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FLOOD RISK PREDICTION FOR BRIDGE INFRASTRUCTURES WITH MACHINE LEARNING

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Abstract Flood prediction is required for infrastructure protection and disaster management. Traditional physics based models are limited in representing complex nonlinear relationships among environmental and infrastructure factors. Machine learning, i.e., Long Short Term Memory, Random Forest, and Support Vector Machine models are evaluated for the prediction of exposure, criticality, and overall risk. The results show that Random Forest provides superior performance for exposure and criticality assessment, while Long Short Term Memory achieves the best performance for overall risk prediction. The findings indicate that different machine learning methods are suited to different flood risk components. A comprehensive approach to flood risk assessment is therefore supported. Valuable information is provided for infrastructure planning, risk reduction, and decision making. Further improvement is expected through the inclusion of additional data sources and combined modeling methods.

Keywords: Flood, Machine learning, Risk prediction, Infrastructure vulnerability, Random Forest, Information Systems, Modeling and Simulation, Applied Mathematics, Computational Mathematics, Computer Science Applications, Artificial Intelligence, Data Science, Big Data.

AMS Mathematics Subject Classification: 68T07; 68T05; 62P12.

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1 Introduction

Floods are among the most severe natural hazards and substantial impacts are imposed on communities, economies, and infrastructure. Increased flood frequency and severity are reported in many regions due to climate change, urban expansion, population growth, and land use change [1]. Therefore, reliable flood risk assessment is required for disaster preparedness and infrastructure protection.Traditional flood risk assessment is based on hydrological models, statistical methods, and expert knowledge. Useful information is provided through these approaches. However, complex relationships among environmental, hydrological, meteorological, and socioeconomic factors are often difficult to represent. As a result, limitations are observed in prediction accuracy and adaptability. Consequently, data driven methods receive increased attention in flood research [2].Machine learning and deep learning methods are widely adopted for flood risk analysis. Complex nonlinear relationships are identified, and large datasets are efficiently analysed. Improved prediction accuracy is therefore achieved, which supports flood management and risk reduction efforts [2]. Deep learning methods, particularly Long Short Term Memory models, are frequently applied in flood prediction studies [3]. Hydrological, meteorological, topographic, and land use data are incorporated into these models. Temporal patterns within flood related data are effectively represented, and improved predictive performance is often reported when compared with conventional approaches [4]. Artificial Neural Network based geospatial models are widely applied in flood forecasting. High resolution environmental data are integrated to support reliable flood prediction [4]. Spatial relationships among flood related factors are effectively represented, and improved performance is achieved across different geographical regions. Therefore, intelligent systems are considered suitable for flood warning and monitoring applications. Flood risk assessment requires the identification of vulnerable areas and exposed assets. Deep learning methods are applied for flood susceptibility mapping and vulnerability assessment. Flood risk maps are produced through the integration of hazard, exposure, and vulnerability indicators [5]. These maps support emergency planning, infrastructure design, and land use management. In data limited regions, useful information is extracted from available datasets, which improves decision making [6].Machine learning methods are also used for flood inundation forecasting. Flood extent, depth, and propagation are estimated with improved accuracy and reduced computation time [7]. As a result, early warning systems and preparedness measures are strengthened.Urban flood risk assessment receives substantial research attention due to the concentration of population, infrastructure, and economic assets. Attention based deep learning models are applied for detailed urban flood risk and damage estimation [7,8]. Machine learning methods are also integrated with hydrodynamic models to improve prediction reliability and assessment accuracy [9]. Consequently, improved strategies for urban planning and infrastructure protection are supported.Deep learning methods are also used for flood severity classification. Image and video data are analysed to identify flood conditions and severity levels [10]. Rapid information is provided for emergency response, and dependence on manual assessment is reduced.Several challenges remain, including computational cost, data quality limitations, and restricted data availability. Recent studies show that lightweight deep learning models reduce computational requirements while maintaining strong predictive capability [10,11]. Further improvements are expected through the integration of remote sensing, geographic information systems, sensor networks, and artificial intelligence methods.Among machine learning approaches, Long Short Term Memory, Random Forest, and Support Vector Machine models show strong potential for flood risk prediction. Long Short Term Memory models represent temporal relationships, Random Forest models perform well in nonlinear environments, and Support Vector Machine models support effective classification and prediction [12,13,14]. Comparative evaluation of these methods remains important for flood risk assessment [15].This study evaluates Long Short Term Memory, Random Forest, and Support Vector Machine models for flood risk prediction as presented in an earlier attempt in a conference version [15]. Their predictive performance is compared for flood hazard assessment. The outcomes support flood management, infrastructure resilience, and disaster risk reduction.

