

Cross-Media Data Fusion and Intelligent Analytics Framework for Comprehensive Information Extraction and Value Mining

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ABSTRACT- The core content of this paper is to analyze the integration of cross-media data and artificial intelligence. The core of the whole paper is to analyze different types of media data such as text, image and video. With the increasing complexity and quantity of multimedia data, it can be seen that traditional methods can no longer meet the current data needs. Therefore, some advanced technologies need to be integrated, such as convolutional neural network (CNN) Long and short memory network (LSTM) and graph neural network (GNN) to extract the data content. Therefore, the core of this paper emphasizes the centralized extraction of innocuous complex data through mixed and multi-transport facilities, and proposes that the framework can enhance information extraction and value mining, and this method can be more applied to the media medical and security fields.

KEYWORDS- Cross-Media Data Fusion, Intelligent Analytics, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM)

1. INTRODUCTION

Digital transformation has profoundly reshaped the media industry, driving changes across four main dimensions. First, user experience has become paramount, with content consumption increasingly tailored to individual preferences. Second, the accessibility of media has expanded content can now be consumed and interacted with anytime, anywhere, and on any device. Third, in contrast to traditional media, applications have emerged as the new face of business, offering dynamic and interactive experiences [1][2][3]. Finally, the fourth shift is the growing emphasis on data capital—organizations must capture, analyze, and maximize the value of data to remain competitive.

The construction of converged media cloud platforms is evolving at a deeper level to meet these transformations. However, this development introduces new challenges, particularly in areas like cross-cloud interoperability, container integration, and modern application platform integration. [4]As media organizations increasingly rely on data to deliver personalized digital services, the competitive advantage in the future will lie in the ability to leverage data-driven insights to enhance digital experiences.

In this context, digital transformation becomes essential for media organizations. Successful transformation is about

becoming data-driven, delivering innovative digital business services, and operating in a multi-cloud world. [5][6][7]Hybrid cloud environments, combining private and public cloud solutions, have become crucial in this transformation. However, adopting a multi-cloud approach brings its own set of complexities. Organizations may struggle with operational silos, the cost and time of migration, and the training requirements for managing multiple cloud environments. [8] Moreover, the open nature of the cloud introduces potential security risks and complicates infrastructure management.

To overcome these challenges, a true hybrid cloud solution is necessary—one that integrates and extends infrastructure and operations across private cloud, public cloud, and edge computing environments. The key to success lies in providing a consistent infrastructure that supports computing, storage, and networking for all business-critical applications. A consistent infrastructure and operational model can help eliminate silos, reduce costs, and ensure that applications are deployed flexibly across different cloud environments. [9] VMware-based solutions, such as those provided by Dell Technologies, offer media customers a unified cloud architecture, operations, and services, enabling seamless migration between private and public clouds.

II. CROSS-MEDIA DATA FUSION

In the traditional data processing of converged media, the data mining channel is usually to process a single data. However, in the era of big data, we are faced with different and diversified complex data from different fields and sources, and these data are composed of multiple modes, and each mode contains different representations. Distribution scale and density in most data studies, it can be seen that how to release more effective data and knowledge from multiple different potentially related data sets is more important, thus essentially differentiating big data from traditional data minin. [10][11] This requires broader and more advanced techniques, such as data mining through machine learning, or artificial intelligence, and organic fusion of knowledge from various kinds of data, which focuses on the fusion of knowledge, rather than a combination of schema and data, this classification pattern more clearly distinguishes the relevance of traditional data fusion across data fusion and database community research.

