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Systematic Review

A Systematic Review of Machine Learning Techniques and Applications in Soil Improvement Using Green Materials

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Abstract: According to an extensive evaluation of published studies, there is a shortage of research on systematic literature reviews related to machine learning prediction techniques and methodologies in soil improvement using green materials. A literature review suggests that machine learning algorithms are effective at predicting various soil characteristics, including compressive strength, deformations, bearing capacity, California bearing ratio, compaction performance, stress–strain behavior, geotextile pullout strength behavior, and soil classification. The current study aims to comprehensively evaluate recent breakthroughs in machine learning algorithms for soil improvement using a systematic procedure known as PRISMA and meta-analysis. Relevant databases, including Web of Science, ScienceDirect, IEEE, and SCOPUS, were utilized, and the chosen papers were categorized based on: the approach and method employed, year of publication, authors, journals and conferences, research goals, findings and results, and solution and modeling. The review results will advance the understanding of civil and geotechnical designers and practitioners in integrating data for most geotechnical engineering problems. Additionally, the approaches covered in this research will assist geotechnical practitioners in understanding the strengths and weaknesses of artificial intelligence algorithms compared to other traditional mathematical modeling techniques.

Keywords: PRISMA; soil improvement; by-product; artificial intelligence; green materials; environmental impact

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1. Introduction

Climate change and environmental impacts are currently challenging topics for the Earth's survival; waste management became a trending issue. Reusing the waste materials in different applications is one of the solutions that help in waste management, where one of the uses is in soil improvement applications, as it is a frequently used material in this industry [1–8]. Some industrial wastes have cementitious properties that could help replace traditional soil-reinforcing materials such as cement, where cement is a direct reason for climate change by a 5% of the carbon dioxide CO_2 emissions through its production [9–11]. Cement manufacture uses 4 Giga joules of energy and emits an equivalent amount of CO_2 into the atmosphere, which accounts for 30% of all CO_2 emissions worldwide from an environmental perceptive [12]. Additionally, because limestone is essential to cement production, a severe shortage may develop over the next five years [13].

Furthermore, due to burning raw materials, fossils, and minerals in the kiln chamber, CO_2 emissions are produced, which have a detrimental impact on the environment [10,14]. Accordingly, using cement alternatives such as industrial waste materials, which are considered pozzolanic materials, is essential to reduce the cement industry's severe environmental impacts and recycle those industrial waste materials. However, the key enrolment is to control the ratio of waste or green materials as soil-treating material to achieve maximum efficiency in soil improvement.

Machine learning is a rapidly growing field that has the potential to revolutionize geotechnical engineering. In particular, it has great potential for improving soil improvement using green materials, which is a critical area of research for sustainable and environmentally friendly construction practices. Machine learning is one of the trending topics that was used in several geotechnical applications such as prediction of retaining wall deflection [15], excavation [16,17], soil behavior [2], Earth retaining structures [18], bearing capacity [19–24], settlement of structures [8,18,20,24–28], liquefaction assessment [29], slope stability and landslide [30,31], and soil characterization [2,3,7,32–37]. That helps geotechnical engineers to control and predict the soil properties and behavior under various loading conditions. In addition, it is used to predict the stress–strain behavior and shear resistance of the after-treatment using waste materials [3,7,15,38,39], which helps in controlling the used ratios of waste materials [5,21]. However, minimizing the error of the prediction model is one of the challenging problems which depends on the algorithm used for predicting [40]. In this article, we will discuss some of the key applications of machine learning in geotechnical engineering for soil improvement, including model accuracy, regression models, and performance.

One of the most significant advantages of machine learning is its ability to improve model accuracy. Machine learning algorithms can use large amounts of data to identify patterns and relationships that may not be apparent to engineers. This can lead to more accurate predictions of soil behavior and the effectiveness of various soil improvement techniques [41,42]. Regression models are a common tool in geotechnical engineering for predicting soil behavior based on various parameters, such as soil type, moisture content, and density. Machine learning algorithms can be used to develop more accurate regression models by identifying complex nonlinear relationships between these parameters and soil behavior. Table 1 shows the used green materials in soil improvement and the used algorithms in data regression with the related accuracy based on R^2 values, which shows in general high acceptable rate for the conducted models. This can lead to more precise predictions of soil performance and the effectiveness of soil improvement techniques. Another important application of machine learning in geotechnical engineering is performance monitoring [43,44]. Machine learning algorithms can analyze large amounts of data from sensors and other sources to identify patterns and trends in soil behavior over time. This can help engineers to identify potential problems early on and make adjustments to soil improvement techniques as needed.

On the other hand, machine learning's most significant drawback is its reliance on large amounts of high-quality data [45]. Machine learning algorithms require vast quantities of data to train effectively, and if these data are incomplete or biased, they can lead to inaccurate or misleading results and its lack of transparency and interpretability [46]. Many machine learning algorithms are "black boxes," meaning that it can be challenging to understand how they arrive at their conclusions [27]. Another potential disadvantage of machine learning is overfitting. Overfitting occurs when a machine learning algorithm is trained too closely on a specific dataset and becomes too specialized to that dataset, leading to poor performance on new data. This can be particularly problematic in cases where the algorithm is used to make predictions about future events or trends based on historical data. In order to avoid overfitting, it is important to carefully design and test machine learning algorithms using a variety of datasets and validation techniques [47,48]. However, this can be time-consuming and expensive, which may limit the practicality of using machine learning in certain applications. Additionally, some machine learning algorithms may lack human oversight, which can lead to unintended consequences or errors if not carefully monitored and controlled by human experts [49,50].

Table 1. Evaluation of algorithms used in data prediction of various green improved soils.

Treated Material	Treatment Material	Data Set	Validation	ML Algorithm	Training R^2	Validation R^2	Program	Test	Source
Clayey Soil	Aluminum Slag	18	K-folded	ANN	0.9997552	1.0000	-	CBR SA AL MPT	[36]
Soil	Fly Ash	-		MLR ANN	0.520 0.638	- 0.8263	R Program	UCS	[1]
SP SW	Soil Geosynthetic	-		GEP	0.977	0.961	SGA	DS	[15]
Clay	NaOH	491		MFFNN CFNN RBNN ENN MLR	0.99999 0.99995 0.99999 0.99070 0.99950	0.9996 0.9939 0.9615 0.9977 0.9994	-	SA AL MPT	[2]
Cohesive Soils	Fly Ash Blast Furnace Slag	283		GMDH ANN	0.986 0.859	0.946 -	MATLAB	UCS	[51]
Clays soil	Fly Ash Ground Granulated Blast Furnace Slag	283		ANN MVR	0.996 0.910	0.982 0.899	MATLAB	UCS	[38]
Clayey Soils	Geopolymer	213		ANN GMDHNN	0.984 0.960	0.949 0.944	MATLAB	UCS	[39]
Sandy Soil	Alkali-Activated Volcanic Ash Blast Furnace Slag			ANN EPR	0.97 0.97	- -	-	UCS	[52]
Cohesionless		123		BPNN	0.946729	0.863041	-	SETT	[20]

Recent developments in machine learning (ML) for civil Engineering focused on addressing the challenges associated with interpreting ML results and the lack of user-friendly tools [47,48]. Explainable ML models were developed to provide transparency and interpretability, allowing users to understand the reasoning behind the predictions. User-friendly tools and interfaces were also created to simplify the implementation and interpretation of ML models for practitioners without extensive ML expertise [45]. These developments aim to facilitate the practical application of ML in civil engineering, supporting tasks such as structural health monitoring, predictive maintenance, risk assessment, and construction process optimization [46]. The advancements in ML for civil engineering provide practitioners, designers, and decision-makers with practical implementations that offer accuracy, interpretability, and ease of use [27].

Indeed, the applications of machine learning in geotechnical engineering are many, such as prediction of settlement [8,20,27], compressive strength [3,38,39,51–53], bearing capacity [22,24], stress–strain behavior [2], and compaction performance [7]. Several studies classified and reviewed machine learning applications in geotechnical engineering for predicting landslide, strength, settlements, bearing capacity, liquefaction, and slope stability [40,54–56]. However, the conducted studies were not including soil improvement using waste materials and did not match its challenges. Therefore, the authors consider lately published research in the emphasized area deficient in a systematic review, where the research flowchart is shown in Figure 1 considering a systematic review paper, merging accessible methods and recent studies is needed. The research framework for machine learning application in soil improvement review in geotechnical engineering can be structured as follows:

1. Identification of keywords and databases: Identify geotechnical applications that were addressed using machine learning. That included the studied problems such

as soil stabilization, liquefaction mitigation, and settlement control, where the keywords were identified and the used relevant databases, including Web of Science, ScienceDirect, IEEE, and SCOPUS, were utilized using a systematic procedure known as PRISMA and meta-analysis (Supplementary Materials).

2. Trend of combined collected data: Identify trend geotechnical applications that were addressed using machine learning for sustainable soil improvement methods using green materials.
3. Commonly used machine learning algorithms: According to collected and filtered articles, the used algorithms were defined, and statistical equations were represented.
4. Performance evaluation: The performance of the developed machine learning models using appropriate performance metrics such as accuracy were stated based on the compared predicted values of the models with the actual performance data in previous research to indicated the advantages and disadvantages of used machine learning algorithms.
5. Overview: The outcome of this study was indicated in the discussion and conclusion sections for representing the critical analysis and perspectives. Continuously improve the machine learning model by incorporating new data and refining the model parameters. This can help to improve the accuracy and reliability of the model over time.

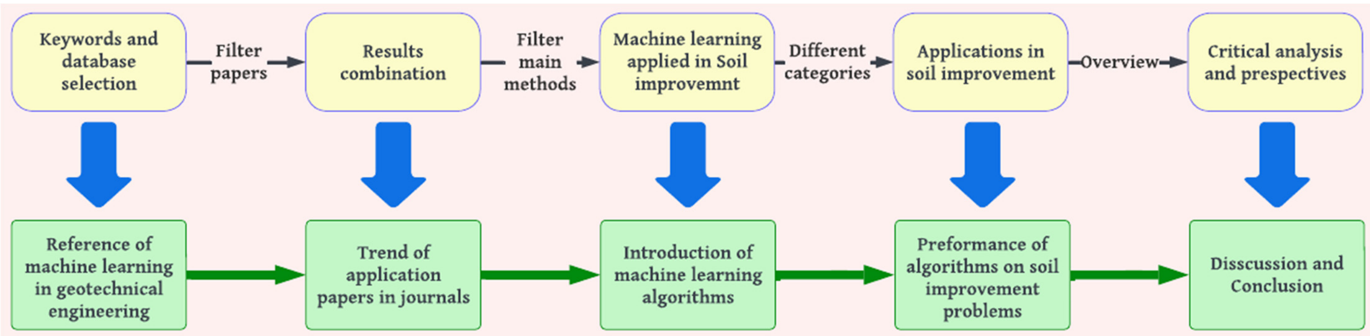

Figure 1. Research framework of ML application in soil improvement review in geotechnical engineering.

Overall, the research framework for machine learning application in soil improvement review in geotechnical engineering involves identifying the problem, collecting and preprocessing data, developing and evaluating machine learning models, selecting the best model, implementing the model in the field, and continuously improving the model. This framework can help to advance the use of machine learning in soil improvement and lead to more efficient and sustainable geotechnical engineering practices.

2. Literature Overview

2.1. Papers Distribution

Since the early 1900s and up to the recent date of this article's writing, over 82,000 research papers were indexed in the field of geotechnical engineering in the Web of Science (WOS). However, when the search was limited to machine learning and soil improvement using waste or recycled materials within the field of geotechnical engineering, only eight articles were found, and the remaining titles were very limited. The distribution of these eight articles according to their publication dates is shown in Figure 2. As Figure 2 illustrates, the number of articles on machine learning applications in soil improvement using waste or recycled materials significantly increased in the last five years, with seven of the eight articles being published during this period, and no articles detected in previous decades. The rapid growth of published articles in the last five years indicates the continuation of this trend, as many papers in 2022 are still under processing.

