LAMPIRAN

INDONESIAN JOURNAL OF ARTIFICIAL INTELLIGENCE AND DATA MINING
إندونيسيان جورنال أوف الذكاء الاصطناعي واستخراج البيانات
PUZZLE RESEARCH DATA TECHNOLOGY
FAKULTAS SAINS DAN TEKNOLOGI
UNIVERSITAS ISLAM NEGERI SULTAN SYARIF KASIM RIAU
Pusat Riset Data Besar Gdg. Laboratorium Lt. 1 FST Jl. HR. Soebrantas KM. 18 No. 155 Pekanbaru Riau 28293
Telp. /Hp: +6285275359942 Website: http://predatech.uin-suska.ac.id/ijaidm Email: ijaidm@uin-suska.ac.id

LETTER OF ACCEPTANCE

Nomor: RO-FST/U.201005/IJAIDM-PRDT/31/2025

Editor Kepala *Indonesian Journal of Artificial Intelligence and Data Mining* (IJAIDM) *Puzzle Research Data Technology* (Predatech) Fakultas Sains dan Teknologi (FST) UIN Sultan Syarif Kasim Riau, menerangkan bahwa paper dengan:

ID Paper	:	37652
Judul	:	**Lithology Prediction Using Deep Learning (ANN) and Schlumberger Resistivity Inversion Data: A Case Study in Eastern Lampung**
Penulis	:	M. Fitrah Ramadhan, Suhendro Yusuf Irianto, Alhada Farduwin
Korespondensi	:	M. Fitrah Ramadhan
Afiliasi	:	Institute Informatics and Business Darmajaya

Telah Diterima pada *Indonesian Journal of Artificial Intelligence and Data Mining* (IJAIDM) Predatech UIN Sultan Syarif Kasim Riau, dan akan diterbitkan pada Volume 8 Nomor 3 November 2025.

Demikian surat keterangan ini dibuat dengan sebenarnya untuk dapat dipergunakan sebagaimana mestinya.

Pekanbaru, 30 Juni 2025
Editor Kepala

Mustakim, S.T., M.Kom.
NIDN. 2002068801

Fitrah Ramadhan

Lithology Prediction Using Deep Learning Artificial Neural Network and Schlumberger Resistivity Inversion Data at Easte...

Institut Teknologi Sumatera

Document Details

Submission ID

trn:oid:::27385:117730929

Submission Date

Oct 21, 2025, 11:28 AM GMT+7

Download Date

Oct 21, 2025, 11:31 AM GMT+7

File Name

Lithology Prediction Using Deep Learning Artificial Neural Network and Schlumberger Resistivity....pdf

File Size

636.1 KB

10 Pages

6,058 Words

36,362 Characters

13% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

Filtered from the Report

- Bibliography
- Quoted Text
- Cited Text
- Submitted works

Exclusions

- 4 Excluded Matches

Match Groups

65 Not Cited or Quoted 13%
Matches with neither in-text citation nor quotation marks

0 Missing Quotations 0%
Matches that are still very similar to source material

0 Missing Citation 0%
Matches that have quotation marks, but no in-text citation

0 Cited and Quoted 0%
Matches with in-text citation present, but no quotation marks

Top Sources

8% Internet sources

9% Publications

0% Submitted works (Student Papers)

Integrity Flags

0 Integrity Flags for Review

No suspicious text manipulations found.

Our system's algorithms look deeply at a document for any inconsistencies that would set it apart from a normal submission. If we notice something strange, we flag it for you to review.

A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.

Match Groups

- **65** Not Cited or Quoted 13%
  Matches with neither in-text citation nor quotation marks
- **0** Missing Quotations 0%
  Matches that are still very similar to source material
- **0** Missing Citation 0%
  Matches that have quotation marks, but no in-text citation
- **0** Cited and Quoted 0%
  Matches with in-text citation present, but no quotation marks

Top Sources

8% Internet sources
9% Publications
0% Submitted works (Student Papers)

Top Sources

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	Internet	**repository.uinsu.ac.id**	1%
2	Publication	**Khumukcham Robindro Singh, Nazrul Hoque, Arnab Kumar Maji, Sabyasachi Mon...**	<1%
3	Internet	**yamanashi.repo.nii.ac.jp**	<1%
4	Publication	**Yunxin Xie, Liangyu Jin, Chenyang Zhu, Weibin Luo, Qian Wang. "Enhanced cross-...**	<1%
5	Internet	**ar5iv.labs.arxiv.org**	<1%
6	Publication	**Thangaprakash Sengodan, Sanjay Misra, M Murugappan. "Advances in Electrical ...**	<1%
7	Publication	**Amit Lathigara, Nirav Bhatt, Paresh Tanna. "Emerging Perspectives and Applicati...**	<1%
8	Publication	**S.P. Jani, M. Adam Khan. "Applications of AI in Smart Technologies and Manufactu...**	<1%
9	Publication	**Oluwatobi Adeleke, Sina Karimzadeh, Tien-Chien Jen. "Machine Learning-Based M...**	<1%
10	Internet	**www.frontiersin.org**	<1%

11 Publication

Atiqur Rahman Ahad, Sozo Inoue, Guillaume Lopez, Tahera Hossain. "Human Acti... <1%

12 Publication

Lu, Yao. "Exploration of Dimensionality Reduction Techniques for Improving Canc... <1%

13 Internet

ejournal.uin-suska.ac.id <1%

14 Internet

openjicareport.jica.go.jp <1%

15 Publication

Dinesh Goyal, Bhanu Pratap, Sandeep Gupta, Saurabh Raj, Rekha Rani Agrawal, I... <1%

16 Internet

www.irjmets.com <1%

17 Publication

Sanisa Trakulmututa, Khin Than Win. "Machine learning in orthodontics: Transfor... <1%

18 Internet

fs.unm.edu <1%

19 Internet

theses.liacs.nl <1%

20 Internet

www.saiie.co.za <1%

21 Internet

journal.uad.ac.id <1%

22 Internet

www.jurnal.iaii.or.id <1%

23 Publication

Chairani -, Suhendro Y. Irianto, Sri Karnila, Adimas -. "Fuzzy Deep Learning Appro... <1%

24 Publication

Pamidi Venkata Durga Kannaiah, Neetish Kumar Maurya. "Machine learning appr... <1%

25	Publication	S.J. Xavier Savarimuthu, Sivakannan Subramani, Alex Noel Joseph Raj. "Artificial I...	<1%
26	Internet	www.icicel.org	<1%
27	Internet	www.sciencegate.app	<1%
28	Publication	Arvind Dagur, Karan Singh, Pawan Singh Mehra, Dhirendra Kumar Shukla. "Artific...	<1%
29	Publication	Gil G. Correia, Denis J. Schiozer. "Reservoir characterization using electrofacies an...	<1%
30	Publication	H.L. Gururaj, Francesco Flammini, J. Shreyas. "Data Science & Exploration in Artifi...	<1%
31	Internet	eprints.lse.ac.uk	<1%
32	Internet	ijsrcseit.com	<1%
33	Internet	jisem-journal.com	<1%
34	Internet	journalofbigdata.springeropen.com	<1%
35	Internet	kth.diva-portal.org	<1%
36	Internet	media.neliti.com	<1%
37	Internet	pmc.ncbi.nlm.nih.gov	<1%
38	Internet	repository.ipmi.ac.id	<1%

