Türkiye Teknoloji ve Uygulamalı Bilimler Dergisi

ISSN: 2528-8652 e-ISSN: 2822-2660 2024, 5(2):70-86
Period Biannually Founded 2017 Publisher Siirt University https://dergipark.org.tr/tr/pub/tubid

Effect of Data Augmentation Method in Applied Science Data-Based Salt Area Estimation with U-Net

Betül AĞAOĞLU*
Computer Engineering Department, Ankara University, Türkiye
https://orcid.org/0000-0002-6539-371X

İman ASKERZADE
Computer Engineering Department, Ankara University, Türkiye
https://orcid.org/0000-0003-4466-8128

Gazi Erkan BOSTANCI
Computer Engineering Department, Ankara University, Türkiye
https://orcid.org/0000-0001-8547-7569

İhsan Tolga MEDENİ
Management Information Systems Department, Ankara Yıldırım Beyazıt University, Türkiye
https://orcid.org/0000-0002-0642-7908

Research Article

Received

29/04/2024

Accepted

26/06/2024

DOI

10.70562/tubid.1474999

Abstract

Oil and natural gas rank first as energy inputs worldwide. Other subsurface resources, such as salt, provide clues to obtaining these natural resources. Salt accumulation areas are subsurface resources used to locate oil and gas fields. Seismic data, which are geological data, provide information for locating underground resources. Manual interpretation of these images requires expert knowledge and experience. This time-consuming and laborious method is also limited by the fact that it cannot be replicated. The limitations of traditional methods have increased the need for faster, more cost-effective, and reproducible solutions. At this point, deep learning technologies, which have achieved great success in recent years, come into play. Deep learning plays a significant role in overcoming the challenges of manual interpretation by providing high accuracy and efficiency in image segmentation. Automating the detection of subsurface reserves in seismic images using artificial intelligence methods reduces time, cost and workload factors. In this study, we aim to detect salt areas in seismic data using the U-net architecture. In addition, the effect of data augmentation methods on the designed system is investigated. The data set used in the system consists of seismic images that are combined together for automatic detection of salt mass. As a result of the study, the Intersection over Union value of the system designed without data augmentation method is 93.90%, while the the Intersection over Union value of the system designed using data augmentation method is 94.45%.

Keywords: Deep learning, CNN, U-net, segmentation, salt reserve, seismic data

*Corresponding Author: betulagaoglu@hitit.edu.tr

1. Introduction

Natural resources are vital for the continuity of human life. Resources such as energy production and precious metals form the basis of modern life and play a critical role in the functioning of economies (1). Oil and natural gas are the main sources of transportation and electricity generation, as well as industrial and commercial activities (2). However, the identification and extraction of these valuable resources is a challenging process (3,4). Large salt deposits have been found in regions where these natural resources are common on the earth's surface (5). Due to its low permeability, salt can be located as it reflects from oil or natural gas reservoir areas (6). Seismic images are widely used to estimate the location of resources. Seismic images provide information about the location of natural resources by visualizing the subsurface structure. These images are obtained using sound waves. The sound waves are reflected from different structures and recorded by an instrument called a geo-phone (7). Inaccurate estimates made with seismic data are attributed to the poor quality of the data, lack of knowledge of the interpreter, and insufficient attention to the preprocessing of the data (3). Demonstrating that the data to be used in reserve estimation are reliable, accurate and high quality data and proving the accuracy of the data is the first and important step in this process. In this step, necessary procedures should be applied and documented. In the process referred to as data verification, factors such as proving the accuracy of the data and its usefulness in the estimation process are determined. After this step, the data is transferred to the computer environment. In this step, which is called data validation, the formation of erroneous, incomplete, repetitive problematic data due to the transfer of data to the computer is prevented (4). The stages of seismic image acquisition are shown in Figure 1.

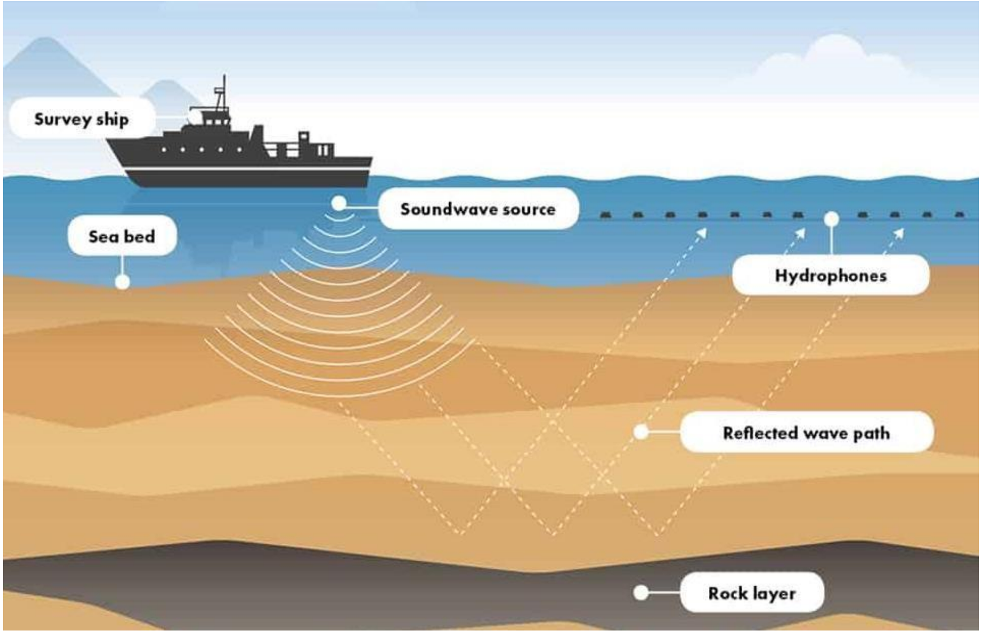

Figure 1. Seismic image collection (8)

Seismic images are an important tool for locating salt domes (9). Salt domes are defined as elevated structures formed by the layering of salts in certain areas of the geological structure (10). These salt dome areas are considered as potential reservoirs where valuable resources such as oil and natural gas can be stored. Figure 2 shows these formations.

