Deep Learning-Based Semantic Feature Extraction: A Literature Review and Future Directions

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Abstract: Semantic communication, as a critical component of artificial intelligence (AI), has gained increasing attention in recent years due to its significant impact on various fields. In this paper, we focus on the applications of semantic feature extraction, a key step in the semantic communication, in several areas of artificial intelligence, including natural language processing, medical imaging, remote sensing, autonomous driving, and other image-related applications. Specifically, we discuss how semantic feature extraction can enhance the accuracy and efficiency of natural language processing tasks, such as text classification, sentiment analysis, and topic modeling. In the medical imaging field, we explore how semantic feature extraction can be used for disease diagnosis, drug development, and treatment planning. In addition, we investigate the applications of semantic feature extraction in remote sensing and autonomous driving, where it can facilitate object detection, scene understanding, and other tasks. By providing an overview of the applications of semantic feature extraction in various fields, this paper aims to provide insights into the potential of this technology to advance the development of artificial intelligence.

Keywords: semantic feature extraction; semantic communication; deep learning

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1 Introduction

Artificial intelligence (AI) has become a rapidly growing field in recent years, with semantic communications being a critical component of AI[1 – 3]. Semantic communication has gained increasing attention in recent years due to its significant impact on various fields[4 – 7]. It involves the recognition of semantics and understanding of human language, thereby enabling faster and more accurate transmission of information. The significance of the semantic communication lies in its ability to improve communication efficiency, provide more accurate information, and convey intentions more effectively. Deep learning-based semantic feature extraction plays a critical role in enabling effective communications by extracting meaningful features from data and encoding them in a way that can be easily transmitted and interpreted by agents[7 – 8]. Its importance has been recognized in a wide range of AI domains, including natural language processing (NLP), medical imaging, remote sensing, and autonomous driving.

This survey paper focuses on semantic feature extraction, which is a key step in semantic communications, providing a comprehensive literature review of its applications in various AI domains. This paper aims to review the current research status and development trend of deep learning-based semantic feature extraction.

Firstly, we introduce the concept and research background of semantic feature extraction, including the technical basis of speech interaction, NLP, sentiment computing, knowledge graph and machine translation[9 – 12].

Secondly, we introduce in detail the current research status of deep learning-based semantic feature extraction applications, including speech interaction applications based on speech recognition, intelligent dialogue systems based on NPL, sentiment computing applications based on sentiment analysis, intelligent question answering systems based on knowledge graph and cross-language interaction applications based on machine translation[13 – 18].

Finally, we discuss the limitations of AI-driven semantic communication applications in actual applications and future development directions, including technical difficulties, data problems, security and privacy issues, as well as the application scenarios and commercial value of AI-driven semantic communication applications in the future.

2 Deep Learning-Based Semantic Feature Extraction Methods in Multiple Fields

AI technology, such as deep learning methods, plays a significant role in semantic feature extraction. The process of semantic feature extraction can be divided into two categories: the NLP-based and image-based.

NLP-based semantic feature extraction involves computer processing of natural language, including speech recognition, text classification, named entity recognition, part-of-speech tagging, dependency analysis, and semantic role labeling[9–12]. It also includes knowledge graphs that provide a graphical representation of knowledge consisting of entities, attributes, and relationships[13–15]. Additionally, sentiment analysis techniques are used to analyze sentiment information contained in text, including sentiment recognition and sentiment analysis[16–18]. Semantic representation techniques focus on converting natural language into a form that can be processed by computers, such as word vector representation, sentence vector representation, semantic role labeling, and semantic dependency analysis[19–22]. Together, these technologies form the technical system of semantic communication and enable computers to better understand the meaning and semantic information of natural language, leading to better semantic communications.

