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Lithology Prediction Using Deep Learning Artificial Neural Network and Schlumberger Resistivity Inversion Data at Eastern Lampung

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ABSTRACT
The Schlumberger geoelectric method has been extensively employed in earth resource exploration due to its capability to identify variations in subsurface resistivity. However, the manual interpretation of geoelectric data inversion results is often subjective and time-consuming. This study aims to automate the lithology identification process by utilizing deep learning techniques, particularly Artificial Neural Networks (ANN), based on the inverted resistivity parameters obtained through the IPI2Win software. The Schlumberger configuration geoelectric data were obtained from survey reports provided by the Ministry of Public Works and Housing (Kementerian Pekerjaan Umum dan Perumahan Rakyat/ PUPR), which conducted geoelectric measurements in East Lampung Regency, Lampung Province, Indonesia. The ANN algorithm demonstrated an average accuracy of 90% in predicting lithology based on resistivity patterns resulting from Schlumberger inversion. Outperforming Support Vectorr Machine (SVM) (87%) and XGBoost (88%). These results confirm the initial hypothesis that ANN can effectively capture the complex relationships between resistivity values and rock types. The present study proposes an integrated approach between geophysics and machine learning with ANN algorithms for lithology prediction based on Schlumberger configuration geophysical inversion data. The present study proposes an integrated approach between geophysics and machine learning with ANN algorithms for lithology prediction based on Schlumberger configuration geophysical inversion data.

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1. INTRODUCTION

Lithology is a key parameter in the exploration of geological resources, particularly for identifying rock formations, assessing hydrocarbon potential, and mitigating geohazard risks such as landslides or seawater intrusion. Traditional approaches such as core drilling analysis or data logging have long been used for lithological interpretation. However, these methods have significant limitations, including high costs, lengthy processing times, and subjectivity in interpretation results [1], [2], [3], [4]. Core drilling analysis requires complex physical extraction of rock cores and manual interpretation that is prone to error [5], [6]. Furthermore, conventional geophysical methods, such as Schlumberger resistivity measurements, frequently yield data that is challenging to translate directly into lithological categories without a robust analytical approach [7]. Challenges in lithological interpretation are of particular concern. According to research [8], factors such as local variations, mineralogical composition, and moisture content can influence the results of rock resistivity interpretation. Additionally, geological interpretation challenges were highlighted in Study [9], which demonstrated that inaccuracies in geophysical surveys can lead to engineering issues in building construction in Nigeria. These structural failures were caused by inaccurate interpretations, necessitating better integration between geotechnical and geophysical disciplines in interpreting subsurface characteristic values.Therefore, integrating geophysical methods with machine learning algorithms is an innovative way to improve the accuracy and efficiency of predicting lithology.