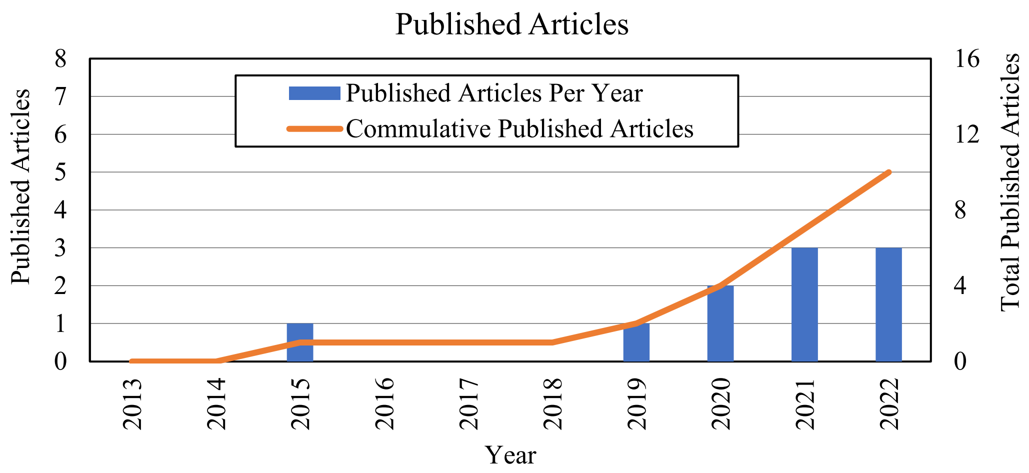

Figure 2. Annual published article distribution concentrating on the ML function in soil improvement (Source: WOS; May 2023 last update for literature research).

For research concern in the soil improvement field of ML, the journals published articles on the corresponding keywords, and the percentage of selected articles amongst the journal sources are shown in Table 2. For the moment, the distribution of journal sources by article number and their specific application conducted from WOS are listed in Table 3. Remarkably, the following research writings were excluded from the research, editor notes, book chapters, master theses, and doctoral dissertations. As illustrated, each journal had one publication, where the journals were closed access.

Table 2. Papers distribution according to the source name in the subject of soil improvement field of ML and corresponding articles (WOS).

No.	Journal Name	N	Ratio (%)	Publication
1	Arabian Journal for Science and Engineering	1	10.00%	[1]
2	Computers and Geotechnics	1	10.00%	[38]
3	Construction and Building Materials	1	10.00%	[57]
4	Engineering with Computers	1	10.00%	[51]
5	Environmental Science and Pollution Research	1	10.00%	[21]
6	Geosynthetics International	1	10.00%	[20]
7	Iranian Journal of Science and Technology—Transactions of Civil Engineering	1	10.00%	[39]
8	Journal of Materials in Civil Engineering	1	10.00%	[52]
9	Materials	1	10.00%	[58]
10	Materials Today: Proceedings	1	10.00%	[6]

Table 3. Improved soil testing research using ML.

Soil Type	Used Material	AI Model	Test	Reference
Clayey Soil	Alum	ANN (K-folded)	CBR Sieve analysis Atterberg limits Compaction test	[36]
Soil	Fly Ash	MLR ANN	UCS	[1]
SP SW	Soil–Geosynthetic	GEP	-	[15]

Table 3. *Cont.*

Soil Type	Used Material	AI Model	Test	Reference
Clay	NaOH	MFFNN CFNN RBNN ENN MLR	Sieve analysis Atterberg limits modified proctor test	[2]
Cohesive Soil	Fly Ash Blast Furnace Slag	GMDH ANN	UCS	[51]
Clays Soil	Fly Ash Furnace Slag Ground Granulated Blast	ANN MVR	UCS	[38]
Clayey Soils	Geopolymer	ANN GMDH-ANN	UCS	[39]
Sandy Soil	Alkali-Activated Volcanic Ash Blast Furnace Slag	ANN EPR	UCS	[52]
Various Soils	Fly Ash	DT RF GBoost	UCS	[58]
Soft Soil	Fly Ash	BM	UCS	[57]

Several ML algorithms are involved in solving soil improvement problems based on statistics retrieval data from WOS, where the main ML methods used in this field are shown in Figure 3. The artificial neural network (ANN), extreme learning machine (ELM), and group method of data handling (GMDH) are the most common algorithms in solving soil improvement challenges. Their applications contain soil parameter inference [5], bearing capacity [24], deformation performance [8], compressive strength prediction [38,39,51,52], etc. Other machine learning algorithms, such as quadratic model (QM) [2] and ternary diagrams (TD) [1], are rarely used [1]. The main ML algorithms' principles and applications are explained in the following sections. The results suggest that combining ML methods with existing databases is a promising engineering research focus.

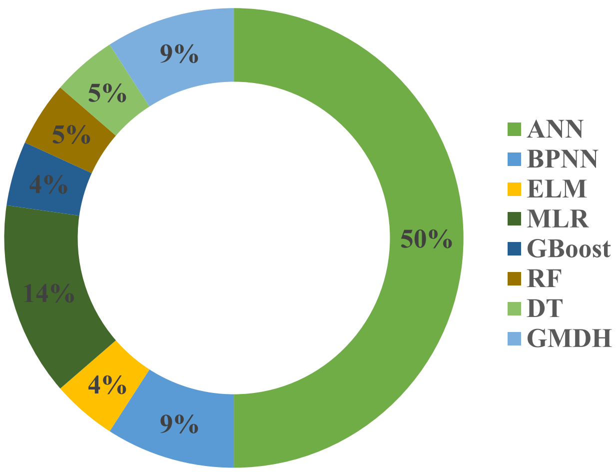

Figure 3. Used ML algorithms to solve soil improvement problems (Source: WOS; May 2023 last update for literature research).

2.2. Applications of ML in the Soil Improvement Industry Using Environmentally Friendly Materials

Various machine learning algorithms were used in predicting compressive strength, deformations, bearing capacity, California bearing ratio, compaction performance, stress–

strain behavior, geotextile pullout strength behavior, and soil classification, as shown in Tables 3 and 4 for improved soil experiments and simulation correspondingly. The ANN algorithm was the most used in the selected articles in this research [1,4,6–8,21,22,38,39,51,52], followed by both MLR [1,6,38], GMDH [39,51], and BPNN [1,4,5] algorithms. In addition, other algorithms were used as ELM [59] and hybrid algorithms [39,57].

Table 4. Improved soil simulation research using ML.

Soil Type	Used Material	AI Model	Test	Reference
SOIL	Geogrid	MLR ANN	Settlement	[28]
Sand	Ferrochrome Slag	ELM	-	[8]
Sand	Peat	MARS	UCS	[33]
Sand (Raft)	Planar Geocell	GRNN BPNN	Settlement	[26]
Sand	Coir	ANN	-	[22]
Geogrid	Imperial Smelting Furnace Slag	ANN	SS ECH Physical TS	[4]
Subgrade	Coal Ash Bagasse Ash Groundnut Shell Ash	ANN MRA	-	[6]
Various Soils	Alum Sludge	ANN	MDD USCS OMC SG PI CBR	[7]
BASE	Quarry Waste	ANN	BC Deformation	[21]

Compressive strength is one of the most critical parameters of soils that define its reflection to load resistance during loading, where both short-term and long-term loading are crucially based on the construction method [5,17,60,61]. However, the indication of the compressive strength of soil requires experience in detection that always has significant uncertainties due to human error in the preparation and installation of the specimens that affect the behavior of soil under loading [8,57,58]. Accordingly, using machine learning algorithms for their high accuracy advantage in detecting compressive strength through simple geotechnical and engineering parameters of soil is an essential solution that avoids the uncertainties in both measuring and predicting the compressive strength [2,53,62]. The algorithms used in the estimate of compressive strength indicated high accuracy for the predictive models depended on Atterberg limits [1,4,5,7,38,39,51], additives ratio [1,4,5,7,38,39,51], compaction test parameters [1], sieve analysis parameters [4], and physical properties [7]. Furthermore, the predicted models generally showed high accuracy over 0.9 for the coefficient of determination R^2 value, where the highest accuracy was for ANN, GMDH, NF- GMDH, NF-GMDH- PSO, BPNN, and ELM. Additionally, it is evident from the results that ANN's coefficient of correlation R^2, which is superior to GMDH- NN's, is higher for both training and testing datasets [39].

California Bearing Ratio CBR is a direct method that controls the designing and construction of pavements, where higher CBR results in fewer paving materials [63–65]. That leads to cost-effective design, construction, and compaction effort [7]. Furthermore, as there was a variation in energy of compaction at each level of soil improvement addition, the test results were corroborated using the ANN algorithm [7]. According to the variance in energy of compaction, the behavior of the soil's physical properties was investigated. In order to choose equipment that will be deployed to fields effectively, Shah et al. [7] studied the transmission of energy from the source to the soil, as well as how compaction affects the soil was investigated. Each method's comparative effort was expressed in terms of dry unit weight and moisture contents in parallel with engineering and geotechnical parameters. ANN was effective with an R^2 value exceeding 0.9 for the prediction of the relationship between the results of the two compaction tests and how compaction affects the soil, which would help in infrastructure and future geotechnical applications using alum sludge waste [7]. Despite the limitation in the generated results by the MLR algorithm, the generated models for CBR assessed an R^2 value of 0.68 as acceptable models. Therefore, ANN outperforms MRA. For estimating soil CBR, ANN and MRA models produced a good agreement with the data. Therefore, these models can be used to reasonably accurately forecast the CBR of soils. Both the MRA and ANN models showed dependable results by estimating the CBR of byproducts with soil stabilized by geogrid [6].

For the trend of using eco-friendly materials in soil improvement, the **compaction performance** of improved soil became essentially to be investigated. Accordingly, several research articles studied the ML applications on compaction performance of improved soil using eco-friendly materials such as; fly ash [1], alum sludge waste [7], kraft paper fiber [53], and palm oil fuel ash [66]. In general, these materials enhanced the compaction performance of the improved soil for both factors maximum dry density MMD and optimum moisture content OMC [1]. By applying the Atterberg limit values, proctor test results, and unconfined compressive strength test UCS values of the fly ash improved samples, multiple regression and ANN analyses were attempted to predict the resistance values of the cured samples. In the strength prediction equations of cured samples, the MLR analyses showed the strongest connection R^2 with a value of 0.88. Low correlation coefficients for the prediction equations in the MLR determination prompted ANN prediction that provided the greatest correlation [1].

Geotechnical engineering recently showed extensive use of ELM in predicting and controlling the **bearing capacity**. Kumar and Samui [67] used the ELM model to analyze a piling foundation's reliability. The study's main goal was to determine how well an extreme learning machine model could forecast a pile's bearing capability when buried in loose soil. The evaluation and prediction of **slope stability** were also carried out by Liu et al. [30] using an extreme learning machine ELM, with significant accurate prediction. In addition, it was demonstrated by Sahu et al. [24] that the created ANN model could explain how inputs affect outputs physically, as seen in the neural interpretation diagram NID. It was found that whereas foundation depth to width was directly related to the reduction factor, inclination angle to internal friction angle α/ϕ was inversely related to RF levels [24] for the data conducted by Sahu et al. [68]. However, it is also possible to conclude that the appropriate pavement design technique even permits incorrect evaluation and analysis of design factors and the design process itself, which can result in uncertain, uncertain design explanations. That is supported by the weak relationships between the constructed and expected structural data [23].

Deformations and settlements are significant challenges for geotechnical engineers to control [69]. Therefore, using machine learning to predict and control settlements is a trending research area in both experimental work [2,8,26,70–73] and/or simulation [19,20,25,27,28]. That helps in better understanding the soil's behavior, especially after improvement using green, by-product, or recycled materials under various loading conditions [27]. The deformations were predicted using machine learning algorithms such as ANN, MLR, and ELM. All derived efficient prediction models with high accuracy. ML was used to calculate the settlement of footing laid on geogrid strengthened soil using ferrochrome slag industrial waste using ANN and ELM, where the models are capable and effective at forecasting settlement [8]. That gives an advantage to ML compared to experimental methods; developed computational models are less time- and money-consuming and considerably reproduce the findings of the experimental study.