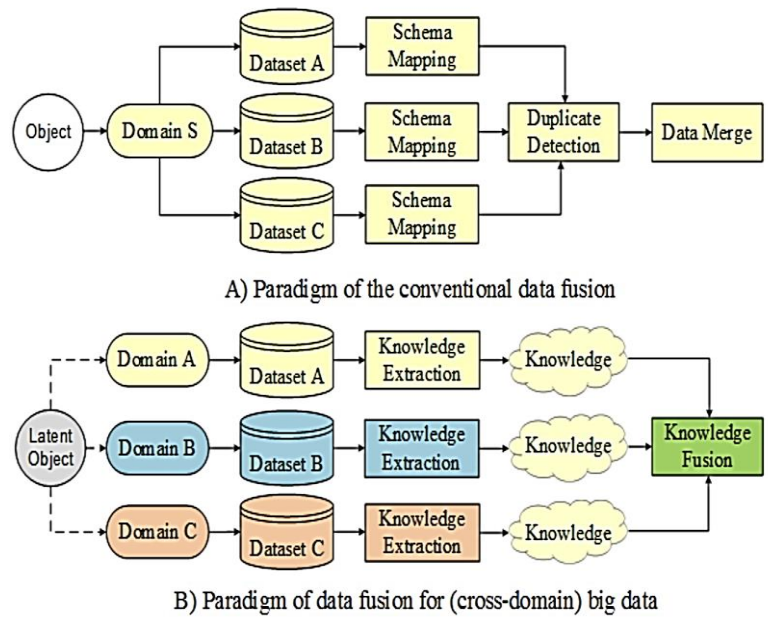


Figure 1: Differences between different cross-domain data fusion and traditional data fusion [48]

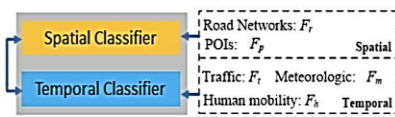
In the above figure 1, illustrates the key distinctions between cross-domain data fusion and traditional data fusion. Traditional data fusion typically involves the integration of data from similar sources or domains, often with a focus on schema matching and database-level integration. In contrast, cross-domain data fusion deals with more complex, heterogeneous data from multiple sources or fields, where the data is multi-modal and contains various representations, distributions, and densities. This requires advanced techniques such as machine learning or artificial intelligence to not only fuse data but also to integrate knowledge across different domains. These differences highlight the evolving complexity of data fusion in the era

of big data, emphasizing the importance of knowledge fusion rather than simply combining data schemas.

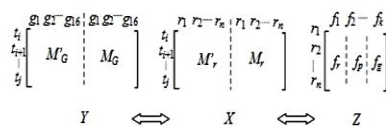
A. Media Data Fusion Methods

In the analysis of this paper, we classify the methods of data into three categories. Firstly, the classification based on stage, the classification based on feature level, and the classification based on semantic data fusion methods are the first, and the last kind of data fusion methods are further divided into four groups in the method tutorial: There are methods based on multi-view learning, methods based on similarity, methods based on probabilistic dependence and methods based on transfer learning [12][13].

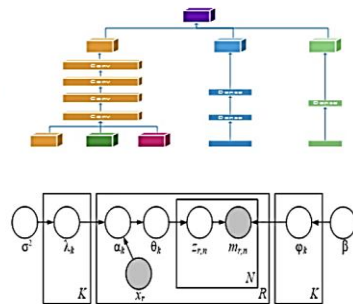
- Stage-based data fusion
- Feature-level-based data fusion
 - Feature concatenation + regularization
 - DNN-based
- Semantic meaning-based fusion



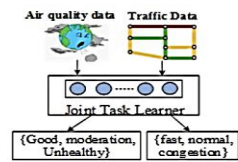
Multi-view learning (Co-training)



Similarity-based (matrix factorization)



Pro. dependency-based (Topic Models)



Transfer Learning-based

Figure 2: Categories of Methods for Cross-Domain Data Fusion[48]

In this method (in Figure 2), the highest-level principles and data processing methods of each method are reduced, and the proportion of technical processing and municipal

problems are also displayed for each method. [14] In addition, the core work of this method round is to explore the fusion methods of different data in a data framework, as

well as the relationship and difference between each data. To help various communities and various fields find data fusion solutions in big data projects and come up with more frontier data solutions.