Several machine learning approaches have been proposed in previous studies for lithology classification. Study [3] utilized geophysical well-log data from nine wells in an Iranian gas field, comprising 44,521 depth-level records with 11 well-log features and four lithology classes. Study [10] employed the same dataset from two gas hydrate exploration wells in the Alaska North Slope (ANS). The well-log data used in these studies were derived from subsurface geophysical surveys and are publicly available. Input features included Gamma Ray (GR), Bulk Density, Neutron Porosity, Density Porosity, Resistivity, and Compressional Velocity. In addition to well-log data, study [5] incorporated image-based Computed Tomography (CT Scan) datasets obtained from rock core samples. That study classified three lithological types—carbonate, sandstone, and shale—with original image dimensions of 1000×1000 pixels, which were resized to 224×224 pixels to meet the input requirements of the Convolutional Neural Network (CNN) model. According on [3], the development of a Residual Convolutional Neural Network (ResCNN) for the classification of Iranian gas fields has been shown to achieve an F1-score of up to 80%, with a particular emphasis on well-log data. This study highlights the importance of feature interpretation (SHAP) and the stability of models against noise. The findings of research [10] demonstrate that supervised learning algorithms, such as neural networks, exhibit an accuracy of up to 90%, while unsupervised learning methods attain approximately 80%. A similar approach can be developed using inverse resistivity data from Schlumberger surveys. Another study introduced RockDNet, a CNN model for lithology classification based on rock core images. However, this study did not integrate geophysical data such as Schlumberger resistivity [5]. The utilisation of Artificial Neural Networks (ANN) was also examined in study [2], which employed core drilling data to identify lithofacies with an accuracy of 88.2% by leveraging the XGBoost algorithm. Nevertheless, this approach is restricted to structural data and does not take into account geophysical data such as Schlumberger resistivity. Despite the noteworthy advancements, there remain notable lacunae in the amalgamation of Schlumberger geophysical data with ANN models that have been optimized through techniques such as Synthetic Over-Sampling Technique (SMOTE) and K-Fold validation. A prevailing tendency in extant studies has been to concentrate on a solitary form of data, such as well logs and rock core images, while neglecting to leverage the full potential of inverse geophysical data as the primary input [1], [7], [11]. Furthermore, lithological class imbalance is frequently disregarded, leading to prediction bias in minority classes [12]. Although SMOTE has been tested on Support Vector Machines (SVM) by research [3], [10], its application in ANN models for lithological data has not been optimal. This study addresses this gap by creating a lithology prediction model that uses IPI2Win software to analyze Schlumberger geophysical resistivity inversion data for ANN training. This approach is further enhanced by the implementation of the SMOTE technique, which addresses imbalanced classes due to lithology, and K-Fold validation, which ensures stability. SMOTE was selected for its capacity to enhance prediction accuracy in minority classes by generating synthetic examples based on interpolation between minority class samples, as opposed to merely duplicating data [13], [14], [15]. Additionally, we will compare the performance of the ANN with other algorithms, such as SVM and XGBoost. This comparison will provide insight into the relative advantages of each method when working with geophysical data.

This study aims to develop a lithology classification model based on the ANN algorithm, utilizing inverted geoelectrical data from the Schlumberger configuration processed using the IPI2Win software. Geoelectrical resistivity measurements typically provide subsurface resistivity variations that can be correlated with specific lithological units. However, manual lithology classification based on resistivity values is often subjective and time-consuming. Therefore, this research proposes a machine learning-based approach to accelerate the classification process and improve its accuracy. The ANN algorithm was selected due to its capability to model complex, non-linear relationships commonly found in geophysical datasets. Furthermore, to address the issue of class imbalance which can lead to biased predictions and poor model performance the Synthetic Minority Over-sampling Technique (SMOTE) was employed. This technique enhances the representation of minority classes, allowing the model to learn more effectively from all available classes. Model validation was conducted using five-fold cross-validation to assess its robustness, consistency, and generalization ability. The results of this study are expected to contribute to the growing application of machine learning techniques in geophysical exploration, particularly in lithology classification using geoelectrical resistivity data.

2. RESEARCH METHOD

This study uses data from a geophysical survey report in East Lampung Regency, Lampung Province. Electrical resistivity is one geophysical method for studying the electrical resistivity properties of rock layers within the earth [16], [17]. The survey was conducted across 24 subdistricts to determine the distribution of lithology, rock outcrops, slope, and orientation of rock layers (strike and dip), as well as local geological structures. In measurements using the Schlumberger configuration, the survey began with a half-spread AB/2 of 1.5 meters, extending up to 400 meters. When the data were deemed insufficient for interpretation at depths greater than 180 meters, the AB/2 spacing was extended to 600 meters at selected locations. The potential electrode spacing (MN/2) is set at 5% of AB/2, with measurements taken at AB/2 distances of 12, 50, and 300 meters. Based on the survey results, the Schlumberger configuration proved to be the most effective method for geophysical investigation [18]. The Schlumberger configuration is used because it provides the most accurate and effective results in data collection compared to other geophysical methods [19], [20], [21]. A total of 500 measurement points were collected during the geophysical survey. However, this study utilized data from 374 measurement points, which yielded two lithological units: extrusive mafic lava and extrusive intermediate pyroclastic deposits. The use of these lithological categories still provided meaningful contributions to lithological classification based on geophysical data [22].

