IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 11 July 2023, accepted 29 July 2023, date of publication 7 August 2023, date of current version 15 August 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3302399

RESEARCH ARTICLE

Knowledge Graph-Based Method for Intelligent Generation of Emergency Plans for Water Conservancy Projects

LIHU WANG[1], XUEMEI LIU[1,2,3], YANG LIU[3], HAIRUI LI[1], JIAQI LIU[3], (Graduate Student Member, IEEE), AND LIBO YANG[2]

[1]School of Management and Economics, North China University of Water Resources and Electric Power, Zhengzhou, Henan 450046, China
[2]School of Information Engineering, North China University of Water Resources and Electric Power, Zhengzhou, Henan 450046, China
[3]Collaborative Innovation Centre for Efficient Utilization of Water Resources, North China University of Water Resources and Electric Power, Zhengzhou, Henan 450046, China

Corresponding author: Xuemei Liu (liuxuemei@ncwu.edu.cn)

This work was supported in part by grants from the National Natural Science Foundation of China (72271091), Projects of Open Cooperation of Henan Academy of Sciences (220901008), and Major Science and Technology Projects of the Ministry of Water Resources (SKS-2022029).

ABSTRACT In response to the issues of poor content correlation and insufficient intelligent decision support in emergency plans for water conservancy projects, a method for intelligent generation of emergency plans based on knowledge graphs is proposed. Utilizing pre-trained language models (PTM) based on entity masking, the accuracy of entity recognition tasks is enhanced by uncovering contextual features surrounding the masked entities. By employing translations, rotations, and superpositions within the vector space, a multiview convolutional neural network (MCNN) is constructed to enhance the accuracy of relation extraction through complementary and integrated feature representation. Integrating PTM with MCNN enables the construction of an emergency entity relationship extraction method based on PTM-MCNN. Neo4j is utilized for storing entity relationship triplets to construct an emergency knowledge graph. Through the utilization of the mutual information criterion, knowledge retrieval and matching are performed to accomplish the intelligent generation of emergency plans. The results indicate that PTM-MCNN achieves high recognition accuracy (F1 score of 92.2%), ensuring the reliability of the generated emergency plans. Related studies can effectively improve the intelligence of emergency management of water conservancy projects.

INDEX TERMS Emergency plan, knowledge graph, water conservancy projects, convolutional neural network, large-scale pre-trained model.

I. INTRODUCTION

Emergency plans constitute the essential foundation for engineering rescue operations and precise decision-making. Transforming the textual content of emergency plans into a knowledge graph and achieving intelligent generation of such plans are pivotal in advancing the level of intelligent emergency management [1]. Currently, emergency plans for water conservancy projects are predominantly stored in the form of physical documents or electronic files, thereby facing issues such as poor content coherence and inadequate intelligent decision support [2], [3]. Therefore, the exploration of methods for constructing an emergency knowledge graph to achieve the intelligent generation of emergency plans is a crucial problem that needs to be addressed in the field of water conservancy project emergency management.

Conventional techniques for generating emergency plans heavily rely on case matching methods, where the similarity between emergency events and a case repository is computed to derive the final emergency plan [4], [5], [6].

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Wang.

The literature [7] presents a case-based reasoning method for emergency decision-making in water conservancy projects, which enhances the efficiency of handling various emergency events. The literature [8] achieves efficient recommendations for industrial water usage plans by leveraging regularized matching methods. Considering the case feature attributes, the literature [9] generates emergency plans for water conservancy projects by calculating case similarity. However, case matching methods suffer from issues such as weak knowledge correlation, inadequate knowledge representation, and limited knowledge application [10], [11], [12], [13].

Introduced by Google in 2012, knowledge graphs possess robust capabilities in information integration, semantic expression, and knowledge application, offering effective solutions for the knowledge-based organization and intelligent utilization of emergency data [14], [15]. The intelligent generation method for emergency plans based on knowledge graphs primarily comprises rule-based methods and deep learning methods [16], [17]. The rule-based approach to constructing knowledge graphs involves leveraging expert-designed rules and logical matching of target knowledge to build the knowledge graph, enabling the intelligent generation of emergency plans [10], [18], [19]. In the domain of hydroelectric engineering management, the literature [20] has developed an ontology-based intelligent search system for emergency plans, which enhances the efficiency and capability of engineering emergency response. Based on the Dirichlet algorithm and distance algorithm, the literature [21] has constructed a knowledge graph for water management, enabling intelligent recommendations of water-related information. Based on the knowledge graph technology, the literature [22] has achieved the generation of urban flood resilience planning by integrating policy documents with real-time data. The rule-based method for constructing knowledge graphs suffers from issues such as cumbersome rule definition, low entity recognition accuracy, and inefficient graph construction [11], [23], [24].

The deep learning-based approach to constructing knowledge graphs leverages deep neural network models for automatic extraction of knowledge triplets, enabling the generation and recommendation of solutions through the construction of knowledge graphs. Deep learning methods offer a solution to the issues encountered in rule-based methods, such as low accuracy in entity recognition and poor efficiency in graph construction [25], [26]. The literature [27] proposes a recommendation method for emergency plans in water diversion projects based on the fusion of bidirectional long short-term memory (BILSTM) and conditional random field (CRF), known as BILSTM-CRF. In literature [28], a knowledge graph construction method based on convolutional neural network (CNN) is proposed for water quality assessment. In literature [29], leveraging the semantic interconnection capability of knowledge graphs, a BILSTM-based knowledge graph for hydroelectric engineering is constructed, enabling intelligent querying and recommendation of hydroelectric knowledge. In literature [30], a knowledge graph platform for climate information retrieval is constructed by integrating relevant data and information from the climate domain. However, deep learning-based methods for constructing knowledge graphs still face challenges such as poor model generalization ability and high data requirements [31], [32], [33].

With the development and integration of big data and deep learning, the pre-trained-based knowledge graph construction approach has been widely applied [15]. Prominent pre-training models include bidirectional encoder representations from transformers (BERT) [34] and generative pre-trained transformers (GPT) [35], [36]. In literature [37], a water resource knowledge graph based on BERT has been constructed, enabling the retrieval and generation of water resource regulation schemes. In literature [38], the fusion of BERT, BILSTM, and CRF has been employed to construct a knowledge graph for hydroelectric equipment failures, known as BERT-BILSTM-CRF, enabling fault analysis and decision support in the field of hydroelectric power. In literature [39], the fusion of BERT and CNN has been employed to construct a knowledge graph for flood prevention, known as BERT-CNN, enabling intelligent recommendations of flood prevention plans and enhancing the efficiency and capability of emergency response. Currently, pre-trained models used for knowledge graph construction still face challenges such as fixed pre-training patterns, low computational efficiency, and inaccuracies in knowledge extraction [40], [41], [42].

Based on the aforementioned discussions, this study proposes an intelligent method for generating emergency plans for water conservancy projects based on knowledge graphs, aiming to address the issues of poor content correlation and insufficient support for intelligent decision-making in emergency plans. The main contributions are as follows:

- Utilizing pre-trained language models (PTM) based on entity masking, the accuracy of entity recognition tasks is enhanced by uncovering contextual features surrounding the masked entities;
- By employing vector space translation, rotation, and superposition, the multi-view convolutional neural network (MCNN) is constructed to achieve feature complementarity and fusion, thereby enhancing the accuracy of relation extraction;
- Combining PTM with MCNN, an entity relation extraction method based on PTM-MCNN is constructed.
- Based on the mutual information criterion, knowledge retrieval and matching are performed to achieve intelligent generation of emergency plans.

The remaining sections of this paper are organized as follows: Section II introduces the relevant work on PTM-MCNN. Sections III and IV provide detailed explanations of the construction process of PTM-MCNN and the process of emergency plan generation. Section V presents the experimental design, results, and discussions. Section VI concludes the paper and suggests future research directions.

II. RELATED WORK

A. PTM

PTM aims to acquire extensive linguistic knowledge through self-supervised learning using text corpora [43]. Early PTM approaches were primarily based on n-grams and rule-based methods. The paper [44] proposed the global vectors model, which performs pre-training by computing word co-occurrence information and global semantic information. The paper [45] introduced the word vector model, which employs self-supervised learning to represent words as continuous vectors for pre-training.

With the advancement of deep learning, literature [46] introduced the transformer model, which employs self-attention mechanism for sequence modeling. The transformer model is capable of effectively capturing long-range dependencies in text and has achieved significant performance improvements in machine translation tasks. Subsequently, the paper [15] introduced BERT, building upon the foundation of the transformer model. BERT employs a strategy of pre-training and fine-tuning, where it undergoes pre-training on a large-scale unsupervised dataset and then fine-tunes on downstream tasks. The groundbreaking innovation of BERT has led to remarkable achievements in various natural language processing tasks, sparking widespread scholarly interest in PTM.

B. CNN

CNN, a feedforward neural network, possesses formidable feature extraction capabilities [47], [48]. The origins of CNN can be traced back to the 1980s. The literature [49] introduced the lenet model for the task of recognizing handwritten digits. This model incorporates convolution and pooling structures and utilizes the backpropagation algorithm for training. With the emergence and advancement of big data, researchers have embarked on exploring deep CNN models. The literature [50] introduced the alexnet model, which achieved significant breakthroughs in the imagenet image classification competition by utilizing multiple convolutional layers and fully connected layers for training.

The initial application of CNN in NLP tasks was primarily focused on text classification. The literature [51] proposed a CNN-based model for text classification, which employs convolutional operations on sentences to extract local features. The model has achieved promising performance on multiple text classification tasks. Subsequently, CNN has been employed for sequence modeling tasks, such as named entity recognition and part-of-speech tagging. The literature [52] presents a CNN-based sequence annotation model that employs convolution and pooling operations on the input sequence to predict labels.

C. MUTUAL INFORMATION

The concept of mutual information was initially introduced by Shannon in 1948 as a measure of the relationship between two random variables in information theory [51]. With the advancement of machine learning and pattern recognition, mutual information has been employed in the field of feature selection. By calculating the mutual information between feature variables and target variables, the degree of correlation between variables is evaluated, enabling the selection of the most relevant features [53]. On the other hand, mutual information is widely employed for feature extraction. By computing the mutual information between different features, one can assess the relevance of the features and select a subset of features with the maximum mutual information [54].

