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Application of Automatic Completion Algorithm of Power Professional Knowledge Graphs in View of Convolutional Neural Network

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ABSTRACT

With the continuous development of electric power informatization, a large amount of electric power data information has been produced. The reasonable application of electric power database is of great significance. Building the automatic completion optimization algorithm of knowledge graphs (KGs) in power professional field provides a method to extract structured knowledge from a large number of power information and images, which has broad application value. The automatic completion algorithm of power professional KGs in view of convolutional neural network (CNN) is conducive to completing the analysis and management of power data, enabling the flexible use of data information generated by the power grid, and bringing ideas for the in-depth exploration and innovation of power grid data information application.

KEYWORDS

Automatic Completion Algorithm, Evolutionary Neural Network, Knowledge Graphs, Power Professional

INTRODUCTION

At present, the rapid development of many fields cannot be separated from power. However, with the innovation and development of energy management systems worldwide, the traditional power field also needs to transform to informationized power; thus, the innovation and transformation of power systems is imperative. Knowledge Graphs (KGs) are an intelligent database system that combines artificial intelligence with traditional databases. It can realise structural management of large-scale knowledge. By integrating KGs with the power professional field, the scattered knowledge points in the power field can be connected. This study proposes an automatic completion algorithm of power professional KGs on the basis of convolutional neural networks (CNNs). This study hopes to provide support for electric power companies to grasp the development trend and construction of the field firmly.

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Research on KGs has always attracted the attention of many experts and scholars. Such research plays an important role in intelligent search (It refers to the one-stop search for all mainstream resources that can be found on the Internet such as web pages, music, games, pictures, movies, and shopping) and decision-making. At present, Hogan (2021) has made a comprehensive introduction to KGs, compared various data models in view of the graphs, and compared the languages used to query and verify KGs. He explained how to use a combination of deductive and inductive techniques to represent and extract knowledge. Finally, he gave the advanced research direction of Knowledge Graphing for the future (Hogan, 2021). Ji (2021) comprehensively reviewed KGs, covering the overall research topics, including KG representation learning, KG knowledge acquisition and completion, time KGs, and knowledge perception application. He reviewed embedding methods, path reasoning, and logic rule reasoning. To promote future research on KGs, he also provided a planning set of datasets and open-source libraries for different tasks (Ji, 2021). Wang (2017) introduced the technology of embedding using only the facts observed in the KGs. He described the overall framework, specific model design, typical training procedures, and advantages and disadvantages of these technologies. He briefly introduced how KG embedding was applied to various downstream tasks, such as KG completion, relationship extraction, question answering, and so on (Wang, 2017). Noy (2019) focused on the KG of five different technology companies and compared their similarities and differences in building and using these maps. He discussed the challenges facing all knowledge-driven enterprises. The KG set discussed here consists of the products searched and the social networks described (Noy, 2019). These studies play an important role in promoting the development of KGs.

Others have different ideas about the above research. Qian (2017) introduced KGs to express explicitly the attacker's arbitrary prior beliefs about any single user. On the basis of the KGs, he formulated the process of anonymisation and privacy reasoning. Experiments on real social network data show that KGs can enhance deanonymisation and inference attacks. This finding shows the effectiveness of KGs as a universal and effective model of attackers' background knowledge for social network attacks and privacy protection (Qian, 2017). Lampropoulos et al. (2020) showed how to improve augmented reality (AR) functions and services when integrating deep learning, semantic networks, and KGs and showed the potential of their combination in developing contemporary, user-friendly, and user-centred intelligent applications. They discussed how the integration of deep learning, semantic web, KGs, and AR can improve the experience quality and service quality of AR applications to promote and improve users' daily lives (Lampropoulos et al., 2020). Li (2019) proposed a process Knowledge Graphs method for process reuse. Under the guidance of the pattern layer of process KGs, he introduced the latent semantic analysis technology to analyse the knowledge of machining process cases and calculate the similarity between process cases. He transformed process instance knowledge into formal representation of structured process KGs and realised the instantiation process of the KG model layer to obtain processed KG data layers (Li, 2019). Rotmensch (2017) derived a disease-symptom graph from her learned parameters, and evaluated and validated the constructed knowledge graph with permission against a manually constructed knowledge graph at Google and input from expert physicians. Research shows that high-quality health KGs can be built directly and automatically from medical records by using basic concept extraction (Rotmensch, 2017). These studies apply KGs to specific applications and study the construction methods of KGs in view of different technologies, further proving the importance of KGs.

The KGs can not only directly show knowledge in the form of connected graphs according to the visual model to obtain the relationship between the knowledge but also realise the accurate search of a large amount of knowledge information in a short time and complete the statistical analysis through the intelligent search function. Building KGs of electric power professional equipment and automatically completing relevant electric power professional knowledge can result in efficient work on relevant electric power equipment knowledge, complete knowledge storage, intelligent retrieval, auxiliary decision-making, and other services in the electric power professional field. In this study, the automatic construction of power equipment KGs and knowledge completion technology are studied on the basis of the CNN algorithm to complete the intelligent query of power equipment-related knowledge. This study provides support for the creation of an intelligent operation and maintenance system for power professional equipment.