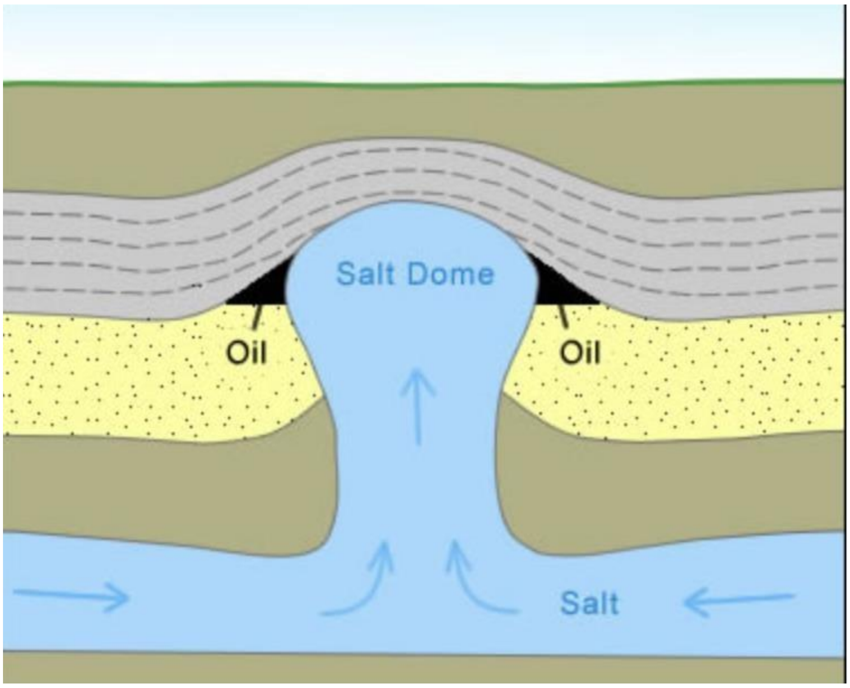

Figure 2. Salt dome (11)

However, manual detection of these salt domes through seismic images is a challenging process (12). The manual detection process is time-consuming, costly and limited in repetition (13). This process requires experts to study seismic images in detail and identify signs of structures such as salt domes. This is a long-term endeavor and often with a high margin of error. In addition, misinterpretation of seismic images can have negative consequences, such as wasted time, cost and effort. Incorrect detections can lead to unnecessary drilling or wrong investments, which can result in significant costs. Moreover, correcting false detections can also require extra time and labor. Therefore, accurate interpretation of seismic imagery and effective detection of salt domes is critical in the process of natural resource exploration and exploitation. It is important to develop and use automated or semi-automated data analysis methods to make this process faster, more accurate and more economical. This will enable the efficient utilization of natural resources and effective management of resources.

Artificial intelligence methods are used to minimize the negative situations experienced in manual reserve estimation. Deep learning, one of the fields of artificial intelligence, has shown high achievements in classification, object detection and image segmentation. It is applied in many fields such as medicine, education, food, geology. With its development and successfully applied methods, deep learning is also used on seismic images to minimize time, cost and user bias (14). It has paved the way not only to speed up seismic processing but also to obtain estimates that are comparable to a group of experts and not based on the opinion of a single expert. Salt detection from seismic images can be considered as a classification, localization and segmentation problem (15). When considered as a classification problem, the salt area is grouped as present or absent (16, 17, 18). When solved as a positioning problem, the area with salt domes is framed (19). For the segmentation problem solution, salt area detection from seismic images is realized by classifying each pixel in the image (15). Models such as U-net, Seg-Net, Resnet, etc. are popularly used to segment salt areas from seismic images (6, 20, 21).

In this study, the U-net model, one of the deep learning methods, is used to detect salt areas that are critical for finding oil and gas deposits. This model is designed to enable detailed analysis of seismic images and precise identification of salt deposits. Unlike traditional neural network architectures, the U-net model has a structure that preserves the size of the input data, which prevents the loss of important features in seismic images. Furthermore, the main objective of the study is to examine the effect of data augmentation method for accurate detection of salt areas using this U-net model. Data augmentation is a widely used method to increase the generalization ability of the model and avoid overfitting in cases of limited training data. In this study, the results obtained by applying data augmentation techniques are observed and the effect of these techniques on the detection of salt areas is evaluated. The results show that data augmentation methods improve the performance of the U-net model and help to identify salt areas more accurately. This study provides an innovative solution to an important problem of the oil and gas industry by introducing a powerful combination of deep learning and data augmentation techniques for analyzing seismic images. The problem is solved by analyzing whether each pixel in the seismic image belongs to a salt field. U-net architecture is proposed to detect salt areas. Using the designed U- net network, 4000 seismic filter images were used for training (3200 trainings, 800 validations) and 18000 seismic images were used for testing. In the other system compared, the number of images used in training was increased to 6400. Within the scope of the study, the publicly available TGS Salt Identification Challenge dataset shared on www.kaggle.com was used (22). The Intersection over Union (IoU) and dice scores for the criticized system show better results both using data replication and when compared with other studies

2. Related Works

U-net is a convolutional neural network model that is widely used in image segmentation and provides effective results. This model segments images based on the principle that each pixel receives a class label (23). One of the reasons why U-net is widely used in the literature is that it can achieve effective results even when the data set is small (24). Zhang et al. (25) focus on the extraction of salt boundaries, which plays an important role in oil and gas exploration by analyzing salt bodies. Traditional methods include sound wave features and edge detection algorithms, which require manual effort. The study uses Convolutional Neural Networks (CNNs), which have evolved as an automatic segmentation method to extract salt boundaries. As a result of the study, higher accuracy was obtained compared to purely CNN methods. Li et al. (26) designed a system for salt area detection using the U-net model directly. In order to improve the accuracy, some modules were added to the system. As a result, it is stated that these modules affect the performance value. Chen et al. (27) improved the architecture by adding different modules to provide a stronger foundation. Spatial Pyramid Sampling (SPS) method was used to select representative samples from the training data. Multimodal Fusion (M2F) module is integrated to extract edge and frequency information from the selected representative samples. Moreover, Local-to-Global (L2G) module is proposed to capture the relationships between pixels in the image. As a result, successful results are obtained using less training data. Zhao et al. (28) builds on the traditional U-Net architecture while adding a special highlight layer to learn boundaries more effectively. The developed model includes a special loss function and measurement metrics to more precisely define the boundaries of salt bodies. This aims to improve the ability to more precisely identify salt bodies in geophysical data by improving segmentation accuracy. The study concludes that Boundary U-Net provides higher accuracy and precision compared to conventional methods.

The U-net model has an architecture consisting of convolutional and convolutional backpropagation layers. Unlike traditional convolutional neural networks, this architecture provides more successful results in detailed segmentation of images (29). Bodapati et al. (15) emphasizes the need to distinguish salt deposits from seismic images in a heuristic way. This approach aims to segment seismic images using a variation of the UNet model. In the study, it was observed that deeper networks extract better features. Moreover, post-processing such as sharpening improves performance. The proposed methodology achieves a higher IoU achievement compared to the Segnet method.

