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# *Graph Neural Networks and Convolutional Neural Networks for Historical Data Analysis: A Survey*

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***Abstract.*** Historical data analysis aims to extract structured knowledge from physical historical materials, documentary historical materials and oral historical materials. The early method developed from visual feature extraction based on convolutional neural network (CNN) to semantic modelling based on knowledge graph (KG), and further evolved into graph neural network (GNN), which significantly improved the reasoning ability of historical relationships. In recent years, GNN-based models, especially the method of integrating structural modelling mechanisms, have promoted the development of historical data analysis tasks. This method has achieved optimal performance in historical document understanding and entity relationship modelling scenarios, and shows strong ability in knowledge representation and reasoning. However, the existing methods still face problems such as limited semantic understanding, difficulty capturing long-range dependencies, and weak handling of dynamic information, which limits the performance and application expansion of the model. This article systematically reviews the analysis methods of historical data, highlights the transition from perception to reasoning. It summaries the development evolution from CNN-based methods to GNN framework-based methods, analyses key technological breakthroughs, and looking forward to the future development trend of multimodal and graph learning.

***Keywords:*** Historical data analysis, Convolutional neural network, Knowledge graph, Graph neural network

## 1. Introduction

With the continuous deepening of artificial intelligence in the field of historical research, historical data analysis has gradually shifted from traditional research to the field of data-driven intelligent analysis. In recent years, deep learning methods have significantly promoted the development of historical data analysis, which exist in various forms like text, images and oral historical materials [1]. Convolutional neural network (CNN) is outstanding in image processing and visual feature extraction [2]. It is widely used in historical document enhancement, layout analysis and cultural relic image recognition. However, it focusses more on local features and is difficult to show the relationship between entities. To make up for this shortcoming, the researchers introduced the knowledge graph (KG) for structured representation and modelled the relationship evolution through the temporal knowledge graph (TKG) [3,4]. On this basis, graph neural networks (GNN) can create

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high-order dependencies between learning nodes to realise knowledge complementation and reasoning [5].

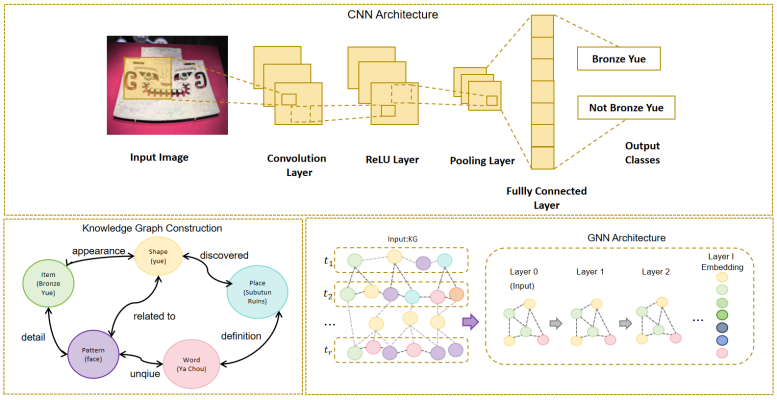



Figure 1. Framework of historical data analysis (CNN–KG–GNN)

As shown in Figure 1, the process moves from feature extraction to relation modeling and finally to reasoning. Historical data analysis requires perception and relational reasoning, which motivates the transition from CNN-based methods to GNN-based approaches. But the existing research is mostly concentrated on a single method and lacks the ability of multi-model collaborative modelling. How to find laws in a small amount of data, find connections in different regions, and open reasoning processes are still urgent problems to be solved in the historical field.

The main contributions of this article are as follows:

• This article systematically sorts out the application of CNN at the historical data.

• Summaries the role of KG and TKG in the structured show of historical data.

• It focusses on analyzing the application of GNN in relational modelling.

• Summaries the challenges facing the current research and explore the possible future development direction.

## 2. Historical data analysis method based on convolutional neural networks

CNN has strong capabilities in visual feature extraction and learning visualisation, so it is widely used in the historical field.

### 2.1. In terms of document image processing

Historical documents usually have blurred patterns, easily appear fading ink, damage and other degradation problems due to time, storage method and so no. Studies have shown that the traditional method has limited performance in complex degradation scenarios, while the CNN method is more robust [6]. Specifically, the deep learning model can distinguish different between text and background, and realise document enhancement and reconstruction to improve the readability of documents.

At the same time, document division and layout analysis are key forecast steps in dealing with historical documents. Because the structure of historical documents is usually complex, to name a few multi-column, tables and hierarchical structures, it will be difficult to achieve the ideal effect of full-page document extraction. Chen et al. proposed a simple method based on CNN, which transforms the segmentation problem into a pixel-level labeling problem [7]. Another method is based on the Faster Region-based Convolutional Neural Network (Faster R-CNN) model, which

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transforms the typesetting analysis content into visual target detection tasks, and automatically identifies and divides different areas in the document [6]. In this way, complex documents can be decomposed into sub-areas with different semantics, and then keep their structural information. However, both methods have the problem of not being able to build a long-distance relationship, and can only be partially patched.

### 2.2. In terms of cultural heritage image recognition

In addition to document processing tasks, CNN is also widely used in the field of cultural heritage image recognition. The goal of such tasks is to extract semantic features from graphics, and then realise the automatic identification and organisation of historical objects. Researchers use generation models to repair damaged documents and improve the quality of visual information from another angle by reconstructing documents [8]. Although this kind of method is different from the traditional CNN model, it also relies on deep visual feature learning, which provides new research ideas for historical image processing.

