# Mechanical Fault Prediction Based on Event Knowledge Graph

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Abstract: Currently, the majority of diagnoses in the field of mechanical faults are performed by experts or expert systems, which require domain experts to guide the completion while having subpar and limited portability. Consequently, we analyzed the current situation of rolling bearing fault, event knowledge graph and convolutional neural network, explored the intelligent fault diagnosis and prediction technology of rolling bearing, introduced event knowledge graph and convolutional neural network in rolling bearing fault diagnosis, provided support for fault diagnosis and prediction, enhanced the accuracy of fault diagnosis and prediction, and enabled the predictive of complex mechanical equations.

## 1 INTRODUCTION

Despite the fact that fault diagnosis technology is an applied and marginal field, the emphasis is transitioning toward information technology, digitalization, and artificial intelligence as a result of technological advancements. The sensitivity and complexity of the large-scale mechanical apparatus have increased. Moreover, calamitous incidents caused by mechanical equipment malfunctions have become more prevalent in recent years as a result of the significant expansion in the complexity of mechanical equipment. Therefore, the use of fault diagnosis and predictive techniques for predictive maintenance of apparatus and equipment is crucial for maintaining the equipment's operation stability and preventing losses due to outages.

Theoretical foundations for fault diagnosis technologies include modern control theory, computer engineering, mathematical statistics, fuzzy set theory, signal processing, pattern recognition, etc. The objective of fault diagnosis is to determine the fault's characteristic description and to detect and isolate the fault based on the various (measurable or unmeasurable) quantities in the system, or some of them, exhibiting characteristics distinct from their normal state when a fault occurs(An, 2008).In the initial stages, manual diagnosis is used. However, the traditional technology of fault diagnosis has been unable to satisfy the actual requirements for the operation of complex mechanical equipment. The prediction model is a crucial component of the technology for predicting mechanical faults. Current fault prediction models include curve fitting models, filtering models, time series models, grey models, artificial neural network models, and fuzzy models.

Knowledge Graph (KG) is a popular form of knowledge representation, published by Google in 2012. It focuses on entities and their relationships, thus representing static knowledge. And existing knowledge graphs in the field of mechanical fault are frequently static graph, where the degree of fault is inferred by associating semantic information with the data(Yan et al., 2022). However, the world contains a vast quantity of event information that conveys dynamic and procedural knowledge, making event-centric knowledge representations such as the Event Knowledge Graph (EKG) essential.

In this paper, in contrast to the conventional approach of using static knowledge graph, we use Event-Ontology(Han et al., 2007) combined with signal data from mechanical fault data sets to construct event knowledge graph. We also utilize the data in the event knowledge graph to construct a convolutional neural network model for fault diagnosis and prediction functions, and then update the event knowledge graph with the results of the diagnosis and prediction.

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This knowledge graph can be utilized for predictive maintenance of machinery and equipment to avoid or minimize downtime, thereby ensuring that machinery and equipment can be utilized for as long as possible.

## 2 RELATED WORK

Currently, mechanical fault prediction (MFP) and diagnosis are usually implemented independently by knowledge graphs or convolutional neural networks. Laibin Zhang et al.(Zhang et al., 2007) proposed a multidimensional fault characteristic parameter model for rotating parts for the purpose of mechanical fault diagnosis technology. Specifically, a fuzzy gray optimal prediction method is proposed to predict short-term faults. The method is able to build a prediction model with a minimum of four data and can effectively handle the nonlinearity of the prediction data. Shi Yu et al.(Yu Shi, 2022) proposed a model for fault diagnosis using a knowledge graph and fuzzy inference. By constructing a knowledge graph of the mechanical fault domain, a fuzzy ontology, and communicating the knowledge graph and fuzzy ontology in a mapping manner, the equipment status can be diagnosed using fuzzy reasoning to derive fault fuzzy values. Although the fuzzy inference model can also accomplish the diagnosis and prediction of mechanical faults, its implementation requires the manual or semi-automatic construction of a fuzzy inference rule base and the setting of thresholds for the addition of inference labels. The rules in the rule repository should not have an excessive number of parameters, as this would reduce the efficacy of inference.

Although Google introduced the Knowledge Graph concept formally in 2012, it has been under development since the Semantic Web was first proposed in 1960. Early knowledge bases, open knowledge graphs, Chinese common knowledge graphs, and domain knowledge graphs are the various types of knowledge graphs(Tian et al., 2021). The event knowledge graph is a dynamic knowledge graph, as opposed to a static knowledge graph, and the data is frequently updated and has a certain timeliness(Zhao et al., 2022); thus, it is difficult to achieve improved results when using inference methods such as fuzzy inference for prediction or diagnosis. Typically, event knowledge graphs employ an ontology-based construction process for knowledge modelling, wherein the top-level representation model of event knowledge graphs is developed first, followed by the refinement of supporting examples. This method is comparable to that of static knowledge graphs. And the method proposed by Zhao Xiaojun et al.(Zhao et al., 2022) for constructing a dynamic military domain graph by processing dynamic data according to data update frequency and usage frequency can better satisfy the requirements of a domain dynamic knowledge graph for high quality and timeliness.

