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ESTIMATION OF SOIL LIQUEFACTION POTENTIAL IN THE DALAMAN RESIDENTIAL AREA USING A SUPERVISED MACHINE LEARNING MODEL

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Abstract

Liquefaction is a critical phenomenon in geotechnical engineering, especially in mixed depositional environments where different soil types coexist. In such environments, assessment of liquefaction potential may be challenging. However, machine learning techniques overcome these challenges. In this study, to estimate the liquefaction potentials of the soils in the Dalaman residential area which is situated in a mixed depositional environment, supervised Multilayer Perceptron (MLP) model has been generated by using seismic parameters from the Chi-Chi and Kocaeli earthquakes and the parameters of the soils affected by these earthquakes. Sensitivity, specificity, accuracy, precision F1 score and AUC have been calculated for training and testing phases in model generation stage and for Dalaman Region. These values have been found to be 77.9%, 91.5, 85.7%, 87.0%, 0.822 and 0.930 in training phase; 80%, 83.1%, 81.8%, 75%, 0.774 and 0.930 in testing phase. For Dalaman residential area, these values have been found as 81.3%, 86.2%, 83.5%, 87.25% and 0.841. When the values from training and testing phase are compared to the results of Dalaman Region, it can be said that the model accurately estimated the liquefaction potentials of the soils in the Dalaman residential area.

Keywords: Liquefaction, Multilayer Perceptron Machine Learning Technique, Mixed Depositional Environment, Dalaman

DALAMAN YERLEŞİM ALANINDAKİ TOPRAK ZEMİNLERİN SIVILAŞMA POTANSİYELİNİN DENETİMLİ MAKİNE ÖĞRENMESİ MODELİ İLE TAHMİNİ

Özet

Sıvılaşma, özellikle karmaşık zemin tiplerinin bir arada bulunduğu karmaşık çökelim ortamlarında, geoteknik mühendisliği açısından kritik bir olgudur. Bu tür ortamlarda sıvılaşma potansiyelinin değerlendirilmesi zorlayıcı olabilir ancak makine öğrenimi teknikleri kullanarak, bu zorluklar kolayca aşılabilir. Bu çalışmada, karışık çökelim ortamında bulunan Dalaman yerleşim alanındaki zeminlerin sıvılaşma potansiyellerini tahmin etmek amacıyla, Chi-Chi ve Kocaeli depremlerine ait sismik parametreler ile bu depremlerden etkilenen zeminlerin parametreleri kullanılarak, denetimli bir makine öğrenimi algoritması olan Çok Katmanlı Algılayıcı (MLP) modeli geliştirilmiştir. Modelin oluşturulma aşamasındaki duyarlılık, özgüllük, doğruluk, kesinlik, F1-değeri ve AUC değeri eğitim aşamasında %77,9, %91,5, %85,7, %87,0, 0.822 ve 0.930 olarak, test aşamasında ise %80, %83,1, %81,8, %75, 0.774 ve 0.930 olarak bulunmuştur. Oluşturulan modelin Dalaman yerleşim alanındaki performans ölçütleri ise %81,3, %86,2, %83,5, %87,25 ve 0.841 olarak bulunmuştur. Bu değerler kıyaslandığında oluşturulan modelin Dalaman bölgesindeki zeminlerin sıvılaşma potansiyelini başarılı bir şekilde tahmin ettiği görülmüştür.

Anahtar Kelimeler: Sıvılaşma, Çok Katmanlı Algılayıcı Makine Öğrenimi Tekniği, Karışık Çökelim Ortamı, Dalaman

Cite

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1. Introduction

The United Nations' concept of "urban resilience against natural disasters" is briefly described as the ability of cities to withstand natural disasters, maintain their functionality and adapt to changing conditions [1]

Seismic soil liquefaction is one of the critical geotechnical hazards within the context of urban resilience due to its severe and catastrophic consequences. Therefore, assessment of the liquefaction hazard of an area is a critical task for the sustainability of any residential area and the safety of the citizens [2].

