SOIL CLASSIFICATION BY USING ARTIFICIAL NEURAL NETWORKS

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

By
ARİF ÖZYANKI

In Partial Fulfilment of the Requirements for the Degree of Master of Science in Civil Engineering

NICOSIA, 2019

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Approval of Director of Graduate School of Applied Sciences

Prof. Dr. Nadire ÇAVUŞ

We certify this thesis is satisfactory for the award of the degree of Masters of Science in Civil Engineering

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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To my Family…

ABSTRACT

Soil properties are very important for the behavior of soils. Determination of the soil properties depends firstly on the classification of the soils. Coarse and fine-grained soils are fined out by sieve analysis. Fine-grained soils classification are done with their grain size distribution which is obtained by hydrometer test as well as their Atterberg limits.

In this thesis, soil classification values have been reached at Atterberg limits values estimated by using Artificial Neural Networks (ANN) training algorithm for fine-grained soils of Turkish Republic of Northern Cyprus. For this study, 108 samples of clay, silt, and sand percentages with liquid limit (LL) and plasticity index (PI) values were used. In the beginning of the study, the LL and PI values were estimated from the grain size distribution values. In the second part of the study soil classifications were found using estimated LL and PI values. In order to obtain the optimum function in ANN model, it was aimed to give high accuracy of the results by using different parameters and the highest correlation coefficient (R^2) values were examined. According to the results of the R^2 values for LL were 0.85 for training, 0.86 for testing, and for PI were 0.80 for test and 0.82 for simulation. In the second and final part of the study, the soil classifications were compared with the estimated soil classifications found from the LL and PI. The results show that 75 out of 88 data used in the training (85.2%) and 18 out of 20 used in the test (90%) were correctly estimated. ANN have been used in engineering areas frequently and reliably in recent years. In particular, the ANN, which are characterized by learning characteristics, can be used successfully in many prediction, estimation and classification processes, including cases where good results cannot be achieved with classical regression methods.

Keywords: Soil classification; Atterberg limits; grain size distribution; fine grained soils; Artificial Neural Networks; correlation coefficient

ÖZET

Zemin özellikleri, zemin davranışları için çok önemlidir. Zemin özelliklerinin belirlenmesi öncelikle zeminlerin sınıflandırmasına bağlıdır. İri ve ince daneli zeminler elek analizi ile belirlenir. İnce daneli zeminler, hidrometre testi ile elde edilen dane dağılımına ve Atterberg limitlerine göre sınıflandırılır.

Bu çalışma ile Kuzey Kıbrıs Türk Cumhuriyeti ince daneli zeminleri için Yapay Sinir Ağları (YSA) algoritması kullanılarak tahmin edilen Atterberg limit değerlerinden, zemin sınıflandırılması değerleri tahmin edilmiştir. Bu çalışmada kil, silt, kum, likit limit (LL) ve plastisite indeksi (PI) değerleri tespit edilen 108 örnek kullanılmıştır. Çalışmanın birinci bölümünde dane dağılımı değerlerinden LL ve PI değerleri tahmin edilmeye çalışılmış olup, ikinci bölümde ise tahmin edilen LL ve PI değerlerinden zemin sınıflandırılmaları bulunmuştur. YSA modeli eğitiminde optimum fonksiyon elde edilmesi için farklı parametreler kullanılarak sonuçların yüksek doğruluk vermesi amaçlanmış ve en yüksek korelasyon katsayısı (R^2) değerlerine bakılmıştır. R^2 değerleri; LL değerlerinde eğitim için kullanılan verilerde 0.85, testte 0.86 ve PI için ise eğitimde 0.80 ve testte 0.82 değerleri elde edilmiştir. İkinci ve sonuç kısmında tahmin edilen LL-PI değerlerinden bulunan zemin sınıfları ile gerçek zemin sınıfları karşılaştırılmıştır. Sonuçlara göre LL-PI değerleri için eğitimde kullanılan 88 veriden 75'i (%85.2) ve testte kullanılan 20 veriden 18'i (%90) doğru tahmin edilmiştir. YSA, son dönemlerde mühendislik alanlarında sıklıkla ve güvenilir bir biçimde kullanılmaya başlanmıştır. Özellikle, öğrenme özelliği ön plana çıkan YSA, klasik regresyon yöntemleri ile iyi sonuçlara ulaşılamayan durumlar dâhil pek çok ön kestirim, tahmin ve sınıflandırma işlemlerinde başarılı bir şekilde kullanılabilmekledir.

Anahtar Kelimeler: Zemin sınıflandırılması; dane dağılımı; ince daneli zemin; Atterberg limitleri; Yapay Sinir Ağları; korelasyon katsayısı

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LIST OF SYMBOLS AND ABBREVIATIONS

ANN:	Artificial Neural Networks
ART:	Adaptive Resonance Theory
CEC:	Cation Exchange
CPT:	Cone Penetration Test
D:	Grain Size
D_r:	Relative Density
FC:	Fines Content
G:	Specific Gravity
H_e:	Effective Depth
LL:	Liquid Limit
M:	Temperature
MDD:	Maximum Dry Density
M_s:	Dry Soil Mass
N:	Percentages of Grain Size Smaller Than D
OM:	Organic Matter
OMC:	Optimum Moist Content
PI:	Plasticity Index
PL:	Plastic Limit
R:	Hydrometer Reading Correction
R^2:	Coefficient of Determination
RBF:	Radial Basis Function
RNN:	Recurrent Neural Network
SL:	Shrinkage Limit
SPT:	Standard Penetration Test
SSE:	Sum of Squares of Model Errors
SST:	Square Sum of The Errors
t:	Sedimentation Time
USCS:	The Unified Soil Classification System
V_k:	Net Input

w:	Weights
x_i:	ANNs Input Values
σ':	Effective Stress
η:	Water Viscosity
ρ_w:	Water Density

CHAPTER 1

INTRODUCTION

1.1. Background

The soil is composed of gravel, sand, silt, and clay as a result of disintegration or by disintegration, transportation, and deposition of rocks. There are several methods to find the properties of soils. The methods followed in the examination of soils are complementary to each other, it is impossible to obtain information about the behavior of soils without determining the properties and changes of soil characteristics. Geotechnical engineers are able to determine which characteristics have the most impact on soil behavior. The soils are heterogeneous. It can be expected to vary within meters. Soils remain under various influences such as loading, dewatering, drying, and freezing over the years. The reactions of the soil in these cases are important both in the use of the soil as a building material and in the structures to be built upon.

Soils can have infinitely different properties due to the composition of its mineral or organic contents. It is difficult to apply probability methods to such a subject. It is also considered that to determine the soil characteristics require long-term and expensive experiments. Therefore, various researchers presented statistical methods in the form of regression analysis in order to determine the soil properties which provide reliable results and also can be obtained rapidly and inexpensively.

The buildings that make up the living areas of people are mostly built on soils. Accurate estimation of the properties of the soils on which these buildings will be build will provide economic gain for the design of the buildings and will guarantee their lives and assets for the people living in it.

The soil classification system has been one of the communication languages among the engineers in geotechnical engineering applications. The determination of soil classification is not eliminating the need for detailed soil investigations and other laboratory tests on soil samples which we determine the engineering properties. However, an engineer can determine the behavior of the soil in the case of structural loads in the application phase by classified soil. It is an inevitable fact that clays, which are frequently encountered in soil mechanics problems, have a wide range in terms of their engineering characteristics.

The grains forming the soil have a very different geometry and are of a wide variety of sizes. Knowing the grain size distribution in the soil plays an important role in determining the index properties of soils. The grain size distribution is the ratio of the weight of the grains of various diameters to the total dry weight of the soil in percent. Soils are divided into two types: coarse-grained soils (gravel and sand) and fine-grained soils (clay and silt). In order to determine the grain size distribution of the coarse-grained soils according to the in diameters, the sieve analysis is carried out and the hydrometer test is performed to determine the grain size distribution of the fine-grained soils according to the diameters.

Research on Artificial Neural Networks (ANN) continues on software and hardware. Today, ANN applications can be found in many areas such as economics, industrial engineering, automation, electronic circuit design, electronic engineering, computer engineering, medicine, various intelligence problems, optical perception, object identification. ANNs have also been successfully utilized in the field of geotechnical and construction engineering with the advancements in computational sciences and in computational power.

ANNs are inspired by biological neurons (nerve cells), resulting in artificially simulated studies of the brain's working system. The distinguishing feature of ANN from other methods of computation is that they perform operations using the learning feature of the human brain. Classical statistical methods recognize that the relationship between dependent and independent variables is linear, which results in insufficiencies as well as inefficiencies in the studies. In geotechnical sciences, parameters are controlled by many variables such as environmental factors, dynamic characteristics, and pore water pressure, where the relationships between these variables may be both linear or non-linear. The interdependent interaction of these features may make it difficult and time-consuming to utilize classical statistical methods. The application of a series of methods developed by ANN provides alternative solutions to the problems in geotechnical sciences or offers supplementary tools to the classical statistical methods in geotechnical studies.

ANN change its structure and weight of the neurons throughout its training and development by randomly distributed input parameters. It has a structure that can adapt itself like a nervous system of a living organism. In other words, it can change its structure and learn according to an internal and external stimulus. In the decision-making stage, the connection weights are activated and find the solution by itself. Therefore, it is not known what the system will do under a certain situation. This is the factor that adds an unknown feature to the system.

The ANN generally generates a set of data sets corresponding to an input data set. In this context, the final ANN model consists of three layers, an input layer where the input data is entered, a hidden layer where the data is processed, and an output layer where the results are obtained. The other important component of the ANN model is the connections between the layers. Each connection has a weight value. The weights of these connections are altered to develop a successful ANN tool throughout its training which provides favorable output results for a given set of input values. The weights generated during training are the values in which necessary information is stored. Although ANN is a proven technology and has a wide variety of usage and implementations in almost all science divisions, it is not entirely known how these weights are calculated and assigned. In this respect, the ANN content has not been fully solved and is criticized for this reason via various researchers.

1.2. Problem Statement

The aim of this study is to explain the estimation of the desired parameters using the learning method of the ANN with the available data. In cases where classical statistical methods such as multiple linear regression are insufficient and there is no linear relationship between variables, ANN can provide solutions to these type of problems and can be utilized successfully. Similarly, the linear relationship between the values of the sieve analysis and the Atterberg values used in the estimation is insufficient, ANN can be used for such a process. Sieve analysis and hydrometer analysis are required to determine whether the soils are fine-grained or coarse-grained, while Atterberg limits are required for the classification of fine-grained soils. Each process is laborious and expensive. The number of processes can be reduced by using sieve analysis values in estimating Atterberg limits.

1.3. Hypothesis

In this thesis, Atterberg limits which are difficult to be predicted by classical statistical methods will be calculated by using ANN and soil classification will be made from these values.

1.4. Research Objectives

The main objective of this thesis is to estimate the Atterberg limits from the grain size distribution values by the ANN method and to determine the soil classification from these estimated values.

To achieve this goal;

i. Training the model of ANN with sieve analysis and Atterberg limits obtained from previous projects in North Cyprus soils.
ii. Simulate the trained model with another set of data with the same characteristics.
iii. Determination of soil classification with estimated Atterberg limit values.
iv. The comparison of the determined soil classifications with the original soil classification.

1.5. Organization of Study

A number of actions have been taken to ensure the success of the identified steps and targets. The flow algorithm showing these steps are shown in Figure 1.1.

The purpose and steps of the study are described in the first chapter. Other similar publications are mentioned in the literature section, which is the Chapter 2. The research area, the methodology of the studies is given in Chapter 3. The modeling process, regression analysis, and other operations are the subjects of Chapter 4. A comparison of previous studies is given in Chapter 5.

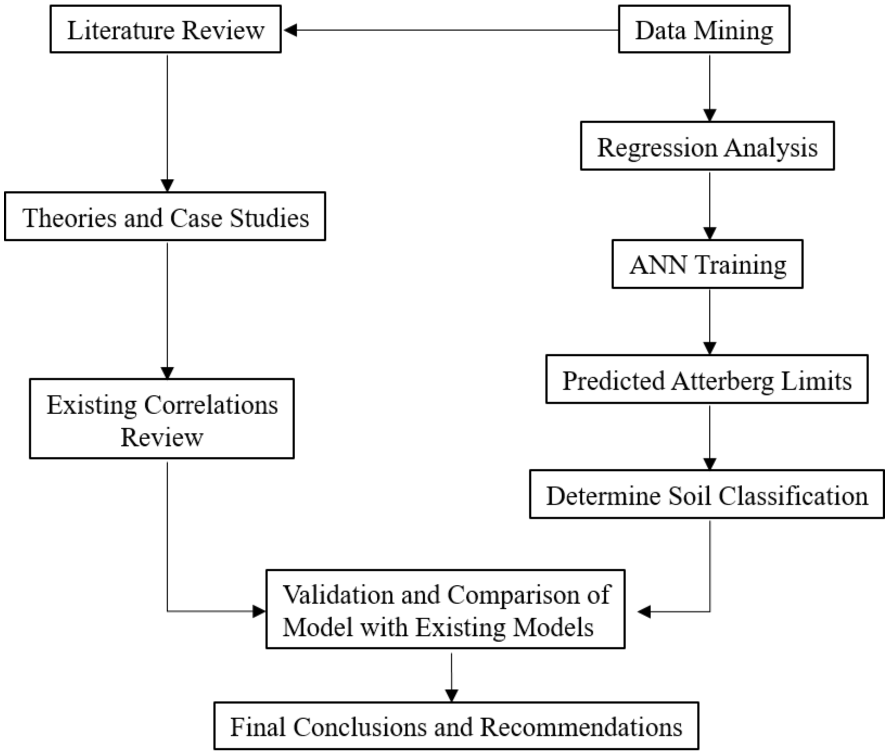


Figure 1.1: Algorithm of the study

CHAPTER 2

LITERATURE REVIEW

2.1. Soil Classification

Soils with a grain size of less than 0.075 mm are defined as fine-grained soils (ASTM D422-63; Holtz et al., 2011). Furthermore, in order to classify a soil sample as a fine-grained soil, more than 50% of its dry weight should be finer than 0.075 mm. Fine-grained soils are a mixture of clay and silt grains. The definition of the size limit between the clay and silt particles is called the clay fraction and this difference is determined to be 0.005 (ASTM D422-63) mm or 0.002 mm (Taylor, 1948). However, the cutoff between clay and silt particles is very narrow. The plasticity properties of silt and clay are a better separator than the particle size (Holtz et al., 2011).

2.2. Atterberg Limit Tests

Albert Atterberg (1911) originally defined six ‘Limits of consistency’ to classify fine-grained soils, but in present engineering applications, only three of the limits, i.e. liquid (LL), plastic (PL) and shrinkage (SL) limits are used. In fact, he was able to define several limits of consistency and he has developed simple laboratory tests to define these limits. PL is the transition limit for soils from semi-solid to plastic, and LL is the transition from the plastic state to the liquid state (Casagrande, 1958; Archer, 1975; PCA, 1992; Campbell, 2001; McBride, 2008; Das, 2010). These soil limits (soil consistency) are the water content rates required for mechanical changes in the soil. The plastic range measured as the plastic limit is the soil behavior limit where soil can return to plastic behavior without fracturing under loading. These limits are used to classify fine-grained soils. Atterberg limits can also be used to understand many soil mechanics and soil physical properties. Some of these features are swelling and shrinkage potentials, shear strength, and compressibility (Archer, 1975; Wroth and Wood, 1978; Campbell, 2001; McBride, 2008; Seybold, et al., 2008). These limits are also indispensable for soil and substructure surveys. While investigating the fundamental properties of soils, many researchers have used these limits. De la Rosa (1979), a research conducted in Florida, said cation exchange capacity (CEC), organic matter (OM) and clay content to cause considerable effects on PI. Studies on the soils in Canada and Nigeria have reported a significant relationship with the clay rate, LL, PL and PI values (Jong, et al., 1990; Mbagwu and Abeh, 1998). In another study, Odell et al. (1960) concluded that the clay content, the montmorillonite ratio in the soil and the OM ratio had a weighty effect on LL and PI. In the study conducted with data on the database on the US, Seybold (2008) noted that the clay content and CEC had a significant impact on LL and PI. Keller and Dexter (2012) stated that there was a correlation between the clay content and LL, PL, and PI values.

2.3. Artificial Neural Network in Geotechnical Engineering

In the studies of civil engineering and geotechnical engineering, ANN has been widely used since early 1990 (Lee and Lee, 1996; Najjar et al., 1996; Yuanyou et al., 1997; Yang and Zhang, 1998; Hurtado et al., 2001; Rafiq et al., 2001; Lee et al., 2003; Basma and Kallas, 2004). In the previous studies, it is observed that ANN is frequently used in estimating the compaction and uplift of pile foundations and axial and lateral load capacities (Goh, 1994, 1996; Chan et al., 1995; Goh et al., 1995; Lee and Lee, 1996; Teh et al., 1997; Abu-Kiefa, 1998; Nawari et al., 1999; Rahman et al., 2001; Hanna et al., 2004; Das and Basudhar, 2006; Ahmad et al., 2007; Shahin and Jaksa, 2009), drilled pole (Goh et al., 2005; Shahin and Jaksa, 2009), foundation settlements (Sivakugan et al., 1998) and anchors embedment (Rahman et al., 2001; Shahin et al., 2004, 2005; Shahin and Jaksa, 2006).

Goh et al. (1995) studied the relative density (D_r) and average effective stress (σ') as input in the ANN model performed on normally loaded and over-consolidated sands. They estimated the Cone Penetration Test (CPT) and cone resistance (q_c) as output. In this study, they used 93 data for training and 74 data for the testing. In this nonlinear relationship, the correlation coefficient was obtained as 0.97 for training and 0.91 for the test.

The prediction of settlements in the foundations is affected by uncertainties, similar to other complex issues of geotechnics. For this purpose, settlements prediction was tested with ANN by some researchers. Sivakugan et al. (1998) predicted the settlement of the shallow foundations on coarse-grained soils with ANN. In the development of the ANN tool, 79 data sets were used where 69 of them were used for training and 10 datasets for testing. Five parameters were used as input values that are applied net pressure, average standard penetration test (SPT) values, foundation width, foundation form and foundation depth.

The ANN method is applied to other applications in earth sciences; retaining walls (Ozturk, 2014; Ghaleini et al., 2018), dams (Ranković et al., 2014; Stojanovic et al., 2016), earthquake (Dindar et al., 2017), geographical information systems (Aslantaş and Kurban, 2007), mining (Rankine and Sivakugan, 2005; Afram et al., 2017), geoenvironmental engineering (Shang et al., 2004), petroleum engineering (Kulga et al., 2018) and rock mechanics (Kanungo et al., 2014).

Traditional statistical methods may be insufficient due to interactions between variables. Prediction of physical properties of soil such as mineralogy, porosity, water content, grain size etc. with statistical methods is difficult (Yingjie and Rosenbaum, 2002). ANN algorithms can be used to estimate/determine various soil characteristics, including soil classification (Cal, 1995).

2.4. Some Existing Correlations

In previous studies, the researchers used the ANN method in the estimation of soil properties and soil classification. Different estimation methods were compared in previous studies with ANN and classical regression analysis methods.

Cal (1995) had classified soil by using LL, PI and clay content. As a result of the study, he classified the clay soils as; heavy clay (I), light clay (II), heavy sub-clay (III), medium sub-clay (IV), light sub-clay (V), and sub-sandy clay (VI).

Günaydın (2009) predicted optimum moist content (OMC) and maximum dry density (MDD) values by using different methods. He used different combinations of fine-grained, sand, gravel, LL and PL values with 126 samples (Table 2.1).

Table 2.1: Models structure used in the study (Günaydın, 2009)

MODEL	INPUTS	STRUCTURE	TRANSFER FUNCTION
I	FG, S, G, G_s, w_L, w_P, ST	7-3-3	tan sig- log sig
II	FG, S, G, w_L, w_P	5-3-2	tan sig- log sig
III	FG, S, G	3-3-2	tan sig- log sig
IV	w_L, w_P	2-6-2	tan sig- log sig
V	w_L, w_P	2-3-1	tan sig- log sig

In the study, Simple-Multiple Analysis and ANN methods were compared. R^2 values were found to be between 0.77-0.78 for multiple linear regression analysis (Equation 2.1), 0.74-0.82 for simple linear regression analysis (Figure 2.1), and 0.67-0.89 for ANN analysis (Figure 2.2).

$$OMC = 0.3802w_L + 2.4513 \;\; R^2 = 0.82 \tag{2.1}$$

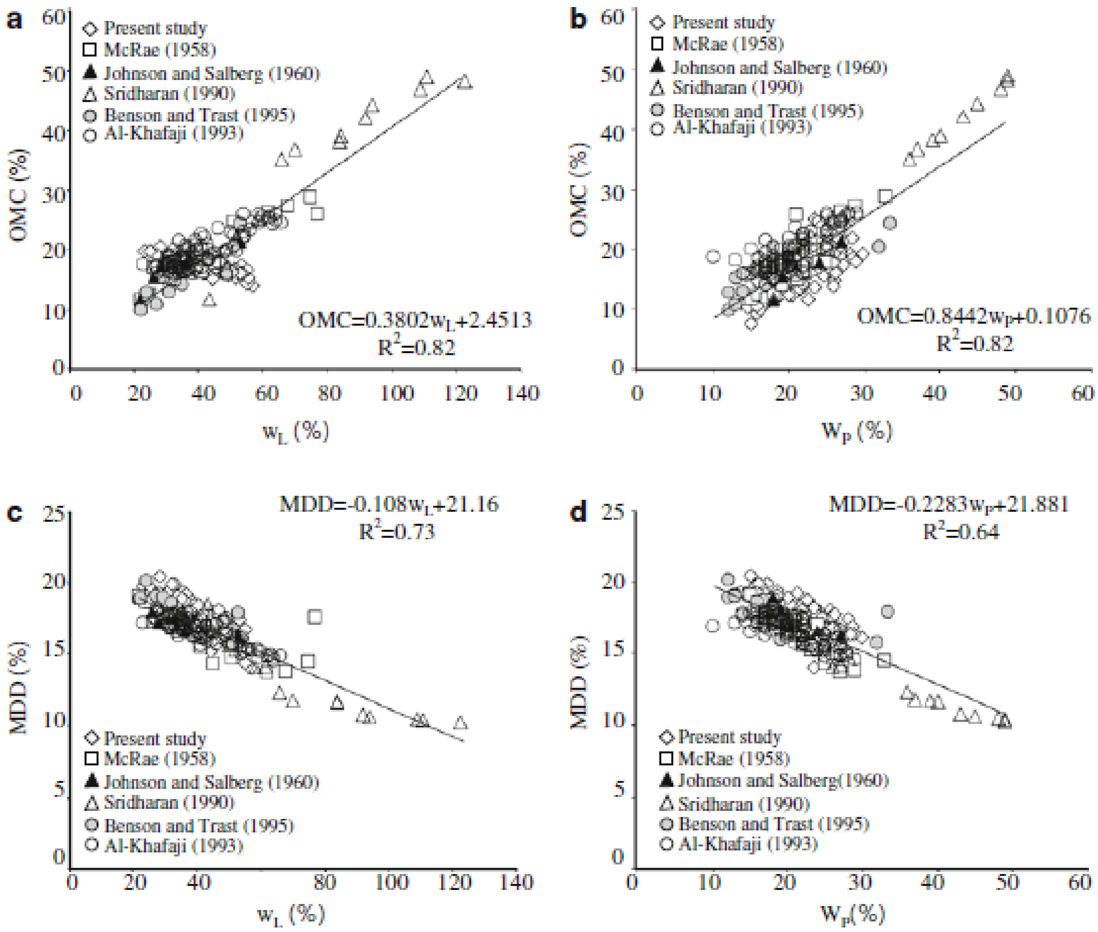


Figure 2.1: Simple linear regression analysis results; a) LL versus OMC, b) PL versus OMC, c) LL versus MD, d) PL versus MDD (Günaydın, 2009)

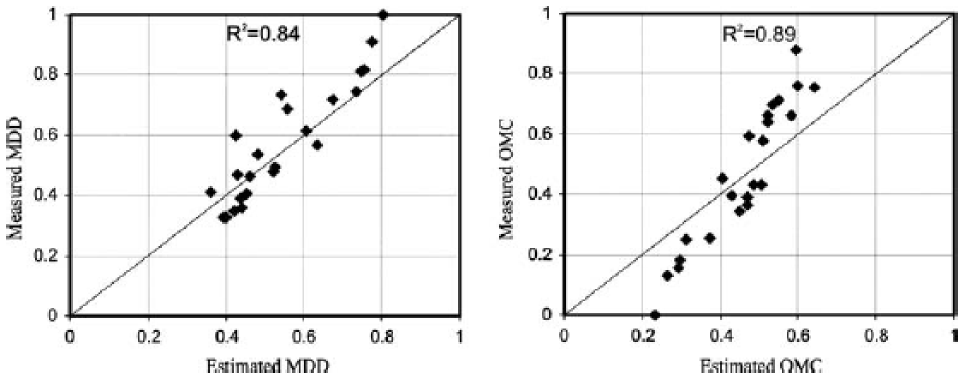


Figure 2.2: Comparison between measured compaction values, and the estimated compaction values by Model II (Günaydın, 2009)

Hassannejad et al. (2015) made soil classification with various ANN approaches to moisture content, LL, PL, and SPT values with 120 samples. They mentioned that the best algorithm to estimate soil classification is the Levenberg-Marquardt algorithm.

Tenpe and Kaur (2015) using ANN techniques calculated the OMC and MDD from LL, PL, and sieve analysis values with 210 samples. According to the ANN model results, the R^2 values for OMC values were 0.85 in the training, 0.76 in the test and 0.95 in the simulation (Figure 2.3 a, b, and c).

