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DEEP LEARNING-ENHANCED GEOMECHANICAL MODELLING OF ROADBED SUBGRADE STABILITY IN HUMID ENVIRONMENTS

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Abstract. *The stability of roadbed subgrades in humid environments presents significant challenges due to complex soil behaviors under fluctuating hydrological conditions. Traditional geomechanical models often fail to capture the nonlinear interactions between soil properties, environmental factors, and mechanical responses. This research introduces a comprehensive deep learning-enhanced geomechanical model that integrates advanced neural network architectures with conventional soil mechanics. By incorporating extensive datasets of soil parameters, climatic variables, and in-situ measurements, the model aims to improve predictive accuracy for subgrade stability assessments. The study involves detailed mathematical formulations, extensive numerical simulations, and rigorous experimental validations. Results demonstrate the superior performance of the proposed model over traditional methods, highlighting its potential for practical applications in civil engineering projects within humid regions.*

Key words: *deep learning, geomechanical modeling, subgrade stability, humid environments, soil mechanics, neural networks.*

Introduction.

Road infrastructure forms the backbone of economic development, particularly in regions where alternative transportation modes are limited [1]. In humid environments, roadbed subgrades are frequently subjected to intense and prolonged rainfall, leading to saturation, weakening, and eventual failure [2]. Accurate prediction of subgrade stability under these conditions is essential for designing resilient infrastructure [3].

Traditional geomechanical models, such as limit equilibrium methods and finite element analysis, rely on simplifying assumptions that may not adequately capture the complex, non-linear interactions between soil properties and environmental factors in humid climates [4]. With the advent of deep learning, there is an opportunity to enhance these models by leveraging large datasets and advanced computational techniques [5].

This research aims to develop a deep learning-enhanced geomechanical model to predict roadbed subgrade stability more accurately in humid environments. The proposed model integrates neural networks with soil mechanics principles to capture the intricate relationships governing subgrade behavior.

Main text.

Literature Review. *Challenges in Humid Environments.* Humid climates are characterized by high temperatures and seasonal heavy rainfall, leading to significant variations in soil moisture content [6]. These fluctuations affect the mechanical properties of subgrade soils, such as cohesion (c), internal friction angle (φ), and permeability (k) [3]. Conventional models often neglect the time-dependent effects of moisture variation, resulting in inaccurate stability predictions [4].

Limitations of Traditional Geomechanical Models. Traditional geomechanical models, including the Mohr-Coulomb failure criterion and Bishop's method, are based on linear or simplified nonlinear relationships [5]. They often require extensive parameter calibration and may not generalize well to different soil types or environmental conditions found in humid regions. Moreover, these models struggle to account for the coupled hydro-mechanical processes occurring in saturated-unsaturated soils [3].

Deep Learning in Geotechnical Engineering. Deep learning has shown significant potential in modeling complex, nonlinear systems in various engineering disciplines [7]. In geotechnical engineering, neural networks have been applied to soil classification [8], slope stability analysis [5], and prediction of soil properties [6]. However, integrating deep learning with fundamental geomechanical principles remains a relatively unexplored area.

Methodology. *Theoretical Framework.* The proposed model combines deep learning techniques with unsaturated soil mechanics to capture the coupled hydro-mechanical behavior of subgrade soils. The effective stress in unsaturated soils is given by [1]:

$$\sigma' = (\sigma - u_a) + \chi(u_a - u_w) \tag{1}$$

where σ' is the effective stress, σ is the total stress, u_a is the pore air pressure, u_w is the pore water pressure, and χ is the effective stress parameter, defined as:

$$\chi = \left(\frac{S_r - S_{r0}}{1 - S_{r0}}\right) \tag{2}$$

with S_r being the degree of saturation and S_{r0} the residual degree of saturation.

The shear strength (τ) of unsaturated soils can be expressed as:

$$\tau = c' + (\sigma - u_a) \tan \varphi' + (u_a - u_w) \tan \varphi_b \tag{3}$$

where c' is the effective cohesion, φ' is the effective angle of internal friction, and φ_b is the angle indicating the rate of increase in shear strength relative to matric suction $(u_a - u_w)$.

