LANDSLIDE PREDICTION OF KERALA USING MACHINE LEARNING

A PROJECT REPORT

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE
OF

MASTER OF TECHNOLOGY
IN
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Submitted by

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CANDIDATE’S DECLARATION

I, AISWARYA PADMADAS (2K21/GTE/03), students of M.Tech (Geotechnical Engineering),hereby declare that the project Dissertation titled **"Landslide prediction of Kerala using machine learning"** which is submitted by me to the Department of Civil Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

Place: Delhi AISWARYA PADMADAS

Date: 22.05.2023

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CERTIFICATE

I hereby certify that the Project Dissertation titled “Landslide prediction of Kerala using machine learning” which is submitted by AISWARYA PADMADAS, Roll No’s – 2K21/GTE/03, Department of Civil Engineering ,Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the 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.

Place: Delhi **Prof. RAJU SARKAR**

Date: 22.05.2023 **SUPERVISOR**

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ABSTRACT

Kerala is known as "God's own country" for its scenic beauty and unique features. Gorgeous landscapes and breathtaking backwaters have always been a blessing for Kerala. Hold of the Western Ghats and Arabian sea favors Kerala for providing torrential rain. But for the past few years, the scenario changed. In August 2018, a low-pressure system around the start of the month was followed by a monsoon depression several days later, resulting in a protracted period of exceptionally heavy rainfall in Kerala, which causes great lose of life and the estimated value of the infrastructure and buildings at $200 billion USD have been washed out. Kerala is experiencing ferocious rain as the effect of different anthropogenic and natural changes; also, the frequency of landslides has increased as a reflection of these. Prediction of those will help in hand for prevention.

This study focuses on developing a model for the prediction of landslides using Logistic Regression (LR), k-Nearest Neighbour (kNN), Naïve Bayes (NB), Decision Tree (DT), Random Forest (RF) and Support vector Machine (SVM); along with deep neural network algorithms like Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) was used, with training (70%), validation (15%), and testing (15%) datasets. Twenty-three factors were considered for the study, but five were eliminated after the multicollinearity test. Even though every model is giving satisfactory results, RF and CNN is giving exceptionally greater results of 0.95 and 0.94 for ROC-AUC and PR-AUC respectively. Not to mention the remarkable result of SVM model with 0.94 (ROC-AUC). Different accuracy checks used were ROC-AUC, PR-AUC, precision, accuracy score, F1-score, and log loss.

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LIST OF SYMBOLS AND ABBREVIATIONS

β	Regression coefficients
p	Probability of landslide occurance
z	Linear combination of factors
β	Regression coefficients
x	independent variables
δ	Standard deviation
δ	Standard deviation
μ	Mean
ω	Weight vector
E	Penalty parameter
α	Precision parameter
u	Bias term
υ_i, υ_i^*	slack variables
LR	Logistic Regression
kNN	K-Nearest Neighbor
NB	Naive Bayes
DT	Decision Tree
RF	Random Forest
SVM	Support Vector Machine
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
SWM	South West Monsoon
FRL	Full Reservoir Level

IMD	India Meteorological Department
IPCC	Intergovernmental Panel on Climate Change
IMD	India Meteorological Department
ROC curve	Receiver Operation Characteristic curve
PR curve	Precision-Recall curve
AUC	Area Under the curve
DEM	Digital Elevation Model
IMD	India Meteorological Department
IMD	India Meteorological Department
WGS	World Geodetic System
UTM	Universal Transverse Mercator
FAO -UNESCO	Food and Agriculture Organization of the United Nations- The United Nations Educational, Scientific and Cultural Organization
SRTM	Shuttle Radar Topography Mission
ORNL DAAC	NASA's Oak Ridge National Laboratory-Distributed Active Archive Center
CHRIPS	Climate Hazards Group InfraRed Precipitation with Station data
CHRIPS	Climate Hazards Group InfraRed Precipitation with Station data
SPI	Stream Power Index
TWI	Topographic Wetness Index
NDVI	Normalized Difference Vegetation Index

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

Landslides significantly damage both people and property. Due to the landslip, numerous ongoing infrastructure projects are stopped. Landslides affected about 4.8 million people worldwide between 1998 and 2007, resulting in an estimated 18000 fatalities. It has been difficult to analyse landslides because of their complexity. For effective prediction and mitigation, a wide range of various areas must work together extensively. Consequently, the outcomes of landslip susceptibility maps can be quite useful. Given the relative youth of the Himalayas, India is one of the nations most frequently hit by landslides, with more than 3000 fatalities reported between 2010 and 2019. The Himalayan range is distinguished by unstable geology with many faults because of its youth. The likelihood of landslides occurring is further increased by additional manmade variables, such as construction projects like dams and power plants.

According to [2], the monsoon season accounts for over 80% of India's yearly precipitation, and the country's population relies on this water for industry, hydration, and agriculture. Any variation in the monsoon rains' timing, length, and intensity has a significant impact on Indians' quality of life. Devastating food catastrophes have occurred in a few different regions of India recently. For instance, Mumbai's fooding on July 26, 2005, when the entire city received 942 mm of rain in one day, was the worst ever recorded [3]. Similar to this, more than 340 mm of rain fell in the state of Uttarakhand on June 17, 2013, causing catastrophic flooding and unprecedented losses in terms of both life and property [4, 5]. Another similar instance is the November 2015 Chennai floods, which cost over 500 lives when Chennai received three times the average rainfall [6]. Extreme rains in India cause an annual loss of $3 billion in agriculture, which accounts for 10% of all economic losses worldwide [7].

Kerala, a relatively tiny state in the southwest of the Indian Peninsula with a total size of 38,863 km2, often receives rain in the sort of of monsoon rain and thundershowers for approximately six months out of the year. Compared to other regions of the Indian subcontinent, Kerala's yearly rainfall varies quite little. But there had at least been one; historians have remarked that 1924 was one of such atypically rainy years, with 3368 mm of rain falling during the course of three weeks. This precipitation event in 1924 specifically took place during the southwest monsoon (SWM) season. Between 1 June and 26 August 2018, during the current SWM rainfall events, 36% more rain fell than usual for that time period (IMD 2018), albeit being 50% less than the 1924 event. Kerala, which is divided into the highland (above 75.0 m), midland (between 7.5 and 75.0 m), and coastal plain (below 7.0 m) physiographic divisions, displays a variety of geomorphic features, including the tall mountain peaks of Anaimudi (2695 m), 41 short-run west-flowing rivers, and a coastal plain dotted with numerous lagoon and barrier systems. For instance, numerous areas of the coastal plains (Vembanadkayal, Kuttanad, and the Kole lands of Thrissur) have a floor that is lower than the mean sea level, according to [8, 9]. In the highland and/or middleland, many of the shortrun rivers have dams and multi-use water storage reservoirs. The catchments of the Western Ghats experienced sporadic episodes of high rainfall (for example, 177.5 mm on August 17, 2018, in Idukki), which brought reservoirs to their Full Reservoir Level (FRL) and forced the release of extra water through flood gates (Duncombe, 2018). A portion of the Pathanamthitta, Alappuzha, Kottayam, Idukki, Ernakulam, Thrissur, and Wayanad districts were flooded as a result of the discharge of extra water. Hundreds of thousands of people had to be relocated to secure shelters as a result of the flooding caused by the dam release that overwhelmed large built-up areas and small towns downstream of the basins. 445 people died as a result of flooding in the Achankovil, Pamba, Manimala, Meenachal, Moovattupuzha, Periyar, and Chalakudi river basins, which also uprooted riverside trees and damaged or destroyed homes, businesses, roads, and other civil infrastructure. The affected land also experienced heavy siltation.

In order to formulate future plans and permits, assess damages, determine the amount of compensation due, and choose the best possible land use and land planning in flood-affected and -prone areas, it is urgently necessary to assess flood inundation [10, 11]. Satellite remote sensing data are an excellent tool in disaster management due to the availability of synoptic views and reviews. However, optically sensed satellite data won't be much use because persistent cloud cover obscured visible and near-infrared sensor acquired images over Kerala throughout SWM season [12]. Additionally, data on the magnitude of floods must be recorded before the water recedes, unlike other natural hazards, or else the traditional indirect-terrestrial flood fingerprints must be found and counted. Cloud-penetrating, active radar sensors operating in the microwave area can be employed for flood inundation studies regardless of cloud cover, as shown by [13–15].

1.2 BRIEF ABOUT LANDSLIDES

A land slide is defined as a situation in which soil, rock mass, or other material slips down a hill. According to [16,17], its process is characterised by the movement, flow, or fall of materials as a result of gravity operating down the slope. It was challenging for experts to come up with a consensus definition for the landslide due to the landslides' extreme intricacy. A thorough research of the region's history landslides is essential for identifying the areas that are more vulnerable to landslip occurrence. This is due to the fact that future landslip events will be more likely to occur in the places that are more likely to be affected by landside disasters. In order to effectively and accurately map previously occurring landslides, Geographic Information System (GIS) techniques can be used [18–22]. Landlsides are mainly classified as 6 by [1]. They are falls, topples,

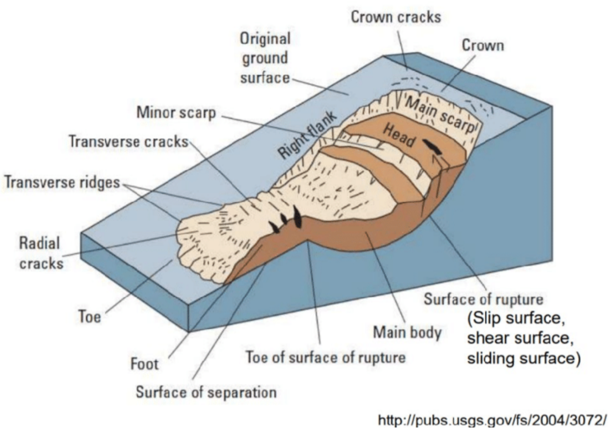


Figure 1.1: Diagram of landslide used for illustration [1]

slides, lateral spreads, flows and complex which is a combinatio of pricipal movement types, it can be of 2 or more. Various parts of these kinds of movement is illustrated [23]

Figure 1.1. [24] listed a number of elements that contribute to landslip tragedies. They can be anthropogenic, physical, geological, or morphological in nature. Either directly or indirectly, they start the landslip. Sometimes, some manmade or man-made elements, such as blasting, volcanoes, dams, etc., can also indirectly contribute to the occurrence of landslides.

1.3 LITERATURE REVIEW

Flood and related mass movement of rock, debris, and earth has constantly threatened humanity. The influence of anthropogenic factors in the same is also a point out of the question; due to the same, vulnerability is difficult to predict [25]. Hundreds of lives are lost yearly due to landslides [21](Yalcin et al., 2011). Fundamental factors affecting landslides can be classified as predisposing, triggering, and acceleration [26]. Lithology and morphology can be considered as predisposing factors [27, 28] and land modification can be regarded as an accelerating factor [29]. When rainwater infiltrates, the groundwater level increases, which reduces the shear strength of the soil; also, the slope instability increases, so as to consider intense rainfall as a triggering factor. [26, 30–35]. For a developing country like India, high population density is an adjunct to hazardous problems [36]. Responsible factors for landslides are plenty; deforestation, construction of roadways and other buildings on the slope, blasting, etc., are examples. Different researchers have studied the influence of socio-economic and geo-environmental factors on landslides [37] but making the ground vulnerable due to the impact of physical and anthropogenic factors was to be discussed in detail.

South India, chiefly Kerala, belongs to a tropical region; receiving 80% of the annual rainfall in the month from June to September [38] and belongs to the landslide-prone hazardous zone, which covers 15% of India's total area [39–42] National Disaster Management Authority 2019. Having the influence of both the Arabian Sea and Western Ghats; with an average population density of 860 persons per square kilometer, is also a topic of discussion regarding dire climatic changes [2,43,44]. 39 Kerala State Emergency Operation Centres have to established around Kerala by Kerala State Disaster Management Authority 2016 as per Kerala State Disaster Management Plan 2016 as this state have been identified as multi-hazard-prone state and landslides are an incessant problem, especially in monsoon season. The current Intergovernmental Panel on Climate Change (IPCC) assessment [45] states that flooding in the Asian monsoon region along with other tropical places is anticipated to increase, and wet extremes are projected to grow more severe in numerous regions where mean precipitation is anticipated to rise. According to several research [7, 46–49], extreme rainfall events would likely become more frequent in India as a result of global warming. Since monsoon depressions are typically linked to extreme events over central India [50], intensification of extreme rainfall events may be related to changes in the dynamics of monsoon depressions [51]. It is unclear, however, if monsoon depressions are to blame for the excessive rainfall occurrences in these models due to the coarse granularity of the international climate models [52]. According to [50] , monsoon depressions are frequently associated with extreme weather over central India, hence amplification of severe thunderstorms may be linked to modifications in the seasonality of monsoon depressions [51]. However, due to the coarse granularity of the worldwide climate models, it is unclear if monsoon depressions account for the high rainfall occurrences in these models [52].

Studies regarding landslide prediction have always been helpful in arresting upcoming problems. These studies were conducted on a note of some assumptions; (i) the probability of occurrence of landslides in the future will be more in the areas which have been subjected to the landslides in the past.; (ii) environmental information and physical models can be used to compute explorations and reports which are an essential source of information for evaluating spatial frequency of landslide occurrence; (iii) evidences of previously occuring landslides can be easily recognized, classified and mapped.; and (iv) experimental, statistical and deterministic models can be applied to evaluate the landslide occurrence, which is primarily governed by physical laws. [15, 53]. Also, these studies as a whole may be classified as quantitative and qualitative approaches [54–57]. Quantitative methods are more frequently used nowadays, which is a data-driven physical approach (by analyzing landslide history and the conditioning parameter for the same) in comparison with seeking expert opinion like qualitative approach [57–61]. Machine learning is simply allowing computers to learn without programming explicitly. ML has shown its supremacy in every science and technology domain and has never failed to deliver high results compared to the traditional approach [28, 62, 63]. LR and kNN are machine learning (ML) algorithms, a multivariant quantitative method used to associate between dependent and independent variables [64–66]. DT is a real problem solver in AI field with discrete dataset [67]. NB's performance is to be said surprising for many classification problems [65]. In order to discover the best separation hyperplane, SVM, a machine learning technique that utilises statistical learning theory, convert the first input field into a better-dimension three [68–70] feature space.RF is a particular kind of classifier that uses multiple trees for sample training and prediction. With sufficient samples, ANN, a complicated and adaptable nonlinear statistical approach, can produce accurate predictions for a classification [71]. A further advantage of ANN is that it implements less onerous information requirements, which is one of its main advantages that is available regarding the nature of the links between the data being processed and its manner of distribution [72]. The fundamental process of RF is creating a decision tree for each collection of features after selecting them at random from the dataset [73, 74].

Logistic regression always has a promising spatial prediction for landslides [75], for which it is widely used [76]. There are works where LR outcompetes more sophisticated methods like artificial neural network (ANN) [77], so LR shows better performance in comparison with multi-criteria decision analysis [78]. k-Nearest Neighbour is a lazy learner algorithm that doesn't learn from the given data set but memorizes. kNN is a simple classifier algorithm that comes in handy for these kinds of works [79]. Naïve Bayes' and Decision Tree is considered as the best 10 algorithms used for the data mining according to IEEE. DT gives great accuracy in landslide model making for the future study and prediction [30, 80]. Similar was confirmed for susceptibility mapping also, which uses the classes of landslides for study [81]. Even though Naïve Bayes' is used in many such works, the accuracy and application is limited [82]. Processing extends of this algorithm for both discrete and continuous dataset with much about of variables is notable [83, 84] , but the consideration of factors taken as independent is not applicable in real life situations [81].

1.4 RESEARCH GAP

From the literature review, this study mainly aims to predict landslides in Kerala using machine learning techniques. There are researches regarding this kind of work for Idukki, Kerala, one of the districts affected by the 2018 flood [44, 48]. But the fact that it was only restricted to Idukki is surprising, without taking into account the dynamic effect's variation at even smaller administrative divisions. Given the 2018 Kerala flood, which was disastrous, according to Kerala State Disaster Management Authority (KSDMA), the whole Kerala needs to be taken for the study, and the same is done here.

Different resercher considered different set of data for these kinds of study and there is no particular mapping system between them. Also a proper understanding about the correlation between these factors are important. Finding the proper dataset of causative factors is important for any kind of studies related to natural hazards, especially landslides. From the literature review, a serious lack of knowledge between those are seen which in return effects for the accuracy of the model developed.

The relationship between the independent and dependent variables can be mapped using machine learning, which makes no assumptions and can be modified to fit the data. Although there are several non-computer science fields where machine learning, or ML, is used, such as investigating the impact of different types of natural disasters, the use of ML to address the problem related to landslides is not consistently demonstrated in the literature. This kind of study is helpful for the authority to take appropriate action against unforeseen mass movements and also put forward the possibility of considering the whole area for research, as the effect of climatic change is unpredictable.

1.5 OBJECTIVES

The following are the primary research goals that have been established for this research work:

1. Understanding more about the causative factors affecting landslides, along with the correlation among.

2. Identity landslide-prone area in the considered study area and make a landslide inventory map from the past landslide events.

3. Predicting the landslide posibility for the study area considering the available dataset using different machine learning algorithms; along with finding the accuracy of those.

4. Coupling more sophisticated, high level machine learning- deep neural networks like ANN and CNN.
5. Developing a system which predicts the possibility of landslide corresponding with the change in environmental conditions as the data is fed.
6. Bringing up a more understandable illustration sytem.

CHAPTER 2

STUDY AREA

The study was conducted in the state of Kerala (10.8505° N, 76.2711° E), India, which spreads over 38,863 km^2 as illustrated in Figure 2.1. Geographically, Kerala shares its border with Tamil Nadu on east and south, north and northeast with Karnataka and the Arabian Sea on the west. Kerala stands in the 21st position in account of the population of India, with 14 districts and one union territory. Being occupied in the southwest corner of India, Kerala is blessed with around 550 km run of Arabian sea and is well protected by Western Ghats, nearly 21856 km2 or 56% of the state's total geographical area, as per Kerala Forest Department.