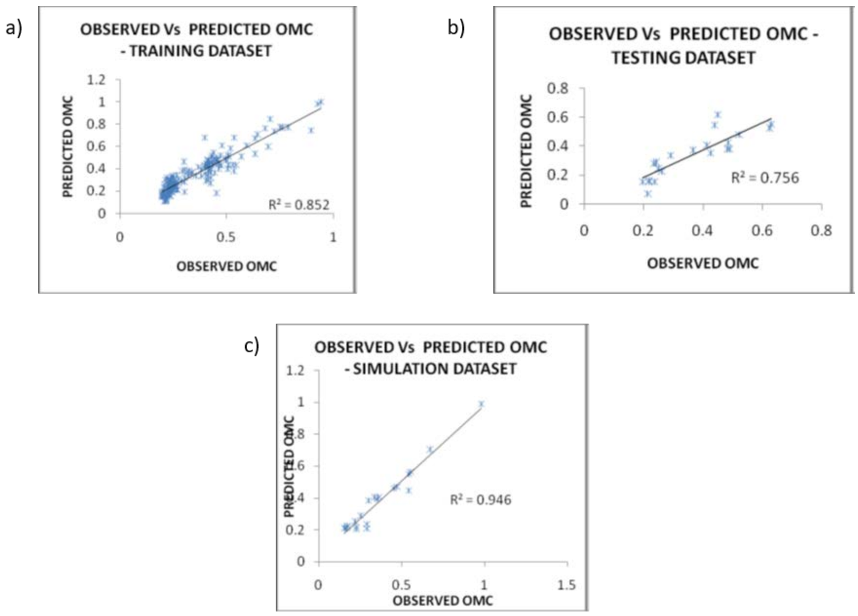


Figure 2.3: Observed OMC vs Predicted OMC values during a) Training, b) Testing, and c) Simulation (Tenpe and Kaur, 2015)

Also, R^2 for MDD values were 0.88 in training, 0.81 in testing and 0.95 in the simulation (Figure 2.4 a, b, and c).

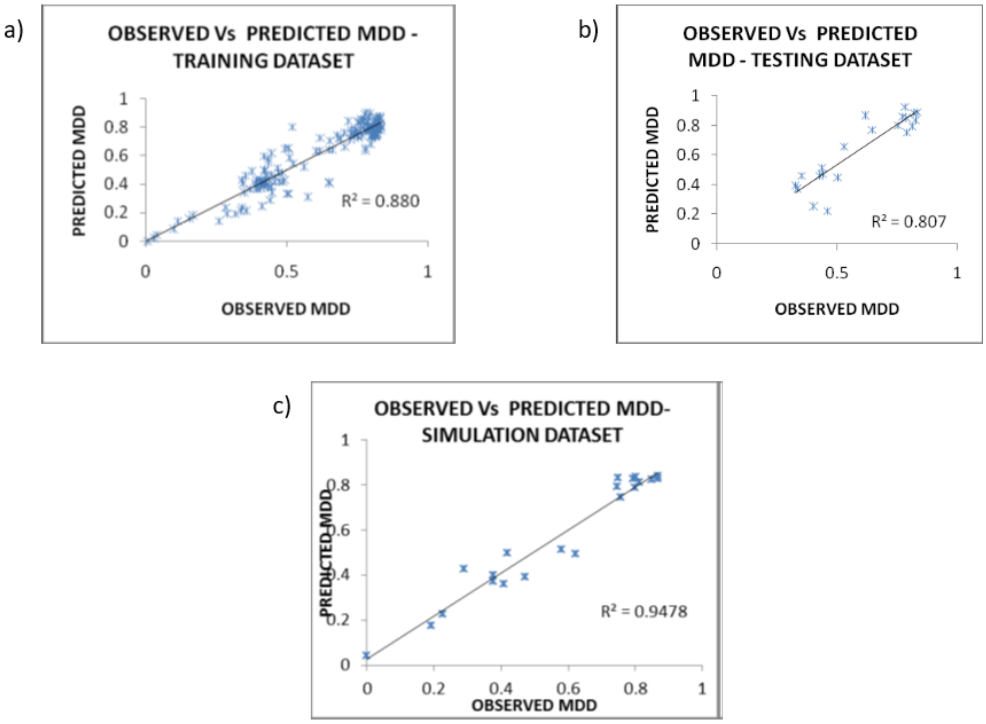


Figure 2.4: Observed OMC vs Predicted MDD values during a) Training, b) Testing, and c) Simulation (Tenpe and Kaur, 2015)

Bahmed et al (2017) were used the LL, the PL and Lime content as input for estimate the PI, the MDD, and the OMC values separately with ANN. In the study they used 280 data collected from previous studies. As shown the Figure 2.5 a, b, and c, the R^2 value for the PI was 0.91, for MDD and OMC were 0.83.

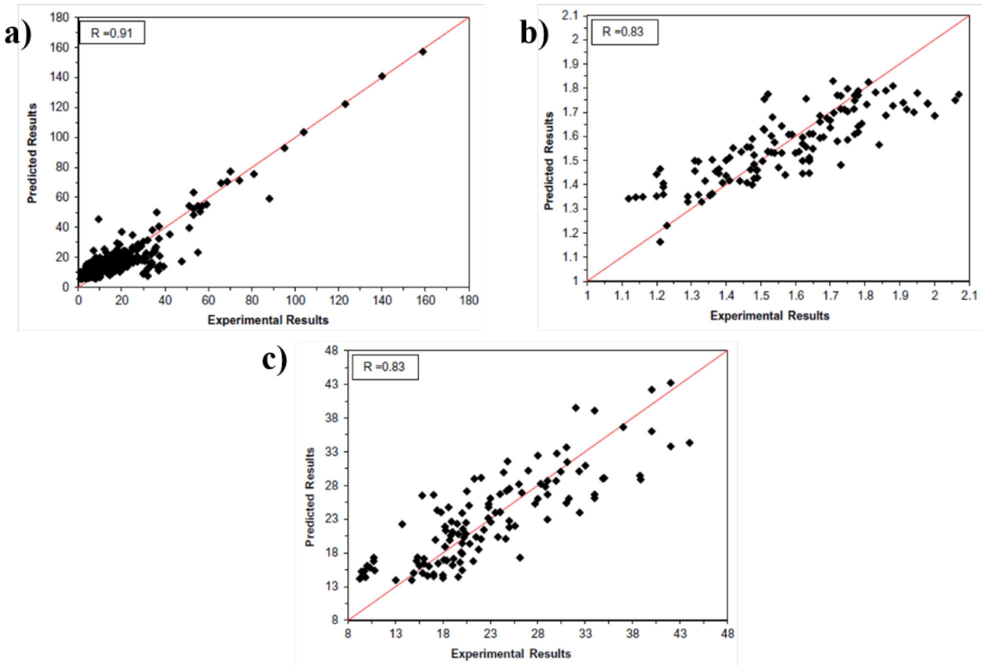


Figure 2.5: a) Experimental LL versus predicted LL, b) Experimental MDD versus predicted MDD, and c) Experimental OMC versus predicted OMC (Bahmed et al., 2017)

Reale et al. (2018) used the CPT values and estimated soil classification with ANN. For this reason, they used 216 data set. For this purpose, they developed two different ANN network. The first network developed to estimate fines content (FC) and second network developed for predicted for both the LL and PI. The R^2 of correlations results were 0.79 for FC, 0.85 for LL, and 0.78 for PI (Figure 2.6 a, b and c).

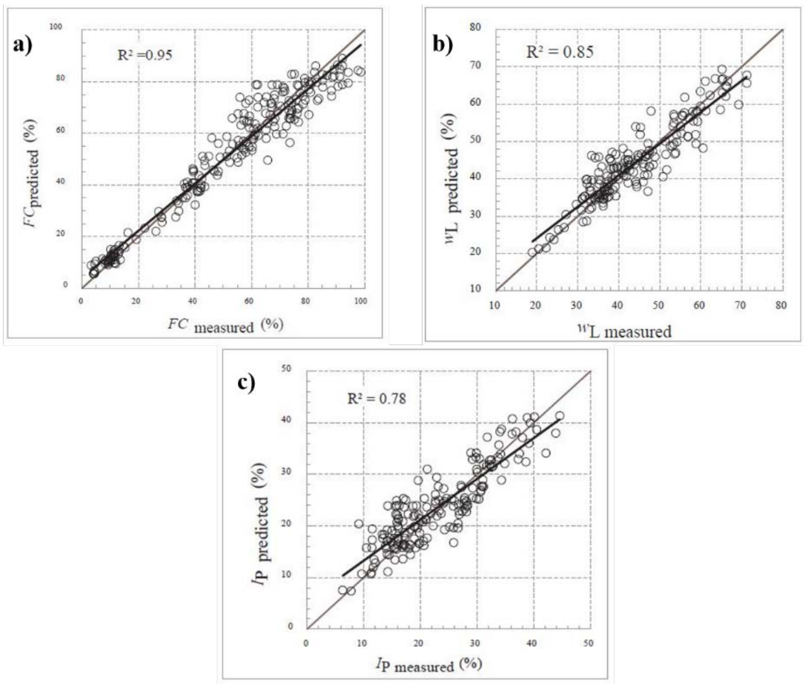


Figure 2.6: a) Measured FC versus predicted FC, b) Measured LL versus predicted LL, c) Measured PI versus predicted PI (Reale et al., 2018)

CHAPTER 3

MATERIALS AND METHODS

3.1. Area of Study

The soil samples and data used in this project were collected from various parts of Cyprus, especially Nicosia. The samples represent the different depth and soil types. The island of Cyprus is the third of the Mediterranean and the largest island of the Eastern Mediterranean with an area of 9251 km^2. The total area of North Cyprus is 3299 km^2.

Intensive investigations were carried out about the geology of Cyprus. However, there is no consensus yet. Ketin (1987) suggested five geological zones from north to south (1) Kyrenia or Five fingers Mountains, (2) Mesaoria Neogen Basin, (3) Troodos Massive, (4) Mamonia Complex, and (5) Limassol Forest Complex and Arakapas Fault Belt (Ketin, 1987). According to the Geological Survey Department of Cyprus, there are four geological zones in Cyprus namely; (1) Kyrenia, (2) Troodos, (3) Mamonia and (4) Circum Troodos Sedimentary Succession (GSD, 2002). Another suggestion about geological zones of Cyprus is made by Atalar (2005) and he divided the island into six geological zones according to geological evolution and emplacement of its geological units: These are; Kyrenia Zone, Mamonia Zone (Mamonia Complex), South Cyprus Zone, Troodos Zone (Troodos Ophiolite), Mesaoria Zone and the Alluviums (Atalar, 2005, 2006) (Figure 3.1).

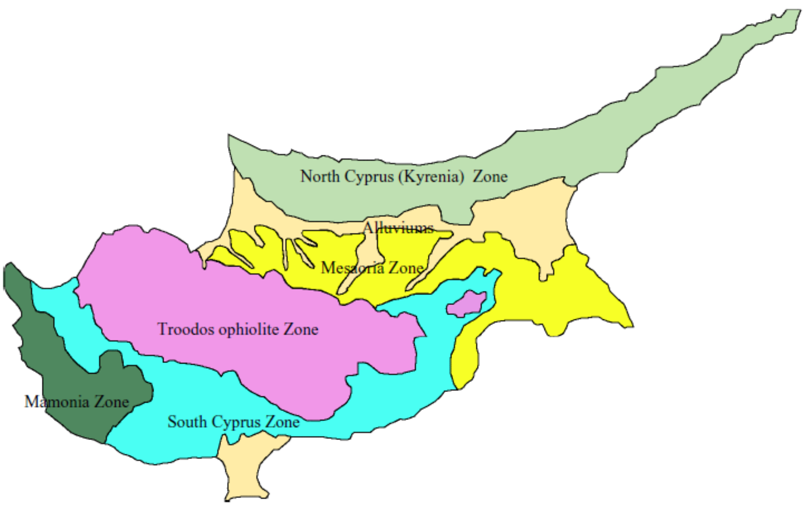


Figure 3.1: Cyprus geological map (Atalar, 2005)

The majority of the Cyprus soils are alluviums and over-consolidated clays (Table 3.1). The alluviums are located between the Kyrenia and Trodos mountain ranges, which are flat and topographically low areas. These represent the soils in the center of Cyprus (Atalar and Das, 2009). Alluvial soils consist of loose-medium density gravel and sand and soft hard silt and clays. The clay size amount in the alluviums is low. The amount of montmorillonite in the alluvium is high. These alluviums have partially high strength when dry. However, their strength is reduced with saturation. These clayey soils have low to intermediate swelling potential in North Cyprus. They were observed especially on the east and west coasts within the old harbors. There are old river beds filled with alluviums on the shoreline and inland.

Mesaoria clay zone; consists of clay with high and very high swelling potential. This group, which is heavily observed in the middle of the Island, have high and extremely high swelling potential (Table 3.1) especially in Nicosia, Famagusta, Larnaca, and Polis. This zone, which is mainly composed marl, also contains calcaremite, conglomerates, limestone, and gravel.

Clays of Değirmenlik (Kythrea) Group; This group includes mostly turbidite rocks. The group consists of gravel, pebbles, greywacke, marl and abyssal turbidites with mostly shallow environmental limestone, chalk, marl, limestone, and gypsum. The tens of meters of clayey units, which are several meters thick in different formations of the Değirmenlik (Kythrea) group, exhibit varied swelling potential. Haspolat (Mia Milia) present intermediate to high swelling potential, Yılmazköy (Skylloura) and Yazılıtepe (Lapatza) formations present high to very high swelling potential (Atalar, 2004).

Bentonitic Clays are formed by pillow lavas (Troodos Ophiolites) and form the first clays of Cyprus. Reaches a thickness of more than 300 meters in South Cyprus. Although 35% of bentonitic clays are calcium montmorillonite with low swelling potential, bentonitic clays have the highest swelling potential of Cyprus clays.

Clays of Momonia Complex are within igneous-volcanic, and metamorphic rocks of the Mamonia Complex of Middle Triassic to Cretaceous ages. Their swelling potential is much less than in the bentonitic clays (Figure 3.2).

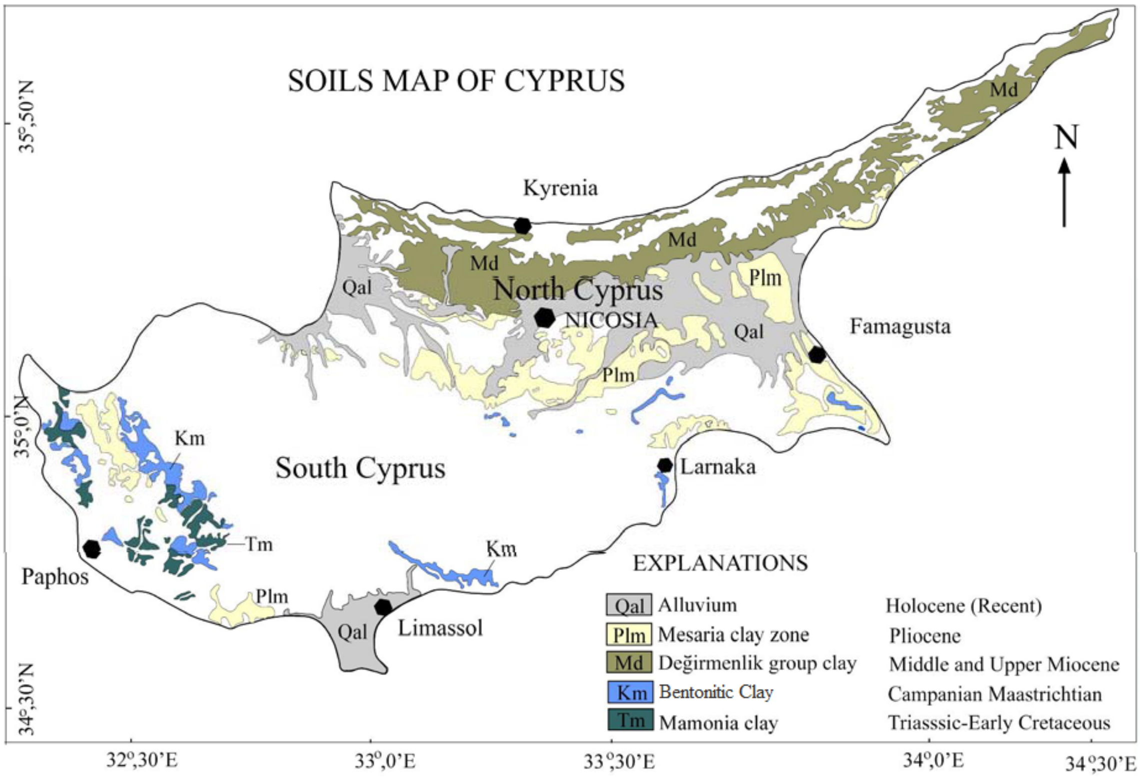


Figure 3.2: Cyprus soils map (Atalar and Das, 2009)

Table 3.1: Swelling potential of Cyprus clays (Atalar and Das, 2018)

Clays	Liquid Limit (LL)	Swelling Potential
Alluvium (North Nicosia)	32-48	Low-Intermediate
Alluvium (South Nicosia)	60-115	High – Extremely High
Mesaoria Clay Zone	52-119	High – Extremely High
Değirmenlik Group Clay	47-88	Intermediate – High
Mamonia Complex	33-167	Intermediate – Extremely High
Bentonitic Clays	55-210	High – Extremely High

3.2 Testing Methods

Soils can be divided into coarse-grained soils and fine-grained soils. In order to make this distinction, the grain size distribution analysis method is used. Grain size distribution analysis is divided into sieve analysis and hydrometer test analysis. If the ratio of the material under the 0.075 mm sieve is less than 50% it is called as coarse-grain soil (Gravel, sand),

and if it is more than 50%, it is called as fine-grained soil (silt, clay). Fine-grained soils are determined by hydrometer analysis after sieve analysis. We need LL and PI values when classifying fine-grained soils. Atterberg limit tests are performed for this purpose.

3.2.1. Grain size distribution

Grain Size Distribution analysis can be defined as the combination of two methods; sieve analysis and hydrometer analysis.

a) *Sieve Analysis Test*

During the analysis of the field works, reports, and projects sieve analysis were performing by using appropriate sieves according to ASTM D6913-17 standards. Samples were dried overnight at 105 ° C to 110 ° C. After the samples were cooled, they took to the sieve and the sieving process is performed. In the process using sieves with different sizes, the amount of sample remaining after each sieve is noted.

b) *Hydrometer Test*

In accordance with ASTM D 422-63 - Standard Test Method for Particle-Size Analysis of Soils standards;

- Samples remaining in the tray after sieve analysis are used for hydrometer analysis. Dispersing agents (Sodium Hexametaphosphate (40 g / L)) is added to the clay and silt grains to prevent them from sticking together and are allowed to soak for 10 minutes.
- The prepared solution is taken up in the precipitation vessel and pure water is added until the volume of the solution is reached.
- The open-end vessel is sealed with a stopper and upend 30 times per minute.
- After the vessel is directed, the cover is removed and time is recorded. After 1 minute 40 seconds the hydrometer is placed in the cylinder for the first reading.
- An identical 1000 ml vessel is filled with distilled water and the hydrometer is calibrated. Hydrometer reading in distilled water should normally be zero. A reading other than that is recorded and used as a hydrometer correction.

- For the first reading of the suspension, the hydrometer is slowly released into the liquid and the value is recorded.
- In the hydrometer test, readings are performed after 30 seconds, 1, 2, 4, 8, 15, 30, 60, 120, 240 and 1440 minutes.
- At each reading, the temperature of the suspension liquid is recorded and after reading, the hydrometer is swirled inside the control vessel.

After the hydrometer test is completed the calculation of the grain size is found by Equation 3.1.

$$D = M\sqrt{\frac{H_e}{t}} \tag{3.1}$$

$$M = \left(\frac{0.3\eta}{g(G-1)\rho_w}\right) \tag{3.2}$$

In where;

D is grain size, M is temperature, η is water viscosity, G is specific gravity, ρ_w water density (g/ml), H_e is effective depth and t is sedimentation time.

For the calculation of percentages of grain size smaller than D;

$$N = \left(\frac{G}{G-1}\right) * \frac{R}{M_s} * 100 \tag{3.3}$$

In where;

R is Hydrometer reading correction, M_s is dry soil mass.

3.2.2. Atterberg limits

Atterberg limits were determined by using distilled water on fine-grained soils. When performing the tests, ASTM D4318-17 (Standard Test Method for LL, PL of soils) standards are followed. The tests are performed with 200 gr soil sample which passes from No.40 (0.425 mm) sieve.

3.3 Artificial Neural Network

3.3.1. Definition of ANN

The basis of the ANNs began in 1942 with the first cell model proposed by McCulloch and Pitts. An ANN is a complex neural network composed of a combination of many simple nerve cells (Lippmann, 1987). Important features of ANNs are solving non-linear problems, having a distributed parallel structure, learning, error tolerance, and generalization. Through to these features are used in many areas. One of the important features of ANNs is learning and generalize this learning. By exploring the relationship between inputs and outputs given to the network, it is able to produce the appropriate outputs against unrecognized data (Garip, 2011).

ANN has a structure that model the functioning of live nervous system. In the live nervous system, the nerve cells receive signals and perform the signal transmission according to the signal they receive (Figure 3.3). The received signals are transmitted to the center of the cell (cell body). When the collected signals exceed the threshold, the signal is transmitted to the other nerve cells via the axon (Akkaya, 2011).

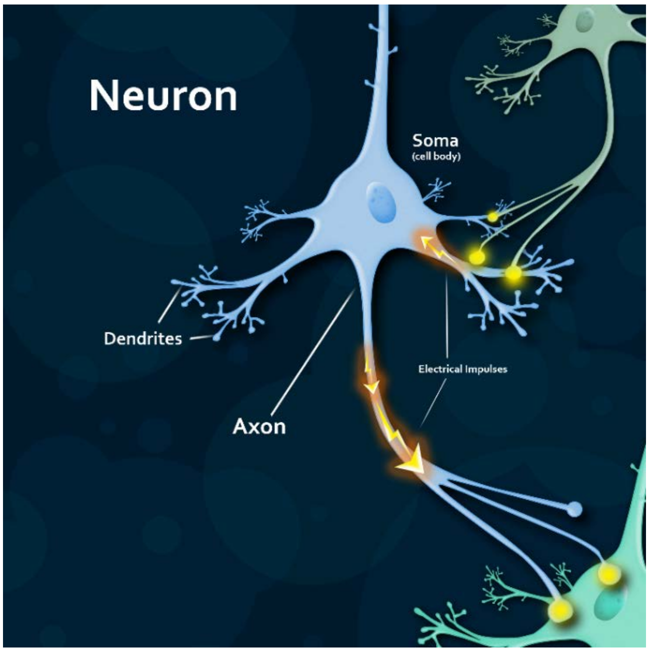


Figure 3.3: Biological nerve cell structure (Brain Education, 2018)

ANN is formed by the combination of many artificial nerve cells. This combination takes place in layers, not arbitrary (Akkaya, 2011).

We can mention about 3 learning strategies used in ANN.

a) Supervised Learning: Supervised learning is a machine learning technique that produces a function through training data. In other words, in this learning technique, the algorithm generates a function that makes a matching function between inputs and outputs (Hinton et al., 1999).
b) Unsupervised Learning: Unsupervised Learning model is a machine learning technique based on observations. In other words, the method tries to perform learning only through inputs without using output data. This method is especially used to collect the data set (Hinton et al., 1999).
c) Reinforcement Learning: Reinforcement Learning, a type of machine learning, demonstrates how an autonomous agent who senses the environment in which it is located and learns to make the right decisions to reach its goal (Johnson et al., 2000).

3.3.2. Main components of ANN

The artificial nerve cell is the basic element of the ANN and is also referred to as the processing element. A processing element consists of five components. These consist of inputs, weights, summing function, transfer function, and output. The similarities between the biological nervous system and the ANN are shown in Table 3.2 (Sağıroğlu et al., 2003).

Table 3.2: Biological Nervous System with similar features of ANN (Sağıroğlu et al., 2003)

Biological Nervous System	**Artificial Neural Network**
Dendrite	Summing Function
Cell Body	Artificial Neuron (Processing Element)
Axons	Transfer Function
Neurons	Artificial Neuron Output
Synapses	Weights

3.3.2.1. Inputs

The inputs are data from outside a neuron, and these data may come from an external neuron or neuron itself to the neuron (Aslay and Üstün, 2013). The basis of network training is input.

3.3.2.2. Weights

The weights are represented by w coefficients showing the effect of input data from the neural nerve on the nerve cell. Each input has a weight. The high weight value indicates that the input is important and the effective rate is high. Low weight values indicate that input is insignificant (Elmas, 2007). Weights are used in the relationship between input and output values (Garip, 2011).

3.3.2.3. Summing function

It calculates the net input from the neuron and different functions can be used to perform this calculation. The most commonly used method is the weighted sum (Hamzaçebi, 2011). The summing function equation is shown in Equation 3.4.

$$V_k = \sum_{i=1}^{n} x_i w_{ki} \tag{3.4}$$

In equation 3.4; V_k is net input, x_i is ANNs input values, w_{ki} is weights (i. input range k. neuron connecting weight), n is number of inputs. The selection of the summing function may vary depending on the problem. The trial and error method is used for the determination of ideal summing function.

3.3.2.4 Activation function

It is the function that keeps the output value against the net input value of the neuron in a certain range. It establishes a bond between the input and output values of the neuron (Haykin and Network, 2004). It processes the total input to the cell and generates the corresponding output. Different functions are used for output generating. Some network models require the use of a derivative function (Öztemel, 2003).