2 Materials and Methods

2.1 Dataset and Risk

In this study, the SEMCOG dataset [11] is utilized to develop flood risk assessment models for bridge infrastructure. The dataset consists of 2,634 bridge records, in which each characterized by various environmental, structural, and operational variables relevant to flood risk analysis. Flood hazard risk is modeled using an indicator-based method, where the overall risk is decomposed into two primary components, i.e., exposure and criticality. Exposure represents the degree to which an asset is subjected to flood hazards, while criticality reflects the importance and potential consequences of failure of a specific bridge. The combined effect of these two indicators yields the overall risk score, which serves as the principal metric for evaluating infrastructure vulnerability.

Figure 1 provides an overview of the dataset and key relationships among the variables. Most bridge assets are classified within the medium risk category. Variable importance analysis indicates that impervious surface percentage and flow accumulation are the most influential

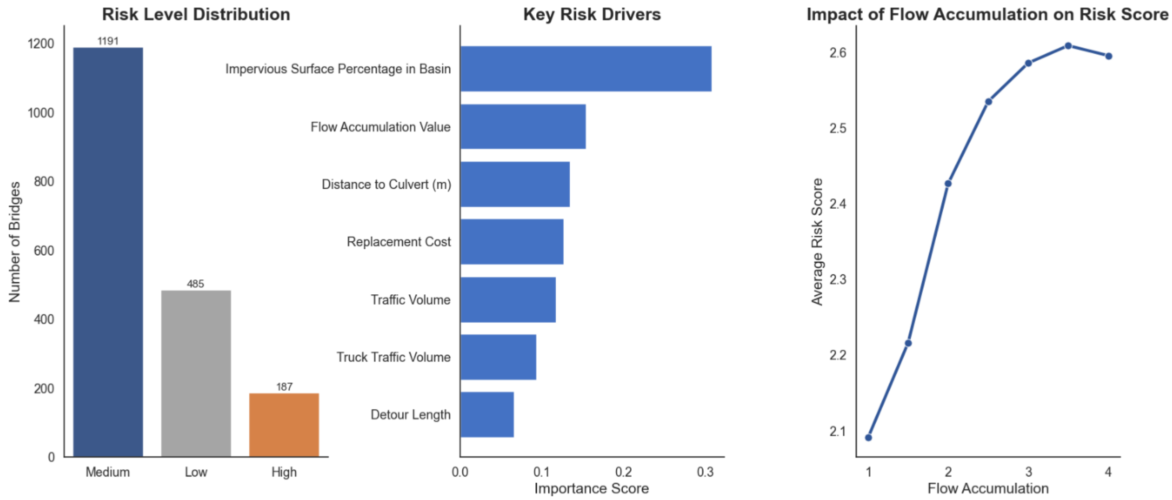

Figure 1: Integrated analytical dashboard presenting the distribution of flood risk levels, the relative importance of predictive features derived from the Random Forest model, and the impact of flow accumulation on the average risk score.

factors in flood risk estimation. The relationship between flow accumulation and risk score shows a nonlinear pattern, with risk values increasing before reaching a stable level. These observations provide insight into the dataset and support the model development process. The dataset includes traffic, infrastructure, hydrological, and environmental variables. These factors are used to estimate exposure and criticality scores. Figure 2 presents the risk assessment methodology. Input variables are used to calculate exposure and criticality scores, which are then combined to determine the overall risk score. This approach incorporates both hazard characteristics and infrastructure vulnerability within the prediction process.

