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Cross-Attention Gated BiLSTM-Enhanced Ensemble Learning for Subset Simulation-Based Probabilistic Slope Stability Analysis

S. Prakash[1*]

[1]Department of Electrical and Electronics Engineering, Aarupadai Veedu Institute of Technology, Vinayaka Missions Research Foundation, Chennai, India. prakash.yours@gmail.com

[1*]Corresponding Author E-mail: prakash.yours@gmail.com

ABSTRACT: Probabilistic Slope Stability Analysis (PSSA) is crucial for understanding the underlying spatial variation in soil parameters which affects slope analysis and design. In recent years, intelligent data-driven systems have become essential for solving complex real-world problems. Hence, this study presents a comprehensive data analysis and prediction framework employing a Cross-Attention Gated BiLSTM model. Data cleaning identifies and removes duplicate soil test records from the dataset and finds the missing values, outliers to ensure data reliability. Subsequently, Exploratory Data Analysis (EDA) is conducted using descriptive statistics and visualizations to uncover patterns and correlations. After extracting, a deep learning-based prediction model, a Cross-Attention Gated BiLSTM is implemented, which leverages bidirectional temporal dependencies and cross-attention mechanisms for enhancing contextual feature learning and improves predictive performance. The model demonstrates significant potential in capturing complex dependencies in sequential data, making it highly suitable for time-series prediction and classification tasks. Implementing Python software with slope stability dataset, the proposed Cross Attention Gated BiLSTM accommodate the actual generation pattern better than existing methods and produce the Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) , R2 value of 0.06, 0.11 and 97% respectively.

Keywords: Slope stability analysis, Cross-Attention Gated BiLSTM, Exploratory Data Analysis, Descriptive Statistics, Visualizations, Data cleaning

1. Introduction

PSSA is a geotechnical engineering that guarantees the dependability and safety of both natural and artificial slopes [1]. Although their widespread use, traditional deterministic approaches frequently fall short in capturing the inherent uncertainties in environmental parameters, loading conditions, and soil qualities. Consequently, probabilistic approaches have become more popular in order to overcome this constraint, providing a more accurate evaluation by calculating the probability of slope failure [2]. Whereas, Subset Simulation (SS) is one of the most effective and potent methods for calculating minor failure probabilities in high-dimensional spaces [3–4]. It's greatly improves computational efficiency by converting the rare event probability estimate problem into a series of more frequent conditional events, and in contrast to rudimentary Monte Carlo approaches [5]. Additionally, the deterministic technique of analysis, the Factor of Safety is defined as the ratio of the Resistive Moment (MR) to the Overturning Moment (MO). The slope is considered as safe when the calculated Factor of Safety (FS) value is greater than unity [6].

Whereas, the reliability index (β) and Probability of Failure (POF) is used to address soil uncertainties, including the inherent geo-graphic variability of soil, in order to assess the geotechnical study and design process [7]. Moreover, the shear strength reduction approach is commonly used in SSA to model soil stress states, slope breakdown processes, and the consequent FS [8-9]. Consequently, the FS at the point of failure is computed as the ratio of the soil's shear strength parameters (effective cohesion and the tangent of the effective friction angle) to individuals needed to bring the slope to failure [10]. To address these challenges, various classification techniques are employed for improved probabilistic slope stability analysis.

Some of the machine learning technique is used to forecast the probabilistic slope stability analysis. Extreme Gradient Boost used to forecast the safety factor of a slope, whether it is made of natural soil or artificial soil. In order to estimate the FS value, Extreme Gradient Boost predict slope by that this model better. The Extreme Gradient Boost technique handle sparse data, implement distributed and parallel computing in a flexible manner. However, its struggle with prediction outside the range of training data, particularly when the soil conditions in the field differ significantly [11]. Additionally, the ensemble bagging model is the most effective method for evaluating and predicting the stability of slopes. Ensemble bagging model is a highly efficient computer technique for managing machine learning and data mining problems. It calculates ten times faster and generates classification results with more accuracy. It successfully avoid over-fitting even when given missing values. Nonetheless, ensemble nature makes it hard to trace individual decision pathways, affecting transparency in slope [12]. Whereas, to evaluate and handle the cross correlation in probabilistic analysis Bootstrap sampling method is used. Probabilistic analysis that physically based susceptibility analysis incorporates cross-correlation between input parameters. Nevertheless, Bootstrap fail to generate values outside the observed range. For variables with heavy tails bootstrap never capture extremes beyond their maximum observed values, thus limiting failure probability estimation [13].