2.1. Data Collection and Geophysical Survey Methodology

This study uses data from a geophysical survey report in East Lampung Regency, Lampung Province. Electrical resistivity is one geophysical method for studying the electrical resistivity properties of rock layers within the earth [16], [17]. The survey was conducted across 24 subdistricts to determine the distribution of lithology, rock outcrops, slope, and orientation of rock layers (strike and dip), as well as local geological structures. In measurements using the Schlumberger configuration, the survey began with a half-spread AB/2 of 1.5 meters, extending up to 400 meters. When the data were deemed insufficient for interpretation at depths greater than 180 meters, the AB/2 spacing was extended to 600 meters at selected locations. The potential electrode spacing (MN/2) is set at 5% of AB/2, with measurements taken at AB/2 distances of 12, 50, and 300 meters. Based on the survey results, the Schlumberger configuration proved to be the most effective method for geophysical investigation [18]. The Schlumberger configuration is used because it provides the most accurate and effective results in data collection compared to other geophysical methods [19], [20], [21]. A total of 500 measurement points were collected during the geophysical survey. However, this study utilized data from 374 measurement points, which yielded two lithological units: extrusive mafic lava and extrusive intermediate pyroclastic deposits. The use of these lithological categories still provided meaningful contributions to lithological classification based on geophysical data [22].

2.2. Inversion of Schlumberger Sounding Data

Based on the results of the geophysical survey conducted in the field, the obtained data represent apparent resistivity values rather than true resistivity values [16]. Therefore, an inversion process is necessary to generate a representative subsurface resistivity model [21], [23], [24]. Inversion is performed because geophysical observation data does not directly provide information about the physical properties of the subsurface. The inversion process aims to construct a realistic and representative subsurface model that can be used for geological interpretation, resource exploration, or understanding the tectonic structure of an area [19]. The inversion process applied to the data in this study is illustrated in Figure 1.

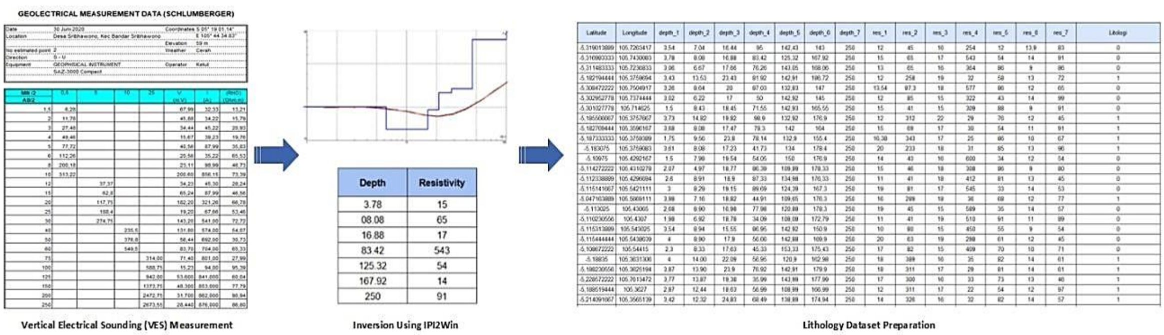


Figure 1. Inversion of Schlumberger Sounding Data

The geophysical measurement process was conducted in the field to obtain apparent resistivity values at various depths. The collected data were then processed through inversion steps using IPI2Win software [23], [24]. The purpose of this inversion stage is to generate a representative accurate resistivity model as a function of depth. This model is the foundation for interpreting subsurface structures and delineating geological layers in the study area [24].