### 2.3. Limitations of convolutional neural networks method

Even, CNN has achieved remarkable results in historical data analysis, there are still certain limitations. CNN focusses more on the extraction of local features, and more at the two-dimensional level, lacking the ability to model the connection between entities and the time dimension. Also it is limited in capturing long-range dependencies and relational structures. Therefore, this limitation requires the introduction of knowledge graph (KG) and GNN to build a more complex model knowledge network, which has become an important direction to further improve the ability of historical data analysis.

## 3. Knowledge graph

KG usually use triplets ( $s$, $r$, $o$ ) to represent entity relationships and transform unstructured data into structured networks. In order to model time changes, temporal knowledge graph (TKG) ( $s$, $r$, $o$, $t$ ) are introduced to portray the evolution of relationships [9]. The existing temporal knowledge graph (TKG) method mainly realises relational reasoning through path modelling and time evolution modelling [10]. Importantly, KG serves as a bridge between feature extraction CNN and relational reasoning GNN, providing a structured representation that connects low-level features with high-level reasoning tasks. However, it shows that the learning ability is limited. By realising efficient modelling and reasoning of complex relationships, researchers further introduce GNN.

## 4. Historical data analysis method based on graph neural network

Nowadays, with the development of historical data from visual recognition to relational modelling and reasoning, GNN has gradually become the core means of processing historical data. Compared with CNN's local feature extraction, GNN can build a network between entities on this basis and support complex reasoning processes. It makes GNN have significant advantages in historical figure analysis, event modelling and knowledge graph reasoning.

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### 4.1. Basic graph neural network method

The basic GNN method is mainly used to model the relationship between people, events, and semantic entities. Such methods are usually based on the graph convolution network (GCN) or the graph attention network (GAT) to represent the learning node through the information of the neighbouring node.

GNN can effectively integrate the contextual information in the diagram structure, thus improving the relationship modelling ability. Studies have shown that in the task of extracting historical text information, the weak supervision of named entity identification method combined with graph structure modelling realises the effective extraction and representation of entity relationships in historical texts [11]. In addition, other studies enhance nodes by introducing historical behaviour information or activating information, thus improving the model's modelling ability of complex relationships [12].

### 4.2. Multimodal graph neural network method

#### 4.2.1. Methods based on circular neural networks

In visual texts with complex architectures, like oracles, this kind of text not only has less data, but also has a weak connection with upper and lower spaces. But the local space is also connected with global semantics. Therefore, static graph neural networks are limited and not enough to cope with complex spatial structures. Recurrent Graph Neural Network (R-GNN) integrates CNN, GNN and Recurrent Neural Network (RNN), while modelling local features and global structures, improving the performance of oracle text classification tasks [13].

#### 4.2.2. Graph Neural Networks for visual question answering model

At the same time, the joint modelling of multi-source data is an important direction of multimodal analysis. Graph Neural Networks for Visual Question Answering (VQA-GNN) proposed by Wang et al. realises the fusion modelling of visual and text information through graph structure reasoning [14]. The method adopts a two-way fusion mechanism to promote information interaction between different modalities, and combines the multi-relational attention mechanism to jointly model cross-modal characteristics, which improves the reasoning ability of the model and alleviates the difference in representation between modes. Compared with basic GNNs, multimodal GNNs can better combine different data sources and work better on complex historical reasoning tasks, as shown in Table 1.

Table 1. summarizes the differences between CNN, GNN, and multimodal GNN methods in historical data analysis

| Method | Focus | Advantage | Limitation |
|---|---|---|---|
| CNN | Local feature extraction | Effective in visual tasks | Cannot model relationships |
| GNN | Structural modeling | Captures relationships | Requires graph structure |
| Multimodal GNN | Cross-modal reasoning | Combines modalities | Computationally expensive |

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## 5. Challenges and future research direction

Although CNN, KG and GNN are widely used in historical data analysis, they still face many challenges.

### 5.1. Data scarcity and labelling difficulties

Compared with modern data sets, historical data lacks large-scale and high-quality annotation samples, which limits the performance of deep learning models. In addition, there are a large number of ancient language expressions, semantic ambiguities and non-standard writing methods in historical texts, which makes the task of entity identification and relationship extraction more difficult, thus affecting the quality of KG.

### 5.2. Problems and development of multi-model fusion and connection

In the existing research framework, CNN is mainly used to extract low-level features from images or text, while GNN is used to model entity relationships and conduct reasoning. However, these two types of models usually adopt phased processing and lack a unified end-to-end learning mechanism, resulting in limited information transmission between feature representation and relationship modelling, affecting the overall performance. Future research can explore a unified fusion framework, collaboratively model the feature extraction ability of CNN and the relationship modelling ability of GNN, and realise all the optimisation from raw data to high-level semantic reasoning.

### 5.3. Challenges at the application level

There are significant differences in historical data in various fields, and it also have huge differences between different dynasties, like different cultural backgrounds and different language systems. Existing models are usually trained based on specific data sets, and the generalisation ability is limited. Therefore, building a model with cross-field adaptability is an important prerequisite for realising the intelligent analysis of historical data. Building a multi-modal unified representation model is conducive to improving the analytical ability and the digitisation of cultural heritage under complex historical scenarios.

## 6. Conclusion

This article systematically sorts out the application of CNN, KG and GNN in historical data analysis from a methodological perspective, and builds an analysis framework from multimodal data to structured knowledge to realise complex relationship modelling and reasoning. Although remarkable progress has been made in relevant research, it still faces challenges in data scarcity and difficulties in multimodal integration. Besides, the model still has room for improvement in terms of interpretability and cross-field generalisation ability. Future research can focus on the unified modelling of multimodal data and the collaborative integration between deep learning models, especially in combining perception and reasoning processes. Combined with the method of interpretable artificial intelligence, it is expected to further enhance the application value of the model in historical research.

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