

Analysis of Piping in Habdat Earthen Embankment Using Hybrid Deep Learning

Subodh Kumar Suman[1]
[1]Assistant Professor, Department of Civil Engineering
Bhagalpur College of Engineering, Bhagalpur, Bihar, India
Avinash Kumar[2]
[2]Assistant Professor, Department of Civil Engineering
Government Engineering College, Sheikhpura, Bihar, India

Abstract- Piping is one of the phenomena of water erosion that causes significant changes in the earthen embankment, resulting in about 90% of earth dam failures. To analyze this issue, this study addresses the critical issue of piping susceptibility in the Habdat Earthen Embankment context using the deep learning approach. Through a comprehensive approach, encompassing data acquisition, data preprocessing (Data cleaning, standardization and normalization), feature extraction, feature selection, and prediction, a robust model is developed for assessing piping occurrences. Leveraging advanced techniques, including the Self-Improved Green Anaconda Optimization (GAO) and hybrid deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), this research achieves enhanced predictive accuracy. Evaluation results indicate the proposed model's superiority consistently outperforming benchmark models in accuracy (0.98), precision (0.99), sensitivity (0.98), specificity (0.97) F1-Score (0.93), MCC (0.99), NPV (0.95), FPR (0.02) and FNR (0.00). The incorporation of GAO and hybrid deep learning not only enhances predictive accuracy, but also showcases adaptability across diverse scenarios. This research contributes significantly to geotechnical engineering, offering a foundation for further research and practical applications in risk assessment, infrastructure planning, and disaster prevention. The findings underscore the potential of innovative optimization and deep learning techniques in robust piping susceptibility assessment.

Keywords— *Piping Susceptibility, Earthen Embankment, Green Anaconda Optimization, Deep Learning.*

INTRODUCTION

A typical kind of water-retaining construction, earthen embankments assist the community in a variety of ways, including holding water for irrigation, and water supply, and protecting people from natural calamities like floods. Seepage pressures can remove fines from a passage between the upstream and downstream sides through a process known as piping. These pipes can cause soil particles to erode and be carried away by the water, creating voids and potentially compromising the stability of earthen embankments. Since it has been determined that piping is the root of roughly 90% of all earthen dam collapses, piping is a crucial procedure in geotechnical engineering. Backward erosion pipe is the cause of 31% of dam failures. Because of the head difference, an embankment serves as a water barrier, allowing water to pass through it from one side to the other. Once the water flow reaches the critical gradient, the soil on the downstream side of the embankment begins to erode. The beginning of piping is indicated by the erosion of the soil on the downstream side of the embankment. Internal erosion causes a pipe channel to develop as it travels upstream from the downstream side, causing internal erosion to undermine an embankment. When the hydraulic gradient is larger than the critical gradient, piping in an earthen embankment begins. During the analysis phase of embankment structures, it's essential to incorporate a probabilistic analysis that accurately represents the spatial variability of soil properties. This ensures both the safety and cost-effectiveness of the design. In the realm of reliability analysis for engineering structures, the First Order Reliability Method (FORM) has been a prevalent choice for several decades. Additionally,

IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
, **UGC CARE Listed (Group -I) Journal Volume 10, Iss 09, 2021**

the RFEM approach has been employed to explore the stochastic nature of hydraulic gradients within earthen dams, factoring in soil permeability variability as a random element. A recent advancement in this field is the Subset Simulation (SS) method, which builds upon the foundation of RFEM. It generates random fields centered around a mean value of the design random variable and utilizes the Markov Chain Monte Carlo (MCMC) technique for random field generation. This approach is known to be more efficient than the Monte Carlo Simulation (MCS) method, requiring fewer samples to achieve the desired accuracy level. Notably, the Subset Simulation method has demonstrated success in reliability and risk analysis for various engineering challenges. Various scholars have also provided various probabilistic methods for forecasting the factors causing piping failure in earthen dams.

