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Systematic review of machine learning based landslide susceptibility mapping

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ABSTRACT

The landslide problem is one type of geohazard which damages both economic and human life loss. This problem needs awareness and creating zonation's to prevent its effect. This study reviews in locations Brazil, India, China, Italy, Turkey, Denmark, Vietnam, Iran, Bhutan, Pakistan, Peru, and Ecuador. These countries are facing landslide problems because their topography is more hilly terrain types. During the studies, different criteria are set to review articles published in the last 5 years from 2018 to June 9, 2023. The research is more focused on a machine learning model to map landslide problems in these selected areas. A field survey is used to validate this landslide susceptible mapping results. Future researchers utilizing machine learning methods to map the area's susceptibility to landslides will benefit from this research. Deep learning and ensembled machine learning will give good results for more datasets.

1. Introduction

Landslide susceptibility mapping is used to minimize risks and damages during the occurrences of landslide problems. Systematic literature reviews on landslide susceptibility mapping are used to know the current and future problems and their solutions. Nowadays machine learning approaches predict and detect landslide problems in large areas.

Different scholars used machine learning algorithms to map landslide susceptibility and predict the triggering factors(Ageenko et al., 2022; Al-Najjar et al., 2021; Ali et al., 2022). This review is used to identify the types of machine learning algorithms which give better performance to predict and map landslide susceptibility in a given location (Aslam et al., 2022).

During the last couple of decades, different landslide susceptibility mapping was done but it depends on the area of problem and data's availability. The landslide causative factors are different on the researcher's side. It affects the maps of the specific area. For a better understanding and warning system, all parameters are used as input for landslide susceptibility mapping. Most developing countries like Ethiopia have no data centers for input to predict geohazard problems and minimize accidents which are caused by landslide problems.

To get the full map of this problem collect and use remote sensing applications for input parameters in mountainous and inaccessible areas during the rainy season and earthquake periods. Different academicians from different areas like computer science, geology, hydrology, geotechnical, geospatial, and other experts give a better understanding of landslide susceptibility mapping in large coverage of problematic areas. Now, the main question that comes from everyone's mind is what is the solution? Researchers have different insights to identify or map landslide problematic areas like machine learning algorithms (i.e., random forest, decision tree, support vector machine, artificial neural network, etc.) Frequency ratio method, Analytical hierarchical method using geographical information system (GIS).

The current study aims to analyze the machine learning approach to map landslide susceptibility mapping, to identify types of algorism give better performance to identify problems from very low to very high susceptibility map (Chowdhury, 2023).

The first aspect of the study searched the literature that allowed us to understand the series of landslide problems in different areas recently and how it has become better. The second stream of literature focused on classifying the best possible machine learning algorism under different scenarios as an outcome of the current solutions.

We mapped the literature to understand what lessons were learned from the past discussed the possible future scenarios and finally provided a future agenda. The main objective of the study is to know landslide susceptibility mapping using a machine learning algorithm, to see the parameters of input for landslide susceptibility mapping using a machine learning algorithm, and to identify which types of machine learning algorithms give good results depending on other parameters.

2. Methods

2.1 Eligibility Criteria

The article had to meet three pre-defined criteria. First, the article had to be published in different journals like Remote sensing, Stochastic Environmental Research and Risk Assessment, Sensors, Civil Engineering and Environmental Systems, Landslides, Symmetry, Arabian Journal for Science and Engineering, Catena, Computers and Geosciences, Geomorphology, Science of the Total Environment, Science of the Total Environment, Modeling Earth Systems and Environment, Stochastic Environmental Research and Risk Assessment, Land, International Journal of Geo-Information, Natural Hazards, Engineering Science, Frontier in Earth Science, Lithosphere, Bulletin of Engineering Geology and the Environment (Ageenko et al., 2022).

The second criterion for the selection of the papers was that the article had to full length and be published in English. Thus, all other publications, such as research notes, editors 'comments, readers' comments, and book reviews were excluded (Ali et al., 2022). The final criterion was that the article had to be based on landslide susceptibility mapping using machine learning theory and/or concept. Concerning this last criterion, it was not just enough for an article to mention landslide susceptibility mapping concept or theory to be selected, but the theory and/or concept needed to be central to the research (Aslam et al., 2022).

Among the different reviews that were assessed in this study, 38 of them described inclusion and exclusion criteria for publication status. Also, 38 reviews mentioned the language of publications as one of the eligibility criteria.

