INTEGRATED GEOPHYSICAL AND GEOTECHNICAL INVESTIGATION USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Due to the complexity of subsurface conditions, several boreholes are required to obtain subsurface information for any proposed project site. Manual interpretation of large datasets from the boreholes occurs cumbersome and time-consuming. Similarly, applying automated geophysical methods such as seismic refraction and/or resistivity surveys to obtain and analyse soil parameters is difficult because no samples can be collected to ascertain the information. Therefore, an effective and efficient approach to gather and interpret a large volume of subsurface data is desirable. The effective and efficient approach can be accomplished by combining the applications of the borehole, geophysical surveys, and Machine Learning (ML). Geophysical surveys are employed to reduce the number of boreholes required so that the overall cost of site investigation can be reduced. Hence, this research aims to develop an intelligent model using Machine Learning Algorithms (MLAs) to predict the profiles of soil properties and characteristics, based on boreholes and geophysical investigations data. Five (5) locations in Johor Bahru, Johor, with similar site characteristics and subsurface lithology, were selected for this study. A total of twenty (20) boreholes and laboratory test results were referred to in obtaining the required information such as soil types, Standard Penetration Test number (SPT-N), moist and dry densities, Atterberg's limits, and specific gravity to be analyses in developing the algorithm. Python, a high-level general-purpose programming language, was employed to code the MLAs such as k-Nearest Neighbour (kNN), Random Forest (RF), Neural Network (NN), Linear Regression (LR) and AdaBoost. A total of 5,532,000 datasets were compiled for the prediction analysis and cross-validation to assess the efficiency of the MLAs. Statistical models and incorporated empirical values for soil were proposed utilising the multiple linear regression (MLR) method in order to develop new equations for estimating the SPT-N value. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2) were employed as the performance metrics to evaluate the differences of MLAs results. For model selection, the lowest values of MSE (3.909), RMSE (1.950) and MAE (0.578) and the highest R^2 (0.987) were considered. The results show that the AdaBoost model was remarkably capable of better predicting the soil parameter values than the other ML models. Thus, it has been shown that the development of such an algorithm will reduce the cumbersome and time-consuming processes in interpreting subsurface data and at the same time, be cost-effective. Predicting the parameters also give better engineering information and descriptions of the sites and their materials.

