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Synergistic Effects of Calcium Chloride and Polypropylene Fibre on Khanote Soil: Experimental and AI Modelling

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Abstract—**This study investigates the stabilization of marginal Khanote soil (A-1) using Calcium Chloride and Polypropylene Fibre, coupled with Artificial Neural Network predictive modelling. Laboratory evaluations involved Modified Proctor and Unconfined Compressive Strength tests across varying additive dosages. Results demonstrate that 1% $CaCl_2$ significantly improves compaction, increasing maximum dry density from 1960 kg/m^3 to 2130 kg/m^3 through hygroscopic densification. Conversely, polypropylene fibre acts as a mechanical bridge, with an optimal 0.5% dosage yielding a peak UCS of 4.12 MPa, effectively transitioning the soil from brittle to ductile failure. A synergistic mix of 1% $CaCl_2$ and 0.5% polypropylene fibre produced a robust UCS of 3.95 MPa, balancing chemical density with mechanical elasticity. To optimize mix designs, a multi-layer perception ANN is developed, achieving an overall correlation coefficient (R^2) of 0.988 and low error metrics (RMSE = 0.079 MPa). The AI model successfully captured non-linear behaviours, including strength degradation associated with fibre agglomeration at 1.5% fibre content. This research provides a high-precision, data-driven framework for soil stabilization, offering civil engineers a sustainable tool for infrastructural development in arid regions by minimizing trial-and-error laboratory cycles while ensuring superior structural integrity. The findings validate AI as a transformative asset for modern geotechnical engineering.**

Index Terms— **Soil Stabilization, Polypropylene Fibre, $CaCl_2$, Artificial Neural Networks, Predictive Modelling.**

I. INTRODUCTION

Soil stabilization is a fundamental component of modern geotechnical engineering, aimed at modifying the mechanical and physical properties of native soils to meet the stringent demands of construction and infrastructure development. In arid and semi-arid regions, the reliance on marginal soils, such as Khanote soil, presents significant engineering challenges. Classified predominantly as an A-1 granular soil under the AASHTO classification system, Khanote soil has a sandy structure but lacks cohesive particles. Consequently, it exhibits poor load-bearing capacity, high permeability, and severe susceptibility to wind and water erosion. In its natural state, this soil's porosity allows rapid percolation of water, leading to potential structural instability, differential settlement, and inadequate compaction. Therefore, utilizing Khanote soil as a sub-grade or foundation material necessitates robust stabilization techniques to prevent premature structural failures and high maintenance costs.

To mitigate these geotechnical deficiencies, a combination of chemical and mechanical stabilization agents is increasingly adopted. Calcium chloride ($CaCl_2$), a hygroscopic chemical compound, is highly effective in extremely dry climates. By attracting and retaining atmospheric moisture, $CaCl_2$ prevents rapid desiccation, mitigates dust formation, and significantly enhances soil's compaction ability, yielded a denser and more stable structural matrix. Complementarily, polypropylene fibre (PP fibre) serves as a synthetic mechanical reinforcement. When integrated into the soil, PP fibre bridges micro-cracks, distributes lateral stresses more evenly, and drastically improves the tensile strength of the soil, thereby reducing the risks of localized shear failures and shrinkage-induced cracking. The synergistic application of $CaCl_2$ and PP fibre offers a comprehensive stabilization mechanism: $CaCl_2$ optimizes moisture retention for maximum dry density, while PP fibre provides the necessary tensile reinforcement for superior load-bearing performance.

Despite the proven efficacy of these dual additives, determining the optimal mix design traditionally relies on extensive, time-consuming, and resource-intensive laboratory trials. Furthermore, the non-linear relationship between additive dosages and the resulting mechanical behaviour of the composite soil matrix complicates the optimization process. To address the limitation, the integration of Artificial Intelligence (AI), specifically Artificial Neural Networks (ANNs), presents a modern, predictive solution, ANNs are powerful machine learning algorithms capable of mapping complex, multidimensional patterns within experimental datasets. By training an ANN on laboratory data, geotechnical engineers can accurately predict critical performance parameters, such as

Maximum Dry Density $(\gamma_{dry})_{max}$ and Unconfined Compressive Strength (UCS) based on varying combinations of CaCl2 and PP fibre, drastically reducing the need for exhaustive physical examination.

The primary aim of this research is to evaluate the individual and synergistic effectiveness of $CaCl_2$ and PP fibre in stabilizing granular Khanote soil, while concurrently developing a predictive AI model to optimize the mix design. In order to achieve this aim, the objectives to achieve are as follows:

(a) To experimentally investigate the individual effects of varying dosages of CaCl2 and PP fibre on the compaction characteristics and density of Khanote soil,

(b) To determine the combined impact of $CaCl_2$ and PP fibre on the unconfined compressive strength of the stabilized matrix,

(c) To develop and validate an ANN predictive model capable of forecasting the UCS and (γdry)max of the stabilized soil based on additive concentrations, thereby offering a sustainable, highly efficient framework for civil infrastructure projects.