Another important feature of U-net is that it does not impose any limitations in terms of system results (30). In other words, it can provide successful results on images of different scales, different problem domains and different data sets. This feature enables U-net to have a wide range of applications. The flexible and effective structure of U-net has made it a preferred model in many studies in image segmentation (31). In particular, the U-net model has been successfully used in fields such as medical imaging, remote sensing, autonomous vehicles, and geology (31, 32, 33, 34) Therefore, the U-net model is widely accepted in the literature as a reliable and effective tool for image segmentation. Karchevskiy et al. (16) designed a U-net with ResNet-50 encoder. As a result of the study, a high accuracy score was obtained. In another study, Zhou et al. (35) worked with some modules added to the U-net neural network. Spatial and Channel-wise Squeeze and Excitation (ScSE), Feature Pyramid Attention (FPA), and their effects on the results were investigated. As a result of the study, it was stated that these modules segmented better than the results obtained without the modules. Many studies have been conducted using different versions of the U-net neural network. Bochu et al. (36) designed a model using a combination of U-net network ResNet18, ResNet34. Later in the study, a second model was developed by combining ResNet34 with VGG16 and inceptionv3. As a result of the study, it was stated that the performance scores of the individual network models were lower than the combined models. Guo et al. (37) presented a deep supervised learning model using edge optimization that makes the edges in the images clearer and more prominent to perform salt body segmentation. As a result of the study, it was stated that the use of the edge optimization process increased the accuracy value. In studies with seismic data, it is seen that the pre-processing processes to be performed before the data is included in the training are important. Chung et al. (38). emphasized the importance of noise removal from salt dome images. The data cleaning process aims to address potential errors, noise and anomalies in the salt dome dataset. This step aims to organize and correct the dataset to obtain more accurate and reliable results. HajNasser et al. (39). MultiResU-Net, a neural network for the identification and quality control of salt bodies is being studied. This work aims to provide an automated approach as an alternative to traditional quality control and manual interpretation. The study is designed to classify salt bodies by efficiently using features at a wide range of resolution levels. The results show that MultiResU-Net has the potential to successfully identify salt bodies and improve quality control processes (40) used the "Mean Teacher" method for semi-supervised salt segmentation. Traditionally, a large amount of labeled data is usually needed to identify salt bodies. However, this study aims to improve model performance by using a larger learning dataset with a limited amount of labeled data. The "Mean Teacher" approach involves a framework in which the model has a network of teachers that is continuously updated and this teacher drives the student model. In this way, a regularization mechanism is provided to smooth and generalize the model's decisions. Semi-supervised learning can improve the performance of the model by combining labeled and unlabeled data. In conclusion, the "Mean Teacher" method is effective in the semi-supervised salt segmentation task and can improve the performance of the model even in the case of limited labeled data. Saad et al. (41) designed a model called Self-Attention Fully Convolutional DenseNet (SA-FC-DenseNet) for automatic salt segmentation. It is based on a fully convolutional DenseNet architecture enriched with the Self-Attention mechanism. The Self-Attention mechanism allows the model to learn the dependencies between pixels at different locations and thus perform more efficient segmentation. The model increases its feature extraction capacity by using dense blocks and full convolution layers. The Self-Attention mechanism aims to be more accurate, especially in identifying fine details of salt bodies. The results of the study show that SA-FC-DenseNet outperforms other methods in automatic salt segmentation and is particularly effective in detecting fine boundaries. Many deep learning methods have also been studied in 3D seismic images. Xu et al. (42) proposed a hybrid semi-supervised model for 3D seismic images.

3. Methodology

Deep learning architectures such as the U-Net model are often effective in image segmentation tasks. Therefore, in this study, a system is designed using the U-Net model. U-Net is an architecture characterized by its encoder-decoder structure and is widely used in biomedical image segmentation. Before training the system, the data set was expanded using data augmentation methods. Data augmentation methods may include techniques such as rotation, horizontal or vertical symmetry, panning, zooming, etc. of the existing images. The aim of these methods is to increase the number of samples in the training dataset and to enable the model to generalize better. Using the same U-Net model, the system was trained again with the data set without data augmentation methods. The results obtained after this training are analyzed to evaluate how the system performance changes under the influence of data augmentation methods. The results are compared with the results obtained in previous similar studies and the impact of data augmentation methods on the system performance. This comparison is important to determine how effective data augmentation methods are and how they can improve system performance.

This study can make a significant contribution to research in this field by systematically examining the effect of data augmentation methods with the U-Net model used in image segmentation and how these methods affect the results obtained compared to previous studies.

3.1. Detail of U-Net architecture

The U-net architecture, a convolutional network approach, is a highly accurate model for performing image segmentation, especially in the medical field. The architecture consists of two parts. Encoder and decoder. The encoder part is in the form of a narrowing path as important connecting features are detected in the image. The decoder is a symmetrically generated path using inverse convolution to ensure precise localization (29). The U-net architecture is shown in figure 3.

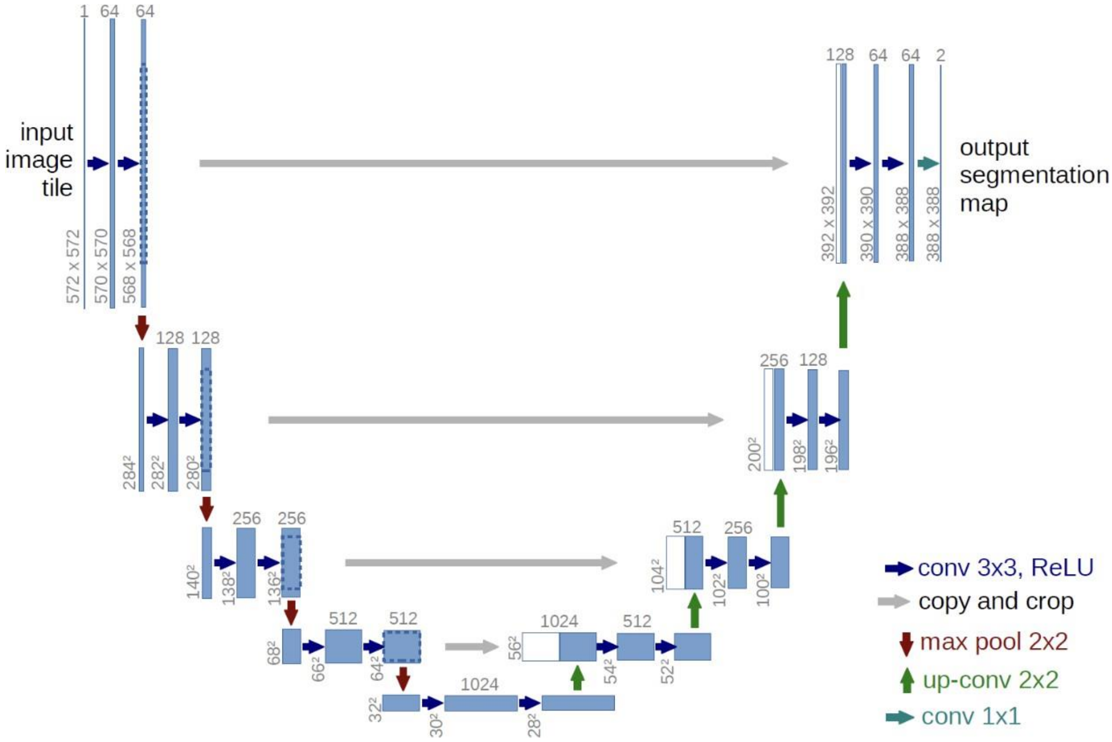

Figure 3. U-net architecture (29)