2.3. Multilayer Perceptron (MLP)

The MLP represents a foundational architecture among feedforward neural networks. It comprises multiple fully connected layers of artificial neurons, typically consisting of one or more hidden layers and a final output layer [25], [26], [27]. Each neuron in this layer performs a computation consisting of a weighted sum of the input signals [28]. In the hidden layer, each neuron similarly computes a weighted sum of its inputs, as follows:

$$z_j = \sum_{i=1}^{n} w_{ji} x_i + b_j \tag{1}$$

Where z_j is the pre-activation value of neuron j, w_{ji} is the weight connecting neuron i in the previous layer with neuron j. x_i is the input value of neuron i and b_j is the bias in neuron j, which helps regulate the computation result [29]. After calculating the weighted sum, the result is passed through an activation function to introduce non-linearity into the model. The activation function used in this study is the Rectified Linear Unit (ReLU) [30]. The Rectified Linear Unit (ReLU) activation function is mathematically expressed as $f(z) = (0, z)$. It outputs zero for negative inputs and preserves positive values, which contributes to faster convergence and enhanced stability during neural network training [31], [32].

2.4. Machine Learning Workflow: From Data Preprocessing to Model Evaluation

This study utilized geophysical inversion data obtained from previous surveys as the dataset. The dataset comprises 17 columns that include spatial features, depth parameters, resistivity values, and lithology labels. Spatial features are represented by latitude and longitude coordinates, while seven depth parameters (in meters) correspond to subsurface layers (Depth 1–7). The seven resistivity values (in ohm·m) measured at each depth (Resistivity 1–7) were also used as prominent input features. As classification targets, the Lithology column includes two main volcanic lithology categories: Extrusive mafic lava (0) and Extrusive intermediate pyroclastic (1). This dataset comprises 374 data points selected from an initial set of 500, which had undergone prior validation as part of this study's data quality assurance process. The input features (X) encompass all variables except the Lithology column: latitude, longitude, depth 1–7, and resistivity 1–7. The lithology label (y) is encoded into numerical values using LabelEncoder to meet the ANN model input requirements. In contrast, numerical features are normalized with StandardScaler to ensure data scale uniformity and improve model training convergence [33]. Resistivity and depth serve as essential parameters for characterizing variations in the electrical properties of subsurface rock formations, which play a significant role in lithological identification [34].