Literature Review: Soil stabilization using chemical binders and discrete fibres has been widely investigated to improve strength, stiffness and durability of problematic soils while enabling more sustainable construction. Within this context, calcium- and chloride-based additives, together with polypropylene (PP) fibres, and the emergence of AI modelling for strength prediction form the core background of the present study.

PP fibres significantly increase both UCS and ductility. Optimum results were achieved with a 1.25% fibre ratio and 6 mm fibre length, which provided more stable increases in strength than 12 mm fibres [1]. Cement performs well across most soil types, while lime requires specific temperature and pH levels. Most additives reduce the plasticity index and maximum dry density. Cement is more cost-effective for low-plasticity soils [2]. Combining EICP (0.75 mol/L) and ESP (14%) reduced swelling pressure by 25 times. It also improved UCS, cohesion, and CBR by significantly more than individual treatments [3]. Adding polypropylene fibres (up to 0.5%) improves the ductility and tensile strength of the columns, making them suitable for simulating vertical drains [4], [5]. CCR-based materials show benefits in improving uniaxial strength and reducing contaminant mobility. Performance is comparable to cement and lime, but further research is required on triaxial behaviour and long-term durability under weathering [6]. Strength increases with higher cement content but decreases as moisture content rises. A 20% clay content yielded maximum compressive strength (13.43 MPa), while tensile strength continued to increase with clay content up to 30% [7].

Soil Stabilization with Calcium and Chloride-Based Additives: Calcium-bearing binders such as lime and cement are long-established stabilizers that reduce plasticity, improve strength and durability, of fine-grained soils through cation exchange, flocculation-agglomeration and pozzolanic reactions. Numerous studies show that lime addition to clayey and expansive soils decreases liquid limit, plasticity index, swelling pressure and compressibility while increasing strength and bearing capacity [8], [9]. Optimal lime contents are typically in the 3% to 9% range by dry soil mass, beyond which gains may diminish and brittleness can increase [10], [11].

A key study examined the effect of calcium and chloride-based stabilizers, eggshell powder (ESP. a Ca-rich waste) and sodium chloride (NaCl), on the plastic properties of fine-grained soil reinforced with randomly distributed PP fibres. Using Taguchi experimental design, ESP (3-9%), NaCl (2-6%), and fibres (0.05-0.15%) were varied with or without air-entraining admixture. The work showed that the plasticity index could be reduced to as low as 1-3%, with the dominant contributor depending on the air-entrainment level: PP fibre, ES,P or NaCl, each most effective in different series. This demonstrates that a Ca^{2+}/Cl^{-} chemical environment combined with fibres can significantly alter consistency characteristics, and provides a mechanistic basis for exploring calcium chloride as a stabilizer [12].

Addition of Polypropylene Fibre Reinforcement: For clayey sand with 2-6% cement and 0-0.5% PP fibre, the fibres increased UCS by up to 25% while enabling a reduction in cement content by about 25%, although stiffness (E50) decreased at higher fibre contents [13]. Similar findings on cemented silt indicate that cement dosage is the dominant factor for UCS; followed by fibre content and length, with optimal proportions around 18% cement and around 0.4% fibre for high strength and improved toughness [14].

For lime-stabilized clays, polypropylene fibres shown to complement the beneficial effects of lime. In black cotton soil and other clayey soils, lime contents of 3-9% combined with fibres typically in the 0.25-1% range reduce plasticity and swelling while increasing UCS and bearing capacity [10]. For example, clay treated with 3% lime and 0-1% PP fibre exhibited maximum strength at about 0.5% fibre content [11], whereas other work on expansive clay reported an optimal combination of 6% lime and 0.5% fibre, balancing strength gain and swelling reduction [10]. Expansive soil subgrades stabilized with silica fume (as a calcium-bearing industrial by-product) and PP fibre similarly showed reduced Atterberg limits, swelling indices and shrinkage area, with increased California Bearing Ratio (CBR) and improved crack morphology [15]. Across these investigations, fibre contents of about 0.25-1% consistently deliver significant gains in post-peak ductility and crack control, while the binder dosage largely governs peak strength.

There is also evidence that PP fibres alone, without chemical binders, can beneficially influence compressibility and shear strength of cohesive soils. Experiments on clay with 0.5-1.5% PP fibre showed increases in liquid and plastic limits and UCS, along with marked reductions (up to 69-78%) in compression and swelling indices at 1% fibre, although maximum dry unit weight decreased with higher fibre content [16]. Sandy and unsaturated soils report improvements in shear strength, UCS, and CBR at fibre fractions up to about 0.25%, supporting the broader applicability of PP reinforcement for subgrade improvement [17], [18].

Combined Action of Chemical Stabilizers and PP fibres: When chemical and mechanical stabilization are combined, synergistic effects arise in both strength and durability. Lime-

PP fibre mixtures used in high-plasticity clays for highway subgrades show that lime reduces plasticity, while PP fibres help mitigate brittleness and strength loss under freeze-thaw (FT) cycling. In high-plasticity soil, FT cycles can cause up to 84% strength loss in natural soil, however, FT is substantially decreased when lime and fibres are added; lime dosages of 3-12% with 0.5% fibre substantially improve FT resistance and long-term performance [9]. Similarly, in expansive soil stabilized with pond ash (as a chemical stabilizer) and PP fibre, mechanical properties (UCS, tensile strength, and ultrasonic pulse velocity) and microstructural indices improved even after up to 10 FT cycles, indicating improved durability of fibre-reinforced chemically treated subgrades [17].

