation.For upcoming work, a number of directions can be considered.

MODEL	**Intersection Over Union Score (IOU)**
Unet-ResNet18	0.86543167
Unet-ResNet34,VGG16,Inception V3	0.8537855
DeepLab V3+	0.86323285
Ensemble Score	0.86996245

Table1: IOU results obtained on trained models.

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