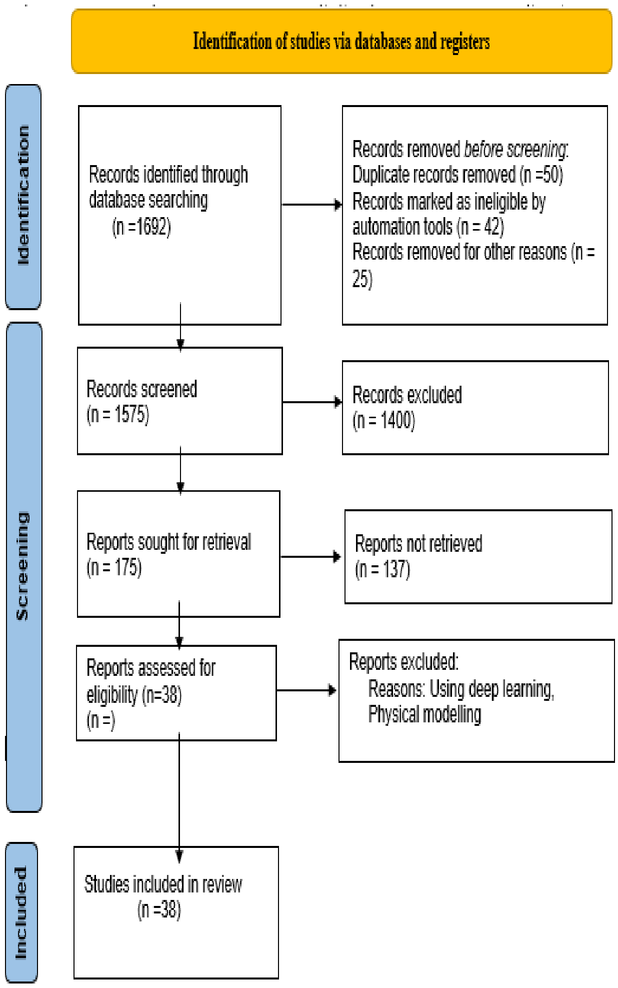

Figure 1. Steps of systematic analysis process of the research

2.2 Search Strategy

For this systematic search, we developed a search strategy to identify relevant literature. This search strategy was tailored to five databases: Scopus, Web of Science, Science Direct, IEEEXPlore, and EBSCO and the search terms used were the following:

“Landslide” and “Susceptibility” and “Mapping” AND “Machine Learning”. All searches spanned from database inception 2018 to June 9, 2023, and included journal articles and conference proceedings, published in English language only. The searching strings with the conditions shows in Table 1.

Table 1. Search strings with the condition

Database name	String	Condition
Web of Science	"Landslide Susceptibility Mapping" AND "Machine Learning"	2018-June 9, 2023
Science Direct	"Landslide Susceptibility Mapping" AND "Machine Learning"	2018-June 9, 2023
Scopus	"Landslide Susceptibility Mapping" AND "Machine Learning"	2018-June 9, 2023
EBSCOhost	"Landslide Susceptibility Mapping" AND "Machine Learning"	2018-June 9, 2023
IEEEXPlor	"Landslide Susceptibility Mapping" AND "Machine Learning"	2018-June 9, 2023

2.3 Information Sources

An extensive literature search was conducted using various databases such as the Web of Science (647), Science Direct (613), Scopus (343), IEEEXPlore (19), and EBSCO (70). Secondly, the citations from the identified articles were traced. Among 1692 publications identified, only those landslide susceptibility mapping studies for machine learning algorithms were selected for analysis. The literature collection was mostly conducted from 2018 to June 9, 2023.

2.4 Selection Process

The selection criteria were based on the PRISMA statement (Pahlevan Sharif et al., 2019). The search mainly focused on the mapping existing literature on landslide susceptibility mapping in the fields of geology, computer science, and civil engineering. The search then narrowed to the subject areas of earth science, geotechnical engineering, and hydrology fields. The search span was from 2018 to June 9, 2023. All articles before 2018 were excluded from the search.

The search was focused on all countries mainly journal articles and conference proceedings that have done landslide susceptibility mapping using machine learning algorism.

2.5 Data Collection Process

The authors of this study then perused the articles and subsequently performed the content analysis. Any conflicts were resolved by discussions among the researchers until a consensus was achieved (Bao et al., 2022).

