"ESTIMATION OF SHEAR STRENGTH OF SOIL USING MACHINE LEARNING TECHNIQUE"

A DISSERTATION

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IN

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Submitted by

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CANDIDATE'S DECLARATION

I, **Ankit Singh, 2K20/GTE/04**, student of M.Tech (Civil Engineering), hereby declare that the project dissertation titled **"Estimation of Shear Strength Parameters Using Machine Learning Technique"** is submitted to the Department of Civil Engineering, Delhi Technological University, Delhi, by me in partial fulfillment of requirement for the award of degree of **Master of Technology (Geotechnical Engineering)**. This thesis is original work done by me and not obtained from any source without proper citation. This project work has not previously formed the basis for award of any degree, diploma, fellowship or other similar title or recognition.

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CERTIFICATE

I hereby certify that project dissertation titled **"Estimation of Strength parameters of soil using Machine Learning Techniques"** submitted by **Ankit Singh, 2K20/GTE/04,** Department of Civil Engineering, Delhi Technological University, Delhi, in partial fulfillment for the award of degree of Master of Technology, is a project work carried out by the student under my supervision. To the best of my knowledge, this work has not been submitted in part or full for any degree or diploma to this university or elsewhere.

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ABSTRACT

Shear strength is a significant criterion used to determine the capability of ground foundation in the design phase of many megaprojects (highways, roads, high-rise buildings) and geotechnical constructions (earth dams, retaining walls). These characteristics are determined through laboratory testing. Because shear strength have such a strong influence on soil carrying capacity, a great number of experimental and theoretical investigations have been conducted to better understand soil strength behaviours.

This study focuses on the creation of machine learning models such as Artificial Neural Network(ANN) Multilayer Perceptron(MLP) and Radial basis Function(RBF) for predicting shear strength of soil using data from TC304 Database. For estimating shear strength, relevant input factors such as Undrained shear strength (USS), vertical effective stress (VES), preconsolidation stress (ps), liquid limit (LL), plastic limit (pl), and natural water content are all metrics in two datasets have been chosen. The most essential variables for predicting soil shear strength using the ML model were determined to be vertical effective stress, pre - consolidation stress, depth, and plastic limit. The effectiveness of the ANN model was assessed using well-known statistical metrics like the mean absolute error (MAE), root mean squared (RMSE), and coefficient of correlation (R). The proposed models were able to learn the intricate relationship between soil strength and their contributing factors effectively.

.

Keywords: Artificial Neural Network(ANN), Multilayer Perceptron(MLP), Radial basis Function(RBF), Undrained shear strength (USS), vertical effective stress (VES), preconsolidation stress (ps), liquid limit (LL), plastic limit (pl), natural water content, mean absolute error (MAE), root mean squared (RMSE), and coefficient of correlation (R).

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Chapter 1 – Introduction

1.1 Soil Shear strength:

Shear strength is described as a soil's ability to resist mobility or slippage when it is subjected to generated stress. Many infrastructure projects rely significantly on this soil feature, including highways, pavements, dams, slope protection, and high-rise skyscrapers (SK et al. 1996). There's not a single engineering situation where soil shear properties aren't a factor. Measuring the soil shear strength is crucial in geotechnical studies.

For more than 250 years, engineers and mathematics have struggled to measure the shear capacity of soils. Firstly Coulomb investigate the concept of shearing strength and he defined soil shear strength as a single term. Later, Mohr proposed the shear hypothesis, which said that material collapse on a plane is impossible without exceeding the maximum shearing strength. Several researchers, including Tresca, Mises, and Griffiths, made substantial contributions to the processes of failure and theories of shear strength in the recent years. Finally, the Mohr Coulomb hypothesis was developed combining Mohr and Coulomb theories as well as two shear strength variables. The Mohr–Coulomb hypothesis is a general characterization of geotechnical materials' shear strength. Both cohesiveness tangent and slope of shearing resistance, as per this theory, are 2 shear components that fluctuate linearly with applied force. The angle of cohesiveness and internal friction angle are determined by the intercept and slope of the tangent of the Mohr - coulomb failure failure envelopes, respectively. (Mollahasani et al 2011).

The Mohr–Coulomb criterion is often used to assess shear strength of soil in slope stability, earth pressure and bearing capacity, and concerns. The Mohr Coulomb failures are caused by strains on the likely rupture plane in earth constructions. The Mohr–Coulomb criteria is defined on the premise of soil collapse on any plane whenever shear stress (Tf) reaches a critical level. Finally, the shearstrength is derived by

$$\tau_f = C + \sigma \tan \phi$$

Where, c is cohesion, σ is lateral stress on the plane under consideration, and f is internal friction intercept.

According to a basic interpretation, deformations are restricted if shear stress on a specific plane is less than crucial tf values. Shear distortions are infinite, and failure in shear occurs when shear stress on given plane exceeds a critical magnitude. Even if the normal stress is 0, the cohesiveness suggests that shear failure requires a shearing stress. The Mohr–Coulomb criterion can be represented in geometric terms. In other words, Mohr's circle can be used to graphically express stress on surface of various orientations, as seen in Fig.1.1 The Mohr circle is formed by lengths corresponding to σ 1 and σ 3, the highest and lowest primary stresses, on the horizontal axis. The 2 stresses presents a circle of a radius of half of $\sigma_1 - \sigma_3$ and a centre of half of $\sigma_1 + \sigma_3$ on the horizontal plane.

To explain a failure condition for sands, using Mohr–Coulomb criterion are a feasible hypothesis to utilise. Sands have no cohesive (C = 0), and the friction angle ranges from 30 to 45 deg based on the surface area or overall shape of the morphologies of the particles.

Clay soils have a smaller angle of friction than sands and are less cohesive. The Mohr - coulomb failure criteria are well applicable to clays, and the change of hydraulic moisture with time is critical for applying this hypothesis.

Many clays have unique characteristics that increase cohesiveness over time during consolidation. Depending on the presence of overconsolidation, this results in increased strength. The Mohr Coulomb criterion may not apply to soft clays since the soil acts more like a viscous fluid than a solid. Because of the reason that confining pressures is supplied to the specimen of Soil conditions can be replicated in a way that surpasses previous testing methods using horizontally equal in-situ conditions in tri-axial testing equipment. Furthermore, by accounting for pore water changes that occurs during the testing operation, the drainage situation can be regulated. Consolidated Drained (CD), Consolidated Undrained (CU), and Unconsolidated Undrained (UU) Undrained testing methodologies can all be used (CD). The Mohr–Coulomb failure hypothesis is commonly used to evaluate the findings of static triaxial testing. The failure envelop is established in this way by plotting Mohr circles with deviator stress and failure stresses. The failure envelope is then used to derive soil shear strength characteristics (c vs. Φ). For the most part, geotechnical investigations consider the failure envelope to be linear instead of nonlinear, as previously stated.

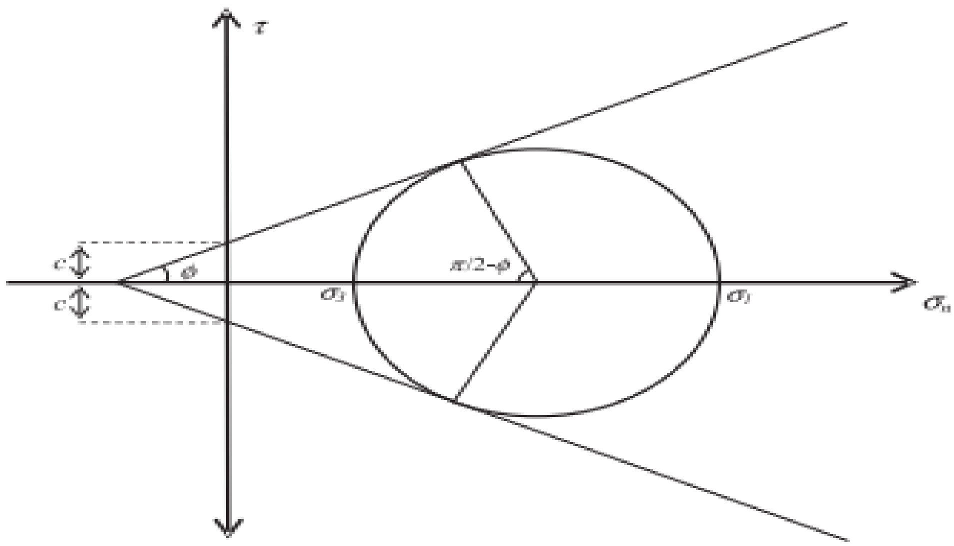


Fig.1.1 Mohr Coulomb critieria Geometrical view (Goktepe et. al. 2008)

This hypothesis has recently been accepted technique for calculating shear strength characteristics for soil subjected static loads. In this hypothesis, the shear envelope is nearly nonlinear; whereas, it is commonly account linear for practical reasons because it is simple and do not introduce substantial inaccuracies (Wood DW et al 1990).

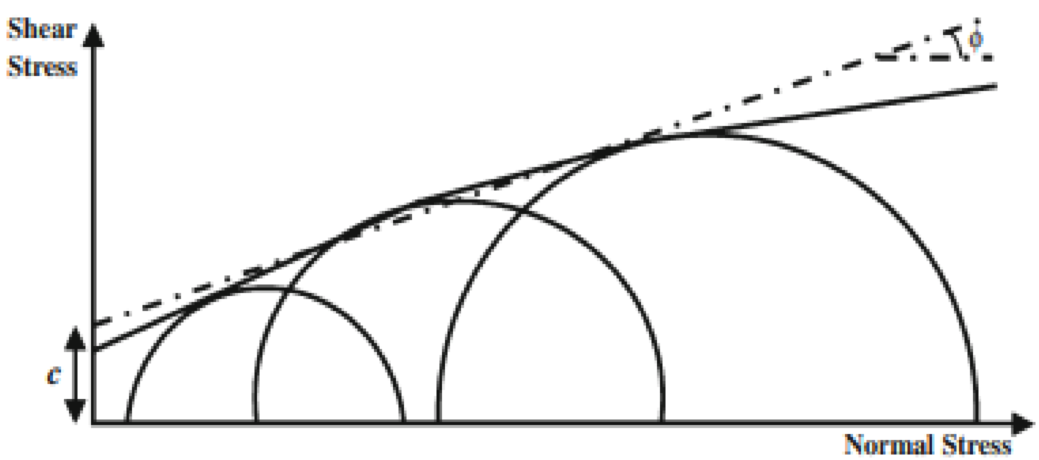


Fig1.2. Mohr circles and failure envelopes (Murthy et. al. 2008).