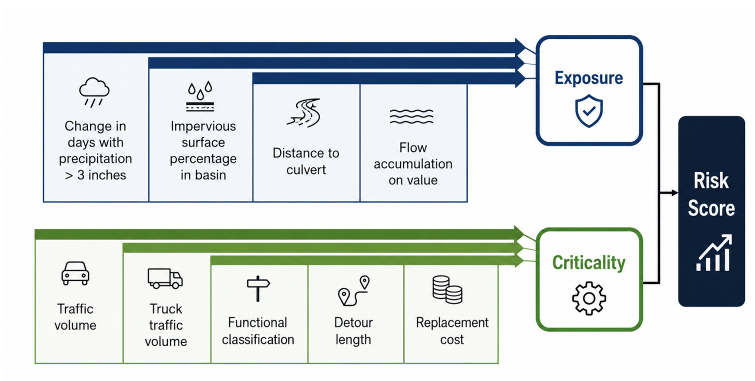

Figure 2: An overview of the input variables used in methodology

2.2 LSTM Model

Long Short Term Memory is a recurrent neural network model designed for sequential data and long range dependency learning. A memory cell, hidden state, and gating units are included in its structure. Information flow is controlled through these gates. The vanishing gradient problem in standard recurrent neural networks is reduced through this design. As a result, improved performance is achieved in time series forecasting and sequence modeling tasks [12]. The memory cell is assigned long term information storage. The hidden state is assigned short term information and output at each time step. Information flow in LSTM is controlled by three gates: input gate i_t, forget gate f_t, and output gate o_t.

The input gate is defined as:

$$i_t = \sigma\left(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}\right) \tag{1}$$

The forget gate is defined as:

$$f_t = \sigma\left(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}\right) \tag{2}$$

The candidate cell state is computed as:

$$\bar{c}_t = \tanh\left(W_{ic}x_t + b_{ic} + W_{hc}h_{t-1} + b_{hc}\right) \tag{3}$$

The cell state is updated as:

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \bar{c}_t \tag{4}$$

The output gate is defined as:

$$o_t = \sigma\left(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}\right) \tag{5}$$

The hidden state is computed as:

$$h_t = o_t \cdot \tanh(c_t) \tag{6}$$

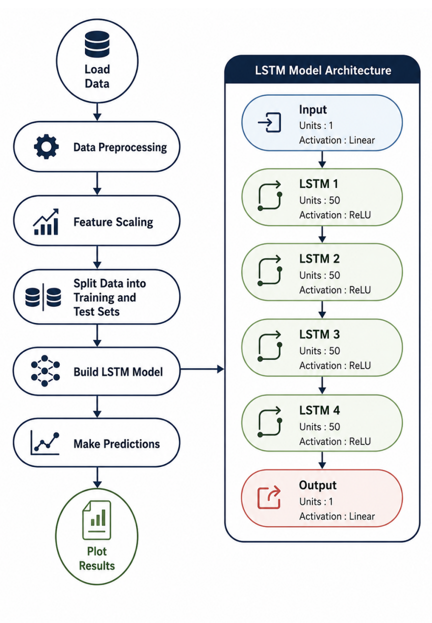

Figure 3: The architecture of the LSTM used in this study

2.3 Random Forest

For a given input feature vector X, prediction in a decision tree is obtained by traversal from the root node R to a leaf node L.

$$\widehat{y}_{DT}(X) = Traverse(R, X) \tag{7}$$

At each internal node, a decision rule is applied based on feature values until a terminal node is reached. The leaf node provides the final output.

$$Traverse(N, X) = \begin{cases} Traverse(LeftChild(N), X) & \text{if } SplitCondition(N, X) \text{ is true} \\ Traverse(RightChild(N), X) & \text{otherwise} \end{cases} \tag{8}$$

Here, $SplitCondition(N, X)$ defines the rule at node N. The functions $LeftChild(N)$ and $RightChild(N)$ define the child nodes.