2.6 Data Items

Every article was carefully read and the information on the research theme/focus, methods, and author/s was recorded on an Excel sheet (Bragagnolo et al., 2020).

3. Results and discussion

Entering the keyword 'Landslide susceptibility mapping' AND 'Machine Learning' as the search criterion resulted in 1692 full-length articles published between 2018 and June 9, 2023 being retrieved.

Among the 1692 articles, 12 were 'editorial' prefaces or commentary articles, and 19 were not available as the authors' affiliated university does not subscribe to these relevant journals. The remaining full-length articles were thoroughly read by each author to confirm their appropriateness.

A further 14 of the retrieved articles were excluded as they were unrelated to personality research. For instance, one article stated that 'Instead of trying to measure personality traits that might be important, [respondents were] simply asked what the term machine learning to them (Bravo-López et al., 2022).

Another article analyzed landslide susceptibility mapping (W. Chen et al., 2018). This left a total of 38 published articles about landslide susceptibility mapping using the machine learning approach (Wei Chen et al., 2018).

3.1 Year of publication

Research papers related to landslide susceptibility mapping in China, Bhutan, India, Peru, South Korea, Pakistan, Ecuador, Vietnam, Italy, Iran, Turkey, Brazil, Algeria, and Denmark increased and decreased between 2018 and June 9, 2023 (Figure 2.), but years like 2018, 2019 and 2021 almost similar paper was produced (Wei Chen et al., 2018; Chen & Yang, 2023; Chen et al., 2022). years like 2020, 2022 and June 9, 2023, increased than the previous year (Fig 2). published papers in number from 2018, 4 in number, 2019, 4 in number, 2020, 7 number, 2021, 4 in number, 2022, 12 in number, and January 1, 2023 to June 9, 2023, 6 in number.

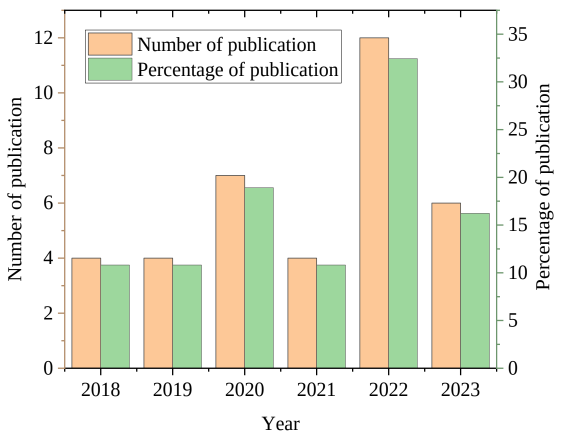

Figure 2. Year of publication on landslide susceptibility mapping from 2018 to June 9, 2023.

3.2 Publishing journals of the research paper

The papers were published in 23 different journals focusing on the Bulletin of Engineering Geology and Environment, Lithosphere, Frontiers in Earth Science, Engineering Science, Natural Hazards, International Journal of Geoinformation, land, Modelling Earth Systems and Environment, Science of the Total Environment, Geomorphology, Geoscience frontiers, Computer and geoscience, catena, Civil engineering and environment, symmetry, sensors, Arabian Journal for science and engineering, Stochastic environment research and risk assessment, Mathematical problems in engineering and Remote sensing (Di Napoli et al., 2020; Fang et al., 2020; Gui et al., 2023). The highest number of publications is found in remote sensing journals which is 26 % (Figure 3) and the lowest number of publications is found in more journals i.e. 14 journals have the lowest publication which is 2 % (Figure 3.).

