AI-Based Prediction of Geotextile Performance and Durability Under Different Soil Conditions

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Abstract

Geotextiles are really important in construction and transportation projects because they help with things like keeping soil separate filtering water draining water making things stronger and stopping erosion. How well geotextiles. How long they last depend on the type of soil they are in how wet the soil is, how much weight is on them what kind of chemicals they are exposed to and what the environment is like. Usually, people test geotextiles in a lab watch how they do in the field and use rules of thumb to figure out how they will work. This can take a long time cost a lot of money and it is hard to know if it will work the same in different types of soil.

Now that we have things like Artificial Intelligence and Machine Learning we can make models that can predict how geotextiles will work and how long they will last based on lots of soil and environmental factors. This study is about making a framework that uses Artificial Intelligence to predict how geotextiles will do in types of soil. We will use things like what kind of soil it's how the soil particles are spread out how wet the soil is, how dense the soil is, how well water can get through the soil how acidic the soil is, what the temperature is, how much pressure is on the soil how strong the soil is and what the geotextile is made of to make our predictions. We will look at things like how strong the geotextile stays how much it stretches, how it lets water through how well it filters, how much it deforms and how long it will last to see how it is doing.

We can use Machine Learning techniques like Artificial Neural Networks, Random Forest Support Vector Regression and Gradient Boosting to make our predictions and compare them using things like how well they fit the data how far off they are from the real values and what percentage they are off. This will help us figure out what the important factors are that affect how geotextiles work and last in different types of soil. This study will show that Artificial Intelligence can be an useful tool for picking the right geotextile materials predicting how long they will last, reducing the need, for experiments and making construction projects more reliable and sustainable.

Keywords: *Artificial Neural Networks; Geotextile; Machine Learning; Soil Conditions; Durability Prediction; Geotechnical.*

1. Today's geotechnical projects often use man-made materials called geosynthetics. These help strengthen soil and make structures last longer, both short-term and long-term.

Geotextiles are a common type of geosynthetic. They're widely used in roads, railways, landfills, and coastal defenses.

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They serve several roles: keeping layers apart, filtering water, draining excess liquid, adding strength, and protecting materials.

How a geotextile behaves under stress doesn't depend on the specific material it's made from.

The soil around it can affect how well it works. Things like the size of the soil particles how much water is in the soil and how acidic the soil is can all impact the Geotextile. So a Geotextile that works well in one place might not work well in another.

Durability is a deal because Geotextiles are often used for a long time. They can be damaged by things like sunlight, chemicals and heavy loads. All these things can affect how strong the Geotextile is and how well it filters water.

Artificial Intelligence can help with this. Machine Learning algorithms can look at a lot of information. Figure out how different factors affect the performance of Geotextiles.

If such algorithms are properly trained, it will be possible to predict the effectiveness of geotextiles. The problem at hand is the use of artificial intelligence to predict geotextile performance and lifespan after placement in the soil. The study will combine geotechnical expertise, the properties of the polymer, and environmental variables to create algorithms that can select appropriate materials and develop strategies for their indefinite use.

2. Background to the Performance of Geotextiles

Polypropylene and polyester are some of the polymers used to make geotextiles. The material's properties are determined by their composition and manufacturing technology.

The main functions of geotextiles include:

2.1. Separation

Separates mixtures of soils with different particle sizes without disrupting water flow through the system.

2.2. Filtration

It involves a precise pore structure that allows water to pass through while blocking soil particles.

2.3. Drainage

The ability of geotextiles to drain under pressure and their resistance to clogging during deformation.

2.4 Reinforcement

Some Geotextiles are used to make soil structures stronger. How well they work depends on things like tensile strength. How well they interact with the soil.

We need to consider all these factors when we are working with Geotextiles and trying to predict their performance and Durability Prediction using Artificial Intelligence and Machine Learning. By doing we can improve the Service Life of Geotextiles and the overall performance of Geotechnical Engineering projects. Geotextile and Soil Conditions are crucial, in determining the Tensile Strength and overall Performance Prediction of these materials.

