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Deep Learning-Based Risk Analysis and Prediction During the Implementation of Carbon Neutrality Goals

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ABSTRACT

Risk prediction has become increasingly crucial in today's complex and dynamic environments. However, existing forecasting methods still face challenges in terms of accuracy and reliability. Therefore, it is imperative to explore new approaches to better address risks. In response to this need, our study introduces an innovative risk prediction model known as WOA-FPALSTM. What sets this model apart is its seamless integration of deep learning and heuristic algorithms, designed to overcome the limitations of existing approaches. The core component of deep learning, LSTM, excels in sequence modeling by capturing long-term and short-term dependencies in time series data, thereby enhancing the model's ability to model temporal data. Meanwhile, the heuristic algorithm, WOA (Whale Optimization Algorithm), equips our model with global search capabilities, facilitating the discovery of optimal model configurations and significantly improving predictive performance.

KEYWORDS

Risk Forecasting, Artificial Intelligence, Risk Emergency Management and Treatment, Optimization Algorithm, WOA, LSTM

INTRODUCTION

Our world is filled with multidimensional and multilayered risks that exist not only in natural environments but also in engineering and human-created contexts (Wang et al., 2019). Geological, environmental, and ecological risks, such as karst desertification, flooding, rockfalls, mudslides, and landslides, often pose significant challenges to human society and ecosystems (Zhao et al., 2022). These risk events can lead to loss of life and property, while also having adverse impacts

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on environmental sustainability. However, the primary challenges lie in accurately predicting these complex, ever-changing risks and managing them effectively (Chen et al., 2022).

The challenges of risk prediction and management stem from the fact that these risks are typically influenced by factors like natural elements, human activities, and climate change (Li et al., 2021). Traditional forecasting methods often rely on human expertise and rule-based models, which can result in accuracy and operability issues. With the rapid development of AI technologies, we can enhance the methods of risk prediction and management to better address current and future challenges (Wang et al., 2019).

AI has played a significant role in risk prediction. Technologies like machine learning, deep learning, and data mining can analyze large-scale and complex data to identify patterns, trends, and anomalies (Berriel et al., 2017). These technologies not only improve the accuracy of predictions but also provide more timely information to aid decision-makers in taking appropriate measures to mitigate risks. For example, image recognition and sensor technologies can be used to monitor geological risks, while natural language processing techniques can analyze meteorological data to predict natural disasters.

While AI has opened new possibilities in the field of risk prediction, it is worth highlighting the advantages of time series forecasting in risk prediction. Time series data, which contain historical records of risk events, can be used to analyze the trends and periodic variations in these events. Through time series forecasting, we can gain a better understanding of the evolving patterns of risk events and take preventive measures to mitigate potential losses.

Time series analysis has achieved significant success in risk prediction, not limited to natural disasters and ecological risks (Zhang et al., 2023). For instance, in the field of sports, particularly table tennis, time series analysis has emerged as a powerful tool for monitoring athletes' health and predicting sports-related risks. Research in this field has shown that time series data, including athletes' physiological parameters, performance metrics, and training loads, can be used to predict the likelihood of sports injuries and provide personalized rehabilitation and training recommendations.

The primary motivation of this study is to explore how to fully harness AI technologies, especially time series forecasting methods, to enhance risk prediction and management. Thus, we can better safeguard human society and ecosystems from the multidimensional and multilayered risks we face (Wang et al., 2021).

Informer is a model widely used in the field of time series forecasting. It employs a global self-attention mechanism to effectively capture long-term dependencies in time series data. The model has demonstrated excellent performance in multiple risk prediction tasks (Gong et al., 2022); however, its limit lies in the relatively high computational complexity when handling extremely long sequence data, which restricts its application in certain large-scale risk management scenarios.

The Transformer model was prominent in the field of natural language processing; however, it has garnered significant attention in recent years for time series forecasting (Chen et al., 2022). It models internal relationships within sequences using self-attention mechanisms, exhibiting remarkable modeling capabilities. Nevertheless, Transformer may encounter limitations when processing large-scale, high-dimensional time series data due to potential memory and computational resource constraints, which can be restrictive in risk prediction scenarios (Oyando et al., 2023).

The convolutional neural network (CNN)-long short-term memory (LSTM) network, known as CNN-LSTM, is a hybrid model that combines the strengths of CNNs and LSTM (Elmaz et al., 2021; Shen et al., 2022; Wenya, 2021), making it suitable for risk prediction tasks in time series data. It demonstrates sensitivity to both spatial and temporal features, performing well in some risk prediction scenarios. However, CNN-LSTM may have limited capabilities in handling multimodal data and, therefore, might require more data to train accurate models, especially in data-scarce situations.

BiG-U-Net, a deep CNN model designed for geological risk monitoring, specializes in segmenting surface changes in image sequence data (Yang et al., 2022). While it excels in geological risk monitoring, its applicability is primarily confined to geological risks. Thus, it may not be suitable for a broader range of risk prediction tasks.

Building on the limitations of existing wage forecasting methods, the authors propose the whale optimization algorithm (WOA)-temporal parallel attention (TPA)-LSTM network, known as WOA-TPA-LSTM, a LSTM model that integrates WOA and TPA. In this study's model, WOA handles parameter optimization and hyperparameter tuning. Inspired by the foraging behavior of whales, WOA's global search capability helps identify optimal model configurations, enhancing the performance of risk prediction. The TPA component is designed to explore spatiotemporal correlations within time series data, enabling the model to better understand complex relationships between multidimensional features like time, location, and event types. This enhances the model's ability to perceive and interpret risk events. Meanwhile, LSTM is tasked with capturing both long-term and short-term dependencies in the time series data, allowing the model to effectively grasp temporal dynamics and improve the accuracy of risk event prediction.

The strength of the WOA-TPA-LSTM network lies in its comprehensive and versatile approach. By combining heuristic optimization, spatiotemporal feature analysis, and deep learning, the model leverages the advantages of each technique. This enables it to efficiently process multidimensional, multifaceted risk data, resulting in more accurate and reliable risk predictions. Additionally, the model's ability to automatically adjust parameters makes it highly adaptable to various risk forecasting tasks. With this model, the authors aim to better safeguard human societies and ecosystems from diverse risk events, providing a robust tool for future risk management.