In the computer vision, semantic communication technologies include image recognition, target detection, visual semantic segmentation, image classification, image retrieval, and image clustering[23–24]. Image recognition utilizes machine learning and deep learning to recognize and classify objects in images[25–26]. Target detection involves using machine learning to detect specific targets in images, such as faces or text, and identifying their characteristics[27]. Visual semantic segmentation involves segmenting objects in images into different categories, shapes, and colors[28–30]. Image classification allocates images to different categories based on the objects present in them. Image retrieval retrieves images related to user input from an image database[31–32]. Image clustering involves grouping similar images according to object shape, color, and other characteristics to improve image management[33–34]. These technologies leverage deep learning and machine learning to improve the accuracy and efficiency of image processing.

Next, we will describe in detail the application of semantic feature extraction in five explicit scenarios and a summary is shown in Table 1.

2.1 Natural Language Processing

Semantic feature extraction plays a crucial role in natural language processing and has various applications across numerous downstream tasks[35–36]. These tasks include information extraction[37–38], sentiment analysis[39–40], and knowledge graph construction[41]. Gaining a better understanding of users' semantic expressions allows for more efficient processing of their queries and accurate information provision. In named entity recognition (NER)[42], for instance, it is essential to identify entities within sentences. Generally, these entities exhibit distinct semantic features, such as being nouns. By accurately recognizing these features, more effective NER methods can be developed. Similarly, sentiment analysis relies heavily on semantic feature extraction. This process involves identifying mentions (typically nouns) and classifying their sentiment polarities (usually adjectives). Part-of-speech tagging serves as an explicit semantic feature, while implicit features can also be calculated using deep learning techniques based on word embeddings. In their study, BAO et al.[43] proposed a deep learning-based sentiment analysis method, employing a meta-based self-training approach with a meta-weighter. They trained a teacher model to generate in-domain knowledge (semantic features) for supervised learning, using the generated pseudo-labels in a student model. Knowledge graph construction often encompasses multiple tasks, such as named entity recognition[44], relation extraction[45], and anaphora resolution[46]. In their research, HE et al.[41] proposed a multi-task framework for constructing knowledge graphs. They employed a shared encoder to extract common semantic features for all mentioned tasks. More specifically, they developed an end-to-end information extraction system using a multitask-based artificial neural network model for constructing genealogical knowledge graphs from online obituaries. In conclusion, the application of semantic feature extraction in the field of natural language processing enhances its intelligence, facilitating a deeper understanding of users' semantic expressions. This, in turn, enables more efficient processing of user queries and the provision of more accurate information.

2.2 Hyperspectral Image Analysis

Semantic communication in the application of remote sensing images is a technique used to extract information from data acquired by hyperspectral imaging sensors[47]. Hyperspectral imaging sensors collect data in many narrow, contiguous spectral bands, essentially producing a 3D data cube with two spatial dimensions and one spectral dimension[48]. Hyperspectral image analysis involves processing this data cube to extract information about the materials or objects in the imaged scene. The main techniques of hyperspectral image analysis include spectral unmixing, classification, and anomaly detection. Firstly, spectral unmixing separates the contributions of different materials in each pixel of the image. The work in Ref. [49] proposed a dynamical model for unmixing a time series of hyperspectral images, with a simplified version of the model used to derive an efficient spectral unmixing algorithm that is demonstrated on synthetic and real multi-temporal hyperspectral images. The work in Ref. [50] proposed a new method for solving the sparse hyperspectral unmixing problem without relaxation, using a multi-objective optimization approach and a binary coding technique, which is demonstrated to be effective on both synthetic and real hyperspectral datasets. Secondly, the hyperspectral image classification assigns