39 Internet

repository.unsri.ac.id <1%

40 Internet

www.coursehero.com <1%

41 Publication

Tsair-Fwu Lee, Jun-Ping Shiau, Chia-Hui Chen, Wen-Ping Yun et al. "A Machine Lea... <1%

42 Publication

Augustine Uhunoma Osarogiagbon, Faisal Khan, Ramachandran Venkatesan, Pau... <1%

43 Publication

Fatih Gurcan. "Linear B-cell epitope prediction for SARS and COVID-19 vaccine des... <1%

Indonesian Journal of Artificial Intelligence and Data Mining (IJAIDM)
Vol. 8, No. 2, July 2025, pp. 427 – 436
p-ISSN: 2614-3372 | e-ISSN: 2614-6150

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

[1*]M. Fitrah Ramadhan, [2]Suhendro Yusuf Irianto, [3]Alhada Farduwin
[1,2]Departement of Informatics, Institute Informatics and Business Darmajaya, Indonesia
[3]Faculty of Industrial Technology, Institut Teknologi Sumatera, Indonesia
Email: [1]mfitrah999@gmail.com, [2]suhendro@darmajaya.ac.id, [3]alhada.farduwin@tg.itera.ac.id

Article Info
Article history:
Received Jun 3rd, 2025
Revised Jul 15th, 2025
Accepted Jul 31th, 2025

Keyword:
Artificial Neural Network
Deep Learning
Lithology Prediction
Schlumberger Geoelectric

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.

Corresponding Author:
M. Fitrah Ramadhan,
Departement of Informatics, Institute Informatics and Business Darmajaya,
Institute Informatics and Business Darmajaya,
JL. Zainal Abidin Pagar Alam no 93, Bandar Lampung, Lampung, Indonesia.
Email: mfitrah999@gmail.com

DOI: http://dx.doi.org/10.24014/ijaidm.v8i2.37652

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.

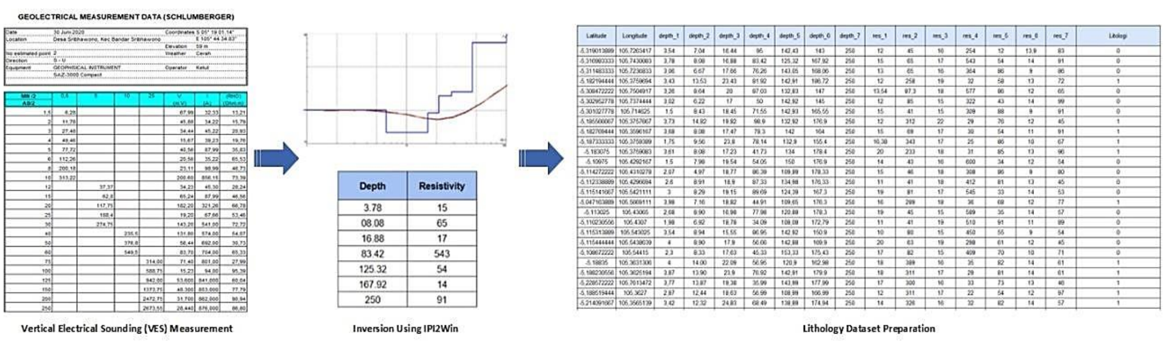


Figure 1. Inversion of Schlumberger Sounding Data

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].

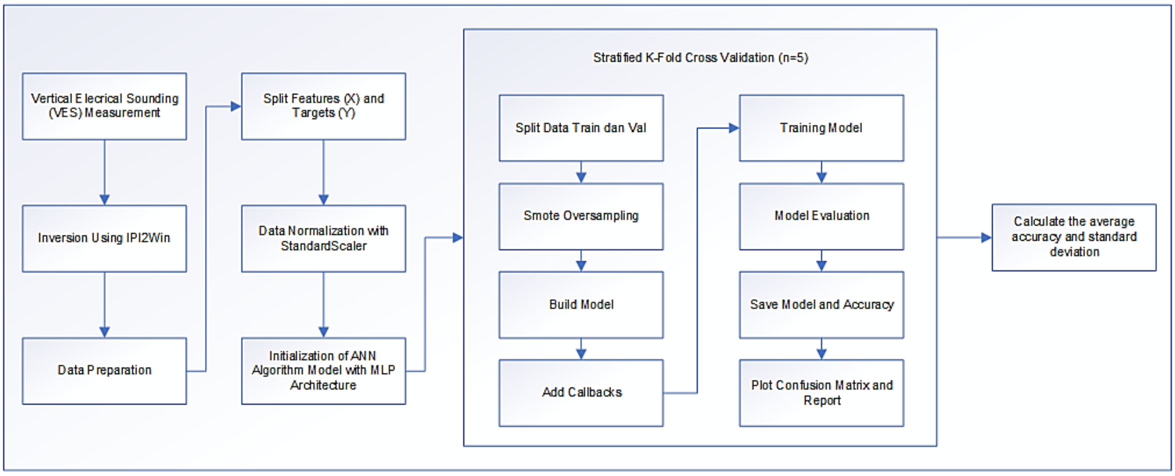


Figure 2. Workflow for Lithology Classification Using MLP

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.

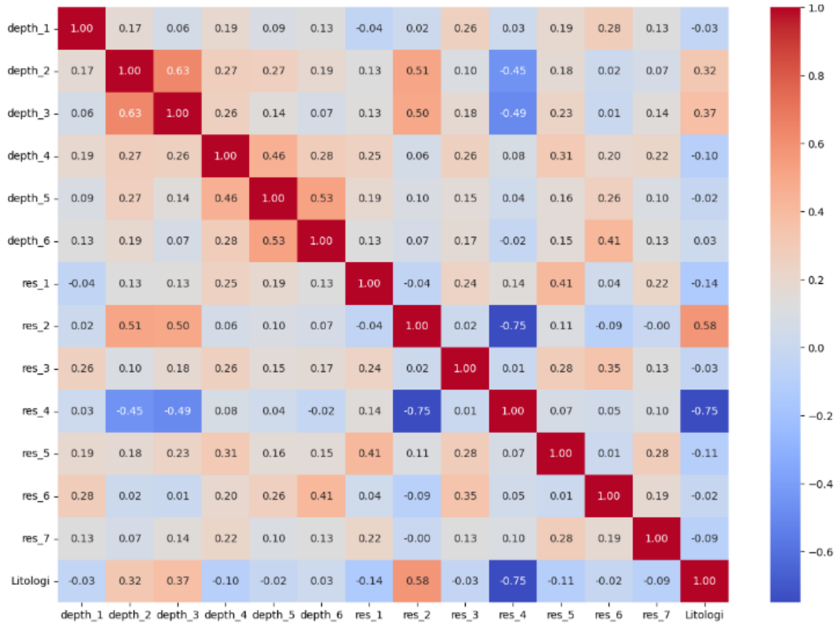
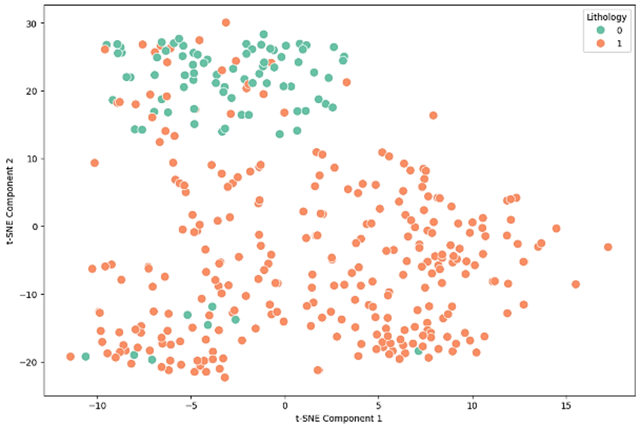