In the field of natural language processing, mutual information was initially employed in semantic relatedness computation. It quantifies semantic correlation by calculating the mutual information of word co-occurrences [55]. Subsequently, mutual information started to be employed in feature selection and text classification tasks. In the context of feature selection, mutual information is utilized to assess the degree of association among word categories. In the context of text classification, mutual information is employed for the computation of feature importance [56]. With the emergence of information extraction tasks, mutual information has begun to play a role in such tasks. By computing the mutual information of entities, one can capture the correlation and dependency between entities, enabling entity querying and information retrieval [57], [58].

III. PTM-MCNN ENTITY RELATIONSHIP EXTRACTION MODEL

A. PTM CONSTRUCTION

The PTM proposed in this study is a deep language model based on self-supervised learning, trained by applying a random masking mechanism to the multi-layer transformer structure. The transformer is a self-attention neural network framework that eliminates recurrent structures and allows for parallel computation. It has the ability to better capture semantic information and exhibits stronger generalization capabilities. PTM employs the technique of randomly masking portions of entities in sentences to extract features from textual information. It consists of an input layer, a feature extraction layer and an output layer. The basic implementation is as follows.

Pretraining strategy: During the pretraining phase, the model is trained to understand the contextual features of masked positions by randomly masking characters in the input sequence. This allows the model to learn the original meaning of the masked positions based on the surrounding context. Currently, conventional pretraining language models, such as BERT, typically employ a masking strategy that involves masking individual characters in the text using a single [MASK] token. However, during the process of extracting emergency entities in water conservancy projects, the naming conventions for entities are complex, diverse, and often involve longer names. If the original masking strategy is still employed, it would be unable to fully mask the entire entity, resulting in model bias when predicting

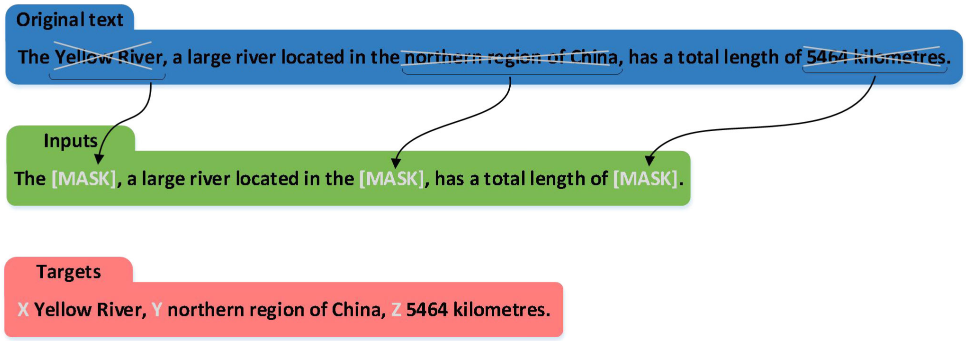


FIGURE 1. The basic process of random [MASK] in the pre-training phase.

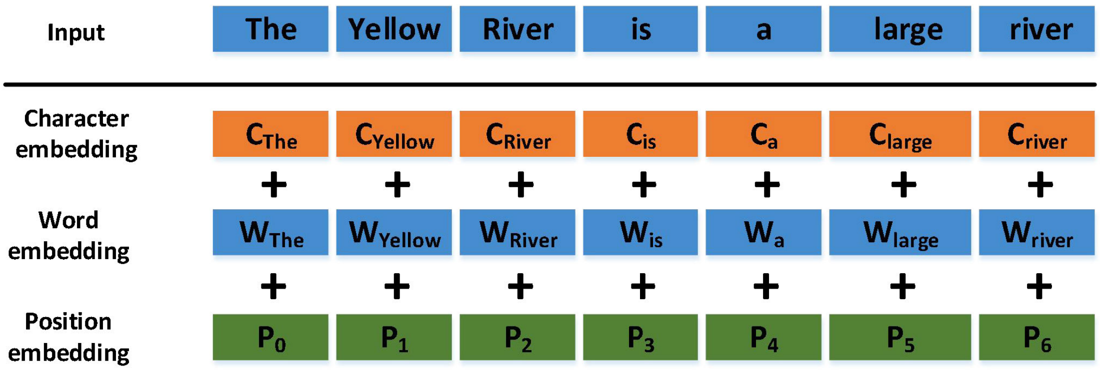


FIGURE 2. Schematic representation of the character embedding, word embedding and location embedding forming the PTM input layer.

the masked words and consequently leading to inaccurate predictions. Therefore, this paper aims to enhance the masking strategy of pre-training language models by employing an entity-level masking approach to mask the text. Firstly, the text is tokenized and entity analysis is performed using an entity lexicon. Then, the entire entity is masked using multiple consecutive [MASK] tokens. Finally, the model is used to predict all the characters replaced by [MASK] tokens, allowing for the extraction of entity-level feature information, thus alleviating biases caused by incomplete semantics during the prediction process. Figure 1 illustrates the basic processing of masking entities in the input text. The random masking strategy is as follows: (1) 80% of the entities in the input sequence are replaced with other entities. (2) 10% of the entities in the input sequence are masked with [MASK]. (3) 10% of the input sequence remains unchanged.

Input layer: As depicted in Figure 2, the input layer of the PTM is composed of three components: character embedding, word embedding, and positional embedding, which are combined together. Character embedding transforms the input text sequence into fixed-dimensional vectors, word embedding encapsulates various word information, and positional embedding enables sequential encoding of the input text sequence.

Feature extraction layer: The feature extraction layer of PTM consists of a 24-layer transformer network, with each layer comprising 6 encoders. The transformer network employs a self-attention mechanism, which calculates the contextual features of words or characters and assigns weights to each word or character accordingly. In such cases, word vectors or character vectors would encompass semantic information that is related to their context. Taking word embeddings as an example, the self-attention mechanism in transformer is defined as follows.

$$f_{attention}(Q, K, V) = Softmax(\frac{QK^T}{\sqrt{d_k}})V, \tag{1}$$

Among them, Q, K and V are matrices of word embeddings. The dot product matrix of Q and K^T represents the degree of correlation for each word. $\sqrt{d_k}$ serves as the scaling factor. Building upon this foundation, multiple self-attention layers are concatenated through a multi-head structure to obtain a more interpretable multi-head attention mechanism. The formula is defined as follows.

$$f_{multihead}(Q, K, V) = [head^1\ head^2\ \ldots\ head^n], \tag{2}$$

$$head^i = f_{attention}(QW_Q^i, KW_K^i, VW_V^i), \tag{3}$$

Among them, the matrix W represents the weight matrix, *head* denotes the number of attention heads, and W_Q, W_K,

W_V represent the weight parameter matrices for Q, K and V, respectively. To expedite the convergence of the model, a residual network is introduced, followed by a normalization process.

Output layer: The output layer of the PTM consists of the results obtained after feature extraction through 24 layers of transformer encoders and decoders. It outputs word vectors that encompass the rich semantic information of the input text.

B. MCNN CONSTRUCTION

The relationships among entities in water conservancy projects' emergency scenarios exhibit intricacy and uncertainty. For extracting complex relationships, conventional approaches commonly employ one-dimensional convolutions for feature extraction. The feature extraction based on one-dimensional convolutions typically captures only local information, leading to limited comprehension of the global context. When performing the classification of entity relationships, employing a multi-view strategy can aid in extracting a broader range of entity relationship features [59]. The main concept of MCNN revolves around manipulating embedding vectors through spatial translation, rotation, and superposition to construct multiple views, which are then subjected to feature extraction using CNN. By performing spatial translation on the embedded vectors, it is possible to alter the relative positions of entities and relationships, thereby capturing entity relationship features at different locations. By applying spatial rotation to the embedded vectors, the angles of entity relationships can be altered, enabling the capture of entity relationship features from different perspectives. After performing spatial translation and rotation, the embedded vectors are combined and fused, enhancing their sensitivity to changes in the position and angle of the input data, thereby increasing the robustness and generalization capability of the model. This study aims to construct three distinct convolutional views, namely spatial translation of entity-relation vectors, spatial rotation of entity-relation vectors, and spatial fusion and superposition of entity-relation vectors. The basic implementation of MCNN is as follows.

Defining entity $e_h \epsilon R^{a\times b'}$ and relation $e_r \epsilon R^{a\times b'}$, where a, b and $b' = b/2$ represent the spatial dimensions of the vectors. Splitting entity e_h and relation e_r into two parts, defined as $e_h = \{h_1, h_2$ and $e_r = \{r_1, r_2$, respectively, with dimensions $h_1, h_2, r_1, r_2 \epsilon R^{a\times b''}$ and $b'' = b/4$. Utilizing vector addition to achieve the translation operation, each component of the vector undergoes a corresponding addition operation, where the size and direction of the translation vector determine the magnitude and direction of the translation. For the vector h_1, it is translated along the direction and magnitude of the translation vector r_1, resulting in the representation $(h_1 + r_1)$. This study constructs four translation vectors, denoted as $(h_1 + r_1)$, $(h_1 + r_2)$, $(h_2 + r_1)$ and $(h_2 + r_2)$. Then, through the vector concatenation, the first convolutional view is formed, defined as follows.

$$V_t = \left[(h_1 + r_1)_{a\times b''}\,;\,(h_1 + r_2)_{a\times b''}\,;\,(h_2 + r_1)_{a\times b''}\,; \right. \\ \left. \times\,(h_2 + r_2)_{a\times b''}\right]_{a*b}, \tag{4}$$

Among them, V_t represents the convolutional view after spatial translation, $(h_1 + r_1)\,\epsilon R^{a\times b''}$ represents the translation of h_1 along the direction and magnitude of r_1 and [;] represents the vector concatenation. Equation (4) can be extended to the case of nonlinear transformations, defined as follows.

$$V_t = V_t + \frac{e^{V_t} - e^{-V_t}}{e^{V_t} + e^{-V_t}}, \tag{5}$$

By combining V_t and a non-linear transformation, the view can be obtained not only through spatial translation but also through spatial rotation. The rotational operation is accomplished by utilizing the inner product of vectors, where the direction and magnitude of the rotating vector determine the angle and amplitude of the rotation. For vector h_1, rotating it along the angle and magnitude of vector r_1 results in vector $(h_1 * r_1)$. The four rotation vectors are represented as $(h_1 * r_1)$, $(h_1 * r_2)$, $(h_2 * r_1)$ and $(h_2 * r_2)$, respectively. By performing vector concatenation, the second form of view transformation is obtained and defined as follows.