Despite advancements in understanding urban resilience, many cities still have problems in the evaluation of geotechnical hazards, particularly seismic soil liquefaction. This gap in research is especially evident in mixed depositional environments where different soil types (clay size to gravel size) coexist due to the activity of different sedimentation processes in a single area [3]. Even though liquefaction is primarily associated with sandy soils, clays and gravels may also liquefy. However, the liquefaction criteria for sandy, clayey and gravelly soils differs from each other [4-6]. Therefore, mixed depositional environments, where sandy, clayey and gravelly soils coexist, present significant challenges in liquefaction analyses due to their heterogeneous nature. The widespread destructions observed in İskenderun during the 6th February 2023 Kahramanmaraş Earthquake sequence in Türkiye [6, 7] highlights the significance of the assessment of the liquefaction hazard in such complex geological settings.

Machine learning (ML) algorithms are powerful tools for the estimation of liquefaction hazard by identifying complex patterns and relationships between geotechnical, geological, and seismic parameters [8-13]. Hoang and Bui [9] used a hybrid model formed of Kernel Fisher discriminant analyses and least squares support vector machine to estimate the earthquake-induced soil liquefaction. Zhang and Wang [10] performed back propagation neural network, support vector machine, decision tree, k-nearest neighbours, logistic regression, multiple linear regression and naive Bayes to estimate soil liquefaction. Zhou et al. [11] published a paper based on the employment of a genetic algorithm and grey wolf optimizer for optimizing RF models to evaluate soil liquefaction potential. Demir and Şahin [12] investigated feature selection methods for soil liquefaction based on tree-based ensemble algorithms using AdaBoost, gradient boosting, and XGBoost. Lee and Hsiung [13] analysed the sensitivity of the MLP model in the seismic soil liquefaction analyses. Studies given above, used various machine learning languages and different algorithms to develop models for estimating liquefaction potentials of the soils using case histories and soils affected from these events for the generation of these models. Although these studies achieved high accuracies in their models, no statement has been found regarding whether these models have been tested in areas other than where their training data were obtained. Given this gap, our study will be estimating the liquefaction susceptibilities of the soils in the Dalaman residential area, a region characterized by a mixed depositional environment shaped by deltaic, fluvial, alluvial, and beach processes [14-16] by a model generated from a completely different geological and tectonic setting.

This study consists of three primary stages:

- Model Development: A predictive ML model is developed using real-world liquefaction case histories [8].
- Liquefaction Potential Estimation: The trained and tested model is applied to the soils of the Dalaman residential area.
- Model Validation: The model's performance is evaluated by comparing the results with the liquefaction susceptibilities of the soils, which have been calculated using conventional methods [17, 18].

2. Site Characterization

Dalaman Basin, which is located in tectonically one of the most active extensional regions in the world [19], has been shaped by the combined activity of both geological and tectonic processes [14, 15]. Elements that contribute to the formation of the basin covers large geological time interval [14, 15]. The Holocene-age units, which fall within the scope of the study area, are associated with the disintegration of the older units and their deposition in the lowland [14, 15]. The most important elements that modify the basin are the basin margin faults and approximately 250km long meandering Dalaman Stream which is formed of different branches [14, 15]. Initial formation of the Basin has begun as a deltaic system by the activity of the Dalaman Stream. This deltaic system shifted southward during the southward progradation of the Dalaman Stream and related continuous sedimentation. Thus, former deltaic environment has been overlain by the sediments of fluvial and alluvial environments [14, 15]. This complex sedimentation forms a mixed depositional environment characterized by laterally and vertically discontinuous soil layers [3]. Geological map of the Dalaman Basin is given in the Figure 1.

3. Materials and Methodology

This study employs an artificial neural network (ANN) to estimate liquefaction potential of Dalaman region.