Training of decision trees is performed by recursive binary splitting. At each node N, an optimal feature F and threshold T are selected to minimize a split criterion.

$$F, T = \arg \min_{\text{feature, threshold}} SplitCriterion(N, F, T) \tag{9}$$

The split criterion is commonly defined through reduction of variance in the target variable within child nodes.

Splitting is continued until a stopping condition is satisfied, such as a maximum depth or a minimum number of samples per node.

For a Random Forest model, prediction for input X is computed as the aggregation of predictions from all decision trees.

$$\widehat{y}_{RF}(X) = \frac{1}{N} \sum_{i=1}^{N} \widehat{y}_{DT_i}(X) \tag{10}$$

Here, N denotes the number of decision trees, and $\widehat{y}_{DT_i}(X)$ denotes the prediction of the i-th tree. This aggregation reduces variance, limits overfitting, and improves predictive performance.

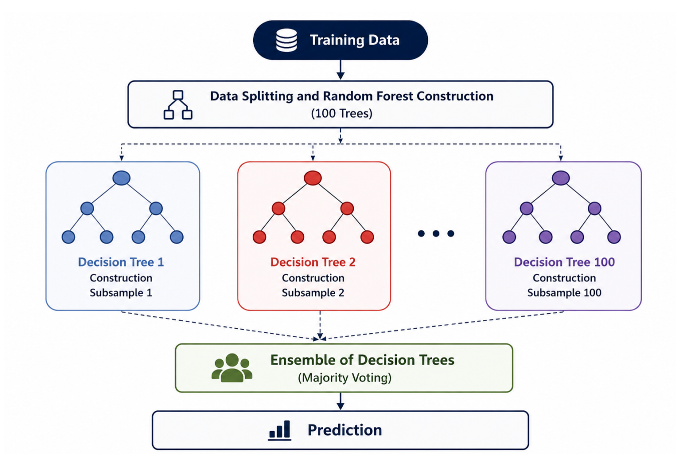

Figure 4: The architecture of the RF used in this study

2.4 SVM

Support Vector Machines (SVM) are used for classification and regression tasks. A linear SVM defines a decision function based on a separating hyperplane.

$$f(x) = \mathbf{w} \cdot \mathbf{x} + b \tag{11}$$

The hyperplane is defined by:

$$\mathbf{w} \cdot \mathbf{x} + b = 0 \tag{12}$$

Classification is determined by the sign of the decision function.

$$\begin{cases} f(x) \geq 0 \Rightarrow \text{class} \ +1 \\ f(x) < 0 \Rightarrow \text{class} \ -1 \end{cases} \tag{13}$$

SVM training is performed by margin maximization with allowance for misclassification in soft margin form. The optimization problem is defined as:

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{N}\xi_i \tag{14}$$

The constraints are given as:

$$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0 \tag{15}$$

For non linearly separable data, the kernel function is applied. The decision function is rewritten using kernel mapping.

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b \tag{16}$$

Here, $K(\mathbf{x}_i, \mathbf{x})$ represents the kernel function, and α_i are Lagrange multipliers.

For regression tasks, SVM is applied to continuous output prediction. The objective function is defined as:

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{N} \updownarrow(y_i - f(\mathbf{x}_i)) \tag{17}$$

The loss function $\updownarrow$ is often defined using an epsilon insensitive form. The solution is obtained through constrained optimization methods such as quadratic programming.

3 Result and Discussion

In this section, the results of the predictive models are presented and discussed. In this study, three machine learning methods, namely RF, LSTM, and SVM, are applied to predict exposure score, criticality score, and overall risk score. The results demonstrate that the developed models effectively capture the patterns within the dataset and provide reliable predictions.