$$V_r = \left[(h_1 * r_1)_{a\times b''}\,;\,(h_1 * r_2)_{a\times b''}\,;\,(h_2 * r_1)_{a\times b''}\,; \right. \\ \left. \times\,(h_2 * r_2)_{a\times b''}\right]_{a*b}, \tag{6}$$

whereas V_r is identical to V_t, $V_r \epsilon R^{a\times b}$ and $(h_1 * r_1)\,\epsilon R^{a\times b''}$ denote the spatial rotation of h_1 along the angle and magnitude of r_1. Thus, the nonlinear transformation approach for V_r is defined as follows.

$$V_r = V_r + \frac{e^{V_r} - e^{-V_r}}{e^{V_r} + e^{-V_r}}, \tag{7}$$

By combining the vectors $(e_h + e_r) \epsilon R^{a\times b'}$ and $(e_h * e_r) \epsilon R^{a\times b'}$ through vector concatenation, a new fused view V_f can be formed, defined as follows.

$$V_f = [(e_h + e_r)_{a\times b'}; (e_h * e_r)_{a\times b'}]_{a*b}, \tag{8}$$

Lastly, the fusion view comprising V_t, V_r and V_f is defined as $V_I = \{V_t, V_r, V_f, I\epsilon\,\{t, r, f\}$. Taking vector V_I as the input of the CNN, a novel multi-view feature augmentation network can be constructed.

C. PTM-MCNN BASED EMERGENCY ENTITY RELATIONSHIP EXTRACTION

PTM-MCNN comprises three main modules: the label annotation module, the feature extraction module, and the entity-relation extraction module. The label annotation module serves as a data standard for training and evaluating the model. The feature extraction module is divided into two parts, namely the pre-training module and the multi-view convolution module. The pre-training module aims to enhance the accuracy of entity extraction by mining the

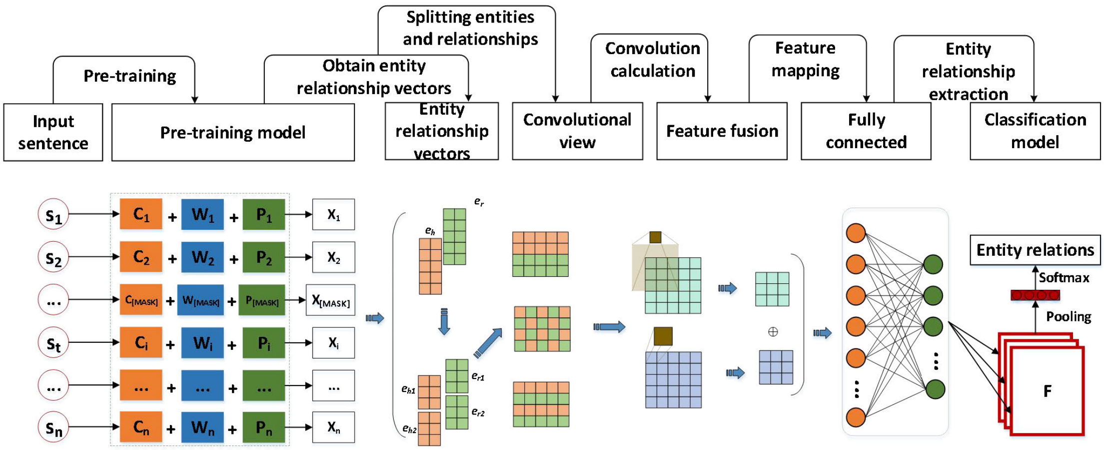


FIGURE 3. Entity relationship extraction process based on PTM-MCNN model.

TABLE 1. Method of marking the text sequence of the emergency plan.

Characters	The	water	level	in	the	main	canal	reaches	the
Label	O	WA-B	WA-I	O	O	MA-B	MA-I	RE-B	O
Entity or relationship		water level				main canal		0	
Characters	guaranteed	level	of	the	levee	and	continues	to	rise
Label	GU-B	GU-I	O	O	LE-B	O	O	O	RI-B
Entity or relationship	guaranteed level				levee				1

semantic features of the text, while the multi-view convolution module enhances the relationship extraction capability by extracting the interaction features of entity relationships. The entity relationship extraction module involves feeding the labeled sequence, which has undergone feature extraction, into a classification model for entity relationship extraction. Figure 3 illustrates the fundamental process of entity relationship extraction using the PTM-MCNN model, as follows:

Label annotation: For a given length of n the emergency plan text $S = \{s^1, s^2, \ldots, s^n$, where s^i denotes the ird character in the text. The label annotation can be represented as a nonlinear mapping, denoted by $k(\cdot)$. The label sequence corresponding to the given text is as follows.

$$L_s = k(S) \tag{9}$$

Among them, $L_s = \{l_s^1, l_s^2, \ldots, l_s^n$ is of the same length as S, and l_s^i represents the label of the ith character in the text. Table 1 provides the emergency plan text sequence, label sequence, and corresponding entity relationship information.

In the sentence, each individual character is assigned a label. The labels can be classified into two categories: entity labels and relation labels. For entity labels, the "BIO" annotation scheme is used to indicate the position of each character within an entity. "B" indicates that the character is at the beginning of an entity, "I" indicates that the character is in the middle or at the end of an entity, and "O" indicates that the character does not belong to any entity. The relationship labels are determined by pre-defined categories of relationships. For example, in Table 1, "WA-B" corresponds to the starting position of the entity "water level," and category "1" represents the relationship "rise".

Feature extraction: For the label annotation sequence $L_s = \{l_s^1, l_s^2, \ldots, l_s^n$, the process of vectorizing L_s is performed using character vectors, word vectors, and positional vectors. Character vectors are employed to capture the precise format, case, and other characteristics of individual characters. Word vectors are utilized to capture the semantic relationships among words. Positional vectors are employed to capture the sequential order and contextual relationships of words within a sentence. Subsequently, the fusion of character vectors, word vectors, and positional vectors is accomplished through vector addition, denoted as $X = \{x_1, x_2, \ldots, x_n$. The PTM-MCNN pre-training module is utilized to extract features from embedded vectors with a length of n, defined as follows.

$$E = f_{ptm}(x_1, x_2, \ldots, x_n), \tag{10}$$

Among them, $E = \{e_1, e_2, \ldots, e_n$ represents the extracted textual features. Next, the extracted textual features are divided into two parts to construct views V_t, V_r and V_f based on spatial translation, rotation, and superposition. Taking view V_t as an example, a 3×3 2D convolution kernel is used for 2D feature extraction, defined as follows:

$$F_{cov} = V_t * \omega_{2D}^2, \tag{11}$$

Among them, $\omega_{2D}^2 \in R^{3\times3}$ represents the 2D convolution kernel, $*$ represents the convolution operator, and F_{cov} represents the feature map obtained after 2D convolution computation. Then, the feature maps are fused using matrix addition and passed through inner product computation to obtain the output.

Entity relation extraction: After performing feature extraction using the PTM-MCNN model, the feature vectors of the text sequences are obtained and defined as F. Using *softmax* to predict the entity relationship label $\hat{y}$ for F, calculate the conditional probability $\hat{p}$ for F belonging to each label class, and assign the maximum $\hat{p}$ value as the predicted class label $\hat{y}$ for F. The calculation formula is defined as follows.

$$\hat{p}(y|F) = softmax(W^{(X)}F + b^{(X)}), \tag{12}$$

$$\hat{y} = argmax(\hat{p}(y|F)), \tag{13}$$

Among them, $W^{(X)}$ represents the weight parameter and $b^{(X)}$ represents the bias parameter. By utilizing the cross-entropy loss function, calculate the loss between the true label and predicted label of the entity relationship. The calculation formula is as follows.

$$L(\theta) = -\frac{1}{N}\sum_i \left(\left(\hat{y}_i log\left(y_i\right)\right) + \left(1-\hat{y}_i\right)\left(1 - log\left(y_i\right)\right)\right), \tag{14}$$

Among them, N represents the number of entity triplets.

IV. KNOWLEDGE GRAPH BASED EMERGENCY PLAN GENERATION

The research focuses on the comprehensive emergency plans at the provincial and municipal levels, as well as 17 specific emergency plans, released by the South-to-North Water Diversion Project in China from 2014 to 2021. The South-to-North Water Diversion Project in China is a large-scale interbasin water resources project implemented to alleviate water scarcity issues in northern China. Since its comprehensive implementation, the project has conveyed a volume of 58.6 billion cubic meters of water, effectively alleviating water scarcity issues in northern China. Leveraging knowledge graph technology, automatic extraction of emergency decision-making knowledge from a large amount of unstructured emergency plan texts and intelligent generation of emergency plans based on actual situations can greatly enhance the efficiency of emergency management for the South-to-North Water Diversion Project. The intelligent generation method of emergency plans based on knowledge graph mainly consists of five stages, namely data preprocessing, ontology construction, entity-relation extraction, knowledge triple storage, and emergency plan generation. The primary objective of data preprocessing is to perform operations such as cleaning, transformation, and normalization on the raw text to enhance the performance and effectiveness of the model. Ontology construction aims to provide a unified semantic framework for describing entities, attributes, and their relationships. The results of entity-relation extraction are used to form the nodes and edges of the knowledge graph. Through knowledge storage, entity-relation triples are presented in the form of a graph. Finally, emergency decision plans are generated through matching and retrieval. Figure 4 illustrates the basic process of the method, which is summarized as follows.

Data preprocessing: For the emergency plan text data, the first step is to remove frequently occurring but semantically insignificant vocabulary to reduce the dimensionality of the feature space and minimize interference from noise on the model. Furthermore, the text data is transformed into numerical vector representations to provide input for model learning.

