IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, July 2026
Impact Factor: 8.2

U-Net Based Salt Segmentation Using Deep Learning for Seismic Image Analysis

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Abstract: *Accurate salt segmentation from seismic images plays a vital role in petroleum exploration and geological interpretation. This paper presents a U-Net Based Salt Segmentation system that automatically detects and segments salt regions using deep learning. The proposed model is implemented using the PyTorch framework and trained on the TGS Salt Identification Challenge Dataset. The U-Net architecture performs pixel-level semantic segmentation through an encoder-decoder network with skip connections, enabling precise identification of salt structures. In addition to segmentation, the system provides quantitative analysis, including salt coverage, salt body count, prediction confidence, and uncertainty estimation. It also generates visualization outputs such as the predicted mask, overlay image, probability heatmap, uncertainty map, and three-dimensional visualization of segmented salt regions. An automatic PDF report generation module summarizes the prediction results and analytical information into a structured report. Experimental results demonstrate that the proposed system provides accurate, reliable, and efficient salt segmentation, reducing manual interpretation effort and supporting improved geological decision-making.*

Keywords: U-Net, Deep Learning, Salt Segmentation, Seismic Images, PyTorch, TGS Salt Dataset, 3D Visualization, Automatic Report Generation.

1. INTRODUCTION

Seismic imaging plays a crucial role in petroleum exploration by providing information about underground geological formations. Accurate identification of salt structures is challenging because salt bodies distort seismic waves and make manual interpretation difficult and time-consuming. Traditional methods rely on expert geologists, increasing both analysis time and operational cost.

Deep learning has significantly improved image segmentation, with the U-Net architecture becoming one of the most effective models for semantic segmentation due to its encoder-decoder structure and skip connections. In this work, a U-Net Based Salt Segmentation system is proposed to automatically detect and segment salt regions from seismic images using the TGS Salt Identification Challenge Dataset. The system also performs quantitative analysis, generates visualization outputs, including 3D visualization, and automatically creates a PDF report containing segmentation results and geological interpretation.

A. Contributions

The major contributions of the proposed work are:

- Developed a U-Net-based deep learning model for automatic salt segmentation.
- Performed quantitative analysis, including salt coverage, salt body count, confidence, and uncertainty estimation.
- Generated visualization outputs such as overlay images, heatmaps, histograms, and 3D visualization.
- Implemented automatic PDF report generation for comprehensive result documentation.
- Developed a Streamlit-based web application for easy image upload, segmentation, visualization, and report download.

The proposed system combines deep learning, visualization, quantitative analysis, and automated reporting into a single application, providing an efficient and user-friendly solution for seismic image interpretation.

II. LITERATURE SURVEY AND RESEARCH GAP

Deep learning has significantly improved semantic image segmentation and has been widely applied in medical imaging, remote sensing, and seismic interpretation. Among various approaches, the U-Net architecture has become one of the most effective models due to its encoder-decoder structure and skip connections, which enable accurate pixel-level segmentation even with limited training data.

Several researchers have enhanced U-Net by incorporating attention mechanisms, residual learning, transfer learning, and data augmentation techniques to improve segmentation accuracy and model generalization. Recent studies have also introduced uncertainty estimation and Test-Time Augmentation (TTA) to increase the reliability of prediction results.

Despite these advancements, most existing methods primarily focus on generating segmentation masks and provide limited support for further analysis. Features such as quantitative salt analysis, confidence estimation, uncertainty visualization, three-dimensional visualization, and automatic report generation are rarely integrated into a single system.

Research Gap

From the reviewed literature, it's miles glaring that modern-day salt segmentation structures in particular emphasize enhancing prediction accuracy even as imparting restrained guide for end result interpretation. Most to be had techniques require customers to manually examine segmentation outputs and put together reviews separately. Furthermore, many current answers lack interactive visualization and user-pleasant interfaces that simplify geological interpretation.

The proposed U-Net Based Salt Segmentation gadget addresses those obstacles through integrating computerized salt segmentation with complete quantitative evaluation, prediction self belief estimation, uncertainty visualization, third-dimensional visualization, geological interpretation, and automated PDF document era. By combining those talents right into a unmarried application, the gadget minimizes guide effort, improves usability, and presents a entire framework for seismic picture evaluation appropriate for sensible geological packages.