METHODOLOGY

The current research focuses on an in-depth analysis of piping phenomena in the context of the Habdat Earthen Embankment. To achieve a comprehensive understanding and accurate predictions, a novel approach involving hybrid Deep Learning techniques has been employed. Within this framework, the research incorporates key factors such as hydraulic conductivity and various soil properties, which collectively contribute to the vulnerability of the embankment to piping. The proposed model consists of five major phases, namely (i) Data Acquisition (ii) Pre-processing, (iii) Feature Extraction, (iv) Feature Selection, and (v) Piping susceptibility Prediction. The overall architecture diagram is depicted in Figure 1.

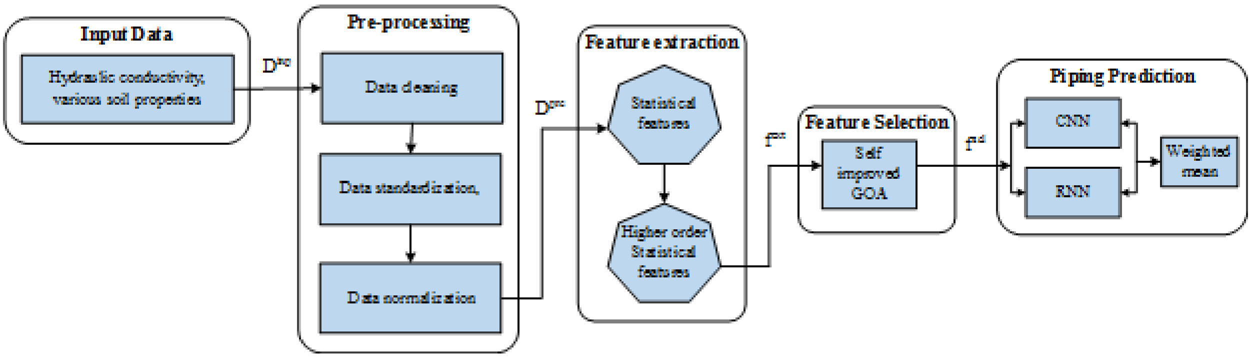

Figure 1- Overall Architecture Diagram

(i) Data Acquisition- The initial step involves the collection of data denoted as D^{inp}. This dataset is meticulously gathered and cross-validated with experimental data sourced from existing literature.

(ii) Pre-Processing- The collected data D^{inp} undergoes a pre-processing stage that encompasses data cleaning, standardization, and normalization processes. The outcome of this stage is the pre-processed dataset, designated as D^{pre}.

(iii) Feature Extraction- From the normalized pre-processed dataset D^{pre}, a range of features is extracted. These features encompass statistical features, denoted as f^{stat}, including mean, median, min-max values, and standard deviation. Additionally, higher-order statistical features f^{h-stat} like skewness and variance are derived from the normalized dataset.

(iv) Feature Selection- The extracted features are subjected to a feature selection process, wherein the Self-improved Green Anaconda Optimization (GAO) technique is utilized. The chosen features resulting from this process are labeled as f^{sel}.

(v) Piping Susceptibility Prediction- The final phase involves the prediction of piping susceptibility. This prediction is facilitated using the optimal features f^{sel} which are employed to train a hybrid deep-learning model. This deep-learning model is composed of two primary components: a Convolutional Neural Network (CNN) and a Recurrent Neural Network (RNN). Upon training these two components, a weighted mean is calculated from their outputs, resulting in a comprehensive prediction of piping susceptibility.
Through the seamless integration of these five phases, the proposed model aims to offer a holistic solution for predicting the susceptibility of piping in the Habdat Earthen Embankment. This innovative approach combines advanced techniques to enhance the accuracy and effectiveness of piping susceptibility assessment.