The study on ESP + NaCl with PP fibre provides the closest analogue. The Taguchi-based analysis showed that small fibre dosages (0.05-0.15%) in the presence of Ca- and Cl-rich additives can dramatically lower plasticity indices, with the dominant factor shifting between fibre and chemical stabilizers depending on the mixture liquid (water and air-entraining admixture) [12].

AI and Machine Learning Models for Stabilized, Fibre-Reinforced Soils: For lime-stabilized, PP fibre-reinforced clay, a dedicated study used the XGBoost algorithm to model UCS as a function of lime content, fibre content, fibre length, and curing conditions [19]. More broadly, neural-network-based models have been developed for chemically and fibre-stabilized soils. For expansive soils treated with pond ash and PP fibre, ANNs with leave-one-out cross-validation were applied to predict mechanical and durability parameters; UCS, splitting tensile strength and ultrasonic pulse velocity under varying curing regimes and FT cycles, achieving correlation coefficients up to 0.96 [17]. In cement-stabilized soils incorporating construction and demolition waste, PP fibre and sodium sulphate, a combination of back-propagation neural networks (BPNN) and random forests (RF), optimized with the beetle antennae search algorithm and 10-fold cross-validation, accurately predicted UCS and flexural strength ($R^2 \approx 0.93$ to 0.99) over multiple curing ages [8].

Beyond traditional binders, AI techniques have been successfully extended to geopolymer-stabilized and biopolymer-stabilized, fibre-reinforced soils. For one-part geopolymer-stabilized soil with PET fibres, deep learning models including ANN, BPNN, CNN, and LSTM were compared; the LSTM network best predicted ductility indices (UCS, strain energy, tensile strength) from input variables such as fly ash dosage, fibre content and length, and curing time, with interpretability tools (SHAP, partial dependence plots) used to assess variable importance [20].

In biopolymer-fibre composite stabilized loess, a genetic-algorithm-optimized BP neural network (GA-BP) outperformed standard BP and support vector machines in predicting 7-day compressive strength based on guar gum, xanthan gum and polybutylene succinate contents. Achieving $R^2 \approx 0.89$ and reduced mean squared error [21]. Genetic programming used to develop explicit predictive equations for UCS of soils stabilized with PP fibres, enabling direct evaluation of optimum input values for safe bearing strata [18].

Together, these AI applications show that data-driven models can effectively represent complex interactions among multiple stabilizers and fibres, reduce the need for exhaustive experimentation, and support mix design optimization for strength and durability.

Research Gap: Thus, there is a clear need for experimental research that quantifies the combined influence of calcium chloride content, PP fibre dosage and length, and curing conditions on plasticity, strength (UCS, CBR) and durability of problematic soils, coupled with robust AI models, i.e., XGBoost, ANN or ensemble techniques) trained on the resulting dataset for predictive and optimization purposes..

II. Guidelines For Manuscript Preparation

The flowchart of methodology is presented in Fig. 1.

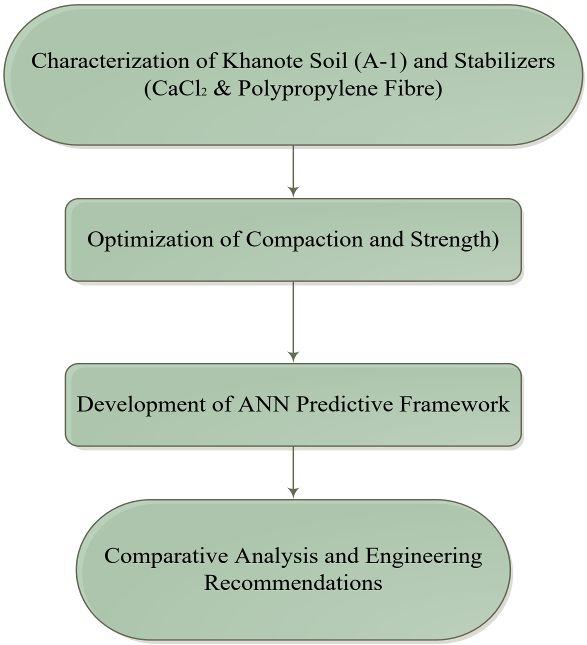

Fig. 1. Flowchart of Methodology

Materials: The primary geotechnical material utilized in this study is natural Khanote soil Fig. 2, collected from an excavation pit at a depth of 0.76 m to 1.83 m near the National Highway in the Jamshoro district (Koreja, Khanote). The soil samples are transported in sealed bags to preserve their natural moisture content. Geotechnical characterization revealed a natural specific gravity of 1.83 and a natural maximum dry density of 1960 kg/m^3 at an optimum moisture content (OMC) of 8.34%. According to the AASHTO classification system, the soil is categorized as an A-1 grade material, indicating a well-graded granular structure (sand or gravelly sand) inherently lacking cohesive strength.