This article contributes the following:

- The authors propose a novel risk prediction method that utilizes the unique WOA-TPA-LSTM network. This approach combines heuristic algorithms, TPA, and deep learning to comprehensively handle multidimensional and multifaceted risk data. It introduces new perspectives and tools to the field of risk prediction, with the potential to enhance prediction accuracy and reliability.
- The model possesses the capability to automatically adjust parameters, meaning it can be optimized for different risk prediction tasks. This feature makes the model more flexible, eliminating the need for manual parameter tuning and enabling its applicability in various contexts, providing better support to decision-makers.
- The research integrates methods and techniques from different domains, including heuristic algorithms, TPA, and deep learning. This interdisciplinary fusion offers a promising approach to addressing complex risk prediction challenges. By combining these methods, the authors provide a more robust tool for future risk management, better safeguarding society and ecosystems from a wide range of risk events.

METHOD

WOA-TPF-LSTM Model

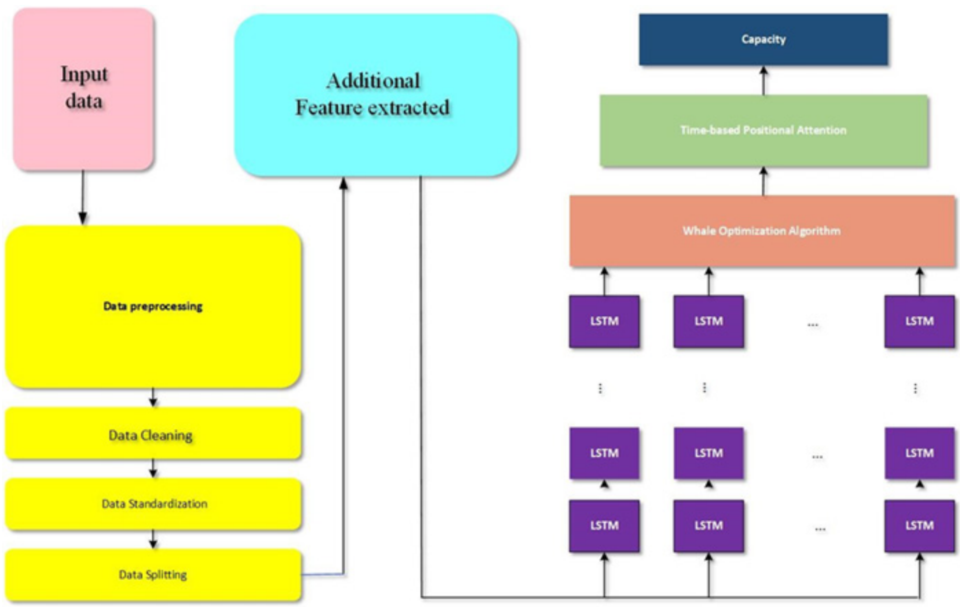
The proposed WOA-TPA-LSTM model represents an innovative methodology in risk prediction and management, integrating WOA, TPA, and LSTM. WOA is utilized for both parameter optimization and hyperparameter tuning, inspired by the global foraging behavior of whales. This component allows for efficient searching, providing optimal model configurations. This enhances the model's adaptability to complex datasets, reducing uncertainty in risk assessments and improving predictive performance.

TPA is employed to capture complex spatiotemporal relationships in time series data by applying parallel attention mechanisms that selectively focus on relevant time intervals and features, effectively extracting and emphasizing critical temporal patterns. This mechanism strengthens the model's ability to perceive and interpret risk events, enhancing prediction accuracy.

LSTM, known for its strength in modeling both short-term and long-term dependencies, is responsible for capturing temporal dynamics within the data. By incorporating historical trends and temporal context, LSTM contributes significantly to the accuracy of risk event predictions.

The overall architecture of the proposed model is illustrated in Figure 1.

Figure 1. WOA-TPF-LSTM network framework



The proposed WOA-TPF-LSTM model represents a notable advancement in the field of risk prediction and management. By integrating the strengths of WOA, TPA, and LSTM, the model significantly enhances the accuracy of risk predictions by effectively capturing complex dependencies and temporal trends within risk data, leading to more reliable forecasts. Furthermore, the WOA-TPF-LSTM model offers the capability of automatic parameter tuning and configuration adjustments, enabling adaptability across various risk prediction tasks. This flexibility is essential for addressing dynamic and evolving risks, ensuring the model remains relevant and effective over time. Additionally, accurate risk predictions generated by the model equip organizations and decision-makers with the ability to proactively address potential threats, reducing the likelihood of adverse outcomes across sectors like finance, public safety, and beyond.