In the design of various structure of geotechnical, accurate estimation of shear strength of soil is a primary concern. These important factors can be measured in the field or in the lab. The most widely preferred lab methods for evaluating the c and φ values are triaxial compression or direct shear test. In the field, tests like the vane test or any other indirect technique are used (Murthy 2008; Mollahasani et al 2011)

Fig1.3 Apparatus for cyclic triaxial test

Fig.1.4 Apparatus for vane shear test

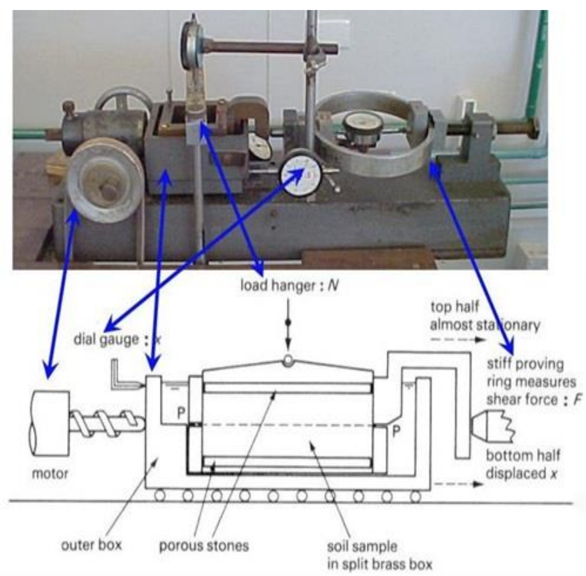


Fig.1.5 Apparatus for Direct shear Test

1.2 The Scope of the Study

However, determining the shear strength experimentally is time-consuming, tedious, and costly. Furthermore, doing testing on each new case is not always feasible due to unavailability of required equipment. Therefore, numerical solutions to estimate soil shear strength have been developed to deal with such complex challenges. Despite the fact that soils are multi-variable, most correlations are created using only one soil index parameters. The functional relationship between soil shear strength and various influencing parameters can be really nonlinear, and formula-based techniques are limited in nonlinear and multivariate modelling. Due to these reasons many studies have been committed to establishing alternative methods to determine soil shear strength, including standard formula-based methods and enhanced data-driven methods. Machine learning based models are proficient at nonlinear modelling and can take into consideration a large number input variables that influence the value of soil shear strength.

1.2 Innovation aimed at

To determine the shear strength, We must follow strict laboratory methods and work with expensive equipment which consumes a lot of time. This research aims to get soil shear strength using machine learning algorithms with a high level of accuracy, which could save capital as well as time to do experimental analysis.

1.3 OBJECTIVE OF THE STUDY

- The major goal of this research is to find the variables that are highly connected with the soil's shear strength.
- To develop a ANN model which will be able to predict undrained shear strength of soil.
- To develop a Multilayer perceptron ML model which will be able to estimate shear strength of soil.
- To develop a Radial Basis function ML model which will be able to estimate shear strength parameters of soil.
- To compare the efficacy of these primary analytic prediction models to laboratory time-

consuming experiments.

- To analyse several prediction models based on statistical factors and determine which model is the best for predicting soil shear strength.

1.4 ANN Model

To solve prediction problem, the Artificial Neural Network (ANN) model employs the creation of algorithms to grasp complex patterns. The ANN is similar to how information is received by the different neurons in the human brain. There are many different Artificial Neural Networks, some of which are listed below. ANNs are made up of interconnected neurons in parallel by synapses. Dendrite and axon are the two basic elements of a neuron. Synapses perform signal processing and dendrites establish the connection between two neurons.

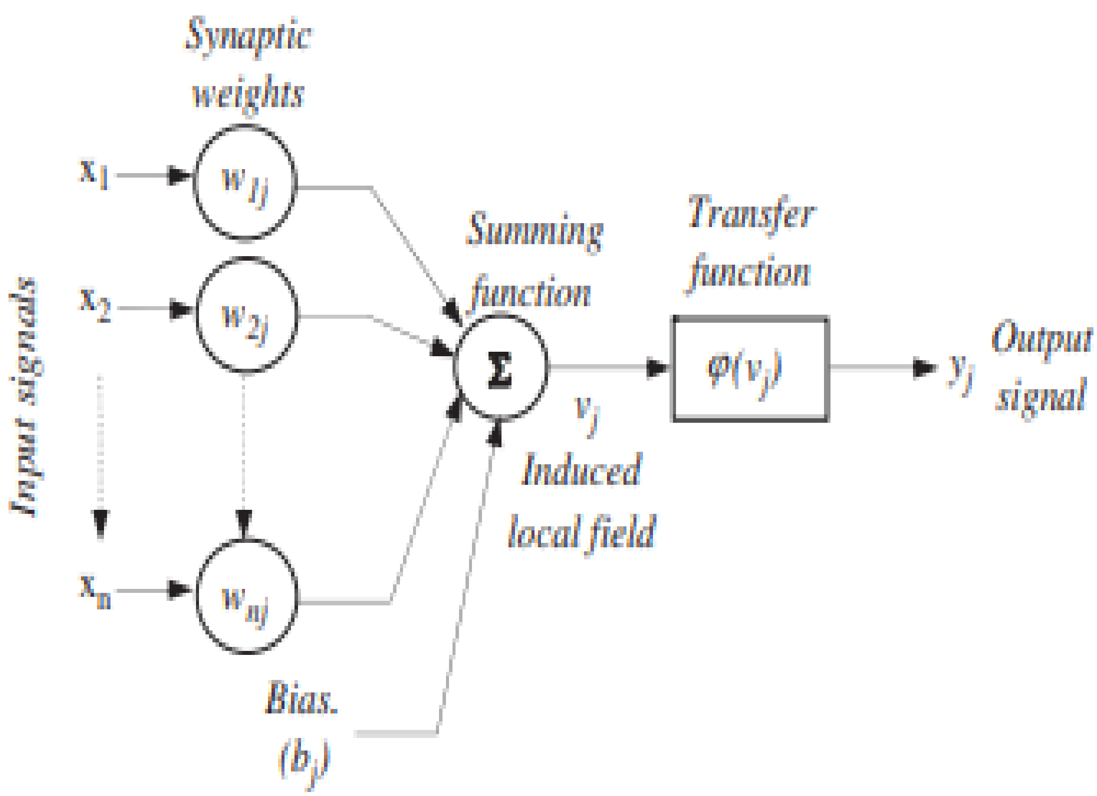


Fig.1.6 Artificial neuron model (Goktepe et. al. 2017)

Axons are long branching that make up the body of a neuron. A neurons is a signal conditioning component that both excites and produces input signals. Figure 1 shows a schematic diagram of an ann model. Following integrating synaptic weights, input signals are gathered, as seen in Fig. The total impulse is then compared to the bias term to calculate the induced local field. In the last phase, an activating function is employed to restrict the mapping range and provide an output. An artificial neuron is represented mathematically as follows:

$$y \quad = \phi(V_j) = \phi\left(\sum_{i=1}^{n=1} x_1 \cdot w_{ij} - b_j\right)$$

where xi is the input, wij is the synapse weight, bj is the bias value, vj is just the induced local fields, j is the activation function, yk is the output signal, n is the previous layer's number of neurons, and k is the processing neuron's index.

I. Multi-layer Perceptron:

The processing unit includes one neuron, synapse weight as well as the bias term is referred to as a perceptron. Multi-layer perceptrons (MLPs) is also called multilayered networks of feedforward neural, are made from three layers: input nodes, more than one hidden layers, and also output layer. Every layer is having set of perceptrons connected in parallel to the layers above and below it. Modeling with MLPs has proven to be successful (learning) mappings that are nonlinear and complex Figure shows an example of an MLP. MLPs are employed to create considered ANN models in this research. The terms ANN and MLP will be used interchangeably in this context.

$$y_i = v_0 + w_1 \times x_1 \; + w_2 \times x_2 \; + \cdots + +w_n \times x_n$$

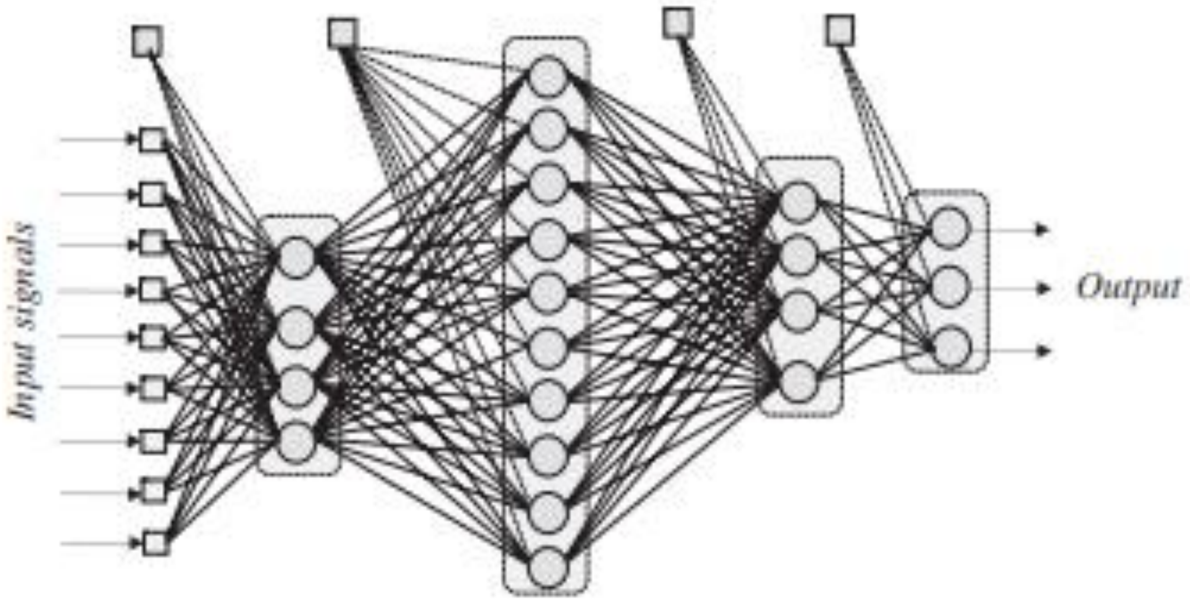


Fig.1.7 Three hidden layers Multilayer perceptron (MLP)

II. Kohenon Network

One of the most basic types of self learning neural networks is Kohonen's networks. Self-organization opens up new options, such as adaptation to previously unknown input data. It appears to become the most natural manner of learning that our brains use, with no clearly defined patterns. Those patterns emerge as a result of the process of learning, which is supplemented by regular effort. The term "Kohonen's networks" refers to net groups that use a competitive learning mechanism, self organizing. We create a signal on net's input and afterwards select the effective neuron, one which fits the input vector the best. Kohonen Network, which is based on unsupervised learning, is utilised in clustering creation. A self-organizing feature map is another name for it (SOFM).

