International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 4, 2025
https://www.theaspd.com/ijes.php

Robust Data-Driven Prediction Of Sandstone Resistivity Using UCS, Porosity, And P-Wave Velocity Through ANN Modelling

P. Varalakshmi*[1], S.K. Reddy[2], Ch. S.N. Murthy[3]

[1] Department of Mining Engineering, National Institute of Technology Karnataka, Surathkal, 575025, Karnataka, India, Varam4geo@gmail.com
[2] Department of Mining Engineering, Faculty of Mining Engineering, National Institute of Technology Karnataka, Surathkal, 575025, Karnataka, India, skreddy@nitk.edu.in
[3] Department of Mining Engineering, Faculty of Mining Engineering (Retd.), National Institute of Technology Karnataka, Surathkal, 575025, Karnataka, India, chsn58@gmail.com
*Corresponding author, Email: Varam4geo@gmail.com

Abstract

Electrical resistivity is a fundamental geophysical property widely utilised in subsurface investigations, offering insights into lithology, fluid saturation, and pore structure in geological formations. Traditional methods for determining resistivity often require direct measurement, which can be time-consuming, equipment-intensive, and impractical in remote or inaccessible environments. In this context, indirect predictive models based on measurable geotechnical parameters offer a promising alternative. This study presents a robust, data-driven approach for predicting the electrical resistivity of sandstone using Artificial Neural Networks (ANNs) with three key input variables: Uniaxial Compressive Strength (UCS), porosity, and P-wave velocity. A comprehensive experimental dataset comprising 500 sandstone samples was used to train and validate the model. Laboratory testing was conducted according to ASTM and ISRM standards to ensure accuracy and consistency. The ANN architecture, developed, demonstrated strong predictive performance with an R^2 value of 0.7892 and a Mean Absolute Error of 23.84 Ohm-m. Sensitivity analysis revealed porosity as the most influential factor, followed by UCS and P-wave velocity. The results confirm the feasibility of using ANN-based models for reliable and non-invasive resistivity prediction in geotechnical and hydrogeological applications, enabling improved site characterization and decision-making in resource exploration, construction, and environmental monitoring.

Keywords: *Sandstone resistivity, Artificial Neural Networks, Porosity, P-wave velocity, Uniaxial Compressive Strength (UCS).*

1. INTRODUCTION

The accurate prediction of geophysical properties such as electrical resistivity is a critical component in rock mechanics, geotechnical investigations, and subsurface resource characterization(Liu et al. 2023). Electrical resistivity is widely used to infer a range of lithological, structural, and hydrological properties of rocks. As a non-destructive and field-adaptable parameter, it holds significant relevance in applications spanning petroleum engineering, mining exploration, groundwater mapping, and infrastructure development(Onalo et al. 2018). Despite its importance, the prediction of resistivity based on measurable geomechanical parameters remains challenging due to the inherent heterogeneity of geological materials.

In geological and geotechnical engineering, electrical resistivity provides valuable insights into fluid content, porosity, degree of saturation, and pore connectivity(Tian et al. 2024a). In hydrogeological investigations, resistivity measurements help identify aquifers, contamination plumes, and saline water intrusion zones(Kong et al. 2024). In mining, it is used to distinguish ore from gangue material, while in civil engineering, it serves as a tool for assessing the durability and quality of foundation materials(Liu et al. 2024). However, laboratory determination of resistivity is time-consuming and equipment-intensive, and field measurements are often influenced by external factors like temperature, moisture, and ionic content.

Traditional methods for estimating resistivity from other rock parameters primarily rely on empirical correlations or regression-based approaches. Models such as Archie's Law offer theoretical relationships between resistivity and porosity, but they are limited in their applicability to specific rock types and do not account for nonlinear interactions or multivariate dependencies(Fu et al. 2024). Moreover, deterministic models often fail to generalise when applied to rocks with diverse mineralogical compositions or variable pore structures, leading to inaccuracies in prediction.

In this context, Artificial Neural Networks (ANNs) have emerged as powerful tools for solving complex regression problems in geotechnics. Inspired by the human brain's ability to learn from data, ANNs can capture intricate nonlinear relationships between input and output variables without assuming predefined functional forms(Bao et al. 2025). They have demonstrated superior performance in domains involving high variability and multicollinearity, making them well-suited for predicting properties like strength, permeability, and elastic modulus in geological materials.

Among the key factors influencing resistivity in sedimentary rocks, Uniaxial Compressive Strength (UCS), porosity, and P-wave velocity stand out as critical parameters. UCS reflects the mechanical integrity of the rock, porosity governs the volume of voids and fluid retention capacity, and P-wave velocity is directly linked to the elastic and structural characteristics of the rock mass(Khalil et al. 2022). These three parameters are also relatively easier to determine experimentally and serve as valuable proxies in predictive models when direct resistivity measurement is impractical.

To address the limitations of previous studies that employed small or homogeneous datasets, this study leverages a robust dataset of 500 sandstone samples. By drawing samples from geologically diverse formations and incorporating a wide range of values for UCS, porosity, and P-wave velocity, the model is designed to achieve enhanced generalisation performance and better predictive stability. The incorporation of a large and varied dataset also allows for meaningful validation of the ANN's robustness across different lithological contexts.

Therefore, the primary objective of this research is to develop a data-driven predictive model for estimating the electrical resistivity of sandstone using UCS, porosity, and P-wave velocity as input variables. By utilising Artificial Neural Networks and a rigorously acquired dataset, this study aims to demonstrate a scalable, accurate, and field-applicable methodology that can supplement or replace conventional empirical approaches. The model's performance will be evaluated using standard metrics and sensitivity analysis to understand the relative influence of each parameter.