AUTOMATIC COMPLETION ALGORITHIM OF POWER PROFESSIONAL KGS

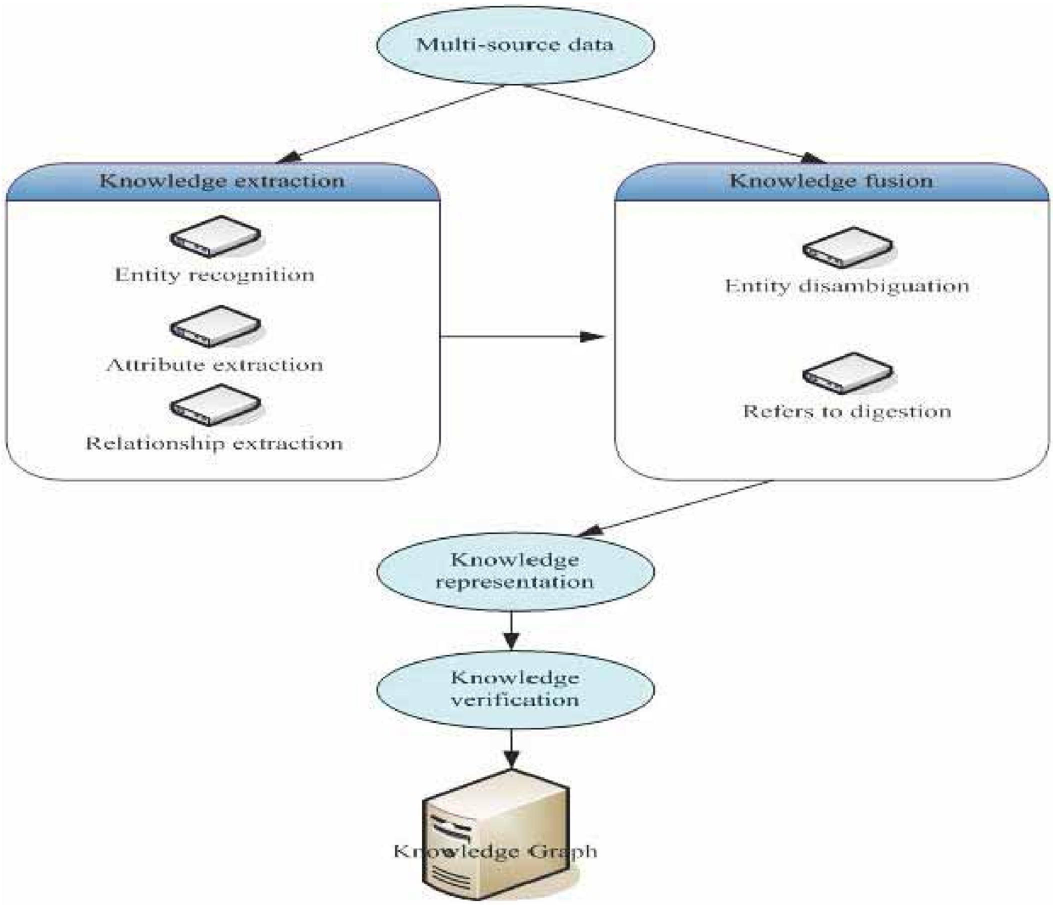
KG-Related Concepts

KG technology has been developing rapidly in recent years and has been increasingly used in the natural language understanding industry, such as in the fields of device reading and knowledge interactive Q&A. KG generalisation is essentially a kind of semantic network where connection points represent entities or attributes and edges represent various semantic relationships among entities and between entities and attributes. Among them, entities refer to objects that exist in the real world and have distinctive features (e.g., apples, footballs). Attributes are information content describing the characteristics of entities, such as total volume, maturity, etc; it is the information content that describes the characteristics of an entity. Connection is the most important feature of KGs; it can achieve the interconnection between things and then provide support for semantic understanding, information retrieval, and other applications. The technology of KG construction mainly includes knowledge extraction, knowledge combination, knowledge demonstration, knowledge authentication, and knowledge logic reasoning. The process framework of KG construction is shown in Figure 1. It forms a remarkably large semantic network diagram. The connection point represents the entity, the edge represents the relationship between the two entities, and the edge and the connection points at both ends form a triple. Head entity, association, and tail entity are its main forms. Power professional KGs can provide services, such as knowledge storage, intelligent search, and assistant decision-making related to the operation and maintenance of power engineering equipment. However, some large-scale KGs, such as the world knowledge base and multilingual knowledge base, are generally incomplete, lacking many effective triples. Therefore, this paper proposes KG to complement and solve these problems. KG complementation is also called link prediction; that is, it predicts and analyses whether a triple is correct knowledge. The method used is mainly based on the entity model of knowledge representation (Gutierrez & Juan, 2021; Tiwari et al., 2021).

Electric power equipment refers to machines that are responsible for the transmission and conversion of electromagnetic energy in a power supply system. It is relatively expensive and has a complicated structure. To ensure the stable operation of a power supply system, daily operation and maintenance management of electric equipment must be conducted. Operation and maintenance management mainly includes online monitoring, status evaluation, common fault prediction, and maintenance of machines. The professional knowledge required by the operation and maintenance management method is complex; thus, one must rely on substantial basic theoretical knowledge and expert experience. Therefore, the professional quality of operation and maintenance personnel has high regulations. To reduce the subjective decision of the operation and maintenance staff in the evaluation and resolution process of the daily operation and maintenance of electric equipment and to improve the operation and maintenance level, a map of power professional knowledge must be built (Wang & Liu, 2019).

Most of the pictures of power professional knowledge are created manually. However, manually created power professional KGs include only the existing basic theory and experience information; the knowledge system is relatively simple, but the content is not rich and colourful, and the relationship between the entity lines of professional knowledge is not fully explored (Chen et al., 2021). Therefore, a solution is needed to complete the manually created power professional KGs automatically.

Figure 1. Construction of KGs



Concepts Related to CNNs

CNNs are a kind of deep neural network containing convolution and structure. Their core content is to use partial perception, weight value sharing, and pooling layers to simplify network parameters and reduce model complexity. CNNs can be considered an upgrade of multilayer perceptron. The difference between them lies in the feature extraction algorithm. The multilayer perceptron adopts the form of full connection layer, whereas the CNN adopts the form of partial connection. CNNs use the form of partial connection to reduce the complexity of the model, thus reducing the risk of multicollinearity (Yamashita, 2018; Cong et al., 2019).

