SLOPE STABILITY ANALYSIS USING ARTIFICIAL NEURAL NETWORK

A

Project Report

Submitted in partial fulfillment of the requirement for the award of the Degree of

"Bachelor of Technology in Civil Engineering"

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CERTIFICATE

We hereby declare that the work presented in the project titled, 'Slope stability analysis using Artificial Neural Network (ANN) ' submitted to Department of Civil Engineering, North Eastern Regional Institute of Science and Technology, Nirjuli, for the award of 'Degree in Civil Engineering' is an authentic record of our work carried out under the guidance and supervision of Dr. Dipika Devi, Associate Professor, North Eastern Regional Institute of Science and Technology. The work presented has not been submitted to any other university or institution.

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CANDIDATES DECLARATION

We hereby declare that our project entitled, "Slope Stability Analysis using Artificial Neural Network" submitted to the Civil Engineering Department of the North Eastern Regional Institute Of Science & Technology (NERIST), is a record of original work done by us under the guidance of Dr. (Mrs.) DIPIKA DEVI, Associate Prof., Department Of Civil Engineering, NERIST, and this project report is submitted in partial fulfillment of the requirement for the award of the Degree of Bachelor of Technology in Civil Engineering.

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ABSTRACT

Analysis of slopes for stability and safety is a major area of concern in civil engineering. This is the reason that so many analysis techniques have been developed so far. Stability of natural slopes and man-made slopes such as roads/railways embankment, hydraulically constructed dams, earth dams etc. is a major issue in geotechnical engineering. The traditional way of slope stability analysis involves the determination of factor of safety for a slope to take safety precautions against any instability. Various researchers worked to develop a new method in which probability of failure or reliability of a slope is calculated. Thus, basically two different approaches of slope stability analysis are available with us– deterministic approach and reliability approach.

Artificial Neural Networks (ANN), usually called neural networks, are very sophisticated modeling techniques which are capable of modeling extremely complex functions. They are used for predicting the outcome of two or more independent variables. Predicting the stability of slopes is a very challenging task for Geotechnical Engineers. They must pay particular attention to geology, ground water and shear strength of the soils in accessing slope stability.

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CHAPTER-1: INTRODUCTION

1.1 SLOPE:

An exposed ground surface that stands at an angle (β) with the horizontal is called slope.

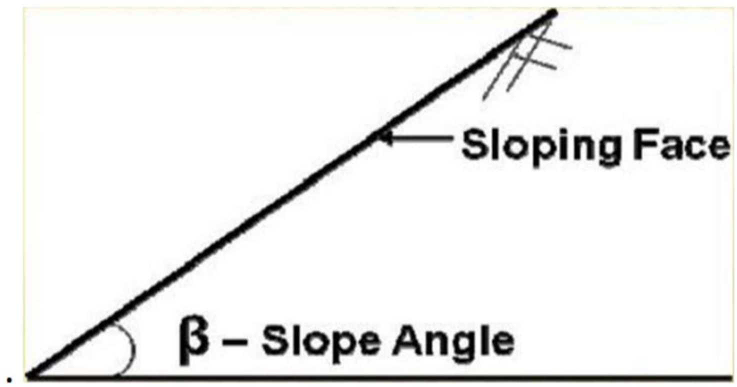


Figure-1: components of a slope
(source:researchgate.net)

Slope may be artificial, that is man-made, as in cuttings and for highways and rail, roads, earth-dams, temporary excavations, landscaping operations for development of sites, etc. Slopes may also be natural, as in landslides and valley, coastal and river cliffs, etc.

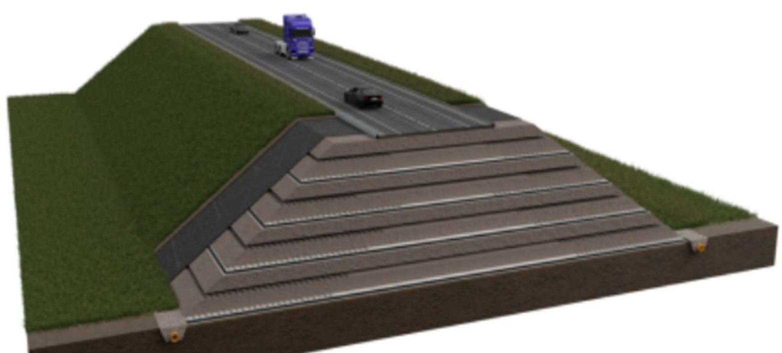


Figure-2: embankments for Highways
(source*:* https://www.abg-geosynthetics.com/civils/highways-and-rail/embankment-consolidation/*)*

Figure-3: embankments for earth-dams.
(source: https://structurae.net/en/structures/dams/zoned-embankment-dams/media)

Figure-4 : River cliffs.
(source:https://www.geoengineer.org/index.php/education/slope-stability/introduction-to-slope-stability)

Figure-5: Valley.
(source: https://structurae.net/en/structures/dams/zoned-embankment-dams/mediahttps://structurae.net/en/structures/dams/zoned-embankment-dams/media)

Landslides are one of the widespread natural hazards which typically occur in the mountainous regions of the world. In recent years, the frequency of landslides has increased causing serious loss to human lives and property. India is one of the countries that is severely prone to landslides, especially in the Himalayan region and the Western Ghats. The Himalayan Mountain chain is one of the most tectonically active and fragile regions of the world. Landslides frequently occur in Northern Indian region of the Himalayas, passes including the states of Jammu and Kashmir, Uttarakhand, Himalaya Himachal Pradesh, Sikkim and Arunachal Pradesh.

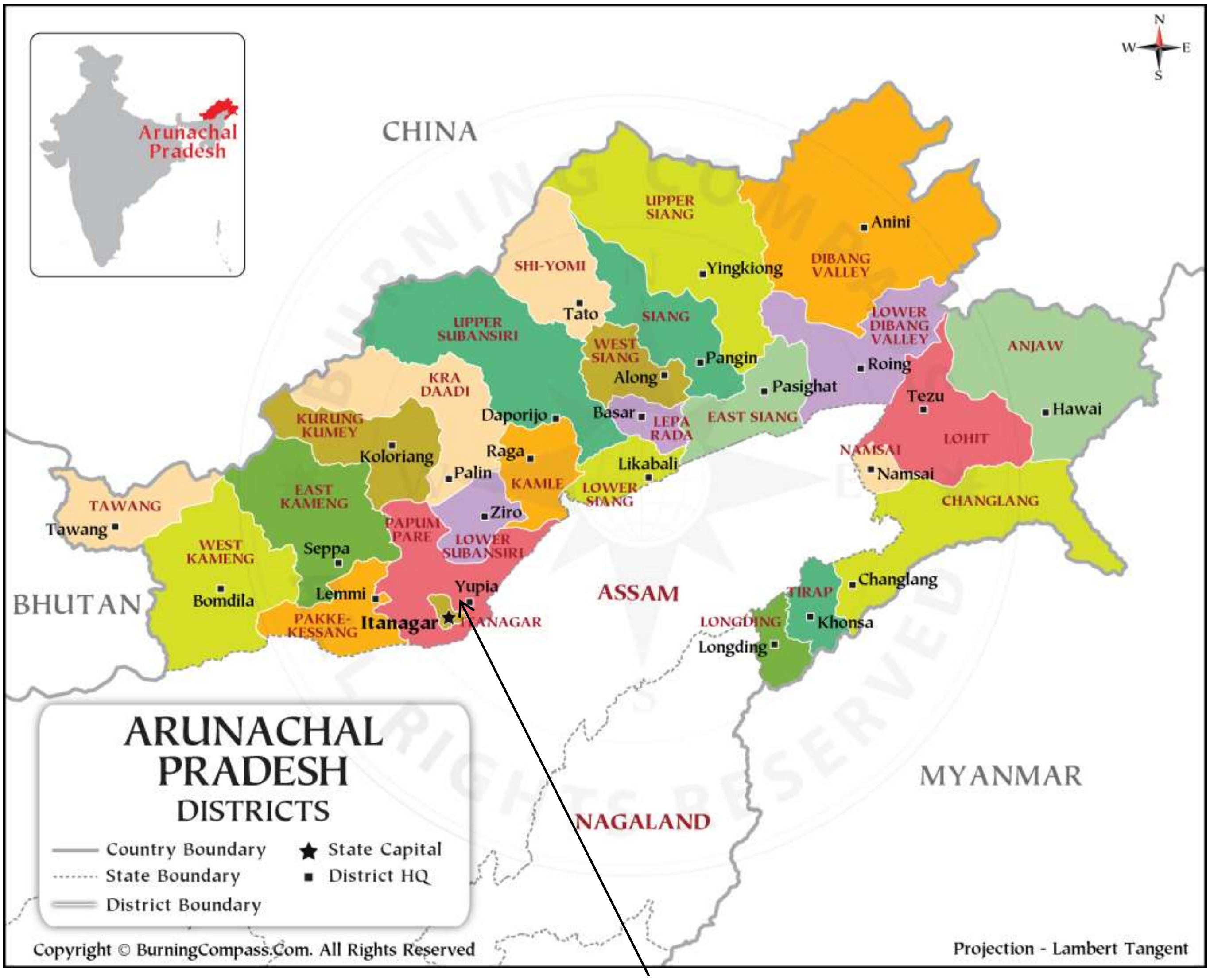


Figure-6 : map of Arunachal Pradesh along with GPS Location of site
(source: BurningCompass.com)

BAGE TINALI

GPS LOCATION :- 27°07'43.8"N 93°44'07.2"E

Figure 7: Test site photo

Figure 8: Test site photo

1.2 Failure of Slopes:

Slope failures occur when driving forces overcome resisting forces. The driving force is typically gravity, and the resisting force is the slope material's shear strength.

When assessing a slope's stability look for indications that physical processes are decreasing shear strength. These include the following:

a) Weak, weathered bedrock, jointed rock, or bedrock that dips parallel to the slope can decrease stability.
b) Droughts, wildfires, and humans can remove vegetation from the slope, decreasing stability.
c) Water in rock joints or in soils can decrease slope stability.
d) Rivers can erode the bottom of the slope, called the toe, decreasing stability. This can occur over time through normal stream action or catastrophically during flood events.
e) Humans modify stability through actions such as excavation of the slope or its toe, loading of the slope or crest, surface or groundwater manipulation, irrigation, and mining.
f) Steeper slopes tend to have greater risks for instability.
g) Soils have variable amounts of shear strength, dependent on factors such as soil texture, pore water, and particle cohesion.
h) Water works in many ways to reduce shear strength. For example, pore water pressure in soils decreases shear strength, and saturated soils are more likely to lead to slope failure. Perched water tables, groundwater seeps, and excessive precipitation are some examples of water sources that may lead to slope failure in certain conditions.

Figure-9: photo of landslide at Balipara-Charduar-Tawang (BCT) road
(source: https://www.independent.co.ug/university-of-maryland-strasburg-to-install-landslide-warning-systems-on-mt-elgon-region/)

Many things can impact the stability of a slope. Just like with stream crossings, all geomorphic factors affecting slope stability should be considered when determining the risk of slope failure.

After the geomorphic factors for each slope crossing have been adequately assessed, these indicators can be fed into our geomorphic framework of slope stability to determine how likely slope failure is at a particular location.