By using the Bayesian interference the PSSA is analysed and performed. Posterior distribution that reflects both sources of knowledge and quantifies uncertainty in parameter estimates. Bayesian interference produces full posterior distributions, capturing variability and parameter correlations ideal for reliability-based design methods. However, high computational demand over high-dimensional parameter spaces is very time-consuming, especially for complex geotechnical models [14]. Whereas, to forecast the PSSA an Adaptive Neuro-Fuzzy Inference System (ANFIS) model is utilized. ANFIS adeptly captures complex nonlinear relationships between soil parameters and factor of safety outcomes, combining neural network learning with fuzzy reasoning. Also, training ANFIS becomes expensive as the number of inputs or fuzzy rules grows. Nevertheless, dimensionality is a significant issue when input variables exceed [15]. Additionally, by Multivariate Adaptive Regression Splines (MARS) model the slope reliability analysis is analysed. MARS is an effective technique for slope reliability analysis based on numerical simulation. Yet, slow and get trapped in local minima, leading to lengthy convergence times and model complexity even for simpler problems [16]. To overcome the limitations of existing methods, a proposed Cross-Attention Gated BiLSTM leverages bidirectional temporal dependencies and cross-attention mechanisms to enhance contextual feature learning and improve predictive performance.

2. Related work

Xu *et al* [17] (2023) have proposed a Support Vector Machine (SVM) method for high-dimensional indirect cross-correlation parameters in slope analysis. It effectively improves the adaptability of the SS in a high-dimensional sample space. To reduce computational effort in slope analysis, the Seismic Collaborative Reliability Evaluation (SCRE) framework integrates SS with the Response Conditioning Method (RCM) to efficiently assess seismic reliability. Nevertheless, increasing model complexity reduces interpretability. This creates a trade-off between transparency and performance that practitioners need to manage effectively.

Ahmad *et al* [18] (2024) have presented an Artificial Neural Network (ANN) for slope reliability and analysis small failure probability level. ANN accurately calculates the slope reliability and greatly improves the efficiency at small failure probability levels. This model intricate, nonlinear relationships between soil parameters and FS more effectively. Yet, ANN method's efficiency is extremely low for issues with low failure probabilities.

Yeh *et al* [19] (2023) have developed a Binary-Addition-Tree algorithm and Monte Carlo simulation based Long Short-Term Memory (LSTM-BAT-MCS), for SSA. The LSTM-BAT-MCS method combines LSTM with specialized sampling for time-dependent reliability in binary-state systems, demonstrating efficient low-error estimation in benchmark network problems. LSTMs automatically learn complex temporal dependencies among multiple input streams, including abrupt or cumulative effects on stability. Nevertheless, training LSTM surrogates typically requires extensive, high-quality time-series data.

Demir *et al* [20] (2025) have proposed a SHapley Additive exPlanations (SHAP) and stacking Ensemble Learning (EL) techniques (SHAP-EL), to classify and predict slope stability. SHAP-EL reduces the risks and damages related to soil slope instability and improve the precision and dependability of soil slope forecasts. SHAP sheds light on the role of geotechnical variables in failure probability predictions, enhancing trust and model transparency. Yet, exact computation of SHAP values is prohibitively slow for large datasets or complex models.

Ahmad *et al* [21] (2024) have presented a Voting Ensemble (VO-ENSM) for failure probability classification. VO-ENSM tends to outperform individual models through error reduction for SSA. Ensemble both homogeneous and heterogeneous predictor enhancing generalization especially when individual learners capture different data patterns in slope analysis. Nonetheless, ensembles obscure individual decision paths, making it hard to trace the geotechnical inputs impact failure predictions.

