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Seismic Data Analysis with Deep Learning Models: Methods, Applications, and Future Perspectives

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Abstract –
Seismic data is a critical source for examining and understanding subsurface structures. It is used in various fields such as oil exploration, geological research, mining, underground infrastructure planning, environmental monitoring, and conservation. The analysis and interpretation of these data are often complex and time-consuming. Deep learning, on the other hand, is recognized for its ability to identify complex patterns in large datasets. Deep learning models can be used to address challenges such as understanding complexity, noise reduction, and feature extraction in seismic data. The role of deep learning methods in seismic data analysis is increasingly significant because these techniques offer the potential to obtain more accurate results and discover new opportunities in seismic interpretation. This contributes to making the seismic interpretation process more efficient and enhancing the understanding of subsurface structures. This study focuses on interpreting seismic data using deep learning methods and examines how deep learning models can be utilized in seismic interpretation. The results of the study demonstrate that deep learning models can effectively address complexity in seismic data and perform automatic feature extraction. These findings highlight the potential of deep learning methods in the field of seismic interpretation and shed light on future research directions.
Keywords – Artificial intelligence; deep learning; seismic data

I. INTRODUCTİON

Understanding complex structures in the energy industry and discovering efficient oil and gas reserves is one of the major challenges for experts [1]. Seismic data analysis and interpretation play a significant role in overcoming this challenge in the industry [2].

Deep learning, a technique from artificial intelligence, has also achieved success in the field of geology [3]. Deep learning models offer potential to surpass traditional methods, obtaining more accurate results and accelerating the exploration process [4].

This review article examines the latest developments in deep learning models for seismic data analysis and reviews their applications in the energy industry.

II. MATERİALS AND METHOD

A. Deep Learning

Deep learning is a powerful learning approach that has emerged as a result of research on artificial neural networks and large datasets [5]. Artificial neural networks, akin to the neural networks in the human brain, are utilized to identify complex relationships and learn patterns [6]. However, deep learning is not confined to simple patterns only; it can also learn multi-layered structures and high-level abstract concepts. Thanks to these characteristics, deep learning models have brought innovations in many fields, especially in areas with large datasets and the need for analyzing complex structures [7].

Some fundamental components of deep learning methods include [8]:

Artificial Neural Networks (ANNs): Deep learning is typically built upon artificial neural networks (ANNs), which often have multi-layered structures. Artificial neural networks are mathematical models that mimic the neural networks of the human brain. Each artificial neuron receives inputs, processes them, and passes the results to other neurons.

Layers: Deep learning models typically consist of consecutive layers. Each layer receives the outputs of the preceding layer, processes them, and passes the results to the next layer. The input layer, hidden layers, and output layer are commonly the basic components of a deep learning model.

Deep Networks: Deep learning models are often referred to as deep networks, which consist of many layers. These networks include multiple hidden layers, providing enough flexibility to model complex relationships.

Activation Functions: Activation functions, used to determine the output of each neuron, provide the non-linearity of the learning process in the network. Commonly used activation functions include ReLU (Rectified Linear Activation), sigmoid, and tanh.

Implementation Methods: Deep learning models are typically trained on large datasets, requiring intensive computational power during the training process. Therefore, specialized hardware such as GPUs with parallel computing capabilities or cloud-based computing resources are commonly used.

These methods form the foundation for a wide range of applications in the field of deep learning and are used to solve complex problems in various disciplines [9].

Deep learning plays a significant role in processing complex and large-scale datasets like seismic data analysis [10]. Seismic data is obtained by recording sound waves used for studying underground geology. It is often large in size and complex in structure, making its analysis challenging with traditional methods [11]. Deep learning models serve as powerful tools to identify patterns and relationships contained within seismic data. Particularly, with their universal feature extraction capabilities, deep learning models can automatically detect significant features in seismic data, enabling more accurate identification of geological structures [12]. Additionally, deep learning techniques can overcome traditional limitations in seismic data analysis, thereby improving the exploration process and accelerating the discovery of new reservoirs [13]. Consequently, the impacts of deep learning on seismic data analysis are increasingly garnering interest among researchers and experts in the energy industry.