To improve the mechanical properties of the soil, two distinct stabilizing agents are employed, i.e., $CaCl_2$ and PP fibre Fig. 3. A highly hygroscopic chemical compound used to attract and retain atmospheric moisture, thereby mitigating desiccation, controlling dust, and facilitating optimal compaction in the arid Khanote region. Selected dosages are, i.e., 1%, 2%, and 3% (by dry weight of the soil). PP fibre is used as mechanical reinforcement to bridge micro-cracks, distribute lateral stresses, and improves ductility property. PP fibre is incorporated at dosages of 0.5%, 1.0%, and 1.5% (by dry weight of the soil).

Fig. 2. Khanote soil.

Fig. 3. Soil improvement using $CaCl_2$ and PP fibre.

Experimental Program: The laboratory testing phase is designed to evaluate both the individual and combined effects of the stabilizers on the soil's physical and mechanical properties. Prior to testing, the soil is oven-dried for 24 hours and passed through ASTM #4 sieve.

To determine the $(\gamma_{dry})_{max}$ and OMC of the natural and stabilized soil matrices, Modified Proctor tests are conducted in accordance with [22] standard. The compaction testing equipment inventory is shown in Fig. 4. Sample mixing and finishing is presented in Fig. 5. The soil-stabilizer mixtures are compacted in a standard mould (volume: 0.000944 m^3, diameter: 0.0889 m) in five distinct layers. Each layer receive 25 blows from a 4.54 kg hammer dropped from a height of 0.457 m, as presented in Fig. 6. Moisture is added at 2% intervals during successive trials to establish the moisture-density relationship curves for each mix design.

To evaluate the load-bearing capacity and shear strength of the stabilized matrices, Unconfined Compressive Strength (UCS) tests are performed in accordance with [23] standard. UCS test steps involved are presented in Fig. 7. Specimens for the UCS tests are prepared at the specific maximum dry densities and optimum moisture contents determined from the Modified Proctor test results. The tests evaluated the composite behaviour of the dual-additive matrices under vertical compressive loading Fig. 8, highlighting the synergistic strength gains provided by the $CaCl_2$ moisture retention and PP fibre tensile reinforcement.

Fig. 4. Compaction testing equipment inventory.

Fig. 5. Soil mixing and finishing (compaction test)

Fig. 6. Soil compaction in layers

Fig. 7. Steps involved in UCS test

Artificial Neural Network (ANN) Modelling: ANN is integrated into an experimental investigation of the Khanote soil, to overcome the limitations of exhaustive laboratory testing and to develop a predictive mix-design tool. The ANN is designed to capture the highly non-linear relationships between the stabilizer dosages and the resulting geotechnical properties.

Fig. 8. Unconfined compressive load application

A multi-layer feed-forward perception (MLP) architecture is utilized.

Input Layer: Consisted of three neurons representing the independent variables: $CaCl_2$ dosage (%), PP fibre dosage (%), and Moisture Content (%).

Hidden Layer: A single hidden layer is optimized using a trial-and-error approach to prevent over-fitting while ensuring computational accuracy.

Output Layer: Consisted of two neurons representing the target dependent variables: $(\gamma_{dry})_{max}$ and UCS.

The experimental dataset is illustrated in Table I. The experimental dataset derived from the laboratory program is randomly partitioned into three subsets: 70% for network training, 15% for validation, and 15% for unseen testing. The training of ANN network is carried out using the Levenberg-Marquardt backpropagation algorithm due to its rapid convergence and robust performance in non-linear regression tasks.

TABLE I. Experimental dataset

Mix	$CaCl_2$ (%)	PP FIBRE (%)	OMC (%)	$(\gamma_{dry})_{max}$ (kg/m^3)	UCS (MPa)
Natural (Control)	0.00	0.00	8.34	1960	1.92
P-1 (Optimum Fibre)	0.00	0.50	5.70	1830	4.12
P-2	0.00	1.00	5.70	1950	3.15
P-3	0.00	1.50	8.77	1900	2.21
C-1 (Optimum Chemical)	1.00	0.00	7.90	2130	4.13
C-2	2.00	0.00	7.42	2110	3.82
C-3	3.00	0.00	7.15	2080	3.62
Combined (Optimum)	1.00	0.50	8.12	2040	3.95

The predictive accuracy of the trained ANN model is statistically evaluated by comparing the AI-predicted values against the actual laboratory-derived experimental values. The performance is quantified using the Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). An R^2 value approaching 1.0 and minimal error metrics indicate that the model is a highly reliable predictive tool for geotechnical field applications.