The structure of a neural network is quite important. A artificial neurons is a simple device that can't achieve much on its own. Complicated processes are only achievable with a network of neurons. Many various architectures have been built to try to emulate the structure and dynamics of the human nervous system due to our lack of information about the specific rules of human brain functioning. The most common network architecture is one-way, one-layer. The reality that almost all neurons must engage in the contest with same rights determines it. As a result, each of these must have the same number of inputs as the entire system.

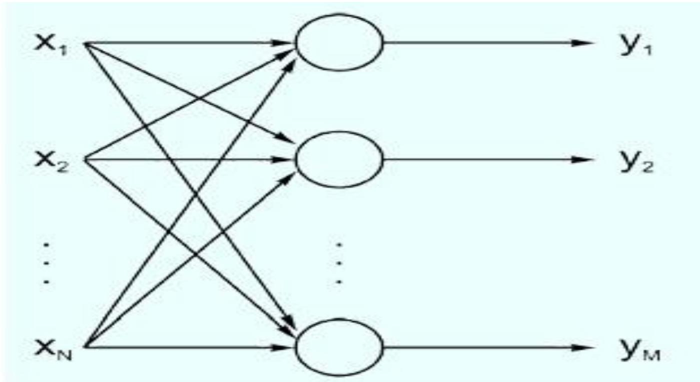


Fig.1.8 Neural Network

III. Radial Basis Function Network

It's also a supervised learning network built on an ANN. As activation functions, it employs radical functions. It has some similarities to MLP. Calculating the values of the hidden layers in each observation is how it's done. The no. of units in hidden layers is also set during RBF learning step.

CHAPTER 2 – REVIEW OF LITERATURE

Since soil shear strength has such a large impact on soil carrying capacity, many experimental and theoretical studies have been done to better comprehend soil strength behaviour. Despite the fact that shear strength concept for unsaturated soils has been developed and appears to be consistent with observed experimental behaviour, laboratory estimations are time - consuming process and labour - intensive, prompting the need for a simpler methods for estimating unsaturated shear strength of soil. Several empirical methodologies have been utilised to achieve this goal.

Linear Genetic Programming, Fuzzy Algorithms, , Artificial Neural Networks (ANN), Support Vector Machine (svm), Random Forests, and other soft computing approaches have been used to solve a wide variety of issues in geotechnical engineering and geoscience in recent years. Artificial neural networks are among the most well known pattern recognition techniques (ANNs). ANNs are often used to predict the behaviour of a variety of civil engineering problems with great success (Shahin et al. 2001). Hirata et al. 1990 employed multiple regression to find out how mechanical behavior and physical parameters of cohesive soils are related, which was one of several research done in attempt to estimate shear strength of soil. To estimate soil shear strength, they used two different regression models. In the very first model, the Atterberg limits were used, while in the second, the Cam–Clay concept was used. The goal of the study was to determine the physical properties of soils whilst accounting for soil classifications and circumstances. In their article, (Miao et al. 1990) reported further research on the strength qualities of unsaturated soils. In this noteworthy study, the hyperbolic formulations of soil strength concept were modelled based on tri-axial shear test data of unsaturated soils. The hyperbolic model's actual utility for geotechnical researchers and engineers was proved by the results of the suctional strength estimation. In 1996, Fredlund et al. proposed a method for predicting unsaturated soil shearing strength value. In their prediction model, they use the soil water interactions curves with saturated soil shear parameters. Once the model has a good estimation of the soil water interactions curves, credible shear function estimates of soil layers can be created. As a result, they were able to construct closed-form solutions characterising the shear characteristics of unsaturated soils in situations when the simple soil water characteristic equation holds true. (Seyhan et al. 1998) devised an Artificial neural network (ANN) approach for stress–strain relationship development of granular materials using CD compression test testing data in 1998. They included dispersion, void ratio, minerology, particle and the effect of confining pressure in the model. As a result, they claimed that they were able to successfully mimic nonlinear stress–strain behaviour at lower strain values using an ANN technique. Habibagahi et al. 2003 employed the ANN technique to evaluate the mechanical characteristics of unsaturated clays. In their ANN model, they employed initial soil parameters and triaxial distortion measurements as input neurons. The output layer of the created model consisted of volumetric deformation, deviator stress, and suction pressure fluctuations. As a result, they successfully used ANN method to replicate the extent of the problem within discussion.

To estimate soil shear capacity for building road, (Tien Bui et al. 2019) created a Machine Learning technique based on Swarm intelligence (LSSVM-CSO). The model took into account sample depth, loam %, wet density of soil, specific gravity , clay %, sand %, plasticity index ,water content, liquid and plastic limit, and liquidity index geotechnical parameters. The findings of this investigation demonstrated that this model was capable of accurately predicting soil shear strength. The Artificial neural networks (ANN), least square - SVM , and regression trees were all outperformed by this model (RT). (Mollahasani et al. 2011) propose a model that estimates the undrained cohesion characteristic (c) of soil using multilayer perceptron (MLP) of ANNs. To calculate the cohesiveness and angle of friction of unsaturated Undrained soil shear strength, (Kanungo et al.2014) used an a regression tree (RT) and artificial neural network (ANN). As input data, the percentages of sand, gravel, clay, silt, plasticity index and dry density are used. Similarly in another study (Kiran et al. 2016) used a Probabilistic Neural to estimate the parameters of shear strength of soil. (Khan et al. 2016) developed a model for calculating the residual strength properties of clay depending on a functional network. To predict the shear capacity of unsaturated soils, Jokar et al.(2017) developed an adaptable neuro-fuzzy inference system. Soft soils' shear strength should be estimated., (Pham et al. 2018) created two hybrid advanced ML strategies for soil shear strength prediction, specifically GANFIS and PANFIS, and compared them to two other benchmarks model, namely ANN and Regressors (SVR). The developed hybrid models beat benchmark models with exceptional prediction accuracy, according to the findings. Many studies have looked into predicting shear strength using machine learning techniques.

According to the recent literature, ml algorithms are particularly effective at estimating soil shear strength. ANN has a wide range of applications in landslide movement monitoring, debris flow projection, , deformation assessment and rock strength , landslide susceptibility mapping, and so on, amongst all of these machine learning approaches. ANNs have recently been used widely in geotechnical engineering to model nonlinear relationships among a set of input parameters and output values due to their ability to simulate nonlinear interactions between a number of input parameters and corresponding outputs.

(Lu et al. 2003) used and grey systems artificial neural networks systems to build slope stability prediction algorithms. (Neaupane KM et al. 2004) used a recursive neural network to track a landslide throughout the Himalaya. The distortion modulus of entire rock specimens can be calculated using this method, (Sonmez et al. 2006) employed ANN. (Das et al. 2011) investigated the performance of two popular machine learning methods, namely SVM and ANN, for predicting soil shear strength under the effects of various input properties and concluded that the performance of SVM and ANN is good but very different under the effects of various input properties. The study also recommended performing a sensitivity analysis to determine the optimum criteria for designing and using machine learning models. To predict intact rock deformation parameters for mechanical excavations, Tiryaki et. al. (2008) used m ultivariable stats, regression trees and artificial neural networks. Baykasolu et al. (2008) employed genetic programming to forecast the compression strength and tensile strength of Gaziantep limestone. (Çanakcı et al. 2009) evaluated the compression strength and tensile strength of Gaziantep basalts using gene expression programming and neural networks and. (Maji et al. 2008) also used the ANN method to forecast the young's modulus of jointed rock. (Rafiai et al. 2011) developed a new set of rock failure criteria using the ANN approach.

In this study , ANN , MLP, RBF used to predict the indirect undrained shear strength capacity of soil, by establishing a correlation between their index properties such as liquid limit(LL), plastic limit(pl), vertical effective stress(VES), preconsolidation stress (ps), sensitivity(St) and natural moisture content.

1) **Liquid Limit**: The liquid limit is simply the point from which the soil starts to act like a liquid due to its high water content. A clay specimen is placed in a standard cup and separated with a spatula to ascertain the liquid limit (groove). Drop the cup containing the specimen till the groove is no longer present. This sample is used to estimate the water content of the soil. The test is repeated, but this time with a higher water content. Low-water-content soil generates more blows, while high-water-content soil produces fewer. On a graph, the number of strikes and the water content are displayed.

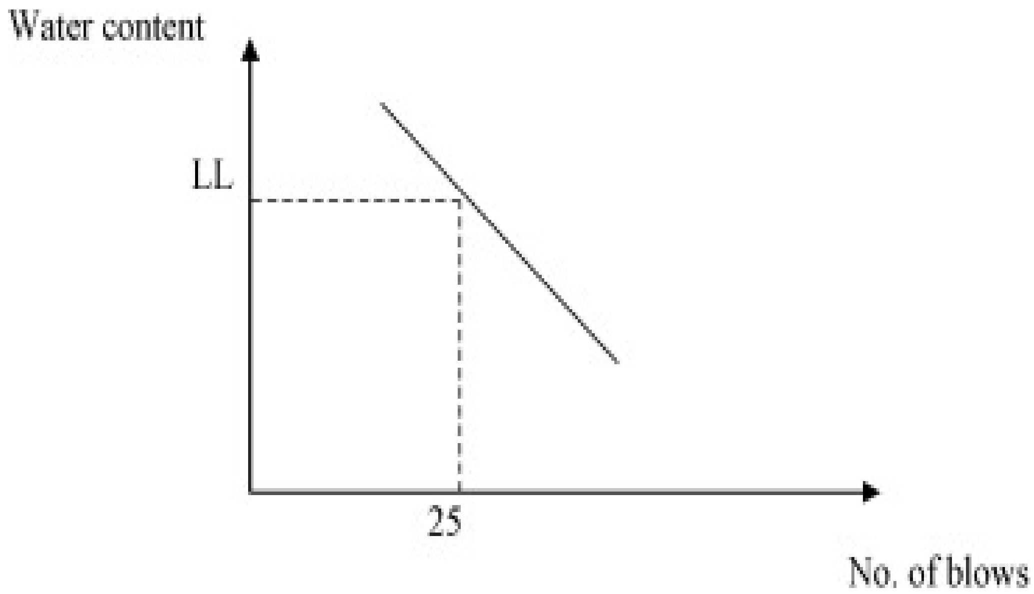


Fig.2.1 liquid limit test. Graph (Rajapakse et. al 2016)

The water content that correlates to 25 blows is known as a clay's liquid limit (LL). Figure shows the liquid limitations for two soils. At a water content of LL1, Soil 1 would attain a liquid-like state. Soil 2 would, but at the other hand, reach this condition at a water content of LL2. LL1 is significantly high than LL2 in Figure. In other words, at low water content, soil 2 lost its shear capacity and becomes more liquid-like than soil 1.