2.5 Erosion Control

Geotextiles may be used to reduce soil erosion by controlling surface runoff and retaining soil particles.

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3. Influence of Soil Conditions on Geotextile Durability

Soil environments are really different. That is why geotextile responses are different too. The big factors related to soil that we looked at in this study are discussed below.

3.1 Soil Type

Soil can be clay or silt or sand or gravel or a mix of these. These types of soil are really different when it comes to the size of the particles and how water can pass through and how they react to chemicals. Soil with small particles like clay can easily block the filters. On the hand soil with big particles like sand can cause more wear and tear on the geotextile.

3.2 Grain-Size Distribution

The way the particles are spread out in the soil determines how the soil and geotextile work together. If the soil particles and the holes in the geotextile are not a match then it can cause problems like blockages or particles moving around.

3.3 Moisture Content

The amount of water in the soil affects how strong the soil is and how the water moves through it and how the soil and geotextile interact. When the soil gets wet and dry times it can also change the soil around it.

3.4 Soil Density and Compaction

When the soil is really packed down it can cause stress on the geotextile. This can happen when the geotextile is being put in. It can cause damage to the geotextile.

3.5 Soil pH and Chemical Environment

The chemicals in the soil can affect how long the geotextile lasts.

The life of a geotextile depends on what the geotextile's made of and what kind of chemicals it is exposed to. The geotextile is affected by the soil it's in. For example the pH of the soil and the chemicals in the soil are things to think about when trying to figure out how long the geotextile will last.

3.6 Confining Pressure

The geotextile that is used under roads and bridges and other big structures is under a lot of pressure. Sometimes this pressure changes and it affects the geotextile. It can make the geotextile thicker or thinner. It can change how water moves through the geotextile and how strong the geotextile is. The geotextile reacts to these changes in ways.

4. Problem Statement

When people want to know how long a geotextile will last they usually do experiments in a laboratory. Look at the results. Laboratory tests are necessary to understand what the geotextile is made of.. It is not possible to test every single type of soil and every possible amount of water and pressure and temperature and exposure, to the environment. This is because there are many different combinations to test.

Furthermore, the relationship between soil characteristics and geotextile degradation is nonlinear and involves interactions between multiple variables. A conventional single-variable approach may therefore provide limited predictive capability.

The research problem can be stated as follows:

How can Artificial Intelligence and Machine Learning techniques be used to predict the performance and durability of geotextiles under different soil and environmental conditions with acceptable accuracy and reliability?

5. Research Objectives

The main goal of this study is to create a framework that uses Artificial Intelligence to predict how well geotextiles will work and last in types of soil.

The specific goals are:

i. To find out what factors from the soil, environment and geotextiles themselves have the impact on how well geotextiles work.
ii. To put together a set of data that includes information from experiments and real-world tests on performance.
iii. To see how the characteristics of the soil affect the performance of geotextiles.
iv. To develop models that use machine learning to predict how geotextiles will work.
v. To compare Artificial Intelligence algorithms to see which ones are best at making predictions.
vi. To figure out what factors have the impact on how long geotextiles will last.
vii. To create a framework for estimating how well geotextiles will work over a period of time and how long they will last.
viii. To give advice, on how to choose the geotextiles for different types of soil environments and geotextile performance.

6. Research Methodology

Our Overall Framework is pretty simple.

It has a lot of steps that we need to follow.

The steps are:

- Data Collection
- Data Preprocessing
- Feature Selection
- Model Development
- Model Training
- Model Validation
- Performance Comparison
- Interpretation
- Durability Prediction

Our Framework can use all sorts of data from laboratory test results to field observations and even data from published experiments and controlled tests.

We can use our Overall Framework to look at all this data and get some information, from the Overall Framework.