1.3 TYPES OF SLOPES:

Slopes may be of two types: Infinite slope and Finite slope. If a slope represents the boundary surface of a semi-infinite soil mass, and the soil properties for all identical depths below the surface are constant, it is called an Infinite slope. If the slope is of limited extent, it is called a Finite slope. Slopes extending to infinity do not exist in nature. The examples of finite slopes are the inclined faces of earth dams, embankments, and cuts etc.

1.3.1 STABILITY OF FINITE SLOPES:

Failure of finite slopes occurs along a surface which is a curve. In stability computations, the curve representing the real surface of sliding is usually replaced by an arc of a circle or logarithmic spiral. Two basic types of failure of a finite slope may occur: (i) slope failure, (ii) base failure.

If the failure occurs along a surface of sliding that intersects the slope at or above its toe, the slide is known as slope failure (or face failure) as shown in Fig-8(d).

If the failure surface passes through the toe, it is known as toe failure (as shown in Fig-8(c)). This occurs when the slope is steep and homogeneous.

If the failure surface passes below the toe portion, it is known as base failure. This generally occurs when the soil below the toe is relatively weak and soft (as shown in Fig-8(b)).

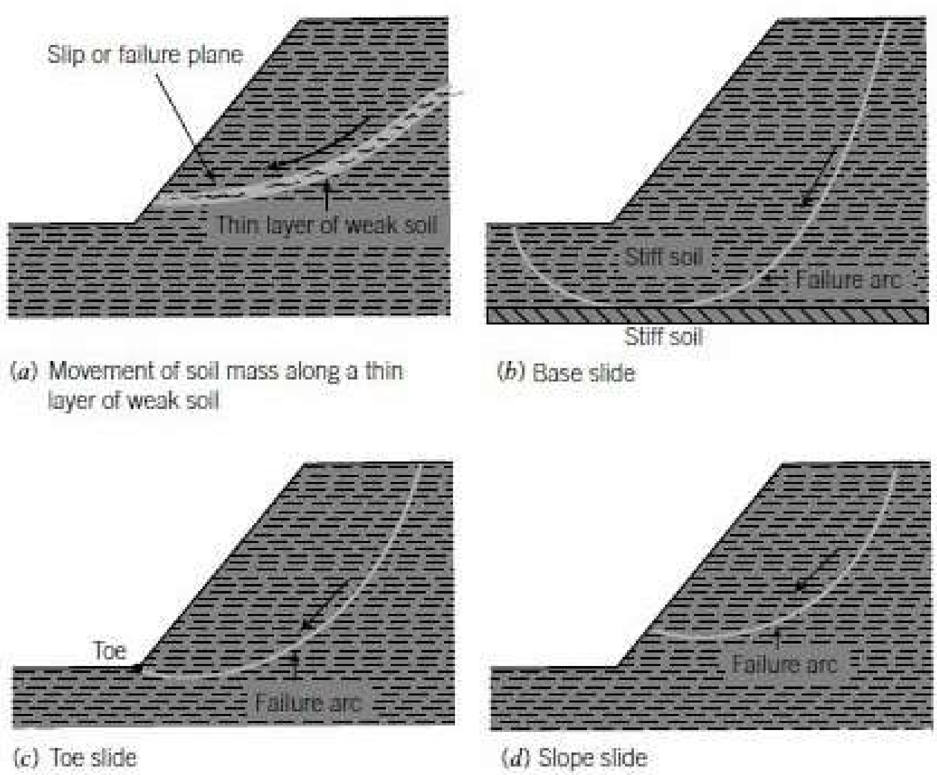


Figure-10: modes of failure for finite slopes.
(source:http://ndl.ethernet.edu.et/bitstream/123456789/90312/12/Chapter%208.2-Slope%20Stability.pdf)

Methods of analysis of finite slopes are: -

a) Culmann's Method of plane failure surface.
b) The Swedish circle Method (Slip circle Method).
c) The Friction circle Method.
d) Bishop’s Method.

a) Culmann considered a simple failure mechanism of a slope of homogeneous soil with plane failure surface passing through the toe of the slope.

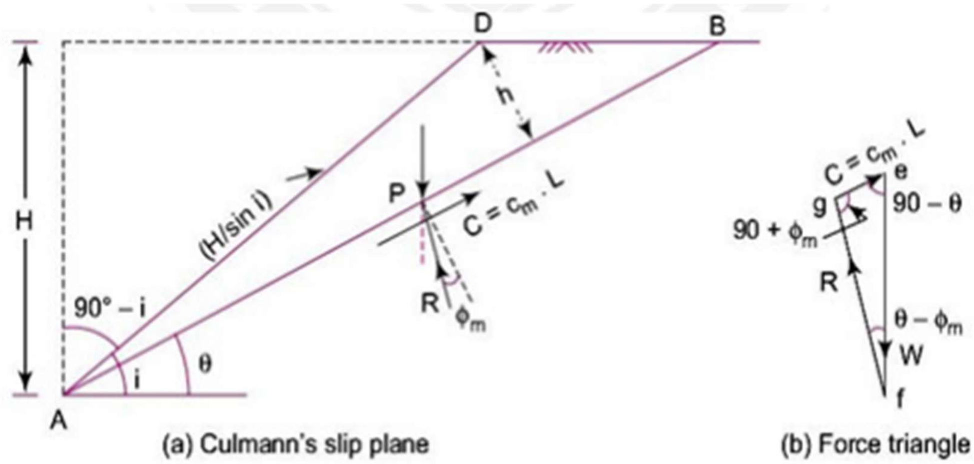


Figure- 11: Culmann’s slip plane and Force triangle (source: B.C. Punmia)

Factor of safety, F $= \frac{\tau_f}{\tau} = \frac{cL + W\cos\theta\tan\varphi}{W\sin\theta}$

Culmann’s method is suitable for very steep slopes.

b) The method, developed by Swedish engineers assumes that the surface of sliding is an arc of a circle. Two cases arise as follows:

- Analysis of purely cohesive soil [$(\emptyset_u = 0)$ analysis]:

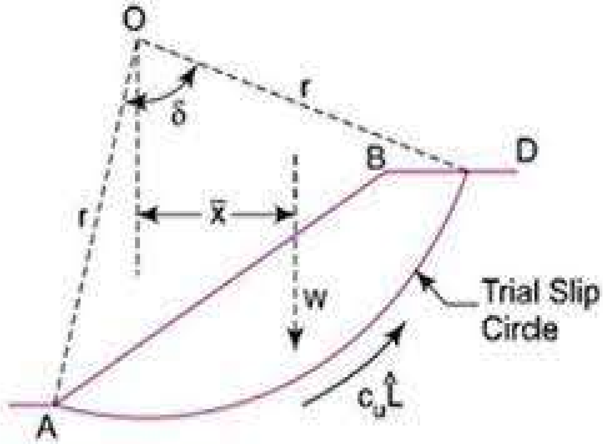


Figure-12: (ϕ_u = 0) Analysis. (source: B.C. Punmia)

Factor of safety, $F = \frac{C_u}{C_m} = \frac{C_u \widehat{L}\ .\ r}{W.\bar{x}}$ where,

$'C_m'$ is the mobilized shear resistance of soil ($\emptyset_u = 0$) and $'C_u'$ is the unit cohesion.

- Analysis of soil possessing both cohesion and friction [(c-ϕ) analysis]:

To test the stability of the slope of a c- ϕ soil, trial slip circle is drawn, and the material above the assumed slip surface is divided into a convenient number of vertical strips or slices. The forces between the slices are neglected, and each slice is assumed to act independently as a column of soil of unit thickness and of width ‘b’.

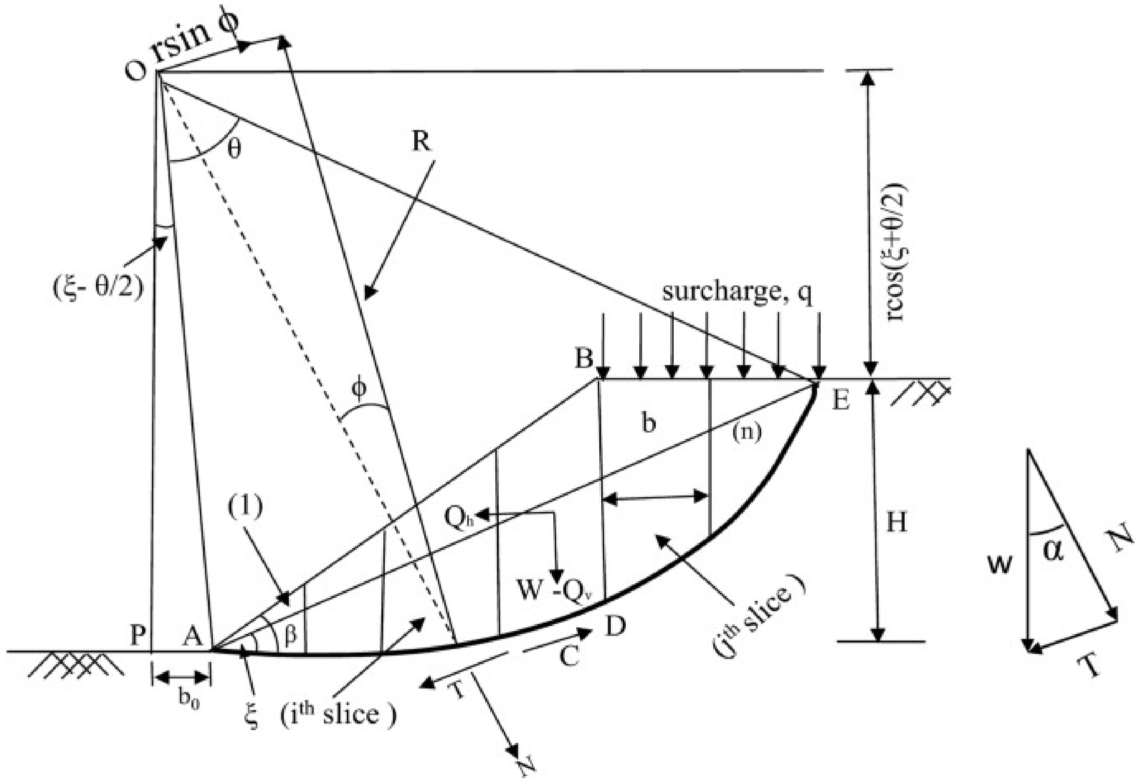


Figure 13: Slip circle method: (c- ϕ) analysis (source: B.C. Punmia)

Factor of safety, $F = \frac{M_R}{M_D} = \frac{c\,\hat{L} + \tan\phi\,\sum N}{\sum T}$

M_D is the driving moment (= $\sum T$ *r).

M_R is the resisting moment.

c) This method uses a total stress-based limit equilibrium approach. In this method the equilibrium of the resultant weight `w', the reaction `p' due to frictional resistance and the cohesive force `c' are considered.