Knowledge graph is a significant infrastructure for AI technology and is essential for computers to accomplish human-like inference and prediction capabilities. Compared with shallow models, deep learning has more obvious advantages in both feature extraction and modeling. Deep learning is better at mining abstract feature representations from original data, and these feature representations usually have better generalization ability. From AlexNet(Krizhevsky et al., 2012), VGGnet(Simonyan and Zisserman, 2014), and GoogLeNet(Szegedy et al., 2015), which participated in the ILSVRC competition and won, it is clear that convolutional neural networks are the undisputed leaders in computer vision and have excellent generalization. Therefore, it is reasonable to assume that convolutional neural networks can contribute new concepts and techniques to the field of mechanical fault diagnosis.

By taking advantage of convolutional neural networks and building CNN models that act directly on time-domain signals, features useful for diagnosis can be learned automatically without manual extraction(Zhang, 2017). Using the upper channel CNN to extract feature information from the vibration signal and the lower channel Bidirectional Gated Recurrent Unit(BiGRU) network to extract the temporal features of the vibration signal from both positive and negative directions enables the diagnosis of faults by combining the benefits of both network models.

Most implementations of the fault prediction function in the aforementioned papers use CNNs for prediction or only KGs for inference, whereas by combining the prediction capability of CNNs with the event attributes of EKGs, we are able to more effectively predict mechanical faults.

## 3 METHODOLOGY

The methodology framework for the mechanical fault prediction model based on event knowledge graph and deep convolutional neural network is depicted in Figure 1.

Four major components comprise the model: the input layer, the EKG layer, the Deep Convolution Neural Networks with Wide First-Layer Kernels (WDCNN) layer, and the output layer. The model input consists of as much data as feasible, including fan end and drive end vibration data, motor revolu-

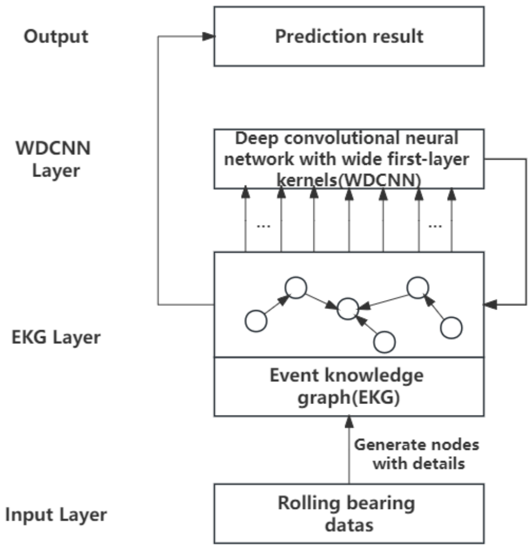


Figure 1: Framework of the prediction system.

tions per minute (RPM), and time series data. The EKG layer then extracts relevant information from the data to establish entities and their relationships. By reading the EKG layer's data, the WDCNN layer performs fault prediction using the pre-trained WDCNN model. When a fault is predicted to be possible, a new entity is added to the EKG, and its relationships with other entities, such as the (entity-fault type) relationship, are established; if no fault is predicted, the corresponding entity's attributes and relationships are merely updated. The output layer obtains the output by reading the attributes and inter-entity relationships of the altered or added entities in the EKG layer.

## 3.1 EKG Layer

In this paper, we constructed the event knowledge graph based on the seven-step method(Noy and Mcguiness, 1995) and the 6H method(Han et al., 2007). At present, the more widely used knowledge graph construction methods are: IDEF-5 method, Skeletal Methontolody, TOVE method, seven-step method(Noy and Mcguiness, 1995) and Methontology method(Fernández-López et al., 1997). In the construction of domain ontologies, the seven-step method and the NeOn Methontology method are now utilized more frequently. Below are brief explanations of the two aforementioned methods: Currently, the most popular methods for building knowledge graphs are the IDEF-5 method, Skeletal Methontolody, TOVE method, seven-step method(Noy and Mcguiness, 1995), and Methontology method(Fernández-López et al., 1997). More frequently, the seven-step method and the NeOn Methontology method are employed in the construction of domain ontologies today. Detailed explanations of the two aforementioned methodologies are provided below.

(i) **Seven-Step Method (Noy and Mcguiness, 1995):** The Stanford University School of Medicine devised this method, which is primarily used for the construction of domain ontologies. The seven stages of the method are: (1) identifying the domain of expertise and scope of the ontology; (2) investigating the possibility of utilizing existing ontologies; and (3) developing the ontology. (3) listing the key terms in the ontology; (4) defining classes and class hierarchies; (5) defining the attributes of classes; (6) defining the constraints of the attributes; (7) generating instances.