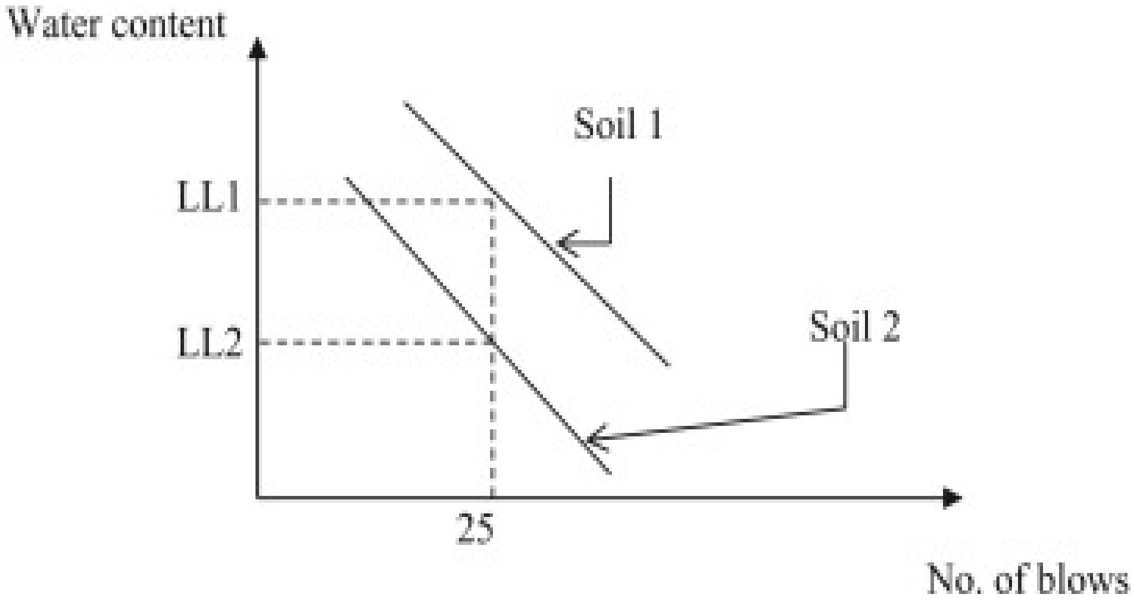


Figure 2.2. Liquid limits for two soils.

2. **Plastic Limit**: The plastic limit of a soil is the water content at which the soil begins to behave like a plastic material. At this moisture content, the soil would collapse when rolled into 3.0mm diameter threads (plastic limit).

Fig.2.3 Sample for determination of Plastic limit

3. **Water content(w%):** The proportion of the weight of water to the weight of solids in a given mass of soil is known as moisture content (w), commonly known as natural water content. In most cases, this ratio is given as a percentage. Water content is 0 whenever voids are filled up by air (dry soil). The most accurate way of detecting the water content is oven drying, which is why it is employed in laboratories.

$$w(\%) = (W_W / W_S) * 100$$

where,
W_W : Weight of water
W_S : Weight of soilds

4. **Vertical effective stress:** Vertical effective stress is the stress that binds particles together. It is held together by the combined effect of total stress and water pressure in the soil. In equation form, it can also be represented as total stress less pore pressure. The total stress at a strata lying at a certain depth below ground level is equal to the full weight of the soil lying just above layer / unit surface of the weight of soil. Effective stress is the fractional stress that sand grains can withstand due to grain-to-grain contact.

Effective Stress (σ') is computed as :

$$\sigma' = \sigma - u_i \sigma'_v = \sigma'_v = \sigma'_h - u_i$$

The effective stress definition was first proposed by Karl Terzaghi. This is a crucial subject in soil mechanics. Shear strength, Change in Volume permeability, and compressibility are all influenced by effective stresses.

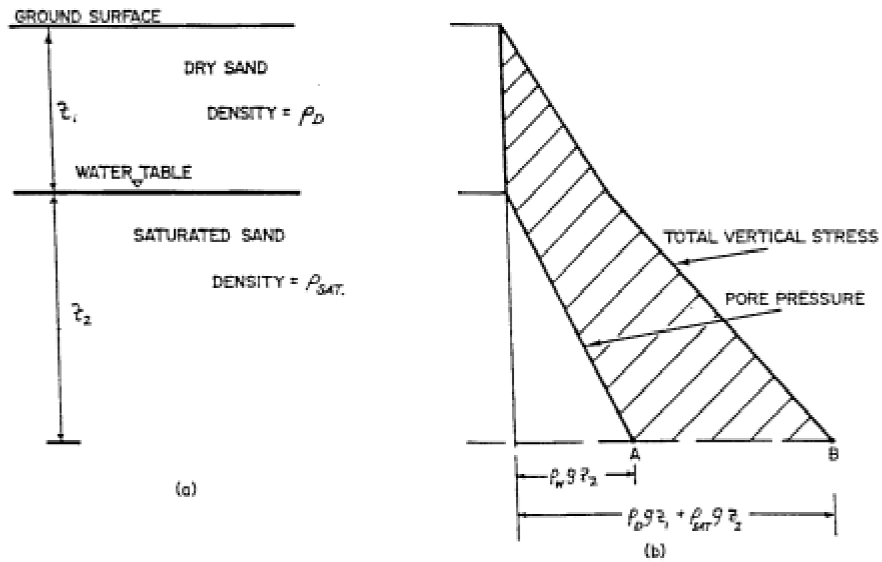


Fig:2.4 Stresses in soil

5. **Preconsolidation stress**: The highest effective vertical overburden pressure that a given soil sample has experienced in the past is known as preconsolidation pressure (Solanki et. al 2008). This value is crucial in geotechnical engineering, especially for determining projected foundation and embankment settlement. Preconsolidation pressure is often referred to as preconsolidation stress. The preconsolidation stress can be used to figure out how much overburden pressure can be applied to a soil without provoking irreversible volume change. Understanding shrinkage behaviour, crack and structure creation, and shear stress resistance all require this type of volume change. Previous pressures as well as other changes in the history of a soil are stored in its structure. If a soil is stressed further than this limit, it will be unable to support the extra load, and the structure would collapse. Depending on type of soil as well as its geological history, this breakdown might result in a variety of outcomes.

Although preconsolidation stress cannot be directly measured, it can be calculated using a variety of methods. Field samples are put through a series of tests, including the constant rate strain test (CRS) and the incremental loading testing (IL). Such tests can be expensive due to the high cost of equipment and the amount of time they take. Every sample must be kept undisturbed and could only pass one test with acceptable findings. It is critical to carry out these experiments carefully in order to obtain an accurate plot. The preconsolidation pressure can be calculated using a variety of approaches based on lab data. The data is commonly plotted as a semilog graph of effective stress versus void ratio.

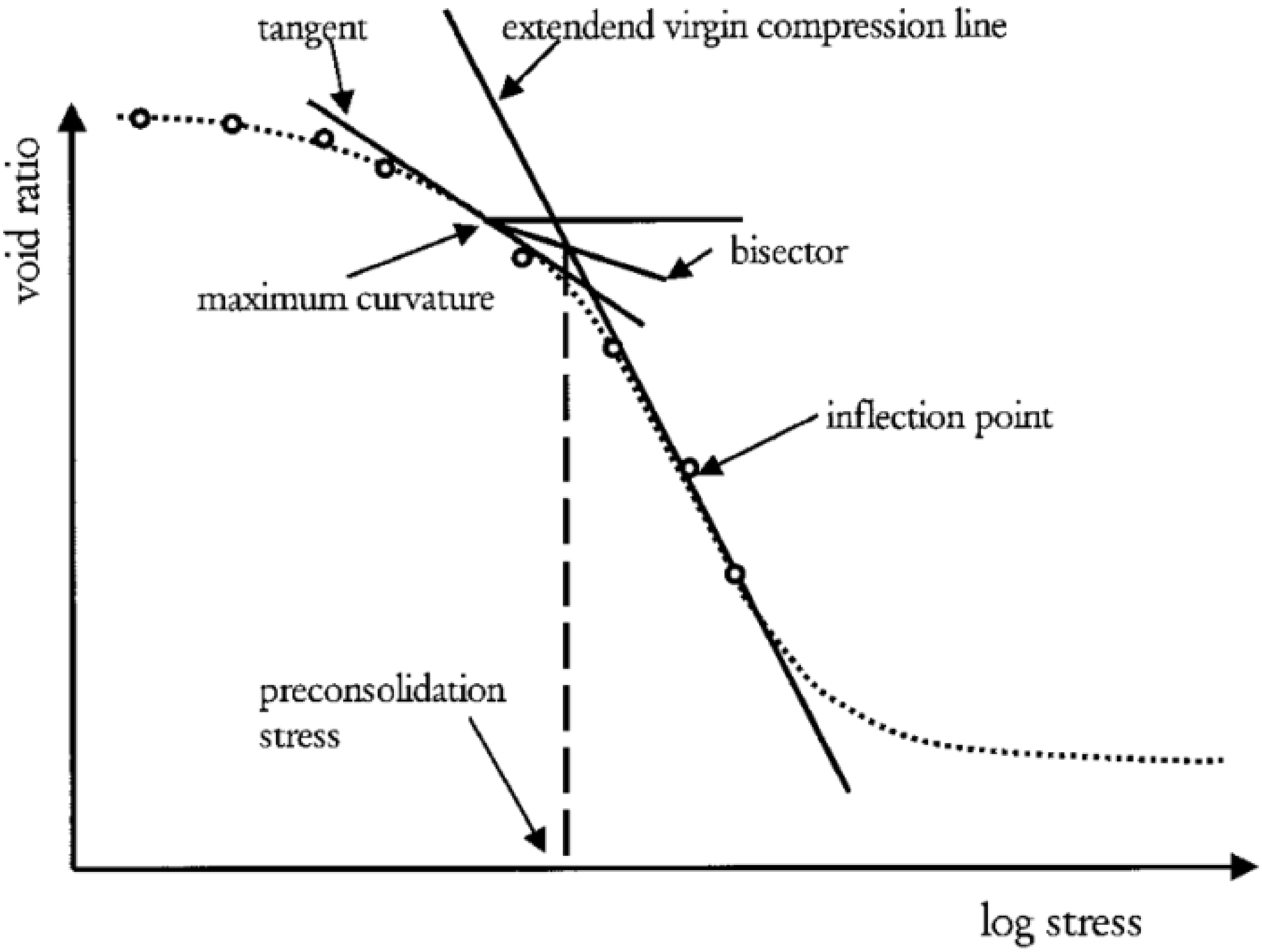


Fig.2.5 Effective stress vs void ratio (Baugartl et. al 2004)

6. **Sensitivity:** When soil is disturbed, such when its remoulded or subject to monotonic or cyclic stress, its sensitivity indicates a drop in shear strength. The ratio of the undrained shear strength of undisturbed soil to the undrained shear strength of remoulded soil at the same water content is known as soil sensitivity.

$$s_t = \frac{\text{USS Undrained Shear strength (undisturbed)}}{\text{USS}_{ur}\text{ Undrained Shear strength (remoulded)}}$$

Terzaghi first used the unconfined compressive strength test to establish the proportion of peak undisturbed strengths to remoulded strength as a quantitative indicator of sensitivity. Unconfined compressive strength test specimens cannot be used because the remoulded strength of certain clays is so low. As a result, the vane shear experiment and the Swedish falling cones experiment are frequently employed.