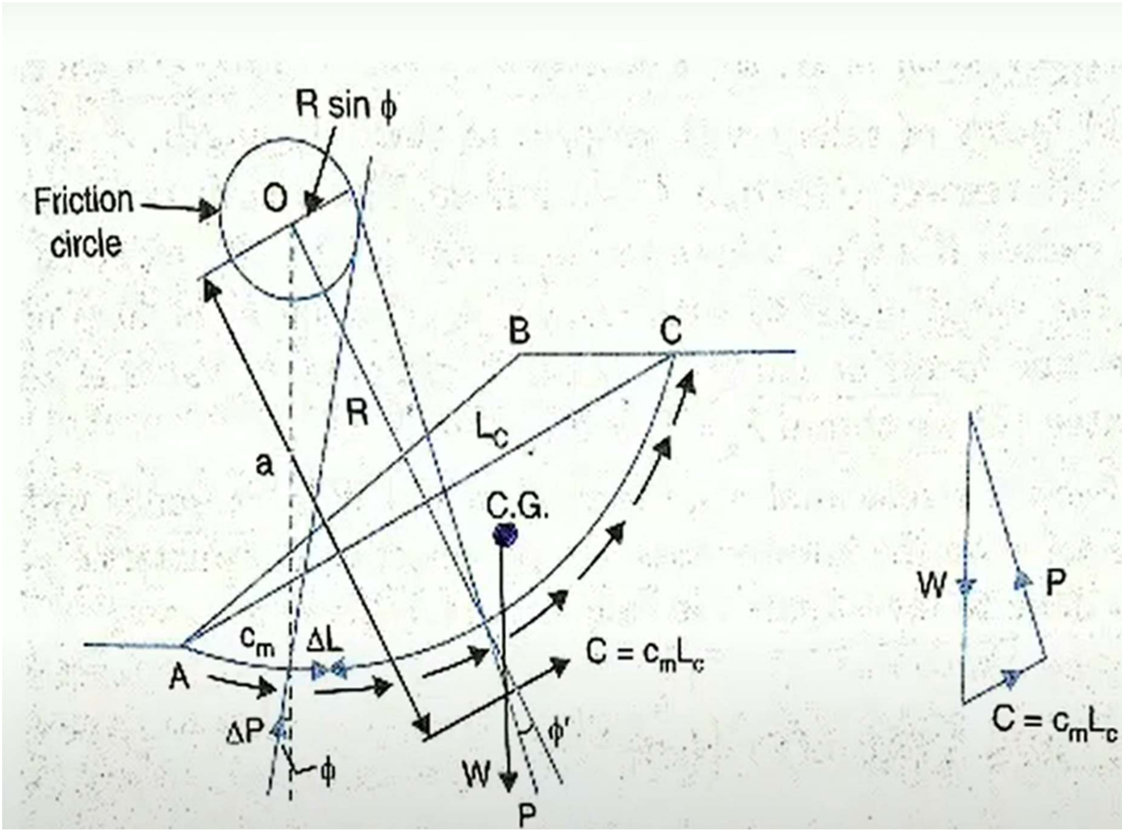


Figure-14: Friction circle analysis and force triangle.(source: B.C.Punmia)

Factor Of Safety (F_c) = $\frac{C_U}{C_m}$ where,

'C_U' is the cohesion value that we obtain from lab.

1.4 Artificial Neural Network (ANN):

An artificial neural network (ANN) is an information processing system that utilizes a mathematical model consisting of interconnected processing units called neurons. These neurons perform complex computations, allowing ANNs to learn, recall, and generalize from training data. By mimicking the structure and function of biological neural networks, ANNs have become a powerful tool in various fields such as machine learning, computer vision, and natural language processing.

An input-output pair is a collection of known input and output values used to train a neural network. These pairs are divided into two separate sets: the learning or training set, and the testing set. The training set is used to teach the neural network and adjust its parameters until it can accurately predict the output values for a given input. Once the neural network has been trained, the testing set is used to evaluate its performance and determine how well it can predict the output values for new, unseen inputs. By using separate training and testing sets, the neural network can be optimized for maximum accuracy and effectiveness.

In general, a neural network is composed of three layers: the input layer, the output layer, and one or more hidden layers in between. The input layer receives input from the external environment and passes it on to the neurons in the hidden layer. The input layer does not perform any computations. The hidden layer, which receives input from the input layer, performs complex computations on the input data and provides the resulting output to the output layer. The output layer consists of neurons that communicate the final output of the neural network to the user or external environment. By using multiple layers with various numbers of neurons, neural networks can learn and analyze complex relationships between inputs and outputs, making them a powerful tool in machine learning and artificial intelligence.

LINEAR REGRESSION METHOD:

In Regression, we plot a graph between the variables which best fit the given data points. The machine learning model can deliver predictions regarding the data. In naïve words, "Regression shows a line or curve that passes through all the data points on a target-predictor graph in such a way that the vertical distance between the data points and the regression line is minimum." It is used principally for prediction, forecasting, time series modeling, and determining the causal-effect relationship between variables. Linear regression is a quiet and simple statistical regression method used for predictive analysis and shows the relationship between the continuous variables. Linear regression shows the linear relationship between the independent variable (X-axis) and the dependent variable (Y-axis), consequently called linear regression. If there is a single input variable (x), such linear regression is called simple linear regression. And if there is more than one input variable, such linear regression is called multiple linear regression. The linear regression model gives a sloped straight line describing the relationship within the variables.

1.5 Objectives:

- To select the site and identify the type of soil.
- To analyze the slope and study its stability using traditional methods.
- To create and verify the ANN Model and analyze the slope stability using the data.
- To analyze stability criteria of any new slope using our prepared ANN model.

CHAPTER-2: LITERATURE REVIEW

[1] Xuzhen et al (2020) studied Machine learning aided stochastic reliability analysis of spatially variable slopes. This paper presents machine learning aided stochastic reliability analysis of spatially variable slopes, which significantly reduces the computational efforts and gives a complete statistical description of the factor of safety with promising accuracy compared with traditional methods. Within this framework, a small number of traditional random finite-element simulations are conducted. The samples of the random fields and the calculated factor of safety are, respectively, treated as training input and output data, and are fed into machine learning algorithms to find mathematical models to replace finite-element simulations. Two powerful machine learning algorithms used are neural networks and the support-vector regression with their associated learning strategies. Several slopes are examined including stratified slopes with 3 or 4 layers described by 4 or 6 random fields. It is found that with 200 to 300 finite-element simulations (finished in about 5 ~ 8 hours), the machine learning generated model can predict the factor of safety accurately, and a stochastic analysis of 105 samples takes several minutes. However, the same traditional analysis would require hundreds of days of computation.

[2]. Chakraborty and Goswami (2015) analyzed Slope Stability prediction using Artificial Neural Network. Artificial neural networks (ANN), usually called neural networks, are very sophisticated modeling techniques which are capable of modeling extremely complex functions. They are used for predicting the outcome of two or more independent variables. Predicting the stability of slopes is a very challenging task for geotechnical engineers. They must pay particular attention to geology, ground water and shear strength of the soils in accessing slope stability. In this paper, a prediction formula has been developed for predicting the factor of safety (FOS) of the slopes using ANN. A total of 110 cases with different geometric and soil conditions were analyzed using Bishop's Simplified Method. Out of these, 100 cases were used to train up the prediction model. The computational method for the training process was a back propagation learning algorithm. The prediction model is validated by comparing the results with the remaining 10 cases.

[3]. Kaur and Sharma (2016). Analysis of slopes for stability and safety is a major area of concern in civil engineering. This is the reason that so many analysis techniques have been developed so far. The traditional way of slope stability analysis involves the determination of factor of safety for a slope to take safety precautions against any instability. Various researchers worked to develop a new method in which probability of failure or reliability of a slope is calculated. Thus, basically two different approaches of slope stability analysis are available with us– deterministic approach and probabilistic (or reliability) approach. In this paper past trends in slope stability analysis are discussed with the evolution of each method. A brief review of available methods has also been presented here along with the advantages and limitations of their use.

[4]. Meng & Mattson (2021). To enable assess slope stability problems efficiently, various machine learning algorithms have been proposed recently. However, these developments are restricted to two-dimensional slope stability analyses (plane strain assumption), although the two-dimensional results can be very conservative. In this study, artificial neural networks are adopted and trained to predict three-dimensional slope stability and a program, Slope Lab has been developed with a graphical user interface. To reduce the number of variables, groups of dimensionless parameters to express stability of slopes in classic stability charts are adopted to construct the neural network architecture. The model has been trained with a dataset from slope stability charts for fully cohesive and cohesive-frictional soils. Furthermore, the impact of concave plan curvature on slope stability that is usually found by excavation in practice is investigated by introducing a dimensionless parameter, relative curvature radius. Slope stability analyses have been conducted with numerical calculations and the artificial neural networks are trained with dimensionless data. The performance of the trained artificial neural networks has been evaluated with the correlation coefficient (R) and root mean square error (RMSE).

[5]. Zhou (2003) expounded the natural factors that affect slope stability and the application principle of Artificial Neural Network in the slope stability analysis. The advantages and disadvantages of general neural network and BP network are analyzed, and the corresponding countermeasures were put forward. ANN is set

up by humans and carries out information processing through continuous or intermittent external input to make state responses. With the development of science and technology, people pay increasing attention to artificial intelligence research, and artificial neural network research is deeper. In recent years, great progress has been made. It can solve the practical problems that are difficult to solve by modern computers in the fields of information, medicine, intelligent robots, biology, transportation, economy and so on. The artificial neural network can adjust, change the behavior of the system, and adapt to the environment through supervised learning and unsupervised learning.

[6]. Pradhan and Lee (2008) carried out landslide risk analysis using artificial neural network model focusing on different training sites.

This paper presents landslide hazard and risk analysis using remote sensing data, GIS tools and artificial neural network model. Landslide locations were identified in the study area from interpretation of aerial photographs and from field surveys. Topographical and geological data and satellite images were collected, processed, and constructed into a spatial database using GIS and image processing. These factors were used with artificial neural networks to analyze landslide hazard. Each factor's weight was determined by the back-propagation training method. Then the landslide hazard indices were calculated using the trained back-propagation weights, and the landslide hazard map was created using tools. Landslide locations were used to verify results of the landslide hazard maps and to compare them. The results of the analysis were verified using the landslide location data and compared with neural network model with all cases. The accuracy observed was 83, 72, 82, 79 and 81% for training sites 1, 2, 3, 4 and 5 respectively. GIS data was used to efficiently analyze the large volume of data, and the artificial neural network proved to be an effective tool for landslide hazard analysis. Further, risk analysis has been performed using DEM, distance from hazard zone, land cover map and damaging objects at risk. DEM was used to delineate the catchments and served as a mask to extract the highest hazard zones of the landslide area. Risk map was produced using map overlying techniques in GIS.

[7]. Khandelwal et al (2022) A stability prediction system that can analyze the slope under both the condition of the soil or rock surface is missing. In this study, artificial neural network technology has been utilized to predict the stability of jointed rock and residual soil slope of the Himalayan region. Database for the artificial neural network was obtained from numerical simulation of several residual soils and rock slope models. Non-linear equations have been formulated by coding the artificial neural network algorithm. An android application has also been developed to predict the stability of residual soil and rock slope instantly. It was observed that the developed android app provides promising results in predicting the factor of safety and stability state of the slopes.