III. PROPOSED SYSTEM

The proposed U-Net Based Salt Segmentation system is designed to automatically identify and segment salt structures from seismic images using deep learning. It integrates image preprocessing, U-Net-based segmentation, quantitative analysis, visualization, geological interpretation, and automatic PDF report generation into a single workflow.

The system accepts a seismic image through a Streamlit-based interface, where the image is preprocessed and passed to the trained U-Net model to generate a binary salt segmentation mask. The predicted output is then analyzed to calculate salt coverage, salt body count, prediction confidence, and uncertainty estimation using Test-Time Augmentation (TTA).

To improve interpretation, the system generates visualization outputs such as the predicted mask, overlay image, probability heatmap, uncertainty heatmap, histogram, and 3D visualization of the detected salt structures. Finally, all prediction results and analytical information are compiled into an automatically generated PDF report for easy documentation.

A. Advantages of the Proposed System

- Automatic pixel-level salt segmentation using the U-Net model.
- Quantitative analysis including salt coverage, salt body count, confidence, and uncertainty estimation.
- Multiple visualization outputs, including 3D visualization.
- Automatic PDF report generation.

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• Interactive Streamlit-based web application for easy image upload and result visualization.

The proposed system provides an efficient and user-friendly solution for seismic image interpretation by combining segmentation, analysis, visualization, and automated reporting within a single application.

IV. METHODOLOGY

The proposed U-Net Based Salt Segmentation system follows a structured workflow for identifying and analyzing salt structures from seismic images. The process includes data preprocessing, U-Net model training, salt segmentation, prediction analysis, visualization, geological interpretation, and automatic report generation.

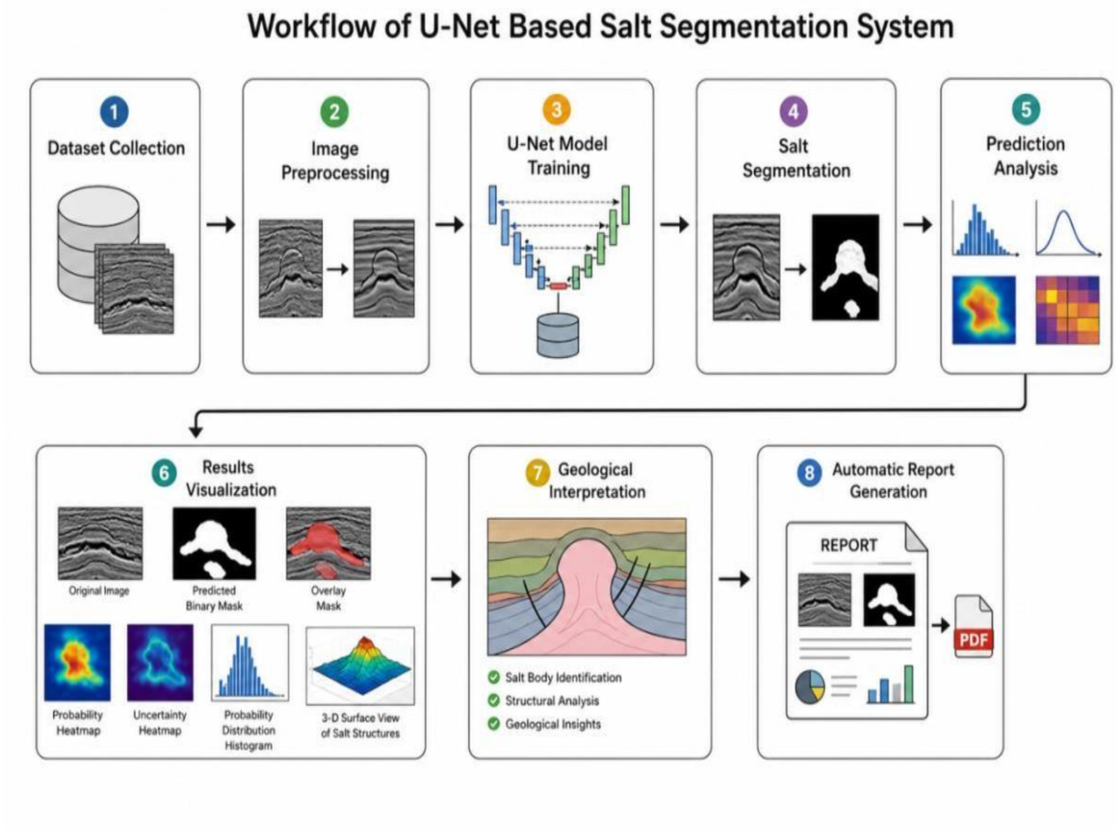

Figure 1.Workflow of the Proposed U-Net Based Salt Segmentation System

A. Dataset Preparation

The model is trained using the TGS Salt Identification Challenge Dataset, which contains grayscale seismic images and corresponding binary masks. The dataset is divided into training and testing sets for model development and evaluation.