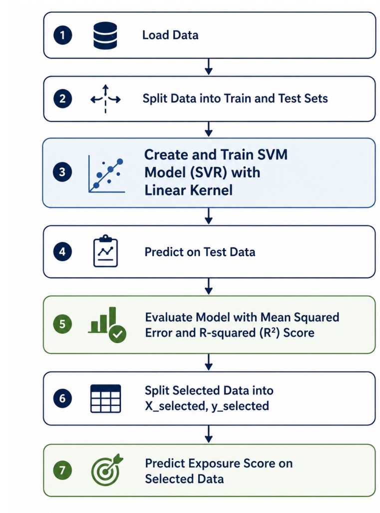

Figure 5: The architecture of the SVM used in this study

3.1 Exposure Score Prediction

The comparative performance of the models for exposure score prediction is illustrated in Figure 6. Instead of individual prediction plots, a consolidated view of model accuracy is provided using Mean Absolute Error (MAE) and Mean Squared Error (MSE), along with the distribution of bridges across exposure levels. As shown in Figure 6, the Random Forest model achieves the best performance, with an MAE of 0.41 and an MSE of 0.25. The LSTM model follows with slightly higher errors (MAE = 0.44, MSE = 0.30), while the SVM model exhibits the highest error values (MAE = 0.47, MSE = 0.33).

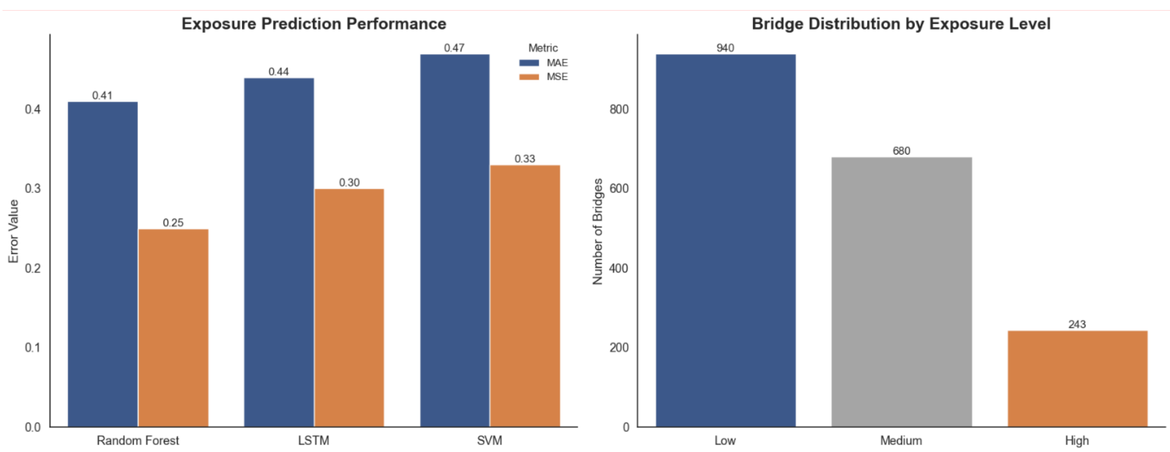

Figure 6: Comparative performance of machine learning models for exposure score prediction, evaluated using MAE and MSE, alongside the distribution of bridges across exposure levels, providing contextual insight into infrastructure vulnerability.

These results highlight the effectiveness of the Random Forest model in capturing nonlinear relationships among input variables, which is particularly beneficial for exposure prediction.

The distribution of bridges based on exposure levels indicates that a significant portion of infrastructure falls within the low-exposure category, while fewer bridges are classified under high exposure. This distribution provides valuable insight into the variability of exposure across the studied system and supports the interpretation of model performance.

Table 1. Exposure score prediction errors

Method	MAE	MSE
Random Forest	0.41	0.25
LSTM	0.44	0.30
SVM	0.47	0.33

3.2 Criticality Score Prediction

The performance of the models for criticality score prediction is presented in Figure 7, where both error metrics and bridge distribution are illustrated. The Random Forest model again demonstrates the highest accuracy, with an MAE of 0.38 and an MSE of 0.11. The LSTM model shows comparable performance (MAE = 0.40, MSE = 0.12), while the SVM model yields slightly higher errors (MAE = 0.41, MSE = 0.13).