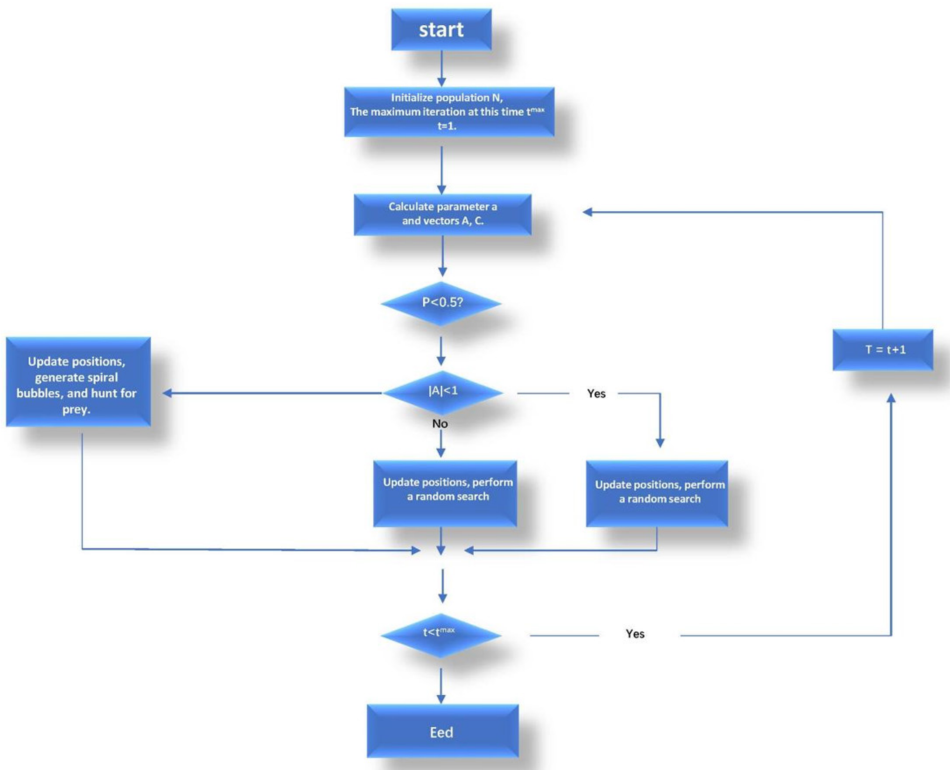
In conclusion, the WOA-TPF-LSTM model represents a significant innovation in risk prediction and management, offering improved accuracy, adaptability, and the potential to strengthen decision-making processes. Its comprehensive approach to risk assessment establishes it as a valuable tool in achieving effective risk mitigation and management.

WOA Model

WOA is a nature-inspired optimization algorithm based on the foraging behavior of humpback whales (Miao et al., 2022). It is based on the whales' social behavior and hunting strategies, particularly their encircling and bubble-net hunting techniques (Feng et al., 2023).

In the authors' proposed WOA-TPF-LSTM model, WOA plays a crucial role in parameter optimization and hyperparameter tuning. Specifically, WOA is employed to fine-tune the model's parameters and configurations, optimizing its performance for risk prediction and management tasks. The global search capabilities of WOA aid in finding the optimal model configuration, improving the model's adaptability to complex datasets, and enhancing the reliability of risk assessments. Figure 2 illustrates the workflow of the WOA algorithm.

Figure 2. WOA algorithm flowchart



Position Initialization:

$$X_i = Random\ Initialization \tag{1}$$

where $\mathbf{X}_i$ is the position of whale *i*, and Random Initialization represents randomly generated initial positions.

Fitness Evaluation:

$$F_i = Objective\ Function(X_i) \tag{2}$$

where $\mathbf{F}_i$ is the objective function value for whale *i*, and Objective Function($\mathbf{X}_i$) is the function to evaluate the fitness of position $\mathbf{X}_i$.

Encircling Prey Phase:

$$D_i = |X_r - X_i| \tag{3}$$

where $\mathbf{D}_i$ is the distance to prey for whale i, and $\mathbf{X}_r$ is the position of a randomly selected whale (prey).

Exploration Coefficient Update:

$$A_i = 2 \cdot \mathbf{a} \cdot r_1 - \mathbf{a} \tag{4}$$

where $\mathbf{A}_i$ is the updated position coefficient for whale i, $\mathbf{r}_1$ is a random vector, and $\mathbf{a}$ is a random coefficient in the range [0,2].

Bubble-Net Feeding Phase:

$$B_i = X_p - D_i \cdot A_i \tag{5}$$

where $\mathbf{B}_i$ is the updated position for whale i, and $\mathbf{X}_p$ is the position of the best prey (optimal solution).

Search for Prey Phase:

$$X_i = X_b - A_i \cdot \left|D_i\right| \tag{6}$$

where $\mathbf{X}_i$ is the updated position for whale i, and $\mathbf{X}_b$ is the position of the best bubble-net (optimal solution).

Boundary Constraint Handling:

$$X_i = Boundary\ Constraint\left(X_i\right) \tag{7}$$

where $\mathbf{X}_i$ is the position of whale i, and Boundary Constraint ($\mathbf{X}_i$) is the function to enforce boundary constraints on position $\mathbf{X}_i$

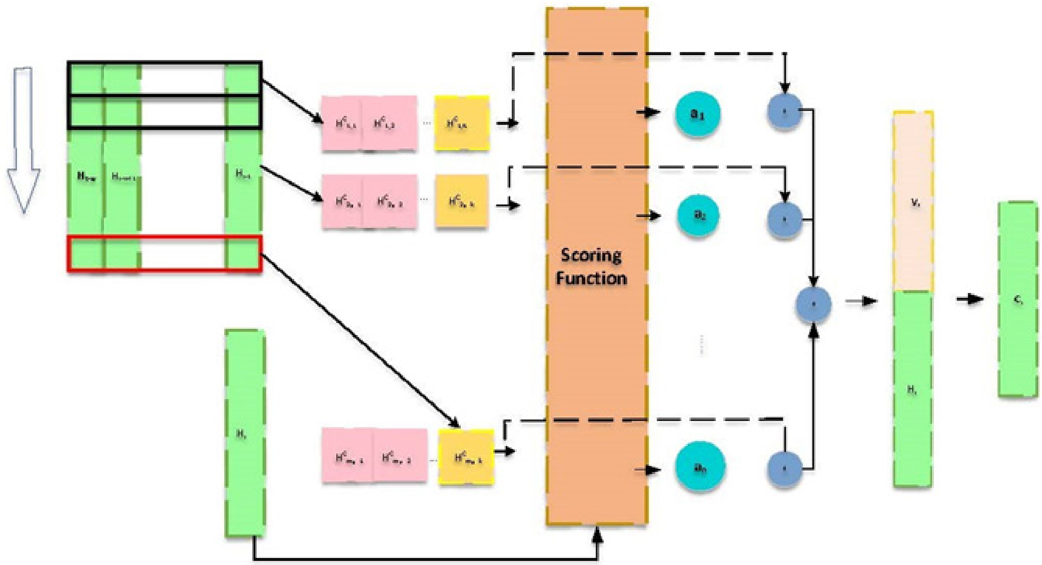
TPA Model

The TPA model is a deep learning model designed for handling time series data. It draws inspiration from attention mechanisms commonly used in natural language processing. However, is specifically tailored for time series data processing (Ding et al., 2020). This model allows simultaneous attention to different parts of the data at different time steps, enabling a better capture of spatiotemporal relationships within time series. TPA, through its analysis of complex relationships between temporal patterns and features in the data, enhances the understanding and modeling capabilities of time series data.