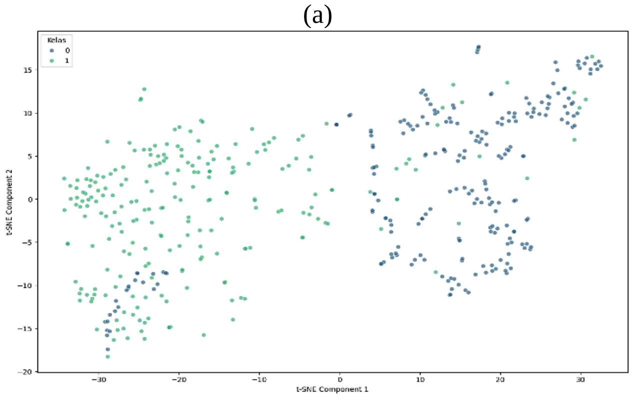
Figure 3. Comparison of Class Distribution Before and After SMOTE Using t-SNE Visualization

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

8 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
22 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
28 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:
10 pyroclastic. Model validation was performed using the Stratified K-Fold Cross Validation approach (n=5).
9 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
15 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	

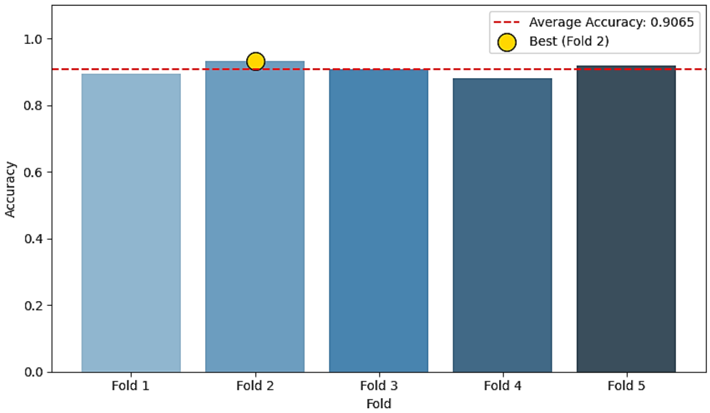


Figure 5. Accuracy of Each Fold in K-Fold Cross Validation

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.

REFERENCES

[1] G. Chen, M. Chen, G. Hong, Y. Lu, B. Zhou, and Y. Gao, "A new method of lithology classification based on convolutional neural network algorithm by utilizing drilling string vibration data," *Energies (Basel)*, vol. 13, no. 4, 2020, doi: 10.3390/en13040888.

[2] M. Yang, Y. Hu, B. Liu, L. Wang, Z. Zhou, and M. Jia, "Application of Artificial Neural Networks for Identification of Lithofacies by Processing of Core Drilling Data," *Applied Sciences (Switzerland)*, vol. 13, no. 21, Nov. 2023, doi: 10.3390/app132111934.

[3] S. H. R. Mousavi and S. M. Hosseini-Nasab, "Residual Convolutional Neural Network for Lithology Classification: A Case Study of an Iranian Gas Field," *Int J Energy Res*, vol. 2024, 2024, doi: 10.1155/2024/5576859.

[4] H. Liang, H. Chen, J. Guo, J. Bai, and Y. Jiang, "Research on lithology identification method based on mechanical specific energy principle and machine learning theory," *Expert Syst Appl*, vol. 189, Mar. 2022, doi: 10.1016/j.eswa.2021.116142.

[5] M. A. M. Abdullah, A. A. Mohammed, and S. R. Awad, "RockDNet: Deep Learning Approach for Lithology Classification," *Applied Sciences (Switzerland)*, vol. 14, no. 13, Jul. 2024, doi: 10.3390/app14135511.

[6] D. Fu, C. Su, W. Wang, and R. Yuan, "Deep learning based lithology classification of drill core images," *PLoS One*, vol. 17, no. 7 July, Jul. 2022, doi: 10.1371/journal.pone.0270826.

[7] R. S. Permana, A. P. Buana, A. Akmam, H. Amir, and A. Putra, "Using the Schlumberger configuration resistivity geoelectric method to estimate the rock structure at landslide zone in Malalak agam," in *Journal of Physics: Conference Series*, Institute of Physics Publishing, May 2020. doi: 10.1088/1742-6596/1481/1/012034.

[8] A. A. Sembiring and A. Akmam, "Damping Factors in the Interpretation of Geoelectric Data (Case Study: Malalak Agam Rock Structure)," *ALSYSTECH Journal of Education Technology*, vol. 2, no. 2, pp. 141–159, May 2024, doi: 10.58578/alsystech.v2i2.3082.

[9] K. D. Oyeyemi *et al.*, "Geoengineering site characterization for foundation integrity assessment," *Cogent Eng*, vol. 7, no. 1, Jan. 2020, doi: 10.1080/23311916.2020.1711684.

[10] H. Singh, Y. Seol, and E. M. Myshakin, "Automated Well-Log Processing and Lithology Classification by Identifying Optimal Features through Unsupervised and Supervised Machine-Learning Algorithms," *SPE Journal*, vol. 25, no. 5, pp. 2778–2800, Oct. 2020, doi: 10.2118/202477-PA.

[11] A. Singh, M. Ojha, and K. Sain, "Predicting lithology using neural networks from downhole data of a gas hydrate reservoir in the Krishna-Godavari basin, eastern Indian offshore," *Geophys J Int*, vol. 220, no. 3, pp. 1813–1837, Mar. 2020, doi: 10.1093/gji/ggz522.

[12] J. J. Marquina-Araujo *et al.*, "Application of Multilayer Perceptron Neural Network in Geological Modeling of Categorical Variables: A Case Study in Peru," *Mathematical Modelling of Engineering Problems*, vol. 11, no. 6, pp. 1463–1472, Jun. 2024, doi: 10.18280/mmep.110607.

[13] F. Gurcan and A. Soylu, "Learning from Imbalanced Data: Integration of Advanced Resampling Techniques and Machine Learning Models for Enhanced Cancer Diagnosis and Prognosis," *Cancers (Basel)*, vol. 16, no. 19, Oct. 2024, doi: 10.3390/cancers16193417.

[14] N. Nnamoko and I. Korkontzelos, "Efficient treatment of outliers and class imbalance for diabetes prediction," *Artif Intell Med*, vol. 104, Apr. 2020, doi: 10.1016/j.artmed.2020.101815.