In the U-Net architecture used in the designed system, the 3x3 convolutional network followed by the ReLU activation function is primarily used in the feature extraction part of the encoder. This convolutional network enables the extraction of features from the input images. The ReLU activation function increases the flexibility of the model by allowing the network to learn non-linear features. After the feature extraction phase, the size of the feature maps is halved. This is achieved by max pooling (43, 44). A 2x2 max pooling process halves the size of the feature maps while preserving important features. This allows the model to learn more specific and salient features. Dropout, a regularization technique used to prevent overfitting of the neural network and to obtain more generalized results, is used in the encoder and decoder parts. Dropout is the random deactivation of some neurons in the network. This allows the network to learn different features and reduces the risk of overfitting. The dropout value of 0.5 means that 50% of each neuron will be disabled in each training iteration. In the decoder part, masks of the trained data are created. At this stage, a 3x3 convolutional network following the ReLU activation function is used. Then, in the output layer, a 1x1 convolution is performed with a sigmoid activation function. The sigmoid activation function generates the segmentation mask that represents the pixel- wise classification. These masks represent the probability that each pixel belongs to a particular class in the image, which allows segmentation to be performed. The resulting model is presented in Fig. 4.

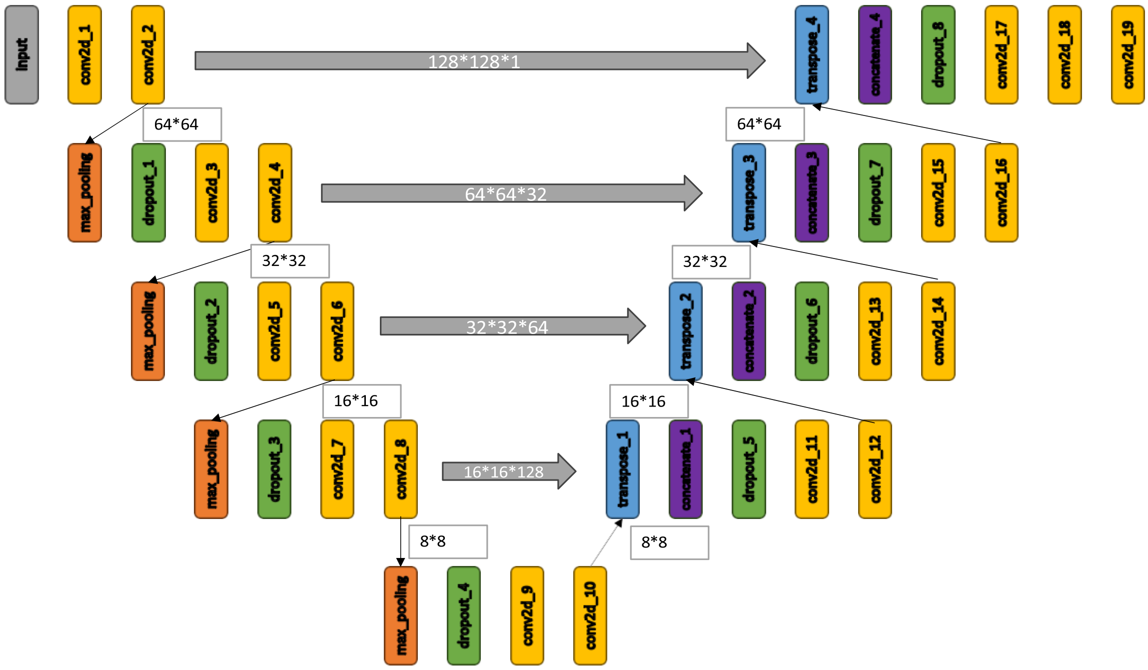

Figure 4. The created U-net based architecture

3.2. Data preprocessing

In order to be passed through the proposed UNET model, the dimensions of the images in the training dataset need to be adapted. This fitting process is usually performed in order to match the size of the images to the expectations of the model. In this context, the training images were uploaded with a size of 101 × 101. However, for the proposed UNET model, 128 × 128 was preferred as the input size. The dimensions of the 101 × 101 images, which are the training data, are resized to 128 × 128.

The up sample function was used for the resizing process. This function is designed to resize images to a specific target size. In particular, the pixel values of the image are preserved by using the preserve range parameter. This parameter ensures that the pixel values do not change during the resizing process and that the data of the original image is preserved. This ensures that the model works with the correct data during the learning process and avoids unwanted changes.

As a result, with these processing steps, the dimensions of the training images are adapted to the expectations of the proposed UNET model and the pixel values are preserved during the resizing process. This is an important step to obtain more consistent and accurate results in order to correctly process the dimensions and data of the model's inputs.

3.3. Data augmentation

In deep learning, data augmentation is a technique used to better generalize the model and improve performance when training data is limited. Data augmentation is used to diversify the available training data. Data augmentation can reduce overfitting and make your model more robust, especially when you have limited data. Data augmentation methods are used to diversify the training data and allow the model to generalize better. There are many methods for data augmentation (45, 46). The most commonly used ones are listed below.

- Random Rotation: Creates new samples by rotating images at random angles.
- Horizontal and Vertical Flipping: New images are obtained by flipping the images horizontally or vertically.
- Random Shifts: New positions are obtained by randomly shifting the images.
- Zoom (Random Zoom): Various samples are obtained by randomly enlarging or reducing the images.
- Random Brightness and Contrast (Random Brightness and Contrast): New samples are created by randomly adjusting the brightness and contrast of the images.
- Color Transformations: Various colored images are obtained by changing the color space of the images or randomly adjusting the color tones.

In the study, the training data set was doubled by taking the horizontal symmetry of each image on the images. The system was also tested by rotating the training data on the horizontal axis. This allows the model to be trained with more data, generally increasing the generalization capability of the model.

3.4. Dataset (Seismic Data)

The dataset was obtained from the TGS Salt Identification Challange on kaggle.com (22) The dataset consists of seismic images acquired from random sites. The images are 101*101 pixels in size. There are mask images where each pixel is classified as salt and sediment. The training folder contains 4000 images and 4000 mask (filter) images. The test folder contains 18000 images with png extension. The dataset also contains the depth information (z) of each image.