(ii) **NeOn Methontology Method (Gomez-Perez and Suárez-Figueroa, 2009):** The core idea of NeOn methodology is to integrate ontologies from different domains into a unified knowledge graph. It is constructed using a "divide-and-conquer" approach, in which the overall problem to be addressed is decomposed into subproblems, and solutions to the overall problem (i.e., the development of the ontology network) are obtained by combining the solutions to the subproblems.

Event-Ontology is defined based on fundamental factors which describe an event. That means the 6H of 'who', 'what', 'where', and 'how' are represented as properties of an event. The property value of "who" is the subject of an event, while the property value of "how" is the subject's action or the event's content. "What" refers to the substance of an event, while "where" and "when" indicate the event's location and time, respectively.(Han et al., 2007).

EKG gave to construct entities and relationships between entities by extracting as much data information as possible in the dataset, such as vibration signal data, fault occurrence locations, fault types, etc. This paper refered to the knowledge graph developed by Liu Xin(Liu, 2019) of Beijing University of Posts and Telecommunications using the improved seven-step methodology. Because mechanical fault event knowledge graph is a type of domain knowledge graph, and in order to share a common understanding of the information structure and make the domain knowledge reusable, it is typically necessary to determine whether there are existing ontologies that can be reused before developing the ontology. The structure Liu proposed is enhanced on the basis of the ontology class hierarchy diagram of this knowledge graph to emphasize the features of the event knowledge graph. By deleting class structures that are not relevant to this paper and adding classes corresponding to the information extracted above, an ontology class hierarchy that better highlights the characteristics of the event knowledge graph is constructed.

### 3.2 WDCNN Layer

The WDCNN layer determines the structure of the model and the parameters of each layer by extracting the vibration signal data from the established knowledge map of mechanical failure events and several preliminary experiments, thus establishing a WDCNN model with the function of diagnosis and prediction of mechanical faults, whose diagnostic function can recognize ten types of failures. As a normal Convolution Neural Network(CNN), WDCNN also has a five-layer structure , which are input layer, convolution layer, pooling layer(or sampling layer), full connection layer and output layer. Among them, the convolution layer and pooling layer are set alternately. In contrast to conventional convolution neural networks, however, WDCNN have a large convolution kernel in the first layer and smaller convolution kernels in subsequent layers. Due to the small number of convolution kernel parameters, WDCNN has a deeper network and can suppress overfitting, so it has a better expressive ability compared with ordinary CNNs. We can also ascertain the applicability of the model's findings by examining the displayed model assessment curves. It implements its prediction function by determining whether mechanical equipment is likely to malfunction based on a threshold value of the difference between predicted and actual values.

### 3.3 Output

In the output layer, mechanical fault diagnosis and prediction results are obtained by retrieving the updated EKG output results, which can be done by clicking on the visualization interface or using query statements.

We implemented the query function of this mechanical fault event knowledge graph in Neo4j. Because of its ability to visualize the entities we create and the relationships between them compared to other databases. In addition, Neo4j can be queried with Cypher statements or simple clicks, which makes it accessible to people who do not have knowledge of database queries. Cypher's fundamental syntax comprises of four distinct sections, each with a unique rule: (1) **Start:** identify the starting node in the graph; (2) **Match:** match the graph pattern to locate subgraphs of the desired data; and (3) **Where:** filter the data based on certain criteria. data; (4) **Return:** deliver the desired results.

## 4 EXPERIMENTAL SETUP

In this section, we discuss all the experimental environments we considered to perform the Event Knowledge Graph of Mechanical Fault Prediction. In the following subsections we discuss: (i) the data set used to build and test; (ii) the metrics used to assess performances; and (iii) the implementation aspects of the proposed EKG of MFP model.

### 4.1 Data Sets Description

The experimental dataset used for this paper is the rolling bearing dataset published by the Rolling Bearing Data Center at Case Western Reserve University(CWRU, 2023). This dataset is presently recognized as the standard dataset for fault diagnosis of rolling bearings worldwide. The investigations in this paper therefore make use of the Normal Baseline, 12k Drive End Bearing Fault, and 12k Fan End Bearing Fault data sets from the CWRU dataset. We used the data in Normal Baseline and 12k Drive End Bearing Fault to construct the event knowledge graph, then train and construct WDCNN using the event knowledge graph's data, and finally use the data in 12k Fan End Bearing Fault to test the generalizability of the established EKG of MFP.

### 4.2 Data Sets Pre-Processing

The initial data set is stored in Matlab (*.mat) files, each file contains fan and drive end vibration data in addition to motor speed.