The activation function may be of different types depending on the function of the neuron. The optimal activation function can be found as a result of the attempts of the network developer, the activation functions can be fixed or adaptable. The most frequently used activation functions are sigmoid and hyperbolic tangent functions (Kakıcı, 2017).

a) Sigmoid Function (logsig): The sigmoid activation function is a continuous and derivative function. It is one of the most frequently used functions in ANN applications due to its non-linearity. This function generates a value between zero and one for each of the input values. The input-output expression of this activation function and the change of the function relative to the input are given respectively in Equation 3.5 and in Figure 3.4.

$$a = \frac{1}{1 + e^{-n}} \tag{3.5}$$

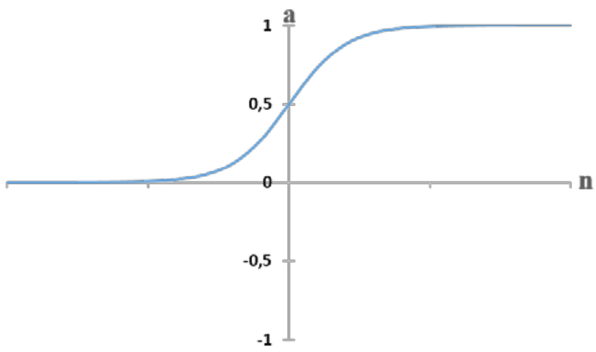


Figure 3.4: Sigmoid activation function

b) Hyperbolic tangent sigmoid function (tansig): For this activation function, the neuron input-output expression is given Equation 3.6 and the change of function are given in Figure 3.5. The dynamic change interval of the function is the range [-1 1] and the function shows a non-linear change in this range depending on the total input of the neuron.

$$a = \frac{e^{n} - e^{-n}}{e^{n} + e^{-n}} \tag{3.6}$$

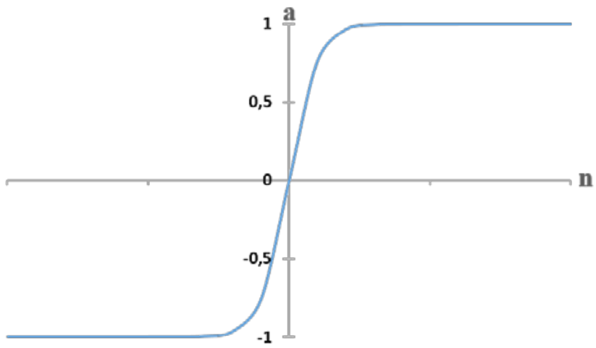


Figure 3.5: Hyperbolic tangent sigmoid function

c) Linear function (purelin): In this activation function, neuron output changes linearly according to the change of neuron inputs. The dynamic change interval is [-1 1]. The input-output characteristic of the function is given in Figure 3.6 and the function description is given Equation 3.7.

$$a = n \tag{3.7}$$

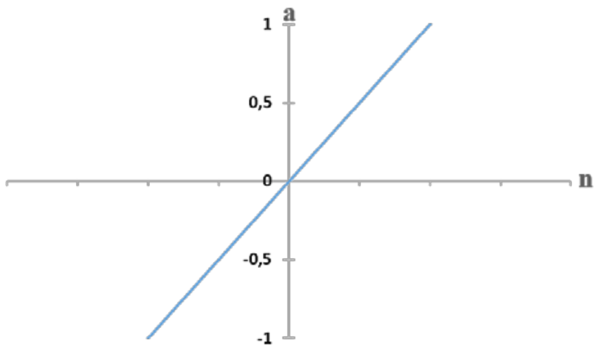


Figure 3.6: Linear (purelin) function

3.3.2.5 Outputs

The output value generated by the activation function. This value can be sent to the outside or to another neuron. The cell can use the generated output as input (Öztemel, 2003).

3.3.3. Neural network types

There are many different types of ANN, such as;

- Adaptive Resonance Theory (ART) Network
- Backpropagation networks
- Radial Basis Function (RBF) Network
- Kohonen Network
- Hopfield Network
- Recurrent Neural Networks (RNN)

3.3.3.1. Adaptive Resonance Theory (ART) Network

ART, based on the functioning of the human brain, was developed by Stephen Grossberg and Gail Carpenter (Figure 3.7). This network consists of a set of neural networks that examine issues such as forecasting and pattern recognition using supervised and unsupervised learning methods.

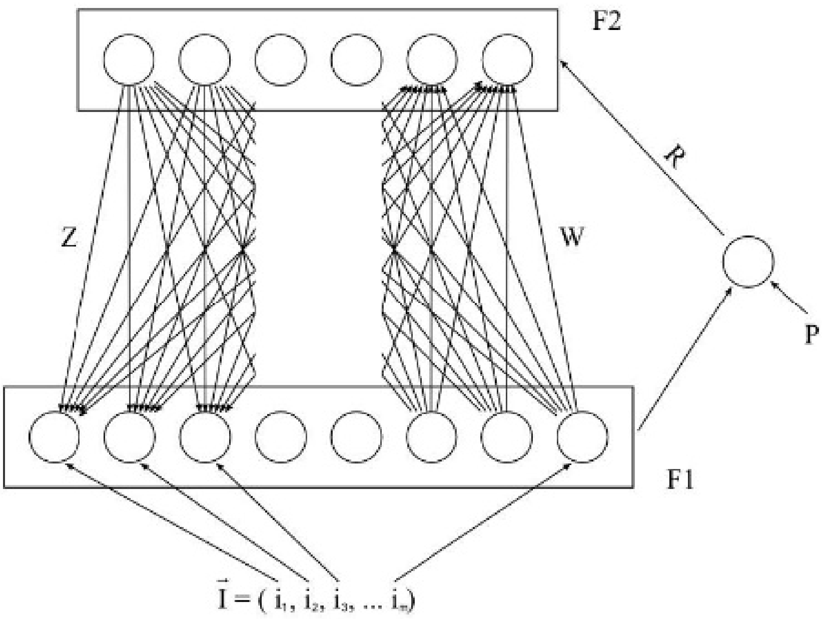


Figure 3.7: Adaptive resonance theory (ART) network structure (Miljkovic, 2010)

The basis of the network is the search for the presented model for a match in the stored categories. If this searching is not giving any matching, the network considers this model as an innovation.

3.3.3.2. Backpropagation networks

Backpropagation network is one of the most used artificial neural network models in engineering applications. The main principle of the Backpropagation network is to minimize the error obtained at the output of the selected network structure and to accordingly change the network weights. In this type of ANN, the processing elements (neurons) are arranged in layers. Each network model consists of at least three layers as input, hidden layer and output.

The backpropagation network model consists of seven learning steps, the first four of which are forward, and the last three steps are backward steps.

1. Defining the network structure: The number of inputs, output, a hidden layer, and neuron numbers is determined.
2. Determination of initial network parameters: The weight and bias to be used in the selected network structure are determined.
3. Identification the learning set to the network: A learning set consisting of inputs and outputs to be used to solve the problem or application is identified to the network.
4. Presence the last output of the network: For each processing element used in the network architecture, the total input, and transfer values are calculated and the last output of the network is the presence.
5. The error between the original value and the network output value is calculated.
6. The error is distributed to backward weights, starting from the output layer.
7. If the error is within acceptable limits, the operation is stopped, otherwise is returned to step 3.

The backpropagation network model tries to reach to minimum error value by increasing or decreasing the weight value it assigns after each approach. It is difficult to estimate the weight values to be used between input and output parameters. The advantage of the system are that the network propagation backwards and changes the weights according to the error rate. As in this study, backpropagation network model is preferred for problems that do not have a linear relationship between input and output parameters.

3.3.3.3. Radial basis function (RBF) networks

RBF networks consist of a 3-layer structure, an input layer, a single hidden layer using the radial functions, and an output layer (Figure 3.8).

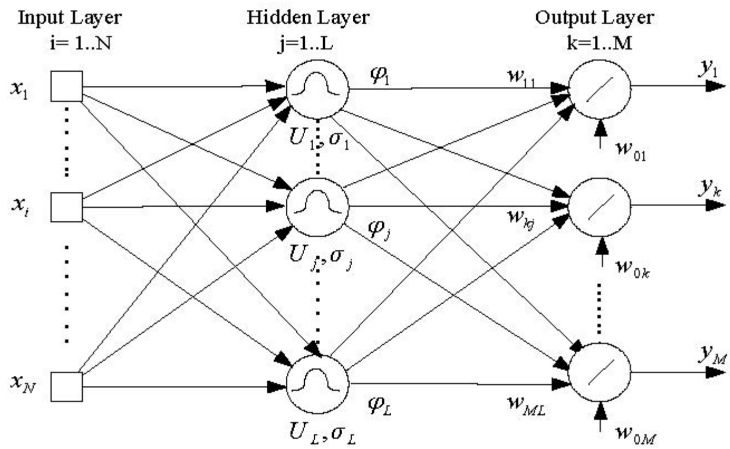


Figure 3.8: RBF network structure (Kaynar et al., 2016)

The working principle of the RBF network is the process of determining the relationship between the input and output by creating linear combinations of the outputs produced by these functions with appropriate weight values by determining RBFs with appropriate width and center values in the hidden layer depending on the input data.

3.3.3.4. Kohonen networks

Kohonen networks aim to cluster data when groups are not initially known. Kohonen networks are a data visualization tool as well as being used for clustering purposes. Kohonen networks are a type of neural network that performs unsupervised learning as there is no output (dependent variable) o be estimated.

3.3.3.5. Hopfield networks

Hopfield network structures are mainly single layer and fully connected neural network structures used for associative purposes. Each unit in the network structure is a simple threshold value processor unit and there is a bi-directional connection weighted between each processor unit pair.

3.3.3.6. Recurrent networks

The Recurrent Neural Network (RNN) is an artificial neural network model where the links between the units form a directed loop. With this loop, a network internal state has been created that allows it to display dynamic temporal behavior. In contrast to feed-forward neural networks, RNNs can use their input memory to process random sequences of inputs (Mikolov, 2010).

CHAPTER 4

DATA ANALYSIS AND RESULTS

A kind of different approaches can be used to provide the relationship between the multivariate data. As a classical method, multivariate regression coefficient estimates can be used. Besides, in these days' ANN are used as an alternative way to this method. This thesis includes 108 data from field works and previous reports, and projects such as Swelling Clay Project (Atalar, 2002; Geotest, 2014; Hussain 2016). These data are compiled according to grain size distribution (% sand, % silt, % clay) and Atterberg limit values. The main aim of this thesis is to predict soil classification with grain size distribution analysis by using ANN. Therefore, at the first phase of this study we predicted liquid limit and plasticity index from grain size distribution with ANN, and in the second phase, we determined soil classification from the Unified Soil Classification System (USCS) chart.

4.1. Data Analysis Methods

There are many methods used to determine the relationship between variables. However, in this study, multiple linear regression and artificial neural network training algorithm methods were used. The coefficient of determination is used as a parameter to determine the degree of accuracy of these methods. If it is necessary to explain this; Coefficient of determination (R^2) is shown in Equation 4.1;

$$R^2 = 1 - \frac{SSE}{SST} \tag{4.1}$$

Where; SSE (Equation 4.2) is the sum of squares of model errors and SST (Equation 4.3) is the square sum of the errors in the model.

$$SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{4.2}$$

$$SST = \sum_{i=1}^{n} (y_i - \bar{y})^2 \qquad (4.3)$$

It is one of the most important parameters used in observing the correspondence between estimated values and actual values. R^2 values descriptive between 0 and +1. Chin (1998) described the accuracy level of R^2 like substantial, more moderate, and weak (Table 4.1).

Table 4.1: Accuracy of coefficient determination (Chin, 1998)

R^2	Desired Value
0.67	Substantial
0.33	More Moderate
0.19	Weak

Data normalization (Equation 4.4) has been applied in order to calculate the predicted values in a healthy and secure way. There are differences between the input and output parameter values. This process was applied to group the data in a certain order and range (between 0 and 1). Another benefit of this process is to reduce the processing time. Is shown in Equation 4.4.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (4.4)$$

4.2. Multiple Linear Regression Analysis

Multiple linear regression is the analysis of being able to explain the relationship between a single dependent variable and multiple independent variables (Equation 4.5). There is a correlation between the dependent and independent variables in this analysis method.

The most general regression equation;

$$Y = a_0 + a_1X_1 + a_2X_2 + \cdots + a_nX_n + e_i \qquad (4.5)$$

Where; X_i are independent, Y_i dependent variables and e_i is error term (Y-Ŷ).

In this study, sand, silt, clay percentages were used as independent variables. Liquid limit and plasticity index were evaluated separately as dependent variables. In Table 4.2 is shown that statistical properties of the data.

Table 4.2: Data properties

	% Sand	**% Silt**	**% Clay**	**LL**	**PI**
Min	0.4	8.7	25.3	26.3	5.1
Max	49.7	51.7	78.0	87.5	56.7
Std. Dev.	12.98	9.55	12.37	15.05	13.81

As is shown in Table 4.3 R^2 values are about 0.38. The comparisons of multiple regression analysis results are shown in Figure 4.1 for LL and Figure 4.2 for PI. That's mean the accuracy of variables being more moderate. This isn't enough for us. Due to this reason, we can't trust this analysis result. In cases where multiple regression analysis is inadequate, the ANN method is used as an alternative method.

Table 4.3: Multiple linear regression analysis results

Dependent Variables	**Independent Variables**			a_0	R^2
	%Sand	**%Silt**	**%Clay**		
LL	7.184287	6.890024	7.788753	-683.325	*0.387924*
PI	7.198396	6.645002	7.507712	-690.861	*0.374896*

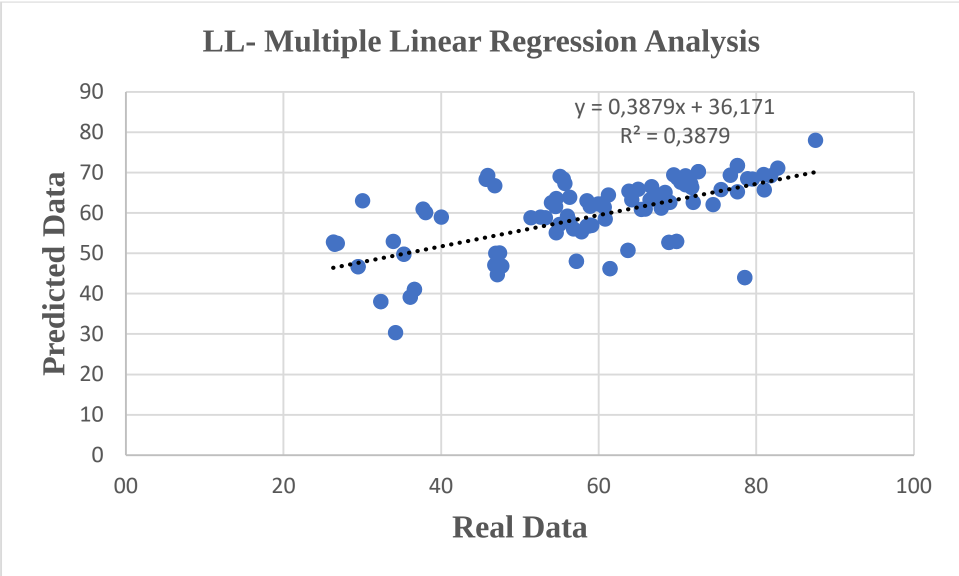
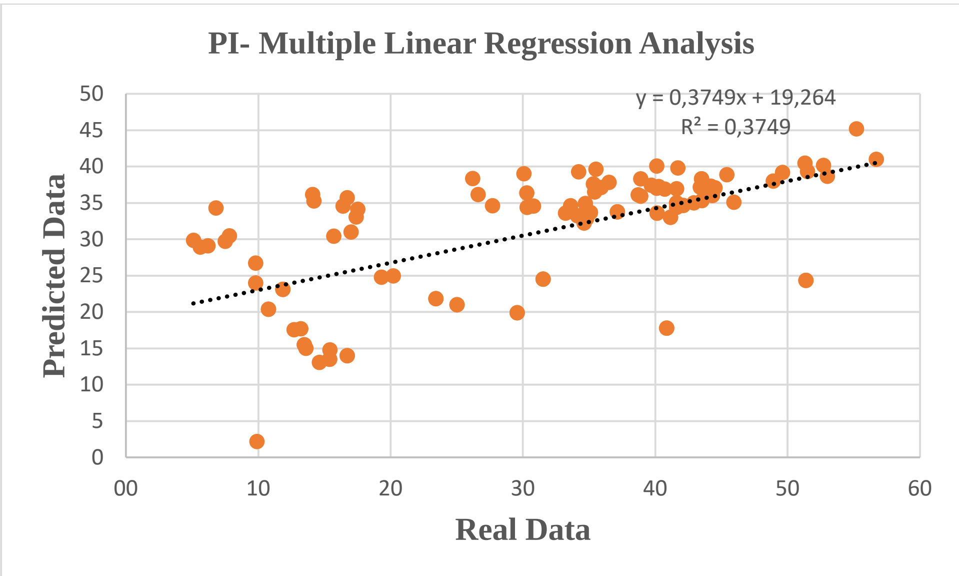


Figure 4.1: Multiple linear regression analysis results for LL



Hata! Yer işareti tanımlanmamış.Figure 4.2: Multiple linear regression analysis results for PI

4.3. Artificial Neural Network Training Algorithm

This study is presented in two separate sections. In the first section, an ANN model was proposed to predict LL and PI by using grain size distribution analysis values. Later, using predicted LL and PI values, classification of soils were determined. Figure 4.3 illustrates the steps adopted in the study for fulfilling above-mentioned procedures.

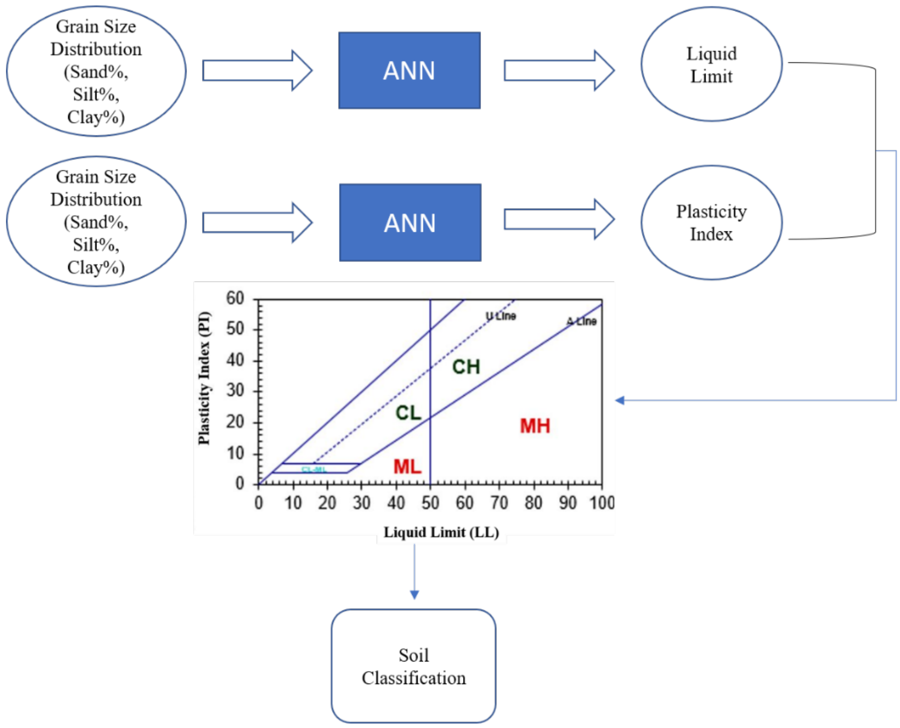


Figure 4.3: Generalized base of the study

4.3.1. Prediction to liquid limit and plasticity index

ANN are computer-based modeling and statistical techniques that mimic the human brain's thinking and acting characteristics. This system consists of the input layer, hidden layers, the output layer, weights (w), and bias (b) as shown in Figure 4.4. Input values for the ANN model are given in the system and multiplied by the corresponding weights. After that, entries with weight sums from all input sources are added to the hidden layers. After data is generated, the hidden layer transfer function is activated and it is calculated as the input layer. This process maintains until the output layer is obtained.

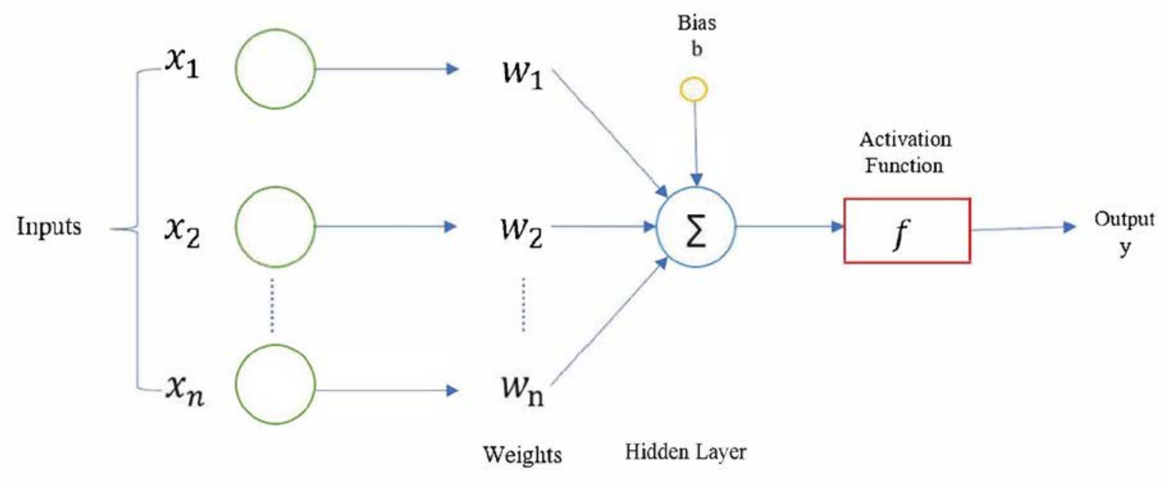


Figure 4.4: The generalized ANN model

4.3.1.1. Preparation of training and test data set

After input and output data are gathered and structured; training and test sets must be established. A total of 108 data were used in this study, 88 were used for the training (Table 4.4) and 20 of them used for the testing (Table 4.5). Normalization has been also applied to the inout and output data sets during the development of the ANN tool.

Table 4.4: Normalized input and output data for training

Input Data			Output Data		
Sand	**Silt**	**Clay**	**LL**	**PL**	**PI**
0.00	0.74	0.64	0.41	0.68	0.28
0.00	0.74	0.64	0.43	0.70	0.29
0.04	0.46	0.83	0.48	0.95	0.22
0.05	0.50	0.79	0.33	0.58	0.24
0.06	0.48	0.80	0.74	0.66	0.68
0.06	0.48	0.80	0.74	0.66	0.68
0.06	0.44	0.83	0.71	0.54	0.71
0.07	0.49	0.78	0.74	0.63	0.70
0.08	0.56	0.72	0.46	0.95	0.21
0.08	0.34	0.89	0.84	0.76	0.74
0.09	0.40	0.84	0.82	0.70	0.76
0.09	0.40	0.84	0.82	0.70	0.76
0.09	0.45	0.79	0.48	0.92	0.24
0.10	0.42	0.81	0.32	0.66	0.18
0.10	0.41	0.77	0.34	0.77	0.15
0.10	0.37	0.85	0.76	0.70	0.68
0.10	0.42	0.75	0.33	0.66	0.20
0.10	0.39	0.83	0.32	0.67	0.17
0.10	0.53	0.72	0.49	0.96	0.23
0.13	0.38	0.75	0.35	0.76	0.16
0.13	0.63	0.60	0.22	0.61	0.09
0.14	1.00	0.30	0.34	0.70	0.18
0.15	0.13	1.00	1.00	0.69	0.97
0.27	0.48	0.60	0.19	0.60	0.05
0.28	0.50	0.58	0.19	0.62	0.05
0.29	0.20	0.81	0.92	0.65	0.90
0.29	0.26	0.75	0.86	0.60	0.85
0.31	0.23	0.77	0.89	0.65	0.86
0.33	0.34	0.66	0.57	0.62	0.50

Table 4.4 Continued

Input Data			Output Data		
Sand	**Silt**	**Clay**	**LL**	**PL**	**PI**
0.34	0.21	0.75	0.91	0.62	0.90
0.35	0.22	0.73	0.87	0.47	0.93
0.36	0.19	0.75	0.71	0.52	0.71
0.36	0.55	0.39	0.13	0.38	0.09
0.36	0.67	0.36	0.61	1.00	0.35
0.37	0.61	0.40	0.12	0.38	0.09
0.38	0.28	0.66	0.84	0.73	0.76
0.39	0.59	0.40	0.71	0.16	0.90
0.39	0.59	0.40	0.71	0.16	0.90
0.40	0.21	0.70	0.74	0.70	0.66
0.41	0.16	0.73	0.73	0.15	0.92
0.41	0.32	0.60	0.06	0.34	0.03
0.42	0.33	0.59	0.69	0.65	0.62
0.42	0.24	0.66	0.80	0.64	0.76
0.42	0.58	0.38	0.70	0.89	0.51
0.42	0.58	0.38	0.70	0.89	0.51
0.42	0.23	0.66	0.63	0.28	0.74
0.42	0.19	0.70	0.72	0.41	0.78
0.44	0.26	0.62	0.67	0.55	0.66
0.49	0.64	0.26	0.50	0.69	0.39
0.50	0.20	0.62	0.69	0.55	0.67
0.52	0.57	0.29	0.15	0.35	0.13
0.54	0.24	0.54	0.79	0.55	0.79
0.54	0.19	0.58	0.69	0.48	0.71
0.54	0.64	0.22	0.05	0.17	0.11
0.54	0.65	0.21	0.57	0.68	0.47
0.54	0.65	0.21	0.57	0.68	0.47
0.54	0.71	0.16	0.85	0.90	0.69
0.57	0.25	0.51	0.64	0.37	0.71
0.57	0.20	0.54	0.75	0.73	0.65
0.58	0.75	0.09	0.17	0.34	0.16
0.58	0.24	0.51	0.65	0.37	0.72
0.59	0.09	0.62	0.66	0.47	0.68
0.60	0.22	0.51	0.68	0.41	0.73
0.60	0.79	0.04	0.16	0.20	0.22
0.61	0.19	0.53	0.55	0.73	0.42
0.62	0.15	0.54	0.66	0.46	0.68
0.63	0.05	0.62	0.73	0.00	1.00
0.63	0.16	0.53	0.70	0.54	0.69

Table 4.4 Continued

Input Data			Output Data		
Sand	**Silt**	**Clay**	**LL**	**PL**	**PI**
0.34	0.21	0.75	0.91	0.62	0.90
0.35	0.22	0.73	0.87	0.47	0.93
0.36	0.19	0.75	0.71	0.52	0.71
0.36	0.55	0.39	0.13	0.38	0.09
0.36	0.67	0.36	0.61	1.00	0.35
0.37	0.61	0.40	0.12	0.38	0.09
0.38	0.28	0.66	0.84	0.73	0.76
0.39	0.59	0.40	0.71	0.16	0.90
0.39	0.59	0.40	0.71	0.16	0.90
0.40	0.21	0.70	0.74	0.70	0.66
0.41	0.16	0.73	0.73	0.15	0.92
0.41	0.32	0.60	0.06	0.34	0.03
0.42	0.33	0.59	0.69	0.65	0.62
0.42	0.24	0.66	0.80	0.64	0.76
0.42	0.58	0.38	0.70	0.89	0.51
0.42	0.58	0.38	0.70	0.89	0.51
0.42	0.23	0.66	0.63	0.28	0.74
0.42	0.19	0.70	0.72	0.41	0.78
0.44	0.26	0.62	0.67	0.55	0.66
0.49	0.64	0.26	0.50	0.69	0.39
0.50	0.20	0.62	0.69	0.55	0.67
0.52	0.57	0.29	0.15	0.35	0.13
0.54	0.24	0.54	0.79	0.55	0.79
0.54	0.19	0.58	0.69	0.48	0.71
0.54	0.64	0.22	0.05	0.17	0.11
0.54	0.65	0.21	0.57	0.68	0.47
0.54	0.65	0.21	0.57	0.68	0.47
0.54	0.71	0.16	0.85	0.90	0.69
0.57	0.25	0.51	0.64	0.37	0.71
0.57	0.20	0.54	0.75	0.73	0.65
0.58	0.75	0.09	0.17	0.34	0.16

Table 4.4 Continued

Input Data			Output Data		
Sand	**Silt**	**Clay**	**LL**	**PL**	**PI**
0.64	0.08	0.58	0.61	0.54	0.59
0.65	0.78	0.00	0.10	0.10	0.20
0.66	0.24	0.43	0.56	0.48	0.56
0.71	0.19	0.43	0.49	0.54	0.44
0.73	0.09	0.49	0.56	0.37	0.61
0.74	0.11	0.47	0.56	0.40	0.60
0.74	0.22	0.37	0.54	0.38	0.58
0.75	0.07	0.49	0.45	0.52	0.41
0.76	0.09	0.47	0.53	0.36	0.59
0.78	0.30	0.27	0.01	0.24	0.02
0.79	0.31	0.26	0.00	0.25	0.01
0.79	0.19	0.35	0.53	0.38	0.57
0.80	0.17	0.35	0.53	0.37	0.58
0.80	0.15	0.37	0.49	0.32	0.55
0.81	0.21	0.32	0.51	0.34	0.57
0.81	0.27	0.26	0.00	0.27	0.00
0.86	0.15	0.32	0.50	0.36	0.54
0.87	0.00	0.43	0.46	0.39	0.48
0.98	0.08	0.26	0.46	0.38	0.49
1.00	0.01	0.30	0.47	0.20	0.59

Table 4.5: Normalized input and output data for test

Input Data			Output Data		
Sand	Silt	Clay	LL	PL	PI
0.06	0.44	0.83	0.71	0.54	0.71
0.07	0.49	0.78	0.74	0.63	0.70
0.08	0.34	0.89	0.84	0.76	0.74
0.09	0.41	0.83	0.47	0.93	0.22
0.10	0.37	0.85	0.76	0.70	0.68
0.10	0.40	0.77	0.34	0.77	0.16
0.29	0.34	0.70	0.89	0.89	0.74
0.36	0.67	0.36	0.61	1.00	0.35
0.42	0.33	0.59	0.69	0.65	0.62
0.49	0.64	0.26	0.50	0.69	0.39
0.52	0.57	0.29	0.15	0.35	0.13
0.54	0.64	0.22	0.05	0.17	0.11
0.54	0.71	0.16	0.85	0.90	0.69
0.58	0.75	0.09	0.17	0.34	0.16
0.60	0.79	0.04	0.16	0.20	0.22
0.62	0.15	0.54	0.62	0.22	0.76
0.65	0.78	0.00	0.10	0.10	0.20
0.79	0.03	0.49	0.53	0.38	0.56
0.87	0.07	0.37	0.44	0.33	0.49
0.91	0.10	0.32	0.53	0.37	0.57

4.3.1.2. Ann structure

Some parameters have been selected for the generation of the ANN model for estimating the output parameters.