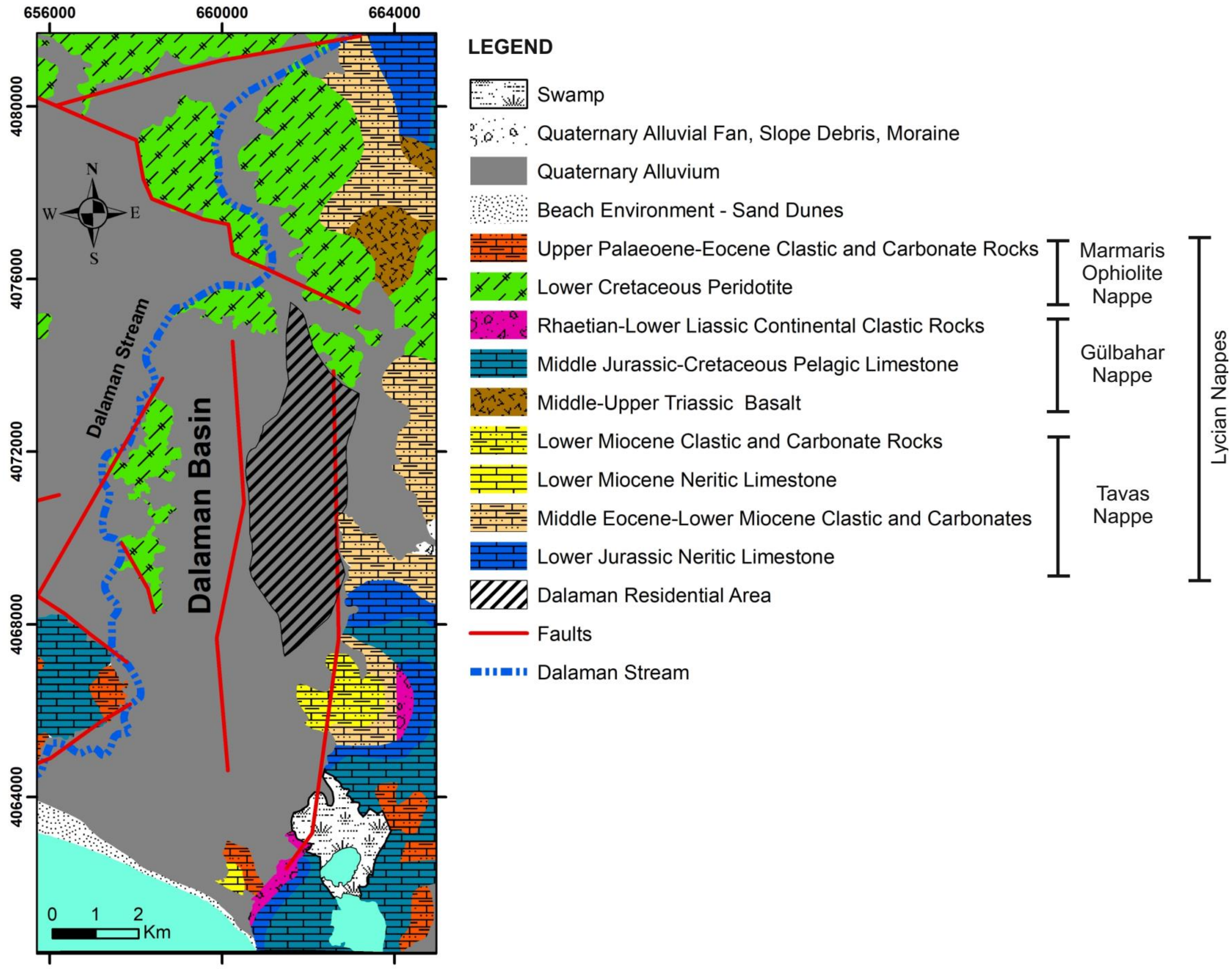

Figure 1. Geological map of the Dalaman Basin. Location of the residential area is indicated by black dashed area. From [18], modified from [20-22].

The methodology consists of data preparation, selection of the neural network model, training and testing the data, estimation of the liquefaction potentials of the soils in the Dalaman residential area and evaluation of the effectiveness of the model. Reliability of the model will be validated in this stage.