EXPERIMENTAL SETUP

The presented model was implemented using MATLAB software. An extensive evaluation of the proposed model was conducted utilizing data sourced from existing literature. Within the collected dataset, 80% was designated for training purposes, while the remaining 20% was reserved for testing. The evaluation process encompassed a range of performance metrics including Accuracy, Precision, Sensitivity, Specificity, F1-score, Negative Predictive Value (NPV), Matthews Correlation Coefficient (MCC), False Positive Rate (FPR), and False Negative Rate (FNR). This comprehensive assessment was carried out by varying the training percentage in performance analysis.
(i) Accuracy- It measures the overall correctness of the model's prediction

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

(ii) Precision- It quantifies the proportion of true positive (TP) predictions among all positive predictions.

$$Precision = \frac{TP}{TP+FP}$$

(iii) Sensitivity- It evaluates the proportion of actual positives that are correctly predicted as positive by the model.

$$Sensitivity = \frac{TP}{TP+FN}$$

(iv) Specificity- It calculates the proportion of actual negatives that are correctly predicted as negative by the model.

$$Specificity = \frac{TN}{TN+FP}$$

(v) F1_Score- It combines both precision and specificity to provide a balanced measure of model performance.

$$F1\_Score = \frac{Presision.Specificity}{Presision + Specificity}$$

(vi) NPV- It assesses the proportion of actual negatives that are correctly predicted as negative.

$$NPV = \frac{TN}{TN+FN}$$

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 10, Iss 09, 2021

(vii) MCC- It takes into account true and false positives and negatives and is useful for imbalanced datasets.

$$MCC = \frac{(TP \times TN - FP \times FN)}{\sqrt{(TP+FN)(TN+FP)(TN+FN)(TP+FP)}}$$

(viii) FPR- It calculates the proportion of actual negatives that are incorrectly predicted as positive.

$$FPR = \frac{FP}{FP+TN}$$

(ix) FNR- It calculates the proportion of actual positives that are incorrectly predicted as negative.

$$FNR = \frac{FN}{FN+TP}$$

PERFORMANCE ANALYSIS

Table 1 presents performance metrics for various models in predicting piping susceptibility in Habdat Earthen Embankment. Each model's accuracy, precision, sensitivity, specificity, F1-Score, Matthews Correlation Coefficient (MCC), Negative Predictive Value (NPV), False Positive Rate (FPR), and False Negative Rate (FNR) are showcased. Figure 2, displays the performance analysis of the proposed model.

	Accuracy	Precision	Sensitivity	Specificity	F1-Score	MCC	NPV	FPR	FR
Proposed	0.98	0.99	0.98	0.97	0.93	0.99	0.95	0.02	0.00
CNN	0.96	0.96	0.96	0.96	0.92	0.96	0.92	0.02	0.00
RNN	0.97	0.95	0.95	0.95	0.92	0.96	0.91	0.02	0.00
MLP	0.92	0.94	0.95	0.93	0.91	0.93	0.88	0.03	0.01
NN	0.90	0.91	0.95	0.91	0.89	0.87	0.84	0.03	0.01
KNN	0.90	0.93	0.87	0.86	0.88	0.86	0.83	0.03	0.01