Prediction for LL values 9 models was developed. The results of those models are shown in Table 4.6. The best-structured model was determined with R^2 values (Figure 4.5).

Table 4.6: ANN models for LL prediction

Model No	Output	Number of Layers	Number of Neurons	Transfer Functions	R^2 Training	R^2 Validation	R^2 Testing	Adjust R^2
1	LL	2	5	Tansig Tansig	0.79	0.59	0.73	0.76
2	LL	2	5	Tansig Logsig	0.73	0.41	0.43	0.65
3	LL	2	5	Logsig Logsig	0.61	0.55	0.52	0.58
4	LL	2	7	Tansig Tansig	0.74	0.89	0.65	0.76
5	LL	2	7	Tansig Logsig	0.67	0.59	0.51	0.64
6	LL	2	7	Logsig Logsig	0.74	0.83	0.89	0.76
7	LL	2	10	Tansig Tansig	0.82	0.88	0.82	0.83
8	LL	2	10	Tansig Logsig	0.77	0.86	0.89	0.79
9	LL	2	10	Logsig Logsig	0.62	0.59	0.62	0.61

Regression analysis results of models are given in Appendix 2.

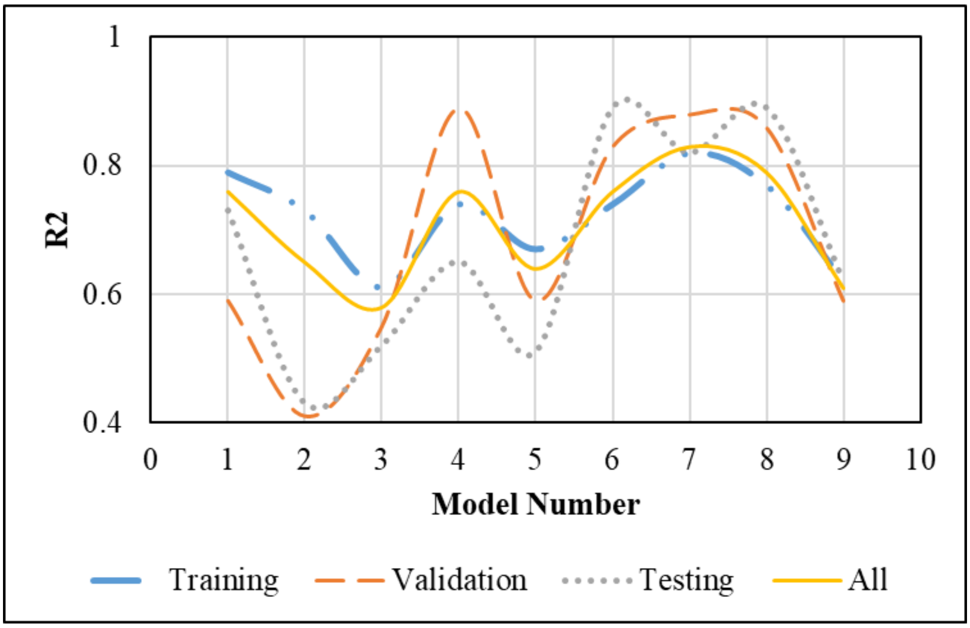


Figure 4.5: Comparison ANN models for predict LL

As shown in Table 4.6 and Figure 4.5, the Model 7 was determined the best structure to solve this problem. Some model's regression analysis results are shown in Figure 4.6a, b, c, and d.

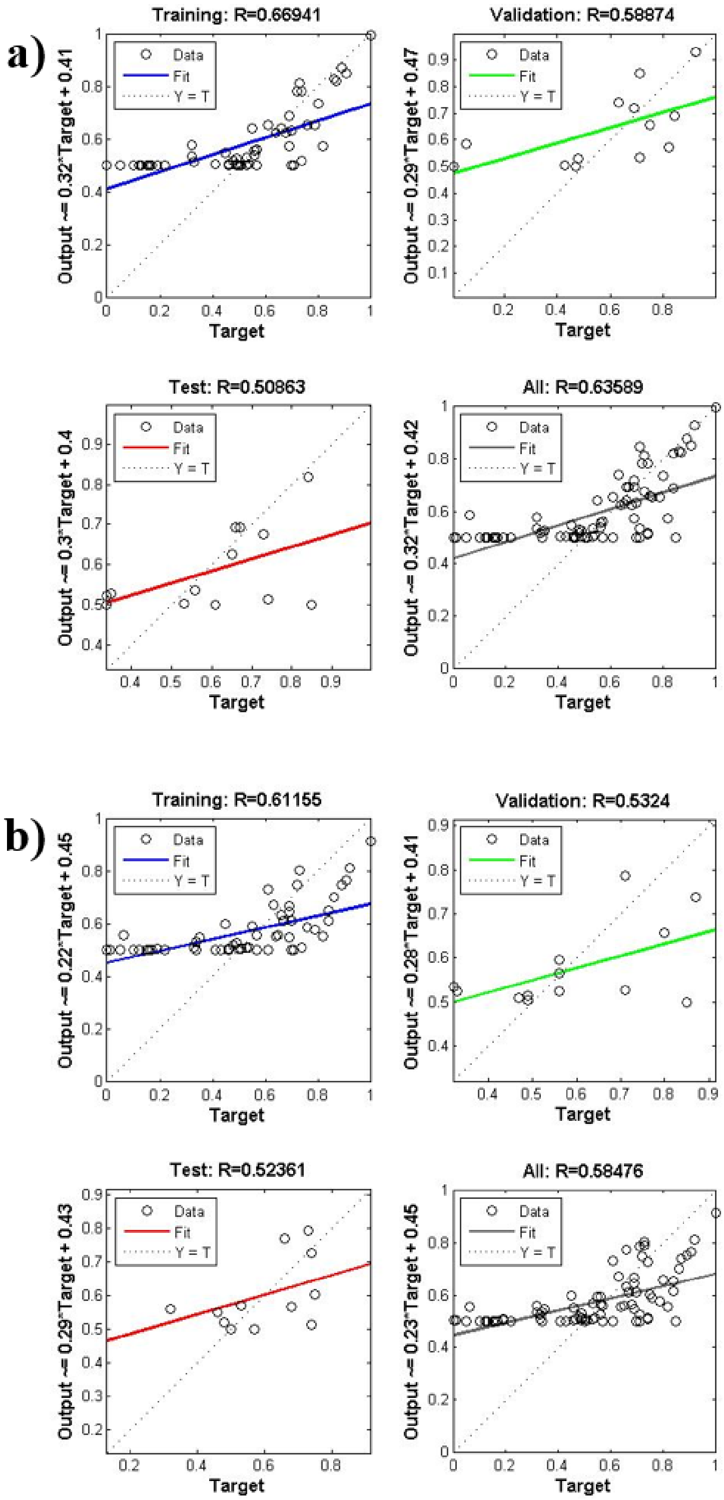


Figure 4.6: Regression analysis results; a) Model 5, and b) Model 3

Prediction for PI values 9 models was developed. The results of those models are shown in Table 4.7. The best-structured model was determined with R^2 values (Figure 4.7).

Table 4.7: ANN models for PI prediction

Model No	Output	Number of Layers	Number of Neurons	Transfer Functions	R2			
					Training	Validation	Testing	Adjust R^2
1	PI	2	5	Tansig Tansig	0.84	0.79	0.7	0.81
2	PI	2	5	Tansig Logsig	0.7	0.61	0.55	0.66
3	PI	2	5	Logsig Logsig	0.69	0.62	0.60	0.66
4	PI	2	7	Tansig Tansig	0.88	0.87	0.88	0.88
5	PI	2	7	Tansig Logsig	0.61	0.64	0.72	0.63
6	PI	2	7	Logsig Logsig	0.63	0.65	0.56	0.61
7	PI	2	10	Tansig Tansig	0.69	0.72	0.64	0.70
8	PI	2	10	Tansig Logsig	0.62	0.69	0.73	0.64
9	PI	2	10	Logsig Logsig	0.67	0.61	0.67	0.65

The regression analysis result of models is given in Appendix 3.

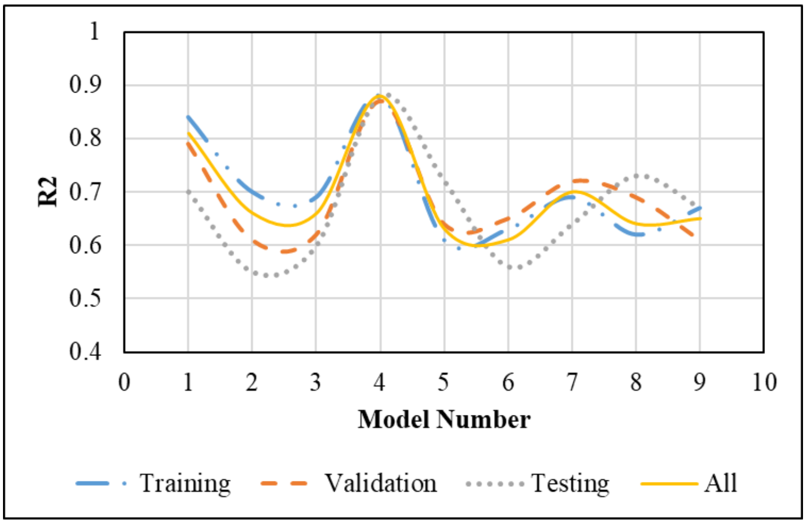


Figure 4.7: Comparison ANN models for predict PI

As shown in Table 4.7 and Figure 4.7, the Model 4 was determined the best structure to solve this problem. Some model's regression analysis results are shown in Figure 4.8a, b, c, and d.

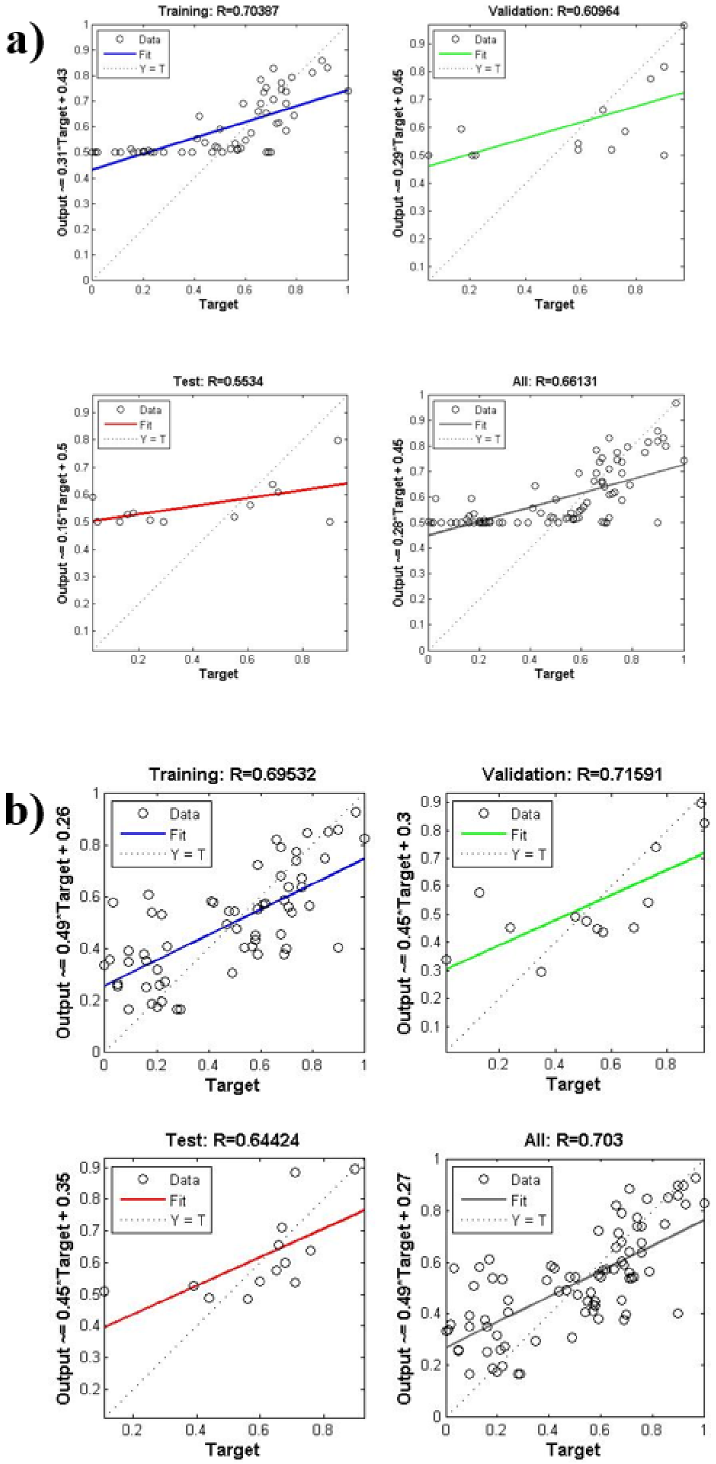


Figure 4.8: Regression analysis results; a) Model 2, and b) Model 7

It has been tried to find optimum values while selecting these parameters that are given in Table 4.8.

Backpropagation feedforward model was used in this study with supervised learning technique. In the development of ANN tool, "nntool" tool which is available as a ready tool in MatLab R2013a software is used. As a result of the models generated by selecting the appropriate number of layers and hidden element values for each output parameter (Figure 4.9), the learning process is trained to achieve optimum results.

Table 4.8 ANN structure parameters

Parameters	Values	
	LL	PI
Input Parameter	3	3
Number of Layers	2	2
Number of Neurons	10	7
Transfer Function	Tansig	Tansig
Network Type	Feed-forward	backpropagation

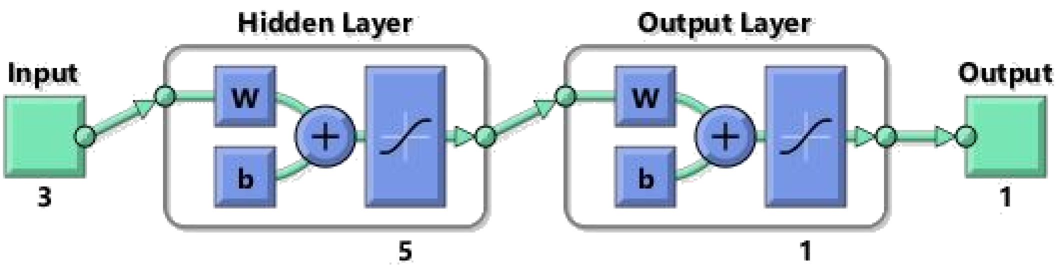


Figure 4.9: ANN model sample

In figure 4.9 Input represents the grain size distribution data, w is weight, b is bias and Output is LL or PI.

4.3.1.3. Ann training

Once the model is created, the system needs to be trained. The data for the training is written in vector format according to the program. In the model 70% of the data were used for the training, 15% for validation and 15% for the test.

a) Liquid Limit Prediction

Predicting of liquid limit values; the data for the training is entered into the system (Figure 4.10) and the predicting process is performed from the program.

The program is called approaches until the calculated values reach the optimum value and the operation stops when the optimum values are reached or the limit values are reached.

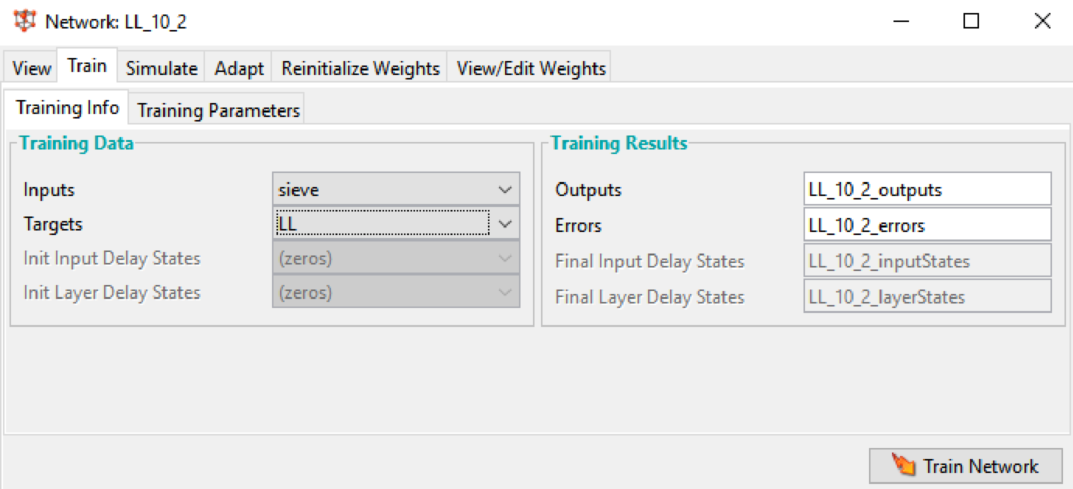


Figure 4.10: Data entry into the network

In order to examine the relationship between the values obtained as a result of the regression and the actual values, the regression graph generated at the end of the process is looked at. In our study, adjusted R^2 values were calculated as 0.82 for the training, 0.82 for the validation, 0.88 for the test, and 0.83 for all data (Figure 4.11).

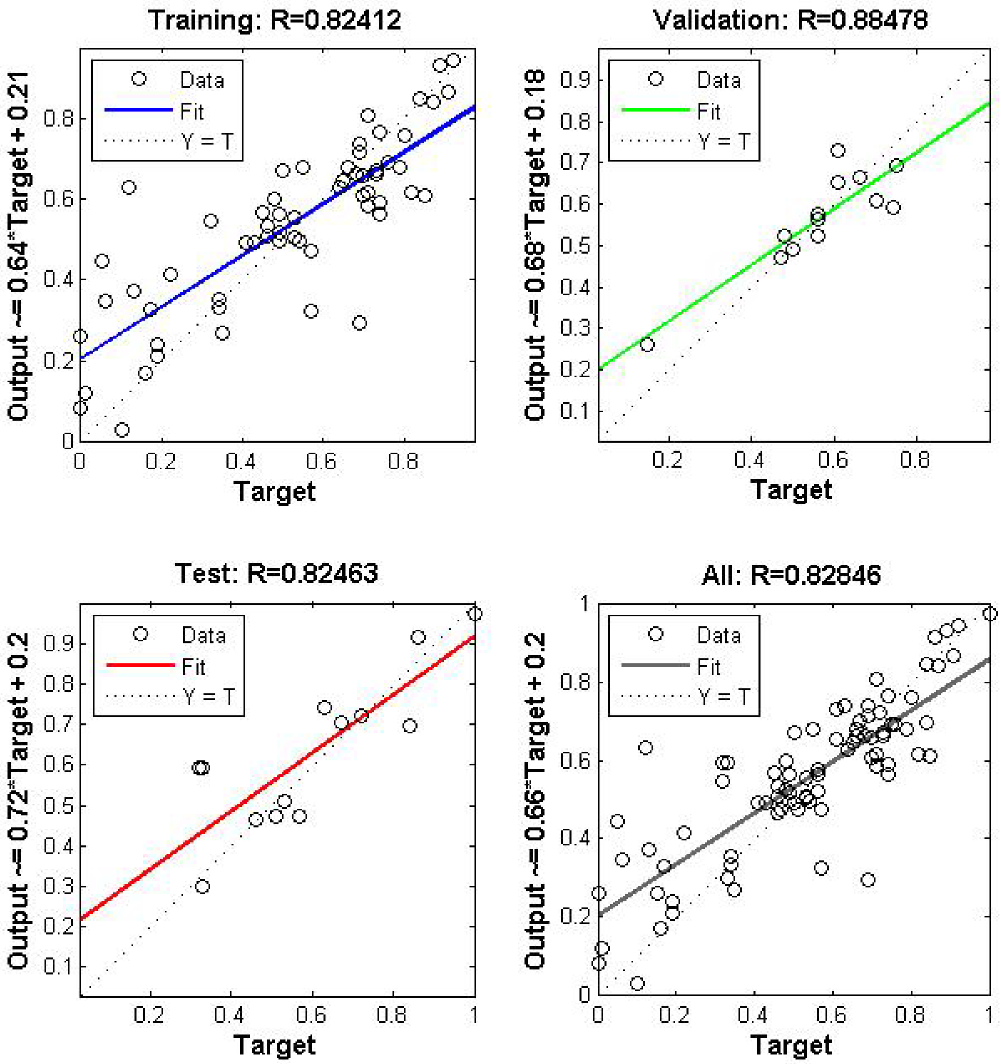


Figure 4.11: Regression analysis result for LL

After checking the predicted values and real data relationship (Table 4.9) we calculated an R^2 value which is found as 0.85.

Table 4.9: Comparison of the training dataset for LL values

LL	LL Predicted	LL	LL Predicted	LL	LL Predicted
0.41	0.49	0.12	0.16	0.61	0.65
0.43	0.49	0.84	0.70	0.10	0.09
0.48	0.60	0.71	0.62	0.56	0.52
0.33	0.36	0.71	0.62	0.49	0.57
0.74	0.76	0.74	0.76	0.56	0.58
0.74	0.76	0.73	0.66	0.56	0.57
0.71	0.76	0.06	0.03	0.54	0.50
0.74	0.57	0.69	0.53	0.45	0.57
0.46	0.53	0.80	0.76	0.53	0.55
0.84	0.85	0.70	0.61	0.01	0.01
0.82	0.62	0.70	0.61	0.00	0.08
0.82	0.62	0.63	0.74	0.53	0.51
0.48	0.52	0.72	0.72	0.53	0.51
0.32	0.55	0.67	0.70	0.49	0.52
0.34	0.35	0.50	0.67	0.51	0.48
0.76	0.69	0.69	0.74	0.00	0.03
0.33	0.30	0.15	0.26	0.50	0.49
0.32	0.59	0.79	0.68	0.46	0.51
0.49	0.50	0.69	0.72	0.46	0.47
0.35	0.27	0.05	0.07	0.47	0.47
0.22	0.42	0.57	0.47		
0.34	0.33	0.57	0.47		
1.00	0.97	0.85	0.61		
0.19	0.21	0.64	0.63		
0.19	0.24	0.75	0.69		
0.92	0.94	0.17	0.33		
0.86	0.91	0.65	0.65		
0.89	0.93	0.66	0.68		
0.57	0.32	0.68	0.66		
0.91	0.87	0.16	0.17		
0.87	0.84	0.55	0.68		
0.71	0.81	0.66	0.66		
0.13	0.14	0.73	0.67		
0.61	0.73	0.70	0.66		
R^2= 0.85					

ANN model trained with training data should be simulated with a test data set. As a result of this operation (Table 4.10), the R^2 value is calculated as 0.86.

Table 4.10: Comparison of the test data set for LL values

LL	**LL Predicted**
0.71	0.66
0.74	0.66
0.84	0.85
0.47	0.59
0.76	0.69
0.34	0.33
0.89	0.85
0.61	0.73
0.69	0.63
0.50	0.67
0.15	0.26
0.05	0.08
0.85	0.61
0.17	0.33
0.16	0.17
0.62	0.66
0.10	0.03
0.53	0.55
0.44	0.50
0.53	0.48
R^2= 0.86	

The relationship with the real and predicted data of LL values is shown in Figure 4.12.