The contribution of the work as follows:

- Data cleaning finds the duplicate, missing values, outliers to ensure data reliability for SS-based PSSA.
- EDA is accompanied using descriptive statistics and visualizations to uncover patterns and correlations based on PSSA.
- The proposed Cross-Attention Gated BiLSTM leverages in both forward and backward direction and cross-attention mechanisms to enhance contextual feature learning and improve predictive performance.

3. Proposed Work

Figure 1 shows the proposed Cross-Attention Gated BiLSTM framework tailored for PSSA, effectively addressing the inherent spatial and temporal variability in soil properties. First, Data cleaning technique to identify and finds the duplicate values for PSSA and the missing values from the slope stability dataset. Then, EDA is accompanied using descriptive statistics and visualizations to uncover patterns and correlations based on SSA. The proposed Cross-Attention Gated BiLSTM model uses a Bidirectional LSTM (BiLSTM) to capture both forward and backward dependencies in sequential input streams such as layered cohesion, friction angle, unit weight, and pore pressure. Next, a cross-attention mechanism dynamically aligns information across these multi-modal streams, enabling the model to selectively focus on salient features mirroring mechanisms successfully applied in geotechnical and seismic prediction contexts.

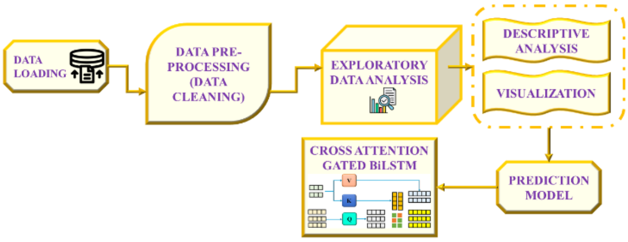

Figure 1: *Block diagram of proposed work*

To improve robustness, a gating layer blends attended features with original BiLSTM outputs, suppressing noise and emphasizing critical signals. This fusion of deep temporal learning, attention-driven integration, and gating enhances both predictive fidelity and interpretability, outperforming models and offering an efficient tool for data-driven slope reliability under uncertainty.

3.1 Data pre-processing by Data cleaning

For PSSA data cleaning is a first step to ensure model accuracy and robustness. This process begins by identifying and removing duplicated or inconsistent soil test records, such as bulk density, cohesion, and internal friction angle. Outliers are detected using statistical methods like box plots or interquartile range and investigated either corrected or excluded if they stem from measurement errors. If few values are missing, it's typically acceptable to impute them using the averages from the same geotechnical unit. However, when a large portion of data is missing, it's suitable to either discard that data entirely. To harmonize scales across different soil parameters, normalization or standardization is applied, particularly when these parameters feed into machine-learning stratification of data grouping by soil layer, geographic location, or test type ensures that the probabilistic inputs used for slope stability modelling accurately reflect the underlying variability and uncertainty in different layers. The processed data is fed as an input to the Exploratory Data Analysis for PSSA.

3.2 Exploratory Data Analysis

In EDA for PSSA, with descriptive statistics computing measures such as standard deviation, skewness, and interquartile range for key geotechnical variables (e.g., cohesion cc, friction angle ϕ, and unit weight γ). These statistics quantify variability and detect anomalies in the Slope Stability Analysis Dataset. Then, visualization techniques including histograms to reveal distribution shapes, box plots to highlight outliers, and scatter plots to explore bivariate relationships. The bivariate relationships are employed to uncover patterns and dependencies. To ground these insights in slope stability theory, the classical infinite slope model is used as a baseline. The slope stability factor F is expressed as:

$$F = \frac{c + (\gamma - m\,\gamma_w) z \tan\phi}{\gamma\, z \sin\alpha \cos\alpha} \quad (1)$$

Where z is the failure depth, α the slope angle, m the saturation ratio, and $\gamma_w$the unit weight of water. By working in statistics e.g., using mean $\pm$ standard deviation values into this equation and overlaying the resulting F distributions, EDA effectively links data variability to a quantitative stability measure.