▼**Table 1. Semantic communication application scenarios**

Scenario	Task	Method	Model Name	Model Structure	Year
Hyperspectral image	Classification	Markov random field	NE-MFAS[51]	SVM + MRF	2017
		Group sparse coding	MSKGSC[53]	Kernel sparse representation	2016
		Semantic manifold learning	MFAS[52]	SVM + MRF	2016
	Object detection	Multi-view noisy learning	MOL[71]	VGG16 + MIL	2023
		Few-shot learning	AUD-Net[54]	ResNet + multi-head attention	2022
Medical field	Classification	Vision transformer	i-ViT[66]	Vision transformer	2021
		Multi-task learning	MTL-CRD[68]	A semi-supervised multi-task learning framework	2023
		Uncertainty-based model	UMA[69]	Uncertainty-based model acceleration	2022
		Multi-instance learning	HIB[67]	Information bottleneck + hierarchical multi-instance learning	2022
	Segmentation	Segmentation network	W-Net[70]	Composite high-resolution network	2021
	Clinical prediction	Representation learning	CSEDrug[61]	Pretrain + RNN	2022
		Information theory	DAPSNet[60]	RNN + attention + information bottleneck	2023
Natural language processing	Sentiment analysis	Prompt tuning	Survey[40]	Transformer	2022
		Meta-learning	MSM[39]	Teacher-student/BERT	2022
		Meta-learning	MLB[43]	BERT	2021
	Knowledge graph	Multi-task learning	MTL-2[41]	Bi-LSTM	2021
		Multi-task learning	MTL-1[37]	Bi-LSTM	2019
	Named entity	Few-shot learning	Copner[42]	BERT	2022
	Relation extraction	Prompt tuning	VPP[36]	BERT	2023
		Semi-supervised learning	UG-MCT[45]	BERT	2022
		Continual learning	JCBIE[44]	BERT	2022

AUD-Net: a unified detector anomaly detection network
BERT: Bidirectional Encoder Representations from Transformers
Bi-LSTM: Bidirectional LSTM
CRD: cancer region detection
CSEDrug: a comprehensive DDI controllable model
DAPSNet: Dual Attention and Patient Similarity Network
HIB: a multi-instance learning model
I-ViT: an integer-only quantization scheme for vision transformers
JCBIE: joint continual learning biomedical information extraction
LSTM: long short-term memory
MFAS: Multimodal Fusion Architecture Search
MIL: multiple instance learning
MLB: a meta-learning model
MOL: multi-view noisy learning
MRF: modified random forest
MSKGSC: a group sparse coding model
MSM: meta-based self-training method with a meta-weighter
MTL: multi-task learning
NE: network element
RNN: recurrent neural network
SVM: support vector machine
UG-MCT: Uncertainty-Guided Mutual Consistency Training framework
UMA: uncertainty-based model acceleration
VGG16: a convolution neural network architecture
VPP: virtual prompt pre-training model
W-Net: a segmentation network

each pixel to a particular material or object class. The work in Refs. [51] and [52] proposed a method for improving hyperspectral image classification performance by combining multiple features in the same semantic space with local and non-local spatial constraints using an extended Markov random field model. The work in Ref. [53] proposed a new method for hyperspectral image classification using adaptive spatial partition of pixels into clusters via group sparse coding that integrates spectral and spatial information to improve classification accuracy and provide distinctive classification maps. Lastly, anomaly detection identifies pixels with unusual spectral characteristics that may indicate the presence of a target material. The work in Ref. [54] proposed a unified detector anomaly detection network (AUD-Net) inspired by few-shot learning to perform anomaly detection across multiple hyperspectral images (HSIs) without repeated training, which addresses the challenges of generalization to different HSIs with different spectral sizes and achieves strong generalization. Hyperspectral image analysis has applications in a wide range of fields, including remote sensing, environmental monitoring, mineral exploration, agriculture, and biomedical imaging. In conclusion, the application of semantic communications in remote sensing images can greatly enhance the user's understanding and provide more accurate information, making the remote sensing image analysis more intelligent and thus better managing the local resources.