Because there is no recorded liquefaction case event in the Dalaman region, there is a need for a dataset to generate the model that will be used to estimate liquefaction susceptibilities of the soils in the Dalaman residential area. Thus, this will be a supervised machine learning algorithm. Dataset used in this study has been obtained from Hanna et al. (2007) [8] and consists of 620 rows formed of seismic parameters of Kocaeli and Chi-Chi earthquakes, parameters of the soils affected by these two earthquakes and the liquefaction conditions of the soils during these earthquakes. Seismic parameters and soil parameters are called as input parameters and the liquefaction cases are called as output parameters [8]. General structure of an ANN is given in the Figure 2.

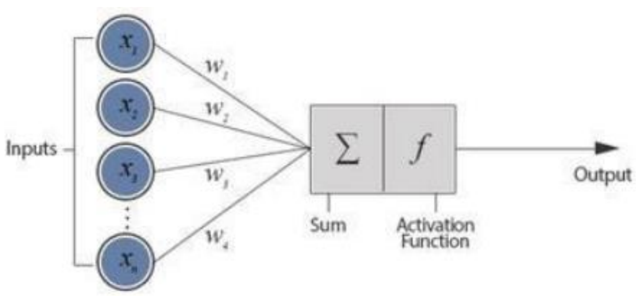

Figure 2. General schematic illustration of ANN [23, 24].

Input parameters that have been used to generate the equation must be completely the same as the parameters which have been used in the estimation of the liquefaction potentials of the soils in the Dalaman Region. Therefore, the dataset provided by [8] has been modified and, depth (z), corrected Standard Penetration

Test (SPT) blow number (N1,60), fine content in percentage (F%), groundwater level (GWL), total stress (σ), effective stress (σ'), moment magnitude of earthquakes, peak ground acceleration (amax) and cyclic stress ratio (CSR) values have been used as the input parameters. Summary of the dataset is given in Table 1.

During the model generation stage, various models have been tried, but the most representative model for the Dalaman residential area has been found to be Multilayer Perceptron (MLP) algorithm. A Multilayer Perceptron (MLP) is a type of ANN composed of multiple layers of interconnected neurons (input layer, hidden layer, output layer). It is widely used for classification and regression tasks due to its ability to learn complex patterns from data [25].

Input parameters have been normalized by using Batch Normalization in order to boost training, to reduce overfitting and to scale the values. Equation of the Batch Normalization is given in Equation 1 [26].

$$x = \frac{\mathrm{x} - \mu\beta}{\sqrt{s^2{}_\beta + \varepsilon}} \tag{1}$$

Then, randomly selected (simple random sampling) approximately 70% of the dataset have been used as training and remaining 30% of them have been used as testing set (69% training-31% testing). Machine Learning Algorithm has been produced by IBM SPSS 27. Software performs the random sampling itself. Since the shuffle option is enabled in the program, the dataset could not be exactly split into 70% and 30%.

Table 1. Small portion of the dataset used to generate the MLP model. Table includes the randomly selected 8 soil layers from the dataset [8].

Z	N1,60	F%	Dw	σ	σ'	M	amax	CSR	Liq.
1.00	6	90.00	0.77	16.30	14.00	7.4	0.40	0.29	No
1.80	8	94.00	0.77	30.90	20.60	7.4	0.40	0.37	No
2.60	7	100.00	0.77	45.60	27.30	7.4	0.40	0.41	No
1.20	7	85.00	2.30	17.70	17.70	7.6	0.18	0.12	No
2.80	6	30.00	2.30	43.50	38.60	7.6	0.18	0.13	Yes
4.20	5	90.00	2.30	70.40	51.80	7.6	0.18	0.16	Yes
6.80	6	99.00	2.30	118.20	74.10	7.6	0.18	0.18	Yes
8.80	7	94.00	2.30	156.30	92.60	7.6	0.18	0.19	Yes

Training type has been selected as Batch training. In order to minimize the error/loss between predicted and actual values, the data has been optimized. Scaled Conjugate Gradient method has been used for the optimization [27].

There is hidden layer between the input layer and the output layer which is formed of multiple neurons which also called as nodes. Each nodes takes data from the input layer and transfer it to the next layer [8]. Our structure is formed of 9 input parameters, 1 hidden layer that is formed of 7 neurons and 1 output layer which consists of 2 results (liquefaction occurs or does not occur).