3.2.1 Descriptive statistics based EDA

In the EDA phase for probabilistic slope stability, the importance is on quantifying the statistical properties of critical soil parameters such as cohesion (c), internal friction angle (ϕ), and unit weight (γ). Core descriptive metrics include means (μ), standard deviations (σ), and coefficients of variation ($v = \frac{\sigma}{\mu}$), which together quantify variability and relative dispersion. For example, when cohesion c follows a lognormal distribution, its log-space parameters are derived using:

$$\sigma_{Inc}^2 = In(v_c^2),\ \mu_{Inc} = In(\mu_c) - \frac{1}{2}\sigma_{Inc}^2 \quad (2)$$

Where $v_c = \frac{\sigma_c}{\mu_c}$. These transformations ensure accurate modelling of skewed or non-negative variables in SS. This descriptive groundwork establishes the foundation for fitting accurate input distributions and for understanding data-driven uncertainty before probabilistic sampling.

3.2.2 Visualization based EDA

In the EDA stage, practitioners leverage visual tools to detect underlying patterns, assess variability, and validate assumptions before conducting probabilistic modelling. A quantitative complement to these visuals is the Pearson correlation coefficient:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\overline{x})^2 \sum_{i=1}^{n}(y_i-\overline{y})^2}} \quad (3)$$

Core visualizations include histograms to inspect the shape and skewness of distributions for cohesion c, friction angle ϕ, and unit weight γ; box plots to reveal outliers and assess dispersion and scatter plots combined in correlation matrices to identify linear or non-linear relationships among variables. The visualized output is fed as an input to the proposed cross Attention Gated BiLSTM method for PSSA.

2.3 Cross-Attention Gated BiLSTM

2.3.1 BiLSTM

BiLSTM is a classification technique under the neural network to classify the SS based PSSA. However, long-term memory issues arise because the original information eventually lost the data. BiLSTM directly led to the development of LSTM models, which are capable of capturing and recalling long-term dependencies. When two hidden states are used in a bidirectional LSTM, the information travels both forward and backward in figure 2.

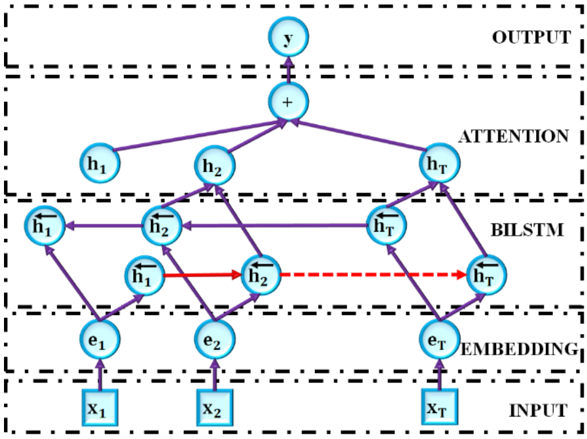

Figure 2: *BiLSTM*

Information passes from the backward to the forward unidirectional LSTM. In principle, Bidirectional Recurrent Neural Network (BRNN) works by breaking down a typical RNN's neurons into bidirectional pathways. To comprehend Bi-LSTM by utilizing its elements and features: LSTM: An RNN type called LSTM is generated to get over the disadvantages of conventional RNNs in terms of identifying long-term dependencies in sequential data for Subset Simulation Based Probabilistic Slope Stability Analysis: .

- **Bidirectional Processing:** Bi-LSTM methods the sequence in both directions instantaneously. The sequence is processed forward by one of its two LSTM layers and backward by the other. Each layer monitors its own hidden statuses and memory cells.
- **Forward Pass:** In the forward pass, the forward LSTM layer receives the input sequence from the first to the last time step.

- **Backward Pass:** The backward LSTM layer receives the input sequence in reverse order, from the last time step to the first, all at once.
- **Combining Forward and Backward States:** Following the completion of the forward and backward passes, at each time step both LSTM layers are combined.

The input and forget gates are responsible for deciding which additional information be kept in the cell state and older information is deleted. The output gate completes the network model's output after the cell state update is complete. This allows the Bi-LSTM output units to spontaneously absorb an illustration that incorporates both historical and future information.