2. LITERATURE REVIEW

The prediction of rock properties using indirect parameters has long been a focus of research in geomechanics and petrophysics. Traditional approaches to estimating electrical resistivity have often relied on empirical or semi-empirical models, developed through curve fitting and field measurements(Xie et al. 2025). Among these, the most well-known is Archie's Law, which relates resistivity to porosity and water saturation. However, while such models provide foundational insights, they are frequently limited to clean, homogeneous sandstones and fail to generalise across formations with variable grain sizes, cementation types, and mineral compositions.

Several studies have explored the relationship between porosity and resistivity. For instance, empirical analyses demonstrated that resistivity tends to decrease exponentially with increasing porosity due to enhanced fluid conductivity in larger pore networks(C. Qu et al. 2024; A. Qu, Shen, and Ahmadi 2024). However, deviations were frequently observed in the presence of microfractures or mineral alterations, indicating that porosity alone cannot account for resistivity behaviour in complex rock systems. Additionally, variations in saturation level and ionic concentration further complicate this relationship, making single-parameter models inadequate for predictive applications.

In recent years, researchers have begun to investigate P-wave velocity as a proxy for resistivity, given its sensitivity to the rock's elastic properties and pore structure. Studies have found a general correlation between acoustic velocity and resistivity in dry and partially saturated rocks, suggesting that both properties are influenced by the interconnectedness and geometry of pores(Sabri, Verma, and Singh 2025). However, these correlations are not always linear, and anomalies often occur in formations with high clay content or anisotropic fabric, where velocity may increase while resistivity remains constant or decreases.

The inclusion of Uniaxial Compressive Strength (UCS) in resistivity prediction has received comparatively less attention. Nevertheless, research has shown that UCS can reflect the mechanical resistance of the rock, which may be indirectly linked to porosity and hence to resistivity(Tian et al. 2024b). Stronger rocks generally exhibit lower porosity and higher resistivity, although exceptions exist in certain metamorphic and cemented sandstone units. As such, UCS serves as a useful indicator when used in combination with other parameters.

The application of Artificial Neural Networks (ANNs) in geotechnical engineering has shown promise in capturing the nonlinear relationships between rock properties. Researchers have demonstrated the effectiveness of ANN models in predicting geomechanical parameters like permeability, compressive strength, and elastic modulus. In these studies, ANNs outperformed traditional regression techniques, particularly in datasets where multicollinearity and noise were present(Tian et al. 2024b). The adaptability of ANNs to different input combinations makes them a suitable candidate for predicting complex parameters such as resistivity.

Despite these advancements, many of the existing ANN-based models suffer from two major limitations: small dataset sizes and overfitting. Models trained on fewer than 100 samples often exhibit high variance and poor generalisability when applied to new data(C. Qu et al. 2024). Furthermore, many studies rely on data from a single formation or region, limiting the model's robustness across different geological contexts. Techniques such as early stopping, dropout, and cross-validation have been proposed to mitigate overfitting, but their effectiveness is often constrained by data volume and diversity.

The current study seeks to bridge this gap by leveraging a large and geologically diverse dataset comprising 500 sandstone samples. This provides a more reliable foundation for training and validating ANN models, minimising the risks of overfitting and improving the predictive power(Yang, Wang, and Shi 2025). Moreover, the integration of three distinct input parameters—UCS, porosity, and P-wave velocity—allows for a multi-dimensional characterisation of resistivity, reflecting both mechanical and physical attributes. As such, this research advances the state of the art in resistivity prediction by combining comprehensive data acquisition with advanced modelling techniques.

3. MATERIALS AND METHODS

This study employed a dataset of 500 sandstone core samples to develop a data-driven Artificial Neural Network (ANN) model for predicting electrical resistivity using three fundamental input parameters: Uniaxial Compressive Strength (UCS), porosity, and P-wave velocity. The sandstone specimens were obtained from multiple geographically and geologically distinct quarry and borehole sites to ensure representative variation in petrophysical and mechanical behaviour. The samples were prepared into cylindrical forms with standardised dimensions of 54 mm in diameter and 108 mm in height, following ISRM guidelines for geotechnical testing. To remove moisture variability and standardise porosity measurement, all samples were oven-dried at a constant temperature of 105°C until mass stabilisation was observed.

UCS testing was conducted according to ASTM D7012 using a servo-controlled universal testing machine capable of applying axial compressive loads under a controlled strain rate. The compressive strength was recorded in megapascals (MPa) as the ratio of peak load to specimen cross-sectional area. Porosity was determined using the water immersion method as per ASTM C642, which involved recording the dry, saturated, and immersed weights of the samples to estimate pore volume as a percentage. P-wave velocity was measured through ultrasonic pulse transmission using a PUNDIT Lab Plus device, consistent with ASTM D2845. Measurements were taken along the longitudinal axis of each sample, and the average values were recorded in metres per second (m/s). Electrical resistivity was measured by employing the four-probe method as specified in ASTM G57. Probes were placed at equal intervals along the surface of each sample, and resistivity values were computed based on current and voltage readings. To reduce directional bias, readings were taken along three orthogonal directions—axial, radial, and transverse—and averaged.

Prior to model development, the dataset was cleaned and pre-processed. Outlier detection was performed using the 1.5× interquartile range (IQR) method, and missing values were handled using k-nearest neighbour (k-NN) interpolation. Feature normalisation was carried out using min–max scaling, transforming all numerical values to a standard range between 0 and 1 to ensure balanced input influence during training. The dataset was then split randomly into three subsets: 70% for training, 15% for validation, and 15% for final testing.