[15] M. Koziarski, "Potential Anchoring for imbalanced data classification," *Pattern Recognit*, vol. 120, Dec. 2021, doi: 10.1016/j.patcog.2021.108114.

[16] W. M. (William M. Telford 1917-1997, *Applied geophysics*. Second edition. Cambridge [England] ; New York : Cambridge University Press, 1990., 1990. [Online]. Available: https://search.library.wisc.edu/catalog/999608560002121

[17] J. M. Reynolds, *An introduction to applied and environmental geophysics*. Chichester ; New York : John Wiley, 1997., 1997. [Online]. Available: https://search.library.wisc.edu/catalog/999809641902121

[18] M. A. Mohammed, N. M. Muztaza, and R. Saad, "The influence of non-collinear electrodes arrangement on a two-dimensional resistivity survey using wenner array," in *Journal of Physics: Conference Series*, IOP Publishing Ltd, Mar. 2021. doi: 10.1088/1742-6596/1825/1/012012.

[19] Y. Palimbong, M. Arisalwadi, E. Agustriani, J. D. Anggraeni, and Kusnadi, "Interpretation of surface structure on artisanal and small scale gold mining areas with geoelectric resistivity method of schlumberger configuration in Sekotong, West Lombok," in *IOP Conference Series: Earth and Environmental Science*, Institute of Physics Publishing, Jan. 2020. doi: 10.1088/1755-1315/413/1/012007.

[20] T. Dahlin and B. Zhou, "A numerical comparison of 2D resistivity imaging with 10 electrode arrays," 2004.

[21] O. R. Hermawan and D. P. Eka Putra, "The Effectiveness of Wenner-Schlumberger and Dipole-dipole Array of 2D Geoelectrical Survey to Detect The Occurring of Groundwater in the Gunung Kidul Karst Aquifer System, Yogyakarta, Indonesia," *Journal of Applied Geology*, vol. 1, no. 2, p. 71, Jul. 2016, doi: 10.22146/jag.26963.

[22] B. Mirzaei, B. Nikpour, and H. Nezamabadi-pour, "CDBH: A clustering and density-based hybrid approach for imbalanced data classification," *Expert Syst Appl*, vol. 164, Feb. 2021, doi: 10.1016/j.eswa.2020.114035.

[23] K. Kalaivanan, B. Gurugnanam, M. Suresh, Karung Phaisonreng Kom, and S. Kumaravel, "Geoelectrical resistivity investigation for hydrogeology conditions and groundwater potential zone mapping of Kodavanar sub-basin, southern India," *Sustain Water Resour Manag*, vol. 5, no. 3, pp. 1281–1301, Sep. 2019, doi: 10.1007/s40899-019-00305-6.

[24] J. S. Ejepu, M. O. Jimoh, S. Abdullahi, I. A. Abdulfatai, S. T. Musa, and N. J. George, "Geoelectric analysis for groundwater potential assessment and aquifer protection in a part of Shango, North-Central Nigeria," *Discover Water*, vol. 4, no. 1, Jun. 2024, doi: 10.1007/s43832-024-00091-z.

[25] G. S. Lumacad and R. A. Namoco, "Multilayer Perceptron Neural Network Approach to Classifying Learning Modalities Under the New Normal," Aug. 2022. doi: 10.36227/techrxiv.20428230.v1.

[26] J. Zhang, T. Wang, Z. Zhang, P. Yan, and X. Li, "QiMLP: Quantum-inspired Multilayer Perceptron with Strong Correlation Mining and Parameter Compression," 2025. [Online]. Available: www.aaai.org

[27] A. Fierravanti, L. Balducci, and T. Fonseca, "Cork Oak Regeneration Prediction Through Multilayer Perceptron Architectures," *Forests*, vol. 16, no. 4, Apr. 2025, doi: 10.3390/f16040645.

[28] A. Tashakkori, M. Talebzadeh, F. Salboukh, L. Deshmukh, and H. Talebzadeh, "Forecasting Gold Prices with MLP Neural Networks: A Machine Learning Approach," *International Journal of Science and Engineering Applications*, Jul. 2024, doi: 10.7753/ijsea1308.1003.

[29] K. A. Rashedi, M. T. Ismail, S. Al Wadi, A. Serroukh, T. S. Alshammari, and J. J. Jaber, "Multi-Layer Perceptron-Based Classification with Application to Outlier Detection in Saudi Arabia Stock Returns," *Journal of Risk and Financial Management*, vol. 17, no. 2, Feb. 2024, doi: 10.3390/jrfm17020069.

[30] O. W. Layton, S. Peng, and S. T. Steinmetz, "ReLU, Sparseness, and the Encoding of Optic Flow in Neural Networks," *Sensors*, vol. 24, no. 23, Dec. 2024, doi: 10.3390/s24237453.

[31] R. K. Vasanthakumari, R. V. Nair, and V. G. Krishnappa, "Improved learning by using a modified activation function of a Convolutional Neural Network in multi-spectral image classification," *Machine Learning with Applications*, vol. 14, p. 100502, Dec. 2023, doi: 10.1016/j.mlwa.2023.100502.

[32] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *J Big Data*, vol. 8, no. 1, Dec. 2021, doi: 10.1186/s40537-021-00444-8.
[33] N. Susanto and H. F. Pardede, "Feature Learning using Deep Variational Autoencoder for Prediction of Defects in Car Engine," in *Proceeding - 2024 International Conference on Information Technology Research and Innovation, ICITRI 2024*, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 311–316. doi: 10.1109/ICITRI62858.2024.10699115.
[34] A. White *et al.*, "Assessing the effect of offline topography on electrical resistivity measurements: insights from flood embankments," *Geophys J Int*, Sep. 2024, doi: 10.1093/gji/ggae313.
[35] J. Ważny, M. Stefaniuk, and A. Cygal, "Estimation of electrical resistivity using artificial neural networks: a case study from Lublin Basin, SE Poland," *Acta Geophysica*, vol. 69, no. 2, pp. 631–642, Apr. 2021, doi: 10.1007/s11600-021-00554-0.
[36] Y. Bai *et al.*, "Understanding and Improving Early Stopping for Learning with Noisy Labels Supplementary A Training details," 2021.