Ontology construction: From the perspective of emergency management analysis, the process of emergency response mainly comprises four stages: forecasting and warning, graded response, emergency handling and post-event support. Forecasting and warning phase encompasses factors such as precipitation, runoff, water level, and reservoir dams. The emergency handling phase involves institutions, responsibilities, and other related aspects. The post-event support phase entails provisions for supplies, equipment, personnel, and more. The ontology of an emergency knowledge graph represents the concepts of emergency and their related relationships, comprising concept nodes and concept relationship edges. The ontology of the emergency knowledge graph constructed in this study primarily encompasses concepts and relationships from five aspects. ① The emergency response process involves four stages: forecasting and early warning, graded response, emergency handling and post-event support. ② Natural objects such as meteorology, hydrology, rivers, etc. ③ Social objects such as institutions and departments. ④ Reservoirs, dams and other water engineering objects. ⑤ Various technical terms in the field of water conservancy.

Entity relationship extraction: The emergency plans for the South-to-North Water Diversion Project in China primarily comprise two types of data: semi-structured tabular data and unstructured textual data. In addition, there are also structured real-time monitoring data. For structured real-time data, it is stored directly using a relational database. For semi-structured tabular data, matching and extraction are performed using regular expressions. For unstructured textual data, extraction is carried out using the PTM-MCNN model. Firstly, the PTM-MCNN model is trained using annotated training dataset. Then, the trained PTM-MCNN model is used to extract entity relationships from unlabeled emergency plan texts. Finally, the extracted entity relationships are integrated to obtain a comprehensive and accurate entity relationship network.

Knowledge storage: This study employs the Neo4j graph database to store the entity relationship triplets. When storing entity nodes, each node is identified by a unique identifier such as an ID or URI. Nodes are labeled to indicate the category of each entity, facilitating the classification and retrieval of nodes. For the storage of relationship edges, the semantic relationships between entities are represented by the types and directions of relationships between nodes. Among them, the starting node of an edge is the head entity, the ending node of an edge is the tail entity, and the type of the edge represents the entity relationship. By storing entity relationship triplets, the semantic relationships and attribute

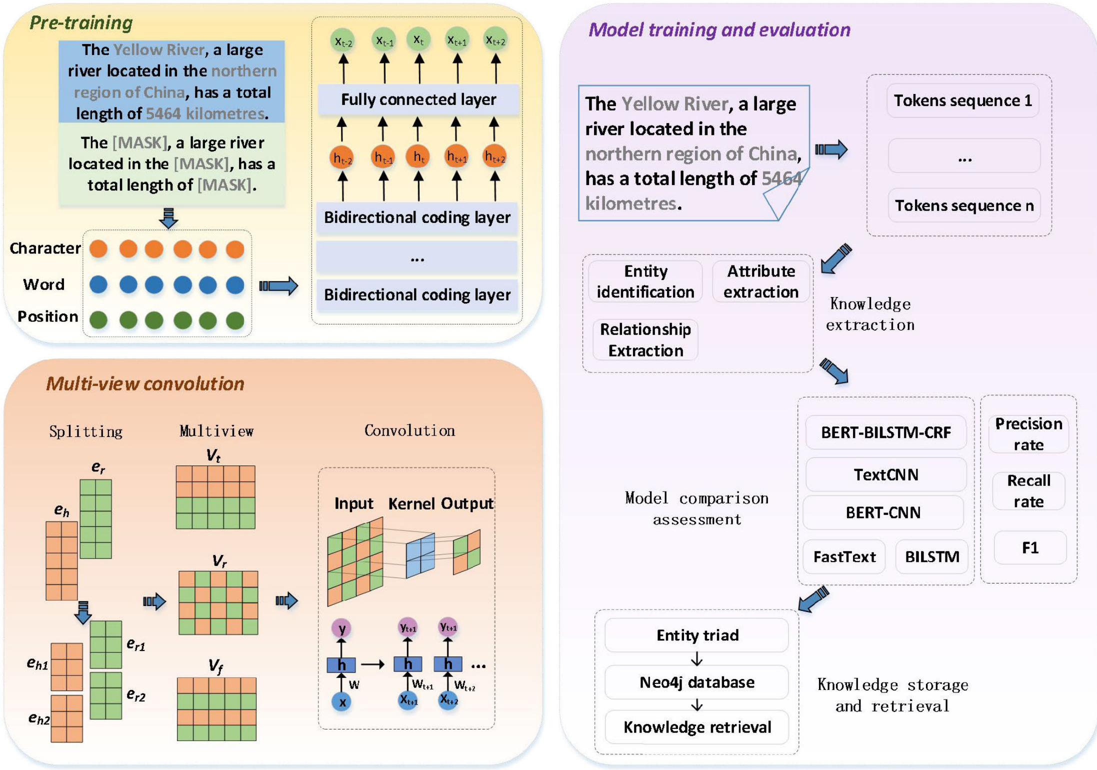


FIGURE 4. Knowledge graph based emergency plan generation process.

information in the knowledge graph are represented in a structured manner. In order to enhance query performance and ensure data consistency, indexes and constraints are created in Neo4j. Indexes facilitate the swift identification of nodes possessing specific attribute values. Constraints ensure the consistency and integrity of data. Furthermore, when dealing with a large volume of imported entity relationship triples, the data can be efficiently loaded into the graph database from external data sources using the bulk import tool provided by Neo4j.

Emergency plan generation: The process of generating emergency plans involves two main stages, namely knowledge retrieval and template matching. The retrieval of emergency knowledge in water conservancy projects can be categorized into two scenarios. The content to be retrieved can be directly obtained from the knowledge graph, and in this case, it is accomplished using the Cypher query language provided by the Neo4j graph database. The Cypher query language offers functionalities such as path traversal and aggregation, demonstrating high efficiency in querying and retrieval. Another scenario arises when the desired content cannot be directly obtained and requires a predefined similarity threshold to be established in advance. Subsequently, employing the mutual information criterion for entity similarity matching, when the input content meets the similarity threshold, the recommendation set will be returned, containing the top 5 solutions with the highest similarity. The formula for calculating the similarity using mutual information is defined as follows.

$$I(E_{in}, E_{fe}) = \sum_{e_{in}\in E_{in}} \sum_{e_{fe}\in E_{fe}} p(e_{in}, e_{fe}) log \frac{p(e_{in}, e_{fe})}{p(e_{in})p(e_{fe})} \quad (15)$$

Among them, E_{in} represents the input entity, E_{fe} represents the entity to be retrieved and $p(\cdot)$ is the joint probability distribution for calculating two random variables. The output of mutual information is the similarity between the two entities. In the template matching phase, the emergency plan templates designed in this study are divided into four sections: forecasting and warning, graded response, emergency handling, and post-event support. The forecast warning includes real-time water level information, meteorological information, and other relevant data within the current area. The graded response includes information on the current response level. Emergency handling encompasses information about organizations, responsibilities, and other relevant details. The post-event support includes information about resources such as supplies, equipment and personnel. Based on the retrieved emergency knowledge, perform entity relationship matching using the emergency plan template and generate and deliver the emergency plan.

V. EXPERIMENT

Knowledge extraction serves as the foundation for constructing a knowledge graph. In this section, the effectiveness of

PTM-MCNN is validated through knowledge extraction tasks on emergency plan data. First, provide an explanation of the datasets, evaluation indexes and baseline models used in the experiment. Then, divide the experiment into four groups to achieve different experimental objectives.

① Conducting knowledge extraction experiments on emergency plan data using the PTM-MCNN model and performing comparative analysis of the experimental results with previous state-of-the-art models to evaluate the effectiveness of the PTM-MCNN model.

② Perform sensitivity analysis experiments on hyperparameters to verify the model's performance sensitivity to hyperparameter settings.

③ Analyze the impact of entity masking-based pre-training tasks and multi-view convolution on the performance of the PTM-MCNN model through ablation experiments.

④ Conducting a case study experiment on intelligent emergency plan generation to meticulously demonstrate how this approach ensures the reliability of emergency plan generation.

A. MODEL PARAMETERS AND DATA

This study utilized the comprehensive emergency plans at the provincial and municipal levels, as well as 17 specialized emergency plans, released by the South-to-North Water Diversion Project in China from 2014 to 2021 as the experimental data. The comprehensive emergency plans at the provincial and municipal levels, as well as the specialized emergency plans, are sourced from the 47 management offices under the South-to-North Water Diversion Project in China. The provincial and municipal emergency plans delineate the unified emergency response procedures for significant risk events within the respective province or city. The process comprises four stages: forecasting and warning, graded response, emergency handling and post-event support. The 17 specialized emergency plans encompass response procedures for 17 major risk events, including flood disasters, fires, traffic accidents, earthquakes, water pollution, and more. After data preprocessing, a total of 733,041 records were obtained, including provincial and municipal emergency plans as well as specialized emergency plans. The emergency plan dataset was divided into training and testing sets with a ratio of 7:3, resulting in 513,128 records in the training set and 219,912 records in the testing set. The baseline models selected for this study encompass widely adopted named entity recognition models and relation extraction models. The baseline models comprise FastText [26], TextCNN [28], BILSTM [30], BERT-BILSTM-CRF [38] and BERT-CNN [39]. Table 2 presents the parameter configurations for each model.

B. EVALUATION OF INDEXES

For model evaluation, this study utilises accuracy, recall and F1 as the evaluation indexes. Accuracy measures the proportion of correctly identified entity relations by the model. Recall measures the ability of the model to correctly identify entity relations. The F1 score is the average of accuracy and recall, used to evaluate the overall performance of the model. The higher the values of accuracy, recall, and F1 score, the better the performance of the model. Precision (P), recall (R), and F1 score are defined as follows:

TABLE 2. Values of the model parameters.