CNNs have the advantages of convenient data entry, simple practice, fewer main parameters, and good scalability. They are widely used in digital image processing, target detection, knowledge representation, and other research directions. In recent years, an increasing number of researchers have used CNNs to solve the text content in the KGs because they are convenient for typing data types. Especially in the field of KG completion, CNNs are used to enhance the ability of the model to obtain the characteristics of triples. Convolution and pooling operations also play a role in feature extraction and are an integral part of CNNs (Khan, 2020; Lindsay, 2021).

In the process of machine learning, for the input data, convolution kernels refer to the main parameters after optimisation. The convolution operation uses the characteristics of partial cognition and interworking of weight values to reduce the complexity of the model. After the convolution operation, the input data can be used for feature acquisition to generate feature graphs. However, the level of these feature graphs is usually high, which is not conducive to model practice. Therefore, to simplify the calculation, data in the feature image must be filtered and the key features must be saved, which is called pooling operation. Pooling results in a feature subgraph of lower dimensions. The pooling operation has two pooling methods: maximum pooling and average pooling (Khan et al., 2019). Its division is based on different aggregation methods. The former one extracts the local highest value, whereas the latter extracts the local mean value (Markiewicz & Koperwas, 2022). It also belongs to the convolution process. The special convolution kernel is used to complete the maximum pooling and average pooling operations. The pooling operation not only maintains the characteristics of mobile balance but also greatly reduces the amount of computation and optimises the phenomenon of multicollinearity.

AUTOMATIC COMPLETION ALGORITHM OF POWER PROFESSIONAL KGS

The continuous emergence of many innovative and cross-research achievements in the field of electric power engineering has prompted the substantial expansion of the technical standard system in the field of electric power engineering. How to describe accurately and track the technical standard system and its changes quickly in this field has become a problem that needs to be solved urgently. It is an important way to obtain technical terms in this field from multiple databases and analyse their relevance. This situation can be projected to the KG field, which is the process of building more classic power professional KGs.

This study uses a three-stage solution that includes semantic modelling of label text documents, semantic association measurement of labels, and structural analysis modelling based on autonomous learning. Figure 2 shows the construction method of power professional KGs. It mainly conducts semantic modelling for label text documents. Generally, tags are likely to imply many kinds of semantics. To grasp the inherent semantic relationship and semantic similarity between label text documents, the linear space model or language expression model is generally used to model semantic association. Given that the description level of the semantic relationship between the two models is limited, the word embedding method is used. Word embedded representation refers to the representation of words and sentences as continuous real value vectors. The actual way is to maximise the co-occurrence probability of keywords by relying on the Skip Gram model. Given that the images caused by tags seriously affect the correlation between words and potential hot spots, a tag topic discussion model is given for description. Parameter estimation is required when calculating probability, and Gibbs sampling is used for this. Although this model can create potential semantic descriptions of labels according to text documents, the occurrence relationship between labels has not been comprehensively considered. It must establish a co-occurrence Internet of Labels and then define label blending according to the Internet to achieve the goal of topic smoothing.

Figure 3 shows the power professional KG completion model based on CNN. It is composed of three parts: associative link feature representation, servo motor encoder based on CNN, and video decoder based on the semantic pairing model. The encoding-and-decoding model is a common architecture in deep learning, which uses the entire process of encoding and decoding to complete the conversion of encoding sequence space vector. The KG completion method in this text is based on the graph embedding generated by the power professional knowledge representation learning, and it is the process of computing the low-dimensional vector representation built by the semantic characteristics of the KGs.

In this study, a CNN-based power professional KG completion algorithm is proposed. Its technical core is the image embedding method of professional knowledge representation and learning. The learning of professional knowledge representation has brought a unified low-level low dimension embedding to top-level word meaning computing, which alleviates the problem of rare graph nodes and greatly improves computing efficiency. It is widely used in many complex word meaning mining

Figure 2. Construction method of power professional KGs

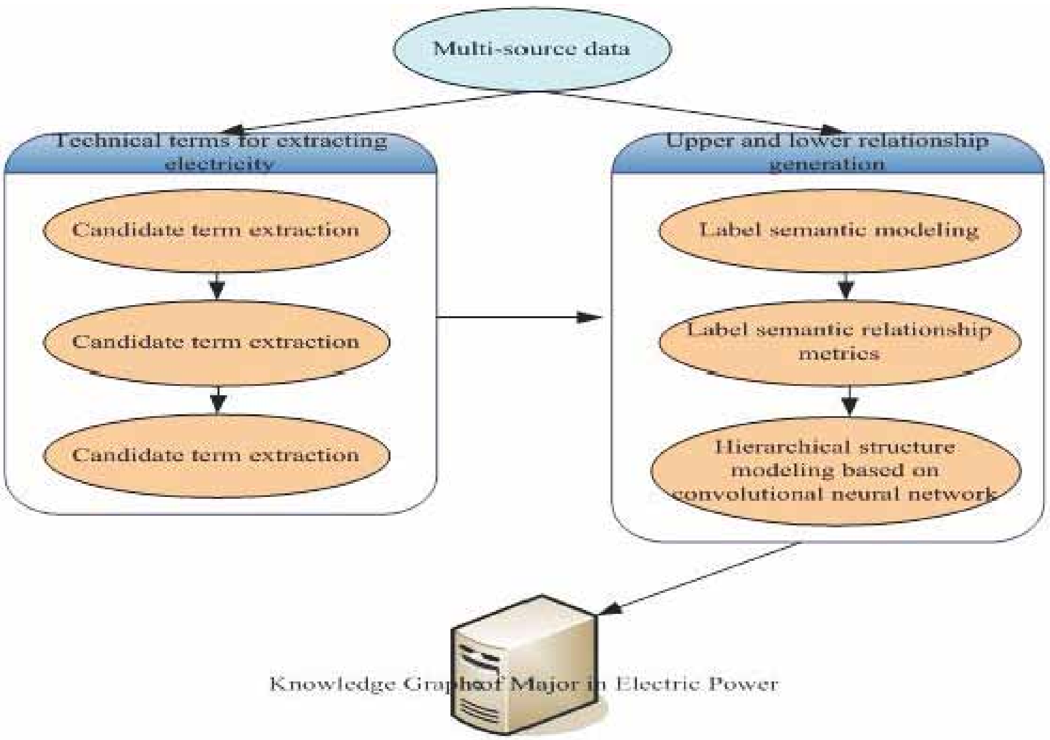
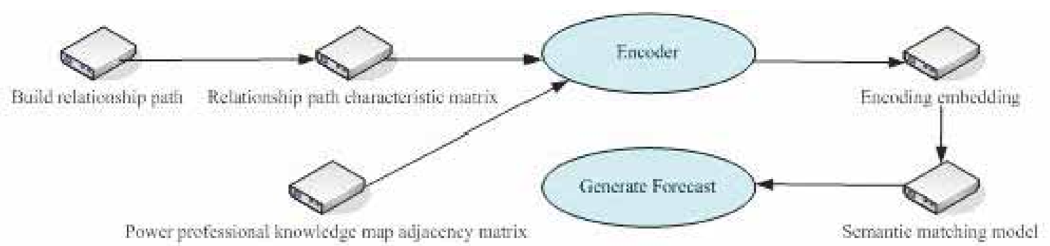