Additionally, the relationship between settlement and the factors of soil internal friction angle, and width, and covering ratio of reinforcement were demonstrated by Soleimanbeigi and Hataf [20], showing that the settlement increment by increasing reinforcement width and decreasing reinforcement covering ratio and soil internal friction angle increase. For the quick estimate of the early settlement of shallow foundations on reinforced cohesion-less soils, the design generated according to the proposed ANN model can be used [27]. With the aim of obtaining more precise findings, the ANN can also be improved by giving the model fresh data sets for the properties of the footing, soil, and reinforcement [25]. The neural network results may be regarded as outperforming conventional methods for settlement prediction because they are based on actual experimental data and do not require any assumptions to make the problem easier to understand [20].

As **geotextile** and **geogrids** are important in the geotechnical industry, new materials such as coir fibers were proposed as an eco-friendly geotextile material [22]. The performance of coir geotextiles was the subject of thorough, in-depth research employing a plate load-testing device. The outcomes showed that coir-reinforcing inclusions improve sand's strength and deformation properties. As a new material used in the soil embankments industry, such as quarry wastes [21], ferrochrome slag [8], and coir fibers [22], it was necessary for utilizing machine learning to conduct the behavior and strength of soil after reinforcement [22,27,72]. When these reinforcing elements are used in practice, the strength of sand beds can be predicted using an ANN model. It was discovered that there was a decent relationship between the model's projected values and the results of the experimental investigation [22]. The model was built on a methodical set of plate load experiments on sand that was not reinforced and sand that was reinforced with coir geotextiles. With the addition of coir reinforcement, the strength and stiffness properties were substantially improved. According to the test results, the ANN model was also established to forecast the strength of sand beds in real-world applications of these reinforcing elements indicating a good correlation between the projected values from the model and the outcomes of the experimental research [22].

The interaction among soil and geotextile and geogrids is crucial for stability and safety in the geotechnical industry. Therefore, machine learning helps predict the optimum **pullout force** of geogrid from soils as a proposed new eco-friendly material for soil improvement [4]. The ANN algorithm was significantly efficient in predicting the pullout force through the variables conducted from the geotechnical and engineering properties of the improved soil [4,19]. However, new data are required to enhance the performance of ANN models [4]. However, important aspects should be considered, as installation damage to geogrids should account for: used strength reduction factors and recognizing the field pullout behavior and the influence of cyclic loading on the behavior of embedded reinforcement in ISFS pulling out [4].

One of the most important and advanced subjects in soil mechanics that focus on soil behavior is **stress–strain behavior**. That defines soil behavior under external forces. Without a doubt, stress–strain behavior is affected by the materials used for soil improvement [74,75], which requires a timesaving and efficient technical way to study, control, and predict the behavior of the improved soil, especially with the large varieties of the eco-friendly materials that involve improving weak soil [27]. In addition, a better understanding of stress–strain behavior allows geotechnical engineers to control settlements and deformations resulting under various conditions of loading [27]. Therefore, ML application was involved in studying the stress–strain behavior of soil improved using green, by-product, and recycled materials such as piling slurry mixed with fibers [5], kraft paper fiber [53], and quarry waste bases [21]. Raja et al. [27] indicated that the created model's sensitivity, generalizability, and robustness are supported by the underlying physical behavior of the geosynthetic reinforced soil foundation GRSF settlement forecast based on existing geotechnical knowledge. Furthermore, the developed ANN model accurately and logically predicts the settlement values, as shown by comparing the predicted and measured foundation settlement [27]. Jiang et al. [5] indicated that the results of this study's unconfined compression test on a modified slurry's stress–strain curve could be accurately fitted by the BPNN. That encourages future research on this crucial topic.

The efficacy of ML-based models to predict the performance of strengthened soils by geopolymer may unquestionably be improved by carrying out further trials under various conditions. In addition, this study focused on considering eco-friendly materials as a significant innovation in our understanding of soils stabilized by geopolymer in predicting unconfined compressive strength [51]. The prediction models were significantly accurate compared to traditional predict mathematical models. However, there was always a **limitation** in the sample number used for input datasets [76]. Therefore, including more data from various soil types and test settings allows the model to be easily retrained to consider a larger variety of data to overcome this constraint [39]. Although ANN results are more accurate, only the optimized network can be displayed. Overall lower values of MAE, RSE, MSE, and RRMSE for trained, validated, and tested dataset are approaching 0, whereas NSE values for trained, validated, and tested dataset corresponding unity show that the ANN model performs better and more efficiently [21].

3. ML Methodology

This study conducted a systematic evaluation and illustrated the current condition of machine learning technology in predicting and controlling the strength of soil improved using green materials. This evaluation was based on the PRISMA technique as recommended by Moher et al. [77], where the method used was the systematic literature review followed as described by both Shamseer et al. [78] and Mardani et al. [79]. Therefore, the goals and what was written in the literature and systematic reviews explained the research topic (Machine Learning Control for Green Materials Used in Soil Improvement Applications). Furthermore, the research questions and goals led to a deeper knowledge of machine learning technology's application in the geotechnical industries. Table 5 presents the research questions, motivations, challenges, and recommendations. This section presents the theory and structure of five ML techniques, including multiple linear regression (MLR), artificial neural network (ANN), extreme learning machine (ELM), and hybrid ML models. The employed approach was explained with schematic diagrams for each step in the process.

Table 5. Research Problems and Motives.

Research Problems	**Motives**
RQ1: How far along is the systematic literature study on employing machine learning in green materials to enhance soil?	Numerous geotechnical applications have successfully used machine learning technology. It is important to comprehend the architecture and key elements of machine learning in applications for soil improvement.
RQ2: How are research publications on this subject distributed by year of publication, author nationalities, publishing house, the goal of employing machine learning in soil improvement using green materials, difficulties, suggested solutions, and contributions?	Machine learning has the potential to enhance difficult tasks in geotechnical applications. Additionally, machine learning may improve the detection of the best engineering ratios for green materials and shear strength, deformation resistance, and stability.
RQ3: What are the obstacles to employing machine learning for soil improvement using green materials for geotechnical applications and why is it important?	Identifying the most effective applications for machine learning in soil improvement is possible.
RQ4: What guidelines may be followed to guarantee the effective use of machine learning to forecast and regulate the strength of improved soil utilizing green materials for geotechnical applications?	It is possible to compile knowledge about machine learning that is successfully used in geotechnical applications.

3.1. Research Objectives

This paper analyzed and summarized the most recent studies on machine learning application in strengthening materials for geotechnical applications. The following are the goals of this systematic literature review:

- To classify and categorize the related and recent research in accordance with various cases of studies;
- To indicate the motives, challenges, and recommendations of machine learning technology with soil improvement using green materials integration to enhance this technique's efficiency;
- To study issues relevant to machine learning incorporation in prediction and controlling the strength of soil improved using green materials and planned solutions in the scope of this research.

3.2. Data Resources

Systematic exploration was achieved using four electronic databases, which were as follows: Web of Science (WOS), ScienceDirect, Scopus, and IEEE Xplore, as shown in Figure 4. The selection of the mentioned electronic databases was based on various articles and conferences published in English only on developing topics, including machine learning applications in soil improvement using green or/and recycled materials.

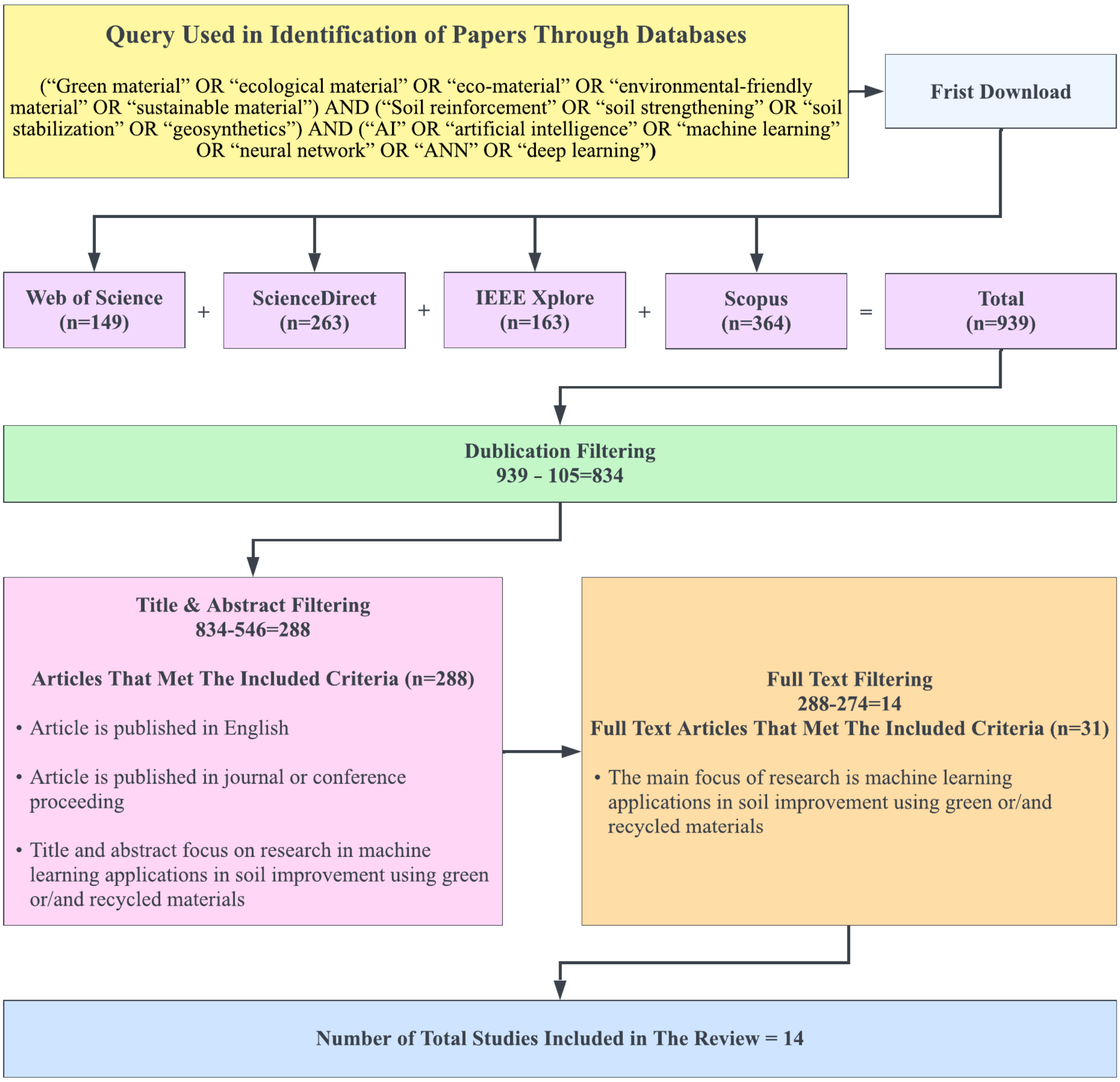

Figure 4. Diagram Outlining the Process for Study Collection, Involving the Search Query and Inclusion and Exclusion Method.

3.3. Study Selection

Selecting relevant studies is difficult, especially when several study areas are being considered. As a result, this step is extremely crucial and might also be the most neglected when researching a particular subject. The first stage involved filtering titles and abstracts to weed out duplicate and irrelevant studies publications [54,56,80]. The second stage of the process involved reading the full texts of the chosen research articles [40,55].

3.4. Systematic Literature Review Search

A query was developed through this study utilizing particular keywords to fulfill the study questions and objectives. Accordingly, it was conducted through this process on the 5th of May 2023 in Web of Science (WOS), ScienceDirect, Scopus, and IEEE Xplore. The used query was '("Waste material" OR "industrial waste" OR "sustainable materials" OR "eco-friendly materials" OR "green buildings" OR "green materials" OR "waste recycling" OR "construction wastes" OR "geopolymer" OR "geosynthetics" OR "geogrid") AND ("Soil reinforcement" OR "soil strengthening" OR "soil stabilization" OR "soil stability" OR "Soil reinforcing" OR "construction" OR "Soil treatment") AND ("AI" OR "artificial intelligence" OR "machine learning" OR "ML" OR "neural network" OR "artificial neural network" OR "ANN" OR "deep learning")". With the database's advanced search option, articles from journals and conferences were selected not considering other selection options, including books and book chapters. It depicted, as shown in Figure 4, the search query, the inclusion and exclusion criteria, and the selection of research publications.