B. The Stage-Based Data Fusion Methods

From the above data methods, it can be seen that there are many different data processing methods in the process of mining different tasks for different data. Therefore, different data and different loose sum methods have no requirements for the consistency of their data processing modes. Therefore, the data fusion method in the opportunity stage can be combined with other data fusion methods as an original method at the beginning [15]. For example, in the process of using road and network data taxi tracks to build a domain map, a graphical model needs to be proposed to fuse the knowledge categories of POS information area maps.

In the second stage, the method based on probabilistic graphic model is adopted in the method framework of the given stage. For example, a city can be divided into various regions according to main roads through map segmentation. Then, the GPS track of the taxi is shot to the area of each different urban road to form a certain area map, where each node is an area edge, representing the commuter road between the two areas, that is, the gathering of taxis in this experiment. From the fusion process of the area map, the knowledge map of road network and taxi trajectory can be seen [16][17][18]. Finally, by identifying and analyzing the breakthrough of area map, different urban road functional zones for detecting and diagnosing traffic anomalies are designed.

C. The Feature-Level-based Data Fusion

It can be seen in this paper that this kind of method is equal, and it is one of the best methods to extract features from different data and complex data. In the extraction process, the sequence can also connect them into a feature resounding, and through each feature resounding, different data are represented for clustering and classification tasks. Finally, the limitations of different fusion methods are proposed through different research on the distribution and scale of data. The method of subclass advanced learning can deal with the problem of feature composure by adding numerical normalization to the objective function. And the weight of the active learning model is close to zero, so the proposed method can be said to be a more advanced and more opportunistic neural network of different data of the same feature representation. [19][20][21][22][23].

III. INTELLIGENT ANALYTICS IN CROSS-MEDIA CONTEXT

A. Traditional Cross-Media Fusion

In recent years, through the continuous growth of different multimodal data, such as images, video texts or some social media frequency clips, in order to understand the core distribution of these heterogeneous data, intelligent cross-media analysis of multimodal data has become one of the important topics of artificial intelligence and multimedia integration to calculate complex data[24]. The goal of transmedia data analysis is to understand the concepts of physical images and symbols, and to infer the hidden more complex multi-state data knowledge map found in

multimedia data, and based on these knowledge maps and transmedia data, artificial intelligence applications are expected to think like human brains, and finally to make certain explanatory and reliable methods.

In recent years, deep neural networks (DNNS) have become the standard solution for a variety of intelligent computing problems. Scholars are increasingly focusing on deep neural networks, which can significantly improve the effectiveness of cross-media data analysis for intelligent computing tasks. Transmedia data analysis aims to deeply understand and precisely calculate the intrinsic properties of entities extracted from multimodal data and their relationship to other interacting entities [25]. DNNS are designed to simulate human learning methods to acquire specific types of knowledge and provide suitable AI tools for intelligent computation of higher-order relationships across modal data.

B. Intelligent Analysis Model Across Media

- **Parallel text Data Collection and Sensing:** Text data sources Large-scale parallel collection technology is used for distributed, real-time, and incremental collection of multilingual text data from global open data sources, including mainstream media and self-media (such as WeChat, Weibo, Zhihu in China, Twitter, and Facebook in foreign countries, etc.) [26].
- **Multi-channel video data crawling and sensing multi-channel distributed crawling technology for seed address URL multi-channel establishment, including login verification, DNS resolution cache, coding, parsing, and download, to achieve the Internet mass view image data distributed cluster collection. [27]** This paper studies the terminal access mode, streaming media format, and decoding technology of mainstream video surveillance manufacturers, and realizes online video stream pulling and decoding.
- **Unified representation of cross-media data knowledge** Deep neural networks has continuously achieved breakthrough success in big data analysis, bringing new ideas to cross-media association representation. [28][29] For different forms of cross-media data representation, a rule-based knowledge graph is constructed, unified structured data is used for representation learning, highly abstract features are extracted through deep neural networks, and cross-media intelligent perception and analysis tasks are carried out based on these abstract features.