B. Seismic Data

Seismic data is a general term for the information collected during the process of gathering data used to understand underground structures and layers on the Earth's surface. These data are commonly used for various purposes such as mapping underground geological formations and structures, locating oil and gas reservoirs, and assessing earthquake hazards [14].

The process of collecting seismic data is typically carried out by underground geophysicists or expert teams. During this process, information about underground structures is gathered using sound waves emitted from the surface. These sound waves reflect off different layers underground, and the properties of the waves are recorded. These recordings are then analyzed to provide information about underground structures [15].

The process of collecting seismic data is typically complex and lengthy, requiring expertise and attention. Therefore, it is usually carried out by expert teams or companies. Data obtained from seismic reflection or seismic refraction methods are collected and recorded using seismic recording devices to acquire seismic data. The obtained seismic data are then processed and analyzed using computer programs. These analyses provide information about the depth, thickness, density, and other properties of underground structures. Processed data are examined and interpreted by geophysicists or experts. These interpretations can be used for various purposes such as mapping underground structures, identifying hydrocarbon reservoirs, and assessing earthquake risks [16].

Seismic data is a crucial tool for many industries and scientific disciplines, playing a critical role in the discovery, assessment, and management of underground resources [17]. It holds particular importance in the petroleum and gas industry, as these data can assist in determining the location and characteristics of hydrocarbon reservoirs. Additionally, seismic data is used in other areas such as assessing earthquake risks, detecting mineral deposits, and discovering underground water sources [18].

C. Some Studies

The analysis of seismic data plays a significant role in the exploration and evaluation processes of underground geophysics [17]. Below is how seismic data can be analyzed using deep learning techniques in the literature and how these analyses can contribute to applications such as the characterization of underground structures and hydrocarbon discovery.

In the study conducted by Guarido, M. et al. [19], semantic segmentation based on U-net was performed with seismic data. Detection of salt deposits using seismic data was carried out. The training and validation ratio was set to 0.8. As a result of the study, an IoU value of 0.8 was obtained.

In the study conducted by Karchevskiy, M. et al. [20], a deep learning method was proposed for salt area detection using seismic data. As the fundamental architecture of the study, a U-Net with a ResNeXt-50 encoder pretrained on ImageNet was employed, along with Spatial-Channel Squeeze & Excitation, Lovasz loss, CoordConv, and Hypercolumn methods. Data augmentation techniques such as horizontal flipping, brightness adjustment, horizontal shifts, and rotations were utilized to increase the dataset. As a result of the study, the model developed with horizontal flipping data augmentation technique achieved a higher performance score.

In the study conducted by Waldeland, A. U. et al. [21], salt classification with Convolutional Neural Networks (CNNs) is investigated. Data augmentation techniques such as random scaling (± 20%), random flips along other axes, random rotations (± 180°), and random tilts (± 15°) were employed to increase the training data. The data were obtained as 3D seismic data from the Barents Sea. The images were classified as salt and non-salt. The study demonstrates how a CNN can be used for the automatic interpretation of salt bodies.

In the study conducted by Liu, B. et al. [22], Se-FPN is proposed for salt area detection. To further integrate information from multiple scales, a Hypercolumns module is appended to the end of the network. The Hypercolumns module, particularly useful for tasks at the pixel level such as visual segmentation, can help achieve better results by providing a more comprehensive and detailed feature space. In the implemented model, an IoU evaluation score of 0.86 was obtained.

In the study conducted by Arogunmati, A. et al. [23], salt area detection was performed using a CNN architecture. As a result, the interpretation time of seismic data using traditional methods was reduced with this study. It was indicated that the designed model could interpret seismic data in a short time with comparable accuracy to minimum human input.

In the study conducted by Guo, J. et al. [24], a deep supervised semantic segmentation model was designed for salt area detection. Edge prediction was added to more accurately predict salt boundaries. Concurrent Spatial and Channel Squeeze & Excitation (scSE) and hypercolumns modules were incorporated into the model. In the dataset used, 4000 training samples were split into a 9:1 ratio for training and validation. The method based on the ResNet-34 backbone achieved an mAP accuracy of 87.39% using 118.88 M parameters on the TGS dataset.