Table 1- Performance Evaluation of Piping Susceptibility Prediction Models

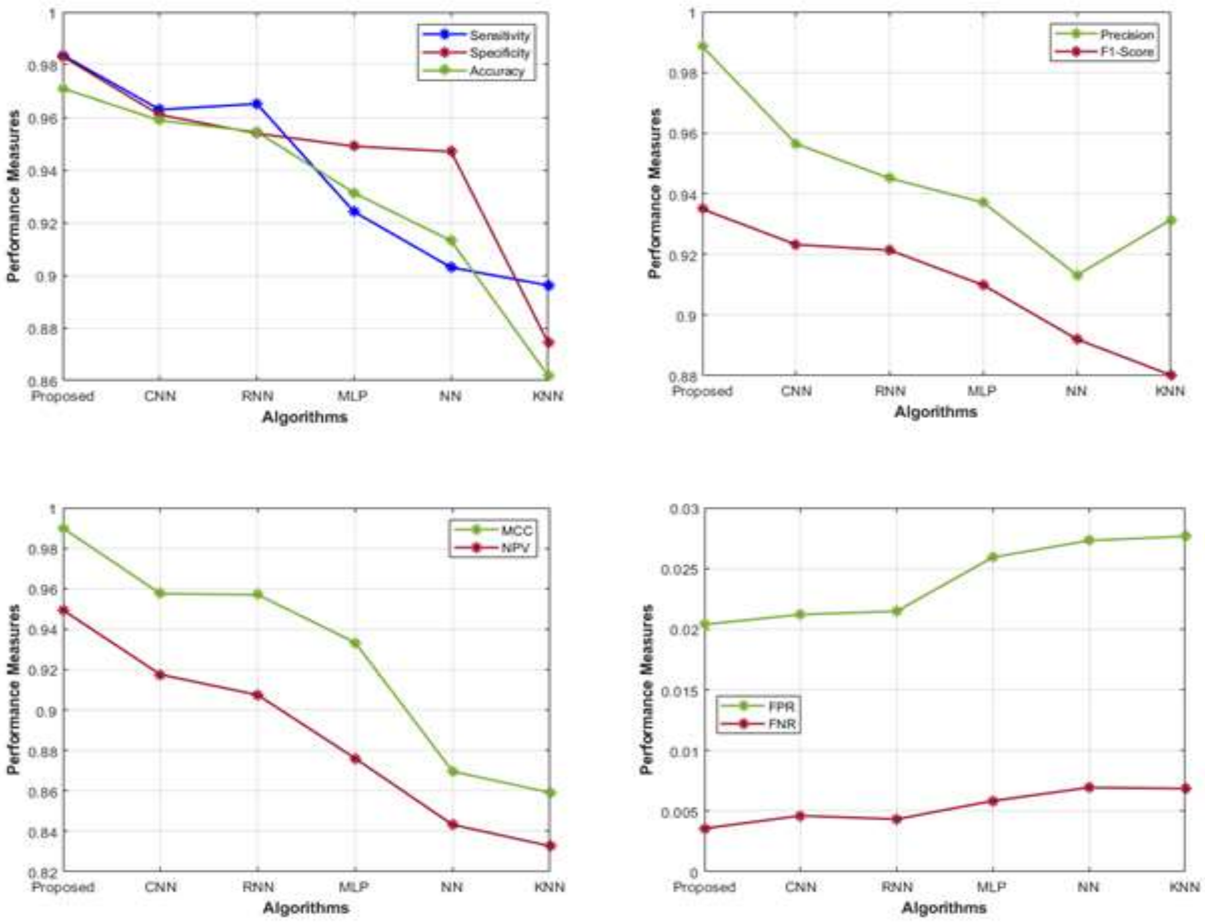

Figure 2- Analysis of the proposed model's performance

The Proposed model achieves high accuracy (0.98) and precision (0.99), signifying its ability to correctly identify susceptible cases. The sensitivity (0.98) and specificity (0.97) demonstrate its balanced recognition of both positive and negative instances. The F1-Score (0.93) indicates good overall performance, while the MCC (0.99) highlights its robustness. Comparatively, the CNN model's accuracy (0.96) and precision (0.96) are slightly lower than the proposed approach. Similarly, the RNN model also shows similar trends, with an accuracy of 0.97 and a precision of 0.95. Other models, such as MLP, NN, and KNN, exhibit progressively lower accuracy, precision, and overall performance. The Proposed hybrid deep learning (CNN and RNN) model outperforms other methods in most metrics, showcasing its effectiveness in piping susceptibility prediction for the Habdat Embankment scenario.