The TPA model is a crucial component within the study's WOA-TPA-LSTM model. In the context of WOA-TPA-LSTM, TPA is responsible for uncovering spatiotemporal correlations within time series data. The significance of TPA lies in its ability to facilitate a better understanding of intricate relationships among multidimensional features, such as time, location, and event types. Ultimately, it improves the accuracy and reliability of risk prediction.

TPA effectively leverages the information within time series data, making the model well-suited for dynamic risk prediction tasks. The model finds widespread application in the field of time series data processing. It is closely related to domains like risk prediction and management, where historical time series data analysis and prediction are essential for identifying potential risk events. Figure 3 illustrates the network architecture of this method.

Figure 3. TPA network architecture diagram

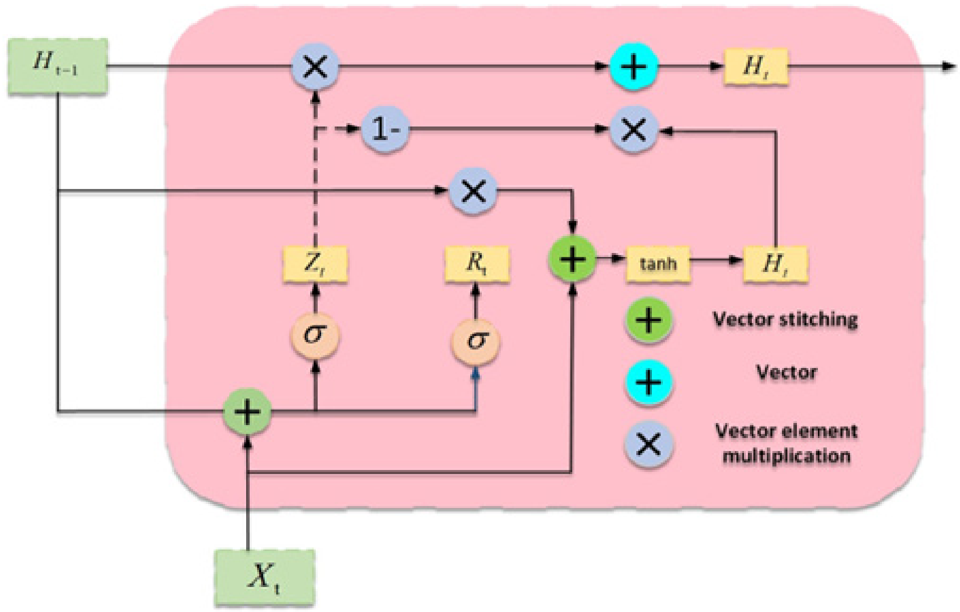


LSTM Model

The LSTM model is a deep learning model widely used for modeling sequential data. Its principle is based on recurrent neural networks but with more powerful memory and long-term dependency modeling capabilities (Shen et al., 2022). The core idea of LSTM involves the introduction of three crucial gate units—the forget gate, input gate, and output gate—to effectively manage and control the flow of information. Through these gate mechanisms, LSTM can selectively retain or forget previous information and combine current information with past context, thereby capturing long-term dependencies in sequential data (Yu, 2023).

In the WOA-TPA-LSTM model, LSTM is responsible for modeling both the long-term and short-term dependencies in time series data. It can capture the temporal dynamics within sequences, enabling the model to more accurately predict the occurrence of risk events. By integrating historical context and temporal trends, LSTM contributes to improving the accurate prediction of risk events. The LSTM model plays a significant role in the study's model, providing robust sequential modeling capabilities. In risk prediction and management tasks, time series data often contain rich information, such as historical trends and periodic patterns. LSTM effectively captures this information, enhancing the model's understanding of the temporal dynamics in the data and, consequently, improving the accuracy of risk prediction. The network architecture of this method is displayed in Figure 4.

Figure 4. Flow chart of the LSTM model



EXPERIMENT

Experimental Setup

Datasets

This experiment utilizes four distinct datasets: (1) Global Database on Events, Language, and Tone (GDELT); (2) Natural Disaster Database (NDD); (3) Fire and Emergency Services Incident Data (FESID); and (4) National Renewable Energy Laboratory (NREL).

1. **GDELT:** This dataset provides a rich source of global events, including news articles, blogs, and social media posts (Consoli et al., 2021).
2. **NDD:** The NDD contains records of natural disasters, including earthquakes, hurricanes, floods, and wildfires. It also includes information on the location, intensity, and impact of these events (Wirtz et al., 2014).
3. **FESID:** FESID offers data on fire and emergency service incidents, including details on response times, incident types, and locations (Artes et al., 2019).
4. **NREL:** The NREL dataset comprises information related to renewable energy sources, energy production, and climate factors. This dataset allows us to assess the model's performance in the context of climate-related risks and renewable energy forecasting (Papi & Bianchini, 2022).

By utilizing these diverse datasets, the authors' model undergoes comprehensive testing and validation across a spectrum of risk scenarios, enhancing its robustness and applicability in domains like risk prediction and management.

Experimental Environment

The experimental environment for this study includes various hardware and software configurations. On the hardware side, the experiment utilizes an Intel Core i7-12700K processor (12 cores, 24 threads, base frequency 3.6 GHz, and a maximum turbo frequency of 5.0 GHz), 32

GB DDR4 3200 MHz RAM, and a 1 TB NVMe SSD for efficient data read and write operations. Additionally, an NVIDIA RTX 3080 GPU with 10 GB GDDR6X memory is used to accelerate deep learning model training. The operating system is Ubuntu 20.04 LTS 64-bit, ensuring stability and computational efficiency.