Hyperparameters	Values
Convolution kernel size	3
Hidden layer dimension	32
Embedding dimension	200
Dropout rate	0.2
Epochs	500

$$P = \frac{T_P}{T_P + F_P} 100\%, \tag{16}$$

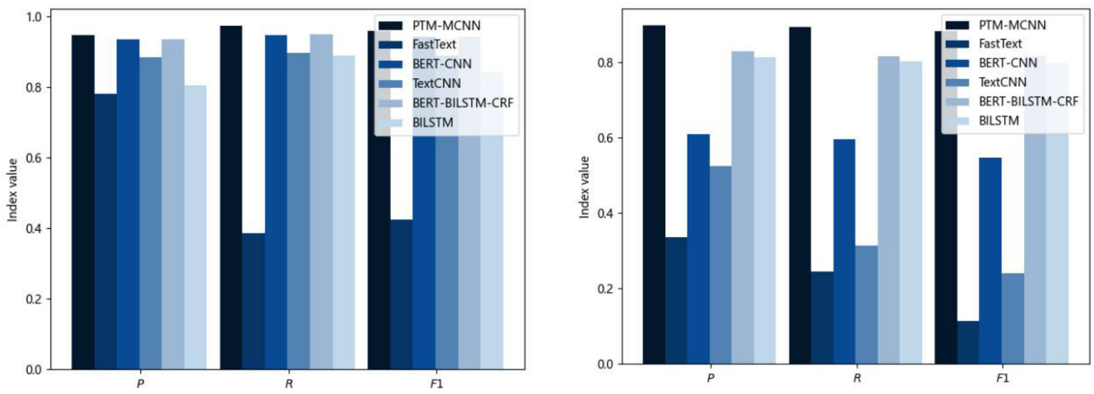
$$R = \frac{T_P}{T_P + F_N} 100\%, \tag{17}$$

$$F1 = \frac{2P \cdot R}{P + R} 100\%, \tag{18}$$

Among them, T_P represents the number of correctly predicted entities, F_P represents the number of predicted entities that are not actual entities and F_N represents the number of entities that were not predicted.

C. KNOWLEDGE EXTRACTION RESULTS AND ANALYSIS

Figure 5 and Table 3 present the experimental results of different models. In terms of entity extraction, FastText exhibits the lowest performance with accuracy, recall and F1 values of 0.780, 0.386 and 0.425, respectively. FastText employs character-level n-gram features to represent text, which exhibits limited capability in understanding complex semantics. BERT-BILSTM-CRF demonstrates superior performance with accuracy, recall and F1 scores of 0.935, 0.949 and 0.941, respectively. BERT-BILSTM-CRF, based on pre-training and bidirectional language modeling, possesses the capability to deeply comprehend the intricate relationships among vocabulary, syntax and semantics, thereby providing a more comprehensive contextual representation. The proposed PTM-MCNN model achieves precision, recall and F1 scores of 0.947, 0.973 and 0.960, respectively. Compared to BERT-BILSTM-CRF, PTM-MCNN achieves an improvement of 1.28% in precision, 2.53% in recall and 2.02% in F1 score. In the domain of water conservancy projects emergency entity extraction, emergency plans exhibit numerous specialized terms and semantic complexities. Conventional pre-trained language models fail to fully comprehend the entire entity, leading to biases in entity extraction by the model. In terms of relation extraction, BERT-BILSTM-CRF achieved accuracy, recall and F1 scores of 0.830, 0.817 and 0.817, respectively, while PTM-MCNN achieved accuracy, recall and F1 scores of 0.898, 0.893 and 0.884, respectively. Compared to BERT-BILSTM-CRF, PTM-MCNN achieved improvements of 8.19% in accuracy, 9.30% in recall and 8.20% in F1 score. Emergency plans exhibit characteristics of complex relationship structures.



(a) Entity extraction assessment results

(b) Results of the relationship extraction assessment

FIGURE 5. Comparison chart of performance levels of each model.

TABLE 3. Comparison of the values of the experimental results for each model.

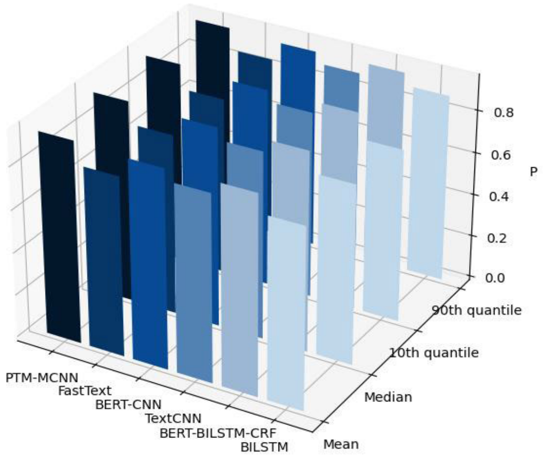
Models	Entity extraction			Relationship extraction		
	P	*R*	*F1*	*P*	*R*	*F1*
PTM-MCNN	**0.947**	**0.973**	**0.960**	**0.898**	**0.893**	**0.884**
FastText	0.780	0.386	0.425	0.337	0.245	0.115
BERT-CNN	0.936	0.948	0.942	0.609	0.597	0.547
TextCNN	0.885	0.897	0.889	0.525	0.315	0.241
BERT-BILSTM-CRF	0.935	0.949	0.941	0.830	0.817	0.817
BILSTM	0.804	0.890	0.842	0.815	0.803	0.798

Our approach in this paper enhances the model's robustness and generalization capacity through vector spatial translation, rotation, and superposition, thereby significantly improving its capability to extract complex relationships. Overall, the proposed PTM-MCNN model in this study consistently outperforms state-of-the-art models in terms of entity relation extraction, indicating its effectiveness in accomplishing the task of extracting emergency entity relations in water conservancy projects.

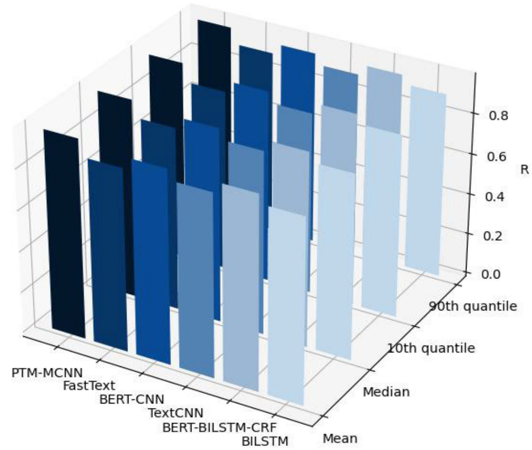
To thoroughly validate the effectiveness of the proposed model, the PTM-MCNN was subjected to 200 statistical experiments, comparing it with the baseline models. The model's performance was evaluated and examined using four statistical variables: mean, median, 10th quantile, and 90th quantile. The mean is used to describe the overall average performance of the model. The median describes the central tendency of the model's performance. Unlike the mean, the median is less sensitive to outliers and better reflects the central trend of the data. The 10th quantile and 90th quantile represent the values at the 10th and 90th percentiles of the data, respectively, and can be used to describe the lower and upper bounds of the data distribution. Figure 6(a)∼(c) present the accuracy, recall and F1 scores of different models and statistical variables in the domain of entity extraction. It can be observed that the mean and median values of BERT-BILSTM-CRF remain around 93%, while the 10th and 90th quantiles remain between 89% and 95%, with a difference of 0.6 between the quantiles. The mean and median values of PTM-MCNN remain around 95%, while the 10th and 90th quantiles remain between 95% and 96%, with a difference of 0.1 between the quantiles. The mean and median of PTM-MCNN surpass those of the BERT-BILSTM-CRF model, while the difference between the 10th and 90th quantiles is smaller for PTM-MCNN compared to BERT-BILSTM-CRF. Indicate that PTM-MCNN exhibits superior average performance to BERT-BILSTM-CRF and is relatively stable. Figure 6 (d)∼(f) present the precision, recall and F1 scores for different models and statistical variables in the context of relation extraction. The mean and median of BERT-BILSTM-CRF remain around 80%, while the 10th and 90th quantiles are maintained at 77% and 82%, respectively, with a difference of 0.5 between the quantiles. The mean and median of PTM-MCNN remain around 89%, while the 10th and 90th quantiles are maintained at 88% and 91%, respectively, with a difference of 0.3 between the quantiles. Indicating that PTM-MCNN outperforms BERT-BILSTM-CRF in relation extraction, exhibiting superior average performance and relative stability.

D. HYPERPARAMETRIC SENSITIVITY ANALYSIS

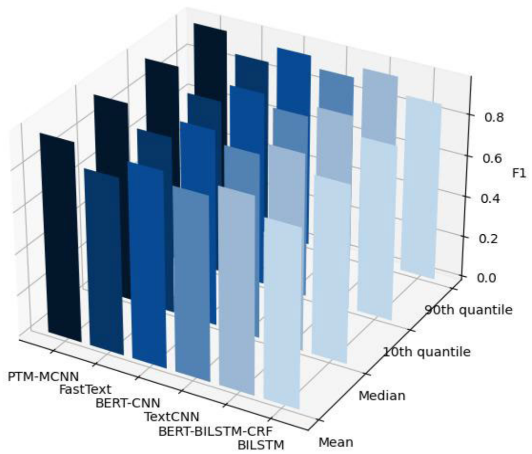
To investigate the impact of hyperparameters on the performance of the PTM-MCNN model, this study conducts a detailed analysis and comparison of several key hyperparameters, including the dimensionality of embedding



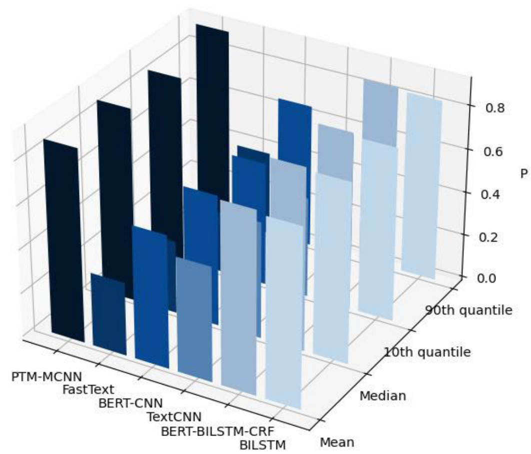
(a) Level of accuracy of entity extraction with different statistical variables for different models



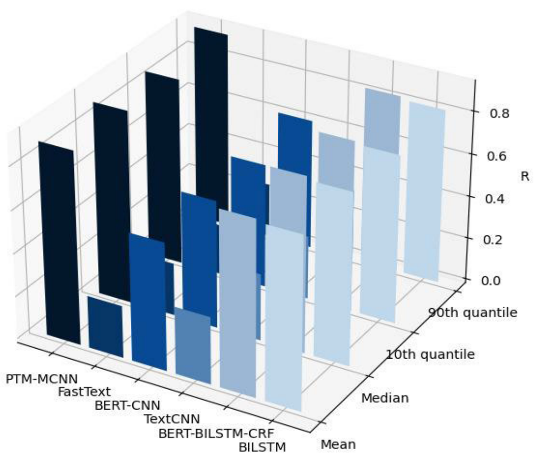
(b) Level of recall of entity extraction with different statistical variables for different models