7. **Undrained shear strength:** Natural saturated clay deposits are frequently loaded (or emptied) at a faster pace than consolidation or draining can occur. In these cases, an optimum undrained situation might be assumed. During undrained loading, the moisture content and volume of the clay stay constant, and extra pore water pressure are created. Undrained shear strength (su) is the shear strength for these kind of conditions**.** The measurement of pore - water pressure is irrelevant when the undrained behaviour of saturated clay soils is examined in terms of the total stresses. The un - drained strength (Su) is considered to be equal to the cohesiveness intercept (cu) of Mohr-Coulomb envelop for total stresses using the S= 0 analysis method. Changes in confining pressure have no effect on the undrained shear strength of the saturated clay soil under these assumptions, as long as the water content remains constant.

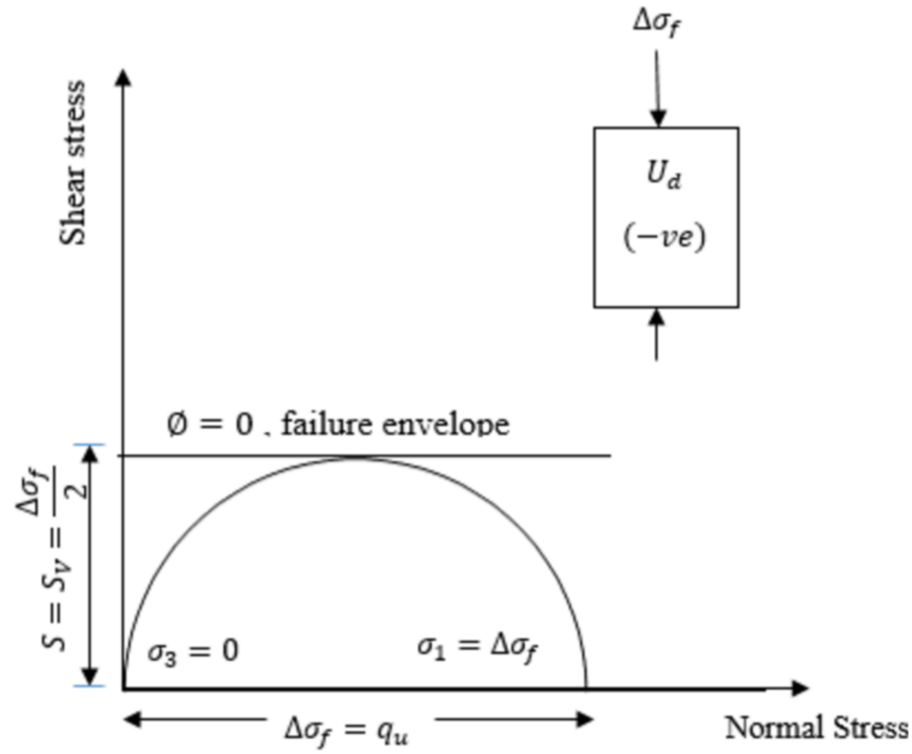


Fig.2.6 Mohr circle for undrained shear strength

The feasibility of the ANN model is tested by merging all of the input data. The cross-validation technique was used to avoid overfitting in ANN models. The collected data is separated into three sets in this method: training, testing, and validation. The connection weights are adjusted using the training set. The validation set is used to assess the network's performance at various phases of learning, and training is terminated once the error begins to rise. Only after the model has been effectively trained the testing set is utilised to evaluate its performance. To construct different models, feed forward back propagation neural network with an activation function that is relu for the hidden layer and output layer were used. The synaptic weight, learning rate, and momentum term were all left configurable. The predictive capacity of ANN models was tested using statistical measures such as MRMS, standard deviation, MSE, and regression, among others. Even though ANNs are effective at predicting outcomes, they have several flaws.

Performance Measures:

The following performance metrics were used to analyse and evaluate the machine l earning models' predictive predictions.

1. **(R^2)Coefficient of Determination:** Closer values to one indicate that this models is likewise better at fitting data.

$$R^2 = 1 - \frac{\sum\left(J_i - \hat{J}_i\right)^2}{\sum\left(J_i - \hat{J}^2\right)^2}$$

The sample mean of (actual target value)/ (anticipated target value) is the bias factor b, and when b = 1, the prediction model is unbiased.

$$b = \frac{1}{n}\sum_{i=1}^{n} \frac{j_i}{\hat{j}_i}$$

2. **(RMSE) Root mean square error:** closer value to zero indicates error in prediction is less

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(j_i - \hat{J}_i\right)^2}$$

3. **(MAPE) Mean Absolute perscentage error:** value closer to zero shows high prediction accuracy

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n} \left|\frac{j_i - \hat{J}_i}{j_i}\right|$$

Where,

j_i and j_i are the actual predicted shear strength and the undrained shear strength respectively

n is the total number of data

j_i is the mean of the actual undrained shear strength

CHAPTER 3 – DATASET USED

The F-clay/7/216 and S-clay/7/168 datasets from the TC304 database were used in this study.
The F-CLAY/7/216, was gathered from 216 field vane test samples collected across 24 separate test sites within Finland. The second dataset, S-Clay/7/162, included 168 field vane test data points from 12 Swedish and 7 Norwegian sites. In this study, the two datasets were integrated and analysed together.
Undrained shear strength (USS), vertical effective stress (VES), preconsolidation stress (ps), liquid limit (LL), plastic limit (pl), and natural water content are all metrics in two datasets (W). The data set is shown in table.

3.1 Datasets Head

LL = liquid limit
PL = plastic limit
w = natural water content
s_v = vertical total stress
s_p = preconsolidation stress
s_u = undrained shear strength
S_t = sensitivity

Depth(m)	LL(%)	PL(%)	w(%)	s'v (kPa)	s'p (kPa)	St	su(test) (kPa)
3.2	70	25	85	30.2	43	11	13
4.6	60	25	75	38.6	60	11	7
5.2	45	20	50	42.2	45	10	7.5
5.5	70	20	80	24.5	25	4	7
6	30	15	75	27	30	2	7
7	80	20	100	32	40	6	12
8	90	15	120	37	40	5	12
3	80	35	110	18	30	12	9
4	75	30	100	23	35	10	11
5	43	20	65	28	30	10	10

6	55	20	80	33	40	11	11
7	25	20	40	38	50	9	8
8	22	20	25	43	50	13	16
1.5	45	20	40	24.2	150	6.5	42
3	80	25	100	33	40	11	15
5	110	25	130	43	50	8	21
6	110	25	120	48	55	8	23
7	80	25	110	53	60	7	25
2.2	69	32.3	75	35.4	105.4	40	19.1
2.7	66.3	31.6	79	37.8	107.8	39.5	20
3.2	60.8	30.2	70	40.3	110.3	39	28.2
3.7	55.2	28.8	62	42.7	112.4	38.5	25
4.2	49.7	27.4	56.7	45.2	115.2	37	22.3
4.7	48.8	27.2	60	47.6	117.6	35	23.7
5.2	48.5	27.1	65.3	50.1	120.1	24.1	31.3
6.2	48	27	52.1	55	127.3	24.2	28.4
7.2	51.8	28	53.5	59.9	140	24	27.8
8.2	55.8	28.9	55.7	64.8	152.3	24	29.9
9.2	68.8	32.2	65	69.7	160	13.5	34.9
10.2	82.4	35.6	77.4	74.6	163	10	34.1
11.2	94.9	38.7	82	79.5	170	10.5	35.1
12.2	107.3	41.8	87.7	84.4	182.3	10.5	23.3
13.2	111.8	42.9	83.9	89.3	185	10	21.1
3	55	25	65	24	48	11	20
4	51	23	60	31	90	9	19
5	75	23	70	38	50	7	18
7	48	23	65	52	65	9	24
8	47	23	70	59	85	13	24
9	55	25	70	66	67	13	23
10	49	23	60	73	110	9	25
11	51	23	60	80	120	8	25
12	55	23	57	87	110	7	27

13	52	22	65	94	100	8	27
5	60	20	100	16.5	22	17	9
7	49	20	80	26.5	28	19	10
2.4	120	50	150	15.6	25	10	8
3.6	52	25	75	20.4	30	9	7
6	80	30	120	30	35	7	16
7	75	30	100	34	48	10	17
8	75	30	100	38	51	12	22
9	90	30	100	42	60	13	24
10	75	30	90	46	75	13	25
11	65	30	75	53	80	14	28
13	60	25	58	67	90	12	34
14	65	25	60	74	130	8	22
16	40	25	35	88	100	6	28
17	52	25	60	95	100	7	30
18	70	25	55	102	140	8	35
2.7	105	25	120	10.1	20	9	5
5.5	70	30	75	19.5	28	5	12
6.5	70	25	65	24.5	35	4	11
7.5	80	30	85	29.5	50	5	14
8.5	65	30	80	34.5	80	7	19
9.5	43	25	50	39.5	60	6	12
10.5	47	25	55	44.5	80	8	15
2.2	79	32	75	28.9	74.3	14	9.3
2.7	74	32	78.5	31.4	62.6	18.6	10.2
2.6	75	32	80.8	31	64.7	19.1	12.2

316*8 columns

Table:3.1 Dataset

Index	Depth(m)	LL(%)	PL(%)	w(%)	s'v (kPa)	s'p (kPa)	St	su(test) (kPa)
count	384.0	384.0	384.0	384.0	384.0	384.0	275.0	384.0
mean	6.977864583333335	68.37317708333326	28.486458333333317	76.46718750000001	48.72421875000003	79.819270833333326	16.293090909090991	19.21223958333336
std	3.8867257018412467	23.86075870687636	7.972817655409252	23.321913773167953	27.33013260511408	48.541082097168555	13.129403240913 43	10.045126960373462
min	0.5	22.0	2.7	17.3	6.9	15.2	2.0	5.0
25%	4.0	51.0	25.0	60.325	31.0	48.150000000000006	8.0	11.775
50%	6.15	68.75	27.0	75.0	43.05	64.9	11.0	16.85
75%	9.0	80.0	32.0	90.0	60.25	100.0	20.0	24.0
max	24.0	201.8	73.9	180.1	212.9	315.6	64.0	75.0

Table 3.2: Descriptive statistics of dataset used

CHAPTER 4 - METHODOLOGY

4.1 Artificial Neural Network.

The technique used involves creating a dataset and visualising it, then designing an architecture for an Artificial Neural Network to predict undrained shear strength, as well as producing an output model. The process includes a graphical depiction of the data collection, as well as identifying the most essential features from the dataset utilizing feature extraction and investigating their interdependencies. Several iterations were carried out in order to find an ANN parameterization with sufficient vitality and generality to tackle the challenge.