Kerala is one of India's states that receives both southwest monsoon (85% of rainfall) and northeast monsoon with copious rain, making the area highly vulnerable to landslide hazards and flooding. The average temperature in the area varies between 27 to 45 degrees Celsius though out the year. The highest point in Kerala is Anai Mudi, with an elevation of 2695 m, and the lowest point is Kuttanad at -2.2m, below sea level. There are 44 rivers in Kerala that are mostly short in length and flow from Western Ghats to the Arabic Ocean but run faster; also, there are 34 backwaters that cover an area of 200 km^2. Slope in the area changes from 00 to 780.

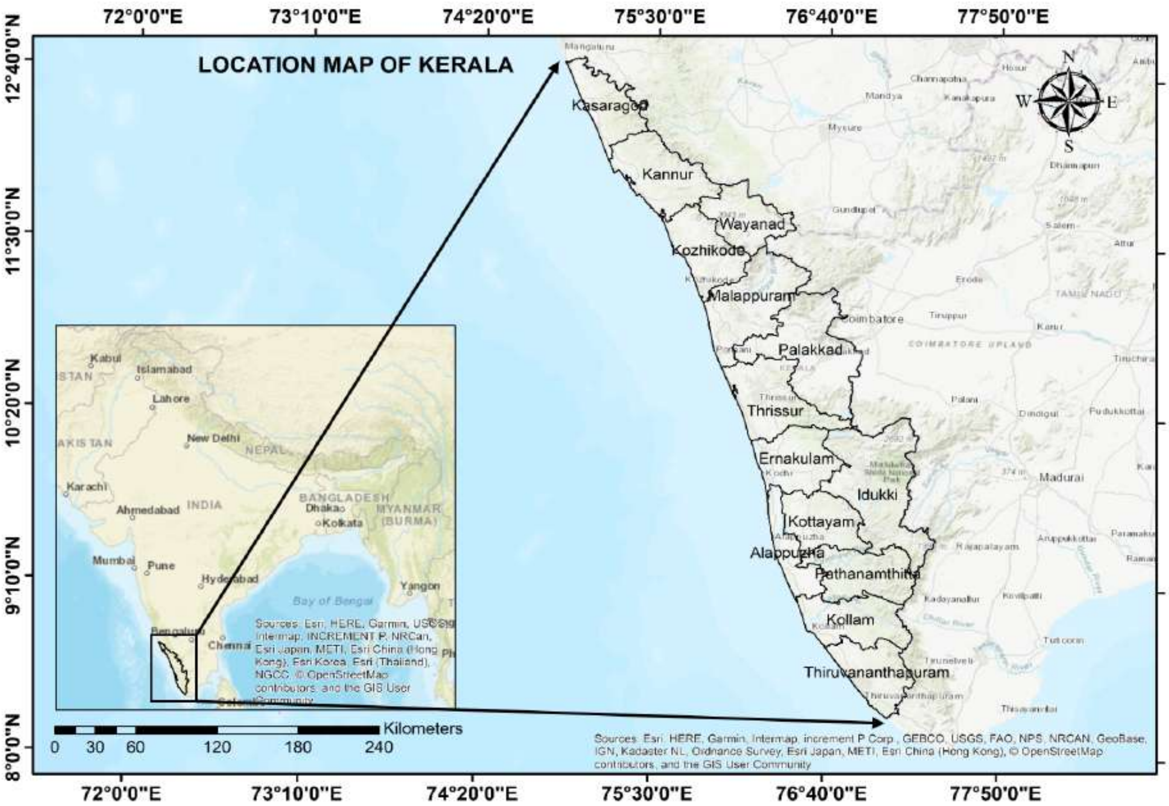


Figure 2.1: Study area

CHAPTER 3

METHODOLOGY

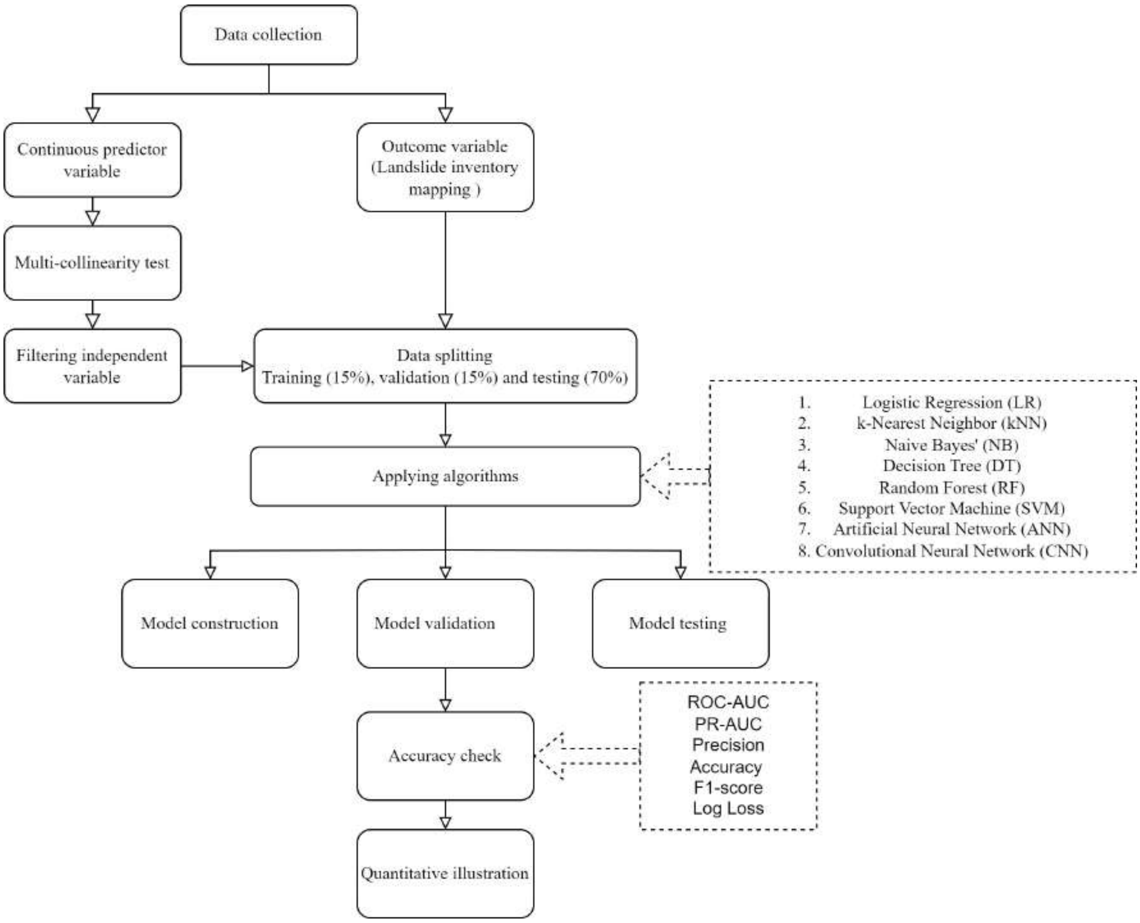


Figure 3.1: Methodology of the proposed study

The technique for this investigation is organised and includes many steps where multivariate models have been used to analyze the past landslide history and present output of future prediction. A flowchart with basics steps adopted is shown in Figure 3.1.

3.1 DATA COLLECTION

Data needed for the study was either collected from appropriate sources or derived from the Digital Elevation Model (DEM) using ArcGIS 10.8. 24 sets of data was used in this study and details of each is mentioned in the proceeding sections. Sources, format and such details are provided in the Table 3.1. All data was collected for atemporal resolution of the past 10 year upto 2021; except landslide data. Whole dataset in projected to the WGS 1984 UTM Zone 43N coordinate system.

Table 3.1: Details of the data used

Sl No	Factors	Sources	Format, resolution and unit
1	Clay content	FAO-UNESCO	GeoTIFF, 30m, meters
2	Deforestation	Derived from LULC (2021) and LULU (2005)	GeoTIFF, 30m, NA
3	Drainage density	Derived from DEM	GeoTIFF, 30m, meters
4	Elevation	NASA SRTM DEM version 3	GeoTIFF, 30m, meters
5	Geology	FAO-UNESCO	GeoTIFF, 30m, meters
6	Geomorphology	Bhukosh-Geological Survey of India	GeoTIFF, 30m, meters
7	Lineament density	Derived from lineament data (BHUVAN)	GeoTIFF, 30m, meters
8	Lithology	Bhukosh-Geological Survey of India	GeoTIFF, 30m, meters
9	LULC (2005)	ORNL DAAC	GeoTIFF,10m, NA
10	LULC (2021)	USGS land use map of Sentinel-2 satellite	GeoTIFF,10m, NA

11	Population density	NASA's SEDEC	GeoTIFF, 30m, people/sq.km
12	Rainfall intensity	CHRIPS	GeoTIFF, 30m, meters
13	Road density	Derived from road map (BHUVAN)	GeoTIFF, 30m, meters
14	Sand Content	FAO-UNESCO	GeoTIFF, 30m, meters
15	Silt Content	FAO-UNESCO	GeoTIFF, 30m, meters
16	Temperature	MODIS	GeoTIFF, 30m, Celsius/year
17	Slope angle	Derived from DEM	GeoTIFF, 30m, degrees
18	Slope aspect	Derived from DEM	GeoTIFF, 30m, degrees
19	Curvature	Derived from DEM	GeoTIFF, 30m, 1/meters
20	Profile curvature	Derived from DEM	GeoTIFF, 30m, 1/meters
21	Curve plan	Derived from DEM	GeoTIFF, 30m, 1/meters
22	Stream Power Index (SPI)	Derived from DEM	GeoTIFF, 30m, Watts/sq.mtr
23	Normalized Difference Vegetation Index (NDVI)	Derived from DEM	GeoTIFF, 30m, NA
24	Topographic Wetness Index (TWI)	Derived from DEM	GeoTIFF, 30m, NA

3.1.1 Lithology

Changes in rock and rock formation influences fluctuation in the various types of geo-hazards [85] [77] [86]. One study by [87] found that the presence of soft lithologies, such as clay, marl, and silt, increased the susceptibility of slopes to landslides. Another study by [88] identified that sedimentary rocks with weak bedding planes and faults were more prone to landslides. In addition, the mineral composition of lithologies can also affect their susceptibility to landslides. For example, the presence of clay minerals in shale and mudstone can increase their tendency to swell and shrink, leading to the development of tension cracks and ultimately landslides [89]. Furthermore, the weathering of lithologies can also influence landslides. For instance, a study by [90] found that the degree of weathering of sandstone and shale can affect the strength and stability of slopes, with heavily weathered slopes being more prone to landslides.

Overall, these studies demonstrate the significant influence of lithology on the occurrence and characteristics of landslides. There are 39 unidentified lithological factors in the state of Kerala. The Figure 3.2 shows the map corresponding.

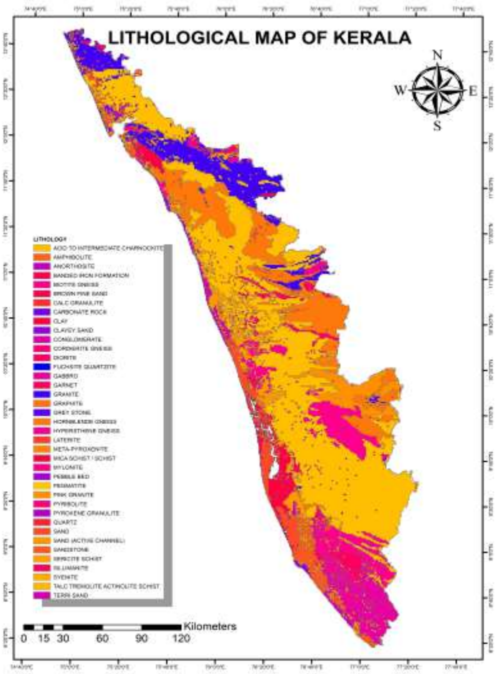


Figure 3.2: Lithology map

3.1.2 Geology

The geological characteristics of a slope can influence its susceptibility to landslides, as well as the type and magnitude of landslides that may occur. When the location is geologically weak with fractured rock, high content of clay minerals or even the presense of slates, phyllites or weathered schists can led to fall due to human interference [37, 91]. Other points to be noted while considering geology is weathering,the degree of weathering of the rock or soil can also influence its stability. Weathering can weaken the rock or soil, making it more prone to sliding. In some cases, weathering can create a layer of weak material within the slope that can act as a sliding plane [87, 88]. The presence of groundwater can influence landslides by increasing pore water pressure within the slope. This can reduce the strength of the rock or soil and make it more prone to sliding [90, 92]. 9 classes for geology was found with different combinations as shown in Figure 3.3.

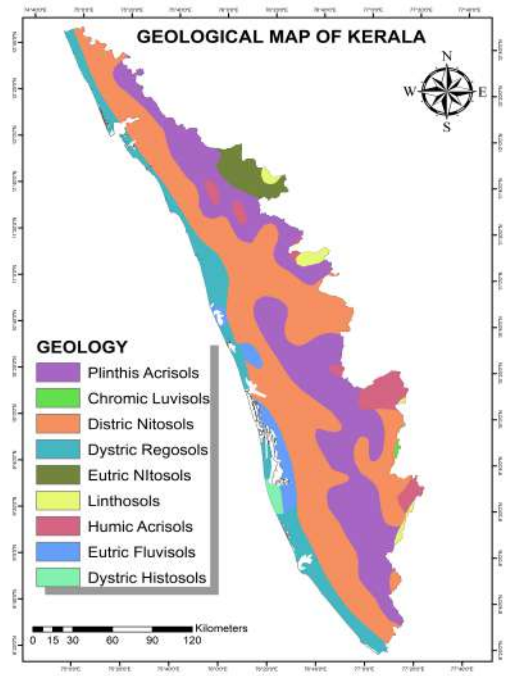


Figure 3.3: Geological map

3.1.3 Drainage density

Drainage density refers to the amount of stream channels, rivers, and other waterways in a given area. High drainage density can increase the likelihood of landslides occurring by reducing the slope's ability to retain moisture and increasing the amount of water that can infiltrate the slope. In addition, high drainage density can increase the amount of pore water pressure within the slope, which can reduce the slope's stability. A number of studies have investigated the relationship between drainage density and landslides. For example, a study by [93] found that drainage density was a significant factor affecting landslide occurrence in Lantau Island, Hong Kong. Similarly, a study by [69] found that there was a positive correlation between drainage density and landslide occurrence in the eastern Black Sea region of Turkey.

As for a state like Kerala with a strong influence of sea and rivers, high drainage density can be a contributing factor to landslides. Density varies from 600 to a few 6000 meters as moving away Figure 3.4.

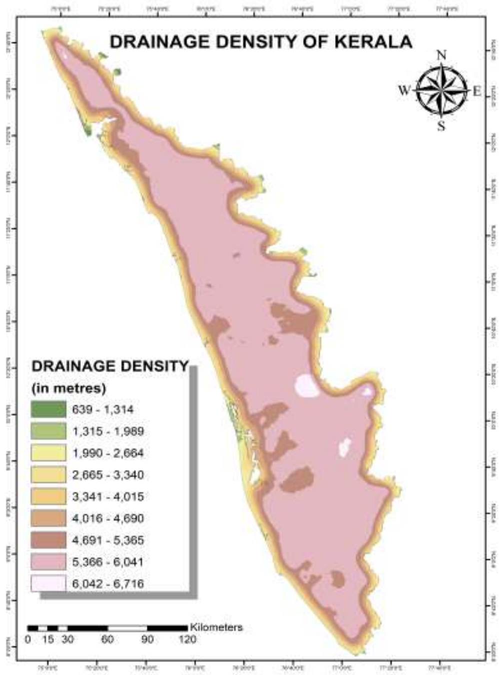


Figure 3.4: Drainage density map

3.1.4 Deforestation

Deforestation can have a significant impact on landslide occurrence. It is known that plant roots can restrain land movement. Deforestation for expanding agricultural land is consideredd a cause of landslides, just as slope cutting [37]. Trees and vegetation help to stabilize slopes and prevent soil erosion by absorbing water and holding the soil in place. When trees are removed, the soil is more susceptible to erosion, and the slope stability can be reduced [53]. This can increase the risk of landslides in deforested areas.

Though deforestation is not much prevail in Kerala as major part of of the state is covered with Western Ghats as illustrated in Figure 3.5. But considering to the points where is it present, and taking into account of landslide points; deforestation have strong influence in landslides too.