Figure 3. Power professional KGs completion model in view of CNN



tasks such as the construction and completion of electric power professional KG, intelligent question answering, etc. When completing power professional KGs, building an embedded system that includes diverse features is a technical key and difficult problem. The completion of a power professional knowledge atlas belongs to the field of machine learning algorithms. The data and various features contained in it are key to determining the performance of models and algorithms.

At this stage, the KG completion method is more focused on obtaining its low dimension embedding, which is used for triplet prediction analysis. The multistep relationship path is one of the features with high value. Therefore, this study selects the relationship link information content between entities as an additional feature when building features. Relational link is the semantic connection implied in KG information. It is the content of the connection structure information involved in the graph data. It can be calculated on such multi-relationship graphs as the power professional KGs. From the perspective of graph network architecture, the prediction and analysis of the relationship between entities are used to see whether edges that can connect the two ends exist. In consideration of the characteristics of KGs as word-meaning graphs, if two entities can be connected indirectly in accordance with other entities and relationships, these two entities can probably be connected through some kind of relationship to form new power KGs. Figure 4 shows the framework of the entity relationship extraction model of power professional KGs.

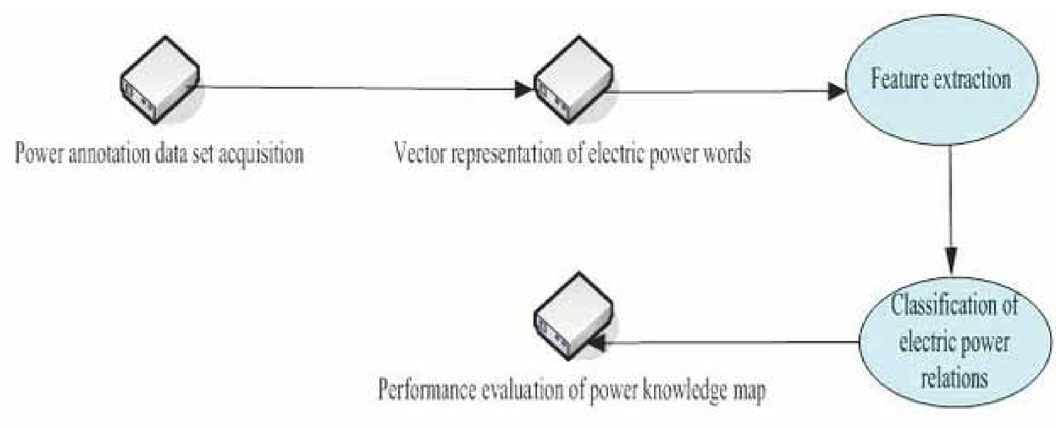
The servo motor encoder is designed as a three-layer neural network structure to build the embedding of power professional KGs, learn the characteristics of the training structure data, and derive the corresponding code representation. On the lowest level of low dimension embedding, the servo motor encoder based on the CNN algorithm is applied to conduct end-to-end learning and training of features. The structure of the relationship graph of the power professional KGs is relatively complex, connecting knowledge and data information; thus, a feature learning algorithm is designed. This method must learn the structural and semantic characteristics of power professional KGs.

The structural characteristics of the network itself and the semantic information contained in the KGs are two characteristics of the KGs. This study uses the relevant feature information of the CNN and brings more learning and training references to the neural network through the semantic information of the power professional KGs to improve the self-learning ability of the power professional KG model. The relation link feature can be used to type the CNN model, and the CNN model can be improved by using the fusion relation type. When the power professional knowledge atlas complements the actual task, feature embedding can be learned in accordance with the model servo motor. This is also a representation of entities and associations in the power professional KGs. In the future, a scoring function formula must be designed to score the relevant triplets and finally screen and rank them according to the score. The design goal of the KG complement model is to make the objective fact triple rank as high as possible in the relevant permutation. The video decoder of the original intention model embeds the features obtained by the automatic encoder into the predictive analysis connection between solid lines for scoring to determine whether it can be included in the existing edge set. In the design of the video decoder, the semantic model is used instead of pure scoring function. This kind of model takes the embedding of entity lines with diversified features as the original way of score calculation, which is more effective than the way of using only scoring functions.