CONCLUSION

In conclusion, this study conducted a comprehensive analysis of piping susceptibility in the context of the Habdat Earth embankment. Through a multi-stage approach including data collection, data preprocessing, feature extraction, feature selection, and prediction, a powerful model has been developed to evaluate the probability of piping occurrence. Utilizing advanced techniques such as self-improved GAO and hybrid deep learning models such as CNN and RNN, the research has made significant progress in predictive accuracy. The results obtained from the evaluation of different prediction models clearly show the superiority of the proposed method. The proposed model consistently outperforms other existing models in terms of accuracy, precision, sensitivity, specificity, F1 Score, MCC, VPN, FPR, and FNR. Combining GAO and hybrid deep learning components not only improves the predictive power of the model but also demonstrates the adaptability of the model to different situations and complex problems. This study makes a significant contribution to the field of piping susceptibility assessment, especially in the geotechnical context. The integration of innovative optimization techniques and hybrid deep learning methods provides a powerful framework for accurate and reliable prediction. The result presented in this study can serve as a basis for further studies and practical applications in risk assessment, infrastructure planning, and disaster prevention in earth embankment systems.

REFERENCES

[1]S. Davidson, P. B.-Q. J. of Engineering, and undefined 2020, “A levee breach induced by internal erosion in Western Australia,” *pubs.geoscienceworld.orgS Davidson, P BakerQuarterly Journal of Engineering Geology and Hydrogeology, 2020*

[2]A. Koulibaly, A. Saeidi, A. Rouleau, M. Q.- Water, and undefined 2020, “Identification of hydraulic parameters influencing the hydraulic erodibility of spillway flow channels,” *mdpi.com*, 2020, doi: 10.3390/w13212950.

[3]A. Mohammed *et al.*, “Experimental and numerical analysis for earth-fill dam seepage,” *mdpi.comAMS Al-Janabi, AH Ghazali, YM Ghazaw, HA Afan, N Al-Ansari, ZM YaseenSustainability, 2020*

[4]R. J. Scheurenberg, “Failure and reconstruction of a small earth dam in residual granites,” *Geotechnics for Developing Africa*, pp. 657–664, Jun. 2020, doi: 10.1201/9781003211174-89/FAILURE-RECONSTRUCTION-SMALL-EARTH-DAM-RESIDUAL-GRANITES-SCHEURENBERG.

[5]B. N. Asthana and D. Khare, “Failure of Embankment Dams,” *Recent Advances in Dam Engineering*, pp. 173–183, 2020, doi: 10.1007/978-3-030-32278-6_8.

[6]M. Sukru Guney, E. Dumlu, M. Okan, Ş. Güney, R. Assistant, and Y. Kalyoncu, “Experimental Study Of The Evolution Of The Breach And The Discharge Through The Breach Resulting From Piping Due To The,” *researchgate.net*, Accessed: Aug. 12, 2020.

[7]G. Hoffmans, L. V. R.-J. of hydraulic Research, and undefined 2018, “Hydraulic approach for predicting piping in dikes,” *Taylor & FrancisG Hoffmans, L Van RijnJournal of hydraulic Research, 2018*.

[8]M. Andreini, P. Gardoni, S. Pagliara, & M. S.-R. E., and undefined 2019, “Probabilistic models for the erosion rate in embankments and reliability analysis of earth dams,” *Elsevier*, Accessed: Aug. 12, 2020.

[9]A. Refaiy, N. AboulAtta, … N. S.-A. S. E., and undefined 2020, “Modeling the effect of downstream drain geometry on seepage through earth dams,” *Elsevier*, Accessed: Aug. 12, 2020.

[10]K. Liu, P. J. Vardon, P. J. Vardon MEng, A. Professor, and M. A. Hicks, “Probabilistic analysis of seepage for internal stability of earth embankments,” *icevirtuallibrary.comK Liu, PJ Vardon, MA HicksEnvironmental Geotechnics, 2018*

[11]“Earthen Embankment Breaching,” *Journal of Hydraulic Engineering*, vol. 137, no. 12, pp. 1549–1564, Dec. 2011, doi: 10.1061/(ASCE)HY.1943-7900.0000498.