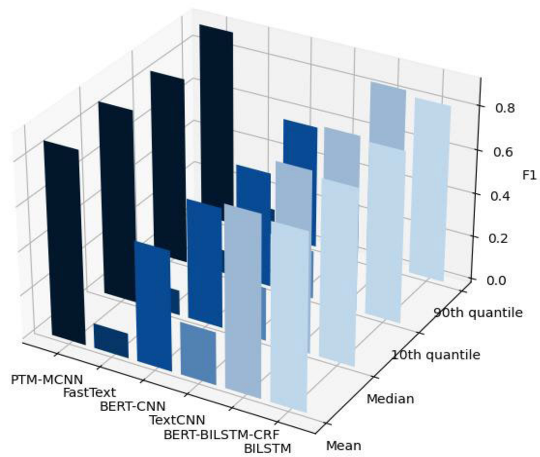
(c) F1 level of entity extraction with different statistical variables for different models



(d) Accuracy level of relationship extraction with different statistical variables for different models



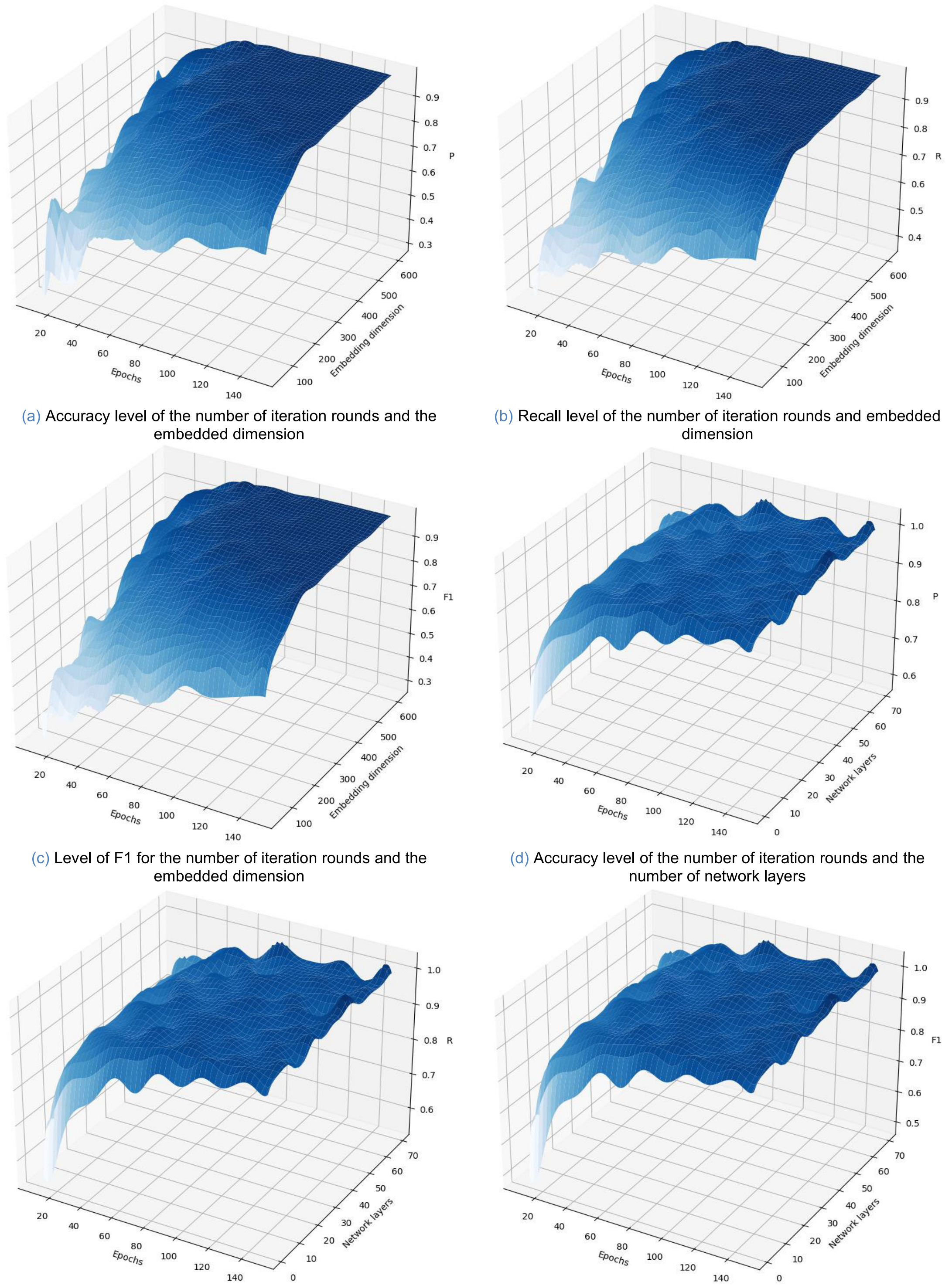
(e) Recall level of relationship extraction with different statistical variables for different models



(f) F1 level of relationship extraction with different statistical variables for different models

FIGURE 6. Model performance levels for different models with different statistical variables.

vectors, the number of layers in the model, and the number of training iterations. The dimensionality of embedding vectors is selected from the set D∈{50, 90, 130, 170, 210, 250, 290, 330, 370, 410, 450, 490, 530, 570, 610}. The number of network layers is chosen from the set L∈{1, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70}. The number of training iterations is selected from the set L∈{10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150}. To ensure experimental



(a) Accuracy level of the number of iteration rounds and the embedded dimension

(b) Recall level of the number of iteration rounds and embedded dimension

(c) Level of F1 for the number of iteration rounds and the embedded dimension

(d) Accuracy level of the number of iteration rounds and the number of network layers

(e) Recall level of the number of iteration rounds and the number of network layers

(f) F1 level of the number of iteration rounds and the number of network layers

FIGURE 7. **Performance level of PTM-MCNN model with different hyperparameters.**

fairness, the settings of the remaining hyperparameters were kept the same as in Section V-A, except for the ones under current investigation. The experimental results are depicted in Figure 7.

Figure 7,(a)∼(c) gives the relationship between the embedding dimension, the number of iteration rounds and the evaluation index. It can be observed that the overall performance of the model is poorer when the number of training

TABLE 4. Comparison results of PTM-MCNN model with variants.

Models	Entity extraction			Relationship extraction		
	P	*R*	*F1*	*P*	*R*	*F1*
PTM-MCNN-CUT	0.927	0.826	0.870	0.867	0.866	0.851
PTM-MCNN-UNI	0.945	0.972	0.959	0.775	0.827	0.784
PTM-MCNN	**0.947**	**0.973**	**0.960**	**0.898**	**0.893**	**0.884**

TABLE 5. Search results and similarity.

Related entities	Entity attributes	Similarity
Level III response standard	1. The water level of the river reaches the warning level. 2. The depth of river scour is 60% of the designed scour depth. 3. Apparent damage occurs to the protection works. 4. The water level of the main canal reaches the alert level. 5. Reservoir dam upstream of the river and canal is in great danger.	0.78
Level I response standard	1. The water level of the river reaches the guaranteed water level. 2. River scour depth reaches the design scour depth. 3. The water level of the main canal reaches the guaranteed water level. 4. The dam upstream of the river may be in danger of dam failure. 5. Disruption of water supply may occur due to damage to the project caused by heavy rainfall and flooding.	0.62
Level IV response standard	1. The water level of the river is 0.5m from the warning level. 2. River scour depth is 40% of the design scour depth. 3. The water level of the main canal is 0.2m from the warning level. 4. Reservoir dam upstream of the river is in general danger.	0.61
Class II response standard	1. The water level of the river is 0.5m from the guaranteed water level of the building. 2. The scour depth of the river channel is 80% of the designed scour depth. 3. The water level of the main canal is 0.2m from the guaranteed water level. 4. Significant danger occurs in the reservoir dam upstream of the river. 5. Damage to the project due to heavy rainfall and flooding may result in a reduction of water supply.	0.60
Flood control standard	1. The design flood standard of river and canal buildings is one in 100 years. 2. The calibrated flood standard for river and canal buildings is one in 300 years. 3. The design flood standard for drainage buildings is one in 50 years. 4. The calibrated flood standard for drainage buildings is one in 200 years.	0.32

iterations is less than 60 and the embedding dimension is less than 300. The overall performance of the model is superior and tends to be stable when the number of iterations is greater than 60 and the embedding dimension is greater than 300. Insufficient number of iterations and lower embedding dimension result in inadequate feature representation capacity of the model, which hinders the comprehensive recognition of contextual information and accurate entity extraction. As the model's embedding dimension and number of iterations increase, its feature representation capacity, generalization ability, and knowledge extraction capability also improve. Figure 7,(d)∼(f) gives the relationship between the number of network layers, the number of iteration rounds and the evaluation index. When the number of network layers is less than 10, the model's performance is poor. However, when the number of network layers exceeds 10, the model exhibits strong generalization ability and tends to stabilize. The experimental results indicate that the number of network layers is also a sensitive hyperparameter. Setting it too high or too low can lead to overfitting or underfitting issues.

E. ABLATION EXPERIMENT

To analyze the impact of entity masking strategy and multi-view strategy on model performance, this study introduces two variant models based on PTM-MCNN: PTM-MCNN-CUT and PTM-MCNN-UNI. PTM-MCNN-CUT represents the removal of the entity masking pre-training task from PTM-MCNN, while PTM-MCNN-UNI represents the removal of the multi-view convolution functionality from PTM-MCNN. The knowledge extraction results of the PTM-MCNN model and its variant models are presented in Table 4.