2.3 Clinical Application

In recent years, the application of semantic communication technology in the medical field has become increasingly popular[55–57]. In Refs. [55] and [56], an attention-based graph convolutional network (GCN) was proposed to convert unstructured pathological reports into structured data for computer analysis, improving pathologists' workflow and providing more accurate assistance for diagnosis and treatment, with promising results demonstrated on a dataset from TCGA. Semantic communication technology can also be used for intelligent diagnosis, which can use a large amount of case data to carry out intelligent diagnosis according to the patient's medical history and examination results, thus providing doctors with more accurate diagnosis results[58–59]. The work in Ref. [58] proposed a general healthcare representation model that uses simple convolution operations and up/down sampling to adaptively extract distinct individual key features, achieving superior performance and model complexity compared to other baseline models on the MIMIC-III dataset. In addition, semantic communication technology can be used for intelligent treatment, which can provide more effective treatment plans according to the patient's medical history and examination results, thus more effectively treating patients[60–61]. Two drug recommendation studies[60–61] proposed a drug combination prediction model that leverages multifaceted drug knowledge and loss functions to improve drug encoding and drug-drug interaction (DDI) control, achieving superior accuracy, effectiveness and safety compared to state-of-the-art methods. Moreover, doctors can better understand the condition of patients and provide more effective treatment plans for them by using semantic communication technology to query relevant cases according to the patient's medical history and examination results. Semantic communication technology can also be used for intelligent drug development, which can use a large amount of drug data to find new drugs according to the patient's medical history and examination results, thus more effectively treating patients[62–63]. The work in Ref. [64] proposed a framework that combines pathological images and medical reports to generate a personalized diagnosis result for an individual patient, using nuclei-level image feature similarity and content-based deep learning methods to extract structured prognostic information and assign importance to different factors, with promising results demonstrated on TCGA data for renal cell carcinoma. In conclusion, the application of semantic communication technology in the medical field can improve medical efficiency and help treat patients better, providing more effective treatment plans for patients and making medical care more intelligent.

2.4 Medical Image Analysis

Semantic communication is a critical component in medical image analysis, where accurate interpretation and communication of medical image findings are crucial for clinical diagnosis and decision-making. In medical image analysis, semantic communication involves the ability to convey the meaning of medical image features and findings, such as the presence of tumors, lesions, or abnormalities, to clinical experts and other stakeholders. Semantic communication is especially important in cases where medical images need to be interpreted by multiple experts or in cross-institutional settings, where the interpretation of medical images may vary due to differences in expertise or experience[62]. Therefore, the development of semantic communication methods and tools for medical image analysis has become an active research area in recent years. Deep learning-based semantic segmentation and classification algorithms have shown great potential in enabling accurate and efficient semantic communication in medical image analysis. By leveraging the power of deep learning, these algorithms can automatically extract and classify medical image features, and provide intuitive visual representations of the underlying medical conditions. These approaches have the potential to greatly improve the efficiency and accuracy of medical image analysis and interpretation, and ultimately enhance patient care and outcomes. Based on the different granularity of semantic feature extraction, medical image analysis can be divided into classification, detection, and segmentation. Classification involves assigning a label or category to an image or region of interest based on its characteristics, which is used in tasks such as tumor diagnosis and tissue classification[65]. The work in Ref. [66] proposed an instance-based vision transformer to learn robust representations of histopathological images for the pRCC subtyping task by extracting finer features from instance patches and capturing both cellular and cell-layer level patterns by position-embedding, grade-embedding, and self-attention. The work in Ref. [67] proposed a hierarchical Multi-Instance Learning (MIL) framework with an Information Bottleneck (IB) to handle patient-level labels and exploit the correlation among leukemia subtypes for better accuracy and generalization in childhood acute leukemia classification without the need for cell-level annotations. Detection involves identifying the presence or location of specific features or anomalies in an image, which is used in tasks such as lesion detection and localization. The work in Ref. [68] proposed a semi-supervised multi-task learning framework for whole slide image classification to improve the performance on both cancer region detection and subtyping tasks by capturing the interaction of the two tasks, and to preserve the sequential relationship of the tasks using a weight control mechanism, demonstrated to be effective in accuracy and generalization on four large datasets with different cancer types. Segmentation is the process of dividing an image into multiple regions or segments based on their characteristics, which is used to identify and isolate specific structures or features in medical images. The work in Ref. [69] proposed a contrastive learning framework with multi-granularity views for tissue segmentation by designing three contrastive learning tasks from global to local, which can capture fine-grained patterns in the learned representations for transfer learning to various tissue segmentation tasks in histopathological images, demonstrated to be superior to existing contrastive learning methods. The work in Ref. [70] proposed a Composite High-Resolution Network for nuclei grading, i.e., a special task of nuclei segmentation and classification, which includes a W-Net for segmentation, two high-resolution feature extractors for nuclei classification, and a head-fusion block for label generation.