[8]. Ray, A., Kumar, V., Kumar, A. et al.(2020) Stability prediction of Himalayan residual soil slope using artificial neural network. Over the past decade, machine learning (ML) techniques have advanced to the point where they can model complex multi-factorial problems such as slope stability analysis. However, there has been little research on the analysis of residual soil slope using ML. The objective of this study is to develop an artificial neural network (ANN) model for evaluating the factor of safety of Shivalik Slopes in the Himalayan Region. The study used data obtained from numerical analysis of a residual soil slope to develop two ANN models with different numbers of input parameters. A four-layer, feed-forward back-propagation neural network with the optimum number of hidden neurons was developed using a trial-and-error method. The predictive performance of the ANN models was evaluated using various performance indices such as coefficient of determination, root mean square error, variance accounted for, and residual error. Both ANN models showed good predictive performance, with the ANN2 model performing better than the ANN1 model. The study concludes that ANN models are reliable and valid computational tools that can be used during the preliminary stage of designing infrastructure projects in residual soil slopes.

[9]. Choobbasti A.J. (2009) presented a study on prediction of soil stability using Artificial Neural Network. In this paper we studied about investigating soil failures is a complex task that requires geologists and

engineers to work together. Geotechnical engineers must consider various geological factors, such as water and soil strength, to assess slope stability.

Artificial neural networks (ANNs) are advanced modeling techniques that can predict slope stability by analyzing different site investigation data. This helps engineers identify areas that may be at risk of failure. ANNs are a promising tool for predicting soil stability and other geotechnical problems.

CHAPTER-3: METHODOLOGY

3.1 PRELIMINARY INVESTIGATION OF SOIL:

The preliminary investigation was carried out to find out the index and engineering properties of the soil by using the following methods.

3.1.1 GRAIN-SIZE ANALYSIS:

The grain size analysis is widely used in classification of soils. The data obtained from grain size distribution curves is used in the design of filters for earth dams and to determine suitability of soil for road construction, airfield etc. Information obtained from grain size analysis can be used to predict soil water movement although permeability tests are generally used. The method is applicable to dry soil passing through 4.75 mm size sieve less than 10 % passing through 75-micron sieve.

Percentage retained on any sieve = $\frac{weigh\ \ of\ soi\ \ retained}{Total\ weigh} * 100\%$

Cumulative percentage retained is equal to the sum of percentages retained on any sieve for all coarser sieves.

Apparatus for Grain-size analysis: -

- IS Sieves (10mm, 4.75mm, 2mm, 1mm, 600 µ, 425 µ, 300 µ, 150 µ, and 75 µ).
- Sieve shaker (Mechanical shaker).
- Oven.
- Trays.
- Weighing balance with accuracy of 0.1% of the mass of the sample.

Figure 15: IS Sieves.
(source: m.made-in-china.com)

Procedure for Grain-size analysis: -

1). For soil samples of soil retained on 75 micron I.S sieve

(a) The proportion of soil sample retained on 75 micron I.S sieve is weighed, and recorded weight of soil sample is as per I.S 2720.

(b) I.S sieves are selected and arranged in the order as shown in the table.

(c) The soil sample is separated into various fractions by sieving through above sieves placed in the above-mentioned order.

(d) The weight of soil retained on each sieve is recorded.

(e) The moisture content of soil if above 5% it is to be measured and recorded.

2). No particle of soil sample shall be pushed through the sieves.

3.1.2 LIQUID LIMIT TEST:

Liquid limit is the water content where the soil starts to behave as a liquid.

In the static cone penetrometer method, the liquid limit is taken as the moisture content at which a standard 30-degree, 80 g cone will penetrate the soil sample 20 mm in approximately 5 sec. The Cone Penetration Test (CPT) is one of the most used site investigation tools in the field of geotechnical engineering for the classification and characterization of soils. The liquid limit of the soil corresponds to the water content of a paste which would give 20 mm penetration of the soil.

Apparatus Required: -

- Cone Penetrometer conforming to IS :11196-1985.
- Weigh Balance, sensitive to 0.01g.
- Containers, non-corrodible and airtight for moisture determination.
- Hot Air Oven, thermostatically controlled, capable of maintaining temperature of 105° to 110° C.

Figure-16: cone penetrometer
(source: https://amzn.eu/d/akrPppi)

Procedure for Cone Penetration test to determine liquid limit of the soil sample: -

1. Take about 150 g of soil sample, passing from 425 micron, and work it well into a paste with addition of distilled water. In the case of highly clayey soils, to ensure uniform moisture distribution, it is recommended that the soil in the mixed state is left for sufficient time (24 hours) in an air-tight container.
2. The wet soil paste shall then be transferred to the cylindrical cup of cone penetrometer apparatus, ensuring that no air is trapped in this process. Finally, the wet soil is levelled up to the top of the cup and placed on the base of the cone penetrometer apparatus.
3. The penetrometer shall be so adjusted that the cone point just touches the surface of the soil paste in the cup clamped in this position. The initial reading is either adjusted to zero or noted down as is shown on the graduated scale. The vertical clamp is then released allowing the cone to penetrate the soil paste under its own weight. The penetration of the cone after 5 seconds shall be noted to the nearest millimeter.

4. If the difference in penetration lies between 14 and 28 mm, the test is repeated with suitable adjustments to moisture either by addition of more water or exposure of the spread paste on a glass plate for reduction in moisture content.
5. The test shall then be repeated at least to have three sets of values of penetration in the range of 20 to 28 mm. The exact moisture content of each trial shall be determined.

3.1.3 STANDARD PROCTOR TEST:

The objectives of compaction are:

- To increase soil shear strength and therefore its bearing capacity.
- To reduce subsequent settlement under working loads.
- To reduce soil permeability making it more difficult for water to flow through.

To assess the degree of compaction, it is necessary to use the dry unit weight, which is an indicator of compactness of solid soil particles in a given volume. The laboratory testing is meant to establish the maximum dry density that can be attained for a given soil with a standard amount of compactive effort.

1) Bulk Density, $\rho = \frac{(M_2 - M_1)}{V}$

2) Dry Density, $\rho_{d=} \frac{\rho}{(1+w)}$

3) Dry density for zero air voids line, $\rho_d = \frac{G*\rho_w}{[1+\left\{\frac{wG}{S}\right\}]}$

'M_1'is the mass of mould used for Proctor test.

'M_2'is the combined mass of mould and compacted soil.

'M' is the mass of wet soil.

'V' is the volume of mould.

'ρ_w' is the density of water.

'G' is the specific gravity of soils.

'w' is the water content.

'S' is the degree of saturation.

Apparatus Required: -

i. Proctor mould having a capacity of 944 cc with an internal diameter of 10.2 cm and a height of 11.6 cm. The mould shall have a detachable collar assembly and a detachable base plate.
ii. Rammer: A mechanical operated metal rammer having a 5.08 cm diameter face and a weight of 2.5 kg. The rammer shall be equipped with a suitable arrangement to control the height of drop to a free fall of 30 cm.
iii. Sample extruder, mixing tools such as mixing pan, spoon, towel, and spatula.

iv. A balance of 15 kg capacity, Sensitive balance, Straight edge, Graduated cylinder, Moisture tins.

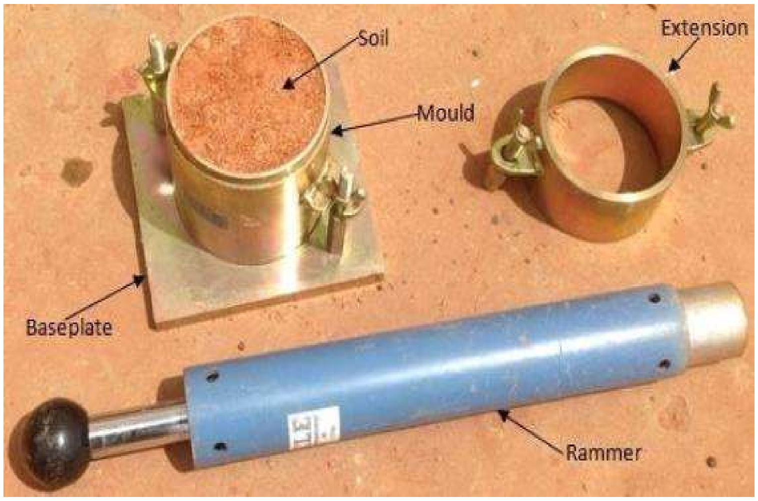


Figure-17: standard proctor test apparatus.
(source: *researchgate.net*)

Procedure for Standard Proctor test: -

1. Take a representative oven-dried sample, approximately 5 kg in the given pan. Thoroughly mix the sample with sufficient water to dampen it with approximate water content of 4-6 %.
2. Weigh the proctor mould without base plate and collar. Fix the collar and base plate. Place the soil in the Proctor mould and compact it in 3 layers giving 25 blows per layer with the 2.5 kg rammer falling through. The blows shall be distributed uniformly over the surface of each layer.
3. Remove the collar; trim the compacted soil even with the top of mould using a straight edge and weigh.
4. Divide the weight of the compacted specimen by 944 cc and record the result as the bulk density (ρ_{bulk}).
5. Remove the sample from mould and slice vertically through and obtain a small sample for water content.
6. Thoroughly break up the remainder of the material until it has passed a no.4 sieve as judged by the eye. Add water in sufficient amounts to increase the moisture content of the soil sample by one or two percentage points and repeat the above procedure for each increment of water added. Continue this series of determination until there is either a decrease or no change in the wet unit weight of the compacted soil.

3.1.4 TRIAXIAL TEST:

Figure-18: Triaxial setup. (source: Geotech. Lab)

A triaxial shear test is a common method to measure the mechanical properties of many deformable solids, especially soil (e.g., sand, clay) and rock, and other granular materials or powders. A. Casagrande developed the triaxial test. It is the most versatile of all the shear stress. Drainage conditions can be controlled, whatever the type of the soil. In the triaxial test, pore water measurements can be made accurately. Volume changes can also be measured. There is no rotation of the principal stresses during the test. The failure plane is not forced. The specimens can fail only on any weak plane or can simply bulge. The stress distribution

on the failure plane is uniform. From the triaxial test data, it is possible to extract fundamental material parameters about the sample, including its angle of shearing resistance, apparent cohesion, and dilatancy angle. These parameters are then used in computer models to predict how the material will behave in a larger-scale engineering application. An example would be to predict the stability of the soil on a slope, whether the slope will collapse or whether the soil will support the shear stresses of the slope and remain in place. Triaxial tests are used along with other tests to make such engineering predictions. The test is carried out on a cylindrical specimen of soil, usually having a length to diameter ratio of 2.

Three types of triaxial tests can be conducted with different combinations of drainage conditions in the two stages of the tests:

(i) Unconsolidated Undrained (UU) Triaxial Test:

In the UU triaxial test, the drainage line valve is kept closed during the two stages. As a result, the pore water of the soil remains in the soil and, hence, the soil remains unconsolidated. Finally, the sample is tested to failure under undrained conditions, i.e., without allowing the pore water pressure to dissipate. If the pore water pressures are measured, the test is denoted as UU test.

(ii) Consolidated Undrained (CU) triaxial Test:

In the CU triaxial test, the drainage line valve is kept open during the first stage and then closed during the second stage. As a result, the pore water drains out of the soil and pore water pressure will dissipate and, hence, the soil will eventually be consolidated. Finally, the sample is tested to failure under undrained conditions by closing the drainage line valve. If the pore water pressures are measured, the test is denoted as CU test.

(iii) Consolidated Drained (CD) Triaxial Test.

In the CD triaxial test, the drainage line valve is kept open during the two stages and. As a result, the pore water drains out of the soil and pore water pressure will dissipate and, hence, the soil will eventually be consolidated. Finally, the sample is tested to failure under drained conditions by opening the drainage line valve and the allowing dissipation of pore water pressure.