From Table 4, it can be observed that in terms of entity extraction, PTM-MCNN achieves precision, recall and F1 scores of 0.947, 0.973 and 0.960, respectively, while PTM-MCNN-CUT achieves precision, recall and F1 scores of 0.927, 0.826 and 0.870, respectively. Compared to the PTM-MCNN-CUT model, the PTM-MCNN model exhibits improvements of 2.16% in precision, 17.80% in recall and 10.34% in F1 score. The removal of the entity masking strategy in the PTM-MCNN-CUT model, based on the PTM-MCNN, has led to a decrease in the ability to extract contextual features of entities, thereby impacting the performance of entity extraction. In terms of relation extraction, PTM-MCNN achieved precision, recall and F1 scores of 0.898, 0.893 and 0.884 respectively, while PTM-MCNN-UNI achieved precision, recall and F1 scores of 0.775, 0.827 and 0.784 respectively. Compared to PTM-MCNN-UNI, PTM-MCNN achieved an improvement of 15.87% in precision, 7.98% in recall and 12.75% in F1 score. The use of a single-view strategy in PTM-MCNN-UNI resulted in a weakened ability to extract relations, thus impacting the accuracy of relation extraction.

F. ANALYSIS OF EMERGENCY PLAN GENERATION RESULTS

Using the "Classification and response standards for flood disasters in the South-to-North Water Diversion Project of China" as a retrieval case, knowledge retrieval and matching were conducted based on the mutual information criterion. The top 5 most relevant entities with the highest similarity in the emergency knowledge graph were returned, and the results are shown in Table 5. The classification and response standards for flood disasters in the South-to-North Water Diversion Project of China consist of four levels, ranging from Level I∼Level IV in descending order. Based on the information presented in Table 5, the hierarchical response standards are essentially included in the returned list of results. The current recommendation results, in conjunction with the actual situation of the South-to-North Water Diversion Project, essentially meet the requirement for accurate generation of emergency plans. The main reasons for the failure of recommendations, in which a few correct contents are not included in the recommendation list, are as follows. ① The inaccurate identification of certain entities by the entity recognition algorithm may be attributed to possible annotation errors during manual data labeling. ② Insufficient training data for the entity recognition model resulted in the inability to accurately identify the relevant entities.

VI. SUMMARIES

Aiming to address the issues of poor content relevance and insufficient intelligent decision support in emergency plans for water conservancy projects, a knowledge graph based intelligent generation model for emergency plans is proposed. The main findings and contributions are summarized as follows.

1) PTM is proposed, which improves the accuracy of entity recognition task by randomly masking partial entities in sentences. Compared to BERT-BILSTM-CRF, our method achieves an increase of 1.28% in accuracy, 2.53% in recall and 2.02% in F1 score for entity recognition task, enabling the extraction of emergency entities in water conservancy projects.

2) By employing vector space translation, rotation, and superposition, MCNN is constructed, which enhances the accuracy of relation extraction. Our approach achieves precision, recall and F1 score of 0.898, 0.893 and 0.884, respectively, making it the top-performing method for relation extraction in terms of overall performance.

3) The extracted emergency entity relation triplets are stored in the Neo4j graph database, forming an emergency knowledge graph in the field of water conservancy projects. The retrieval of emergency knowledge and the generation of emergency plans are accomplished using the mutual information criterion.

However, the current approach in this paper fails to take into account the multimodal information present in emergency plan data, which results in a gap between the emergency plans generated using knowledge graphs and their practical application in engineering projects. Future research will focus on addressing the challenges posed by the multimodal aspects of emergency plans.

REFERENCES

[1] H. Kreibich, A. F. Van Loon, and K. Schröter, "The challenge of unprecedented floods and droughts in risk management," *Nature*, 2022, vol. 608, no. 7921, pp. 80–86.

[2] H. Li, F. Li, J. Zuo, J. Sun, C. Yuan, L. Ji, Y. Ma, and D. Yao, "Emergency decision-making system for the large-scale infrastructure: A case study of the south-to-north water diversion project," *J. Infrastruct. Syst.*, vol. 28, no. 1, Mar. 2022, Art. no. 04021051.

[3] E. Z. Berglund, S. Buchberger, M. Cunha, K. M. Faust, M. Giacomoni, E. Goharian, Y. Kleiner, J. Lee, A. Ostfeld, F. Pasha, J. E. Pesantez, J. Saldarriaga, E. Shafiee, L. Spearing, J. E. van Zyl, and Y. C. E. Yang, "Effects of the COVID-19 pandemic on water utility operations and vulnerability," *J. Water Resour. Planning Manage.*, vol. 148, no. 6, Jun. 2022, Art. no. 04022027.

[4] M. Asif and J. Ahmed, "A novel case base reasoning and frequent pattern based decision support system for mitigating software risk factors," *IEEE Access*, vol. 8, pp. 102278–102291, 2020.

[5] J. Dong, X. Li, C. Xu, X. Yang, G. Yang, X. Wang, and M. Wang, "Dual encoding for video retrieval by text," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 44, no. 8, pp. 4065–4080, Aug. 2022.

[6] I. Wennman, C. Jacobson, E. Carlström, A. Hyltander, and A. Khorram-Manesh, "Organizational changes needed in disasters and public health emergencies: A qualitative study among managers at a major hospital," *Int. J. Disaster Risk Sci.*, vol. 13, no. 4, pp. 481–494, Aug. 2022.

[7] F. Li, P. Zhang, X. Huang, J. Sun, and Q. Li, "Emergency decision-making for middle route of south-to-north water diversion project using case-based reasoning and prospect theory," *Sustainability*, vol. 14, no. 21, Oct. 2022, Art. no. 13707.

[8] B. Yang, W. Zheng, and X. Ke, "Forecasting of industrial water demand using case-based reasoning—A case study in Zhangye City, China," *Water*, vol. 9, no. 8, p. 626, Aug. 2017.

[9] S. Basu, S. Roy, and S. DasBit, "A post-disaster demand forecasting system using principal component regression analysis and case-based reasoning over smartphone-based DTN," *IEEE Trans. Eng. Manag.*, vol. 66, no. 2, pp. 224–239, May 2019.

[10] J. Wang, X. Wang, C. Ma, and L. Kou, "A survey on the development status and application prospects of knowledge graph in smart grids," *IET Gener., Transmiss. Distrib.*, vol. 15, no. 3, pp. 383–407, Feb. 2021.

[11] X. Chen, S. Jia, and Y. Xiang, "A review: Knowledge reasoning over knowledge graph," *Expert Syst. Appl.*, vol. 141, Mar. 2020, Art. no. 112948.

[12] E. Persson and M. Granberg, "Implementation through collaborative crisis management and contingency planning: The case of dam failure in Sweden," *J. Risk Res.*, vol. 24, no. 10, pp. 1335–1348, Oct. 2021.

[13] X. Zheng, B. Wang, Y. Zhao, S. Mao, and Y. Tang, "A knowledge graph method for hazardous chemical management: Ontology design and entity identification," *Neurocomputing*, vol. 430, pp. 104–111, Mar. 2021.

[14] Z. Li, Zhao et al., "Transo: A knowledge-driven representation learning method with ontology information constraints," *World Wide Web*, vol. 26, no. 1, pp. 297–319, 2023.

[15] X. Zhu, Z. Li, X. Wang, X. Jiang, P. Sun, X. Wang, Y. Xiao, and N. J. Yuan, "Multi-modal knowledge graph construction and application: A survey," *IEEE Trans. Knowl. Data Eng.*, early access, Nov. 23, 2022, doi: 10.1109/TKDE.2022.3224228.

[16] L. T. H. Lan, T. M. Tuan, T. T. Ngan, L. H. Son, N. L. Giang, V. T. N. Ngoc, and P. V. Hai, "A new complex fuzzy inference system with fuzzy knowledge graph and extensions in decision making," *IEEE Access*, vol. 8, pp. 164899–164921, 2020.

[17] X. Chai, "Diagnosis method of thyroid disease combining knowledge graph and deep learning," *IEEE Access*, vol. 8, pp. 149787–149795, 2020.

[18] Q. Lin, R. Mao, J. Liu, F. Xu, and E. Cambria, "Fusing topology contexts and logical rules in language models for knowledge graph completion," *Inf. Fusion*, vol. 90, pp. 253–264, Feb. 2023.

[19] B. Xue and L. Zou, "Knowledge graph quality management: A comprehensive survey," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 5, pp. 4969–4988, May 2023.

[20] R. Zhu, X. Wu, Y. Hu, Y. Chen, and B. Liu, "OEIS: Knowledge graph based intelligent search system in ocean engineering," in *Proc. 10th Int. Conf. Adv. Cloud Big Data (CBD)*, Nov. 2022, pp. 151–156.

[21] I. Tiddi and S. Schlobach, "Knowledge graphs as tools for explainable machine learning: A survey," *Artif. Intell.*, vol. 302, Jan. 2022, Art. no. 103627.

[22] X. Ye, S. Wang, Z. Lu, Y. Song, and S. Yu, "Towards an AI-driven framework for multi-scale urban flood resilience planning and design," *Comput. Urban Sci.*, vol. 1, no. 1, pp. 1–12, Dec. 2021.

[23] J. Zhang, J. Huang, J. Gao, R. Han, and C. Zhou, "Knowledge graph embedding by logical-default attention graph convolution neural network for link prediction," *Inf. Sci.*, vol. 593, pp. 201–215, May 2022.

[24] H. Li, Y. Wang, S. Zhang, Y. Song, and H. Qu, "KG4 vis: A knowledge graph-based approach for visualization recommendation," *IEEE Trans. Vis. Comput. Graphics*, vol. 28, no. 1, pp. 195–205, Jan. 2022.

[25] G. Lampropoulos, E. Keramopoulos, and K. Diamantaras, "Enhancing the functionality of augmented reality using deep learning, semantic web and knowledge graphs: A review," *Vis. Informat.*, vol. 4, no. 1, pp. 32–42, Mar. 2020.

[26] S. Muñoz and C. A. Iglesias, "A text classification approach to detect psychological stress combining a lexicon-based feature framework with distributional representations," *Inf. Process. Manage.*, vol. 59, no. 5, Sep. 2022, Art. no. 103011.

[27] X. Liu, H. Lu, and H. Li, "Intelligent generation method of emergency plan for hydraulic engineering based on knowledge graph—Take the south-to-north water diversion project as an example," *LHB*, vol. 108, no. 1, Dec. 2022, Art. no. 2153629.

[28] J. Yan, Q. Gao, Y. Yu, L. Chen, Z. Xu, and J. Chen, "Combining knowledge graph with deep adversarial network for water quality prediction," *Environ. Sci. Pollut. Res.*, vol. 30, no. 4, pp. 10360–10376, Sep. 2022.