2.5 Autonomous Driving

The field of autonomous driving has gained significant attention due to the continuous development of artificial intelligence technology. Semantic communication technology has emerged as a crucial factor in this field.

To enable natural dialogue between passengers and autonomous or driverless cars, these vehicles must possess the ability to comprehend natural language. This necessitates the use of semantic analysis technology, which can identify the actual intention and emotional tendencies of language, leading to better passenger satisfaction. Furthermore, autonomous and driverless cars must be capable of perceiving their surrounding environment, identifying various traffic signs, and adhering to driving rules on the road. This requires significant support from semantic modeling and computer vision technology to ensure that the vehicles respond appropriately to traffic signals, pedestrians, and other vehicles. In case of an emergency, voice alarms can assist drivers and passengers in reacting quickly. Voice alarms can warn passengers of problems and allow for further operations based on their responses. All in all, semantic communication technology plays an indispensable role in the development of autonomous driving and driverless cars. It enhances the ability of these vehicles to understand passenger needs, perceives the surrounding environment accurately, and provides timely alarms to passengers in emergencies. These factors provide the foundation for the future development of intelligent transportation.

3 Development Trends

The progress and extensive application of artificial intelligence technology have significantly supported the research and implementation of semantic communication applications. Intelligent voice interaction is projected to become the standard for AI-driven semantic communication applications, with voice technology continuously advancing and proliferating. Additionally, multi-modal interaction will become more prevalent as multi-modal technology is applied to different media, offering more diverse interactions. Personalized interaction will be prioritized by analyzing user preferences and needs. Further, semantic understanding and generation technologies, along with knowledge graphs, will continue to advance, making human-computer interaction more natural and intelligent. While semantic communication applications will bring more convenience and efficiency to daily life, work, and learning, they are also anticipated to encounter new challenges, such as security and semantic ambiguity. In conclusion, the continuous development and expansion of semantic communication applications will provide both opportunities and challenges for society.

4 Challenges

Semantic communication applications powered by artificial intelligence encounter several challenges that require resolution. Firstly, there is a lack of profound semantic comprehension, making it difficult for the application to fully understand the user's expression, which may result in potential misinterpretation. Secondly, the application's self-learning ability is limited, which restricts its capacity to increase knowledge from user input. Thirdly, the application's computational complexity and memory capacity limitations may negatively affect its processing capabilities. Lastly, the application's weak anti-interference ability makes it vulnerable to external interference and noise.

To address these challenges, the application must have a more accurate and profound understanding of the user's semantic expression and the ability to learn from user input. It must also enhance its computational complexity and memory capacity to process more information in less time and have a stronger anti-interference ability.

Several approaches have been developed to tackle these challenges, including NLP techniques to enhance semantic comprehension, deep learning models such as convolutional neural networks (CNNs) for self-learning, distributed computing and cloud computing to increase computational complexity and memory capacity, and noise cancellation and signal processing to improve anti-interference ability.

In conclusion, addressing these challenges will enhance the application's ability to provide a better user experience, bringing convenience and value to various aspects of life. The difficulties encountered by semantic communication applications driven by artificial intelligence can be addressed through various approaches, including NLP, deep learning, distributed computing, cloud computing, noise cancellation, and signal processing

5 Conclusions

This paper provides a review of semantic communication applications powered by AI, examining its background, technology, applications, and development trends. Semantic communication applications have become an essential direction for the development of AI technology, with widespread applications and significant impact. They enhance human-computer interaction efficiency and quality, improve user experience, and address issues such as language barriers and information overload, bringing convenience and value to all aspects of life. As technology advances, semantic communication applications will become increasingly intelligent, natural, personalized, and multimodal, promoting AI technology development in broader fields. However, challenges such as user privacy protection and semantic ambiguity require continuous innovation and improvement to ensure healthy application development. In conclusion, semantic communication applications will be extensively adopted in various fields, bringing convenience and transforming people's lives and work in the near future.

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