7. Dataset Development

A synthetic dataset comprising 300 observations was developed to demonstrate the application of artificial intelligence and machine learning techniques for predicting geotextile performance under different soil and environmental conditions. The dataset was designed to represent plausible variations in soil characteristics, environmental exposure, and geotextile properties.

The dataset included ten predictor variables covering soil, environmental, and geotextile-related characteristics. The predicted output variable was tensile strength retention (%), which represents the percentage of the initial tensile strength retained by the geotextile after exposure to the specified conditions.

The input and output variables used in the analysis are presented in Table 1.

Table 1. Input and output parameters used for AI-based prediction

Parameter	**Type**	**Unit**
Soil Type	Categorical	-
Moisture Content	Numerical	%
Dry Density	Numerical	g/cm³
Permeability	Numerical	mm/s
Soil pH	Numerical	-
Confining Pressure	Numerical	kPa
Temperature	Numerical	°C
Exposure Duration	Numerical	days
Polymer Type	Categorical	-
Geotextile Thickness	Numerical	mm
Initial Tensile Strength	Numerical	kN/m
Tensile Strength Retention	**Target variable**	**%**

The target variable for prediction was tensile strength retention (%), while the remaining ten parameters were used as predictor variables.

7.1 Synthetic Data Generation

Since a publicly available experimental dataset containing all the required soil, environmental and geotextile parameters was unavailable for this methodological illustration, a synthetic dataset was created using physically permissible parameter ranges.

The dataset was composed of four soil classes (Sand, Silt, Clay and Loam) and three polymer classes (Polypropylene (PP), Polyethylene Terephthalate (PET) and Polyethylene (PE)).

The numerical parameters were created within engineering reasonable ranges. Moisture content was selected within the range of approximately 5% to 35%, dry density was selected between 1.35 and 2.05 g/cm³, permeability was selected between 0.02 and 2.0 mm/s, soil pH was selected between 5 and 9, confining pressure was selected between 20 and 300 kPa, temperature was selected between 10 and 55°C, exposure time was selected between 30 and 3650 days, geotextile thickness was selected between 0.5 mm and 3.0 mm, and initial tensile strength was selected between 15 kN/m and 80 kN/m.

Tensile strength retention was selected as the target response, based on the combined effect of the input parameters and a controlled random element to describe the variability in the data.

7.2 Data Preprocessing

Before building the model, dataset was subjected to various data preprocessing techniques and methods. Any variables (soil type, polymer type) that were in a categorical form, were converted into variables using categorical encoding.

Numerical variables were standardized where required by the respective machine learning algorithm.

The complete dataset containing 300 observations was divided into two subsets. Eighty percent of the observations (240 records) were used for model training, while the remaining 20% (60 records) were used for independent testing. The data partitioning was performed using a fixed random state to ensure reproducibility.

7.3 Machine Learning Models

Four machine learning approaches were evaluated for predicting tensile strength retention:

i. Linear Regression
ii. Random Forest Regression
iii. Support Vector Regression (SVR)
iv. Gradient Boosting Regression

Linear Regression was included as a baseline model to establish the relationship between the predictor variables and tensile strength retention. Random Forest and Gradient Boosting were selected because of their ability to model nonlinear relationships and interactions among variables. Support Vector Regression was included because of its effectiveness in regression problems involving relatively complex relationships between input variables and the target response.

Each model was trained using the training dataset and subsequently evaluated using the independent testing dataset.

7.4 Model Evaluation

The predictive performance of each model was evaluated using three commonly used regression metrics: coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE).

The coefficient of determination was used to measure the proportion of variation in tensile strength retention explained by the model. RMSE was used to quantify the magnitude of prediction errors, with greater penalties assigned to larger errors. MAE was used to represent the average absolute difference between observed and predicted values.