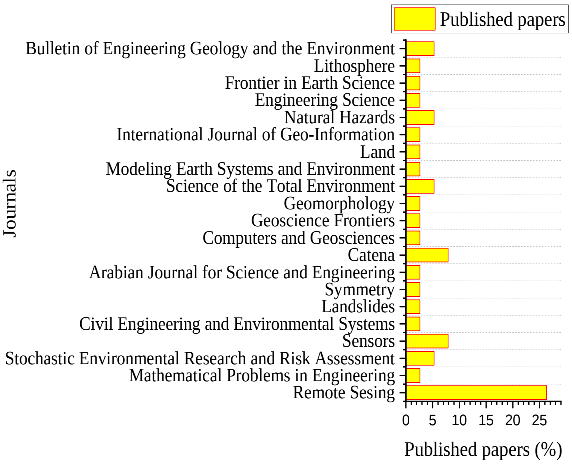

Figure 3. Journal with landslide susceptibly mapping publications

3.3 Size of the study area

The size of the study area mentioned in the research is categorized in Figure 4. The highest number of research papers covers around 58,000 square kilometres of area, in China. Papers published in Italy, Iran, Turkey, and Denmark have less than 1000-kilometre square coverage. Brazil and Vietnam have between 1000 – 2000 kilometres square coverage. Ecuador, India, Pakistan, and Bhutan have between 2000 to 10,000 kilometres square coverage (Hamid et al., 2022; Hong et al., 2020; Kadavi et al., 2018; Kavzoglu & Teke, 2022). The size of the study area was always determined by the researchers and its natural boundaries to get sample points. this may change the susceptibility zones and visualize more accurate areas of landslide susceptibility.

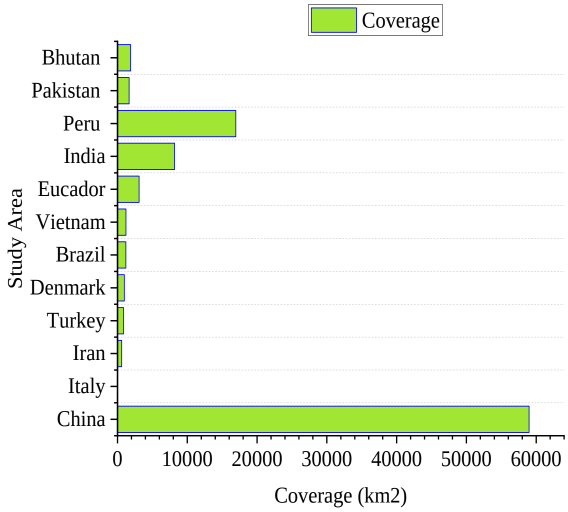

Figure 4. Size of the study area in square kilometers

3.4 Landslide conditioning factors

The landslide conditioning factors used to construct the susceptibility mapping which is used in this systematic literature review paper are Digital elevation model (DEM), Slope, Aspect, Geomorphologic units, Landslide point density, Distance from the road, Distance from the residential area, cumulative rainfall, Distance from the river system, Lithological unit, Geology, Elevation, Altitude, normalized differential vegetation index (NDVI), Standardized precipitation index (SPI), Topographic position index (TPI), Terrain ruggedness index (TRI), topographic wetness index (TWI), distance to fault, plan curvature, and plan profile (Kumar et al., 2023; Li et al., 2022; Liang et al., 2021; Liang et al., 2020). Some of the landslide condition factors are shown in Figure 5.

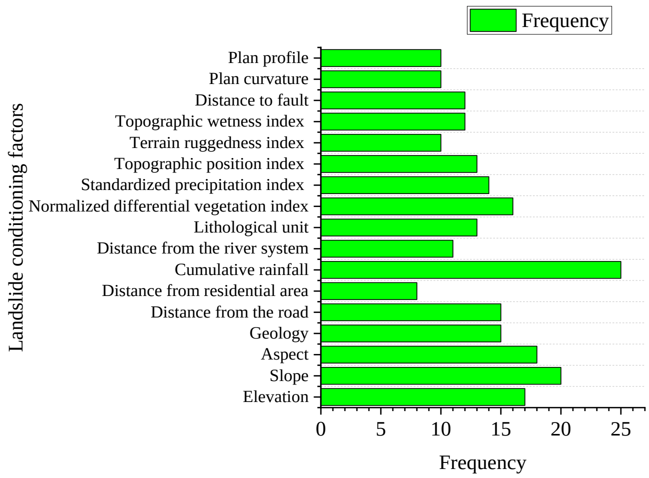

Figure 5. Frequency of conditioning factors

3.5. Characteristics of inventory database

In these areas, most of the landslide susceptibility map is prepared using field survey data. Thirty-eight literatures have used field survey data for preparing landslides susceptibility maps and others used secondary data. google images using Google Earth images are used for inventory databases for the selected areas (Miao et al., 2023; Pham et al., 2020; Rane & Vincent, 2021; Roy et al., 2019). The types of inventory data in this research area are divided in their frequency based on their size from 0 to 500 frequencies 23, 501 to 1,000 frequencies 8, and 2,501 to 10,000 frequency 2. The size of the inventory database has effects on the prediction capacity of the machine learning algorithms but due to the topography and other economic issues getting a large amount of database is difficult. For training and testing purposes, data size from 0 to 500 landslide points was used in 23 selected papers (Figure 6.).