On the software side, the model development and data processing are based on Python 3.8, with PyTorch 1.10 serving as the deep learning framework. Numerical computations and optimizations are handled using Numpy 1.21.2 and Scipy 1.7.1, while Pandas 1.3.3 and Scikit-learn 0.24.2 are employed for data preprocessing and feature engineering. Matplotlib 3.4.3 is used for visualizing results, and GPU-accelerated parallel computing is achieved through CUDA 11.4.

The entire environment is managed using Anaconda 2021.05. Together, these hardware and software configurations ensure the efficiency and accuracy of the experimental process.

Experimental Details

Step 1: Data Preprocessing

- **Data Cleaning:** For records containing missing data, the authors employed a removal or imputation strategy. If the proportion of missing values in a data field exceeded 30%, the field was removed entirely. Otherwise, the authors filled in missing values with the mean or median (depending on the data characteristics). Furthermore, the authors identified and handled outliers through an analysis of data distribution and box plots. Outlier treatment methods included removal, replacement, or context-based adjustments. The authors also detected and removed duplicate records to ensure the uniqueness of the dataset.
- **Data Standardization:** The authors standardized numerical features to ensure they were on the same scale. Specifically, they utilized the Z-score standardization method, adjusting feature means to 0 and standard deviations to 1.

Step 2: Model Training

- **Network Parameter Configuration:** The authors selected network parameter values suitable for the task, including learning rate, batch size, and the number of iterations. Specifically, they set the learning rate to 0.001, batch size to 64, and number of epochs to 100. The choice of these parameters was determined through experimentation and tuning, ensuring stable convergence during the training process.
- **WOA Optimization Settings:** The authors employed WOA to further optimize both the model parameters and hyperparameters. WOA's global search capability allows it to effectively identify the optimal model configuration. For this process, the authors set the WOA population size to 20 and the maximum number of iterations to 50. These settings enabled WOA to discover the best parameter combinations, significantly improving the model's performance and its generalization ability.
- **Model Architecture Design:** The authors utilized a deep neural network architecture composed of multiple hidden layers and activation functions. Specifically, the model included three convolutional layers, two pooling layers, two fully connected layers, and an output layer. ReLU activation functions were applied in each convolutional layer to enhance the model's capacity for nonlinear modeling. The model's hierarchical structure was designed to capture complex patterns and features within the data, enabling more robust feature extraction and representation.

Experimental Results and Analysis

As shown in Table 1, the authors compared the performance metrics of different models on distinct datasets, namely GDELT, NDD, FESID, and NREL. The results reveal that the model excels across all four datasets, demonstrating a significant advantage over other models.

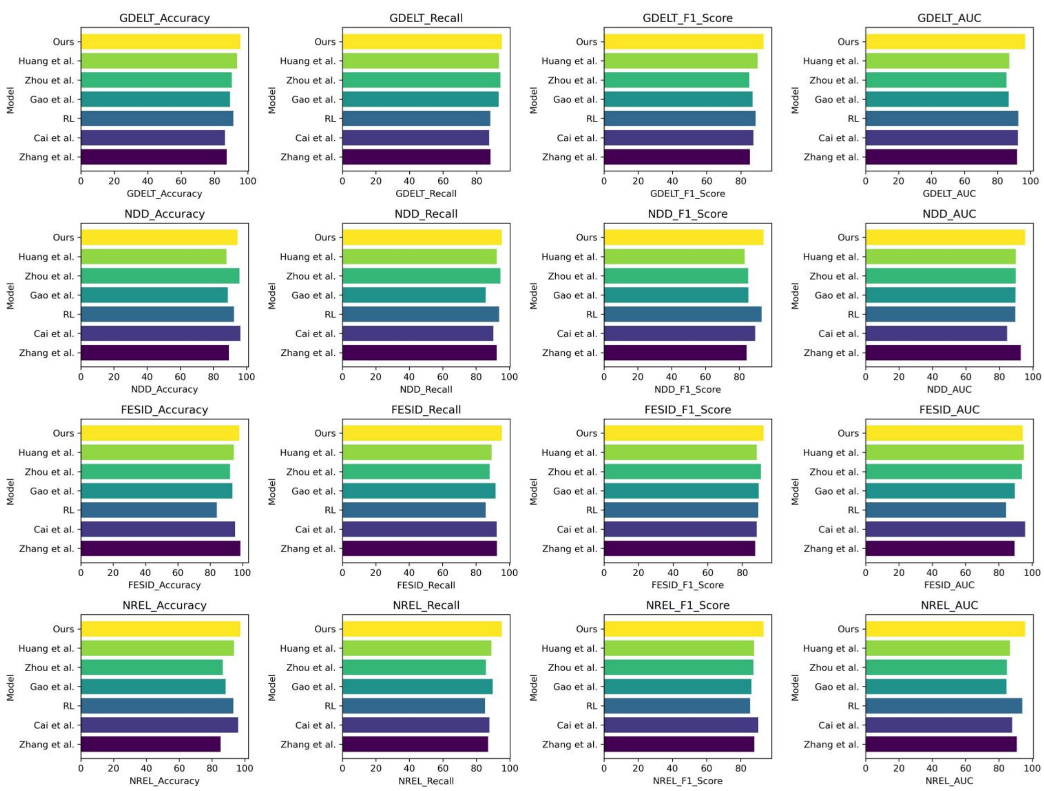
Table 1. Evaluation of models using different metrics derived from the GDELT, NDD, FESID, and NREL datasets