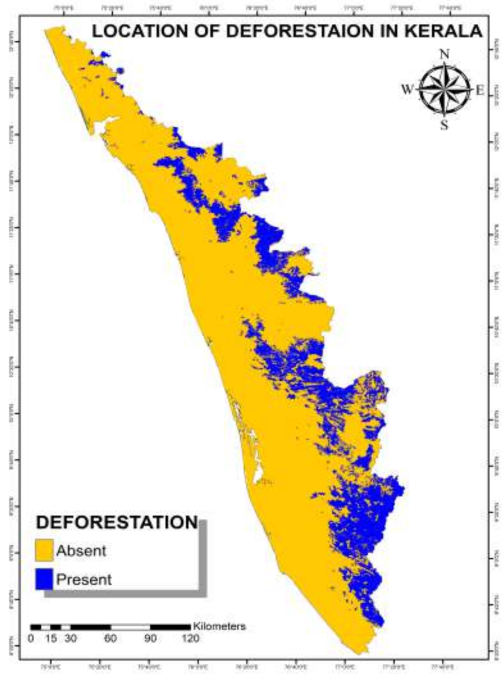


Figure 3.5: Deforestation map

3.1.5 Road density

By modifying the natural drainage patterns, causing more erosion, and affecting the stability of the slope, roads can have a substantial impact on the occurrence of landslides. For road construction, materials will be removed from the foot causing serios stability problems [44, 94]. Roads can affect slope stability through changes in soil moisture, surface water runoff, and alterations to the natural drainage patterns [95]. Road density was considered as the density of roads were an important factor at a single point. It is clear from the map that there are no much road access in mountain ranges. Map is shown in Figure 3.6

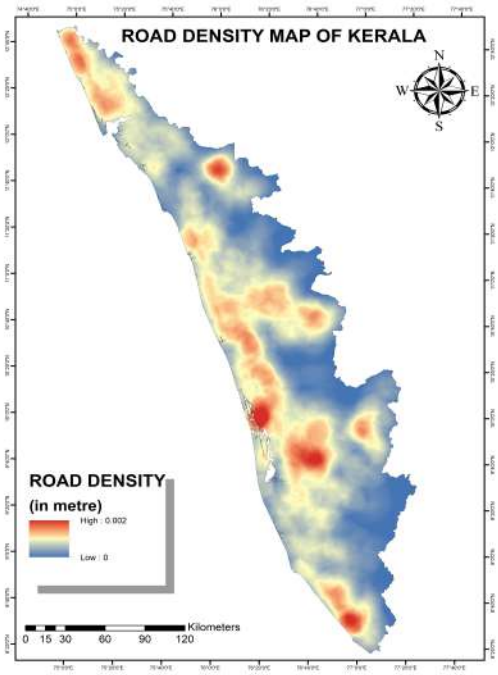


Figure 3.6: Road density map

3.1.6 Rainfall intensity

Rainfall is a significant factor in the occurrence of landslides, as it can increase the weight of soil and rock and reduce their strength, leading to slope instability. High-intensity rainfall can also increase the pore water pressure in soil, reducing the effective stress and shear strength, which can trigger landslides [96]. Moreover, long-term rainfall patterns can contribute to soil saturation and changes in vegetation, leading to an increased susceptibility to landslides. Many studies have investigated the relationship between rainfall and landslides. For example, one study in Taiwan found that rainfall intensity was the most significant factor in landslide occurrence [97]. Another study in Italy found that rainfall played a significant role in triggering landslides, especially during extreme rainfall events [98]. Additionally, research has shown that changes in rainfall patterns due to climate change may lead to an increased frequency of landslides in certain regions [99].

Overall, rainfall is a crucial factor to consider in landslide susceptibility and risk assessment, and it is important to understand its influence on the stability of slopes and the potential for landslides to occur. For a state like Kerala were the annual average rainfall is about 3107mm (7,030 crore m^3 of water), rainfall intensity is a serious problem to be look forward to (Figure 3.7).

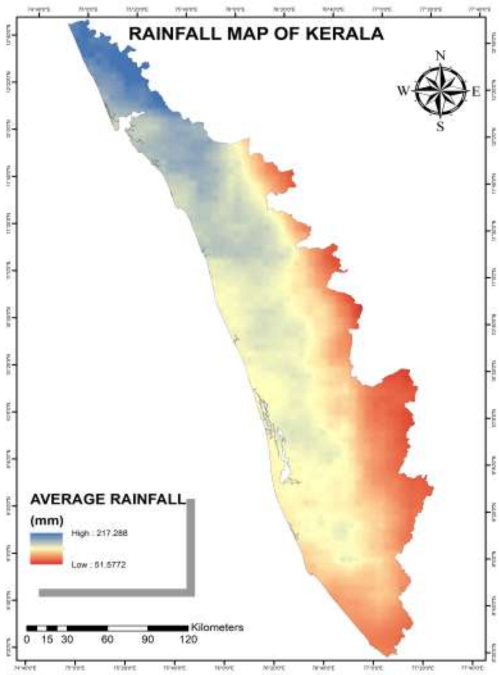


Figure 3.7: Rainfall intensity map

3.1.7 Elevation

The elevation is most crucial topographic factor determining slope angle which effects slides [44]. Steeper slopes are more prone to landslides, particularly when combined with other factors such as heavy rainfall or seismic activity [37]. High elevations in mountainous regions also increase the likelihood of landslides due to the presence of rock outcrops, cliffs, and steep slopes. Additionally, elevation can affect soil moisture, with higher elevations often experiencing cooler and wetter conditions that increase the likelihood of landslides [100]. Highest elevation in Kerala is of 2694 meters from mean sea level. But also, Kuttanad (District of Alappuzha and Kottayam) is about 2.2 meters below sea level which makes the locality highly suspectible for flood with even a small rain(Figure 3.8).

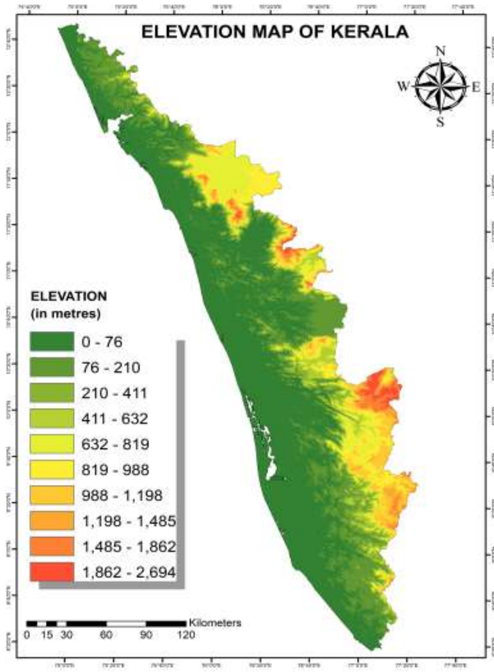


Figure 3.8: Elevation map

3.1.8 Temperature

Temperature can also influence landslides by affecting the stability of slopes. For example, freezing and thawing cycles can cause soil to expand and contract, which can weaken the slope and increase the likelihood of a landslide. Similarly, high temperatures can cause soil to dry out and become more brittle, which can also increase the likelihood of slope failure [101]. Temperature can also indirectly affect landslides by influencing factors such as vegetation growth and the amount and intensity of rainfall. Also, changes in shear bands due to frictional heating for clayey materials caused landslides from the secondary phase of creep [102]. Kerala neither experience extreme summer nor winter, so the average temperature ranges between 27 to 45;though not to avoid the fact that there are places in Kerala with acute winter and summer like Idukki and Palakkad respectively. Map is shown in Figure 3.9

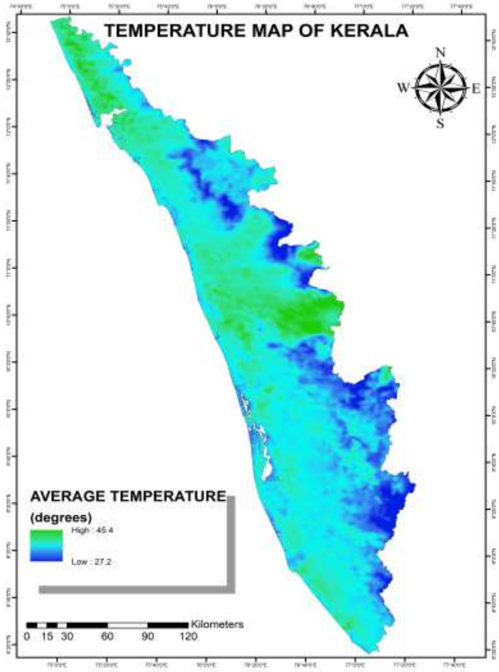


Figure 3.9: Temerature map

3.1.9 Land Use/Land Cover(LULC)

Land Use/Land Cover (LULC) changes can have significant impacts on the stability of slopes and the occurrence of landslides. Human activities such as deforestation, urbanization, and agricultural practices can alter the natural state of the land, leading to changes in soil structure, vegetation cover, and drainage patterns, which in turn affect the susceptibility of slopes to landslides. For example, deforestation can increase soil erosion, decrease the binding capacity of roots, and reduce the stability of the slope. Urbanization can lead to the removal of vegetation and soil compaction, which can increase runoff and decrease infiltration, leading to higher pore water pressure and higher likelihood of landslides. Agriculture can also have similar effects, with soil compaction and waterlogging leading to higher susceptibility to landslides [103]. Large portion of Kerala is covered with water bodies as there are numerous rivers in Western Ghats region as shown in Figure 3.10.

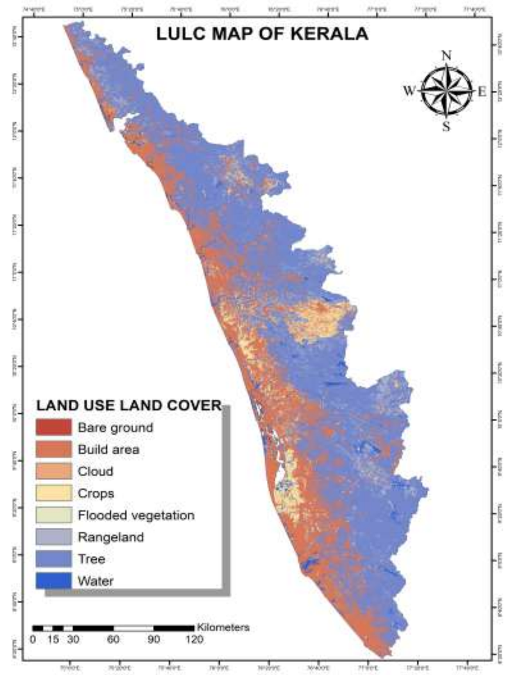


Figure 3.10: Land Use/Land Cover (LULC) map

3.1.10 Geomorphology

Geomorphology, the study of landforms and their evolution, plays an important role in understanding the occurrence and distribution of landslides. Factors such as slope angle, slope aspect, slope curvature, and topography can all influence the potential for landslides. In addition, the presence of certain landforms, such as valleys, ridges, and scarps, can be indicators of past landslides or potential landslide activity. The presence of erodible fines and deposits of coarse gravels with cemented nature triggers landslides [104]. The geomorphological features, such as ridges, valleys, and drainage systems, also play a role in landslide occurrence and propagation. The interaction between these features, such as drainage diversion by ridges and valleys, can affect the hydrological conditions and trigger landslides. Moreover, the degree of slope inclination, curvature, and aspect orientation can contribute to the instability of the slopes [105]. 18 geomorphological (Figure 3.11)classes are there in Kerala, which also include a great range of coastal plain as Kerala shares border with Arabian Sea.

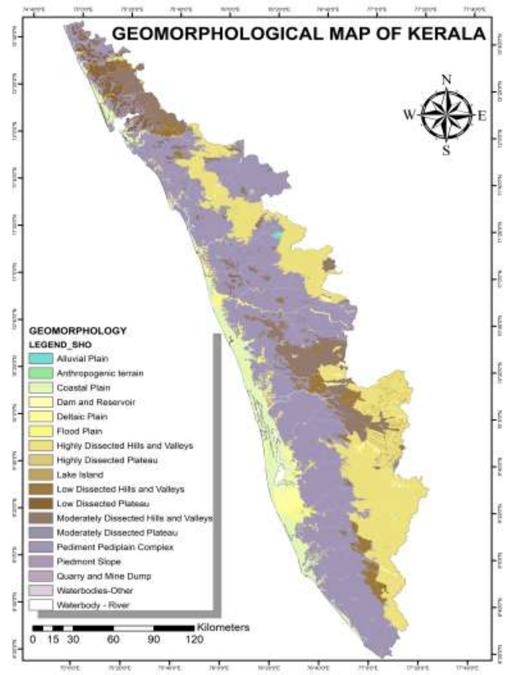


Figure 3.11: Geomophological map

3.1.11 Lineament Density

Lineament density is a geo-environmental factor which can be an important factor in landslide occurrence, as fractures and faults in the bedrock can provide pathways for water infiltration and can weaken the stability of slopes [106]. Higher lineament density can lead to a higher chance of landslides [107]. This factor doesn't seem to effect to the study area much. Value of the factor changes from 0 to a few 0.0004 meters Figure 3.12.

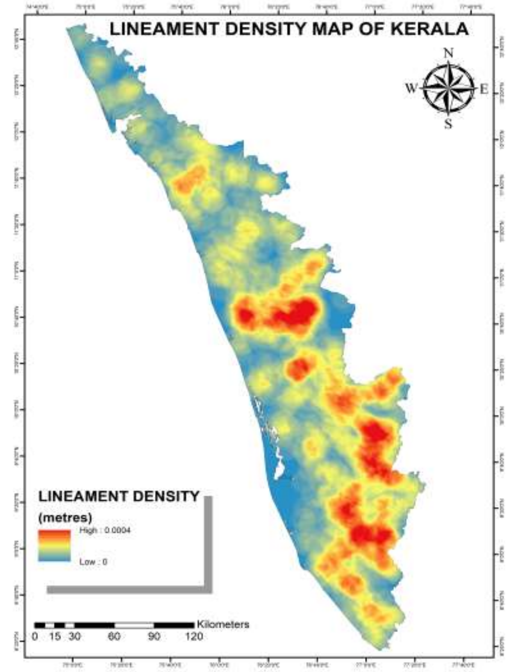


Figure 3.12: Lineament density map

3.1.12 Slope angle

Slope angle is a key factor that can influence landslides. In a way, it indicates the relation between shear stress and shear strength [44].Generally, as slope angle increases, the likelihood of landslides also increases. This is because steeper slopes are more prone to soil and rock instability, and the force of gravity pulling downhill is greater [53].Research has shown that there is a threshold slope angle beyond which landslides become more frequent and severe. The exact threshold varies depending on factors such as geology, soil properties, and rainfall patterns, but studies have suggested a range of threshold slope angles from 25 to 40 degrees [87]. Kerala is particularly known for it's mountain ranges along border to Tamil Nadu. Starting from 0, slope angle increases to almost 79^o, which make those places very vulnerable for landslides. Map is shown in Figure 3.13

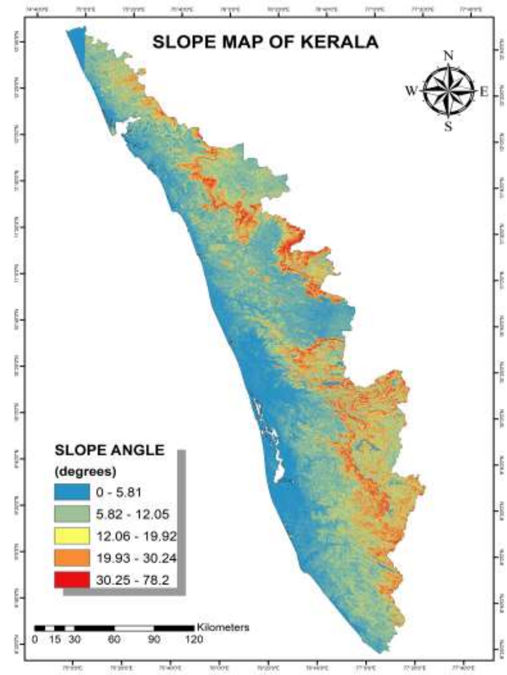


Figure 3.13: Slope angle map

3.1.13 Population density

Population density can have an influence on landslides as human activities such as urbanization and construction can alter the natural landscape and destabilize slopes [76]. Higher population densities can also increase the likelihood of people living in areas prone to landslides, leading to greater exposure and vulnerability. Population of Kerala is around 33,406,061 spread over 38,852 sq km, which gives an average density of 860 person/sqkm, as illustrated in Figure 3.14.

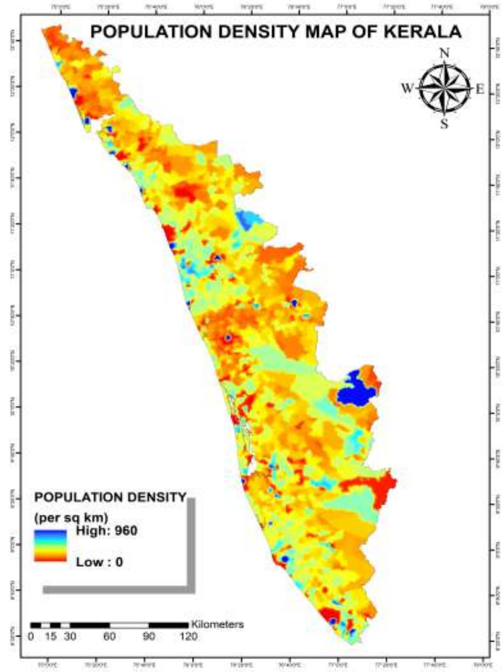


Figure 3.14: Population density map

3.1.14 Content of silt, clay and sand

Soil properties such as silt, clay, and sand content can influence the occurrence and behavior of landslides. The resistance of soil and texture classes can be better understood from the percent of clay, sand and silt [37, 108] Silt and clay can contribute to landslides by increasing the water-holding capacity of soils and decreasing soil strength, while sand content can increase the drainage capacity of soils and provide additional strength.

Studies have shown that high silt and clay content can increase the susceptibility of slopes to landslides. For example, a study in Taiwan found that slopes with high clay content were more susceptible to landslides triggered by rainfall events [90]. Similarly, a study in Brazil found that high silt and clay content were the most important factors influencing the occurrence of shallow landslides in a mountainous area [66]. On the other hand, high sand content can also affect landslide occurrence. For example, a study in Italy found that slopes with high sand content were more susceptible to debris flows triggered by intense rainfall [109]. The map showning content of silt, clay and sand is illustrated as Figure 3.15, Figure 3.16 and Figure 3.17 respectively.