This study proposes the application of the automatic completion algorithm of power professional KGs on the basis of the CNN, which involves the following formulae:

$$\mathrm{Rank}_{e} = \left|\left\{c\epsilon' \setminus \left\{e\right\} : \varnothing\left(k,y,c\right) > \varnothing\left(k,y,e\right)\right\}\right| + 1\,, \tag{1}$$

Figure 4. Entity relationship extraction model of power professional KGs



where e is the target tail entity of electric power discipline, Rank_e is the ranking of the target tail entity of electric power discipline, and (k, y, c) denotes the test triplet

$$\mathrm{Rank}_e = \left|\left\{c\epsilon' \setminus \{e\} : \varnothing(k,y,c) > \varnothing(k,y,e) \wedge (k,y,c) \notin T\right\}\right| + 1, \tag{2}$$

$$R_{a,b} = (W*\acute{A})_{a,b} = \sum_m \sum_n W_{a+m,b+n} \acute{A}_{m,n}, \tag{3}$$

where R denotes convolved feature graphs, dimensions in a and b represent feature graphs, W denotes input data, A denotes the convolution kernel, and m and n are convolution kernel dimensions

$$U_d^f = ,(\sum_r U_r^{f-1} * \acute{A}_d^f), \tag{4}$$

where , is the activation function, r is the number of electric power specialty characteristic maps, U is the characteristic diagram of electric power discipline, U_d^f is the characteristic diagram of the f convolution layer obtained after convolution, and $*$ is the convolution operation

$$\hat{p} = S^J p, \tag{5}$$

where P is the original vector of electric power discipline, $\hat{p}$ is the transformed vector, and S^J is the transposition of the characteristic matrix

$$p_a \tilde{*} p_b = S\left((S^J p_a) \odot (S^J p_b)\right), \tag{6}$$

where $\tilde{*}$ is the convolution operation on the electric power characteristic diagram, and $\odot$ is the Hadamard product

$$J_a = \mathrm{Range}(Q_a) = \mathrm{dom}(Q_{a+1}), \tag{7}$$

where $\mathrm{dom}(Q_{a+1})$ is the knowledge field, $\mathrm{Range}(Q_a)$ is the knowledge field range, and J_a is the entity node

$$k_{i,Q_{(u)}} = \begin{cases} 1, & u = i \\ 0, & otherwise \end{cases}, \tag{8}$$

where $k_{i,Q_{(u)}}$ is the probability of node u reaching node i

$$k_{i,Q_{(u)}} = \sum_{u' \in \mathrm{range}(Q')} k_{i,Q_{(u)}} \bullet Q(u \mid u'; E_a), \tag{9}$$

$$h_u\left(K_a^{(A)}, K_b^{(A)}\right) = \sum_{e \epsilon E} \sum_{b \epsilon L_a'} \frac{\operatorname{conv}\left(T_0 K_a^{(A)}, T_e^A K_b^{(A)}\right)}{\left|L_a^e\right|}, \tag{10}$$

where T_e^A is the relation-based weight matrix

$$T_e^{(A)} = D \oplus dX_{de}^{(A)}, \tag{11}$$

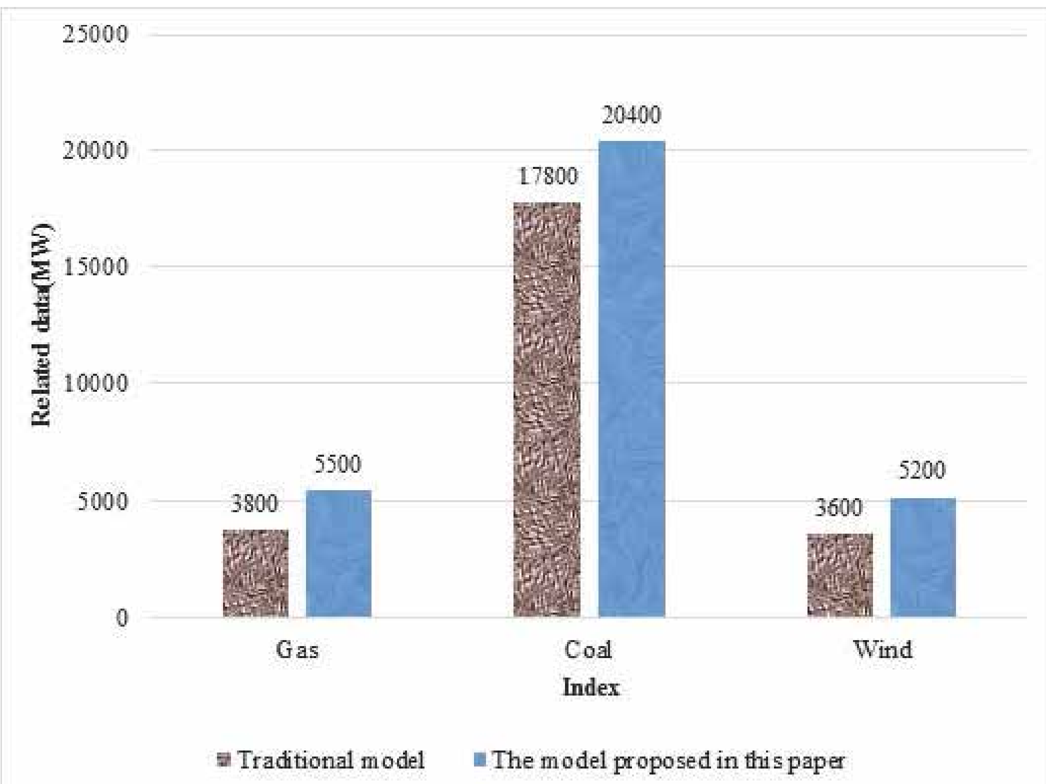
where $\oplus$ denotes matrix splicing, and $X_{de}^{(A)}$ is the decomposed power vector.