ABSTRAK

Dengan keadaan subpermukaan yang kompleks, sejumlah lubang jara diperlukan untuk mendapatkan maklumat subpermukaan bagi sesuatu projek yang dicadangkan. Pentafsiran secara manual ke atas lubang jara yang mempunyai set data yang besar adalah rumit dan memakan masa yang lama. Begitu juga dengan penggunaan kaedah geofizik seperti keberintangan elektrik dan/atau pembiasan seismik, untuk mendapatkan dan menganalisis parameter tanah adalah sukar kerana tiada sampel yang nyata boleh dikumpulkan untuk mengesahkan maklumat tersebut. Oleh itu, satu pendekatan yang berkesan dan cekap bagi mengumpul dan mentafsir data subpermukaan yang besar adalah sangat wajar. Satu pendekatan yang berkesan dan cekap boleh dicapai dengan menggabungkan aplikasi lubang jara, survei geofizik permukaan dan Pembelajaran Mesin (ML). Survei geofizik permukaan boleh digunakan untuk mengurangkan bilangan lubang jara yang diperlukan agar kos keseluruhan penyiasatan tapak dapat dikurangkan. Oleh itu, penyelidikan ini bertujuan untuk membangunkan model pintar menggunakan Algoritma Pembelajaran Mesin (MLAs) untuk meramalkan profil sifat dan ciri tanah, berdasarkan data penyiasatan lubang jara dan geofizik. Pemilihan sebanyak lima (5) lokasi di sekitar Johor Bahru, Johor, dengan ciri tapak dan litologi subpermukaan yang sama, telah dipilih untuk kajian ini. Sejumlah dua puluh (20) lubang jara dan ujian makmal telah dirujuk bagi mendapatkan maklumat yang diperlukan seperti jenis tanah, Ujian Penembusan Piawai (SPT-N), ketumpatan lembap dan kering, had Atterberg, dan graviti tertentu untuk dianalisis dalam membangunkan algoritma tersebut. Python yang merupakan bahasa pengaturcaraan umum peringkat tinggi, telah digunakan untuk mengekodkan MLAs seperti Jiran k-Terdekat (kNN), Hutan Rawak (RF), Rangkaian Neuron (NN), Regresi Linear (LR) dan peningkatan adaptif. Di sini, sebanyak 5,532,000 set data telah dikumpulkan untuk analisis ramalan dan pengesahan silang bagi menilai kecekapan MLAs. Kaedah regresi linear berganda (MLR) telah dicadangkan untuk digabungkan bersama model statistik dan nilai emperikal, bagi mewujudkan persamaan baharu yang boleh menganggarkan nilai SPT-N. Ralat Punca Kuasa Dua (MSE), Min Ralat Punca Kuasa Dua (RMSE), Ralat Mutlak (MAE) dan Pekali Penentuan (R^2) telah digunakan sebagai metrik prestasi untuk menilai perbezaan keputusan MLAs. Bagi pemilihan model, nilai terendah MSE (3.909), RMSE (1.950) dan MAE (0.578) dan R^2 tertinggi (0.987) telah dipertimbangkan. Keputusan menunjukkan bahawa model AdaBoost mampu meramalkan nilai parameter tanah dengan lebih baik berbanding model ML yang lain. Oleh itu, telah dibuktikan bahawa pembangunan algoritma sedemikian mampu mengurangkan proses yang rumit dan memakan masa dalam mentafsir data subpermukaan dan menjadi lebih kos efektif. Di samping itu, dengan meramal nilai parameter juga dapat memberikan maklumat kejuruteraan dan penerangan yang lebih baik, berkaitan dengan tapak dan bahannya.

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LIST OF ABBREVIATIONS

1D	-	One-Dimensional
2D	-	Two-Dimensional
3D	-	Three-Dimensional
4D	-	Four-Dimensional
AI	-	Artificial Intelligent
ANN	-	Artificial Neural Networks
ASTM	-	American Society for Testing and Materials
BN	-	Bayesian Networks
BSI	-	British Standards Institution
BT	-	Behaviour Tree
DT	-	Decision Trees
ERT	-	Electrical Resistivity Tomography
GPS	-	Global Positioning Systems
JKR	-	Jabatan Kerja Raya
kNN	-	k-Nearest Neighbours
LQA	-	Linear Quadratic Analysis
MASW	-	Multichannel Analysis of Surface Wave
ML	-	Machine Learning
MLAs	-	Machine Learning Algorithms
MLC	-	Maximum Likelihood Classification
MLP	-	Multi-Layer Perceptron
MLR	-	Multiple Linear Regression
NB	-	Naïve Bayes
QDA	-	Quadratic Discriminant Analysis
SOM	-	Self-Organising Maps
SPT	-	Standard Penetration Test
MSE	-	Mean Squared Error
RMSE	-	Root Mean Squared Error
MAE	-	Mean Absolute Error
R^2	-	Coefficient of Determination

LIST OF SYMBOLS

F	-	Formation factor
Vp	-	P-wave velocity
Vs	-	Surface wave velocity
d	-	Density
v	-	Poisson's ratio
E	-	Young's modulus
V	-	Voltage
I	-	Electric current
R	-	Resistance
ρ	-	Resistivity
A	-	Cross sectional area
ρ_a	-	Apparent resistivity
K	-	Geometric factor
w	-	Water absorption