2.3.2 Cross-Attention Gated BiLSTM

In this advanced PSSA framework, SS is used to efficiently estimate very low failure probabilities by decomposing them into a sequence of more probable intermediate events. To model the complex relationships between geotechnical inputs and slope performance, a Cross-Attention Gated BiLSTM is embedded within the subset simulation loop, effectively acting as a surrogate evaluator for the limit-state function.

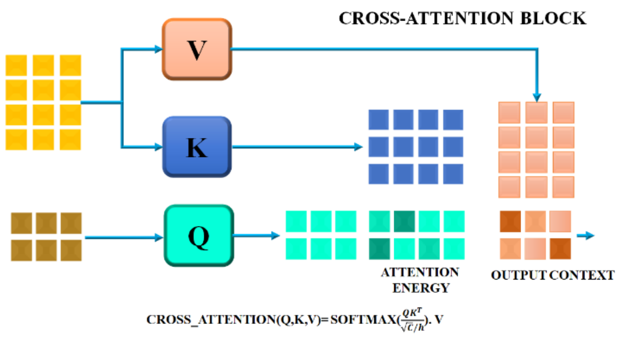

Figure 3: *Cross-Attention block*

At each subset stage, the Bidirectional LSTM processes sequential soil parameters cohesion c, friction angle ϕ, unit weight γ in both time directions, producing forward $\overrightarrow{h_t}$and backward $\overleftarrow{h_t}$ hidden states. These are concatenated into H_t. simultaneously; a secondary feature stream (e.g., pore water pressure time series) is processed, and then integrated with H_t via a cross-attention mechanism in figure 3:

$$A_t = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

This mechanism adaptively aligns and weights relevant features across modalities, ensuring the model focuses on critical patterns. To refine the fused representation, a sigmoid gate is applied:

$$G_t = \sigma\left(W_g[H_t; A_t] + b_g\right), \tag{5}$$

$$\widetilde{H_t} = G_t \odot A_t + (1 - G_t) \odot H_t \tag{6}$$

The gated representation is then passed through dense layers to estimate the limit-state output $Y = h(X)$.

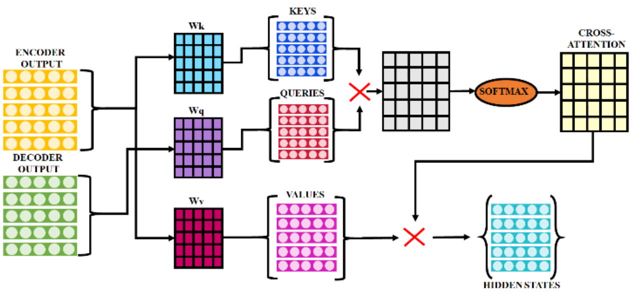

Figure 4: *Cross Attention mechanism*

Embedding a deep attention-based surrogate into the SS loop further improves effectiveness and enables accurate estimation of extremely low failure possibilities, while capturing complex temporal and cross-modal interactions in geotechnical parameters. By using the proposed Cross Attention Gated BiLSTM enhances efficiency and enables accurate estimation of extremely low failure probabilities.

4. Result and discussion

In result and discussion section the PSSA are predicted using the proposed Cross Attention Gated BiLSTM. Also, the slope stability analysis dataset is taken from the kaggle.com implemented using Python software.

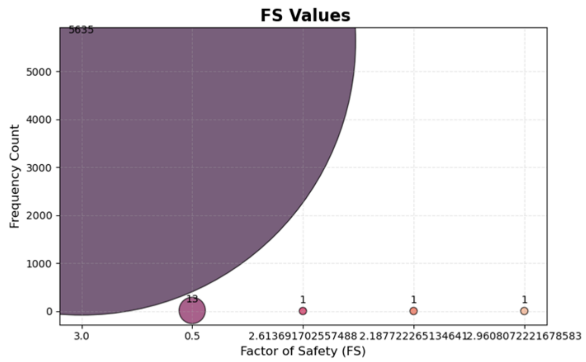

Figure 5: *FS values*

Figure 5 shows the FS values for the SS based PSSA. The X-axis indicates the FS and Y-axis indicates the frequency count. X-axis have the value of 3 to 2.9 and Y-axis have the frequency count of 1000 to 6000. The FS value is high in 3 to 2.6 and the frequency count is 5635.