The equations used were:

R^2

$$R^2 = 1 - \Sigma(y_i - \hat{y}_i)^2 / \Sigma(y_i - \bar{y})^2$$

RMSE

$$RMSE = \sqrt{[(1/n) \Sigma_{i=1}^{n} (y_i - \hat{y}_i)^2]}$$

MAE

$$MAE = (1/n) \Sigma_{i=1}^{n} |y_i - \hat{y}_i|$$

where y_i represents the observed value, $\hat{y}_i$ represents the predicted value, $\bar{y}$ represents the mean observed value, and n represents the number of observations.

8. Results and Discussion

8.1 Model Prediction Performance

The performance of the four machine learning models on the testing dataset is presented in Table 2.

Table 2. Predictive performance of the machine learning models

Model	**R^2**	**RMSE**	**MAE**
Linear Regression	**0.9423**	**2.466**	**1.823**
SVR	0.9013	3.226	2.581
Gradient Boosting	0.8916	3.380	2.726
Random Forest	0.8274	4.266	3.216

The results indicate that all four models were capable of predicting tensile strength retention from the selected input parameters. Among the evaluated models, Linear Regression produced the highest R^2 value of 0.9423 and the lowest RMSE and MAE values of 2.466 and 1.823, respectively.

The SVR model achieved an R^2 of 0.9013, followed by Gradient Boosting with an R^2 of 0.8916. Random Forest produced an R^2 of 0.8274 and comparatively higher prediction errors.

The comparatively strong performance of Linear Regression in this synthetic dataset suggests that the generated target variable contains a substantial linear component associated with the selected input parameters. However, this finding should not be interpreted as evidence that linear regression will necessarily outperform nonlinear machine learning methods for experimentally measured geotextile data.

9. Data Preprocessing

When we look at experimental data, we often find that it has some problems. The data may have missing values the units may not be the same there may be outliers. There could be errors in the measurements. So, when we do data preprocessing, we need to do a thing.

i. We have to remove or fix the missing observations in the data.
ii. We have to find the values that're abnormal or really extreme.
iii. We have to make sure that all the measurement units are the same.
iv. We have to make sure the numerical variables are on the scale.
v. We have to encode the variables like the type of soil and the type of polymer.
vi. We have to analyze how the features, in the data correlate with each other.
vii. We have to split the data into training and testing datasets.

A typical dataset could be split into 70 percent training data 15 percent validation data and 15 percent testing data. We could use k-fold cross-validation if the dataset is pretty small.

10. Machine Learning Models

10.1 Artificial Neural Network

Artificial Neural Networks are really good for problems that're not straightforward and have a lot of things going on at the same time. You can think of an Artificial Neural Network like this:

$$y = f(WX + b)$$

where X is the information, you put in W is the weight of the model b is like a starting point f is the function that helps figure things out and y is what the Artificial Neural Network thinks will happen.

10.2 Random Forest

Random Forest is a way of making predictions by using a lot of decision trees. It is good at handling problems where things are connected in ways. Random Forest can also deal with data, which is data that is not very accurate. It can tell you which pieces of information are the most important.

10.3 Support Vector Regression

Support Vector Regression is a choice when you have a problem that is not straightforward and you do not have a lot of data. It can help you make predictions even with a small amount of information.

10.4 Gradient Boosting

Gradient Boosting is a way of making predictions by building a series of decision trees. Each tree tries to fix the mistakes of the tree before it. Gradient Boosting is really good at making predictions when you have data that is well organized like the kind of data you find, in engineering.

11. Model Evaluation

11.1 Coefficient of Determination

$$R^2 = 1 - [\Sigma(y_i - \hat{y}_i)^2 / \Sigma(y_i - \bar{y})^2]$$

A value closer to 1 indicates stronger agreement between predicted and observed values.

11.2 Root Mean Square Error

$$RMSE = \sqrt{[(1/n)\ \Sigma(y_i - \hat{y}_i)^2]}$$

Lower RMSE indicates better prediction accuracy.