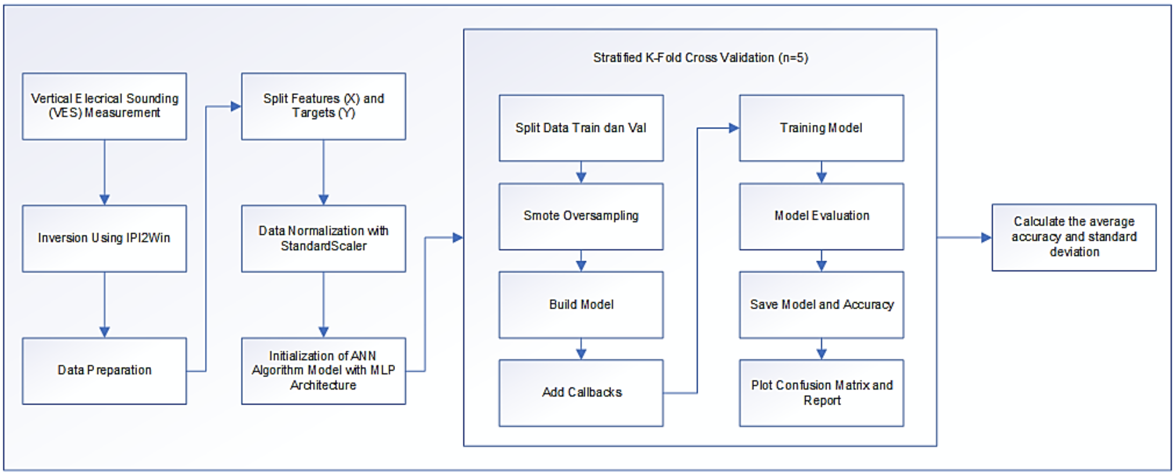


Figure 2. Workflow for Lithology Classification Using MLP

Figure 2 illustrates that the ANN model used in this study was designed based on the MLP architecture, which consists of two hidden layers [35]. The first layer consists of 128 neurons with a ReLU activation function, followed by BatchNormalization and Dropout (dropout rate=0.3), while the second layer has 64 neurons with a similar configuration. The model was compiled with Adam optimization (learning rate=0.001) and accuracy metrics. To address the class imbalance in the training data, the SMOTE was applied in each training iteration. Model validation was performed using the Stratified K-Fold Cross Validation approach (n=5), ensuring that class distribution remained consistent across each data split. During training, the EarlyStopping and ReduceLROnPlateau callbacks were used to prevent overfitting and dynamically adjust the learning rate [36]. The model was trained for 50 epochs with a batch size of 32. Model performance evaluation included accuracy, confusion matrix, and classification report (precision, recall, F1-score). The results showed the average accuracy from 5 folds, with visualization of the confusion matrix for classification error analysis. Each fold stored the best model for potential inference use.

3. RESULT AND ANALYSIS

This study uses geophysical survey data from Schlumberger configuration measurements in the East Lampung region of Lampung Province. The data obtained was then inverted using IPI2Win software to produce subsurface resistivity values. Each dataset is accompanied by lithological information derived from geophysical measurements, such as the latitude and longitude of the measurement area, depth, and resistivity values at each measurement depth. In the data preprocessing stage, lithological classes were coded into numerical values. Additionally, to address data imbalance, the SMOTE was applied to generate synthetic samples in the minority class. Modeling was performed using the ANN algorithm with a MLP approach. Model training was conducted using Adam optimization with a cross-entropy loss function. To evaluate performance and ensure generalization, cross-validation with five folds was applied, and model performance was assessed based on accuracy, precision, recall, and F-1 score metrics. The analysis process began with data collection and data inversion using IPI2Win software. The correlation matrix in Figure 3 was used to identify linear relationships between features that indicate multicollinearity among several variables. Variables res_4, res_5, res_6, and res_7 have a high correlation, while variables depth_3 and depth_4 also show a strong relationship. However, there is a significant negative relationship between the lithology variable and several resistivity variables. The relationships between variables, particularly between lithology and resistivity values, provide important insights into the geological dynamics within the dataset. Selecting the appropriate machine learning algorithm is crucial for subsurface lithology classification. This study employs an ANN algorithm, which handles multicollinearity relatively better than traditional linear models.