Apparatus required: -

- Triaxial Shear Test Apparatus.
- Triaxial Shear Test Setup.
- 3.8 cm (1.5 inch) internal diameter 12.5 cm (5 inches) long sample tubes.
- Rubber Ring.
- Open ended cylindrical section.
- Weighing balance.

Procedure: -

(1) A cylindrical specimen of soil having size length to diameter as 78 mm by 36 mm is placed on a saturated porous disc resting on the pedestal of the triaxial cell.

(2) The specimen is encased in a rubber membrane and sealed to the pedestal using rubber O-rings.

(3) The triaxial cell is filled with water at the required cell pressure, σ_c, with the drainage line valve closed.

(4) The cell pressure is held constant, and the pore water pressure measurement device can be attached to the specimen through the pressure connections.

(5) Additional axial stress, called the deviator stress (σ_d), is then applied through the ram gradually with the drainage line valve kept close, and measured with a proving ring until 15% axial strain was reached.

(6) The above steps are repeated using a different sample.

For an undrained test, the volumetric change (ΔV_0) is zero and the cross-sectional area (A) of the specimen at any stage during shear is given by:

$$A = A_0 / (1 - \epsilon_l)$$

where, A_0 = cross sectional area of original sample

ϵ_l = axial strain in the sample

The minor principal stress (σ_3) is equal to the cell pressure (σ_c). The major principal stress (σ_1) is equal to the sum of the cell pressure and the deviator stress. Thus,

$$\sigma_1 = \sigma_3 + (\sigma_1 - \sigma_3) = \sigma_3 + \sigma_d$$

The deviator stress at failure ($\sigma_1 - \sigma_3$) is known as the compressive strength of the soil.

3.2 ANN ARCHITECTURE AND TRAINING ALGORITHM:

Artificial Neural Network (ANN) usually called neural networks, are very sophisticated modelling techniques which are capable of modelling extremely complex functions. They are used for predicting the outcome of two or more independent variables.

In this project, 110 slope cases having different geometrical and slope parameters will be selected whose various soil parameters are knowns. These slope parameters will be used to analyze the various slopes using Bishop's Simplified Method to find the FOS. Out of these, 100 cases will be used to develop the prediction model using ANN. In the proposed model, several important parameters including, height of the slope (H), cohesion (C), angle of internal friction (φ), angle of the slope (β) and unit weight of soil (γ) will be used as input parameters whereas the FOS will be use as the target value. The computational method for the training process was a back propagation learning algorithm. The prediction model will be validated by comparing the results with the remaining 10 cases. The ANN model will be prepared in Google Collab.

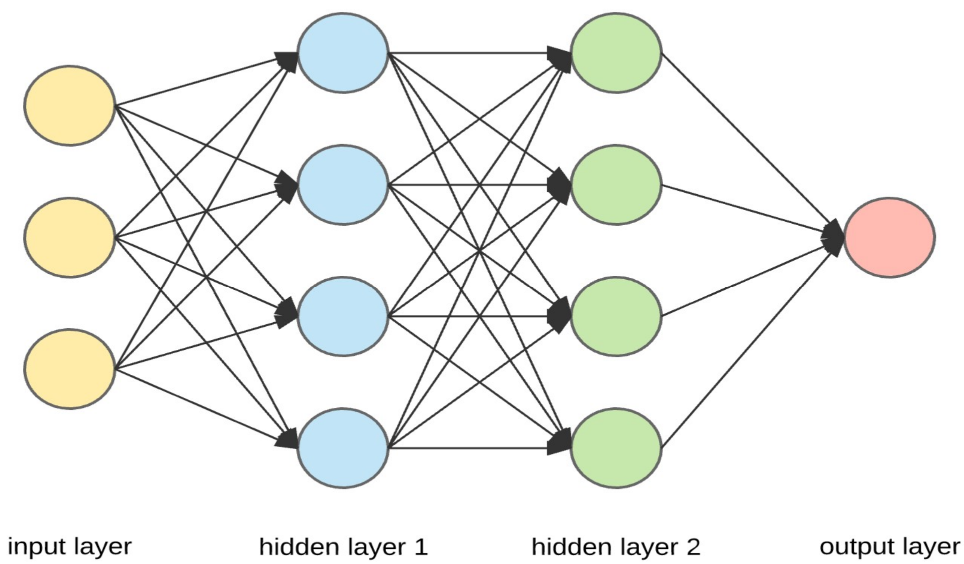


Figure 19: Network architecture diagram in ANN
(source: researchgate.net)

A typical neural network structure used in this study is shown in Fig-21. As shown in figure, the ANN structure consists of an input layer, one hidden layer, and an output layer. Each layer has its corresponding neurons and weight connections. It has been shown that ANNs with one hidden layer can approximate any function given that sufficient degrees of freedom are provided. The input represents the random variables X in the input layer. The output consists of a single neuron representing the response surface. To determine the determine this number. It is normally determined by a trial-and-error process, so this number will be optimized during the training process. The initial number is picked by guesswork and experience. If the network has trouble learning, further neurons can be added to the hidden layer and the process is repeated until the performance of the trained model is acceptable.

3.3 ANN Dataset:

Table 3.3.1: Dataset for ANN model.

Density	C	Phi	H	slope angle	FS
1.4	0.36	26	50	30	1.934
1.5	0.7	27	50	30	2.279
1.6	0.7	35	50	30	2.543
1.4	0.63	15	55	40	1.855
1.5	1.12	16	55	40	2.01
1.6	1.2	18	55	40	2.279
1.4	0.7	0	60	50	1.78
1.5	1.26	0	60	50	1.8
1.6	1.33	15	60	50	2.332
1.4	0.91	0	65	60	1.553
1.5	1.28	0	65	60	1.7
1.6	1.33	10	65	60	2.253
1.4	0.36	26	50	30	1.567
1.5	0.7	27	50	30	1.821
1.6	0.7	35	50	30	2.326
1.4	0.63	15	55	40	1.449
1.5	1.12	16	55	40	1.567
1.6	1.2	18	55	40	2.154
1.4	0.7	0	60	50	1.384
1.5	1.26	0	60	50	1.529
1.6	1.33	15	60	50	2.18
1.4	0.91	0	65	60	0.967
1.5	1.28	0	65	60	1.44
1.6	1.33	10	65	60	2.14
1.4	0.36	26	50	30	1.061
1.5	0.7	27	50	30	1.416
1.6	0.7	35	50	30	2.314
1.4	0.63	15	55	40	0.936
1.5	1.12	16	55	40	1.11
1.6	1.2	18	55	40	2.091
1.4	0.7	0	60	50	0.5
1.5	1.26	0	60	50	1.064
1.6	1.33	15	60	50	2.047
1.4	0.91	0	65	60	0.384
1.5	1.28	0	65	60	1.06
1.6	1.33	10	65	60	2.018
1.4	0.36	26	50	30	0.896

1.5	0.7	27	50	30	1.427
1.6	0.7	35	50	30	2.507
1.4	0.63	15	55	40	0.869
1.5	1.12	16	55	40	1.26
1.6	1.2	18	55	40	2.066
1.4	0.7	0	60	50	0.641
1.5	1.26	0	60	50	0.981
1.6	1.33	15	60	50	1.982
1.4	0.91	0	65	60	0.316
1.5	1.28	0	65	60	0.971
1.6	1.33	10	65	60	0.954
1.4	0.36	26	50	30	1.934
1.5	0.7	27	50	30	2.279
1.6	0.7	35	50	30	2.543
1.4	0.63	15	55	40	1.855
1.5	1.12	16	55	40	2.01
1.6	1.2	18	55	40	2.279
1.4	0.7	0	60	50	1.78
1.5	1.26	0	60	50	1.8
1.6	1.33	15	60	50	2.332
1.4	0.91	0	65	60	1.553
1.5	1.28	0	65	60	1.7
1.6	1.33	10	65	60	2.253
1.4	0.36	26	50	30	1.567
1.5	0.7	27	50	30	1.821
1.6	0.7	35	50	30	2.326
1.4	0.63	15	55	40	1.449
1.5	1.12	16	55	40	1.567
1.6	1.2	18	55	40	2.154
1.4	0.7	0	60	50	1.384
1.5	1.26	0	60	50	1.529
1.6	1.33	15	60	50	2.18
1.4	0.91	0	65	60	0.967
1.5	1.28	0	65	60	1.44
1.6	1.33	10	65	60	2.14
1.4	0.36	26	50	30	1.061
1.5	0.7	27	50	30	1.416
1.6	0.7	35	50	30	2.314
1.4	0.63	15	55	40	0.936
1.5	1.12	16	55	40	1.11
1.6	1.2	18	55	40	2.091
1.4	0.7	0	60	50	0.5

1.5	1.26	0	60	50	1.064
1.6	1.33	15	60	50	2.047
1.4	0.91	0	65	60	0.384
1.5	1.28	0	65	60	1.06
1.6	1.33	10	65	60	2.018
1.4	0.36	26	50	30	0.896
1.5	0.7	27	50	30	1.427
1.6	0.7	35	50	30	2.507
1.4	0.63	15	55	40	0.869
1.5	1.12	16	55	40	1.26
1.6	1.2	18	55	40	2.066
1.4	0.7	0	60	50	0.641
1.5	1.26	0	60	50	0.981
1.6	1.33	15	60	50	1.982
1.4	0.91	0	65	60	0.316
1.5	1.28	0	65	60	0.971
1.6	1.33	10	65	60	0.954
1.4	0.36	26	50	30	1.934
1.5	0.7	27	50	30	2.279
1.6	0.7	35	50	30	2.543
1.4	0.63	15	55	40	1.855

CHAPTER-4: RESULT AND ANALYSIS:

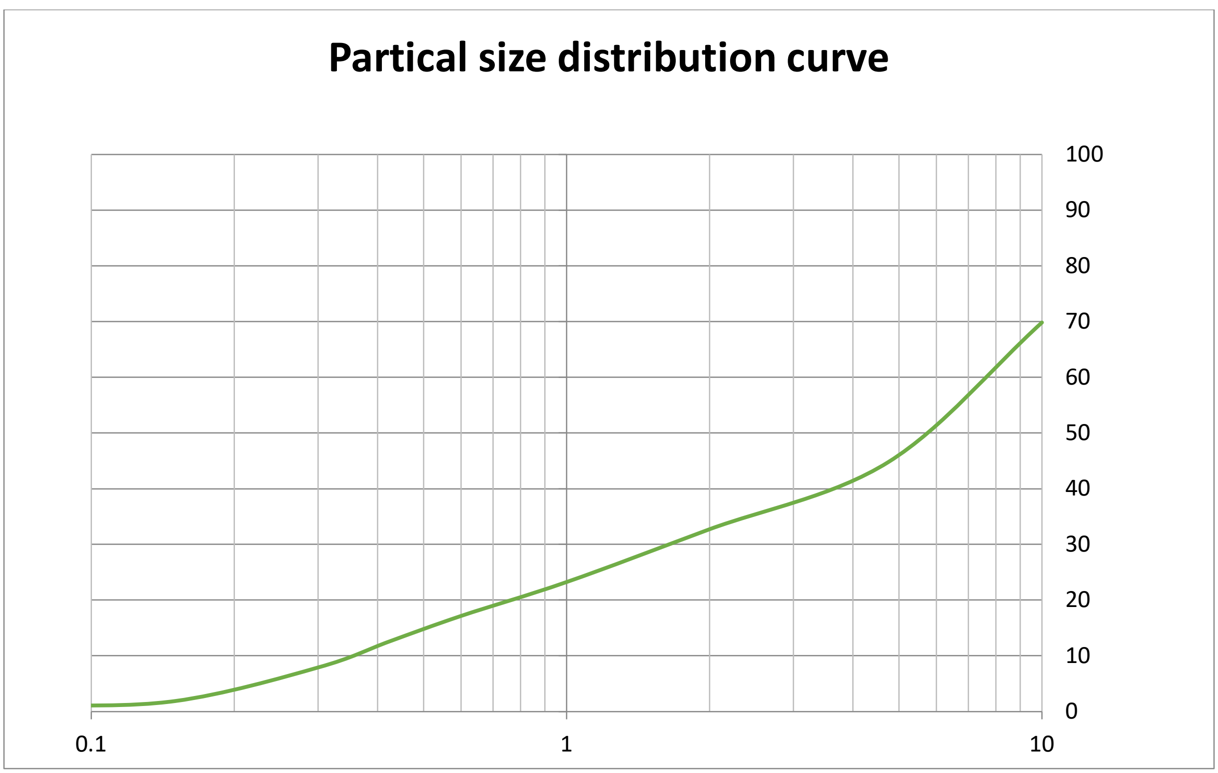
4.1 GRAIN-SIZE ANALYSIS: -

Sample Details: -

Weight of Sample taken for Sieve Analysis = 500gms.