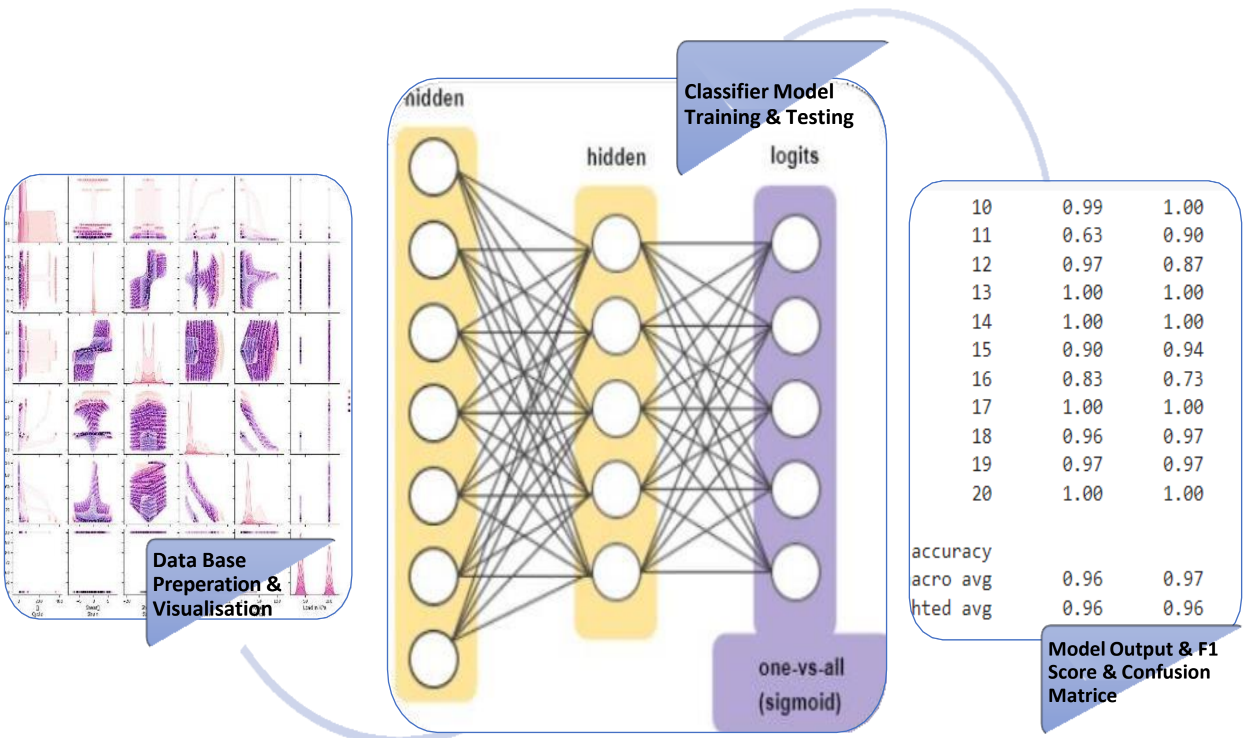


Fig.4.1 Representation of Methodolgy

4.2 NETWORK TRAINING –

It is required to train the network using input-output pairs prior to the practical applications. The connection weights values are fixed at the end of this process. Following an iterative method, the training entails lowering the variance or error E between the realised network output and the target or desired output. A training process is used to identify the optimal weight matrix and bias, which minimises a preset error function, commonly of the type E=(On-Ot) 2, where On is the network output at a specific output node and Ot is the desired output at the same node.

The computation is done for each training pattern's output neurons, and then for all training patterns. Training is the process of adapting the connection weights of an ANN through a continual simulation process by the environment in which it has been incorporated. Unsupervised and supervised training are the two main types of training. A supervised training approach necessitates the involvement of a teacher in the training process, implying a high number of input and output samples in order to iteratively optimise the connection weights and bias of each node. An unsupervised training algorithm, on the other hand, does not require the support of a teacher. Just an input data set is given to the ANN during training, and it automatically resizes its connection weights to group the input sequence into classes with comparable attributes.

In this study ANN model training is done using python libraries like keras, Tensorflow, Numpy, Pandas, Matlpotlib, SkLearn and sequential modelling is used

The steps in the training procedure of RBF are as follows:

1. **Forward Propagation:**
   Multiply the inputs by the weights (just use random numbers as weights)
   Let Y = W1x1+W2x2+W3x3 = Wixi .
   To calculate the neuron's output, run the result via a sigmoid algorithm. To normalise the result between 0 and 1, use the Sigmoid function: (1/(1 + (e-y)))

2. **Back Propagation**

Determine the error, which is the difference between the actual and intended output. Adjust the weights based on the error by multiplying the error with the input and then with the Sigmoid curve's gradient:

Weight += Error Input Output (1-Output), with Output (1-Output) being the sigmoid curve's derivative.

Step 1: Import required python libraries as shown in fig:

```
import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LeakyReLU,PReLU,ELU
from keras.layers import Dropout

import tensorflow as tf
import numpy as np
import pandas as pd
import sklearn
from sklearn.metrics import confusion_matrix
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.layers.experimental.preprocessing import Normalization
import matplotlib
import matplotlib.pyplot as plt
```

Fig.4.2 Python Libraries

Step 2: Define a Sequential model.

```
NN_model = Sequential()
```

Fig.4.3 Defining sequential mode

Step 3: Add a Dense layer with relu activation function. In this ANN model 1 input layer, three hidden layers and 1 output layer with relu activation function is developed

```
# The Input Layer :
NN_model.add(Dense(128, kernel_initializer='normal',input_dim = X_train.shape[1], activation='relu'))

# The Hidden Layers :
NN_model.add(Dense(256, kernel_initializer='normal',activation='relu'))
NN_model.add(Dense(256, kernel_initializer='normal',activation='relu'))
NN_model.add(Dense(256, kernel_initializer='normal',activation='relu'))
#The Output Layer :
NN_model.add(Dense(1, kernel_initializer='normal',activation='linear'))
```

Fig.4.4 Layers in ANN model

Step 4: Compile the model with an optimizer and loss function. In this model adam optimizer and Mean absolute error loss is used.

```
# Compile the network :
NN_model.compile(loss='mean_absolute_error', optimizer='adam',metrics=['mean_absolute_error'])
NN_model.summary()
```

Fig.4.5 Optimizer and loss function

Step 5: Fit the model to the dataset.

```
# Fitting the ANN to the Training set
model_history=NN_model.fit(X_train, y_train,validation_split=0.25, batch_size = 10, epochs = 100)
```

Fig.4.6 Dataset Fitting

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 128)               1024

 dense_1 (Dense)             (None, 256)               33024

 dense_2 (Dense)             (None, 256)               65792

 dense_3 (Dense)             (None, 256)               65792

 dense_4 (Dense)             (None, 1)                 257

=================================================================
Total params: 165,889
Trainable params: 165,889
Non-trainable params: 0
_________________________________________________________________
Epoch 1/100
16/16 [==============================] - 1s 19ms/step - loss: 9.6393 - mean_absolute_error: 9.6393 - val_loss: 8.3967 - val_mean_absolute_error: 8.3967
Epoch 2/100
16/16 [==============================] - 0s 7ms/step - loss: 6.6481 - mean_absolute_error: 6.6481 - val_loss: 4.9200 - val_mean_absolute_error: 4.9200
Epoch 3/100
16/16 [==============================] - 0s 7ms/step - loss: 5.4721 - mean_absolute_error: 5.4721 - val_loss: 4.4099 - val_mean_absolute_error: 4.4099
Epoch 4/100
16/16 [==============================] - 0s 6ms/step - loss: 4.8244 - mean_absolute_error: 4.8244 - val_loss: 5.1106 - val_mean_absolute_error: 5.1106
Epoch 5/100
```

Fig.4.7 Model training

The steps in the training procedure of MLP are as follows:

1. Step1. : Import required python libraries as shown:

```python
from sklearn.neural_network import MLPRegressor
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Fig.4.8 Python libraries import

2. Step2. Splitting the dataset into train and test dataset. We have set aside 30% of the data for

testing the trained model's accuracy. The input data is further adjusted to ensure that it is standard normally distributed, centred around zero, and has variance in the same order in both the train and test datasets.

```
x_train, x_test, y_train, y_test = train_test_split(xi, y, test_size = 0.3, random_state = 0)
```

Fig.4.9 Setting of data for classifiers

3. Step3. Scale the data

```
scaler = StandardScaler()
xi = scaler.fit_transform(x)
```

Fig.4.10 Scaling the data

4. Step4. Three hidden layers, each with 64 neurons, are simulated in the code below. The model has a total of five layers, including the output and input layers. If no optimiser is given, the default optimiser is "Adam," which can handle a rather large dataset.

```
reg = MLPRegressor(hidden_layer_sizes= (64,64,64), activation = "relu", alpha = 0.0001, batch_size = 'auto',
                   learning_rate = 'constant', learning_rate_init = 0.001,
                   random_state = 1, max_iter = 2000).fit(x_train,y_train)
```

Fig.4.11 MLP modelling

5. Step5. The training set is used to forecast the target data of the reserve test dataset, which the model has never seen before, in the code below.

```
J = reg.predict(x_test)
```

Fig.4.12 Predicting training dataset

CHAPTER 5 – RESULTS AND DISCUSSION

5.1 Exploratory Data Analysis:

Pairplot visualisation is useful when doing exploratory data analysis (EDA). When the variables are continuous or categorical, Pairplot visualises them to reveal their relationship. Plot pairwise interconnections in a data collection. Pair plot is a high-level interface for constructing visually beautiful and educational statistical visualisations in the Seaborn library. The differences in each plot may be seen in Figure shows the Undained shear strength relationship with vertical effective stress (VES), preconsolidation stress (ps), liquid limit (LL), plastic limit (pl), sentivity,, and natural water content below, The darker shades of color depicts the data points associated with high undrained shear strength of soil and the lighter shades shows the lower value of undrained shear strength associated with it. In the first column graphical representation of data of the depth is shown with with vertical effective stress (VES), preconsolidation stress (ps), liquid limit (LL), plastic limit (pl), sentivity,, and natural water content , undrained shear strength below. Similarly, the second column shows the data of liquid limit (LL) which is plotted with vertical effective stress (VES), preconsolidation stress (ps), depth , plastic limit (pl), sentivity,, and natural water content , undrained shear strength below is shown. The third column shows the data of plastic limit (pl)which is plotted against vertical effective stress (VES), preconsolidation stress (ps), depth , plastic limit (pl) , sentivity, and natural water content , undrained shear strength is shown below. Fourth column shows the data of natural water content which is plotted against vertical effective stress (VES), preconsolidation stress (ps), depth , plastic limit (pl) , sentivity, plastic limit (pl) and, undrained shear strength is shown below. Fifth column shows the data of vertical effective stress (VES) which is plotted against vertical effective stress (VES), preconsolidation stress (ps), depth , plastic limit (pl) , sentivity, plastic limit (pl) and, undrained shear strength is shown below. Sixth column shows the data of undrained shear strength which is plotted against vertical effective stress (VES), preconsolidation stress (ps), depth , plastic limit (pl) , sentivity, plastic limit (pl) and, vertical effective stress (VES) is shown below. Seventh column shows the data of sentivity which is plotted against vertical effective stress (VES), preconsolidation stress (ps), depth , plastic limit (pl) , undrained shear strength , plastic limit (pl) and, vertical effective stress (VES) is shown below.