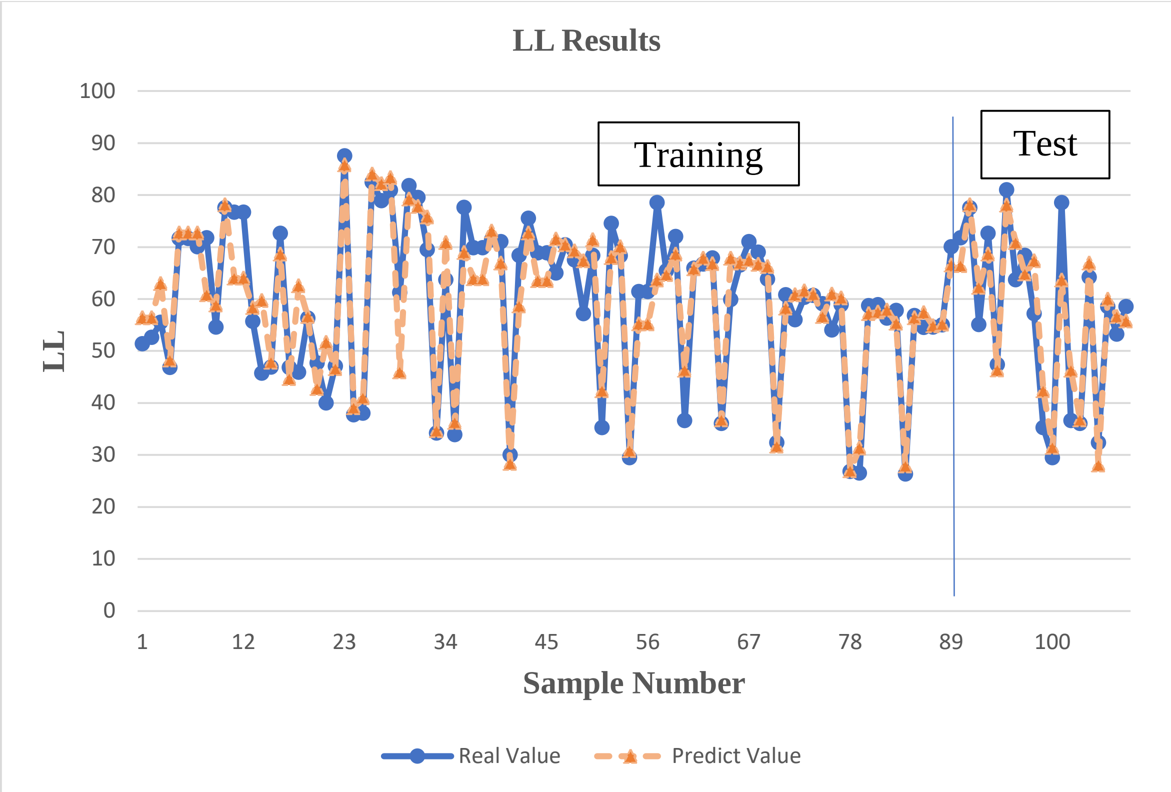


Figure 4.12: Comparison between real and predict data for LL

b) Plasticity Index Prediction

Predicting of plasticity index values; the data for the training is entered into the system (Figure 4.13) and the predicting process is performed from the program.

The program operates until the calculated values reach the optimum values and it stops the operation once the desired values are predicted (optimum values); in other words, the program stops once the plasticity index values are predicted favorably.

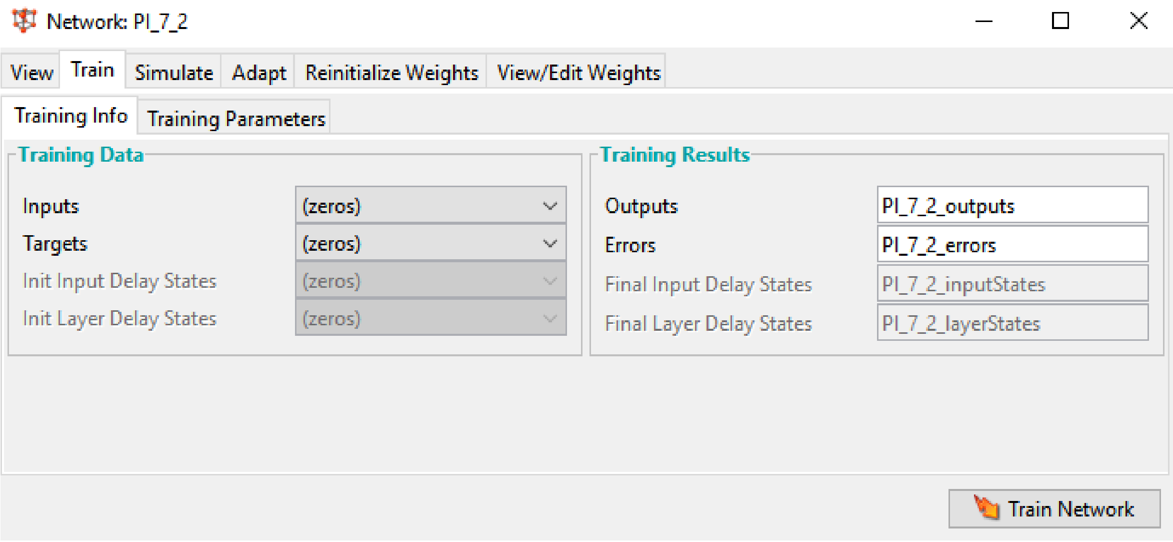


Figure 4.13: Data entry into the network

In order to examine the relationship between the actual values and the predictions, the regression graph is plotted at the end of the training process. In our study, adjusted R^2 for PI values were calculated as 0.86 for the training, 0.87 for the validation, 0.88 for the test, and 0.87 for all data (Figure 4.14).

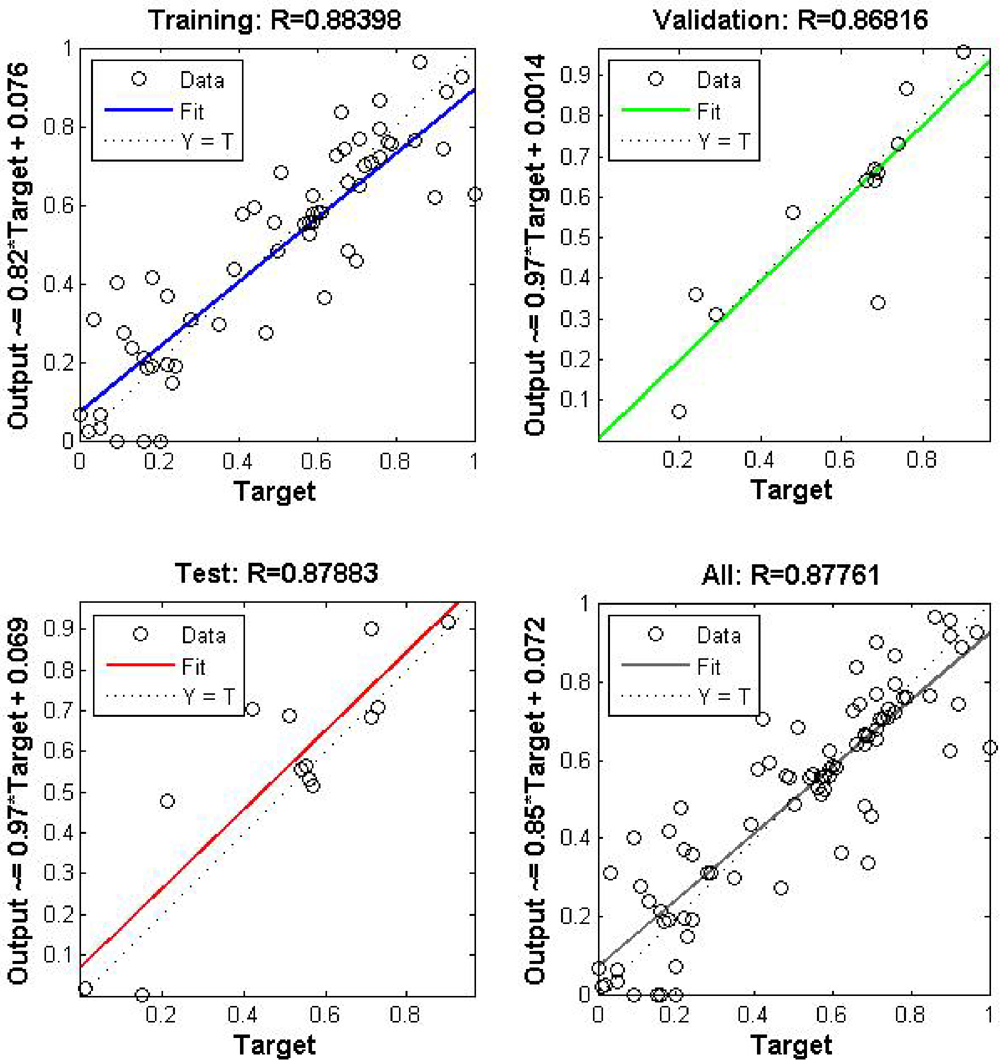


Figure 4.14: Regression analysis result for PI

After checking the predicted values and real data relationship (Table 4.11) we calculated an R^2 value for PI which was 0.81.

Table 4.11: Comparison of training data set for PI values

PI	PI Predicted	PI	PI Predicted	PI	PI Predicted
0.28	0.31	0.09	0.40	0.59	0.63
0.29	0.31	0.76	0.72	0.20	0.07
0.22	0.37	0.90	0.62	0.56	0.53
0.24	0.24	0.90	0.62	0.44	0.60
0.68	0.68	0.66	0.84	0.61	0.58
0.68	0.68	0.92	0.74	0.60	0.58
0.71	0.65	0.03	0.03	0.58	0.53
0.70	0.46	0.62	0.36	0.41	0.58
0.21	0.25	0.76	0.79	0.59	0.58
0.74	0.71	0.51	0.49	0.02	0.03
0.76	0.87	0.51	0.49	0.01	0.02
0.76	0.87	0.74	0.73	0.57	0.55
0.24	0.19	0.78	0.76	0.58	0.56
0.18	0.42	0.66	0.64	0.55	0.57
0.15	0.00	0.39	0.44	0.57	0.51
0.68	0.48	0.67	0.74	0.00	0.07
0.20	0.00	0.13	0.24	0.54	0.56
0.17	0.19	0.79	0.76	0.48	0.56
0.23	0.15	0.71	0.77	0.49	0.56
0.16	0.00	0.11	0.28	0.59	0.56
0.09	0.00	0.47	0.27		
0.18	0.19	0.47	0.27		
0.97	0.93	0.69	0.34		
0.05	0.03	0.71	0.68		
0.05	0.07	0.65	0.73		
0.90	0.96	0.16	0.21		
0.85	0.79	0.72	0.70		
0.86	0.96	0.68	0.67		
0.50	0.49	0.73	0.71		
0.90	0.92	0.22	0.20		
0.93	0.89	0.42	0.71		
0.71	0.90	0.68	0.66		
0.09	0.00	1.00	0.63		
0.35	0.30	0.69	0.66		
R^2= 0.81					

ANN model trained with training data should be simulated with a test data set. As a result of this operation (Table 4.12), the R^2 value for PI is calculated as 0.82.

Table 4.12. Comparison of the test data set for PI values

PI	PI Predicted
0.71	0.59
0.70	0.64
0.74	0.79
0.22	0.25
0.68	0.60
0.16	0.22
0.74	0.45
0.35	0.47
0.62	0.50
0.39	0.43
0.13	0.30
0.11	0.28
0.69	0.63
0.16	0.29
0.22	0.32
0.76	0.70
0.20	0.24
0.56	0.59
0.49	0.59
0.57	0.56
R^2= 0.82	

The relationship with the real and predicted data of PI is shown in Figure 4.15.

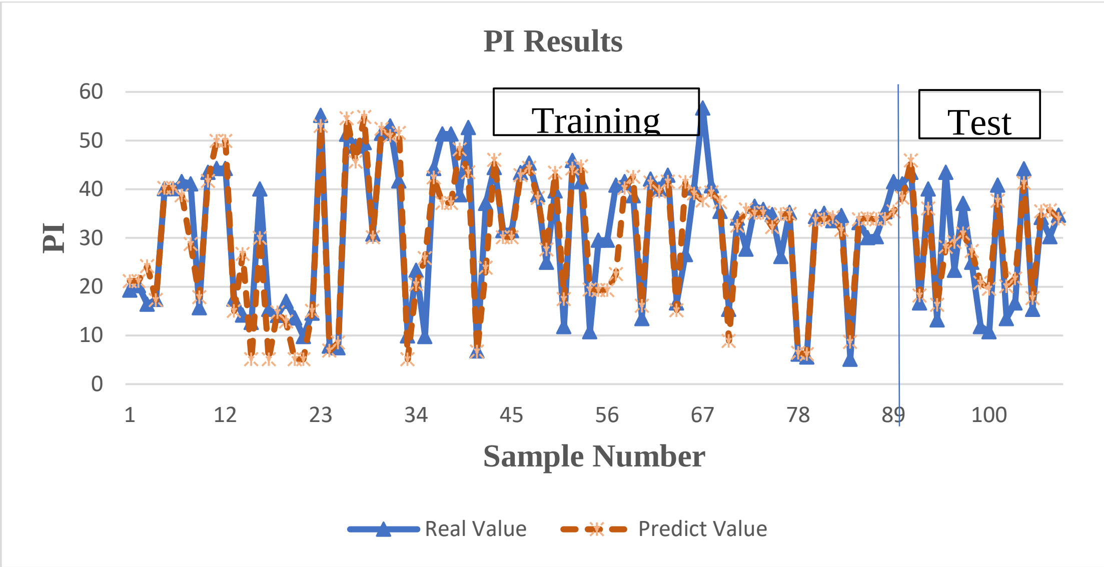


Figure 4.15: Comparison between real and predict data for PI

4.3.2. Determination of soil classification

The second part of the study includes finding the soil classification by using predicted LL and PI values. We used USCS Chart (Figure 4.16) for determined soil classification. When fine-grained soils are classified, some letters are taken according to some conditions depending on LL and PI values. These;

- L is low plasticity
- H is high plasticity

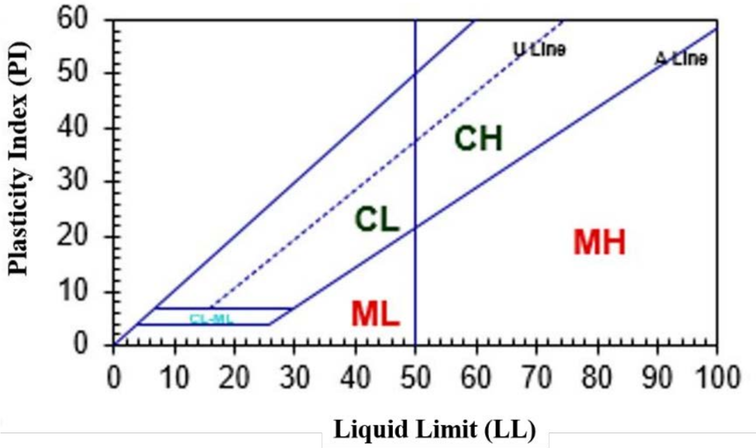


Figure 4.16: Unified Soil Classification System Symbol Chart (Wagner, 1957)

In this part of the study, the real data (Figure 4.17 and Figure 4.18) and the predicted data (Figure 4.19 and Figure 4.20) are classified separately with the aid of the classification chart.

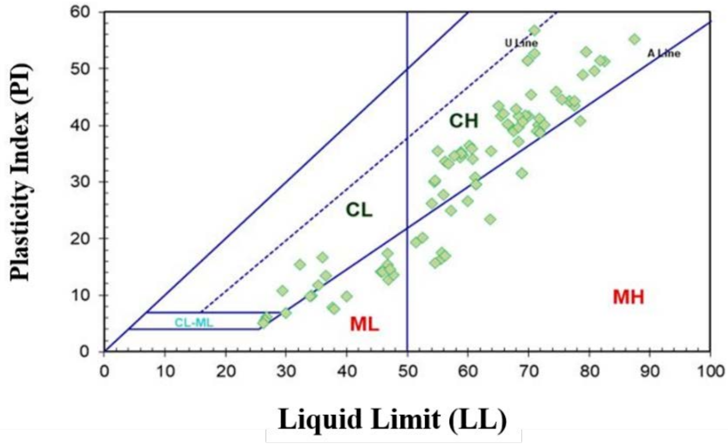


Figure 4.17: Real data set classification which used for training

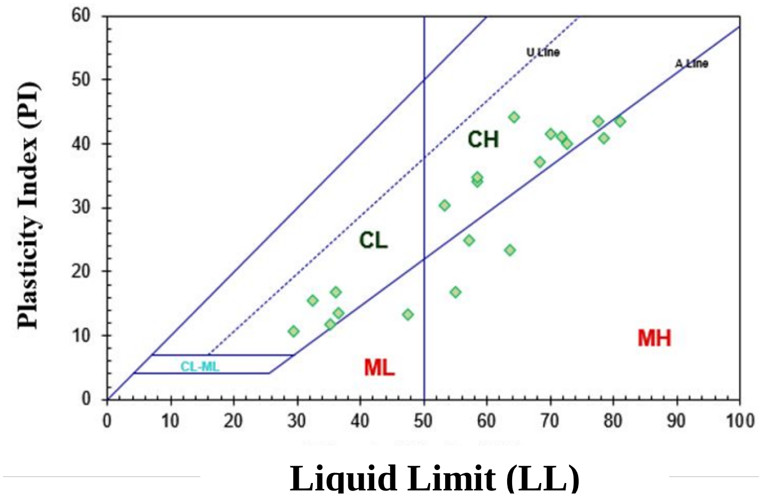


Figure 4.18: Real data set classification which used for testing

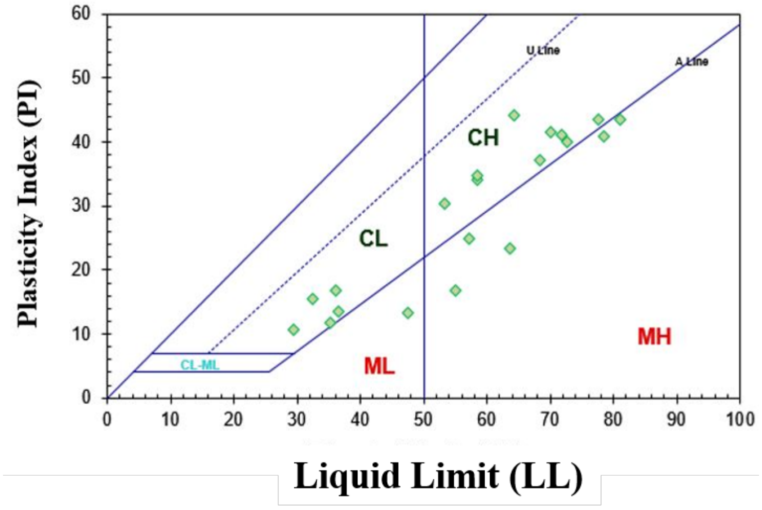


Figure 4.19: Predicted data set classification which used for training

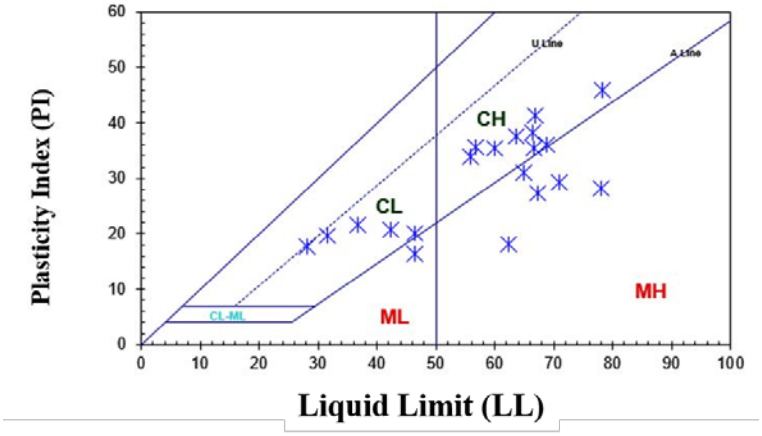


Figure 4.20: Predicted data set classification which used for testing

Table 4.13 and Table 4.14 are prepared so that the accuracy of adaptation of the study done can be better understood. The table is divided into two parts (True and False) and the real soil classification and the predicted soil classification are compared. True (T) represents that the real soil classification and predicted soil classification are the same, and if it is false (F), it represents that the real soil classification and predicted soil classification are different.

Table 4.13: Comparison of soil classification with training data set

Real	Predicted	True/False	Real	Predicted	True/False
M H	M H	T	C H	C H	T
M H	M H	T	C H	C H	T
M H	M H	T	M L	C L	F
M L	M L	T	C H	M H	F
C H	C H	T	C H	C H	T
C H	C H	T	M H	M H	T
C H	C H	T	M H	M H	T
C H	M H	F	C H	C H	T
M H	M H	T	C H	C H	T
C H	M H	F	C H	C H	T
C H	C H	T	M H	M H	T
C H	C H	T	C H	C H	T
M H	M H	T	C L	C L	T
M L	M H	F	C H	C H	T
M L	M L	T	C H	C H	T
C H	M H	F	C L	C L	T
M L	M L	T	M H	M H	T
M L	M H	F	M H	M H	T
M H	M H	T	M H	M H	T
M L	M L	T	C H	C H	T
M L	M H	F	C H	C H	T
M L	M L	T	C L	M L	F
C H	C H	T	C H	C H	T
M L	M L	T	C H	C H	T
M L	M L	T	C H	C H	T
C H	C H	T	C L	C L	T
C H	C H	T	M H	C H	F
C H	C H	T	C H	C H	T
C H	C L	F	C H	C H	T
C H	C H	T	C H	C H	T
C H	C H	T	C H	C H	T
C H	C H	T	C L	C L	T
M L	M L	T	C H	C H	T
M H	M H	T	C H	C H	T
M L	C L	F	C H	C H	T
C H	C H	T	C H	C H	T
C H	C H	T	C H	C H	T
C H	C H	T	C H	C H	T

Table 4.13 Continued

Real	Predicted	True/False	
C H	C H	T	
C L	C L	T	
C L	M L		F
C H	C H	T	
C H	C H	T	
C H	C H	T	
C H	C H	T	
C L	C L	T	
C H	C H	T	
C H	C H	T	
C H	C H	T	
C H	C H	T	
75 True/13 False = %85.22 Accuracy			

As a result of the data used for training, 75 of the 88 classifications were found to be correct in the soil classifications. This gives an accuracy of about 85%.

Table 4.14: Comparison of soil classification with test data set

Real	Predicted	True/False	
C H	C H	T	
C H	C H	T	
C H	C H	T	
M H	M H	T	
C H	C H	T	
M L	M L	T	
M H	M H	T	
M H	M H	T	
C H	M H		F
M H	M H	T	
C L	C L	T	
C L	C L	T	
M H	C H		F
C L	C L	T	
C L	C L	T	
C H	C H	T	

Table 4.12 Continued

Real	Predicted	True/False
C L	C L	T
C H	C H	T
C H	C H	T
C H	C H	T
18 True/2 False = %90.00 Accuracy		

As a result of the data used for training, 18 of the 20 classifications were found to be correct in the soil classifications, which gives an accuracy of about 90%.

4.4. Results

The determination of soil classification has an important place in geotechnical engineering which is one of the most important areas of civil engineering. As mentioned in Chapter 2, different soil characteristics play an effective role in determining the soil classification. Some of these features are in a linear relationship with each other. However, there is no linear relationship between grain size distribution values and LL-PI values used in this study. We can reach this result with multiple linear analysis results.

In the previous studies, the values of R^2, which are estimated different soil properties performing using different input parameters, vary in the range of 0.67-0.97. The data used in this thesis were derived from the North Cyprus clays described in Chapter 3, from the Değirmenlik Group Clay, Mesaoria Zone, and Alluvium groups. As a result of these studies, R^2 values vary between 0.81 and 0.87. Besides, it is concluded that the accuracy ranges from 85% to 90% in the soil classification.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

ANN, which is becoming more widespread in the fields of science and engineering, is also a useful method in geotechnical engineering fields. This study presents the advantages of using ANN in cases where classical regression methods are inadequate. In total, 108 data sets are used in the development of the ANN tool. It was aimed to maximize the validity of the program with selected examples from North Cyprus.

The following conclusions can be reached as a result of the studies carried out;

1. There is no direct relationship between the liquid limit and plasticity index and sieve analysis values.
2. The tansig transfer function among the transfer functions for the data used in this study enabled us to achieve better results than the logsig transfer function.
3. As a result of the study with ANN, a connection could be made between the parameters that are not directly related.
4. By using the ANN method, we can reach the sieve analysis values and the Atterberg values with a high accuracy rate.
5. There is a higher connection between the LL values and the sieve analysis values than PI values.
6. The validity and accuracy of the system have been tested by making the soil classification with the LL and PI values as a result of the ANN.
7. ANN can successfully apply in engineering problems that are more affected by variables such as soil properties.
8. No attempt was made to find the relationship of different soils.