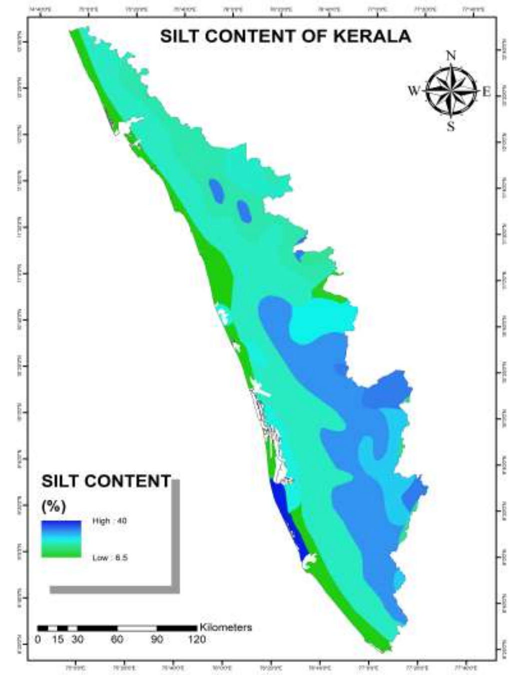


Figure 3.15: Silt content map

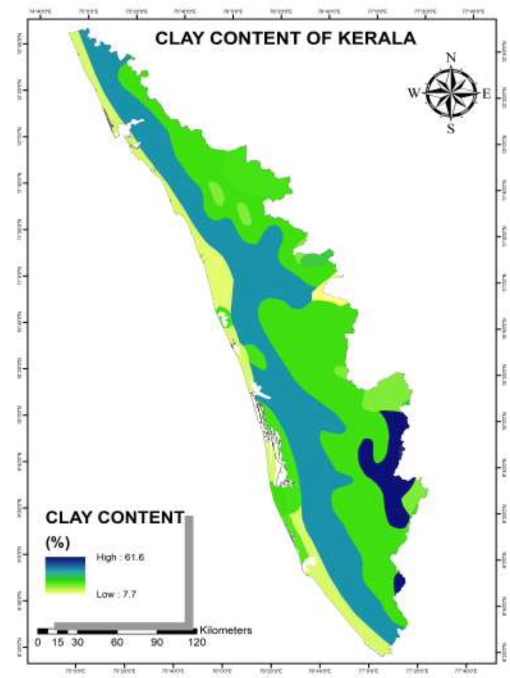


Figure 3.16: clay content map

3.1.15 Stream Power Index (SPI), Topographic Wetness Index (TWI) and Normalized Difference Vegetation Index (NDVI)

SPI is a measure of the ability of water to erode soil and rock. It takes into account both the slope and the drainage area of a particular point on a landscape. Higher SPI values indicate greater erosive potential and are generally associated with higher landslide

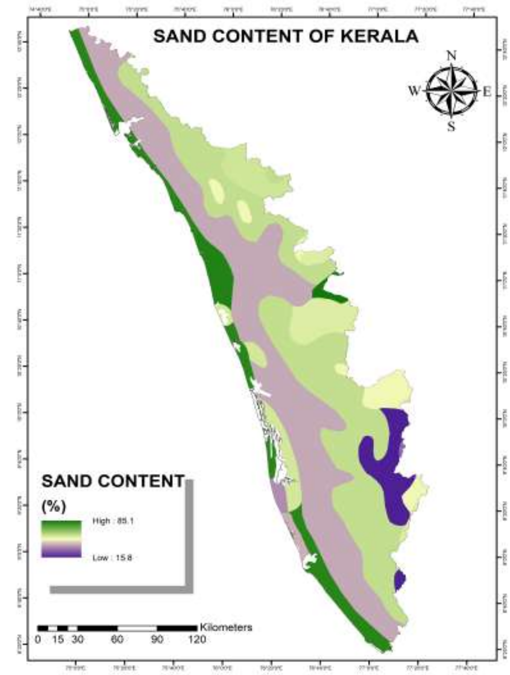


Figure 3.17: Sand content map

susceptibility (Figure 3.18). TWI is a measure of the ability of a landscape to retain water. It is calculated by dividing the upslope contributing area by the slope angle. Higher TWI values indicate greater water accumulation and saturation, which can increase the likelihood of landslides (Figure 3.19). NDVI is a measure of vegetation greenness and density, and is commonly used to assess vegetation cover and health. Higher NDVI values are associated with greater vegetation cover and health, which can help stabilize slopes and reduce the likelihood of landslides (Figure 3.20).

Studies have found that SPI and TWI are positively correlated with landslide occurrence, while NDVI is negatively correlated. For example, [110] found that SPI and TWI were significant predictors of landslide occurrence in the Three Gorges Reservoir Area in China, while NDVI had a negative correlation with landslide occurrence. Another study found that SPI and TWI were important predictors of landslide occurrence in a mountainous area in Japan, while NDVI was not significant [26].

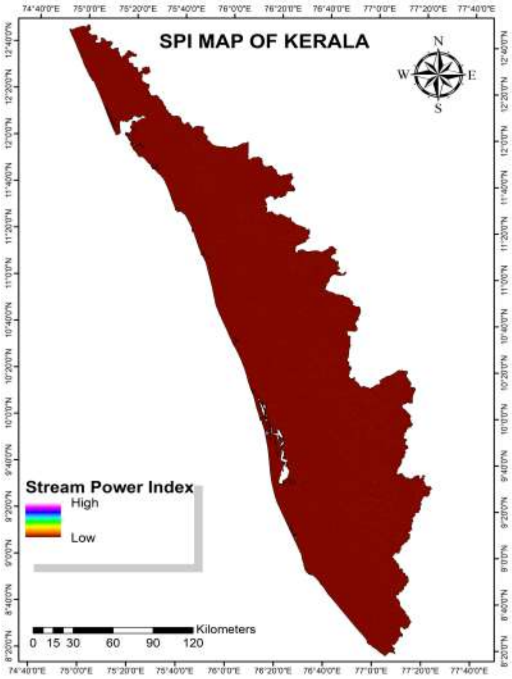


Figure 3.18: Stream Power Index (SPI) map

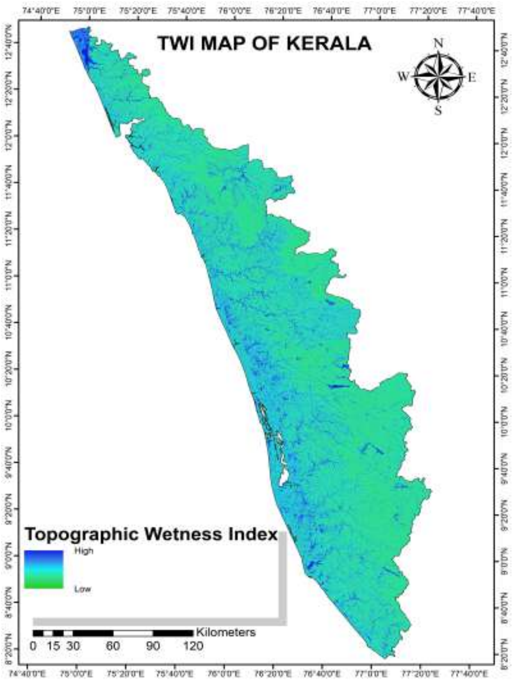


Figure 3.19: Topographic Wetness Index map

3.1.16 Curvature, profile curvature and curve plan

Curvature (Figure 3.21), profile curvature (Figure 3.23), and curve plan (Figure 3.22) are topographic measures that can influence landslide occurrence. These measures are calculated based on the topography of an area and can provide insights into the

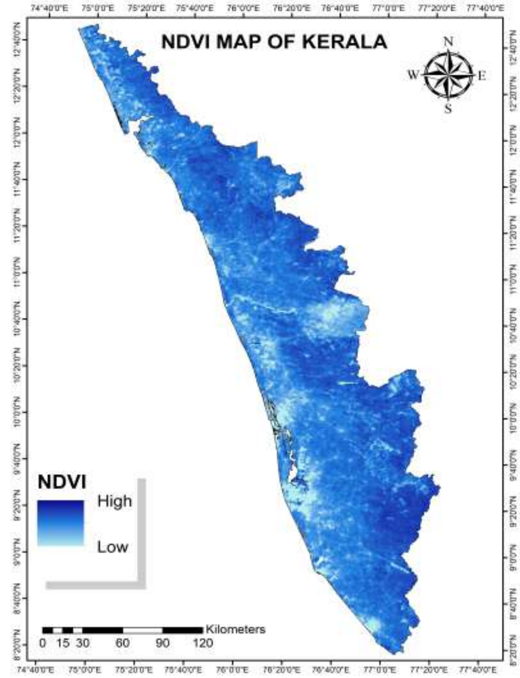


Figure 3.20: Normalized Difference Vegetation Index (NDVI) map

shape and curvature of the landscape.

Curvature refers to the amount of surface curvature in a given area, and it can be classified as positive (convex), negative (concave), or flat. Profile curvature is the curvature along a line that is perpendicular to the contour lines of the topography, while curve plan is the curvature along a line that is parallel to the contour lines. Studies have shown that areas with high positive curvature, particularly in steep slopes, are more prone to landslides. Positive curvature can cause soil or rock to be more susceptible to erosion, leading to instability and eventual landslide occurrence. On the other hand, flat or negative curvature areas are less susceptible to landslides. Profile curvature can also affect landslide occurrence. Areas with high positive profile curvature indicate areas where the slope angle changes abruptly, increasing the risk of instability and landslides. Curve plan can also provide information about the direction of slope, which can affect the distribution of landslide occurrence.

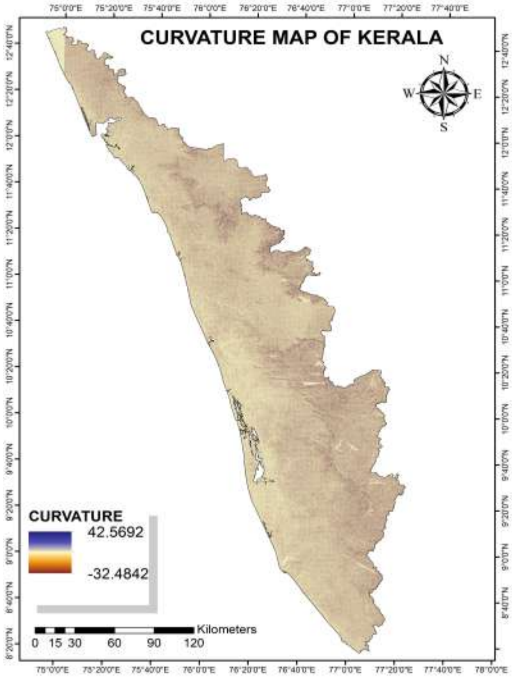


Figure 3.21: Curvature map

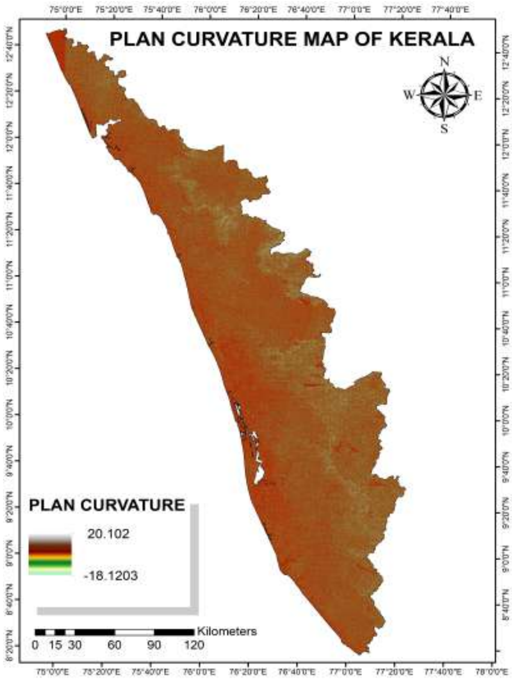


Figure 3.22: Plan curvature map

3.1.17 Slope aspect

Slope aspect can have a significant effect on the occurrence of landslides. For example, in a study conducted by [111], it was found that slopes with a northern aspect were more susceptible to landslides compared to those with a southern aspect. This is

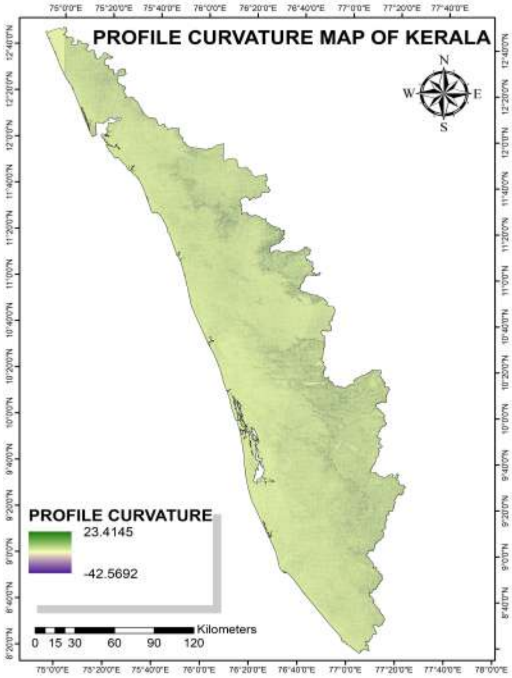


Figure 3.23: Profile curvature map

because northern slopes receive less sunlight, leading to more moisture retention and slower evaporation rates, which can increase soil saturation and instability. Another study b [60] also found that slope aspect played an important role in landslide occurrence, with south-facing slopes having a lower susceptibility to landslides compared to north-facing slopes. The authors attributed this to the higher solar radiation on south-facing slopes, leading to faster evapotranspiration and lower soil moisture content. Map is shown in Figure 3.24

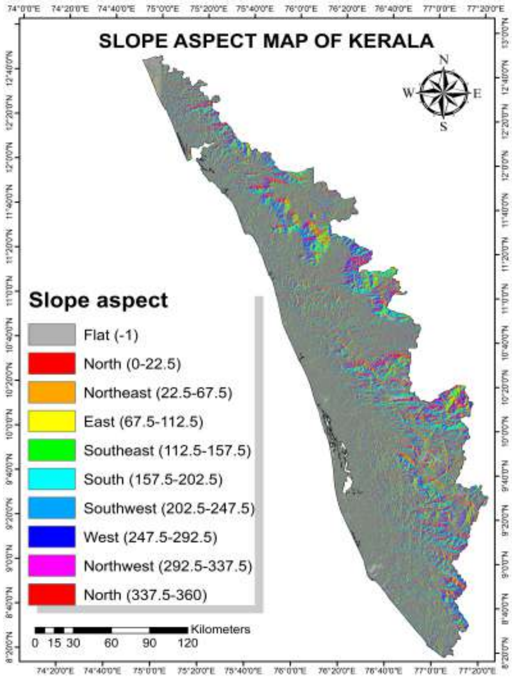


Figure 3.24: Slope aspect map

3.2 LANDSLIDE INVENTORY MAPPING

Landslide inventory mapping (Figure 3.25) was done by the proper understanding of the past and present landslides. It is the process of identifying, documenting, and mapping landslides in a particular area. It involves the systematic collection and analysis of data related to landslides, such as their location, size, type, and other relevant characteristics. It can be done for various uses, such as understanding the susceptibility, hazard and risk assessment, investigating the distribution pattern and type, or maybe finding the probability of landslides with respect to the factors [112]). Landslide inventory mapping can be included by the location, date of occurrence and the type of mass movement. The parameters that must be selected for the map preparation depend on the work. For the work done, landslide data was collected from Bhukosh-Geological Survey of India. 3142 data points were collected, most of them because of the rise in pore pressure due to the intense rain. Of the data collected, 83% was due to debris, 10.3 by rock, and 3.4 by soil. The translational movements were mostly sliding (66%), flow (29%), and subsidence (2.3%). When it comes to failures, it was due to shallow translational, rotational and planar, and a few by deep rotational mechanisms. Among the collected data, 70% was taken for training and 15% for validation and testing.

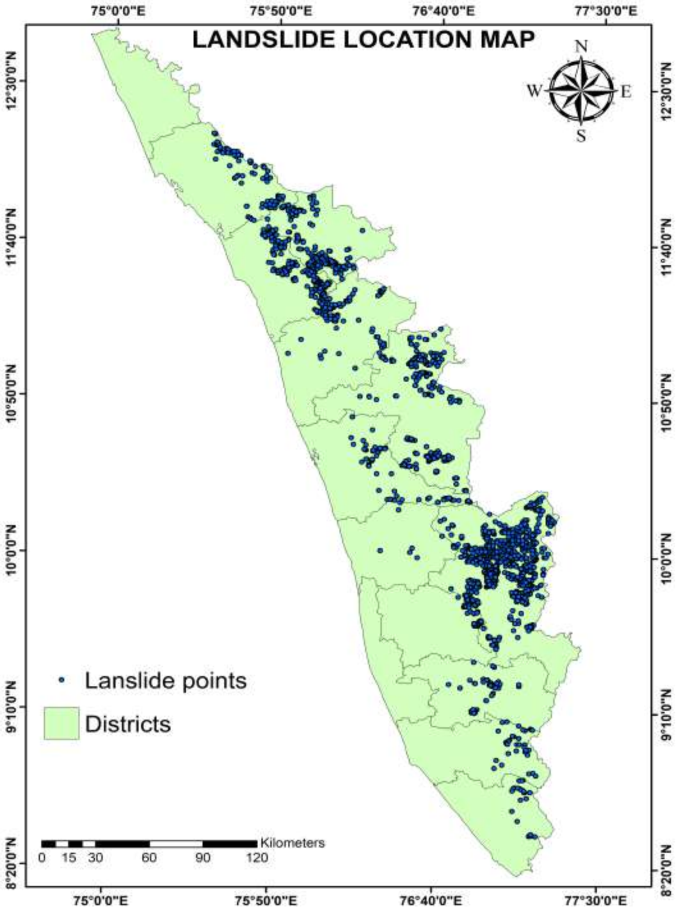


Figure 3.25: Landslide inventory map

3.3 MULTICOLLINEARITY TEST

Multicollinearity refers to a high degree of correlation between independent variables in a statistical model. Multicollinearity (or collinearity) can occur when there is a linear relationship between one independent factor for a regression model to another [113]. In the context of assessing landslide causative factors, it is important to test for multicollinearity among the variables to ensure the reliability and interpretability of the model results [95]. The basic point of any linear regression model is finding perfect regression coefficients representing the data. Consider the equation:

$$y = \beta_0 + \beta_1 + \beta_2 + ... + \beta_p \tag{3.1}$$

These regression coefficients represent the slope of each variable used, and for those to be optimal, the squared error value should be low.

$$\beta = (X^T X)^{-1} X^{-1} y \tag{3.2}$$

where β is the vector that includes the regression coefficients and X is the matrix with predicting variables. $X^T X$ should be invertible in order to find β, which is the assumption taken. But if any multicollinearity is present, the term $X^T X$ won't be invertible.