In addition, intelligent analysis algorithms, such as convolutional neural networks (CNN), Long short-term memory networks (LSTM), and graph neural networks (GNN), play a crucial role in cross-media analysis. Convolutional neural networks (CNNS) are usually used to process image and video data, extract spatial features through their deep structure, and are widely used in tasks such as image classification, object detection and video content understanding. [30][31][32][33] In cross-media analysis, CNN can be combined with other modal data (such as text and audio) to carry out multi-modal learning and improve the understanding of multimedia content. Long short-term memory networks (LSTMS) perform well when processing time series data, especially dynamic information in video. LSTM can effectively capture the temporal relationship between video frames, and is suitable for sentiment analysis, video summarization and event detection.

Graph neural networks (GNN) are particularly suitable for processing data with graph structure, such as user and item relationships in social networks, recommendation systems. In cross-media analysis, GNN can combine information from different modes to achieve more accurate recommendations and predictions by modeling multi-dimensional relational data. By applying these intelligent analysis algorithms to the fusion of cross-media data, the accuracy of information extraction and the depth of value mining can be significantly improved, thus providing more efficient decision support and user experience optimization for various application scenarios.

IV. APPLICATIONS OF THE FRAMEWORK

With the rapid development of multimedia and network technology, massive cross-media data such as images, videos, and texts are growing rapidly. [34] They are multi-source heterogeneous and interrelated, which makes data representation, information retrieval, knowledge discovery, and semantic reasoning face cross-media and cross-data source challenges. How to learn from the cross-media characteristics of the human brain and recognizing the external world across different sensory information such as vision, hearing, and language is crucial for improving the perceptual-cognitive ability and intelligence level of the computer [35][36]. It can be seen that the tasks and objectives of cross-media analytical reasoning technology in "Artificial Intelligence 2.0" are introduced, and then our relevant research progress is highlighted, including fine-grained image classification, cross-media retrieval, text image generation, video description generation, etc.

Diao, Huang, and Wan [20] analyzed Early detection of cervical adenocarcinoma using immunohistochemical staining patterns through computer vision technology, a method for early cervical adenocarcinoma detection based on immunohistochemical staining pattern and computer vision technology was proposed. In this study, computer vision technology was used to analyze the features of immune histochemical staining images and automatically identify the cell and tissue features associated with cervical adenocarcinoma, providing an efficient and accurate means of early diagnosis. The method not only improves the sensitivity of detection, but also reduces the error caused by human factors through deep learning analysis of staining patterns. The study shows that the combination of computer vision and immunohistochemistry can significantly improve the accuracy of early screening for cervical adenocarcinoma, promote the development of early cancer detection technology, and provide technical support for personalized medicine.

A. Cross-Media Medical Imaging Cases

In recent years, the prediction and recognition of cancer has been an important research direction in the field of medical image analysis, especially with the promotion of multi-modal medical image fusion technology, the related

research has made remarkable progress. Traditional medical imaging techniques, such as CT, MRI and PET, have different advantages, but the image of a single mode is often unable to fully capture the complex features of the lesion, which limits the accuracy and precision of early cancer diagnosis [37][38][39]. Therefore, the use of multimodal image fusion technology to synthesize information from different sources has become an important method to improve the accuracy of cancer prediction and recognition.

In this context, artificial intelligence (AI), especially deep learning technology, is widely used in medical image analysis[40]. Diao et al. [20] in their In Fusion, a cancer prediction and recognition method based on multimodal medical image fusion is proposed. The study combines multiple deep learning models, such as convolutional neural networks (CNNs) and self-attention Mechanisms, to enhance the model's ability to process multimodal data and optimize the accuracy of cancer diagnosis.