AUTOMATIC COMPLETION EXPERIMENT OF POWER PROFESSIONAL KGS

To verify the effect of the automatic CNN-based completion algorithm of power professional KGs in power equipment, this study conducted corresponding experiments. The relevant experimental results are as follows:

Installed capacity refers to the sum of the maximum power of all steam turbines or hydroelectric generating units often equipped in thermal power plants or hydropower stations. It is one of the key indicators that show the scale of a thermal power plant or hydropower station project and the production of electric power projects. The installed capacity is mainly based on the demand of the capital construction

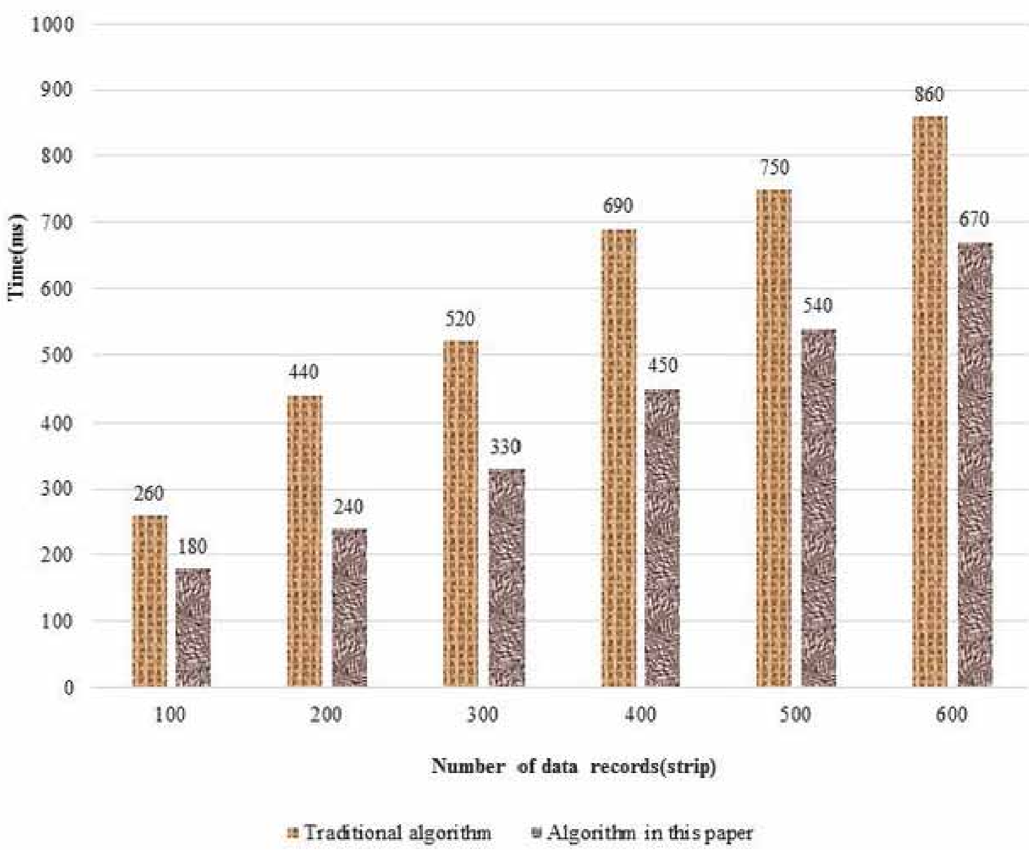
Figure 5. Comparison of installed capacity between traditional mode and the model in this chapter



development plan of the power industry, which is determined by the power group or other relevant technical departments through comprehensive analysis of various aspects of different plans. The installed capacity of the power system in a certain area using the traditional model and the model proposed in this study after knowledge completion are tested and compared. Figure 5 shows the statistical chart of the comparison of installed capacity between the traditional model and this model. Overall, the total installed capacity of the power supply under the knowledge completion model of the CNN proposed in this study is 31,100 MW, which is remarkably higher than the 25,200 MW under the traditional model. The total installed capacity of the proposed algorithm is about 23.41% higher than that of the traditional model. Specifically, the installed capacity of wind power in this region under the traditional model planning is only 3,600 MW, whereas the installed capacity of wind power in this region has increased by 1,600 MW after knowledge supplementation. Under the traditional model planning, the gas turbine assembly capacity in this region is only 3,800 MW, but after knowledge improvement, the gas turbine assembly capacity in this region increased by 1,700 MW. Under the traditional model planning, the gas turbine assembly capacity in this region is only 17,800 MW, but after knowledge improvement, the gas turbine assembly capacity in this region increased by 2,600 MW. After knowledge completion based on CNN, power resource allocation is considerably optimised.

The comparison experiment of the operation time required for grid data processing between the algorithm proposed in this study and a traditional algorithm is shown in Figure 6. With the algorithm proposed in this text, the power grid operation time is considerably shorter than the traditional model.

Figure 6. Comparison of grid operation time between traditional algorithm and algorithm proposed in this chapter



Under the traditional algorithm, the power system needs 260 ms to process 100 pieces of data, whereas under the CNN-based knowledge completion algorithm, it needs only 180 ms. The algorithm proposed in this study is 80 ms faster than the traditional algorithm. With the increase of data processing times, the running time of the power system based on the CNN knowledge completion algorithm proposed in this study does not fluctuate considerably. Compared with that of traditional algorithms, the running time required for processing data is shorter and more stable. This finding proves that the knowledge completion algorithm based on CNN is effective in terms of the running time of power grid data processing. For the power system, the faster the processing speed is, the higher the efficiency is, which is crucial to providing decision making or finding faults.

By using the proposed CNN-based knowledge completion algorithm, 500 test sample images are tested for fault detection, including 380 fault sample images and 120 normal sample images. The failure sample rate is 76%, and the normal sample rate is 24%. Figure 7 shows the statistical diagram of the results of the CNN-based knowledge completion algorithm for power equipment fault detection. A total of 380 sample images have faults; 377 are correctly detected, and three are incorrectly detected. The correct recognition rate of sample detection is 99.21%. In addition, all normal sample images are correctly detected, and the correct recognition rate of sample detection is 100%. The proposed CNN-based knowledge completion algorithm has a high recognition accuracy rate for power equipment fault detection, and the recognition accuracy rate for normal samples and fault samples reaches higher than 99%, which greatly improves the accuracy rate in specific industrial production operation processes. In the subsequent practical application, with the accumulation of data samples, the accuracy of recognition and classification must be further improved.