Calculating VIF (Variance Inflation Factor) and Tolerance is the simplest method to find multi collinearity.VIF measures the degree of multicollinearity by assessing how much the variance of an estimated regression coefficient is inflated due to collinearity. VIF is calculated by taking a particular variable and regressing it with others. It estimates how much the variance of a coefficient is inflated. Tolerance is the reciprocal of VIF (1/VIF), and it represents the proportion of variance in a variable that is not explained by other independent variables. Tolerance values below a certain threshold indicate high multicollinearity.

$$VIF = \frac{1}{1 - R^2} \tag{3.3}$$

$$Tolerance = 1 - R^2 \tag{3.4}$$

Factors with VIF>5 and Tolerance>0.2 [37] was wiped out.

3.4 ALGORITHMS USED

Supervised regression is used for the analysis of the data in this study, which was done using 8 machine learning models (6 classification algorithms and 2 deep learning algorithms). For model development, dataset is classified as 3. Training (70%), validation (15%) and testing (15%). Programming interface used is Python and tuning have been done until better accuracy is achieved. Pre-processeing of data is also been done to greater accuracy.

3.4.1 Logistic Regression (LR)

Logistic regression was first introduced in the late 1960s [114]; from the basics of the central mathematical concept for the logit-natural logarithm [115]. LR is a multivariate regression method [44] for studying and validating the relation between categorical outcome variable (dependent factor) and continuous predictor variable (independent factor) [62]; by finding the best fit algorithm; which also provide with low error [116]. According to the logit-natural algorithm; LR can be quantitatively calculated as:

$$p = \frac{1}{1+e^{-z}} \tag{3.5}$$

here p is the probability of landslide occurrence. It forms the shape of a S curve and varies between 0 and 1. z is the linear combination of the factors taken and can be expressed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n = \ln \frac{p}{1-p} \tag{3.6}$$

β_o is the intercept condition, and β_1, β_2, $\ldots \beta_n$ are the regression coefficients which indicates the augmentation coefficient for independent variables $x_1, x_2 \ldots x_n$. Also, the term $\frac{p}{1-p}$ is odd or likelihood ratio. also y is the outcome variable. [77, 117, 118]. Bivariate models are generated by fitting between the variable of interest and each distinct covariate in the forward iterative approach.The working model is then updated with the most important covariate. The most important covariate is kept in the working model at each subsequent stage as new variables are introduced one at a time. As a result, the effects of the previously introduced covariates are accounted for while each additional covariate is modelled. No additional covariates are included in the model if none are found to be significant at a predetermined level of confidence [119].

3.4.2 K Nearest Neighbor (kNN)

kNN is a lazy learner classification algorithm, as it is not learning anything; that is widely used due to its simple implementation and distinguished performance [120]. kNN model use object classification to distinguish between both in this problem. By using the Euclidean distance function, algorithm can classify unknown entities with similar properties [121]. The basic assumption of the algorithm is that the variables used should come under the same class irrespective of the weight subordinate. The Euclidean equation can be explained as:

$$d(p,q) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \tag{3.7}$$

here p and q are the independent variables in n dimension. kNN techniques calculates the weights of each parameter and each sum up over for landslide events.

$$L_p = \sum_{i=1}^{k} W_{i,p} m_i \tag{3.8}$$

m_i is the independent variable and $W_(i,p)$ is the pixel weight and corresponding L_p is the landslide prediction. The number of neighbors thus formed will be changed for better accuracy and reliability [122].

3.4.3 Naïve Bayes' (NB)

Naïve Bayes' combines Bayes' theorem of conditional probability and Naïve's assumption of independence [98]. Also, this model gives equal priority to every factor taken. Considering the assumption of factors being completely independent to each other is practically, this model is always open for modification [123, 124] which is also called as conditional independence assumption. As NB doesn't need any intricated parameter for iteration, it has good computational efficiency and low variance [119]. The primary benefit of the NB classifier is its simplicity in construction, as it does not require complex iterative parameter estimation methods. Moreover, the NB classifier demonstrates resilience towards noise and irrelevant attributes [110].Posterior probability in this case is:

$$y = argmaxP(y_i) \prod_{i=1}^{n} P\frac{x_i}{y_i} \tag{3.9}$$

Also, conditional probability is:

$$P(x_i \mid y_i) = \frac{1}{\sqrt{2\pi\delta}} e^{-\frac{(x_i-\mu)^2}{2\delta^2}} \tag{3.10}$$

Here x_i is the predictor variable and y_i is the outcome variable. Whereas μ is mean and δ is standard deviation [84, 110, 125].

3.4.4 Decision Tree (DT)

DT is capable of identifying non-addictive and non-linear relationships between predictor variable and outcome variable [126]. It is a non-parametric model used to make tree like structure in hierarchical model [96, 105]. DT can simply be described with a tree form, where root note which represent top prioritised predictor variable. From which it splits to decision nodes (internal nodes), then to terminal nodes (leaf nodes). A binary decision will be taken in each node, which further split it into required. The taller the tree, higher the accuracy [116, 126]. Even though with complex relationship between the variables, DT wins to create a model; which is in fact considered as one of the greatest advantages [127]. Also the ability to tackle with both continuous and categorical value should be noted [128]. Categorizing factors with their importance and easily understandable result construction are other advantages of DT. Considering the hypothesis of predictor variables being independent, basic DT algorithms in practise are, classification and regression tree (CART) [129], Iterative Dichotomizer version 3 (ID3) [130] and C4.5 [131]. Also, each algorithm uses entropy and information gain as follows [132]:

$$H(D) = -\sum_{i=1}^{n} P_i \log_2 P_i \tag{3.11}$$

where H is entropy (considering Boltzmann's H-theorem) [43]. It is written with a consideration of having n classes with D domain. Information gain measures the reduction to be expected in entropy [133], and it is defined as:

$$Gain(D,A) = H(D) - \sum_{v \in Values(A)} \frac{|D_v|}{|D|} H(D_v) \tag{3.12}$$

here $Value(A)$ is the domain of predictor attribute $(A).D_v \subseteq D$ for each $v = Value(A)$.

3.4.5 Random Forest (RF)

Random Forest, developed by Breiman in 2001, is a ensemble and supervised model which uses decision tree to use independently connect subset with bootsrapping [134]. The bootstrap aggregating, or bagging, method is a general strategy that the teaching algorithm for random forests uses to train tree learners. RF can handle categorical and continuous data as well as data with several dimensions [135]. Random selection is utilised at each split node and is known to provide great accuracy rates for outliers in predictors since it is based on two data items, namely proximities and out-of-bag (OOB) data [73]. In every step of RF, each hyper parameter is split properly. The biggest advantage of using RF is the elimination of overfitting. It exhibits excellent robustness with regard to big feature sets, hence it is not necessary to pre-select variables;it doesn't increase the possibility of overfitting; achieving excellent performance often requires minimal fine-tuning of parameters and it provides metrics indicating the importance of variables. RF is highly recommended for high-dimensional problems with nonlinear factors [64].

3.4.6 Support Vector Machine (SVM)

A fairly recent supervised teaching technique called Support Vector Machines is based on the structural risk reduction principle and statistical learning theory. SVM implicitly converts the original space of input into a highly dimensional space of features using the training data [70].The best hyper plane in the property space is then found by maximising the margins of the class boundaries. Support vectors are used as training vertices that are greatest to the ideal hyperplane. The classification of fresh data can be done using the decision surface once it has been received [68].

Consider x_i as input dataset and y_i and output corresponding for $i = 1,2,3,...,n$. The optimization function for finding the optical hyperplane is minimizing the equation [70, 136]:

$$Minimize \frac{1}{2}||\omega||^2 + E\sum_{i=1}^{n} \upsilon_i + \upsilon_i^* \tag{3.13}$$

this should be subject to:

$$y_i - \omega\varphi(x_i) - u \leq \alpha + \upsilon_i \tag{3.14}$$

$$\omega\varphi(x_i) + u - y_i \leq \alpha + \upsilon_i^* \tag{3.15}$$

$$\upsilon_i, \upsilon_i^* \geq 0 \tag{3.16}$$

here, ω, E, α, u and $\varphi(x_i)$ are weight vector, penalty parameter, precision parameter, bias term and kernal funtion respectively. Where as υ_i, υ_i^* are slack variables [136].

3.4.7 Artificial Neural Network (ANN)

It is feasible to model a network of connected nodes using artificial neural networks for issues like landslides when relationships between the causes and effects are complex. In the literature, numerous neural network algorithms have been put forth. Multi-layer perceptron (MLP) neural networks and radial basis function (RBF) neural networks are the two most widely used ANNs in landslip analysis.The MLP Neural Nets' structure, activation strategies, and connection weight updating techniques all have an impact on how well they work [137]. According to [138], A layer of input, any number of layers that are hidden, and a result layer are common components of ANNs. While the total amount of input neurons is equal to utilising specific training data, the quantity of landslip variables selected for reconditioning and the number of concealed neurons are calculated. The connection of parameters connecting the The back-propagation approach with two phases was used to initialise the concealed input neuron, undetected, and output neurons. Forward transmission of the input occurs through the layers during the forward phase, producing an output layer response. Estimated between-target and between-output and response values gap. The connection weights were adjusted in the backward phase to reduce the difference.

Using artificial neural networks for multi-source segmentation involves two stages: the classifying stage and the training step, during which the internal weights are changed. The back-propagation approach typically trains the system until a specific minimal error among the desired and observed outputs of the network is reached. The network is utilised as a feed-forward structure after training to create a classification for all the data [139].

3.4.8 Convolutional Neural Network (CNN)

A hot topic in machine learning is deep learning. Additionally, a well-known deep learning model that draws its inspiration from the biological vision system is the convolutional neural network (CNN). The "Neocognitron" – the forerunner of CNN – was suggested by [140]. Then, in the 1990s, LeCun and his colleagues introduced the contemporary CNN framework, which they later refined. CNN multi-layer neural networks are capable of obtaining an image's key feature representations. As a result, these networks are capable of identifying visual rules in an image without the use of a sophisticated rule created by an expert [141]. Each "hidden" layer in a CNN typically consists of convolutional and pooling layers, with convolutional layers serving as the primary structural component of any CNN [142].

The deep learning community continues to debate the ideal design for a CNN to achieve the highest performance depending on the application [143]. It includes a fully connected layer, two learnt convolutional layers, two pooling layers with an average and a maximum pooling, and two pooling layers. Change detection in the potential landslip zones can be done using CNN.From the binary image of the potential landslip area, the binary image of the modified area was created. The range of suspect locations in the binary image of the changing area has been narrowed from the potential landslip areas to the zone where the changes primarily take place [144].

3.5 ACCURACY CHECK

The basic elements of accuracy check are: true positive TP (accurately classified positive cases), true negative TN (accurately classified negative cases), false positive FP (negative cases classified as positive), and false negative FN (positive cases classified as negative) [108]. These elements are used in the confusion matrix with positivity in the y-axis and predictions in the x-axis for the calculation of the following:

$$TruePositiveRate(TPR) = \frac{TP}{TP+FN} \tag{3.17}$$

$$TrueNegativeRate(TNR) = \frac{TN}{TN+FP} \tag{3.18}$$

$$FalseNegativeRate(FNR) = \frac{FN}{FN+TP} \tag{3.19}$$

$$FalsePositiveRate(FPR) = \frac{FP}{FP+TN} \tag{3.20}$$

$$PositivePredictiveValue(PPV) = \frac{TP}{TP+FP} \tag{3.21}$$

Receiver operating characteristics (ROC) curve: ROC plotted with TPR against FPR. It is a plot of the power as a function of the Type I Error of the decision rule. The area under the curve (AUC) give the 2D area under the ROC, which represents the probability of possibility directly. Here AUC is classification-threshold-invariant is used as it can measure the quality of model prediction [107].

Precision-Recall (PR) curve: Precision (PPV) and recall (TPR) are the 2 fundamental terms by which the accuracy can be calculated on a minority scale [22]. PR curve is a plot of precision on the y-axis and recall on x-axis. PR-AUC summarizes the threshold values in the curve to a single score.

Precision: is the degree by measurement under the same condition gives the same result. It implies the variation level in the values for different measurement. Precision is same as positive predictive value.

F1-Score: through the harmonic means; it combines precision and recall. It can be expressed by the following equation:

$$F1 - Score = 2 * \frac{(Precision * Recall)}{Precision + Recall} \tag{3.22}$$

Accuracy score: accuracy is a matric describing how the model works for all classes. It can be calculated as the ratio of all correct predictions with total predictions.

$$Accuracy = \frac{Truepositive + Truenegative}{Truepositive + Truenegative + Falsepositive + Falsenegative} \tag{3.23}$$

Log Loss: shows the closeness of the predicted probability with the actual value. The log-loss value also increases when the value deviates from the original value.

$$Logloss = -\frac{1}{N}\sum_{i=1}^{N}[y_i \ln(p_i) + (1 - y_i)\ln(1 - p_i)] \tag{3.24}$$

here N is the number of observations, y is the actual value of observation and p is predicted value of observation.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 MULTICOLLINEARITY TEST

The outcomes of the multicollinearity test are depicted in Figure 4.1and Figure 4.2. From the results obtained, factors that increase VIF than 5 and tolerance greater than 0.2 is neglected. As per the results; for the development of models, factors like clay content, sand content, curve profile, curve plan and curvature have been removed.

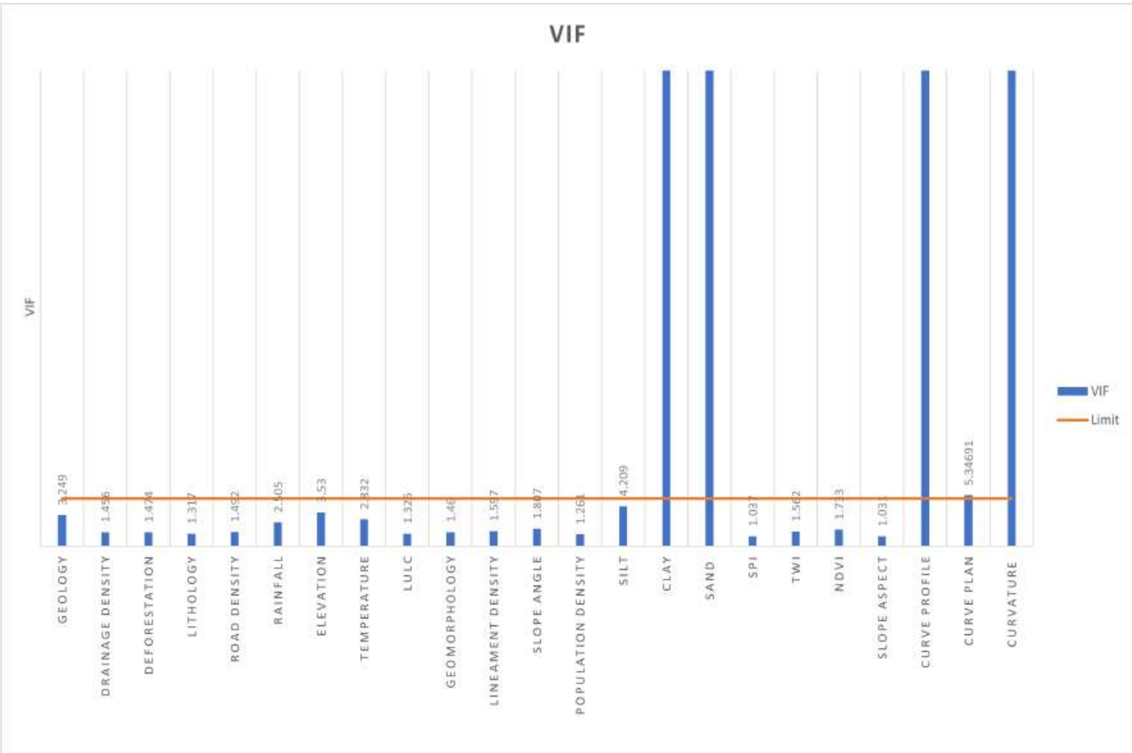


Figure 4.1: VIF value of each factor considered for the analysis with limit.