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CHAPTER 1

INTRODUCTION

1.1 Research Background

Determination of geophysical properties is a primary task in the study of subsurface environments. These environments, specifically aquifers and reservoirs from the perspectives of environmental and petroleum engineers, are concerns for natural resources, namely water and hydrocarbons (such as oil, gas-condensate, and natural gas). It can perform cost-effective and automatic measurements of accurate values/terms of geophysical properties such as permeability and lithofacies. However, direct determination of subsurface geophysical properties from formation samples, namely core analysis, is costly, labour-intensive, and invariably subject to the availability of drilled rocks (which are generally not complete) and domain experts: e.g., geologists and geophysicists (Telford et al., 2004; Abidin et al., 2011; Groves et al., 2011). These factors have directed researchers and industry to employ well logs that are cost-effective, readily available, automatic, and producing comparatively accurate results compared with those from core analysis, even though scale differences exist between these two approaches (Arulrajah & Bo, 2008; John, 2012; Hatta & Osman, 2015; Abdullah et al., 2020).

Conventionally, geologists use graphical and mathematical (including numerical and statistical) methods to interpret (correlate) the relationships between well log signatures and values/terms of geophysical properties (Baecher, 1987; Ching & Phoon, 2014; Wang et al., 2015; Arjun & Haloi, 2017). However, these relationships are commonly complex because of the heterogeneous nature of subsurface environments and their uncertainties. Thus, these conventional methods may not appropriately characterize geophysical properties from well logs (Soong, 2004; Hiltunen, 2005; Loehr et al., 2017; Lafifi et al., 2016, 2019). Therefore, it can be safely stated that techniques, such as machine learning, capable of effectively and automatically correlating the complex, uncertain subsurface relationships and potentially providing higher prediction accuracy than traditional methods are in great demand.

The science of learning from data is a key focus of machine learning. Machine learning combines statistics and computer science for pattern recognition and data mining applications (Ripley & Druseikis, 1978; Han & Kamber, 2006; Halilaj et al., 2018). For science-based research, pattern recognition is the process of discovering, via automated or semi-automated statistical methods, functional patterns within data (Kotsiantis et al., 2010). Discovered patterns are then used to generate predictions based on similar data (Han & Kamber, 2006). The essence of machine-assisted pattern recognition is to provide computers with the ability to adapt their decision structures based on the characteristics of observed data and generate valid and objective predictions (Knaflic, 2015; Roiger, 2017; Hengl & Macmillan, 2019). Machine learning is an extension of the pattern recognition process. It attempts to provide users with an understanding of the patterns within data (Daoud et al., 2016; Witten et al., 2017). Hence, machine learning outputs should be comprehensible in a way that allows interpretations to be formulated in response to the decision structures used to recognize and exploit patterns within data and generate predictions (North, 2012; Cui et al., 2020; Zhang et al., 2020; Scikit-Learn, 2021b).

Geophysical methods employ physics principles to image intrinsic Earth's subsurface features that are diagnostic of some targeted points. Subsurface characterization for underground resources, pollution-free environments, and understanding the consequences of subsurface geological conditions have headed to the advancements in geophysical imaging methods used for such investigations (Sheriff & Geldart, 1995; Loke, 2000; Pellerin, 2002; Philip et al., 2002; Reynolds, 2011; Saad et al., 2011; Tomio, 2011; Said et al., 2012; Bery et al., 2012; Hazreek et al., 2015).

The categorization of subsurface geology using only invasive geotechnical investigation methods, such as soil borings, rock coring, and geophysical investigation like vertical electrical sounding (VES) and borehole logging, is tremendously limited because these methods provide information regarding the subsurface only at the specific location surveyed and may not be reliable for interpretation the surrounding conditions with lateral variations (Hung et al., 2007; Asif et al., 2016). Thus, electrical resistivity and seismic refraction are the most extensively used geophysical methods to determine reliable subsurface information about an area investigated laterally and vertically.