Hyperbolic tangent activation function has been used in the hidden layers (Equation 2) [28]. Because hyperbolic tangent function is zero centred and it transforms the input parameters to values between -1 and 1, it enables the model to learn better [29]. Output layer is formed of two neurons. Because the liquefaction condition is categorical (either liquefaction occurs or does not occur), Softmax activation function has been used in output layer [30, 31]. Equation of the Softmax activation function is given in Equation 3 [32]. Schematic illustration of the generated model is given in the Figure 3.

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$

$$\sigma(\vec{x})i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \tag{3}$$

The second stage is the validation of the generated model using the data from Dalaman Basin. For this reason, liquefaction potentials of the 298 soil layers from the Dalaman Basin have been calculated using the simplified method [17]. Equations used to calculate the liquefaction potentials of the soils are given in Equations 4-11.

$$CRR_{7.5} = \left(\frac{1}{34 - N_{1,60f}}\right) + \left(\frac{N_{1,60f}}{135}\right) + \left(\frac{50}{\left(10N_{1,60f} + 45\right)^2}\right) - \left(\frac{1}{200}\right) \tag{4}$$

$$\mathrm{CSR} = \left(\frac{\mathrm{M} - 1}{10}\right)\left(\frac{\sigma}{\sigma'}\right)(\mathrm{a_{max}})\mathrm{r_d} \tag{5}$$

$$a_{max} = (0.4)S_{DS} \quad (6)$$

$$\mathrm{r_d} = 1.0 - 0.00765\mathrm{z} \text{ if } \mathrm{z} \leq 9.15m \quad (7)$$

$$\mathrm{r_d} = 1.174 - 0.0267\mathrm{z} \text{ if } 9.15\mathrm{m} < \mathrm{z} \leq 9.15m \quad (8)$$

$$\mathrm{MSF} = 10^{2.24}/\mathrm{M_w}^{2.56} \quad (9)$$

$$\mathrm{CRR} = \mathrm{CRR}_{7.5}\,.\,\mathrm{MSF} \quad (10)$$

$$FoS = \left(\frac{CRR}{CSR}\right) \quad (11)$$

After the calculation of Cyclic Resistance Ratio and Cyclic Stress Ratio, Factor of Safety (FoS) values have been obtained for the soils in the study area. Soils with FoS values greater than 1.1 are classified as non-liquefiable and soils with FoS values lower than 1.1 are classified as liquefiable [33, 34].

298 Soil layers have been imported into the generated model and the calculated FoS values (Liquefaction potentials of the soils) have been compared with the estimated values.

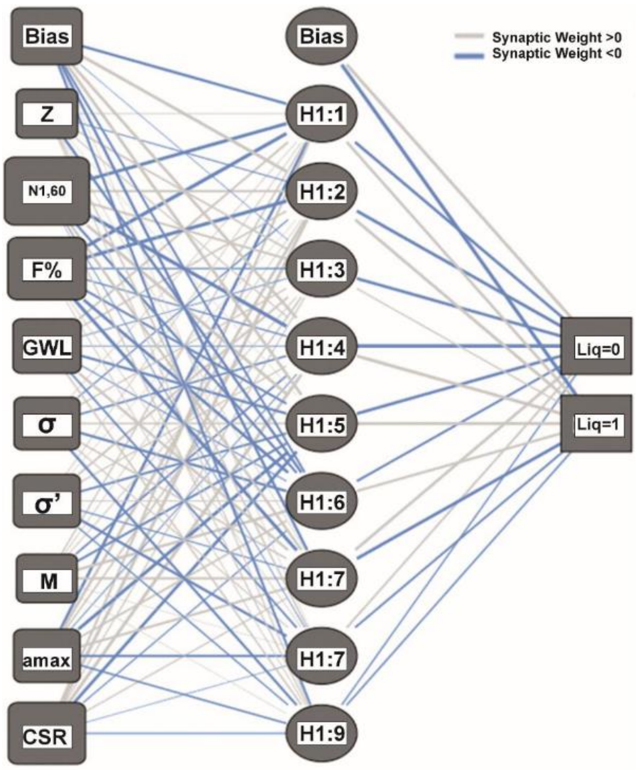

Figure 3. Schematic illustration of the generated MLP model.