B. Image Preprocessing

Input seismic images are resized to 128 × 128 pixels, normalized, and converted into tensor format before being provided to the U-Net model.

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C. U-Net Model Development

The U-Net architecture performs pixel-level semantic segmentation using an encoder-decoder network with skip connections. The model is trained using the Binary Cross-Entropy loss function and the Adam optimizer.

D. Salt Segmentation and Analysis

The trained model generates a binary salt mask from the input image. The system then calculates salt coverage, salt body count, prediction confidence, and uncertainty estimation using Test-Time Augmentation (TTA).

E. Visualization and Report Generation

The system generates visualization outputs, including the predicted mask, overlay image, heatmaps, histogram, and 3D visualization. It also creates an automatic PDF report containing the segmentation results, analysis, and geological interpretation.

Workflow:

Seismic Image → Preprocessing → U-Net Segmentation → Quantitative Analysis → Visualization → Automatic PDF Report Generation

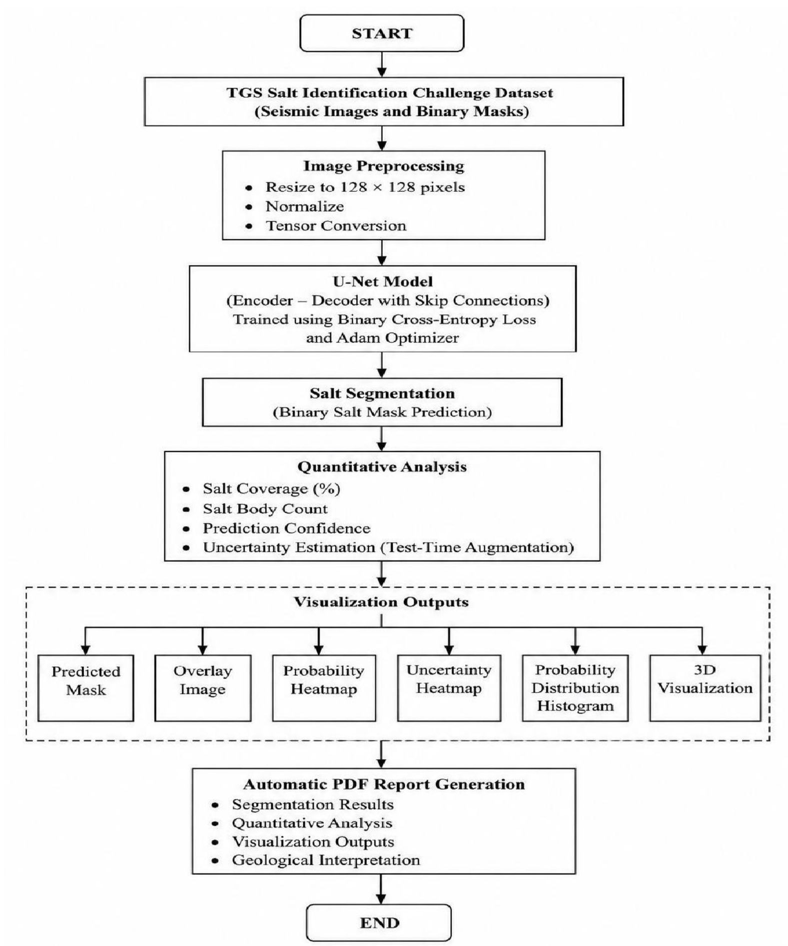

Figure. 2. Methodology of the Proposed U-Net Based Salt Segmentation System.

DOI: 10.48175/IJARSCT-37880

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V. SYSTEM ARCHITECTURE AND DESIGN

The proposed U-Net Based Salt Segmentation system follows a modular architecture that integrates image preprocessing, deep learning-based segmentation, quantitative analysis, visualization, and automatic report generation into a single workflow. The architecture consists of five major modules: User Interface, Image Preprocessing, U-Net Segmentation, Analysis and Visualization, and Report Generation.