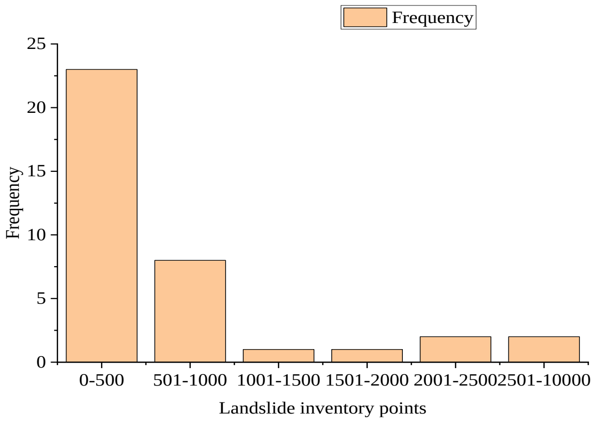

Figure 6. Number of landslide locations in the inventory database

3.6. Publication based on database

In this systematic literature review, five types of source databases were used i.e. Scopus, Web of Science, Science Direct, IEEEXPlor, and EBSCOhost (Shirzadi et al., 2018; Su et al., 2021; Sun et al., 2020; Thai Pham et al., 2019). Based on the source more published papers were found in Web of Science and Science Direct which is greater than 35 %. Small published papers were found in IEEEXPlor (Figure 7.).

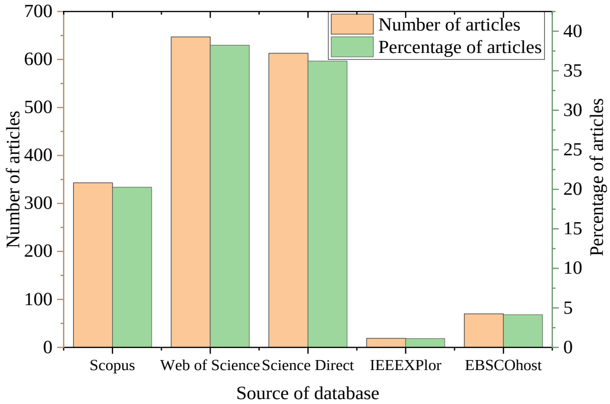

Figure 7. Publication based on database

3.7. Publication based on study area

The selected papers were studied in different countries like Algeria, South Korea, China, Italy, Iran, Turkey, Denmark, Brazil, Vietnam, Ecuador, India, Peru, Pakistan, and Bhutan. Most of the published papers were done in China and India, which is 52 % and 7 %, respectively (Figure 8.) (Ullah et al., 2022; Wang et al., 2020; Wang et al., 2023; Wu et al., 2020).

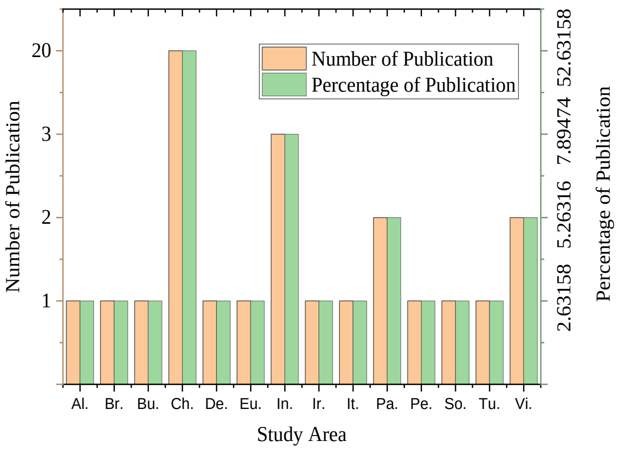

Figure 8. Publication based on study area

Where: Algeria (Al.), South Korea (So.), China (Ch.), Italy (It.), Iran (Ir.), TurkeyTu.), Denmark (De.), Brazil (Br.), Vietnam (Vi), Ecuador (Eu.), India (In.), Peru (Pe.), Pakistan (Pa.), and Bhutan (Bu.).