The experimental object of this paper is a deep groove ball bearing SKF6205 model drive end bearing. The faulty bearing is machined by EDM with a system sampling frequency of 12kHz, and it is separated into three categories based on its damaged parts: inner race, outer race, and ball, and four categories based on its fault diameters: 0.007, 0.014, 0.021, and 0.028 inches. However, due to the lack of outer race damage data for the 0.028 inch diameter portion, the 0.007, 0.014, and 0.021 damage diameters were selected, for a total of $3\times3$ fault states. As outer race damage is a stationary damage, the location of the fault in relation to the bearing load zone has a direct impact on the vibratory response of the motor/bearing system. The outer race fault location chosen for this research is in the 6 o'clock direction (directly within the load zone). The data sets used are shown in the Table 1 and Table 2.

Then, the data set is randomly partitioned into train, valid, and test, and the partitioning ratio is set to 0.7: 0.1: 0.2 so that training and test set samples

Table 1: Normal Baseline Data.

| Motor Load (HP) | Approx. Motor Speed (rpm) | Normal Baseline Data |
|---|---|---|
| 0 | 1797 | 97.mat |
| 1 | 1772 | 98.mat |
| 2 | 1750 | 99.mat |
| 3 | 1730 | 100.mat |

do not overlap. In each experiment, 1024 data are utilized for fault diagnosis.

In addition, there are 10 fault categories that have been artificially specified, corresponding to 1 fault-free status and 9 fault statuses with three fault locations (inner_race, ball, outer_race) and three fault diameters (0.007, 0.014, 0.021) in two combinations. Table 3 lists the types corresponding to these fault status.

Due to the fact that the subsequent query includes bearing location, motor load horsepower (HP), motor speed, bearing operation status, fault diameter (in fault status), fault occurrence location (in fault status), and fault name, etc., the corresponding data columns are added to the data set and output as excel (.csv) files.

Before conducting fault prediction, it is necessary to obtain new data. In this paper, we utilize the data in the 12k DriveEndBearingFaultData file with the split ratio set to [train: valid: test]=[0.1: 0.1: 0.80], presume the data in the test section to be recently collected data, and transform the imported data into a format acceptable by the model input layer.

## 4.3 Metrics

The purpose of this paper is to accomplish supervised diagnosis and prediction of mechanical faults. Accuracy and loss curves are frequently used as crucial metrics for evaluating the efficacy of machine learning models, and loss curves can reflect the dynamic trend of network training. To evaluate the diagnostic and predictive quality of the WDCNN model developed in this paper for bearing faults, we observe the loss curve to determine whether the model converges and fits, and the acc curve to determine the model's applicability for bearing fault prediction.

## 4.4 Implementation Details

The construction of EKG and the establishment of WDCNN are carried out using the methodologies described above.

**EKG Construction:** First, we analyzed the data in the CWRU bearing fault dataset and identify the key terms in the ontology; then, we defined the classes and the class hierarchy based on these terms. We used a combination of top-down and bottom-up approaches and referred to the ontology class hierarchy of the knowledge graph created by Xin Liu of Beijing University of Posts and Telecommunications(Liu, 2019) to define classes and class hierarchies in the EKG. Analysis of the CWRU rolling bearing dataset from the bottom-up layer provides access to the important terms in the field of rolling bearing faults: bearing operating part, bearing physical component, bearing fault type, bearing operating status, bearing operating conditions, bearing protection methods, etc., which can all be used as concepts extracted from the top-down layer to construct the ontology. The bottom stratum of data contains bearing fault diameters, time series data, fault varieties, etc. Therefore, the bearing operation status can be divided into two categories: normal and abnormal, with the fault status subdivided further into fault vibration signal, fault diameter, etc. In summary, the class hierarchy can be deduced as follows: A rolling bearing includes several categories of operating part, physical component, operating status, faults, and bearing protection methods. The operating status contains subcategories for normal state and abnormal state. The normal state subcategory contains normal state signal data, while the abnormal state subcategory contains fault signal data and specific fault type. The operating condition also includes motor load horsepower and motor speed.

Then, to facilitate subsequent query functions and data updates, we specify the class's data attributes and relational attributes, upon which we define the constraints for each attribute. Instances are subsequently created in the Neo4j graph database to conclude the construction of the bearing fault event knowledge graph.

**WDCNN Establishment:** The purpose of establishing a convolutional neural network in this paper is to realize the diagnosis and prediction of mechanical faults, using tensorflow in python to establish the initial CNN and then selecting the WDCNN with superior performance based on a series of preliminary experiments. The WDCNN consists of five convolutional layers, five pooling layers, one full connection and one Softmax layer. Following are the parameters of the convolutional neural network: The size of the first convolutional kernel is $64\times11$ with a $16\times11$ stride size, the size of the remaining convolutional layers is $3\times11$ with a $2\times11$ stride size, and the size of each of the five pooling layers is $2\times11$ with a $2\times11$ stride size. In addition, the Softmax layer is configured to generate 10 outputs for 10 bearing fault states. The parameters of the WDCNN model used in the experiments are shown in Table 4.