Effectiveness of a machine learning model is evaluated via performance metrices. Accuracy, Precision, Sensitivity, Specificity, F1-Score and Receiver Operating Characteristic (ROC) Curve are types of performance metrices [35]. Definitions of each performance metrices are given below.

Accuracy: Proportion of the correct estimations (Equation 12). [35].

$$Accuracy = \frac{\mathrm{TP + TN}}{TP + TN + FP + FN} \quad (12)$$

Precision: The fraction of correctly predicted positive cases out of all predicted positives (Equation 13). [35].

$$Precision = \frac{\mathrm{TP}}{TP + FP} \quad (13)$$

Sensitivity: The proportion of actual positive cases correctly identified (Equation 14). [35].

$$\mathrm{Sensitivity} = \frac{\mathrm{TP}}{TP + FN} \quad (14)$$

F1-Score: Harmonic mean of precision and sensitivity (Equation 15). [35].

$$F1 = \frac{\text{Precision x Sensitivity}}{Precision + Sensitivity} \quad (15)$$

Specificity: The proportion of actual negative cases correctly identified (Equation 16). [35].

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{TN + FP} \quad (16)$$

ROC Score: Measures a model's ability to distinguish between classes using probability scores. (Equations 17-19) [35].

$$TPR = \frac{TP}{TP + FN} \quad (17)$$

$$FPR = \frac{FP}{FP + TN} \quad (18)$$

$$\int_0^1 TPR(FPR)d(FPR) \quad (19)$$

TP, TN, FP, FN are True Positive, True Negative, False Positive and False Negative respectively. [35].

4. Results and Discussions

Sensitivity, specificity, accuracy, precision and F1 score during the generation of the model have been found as 77.9%, 91.5, 85.7%, 87.0% and 0.822 respectively for training phase; and 80%, 83.1%, 81.8%, 75% and 0.774 respectively for testing phase. Confusion metrices are given in Table 2 and performance metrices are given in Table 3 for model generation stage.

Sensitivity, specificity, accuracy, precision and F1 score have been seen to be 81.3%, 86.2%, 83.5%, 87.25% and 0.841 respectively when the soils in the Dalaman Region have been imported to the equation. Confusion metrices are given in Table 4 and performance metrices are given in Table 5 for the validation stage.

Table 2. TP, TN, FP, FN values for the model generation stage

Confusion Matrix	Training Phase	Testing Phase
True Positives (TP)	141	60
True Negatives (TN)	225	98
False Positives (FP)	21	20
False Negatives (FN)	40	15

Table 3. Performance metrices for the model generation stage

Performance Metrics	Training Phase	Testing Phase
Sensitivity	77.90%	80.00%
Specificity	91.50%	83.10%
Accuracy	85.70%	81.80%
Precision	87.00%	75.00%
F1 Score	0.822	0.774

Table 4. TP, TN, FP, FN values obtained from the Dalaman Region

Confusion Matrix	Number
True Positives (TP)	130
True Negatives (TN)	119
False Positives (FP)	19
False Negatives (FN)	30

Table 5. Performance metrices for the Dalaman Region

Performance Metrics	Value
Sensitivity	81.30%
Specificity	86.20%
Accuracy	83.50%
Precision	87.25%
F1 Score	0.841

In the case of liquefaction potential analysis, sensitivity is generally more significant than specificity, especially in situations where the risk of missing a liquefaction hazard is high. Missing a liquefaction event can result in significant damage and safety concerns, however, missing a non-liquefaction case does not result in a damage and safety concern.

The sensitivity value in the Dalaman region is higher than in both the training and testing phases. This clearly shows that the model is more successful in identifying liquefiable soil layers in the Dalaman region.

Specificity shows a trend as 91.40% (Training phase), 86.2% (Dalaman), 83.10% (Testing phase). This suggest that the model is realistic in the testing phase and Dalaman Region.