3.5. Evaluation Criteria

Segmentation performance can be evaluated with various metrics. Different techniques have been used for the results in previous studies. Due to the importance of metrics that characterize the areas of overlap (number of true positives, number of false positives, number of false negatives), positive- based metrics are generally prioritized in segmentation studies. The most common performance evaluation metrics for segmentation with seismic data are IoU, Dice Overlap Index or Dice Similarity Coefficient (Dice Score) (47,48).

3.5.1. IoU

IoU is a metric used to evaluate the performance of an object detection or image segmentation (49).

- **Intersection:** Refers to the common area between the real object and the predicted object.

- **Union:** The sum of the areas of the real object and the predicted object.

IoU divides these two values by each other. This metric takes a value between 0 and 1. The closer it is to 1, the closer the prediction is to the true object. In the ideal case, an IoU of 1 means that the two regions completely overlap. The use of IoU is particularly common in tasks such as object detection and image segmentation. IoU is often used to evaluate how well the model performs with a quantitative measure.

3.5.2. Dice Overlap Index/Dice Similarity Coefficient (Dice Score)

The Dice Overlap Index or Dice Similarity Coefficient is a frequently used measure in applications such as image segmentation. In particular, it is used to measure how well the segmentation map that is the output of an algorithm matches the actual (reference) segmentation map (50).

The Dice Similarity Coefficient is calculated with the following formula;

$$Dice = \frac{2*IX \cap YI}{IXI+IYI} \qquad (1)$$

where;

- X and Y are the model predicted segmentation map and the actual (reference) segmentation map, respectively.
- The symbol I.I refers to the number of elements of the cluster.
- XY denotes the intersection of the two clusters.

Dice Similarity Coefficient takes a value between 0 and 1. The closer it is to 1, the better the agreement between the model's predictions and the actual segmentation. In the case of a complete overlap (intersection), the Dice value reaches 1. If there is no overlap (i.e. both the model predicted and the actual segmentation map are empty), the Dice value is 0. The Dice Similarity Coefficient is often preferred in areas such as image segmentation, especially in imbalanced classification problems (i.e. imbalances between non-object areas and object areas) (51).

3.6. Architectural structure

The most important feature of the U-net network model is that it can achieve high performance with little data. In this study, the effect of image duplication on the performance of the system is studied. In artificial intelligence applications, there are several options to optimize the simultaneous processing and learning of the data set during model training. These options include parameters such as number of epochs, batch size and activation functions. Changing these parameters can affect the success performance of the model. The hyper-parameters used in the study are given in Table 1.

Table 1. Hyper-parameters used in the model

Input size	128*128*1
Optimizer	Adam
Batch size	64
Epoch	200
Loss fun.	BCEWithLogitsLoss()
Score Metric	IoU Dice Score

4. Results and Discussion

There are many studies in the literature using seismic images for reserve determination. In these studies, segmentation methods are used to match each pixel in the images with a class label. In this context, in this study, U-net architecture is used in seismic images for the detection of salt fields. The 101x101x1 images in the dataset were resized to 128x128x1 for better generalization and learning of the model.

In the study, the salt area was calculated on the training data and masks before training. The ratio of the number of salt pixels in the masks to the total pixels was calculated and graded between 0 and 10. The higher the number of salt pixels in the image, the higher the score. If 0 means no salt area and 10 means the whole image consists of salt. The results are shown in Figure 5. According to the figures, it is seen that the data set distribution rates are not regular. It is understood that there are fewer images with salt areas.

In a deep learning system designed with seismic images, depth information is often important. Depth information includes information such as the thickness and location of layers beneath the earth's surface. Seismic images are often used to study subsurface structures, and in this case, depth information can provide valuable information about the location and characteristics of the structures. Especially in applications such as oil and gas exploration, deep learning models working with seismic images can often use depth information to better understand and identify subsurface formations. Depth information can provide more insights into the thickness, density and other properties of the subsurface layers. When the depth information of the train and test data in the depths.csv file given in the dataset was processed, it was seen that the majority of the images were within the average value range. The depth information of the images in the dataset is shown in Figure 6.

In the experimental study, a U-net network model was designed on Kaggle.com's site using GPU P100 16 GB Ram. In the designed system, 20% of the training data was allocated as validation. During the training process, the 'EarlyStopping' method was used to prevent overfitting and optimize the training duration. The patience parameter was set to 100 in the EarlyStopping method. In this way, the training was stopped at the point where the model showed its best performance. In the study, the data was first trained in the system designed without using data augmentation methods. Figure 7 below shows visualizations for salt area detection performed by the model. The salt area is seen in red as predicted by the green system.