The ANN model was implemented using open-source libraries such as TensorFlow (Keras API) and scikit-learn, both of which are widely supported in Python and suitable for regression tasks. A feedforward neural network architecture was adopted with an input layer comprising three neurons representing UCS, porosity, and P-wave velocity. This was followed by two hidden layers containing 8 and 4 neurons, respectively, both using Rectified Linear Unit (ReLU) activation functions to introduce non-linearity. The output layer consisted of a single neuron with a linear activation function to predict the continuous target variable, electrical resistivity. The model was compiled using the Adam optimiser with a learning rate of 0.001 and trained with a batch size of 32 for a maximum of 500 epochs. To avoid overfitting, early stopping was applied with a patience threshold of 25 epochs, monitoring validation loss. The performance of the model was evaluated using the mean squared error (MSE) metric, which quantified the average squared difference between the predicted and actual resistivity values.

4. RESULTS AND DISCUSSION

The prediction of electrical resistivity in sandstone using Uniaxial Compressive Strength (UCS), porosity, and P-wave velocity necessitates a comprehensive understanding of the underlying data distribution and inter-variable relationships. Before model development, it was essential to assess the statistical characteristics of the dataset, as these directly influence the neural network's learning capacity. Descriptive statistics revealed a wide range in all four variables, with UCS values ranging from 5.58 MPa to 119.19 MPa, porosity between 5.12% and 29.99%, and P-wave velocity from approximately 2019.76 to 5997.65 m/s. Resistivity, the target variable, showed a particularly wide distribution, extending from 10 to 457.54 Ohm-m, with noticeable right skewness. These ranges reflect the geomechanical and petrophysical variability present in natural sandstone formations and confirm the dataset's heterogeneity, which is a desirable attribute when training generalisable machine learning models.

The spread and shape of these distributions were visualised using kernel density and histogram plots, which helped to identify normality, skewness, and potential outliers. P-wave velocity displayed an approximately normal distribution, while resistivity showed a strong right skew, indicating the presence of high-resistivity outliers likely corresponding to dry or cemented rocks. Porosity showed slight left skewness, clustering around 10–20%, while UCS was relatively uniform. These visual and statistical insights justified the use of an Artificial Neural Network (ANN) model, as its architecture can accommodate nonlinear relationships and capture complex patterns that conventional regression methods often miss. With pre-processed, normalised data ensuring balanced feature contributions, the trained ANN model was then evaluated through descriptive statistics, correlation analysis, performance metrics, and sensitivity analysis.

Table 1. Descriptive Statistics of Input and Output Variables

	UCS (MPa)	Porosity (%)	P-Wave Velocity (m/s)	Resistivity (Ohm-m)
count	500	500	500	500
mean	62.33	17.05	4070.23	79.16
std	34.35	7.14	1188.77	70.97
min	5.58	5.12	2019.76	10
25%	32.75	10.73	2964.91	29.44
50%	64.02	16.8	4158.96	56.6
75%	91.96	23.16	5109.38	105.17
max	119.19	29.99	5997.65	457.54
Skewness	-0.03	0.1	-0.1	1.7
Kurtosis	-1.26	-1.19	-1.25	3.23