Specifically, the study used CT and MRI image data to extract image features through convolutional neural networks and then integrated the information of the two modes through feature fusion technology to obtain more comprehensive lesion information. In addition, the study also explored the impact of different fusion strategies (such as early fusion and late fusion) on cancer recognition results and found that multi-modal fusion can effectively improve the recognition ability of the lesion area, especially in the case of poor image quality or more noise, the fusion model showed stronger robustness[41][42][43].

Combining artificial intelligence and multi-modal image fusion, the current research direction is gradually moving towards more refined image processing and intelligent diagnosis methods. Through the continuous optimization of deep learning technology, the future medical image analysis system will not only provide more efficient cancer diagnosis schemes, but also realize more accurate personalized medical services in clinical applications. The development of this field is expected to bring great breakthroughs for the early screening and precision treatment of cancer and promote the deep integration of medical imaging technology and artificial intelligence.

The purpose of the cross-media intelligent medical image interpretation system is to establish an intelligent medical image interpretation system so that users can quickly acquire medical image knowledge, pathological knowledge, and health knowledge according to their own needs. [44][45]Users can input their images provided by existing hospitals into the system, and the system analyzes the images and returns to the user's similar organ images and related text description information (anatomical knowledge and working principle of the organ, etc.) so that users can initially understand the geometric shape of an organ, its functional structure, and the severity of the lesions. To provide services for patients, medical workers, and scientific researchers.



Figure 3: Two Images, Same Injury[49]

In the above figure 3, file sharing makes it easy to store and compare different digital images when treating patients, says Project managers Terje Hellemo (Helse Nord Fresk) and Rune Grov Eilertsen (Radiology Management Center) [49]. In addition, Diao et al. [20] discussed the important role of artificial intelligence in personalized medicine, especially combining advanced medical imaging technology to improve the accuracy of disease diagnosis and treatment. The study pointed out that through AI technology such as deep learning, medical image data can be automatically analyzed and interpreted, from which subtle pathological characteristics can be extracted, and combined with clinical information of patients, to provide data support for the development of personalized treatment plans[46][47] AI not only improves the accuracy of early disease identification but also predicts patients' responses to different treatments based on image characteristics, promoting the development of personalized drugs and the progress of precision therapy. In recent years, short-term price forecasting, especially in the field of electricity trading market and finance, has become an important research topic. The "hybrid stacking method" proposed by Chen et al. [37] is applied to the short-term price prediction of the power trading market, which significantly improves the accuracy and reliability of the prediction by combining various machine learning models. This method adopts the framework of stacked ensemble learning, utilizes the advantages of multiple models to optimize the prediction results, and can effectively deal with the market volatility and complex nonlinear characteristics. This method not only has an important impact on real-time decision-making in the electricity market, but also provides a new perspective for short-term price forecasting in the financial field. In the financial markets, especially the stock and commodity markets, the application of artificial intelligence (AI) technology has gradually become a core tool for improving forecast accuracy and market analysis capabilities(Figure 3). AI, especially deep learning and ensemble learning methods, are capable of processing large and complex data sets, capturing weak signals in market trends, and playing an important role in high-frequency trading and risk management. Advances in converged media technology have also further enhanced the diversity

and real-time flow of information in financial markets, enabling AI to conduct sentiment analysis and trend prediction through multi-modal data (such as news, social media, financial statements, etc.), so as to more accurately predict market changes.

Combining the research direction of finance and converged media is not only a theoretical innovation, but also a breakthrough in practical application. Through the integration of big data and artificial intelligence technologies, especially integrated learning and large language models, more significant results will be achieved in the future in the fields of short-term price prediction, risk assessment and investment decision-making in financial markets. The research of Chen et al. [47] provides valuable technical reference for this field and promotes the deep application and optimization of AI technology in actual trading systems. This shows that the combination of AI and medical imaging has broad application prospects in the future of personalized medicine.