5.2. Recommendations

1. This study was carried out only on North Cyprus soils, especially on the clays. Work areas and parameters can be expanded during future work.
2. Similar work within the same soil groups will point out the relationship of the soils with different swelling potential

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APPENDICES

Appendix 1: Samples used in this study

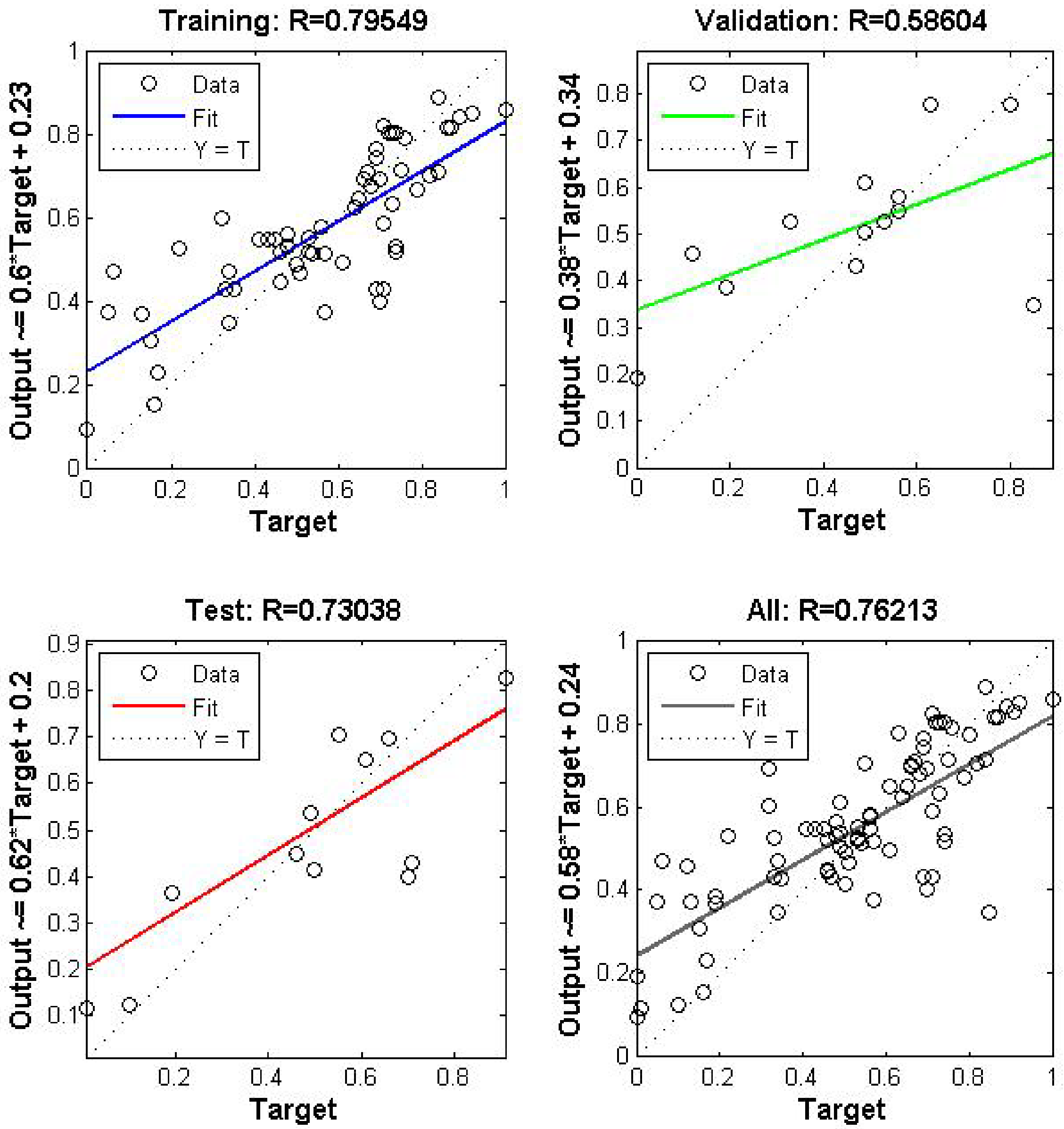
INPUTS			OUTPUTS	
Sand	**Silt**	**Clay**	**LL**	**PI**
49.7	9.3	41.0	55.0	35.4
48.9	12.1	39.0	54.6	30.3
45.2	12.8	42.0	58.5	34.7
43.3	8.7	48.0	54.5	30.1
43.2	11.9	45.0	53.2	30.3
42.9	15.2	42.0	56.8	33.2
40.4	17.6	42.0	57.8	34.6
40.0	15.0	45.0	56.3	33.6
39.9	16.1	44.0	58.9	35.1
39.2	16.8	44.0	58.7	34.4
39.1	9.9	51.0	58.5	34.2
37.6	12.4	50.0	58.9	35.3
37.4	11.6	51.0	54.0	26.2
36.8	18.2	45.0	59.1	34.8
36.7	13.3	50.0	60.7	35.9
36.5	12.5	51.0	60.3	36.5
35.3	16.7	48.0	56.0	27.7
32.8	19.2	48.0	60.8	34.1
32.0	12.1	56.0	63.8	35.5
31.6	15.4	53.0	69.0	40.7
31.3	10.7	58.0	71.0	56.7
30.8	15.2	54.0	64.2	44.2
30.8	15.2	54.0	66.5	40.3
30.3	16.7	53.0	59.9	26.6
29.8	18.2	52.0	67.9	42.9
29.6	12.4	58.0	66.7	40.1
29.1	18.9	52.0	65.9	42.1
28.7	17.3	54.0	72.0	38.7
28.7	19.3	52.0	65.4	41.6
27.0	17.0	56.0	68.3	41.6

INPUTS			OUTPUTS	
Sand	**Silt**	**Clay**	**LL**	**PI**
22.2	19.9	58.0	67.5	38.9
21.2	16.8	62.0	70.4	45.4
21.2	18.8	60.0	65.0	43.4
21.1	19.0	60.0	75.5	44.5
20.4	15.6	64.0	71.0	52.7
20.2	17.8	62.0	71.4	38.9
19.2	20.8	60.0	77.6	44.3
18.2	16.8	65.0	69.5	41.7
17.7	18.3	64.0	79.5	53.0
17.3	17.7	65.0	81.8	51.5
16.5	23.5	60.0	61.2	30.8
15.5	18.5	66.0	80.9	49.6
14.9	20.1	65.0	78.9	48.9
14.8	23.2	62.0	81.0	43.5
14.7	17.3	68.0	82.7	51.3
7.6	14.4	78.0	87.5	55.2
40.4	20.4	39.2	26.3	5.1
39.1	21.9	39.0	26.5	5.6
38.9	21.8	39.3	26.8	6.2
32.6	42.1	25.3	32.3	15.4
30.2	42.5	27.3	36.1	16.7
29.1	41.1	29.8	36.6	13.5
27.2	39.1	33.7	78.5	40.9
27.1	36.1	36.8	29.5	10.8
27.1	36.7	36.2	61.4	29.6
26.2	33.3	40.5	35.3	11.8
24.6	36.3	39.1	57.2	25.0
21.1	33.5	45.4	68.9	31.5

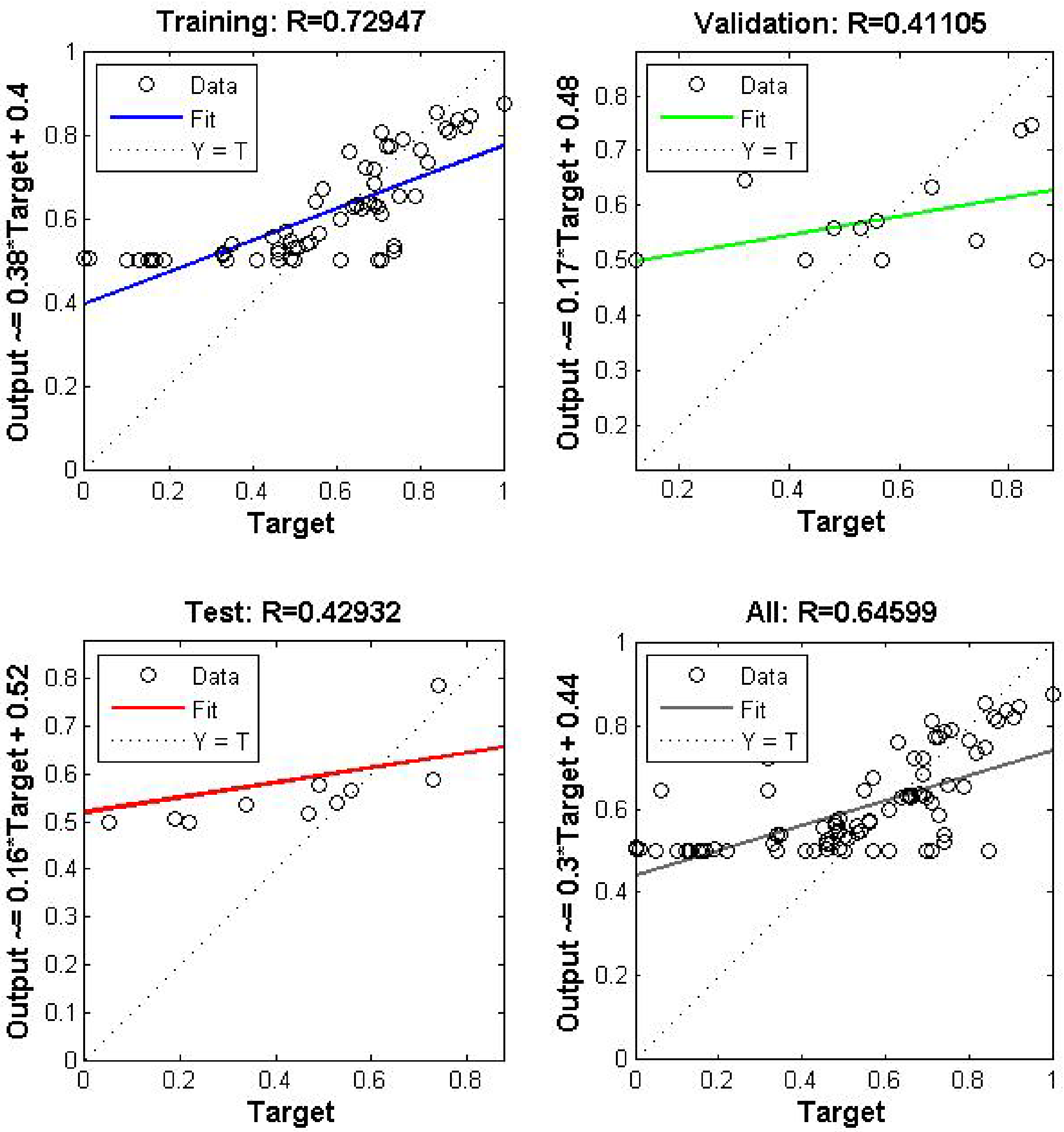
INPUTS			OUTPUTS	
Sand	**Silt**	**Clay**	**LL**	**PI**
5.3	26.3	66.0	46.9	12.7
21.0	22.8	56.2	68.4	37.1
20.7	22.3	57.0	30.0	6.8
19.6	34.2	46.2	69.9	51.4
18.5	35.0	46.5	33.9	9.8
18.3	32.5	46.0	34.2	9.9
18.3	37.6	44.1	63.7	23.4
14.0	30.0	56.0	38.0	7.5
13.8	29.2	57.0	37.7	7.8
7.3	51.7	41.0	47.1	14.6
7.0	25.2	65.0	47.7	13.6
7.0	36.0	57.0	40.0	9.8
5.5	26.1	66.0	47.4	13.2
5.4	26.9	65.0	46.8	15.4
5.4	25.6	69.0	45.9	14.1
5.4	31.6	63.0	56.3	17.0
5.3	24.7	70.0	72.6	40.1
5.3	26.7	68.0	45.7	14.2
4.8	28.2	67.0	55.7	17.5
4.6	26.4	69.0	55.1	16.7
4.6	26.0	69.4	76.7	44.3
4.5	23.5	72.1	77.6	43.5
4.4	32.6	63.0	54.6	15.7
4.1	29.7	66.2	71.8	41.2
3.3	27.7	69.0	70.0	41.6
3.1	29.4	67.5	71.7	40.1
2.9	30.1	67.0	46.8	17.4
2.5	28.5	69.0	55.5	16.4
0.4	40.6	59.0	51.4	19.3
0.4	40.4	59.2	52.6	20.2

INPUTS			OUTPUTS	
Sand	**Silt**	**Clay**	**LL**	**PI**
30.2	42.5	27.3	36.1	16.7
29.1	41.1	29.8	36.6	13.5
27.2	39.1	33.7	78.5	40.9
27.1	36.1	36.8	29.5	10.8
27.1	36.7	36.2	61.4	29.6
26.2	33.3	40.5	35.3	11.8
24.6	36.3	39.1	57.2	25.0
21.1	33.5	45.4	68.9	31.5
21.0	22.8	56.2	68.4	37.1
19.6	34.2	46.2	69.9	51.4
18.3	37.6	44.1	63.7	23.4
5.3	24.7	70.0	72.6	40.1
4.6	26.0	69.4	76.7	44.3
4.5	23.5	72.1	77.6	43.5
4.1	29.7	66.2	71.8	41.2
3.3	27.7	69.0	70.0	41.6
3.1	29.4	67.5	71.7	40.1

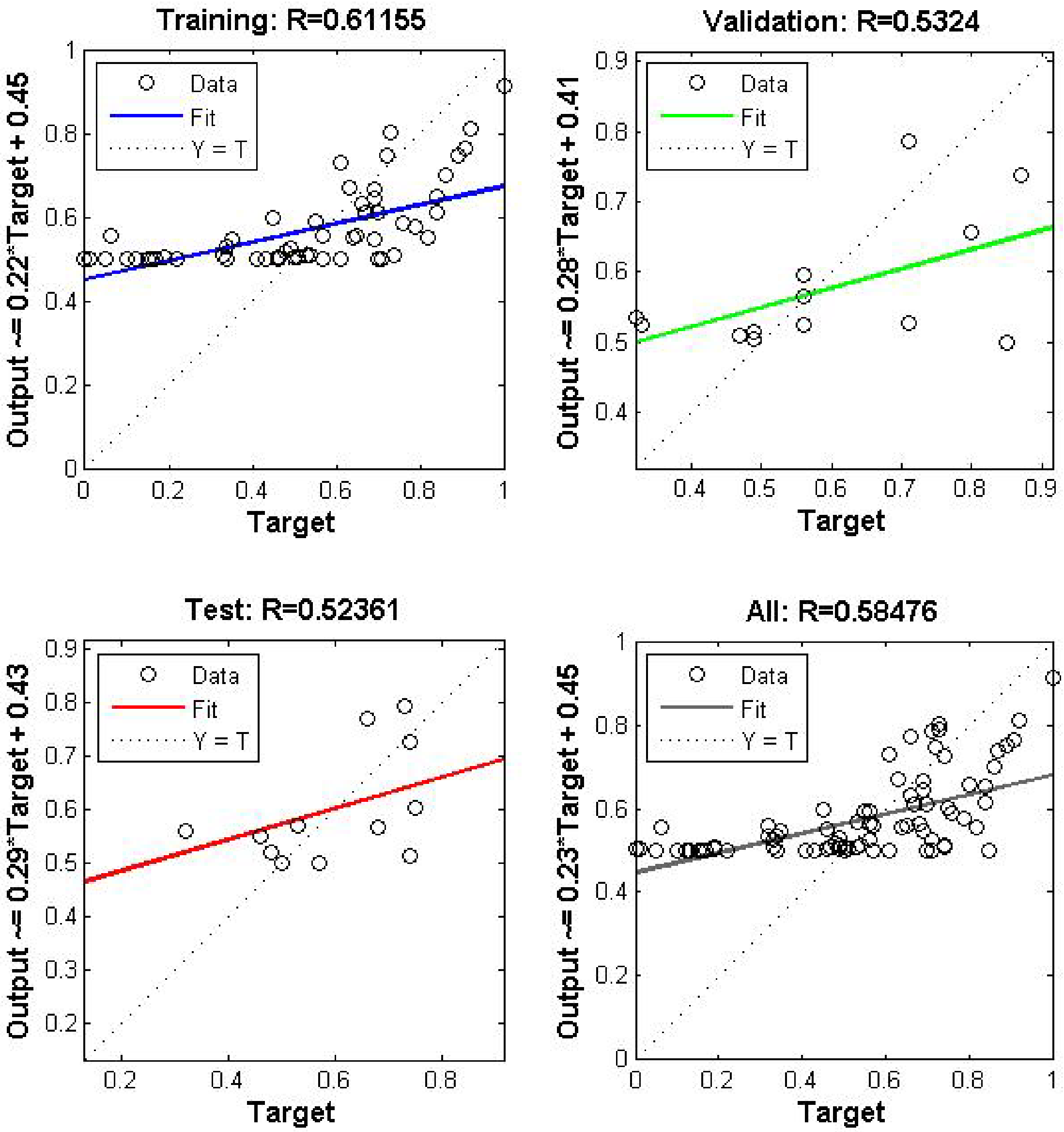
Appendix 2: Regression analysis results for LL



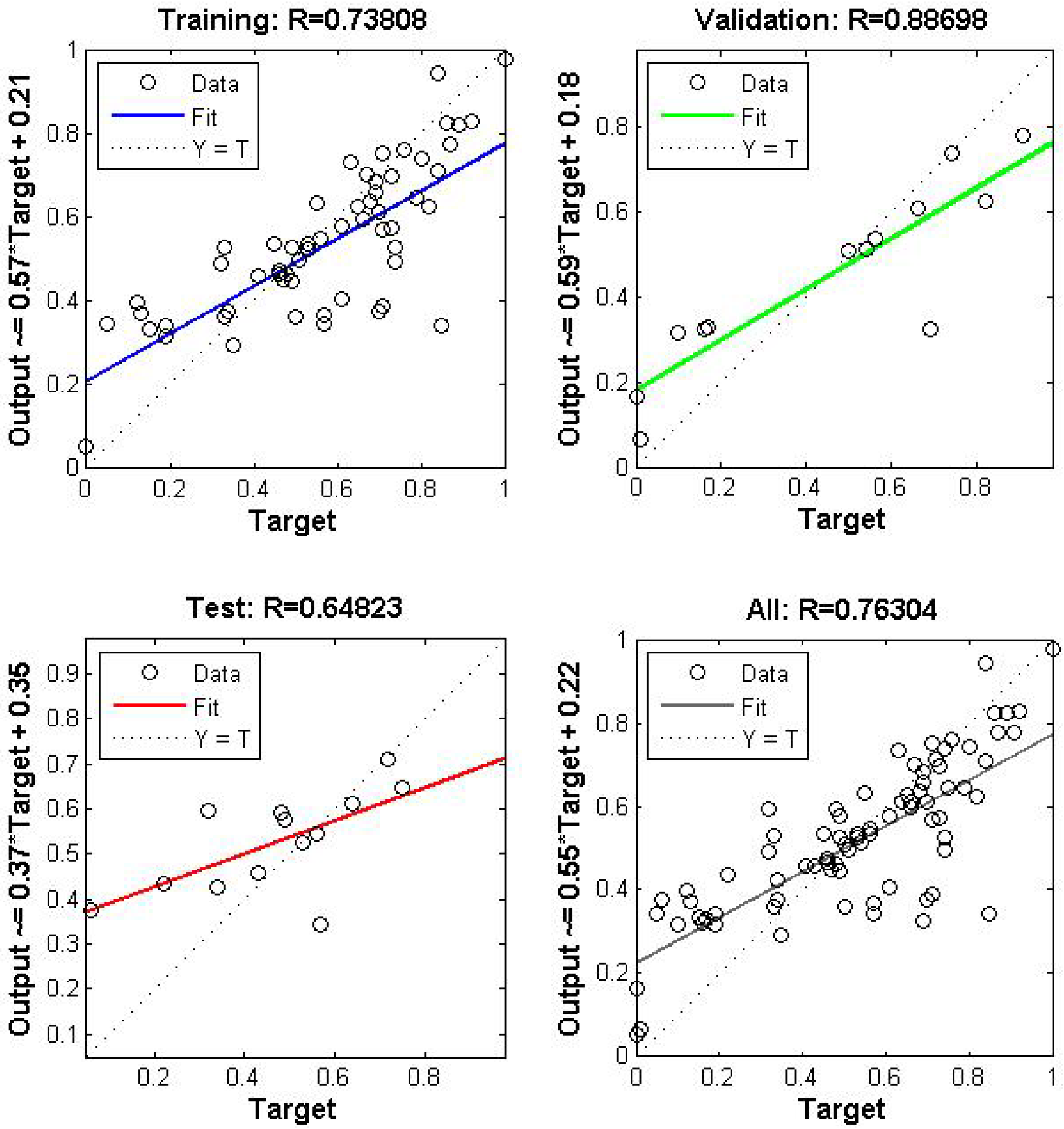
MODEL 1


Training: R=0.72947
Validation: R=0.41105
Test: R=0.42932
All: R=0.64599
Data
Fit
Y = T
Output ~= 0.38*Target + 0.4
Output ~= 0.17*Target + 0.48
Output ~= 0.16*Target + 0.52
Output ~= 0.3*Target + 0.44
Target

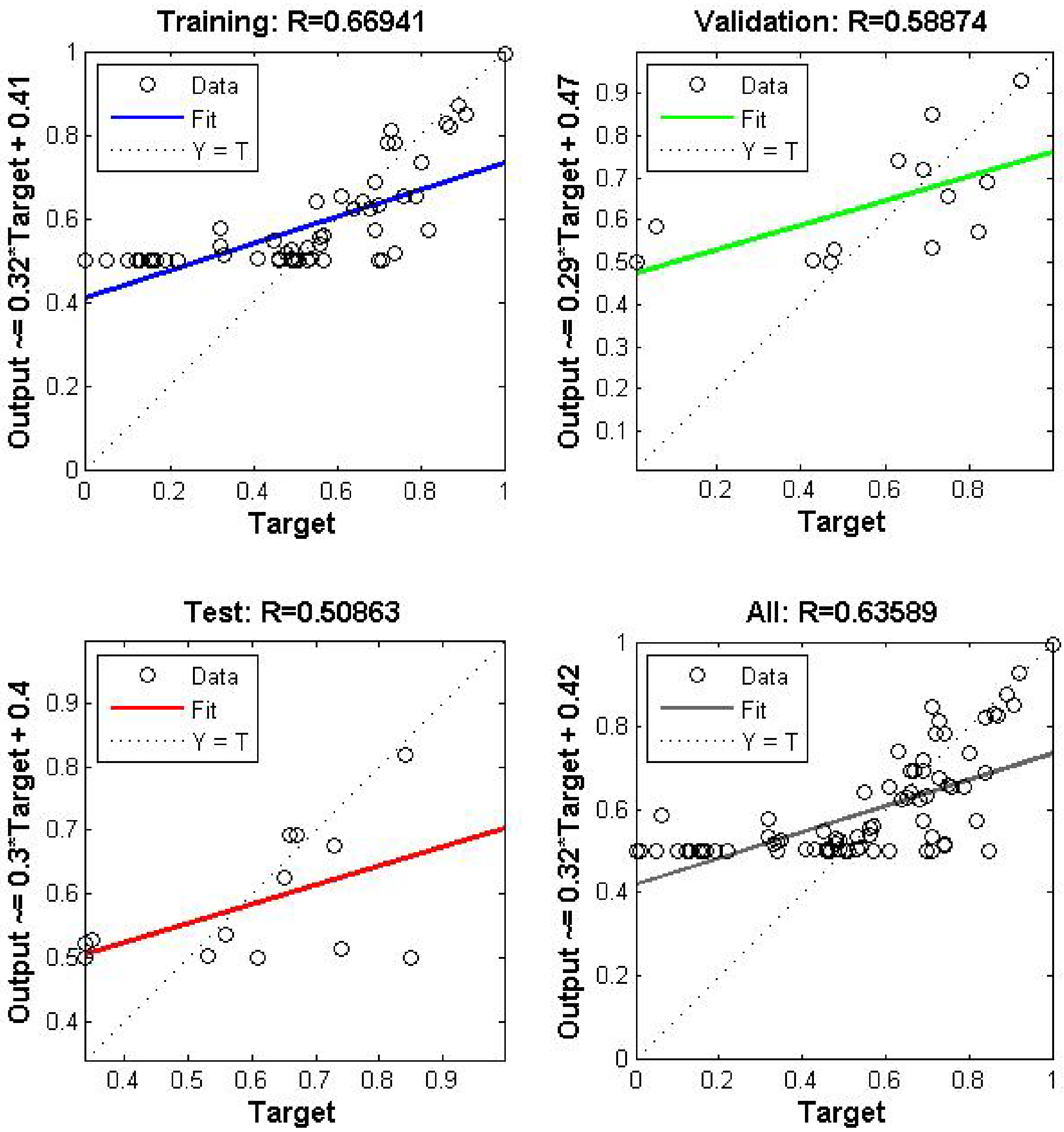
MODEL 2


Training: R=0.61155
Output ~= 0.22*Target + 0.45
Target
Data
Fit
Y = T
Validation: R=0.5324
Output ~= 0.28*Target + 0.41
Target
Data
Fit
Y = T
Test: R=0.52361
Output ~= 0.29*Target + 0.43
Target
Data
Fit
Y = T
All: R=0.58476
Output ~= 0.23*Target + 0.45
Target
Data
Fit
Y = T