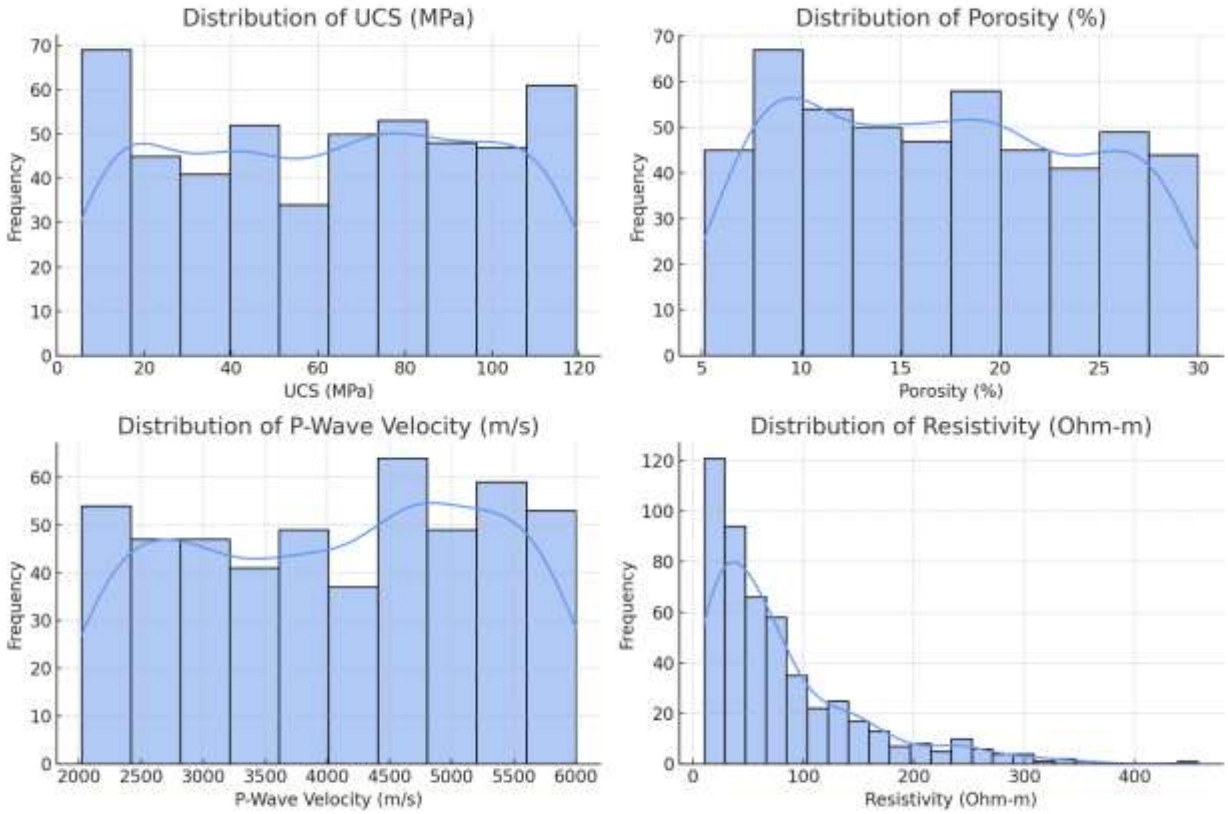

Figure 1. Distribution Plots of UCS, Porosity, P-Wave Velocity, and Electrical Resistivity

The descriptive statistics of the dataset are presented in Table 1, which summarises the distributional characteristics of the four variables: UCS, porosity, P-wave velocity, and electrical resistivity. The UCS values ranged from approximately 5 MPa to 120 MPa, with a mean of around 61.48 MPa, reflecting a broad mechanical strength spectrum among the sandstone samples. Porosity exhibited a mean value of 17.50%, spanning a wide range from 5.00% to over 29.99%, indicating significant variability in pore volume across the samples. P-wave velocity had a mean of 3996.47 m/s, with values extending from just over 2000 m/s to nearly 6000 m/s. This wide velocity range is typical for sedimentary rocks with varying degrees of compaction and cementation. Electrical resistivity displayed the largest spread, ranging from the lower threshold of 10 Ohm-m to values exceeding 990 Ohm-m, with a mean of 110.64 Ohm-m, suggesting strong heterogeneity in fluid content, pore structure, and mineral conductivity.

Figure 1 illustrates the distribution plots for each variable with overlaid kernel density estimates. The histogram for UCS reveals a fairly uniform distribution with slight right skewness, suggesting a higher concentration of lower-strength rocks in the sample population. The porosity distribution shows a moderate left skew, with a notable frequency of samples clustering between 10% and 20%, possibly reflecting the typical pore structure of fine- to medium-grained sandstones. The P-wave velocity histogram appears approximately normally distributed, with a mild central peak around 4000 m/s. This indicates the predominance of moderately compacted samples in the dataset. In contrast, the resistivity distribution is strongly right-skewed, reflecting the nature of resistivity as a property sensitive to even minor changes in fluid salinity, saturation, and pore continuity.