The workflow begins when the user uploads a seismic image through the Streamlit-based web interface. The uploaded image is validated, resized to the required input size, normalized, and converted into tensor format before being passed to the trained U-Net model for prediction.

The U-Net segmentation model forms the core of the system. It uses an encoder-decoder architecture with skip connections to extract image features and generate an accurate binary segmentation mask representing the detected salt regions. The skip connections preserve spatial information, resulting in better localization of salt boundaries.

After segmentation, the predicted mask is processed by the analysis module, which calculates important parameters such as salt coverage percentage, number of salt bodies, prediction confidence, and uncertainty estimation using Test-Time Augmentation (TTA). These values help evaluate the quality and reliability of the segmentation results.

The visualization module generates several outputs, including the predicted mask, overlay image, probability heatmap, uncertainty heatmap, histogram, and 3D visualization, enabling users to interpret the detected salt structures more effectively. Finally, the report generation module automatically compiles the segmentation results, analytical statistics, visualizations, and geological interpretation into a structured PDF report that can be downloaded by the user.

System Architecture:

User → Streamlit Interface → Image Preprocessing → U-Net Model → Salt Segmentation → Quantitative Analysis → Visualization → Automatic PDF Report Generation

VI. IMPLEMENTATION

The proposed U-Net Based Salt Segmentation system was implemented using Python by integrating deep learning, image processing, visualization, and report generation modules into a single application.

A. Development Environment

The system was developed using Python and PyTorch for model implementation and training. A Streamlit interface was used for user interaction, while OpenCV, NumPy, Matplotlib, and Pillow were used for image processing and visualization. The application was developed using Visual Studio Code.

B. U-Net Model Implementation

The U-Net model was trained on the TGS Salt Identification Challenge Dataset using seismic images and binary masks. The model employs an encoder-decoder architecture with skip connections and was optimized using the Binary Cross-Entropy loss function and the Adam optimizer.

C. Prediction and Analysis

The uploaded seismic image is preprocessed and passed through the trained model to generate binary salt mask. The system calculates salt coverage, salt body count, prediction confidence, anuncertainty estimation to evaluate the segmentation results.

D. Visualization and Report Generation

The system generates visualization outputs, including the predicted mask, overlay image, probability heatmap, uncertainty heatmap, histogram, and 3D visualization. It also creates an automatic PDF report containing the segmentation results, analysis, and geological interpretation.

E. Performance Evaluation

The proposed model was evaluated using Dice Coefficient, Intersection over Union (IoU), and Precision. The results demonstrate reliable segmentation performance and effective identification of salt structures from seismic images.

VII. RESULTS AND DISCUSSION

The proposed U-Net Based Salt Segmentation system was successfully implemented and evaluated using the TGS Salt Identification Challenge Dataset. The trained U-Net model accurately identified salt regions and generated binary segmentation masks with reliable boundary detection.

The developed application enables users to upload seismic images and obtain segmentation results in real time. It automatically calculates salt coverage, salt body count, prediction confidence, and uncertainty estimation, providing meaningful information about the detected salt structures.

To improve interpretation, the system generates visualization outputs, including the predicted mask, overlay image, probability heatmap, uncertainty heatmap, histogram, and 3D visualization. An automatic PDF report is also generated, summarizing the segmentation results, quantitative analysis, and geological interpretation.

The performance of the proposed model was evaluated using Dice Coefficient, Intersection over Union (IoU), and Precision. The experimental results demonstrate that the system provides accurate and reliable salt segmentation while integrating visualization, quantitative analysis, and automated reporting into a single user-friendly application.

VIII. CONCLUSION AND FUTURE WORK

The proposed U-Net Based Salt Segmentation system was successfully implemented and evaluated using the TGS Salt Identification Challenge Dataset. The trained U-Net model accurately segmented salt regions and generated reliable binary masks from seismic images.

The developed application allows users to upload seismic images and obtain segmentation results in real time. It automatically calculates salt coverage, salt body count, prediction confidence, and uncertainty estimation, providing valuable insights into the detected salt structures.

To improve result interpretation, the system generates visualization outputs such as the predicted mask, overlay image, probability heatmap, uncertainty heatmap, histogram, and 3D visualization. An automatic PDF report is also generated, containing the segmentation results, quantitative analysis, and geological interpretation.

The model was evaluated using Dice Coefficient, Intersection over Union (IoU), and Precision. The experimental results demonstrate that the proposed system provides accurate segmentation, reliable analysis, and an efficient solution for seismic image interpretation.

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