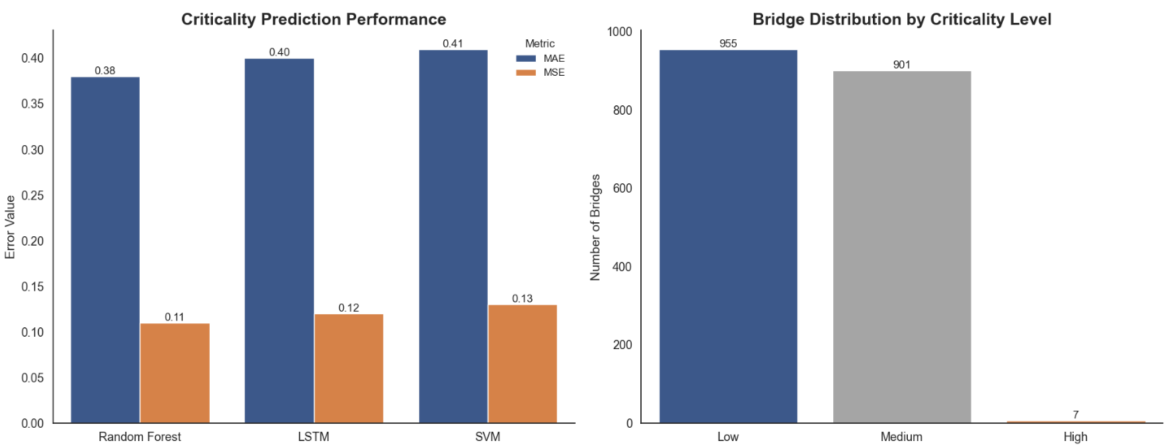

Figure 7: Comparative performance of machine learning models for criticality score prediction, evaluated using MAE and MSE, along with the distribution of bridges across criticality levels.

These findings indicate that Random Forest remains a robust method for modeling infrastructure-related characteristics, particularly when dealing with complex interactions among features. The distribution of bridges across criticality levels shows that most assets fall within low and medium categories, while only a small proportion is classified as highly critical. This suggests that while the majority of bridges demonstrate moderate resilience, a subset of infrastructure requires focused attention for risk mitigation. The results are summarized in Table 2. as follows.

Table 2. Criticality score prediction errors

Method	MAE	MSE
Random Forest	0.38	0.11
LSTM	0.40	0.12
SVM	0.41	0.13

3.3 Risk Score Prediction

The overall performance of the predictive models for risk score estimation is illustrated in Figure 6, which provides a combined view of model accuracy and bridge distribution across risk levels. Unlike the previous cases, the LSTM model achieves the best performance for risk prediction, with an MAE of 0.31 and an MSE of 0.11. The Random Forest model shows slightly higher errors (MAE = 0.33, MSE = 0.12), while the SVM model produces comparable MAE (0.32) but a higher MSE (0.14), indicating lower prediction stability. The improved performance of LSTM in this case can be attributed to its ability to model complex relationships between exposure and criticality components, which together define the overall risk score.