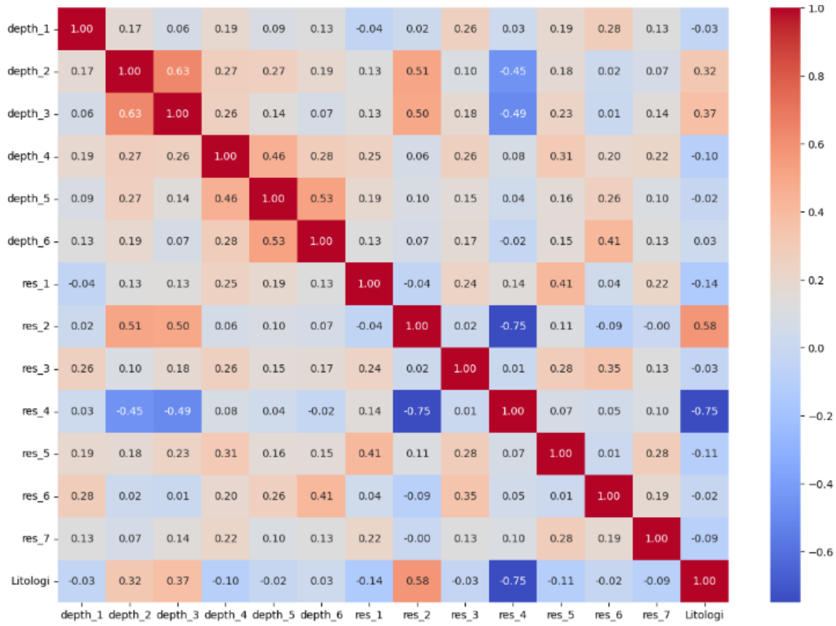
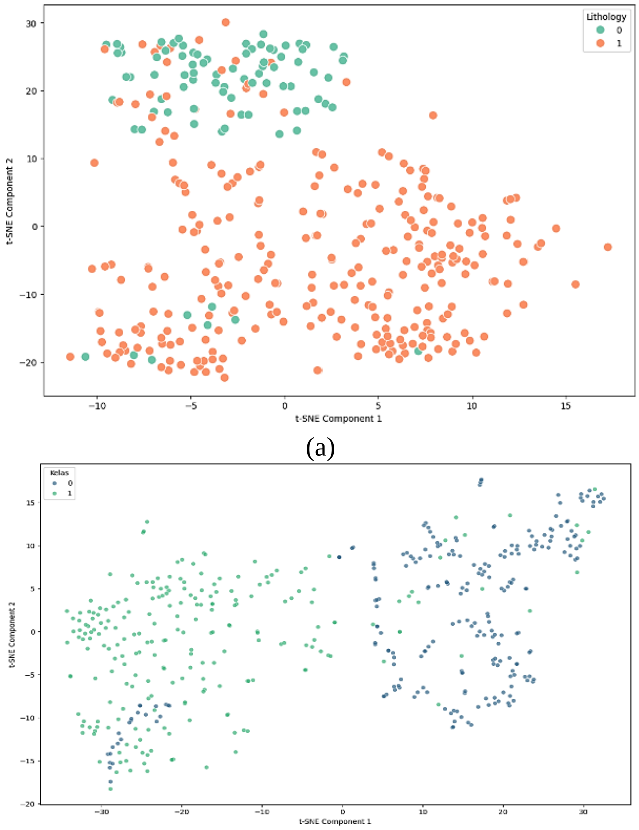


Figure 3. Comparison of Class Distribution Before and After SMOTE Using t-SNE Visualization

This study utilized the ANN algorithm to identify and classify lithological units derived from geoelectrical inversion data. Class distribution was visualized using the t-SNE technique before model training as part of preliminary data analysis. Figure 4 presents visualization results that reveal the spatial distribution of classes and support the assessment of class balancing techniques, such as SMOTE. These methods improved model performance by reducing bias toward majority classes and enhancing generalization. Additionally, feature correlations were examined to ensure input independence. The results demonstrate that machine learning techniques can significantly contribute to subsurface characterization when combined with appropriate preprocessing and interpretation strategies. Furthermore, integrating geological context into feature selection helped improve the relevance and physical interpretability of the classification outcomes. This approach highlights the potential for data-driven models to complement traditional geological analysis in complex subsurface environments. Such integration opens new opportunities for more accurate and efficient subsurface modeling, especially in areas with limited direct observations.



(a)

(b)

Figure 4. Comparison of Class Distribution Before and After SMOTE Using t-SNE Visualization

As shown in Figure 4, panel (a) displays the original class distribution before SMOTE, whereas panel (b) presents the balanced class distribution following SMOTE application. This technique mitigated class imbalance by generating synthetic samples for the minority class, achieving a more uniform distribution across the feature space. However, this also increases the complexity of the data structure, which may hinder class separability by machine learning models. Therefore, tailored approaches such as SMOTE parameter optimization and appropriate algorithm selection are necessary to maximize the effectiveness of this method. The results indicate that SMOTE is an effective method for mitigating class imbalance. Nevertheless, careful application is required to minimize risks such as overfitting and introducing unnecessary data complexity. After observing the distribution of data before and after the application of SMOTE through t-SNE visualization, the next step is to apply a machine learning algorithm using the MLP ANN algorithm. Model validation was carried out using the Stratified K-Fold Cross Validation (n=5) approach, with the results shown in Table 1.