The cross-media intelligent medical image interpretation system is an intelligent medical image interpretation system that can enable users to quickly acquire medical image knowledge, pathological knowledge and health knowledge according to their own needs. It is mounted on the system platform for the medical data retrieval methods based on text, voice and image respectively, and realizes the visualization of 3D medical image data[40][41][42]. This technology has reduced the average post-processing time of multi-risk organ image painting from 25-35min to 2-3min in the application of the head and neck radiotherapy system of UCLA Radiotherapy Center and the First Affiliated Hospital of Xi'an Jiaotong University, and the number of technician clicks from 100+ times to 4 times, greatly improving the post-processing efficiency of images in clinical work, and ranking second in the world in the International AAPM2019 competition.

B. Ai Video Intelligence Analysis Technology

Media video intelligence analysis technology mainly relies on deep learning and computer vision two core technologies. The principle is to access a variety of cameras and DVR, DVS and streaming media servers, and other video equipment, and through intelligent image recognition and processing technology, active early warning of various

security events, through real-time analysis, the alarm information to the integrated monitoring platform and client[42]. Specifically, the intelligent video analysis system "finds the enemy situation" and "sees" the surveillance target in the field of view through the camera in real-time, and at the same time determines whether there is a security threat to the behavior of these monitored targets through its intelligent recognition algorithm. Timely to the integrated monitoring platform or background management personnel through voice, video, and other types of alarm.

There are usually two kinds of AI video intelligent analysis technology used in video surveillance solutions, the first is a front-end solution based on intelligent video processors. In this mode, all target tracking, behavior judgment, and alarm triggering are completed by the front-end intelligent analysis equipment, and only the alarm information is transmitted to the monitoring center through the network. [43][44][45] The second is a back-end intelligent video analysis solution based on industrial computers. In this mode, all front-end cameras only have the basic video capture function, and all video analysis must be gathered to the back end or key nodes by the computer unified processing. In the market, the first way is mostly used, and the video analysis device is placed after the IP camera, which can effectively save the bandwidth occupied by the video stream. The solution based on industrial computers can only control a few key monitoring points, and the computer performance and network bandwidth requirements are relatively high.

In the process of video intelligent analysis, it is necessary to preprocess the video, such as de-noising, enhancement, etc., to improve the video quality. Then, the object in the video is detected, tracked, and identified by the deep learning model. These targets can be faces, objects, behaviors, etc. [45][46][47] Finally, through the analysis of the identification results, the key information in the video is extracted to provide support for the subsequent intelligent application.

V. CONCLUSION

The rapid evolution of cross-media data, encompassing diverse sources such as images, videos, text, and audio, presents both immense opportunities and significant challenges for intelligent analytics. The integration and fusion of these heterogeneous data types are crucial for extracting valuable insights and enhancing decision-making processes. In this context, advanced machine learning algorithms, such as convolutional neural networks (CNN), long short-term memory networks (LSTM), and graph neural networks (GNN), play pivotal roles in bridging the gap between different media modalities. These intelligent analysis techniques enable the effective handling of cross-media data, allowing for more accurate information extraction, deeper value mining, and enhanced user experiences. The development of robust frameworks for cross-media data fusion and analytics will be key to advancing fields ranging from media content analysis to personalized healthcare, security surveillance, and beyond. As media organizations, healthcare systems, and other industries continue to leverage the power of cross-media data, the need for efficient, scalable, and secure data integration strategies becomes increasingly important.

Hybrid and multi-cloud solutions, combined with consistent infrastructure models, can provide the flexibility and operational efficiency required for seamless data fusion across diverse environments. The future of cross-media data fusion lies in the ability to integrate different data types with minimal friction, ensuring that insights can be drawn from a holistic view of interconnected information. By continuously advancing the underlying technologies and methodologies, organizations can unlock new opportunities for innovation and create more personalized, data-driven solutions that meet the demands of today's dynamic digital landscape.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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