In the study conducted by Zhou, H. et al. [25], a variant of the U-Net network is proposed for detecting salt areas in seismic data. The designed model incorporates scSE (Concurrent Spatial and Channel Squeeze & Excitation), FPA

(Feature Pyramid Attention), and AG (Attention-Guided) modules. The proposed neural network architecture has been validated with real data examples obtained from the Gulf of Mexico, corroborated with interpretations by experienced experts. As a result of the conducted studies, it was noted that the overall performance of the proposed neural network was enhanced, and its ability to successfully detect subtle salt features was promising.

In the study conducted by Zhao, Y. and colleagues [26], a deep neural network model is proposed to address the challenges associated with manual interpretation of seismic images due to their complex structures. The designed system incorporates an independent decoder called boundary decoder within a U-Net-based framework. The newly developed network is named U-Net with Boundary Decoder (BU-Net). According to the results of the study, an approach that could increase IoU by 2.6% in experimental evaluation is proposed, emphasizing that this approach could significantly optimize the semantic boundaries and details of salt bodies.

In the study conducted by HajNasser, Y. [27], a deep neural network introduces a new machine learning approach. The aim of the study is to highlight the benefits of using machine learning with the MultiResU-Net network. The designed system proposes a closed-loop machine learning workflow aiming to combine machine learning predictions with the interpretation experience of geophysical engineers.

The method proposed by Chung, Y. and colleagues [28] is a new interactive segmentation model. This method utilizes a two-component distance map consisting of automatically segmented results and user-labeled pixels. Additionally, a structural map is extracted from the image and presented as input to this automatic segmentation model. As a result of the study, it is noted that with a data cleaning technique removing samples with incorrect labels, IoU reached 91.81%.

In the study conducted by Konuk, T. and the team [29], a type of neural network model that differs from traditional deep learning approaches is focused on, namely Bayesian neural networks. The Bayesian approach is based on probability theory to model uncertainties and probabilities. Therefore, Bayesian neural networks provide accurate salt probability values and quantitative uncertainties in both data and model parameters. The study also proposes a new approach to reduce the complexity and computational requirements of traditional Bayesian neural networks. This approach utilizes an architecture that combines deterministic and probabilistic layers. The designed architecture allows the model to account for uncertainties and to be trained faster and more efficiently. It is noted that the developed model achieved high performance on two different seismic datasets.

In the study conducted by Arsha, P. V. and colleagues [30], a deep neural network model called Mask R-CNN is proposed. Mask R-CNN not only determines the positions and classes of objects in object detection tasks but also performs detailed masking of objects at the pixel level. The developed model accepts a seismic image as input and performs the necessary pixel classification. The results obtained indicate that the model outperforms traditional CNN networks developed in this field.

In the method proposed by Chung, Y. and colleagues [31], the aim is to clean the dataset containing noisy labels using the Kullback-Leibler Divergence (KL) and Noise Robust Loss functions. As a result of the method, it is noted that the segmentation performance improves without heavily noisy labels.

In the study conducted by Zhang, H. and colleagues [32], a new deep learning-based interactive segmentation method is proposed for extracting salt boundaries. To incorporate interaction points into the method, positive and negative points are transformed into two Euclidean Distance Maps (EDMs) combined with seismic images to train a CNN model. The model consists of a U-net and a Pyramid Pooling Module (PPM). Subsequently, a graph cut algorithm is used to refine the probability maps predicted by the CNN model and then update the salt boundaries. Some field examples indicate that the proposed method outperforms fully automatic CNN methods with higher fundamental matching degrees.

In the study conducted by Li, H. and the team [33], a deep supervision-based salt rock segmentation method is proposed using the U-Net model. By employing transfer learning, a pre-trained model loaded with ResNeSt is utilized as the backbone of the encoder. To further enhance accuracy, OCNet and scSE modules are added to the decoder. Application of the developed model to datasets resulted in a single-model precision of 87.32% mAP.