Fig. 5.1 Relationship between parameters

5.2 Correlation anlysis:

The spearman's rank correlation coefficient(rs) was used to determine the interrelations between each pairwise variable, and then a statistic table containing all correlation coefficient(rs) was used to establish the interrelations among each pairwise variable, and finally a correlation table was created. The correlation of all parameters according to the rs(absolute value) dropping at different intervals was clearly described in the table.

Preconsolidation stress is strongly correlated with undrained shear strength (rs = 0.724), whereas lateral effective stress is significantly correlated with undrained shear strength (rs = 0.44). Undrained shear strength seems to be almost independent of the Liquid limit and Plastic Limit (rs 0.04), as shown in table.

Table 5.1 Correlation between different parameters

index	**Depth(m)**	**LL(%)**	**PL(%)**	**w(%)**	s'v (kPa)	s'p (kPa)	**St**	**su(test) (kPa)**
Depth(m)	1.0	-0.12163089825059062	-0.22040510588244694	-0.29010063903440186	0.8820831690508216	0.5321823907229958	-0.2537742819024459	0.37676567398798844
LL(%)	-0.12163089825059062	1.0	0.5920833289295798	0.8195062164553357	-0.23699182534174665	-0.16113572721415623	-0.05930415420758304	0.0441905204742231
PL(%)	-0.22040510588244694	0.5920833289295798	1.0	0.561937912260736	-0.2943003689814528	-0.1714749361173215	0.3199528143600619	-0.023909269331419177
w(%)	-0.29010063903440186	0.8195062164553357	0.561937912260736	1.0	-0.4422293481573278	-0.41835034264763454	0.1410600648095956	-0.17520515725683974
s'v (kPa)	0.8820831690508216	-0.23699182534174665	-0.2943003689814528	-0.4422293481573278	1.0	0.6983145144757056	-0.21064239329537357	0.44723518618267444

s'p (kPa)	0.5321823907229958	-0.16113572721415623	-0.1714749361173215	-0.41835034264763454	0.6983145144757056	1.0	-0.20250856591358332	0.7247666499161579
St	-0.2537742819024459	-0.05930415420758304	0.3199528143600619	0.1410600648095956	-0.21064239329537357	-0.20250856591358332	1.0	-0.20995302757108938
su(test) (kPa)	0.37676567398798844	0.0441905204742231	-0.023909269331419177	-0.17520515725683974	0.44723518618267444	0.7247666499161579	-0.20995302757108938	1.0

5.3 Heat-Maps:

A heat map is a two-dimensional graphical depiction in which various colours represent various values. A simple heat map can be used to quickly visualise data. High detailed heat maps allow the observer to interpret more complex data sets. Heat maps can be displayed in a variety of ways, but they all have one thing in common: they use colour to indicate correlation between the two sets that would be much more difficult to understand if presented mathematically in a worksheet. The higher shades of light green colour demonstrate a significant positive correlation with the extracted features, whilst the darker shades of red and orange colors show a strong negative correlation with the features under investigation.

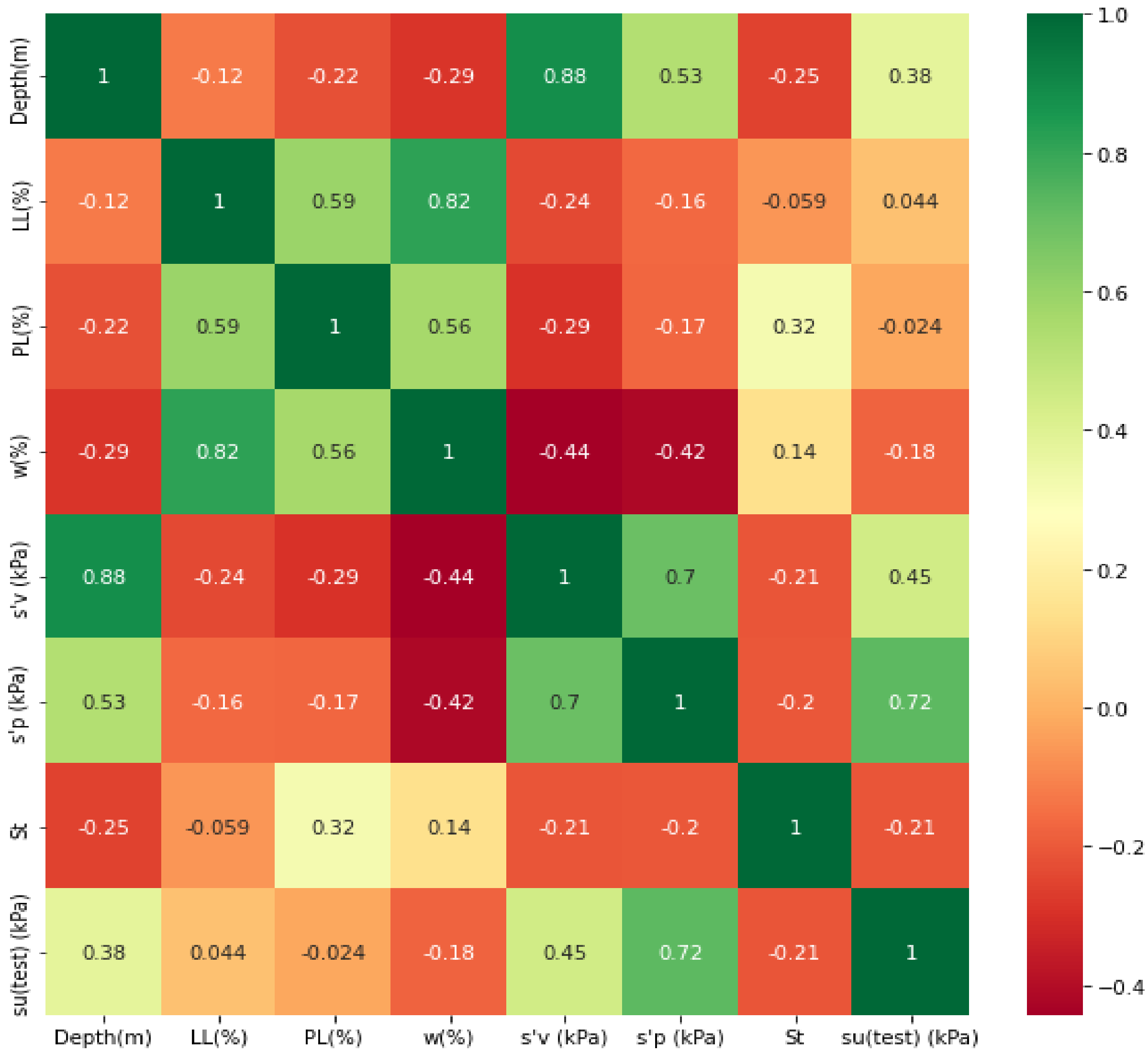


Fig.5.2 Undrained shear strength correlation matrix

5.4 Feature Importance:

The phrase "feature importance" refers to a collection of approaches for assigning scores to input qualities in a predictive model, reflecting the relative importance of each piece of information for making a prediction. For problems requiring the prediction of a numerical value, known as regression, and problems involving the prediction of a class label, known as classification, feature significance scores may be computed. The ratings are helpful and may be used to a variety of scenarios in a predictive modeling issue, including A better comprehension of the information. To get a better grasp of a model, The number of input features is being reduced. The significance of features in a dataset may be used to get insight into it. The relative ratings mayreveal which characteristics are most important to the target and, conversely, which ones are least important. A domain expert may understand this and utilize it as a starting point for collecting additional or different data. The model may be deciphered using feature significance scores. A predictive model that has been fitted to the dataset is used to compute the majority of significance ratings. Examining the significance score while making a prediction provides insight into that specific model and which attributes are mos timportant and least important to the model.

Figure 1 depicts the multiple feature parameters and their overall average weight (percent). Preconsolidation stress (53.8%) is the most critical feature variable in the current ANN model, followed by Vertical effective stress (12%), Depth (10%), and plastic limit (9%). . This finding provides important overview of the characteristics of clays' undrained shear strength, and similar results on sensitivity were also published in (D'Ignazio et al. 2016).