Table - 4.1 1: Sieve analysis datasheet

S. No.	I.S. Sieve No	Weight retained in gms	Cumulative weight retained in gms	Percent (%) weight retained	Percent (%) weight passing
1	10 mm	150.91	150.91	30.18	69.81
2	4.75mm	125.13	276.04	55.22	44.78
3	2mm	60.29	336.33	67.28	32.72
4	1mm	47.27	383.6	76.74	23.26
5	600 µ	30.46	414.06	82.83	17.17
6	425µ	22.63	436.69	87.36	12.64
7	300µ	23.81	460.5	92.12	7.88
8	150µ	29.99	490.49	98.12	1.88
9	75µ	4.59	495.08	99.04	0.96
10	PAN	4.83	499.90	100	0



D_{60} = 7.942369157 $C_u = \frac{D6}{D10} = 22.3305831$

D_{30} = 1.712473573 $C_c = \frac{D30^2}{D10*D60} = 1.038120296$

D_{10} = 0.355672269

The above graph shows, as the particle size increases the percentage finer also increases. From the graph the values of D_{10}, D_{30} and D_{60} were found to be 0.355672269, 1.712473573, and 7.942369157and then theuniformity coefficient and curvature coefficient was found to be 22.3305831 and 1.038120296. From the above results the soil is a well-6 graded soil.

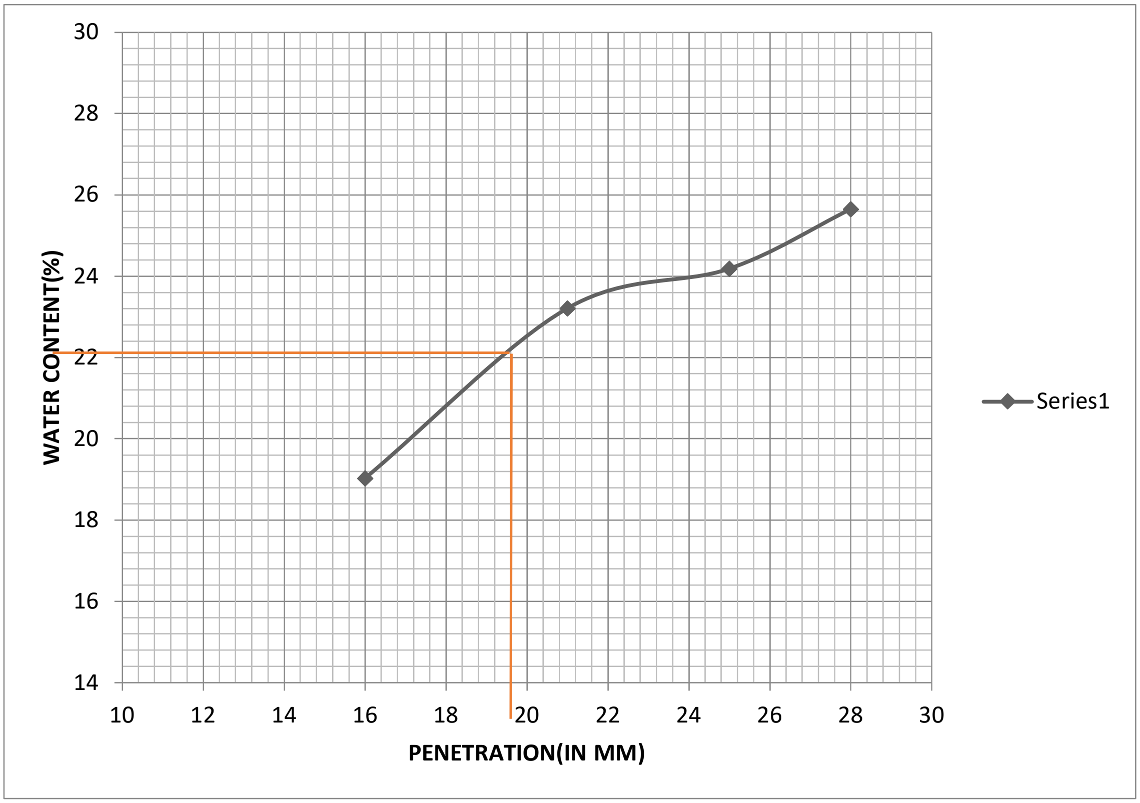
4.2 LIQUID LIMIT TEST: -

Table-4.2 1: Liquid limit datasheet

container no.	1	2	3	4	5	6	7	8
wt. of container + lid w1	10.05	9.64	8.94	8.59	6.28	6.79	4.2	6.2
Wt. of container + lid + wet sample, W2	48.69	45.94	49.32	44.49	41.81	44.42	32.85	33.88
Wt. of container + lid + dry sample, W3	40.75	38.69	41.65	37.78	34.89	37.09	28.22	29.5
Wt. of dry sample = W3 – W1	30.7	29.05	32.71	29.19	28.61	30.3	28.65	27.68
Wt. of water in the soil = W2 – W3	7.94	7.25	7.67	6.71	6.92	7.33	4.63	4.38
Water content (%) = (W2 – W3) / (W3 – W1) ´ 100	26.4	24.95	23.44	22.98	24.18	24.19	19.27	18.79
AVERAGE WATER CONTENT (%)	W1	=	23.025					

Table- 4.2 2 : Depth of penetration for different water content.

SL. NO	WATER CONTENT(%)	PENETRATION(IN MM)
1.	19.03	16
2.	23.21	21
3.	24.185	25
4	25.65	28



From the above experiment, the Liquid limit was found to be 22.374.

Table- 4.2 3 : Plastic limit datasheet

Determination number	1	2	3
Container number	I	II	III
Weight of container, g	25.55	24.65	25.40
Weight of container + Wet soil, g	29.40	27.60	29.35
Weight of container + Oven dry soil, g	28.30	26.90	28.50
Weight of water, g	1.10	0.70	0.85
Weight of oven dry soil, in g	2.75	2.25	3.10
Water content (%)	40.00	31.19	27.42

From the above experiment, the Plastic limit was found to be 32.84%

4.3 TRIAXIAL TEST: -

Readings recorded and other evaluated values in the Triaxial test are given in the following tables.

Sample height = 76 mm

Sample diameter = 38 mm

Sample cross sectional area A_0 = 1134 mm^2

1) Cell Pressure = 0.5 kg/cm^2

Table-4.3 1 : Triaxial test datasheet

Dial Gauge	Deformation (in mm)	P. R. R	Load (kN)	Strain	**Actual Area(m^2)**	Corrected Area(m^2)	Cell Pressure (kN/m^2)	**Deviator stress** (kN/m^2)	σ 1	σ 3
0	0	0	0	0	0.001134	0.001134	50	0	50	50
20	0.2	4	0.00844	0.000262	0.001134	0.001134297	50	7.440730794	57.44073079	50
40	0.4	5	0.01055	0.000524	0.001134	0.001134595	50	9.298476014	59.29847601	50
60	0.6	8	0.01688	0.000786	0.001134	0.001134892	50	14.87366166	64.87366166	50
80	0.8	11	0.02321	0.001048	0.001134	0.00113519	50	20.44592233	70.44592233	50
100	1	15	0.03165	0.00131	0.001134	0.001135487	50	27.87349074	77.87349074	50
120	1.2	19	0.04009	0.001572	0.001134	0.001135785	50	35.29715919	85.29715919	50
140	1.4	23	0.04853	0.001834	0.001134	0.001136084	50	42.71692767	92.71692767	50
160	1.6	26	0.05486	0.002096	0.001134	0.001136382	50	48.27602596	98.27602596	50
180	1.8	29	0.06119	0.002358	0.001134	0.00113668	50	53.83219928	103.8321993	50
200	2	36	0.07596	0.00262	0.001134	0.001136979	50	66.80862857	116.8086286	50
250	2.5	48	0.10128	0.003275	0.001134	0.001137726	50	89.01967196	139.019672	50
300	3	56	0.11816	0.00393	0.001134	0.001138474	50	103.7880346	50	50
350	3.5	62	0.13082	0.004585	0.001134	0.001139223	50	114.8326193	57.44073079	50
400	4	65	0.13715	0.00524	0.001134	0.001139973	50	120.3098183	59.29847601	50
450	4.5	75	0.15825	0.005895	0.001134	0.001140725	50	138.7276157	64.87366166	50

500	5	84	0.17724	0.00655	0.001134	0.001141477	50	181.0318784	153.7880346	50
550	5.5	98	0.20678	0.007205	0.001134	0.00114223	50	210.4491672	164.8326193	50
600	6	114	0.24054	0.00786	0.001134	0.001142984	50	230.6033234	170.3098183	50
700	7	135	0.28485	0.00917	0.001134	0.001144495	50	248.8870595	188.7276157	50
750	7.5	196	0.41356	0.009825	0.001134	0.001145252	50	361.1082654	205.2725556	50
800	8	130	0.2743	0.01048	0.001134	0.00114601	50	239.3521481	231.0318784	50
850	8.5	121	0.25531	0.011135	0.001134	0.001146769	50	222.6341474	260.4491672	50

$\sigma_3 = 50\ kN/m^2 = 0.5\ kg/cm^2$.

$\sigma_1 = 411.1083\ kN/m^2 = 4.11\ kg/cm^2$.

DEVIATRIC STRESS = $361.1083\ kN/m^2 = 2.6714\ kg/cm^2$.