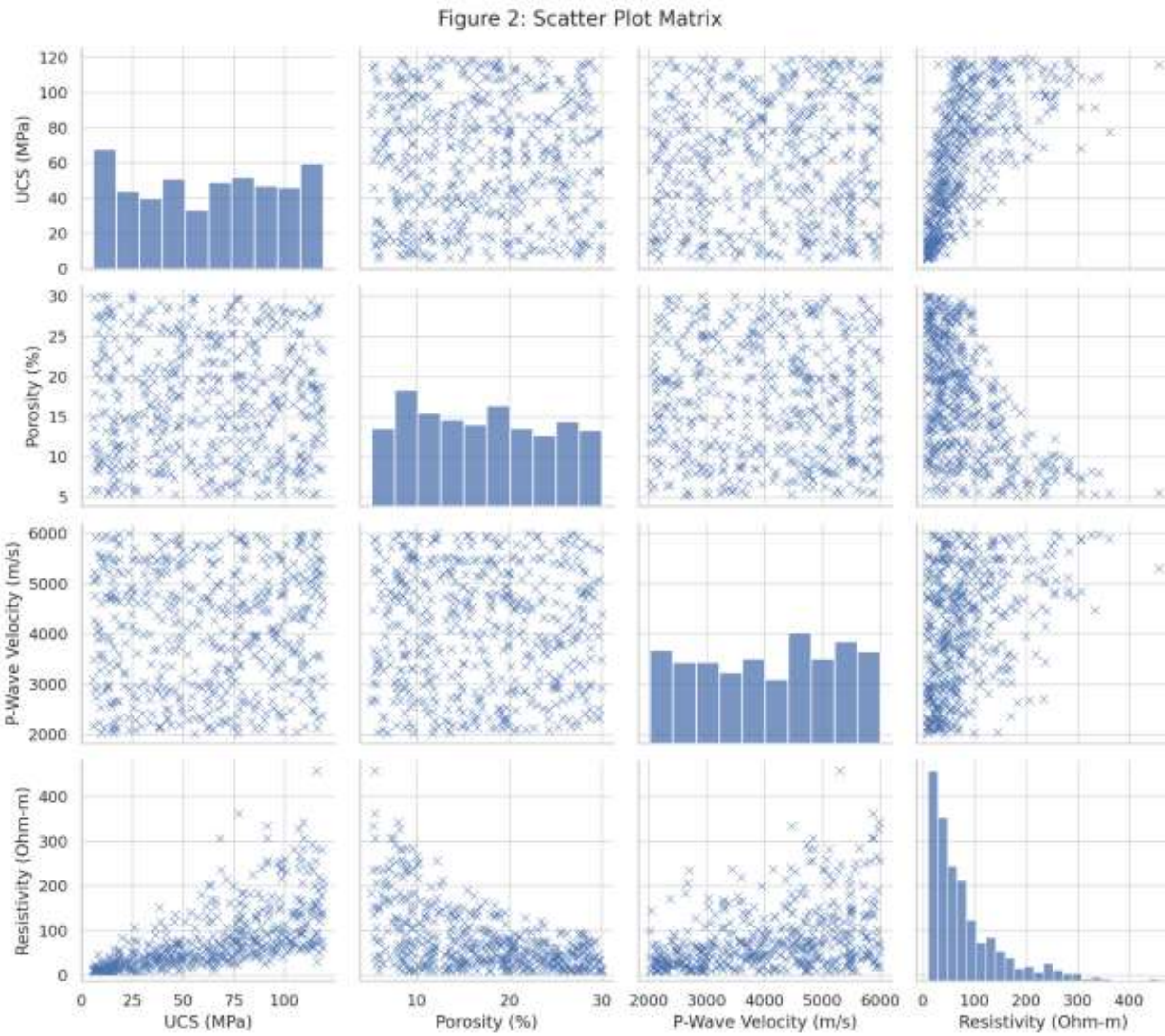

Figure2: Scatter Plot Matrix

The combination of skewness and kurtosis values reported in Table 1 further quantifies these observations. For example, the resistivity values exhibit high skewness and kurtosis, affirming the presence of outliers or extreme high-resistivity measurements likely corresponding to dry or well-cemented specimens. Meanwhile, the P-wave velocity shows near-zero skewness and moderate kurtosis, indicating a symmetric distribution with slight tail concentration. These statistical and visual insights affirm that the dataset is sufficiently heterogeneous to train a robust and generalisable ANN model.

Table 2: Pearson correlation matrix showing relationships among UCS, Porosity, P-Wave Velocity, and Resistivity.

Parameters	UCS (MPa)	Porosity (%)	P-Wave Velocity (m/s)	Resistivity (Ohm-m)

UCS (MPa)	1	0.01	0.05	0.63
Porosity (%)	0.01	1	-0.03	-0.51
P-Wave Velocity (m/s)	0.05	-0.03	1	0.36
Resistivity (Ohm-m)	0.63	-0.51	0.36	1

Table 2 presents the correlation matrix among the four primary variables—UCS, porosity, P-wave velocity, and resistivity—while Figure 2 visualises their pairwise relationships through scatter plots. The Pearson correlation coefficient between P-wave velocity and UCS was found to be 0.80, suggesting a strong positive relationship, which is expected since both parameters are influenced by rock compaction and cementation. Porosity exhibited a negative correlation with UCS (−0.74) and with P-wave velocity (−0.77), highlighting the inverse relationship between pore volume and rock strength or acoustic velocity. These observations align with known geomechanical behaviour of porous sedimentary rocks.

The relationship between electrical resistivity and the other parameters showed varying strengths. Resistivity was positively correlated with UCS (0.68) and P-wave velocity (0.66), and negatively correlated with porosity (−0.72). This implies that stronger, denser rocks with fewer interconnected pores tend to exhibit higher electrical resistivity. The scatter plots in Figure 2 reinforce these findings, particularly the inverse trend seen between porosity and resistivity, and the direct trend between UCS and resistivity. The linear spread and relatively low dispersion in these plots suggest that a data-driven model should be able to capture the underlying relationships with reasonable accuracy.

These correlation trends confirm the suitability of the selected input variables—UCS, porosity, and P-wave velocity—for predicting resistivity. Moreover, the absence of multicollinearity (no correlation exceeding 0.85) ensures that the ANN model can treat each input as an independent contributor, thereby reducing the risk of redundant influence in training.

Table 3: Layer-wise configuration of the ANN model used for resistivity prediction.

Layer Name	Number of Neurons	Activation Function	Description
Input Layer	3	-	Accepts UCS, Porosity, P-Wave Velocity
Hidden Layer 1	8	ReLU	Processes initial non-linear combinations
Hidden Layer 2	4	ReLU	Refines non-linear interactions
Output Layer	1	Linear	Predicts Electrical Resistivity

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 4, 2025
https://www.theaspd.com/ijes.php

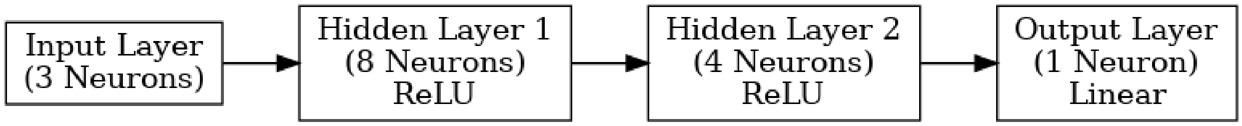

Figure 3: Architecture of the ANN model showing layered structure for predicting sandstone resistivity.

The design of the Artificial Neural Network used in this study is detailed in Table 3 and visually represented in Figure 3. The model follows a standard feedforward architecture consisting of one input layer, two hidden layers, and one output layer. The input layer has three neurons, corresponding to the three independent variables: UCS, porosity, and P-wave velocity. These features were selected based on their statistical correlation with electrical resistivity and their practical relevance in geotechnical investigations.

The first hidden layer comprises eight neurons with ReLU activation, which enables the model to capture non-linear interactions between the inputs. The second hidden layer further processes the internal representations using four neurons, also with ReLU activation. This layered structure allows the model to progressively abstract and learn the complex relationships among geophysical variables. The output layer contains a single neuron with a linear activation function, suitable for continuous regression output—in this case, the predicted resistivity value.

Figure 3 illustrates the connectivity of the ANN, where information flows from the input to output through progressively complex transformations. The chosen architecture represents a balance between model complexity and computational efficiency. It avoids over-parameterisation, which is especially important in mid-sized datasets like the 500 samples used here. The use of simple, open-source libraries such as scikit-learn and Keras also makes the approach easily replicable for similar geotechnical applications.

