

Brief Report

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Overview of Deep Learning Research

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Brief Report

Overview of Deep Learning Research

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Abstract: Deep learning, as a strong trend in the fields of machine learning and artificial intelligence, is not only a hot topic in current academic research, but also a key force driving technological progress. As one of the latest trends in artificial intelligence research, deep learning has become one of the most eye-catching scientific research trends today due to its powerful data processing capabilities and pattern recognition accuracy. This paper summarizes the deep learning model and summarizes the application of deep learning in many fields.

Keywords: deep learning; deep mental network; literature review

1. Introduction

Deep learning is an important branch of machine learning that was introduced in 1986 and began to be used in artificial neural networks in 2000.

Deep learning is the process of learning the inherent patterns and expression levels of sample data, using multi-layer neural networks to automatically learn and extract features from the data, thereby achieving tasks such as prediction, classification, and recognition of the data.

In recent years, the field of deep learning has witnessed unprecedented technological innovation and theoretical breakthroughs. New deep learning models and technologies are emerging like mushrooms after rain, constantly surpassing advanced machine learning algorithms and even early deep learning techniques. These advances include but are not limited to the widespread application of convolutional neural networks (CNNs) in image recognition, the outstanding performance of recurrent neural networks (RNNs) and their variants such as long short-term memory networks (LSTMs) in natural language processing tasks, and the pioneering work of generative adversarial networks (GANs) in image generation and style transfer.

2. The Five Major Models of Deep Learning

2.1. Convolutional Neural Networks

Convolutional neural networks is a deep learning models specifically designed for processing grid data, especially suitable for image data processing. CNN achieves automatic extraction and classification of image features through structures such as convolutional layers, pooling layers, and fully connected layers. Among them, the convolutional layer extracts local features of the image through convolution operations; the pooling layer reduces the dimensionality and computational complexity of data through downsampling operations; the fully connected layer maps the extracted features to the category space to achieve classification tasks. CNN has excellent performance in fields such as image classification and object detection.

2.2. Recurrent Neural Networks

Recurrent neural network is a deep learning model used for processing sequential data. Unlike CNN, RNN can capture temporal dependencies in sequential data, making it suitable for processing data with temporal features such as image sequences and speech sequences. RNN introduces a cyclic connection structure to enable the network to remember historical information and consider the

influence of historical information in current decision-making. However, traditional RNNs face an undeniable problem of gradient vanishing or exploding when dealing with long sequence data. To address this issue, researchers have proposed variants such as Long Short Term Memory Networks (LSTM) and Gated Recurrent Units (GRU) to improve the performance of RNNs in processing long sequence data.

2.3. Long Short Term Memory Network

LSTM is a variant of RNN proposed by researchers to solve the problem of gradient vanishing or exploding in recurrent neural networks when processing long sequence data. It introduces gating mechanisms (forget gate, input gate, and output gate) to address the gradient vanishing and exploding issues in traditional RNNs. LSTM, by introducing gating mechanisms and memory units, enables the network to remember long-term information and forget useless information, better capturing long-term dependencies in sequence data. Therefore, it performs well in processing long sequence data.

2.4. Generative Adversarial Networks

Generative Adversarial Model is a deep learning model primarily used for data generation tasks, consisting of two networks: Generator and Discriminator. The generator is responsible for generating data samples that are as realistic as possible, while the discriminator is responsible for accurately determining whether the input data is real or generated by the generator. The generator is responsible for capturing the distribution of sample data, while the discriminator is generally a binary classifier that determines whether the input is real data or generated samples. The optimization process of this model is a "binary minimax game" problem, in which one party (discriminator or generator) is fixed during training, the parameters of the other party are updated, and iteration is alternated, forming an adversarial relationship between the two. Through this adversarial training, the generator gradually learns to generate high-quality data, such as images, audio, etc.

2.5. Transformer Network

The Transformer model is a deep learning model based entirely on attention mechanisms, abandoning traditional RNN and CNN structures. Transformer achieves efficient processing and understanding of sequential data through techniques such as self-attention and positional encoding.

3. The Application of Deep Learning

As a key branch of the field, deep learning has achieved significant results in many areas such as image recognition and speech recognition due to its powerful feature learning and classification capabilities.