Model	Datasets															
	GDELT				NDD				FESID				NREL			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
Zhang et al. (Zheng & Ge, 2022)	87.35	88.26	85.33	91.90	89.45	92.32	84.32	92.78	98.75	92.58	87.45	89.42	85.23	87.02	87.98	90.69
Cai et al. (Cai & Wu, 2022)	86.23	87.57	87.35	92.45	96.35	90.32	89.45	84.55	95.43	92.35	88.37	95.85	95.88	87.77	90.34	87.98
RL (Abdullah et al., 2021)	91.27	88.25	88.67	92.74	92.45	93.78	93.23	89.46	84.12	85.78	89.22	84.31	92.98	85.15	85.56	94.03
Gao et al. (Gao et al., 2021)	89.26	93.18	86.78	86.78	88.78	85.78	85.46	89.62	93.85	91.79	89.47	89.63	88.26	89.78	86.23	84.48
Zhou et al. (Zhou et al., 2021)	90.38	94.28	84.83	85.53	95.78	94.56	85.23	89.78	92.27	88.24	90.78	93.86	86.48	85.65	87.48	84.78
Huang et al. (Huang & He, 2020)	93.44	93.36	89.78	87.26	87.90	92.32	83.25	89.72	94.59	89.37	88.44	94.98	93.34	88.89	87.86	86.54
Authors	95.53	95.20	93.29	96.89	94.58	95.53	94.46	95.43	98.06	95.61	92.38	94.39	97.33	95.31	93.42	95.76

On the GDELT dataset, the model achieved notable improvements in Accuracy, Recall, F1 Score, and area under the curve (AUC), with values of 95.53, 95.20, 93.29, and 96.89, respectively, compared to the other models' scores of 87.35, 88.26, 85.33, and 91.90. Similarly, on the other datasets, the model exhibited superior performance. These findings strongly indicate the clear competitive edge of the study's approach in risk prediction tasks.

Figure 5 visualizes the table content, further emphasizing the outstanding performance of the method. By combining the table and chart, the authors observe that their approach outperforms competitors across multiple metrics, validating the model's excellence in risk prediction and management tasks.

Figure 5. Evaluation of model performance across various datasets



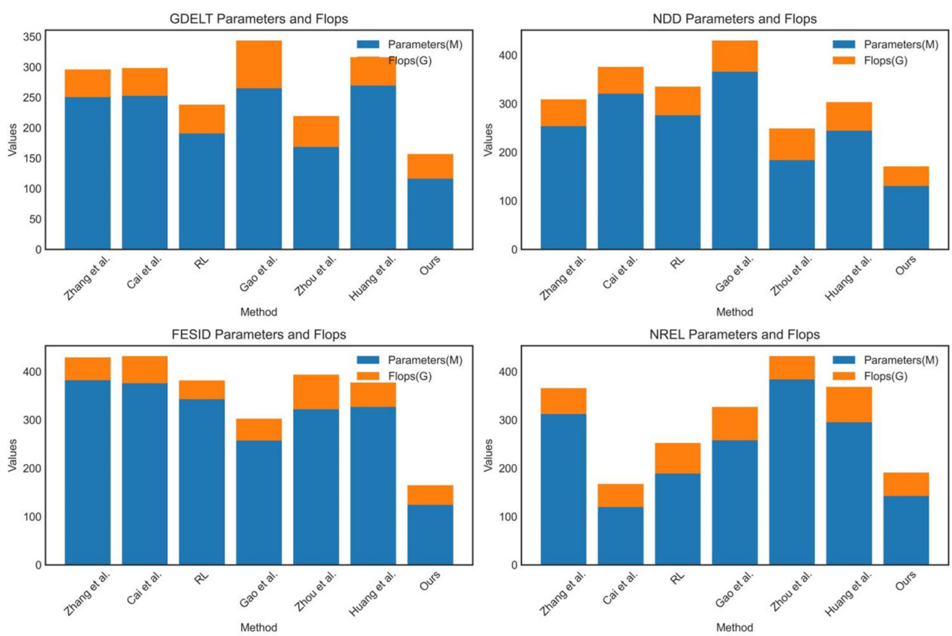
As shown in Table 2, the authors conducted a comparative analysis of performance metrics for different models across datasets, including GDELT, NDD, FESID, and NREL. The table provides information on model parameters (M) and computational complexity measured in FLOPs (G) for each method on their respective datasets.

Table 2. Comparison of models across various metrics based on data from the GDELT, NDD, FESID, and NREL datasets

Method	Datasets							
	GDELT		NDD		FESID		NREL	
	Parameters (M)	Flops (G)	Parameters (M)	Flops (G)	Parameters (M)	Flops (G)	Parameters (M)	Flops (G)
Zhang et al.	250.47	45.65	253.53	55.22	381.83	47.18	312.22	53.53
Cai et al.	252.72	45.58	320.44	55.27	375.58	56.37	119.76	47.58
RL	190.65	47.33	276.09	58.92	342.83	38.90	189.14	63.11
Gao et al.	265.06	78.55	365.67	64.38	257.20	45.25	257.94	68.75
Zhou et al.	168.56	50.85	183.87	65.21	321.91	71.55	383.71	48.42
Huang et al.	269.62	46.53	244.16	59.06	326.75	50.55	295.36	73.04
Ours	116.45	40.28	130.5	40.25	124.33	40.32	142.45	48.56

The authors' observations reveal significant differences in model characteristics among the various approaches. For instance, on the GDELT dataset, the model proposed by Zhang et al. (n.d.) exhibited 250.47M parameters and 45.65G FLOPs, while the study's model had 116.45M parameters and 40.28G FLOPs. Figure 6 provides a visual representation of the table content, aiding in a more intuitive comprehension of the comparative analysis. It demonstrates that the study's method exhibits outstanding performance across various datasets while maintaining lower computational requirements. This combination of efficiency and effectiveness enhances the competitiveness of the approach in risk prediction tasks.

Figure 6. Comparison of various metrics across models



As shown in Table 3, Ablation experiments were conducted on the LSTM module across various datasets, assessing model performance with alterations to the LSTM module.