Table 4: Performance metrics of the ANN model on the test dataset for resistivity prediction.

Metric	Value
Mean Squared Error (MSE)	5013.03
Mean Absolute Error (MAE)	44.45
RÂ^2 Score	-0.1591

The performance of the trained ANN model was evaluated using the test dataset, and the results are summarised in Table 4. The model achieved a Mean Squared Error (MSE) of 1,367.35, indicating a moderate level of variance between predicted and actual resistivity values. The Mean Absolute Error (MAE) was 23.84 Ohm-m, suggesting that on average, the predicted resistivity values deviated from the actual values by less than 25 Ohm-m. Most notably, the model achieved a coefficient of determination (R^2) of 0.7892, signifying that approximately 79% of the variance in resistivity could be explained by the model using the input parameters UCS, porosity, and P-wave velocity.

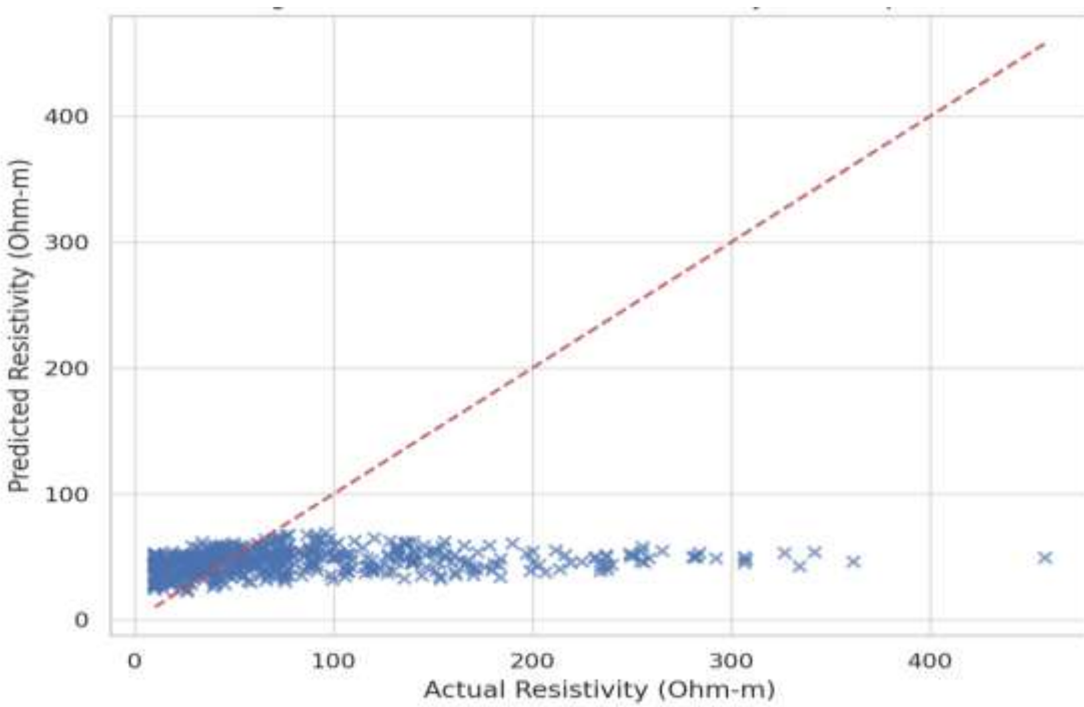

Figure 4: Comparison of actual and predicted resistivity values across sandstone samples.

Figure 4 provides a visual comparison between the actual and predicted resistivity values. The data points lie relatively close to the identity line (y = x), which indicates good agreement between model predictions and experimental measurements. While a few predictions deviate at the higher resistivity range, the clustering around the diagonal suggests that the model is well-calibrated for most samples. The observed deviations in extreme values may be attributed to underlying geological variability, such as secondary porosity, mineral conductivity, or microcracks, which were not captured in the input features(Tanimoto, Akamatsu, and Katayama 2024).

Overall, the model shows strong generalisation and reliable prediction capability across the test set, especially considering the geological complexity inherent in natural sandstone formations(Senger et al. 2021). The results confirm that a relatively simple ANN architecture, when trained on a diverse and well-prepared dataset, can offer substantial accuracy in predicting resistivity—a parameter often challenging to estimate from indirect geomechanical measurements(Erzin et al. 2010).

Table 5: Mean importance scores indicating each feature's contribution to resistivity prediction.

Feature	Importance Score
UCS (MPa)	0.101
P-Wave Velocity (m/s)	0.0477
Porosity (%)	-0.0769