3.8. Distribution of database

Based on Figure 9. more papers are published in Remote Sensing journals and the database is Web of Science and Science Direct, publisher was MDPI (Ye et al., 2022; Yu et al., 2023; Zeng et al., 2023; Zhao et al., 2021; Zhou et al., 2018). Also, more than 100 citation published research papers has shown in Table 2.

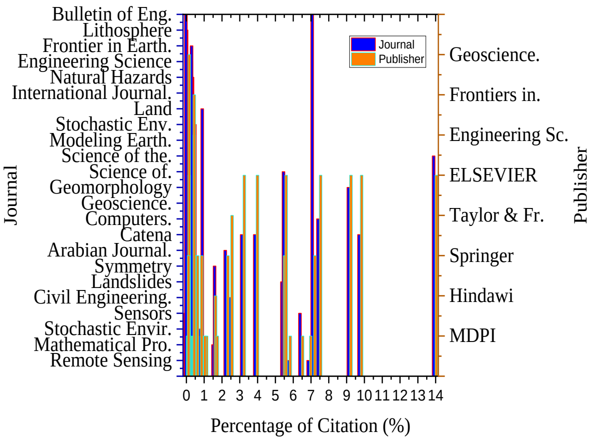

Figure 9. Distribution of database

This literature review and meta-analysis revealed different aspects of landslide susceptibility mapping research in different parts of the world like China, Italy, Denmark, India, Peru, Pakistan, Vietnam, Turkey, and Brazil, especially, the commonly used input data and methods, acquired map accuracy and the relationship between map accuracy and input data characteristics.

Results depicted that there is a variety of methods used in literature but the application of machine learning is limited. Landslide susceptibility mapping research has an increasing trend in such countries.The landslide susceptibility mapping is also limited to some specific regions. The hilly region faces landslides during the rainy season. This is because the death toll and economic loss are confined to these regions.

However, there is a need to assess the landslide characteristics of the other regions because the excluded areas may face serious landslides in future because of climate change-induced extreme rainfall.

In China, Brazil, Italy, Vietnam, and India, morphological factors are most commonly used followed by hydrological and land cover factors. Emphasis should also be given to geological and geotechnical factors as the region is composed of complex geological formations and landslides are rainfall-induced.

Table 2. Research Publication which has more than 100 citations

No.	Title of the papers	Citations	Year	Reference
1	Landslide susceptibility modelling using GIS-based machine learning techniques for Chongren County, Jiangxi Province, China	303	2018	26
2	Application of alternating decision tree with AdaBoost and bagging ensembles for landslide susceptibility mapping	212	2020	25
3	A random forest model of landslide susceptibility mapping based on hyperparameter optimization using Bayes algorithm	199	2020	23
4	Integration of convolutional neural network and conventional machine learning classifiers for landslide susceptibility mapping	162	2020	22
5	Novel hybrid artificial intelligence approach of bivariate statistical-methods-based kernel logistic regression classifier for landslide susceptibility modelling	155	2019	36
6	Application of Ensemble-Based Machine Learning Models of Landslide Susceptibility Mapping	150	2018	8
7	Novel GIS Based Machine Learning Algorithms for Shallow Landslide Susceptibility Mapping	140	2018	18
8	A Novel Ensemble Approach for Landslide Susceptibility Mapping (LSM) in Darjeeling and Kalim Pong Districts, West Bengal, India	125	2019	5
9	Modelling landslide susceptibility using LogitBoost alternating decision trees and forest by penalizing attributes with the bagging ensemble	120	2020	24
10	Machine learning ensemble modelling as a tool to improve landslide susceptibility mapping reliability	118	2020	16

For landslide susceptibility mapping, random forest, logistic regression, support vector machine, and decision are more frequently used methods in these research areas or countries. Following the global landslide analysis methods, emphasis should be given to machine and deep learning algorithms to get a more accurate and realistic result. This research applicable for early understand of machine learning for landslide susceptibility mapping and early warning system in data accessibility areas.

Some specific recommendations from this research are as follows:

- Mapping landslide risk using physically-based techniques as well as machine and deep learning algorithms.
- For validation, use laboratory tests related to geotechnical engineering.
- To reduce the impact of size, increase the number of datasets.
- Creating a database on landslides and updating it frequently for additional tropical nations, such as Ethiopia.
- Making an effort to create a micro-scale national map of landslide susceptibility.
- Creating policies for mapping inventories and landslide susceptibility.
- Separating training and testing data according to certain guidelines and making note of them expressly in the study.
- Mapping landslip susceptibility using slope units.

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