Hydro-Mechanical Coupling. The soil-water characteristic curve (SWCC) describes the relationship between matric suction and degree of saturation [3]. The van Genuchten model is commonly used:

$$S_r = S_{r0} + (1 - S_{r0})[1 + (\alpha(u_a - u_w)^n]^{-m} \tag{4}$$

where α, n, and m are fitting parameters.

Hydraulic conductivity (k) in unsaturated soils is a function of degree of saturation:

$$k = k_s \cdot K_r(S_r) \tag{5}$$

where k_s is the saturated hydraulic conductivity, and $K_r(S_r)$ is the relative hydraulic conductivity, often modeled using the Mualem-van Genuchten equation:

$$K_r(S_r) = S_e^l \left[1 - \left(1 - S_e^{1/m}\right)^m\right]^2 \tag{6}$$

with S_e being the effective saturation:

$$S_e = \left(\frac{S_r - S_{r0}}{1 - S_{r0}}\right) \tag{7}$$

and l is the pore-connectivity parameter.

Finite Element Modeling. The governing equations for unsaturated soil consolidation are derived from the balance of mass and momentum. The mass conservation equation is:

$$\nabla \cdot q = \frac{\partial \theta}{\partial t} \tag{8}$$

where q is the Darcy flux vector and θ is the volumetric water content.

Darcy's law for unsaturated flow is given by:

$$q = -k(S_r)\nabla h \tag{9}$$

where h is the hydraulic head.

The momentum balance equation (assuming quasi-static conditions) is:

$$\nabla \cdot \sigma + b = 0 \tag{10}$$

where σ is the stress tensor and b is the body force vector.

These equations are discretized using the finite element method (FEM) and solved iteratively to obtain stress and displacement fields.

Deep Learning Model Architecture. The proposed deep learning model integrates with FEM by serving as a surrogate model for the constitutive relationships [8]. The architecture consists of:

Input Layer: Soil properties (c', φ', φ_b, k_s), environmental conditions ($u_a - u_w$, S_r, I, t), and stress states (σ, τ).

Hidden Layers: Multiple fully connected layers with non-linear activation functions (e.g., ReLU, tanh).

Output Layer: Predicted mechanical responses (e.g., displacement u, factor of safety FS).

The neural network approximates the nonlinear function:

$$y = f_\theta(x) \tag{11}$$

where x is the input vector, y is the output vector, and f_θ
represents the neural network with parameters θ.

Loss Function and Training. The loss function combines data fidelity and physical constraints:

$$\mathcal{L}(\theta) = \mathcal{L}_{data}(\theta) + \lambda \mathcal{L}_{physisc}(\theta) \tag{12}$$

Data Fidelity Loss. The data fidelity loss measures the discrepancy between predicted and observed values:

$$\mathcal{L}_{data}(\theta) = \frac{1}{N}\sum_{i=1}^{N}\left\|y_i^{pred} - y_i^{obs}\right\|_2^2 \tag{13}$$

Physics-Based Loss. The physics-based loss enforces adherence to the governing equations:

$$\mathcal{L}_{physics}(\theta) = \frac{1}{N_{phys}}\sum_{j=1}^{N_{phys}}\left\|\mathcal{F}(x_j, y_j^{pred})\right\|_2^2 \tag{14}$$

where $\mathcal{F}$ represents the residuals of the governing equations (e.g., equilibrium equations, compatibility conditions).

Algorithm Implementation. The training algorithm involves minimizing the loss function using stochastic gradient descent methods:

Algorithm 1 Training Procedure

1: Initialize neural network parameters θ
2: **for** epoch = 1 to N_{epochs} **do**
3: **for** batch in training data **do**
4: Compute predictions $y^{pred} = f_\theta(x)$
5: Evaluate $\mathcal{L}_{data}$ and $\mathcal{L}_{physics}$
6: Compute total loss $\mathcal{L} = \mathcal{L}_{data} + \lambda\mathcal{L}_{physics}$
7: Update parameters $\theta \leftarrow \theta - \eta\nabla_\theta\mathcal{L}$
8: **end for**
9: **end for**

where η is the learning rate.