In Table 1, class 0 represents Extrusive: mafic: lava, and class 1 represents Extrusive: intermediate: pyroclastic. Model validation was performed using the Stratified K-Fold Cross Validation approach (n=5). The model consists of two hidden layers with the first layer having 128 neurons and the second layer using 64 neurons to gradually reduce complexity and prevent overfitting, resulting in an average accuracy of 90.65% with a standard deviation of ±1.87%. These results indicate that the ANN model performs excellently and stably, with all folds achieving an accuracy of over 85%. Although minor variations were observed across folds (accuracy range: 88.00%–93.33%), the EarlyStopping and ReduceLROnPlateau callbacks were employed during training to prevent overfitting and enable dynamic learning rate adjustment. The model was configured with the Adam optimizer (learning rate = 0.001) and SMOTE to address class imbalance. Although the ANN algorithm achieved an average accuracy of 90.65%, based on the data in Table 1. There is variation in performance between classes, where Class 1 (Extrusive intermediate pyroclastic) has very high precision and recall values exceeding 90% due to the larger amount of data and dominant resistivity patterns, as well as unique resistivity values. Class 0 (Extrusive mafic lava), although it has a relatively high recall rate, has a lower precision rate, resulting in the model incorrectly predicting some samples. The primary cause of the model's inaccuracy in prediction is that some pyroclastic data overlap, particularly the resistivity values res_4 and res_6. Additionally, vertical and lateral lithological variations in the East Lampung region cause smooth resistivity transitions, making the boundaries between lithological units not always clearly reflected as sharp changes in the resistivity profile. This makes explicit class separation challenging, especially in transition zones. Figure 5 presents the accuracy of each fold in the K-Fold cross-validation.

Table 1. Evaluation Results of the ANN Model with SMOTE Based on 5-Fold Cross-Validation

Fold	Class	SMOTE		Precision	Recall	F1-Score	Support	Accuracy
		Before	After					
1	0	68	231	0.7143	0.8824	0.7895	17	0.8933
	1	231	231	0.9630	0.8966	0.9286	58	
2	0	68	231	0.8333	0.8824	0.8571	17	0.9333
	1	231	231	0.9649	0.9483	0.9565	58	
3	0	68	231	0.7778	0.8235	0.8000	17	0.9067
	1	231	231	0.9474	0.9310	0.9391	58	
4	0	68	231	0.6667	0.9412	0.7805	17	0.8800
	1	231	231	0.9804	0.8621	0.9174	58	
5	0	68	232	0.7619	0.9412	0.8421	17	0.9189
	1	232	232	0.9811	0.9123	0.9455	57	

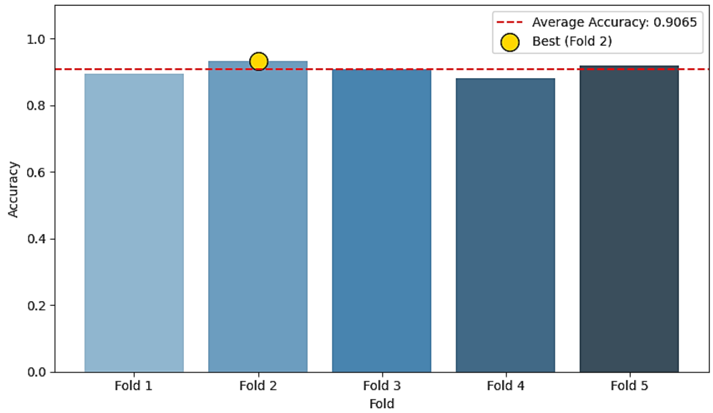


Figure 5. Accuracy of Each Fold in K-Fold Cross Validation

The same dataset was used to evaluate the performance of additional machine learning algorithms, specifically, the SVM and XGBoost, to compare model accuracy and stability in lithology classification based on geoelectrical inversion data. Table 2 presents the average accuracy results for the three algorithms, providing a comparative overview of the effectiveness of the ANN, SVM, and XGBoost on the identical dataset.