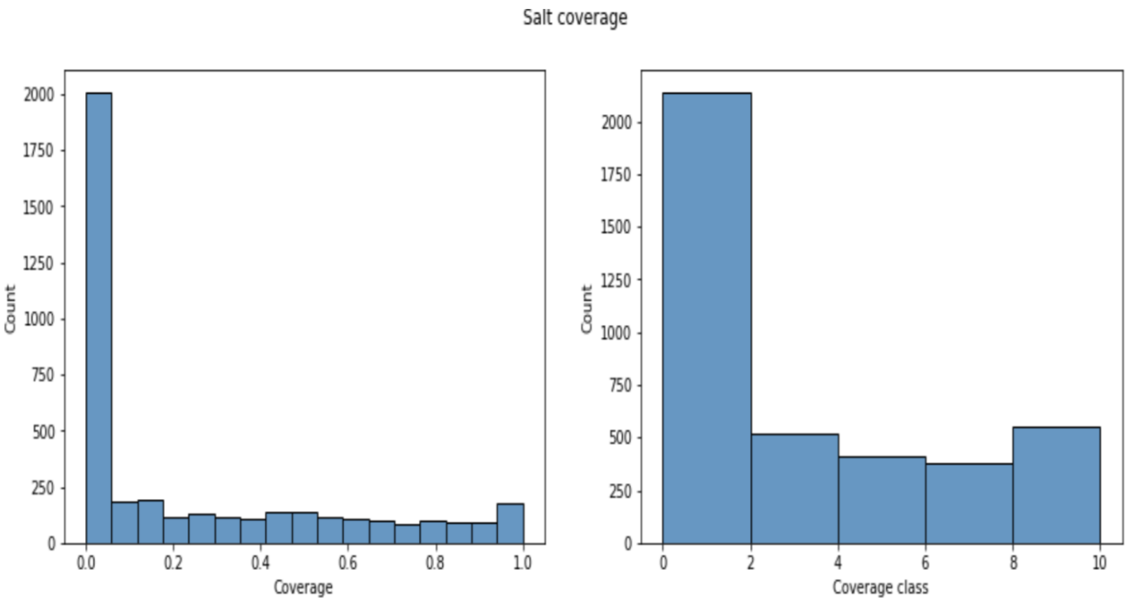

Figure 5. Salt ratio and grading in seismic images in the dataset

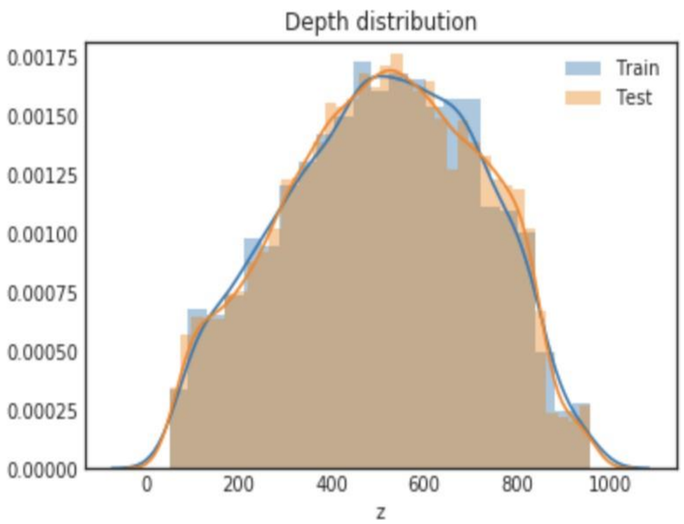

Figure 6. Depth distributions of train and test data

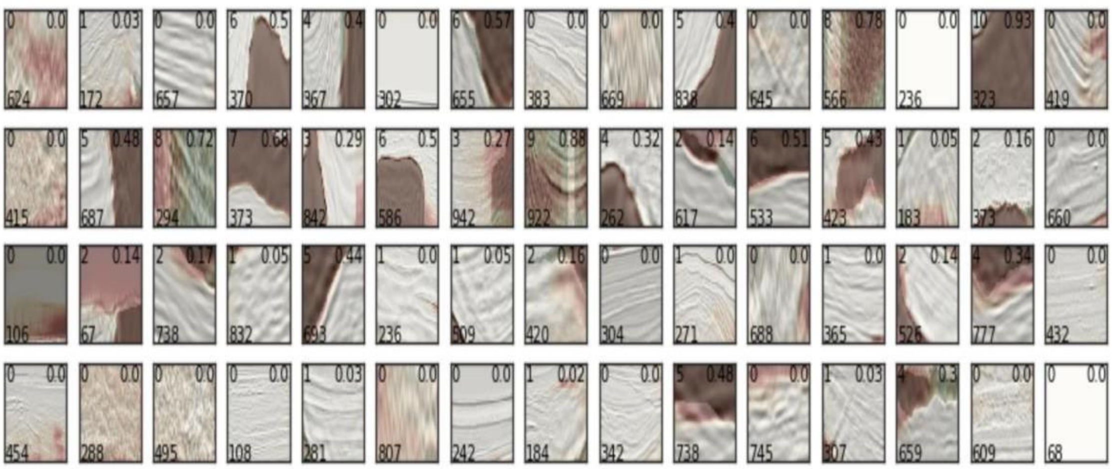

Figure 7. Prediction result images of the system without data augmentation methods

The accuracy value of the system designed without using data augmentation method is 93.08% and the loss value is 14.52%. The graph of the result is shown in Figure 8.

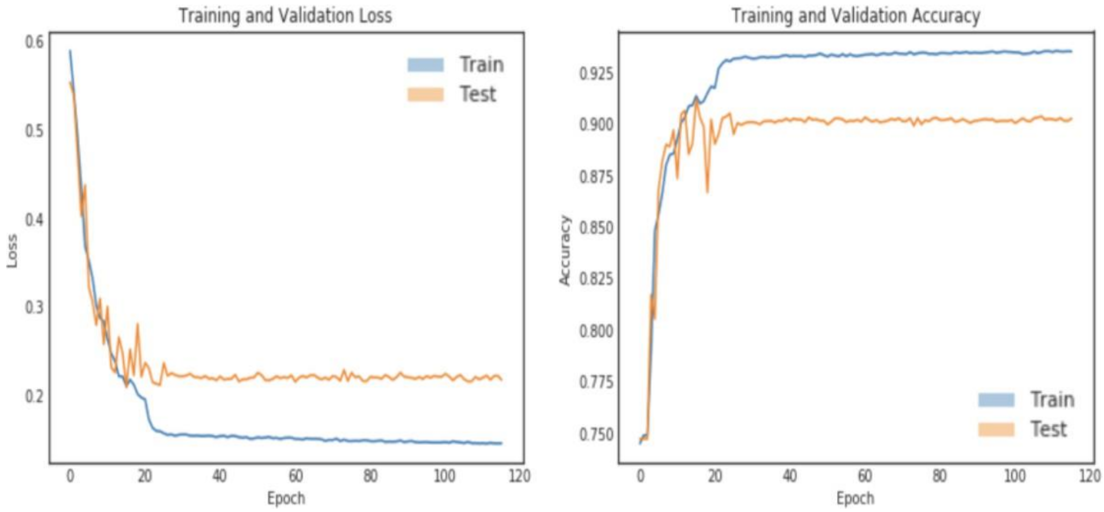

Figure 8. Loss and accuracy graph of the system without data replication

In the rest of the study, the training data set was increased to 6400 images by using data augmentation methods over the data set. The system was trained again using the specified hyperparameters exactly. Figure 9 below shows the images for salt area detection performed by the model.

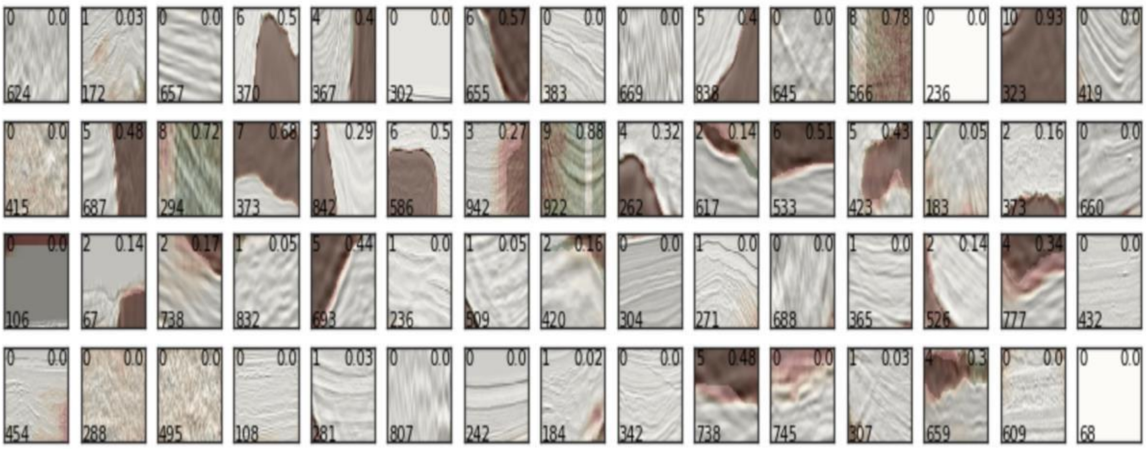

Figure 9. Prediction result visualizations using data replication

The accuracy value of the system designed using the data replication method is 94.46% and the loss value is 12.02%. The graph of the result is shown in Figure 10.