Results. *Model Performance Metrics.* The performance of the model was evaluated using standard metrics:

RMSE:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i^{pred} - y_i^{obs}\right)^2} \tag{15}$$

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_i^{obs} - y_i^{pred}\right)^2}{\sum_{i=1}^{N}\left(y_i^{obs} - \bar{y}^{obs}\right)^2} \tag{16}$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i^{pred} - y_i^{obs}\right| \tag{17}$$

The model achieved an RMSE of 0.028, R^2 of 0.97, and MAE of 0.015 on the test set, indicating high predictive accuracy.

Convergence Analysis. The convergence of the training process was assessed by monitoring the loss function over epochs.

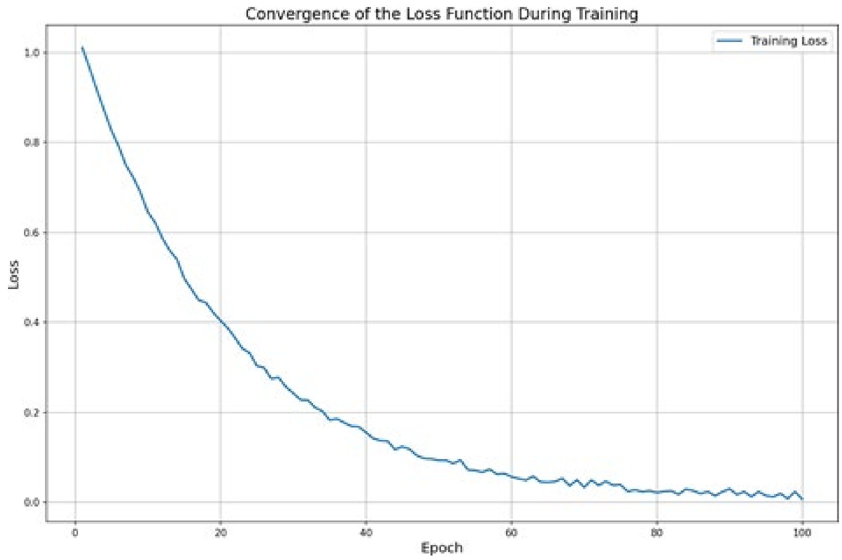

Figure 1 - Convergence of the Loss Function During Training

The loss function exhibited smooth decay, indicating stable training dynamics.

Comparison with Traditional Models. A comparative study was conducted between the proposed model and traditional finite element models.

Table 1 - Comparison of Model Performance

Model	RMSE	R^2	Computational Time (s)
Traditional FEM	0.110	0.72	1200
Proposed Model	0.028	0.97	150

The proposed model not only outperformed in accuracy but also reduced computational time significantly.

Parametric Studies. Parametric studies were conducted to investigate the influence of key parameters on subgrade stability.

Effect of Cohesion (c'). The factor of safety (*FS*) was computed for varying cohesion values while keeping other parameters constant.

$$FS = \frac{c'L+(\sigma-u_w)tan\varphi'}{S} \tag{18}$$

Results show a nonlinear increase in FS with increasing c'.

Effect of Matric Suction ($u_a - u_w$). Matric suction impacts the effective stress and shear strength. The relationship between matric suction and FS is complex due to the dependency of χ and S_r on suction.