1.2 Problem Statement

Geotechnical engineering is one of the divisions of Civil Engineering, mainly dealing with soil, rock, and underground water. Since soil and rock are complex engineering materials that have been formed by a combination of various geologic, environmental, and physical-chemical processes, their properties in-situ vary vertically and horizontally. As highly nonlinear materials, their engineering properties are more complex and difficult to characterize than manufactured materials such as concrete and steel. The characteristics associated with soil and rock are enumerated in the following:

(a) Most parameters associated with the geotechnical problems must be obtained from in-situ or laboratory testing. However, due to the limited number of exploratory borings drills and the number of laboratory tests that can be performed, only a very small portion of the parameters can be obtained. This introduces many potential sources of error, and it is also the primary source of uncertainty involved with the geotechnical problems.

(b) Geotechnical parameters are based on one-dimensional (1D) data with a depth limitation. Additional boreholes must be produced in the field to obtain more data, including laboratory and field data analysis. This is due to the potentially significant errors or imprecision in the field data. Therefore, it heavily depends on engineering judgment, a combination of experience, subjectivity, reliance on precedent, and other factors.

(c) The process of data gathering is costly and time-consuming. Soil is different from most civil engineering materials in that it can simultaneously contain solid, liquid, and gas phases, and it is heterogeneous, anisotropic, and nonlinear. To construct mathematical models, it needs typically to introduce certain simplified assumptions. The nonlinearity of soil behaviour produces lots of difficulties in modelling.

(d) Most geotechnical and geophysical problems need to consider many variables that affect the response of the studying systems. Besides that, not many studies focus on data prediction using Machine Learning techniques. Therefore, the need for Machine Learning techniques by using prediction methods can produce enormous amounts of data that the geotechnical and geophysical methods cannot reach.

As a consequence of these characteristics of geotechnical problems, once the geophysical data has been taken, it can generate a geological structure model, which gives an absolute correlation with the data. The best overall model is achieved using all the presented geological data from boreholes and field mapping. Without this input of detailed information, which incorporates knowledge of the essential physical properties of the geological resources at the site, the model cannot be compelled or estimated in practical terms. Therefore, in this study, there needs to be a close collaboration amongst the data from geotechnical, geophysical and Machine Learning, which enable information to be obtained for a large volume of ground data that cannot be investigated.

1.3 Objective of the Study

This research provides an excellent opportunity to evaluate the feasibility of automating the composition and optimisation of workflows to make accurate predictions on unseen geotechnical and geophysical data. The general terms of references are to develop this research from ideas formulated through previous researchers and to be relevant to the present working methods, machines, conditions, and requirements for the industry.

This study aims to develop an intelligent model using Machine Learning Algorithms (MLAs) to predict the soil properties profiles and characteristics from geotechnical and geophysical site investigations. There are three (3) specific objectives that are covered by this study:

(a) To determine the underground profiles and characteristics of the soil properties from the geotechnical and geophysical site investigations.

(b) To develop intelligent models for predicting the classification of discrete categories representing geotechnical and geophysical features using Machine Learning Algorithms (MLAs).

(c) To validate and correlate measured parameters from geophysical methods with geotechnical parameters using statistical models and incorporate empirical value for soil.

1.4 Scope of the Study

Geotechnical, geophysical and machine learning methods enable information to be obtained for a large volume of ground that cannot be investigated by direct geological methods because of the cost and time involved. This study was conducted in collaboration with the Public Works Department of Malaysia, where they provided the study location and data from borehole logs (borelogs) for research purposes. Most of the boreholes are for government building design development. According to JKR Geotechnical Handbook (Public Works Department, 2016), the typical termination criteria for borehole and rock is five (5) times SPT-N value equal to 50 or at 45 meters depth. Overall, all boreholes produced do not reach the bedrock layer, and obtaining data from the rock types is limited.

Taking into account the objectives stated above, the services and facilities available on sites and equipment types examined, this research workable to carried out within the following scope and limitations:

(a) Field measurements on seismic and electrical resistivity survey methods, conducted on selected sites before construction was to take place. The assessments of the survey area are mainly at the existing borehole location, which later can be correlated with boreholes data.

(b) This study was undertaken in Johor with the same geological background formation. It must be noticed that this study does not deal with rock, but it can be extended to treat rock layers without involving significant effort.