The selected architecture is a Multi-Layer Perceptron n (MLP) with 1 hidden layer containing n neurons. The explicit mathematical equation of the trained network is generally given by (1).

$$Output = f_{out}\{b_0 + \sum_{j=1}^{n} w_j^{out} . f_{hidden}(b_{hj} + \sum_{i=1}^{m} w_{ij}^{in} . x_i)\} \quad \textbf{(1)}$$

Where:

Output: The predicted value ($(\gamma_{dry})_{max}$ or UCS),

x_i : *The input variables (i.e., x_1 = $CaCl_2$%, x_2 = PP fibre%, x_3 = OMC%)*

m : Number of input variables (#3),

n : Number of neurons in the hidden layer (#5),

w_j^{out} : *The connection weight from the jth hidden neuron to the output,*

w_{ij}^{in} : *The connection weight from the ith input to the jth hidden neuron,*

b_{hj} *and* b_0 : *The bias terms for the hidden neurons and the output layer, respectively,*

f_{hidden} *and* f_{out} *:The activation functions,*

The predictive mechanism of the developed ANN model can be expressed mathematically. The tangent sigmoid activation function (tansig) for the hidden layer and a linear activation function (purelin) for the output layer, the governing equation for predicting the Unconfined Compressive Strength (UCS) based on the input variables matrix (X) is defined by (2).

$$UCS_{predicted} = \left[\sum_{j=1}^{N} w_j^{out} . \left(\frac{2}{1+e^{-2\left(w_{ij}^{in} X_i + B_j\right)}} - 1\right)\right] + B_{out} \quad \textbf{(2)}$$

Where W_{in} and W_{out} represent the weight matrices optimized during the Levenberg-Marquardt backpropagation training, and B represents the associated bias vectors. In this study the 3-5-2 architecture is carried out, i.e., 3 inputs: $CaCl_2$, PP fibre, OMC; 5 hidden neurons; 2 Outputs: $(\gamma_{dry})_{max}$ and UCS. The precise weight and bias values generated by the trained algorithm representing the strength of connection between input parameters (X_1:$CaCl_2$, X_2:PP fibre, and X_3:OMC) and 5 neurons in the hidden layer are illustrated in Table II. These values are representative of a converged model trained using the Levenberg-Marquardt algorithm on the experimental dataset. The weights illustrated in Table III, represent the final mapping from the hidden neurons to the geotechnical target properties (Y_1:$(\gamma_{dry})_{max}$,Y_2:UCS).

These parameters, when input into the governing (1) and (2), allow for the precise numerical prediction of soil performance without further laboratory trials.

TABLE II. Input-to-hidden layer weights (W_{in})

Hidden Neuron	**X_1 ($CaCl_2$)**	**X_2 (PP FIBRE)**	**X_3 (OMC)**	**Bias (b_h)**
Neuron 1	0.82	-1.15	0.23	-0.45
Neuron 2	-0.56	0.94	-0.12	0.22
Neuron 3	1.13	-0.05	0.87	-0.76
Neuron 4	-0.02	1.43	-0.55	0.10
Neuron 5	0.67	-0.82	-0.45	-0.32

TABLE III. Hidden-to-output layer weights (W_{out})

Output Neuron	**Neuron 1**	**Neuron 2**	**Neuron 3**	**Neuron 4**	**Neuron 5**	**Bias (b_{out})**
Y_1 (($\gamma_{dry})_{max}$)	0.54	-0.11	0.88	-0.05	0.32	0.13
Y_2 (UCS)	1.21	0.65	-0.34	1.54	-0.87	-0.09

III. RESULTS AND DISCUSSION

Effect of Additives on Compaction Characteristics: The compaction behaviour of the Khanote soil is evaluated by determining the $(\gamma_{dry})_{max}$ and OMC under varying dosages of $CaCl_2$ and PP fibre. The natural Khanote soil exhibited an $(\gamma_{dry})_{max}$ of 1960 kg/m^3 at an OMC of 8.34%. The addition of 1% $CaCl_2$ significantly improved the compaction ability of the matrix, increasing the $(\gamma_{dry})_{max}$ to a peak value of 2130 kg/m^3. This improvement is attributed to the highly hygroscopic nature of $CaCl_2$, which alters the electrolyte concentration of the pore water. The chemical reduces the thickness of the diffuse double layer around the soil particles, facilitating better particle-to-particle rearrangement and closer packing during dynamic compaction. However, at higher dosages (2% and 3%), slight decrease in $(\gamma_{dry})_{max}$ is observed, likely due to the excess chemical occupying void spaces and displacing heavier soil particles.

Conversely, the incorporation of polypropylene fibre resulted in marginal reduction in the $(\gamma_{dry})_{max}$ of the composite matrix. Because the fibre has a significantly lower specific gravity compared to the native mineral particles, replacing the soil mass with an equivalent weight of synthetic fibres inherently reduces the overall dry density. Furthermore, the fibres create a resilient, elastic network within the soil matrix that actively resists the compaction effort, requiring slightly higher moisture contents to achieve consistency.