The proposed knowledge completion algorithm in this study is used for the fault detection of some main power equipment parts to verify the effect of knowledge completion. Figure 8 shows the comparative statistical diagram of the classification effect of power equipment fault detection. The average accuracy of the proposed knowledge completion algorithm for each key part reaches higher than 97%. The average accuracy of the disconnector, arrester, circuit breaker, current transformer, voltage transformer, and bushing is 98.47%, 97.52%, 98.21%, 97.78%, 97.33%, and 98.89%, respectively. Under the traditional algorithm, the average fault accuracy of these parts is only about 92%–93%. The proposed CNN-based

Figure 7. Results of power equipment fault detection using knowledge completion algorithm in view of CNN

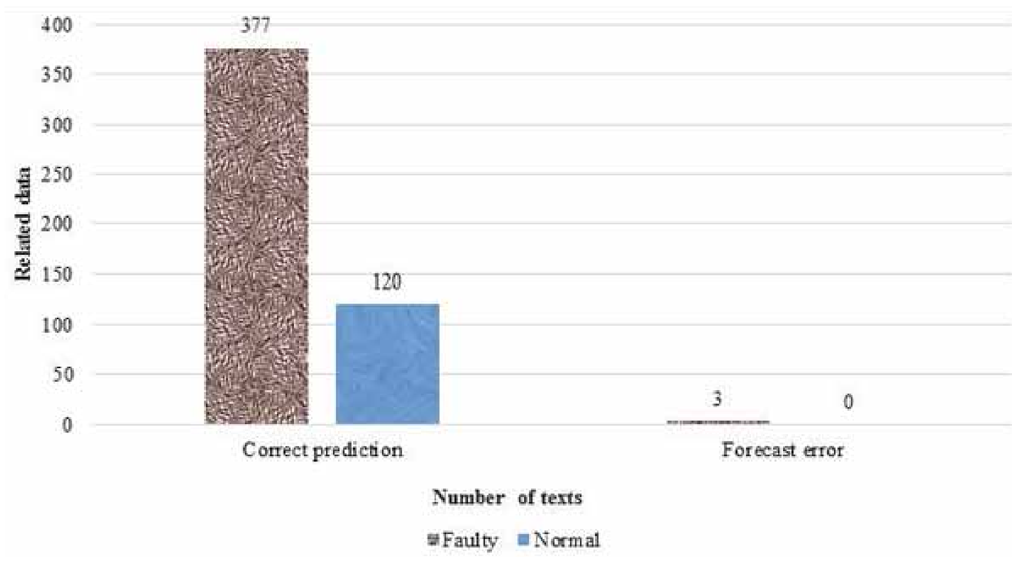
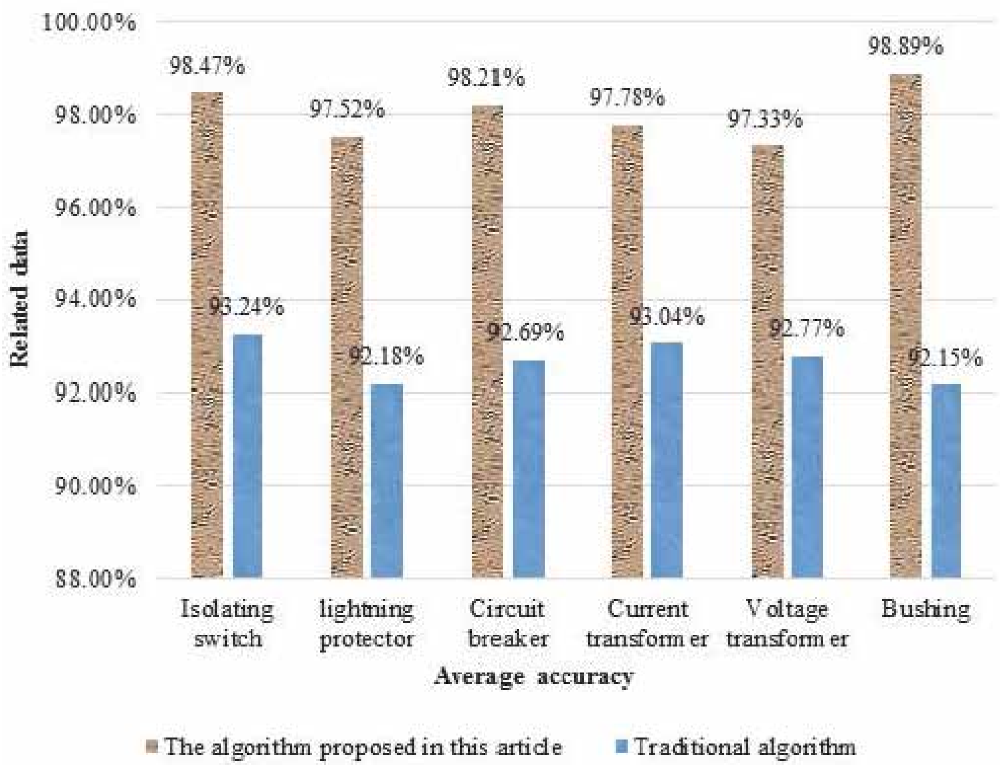


Figure 8. Comparison of classification effects of power equipment fault detection



knowledge completion algorithm remarkably improves the accuracy of fault detection for key parts compared with traditional algorithms. This result provides crucial support for staff decision making in actual testing work and can greatly meet the needs of actual work.