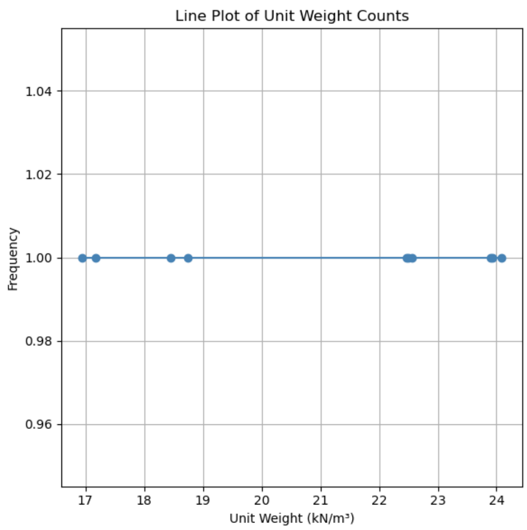

Figure 6: *Line plot of unit weight count*

Figure 6 shows the line plot of unit weight counts. X-axis indicates the unit weight and Y-axis indicates the frequency for PSSA. Soil densities ranging from approximately 17 to 24 kN/m³, which are typical values for various soils (e.g., clays ~17–20, sands ~18–23 kN/m³).Y-axis all data points lie at frequency = 1, indicating each sampled unit weight occurs exactly once in the slope stability analysis dataset

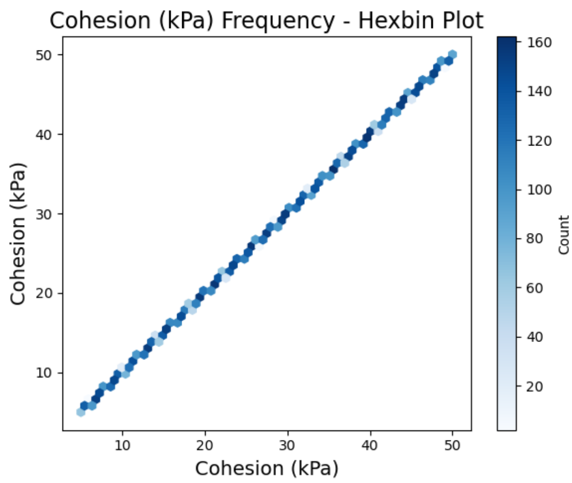

Figure 7: *Cohesion frequency- Hexbin plot*

Figure 7 shows the cohesion frequency-Hexbin plot for PSSA. X-axis and Y-axis indicates the cohesion (kPa) have the value of 10 to 50. It have the vibration in the vales from 10 to 50 it is mentioned in hexbin plot.

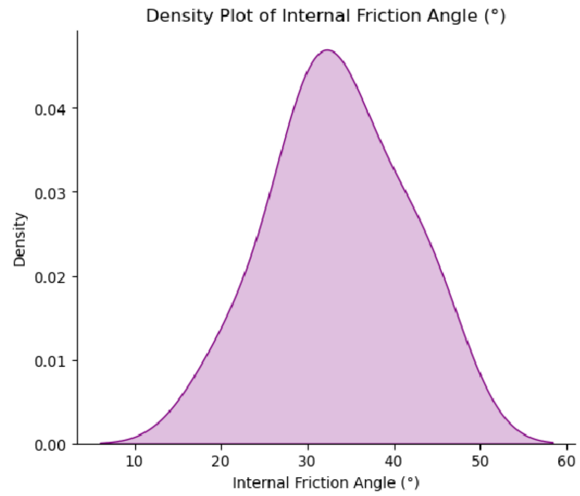

Figure 8: *Density plot of internal friction angle*

Figure 8 shows the density plot of internal friction angle for PSSA. Here, the X-axis indicates the internal friction angle and Y-axis indicates the density. The internal friction angle ranges from 10^0 to 60^0 and the density value ranges up to 0.05. The internal friction value rise in 10^0, it is peak in 30^0 at that time density value is 0.05and decreased up to 59^0 respectively.