3.5. Eligibility Methodologies

This research focused on machine learning applications for soil improvement utilizing green or/and recycled materials, and it included all papers that met the requirements given in Table 6 and Figure 4. Figure 5 shows how the study landscape was divided into three categories, with traditional taxonomy as the main focus for soil development applications employing eco-friendly or recycled resources. These divisions were made after a careful examination of the review literature sources. After duplicate research articles were removed, studies that did not fit the criteria were discarded [20,29]. Similar to that, a study was taken into account for this evaluation provided it successfully satisfied the requirements mentioned in Table 4.

Table 6. Eligibility Criteria for Inclusion and Exclusion.

Criteria	Identified Standards	Grey Literature
Inclusion	Review papers relevant to the use of machine learning applications in soil improvement using green or/and recycled materials Research papers focused on machine learning applications that are related to soil improvement utilizing green or/and recycled materials (new system designs, framework, scheme, new model, and application of the new algorithm). Analysis of the applications and advantages of machine learning in soil restoration projects that utilize environmentally friendly or recycled materials	According to scientific studies, machine learning has significantly improved soil improvement applications.
Exclusion	Books, book chapters, and theses: • Articles not written in English • Unrelated articles	Theses, books, and book chapters that were not related to the articles on the topic were also excluded.

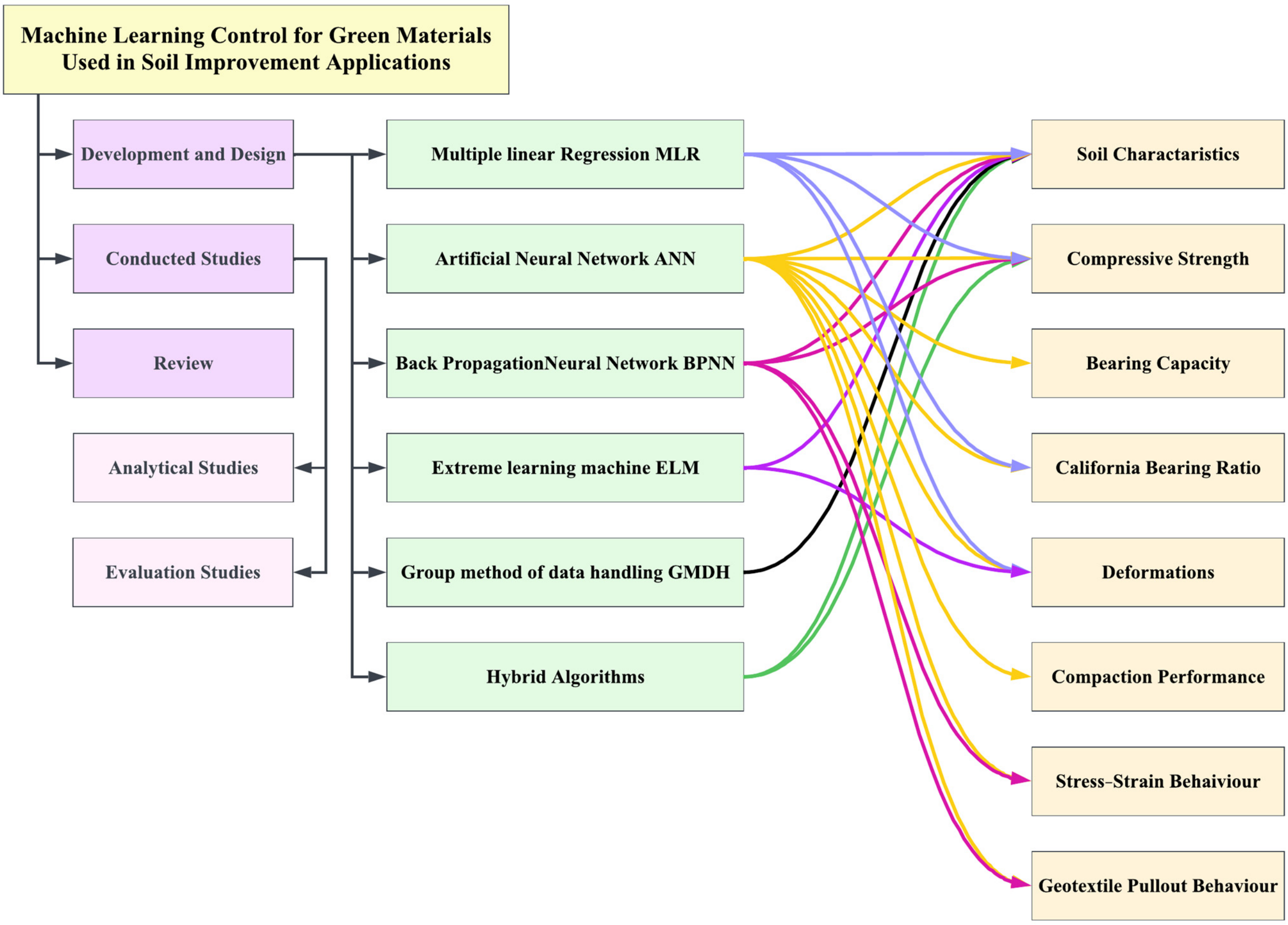

Figure 5. Taxonomy illustration of machine learning technology's application in the geotechnical and construction industries.

4. Coherence Taxonomy

This section lists the relevant research papers' categories and subcategories. The definitions of each subcategory are based on the categorization of research articles and the various eco-friendly soil improvement options. This is shown in Figure 5 and serves as the framework for the definitions of each category.

4.1. Machine Learning Algorithms Used

4.1.1. Multiple Linear Regression (MLR)

The correlation coefficient and nature of the link between the input and output variables are often calculated in regression models. Although the least squares method is commonly used to fit linear regressions, alternative strategies may be utilized, such as lowering the "lack of fit" in various norms or the multi-objective version of the least squares loss function as in ridge regression. Basic and multiple linear regression are the two varieties of linear regression. If the objective is to forecast the linear correlation between one predictor and one criterion variable, the model is referred to as simple linear regression (SLR). As demonstrated in the MLR model architecture in Figure 6, the model is referred to as multiple linear regression (MLR) if the objective is to forecast the linear correlation between two or more predictors and yet another criterion variable. The MLR is the most common kind of linear regression analysis, noting that every value of the independent variable is linked with a value of the dependent variable.

MLR determines the degree of correlation between two or more independent variables (predictors) and a single response variable (dependent variable). It is crucial to keep in mind that the MLR looks at a correlation in terms of a straight line that correctly forecasts each data point that comprises both the goal and output variables [81]. An MLR model's general form is derived as in Equation (1) [81,82];

$$\hat{Y} = a_0 + \sum_{j=1}^{m} a_j X_j \quad (1)$$

where $a_0, a_1, a_2, \ldots ; a_m$ are partial regression coefficients, $\hat{Y}$ is the output of the model, and X_j is its variable of the independent input.

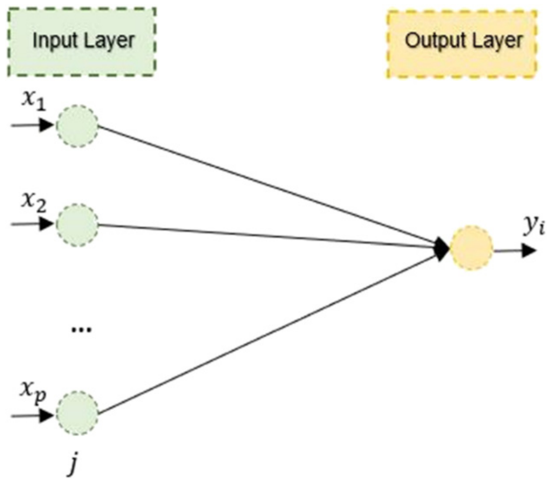

Figure 6. The model architecture of MLR [83].

4.1.2. Artificial Neural Network ANN

ANN is well known as a tool for modeling the complicated multi-criteria systems that are a part of approximation problems. Three layers comprise the ANN (artificial neural network) process: a layer of input, hidden or more layers, and a layer of output. Each hidden layer is linked to the other layers using a transfer function, weights, and biases, as shown in the general ANN structure in Figure 7 [81]. The main component of each layer is the neurons, where each neuron has numerical information that may be referred to as weights. First, the error is identified by looking at the intended output and input values [84,85]. Then, the weights and biases are tuned using an internal training technique to minimize the error by observing the error function. Up until the desired accuracy is attained, the model is trained. Moreover, the output values are validated using that trained model [81].

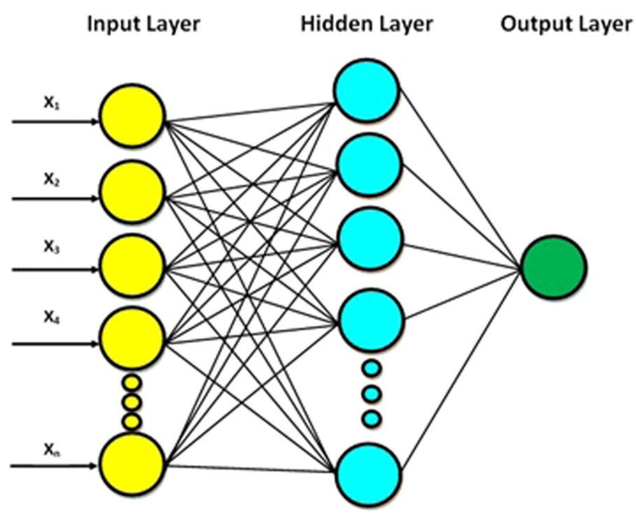

Figure 7. Artificial neural networks structure [81].

Equation (2) illustrates the mathematical relationship among every hidden layer and the independent variables [85]. The p vector of independent variables is x = $[x_1, \ldots, x_p]^T$, each independent variable's matching weights vector is $w_i = [w_i, 1, \ldots, w_i, p]^T$, and σ is activation function that is nonlinear. Sigmoidal function is utilized as the activation function in regression applications for ANN algorithm [86–88], as shown in Equation (3). The anticipated output $\hat{Y}$ is coupled to the hidden neurons h in the same manner as shown in Equation (4) [86], where the hidden neuron vector h = $[h_1, \ldots, h_k]^T$ and set of weight vectors β = $[\beta_1, \ldots, \beta_k]^T$. Despite the fact that g may be a nonlinear function in this case, Equation (5)'s identity matrix is commonly taken for granted.

$$h_i = \sigma\left(w_i{}^T x\right) \tag{2}$$

$$\sigma\left(w_i{}^T x\right) = \frac{1}{1 + e^{w_i{}^T x}} \tag{3}$$

$$\hat{Y} = g\left(\beta^T h\right) \tag{4}$$

$$\hat{Y} = \beta^T h \tag{5}$$

In order to reduce a rate of prediction error for a specific dataset used for training, the weight factors w and β must have the proper values for training neural networks. Regularly, the root-mean-squared error RMSE, where Y_i the output that was observed or measured for observation i, and $\hat{Y}_i$ are the output that was predicted, and N is the observations number or points of data in the training dataset, which gives an adequate measure of error. The identification of weight factors in neural network models is a crucial step in their development. One well-used numerical technique for this purpose is the Levenberg–Marquardt algorithm [84]. Neural network models have a large number of fitting parameters, which makes it easier to identify nonlinear correlations between the independent variable, making them a powerful tool for regression analysis. However, caution must be exercised in the use of neural networks with multiple hidden neurons and/or layers as they are prone to overfitting data, leading to errors in generalization [85,86]. To mitigate this issue, cross-validation should be employed to optimize the hyperparameters' size of a neural network [89].