In the model designed by Geng, Z. and colleagues [34], the "Mean Teacher" method is adopted for semi-supervised salt segmentation. In this approach, both a student model and a teacher model are utilized. While the student model is optimized using a combination of supervised loss and unsupervised consistency loss, the teacher model serves as a kind of average of the student model. This approach aims to leverage unlabeled data to extract more information. The research concludes that semi-supervised salt segmentation methods outperform the supervised baseline even in cases where labeled training data is insufficient. This highlights the potential of semi-supervised approaches in salt segmentation.

In the study proposed by Saad, O.M. and the team [35], the focus is on three-dimensional (3D) salt segmentation. They developed a highly generalized fully convolutional DenseNet for automatic salt segmentation. This framework, utilizing deep learning techniques, enables the automated detection and classification of salts in seismic images. The proposed framework is a supervised technique and has shown robust performance when applied to a new dataset using transfer learning and a small amount of training data. It has been reported to enable the training of a model that can better generalize to a new dataset by leveraging information obtained from another dataset.

In the study conducted by Lakshmi Devi N. and colleagues [36], the focus is on salt segmentation. The study proposes two new models that are more effective than existing models with low detection rates. The primary model consists of a combination of UNet with ResNet-18 and ResNet-34, while the secondary model consists of a combination of UNet with ResNet-34, VGG16, and Inceptionv3. These models are utilized to identify salt regions from seismic data. The research concludes that the proposed ensemble model outperforms individual network models and achieves better salt segmentation results.

In the study conducted by Bodapati, J.D. and the team [37], an effective approach is introduced to identify salt accumulation areas from seismic images. In this approach utilizing semantic segmentation, each pixel is determined whether it belongs to a salt accumulation area. The study employs an enhanced version of the UNet architecture. The proposed method is based on a network structure comprising a combination of the UNet model along with ResNet and DenseNet architectures. This design is aimed at achieving better generalization ability and improved performance. It is noted that the proposed model yields a significant performance improvement compared to other baseline models.

III. Results

This study aims to investigate the potential of analyzing and interpreting seismic data using deep learning techniques. The results indicate that deep learning models have a significant impact on understanding the complexity of seismic data and characterizing subsurface structures. In the conducted studies, it is observed that deep learning methods provide higher accuracy and performance compared to traditional approaches. The methods and results of the research studies are presented in Table 1.

Table 1. Some of the studies

Referans	Method	Result
19	U-Net	0,8 (IoU)
20	ResNeXt-50+Module data augmentation	The use of data augmentation has increased performance
21	CNN+ data augmentation	High performance
22	Se-FPN+Hypercolumn module	0,86 (IoU)
23	CNN	High performance
24	ResNet-34	%87,36 mAP
25	U-Net+Module	High performance
26	BU-Net	It increased IoU by 2.6%
27	MultiResU-Net	High performance
28	Interactive segmentation model	%91,81 (IoU)
29	Bayesian Neural Network	High performance
30	Mask R-CNN	Successful compared to CNN
31	Kullback-Leibler Divergence (KL) and Noise Robust Loss function	High performance
32	U-Net+PPM	Successful compared to CNN
33	ResNeSt+Module	%87,32 mAP
34	Mean Teacher	High performance
35	DenseNet	High performance
36	ResNet-34+VGG16+InceptionV3	High performance
37	ResNet+DenseNet	High performance

IV. Discussion

Our study addresses the impact and potential of deep learning methods on seismic interpretation. It demonstrates that deep learning models can effectively handle the complexity of seismic data and perform automatic feature extraction. However, challenges such as the large amount of data and computational power required for training deep learning models are also highlighted. Specifically, the findings of this study suggest that, compared to traditional seismic interpretation methods, deep learning models can provide more accurate and consistent results. Nevertheless, further research and development are needed for the full adoption of deep learning models in seismic interpretation. The conclusion of this study highlights the future potential of deep learning methods in the field of seismic interpretation.

V. Conclusion

The importance of adopting deep networks like UNet and ResNet, as well as hybrid approach models, is underscored in the findings of this study. Deep networks such as UNet stand out for their high learning capacity and flexible architectures, while hybrid approach models combine different feature extraction and merging strategies to offer a more comprehensive solution. By employing these methods, better results are expected to be achieved in complex problems such as seismic data analysis and petroleum reservoir estimation. These findings indicate the potential benefits of widespread use of deep learning techniques in future underground resource research.

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