Moreover, the Adadelta optimization algo-

Table 2: 12k Drive End Bearing Fault Data.

| Fault Diameter | Motor Load (HP) | Approx. Motor Speed (rpm) | Inner Race | Ball | Outer Race Position Relative to Load Zone (Load Zone Centered at 6:00) | | |
|---|---|---|---|---|---|---|---|
| | | | | | Centered @6:00 | Centered @3:00 | Centered @12:00 |
| 0.007” | 0 | 1797 | 105.mat | 118.mat | 130.mat | 144.mat | 156.mat |
| | 1 | 1772 | 106.mat | 119.mat | 131.mat | 145.mat | 158.mat |
| | 2 | 1750 | 107.mat | 120.mat | 132.mat | 146.mat | 159.mat |
| | 3 | 1730 | 108.mat | 121.mat | 133.mat | 147.mat | 160.mat |
| 0.014” | 0 | 1797 | 169.mat | 185.mat | 197.mat | * | * |
| | 1 | 1772 | 170.mat | 186.mat | 198.mat | * | * |
| | 2 | 1750 | 171.mat | 187.mat | 199.mat | * | * |
| | 3 | 1730 | 172.mat | 188.mat | 200.mat | * | * |
| 0.021” | 0 | 1797 | 209.mat | 222.mat | 234.mat | 246.mat | 258.mat |
| | 1 | 1772 | 210.mat | 223.mat | 235.mat | 247.mat | 259.mat |
| | 2 | 1750 | 211.mat | 224.mat | 236.mat | 248.mat | 260.mat |
| | 3 | 1730 | 212.mat | 225.mat | 237.mat | 249.mat | 261.mat |
| 0.028” | 0 | 1797 | 3001.mat | 3005.mat | * | * | * |
| | 1 | 1772 | 3002.mat | 3006.mat | * | * | * |
| | 2 | 1750 | 3003.mat | 3007.mat | * | * | * |
| | 3 | 1730 | 3004.mat | 3008.mat | * | * | * |

Table 3: 10 types of fault names.

| diameter\position | inner_race | ball | outer_race |
|---|---|---|---|
| 0.007 | 1 | 2 | 3 |
| 0.014 | 4 | 5 | 6 |
| 0.021 | 7 | 8 | 9 |
| normal (no fault) | | 0 | |

Table 4: Parameters of WDCNN.

| No. | Network layers | kernel_size /stride_size | Number of kernels | output (width × depth) |
|---|---|---|---|---|
| 1 | Convolutional layer1 | 64×1/16×1 | 16 | 128×116 |
| 2 | Pooling layer | 2×11/2×11 | 16 | 64×116 |
| 3 | Convolutional layer | 3×11/1×11 | 32 | 64×132 |
| 4 | Pooling layer | 2×11/2×11 | 32 | 32×132 |
| 5 | Convolutional layer | 3×11/1×11 | 64 | 32×164 |
| 6 | Pooling layer | 2×11/2×11 | 64 | 16×164 |
| 7 | Convolutional layer | 3×11/1×11 | 64 | 16×164 |
| 8 | Pooling layer | 2×11/2×11 | 64 | 8×164 |
| 9 | Convolutional layer | 3×11/1×11 | 64 | 6×164 |
| 10 | Pooling layer | 2×11/2×11 | 64 | 3×164 |
| 11 | full connection | 100 | 1 | 100×11 |
| 12 | Softmax | 10 | 1 | 10 |

rithm(Zeiler, 2012) has been used to revise the weights in this paper. The Adadelta optimization algorithm is an improvement of the Adagrad optimization algorithm, in which the exponentially weighted average of the squares of the gradients is used instead of the sum of squares of all gradients for each dimension, thereby avoiding the problem that the update magnitude gradually tends to zero in the late training period; the exponentially weighted average of the squares of the updates dynamically replaces the global scalar learning rate, thereby avoiding truncation.

# 5 RESULT AND DISCUSSION

In this section, we discuss the query function implemented by the bearing fault EKG and the performance of WDCNN in terms of loss and accuracy of fault diagnosis and prediction.

## 5.1 Query Functions of Bearing Fault EKG

In this paper, we present four kinds of most prevalent query functions based on the Cypher query pattern and the visual interface provided by Neo4j. Analysis of the constructed event knowledge graph of bearing fault can identify the subclass or subclasses of entities that the entity being queried falls under. By pressing on nodes, the data attributes associated with nodes and the relationships between nodes can be queried based on the visual interface.