4.1.3. Back Propagation Neural Network BPNN

BPNN is a form of ANN algorithm evaluated within the context of supervised learning. Typically, the BPNN adjusts the weights by rerouting the output layer to the input layer [90,91]. In addition, each layer of the ANN employs examples and exercises to aid learning, similar to humans [92]. Any model could train to manipulate well using a two-layer back propagation network (BPNN) with nonlinear function as first layer's function and linear as the second layer's function. The variables are initially received by the input layer after being brought into the network from a new external dataset. They are then progressively relayed via any hidden layers and eventually sent to the output layer. Information is stored and conveyed through a network utilizing the feed-forward technique via a linear or nonlinear pattern of the independent vector, weights, biases, and transfer functions [26]. The prediction results are then obtained. Figure 8 illustrates a typical three-layer BPNN architecture. The ANN model still suffers from local minima or over-fitting issues, which lowers the accuracy of its predictions [93]. BPNN is defined in Equations (6) and (7) for the input and output relationship [5,26].

$$p = p_1W_1 + p_2W_2 + \ldots\ p_nW_n \tag{6}$$

$$a = f(net) = \frac{1}{1 + e^{-net}} \tag{7}$$

where the network's input vector is $p_i, p_2, \ldots p_n$, the connection weight is $W_i, W_2, \ldots W_n$ for each input vector, and the output is a.

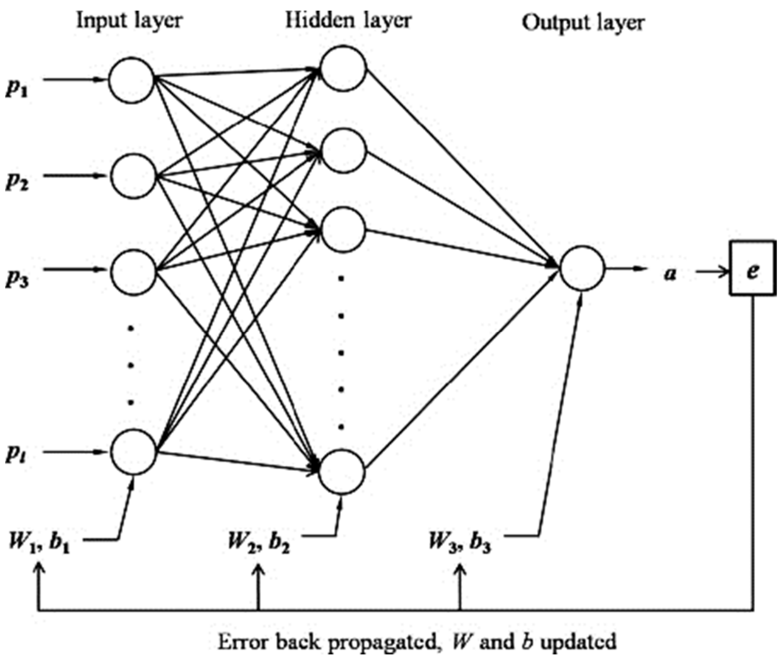

Figure 8. Architecture of BPNN model [93].

4.1.4. Extreme Learning Machine ELM

Huang et al. [94] developed a unique learning method with single-hidden layer feed-forward neural networks (SLFFNNs) called extreme learning machine (ELM), which chooses hidden nodes at random and calculates the output weights of SLFFNNs analytically. The least-squares-based learning approach for generalized SLFFNNs served as the foundation for ELM, an estimator for regression, classification, clustering, and approximation of function problems. Since the hidden layer's weights in the ELM randomly can be initialized, only the output layer's weights need to be optimized [95]. Innovative learning algorithms for feed-forward single-layer neural network include ELM.

For SLFFNN training with K of hidden neurons and in conjunction with the function of activation vector a(x) for learning N of distinct samples (x_i, t_i), where:

$$a(x) = (a_1(x), a_2(x), \ldots, a_K(x)) \tag{8}$$

$$x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]T \in R_n \tag{9}$$

$$t_i = [t_{i1}, t_{i2}, \ldots, t_{in}]T \in R_m \tag{10}$$

If SLFFNNs for N samples can roughly set a zero error, then:

$$\sum_{j=1}^{N} ||y_j - t_j|| = 0 \tag{11}$$

where actual output y of the SLFFNN, and parameters β_i, w_i, and b_i exist such that:

$$\sum_{i=1}^{K} \beta_i a_i \left(w_i \cdot x_j + b_i \right) = t_j, j = 1, \ldots, N \tag{12}$$

where weight vector $w_i = [w_{i1}, \ldots, w_m]^T$ that connects the hidden ith neuron and the input neurons, the connecting weight vector $\beta_i = [\beta_{i1}, \ldots, \beta_m]^T$ of the hidden ith neuron and the output neurons, and the threshold of the hidden ith neuron b_i, as described by Huang et al. [94]. Equation (12)'s control $w_i x_j$ designates the inner product of w_i and x_j. The following is a condensed form of the above N equations:

$$H\beta = T \tag{13}$$

where the hidden-layer output matrix H, the hidden jth neuron's output concerning is the matrix of output weights x_i,, and the matrix of targets T are as described by Huang et al. [94] and Sun et al. [96], where the architecture of model of ELM is indicated in Figure 9. As a result, it is anticipated to learn more quickly and execute more generally. Simply said, it is a more advanced feed-forward neural network with a faster learning rate than any similar network. Extreme learning machine (ELM)'s fundamental operation working principal flow starts by random assign for data to calculate the hidden layer output, the output weights are then calculated, which are used to predict the testing data [8].

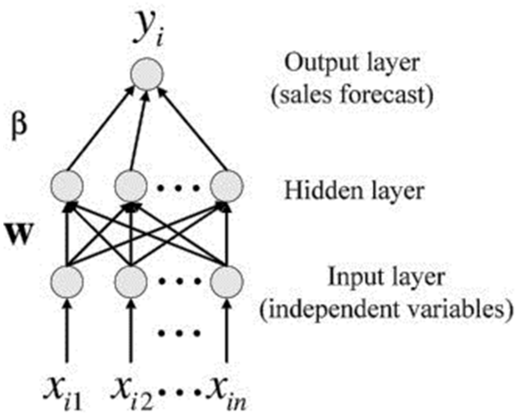

Figure 9. Architecture of ELM model [96].

4.1.5. Group Method of Data Handling (GMDH)

The modelling approach known as the GMDH-type neural network algorithm finds the correlations between the variables utilized. From a time series viewpoint, the algorithm learns how the lags are related [39,51]. It automatically chooses the algorithm to use after learning the relationships. Ivakhnenko [97] built a high-order polynomial by first using GMDH. The Ivakhnenko polynomial is represented by Equation (14).

$$y = a + \sum_{i=1}^{m} b_i \cdot x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} c_{ij} \cdot x_i \cdot x_j + \sum_{i=1}^{m}\sum_{i=1}^{m}\sum_{k=1}^{m} d_{ijk} \cdot x_i \cdot x_j \cdot x_k + \ldots \tag{14}$$

where variables number m, and the polynomial coefficients a, b, c, d, . . . are, commonly known as the weights of variables. In this case, the regressed lagged time series are x_i and x_j, and the response variable is y. The terms are typically employed in calculations up to square terms, as shown in Equation (15).

$$y = a + \sum_{i=1}^{m} b_i \cdot x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} c_{ij} \cdot x_i \cdot x_j \tag{15}$$

All pairwise combinations of p-lagged time series are taken into consideration by the GMDH algorithm. Consequently, every combination involves every neuron [98]. Using these two inputs, a model is created to predict the intended output. In other terms, a neuron receives two input variables and outputs one result. In Equation (15), where m = 2, Ivakhnenko's polynomial specifies the model's structure. Each model must estimate six coefficients according to this specification. There are many levels in the GMDH algorithm, each of which contains neurons. The quantity of input variables determines layer's neurons number. For example, if we suppose that there are p input variables, then there are h-p neurons since all pairwise patterns of input variables $\binom{p}{2}$ are included. Figure 10 shows the GMDH algorithm's design when there are three layers and four inputs.

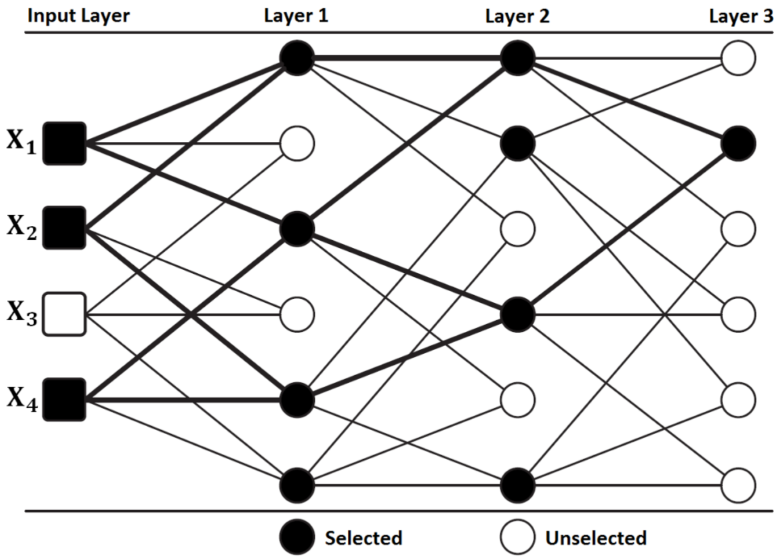

Figure 10. Architecture of GMDH model [98].

The layer's nodes in the GMDH architecture depicted in Figure 10 is six because there are four inputs per layer. The algorithm's first layer is currently present [98]. Every neuron estimates the coefficients of Equation (15). The desired output is anticipated using each neuron's estimated coefficients and input variables. External criteria are used to determine which p neurons are chosen and which h-p neurons are removed from the network [97]. Figure 10 shows the selection of four neurons while removing two from the network. Selected outputs neurons are used as the inputs for the subsequent layer. Up until the final layer, this process is repeated [39,51]. Then, only one neuron is chosen for the final layer. The predicted value for the given time series is the output derived from the final layer. Figure 11 shows a flowchart of the algorithm [97].

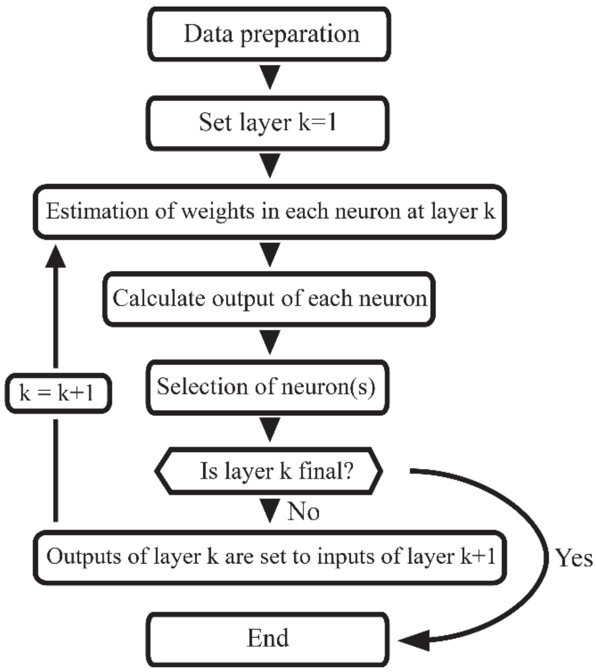

Figure 11. Flowchart of GMDH model [98].