[12]W. gang Zhang, J. hao Wu, X. Gu, L. Han, and L. Wang, “Probabilistic stability analysis of embankment slopes considering the spatial variability of soil properties and seismic randomness,” *J Mt Sci*, vol. 19, no. 5, pp. 1464–1474, May 2020, doi: 10.1007/S11629-021-6981-2.

[13]J. Belo, J. L. da Silva, P. de Q.- Sustainability, and undefined 2020, “Reliability Analysis of an Embankment Built and Reinforced in Soft Ground Using LE and FE,” *mdpi.com*, Accessed: Aug. 12, 2020.

[14]A. Mouyeaux, C. Carvajal, P. Bressolette, … L. P.-E., and undefined 2019, "Probabilistic analysis of pore water pressures of an earth dam using a random finite element approach based on field data," *Elsevier*, Accessed: Aug. 12, 2020.
[15]T. Pham, X. Guo, D. D.-T. Geotechnics, and undefined 2020, "Internal stability analysis of column-supported embankments: Deterministic and probabilistic approaches," *Elsevier*, Accessed: Aug. 12, 2020.
[16]X. Xue, X. Yang, X. C.-A. G. Slovenica, and undefined 2014, "Estimating piping potential in earth dams and levees using generalized neural networks," *fg.uni-mb.siX Xue, X Yang, X ChenActa Geotechnica Slovenica, 2014.*
[17]H. Xue, F. Dang, Y. Li, X. Yin, and M. Lei, "Development of Piping Analysis Method for Embankment Including Time-Dependent Change in Permeability Coefficient," *International Journal of Geomechanics*, vol. 21, no. 6, Jun. 2020, doi: 10.1061/(ASCE)GM.1943-5622.0001942.
[18]Y. A. Sharif, M. Elkholy, M. Hanif Chaudhry, and J. Imran, "Experimental Study on the Piping Erosion Process in Earthen Embankments," *Journal of Hydraulic Engineering*, vol. 141, no. 7, Jul. 2015, doi: 10.1061/(ASCE)HY.1943-7900.0001019.
[19]Y. Chen, W. Chen, S. Janizadeh, … G. B.-G., and undefined 2020, "Deep learning and boosting framework for piping erosion susceptibility modeling: spatial evaluation of agricultural areas in the semi-arid region," *Taylor & FrancisY Chen, W Chen, S Janizadeh, GS Bhunia, A Bera, QB Pham, NTT Linh, AL BalogunGeocarto International, 2020.*
[20]H. Tao and J. Tao, "Quantitative analysis of piping erosion micro-mechanisms with coupled CFD and DEM method," *Acta Geotech*, vol. 12, no. 3, pp. 573–592, Jun. 2017, doi: 10.1007/S11440-016-0516-Y.
[21]W. Wu, "Simplified Physically Based Model of Earthen Embankment Breaching," *Journal of Hydraulic Engineering*, vol. 139, no. 8, pp. 837–851, Aug. 2013, doi: 10.1061/(ASCE)HY.1943-7900.0000741.
[22]S. S. Band *et al.*, "Evaluating the efficiency of different regression, decision tree, and bayesian machine learning algorithms in spatial piping erosion susceptibility using ALOS/PALSAR," *mdpi.comSS Band, S Janizadeh, S Saha, K Mukherjee, SK Bozchaloei, A Cerdà, M Shokri, A MosaviLand, 2020.*
[23]J. Ribas, J. Severo, L. Guimaraes, K. P.-E. Reports, and undefined 2020, "A fuzzy FMEA assessment of hydroelectric earth dam failure modes: A case study in Central Brazil," *Elsevier*, Accessed: Aug. 12, 2020.