**Rolling Bearing Operation Status and Physical Components and Other Parameters:** This query searches for entities and their vibration_signal_data/ fault_vibration_signal_data data attributes that belong to the Normal or Abnormal subclasses of the operating_status class. Figure 2 depicts the query result when the operation status is normal, while Figure 3 depicts the query result when the operation status is abnormal.

**Rolling Bearing Fault Type and Fault Position:** The query is for the ”where” attribute in the event

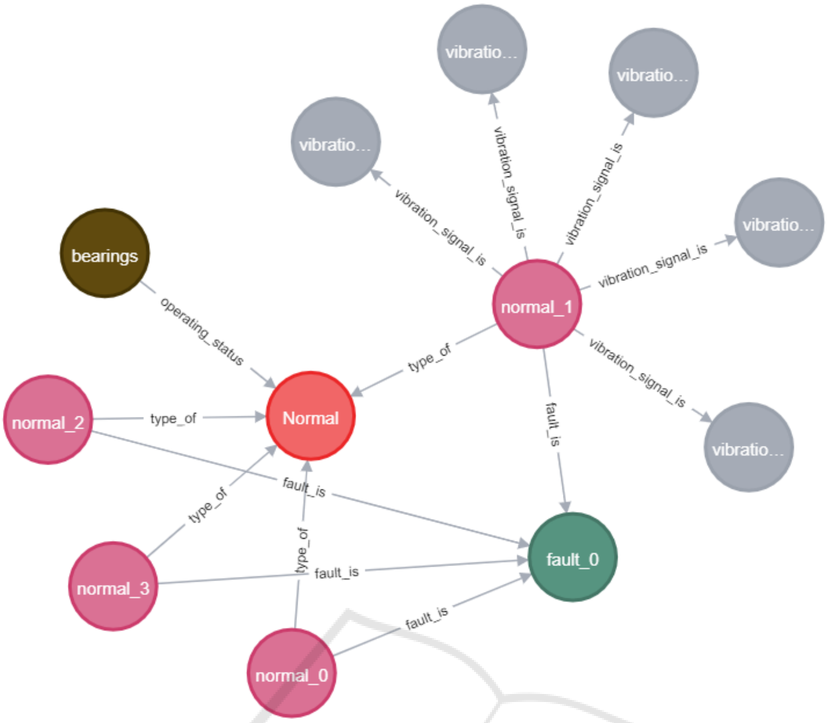


Figure 2: Query result of normal status.



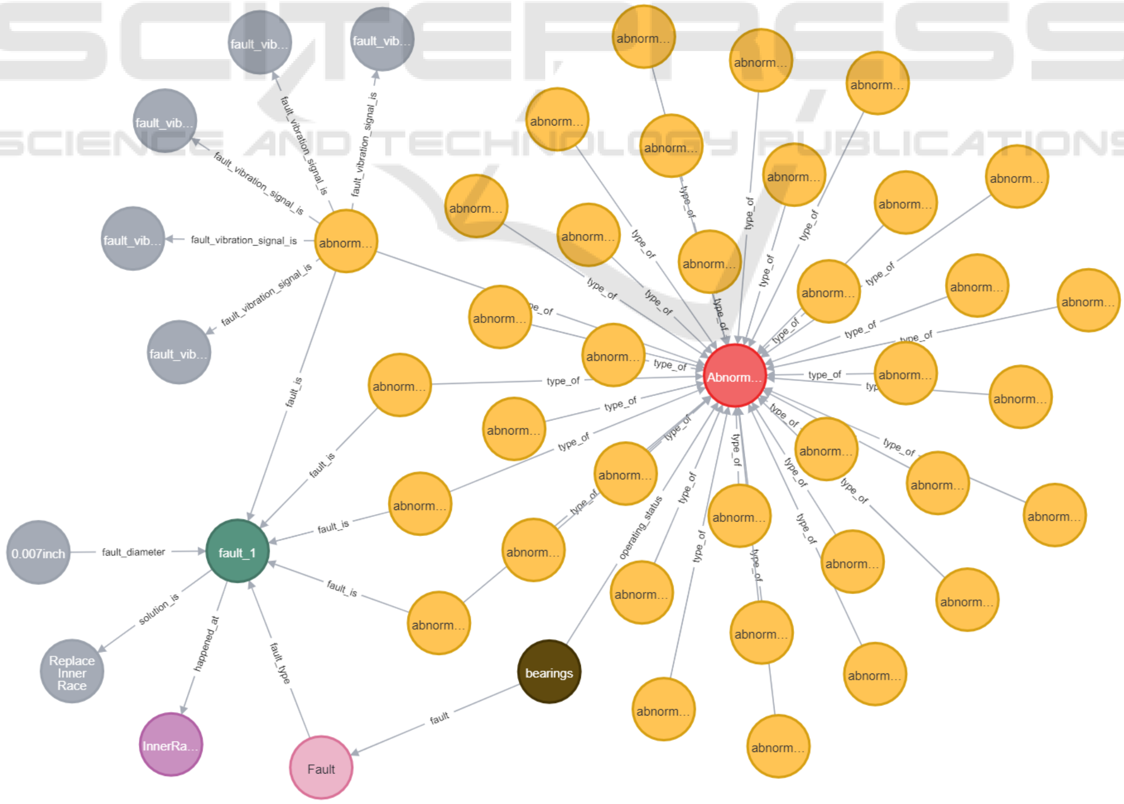


Figure 3: Query result of abnormal status.