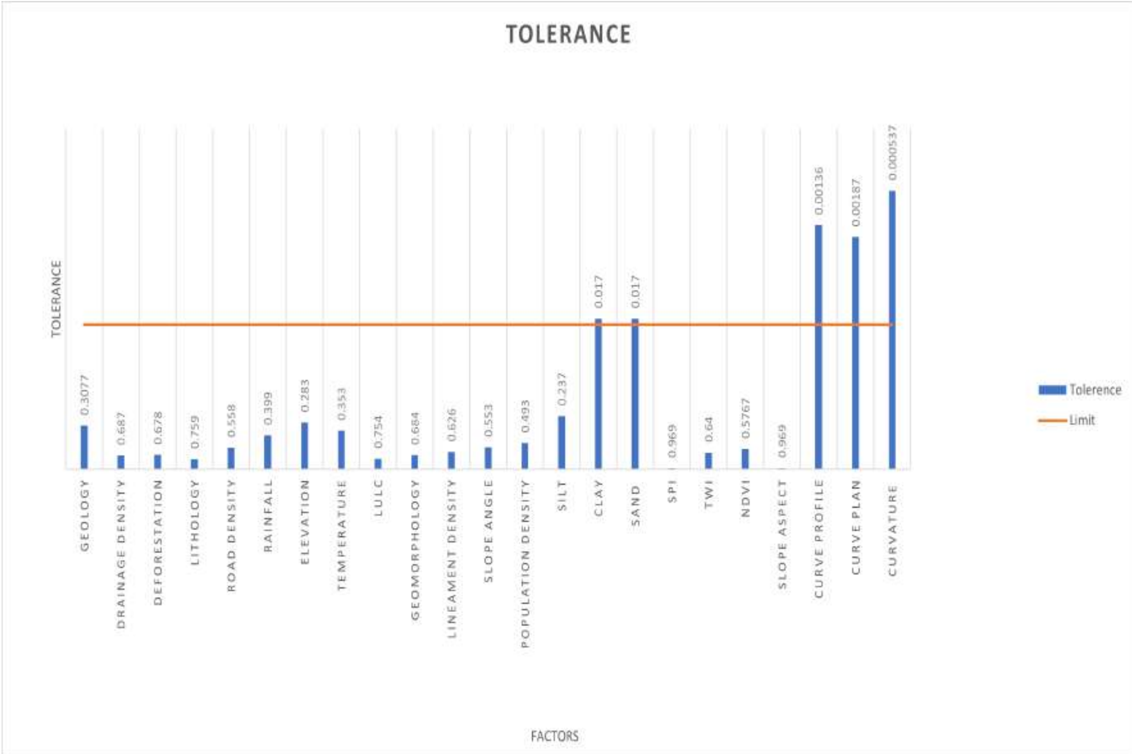


Figure 4.2: Tolerance value of each factor considered for the analysis with limit.

4.2 ALGORITHMS DEVELOPED

For the development of models, only 18 factors were taken considering the results from multicollinearity test. The material was randomly dispersed and divided into three categories: training (70%), validation (15%), and testing (15%). To better comprehend the facts needed by the model; the data fed in was pre-processed and scales were corrected. The values of TN, TP, FN and FP for LR, kNN, DT, RF, SVM, NB, ANN and CNN for training, validation and testing is shown in Figures 4.3 to 4.5 respectively. Each model undergoes 6 accuracy check such as ROC-AUC, PR-AUC, Precision, Accuracy score, F1-score and Log-Loss. For the calulation of same, TPR, TNR, FPR, FNR, PPV is also calculated for 8 algorithms. As per the results, RF and CNN shows higher accuracy with 0.95 in ROC-AUC. Similar good results were shown by SVM too with a score of 0.94 in ROC-AUC. The other models show good enough results such as 0.89 for DT (ROC-AUC), 0.81 for NB (ROC-AUC) and not to mention 0.92 by ANN. PR and ROC curves for different models are illustrated from Figures 4.6 to 4.13. Considering the other accuracy checks done, ROC-AUC and PR-AUC showing better results. Also surprisingly log loss score for the models where respectable, espcially for kNN which doesn't show better results in other methods. Illustration of each score is given in Figures 4.14 to 4.19. Quantitave illustation is something which gives better understanding from every level. Illustation of only models with higher accuracy was done for comparison purpose Figures 4.10, 4.21 and 4.22.

Figure 4.3: TN, FP, FN and TP values corresponding for training dataset for models developed.

Due to the high growth of geo-environmental variations and socio-economic activities; earth is becoming more vulnerable and frequency of landslides are increasing. Proper understanding about the occurrence of the same has prime importance in getting ready for dilemma. Research on landslides has always been an intriguing subject; in Kerala, the frequency of catastrophic falls rose following the 2018 Kerala flood, which attracted global attention. It is evident from the map plotted that mountainous places are more susceptible to landslides, and since mountains make up a significant portion of Kerala, this study is quite pertinent. Talking about mountains in Kerala; they are highly seismically active tectonic faults and folds [38]. This Western Ghats covers a vast area of Kerala, and as study area belongs to a tropical region, rainfall is quite normal there. But the effect of global climate change and other anthropogenic activities like deforestation pays the way for an increase in average daily rainfall, which in turn led to landslides.

Land becomes unstable when the pore water pressure increase to greater level

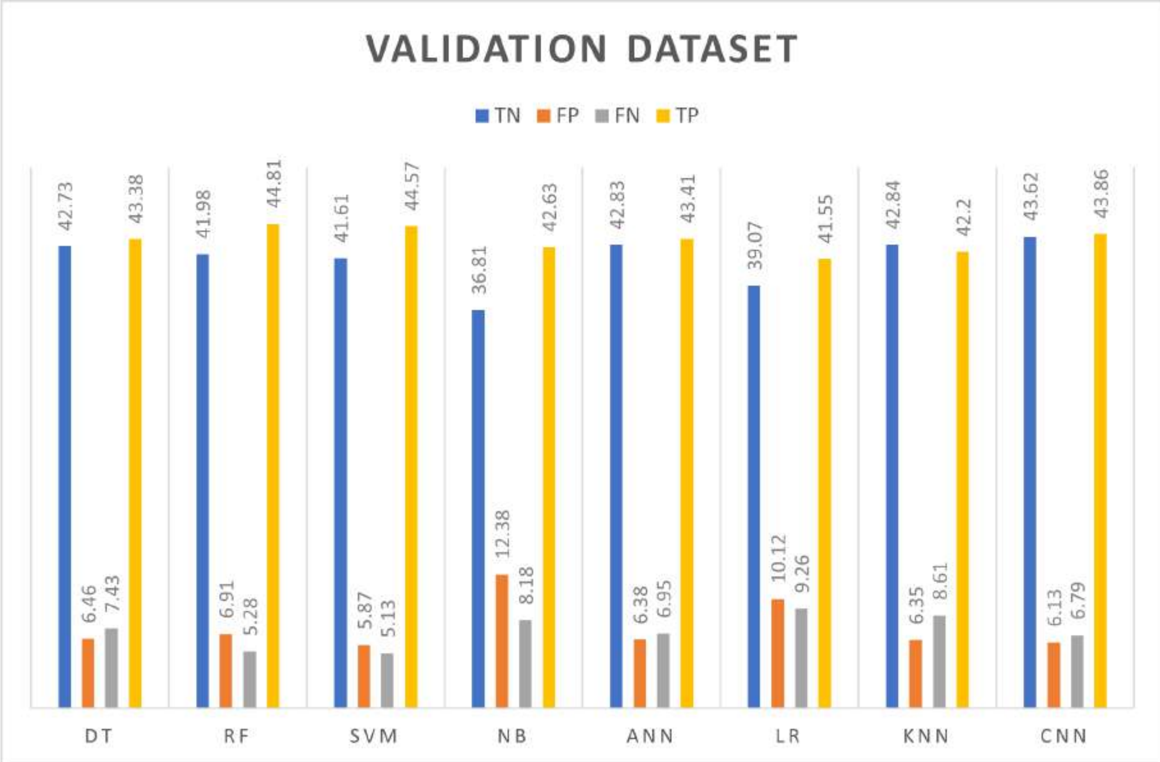


Figure 4.4: TN, FP, FN and TP values corresponding for validation dataset for models developed.

as the shear strength reduces; so, the effect of rainfall in landslides. Confirming to the results from the test, factors like clay content and sand content have been removed for the preparation of model which gave good results against. With the models used, all 8 models showed satisfactory results with the dataset. RF and CNN model was showing a maximum accuracy of 0.95 for testing with ROC-AUC and SVM was 0.94 with ROC-AUC. There is no much change in the accuracy with training dataset and testing dataset, except for DT and in some sections for SVM. Though kNN is considered as the laziest amoung, surprisingly it was showing good results . But results of NB wasn't satisfied as expecting; but the fact that Log-Loss value of the model is 0.37 for testing, which is one of the lowest in determined. Even though the change is not so high; there is a possibility of overfitting for DT model as accuracy reduced from a score of 0.97 to 0.87. Overfitting and underfitting can be interpreted differently; in this case, both models were tuned continuously for better accuracy. In comparison to the benchmark models, the results demonstrate a lower spectrum by ANN for prediction; might that be because of the ranges of values. Despite the proposed ML predictive model for landslide prediction's high accuracy, the present investigation has some restrictions that could be taken into

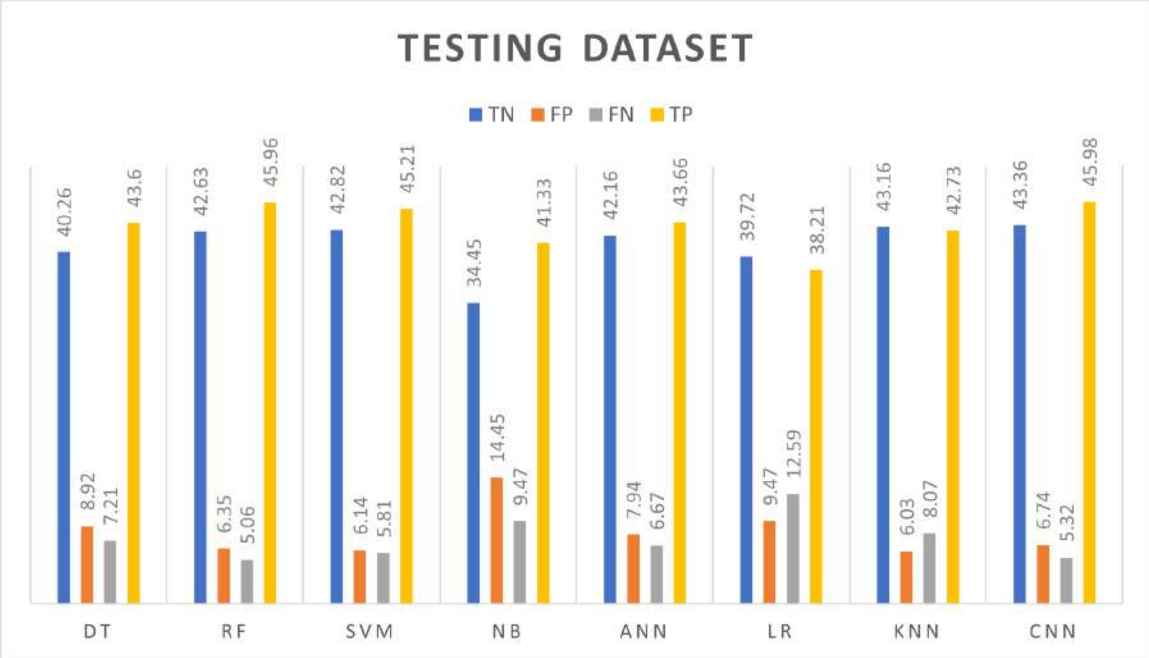
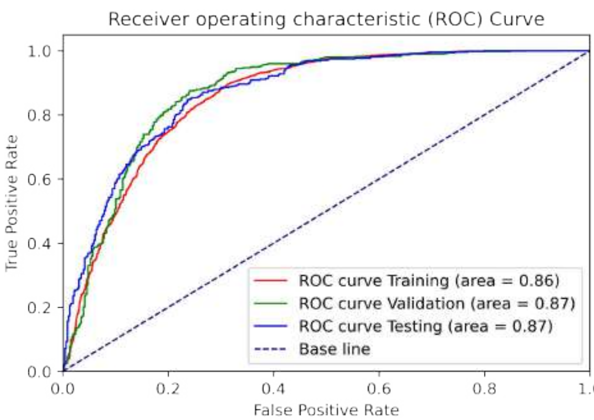


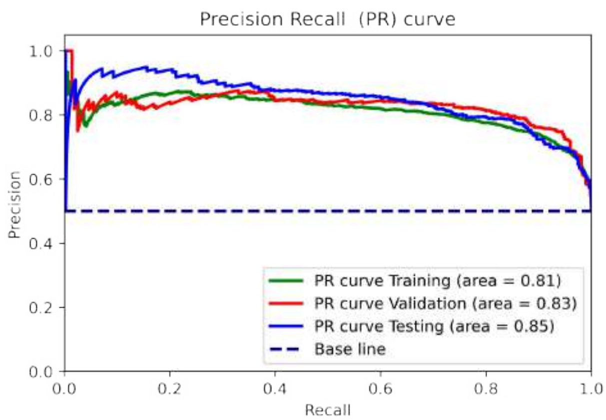
Figure 4.5: TN, FP, FN and TP values corresponding for testing dataset for models developed.

account in subsequent studies.

While others, such as neural networks or support vector machines, may be more difficult to comprehend, certain models, such as decision trees or linear regression, have intrinsic interpretability. Point up the benefits and drawbacks of each model in terms of its capacity to be interpreted and the insights it offers. [37] was mentioning greatly about the effect of quarrying in which results in the possibility of landslides as like [9], but the availability of those data was challenging, so it is missing.