11.3 Mean Absolute Error

$$MAE = (1/n)\ \Sigma|y_i - \hat{y}_i|$$

MAE represents the average magnitude of prediction error.

11.4 Mean Absolute Percentage Error

$$MAPE = (100/n)\ \Sigma|(y_i - \hat{y}_i)/y_i|$$

MAPE provides an interpretable measure of relative prediction error, although care is needed when observed values approach zero.

12. Proposed Experimental Design

To improve the reliability of the proposed model, controlled laboratory experiments can be conducted using different soil conditions.

The study may consider sandy, clayey, and silty soils under low, medium, and high moisture conditions, multiple stress levels, and different exposure durations. The actual experimental levels should be selected based on laboratory capabilities, applicable standards, and the intended application.

13. Performance Prediction

The trained AI model can be used to predict how geotextiles will perform in soil conditions. When given information about the soil type how moisture it has, how dense it is when dry its pH level, the pressure, around it the temperature, the type of polymer used and the original strength when pulled the model can predict how much strength the geotextile will keep and other performance measures.

14. Durability and Service-Life Prediction

One of the important uses of AI is figuring out how long geotextiles will last over time. If the strength of the geotextiles is checked over time the model can understand how time starting strength, environment, moisture, pressure, temperature, chemicals and the strength that is seen are connected.

The life of the geotextile can be guessed as the time it takes for the geotextile to get to a level of performance.

15. Expected Results and Discussion

The new study will show that AI models can really understand the connections between the soil and how geotextiles work.

It seems likely that the type of soil how much water is in the soil the pressure on the soil the kind of polymer used and how long the soil is exposed to conditions will all help make more accurate predictions.

When we look at all these things together like the soil and the environment, we should get predictions than if we just look at one thing at a time.

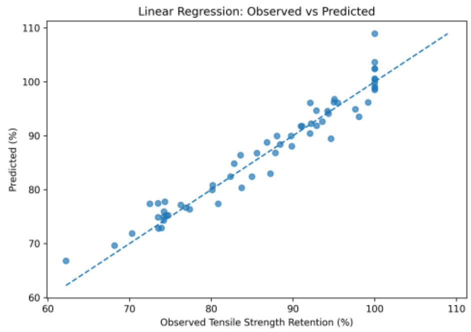
We should only talk about the numbers when we have done some experiments or collected data from the field and taken a close look at it.

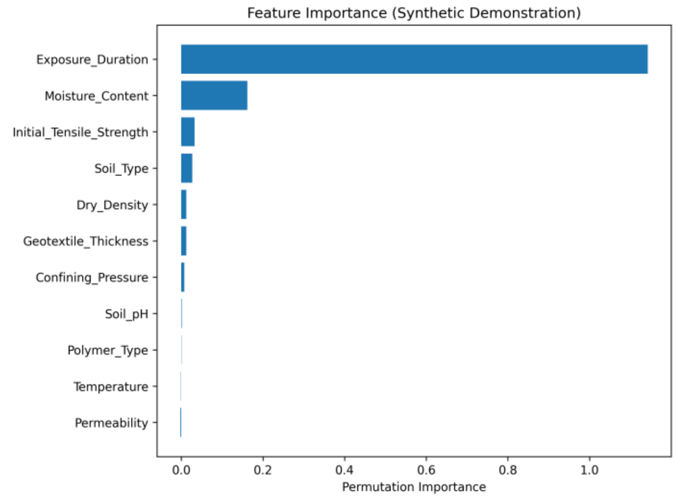
We should not say that a model is accurate unless we have really tested it and seen the results, for ourselves.

16. Feature Importance and Explainable AI

We want to know which variables are really important when we make predictions. There are some methods, like SHAP that can help us understand how each parameter contributes to the result.

We have to look at the model we trained to see which parameters are really influential. We should not just guess which ones are important before we even start.