CONCLUSION

Nowadays, the amount of information on the Internet is growing explosively. KGs can transform unstructured and semi-structured information into structured knowledge, provide information directly and clearly, and improve the efficiency of using Internet resources. KG completion obtains entity and relation vectors through knowledge representation and learning and plays an important role in link prediction, triad classification, and other tasks. To promote the power system to move towards automation and intelligence, electric power artificial intelligence technology must be explored. Given that KGs have many advantages in knowledge organisation, this study combines KGs with the power field to build KGs of power equipment and proposes to use CNN technology to complete the KGs of power equipment automatically. The experimental results show that the proposed algorithm considerably improves power resource allocation, power grid operation time, and power equipment fault detection in comparison with traditional algorithms, thus verifying the effectiveness of the proposed algorithm. However, this research is limited in terms of personal ability; at this stage, the experimental samples are not enough, the scope of the experiment is not wide enough, and the research results still lack certain scientificity and credibility. Therefore, in the future, more in-depth and extensive experiments must be carried out to obtain more accurate experimental results.

REFERENCES

Chen, S., Xiao, H., He, W., Mou, J., Siponen, M., Qiu, H., & Xu, F. (2021). Determinants of individual knowledge innovation behavior: A perspective of emotion, knowledge sharing, and trust. [JOEUC]. *Journal of Organizational and End User Computing*, *33*(6), 1–24. doi:10.4018/JOEUC.20211101.oa27

Cong, I., Soonwon, C., & Mikhail, D. L. (2019). Quantum CNNs. *Nature Physics*, *15*(12), 1273–1278. doi:10.1038/s41567-019-0648-8

Gutierrez, C., & Juan, F. S. (2021). Knowledge Graphs. *Communications of the ACM*, *64*(3), 96–104. doi:10.1145/3418294

Hogan, A., Blomqvist, E., Cochez, M., D'amato, C., Melo, G. D., Gutierrez, C., Kirrane, S., Gayo, J. E. L., Navigli, R., Neumaier, S., Ngomo, A.-C. N., Polleres, A., Rashid, S. M., Rula, A., Schmelzeisen, L., Sequeda, J., Staab, S., & Zimmermann, A. (2021). Knowledge graphs. *ACM Computing Surveys*, *54*(4), 1–37. doi:10.1145/3447772

Ji, S. X., Pan, S., Cambria, E., Marttinen, P., & Yu, P. S. (2021). A survey on knowledge graphs: Representation, Acquisition, and Applications. *IEEE Transactions on Neural Networks and Learning Systems*, *33*(2), 494–514. doi:10.1109/TNNLS.2021.3070843 PMID:33900922

Khan, A. (2020). A survey of the recent architectures of deep CNNs. *Artificial Intelligence Review*, *53*(8), 5455–5516. doi:10.1007/s10462-020-09825-6

Khan, A. N., Cao, X., & Pitafi, A. H. (2019). Personality traits as predictor of m-Payment systems: A SEM-neural networks approach. [JOEUC]. *Journal of Organizational and End User Computing*, *31*(4), 89–110. doi:10.4018/JOEUC.2019100105

Lampropoulos, G., Euclid, K., & Konstantinos, D. (2020). Enhancing the functionality of augmented reality using deep learning, semantic web and knowledge graphs: A review. *Visual Informatics*, *4*(1), 32–42. doi:10.1016/j.visinf.2020.01.001

Li, X. L. (2019). Process Knowledge Graph construction method for process reuse. *Xibei Gongye Daxue Xuebao/ Journal of Northwestern Polytechnical University, 37*(6), 1174-1183.

Lindsay, G. W. (2021). Convolutional neural networks as a model of the visual system: Past, present, and future. *Journal of Cognitive Neuroscience*, *33*(10), 2017–2031. doi:10.1162/jocn_a_01544 PMID:32027584

Markiewicz, M., & Koperwas, J. (2022). Evaluation platform for DDM algorithms with the usage of non-uniform data distribution strategies. [IJITSA]. *International Journal of Information Technologies and Systems Approach*, *15*(1), 1–23. doi:10.4018/IJITSA.290000

Noy, N., Gao, Y., Jain, A., Narayanan, A., Patterson, A., & Taylor, J. (2019). Industry-scale Knowledge Graphs: Lessons and challenges: Five diverse technology companies show how itow done. *ACM Queue; Tomorrow's Computing Today*, *17*(2), 48–75. doi:10.1145/3329781.3332266

Qian, J. W., Li, X.-Y., Zhang, C., Chen, L., Jung, T., & Han, J. (2017). Social network de-anonymization and privacy inference with Knowledge Graph model. *IEEE Transactions on Dependable and Secure Computing*, *16*(4), 679–692. doi:10.1109/TDSC.2017.2697854

Rotmensch, M., Halpern, Y., Tlimat, A., Horng, S., & Sontag, D. (2017). Learning a health Knowledge Graph from electronic medical records. *Scientific Reports*, *7*(1), 1–11. doi:10.1038/s41598-017-05778-z PMID:28729710

Tiwari, S., Fatima, N. A. A., & Devottam, G. (2021). Recent trends in Knowledge Graphs: Theory and practice. *Soft Computing*, *25*(13), 8337–8355. doi:10.1007/s00500-021-05756-8

Wang, H. F., & Liu, Z. Q. (2019). An error recognition method for power equipment defect records based on Knowledge Graph technology. *Frontiers of Information Technology & Electronic Engineering*, *20*(11), 1564–1577. doi:10.1631/FITEE.1800260

Wang, Q., Mao, Z., Wang, B., & Guo, L. (2017). Knowledge Graph embedding: A survey of approaches and applications. *IEEE Transactions on Knowledge and Data Engineering*, *29*(12), 2724–2743. doi:10.1109/TKDE.2017.2754499

Yamashita, R., Nishio, M., Do, R. K. G., & Togashi, K. (2018). Convolutional neural networks: An overview and application in radiology. *Insights Into Imaging*, *9*(4), 611–629. doi:10.1007/s13244-018-0639-9 PMID:29934920

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