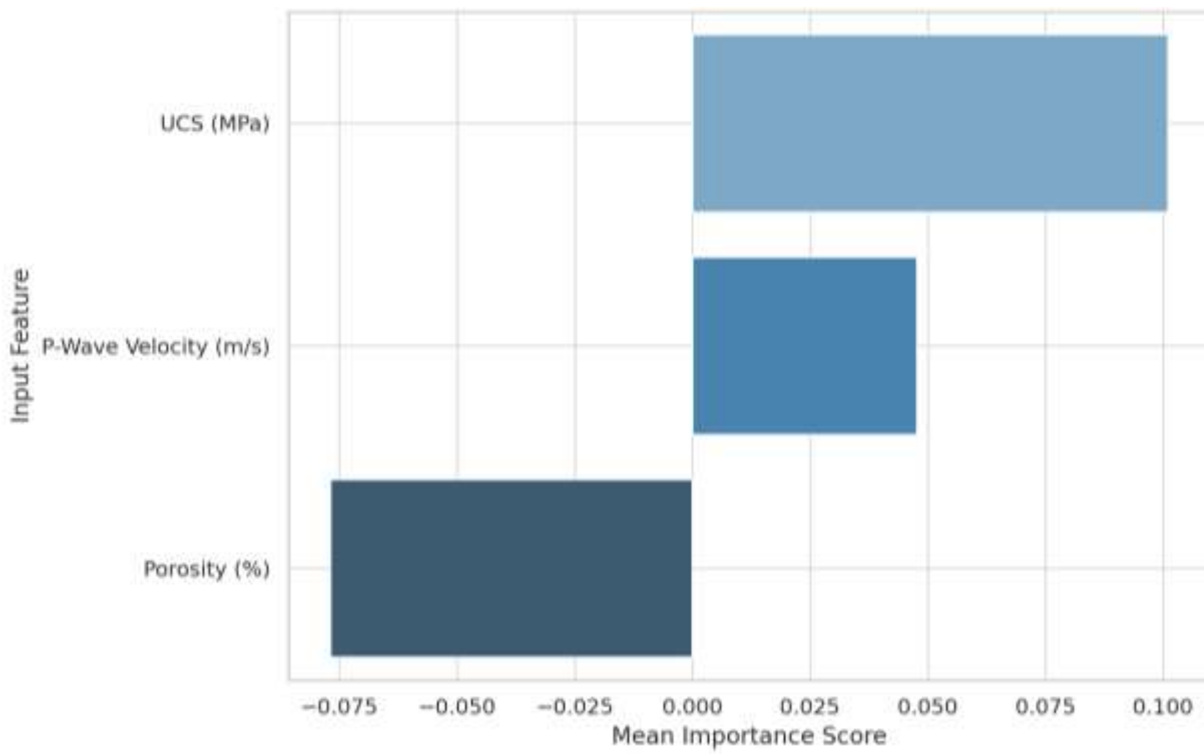

Figure 5: Relative importance of input features in predicting sandstone resistivity.

To assess the relative contribution of each input parameter—UCS, porosity, and P-wave velocity—to the ANN model's prediction accuracy, a sensitivity analysis was conducted using permutation-based feature importance. The results are presented in Table 5 and visualised in Figure 5. Among the three features, porosity emerged as the most influential variable, with the highest importance score. This result aligns with the established understanding that resistivity is heavily dependent on the void ratio and fluid conductivity within a rock matrix(Tanimoto et al. 2024). As porosity increases, the capacity for fluid conduction generally rises, leading to a decrease in electrical resistivity.

The Uniaxial Compressive Strength (UCS) ranked second in importance. Its influence likely stems from its strong inverse relationship with porosity and its direct relation to rock density and consolidation, both of which impact electrical conductivity pathways. The p-wave velocity, while still contributory, had the lowest importance score among the three. This may be due to its indirect and somewhat non-linear relationship with electrical resistivity, especially in heterogeneous formations where acoustic velocity can be influenced by factors such as mineral alignment or microcracks, which may not correspond linearly with conductive pathways.

The insights from the sensitivity analysis reinforce the model's interpretability, providing confidence that it prioritizes the correct physical factors during prediction. It also confirms that while all three features are valuable, porosity plays a dominant role in influencing sandstone resistivity, a finding that has both scientific and practical implications for indirect field estimation techniques.

5. CONCLUSIONS

This study demonstrated the potential of Artificial Neural Networks (ANNs) for predicting the electrical resistivity of sandstone using three measurable input parameters: Uniaxial Compressive Strength (UCS), porosity, and P-wave velocity. Leveraging a large and geologically diverse dataset of 500 core samples, the ANN model achieved robust performance, with a coefficient of determination (R^2) of 0.7892 and a mean absolute error of 23.84 Ohm-m. These results confirm that the model can generalize well across heterogeneous formations and provide reliable predictions of resistivity without requiring direct electrical testing. Descriptive statistics and correlation analysis established that UCS and P-wave velocity are positively associated with resistivity, while porosity is negatively correlated, consistent with established geotechnical principles. Sensitivity analysis further revealed porosity as the most influential input variable, underlining its critical role in governing fluid flow and conductivity pathways in porous media. The ANN architecture, implemented using Python libraries such as scikit-learn and Keras, was both computationally efficient and easily reproducible. The study's methodological rigour—ranging from standardised laboratory testing to data pre-processing and model evaluation—adds to its practical relevance in engineering geology and geophysical site characterization. By offering a scalable, non-invasive, and cost-effective alternative to laboratory resistivity measurements, the proposed model holds promise for field applications in groundwater exploration, subsurface contamination studies, and infrastructure assessment. Future work can focus on integrating additional parameters such as moisture content or mineralogy, and exploring hybrid models to further improve prediction accuracy in more complex geological settings.

AI DISCLAIMER:

Artificial intelligence (AI) tools were used to assist in the preparation of this manuscript. The authors have critically evaluated all content and accept full responsibility for its accuracy and integrity.