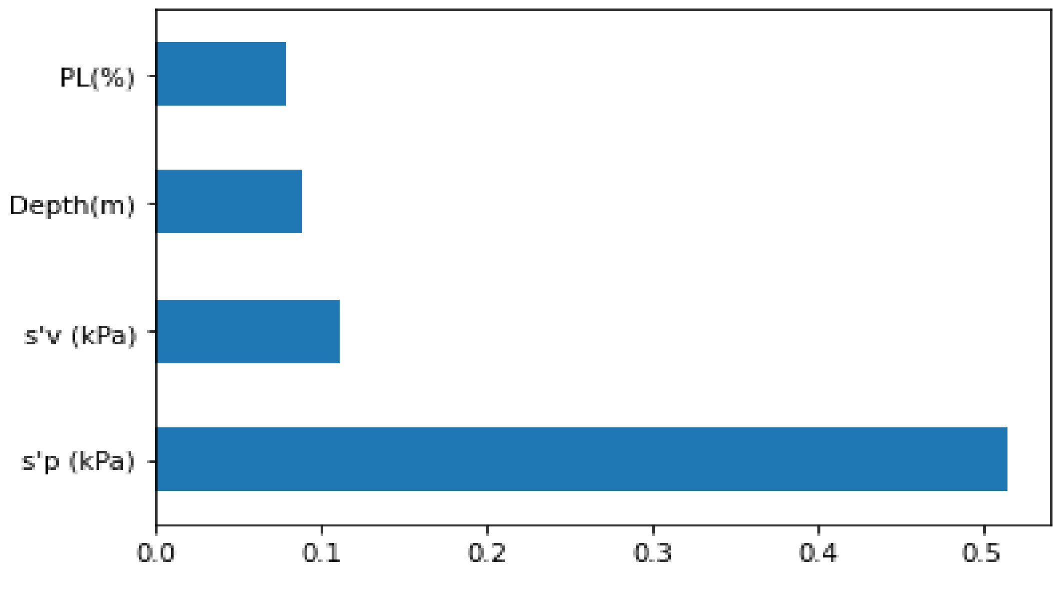


Fig. 5.3 Highly correlated factors with Undrained shear strength

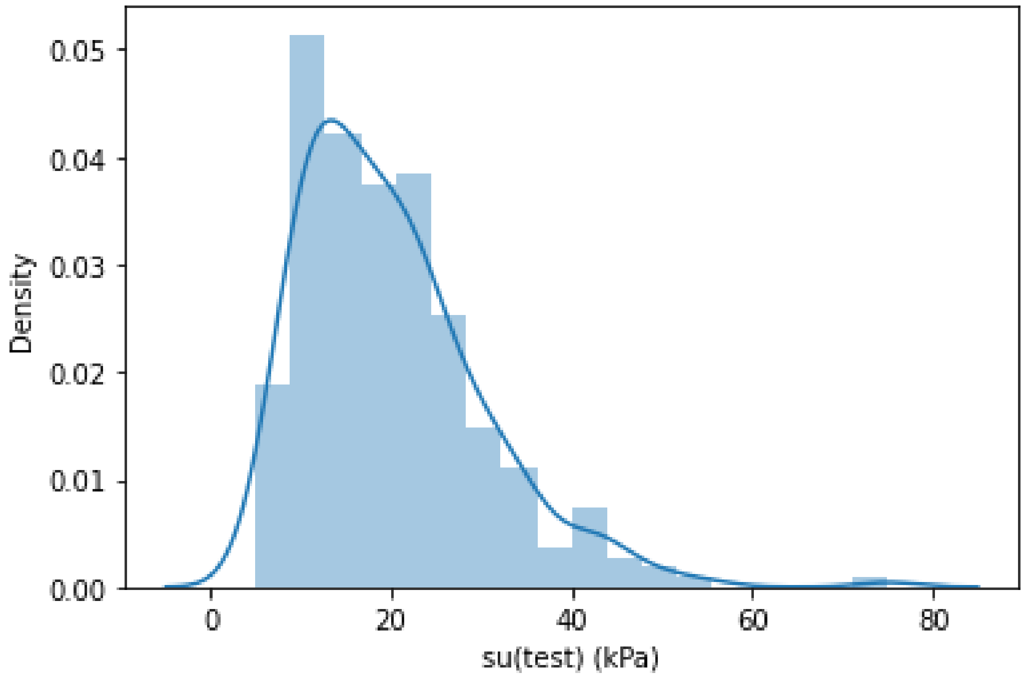


Fig 5.4 Undrained shear strength distribution

ANN Model Evaluation

The ANN Model_1 & Model_2 are trained for predicting the Undrained shear strength of soil by correlating it with various other parameters. RBF Model having 1 input layer, 3 hidden layer and 1 output layer, the model successfully achieved the , accuracy: 0.9112, auc: 0.9298, val_loss: 0.0930, val_accuracy: 0.9136, val_auc: 0.9333 Fig   shows the accuracy and loss of model with respect to 40 epochs.

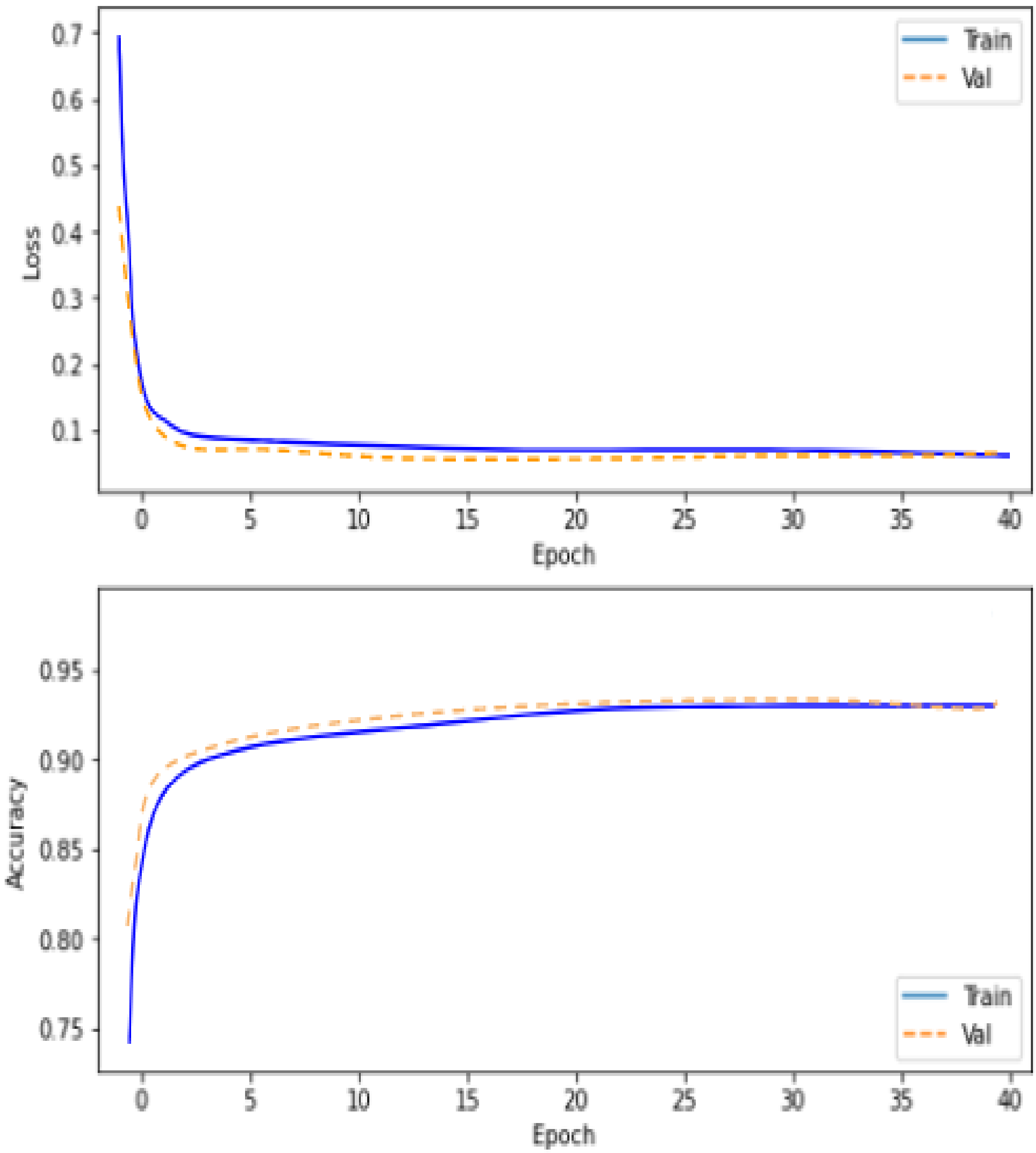
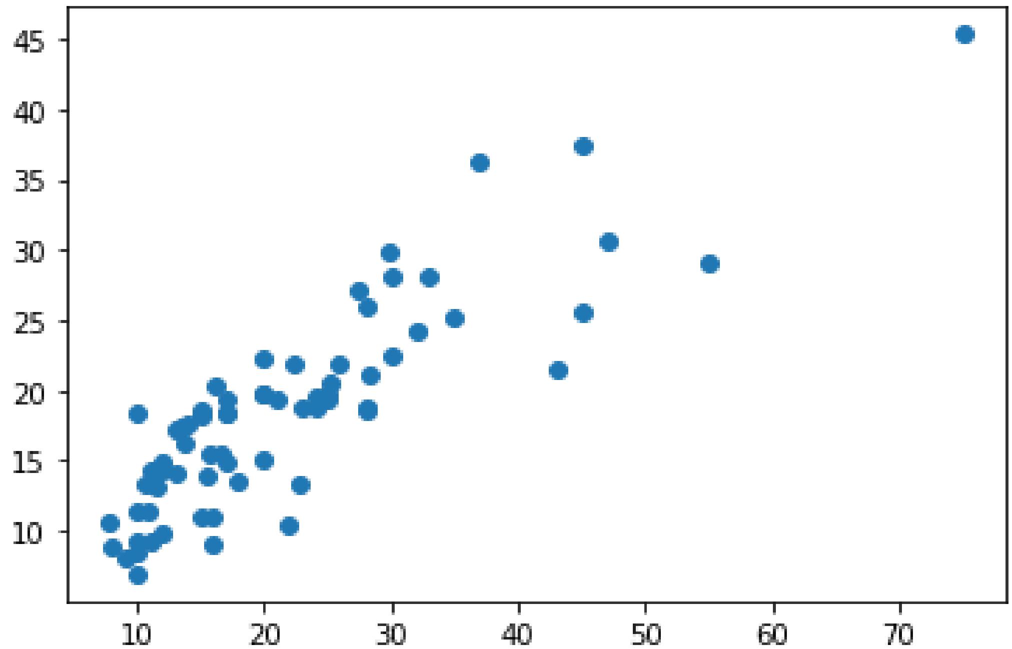


Fig 5.5 : Accuracy and loss of RBF Model

MLP model have three hidden layers, each with 64 neurons, are simulated . The model has a total of five layers, including the output and input layers. The default optimiser "Adam," is used which can handle a large dataset. The model successfully achieved the R^2: 0.8821**, RMSE: 3.60, MAPE: 10.93.** Fig 5.5 shows the graph between predicted undrained shear strength and expermiantal undrained shear strength.

Predicted USS



Experimental USS

Fig. 5.6 Predicted USS vs Experimental USS

CHAPTER 6 – CONCLUSION

From the above study, it can be concluded that the determining the shear strength of soil is crucial in geotechnical analysis. Shear strength is an important factor for the cosntruction of many large-scale infrastructure projects, such as highways, pavements, earth dams, retaining walls, and high-rise skyscrapers. Determining the shear strength experimentally is time-consuming, tedious, and costly. Furthermore, doing testing on each new case is not always feasible due to unavailability of required equipment. Thus modeled ANN Machine learning technique can serve as providing the prediction of undrained shear strength of soil on providing standard inputs with a acceptable level of accuracy under the confidence interval, [f1 score of 0.91 for model_1 & fi score of 0.88 for model_2] this can serve as a quick and reliable prediction of the shear strength of soil, in place of conducting the actual cumbersome tests. These trained models can be deployed as end-to-end projects like websites and software for the welfare of mankind.

CHAPTER 7 – REFERENCES

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