2) Cell Pressure = 1.0 kg/cm^2

Table-4.3 2 : Triaxial test datasheet 2

Dial Gauge	Deformation (in mm)	Load (Kn)	P.R.R	**Area (m^2)**	Strain	Corrected Area(m^2)	Cell Pressure (kN/m^2)	Deviator stress (kN/m^2)	σ 1	σ 3
0	0	0	0	1133.54	0	1133.54	100	0	100	100
20	0.2	0.02532	12	1133.54	0.000263	1133.54	100	22.33123	122.3312	100
40	0.4	0.03798	18	1133.54	0.000526	1133.54	100	33.48802	133.488	100
60	0.6	0.05275	25	1133.54	0.000789	1133.54	100	46.49889	146.4989	100
80	0.8	0.07385	35	1133.54	0.001053	1133.54	100	65.08131	165.0813	100
100	1	0.09495	45	1133.54	0.001316	1133.54	100	83.65392	183.6539	100
120	1.2	0.11183	53	1133.54	0.001579	1133.54	100	98.49977	198.4998	100
140	1.4	0.1266	60	1133.54	0.001842	1133.54	100	111.4798	211.4798	100
160	1.6	0.13715	65	1133.54	0.002105	1133.54	100	120.7379	220.7379	100
180	1.8	0.15192	72	1133.54	0.002368	1133.54	100	133.7052	233.7052	100
250	2.5	0.16247	93	1133.54	0.002632	1133.54	100	142.9526	242.9526	100
300	3	0.19623	105	1133.54	0.003289	1133.54	100	172.5431	272.5431	100

350	3.5	0.25109	119	1133.54	0.004605	1133.54	100	220.4895	320.4895	100
400	4	0.27852	132	1133.54	0.005263	1133.54	100	244.4149	344.4149	100
450	4.5	0.31228	148	1133.54	0.005921	1133.54	100	273.8597	373.8597	100
500	5	0.33549	159	1133.54	0.006579	1133.54	100	294.0195	394.0195	100
550	5.5	0.3587	170	1133.54	0.007237	1133.54	100	314.1523	414.1523	100
600	6	0.38613	183	1133.54	0.007895	1133.54	100	337.9516	437.9516	100
700	7	0.40934	202	1133.54	0.008553	1133.54	100	358.028	458.028	100
750	7.5	0.42622	213	1133.54	0.009211	1133.54	100	372.5447	472.5447	100
800	8	0.44943	221	1133.54	0.009868	1133.54	100	392.5709	492.5709	100
850	8.5	0.46631	212	1133.54	0.010526	1133.54	100	407.0447	507.0447	100

σ 3 = 100 kN/m^2 = 1 kg/cm^2.

σ 1 = 507.0447 kN/m^2 = 5.070447 kg/cm^2.

DEVIATRIC STRESS = 407.044 kN/m^2 = 4.07044 kg/cm^2.

3) Cell Pressure = 1.5 kg/cm^2

Table-4.3 3 : Triaxial test datasheet 3

Dial Gauge	Deformation (in mm)	Strain	P.R.R.	Load (kN)	**Area (m^2)**	Cell Pressure (kN/m^2)	Corrected Area(m^2)	Deviator stress (kN/m^2)	σ 3	σ 1
0	0	0	0	0	1133.54	150	0.001134	0	150	150
20	0.2	0.000263	4	0.008673	1133.54	150	0.001134	7.649262	150	157.6493
40	0.4	0.000526	8	0.017346	1133.54	150	0.001134	15.2945	150	165.2945
60	0.6	0.000789	15	0.032524	1133.54	150	0.001134	28.66963	150	178.6696
80	0.8	0.001053	26	0.056375	1133.54	150	0.001135	49.68094	150	199.6809
100	1	0.001316	35	0.075889	1133.54	150	0.001135	66.86057	150	216.8606
120	1.2	0.001579	45	0.097572	1133.54	150	0.001135	85.94094	150	235.9409
140	1.4	0.001842	53	0.114918	1133.54	150	0.001136	101.1926	150	251.1926
160	1.6	0.002105	60	0.130095	1133.54	150	0.001136	114.5275	150	264.5275
180	1.8	0.002368	67	0.145273	1133.54	150	0.001136	127.8553	150	277.8553
200	2	0.002632	73	0.158283	1133.54	150	0.001137	139.2683	150	289.2683
250	2.5	0.003289	88	0.190807	1133.54	150	0.001137	167.7744	150	317.7744
300	3	0.003947	101	0.218994	1133.54	150	0.001138	192.4321	150	342.4321
400	4	0.005263	125	0.271032	1133.54	150	0.00114	237.8439	150	361.3451
450	4.5	0.005921	134	0.290546	1133.54	150	0.00114	254.8001	150	387.8439

500	5	0.006579	150	0.325239	1133.54	150	0.001141	285.0352	150	404.8001
550	5.5	0.007237	166	0.359931	1133.54	150	0.001142	315.23	150	465.23
600	6	0.007895	180	0.390286	1133.54	150	0.001143	341.5892	150	491.5892
650	6.5	0.008553	194	0.420642	1133.54	150	0.001143	367.9131	150	517.9131
700	7	0.009211	206	0.446661	1133.54	150	0.001144	390.4114	150	540.4114
750	7.5	0.009868	217	0.470512	1133.54	150	0.001145	410.9855	150	560.9855
800	8	0.010526	239	0.518213	1133.54	150	0.001146	452.3515	150	602.3515
850	8.5	0.011184	235	0.50954	1133.54	150	0.001146	444.485	150	594.485

σ 3 = 150 kN/m^2 = 1.5 kg/cm^2.

σ 1 = 602.3515 kN/m^2 = 6.023515 kg/cm^2.

DEVIATRIC STRESS = 452.3515 kN/m^2 = 4.523515 kg/cm^2.

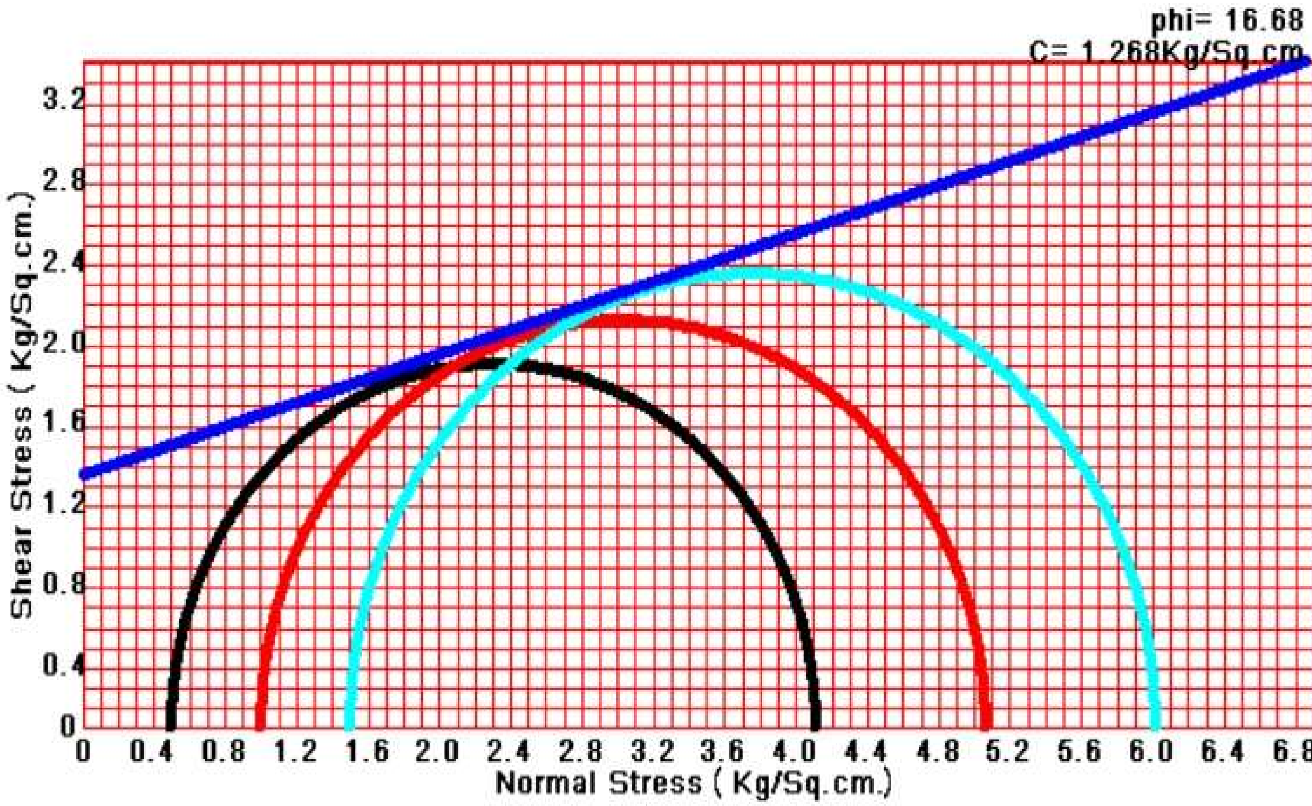


Figure 20: Mohr's circle.

The Mohr's circle as shown in Figure 20 has been obtained by using CASTeR software.

From the Mohr's circle we get cohesion value of the soil = 1.268Kg/cm^2 and angle of internal friction (ϕ) = 16.68°.

4.4 STANDARD PROCTOR TEST: -

Table-4.4 2: Standard Proctor test datasheet

water in (%)	Water content (mL):	Empty Wt. (g):	Volume of mould:	Wt. of soil + Wt. of mould (g):	Wt. of compact soil (g):	Bulk density:	Dry density:	Moisture content:
5	175	5070	1000	6857	1787	1.787	1.706	4.745
6	210	5070	1000	6897	1827	1.827	1.728	5.715
7	245	5070	1000	6949	1879	1.879	1.762	6.6
8	280	5070	1000	6981	1911	1.911	1.776	7.58
9	315	5070	1000	7021	1951	1.951	1.813	7.62
10	350	5070	1000	7067	1997	1.997	1.841	8.455
11	385	5070	1000	7101	2031	2.031	1.854	9.495
12	420	5070	1000	7143	2073	2.073	1.879	10.325
13	455	5070	1000	7196	2126	2.126	1.844	15.25
14	490	5070	1000	7182	2112	2.112	1.836	15.005
15	525	5070	1000	7171	2101	2.101	18,201	15.43
16	560	5070	1000	7162	2092	2.092	1.803	16.035

17	595	5070	1000	7154	2084	2.084	1.784	16.77

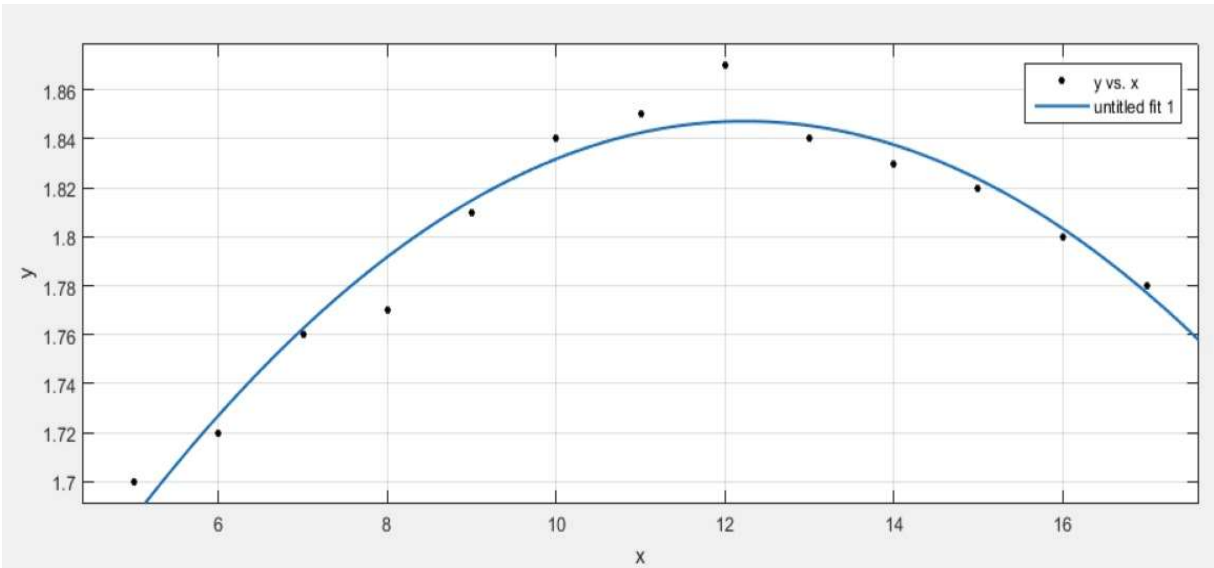


Figure 21: Compaction curve

The above graph shows, as the water content increases the dry density increases up to a limit afterwards it decreases. The optimum moisture content and the maximum dry density were found to be 12% and 1.88 g/cm^3.