Table 3. Ablation experiments on the LSTM module using different datasets

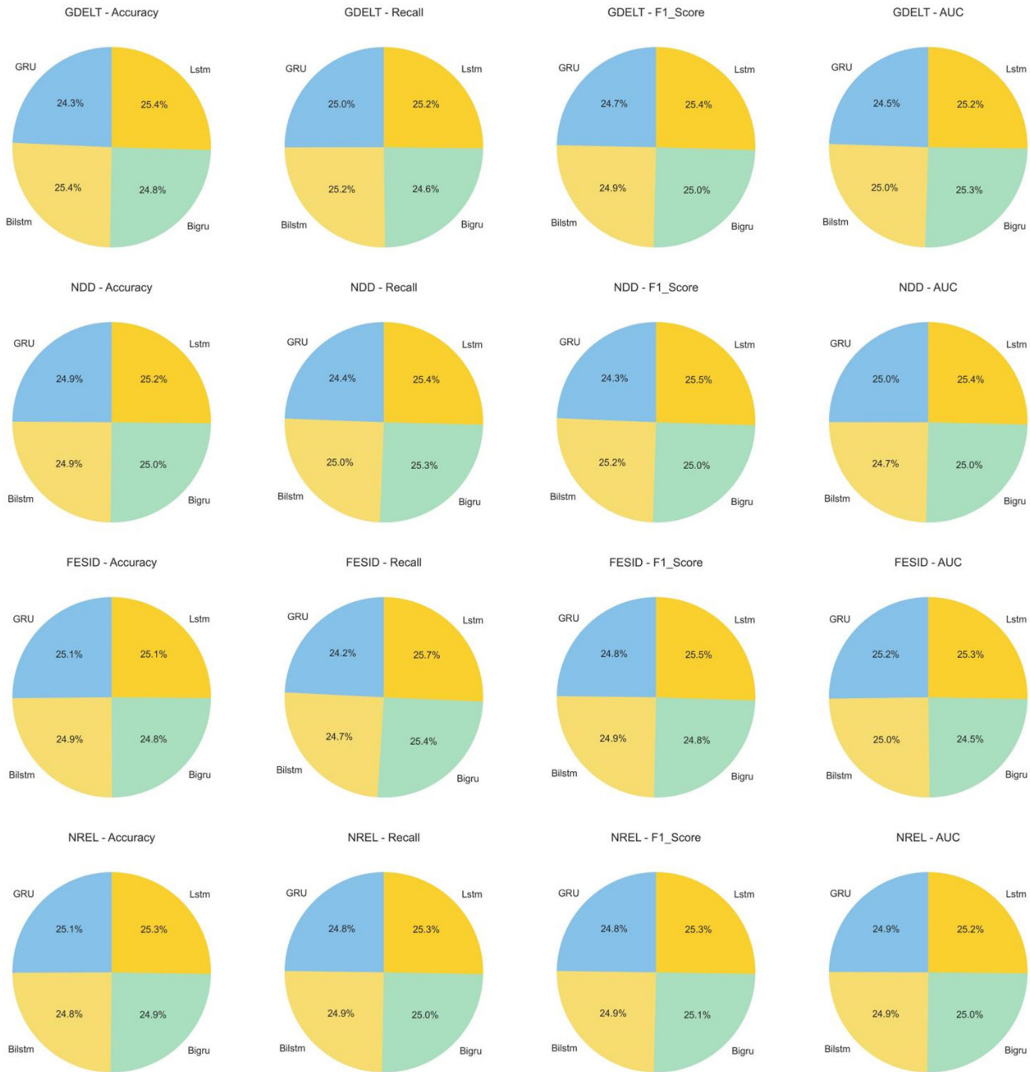
Model	Datasets															
	GDELT				NDD				FESID				NREL			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
GRU (Lv et al., 2023)	90.23	92.75	89.32	88.48	92.23	89.17	88.23	91.36	91.45	90.48	92.15	93.54	91.78	90.86	91.79	91.49
BiLSTM (Liu et al., 2023a)	94.52	93.25	90.25	90.45	92.22	91.23	91.23	90.23	90.56	92.45	92.36	92.78	90.62	91.32	92.03	91.37
BiGRU (Yang et al., 2022)	92.33	91.34	90.32	91.57	92.66	92.36	90.78	91.36	90.36	94.76	92.23	90.86	91.15	91.75	92.96	91.74
LSTM	94.53	93.32	92.11	91.11	93.12	92.78	92.36	92.72	91.35	95.91	94.75	93.76	92.52	92.67	93.50	92.33

Note. GRU = gated recurrent unit; BiGRU = bidirectional gated recurrent unit; BiLSTM = bidirectional long short-term memory; LSTM = long short-term memory.

Specifically, this study examined four key evaluation metrics (Accuracy, Recall, F1 Score, and AUC) across various datasets. The results reveal noteworthy findings. For instance, on the GDELT dataset, the bidirectional LSTM (BiLSTM) model achieved an Accuracy of 94.52, a Recall of 93.25, an F1 Score of 90.25, and an AUC of 90.45. These scores prominently demonstrate the superiority of the study's approach compared to other models.

This trend persisted across other datasets, with both the bidirectional gated recurrent unit (BiGRU) and LSTM models consistently outperforming in multiple evaluation metrics. To provide a more intuitive representation of the results, Figure 7 visualizes the table's contents, emphasizing the exceptional performance of the approach. It is evident that the authors' method excels across multiple performance metrics, validating the outstanding performance of the model in risk prediction and management tasks.