17. Advantages of the Proposed AI Approach

The AI-based approach can provide reduced experimental requirements, faster prediction, nonlinear modeling capability, improved material selection, durability assessment, and support for sustainable infrastructure planning.

18. Limitations

The quality of the training data is really important for AI-based prediction to work well. If a model is trained on one type of soil or one kind of geotextile polymer it may not work very well in other situations. The data from experiments can have mistaken and things that do not match. To predict how long something will last, we need data that shows how it changes over time. AI predictions should be used along, with laboratory testing, field validation, engineering judgment and the standards that are supposed to be followed. The AI-based prediction should help not replace, the ways we make sure things are safe and work well.

19. Practical Applications

The proposed AI framework can be applied to highway and pavement construction, railway infrastructure, embankment stabilization, landfill engineering, drainage systems, coastal engineering, riverbank protection, retaining structures, erosion-control systems, and ground improvement projects.

20. Future Scope

Future studies should focus on creating databases with large amounts of field data and clear end points. Scientists may need to use learning models when working with these databases. Combining formulas with machine learning can lead to simpler and more accurate predictions.

We can use Internet of Things sensors—and their digital twins—to check how well geotextiles perform. These sensors will gather real-time data on temperature, moisture, stress, and shape changes in the field. Artificial Intelligence can analyze this data to estimate how long geotextiles will last. With Probabilistic AI, we get a range of likely outcomes instead of just one prediction.

The goal of this study is to build an AI system that forecasts how geotextiles behave and how long they last in different soil types.

Geotextile performance is affected by many factors: soil type and grain size, water levels, compaction, pressure, soil chemistry, temperature, exposure time, and the geotextile material itself.

Current testing methods are useful for this research. But running many tests for different scenarios can take too much time and money.

Tools like Artificial Neural Networks, Random Forest, Support Vector Regression, and Gradient Boosting can help spot patterns between these factors. Using a database with details on soil and material traits, AI models can predict tensile strength, water flow, deformation, filtration ability, and lifespan of geotextiles.

This solution will influence how engineers choose geotextiles, plan maintenance, and design roads and infrastructure. To pick the best AI models, it's important to gather lab results and field data, then compare them with actual test outcomes.

More work is needed in building better databases, testing models in real-world conditions, improving AI transparency, measuring prediction uncertainty, and linking AI with physical sciences**.** This will support smarter infrastructure and advanced building materials.

References

Breiman, L. (2001). Random forests. *Machine Learning, 45*, 5–32.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning, 20*, 273–297.

Das, B. M., & Sobhan, K. (2018). *Principles of geotechnical engineering*. Cengage Learning.

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *The Annals of Statistics, 29*(5), 1189–1232.

Giroud, J. P. (2010). Development of criteria for geotextile and granular filters. In *Proceedings of the International Conference on Geosynthetics*.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

Holtz, R. D., Christopher, B. R., & Berg, R. R. (1997). *Geosynthetic design and construction guidelines*. Federal Highway Administration.

International Organization for Standardization. (n.d.). *ISO 10318-1: Geosynthetics—Terms and definitions*.

Koerner, R. M. (2012). *Designing with geosynthetics* (6th ed.). Xlibris Corporation.

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. In *Advances in neural information processing systems* (Vol. 30).

Palmeira, E. M. (2009). Soil-geosynthetic interaction: Modelling and analysis. *Geotextiles and Geomembranes, 27*(5), 368–390.

Shukla, S. K. (2016). *An introduction to geosynthetic engineering*. CRC Press.

ASTM International. (n.d.). *ASTM D4491: Standard test methods for water permeability of geotextiles by permittivity*.

ASTM International. (n.d.). *ASTM D4595: Standard test method for tensile properties of geotextiles by the wide-width strip method*.

ASTM International. (n.d.). *ASTM D4759: Standard practice for determining the specification conformance of geosynthetics*.