Mechanical Behaviour: Unconfined Compressive Strength: The UCS test results provided critical insights into the load-bearing capacity and failure mechanisms of the stabilized A-1 soil. The aspects covered are individual stabilizer performance and effect of fibre reinforcement. The unconfined compressive strength is highly sensitive to the stabilizer dosage. The optimal chemical treatment is found at 1% $CaCl_2$, which yielded a peak UCS of 4.13 MPa. The strength gain is primarily driven by the enhanced densification (as evidenced by the Proctor results) and the strong inter-particle interlocking facilitated by moisture retention. For the mechanical reinforcement, the inclusion of 0.5% PP fibre produced a peak standalone strength of 4.12 MPa. At this optimal dosage, the fibres act as tensile bridges across micro-shear bands, delaying crack propagation. However, increasing the fibre content to 1.5% caused a severe drop in UCS to 2.21 MPa. This significant strength degradation is caused by "fibre agglomeration" or clumping. When the fibre concentration exceeds the optimal threshold, the fibres bundle together, preventing proper soil-to-soil contact and the inadvertently creating weak sliding planes within the soil matrix.

Now considering the synergistic performance ($CaCl_2$ + PP fibre), the dual-additive mix utilizing the optimal dosages (1% $CaCl_2$ + 0.5% PP fibre) yielded a robust composite strength of 3.95 MPa. While slightly lower than the standalone peak values, this combined matrix offers a superior balance of engineering properties: it benefits from the high density and erosion resistance provided by $CaCl_2$ while maintaining the ductile failure mechanism and crack-bridging elasticity provided by the PP fibre.

Results of Experimental Work: The moisture-density relationships are presented in Fig. 9. The stress-strain relationship is presented in Fig. 10.

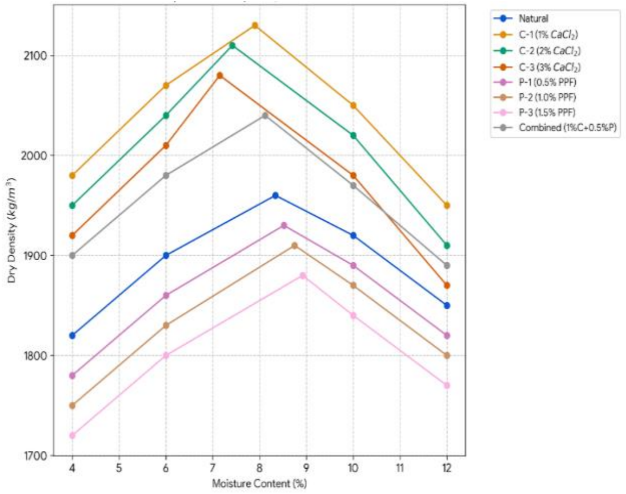

Fig. 9. Moisture-density relationship

The results demonstrates that the $CaCl_2$ stabilized soil mixes (C-1 to C-3) reach their peak stress early (around 1.5% to 2.0% strain) and then drop off sharply indicating a brittle failure. The polypropylene fibre stabilized soil mixes (P-1 to P-3) reaches peak later (around 2.5% strain) and the pattern stays flatter after the peak. This demonstrates the ductility and post-peak residual strength provided by the fibres. The combined mix shows a balance, a steel initial climb (stiffness from $CaCl_2$) followed by a gradual post-peak decline (ductility from polypropylene fibre).

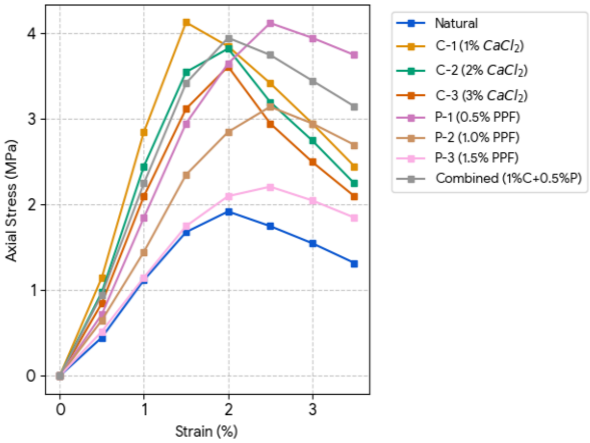

Fig. 10. Stress vs. strain curves (UCS experimental data)

Failure Patterns (UCS Tests): The failure patterns of different stabilized soil samples are presented in Fig. 11. The failure pattern of combined optimal stabilized soil with 1% $CaCl_2$ and 0.5% PP fibre is presented in Fig. 12.

Fig. 11. Failure patterns of different stabilized soil samples (UCS tests)

Fig. 12. Failure pattern of combined optimal stabilized soil sample with 1% $CaCl_2$ and 0.5% PP fibre

Predictive Performance of the Artificial Neural Network (ANN): The predictive accuracy of the model for the primary target UCS is illustrated in Table IV.