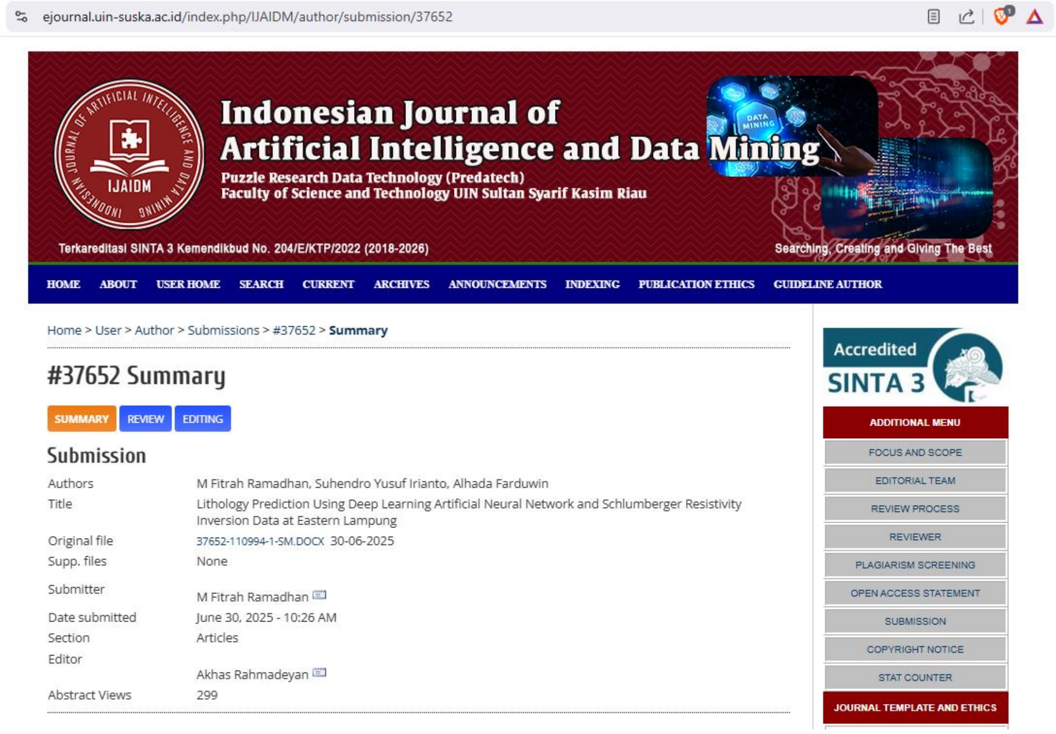
BIBLIOGRAPHY OF AUTHORS

M. Fitrah Ramadhan is a graduate student in the Master Program in Computer Science at the Darmajaya Institute of Information Technology and Business (IIB Darmajaya), Bandar Lampung. His research interests include Artificial Intelligence and Machine Learning, their applications in decision-making systems and intelligent data analysis, and their interconnection with Software Engineering. He is actively involved in developing technology solutions based on artificial intelligence and participates in various research projects to produce practical innovations in the digital world.

Suhendro Yusuf Irianto is a lecturer in the Master of Information Technology Program at the Darmajaya Institute of Information Technology and Business (IIB Darmajaya) in Bandar Lampung. His research interests include Artificial Intelligence and Machine Learning and their applications in decision-making systems and intelligent data analysis. He has published several articles in national and international journals on using artificial intelligence technology for practical solutions across various fields. As an educator, he actively mentors graduate students in developing innovative AI-based research projects.

Alhada Farduwin is a lecturer in the Geophysical Engineering Study Program at the Institut Teknologi Sumatera (ITERA) in Lampung. His areas of expertise include seismic and rock physics, focusing on applying geophysical methods in natural resource exploration and subsurface characterization for geotechnical applications. He is actively involved in research to develop seismic interpretation techniques, rock physical property analysis, and earth structure evaluation relevant to energy exploration and geotechnical risk mitigation.

LAMPIRAN BUKTI SUBMIT JURNAL



ejournal.uin-suska.ac.id/index.php/IJAIDM/author/submission/37652

Indonesian Journal of Artificial Intelligence and Data Mining

Puzzle Research Data Technology (Predatech)
Faculty of Science and Technology UIN Sultan Syarif Kasim Riau

Terkareditasi SINTA 3 Kemendikbud No. 204/E/KTP/2022 (2018-2026)

Searching, Creating and Giving The Best

HOME ABOUT USER HOME SEARCH CURRENT ARCHIVES ANNOUNCEMENTS INDEXING PUBLICATION ETHICS GUIDELINE AUTHOR

Home > User > Author > Submissions > #37652 > **Summary**

#37652 Summary

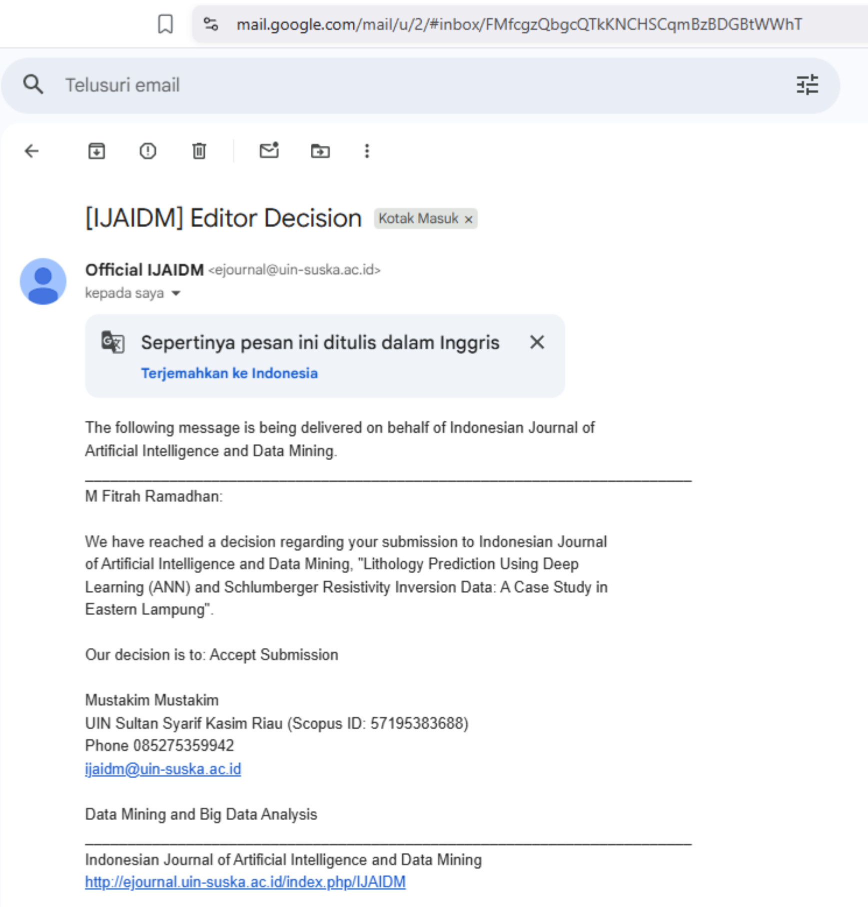
SUMMARY REVIEW EDITING

Submission

Authors	M Fitrah Ramadhan, Suhendro Yusuf Irianto, Alhada Farduwin
Title	Lithology Prediction Using Deep Learning Artificial Neural Network and Schlumberger Resistivity Inversion Data at Eastern Lampung
Original file	37652-110994-1-SM.DOCX 30-06-2025
Supp. files	None
Submitter	M Fitrah Ramadhan
Date submitted	June 30, 2025 - 10:26 AM
Section	Articles
Editor	Akhas Rahmadeyan
Abstract Views	299

Accredited SINTA 3

ADDITIONAL MENU
FOCUS AND SCOPE
EDITORIAL TEAM
REVIEW PROCESS
REVIEWER
PLAGIARISM SCREENING
OPEN ACCESS STATEMENT
SUBMISSION
COPYRIGHT NOTICE
STAT COUNTER
JOURNAL TEMPLATE AND ETHICS



mail.google.com/mail/u/2/#inbox/FMfcgzQbgcQTkKNCHSCqmBzBDGBtWWhT

Telusuri email

[IJAIDM] Editor Decision Kotak Masuk

Official IJAIDM <ejournal@uin-suska.ac.id>
kepada saya

Sepertinya pesan ini ditulis dalam Inggris
Terjemahkan ke Indonesia

The following message is being delivered on behalf of Indonesian Journal of Artificial Intelligence and Data Mining.