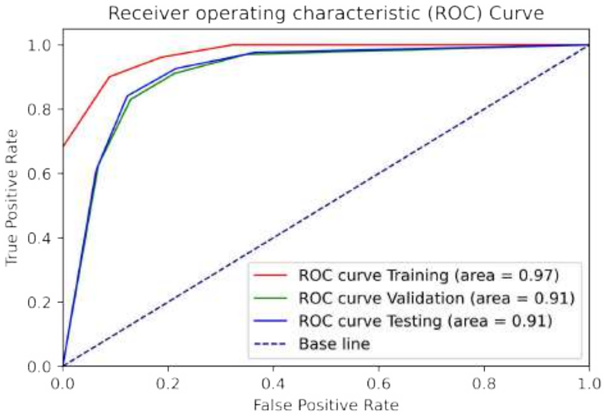


((a)) ROC curve of LR

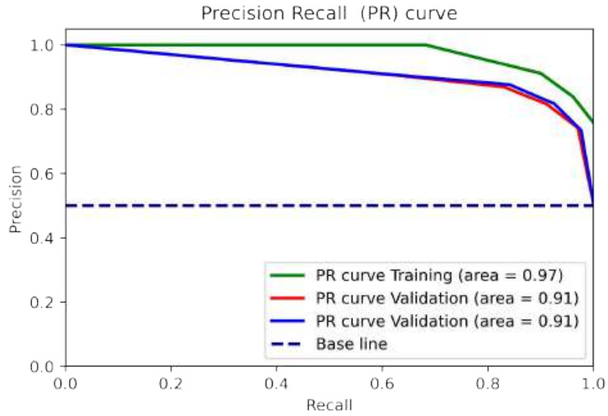


((b)) PR curve of LR

Figure 4.6: ROC and PR curve of LR

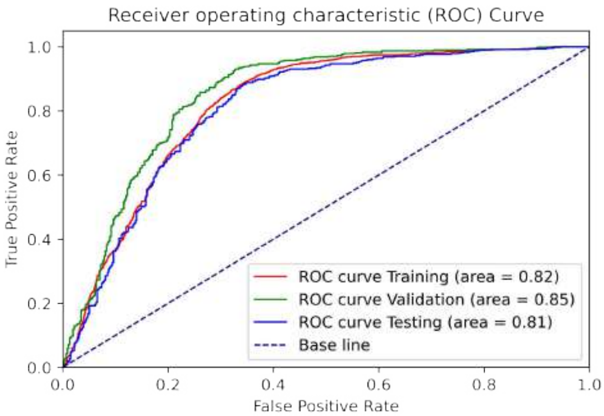


((a)) ROC curve of kNN

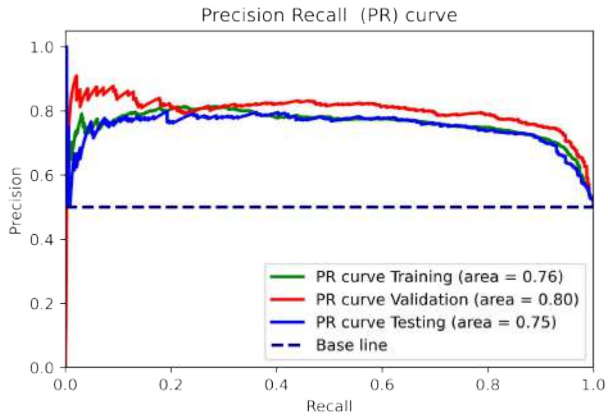


((b)) PR curve of kNN

Figure 4.7: ROC and PR curve of kNN

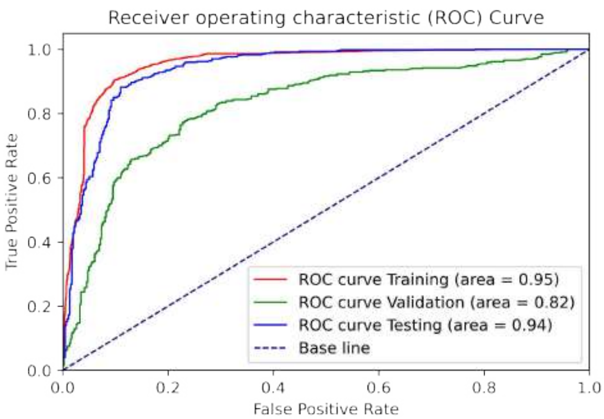


((a)) ROC curve of NB

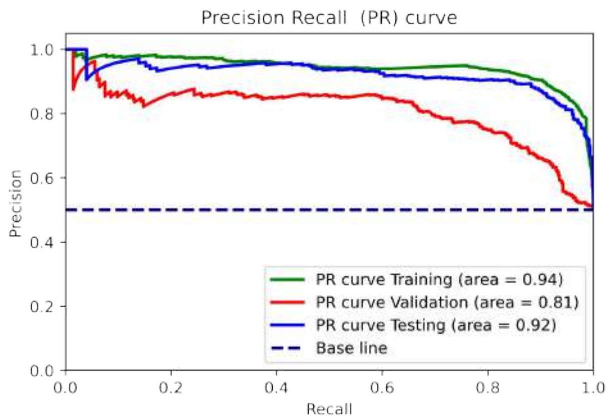


((b)) PR curve of NB

Figure 4.8: ROC and PR curve of LR

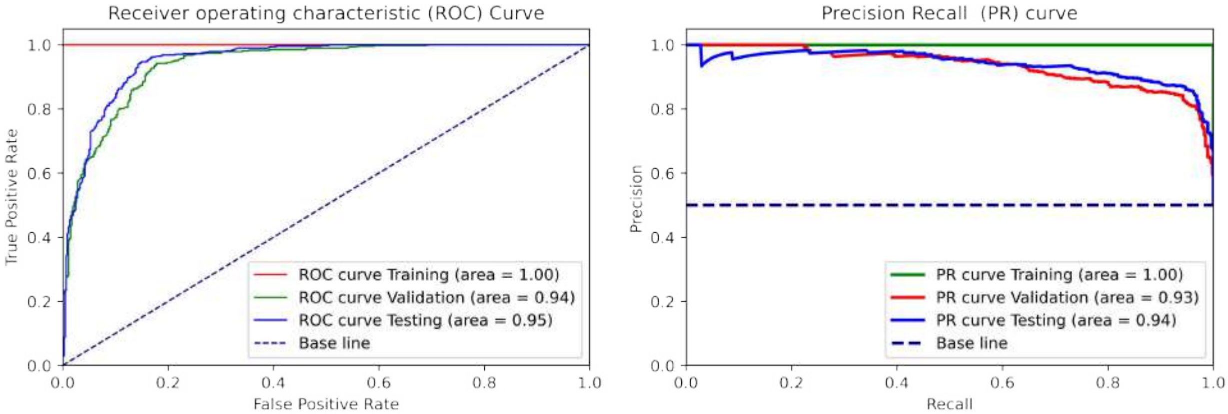


((a)) ROC curve of SVM



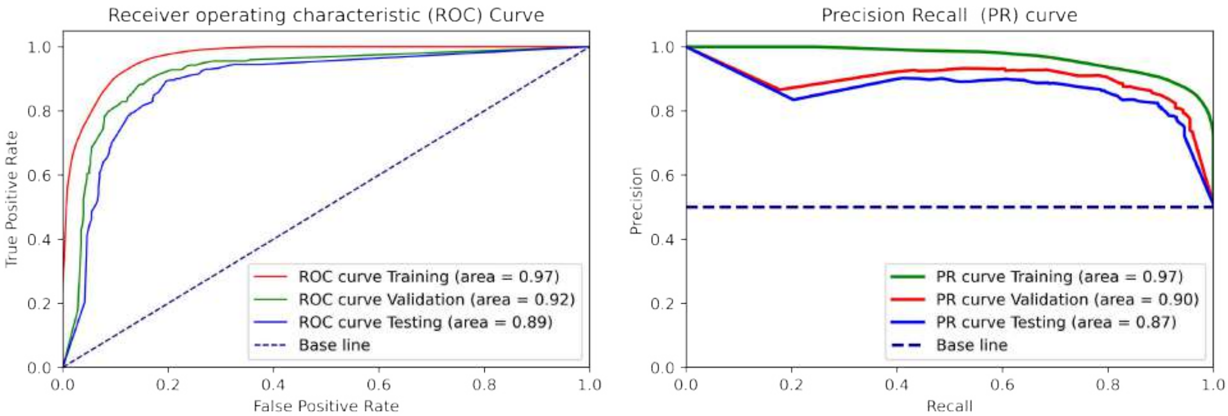
((b)) PR curve of SVM

Figure 4.9: ROC and PR curve of SVM



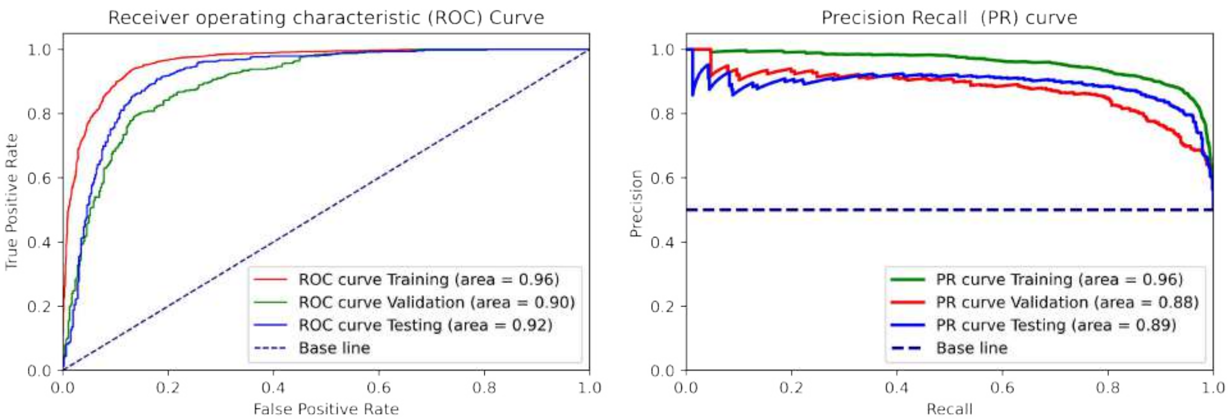
((a)) ROC curve of RF **((b)) PR curve of RF**

Figure 4.10: ROC and PR curve of RF



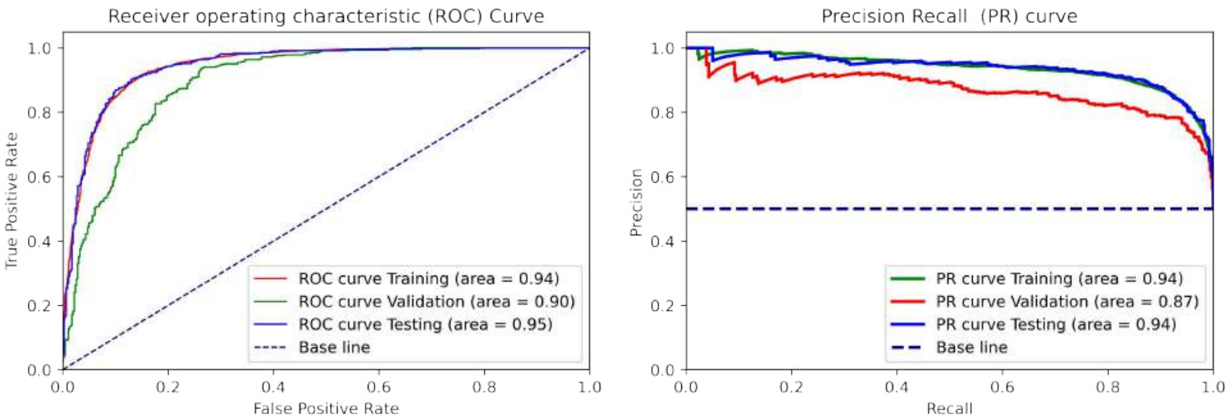
((a)) ROC curve of DT **((b)) PR curve of DTR**

Figure 4.11: ROC and PR curve of DT



((a)) ROC curve of ANN **((b)) PR curve of ANN**

Figure 4.12: ROC and PR curve of ANN



((a)) ROC curve of CNN **((b)) PR curve of CNN**

Figure 4.13: ROC and PR curve of CNN

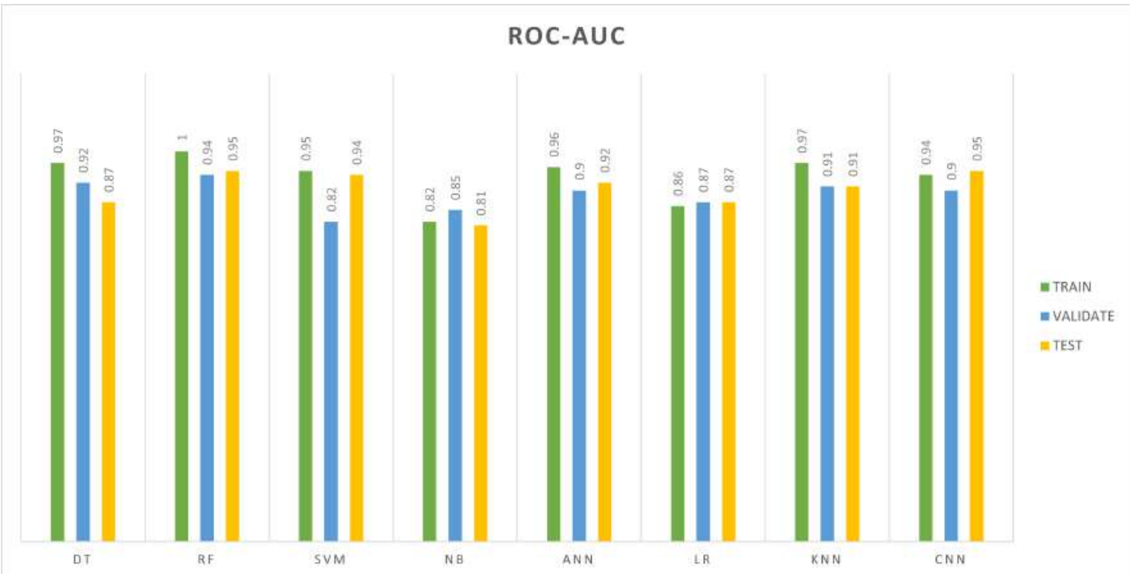


Figure 4.14: ROC-AUC for different models while training, validation and testing.

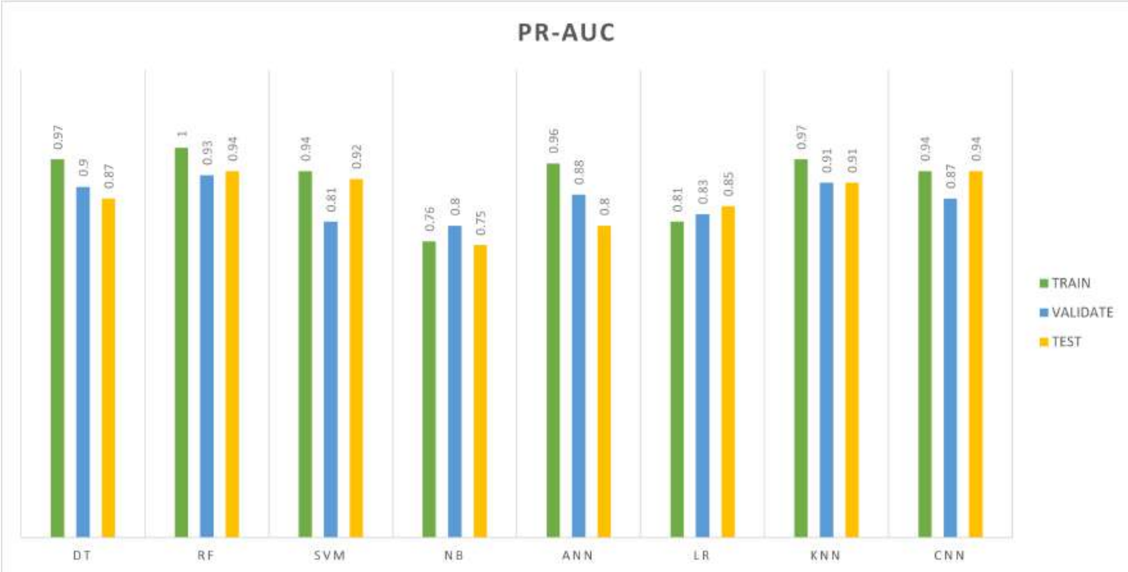


Figure 4.15: PR-AUC for different models while training, validation and testing.

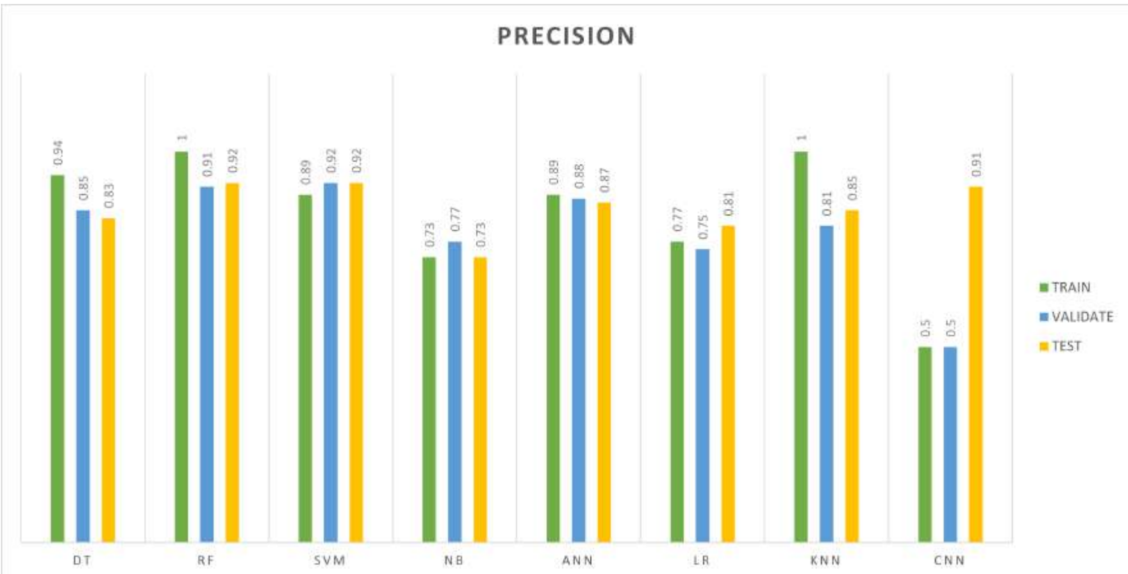


Figure 4.16: Precision for different models while training, validation and testing.

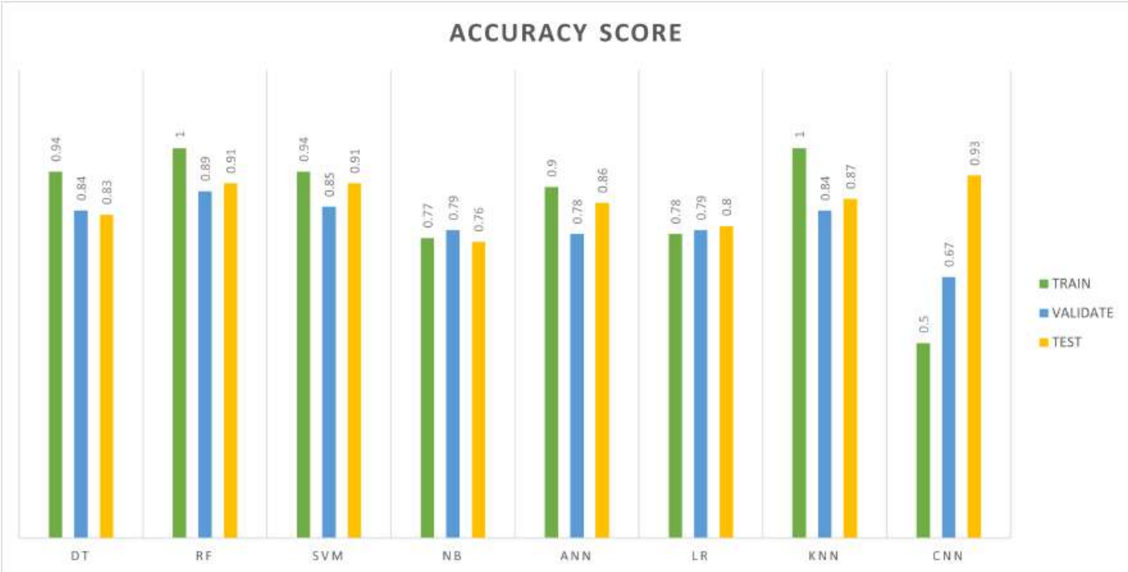


Figure 4.17: Accuracy score for different models while training, validation and testing.