[29] Y. Cao et al., "Optimizing the power station project management using knowledge graphs," *Distrib. Gener. Alternative Energy J.*, vol. 36, no. 2, pp. 113–124, 2021, doi: 10.13052/dgaej2156-3306.3622.

[30] J. Wu, F. Orlandi, D. O'Sullivan, and S. Dev, "LinkClimate: An interoperable knowledge graph platform for climate data," *Comput. Geosci.*, vol. 169, Dec. 2022, Art. no. 105215.

[31] J. M. Rožanec, B. Fortuna, and D. Mladenić, "Knowledge graph-based rich and confidentiality preserving explainable artificial intelligence (XAI)," *Inf. Fusion*, vol. 81, pp. 91–102, May 2022.

[32] A. Mohammed and R. Kora, "A comprehensive review on ensemble deep learning: Opportunities and challenges," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 35, no. 2, pp. 757–774, Feb. 2023.

[33] G. Menghani, "Efficient deep learning: A survey on making deep learning models smaller, faster, and better," *ACM Comput. Surveys*, vol. 55, no. 12, pp. 1–37, Dec. 2023.

[34] W. Hu, L. He, H. Ma, K. Wang, and J. Xiao, "KGNER: Improving Chinese named entity recognition by BERT infused with the knowledge graph," *Appl. Sci.*, vol. 12, no. 15, p. 7702, Jul. 2022.

[35] Y. Yang, Y. Li, and X. Quan, "UBAR: Towards fully end-to-end task-oriented dialog system with GPT-2," in *Proc. AAAI Conf. Artif. Intell.*, vol. 35, no. 16, 2021, pp. 1–9.

[36] P. Liu, "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing," *ACM Comput. Surv.*, vol. 55, no. 9, pp. 1–35, 2023.

[37] J. Liang, J. Xie, X. Wang, S. Wang, and M. Yu, "Visualization of multi scenario water resources regulation based on a dualistic water cycle framework," *Water*, vol. 14, no. 7, p. 1128, Apr. 2022.

[38] F. Meng, S. Yang, J. Wang, L. Xia, and H. Liu, "Creating knowledge graph of electric power equipment faults based on BERT–BiLSTM–CRF model," *J. Electr. Eng. Technol.*, vol. 17, no. 4, pp. 2507–2516, Jul. 2022.

[39] T. Papadimos, S. Andreadis, I. Gialampoukidis, S. Vrochidis, and I. Kompatsiaris, "Flood-related multimedia benchmark evaluation: Challenges, results and a novel GNN approach," *Sensors*, vol. 23, no. 7, p. 3767, Apr. 2023.

[40] A. Zhao and Y. Yu, "Knowledge-enabled BERT for aspect-based sentiment analysis," *Knowl.-Based Syst.*, vol. 227, Sep. 2021, Art. no. 107220.

[41] J. Yang, X. Yang, R. Li, M. Luo, S. Jiang, Y. Zhang, and D. Wang, "BERT and hierarchical cross attention-based question answering over bridge inspection knowledge graph," *Expert Syst. Appl.*, vol. 233, Dec. 2023, Art. no. 120896.

[42] S. Yoo and O. Jeong, "Automating the expansion of a knowledge graph," *Expert Syst. Appl.*, vol. 141, Mar. 2020, Art. no. 112965.

[43] Z. Zhang, "CPM: A large-scale generative Chinese pre-trained language model," *AI Open*, vol. 2, pp. 93–99, Jan. 2021.

[44] J. Pennington, R. Socher, and C. Manning, "Glove: Global vectors for word representation," in *Proc. Conf. Empirical Methods Natural Lang. Process. (EMNLP)*, 2014, pp. 1532–1543.

[45] Z. Ma, W. Zheng, X. Chen, and L. Yin, "Joint embedding VQA model based on dynamic word vector," *PeerJ Comput. Sci.*, vol. 7, p. e353, Mar. 2021.

[46] K. Han, A. Xiao, E. Wu, J. Guo, C. Xu, and Y. Wang, "Transformer in transformer," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 34, 2021, pp. 15908–15919.

[47] X. Xiong, T. Zhu, Y. Zhu, M. Cao, J. Xiao, L. Li, F. Wang, C. Fan, and H. Pei, "Molecular convolutional neural networks with DNA regulatory circuits," *Nature Mach. Intell.*, vol. 4, no. 7, pp. 625–635, Jul. 2022.

[48] Z. Han, M. Jian, and G.-G. Wang, "ConvUNeXt: An efficient convolution neural network for medical image segmentation," *Knowl.-Based Syst.*, vol. 253, Oct. 2022, Art. no. 109512.

[49] R. Ameri, A. Alameer, S. Ferdowsi, K. Nazarpour, and V. Abolghasemi, "Labeled projective dictionary pair learning: Application to handwritten numbers recognition," *Inf. Sci.*, vol. 609, pp. 489–506, Sep. 2022.

[50] S. Shi, L. Xu, W. Gong, B. Chen, B. Chen, F. Qu, X. Tang, J. Sun, and J. Yang, "A convolution neural network for forest leaf chlorophyll and carotenoid estimation using hyperspectral reflectance," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 108, Apr. 2022, Art. no. 102719.

[51] Y. Zhou, J. Li, J. Chi, W. Tang, and Y. Zheng, "Set-CNN: A text convolutional neural network based on semantic extension for short text classification," *Knowl.-Based Syst.*, vol. 257, Dec. 2022, Art. no. 109948.

[52] M. Erzina, A. Trelin, O. Guselnikova, A. Skvortsova, K. Strnadova, V. Svorcik, and O. Lyutakov, "Quantitative detection of α1-acid glycoprotein (AGP) level in blood plasma using SERS and CNN transfer learning approach," *Sens. Actuators B, Chem.*, vol. 367, Sep. 2022, Art. no. 132057.

[53] J. Wang, W. Xu, X. Fu, G. Xu, and Y. Wu, "ASTRAL: Adversarial trained LSTM-CNN for named entity recognition," *Knowl.-Based Syst.*, vol. 197, Jun. 2020, Art. no. 105842.

[54] Z. Wang, P. Ma, Z. Chi, D. Li, H. Yang, and W. Du, "Multi-attention mutual information distributed framework for few-shot learning," *Expert Syst. Appl.*, vol. 202, Sep. 2022, Art. no. 117062.

[55] Y. Wang, W. Pang, and Z. Jiao, "An adaptive mutual K-nearest neighbors clustering algorithm based on maximizing mutual information," *Pattern Recognit.*, vol. 137, May 2023, Art. no. 109273.

[56] P. Teisseyre and J. Lee, "Multilabel all-relevant feature selection using lower bounds of conditional mutual information," *Expert Syst. Appl.*, vol. 216, 2023, Art. no. 119436.

[57] S. Yang, B. Cai, T. Cai, X. Song, J. Jiang, B. Li, and J. Li, "Robust cross-network node classification via constrained graph mutual information," *Knowl.-Based Syst.*, vol. 257, Dec. 2022, Art. no. 109852.

[58] O. A. M. Salem, F. Liu, Y.-P.-P. Chen, A. Hamed, and X. Chen, "Fuzzy joint mutual information feature selection based on ideal vector," *Expert Syst. Appl.*, vol. 193, May 2022, Art. no. 116453.

[59] X. Huang, Y. Ye, X. Yang, and L. Xiong, "Multi-view dynamic graph convolution neural network for traffic flow prediction," *Expert Syst. Appl.*, vol. 222, Jul. 2023, Art. no. 119779.

[60] G. Lee, S. Lee, and C. Lee, "Inventor–licensee matchmaking for university technology licensing: A fastText approach," *Technovation*, vol. 125, Jul. 2023, Art. no. 102765.

LIHU WANG received the M.S. degree from the North China University of Water Resources and Electric Power, in 2022, where he is currently pursuing the Ph.D. degree in management science and engineering.

His research interests include knowledge graph, intelligent cloud computing, machine learning, and deep learning. From 2019 to 2022, three first-class scholarships, one national scholarship, and third prize at provincial level in the internet plus national entrepreneurship competition.

XUEMEI LIU received the M.S. degree from the Beijing University of Aeronautics and Astronautics, Beijing, China, in 1992, and the Ph.D. degree from Northwestern Polytechnical University, Xi'an, China, in 2008. Then, she spent several years as a Postdoctoral Researcher with the Beijing University of Aeronautics and Astronautics. She is currently a Professor and a Ph.D. Supervisor with the North China University of Water Resources and Electric Power. Her current research interests include data mining, machine learning, virtual reality, and intelligent water conservancy.

YANG LIU was born in Kaifeng, Henan, China, in 1979. She received the B.S. degree in computer application technology from the University of Shanxi, Taiyuan, in 2002, the M.S. degree in computer application technology from the University of Electronic Science and Technology of China, Chengdu, in 2005, and the Ph.D. degree in information and signal processing from the Institute of Optoelectronics Technology, Chinese Academy of Sciences, Chengdu, in 2012.

From 2002 to 2005, she was with the Tenth Research Institute of China Electronics Technology Group and became a Software Engineer. Since 2012, she has been with the North China University of Water Resources and Electric Power. In 2015, she was an Associate Professor and a Postgraduate Tutor. She has published more than 30 papers, including more than 20 papers included by SCI and EI, and presided more than 20 scientific research projects. Her research interests include intelligent water conservancy, machine learning, and mathematical sequence analysis.

HAIRUI LI received the M.D. degree from the North China University of Water Resources and Electric Power, in 2015, where he is currently pursuing the Ph.D. degree in management science and engineering. His research interests include operational management of hydraulic engineering, data mining, and machine learning techniques.

JIAQI LIU (Graduate Student Member, IEEE) received the M.S. degree from the North China University of Water Resources and Electric Power, in 2021, where he is currently pursuing the Ph.D. degree in hydraulic engineering. His research interests include knowledge graph and smart water conservancy.

LIBO YANG received the B.S. and M.S. degrees in computer science from the North China University of Water Resources and Electric Power, Zhengzhou, China, in 2004 and 2011, respectively, where he is currently pursuing the Ph.D. degree. His current research interests include machine learning, pattern recognition, data mining, and information management.