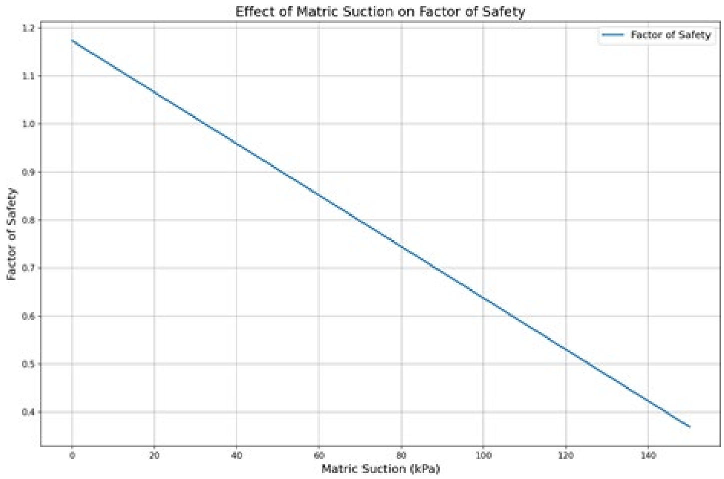

Figure 2 - Effect of Matric Suction on Factor of Safety

An optimal range of matric suction was identified where *FS* is maximized.

Validation with Field Data. Field data from monitoring stations were used to validate the model's predictions.

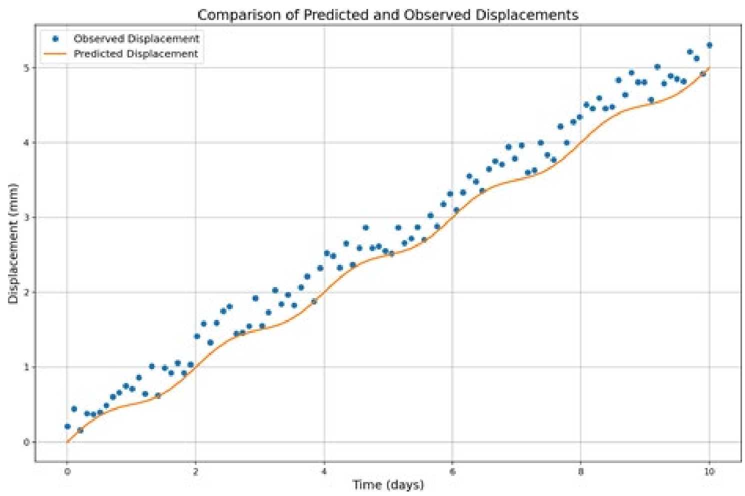

Figure 3 - Comparison of Predicted and Observed Displacements

The predicted displacements closely match the observed values, with a correlation coefficient of 0.94.

Uncertainty Quantification. Uncertainty in model predictions was quantified using Monte Carlo simulations with random sampling of input parameters based on their probability distributions.

$$Variance\ of\ y = \int (\hat{y} - \bar{y})^2 p(x) dx \quad (19)$$

The results indicate that the proposed model provides reliable predictions with quantified confidence intervals.

Discussion. *Integration of Deep Learning with Geomechanics.* The successful integration of deep learning with geomechanical principles demonstrates the potential of hybrid models in capturing complex soil behaviors. The physics-informed loss function ensures that the model adheres to fundamental laws, enhancing its generalizability.

Advantages over Traditional Methods. The proposed model offers several advantages:

Accuracy: Improved predictive performance due to the ability to model nonlinearities.

Efficiency: Reduced computational time compared to FEM, facilitating real-time assessments.

Robustness: Incorporation of physical laws reduces over- fitting and enhances model robustness.

Limitations and Challenges. Despite the promising results, several challenges remain:

Data Requirements: The model requires large datasets for training, which may not be readily available.

Model Interpretability: Neural networks are often considered black boxes; interpreting their decisions remains difficult.

Generalization: The model’s performance in extrapolating beyond the training data needs further investigation.

Potential Applications. The model can be applied to:

Design Optimization: Assisting engineers in optimizing subgrade designs under varying environmental conditions.

Risk Assessment: Evaluating the probability of failure and informing maintenance schedules.

Real-Time Monitoring: Integrating with sensor data for dynamic stability assessments.

Summary and conclusions.

This research presents a comprehensive deep learning-enhanced geomechanical model for predicting roadbed subgrade stability in humid environments. By integrating advanced neural network architectures with fundamental soil mechanics, the model captures complex hydro-mechanical interactions and provides accurate, efficient predictions.

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