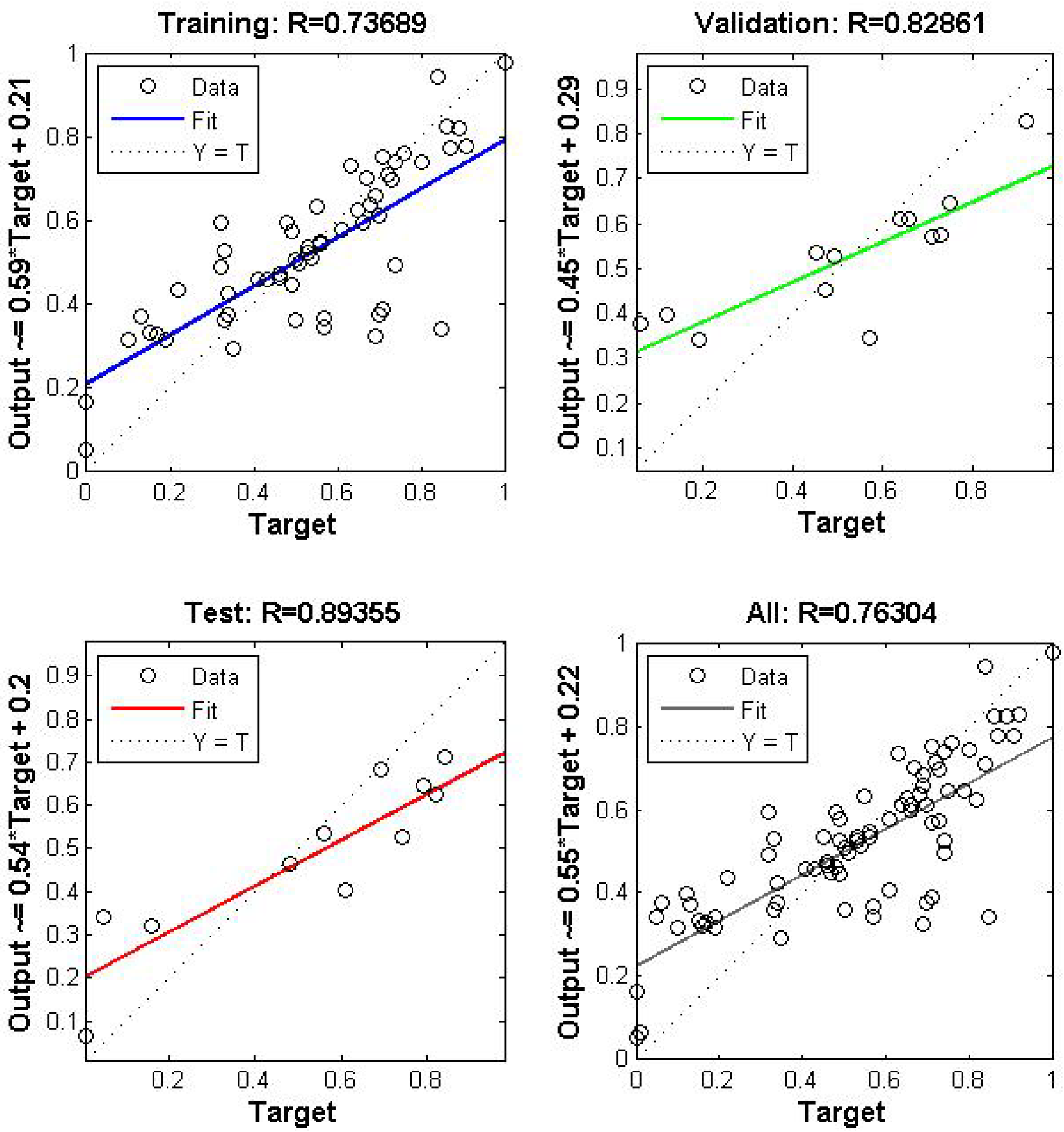
MODEL 3


Training: R=0.73808
Output ~= 0.57*Target + 0.21
Data
Fit
Y = T
Target
Validation: R=0.88698
Output ~= 0.59*Target + 0.18
Data
Fit
Y = T
Target
Test: R=0.64823
Output ~= 0.37*Target + 0.35
Data
Fit
Y = T
Target
All: R=0.76304
Output ~= 0.55*Target + 0.22
Data
Fit
Y = T
Target

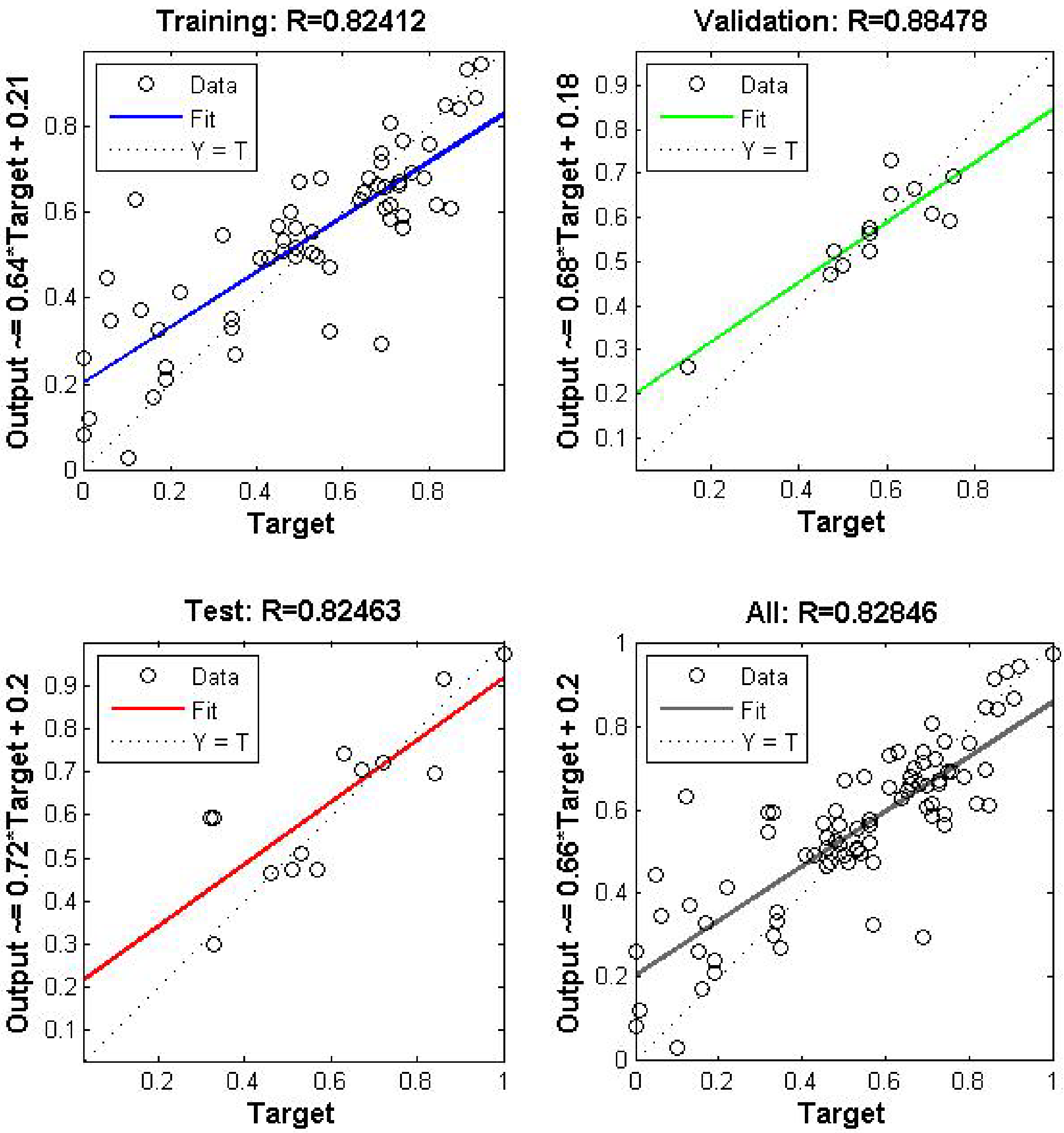
MODEL 4


Training: R=0.66941
Output ~= 0.32*Target + 0.41
Target
Data
Fit
Y = T
Validation: R=0.58874
Output ~= 0.29*Target + 0.47
Target
Data
Fit
Y = T
Test: R=0.50863
Output ~= 0.3*Target + 0.4
Target
Data
Fit
Y = T
All: R=0.63589
Output ~= 0.32*Target + 0.42
Target
Data
Fit
Y = T

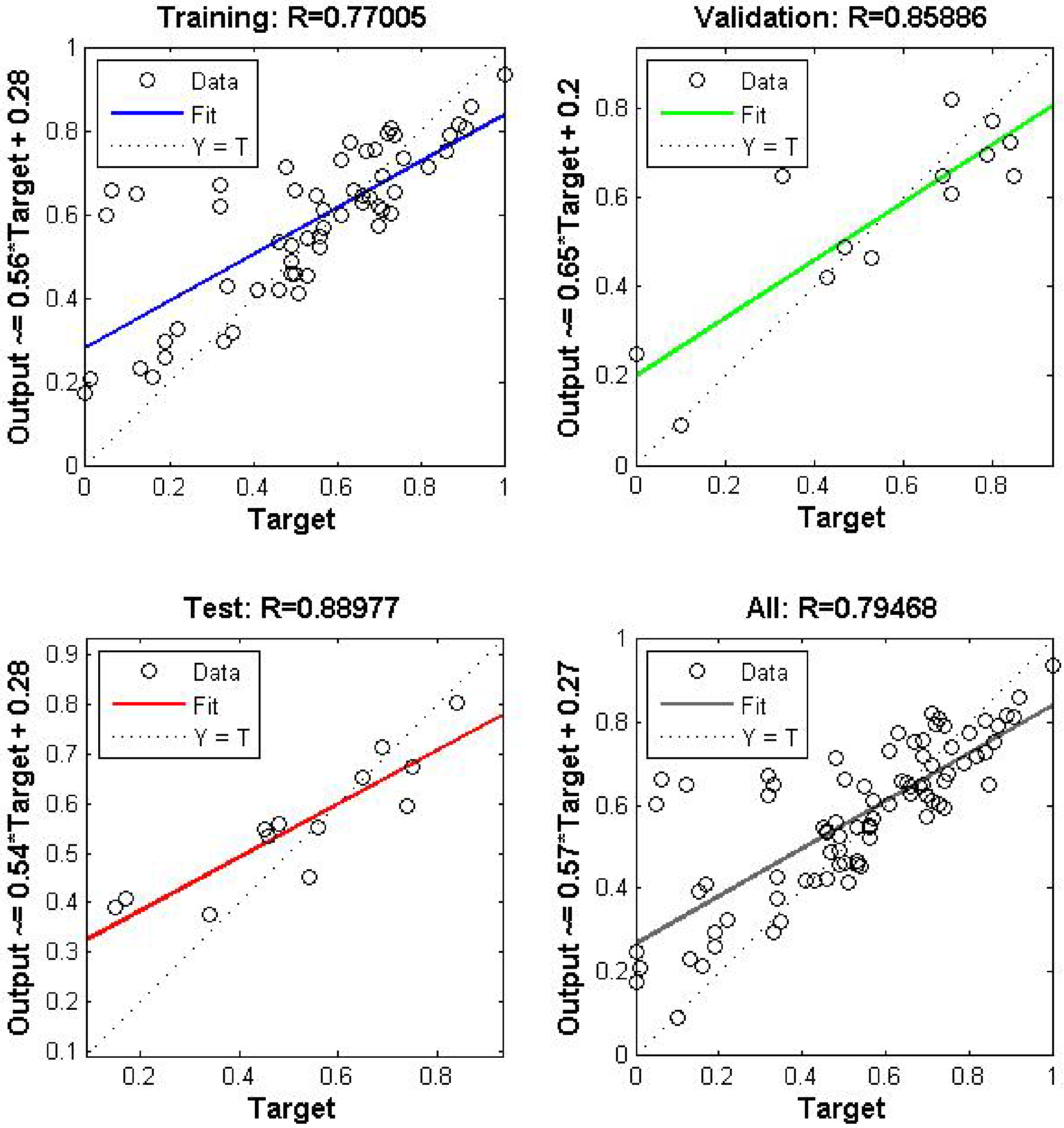
MODEL 5


Training: R=0.73689
Validation: R=0.82861
Test: R=0.89355
All: R=0.76304
Data
Fit
Y = T
Output ~= 0.59*Target + 0.21
Output ~= 0.45*Target + 0.29
Output ~= 0.54*Target + 0.2
Output ~= 0.55*Target + 0.22
Target

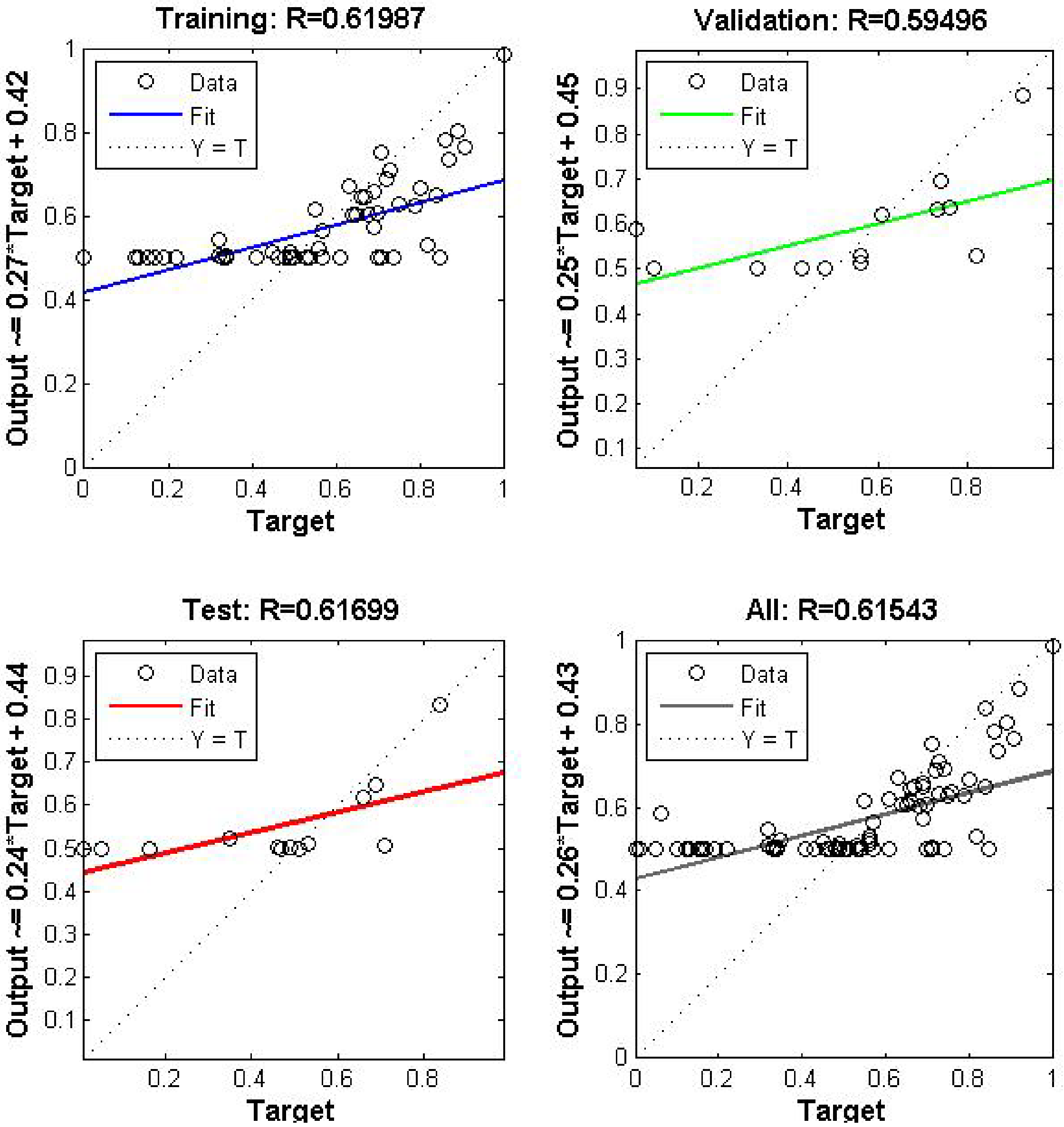
MODEL 6


Training: R=0.82412
Output ~= 0.64*Target + 0.21
Target
Data
Fit
Y = T
Validation: R=0.88478
Output ~= 0.68*Target + 0.18
Test: R=0.82463
Output ~= 0.72*Target + 0.2
All: R=0.82846
Output ~= 0.66*Target + 0.2

MODEL 7

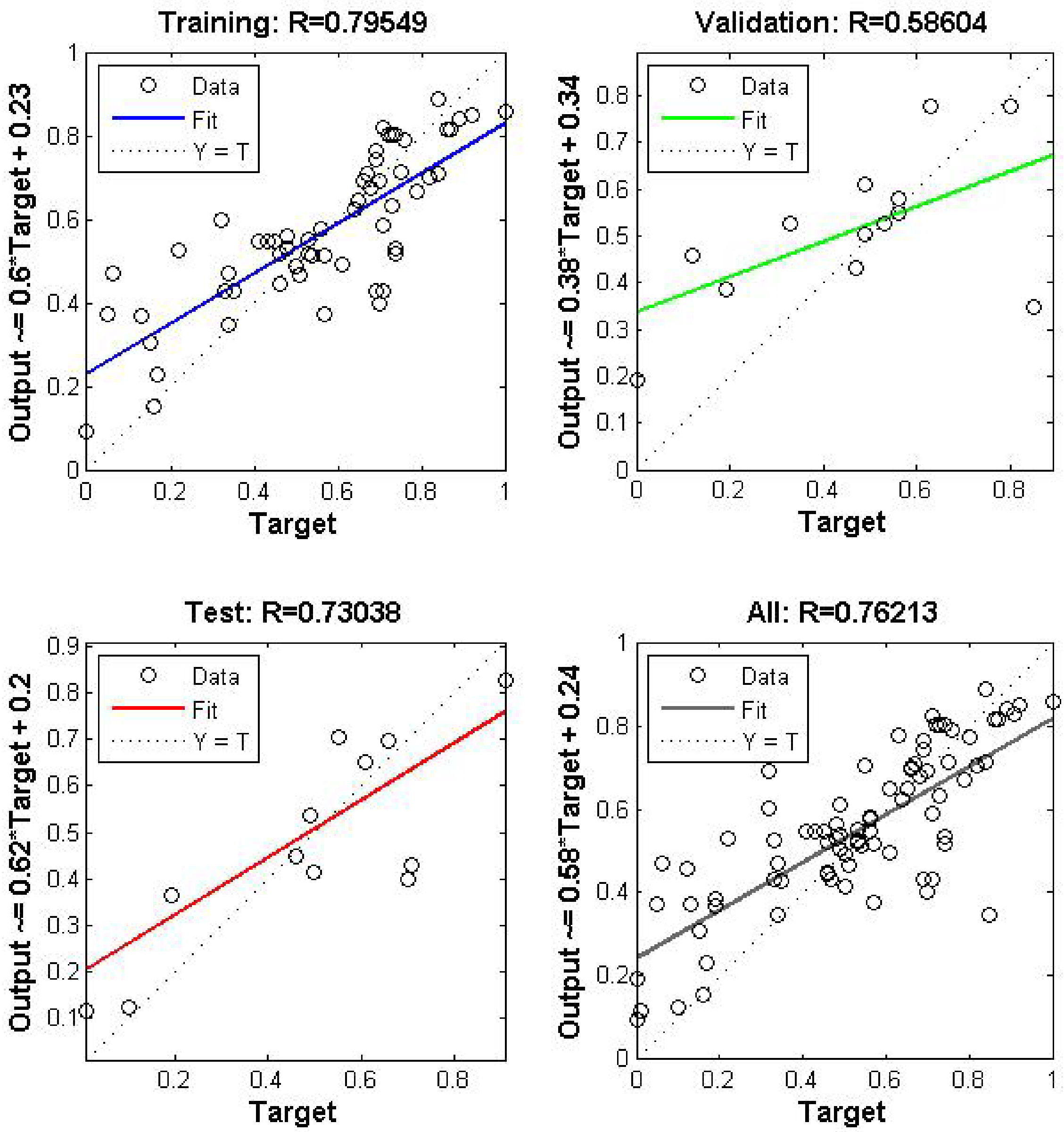

Training: R=0.77005
Data
Fit
Y = T
Output ~= 0.56*Target + 0.28
Target
Validation: R=0.85886
Data
Fit
Y = T
Output ~= 0.65*Target + 0.2
Target
Test: R=0.88977
Data
Fit
Y = T
Output ~= 0.54*Target + 0.28
Target
All: R=0.79468
Data
Fit
Y = T
Output ~= 0.57*Target + 0.27
Target

MODEL 8

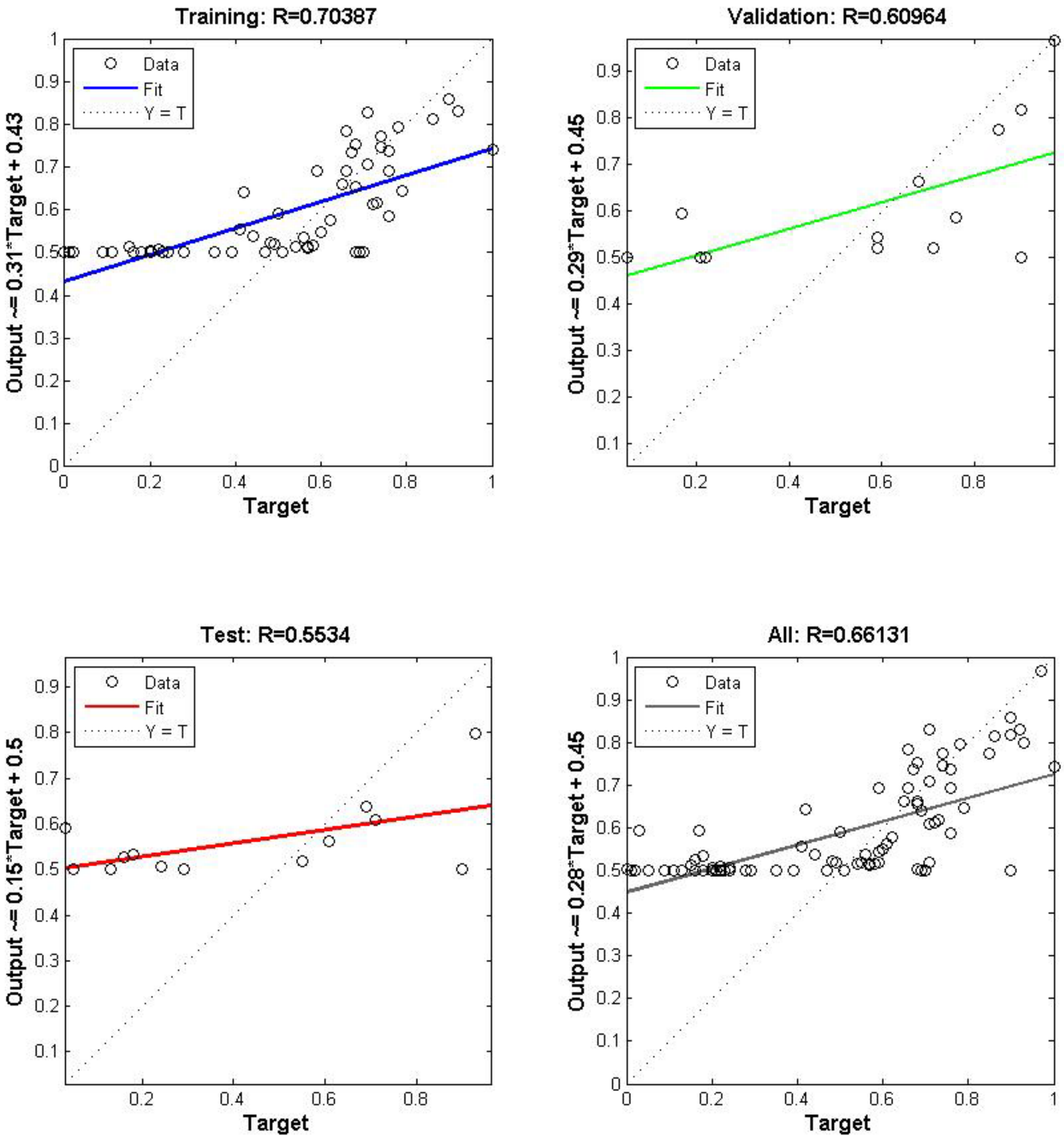

Training: R=0.61987
Validation: R=0.59496
Test: R=0.61699
All: R=0.61543
Data
Fit
Y = T
Output ~= 0.27*Target + 0.42
Output ~= 0.25*Target + 0.45
Output ~= 0.24*Target + 0.44
Output ~= 0.26*Target + 0.43
Target

MODEL 9

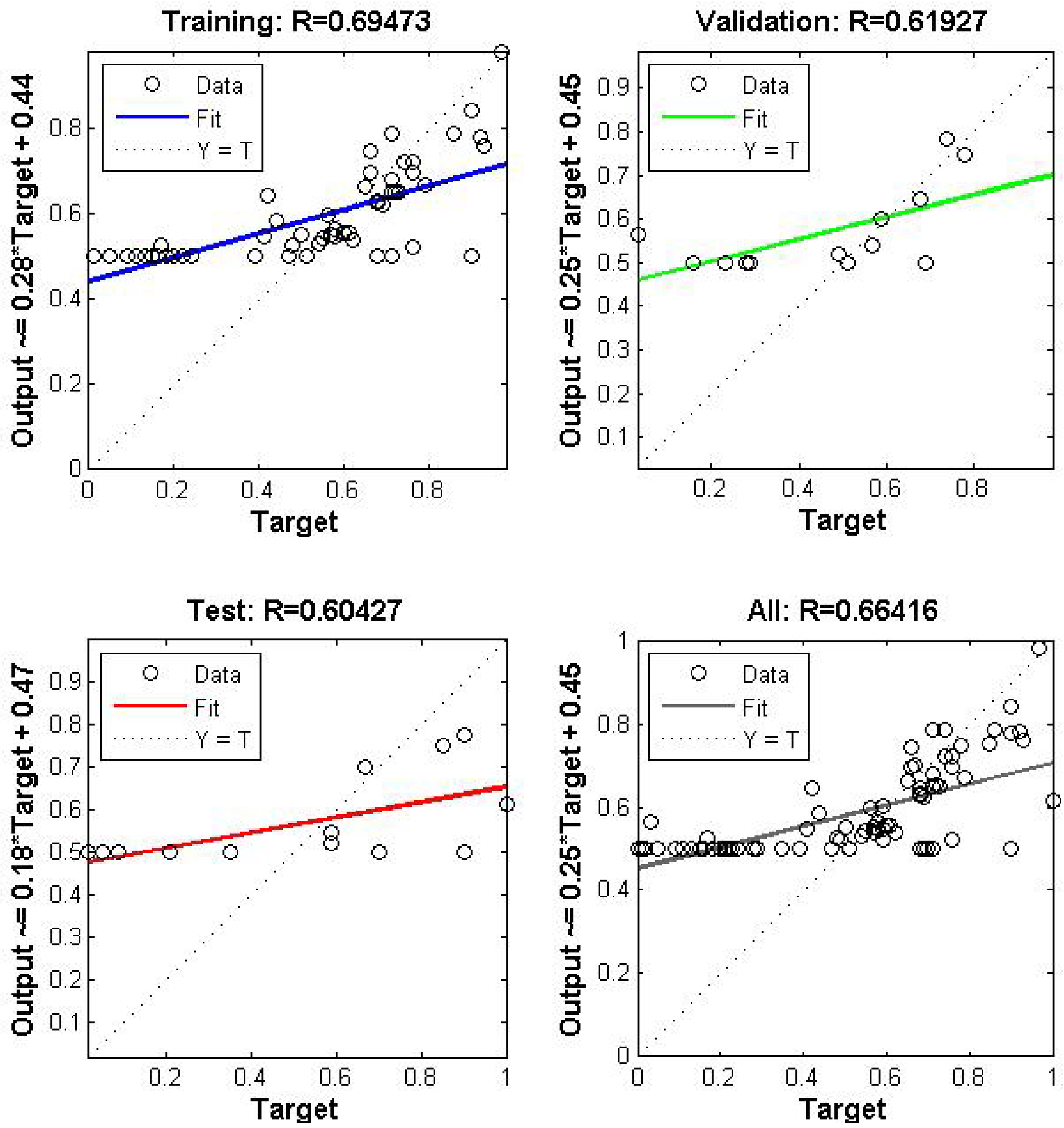
Appendix 3: Regression analysis results for PI