M Fitrah Ramadhan:

We have reached a decision regarding your submission to Indonesian Journal of Artificial Intelligence and Data Mining, "Lithology Prediction Using Deep Learning (ANN) and Schlumberger Resistivity Inversion Data: A Case Study in Eastern Lampung".

Our decision is to: Accept Submission

Mustakim Mustakim
UIN Sultan Syarif Kasim Riau (Scopus ID: 57195383688)
Phone 085275359942
ijaidm@uin-suska.ac.id

Data Mining and Big Data Analysis

Indonesian Journal of Artificial Intelligence and Data Mining
http://ejournal.uin-suska.ac.id/index.php/IJAIDM

LAMPIRAN HASUK REVIEW PAPER

ejournal.uin-suska.ac.id/index.php/IJAIDM/author/submissionReview/37652

#37652 Review

SUMMARY REVIEW EDITING

Submission

Authors	M Fitrah Ramadhan, Suhendro Yusuf Irianto, Alhada Farduwin
Title	Lithology Prediction Using Deep Learning Artificial Neural Network and Schlumberger Resistivity Inversion Data at Eastern Lampung
Section	Articles
Editor	Akhas Rahmadeyan

Peer Review

Round 1

Review Version	37652-110995-2-RV.DOCX 30-06-2025
Initiated	30-06-2025
Last modified	15-07-2025
Uploaded file	Reviewer A 37652-111776-1-RV.PDF 15-07-2025

Editor Decision

Decision	Accept Submission 03-08-2025
Notify Editor	Editor/Author Email Record 03-08-2025
Editor Version	37652-110996-1-ED.DOCX 30-06-2025
Author Version	37652-112011-1-ED.DOCX 19-07-2025 DELETE 37652-112011-2-ED.DOCX 22-07-2025 DELETE
Upload Author Version	Choose File No file chosen Upload

Indonesian Journal of Artificial Intelligence and Data Mining (IJAIDM)
Vol 5, No.1, March 2022, pp. 1 – 10
p-ISSN: 2614-3372 | e-ISSN: 2614-6150

Lithology Prediction Using Deep Learning (ANN) and Schlumberger Resistivity Inversion Data: A Case Study in Eastern Lampung

Article Info

Article history:
Received May 12th, 2019
Revised Jun 20th, 2020
Accepted Jul 26th, 2020

Keyword:
ANN
Lithology Prediction
Schlumberger Geoelectric

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 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.

Corresponding Author:

1. INTRODUCTION (10 PT)

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]. Therefore, integrating geophysical methods with machine learning algorithms is an innovative way to improve the accuracy and efficiency of predicting lithology.

A considerable number of studies have employed machine learning techniques for the purpose of lithology classification. 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 [8] demonstrate that supervised learning algorithms, such as neural networks, exhibit an accuracy of up to 90%, while unsupervised learning

Commented [Pro1]: The introduction is well-structured, starting from the problem statement, transitioning to digital solutions, critically reviewing past studies, and concluding with a clear statement of novelty and contribution.

Commented [Pro2]: The paper clearly outlines that the integration of inverse geophysical data with ANN and class imbalance handling techniques (SMOTE) has not been comprehensively explored in previous research.

Commented [Pro3]: Although the introduction mentions that traditional methods are costly and subjective, it would be stronger if supported with real data or practical examples (e.g., exploration costs or cases of misinterpretation) to emphasize the urgency.

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 artificial neural network (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], [9]. Furthermore, lithological class imbalance is frequently disregarded, leading to prediction bias in minority classes [10]. Although SMOTE has been tested on Support Vector Machines (SVM) by research [3], [8], its application in Artificial Neural Networks (ANN) models for lithological data has not been optimal.

Commented [Pro4]: The review of previous studies is generally informative but quite dense. It would be clearer if organized into subtopics such as: (a). Studies using well-log and core image data (b). CNN and ANN applications. (c). Techniques for handling class imbalance and model validation. (d). Limitations in the use of Schlumberger resistivity data.

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 [11], [12], [13]. 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.

Add paragraph

Commented [Pro5]: While the research direction is clear, it would be better to include a specific sentence stating the study's main objective, such as: *"This study aims to develop a lithology classification model based on ANN using Schlumberger resistivity inversion data, optimized through SMOTE and validated via K-Fold cross-validation."*

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 [14], [15]. 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 [16]. The Schlumberger configuration is used because it provides the most accurate and effective results in data collection compared to other geophysical methods [17], [18], [19]. 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 [20].

Commented [Pro6]: The methodology is quite good and structured

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 [14], [15]. 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 [16]. The Schlumberger configuration is used because it provides the most accurate and effective results in data collection compared to other geophysical methods [17], [18], [19]. 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 [20].

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 [14]. Therefore, an inversion process is necessary to generate a representative subsurface resistivity model [19], [21], [22]. 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 [17]. The inversion process applied to the data in this study is illustrated in Figure 1.

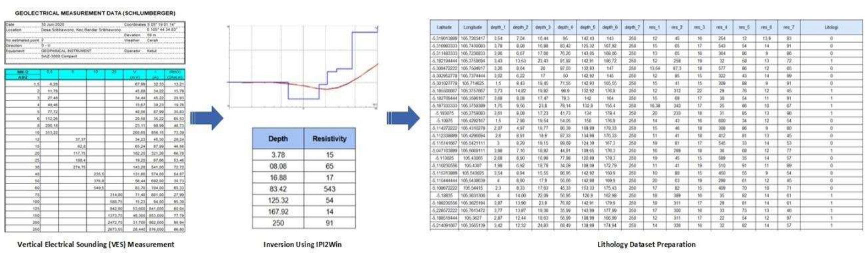


Figure 1. Inversion of Schlumberger Sounding Data

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 [21], [22]. 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 [22].

2.3. Multilayer Perceptron (MLP)

The Multilayer Perceptron (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 [23], [24], [25]. Each neuron in this layer performs a computation consisting of a weighted sum of the input signals [26]. 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 [27]. 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) [28]. 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 [29], [30].

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 [31]. 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 [32].