When accuracy values of three different phases are evaluated, the accuracy in the Dalaman region is higher than in the testing phase but slightly lower than in the training phase. Performing better than the test phase indicates that the model works well in real-world conditions.

The precision in Dalaman is significantly better than the one in testing phase (75.00%) and close to the training phase (87.00%). This means that, when the model predicts liquefaction, the likelihood of it being correct is very high. The precision value in the Dalaman region is one of the strongest indicators of model reliability.

The F1 score in Dalaman is higher than in both the training and testing phases. An increase in the F1 Score indicates that the model maintains a good balance between sensitivity and precision.

Receiver Operating Characteristics (ROC) curve of the training phase of the model generation stage has been given in Figure 4. The area under the ROC curve (AUC) for both the liquefaction and non-liquefaction groups have been found to be 0.930. These values indicate a high level of accuracy and a strong ability of the model to distinguish the two groups, with values close to 1.0 which represents optimal performance. [35]

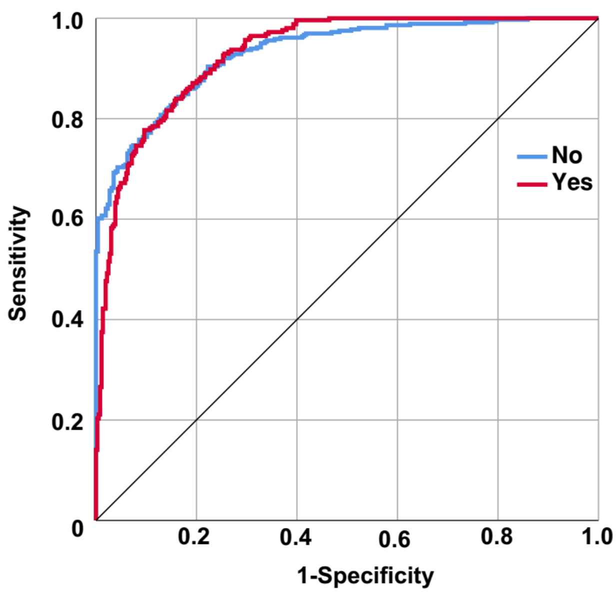

Figure 4. ROC curve for the generated MLP model.

Significance levels of the input parameters for the liquefiabilities of the soils have been calculated and given in Figure 5.

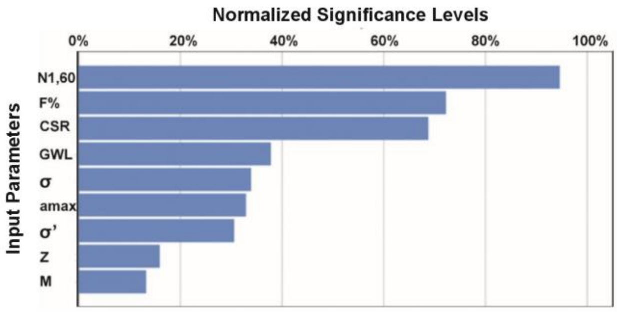

Figure 5. Significance levels of the input parameters in terms of liquefaction phenomena in the Dalaman Region.

The most significant input parameter has been found to be the SPT blow number (N1,60) and the least significant parameter has been found to be earthquake magnitude. The great significance level of the SPT blow number is as expected because it is directly related with the strength of the soil. Such low significance level for the earthquake magnitude is because of the use of only Mw=7.5 earthquake in the estimation of the liquefaction potential of the Dalaman Region and use of only Mw=7.4 and 7.6 earthquakes during the generation of the model. When these values are compared to the significance levels of the Zhang and Wang (2021) [10] it can be said that high significance levels of N1,60, F% and CSR values in this study are compatible with the high significance levels of qc, F% and CSR values in the Zhang and Wang (2021). Moreover, low significance level of earthquake magnitude seems compatible with the one in Zhang and Wang (2021) [10]. In future studies, the produced model can be expanded by adding new liquefaction case histories occurring at different earthquake magnitudes to the data set and the new model can be used to estimate liquefaction potentials of soils for different earthquake magnitudes.