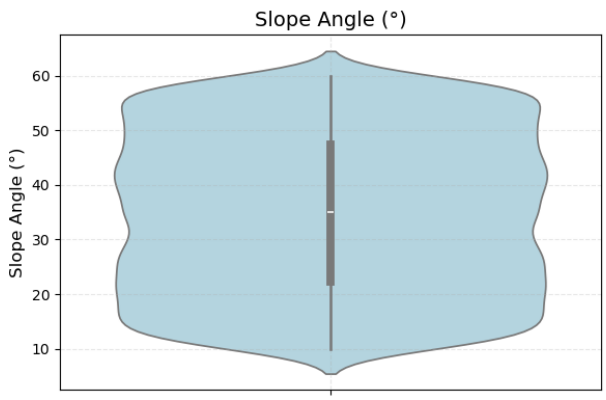

Figure 9: *Slope angle*

Figure 9 shows the slope angle for PSSA. The slope value is from 10^0 to 60^0 and it is high in the range 25^0 to 50^0. The slope value calculates the soil properties according to the ranges in depth.

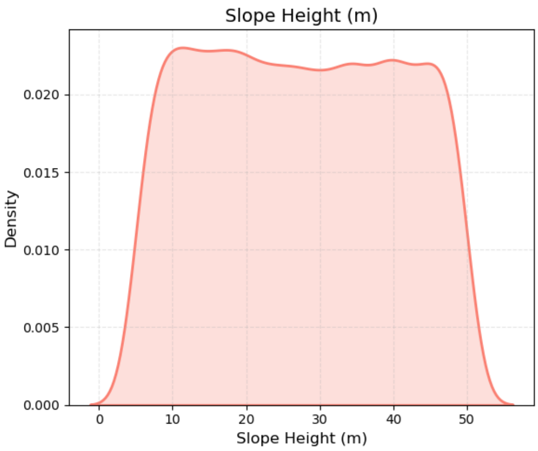

Figure 10: *Slope height (m)*

Figure 10 shows the slope height (m) for PSSA. X-axis indicates the slope height and Y-axis indicates the density. Slope height is calculated in meters and the density is up to 0.020. Analysis is high in 10m, its increased and decreased up to 50 m to finds the soil properties height.

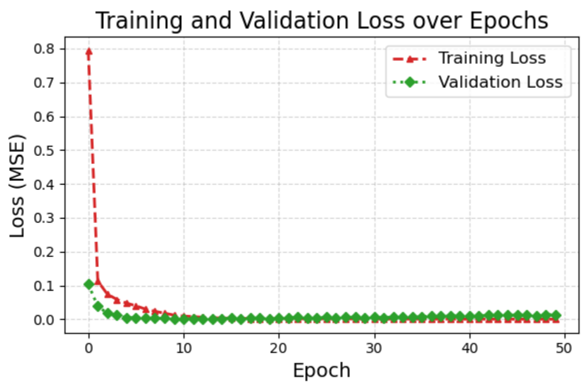

Figure 11: *Training and validation loss over Epochs*

Figure 11 shows the training and validation loss over epochs. For model loss the X-axis indicates the epochs which is up to 50 epochs and Y-axis indicates the loss which is up to 0.8. Training and validation loss is reliably declining in training and validation loss, representing improved learning and reduced error.

4.1 Performance Criteria

The model performance is measured using a statistical evaluation for PSSA, including coefficient of determination (R^2), RMSE, MAE, and MSE. The PSSA criterion formulas are shown below.

$$MSE = \frac{\sum_{i=1}^{m}[x_i - \widehat{x_i}]}{m} \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}[x_i - \widehat{x_i}]2}{m}} \quad (8)$$

$$R^2 = [\frac{1}{M}\frac{\sum_{j=1}^{M}[(Y_j - \bar{Y})(X_j - \overline{X})]}{\sigma_y \sigma_x}]^2 \quad (9)$$