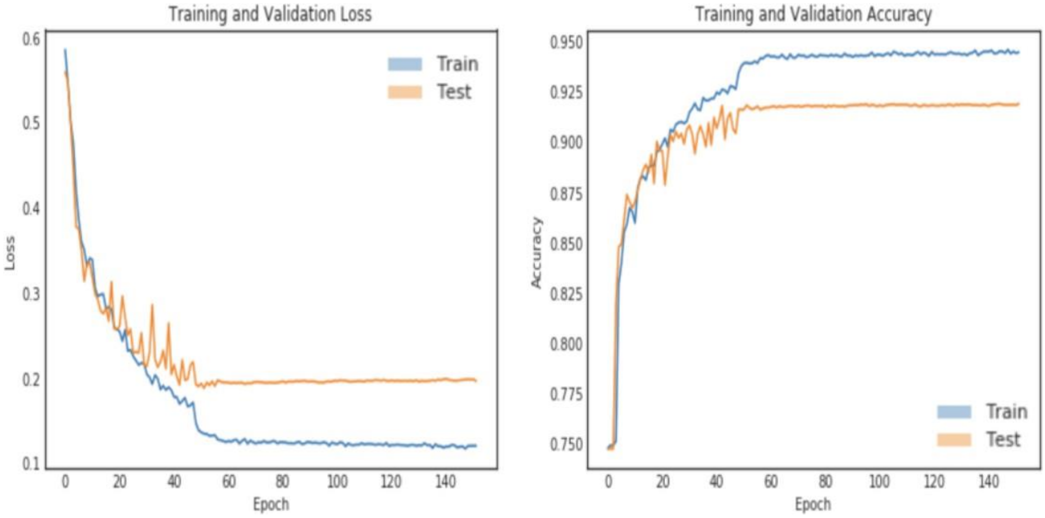

Figure 10. Loss and accuracy graph of the system using data replication

When the U-net model was used to detect salt areas, it was observed that the model trained on seismic images without data augmentation achieved an IoU score of 93.90%. However, when the same model was trained using data augmentation, the IoU score was 94.45%. These results show that data augmentation improves the accuracy of the model and helps it detect salt areas more effectively. The results obtained are presented in Table 1.

Table 2. Model results

Model U-net	IoU	Dice
Data augmentation is not used	93.90%	94.63%
Data augmentation used	94.45%	95.32%

The results obtained in the study were compared with the studies working with the same data set. The comparison is given in Table 2.

Table 3. Comparison of salt field segmentation results with other studies

Studies	Guarido, M. (52)	Liu, B. (53)	Chung, Y. (54)	Study Presented
IoU Score	80%	86%	91.81%	94.45%

The model obtained after the training process was analyzed in the test environment by making the necessary configurations. The results obtained showed an acceptable level of success in the literature. In the rest of the study, the images were duplicated by applying data duplication methods to the training data. These results show that the data augmentation method is successful in segmenting the images accurately.

5. Conclusion

The development of deep learning techniques has played a significant role in seismic data analysis and the detection of subsurface structures. Particularly in the oil and gas industry, the accurate and rapid identification of underground natural resources is of great importance. The segmentation of subsurface structures from seismic images is a critical part of this process, and the proper processing of data directly impacts decision-making processes. However, the limited and imbalanced nature of seismic data can negatively affect the generalization capability of such models. At this point, data augmentation techniques are frequently used to prevent overfitting and enhance the model's performance.

Data augmentation methods are used to reduce overfitting and provide better learning. This study shows that data augmentation methods used in seismic data have a positive effect on the results. In addition, automating the process of salt detection from seismic images with this study will save time, money and effort. This is of great importance for the oil and gas industry, making the reserve determination processes more efficient and accurate. This study demonstrates the effectiveness of data augmentation methods in the segmentation of seismic images, contributing to the literature in this field. Additionally, the high IoU values obtained allow for more accurate and reliable analysis of seismic data, thus providing valuable insights for research in geophysics and energy sectors. In future studies, the U-net model will be improved and the IoU parameter obtained will be further increased.

References

1. Hubbert MK. Energy resources: a report to the Committee on Natural Resources of the National Academy of Sciences–National Research Council. Washington, DC: National Academy of Sciences-National Research Council; 1962. Report No.: PB-222401.
2. Economides MJ, Wood DA. The state of natural gas. J Nat Gas Sci Eng. 2009;1(1-2):1-13.
3. Özkan YZ, Akbaba MA. Örneklemeden rapor etmeye adım adım maden kaynak tahmini. Jeoloji Müh Derg. 2013;37(2):141-58.
4. Coombes J. The art and science of resource estimation: a practical guide for geologists and engineers. Coombes Capability; 2008.
5. Asjad A, Mohamed D. A new approach for salt dome detection using a 3D multidirectional edge detector. Appl Geophys. 2015;12(3):334-42.
6. Wu X, et al. FaultSeg3D: Using synthetic data sets to train an end-to-end convolutional neural network for 3D seismic fault segmentation. Geophysics. 2019;84(3):IM35-IM45.
7. Shafiq MA, et al. Detection of salt-dome boundary surfaces in migrated seismic volumes using gradient of textures. In: SEG International Exposition and Annual Meeting. SEG; 2015.
8. [Internet] Marine seismic surveys: what you need to know. 2024. Available from: https://energyproducers.au/fact_sheets/marine-seismic-surveys-what-you-need-to-know/
9. Di H, Wang Z, AlRegib G. Deep convolutional neural networks for seismic salt-body delineation. In: AAPG Annual Convention and Exhibition; 2018. Vol. 2018.
10. Shafiq MA, et al. Salsi: A new seismic attribute for salt dome detection. In: 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE; 2016.
11. [Internet] Salt domes. 2024. Available from: https://geology.com/stories/13/salt-domes/#google_vignette
12. Babakhin Y, Sanakoyeu A, Kitamura H. Semi-supervised segmentation of salt bodies in seismic images using an ensemble of convolutional neural networks. In: Pattern Recognition: 41st DAGM German Conference, DAGM GCPR 2019, Dortmund, Germany, September 10–13, 2019, Proceedings 41. Springer International Publishing; 2019.
13. Karslı S. Son gelişmeler ışığında Türkiye'de kaya gazı. Journal of the Institute of Science & Technology. 2015;5(3).

14. Halpert A, Clapp RG. Salt body segmentation with dip and frequency attributes. Stanford Exploration Project. 2008;113:1-12.