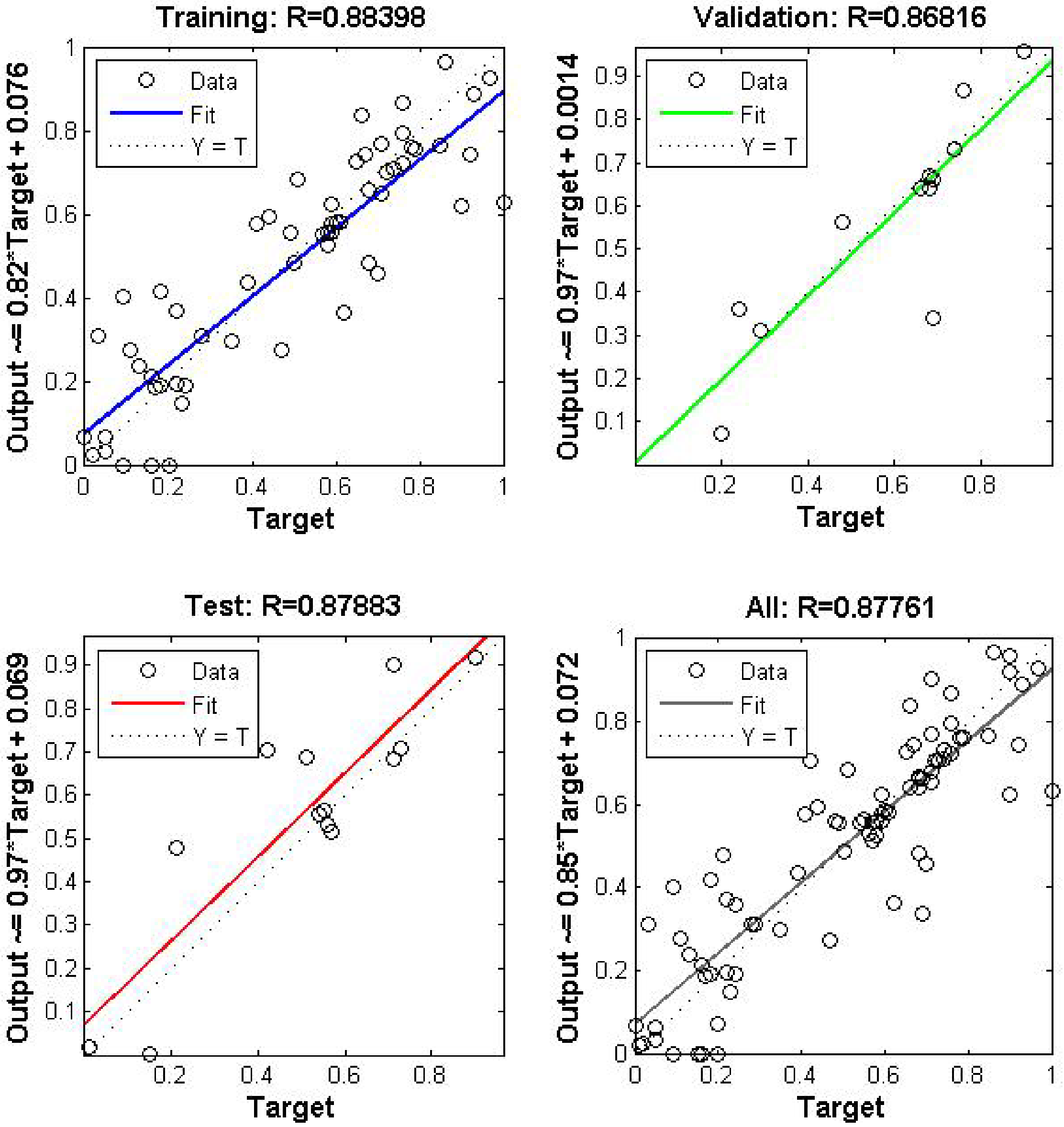
MODEL 1


Training: R=0.70387
Output ~= 0.31*Target + 0.43
Target
Data
Fit
Y = T
Validation: R=0.60964
Output ~= 0.29*Target + 0.45
Target
Data
Fit
Y = T
Test: R=0.5534
Output ~= 0.15*Target + 0.5
Target
Data
Fit
Y = T
All: R=0.66131
Output ~= 0.28*Target + 0.45
Target
Data
Fit
Y = T

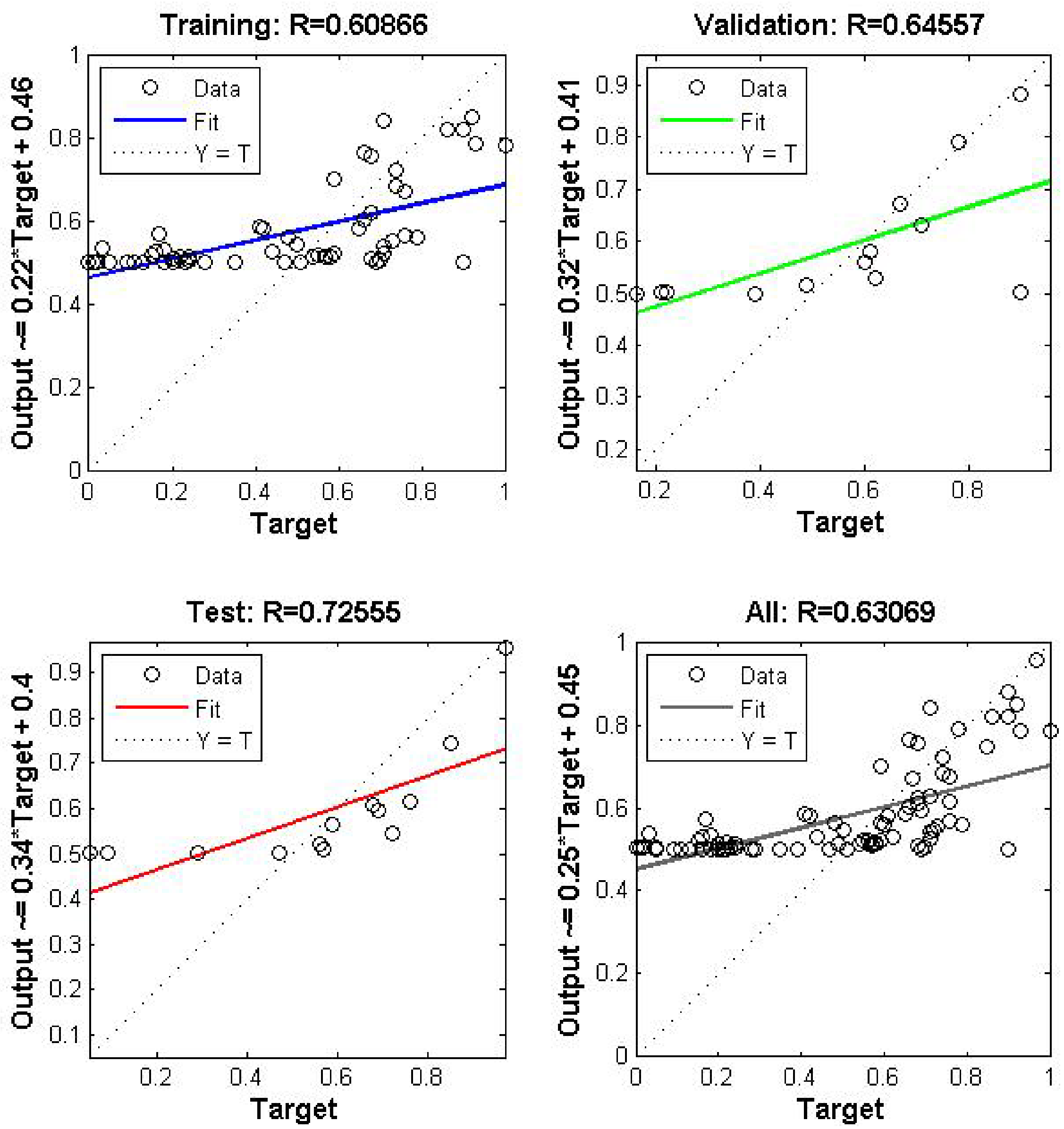
MODEL 2


Training: R=0.69473
Data
Fit
Y = T
Output ~= 0.28*Target + 0.44
Target
Validation: R=0.61927
Output ~= 0.25*Target + 0.45
Test: R=0.60427
Output ~= 0.18*Target + 0.47
All: R=0.66416
Output ~= 0.25*Target + 0.45

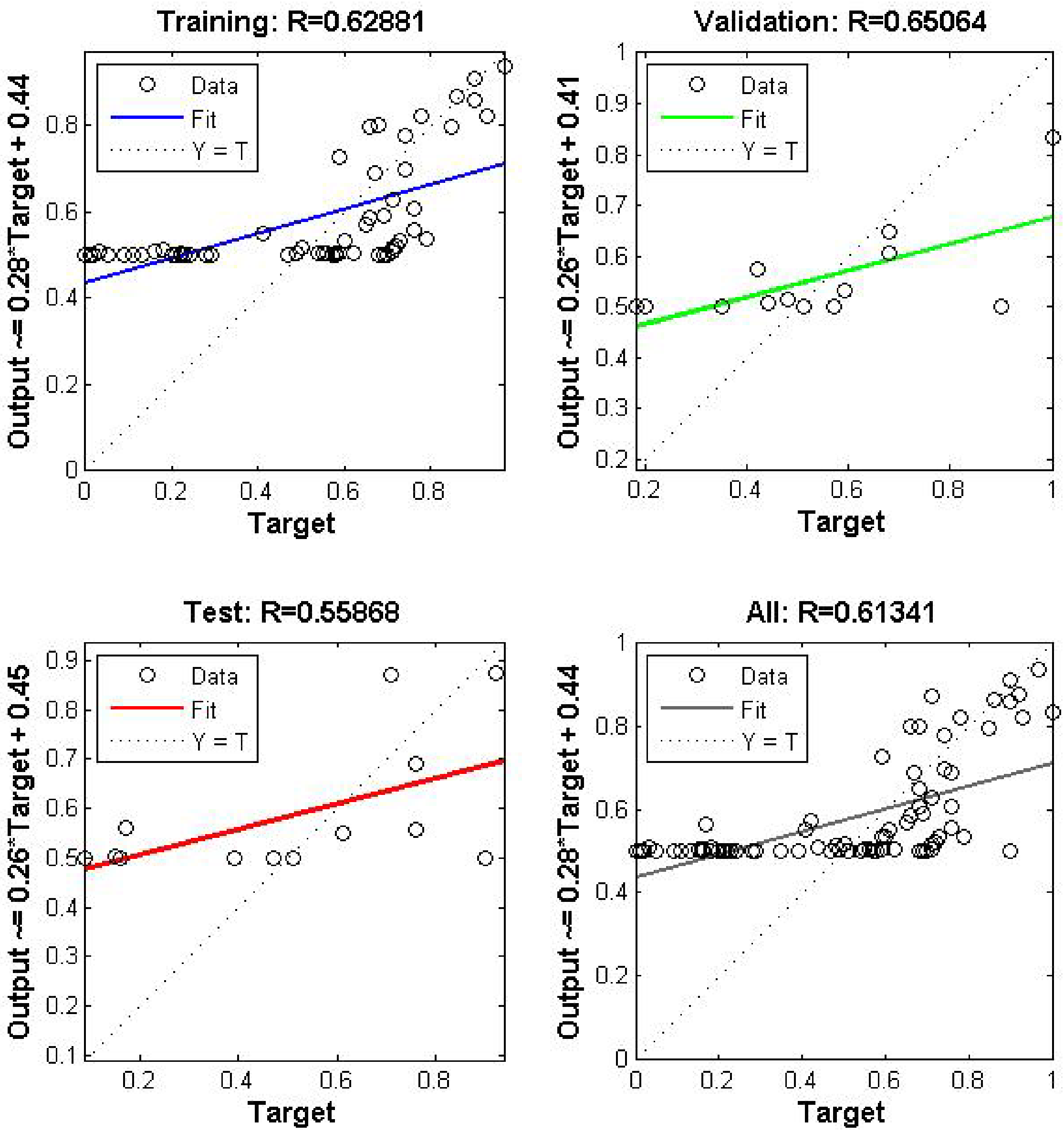
MODEL 3


Training: R=0.88398
Output ~= 0.82*Target + 0.076
Target
Data
Fit
Y = T
Validation: R=0.86816
Output ~= 0.97*Target + 0.0014
Test: R=0.87883
Output ~= 0.97*Target + 0.069
All: R=0.87761
Output ~= 0.85*Target + 0.072

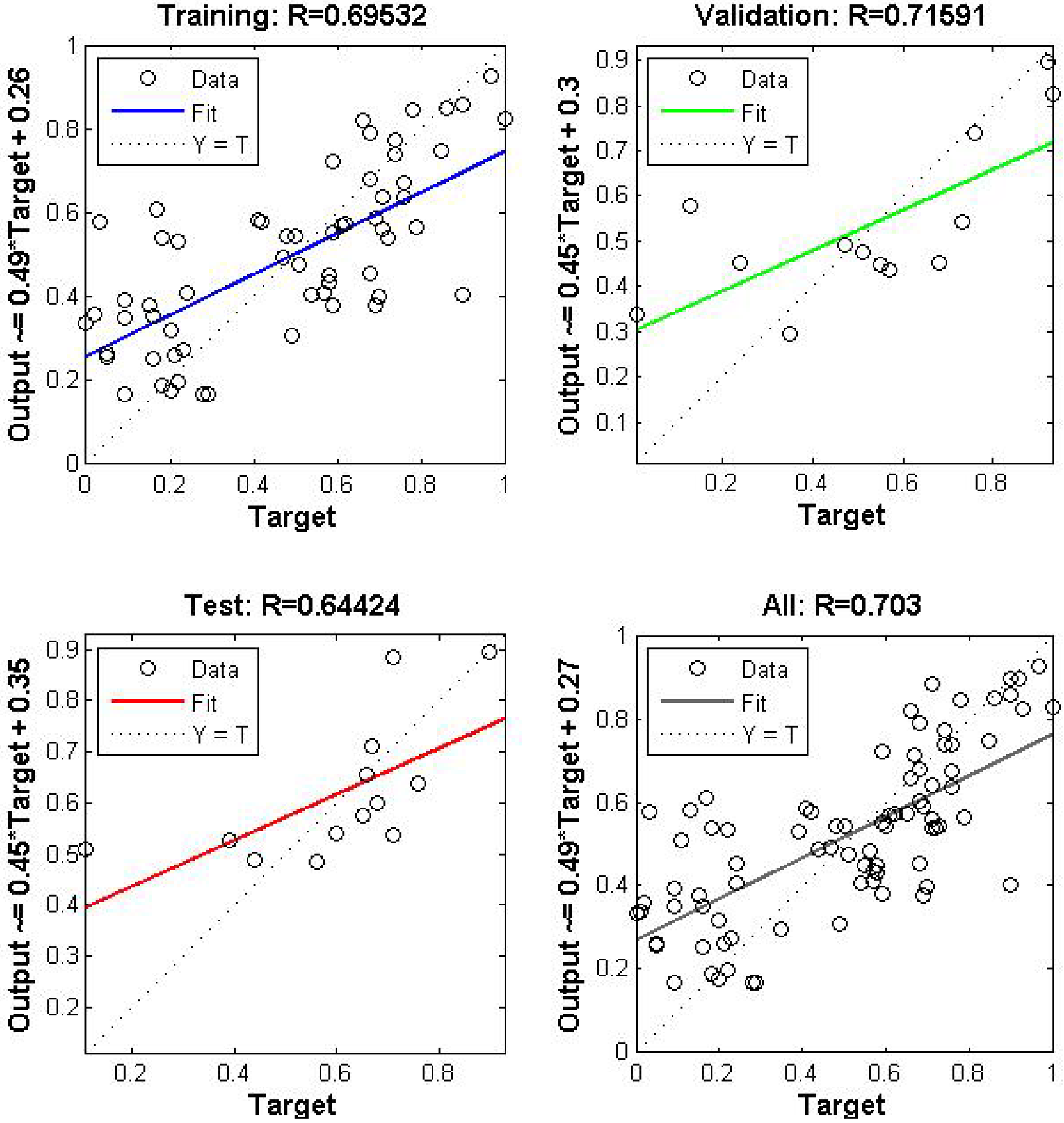
MODEL 4


Training: R=0.60866
Output ~= 0.22*Target + 0.46
Target
Data
Fit
Y = T
Validation: R=0.64557
Output ~= 0.32*Target + 0.41
Test: R=0.72555
Output ~= 0.34*Target + 0.4
All: R=0.63069
Output ~= 0.25*Target + 0.45

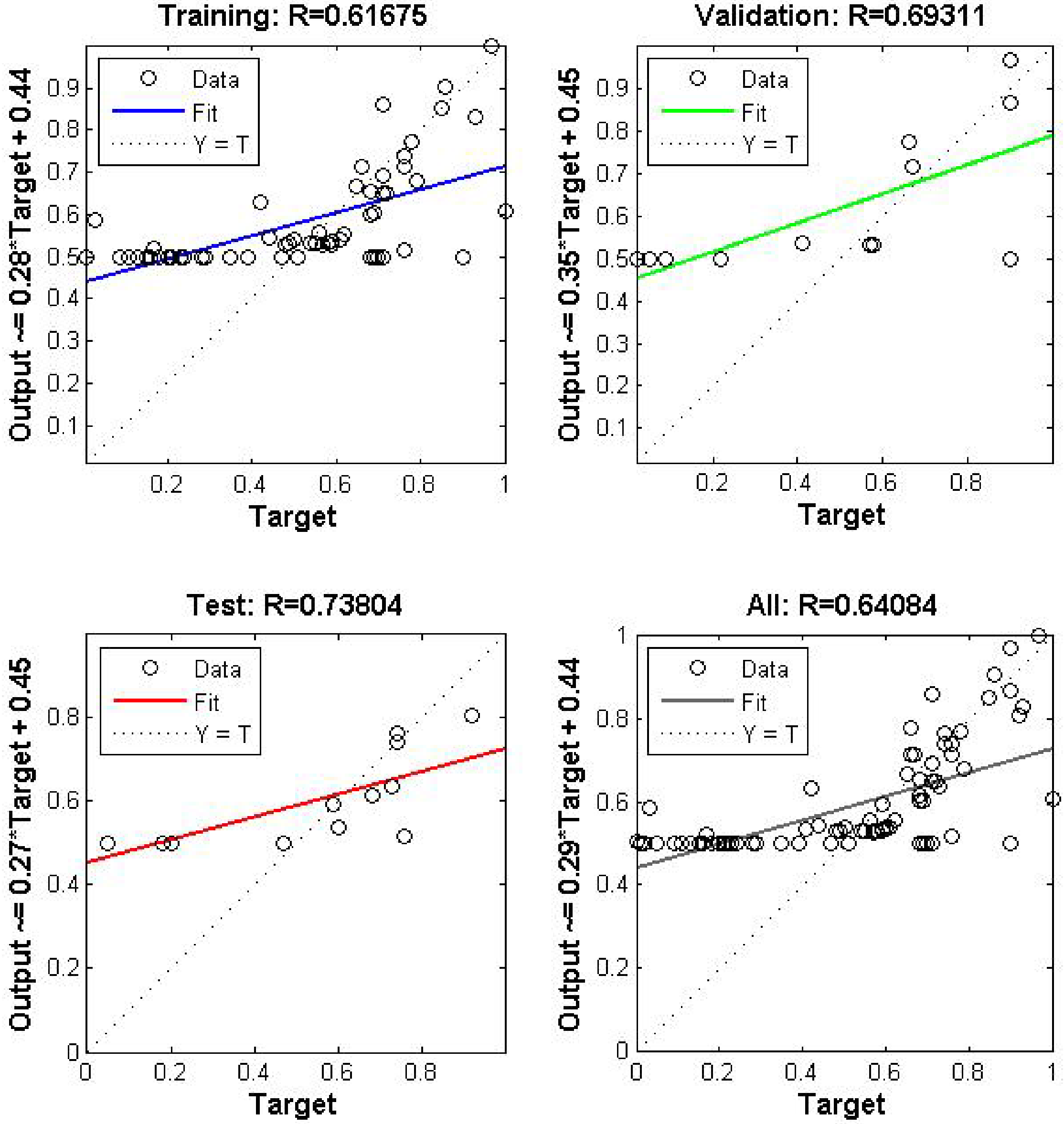
MODEL 5


Training: R=0.62881
Data
Fit
Y = T
Output ~= 0.28*Target + 0.44
Target
Validation: R=0.65064
Output ~= 0.26*Target + 0.41
Test: R=0.55868
Output ~= 0.26*Target + 0.45
All: R=0.61341
Output ~= 0.28*Target + 0.44

MODEL 6

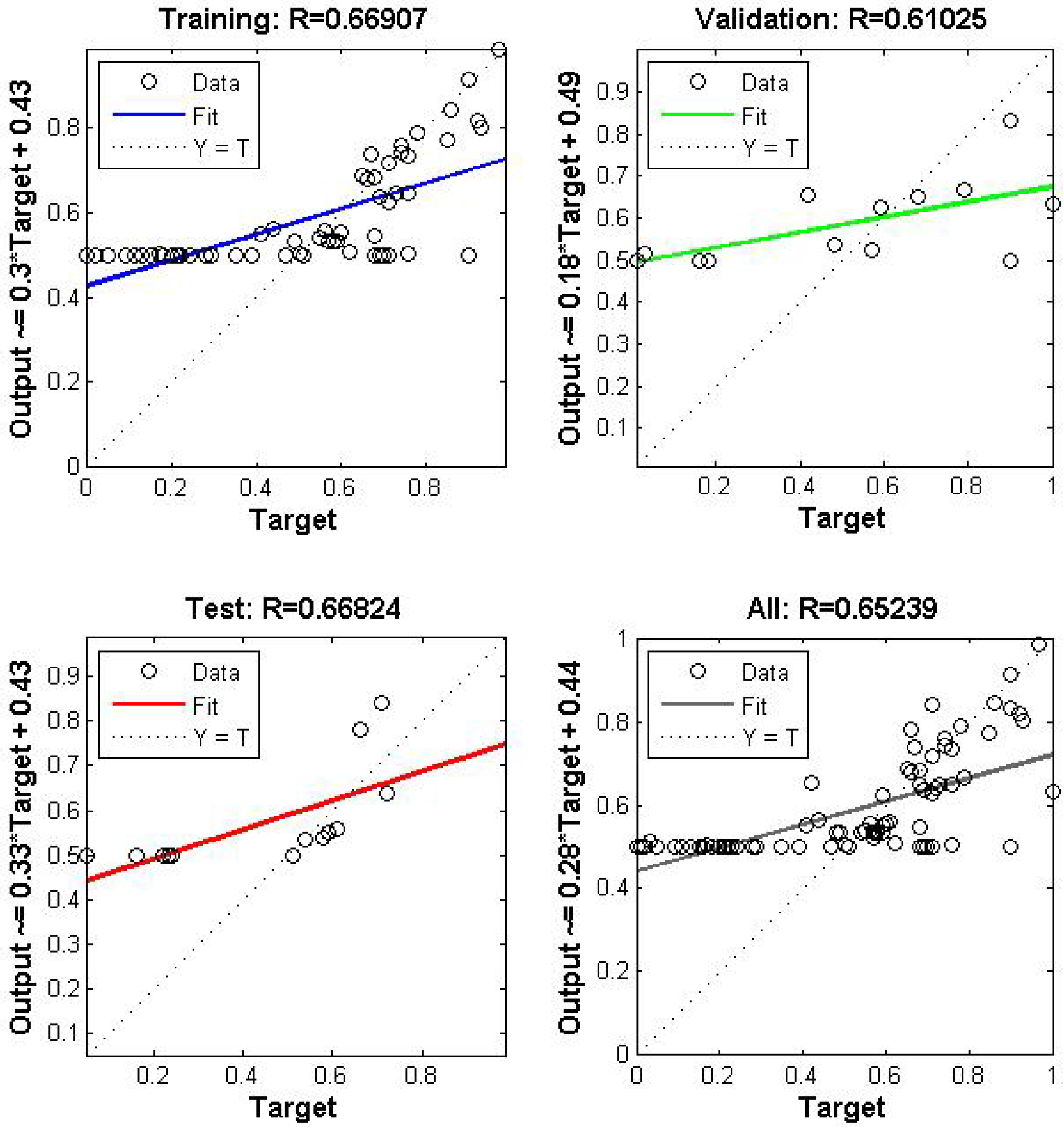

Training: R=0.69532
Output ~= 0.49*Target + 0.26
Data
Fit
Y = T
Target
Validation: R=0.71591
Output ~= 0.45*Target + 0.3
Test: R=0.64424
Output ~= 0.45*Target + 0.35
All: R=0.703
Output ~= 0.49*Target + 0.27

MODEL 7



Training: R=0.61675
Data
Fit
Y = T
Output ~= 0.28*Target + 0.44
Target
Validation: R=0.69311
Data
Fit
Y = T
Output ~= 0.35*Target + 0.45
Target
Test: R=0.73804
Data
Fit
Y = T
Output ~= 0.27*Target + 0.45
Target
All: R=0.64084
Data
Fit
Y = T
Output ~= 0.29*Target + 0.44
Target

MODEL 8



Training: R=0.66907
Output ~= 0.3*Target + 0.43
Target
Data
Fit
Y = T
Validation: R=0.61025
Output ~= 0.18*Target + 0.49
Target
Data
Fit
Y = T
Test: R=0.66824
Output ~= 0.33*Target + 0.43
Target
Data
Fit
Y = T
All: R=0.65239
Output ~= 0.28*Target + 0.44
Target
Data
Fit
Y = T

MODEL 9

THESIS

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