Figure 4: Query result of fault type and position.

knowledge graph, and there are two querying methods: (i) directly querying the fault type and returning the fault type node directly; (ii) transforming it into a query for the ”happened_at” relationship query, which returns the type of fault that occurred on the physical component. The query result for the fault type ”fault_7” is illustrated in Figure 4.

**Rolling Bearing Fault Type and Solution:** The query aims to identify a solution based on the type of defect, which can be translated into a query for the ”solution_is” relationship for the starting node specified. Take the fault type ”fault_5” as an example, the result of its fault solution query is shown in Figure 5.

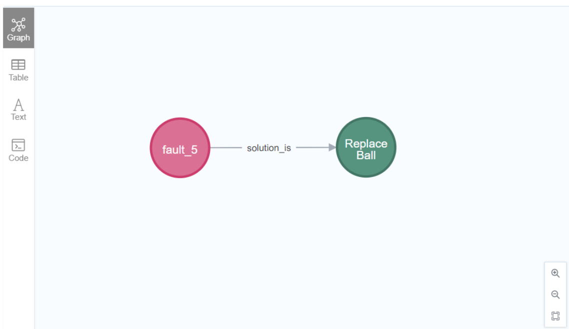


Figure 5: Query result of fault type and solution.

**Rolling Bearing Physical Components and Maintenance Methods:** The query intends to identify the corresponding maintenance solution based on the physical components of the rolling bearing, i.e., specify the starting node as a physical component entity and locate the end node with the relationship ”maintenance_method_is”. Figure 6 depicts the result of the maintenance method inquiry regarding the inner race malfunction.

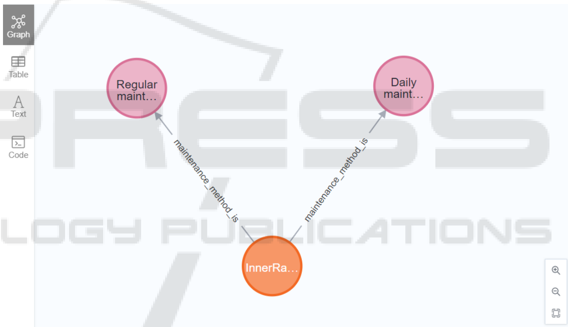


Figure 6: Query result of physical components and maintenance methods.

## 5.2 WDCNN Evaluation

The dataset is trained using a deep convolutional neural network constructed according to Section 4.5, with the learning rate of Adadelta set to 1.0 and the number of training epochs set to 500. Figure 7 and Figure 8 depict the loss and accuracy curves for each training and test, respectively.

With a decent fit, the recognition rate of the convolutional neural network exceeds 99.8% on the training dataset and 97% on the test dataset, as depicted in the figures. The experimental results demonstrate that WDCNN has a strong ability to recognize the test sample data.

The WDCNN model established in the preceding section is applied to assess the test data and calculate the average loss and accuracy values for the newly

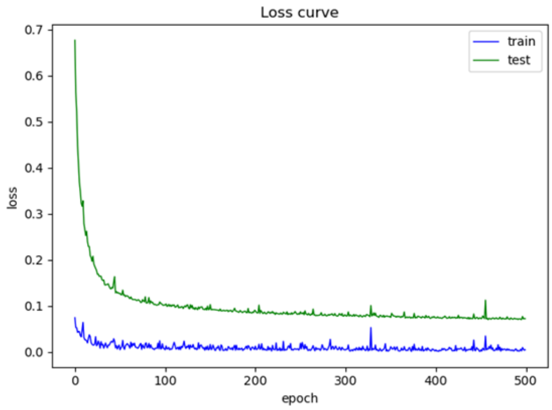


Figure 7: Loss curve of training.

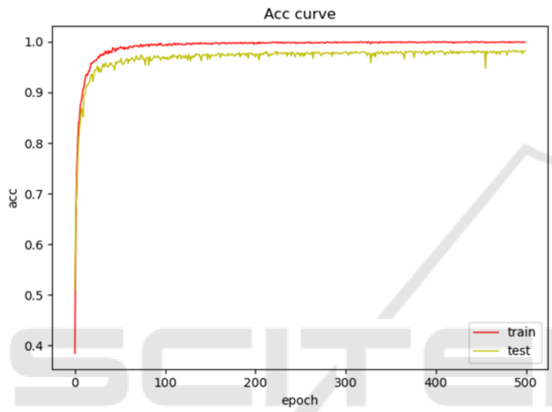


Figure 8: Accuracy curve of training.

collected data. If the average loss in the test history is greater than 0.2 or the accuracy is less than 0.5, then the operating status of the bearing is "Abnormal" if the final average loss is greater than 0.2 or the accuracy is less than 0.5 based on the test history, and "Normal" otherwise. The prediction effect is illustrated in Figures 9 and 10.