4.1.6. Hybrid Algorithms

The exploratory self-organize technique is used to build the network of the neuro-fuzzy group method of data handling NF-GMDH [99,100]. This network can be combined with several iterative and evolutionary techniques. Additionally, as illustrated in Equation (16) [101], a condensed rule of fuzzy is used to advance the network of GMDH-based. Output y is w_k if z_1 and z_2 are G_{k1} and G_{k2}, respectively.

$$G_{kj}(z_j) = exp(-\left(z_j - a_{kj}\right)^2/b_{kj}\right) \tag{16}$$

In the context of the jth input parameter for the fuzzy rule, G_{kj}, which is connected to the Gaussian function, is used. The values of a_{kj} and b_{kj} are fixed for every rule. The definition of y is shown in Equation (17), where w_k corresponds to the kth fuzzy rule's true value [99,102].

$$y = \sum_{k=1}^{K} u_k w_k \tag{17}$$

$$u_k = \prod_j G_{kj}(z_j) \tag{18}$$

Each neuron in the GMDH-based neuro-fuzzy model has a single output and two inputs. Each layer's output is regarded as the subsequent layer's input. The parameter of final output is conducted using the final layer's outputs average [103,104]. The n−1th model's output variables in the q − 1th layer predicted from the variables of input generated from the models of nth and layer qth. It defines the computational form for calculating the μ_k^{qn}. Equation (19) has w_k^{qn}, the equivalent weighted coefficient for the model nth in the qth layer, and q_{nk}, the kth Gaussian function. The input variable ith from the model nth and layer qth is also employed, along with the Gaussian parameters a_k^{qn} and b_k^{qn}. The final result is also stated, as shown in Equation (20).

$$y^{qn} = f\left(y^{q-1,n-1}, y^{q-1,n}\right) = \sum_{k=1}^{K} \mu_k^{qn}.w_k^{qn} \tag{19}$$

$$\mu_k^{qn} = \exp - \frac{\left(y^{q-1,n-1} - a_{k,1}^{qn}\right)^2}{b_{k,1}^{qn}} - \frac{\left(y^{q-1,n} - a_{k,2}^{qn}\right)^2}{b_{k,2}^{qn}} \tag{20}$$

As stated in Equation (21), the inaccuracy of each iteration during the training phase of the neuro-fuzzy GMDH may be computed, where y^* is the amount predicted [51].

$$Er = \frac{(y^* - y)^2}{2} \tag{21}$$

Gaussian variables and the fuzzy rule's weighting parameters are unknown in each partial description (PD). The PDs coefficients was optimized using a technique of particle-swarm optimization (PSO) forming the NF-GMDH-PSO model. In this method, each solution to the issue is represented by a "particle," which is a bird in the search space. Each particle receives a strength value calculated from the strength function. The bird that is nearer to the food source, thus, has a higher strength value. A vector of velocity that depicts the direction and speed of each bird's movement is also shown. Each bird alters its path during optimization based on studies in cognitive and social sciences [102]. The PSO algorithm uses particles to represent potential solutions to the optimization issue. The solution space dimension d, and the ith particle in the sth iteration possess the position vector $X_i^s = x_{i1}^s, x_{i2}^s, \ldots x_{id}^s$ and velocity vector $V_i^s = v_{i1}^s, v_{i2}^s, \ldots v_{id}^s$. The particle ith at a x position in the PSO algorithm improves its position using Equation (8) where v_{k+1}^i indicates the ith particle's improved velocity that was predicted from Equation (23), where velocity value in the kth iteration is v_k^i, the two numbers random between zero and one r_1 and

r_2, the ith particle best position of p_k^i, and best particle position p_k^g. Cognitive parameter c_1 and social parameter c_2 are known as factors of trust because they affect how much people trust particle flow and swarm movement [105]. The parameter if inertia weight w is crucial to the PSO algorithm's convergence. According to Equation (10), where w_{min} is the w minimum value, w_{max} is the w maximum value, and k_{max} is the maximum number of iterations, this parameter decreases as the number of iterations increases [51].

$$x_{k+1}^{i} = x_k^i + v_{k+1}^{i}.\Delta t \tag{22}$$

$$v_{k+1}^{i} = w_k v_k^i + c_1 r_1 \left(p_k^i - x_k^i\right) + c_2 r_2 \left(p_k^g - x_k^i\right) \tag{23}$$

$$w_{k+1} = w_{max} - \frac{w_{max} - w_{min}}{k_{max}} k \tag{24}$$

Due to the concurrent operation of the neuro fuzzy GMDH (NF-GMDH) and PSO algorithms, each partial description (PD) is optimized by the PSO approach for six unknown parameters of the Gaussian function. The integration of the PSO algorithm with the NF-GMDH network is shown in Figure 12. Three fuzzy rules were applied to each PD. The NF-GMDH-PSO-based model includes eight input parameters and one output. The training process provided 15 incomplete descriptions in the first layer. The second layer then produced 15 PDs from the previous layer. Achieving the fewest errors throughout the training phase would allow this procedure to proceed.

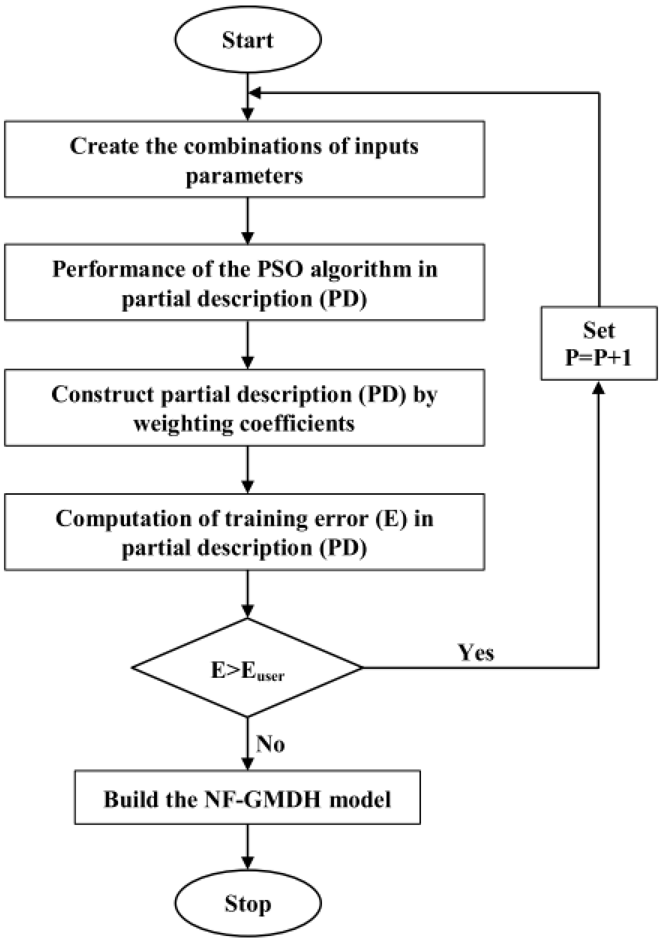

Figure 12. Flowchart of NF-GMDH-PSO model [98].

4.1.7. Accuracy and Performance Evaluation for Models

It was crucial to employ error equations as a comparison element in order to assess the accuracy of various anticipated models. Numerous artificial intelligence models were assessed using the three most used statistical indices: variance account for, coefficient determination R^2, and root mean squared error RMSE. It was evident from the simulation results and the generated index values for the training and test sets that the suggested models were accurate. Therefore, a new, practical equation that can precisely anticipate the desired elements, such as shear strength, may be created using provided models with the best statistical indices values. Along with the coefficient of determination of mean square error R^2 value, the root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE), normalized root mean square error (nRMSE), and normalized mean absolute error (nMAE) were determined. Comparable measures were used by several research [89,106] in the literature to assess the effectiveness of the model's prediction abilities. These metrics are expressed using equations from 25 and 29, where m is the number of observations in the dataset, $\hat{Y}$ is the observed output (experimental value), and is the forecast output.

$$SE = \frac{1}{\mathrm{N}} \sum_{i=1}^{N} \left(Y - \hat{Y}\right)^2 \tag{25}$$

$$RMSE = \sqrt{\frac{1}{\mathrm{N}} \sum_{i=1}^{N} \left(Y - \hat{Y}\right)^2} \tag{26}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \left|Y - \hat{Y}\right| \tag{27}$$

$$nRMSE = RMSE/Y_{mean} \times 100 \tag{28}$$

$$nMAE = MAE/Y_{mean} \times 100 \tag{29}$$

Coefficient of determination R^2 and scatter index SI are also methods of models' evaluation, where Equations (30) and (31) are for SI and R^2, respectively. Also, the range of the scatter index for model evaluation is shown in Figure 13, where the lesser the value, the better the model [107]. In addition, T-statistics T_{stat} and expanded uncertainty U_{95} are also used for model evaluation, as shown in Equations (32) and (33) [45].

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \left(Y_p - Y_e\right)^2}{\sum_{i=1}^{N} \left(Y_e - \hat{Y}_e\right)^2} \tag{30}$$

$$SI = RMSE/\hat{Y}_e \tag{31}$$

$$T_{stat} = \sqrt{\frac{(n-1)MBE^2}{RMSE^2}} \tag{32}$$

$$U_{95} = 1.96\sqrt{SD^2 + RMSE^2} \tag{33}$$

$$MBE = \frac{\sum_{i=1}^{N} \left(Y_p - Y_e\right)}{n} \tag{34}$$

$$SD = \sqrt{\frac{\sum_{i=1}^{N} (X_i - AM)^2}{N-1}} \tag{35}$$

$$AM = \frac{1}{N}\sum_{i=1}^{N} X_i \quad (36)$$

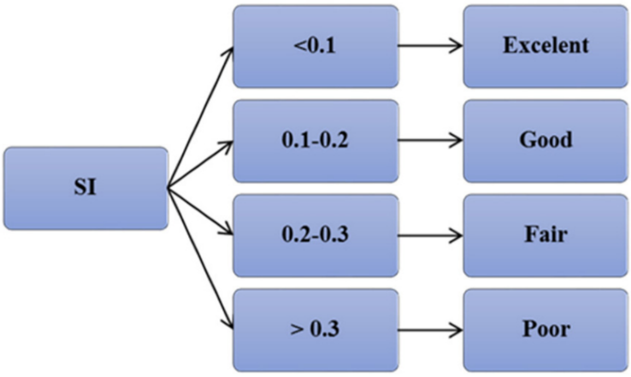

Figure 13. The ranges of scatter index SI for model evaluation [107].

4.2. Green Soil Reinforcing Materials

Due to their impulsive deformation and shriveling characteristics, marine clay soil kinds are considered to be the most precarious and vulnerable in the global building business. If structures are constructed in wet environments, the consolidation phenomenon has an adverse effect on their performance. Due to their high moisture content, soil particles lose contact under loading and become loose, which causes soil shear failure. For structures erected on expansive soil as depicted in Figure 14, innumerable building damages were already seen during unexpected soil deformation and shrinkage [108].

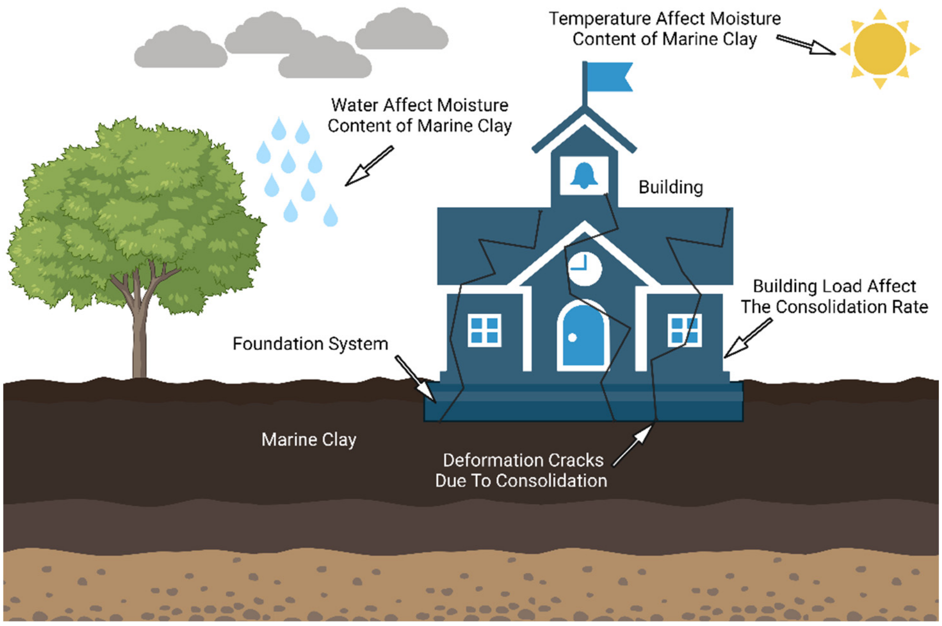

Figure 14. Structural failure as a result of the marine clay soil properties.