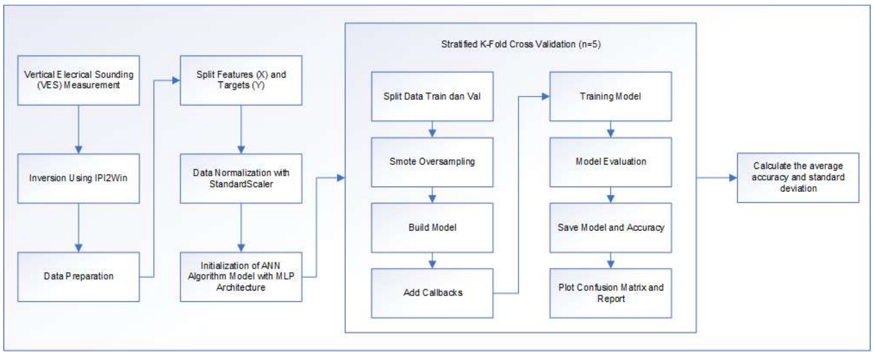


Figure 2. Workflow for Lithology Classification Using Multi-Layer Perceptron (MLP)

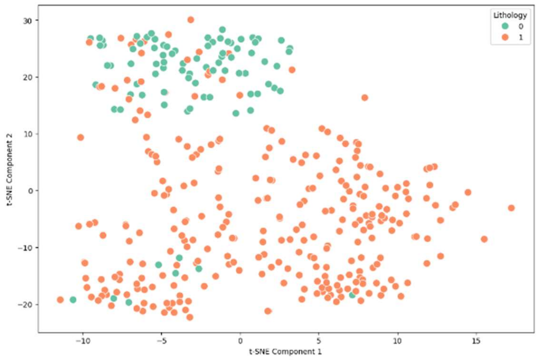
Figure 2 illustrates that the Artificial Neural Network (ANN) model used in this study was designed based on the Multi-Layer Perceptron (MLP) architecture, which consists of two hidden layers [33]. The first layer consists of 128 neurons with a ReLU activation function, followed by BatchNormalization 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 (Synthetic Minority Over-sampling Technique) 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 [34]. 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. RESEARCH METHOD

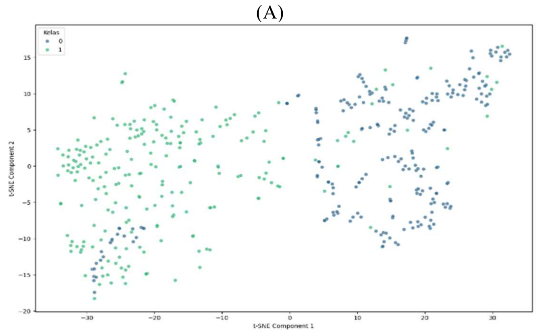
This study utilized the artificial neural network (ANN) algorithm to identify and classify lithological units derived from geoelectrical inversion data. Class distribution was visualized using the t-SNE technique before model training as part of preliminary data analysis. Figure 3 presents visualization 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.

Commented [Pro7]: results and analysis

Commented [Pro8]: You should also include some important processes in ML such as, data collection, preprocessing and modelling.



(A)



(B)

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

As shown in Figure 3, 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 Multi-Layer Perceptron (MLP) Artificial Neural Network (ANN) algorithm. Model validation was carried out using the Stratified K-Fold Cross Validation (n=5) approach, with the results shown in Table 1.

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	

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), resulting in an average accuracy of 90.65% with a standard deviation of ±1.87%. These results indicate that the Artificial Neural Network (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. Figure 4 presents the accuracy of each fold in the K-Fold cross-validation.

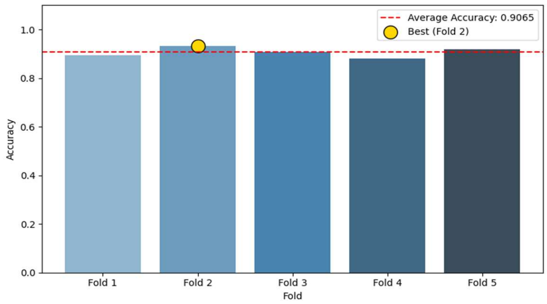


Figure 4. Accuracy of Each Fold in K-Fold Cross Validation

The same dataset was used to evaluate the performance of additional machine learning algorithms, specifically, the Support Vector Machine (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 Artificial Neural Network (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 Artificial Neural Network (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 Support Vector Machine (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. Comparison of Results with Existing Models from Previous Studies

Model	Dataset	Accuracy	Keterangan
Convolutional Neural Network (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.
Artificial Neural Network (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.

Table 2 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.

4. CONCLUSION

Commented [Pro9]: OK

The study highlights the effectiveness of integrating geoelectrical inversion data from the Schlumberger configuration with an Artificial Neural Network (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 Artificial Neural Network (ANN) outperformed conventional machine learning algorithms, including Support Vector Machine (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.

REFERENCES

Commented [Pro10]: Good

[1] G. Chen, M. Chen, G. Hong, Y. Lu, B. Zhou, and Y. Gao, "A new method of lithology classification based on convolutional neural network algorithm by utilizing drilling string vibration data," *Energies (Basel)*, vol. 13, no. 4, 2020, doi: 10.3390/en13040888.

[2] M. Yang, Y. Hu, B. Liu, L. Wang, Z. Zhou, and M. Jia, "Application of Artificial Neural Networks for Identification of Lithofacies by Processing of Core Drilling Data," *Applied Sciences (Switzerland)*, vol. 13, no. 21, Nov. 2023, doi: 10.3390/app132111934.

[3] S. H. R. Mousavi and S. M. Hosseini-Nasab, "Residual Convolutional Neural Network for Lithology Classification: A Case Study of an Iranian Gas Field," *Int J Energy Res*, vol. 2024, 2024, doi: 10.1155/2024/5576859.

[4] H. Liang, H. Chen, J. Guo, J. Bai, and Y. Jiang, "Research on lithology identification method based on mechanical specific energy principle and machine learning theory," *Expert Syst Appl*, vol. 189, Mar. 2022, doi: 10.1016/j.eswa.2021.116142.

[5] M. A. M. Abdullah, A. A. Mohammed, and S. R. Awad, "RockDNet: Deep Learning Approach for Lithology Classification," *Applied Sciences (Switzerland)*, vol. 14, no. 13, Jul. 2024, doi: 10.3390/app14135511.

[6] D. Fu, C. Su, W. Wang, and R. Yuan, "Deep learning based lithology classification of drill core images," *PLoS One*, vol. 17, no. 7 July, Jul. 2022, doi: 10.1371/journal.pone.0270826.

[7] R. S. Permana, A. P. Buana, A. Akmam, H. Amir, and A. Putra, "Using the Schlumberger configuration resistivity geoelectric method to estimate the rock structure at landslide zone in Malalak agam," in *Journal of Physics: Conference Series*, Institute of Physics Publishing, May 2020. doi: 10.1088/1742-6596/1481/1/012034.

[8] H. Singh, Y. Seol, and E. M. Myshakin, "Automated Well-Log Processing and Lithology Classification by Identifying Optimal Features through Unsupervised and Supervised Machine-Learning Algorithms," *SPE Journal*, vol. 25, no. 5, pp. 2778–2800, Oct. 2020, doi: 10.2118/202477-PA.

[9] A. Singh, M. Ojha, and K. Sain, “Predicting lithology using neural networks from downhole data of a gas hydrate reservoir in the Krishna-Godavari basin, eastern Indian offshore,” *Geophys J Int*, vol. 220, no. 3, pp. 1813–1837, Mar. 2020, doi: 10.1093/gji/ggz522.