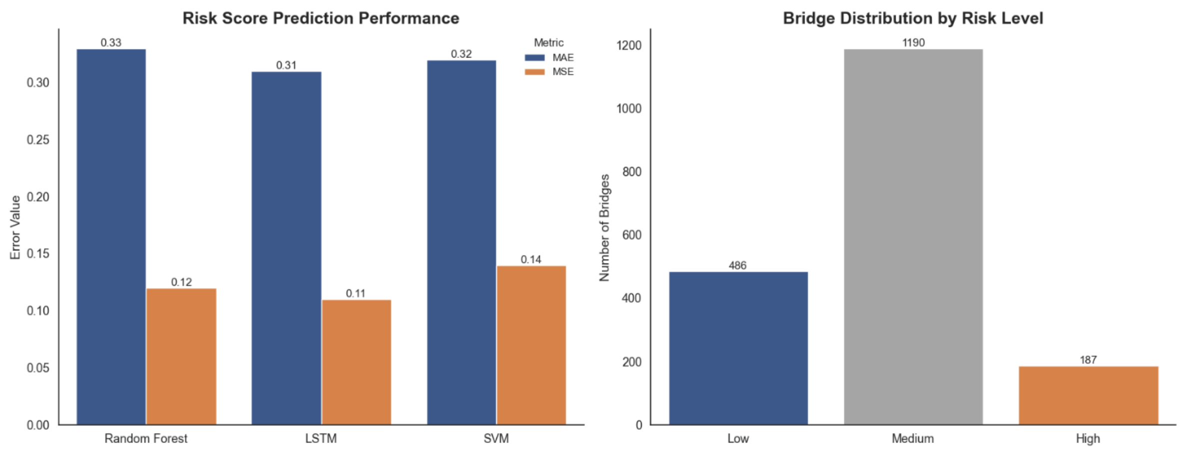

Figure 8: Comparative performance of machine learning models for overall risk score prediction, evaluated using MAE and MSE, together with the distribution of bridges across risk levels.

The bridge distribution shown in Figure 8 indicates that the majority of bridges fall within the medium-risk category, followed by smaller portions in low- and high-risk groups. Although the high-risk category contains fewer bridges, these assets represent critical points of vulnerability and are essential targets for intervention strategies. The quantitative results are summarized in Table 3.

Table 3. Risk score prediction errors

Method	**MAE**	**MSE**
Random Forest	0.33	0.12
LSTM	0.31	0.11
SVM	0.32	0.14

The comparative analysis of the developed machine learning models across exposure, criticality, and overall risk prediction reveals clear patterns in model performance and their applicability to different components of flood risk assessment. The Random Forest model consistently demonstrates strong predictive capability for both exposure and criticality scores, indicating its effectiveness in capturing nonlinear relationships and complex interactions among infrastructure and environmental variables. In contrast, the LSTM model shows superior performance in predicting the overall risk score, which is likely due to its ability to model intricate dependencies between exposure and criticality components that jointly define risk. Although the SVM model provides reasonable predictions, it generally yields higher error values, suggesting that it is less effective in modeling the complexity of the dataset compared to the other approaches. In addition the integration of bridge distribution analysis with prediction accuracy provides essential insights into the structural characteristics. The results indicate that a large proportion of bridges are concentrated in low to medium exposure and criticality categories, while only a smaller subset falls within high-risk classifications. Moreover, the dominance of the medium-risk category in overall risk distribution highlights the presence of widespread moderate vulnerability rather than extreme localized risk. This combined analytical perspective not only validates the effectiveness of the predictive models but also enhances the interpretability of the results by linking statistical performance with real-world infrastructure conditions. Consequently, the proposed approach offers a comprehensive and practical approach for flood risk assessment, which can support decision-makers in prioritizing mitigation strategies and improving infrastructure resilience. For future work applying further advanced methods, e.g., [16] is proposed.

Conclusion

The effectiveness of machine learning methods, including Random Forest, Long Short Term Memory, and Support Vector Machine, is demonstrated for flood risk prediction based on exposure, criticality, and overall risk estimation. Higher performance for exposure and criticality prediction is achieved by Random Forest. This result is linked to its ability to represent nonlinear relationships in environmental and infrastructure variables. Improved performance for overall risk estimation is achieved by Long Short Term Memory. This result is associated with its capability to represent combined effects across multiple risk factors. The integration of model evaluation with infrastructure level assessment provides a structured interpretation of flood risk patterns. Most bridges are classified under moderate risk, while a smaller subset is identified as high risk and is considered for priority action. Location based data integration with machine learning methods is applied to support flood risk assessment. The generated information is used for infrastructure planning, disaster preparedness, and risk reduction. The approach is also used to support resilient infrastructure design. Future work is directed toward the inclusion of additional data sources such as hydrological measurements and remote sensing data. Hybrid models and explainable learning methods are considered to improve accuracy and interpretability. Further development is expected to enhance flood risk prediction across different environmental and geographical conditions. Improved analytics is expected to support flood hazard prediction, interpretation, and mitigation under changing climate and urban conditions.

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