4.2.1. Fly Ash

In coal-burning power plants, fly ash is mostly created during the energy production process [109]. Fly ash is collected using an electrostatic or mechanical precipitator [110–113]. Although landfilling is a common method of disposing of fly ash, rising disposal costs and significant environmental concerns regarding the leaching of latent toxic substances from the ash to soil, surface water, and groundwater [114–116] make the utilization of fly ash a more appealing alternative to direct landfilling [117]. Industrial waste is frequently utilized as a stabilizer to lessen the negative effects on engineering properties of weak soils through reactions with soil particles that improve the engineering qualities of the soils [118]. Accordingly, fly ash behavior was covered by previous research. The addition of fly ash to the soft soils such as marine clay and soft clay soils changed the micro-mechanical and macro-mechanical properties after treatment [118]. The apparent cohesion and angle of internal friction of fly ash are plotted against various moisture contents, where the apparent cohesion increases with the moisture content increment, where reaching its maximum value at the optimum moisture level before progressively declining again beyond it. Obviously, the fly ash grains lost contact force with the generated pore water pressure. Additionally, the moisture content of the molding was slightly reduced by the friction angle by up to 25%; however, it reduced significantly as the water content reached 30% [119]. That increased the unconfined compressive strength dramatically, where the USC increased significantly as the soil texture improved for resisting loads [120]. Despite the clay type, fly ash addition improved the shear strength of high and low plasticity clays, where the same trend was assessed even with quarry dust addition [121]. The unconfined shear strength gradually increased by improvement using fly ash content up to 30% [122]. The shear strength of palm oil fly ash POFA reinforced soil shear strength significantly increased compared to the non-reinforced soil as shown in [123]. The minimum increase was 10 kPa after reinforcement using POFA. Furthermore, both cohesion and internal fiction angle increase significantly at least by 50%. Additionally, both values increased as the vertical pressure increased by 10%, which could be related to matric suction caused by the effect of the vertical pressure [123].

Soft soils such as soft clay shown improvement in the resistance for deformation after using palm oil fly ash POFA. Both saturation degrees 100% and 50% showed a decreasing in deformation values and rates by the increase in POFA ratio. Furthermore, the maximum decrement in deformation was by 50% for 20% POFA sample. That illustrates the benefit using POFA in deformation reduction for geotechnical and construction applications. This is explained by the fact that the water molecules in the inter-particle gaps in the soft soil were only partially filled up at the time of partial saturation, allowing the soil POFA composite to contract before the loading was applied. This indicates that a larger POFA percent is needed to fill up these voids in order to strengthen the soil POFA composite matrix [123].

4.2.2. Natural Pozzolans

Natural pozzolans are typically included in concrete mixtures to help calcium hydroxide (CH) transformation into calcium silicate hydrate that is the source of concrete strength. As stated in ASTM C-618 [124], class N is made of raw or calcined natural pozzolans. However, manufactured materials are used more frequently than raw pozzolans in typical dispensation such as calcined clay, calcined shale, and natural metakaolin. Although calcined shale also has some cementing or hydraulic properties, it is used in general construction with other pozzolans [125]. Meanwhile, most of kaolin clay content is calcined at a low temperature, followed by grinded to an average particle size of between 1 and 2 µm, to create metakaolin. Comparing it to silica fume, it is roughly ten times coarser in diameter but about ten times finer than cement [126]. Compressive strengths developed by time and the increment of added calcined shale ratio for strengthened soil samples [127]. The results showed some fluctuation in compressive strength. However, the compressive strength increased significantly for the treated samples compared to the control samples [127,128]. Furthermore, the strength increased as the pozzolanic activity increased by time and, as a result, the pores size inside the treated soil samples decreased [127]. The curing time has a significant effect on the mechanical and physical properties of the calcined shale replacement in concrete and geotechnical industries. Throughout the whole one-year testing period, the amount of Portland cement replacement at 30% was obtained with the highest compressive and bending strengths [129]. The findings showed that as specimens age, their densities rise. Due to the curing regime adopted in this research, which is a water and sea water curing regime, this may be the result of the continuous hydration process of cement in the presence of a continual water supply [125].

4.2.3. Slags

Slags are a byproduct of heavy metals industries such as iron, copper, aluminum, zinc, etc., where it produces ground granulated blast furnace slag (GGBFS), copper slag, aluminum slag, and zinc slag [4,52,130,131]. Slag materials were used in geotechnical applications and specially in soil improvement as a process of sustainable byproduct recycle and reduction in environmental impact [132,133]. In addition, slags are byproducts that were investigated as a potential source of pozzolanic material [134,135]. GGBFS is obtained during the manufacturing of iron and steel in the blast furnace, where iron ore, calcium carbonate, and coke are heated at a specific temperature of about 1500 °C. While these materials soften in the blast furnace, GGBFS is formed as a side-product. GGBFS contains calcium silicates and aluminates, which make it a good pozzolanic material for soil stabilization. It was shown to have good mechanical properties and durability when used in combination with other materials such as fly ash or rice husk. Several studies investigated the use of GGBFS, where the addition of GGBFS improved the compressive strength and workability of geopolymer concrete while reducing its environmental impact [2,134]. Additionally, copper slag is a by-product of the copper smelting process, which is generated in large quantities worldwide. It is a granular material that consists of non-ferrous particles, iron, and silica [136]. Furthermore, aluminum slag is a byproduct of the aluminum smelting process and is generated during the refining of aluminum from bauxite ore. It is a complex mixture of various compounds, including metallic aluminum, alumina, and other metal oxides [36]. However, it typically contains between 10% and 30% metallic aluminum, making it a valuable resource for recycling and reuse. Zinc slag is also a byproduct of the zinc smelting process and is generated during the refining of zinc from zinc ore [4]. It is a complex mixture of various compounds, including metallic zinc, iron, and other metal oxides. The composition of zinc slag varies depending on the source material and the specific smelting process used. However, it typically contains between 10% and 20% metallic zinc, making it a valuable resource for recycling and reuse [4].

Due to its chemical composition, slag was found to exhibit pozzolanic properties, which make it suitable for use as a partial replacement for cement and lime in various geotechnical applications [4]. The pozzolanic property of copper slag arises from its high content of silica and alumina, which react with calcium hydroxide in the presence of water to form calcium silicate hydrate (C-S-H) gel. This gel contributes to the strength and durability of stabilized soils [4,38,52]. In addition to its pozzolanic properties, slag was also found to improve the engineering properties of soil when used as a stabilizing agent. Studies showed that adding copper slag to soil can increase its strength and reduce its compressibility [4]. This is due to the fact that slag particles fill the voids between soil particles, resulting in denser soil with improved load-bearing capacity. Despite its potential benefits, there are also some concerns associated with the use of slag in construction applications. One major concern is the potential leaching of heavy metals from slag into groundwater or surface water sources. Therefore, it is important to conduct proper testing and analysis before using slag in construction projects to ensure that it meets environmental regulations and does not pose any health risks [4,38,52]. Overall, slag showed promise as a sustainable alternative material for use in construction applications due to its pozzolanic properties and ability to improve soil engineering properties. However, further research is needed to fully understand its potential benefits and limitations before widespread adoption can occur. Further research is needed to fully explore its potential uses and to optimize its properties for specific applications [4,38,52].

4.2.4. Rice Husk

Rice husk is an agricultural waste material that was investigated as a potential source of silica in geopolymer concrete. It is obtained during the processing of rice and is mainly used as a fuel for electricity production. Rice husk contains amorphous and partially crystalline phases, with a higher content of silica compared to other agricultural waste materials [14,137]. The high silica content of rice husk makes it an attractive alternative to traditional sources of silica such as fly ash or GGBFS [118]. When used in combination with other materials such as fly ash or GGBFS, rice husk was shown to improve the mechanical properties and durability of geopolymer concrete. However, its availability may be limited in some regions, which can affect its use as a sustainable material for construction. Several studies investigated the use of rice husk in geopolymers as soil improvement material, where the effect of rice husk ash on the mechanical properties and durability of improved soil was investigated. The addition of rice husk ash improved the compressive strength of the improved soil [14], and it improved the mechanical properties and durability of improved soil while reducing its environmental impact [130]. Despite its potential benefits, there are also some limitations to using rice husk in geopolymer-improved soil. One major limitation is its availability, which may be limited in some regions where rice production is not prevalent [14]. Additionally, there may be concerns about the quality and consistency of rice husk obtained from different sources, which can affect its suitability for use in construction applications [138]. Nonetheless, research on the use of rice husk in geopolymer-improved soil continues to explore its potential benefits and limitations as a sustainable material for geotechnical applications [130,138–140].

4.2.5. Coir

Coir is a natural material that was used for various applications, including soil stabilization. Coir is a fibrous material that is obtained from the outer husk of coconut fruit. It is a renewable resource and has several advantages over other materials used for soil stabilization [141]. According to Rowell et al. [142], coir has a lasting service life of 4–10 years, making it an ideal material for long-term soil stabilization projects. One of the unique properties of coir is its tensile strength in wet conditions. Babu S and Vasudevan K [142] found that coir exhibits higher tensile strength when it is wet, making it an effective material for soil stabilization in areas with high moisture content. Coir also has good water retention properties, which can help improve the moisture content of the soil and reduce compaction effort during construction [22]. In addition to its technical properties, coir is also an environmentally friendly material. It is biodegradable and does not release harmful chemicals into the environment [143–147]. The use of coir as a natural material for soil stabilization can help reduce the carbon footprint associated with traditional methods that rely on synthetic materials [22]. Overall, coir is a versatile and sustainable material that can be used for various applications, including soil stabilization. Its unique properties make it an effective alternative to traditional methods while also promoting environmental sustainability [141].

5. Classification of Research Articles

The final research articles are categorized and discussed in this section based on the following criteria: (1) publication year, (2) nationalities of author, (3) house or journal of publishing, (4) goal of using machine learning in soil improvement applications using green or/and recycled materials and article contributions, and (5) type of problems and suggested solutions. The article publications trend across the four databases IEEE Xplore, ScienceDirect, Scopus, and WOS from 2013 to 2022, although the search was not limited by duration and no records before 2015 were used, as illustrated in Figure 15. The number of publications is increasing annually. As a result, researchers' interest in blockchain technology for healthcare applications recently grew. In 2021, machine learning in soil improvement applications using green or/and recycled materials grew, and more research is anticipated.

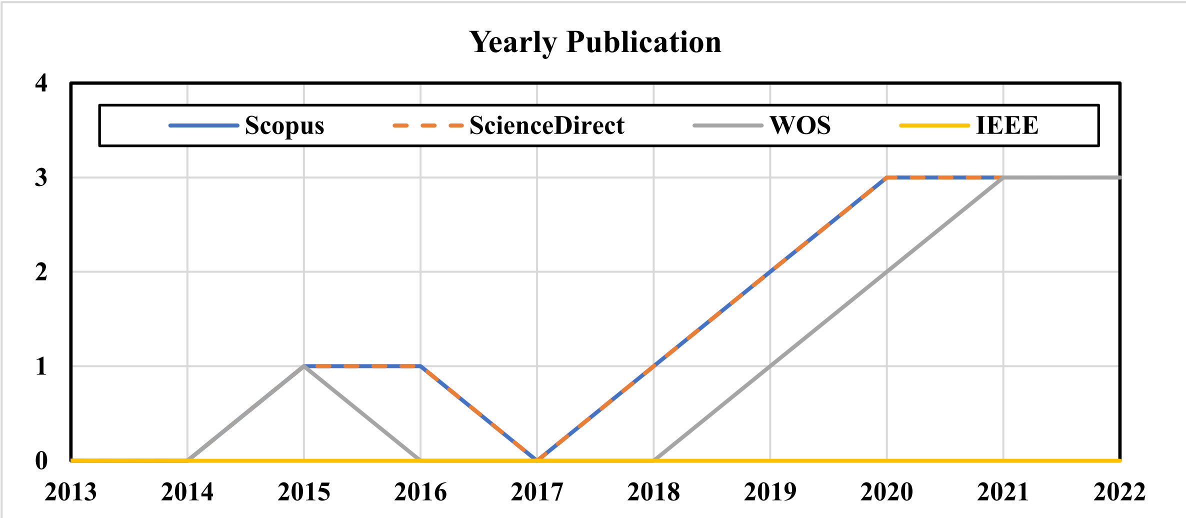

Figure 15. Trending of publication as per IEEE Xplore, ScienceDirect, Scopus, and WOS databases.