4.5 Angle of slope: -

To discover the angle of the slope, the first step was to determine the distance between the points. Then, we utilized the vast resources available through Google Earth to ascertain the height. Armed with this information, we then applied the elegant principles of basic trigonometry to find the angle of slope.

Table-4.5.3: Computation of angle of slope.

Station No.	Horizontal Distance (m)	Height (m)	Slope angle (°)
1	1.588	138	59
2	1.594	142	62
3	1.684	150	60
4	1.774	158	61
5	1.852	165	60
6	1.965	175	59

To find the angle of the slope, we use the formula:

angle = arctan (height / distance)

angle = arctan (138 / 1.588)

angle = 59 degrees.

4.6 Height of slope: -

A Geographic Information System (GIS) is a computer system that analyzes and displays geographically referenced information. It uses data that is attached to a unique location.

Using this method, we can calculate the height (or elevation) of our site as well as information for any specific locations on the earth surface.

As shown in the figure below, the height of the slope is calculated to be 138.156 meters respectively.

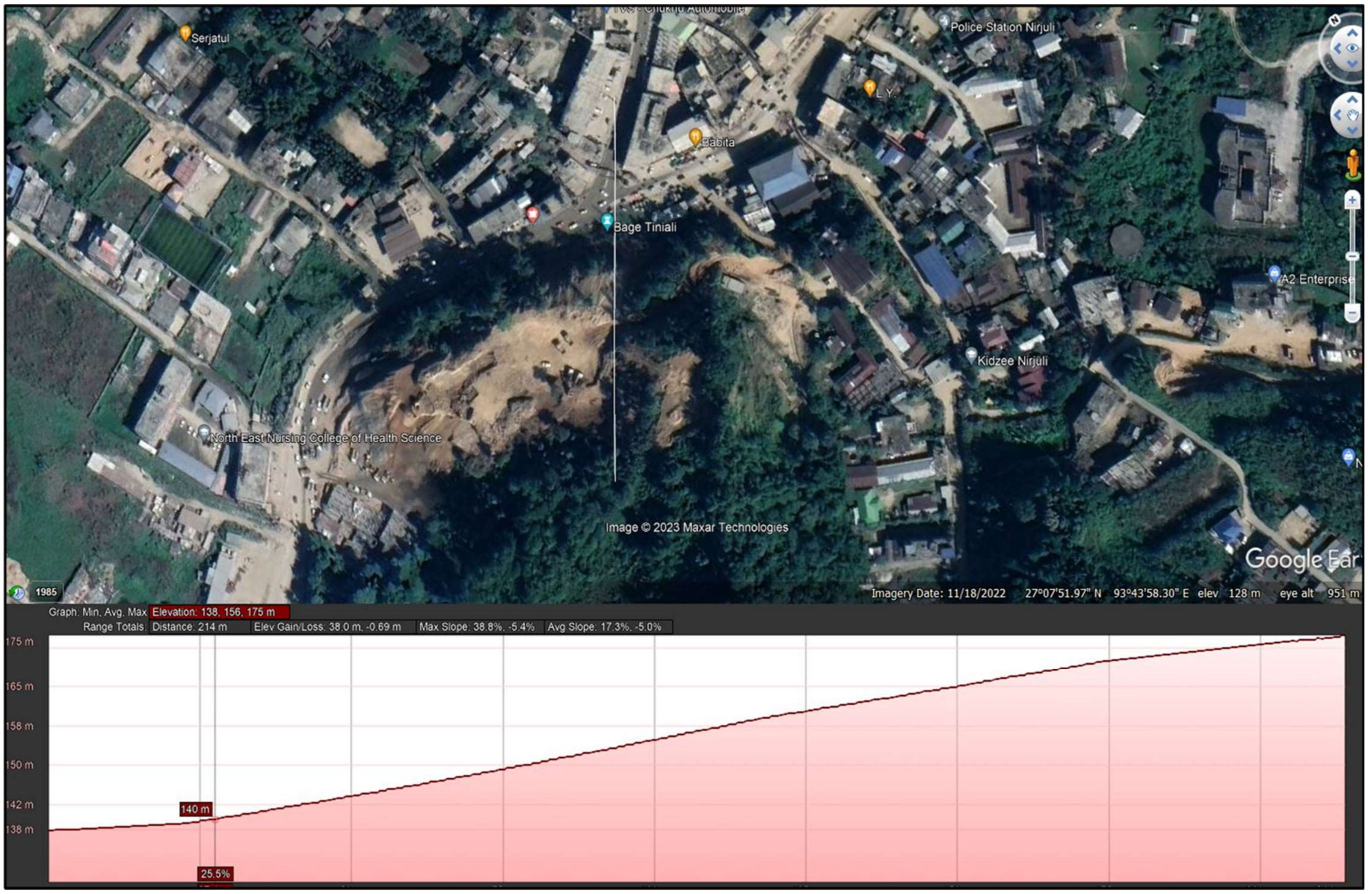


Figure 22: GIS photo of our site.

4.7 ANN Model Program: -

```
from google.colab import drive
drive.mount('/content/drive')

    Mounted at /content/drive

import pandas as pd
df = pd.read_csv('/content/100 DATA.csv')

df
```

	Density	C	Phi	H	slope angle	FS
0	1.4	0.36	26	50	30	1.934
1	1.5	0.70	27	50	30	2.279
2	1.6	0.70	35	50	30	2.543
3	1.4	0.63	15	55	40	1.855
4	1.5	1.12	16	55	40	2.010
...	...	...	...	...	...	...
95	1.6	1.33	10	65	60	0.954
96	1.4	0.36	26	50	30	1.934
97	1.5	0.70	27	50	30	2.279
98	1.6	0.70	35	50	30	2.543
99	1.4	0.63	15	55	40	1.855

100 rows × 6 columns

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

X = df.drop('FS', axis=1)
y = df['FS']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)

model = LinearRegression()
model.fit(X_train, y_train)

▾ LinearRegression
LinearRegression()

y_pred = model.predict(X_test)

import pickle

filename = 'finalized_model.sav'
pickle.dump(model, open(filename, 'wb'))

# load the model from disk
loaded_model = pickle.load(open(filename, 'rb'))
z =np.array([[2.02, 1.268,16.68 ,138.156,59]])
ans_predict = loaded_model.predict(z)

print(ans_predict)

    [4.12569209]
    /usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but LinearRegressio
      warnings.warn(
```

```
from sklearn.metrics import mean squared error, r2_score
mse = mean squared_error(y_test, y_pred)

r=r2_score(y_test, y_pred)
printf('mean squared error:',mse)
print("R-squared:", r2)

Mean squared error: 0.15117944466886843

R-squared: 0.8834918442183565

from sklearn.metrics import mean absolute_error, r2_score

mae = mean absolute_error(y_test, y_pred)
r2=r2_score(y_test,y_pred)

print("Mean absolute error:', mae)

print("R-squared:, r2)

Mean absolute error: 0.3201731990475847

R-squared: 0.8834918442183565
```

Through this project, we endeavor to demonstrate the remarkable capabilities of artificial neural networking to ascertain the factor of safety of slopes by utilizing various soil properties such as density, cohesion, height of slope, angle of internal friction, and slope angle. To achieve this, we commence by training our ANN models with a plethora of data procured from a reputable thesis paper, since conducting experimentation to generate the required data is unfeasible due to time constraints. For testing, we incorporate the values derived from our experiments. Once the ANN has generated a reliable model, we input the properties of soil for the location of interest and obtain the factor of safety with ease and precision.

CHAPTER-5: DISCUSSION AND CONCLUSION:

In this project, we present a cutting-edge approach to slope stability analysis in the challenging terrain of Bage Tinali, Nirjuli, Arunachal Pradesh. Through a rigorous process of in situ and laboratory testing, we compiled a vast dataset of slope stability data, including a wide range of soil parameters. This data was then carefully curated and analyzed to identify the factors that cause slopes to become unstable, allowing for the creation of a highly sophisticated input data set for their artificial neural network (ANN) system.

Using this advanced tool, we were able to accurately predict the factor of safety (FOS) of residual slopes to be 4.125 (with an impressive accuracy rate of approximately 88%), validating the effectiveness of the approach. To assess the predictive performance of this model, we used the performance indices R2, which demonstrated the excellent predictive performance of both ANN models.

One of the major advantages of utilizing ANN is its ability to continuously absorb new patterns and incorporate more training datasets over time, making it an economically viable and highly manageable approach compared to traditional experimental methods. In conclusion, this paper highlights the tremendous potential of ANN in slope stability analysis and geotechnical engineering and underscores the need for continued research and development in this field.

CHAPTER-6: FUTURE SCOPE:

As neural networks continue to grow, their potential to solve increasingly complex problems becomes more feasible. Doubling every 2.4 years, their power is becoming more accessible to the masses. One key area of development is integration with complementary technologies. Another area is the sheer complexity of neural nets, which can be scaled up in terms of power and speed to produce more efficient algorithms capable of processing large amounts of data with fewer examples.

Neural nets are also expected to expand horizontally, being applied to more diverse applications in various industries. However, there is a risk of obsolescence if neural nets cannot keep up with the pace of technological advancements, and developers and consumers may gravitate toward new approaches that offer more potential for solving complex problems.

Overall, the future of neural nets is likely to involve continued advancements in processing power, expansion into new applications and industries, and integration with complementary technologies, all while addressing challenges such as data privacy, algorithm bias, and ethical considerations.

Neural networks can now pick stocks, evaluate marketing prospects, approve loans, deny credit cards, tweak control systems, and inspect work. However, the future holds even more exciting possibilities. Neural networks need faster hardware and must become part of hybrid systems that also utilize fuzzy logic and expert systems. It is then that they will be able to hear speech, read handwriting, and formulate actions. They will become the intelligence behind robots who never tire nor become distracted. This technology will become the leading edge in an age of "intelligent" machines, revolutionizing the way we approach complex problems and making our lives more efficient and convenient.

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