Table 2. Comparison of Results Across Machine Learning Algorithms Using the Same Dataset

Model	Precision	Recall	F1-Score	Accuracy
ANN	0.85	0.90	0.87	0.90
SVM	0.82	0.82	0.82	0.87
XGBoost	0.84	0.85	0.84	0.88

According to the results in table 2, the ANN achieved the highest classification performance in lithology identification, with an accuracy of 90% and an F1-score of 0.87. This result surpassed the SVM, which recorded 87% accuracy and an F1-score of 0.82, and XGBoost, which yielded 88% accuracy and an F1-score of 0.84. The effectiveness of ANN can be attributed to its capacity to model complex, non-linear relationships in geophysical features such as depth and resistivity. While SVM and XGBoost provide strong alternatives, the results indicate that ANN offers superior stability and performance in handling imbalanced lithology classification tasks.

Table 3 presents the evaluation results of four machine learning models using geotechnical and drilling data adapted from previous studies. The CNN model achieved an accuracy of 0.90 using drill string vibration data. The DANN model exhibited superior performance, with an accuracy exceeding 0.92, based on RGB image representations of drilling data obtained from an indoor core drilling machine. In comparison, the ANN model achieved a lower accuracy of 0.66 when trained on diamond drilling records. The proposed approach, which leveraged geophysical inversion data from the Schlumberger configuration, attained an accuracy of 0.90, demonstrating its effectiveness for lithology classification. This study's main novelty lies in applying a machine learning model based on geoelectrical inversion data from the Schlumberger configuration for lithology prediction. Unlike models that rely on direct drilling parameters such as vibration or torque, this approach utilizes resistivity values obtained through inversion, which represent subsurface geophysical properties. The dataset exhibits distinct spatial characteristics and vertical resolution compared to those used in previous studies, offering a novel perspective on lithology identification based on geophysical data. This approach opens new possibilities for geophysical surveys to classify rock formation lithology.

Table 3. Comparison of Results with Existing Models from Previous Studies

Model	Dataset	Accuracy	Information
CNN [1]	Drill string vibration data	0.90	This study introduces a new method for real-time identification of rock formation lithology using drill string vibration data obtained during the drilling process.
Deep Artificial Neural Networks (DANN) [2]	Indoor core drilling machine	> 0.92	This research converts drilling data (torque, WOB, rotational speed) into an RGB image-like representation.
ANN [3]	Diamond Drilling Records	0.66	This study uses diamond drilling records, rock samples, and other related reports that prove categorical variables.
Proposed model	Geoelectrical Inversion Data	0.90	This study utilizes Schlumberger-configured geoelectrical data inverted into a structured dataset.

4. CONCLUSION

The study highlights the effectiveness of integrating geoelectrical inversion data from the Schlumberger configuration with an ANN to develop robust lithology prediction models. Using Stratified K-Fold Cross-Validation (k=5), the model achieved an average classification accuracy of 90.65%. The ANN outperformed conventional machine learning algorithms, including SVM and XGBoost, modeling complex, non-linear associations among resistivity parameters, depth, and lithological classes. This performance advantage was maintained even under imbalanced data conditions, where class distribution was adjusted using the SMOTE technique. Unlike prior studies that predominantly utilized drilling records or image-based features, this research employs geoelectrical inversion data generated by IPI2Win as the primary input for model development. This conceptual shift introduces a novel framework for geophysical data-driven lithology classification, offering advantages in terms of speed, cost-efficiency, and objectivity in identifying subsurface rock types. Consequently, this study contributes to advancing artificial intelligence applications in geological resource exploration, particularly in areas with limited direct drilling data. Furthermore, it demonstrates potential as a decision-support tool for subsurface analysis in geophysics and sustainable energy exploration. This research can be further developed using larger datasets from various geographical regions. This will improve the model's generalization ability and enable comprehensive evaluation of the model's performance on various subsurface geologies. To address the common issue of class imbalance in lithology datasets caused by uneven rock type distribution, future research can explore other oversampling techniques. Future developments will deepen the application of Artificial Intelligence in subsurface lithology modeling and support broader applications in automated geological interpretation and sustainable resource exploration.

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