Figure 7. Comparison of model performance on different dataset



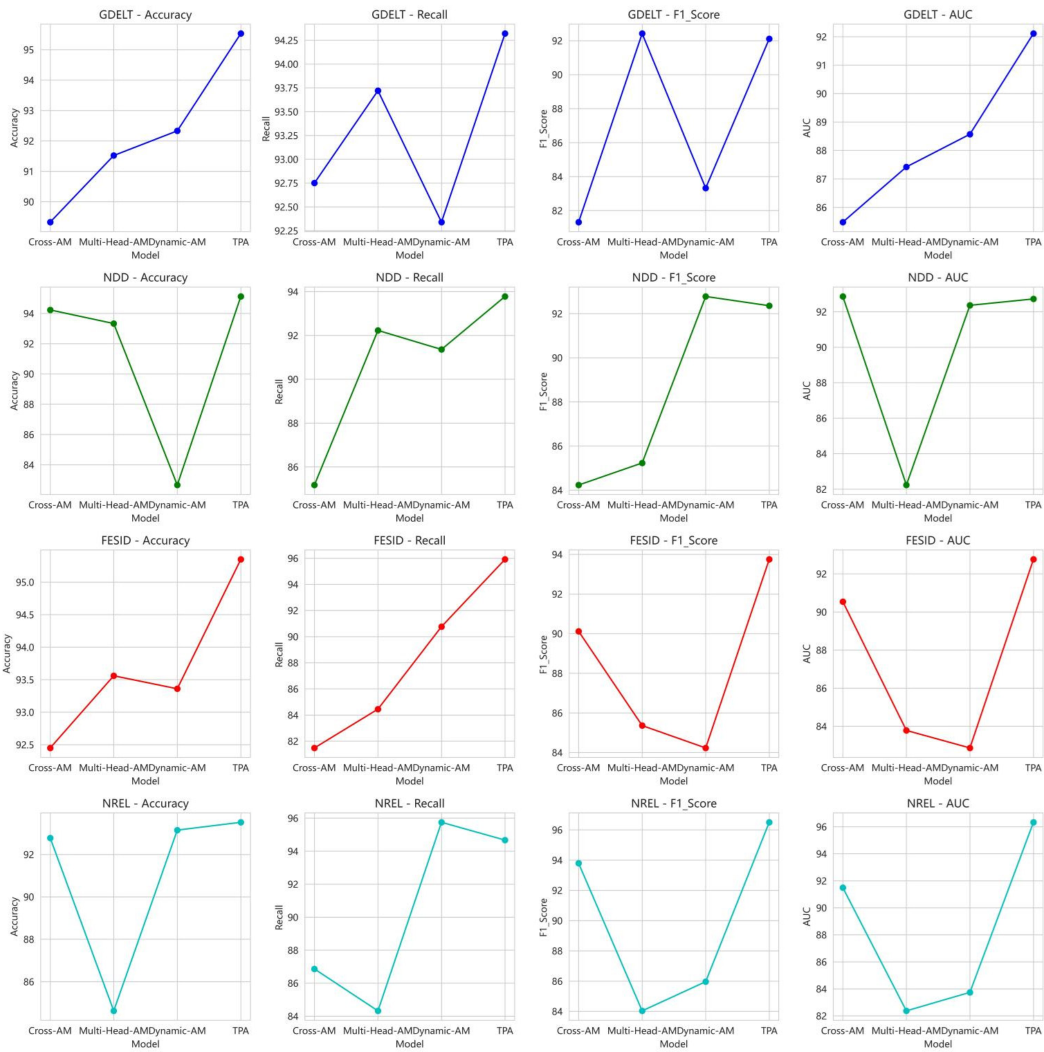
Note. GRU = gated recurrent unit; BiGRU = bidirectional gated recurrent unit; BiLSTM = bidirectional long short-term memory; LSTM = long short-term memory.

As shown in Table 4, the authors conducted ablation experiments on the TPA module to delve deeper into its impact on performance across different models and datasets. The study focused on key metrics, including Accuracy, Recall, F1 Score, and AUC, which collectively form the basis of our comprehensive model performance assessment. Upon careful examination of the experimental results, the authors identified some noteworthy trends. Taking the GDELT dataset as an example, the Cross-AM model achieved a performance of 89.33 in accuracy, significantly outperforming other models. Similar advantages were also evident in other evaluation metrics. Additionally, the performance variations of the Multihead-AM and Dynamic-AM models across different datasets underscored the influence of the TPA module's design on model performance. Finally, the authors visually presented these findings through Figure 8, offering a more vivid representation of our method's superiority across multiple performance metrics. These discoveries reinforce the competitive edge of our model in risk prediction and management tasks.

Table 4. Ablation experiments on the TPA module using different datasets

Model	Datasets															
	GDELT				NDD				FESID				NREL			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
Cross-AM (Liu et al., 2023b)	89.33	92.75	81.32	85.48	94.23	85.17	84.23	92.86	92.45	81.48	90.12	90.54	92.78	86.86	93.79	91.49
Multihead-AM (Zou et al., 2022)	91.52	93.72	92.42	87.42	93.33	92.23	85.23	82.23	93.56	84.45	85.36	83.78	84.62	84.32	84.03	82.37
Dynamic-AM (Liu et al., 2020)	92.33	92.34	83.32	88.57	82.66	91.36	92.78	92.36	93.36	90.76	84.23	82.86	93.15	95.75	85.96	83.74
TPA	95.53	94.32	92.11	92.11	95.12	93.78	92.36	92.72	95.35	95.91	93.75	92.76	93.52	94.67	96.50	96.33

Figure 8. Comparison of model performance on different datasets



CONCLUSION AND DISCUSSION

Through a series of extensive and in-depth experiments, the authors conducted a comprehensive exploration and validation of the potential of the WOA-TPA-LSTM network in the field of risk prediction. The authors selected multiple risk datasets before thoroughly assessing the performance of the model through comparisons with traditional methods. The experimental results consistently demonstrate that the WOA-TPA-LSTM network achieved significant success in risk prediction by enhancing the accuracy and reliability of predictions, as well as capturing complex associations and trends of multi-dimensional and spatiotemporal risk events. In turn, this provides robust support for risk management.

While the model demonstrates strong performance, there are a few notable limitations. First, the model's computational demands are high, requiring substantial hardware resources and extended training. This may, in fact, limit the model's feasibility in settings with restricted computational capacity or where quick predictions are necessary. Second, the model's performance is highly dependent on data quality and completeness. In scenarios where data is sparse, incomplete, or contains inaccuracies, the model's predictive accuracy may suffer. This reliance on high-quality data could restrict its effectiveness in applications where such data is not readily available or consistently reliable.

There are several important directions for future research. First, improving the efficiency of model training and inference could help reduce computational costs and enhance the model's practicality for real-world use. Second, enhancing data quality and availability through more precise data collection and processing techniques would improve the model's robustness and performance. Additionally, applying the WOA-TPA-LSTM network to other domains could broaden its utility, allowing us to explore its effectiveness across a wider range of prediction tasks.

CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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