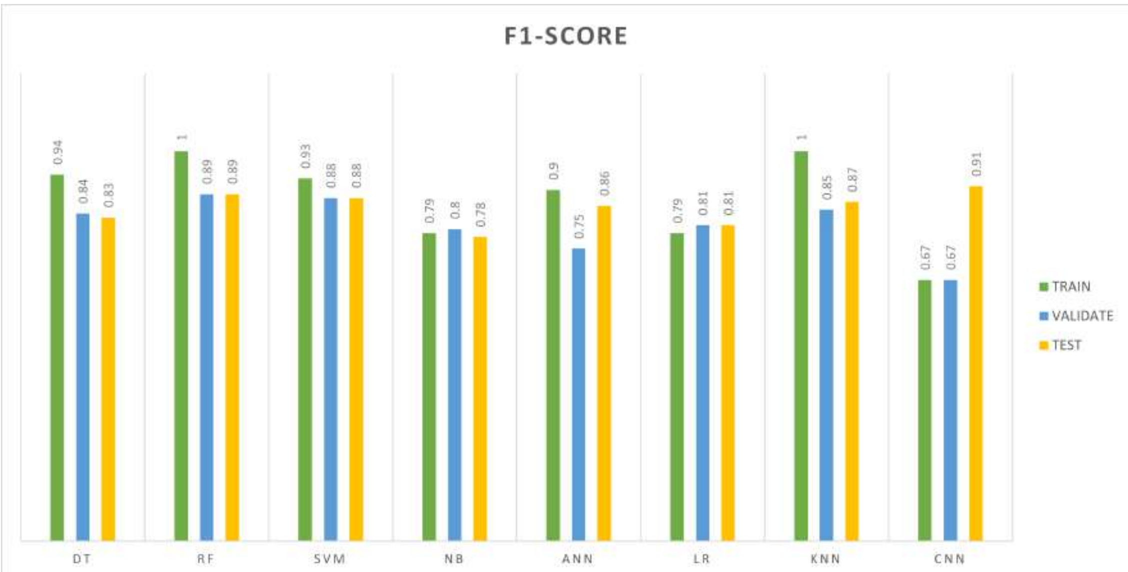
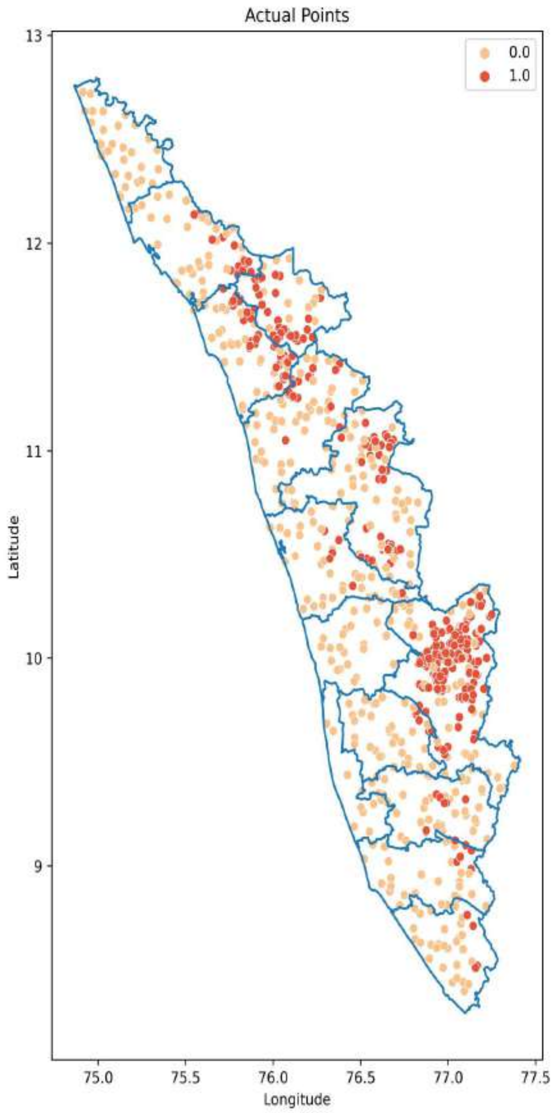
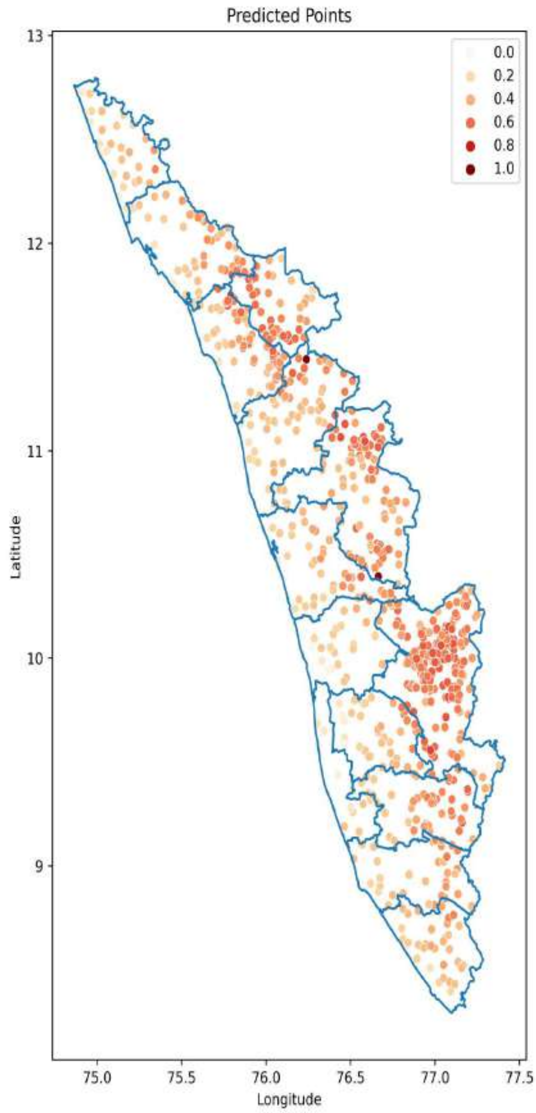


Figure 4.18: F1-score for different models while training, validation and testing.

Figure 4.19: Log-Loss for different models while training, validation and testing.

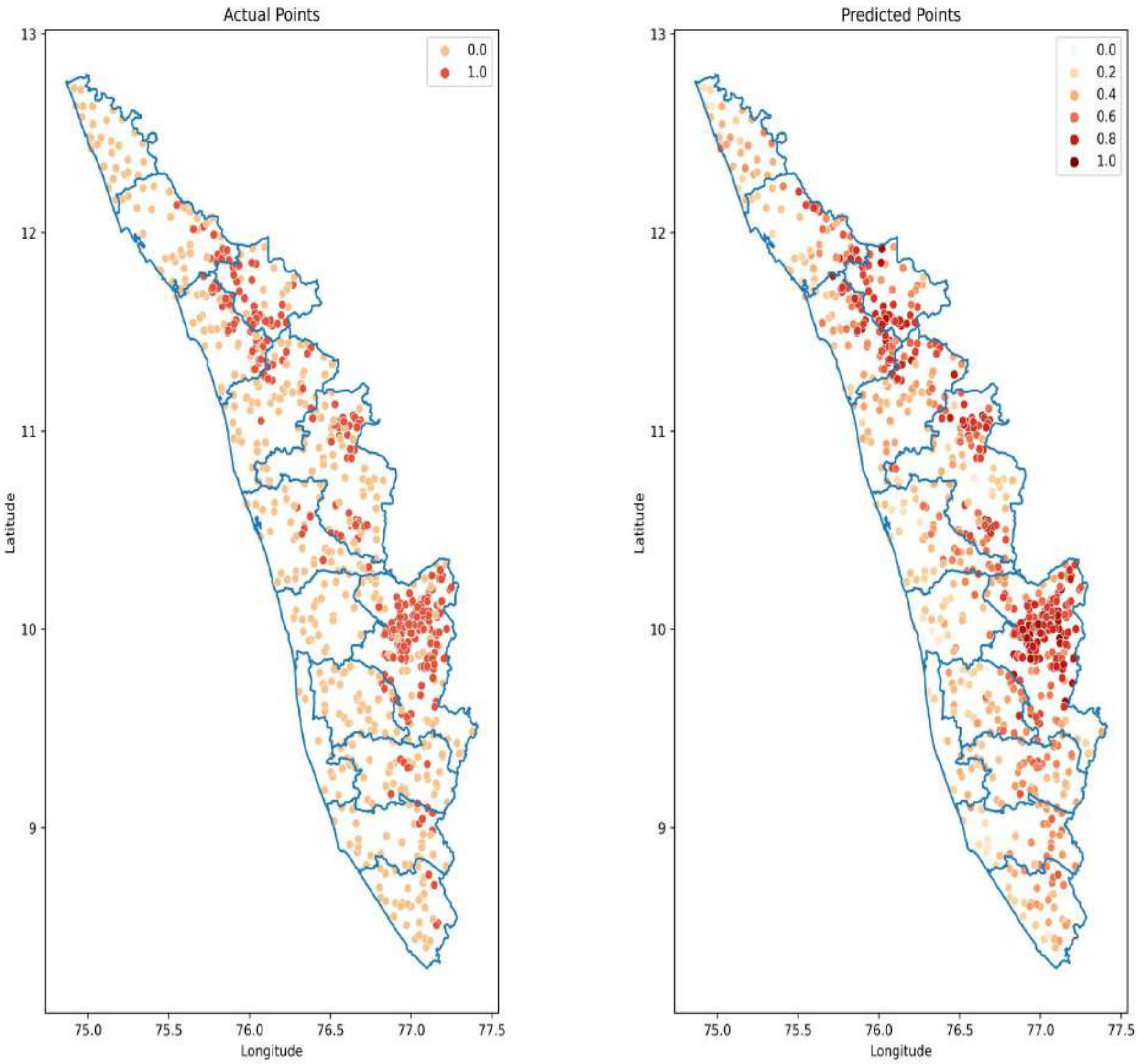


((a)) Actual points



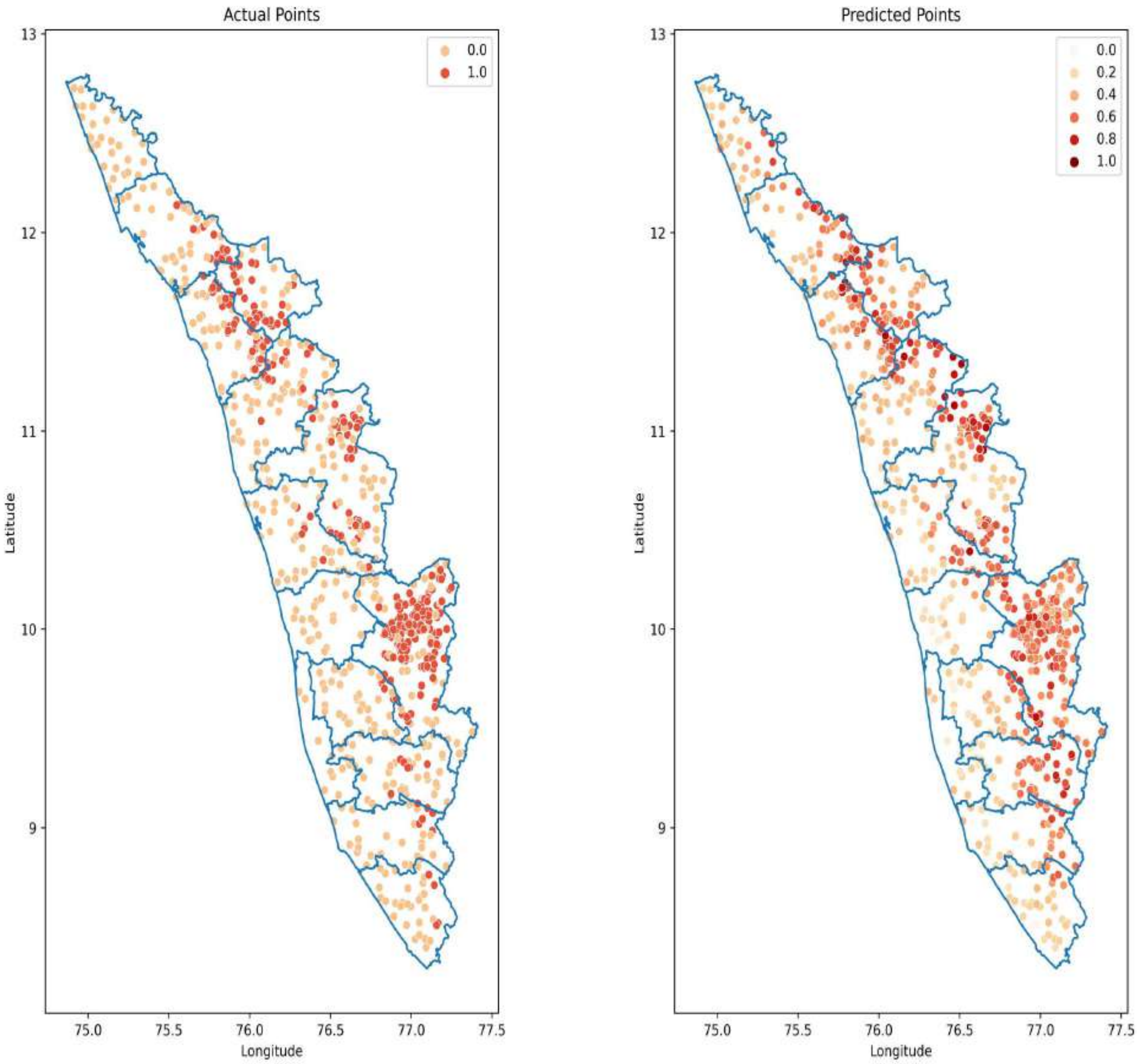
((b)) Predicted points

Figure 4.20: Map showing actual and predicted points of landslides using RF.



((a)) Actual points **((b)) Predicted points**

Figure 4.21: Map showing actual and predicted points of landslides using SVM.



((a)) Actual points **((b)) Predicted points**

Figure 4.22: Map showing actual and predicted points of landslides using CNN.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

For recent decades, landslides have been a threat for the life and livelihood to a greater extent. Human beings, the master of environment, have led to several issues which are not to be forgotten. Predicting the occurrence of any such hazards can help in setting the preventive measure for the same on the whole. It can be well accomplished with the help of proper abet of data and techniques. In this research work, landslide prediction is done for whole Kerala with LR, kNN, DT, RF, SVM, NB, ANN and cNN. 18 factors were considered for the same after multicollinearity test were considered for the same. Though all creditable; limitation of the study should also be mentioned. Those are as follows

- The sparse number of recorded reference landslides (as is typically the case)
- The input database's quality was significantly impacted by the spatial detail of satellite sensor imagery and the overall quality of the DEM data
- In order to manage the data during landslip susceptibility evaluations, the prediction model required strong processors. Specifically because it matches and benefits from the spatially broad character of the landslide phenomena itself, the ML module of the methodology provides essential benefits for vulnerability to landslide mapping.

However, the suitability of the available processors must be considered in order to perform landslip prediction analysis for upcoming scientific studies involving, for example, significantly higher spatial resolution images.

The following may be considered as the future scope of this study:

- More sophisticated machine learning models can be created by researchers and designed specifically for landslip prediction. To increase accuracy and produce more accurate predictions, these models can be modified to include additional geographical information, climate variables, and previous landslip records.

- Early warning systems for landslides can incorporate machine learning techniques. These systems are capable of sending timely notifications to areas at risk of landslides, allowing for evacuation and preventive steps. They do this by continuously analysing real-time sensor data, weather patterns, and geological conditions.

- For the purpose of predicting landslides, remote sensing technology like satellite imaging and LiDAR data can be a great resource. These sizable datasets may be automatically analysed using machine learning techniques, which also allow for the accurate detection of topographical changes and possible landslip hotspots.

- Machine learning may be used to analyse how climate change is affecting the frequency and severity of extreme weather events that are linked to climate change. Models can forecast how climate change will affect the likelihood and distribution of landslides in various places by examining historical data and climatic projections.

- Geotechnical engineering slope stability analysis and design can benefit from the use of machine learning. Engineers can develop more efficient landslip mitigation solutions by applying machine learning algorithms into slope stability models to better comprehend the intricate connections between soil parameters, slope geometry, and triggering factors.

- Systems for planning land use and urban development can be developed with the use of machine learning techniques. In order to minimise the risk of landslides, these systems may analyse a variety of elements, including soil type, topography, and historical landslide data. They then offer recommendations on safe construction techniques, infrastructure development, and zoning laws.

- Accurate landslip prediction can be improved by integrating data from various sources, including meteorological, geological, and ground sensor data. When analysing multiple datasets at once, it may be difficult to spot complicated patterns and correlations. Data fusion techniques might help.

- By analysing and visualising landslip data in an accessible way, machine learning can support programmes for public awareness and education. To help with community readiness and response planning, predictive models and risk maps can be created to communicate possible landslip dangers to the public.

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PUBLICATIONS/CONFERENCES

1. Conference paper accepted for presentation and publication.

ICMESS

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3rd International Conference on Management, Engineering and Social Science

Organized by: Institute For Engineering Research and Publication (IFERP)

06TH & 07TH APRIL 2023 DELHI

31st March 2023

Letter Of Acceptance

Abstract Id: ICMESS-2023_DEL_0141
Abstract Title: Landslide Prediction of Kerala Using Machine Learning Algorithms
Author: Aiswarya Padmadas
Co-Authors: Raju Sarkar

Dear Aiswarya Padmadas

Congratulations!!

The scientific research paper reviewing committee of **3rd International Conference on Management, Engineering and Social Science (ICMESS-2023), Hybrid Conference**" scheduled to take place on the **6th & 7th April 2023** organized by **Institute For Engineering Research and Publication (IFERP)** at **Delhi** is pleased to inform your research paper titled **"Landslide Prediction of Kerala Using Machine Learning Algorithms"** has been accepted after our double-blind peer review process for presenting paper at ICMESS 2023. Authors and speakers are recommended to proceed for registration to confirm their slots in relevant scientific sessions by following the link: https://www.icmess.in/registration.php

Acceptance Status: Yes

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No of authors per paper is limited, only 4 authors (inclusive of Guide) per paper. If exceeds must pay Rs.200 per head
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3rd INTERNATIONAL CONFERENCE ON MANAGEMENT, ENGINEERING AND SOCIAL SCIENCE (ICMESS-2023)

06th & 07th April 2023 | Delhi, India

Certificate No: IFERP20230607-141

This is to Certify that Aiswarya of Delhi Technological Univerisity presented his/her worthy presentation titled *Landslide Prediction of Kerala Using Machine Learning Algorithms*

during the "3rd International Conference on Management, Engineering and Social Science (ICMESS-2023)" organized by Institute For Engineering Research and Publication (IFERP) held on 06th & 07th April 2023 in Delhi, India.

Mr. Siddth Kumar Chhajer
MD & Founder, IFERP
Technoarete Group

Mr. Rudra Bhanu Satpathy
CEO & Founder, IFERP
Technoarete Group

2. Conference paper accepted for presentation and publication.

AMPT 2023

to me

May 19, 2023, 12:15 PM (1 day ago)

Dear Participant,

Thanks, we have received your manuscript titled

"Prediction of landslides in Kerala using Machine Learning"

Your manuscript has been accepted for presentation and publication process in AMPT 2023 conference at NIT Jamshedpur.

Participants must pay a separate registration fee for each of the papers submitted as applicable.

Online mode is only applicable for foreign residents. Indian citizens must attend the conference in offline mode only.

For further updates visit our website: http://www.ampt.in/

Thanks and Regards

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