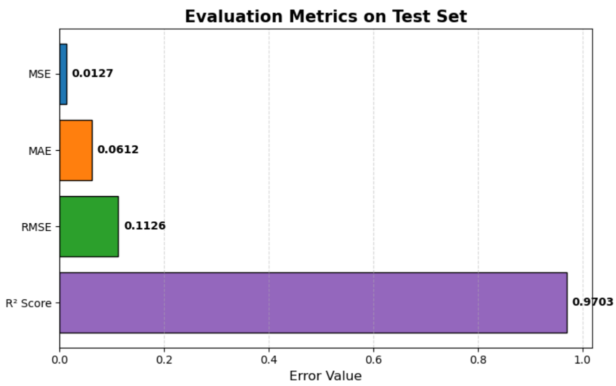

Figure 12: *Evaluation metrics on test set*

Figure 12 shows the evaluation metric on test set comparison for PSSA. The Y-axis indicates the MAE, RMSE, MAPE and MSE, X-axis indicates the error value. The MAE value is 0.0612, RMSE value is 0.1126, R2 value is 0.9703 and MSE value is 0.0127 for PSSA.

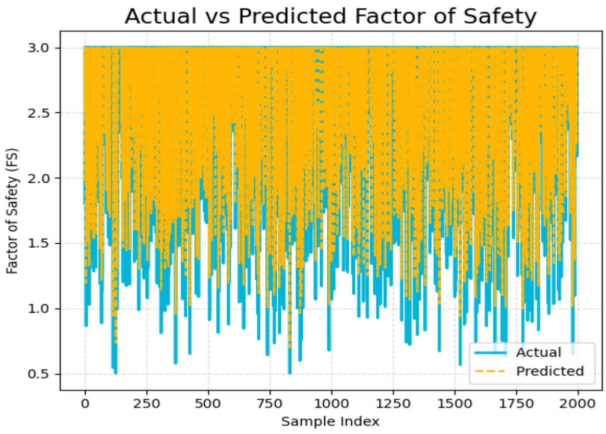

Figure 13: *Actual vs predicted FS*

Figure 13 shows the actual vs predicted FS wave plot for PSSA. The X-axis indicates the sample index it is up to 2000 and Y-axis indicates the values up to 3. The yellow color shows the predicted value and blue color indicates the actual value for the PSSA.

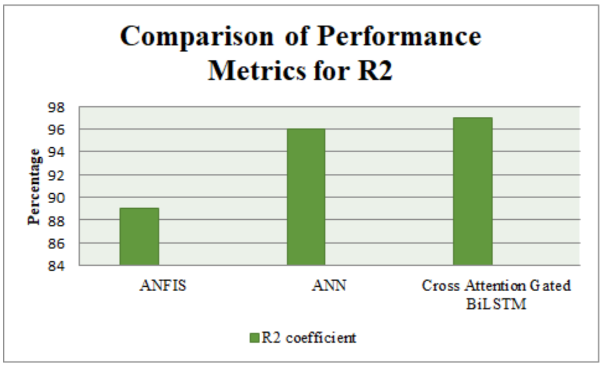

Figure 14: *Comparison of performance metrics for R2*

Figure 14 shows the comparison of performance metrics for R2. The proposed Cross Attention Gated BiLSTM have the higher value of 97%, the ANFIS [15] have the value of 89% and ANN have the value of 96% [18]. ANFIS and ANN R2 value is low compared to the proposed Cross Attention Gated BiLSTM method.

5. Conclusion

This work demonstrates the effectiveness of an end-to-end incorporating data pre-processing, EDA, and an advanced Cross-Attention Gated BiLSTM model for robust prediction tasks. The data cleaning stage effectively analyse data reliability. Additionally, the processed data are visualized and descriptive statistics the uncover patterns and correlations using EDA. By integrating attention mechanisms with bidirectional LSTM, the model successfully captures both forward and backward contextual relationships and selectively focuses on relevant features. The results validate the superiority of the proposed architecture in handling sequential data and improving prediction performance for PSSA. The proposed cross Attention Gated BiLSTM achieved the MAE value is 0.0612, RMSE value is 0.1126, MSE value of 0.0127 and R2 value of 97% for PSSA as a greater performance in contrast to the surviving methods.

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