5.1. Distribution by Year of Publication

Distribution according to publication year is shown in Figure 16, which shows how research publications are distributed among digital databases and taxonomy categories. Four major areas comprise the systematic literature review: design and development, studies of assessment, analytical investigations, and review papers. In general, no review and analytical studies were conducted through this research, where 14 articles were categorized as ten development and design and two assessment studies. WOS published five development and design articles and two assessment studies, whereas both ScienceDirect and Scopus published ten development and design and two assessment studies. Finally, IEEE Xplore was out of interest in the current research topic.

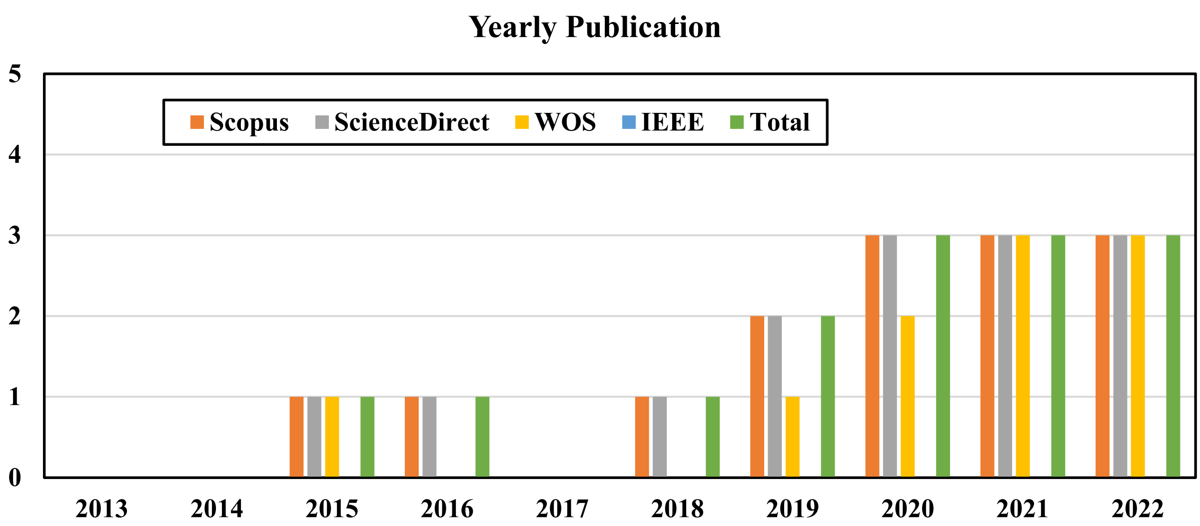

Figure 16. Trending of publication as per IEEE Xplore, ScienceDirect, Scopus, and WOS databases.

5.2. Distribution by Author Nationality

Figure 17 shows how machine learning is used to develop soil improvement applications employing green or/and recycled materials in five different countries, along with the authors' nationalities. It was noticed that pertinent studies were carried out in nations where machine-learning applications were being explored. The 14 publications in machine learning based on soil improvement applications employing environmentally friendly or recycled materials have a nationality distribution that revealed the most productive writers are from India and Iran by 6 and 3, respectively, while one each were from Australia, China, Pakistan, Turkey, and UK.

Figure 17. Nationality of the authors of published articles as per IEEE Xplore, ScienceDirect, Scopus, and WOS databases.

5.3. Distribution by Publishing House or Journal

According to publishers' publications and scientific conferences, the research articles were categorized, as shown in Table 7. In the comprehensive review, this new categorization concept was utilized to help researchers focus on the journals pertinent to the topic of a specific research.

Table 7. Articles categorization by publishers.

ID.	Journals and Conferences Titles	Publisher	Source
1	Advances in Civil Engineering	Hindawi	[5]
2	Arabian Journal for Science and Engineering	Springer	[1]
3	Computers and Geotechnics	Elsevier	[38]
4	Construction and Building Materials	Elsevier	[7]
5	Emerging Trends in Engineering, Science and Technology for Society, Energy and Environment	Taylor and Frances	[22]
6	Engineering with Computers	Springer	[51]
7	Environmental Science and Pollution Research	Springer	[21]
8	Geotextiles and Geomembranes	Elsevier	[4]
9	Innovative Infrastructure Solutions	Springer	[8]
10	Iranian Journal of Science and Technology—Transactions of Civil Engineering	Springer	[39]
11	Journal of Materials in Civil Engineering	ASCE	[52]
12	Materials Today: Proceedings	Elsevier	[6]
13	Construction and Building Materials	Elsevier	[57]
14	Materials	MDPI	[58]

5.4. Distribution by Use of Machine Learning in Soil Improvement and Stabilization Applications

According to the systematic review, machine learning algorithms were employed in a various soil improvement application after treatment using green, recycled, and by-product materials to address several concerns: (1) assessment of green, recycled, and by-product materials as soil-improving materials, (2) samples number or dataset size, (3) limited used algorithms, (4) limitation of algorithms, (5) optimization of neural network architecture, (6) loading conditions, and (7) soil type, as shown in Figure 15. Each research article distribution according to contributions of author is shown in Table 8. By using machine learning in environmentally friendly soil improvement applications, (1) new provided innovative system designs five articles [1,8,21,39,52], (2) new framework 1 article [1], new scheme 1 article [4,57], prediction models 14 articles [1,4–8,21,22,38,39,51,52], and new algorithm application four articles [1,8,39,51]. This systematic study was used to conduct the following analysis to use machine learning in the green soil improvement industry. Table 9 demonstrates that the majority of papers employed in machine learning to enhance (1) prediction of the used ratio green materials effect on soil improvement, (2) prediction of shear strength, (3) prediction of deformations, (4) resistance prediction, and (5) prediction of soil behavior and interaction. Because machine-learning technology involves specialized applications, authors listed a variety of machine-learning-related uses in the green soil improvement industry. As a result, this scientific field will be mentioned frequently.

Table 8. Contribution of the articles.

No.	Contributions	References
1	New system designs	[1,8,21,39,52]
2	Framework	[1]
3	Scheme	[4,57]
4	New model	[1,4–8,21,22,38,39,51,52,57,58]
5	Application of the new algorithm	[1,8,39,51,57,58]

Table 9. Purpose of ML usage in soil improvement using green, by-products, and recycled materials.

No.	Contributions	References
1	Improving prediction resistance	[1,4–8,21,22,38,39,51,52]
2	Improving the prediction of deformations	[4–8,21,22]
3	Improving prediction of shear strength	[1,5,38,39,51,52,57,58]
4	Improving prediction of the used ratio green materials effect on soil improvement	[1,4–8,21,22,38,39,51,52]
5	Improving prediction of soil behavior and interaction	[4,6–8,21,22]

6. Discussion

Machine learning algorithms are still limited in controlling and predicting the behavior of the eco-friendly improved soil. In addition to the trend of climate change's effect on earth, it became essential to use ML in this trend. In addition, there are efficient algorithms not used through the conducted studies through this research, such as support vector regression (SVR), gradient boost trees (GBoost), extreme gradient boost tree (xGBoost), decision trees (DT), adaptive neuro-fuzzy inference system (ANFIS), and others, despite their efficient prediction in other studies on deformation [17,18,24,26], stress–strain [38,148], compressive strength [36], and other areas of study [27,76,131,149]. Therefore, more research in this area is required to understand the mathematical meaning and model architecture that would help researchers select the best algorithm application in the eco-friendly geotechnical industry. The selections of the algorithms depend on the input features used for building the models, otherwise.

Despite the wide variations of the eco-friendly materials proposed for soil improvement, the research of machine learning applications in this area was very limited. Green, by-product, and recycled materials such as fly ash [122,150–153], palm oil fly ash [66,154–159], rice husk [17,137,160,161], coal fly ash [162], coir fibers [141], calcined shale [128,163–165], aluminum sludge [7,36], aluminum dross [166], bamboo fibers [19,31,72], rubber [75], etc., and their combination were open for unlimited mixtures for reinforcing and improving soils and reduction in the climate change impact. Using these materials opens the need for efficient and timesaving mathematical tools to control and predict their effect on soils after improvement, especially with current humanity improvement challenges.

7. Data Extraction and Summarization

Twelve papers were conducted and assessed at this stage of the review process, during which important information was acquired. The papers that were selected for fulfilment were all divided into different applications of soil stabilization and soil improvement using different ratios of different green, by-products, and recycled materials, where the applications were: soil characterization, bearing capacity, deformation, compressive strength, pullout strength, California bearing ratio, compaction, and stress–strain behavior. Articles distribution in the subject of machine learning application in soil improvement according to the titles of the conferences and journals, the publication year, the methodology used, the research objectives, and the results and conclusions were some of the criteria used to evaluate and summarize the papers, as shown in Table 10.

Table 10. Distribution of articles on the topic of ML technique in soil improvement according to the areas of application.

No.	Area	Total	Ratio
1	Engineering	14	100.0
2	Materials Science	12	85.7
3	Environmental Sciences Ecology	7	50.0
4	Computer Science	7	50.0
5	Construction Building Technology	5	35.7

8. Conclusions

In this research, studies about machine-learning applications in green soil improvement over a 10-year period (1 January 2013 to 5 May 2023) were systematically reviewed. The research motivation of this work was the trend of machine learning and the massive environmental impact of the by-product and waste materials and, therefore, how both can be used in geotechnical applications for green soil improvement. Furthermore, there is limited research on this area (14 articles), the used algorithms and their limitations, the collected data from the experiments, soil types, and the targeted output. This comprehensive review focused on key aspects including the selection process for the latest articles, an analysis of the existing papers in the field using a taxonomy approach, and a discussion of previous research endeavors, challenges, and motivations. Despite the limited number of studies available in this area, the current data play a crucial role in combating future outbreaks of a similar nature and overcoming these difficulties, as geotechnical engineers and researchers. In addition, studies should consider how our respected area can be an asset in the near future. From the perspectives of geotechnical engineering, integrating other technologies, such as AI, ML, and different analysis procedures, can contribute to making a difference. Despite the outstanding potential of and vast interest in machine-learning applications, it was concluded that its impact on healthcare remains in green soil improvement applications are yet to be developed. The majority of the studies on in green soil improvement applications based on machine learning continue to remain in the form of novel concepts and in green operating by-products. The future of machine-learning applications in green soil improvement has the immense potential to exert a significant positive effect on sustainable and efficient green soil improvement.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su15129738/s1, PRISMA 2020 Main Checklist [167].

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Abbreviations

AL	Atterberg limits
ANFIS	Adaptive Neuro-Fuzzy inference system
ANN	Artificial neural network
ASCE	American Society of Civil Engineers
BC	Bearing capacity
BM	Bayesian model
BPNN	Back Propagation Neural Network
CBR	California Bearing Ratio
DT	Decision Trees
DS	Direct Shear
ECH	Electrochemical test
ELM	Extreme learning machine
GBoost	Gradient boost tree
GMDH	Group method of data handling
IEEE	Institute of Electrical and Electronics Engineers
MAE	Mean absolute error
MDD	Maximum dry density
MDPI	Molecular Diversity Preservation International
ML	Machine Learning
MLR	Multiple linear Regression
MPT	Modified proctor test
MRA	Multiple Regression Analysis
NID	Neural interpretation diagram
nMAE	Normalized mean absolute error
nRMSE	Normalized root mean square error
NF GMDH	Neuro-fuzzy GMDH
OMC	Optimum moisture content
PD	Partial description
Phy	Physical
PI	Plasticity Index
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSO	Particle-Swarm Optimization
USCS	Unified soil classification system
R^2	Coefficient of determination
RF	Random Forest
RMSE	Root mean square error
RSE	Root square error
RRMSE	Relative root mean square error
RQ	Research question
SETT	Settlement
SD	ScienceDirect
SG	Specific Gravity
SGA	Simple Genetic Algorithm
SI	Scatter index
SS	Shear strength
SVR	Support vector regression
SA	Sieve Analysis
TS	Tension strength
T_{stat}	T-statistics
U_{95}	Expanded uncertainty
WOS	web of science
xGBoost	eXtreme Gradient boost tree

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