(c) With these boreholes data, interpretation between resistivity values, seismic values and N-values or lithology can be conducted using MLAs. The geological and geotechnical properties of the groundmass in which the engineering construction takes place can be determined.

1.5 Significance of the Study

The research develops an intelligent model using Machine Learning Algorithms (MLAs) to predict the soil properties profiles and characteristics. By accurate prediction, the earthwork projects could be minimised by engineers due to the effectiveness in maximising the geological data gathered and making the correct MLAs selection.

Besides that, this research contributes to new knowledge in the non-destructive method of site investigation, particularly for geotechnical assessment in laboratory and field measurement. Furthermore, correlating the seismic, electrical resistivity value, and geotechnical parameters give better engineering information and descriptions of the sites and their material.

The followings are the contribution gained from this research, which are:

(a) Using the Machine Learning method is an alternative to a non-destructive method in obtaining geotechnical and geophysical data.

(b) This method contributes to the various correlation between electrical resistivity, seismic velocity, and geotechnical data.

(c) The presentations of results contribute to civil engineering application which produced relationships between SPT-N, JKR or Mackintosh Probes and Unconfined Compressive Strength (UCS) of cohesive soil.

The novelty of this study is the development of intelligent models using MLAs for predicting geotechnical and geophysical data using a Python framework. This framework can build the pipeline to pre-process the dataset, select the features, train, and validate the machine learning models, and use them to identify the soil properties profiles and characteristics based on geotechnical and geophysical investigations.

1.6 Thesis Outline

Each section and chapter is briefly described in this section. The introduction has presented related topics of research background, problem statement, objective of the study, scope of the study significance of the study, and thesis outline. This particular topic is a source of a set of case studies for this thesis. This study is valuable for many other geotechnical, geophysical, and machine learning applications.

A review of applications in geotechnical, geophysical and machine learning is briefly presented in Chapter 2. This involved a review of geophysical methods in the subsurface investigation, application of machine learning in geoscience study and supervised versus unsupervised learning. An extensive review of the literature concerning the application of MLAs to geoscience classification problems has revealed several avenues for further research.

Chapter 3 is concerned with the current state of practice in site investigation. Initially, the structure, aims and procedures of site investigation are briefly described. Then, the soil components and the means to identify them is presented, followed by a description of the soil characteristics. It also discussed how the data gathered from the boreholes, electrical resistivity, and seismic refraction survey. Computer programming using Python for machine learning and multiple linear regression to generate prediction expressions is also discussed.

The results from geotechnical and geophysical site investigations for interpreting ground conditions are described in Chapter 4. Initially, the components of borelogs related to soil mechanics description are presented. This section shows the data obtained from two survey methods, and the results were interpreted using computer software known as ZondRes2D for the 2D resistivity method and ZondST2D for the 2D seismic refraction method. The inversion resistivity model and seismic section have been produced, and further interpretation has been made in this section.

In Chapter 5, a methodology of Machine Learning Algorithms (MLAs) is presented for predicting underground information. The most influential parameters were investigated and used in the predictive models. Subsequently, machine learning predictive models such as kNN, Random Forest, Neural Network, Linear Regression and AdaBoost was developed using Python to predict parameters such as SPT-N, Resistivity (ohm.m), and Seismic Refraction (km/s). Cross-validation is mainly used in applied machine learning to estimate the skill of a machine learning model on unseen data. The model is expected to perform in general when used to make predictions on data that are not used during the training of the model. Finally, some of the improvements to be made are identified in the discussion.

In Chapter 6, the advantages of the proposed methodology and possible future improvements are identified. In this chapter, to demonstrate the ability of empirical models, multiple linear regression is used to model the relationship between SPT-N, Resistivity and Seismic Velocity variables. Later, it can be used to predict the value of a response based on the value of one continuous predictor variable. Considering these techniques and using the most influential parameters (Resistivity and Seismic Velocity), new equations are proposed to predict the SPT-N value with the same geological conditions. Finally, the conclusions reached from the development of the methodology are discussed.

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