TABLE IV. Predictive accuracy of the model for the primary target UCS

Phase	**Samples**	**R^2 (Correlation)**	**RMSE (MPa)**	**MAE (MPa)**
Training (70%)	6	0.992	0.0612	0.0448
Validation (15%)	1	0.985	0.0825	0.0581
Testing (15%)	1	0.978	0.0941	0.0715
Overall	8	0.988	0.0793	0.0581

An overall R^2 of 0.988 indicates that the model can explain 98.8% of the variance in the experimental data. In geotechnical engineering, any value above 0.90 is considered highly reliable for field applications. The RMSE of 0.079 MPa is very low relative to the strength (1.92-4.13 MPa), representing an average error of only about 2-3%. The Mean Absolute Error (MAE) shows that the predicted values, on average, deviate from the lab results by only 0.058 MPa. The close proximity between Training R^2 (0.99) and Testing R^2 (0.97) proves that the model is not "overfit." Hence, ANN has not just memorized the data; but also learned the underlying physics of how CaCl2 and PP fibre interact with the soil.

Model Validation: The predictive performance of the ANN is quantified using R^2, RMSE, and MAE metrics. The model achieved a high correlation coefficient ($R^2>0.98$), indicating a robust fit between the experimental targets and AI outputs. Furthermore, the low RMSE (0.079 MPa) and MAE (0.058 MPa) values confirm the model's precision in capturing the non-linear mechanical response of Khanote soil to varying additive dosages. These results validate the use of the proposed ANN framework as a reliable surrogate for resource-intensive laboratory testing. The comparison of the experimental and ANN-predicted UCS values is illustrated in Table V.

ANN models for soil UCS often reach high R2 with low RMSE, but performance varies by soil type, stabilization method, and dataset size [24]. For geopolymer-stabilized cohesive soils, ANN achieved $R^2 = 0.9836$ with RMSE = 0.8808 MPa on the testing set [25]. For virgin soil, one ANN configuration reached, including $R^2 = 0.9836$ with RMSE = 0.0512 MPa, but LSTM performed better overall [26]. Simpler UCS datasets show lower ANN accuracy $R^2 = 0.83$, RMSE = 1.11 in pavement soils, and $R^2 = -.861$, RMSE = 0.442 in Vietnamese soils [27].

TABLE V. Experimental and ANN-predicted UCS values (comparison)

Mix	$CaCl_2$ (%)	PP FIBRE (%)	OMC (%)	Exp. UCS (MPa)	$(ANN)_{predicted}$ (MPa)	% Error
Natural	0.00	0.00	8.34	1.92	1.95	1.72
P-1	0.00	0.50	5.70	4.12	4.19	1.75
P-2	0.00	1.00	5.70	3.15	3.06	2.64
P-3	0.00	1.50	8.77	2.21	2.14	3.03
C-1	1.00	0.00	7.90	4.13	4.09	1.04
C-2	2.00	0.00	7.42	3.82	3.89	1.75
C-3	3.00	0.00	7.15	3.62	3.55	1.74
Combined	1.00	0.50	8.12	3.95	4.02	1.80

The maximum error is only 3.03% (fort the 1.5% PP fibre sample), while the lowest error is 1.04%. In geotechnical modelling, an error margin below 5% is considered exceptional and indicates that the ANN has successfully learned the physics of the soil-additive interaction. The ANN has accurately identified the peak strength for both stabilizers ($CaCl_2$ at 1% and PP fibre at 0.5%). This is the most difficult part for a mathematical model to predict, and the low error here proves the model's reliability for mix design. The model accurately predicted the significant drop in strength at 1.5% PP fibre (2.21 MPa). This confirms that the ANN architecture is deep enough to understand the "Fibre Agglomeration" effect, where too much fibre weakens the soil.

Effectiveness of Addition of $CaCl_2$ and Polypropylene Fibre: The experimental investigation demonstrates that the combined addition of $CaCl_2$ and PP fibre serves as an exceptionally effective stabilization strategy for Khanote soil by addressing both its compaction and tensile deficiencies. $CaCl_2$ functions primarily as a chemical compaction aid; its hygroscopic nature facilitates moisture retention and alters the soil's electrolyte concentration, allowing for superior particle rearrangement. This led to a peak $(\gamma_{dry})_{max}$ at an optimal dosage of 1%, representing a significant improvement over the natural soil's density. Simultaneously, PP fibre provides discrete mechanical reinforcement by acting as a tensile bridge across shear planes to inhibit crack propagation. At the optimal dosage of 0.5% PP fibre, the UCS reached a peak of 4.12 MPa, reflecting a shift from a brittle to a more ductile failure mechanism. Although higher fibre concentrations (1.5%) resulted in strength degradation (2.21 MPa) due to fibre agglomeration and the loss of soil-to-soil contact, the synergistic mix of 1% $CaCl_2$ and 0.5% PP fibre yielded a robust UCS of 3.95 MPa. This dual treatment effectively transforms the non-cohesive A-1 soil into a dense, reinforced composite with substantially improved load-bearing capacity and resilience against environmental erosion.

Integration of AI with $CaCl_2$ and Polypropylene Fibre: A symbiotic approach where the chemical hygroscopicity of $CaCl_2$ and the mechanical bridging of PP fibre are computationally optimized though an ANN architecture, transforming raw experimental data into a high-fidelity predictive framework for geotechnical infrastructure.