Hanna et al. [8] provided the dataset including soil parameters and seismic parameters related with the Kocaeli and Chi-Chi Earthquakes. A General Regression Neural Network (GRNN) model has been proposed for the estimation of the liquefaction potentials of the soil in this study. The proposed model has a sensitivity, specificity and overall estimation values equals 98%, 99% and 99% for Taiwan earthquake; 98%, 96% and 97% for Kocaeli Earthquake. The model is different from the MLP model and they have used much more input parameters for the generation of the model. However, because of the limited input parameters within the Dalaman Region, number of the input parameters proposed in the dataset of Hanna et al [8] has been decreased in this study to ensure the uniformity of the datasets. Therefore, it is normal to have lower performance metrices than the one in the [8] is normal.

The studies conducted by Samui and Sitharam [36] and Lee and Hsiung [13] provide significant contributions about how AI-based models can be effectively used in the estimation of the soil liquefaction. Samui and Sitharam [36] has generated MLP and Support Vector Machine models for the estimation of the liquefaction potentials of the soils using soil and seismic parameters from the Chi-Chi Earthquake. However, the dataset does not comprise the soil and seismic parameters from 1999 Kocaeli Earthquake. Even if the generated models have high performances in the training and testing phases, the generated models have approximately 20-25% less performance in the estimation of liquefaction potentials in the global data which means the model does not represent the global data. This is probably because of the number of the data used in the model generation and points the significance of the data diversity. Our paper discusses a MLP model generated by using an extended dataset and performance of the model in the model generation stage is compatible with the performance of the model during the validation stage.

Lee and Hsiung [13] studied the sensitivity analyses on MLP for the recognition of liquefaction cases. According to the study sensitivities of the training and testing phases are found to be 98.9% and 91.2% respectively. The overall performance of the model is stated as 96.6%. However, even if it is not stated in the text the model seems that it has not been validated in a different site in which the liquefaction potentials of the locations are known.

Differences between the results of scientific studies will contribute to the development of science. In order for these studies to progress, more datasets need to be created and made available. Therefore, it is essential to properly record the liquefaction cases that have occurred in earthquake scenarios.

The paper offers practical tool for the estimation of liquefaction potentials of soil based on different input parameters. The model can deal with large dataset.

The MLP model can be used for preliminary study to have an idea about the liquefaction susceptibilities of the locations. However, by strengthening the model by using more input parameters engineers and urban planners may design structures compatible with the concept of "urban resilience against natural disasters" of United Nations. Moreover, designers may avoid from unnecessary efforts by avoiding construction in vulnerable zones. This may reduce the cost of projects.

The model can be shared with the local administrative authorities.

5. Conclusion

Liquefaction is an earthquake induced soil problem which results in undesired destructive consequences for the engineering structures and thus for the humanity. Thus, assessment of the liquefaction potentials of the soils is a significant task for engineers. Mixed depositional environments are common worldwide and hosts important settlements. For such mixed depositional environments, this process may be challenging because of the occurrence of different soil types together. By the increased use of machine learning techniques, many tasks are started the be solved easily. Estimation of the liquefaction potentials of the soils is one of these applications of machine learning techniques. MLP machine learning technique has been used in this study to estimate the liquefaction potentials of the soils in a mixed depositional environment. According to the results, this method has performed satisfactory results. Thus, it can be stated that MLP model can be used to estimate the liquefaction potentials of the soils in mixed depositional environments. At least it can be used as a preliminary study to understand the liquefaction susceptibilities of the soils.

6. Acknowledgment

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7. Declarations and Data Availability

This article was produced from Orkun TÜRE's Ph.D. thesis entitled "Determination of the Geo-Engineering Properties and Liquefaction Potential of the Quaternary Deposits of Dalaman-Muğla/SW Anatolia". These is no competing interest between the authors. No grants or funds were received. All rights of the data used within the scope of this study belongs to the site investigation companies and the Dalaman Municipality. Therefore, data must be requested from the site investigation companies that have been mentioned in the Acknowledgment part.

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