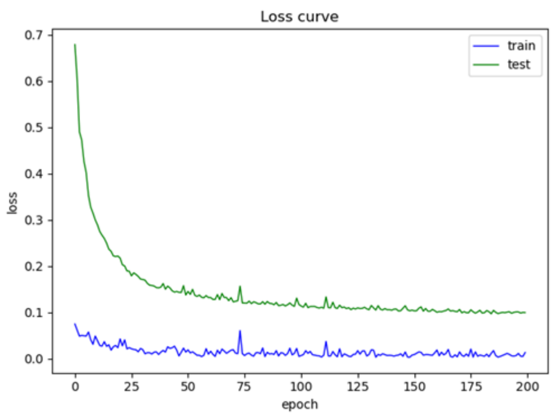


Figure 9: Loss curve of prediction.

Then, we evaluate the function of the constructed

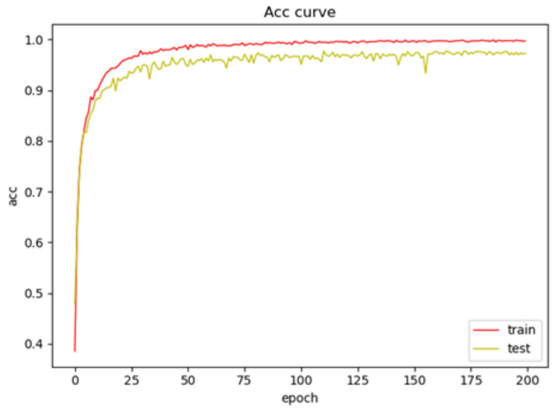


Figure 10: Accuracy curve of prediction.

model to create new nodes based on the prediction results, using "normal" as an example of a prediction result. We constructed a new node with the name "new_normal" under the class "normal_type" in the diagram. Establish the "type_of" relationship between this node and the "Normal" entity within the "operating_status" class. Establish the "fault_is" relationship between this node and the "fault_0" entity within the "fault_details" class. The newly constructed node is queried in the manner depicted in Figure 11. Similar to the status of "Normal", when the running state is "Abnormal", create a new node with the name "new_abnormal" under the class "abnormal_type" in the diagram. Establish the "type_of" relationship between this node and the "Abnormal" entity within the class "operating_status".

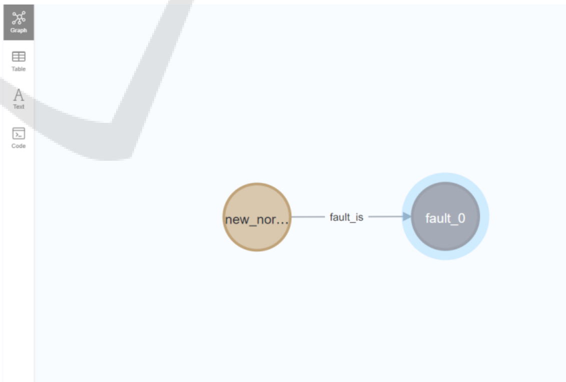


Figure 11: New node of predicted results.

## 6 CONCLUSION

In this paper, we focused on the analysis of faults in rolling bearings, event knowledge graphs, and the current state of convolutional neural networks, as well as fault diagnosis and prediction techniques for rolling bearings. Based on the characteristics of the mechanical fault field and the data collected from the CWRU rolling bearing data center, we extract the relationship between entities and entities using a seven-step process, store the obtained entities and inter-entity relationships in the Neo4j graph database to complete the construction of the bearing fault event knowledge graph, and implement the four types of visual query functions based on the constructed event kdb. Then, we construct a deep convolutional neural network with a wide convolutional kernel on the first layer in order to diagnose the operational status of rolling bearings. The experimentally established WDCNN model has an accuracy rate of greater than 99.8% on the training dataset and greater than 97.3% on the test dataset. Finally, we predict bearing faults by combining an event knowledge graph with a deep convolutional neural network. By acquiring newly collected data during rolling bearing operation, setting fault thresholds, and applying WDCNN to predict and analyze them, new nodes and their relationships are added to the event knowledge graph.

In rolling bearing fault diagnosis, the introduction of the event knowledge graph and convolutional neural network provides support for fault diagnosis and prediction, enhances the accuracy of fault diagnosis and prediction, and reduces the need for expertise and expert system domain knowledge.

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