[10] J. J. Marquina-Araujo *et al.*, “Application of Multilayer Perceptron Neural Network in Geological Modeling of Categorical Variables: A Case Study in Peru,” *Mathematical Modelling of Engineering Problems*, vol. 11, no. 6, pp. 1463–1472, Jun. 2024, doi: 10.18280/mmep.110607.

[11] F. Gurcan and A. Soylu, “Learning from Imbalanced Data: Integration of Advanced Resampling Techniques and Machine Learning Models for Enhanced Cancer Diagnosis and Prognosis,” *Cancers (Basel)*, vol. 16, no. 19, Oct. 2024, doi: 10.3390/cancers16193417.

[12] N. Nnamoko and I. Korkontzelos, “Efficient treatment of outliers and class imbalance for diabetes prediction,” *Artif Intell Med*, vol. 104, Apr. 2020, doi: 10.1016/j.artmed.2020.101815.

[13] M. Koziarski, “Potential Anchoring for imbalanced data classification,” *Pattern Recognit*, vol. 120, Dec. 2021, doi: 10.1016/j.patcog.2021.108114.

[14] W. M. (William M. Telford 1917-1997, *Applied geophysics*. Second edition. Cambridge [England] ; New York : Cambridge University Press, 1990., 1990. [Online]. Available: https://search.library.wisc.edu/catalog/999608560002121

[15] J. M. Reynolds, *An introduction to applied and environmental geophysics*. Chichester ; New York : John Wiley, 1997., 1997. [Online]. Available: https://search.library.wisc.edu/catalog/999809641902121

[16] M. A. Mohammed, N. M. Muztaza, and R. Saad, “The influence of non-collinear electrodes arrangement on a two-dimensional resistivity survey using wenner array,” in *Journal of Physics: Conference Series*, IOP Publishing Ltd, Mar. 2021. doi: 10.1088/1742-6596/1825/1/012012.

[17] Y. Palimbong, M. Arisalwadi, E. Agustriani, J. D. Anggraeni, and Kusnadi, “Interpretation of surface structure on artisanal and small scale gold mining areas with geoelectric resistivity method of schlumberger configuration in Sekotong, West Lombok,” in *IOP Conference Series: Earth and Environmental Science*, Institute of Physics Publishing, Jan. 2020. doi: 10.1088/1755-1315/413/1/012007.

[18] T. Dahlin and B. Zhou, “A numerical comparison of 2D resistivity imaging with 10 electrode arrays,” 2004.

[19] O. R. Hermawan and D. P. Eka Putra, “The Effectiveness of Wenner-Schlumberger and Dipole-dipole Array of 2D Geoelectrical Survey to Detect The Occurring of Groundwater in the Gunung Kidul Karst Aquifer System, Yogyakarta, Indonesia,” *Journal of Applied Geology*, vol. 1, no. 2, p. 71, Jul. 2016, doi: 10.22146/jag.26963.

[20] B. Mirzaei, B. Nikpour, and H. Nezamabadi-pour, “CDBH: A clustering and density-based hybrid approach for imbalanced data classification,” *Expert Syst Appl*, vol. 164, Feb. 2021, doi: 10.1016/j.eswa.2020.114035.

[21] K. Kalaivanan, B. Gurugnanam, M. Suresh, Karung Phaisonreng Kom, and S. Kumaravel, “Geoelectrical resistivity investigation for hydrogeology conditions and groundwater potential zone mapping of Kodavanar sub-basin, southern India,” *Sustain Water Resour Manag*, vol. 5, no. 3, pp. 1281–1301, Sep. 2019, doi: 10.1007/s40899-019-00305-6.

[22] J. S. Ejepu, M. O. Jimoh, S. Abdullahi, I. A. Abdulfatai, S. T. Musa, and N. J. George, “Geoelectric analysis for groundwater potential assessment and aquifer protection in a part of Shango, North-Central Nigeria,” *Discover Water*, vol. 4, no. 1, Jun. 2024, doi: 10.1007/s43832-024-00091-z.

[23] G. S. Lumacad and R. A. Namoco, “Multilayer Perceptron Neural Network Approach to Classifying Learning Modalities Under the New Normal,” Aug. 2022. doi: 10.36227/techrxiv.20428230.v1.

[24] J. Zhang, T. Wang, Z. Zhang, P. Yan, and X. Li, “QiMLP: Quantum-inspired Multilayer Perceptron with Strong Correlation Mining and Parameter Compression,” 2025. [Online]. Available: www.aaai.org

[25] A. Fierravanti, L. Balducci, and T. Fonseca, “Cork Oak Regeneration Prediction Through Multilayer Perceptron Architectures,” *Forests*, vol. 16, no. 4, Apr. 2025, doi: 10.3390/f16040645.

[26] A. Tashakkori, M. Talebzadeh, F. Salboukh, L. Deshmukh, and H. Talebzadeh, “Forecasting Gold Prices with MLP Neural Networks: A Machine Learning Approach,” *International Journal of Science and Engineering Applications*, Jul. 2024, doi: 10.7753/ijsea1308.1003.

[27] K. A. Rashedi, M. T. Ismail, S. Al Wadi, A. Serroukh, T. S. Alshammari, and J. J. Jaber, “Multi-Layer Perceptron-Based Classification with Application to Outlier Detection in Saudi Arabia Stock Returns,” *Journal of Risk and Financial Management*, vol. 17, no. 2, Feb. 2024, doi: 10.3390/jrfm17020069.

[28] O. W. Layton, S. Peng, and S. T. Steinmetz, “ReLU, Sparseness, and the Encoding of Optic Flow in Neural Networks,” *Sensors*, vol. 24, no. 23, Dec. 2024, doi: 10.3390/s24237453.

[29] R. K. Vasanthakumari, R. V. Nair, and V. G. Krishnappa, "Improved learning by using a modified activation function of a Convolutional Neural Network in multi-spectral image classification," *Machine Learning with Applications*, vol. 14, p. 100502, Dec. 2023, doi: 10.1016/j.mlwa.2023.100502.

[30] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *J Big Data*, vol. 8, no. 1, Dec. 2021, doi: 10.1186/s40537-021-00444-8.

[31] N. Susanto and H. F. Pardede, "Feature Learning using Deep Variational Autoencoder for Prediction of Defects in Car Engine," in *Proceeding - 2024 International Conference on Information Technology Research and Innovation, ICITRI 2024*, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 311–316. doi: 10.1109/ICITRI62858.2024.10699115.

[32] A. White *et al.*, "Assessing the effect of offline topography on electrical resistivity measurements: insights from flood embankments," *Geophys J Int*, Sep. 2024, doi: 10.1093/gji/ggae313.

[33] J. Ważny, M. Stefaniuk, and A. Cygal, "Estimation of electrical resistivity using artificial neural networks: a case study from Lublin Basin, SE Poland," *Acta Geophysica*, vol. 69, no. 2, pp. 631–642, Apr. 2021, doi: 10.1007/s11600-021-00554-0.

[34] Y. Bai *et al.*, "Understanding and Improving Early Stopping for Learning with Noisy Labels Supplementary A Training details," 2021.