15. Bodapati JD, Sajja RK, Naralasetti V. An efficient approach for semantic segmentation of salt domes in seismic images using improved UNET architecture. Journal of The Institution of Engineers (India): Series B. 2023;104(3):569-78.

16. Karchevskiy M, Ashrapov I, Kozinkin L. Automatic salt deposits segmentation: A deep learning approach. arXiv preprint arXiv:1812.01429. 2018.

17. Ozdemir C, Dogan Y, Kaya Y. A new local pooling approach for convolutional neural network: local binary pattern. Multimedia Tools and Applications. 2024;83(12):34137-51.

18. Ozdemir C. Classification of brain tumors from MR images using a new CNN architecture. Traitement du Signal. 2023;40(2).

19. Njima W, et al. Deep learning based data recovery for localization. IEEE Access. 2020;8:175741- 52.

20. Badrinarayanan V, Kendall A, Cipolla R. SegNet: A deep convolutional encoder-decoder architecture for image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2017;39(12):2481-95.

21. Zhu H, et al. Training a seismogram discriminator based on ResNet. IEEE Transactions on Geoscience and Remote Sensing. 2020;59(8):7076-85.

22. [Internet] TGS Salt Identification Challenge. Kaggle. 2024. Available from: https://kaggle.com/competitions/tgs-salt-identification-challenge

23. Özdemir C. Meme ultrason görüntülerinde kanser hücre segmentasyonu için yeni bir FCN modeli. Afyon Kocatepe Üniversitesi Fen ve Mühendislik Bilimleri Dergisi. 2023;23(5):1160-70.

24. Siddique N, et al. U-Net and its variants for medical image segmentation: A review of theory and applications. IEEE Access. 2021;9:82031-57.

25. Zhang H, et al. SaltISCG: Interactive salt segmentation method based on CNN and graph cut. IEEE Transactions on Geoscience and Remote Sensing. 2022;60:1-14.

26. Li H, et al. Deep learning-based model for automatic salt rock segmentation. Rock Mechanics and Rock Engineering. 2022;55(6):3735-47.

27. Chen X, et al. A stronger baseline for seismic facies classification with less data. IEEE Transactions on Geoscience and Remote Sensing. 2022;60:1-10.

28. Zhao Y, et al. Boundary U-Net: A segmentation method to improve salt bodies identification accuracy. In: Frontier Computing: Proceedings of FC 2020. Springer Singapore; 2021.

29. Ronneberger O, Fischer P, Brox T. U-Net: Convolutional networks for biomedical image segmentation. In: Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III. Springer International Publishing; 2015.

30. Fabijańska A. Segmentation of corneal endothelium images using a U-Net-based convolutional neural network. Artificial Intelligence in Medicine. 2018;88:1-13.

31. Du G, et al. Medical image segmentation based on U-Net: A review. Journal of Imaging Science & Technology. 2020;64(2).

32. Wang H, Miao F. Building extraction from remote sensing images using deep residual U-Net. European Journal of Remote Sensing. 2022;55(1):71-85.

33. Tran L-A, Le M-H. Robust U-Net-based road lane markings detection for autonomous driving. In: 2019 International Conference on System Science and Engineering (ICSSE). IEEE; 2019.

34. Fan W, et al. Stochastic reconstruction of geological reservoir models based on a concurrent multi-stage U-Net generative adversarial network. Computers & Geosciences. 2024;105562.

35. Zhou H, et al. Salt interpretation with U-SaltNet. In: SEG International Exposition and Annual

Meeting; 2020. SEG.

36. Bochu RR, Buddha NK. Salt segment identification in seismic images of earth surface using deep learning techniques. In: 2023 Second International Conference on Electronics and Renewable Systems (ICEARS). IEEE; 2023.
37. Guo J, et al. A deep supervised edge optimization algorithm for salt body segmentation. IEEE Geoscience and Remote Sensing Letters. 2020;18(10):1746-50.
38. Chung Y, Lu W, Tian X. Data cleansing for salt dome dataset with noise robust network on segmentation task. IEEE Geoscience and Remote Sensing Letters. 2022;19:1-5.
39. HajNasser Y. MultiResU-Net: Neural network for salt bodies delineation and QC manual interpretation. In: Offshore Technology Conference; 2021. OTC.
40. Geng Z, et al. Semisupervised salt segmentation using mean teacher. Interpretation. 2022;10(3):SE21-SE29.
41. Saad OM, et al. Self-attention fully convolutional dense nets for automatic salt segmentation. IEEE Transactions on Neural Networks and Learning Systems. 2022.
42. Xu Z, et al. 3D Salt-HSM: Salt segmentation method based on hybrid semi-supervised and multi- task learning. IEEE Transactions on Geoscience and Remote Sensing. 2023.
43. Özdemir C. Avg-topk: A new pooling method for convolutional neural networks. Expert Systems with Applications. 2023;223:119892.
44. Dogan Y. A new global pooling method for deep neural networks: global average of top-K max-pooling. Traitement du Signal. 2023;40(2).
45. Shorten C, Khoshgoftaar TM. A survey on image data augmentation for deep learning. Journal of Big Data. 2019;6(1):1-48.
46. Ozdemir C, Dogan Y, Kaya Y. RGB-Angle-Wheel: A new data augmentation method for deep learning models. Knowledge-Based Systems. 2024;291:111615.
47. Civitarese, D., Szwarcman, D., Brazil, E.V. and Zadrozny, B., 2019. Semantic segmentation of seismic images. arXiv preprint arXiv:1905.04307.
48. ul Islam MS. Using deep learning based methods to classify salt bodies in seismic images. Journal of Applied Geophysics. 2020;178:104054.
49. Rezatofighi H, et al. Generalized intersection over union: A metric and a loss for bounding box regression. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 2019.
50. Bertels J, et al. Optimizing the Dice score and Jaccard index for medical image segmentation: Theory and practice. In: Medical Image Computing and Computer Assisted Intervention–MICCAI 2019: 22nd International Conference, Shenzhen, China, October 13–17, 2019, Proceedings, Part II. Springer International Publishing; 2019.
51. Eelbode T, et al. Optimization for medical image segmentation: Theory and practice when evaluating with Dice score or Jaccard index. IEEE Transactions on Medical Imaging. 2020;39(11):3679-90.
52. Guarido M, Li J, Cova R. Machine learning in geoscience: Using deep learning to solve the TGS Salt Identification challenge. CREWES Research Report. 2018;30:14.1–14.12.
53. Liu B, et al. Image segmentation of salt deposits using deep convolutional neural network. In: 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC). IEEE; 2019.
54. Chung Y, Lu W, Tian X. Interactive segmentation using prior knowledge-based distance map. In: 2021 8th International Conference on Information, Cybernetics, and Computational Social Systems (ICCSS). IEEE; 2021.