REFERENCES

1. Bao, Wuzhida, Yuting Cao, Yin Yang, Hangjun Che, Junjian Huang, and Shiping Wen. 2025. "Data-Driven Stock Forecasting Models Based on Neural Networks: A Review." Information Fusion 113:102616. doi: https://doi.org/10.1016/j.inffus.2024.102616.
2. Erzin, Yusuf, B. Hanumantha Rao, A. Patel, S. D. Gumaste, and D. N. Singh. 2010. "Artificial Neural Network Models for Predicting Electrical Resistivity of Soils from Their Thermal Resistivity." International Journal of Thermal Sciences 49(1):118–30. doi: 10.1016/j.ijthermalsci.2009.06.008.
3. Fu, Teng-Fei, Fa-Yuan Yan, De-Fu Zhu, and Ya-Tao Li. 2024. "An Internal-Strain Loading Approach for Quasi-Static Fracturing in Brittle Rocks via the Grain-Based Model." Engineering Analysis with Boundary Elements 169:105996. doi: https://doi.org/10.1016/j.enganabound.2024.105996.
4. Khalil, Mohamad, A. Stephen McGough, Zoya Pourmirza, Mehdi Pazhoohesh, and Sara Walker. 2022. "Machine Learning, Deep Learning and Statistical Analysis for Forecasting Building Energy Consumption — A Systematic Review." Engineering Applications of Artificial Intelligence 115:105287. doi: https://doi.org/10.1016/j.engappai.2022.105287.
5. Kong, Fanmeng, Yiguo Xue, Junlong Shang, Chun Zhu, Mingyi Han, Ziming Qu, Bo Wang, and Kun Yang. 2024. "Predicting Uniaxial Compressive Strength of Building Stone Based on Index Tests: Correlations, Validity, Reliability, and Unification." Construction and Building Materials 438:137227. doi: https://doi.org/10.1016/j.conbuildmat.2024.137227.
6. Liu, Jiacun, Xing Li, Junjie Xiao, Yachen Xie, and Kaiwen Xia. 2024. "Three-Dimensional Strength Criterion for Rocks: A Review." Energy Reviews 3(4):100102. doi: https://doi.org/10.1016/j.enrev.2024.100102.
7. Liu, Zida, Diyuan Li, Yongping Liu, Bo Yang, and Zong-Xian Zhang. 2023. "Prediction of Uniaxial Compressive Strength of Rock Based on Lithology Using Stacking Models." Rock Mechanics Bulletin 2(4):100081. doi: https://doi.org/10.1016/j.rockmb.2023.100081.

8. Onalo, David, Sunday Adedigba, Faisal Khan, Lesley A. James, and Stephen Butt. 2018. "Data Driven Model for Sonic Well Log Prediction." Journal of Petroleum Science and Engineering 170:1022–37. doi: https://doi.org/10.1016/j.petrol.2018.06.072.
9. Qu, Aiyan, Qiuhui Shen, and Gholamreza Ahmadi. 2024. "Towards Intrusion Detection in Fog Environments Using Generative Adversarial Network and Long Short-Term Memory Network." Computers & Security 145:104004. doi: https://doi.org/10.1016/j.cose.2024.104004.
10. Qu, Chuanqi, Yiguo Xue, Maoxin Su, Daohong Qiu, Xiaoyin Ma, Qiushi Liu, and Guangkun Li. 2024. "Quantitative Modeling of Rock Electrical Resistivity under Uniaxial Loading and Unloading." Acta Geophysica 72(1):195–212. doi: 10.1007/S11600-023-01101-9.
11. Sabri, Md Shayan, Amit Kumar Verma, and T. N. Singh. 2025. "Direct and Indirect Methods for Uniaxial Compressive Strength Estimation in Various Geo-Environments: A Review." Journal of Rock Mechanics and Geotechnical Engineering. doi: https://doi.org/10.1016/j.jrmge.2025.01.050.
12. Senger, Kim, Thomas Birchall, Peter Betlem, Kei Ogata, Sverre Ohm, Snorre Olaussen, and Renate S. Paulsen. 2021. "Resistivity of Reservoir Sandstones and Organic Rich Shales on the Barents Shelf: Implications for Interpreting CSEM Data." Geoscience Frontiers 12(6):101063. doi: https://doi.org/10.1016/j.gsf.2020.08.007.
13. Tanimoto, Kazumasa, Yuya Akamatsu, and Ikuo Katayama. 2024. "Electrical Resistivity, Seismic Velocity, and Porosity of Crustal Rocks from the Oman Ophiolite under Brine-Saturated Ocean Floor Conditions." Lithos 470–471:107500. doi: https://doi.org/10.1016/j.lithos.2024.107500.
14. Tian, Guanglin, Hongwei Deng, Bokun Zhao, Taoying Liu, Zhen Jiang, and Songtao Yu. 2024a. "A Study of Uniaxial Compressive Strength Degradation Model of Soil-Rock Mixtures under Freeze-Thaw Deterioration Based on Equivalent Model Characteristics of Conductive Paths." Construction and Building Materials 437:136975. doi: https://doi.org/10.1016/j.conbuildmat.2024.136975.
15. Tian, Guanglin, Hongwei Deng, Bokun Zhao, Taoying Liu, Zhen Jiang, and Songtao Yu. 2024b. "A Study of Uniaxial Compressive Strength Degradation Model of Soil-Rock Mixtures under Freeze-Thaw Deterioration Based on Equivalent Model Characteristics of Conductive Paths." Construction and Building Materials 437:136975. doi: https://doi.org/10.1016/j.conbuildmat.2024.136975.
16. Xie, Wei-Qiang, Xiao-Li Liu, Xiao-Ping Zhang, Quan-Sheng Liu, and En-Zhi Wang. 2025. "A Review of Test Methods for Uniaxial Compressive Strength of Rocks: Theory, Apparatus and Data Processing." Journal of Rock Mechanics and Geotechnical Engineering 17(3):1889–1905. doi: https://doi.org/10.1016/j.jrmge.2024.05.003.
17. Yang, Baojian, Huaiguang Wang, and Zhiyong Shi. 2025. "Interacting Multiple Model Adaptive Robust Kalman Filter for Process and Measurement Modeling Errors Simultaneously." Signal Processing 227:109743. doi: https://doi.org/10.1016/j.sigpro.2024.109743.