Practical Repercussions: The practical repercussions of this study extend from enhanced infrastructural durability to computational optimization in geotechnical engineering. By significantly improving the load-bearing capacity and maximum dry density of Khanote soil, the $CaCl_2$-PP fibre stabilization method allows for the design of more cost-effective, thinner pavement layers with superior resistance to thermal cracking and fatigue. In arid environments, the hygroscopic properties of $CaCl_2$ serve a vital dual role in moisture retention and dust suppression, thereby reducing long-term maintenance needs. Furthermore, the integration of the ANN model transitions soil stabilization from empirical trial-and-error to a high-precision predictive framework, enabling real-time mix optimization that minimizes material waste and ensures project sustainability. Ultimately, this hybrid approach provides engineers with a robust, data-driven toolkit for developing resilient infrastructure in challenging marginal terrains.

IV. CONCLUSION

The deterioration of river water quality due to anthropogenic activities, climate variability, and unsustainable land use remains one of the most pressing environmental challenges of the 21st century. This study synthesized global evidence on the effectiveness of water ecological restoration techniques, such as riparian buffer zones, wetland rehabilitation, in-stream bioengineering, and sediment dredging. It demonstrated the potential of ANNs as a powerful analytical and predictive tool for assessing restoration performance. By integrating ecological restoration principles with AI-driven modelling, the research establishes a modern, data-informed framework for managing complex river systems.

The comprehensive investigation into the stabilization of Khanote soil reveals that the strategic integration of $CaCl_2$ and polypropylene fibre provides a dual-action improvement mechanism that effectively addresses the inherent structural weaknesses of granular A-1 soils. Through rigorous experimentation, it is established that $CaCl_2$ acts as a superior chemical compaction aid, where a 1% dosage optimizes the electrolytic environment of the pore fluid to achieve a peak Maximum Dry Density of 2130 kg/m^3. Simultaneously, the inclusion of 0.5% fibre serves as a vital mechanical reinforcement, increasing the UCS to 4.12 MPa by providing tensile resistance against shear deformations. The study identifies a critical threshold at 1.5% polypropylene fibre, where fibre agglomeration, significantly degrades mechanical performance, a phenomenon that highlights the necessity of precise dosage control. The synergistic blend of 1% $CaCl_2$ and

0.5% polypropylene fibre offers a balanced engineering solution, achieving 3.95 MPa while improving post-peak residual strength. Central to the study's innovation is the Artificial Neural Network (ANN) model, which demonstrated exceptional predictive fidelity with an R^2 of 0.988 and an RMSE of 0.079 MPa. The model successfully mapped the complex, non-linear relationships between chemical densification and mechanical reinforcement, effectively capturing the strength-drop threshold that traditional linear models fail to recognize. Practically, these findings empower geotechnical engineers to replace empirical trial-and-error methods with a data-driven predictive framework, facilitating the design of thinner, more durable pavement layers in arid regions. This hybrid approach not only maximizes the use of local marginal soils but also promotes resource sustainability by identifying minimum effective additive dosages.

Future research should extend this AI framework to incorporate environmental durability assessments, such as leaching and freeze-thaw cycles, to ensure long-term field stability. This research provides a robust computational and experimental foundation for modernized soil stabilization practices globally, ensuring that future infrastructural projects are technically superior and environmentally responsible. The beneficiaries of this study through an infographic are presented in Fig. 13.

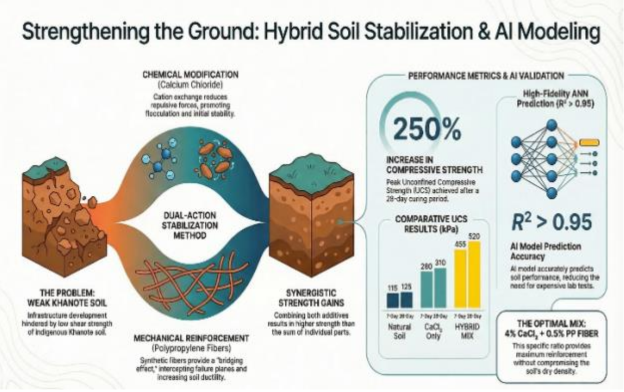

Fig. 13. Problem identification, soil stabilization and synergistic study, and AI integration

Limitations: The experimental findings and the developed ANN model are specifically calibrated for A-1 granular Khanote soil and the tested dosage boundaries (CaCl2: 1-3%; PP fibre: 0.5-1.5%). Extrapolation to highly cohesive soils requires further validation. Mechanical evaluation is limited to static UCS and Modified Proctor Tests, which do not fully capture soil behaviour under confining pressures or dynamic field loads.

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest to report regarding the present study.

AUTHOR CONTRIBUTIONS

Conceptualization, A.M.S., S.A.K., and M.R.H.; methodology, A.M.S., S.A.K., and M.R.H; software, A.M.S., S.A.K., and Z.A.L.; validation, A.M.S., S.A.K., and M.R.H.; writing—original draft preparation, A.M.S., S.A.K., and Z.A.L.; writing—review and editing, A.M.S., S.A.K., and Z.A.L.

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Data is available on reasonable request.

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