3.1. Image Recognition Field

For image recognition, deep learning uses a convolutional neural network structure to perform multi-level feature extraction and classification on images. This processing method significantly improves the accuracy of image recognition and provides impetus for the development of fields such as face recognition and object detection. Traditional image recognition mainly relies on manually designed feature extractors, but these methods have limited accuracy and efficiency in processing complex and variable image data.

The image classification method based on CNN usually includes steps such as data preprocessing, model construction, training, and testing. In the data preprocessing stage, it is necessary to perform operations such as scaling, cropping, and normalization on the images to improve the model's generalization ability. In the model construction phase, classic CNN architectures such as AlexNet, VGGNet, ResNet, etc. are usually used as benchmark models and

fine tuned according to specific tasks and data characteristics. During the training phase, the model parameters are optimized using the backpropagation algorithm to achieve high accuracy on the training set. During the testing phase, the trained model is applied to the test set to evaluate its generalization ability and performance. By using the relu incentive algorithm and convolution function, the program can automatically recognize different things or similar things with different features [7].

A facial recognition system is a typical image recognition application aimed at achieving identity verification or recognition by comparing the input facial image with the facial images in the database. Deep learning algorithms have played an important role in facial recognition systems. In facial recognition systems, CNN is commonly used as a feature extractor to extract high-level feature representations from input facial images. Then, metric learning methods such as cosine similarity and Euclidean distance are used to calculate the similarity between the input image and the images in the database. Finally, based on the similarity threshold, determine whether the input image belongs to a face in the database or identify its identity. Speech recognition field

3.2. *Speech Recognition Field*

The application process of deep learning in speech recognition usually includes five steps: speech signal acquisition, preprocessing, feature extraction, model training, recognition, and testing. Among them, in the feature extraction stage, traditional methods such as MFCC and LPCC are more sensitive to noise and require additional preprocessing steps. The processing effect on non-speech signals is poor, while deep learning models such as CNN and DNN directly extract high-level features from speech signals, reducing reliance on traditional feature extraction methods. GNNs have proven to be a valuable asset for text classification tasks, thanks to their capability to handle non-Euclidean data efficiently. By introducing an adaptive graph construction strategy and efficient graph convolution operation, the accuracy and efficiency of text classification are effectively improved[27].

In speech recognition, DNN can be used for acoustic modeling, replacing traditional GMM models to model the observation probability of speech. Through DNN, the time-domain and frequency-domain features of speech signals can be better captured, improving the accuracy of speech recognition. CNN models the spectral characteristics of speech signals, effectively removing pronunciation differences and facilitating acoustic modeling of speech. RNN can be used to model the temporal dynamic correlation of speech signals. Variants of RNNs, such as Long Short Term Memory Networks (LSTM) and Gated Recurrent Units (GRU), solve the gradient vanishing problem of simple RNNs and further improve the performance of speech recognition. Deep learning technology can achieve the fusion of speech signals with other sensor information, text information, and other data, improving the perception ability of speech recognition systems for environmental information. Peng X, Xu Q, Feng Z, et al. explore an automatic news generation and fact-checking system based on language processing, aimed at enhancing the efficiency and quality of news production while ensuring the authenticity and reliability of the news content[12].

3.3. *Image Generation Field*

In the field of image generation, deep learning models can automatically learn the features of images by simulating neural networks in the human brain, thereby generating high-quality images. GANs have achieved significant success in image generation, style transfer, image enhancement, and other areas. For example, GANs can generate realistic images of faces, animals, buildings, and other objects. VAEs have achieved significant success in image generation, compression, and other areas. For example, VAEs can generate high-quality images while preserving the details and texture of the images. RNNs and their variants have achieved significant results in tasks such as text-to-image generation. For example, by providing descriptive text, corresponding images can be generated. Liu D, Waleffe R, Jiang M, et al have developed a framework called GraphSnapShot, which has been proven an useful tool for graph learning acceleration. GraphSnapShot is a framework for fast cache, storage, retrieval and computation for graph learning. It can quickly store and update the local

topology of graph structure and allows us to track patterns in the structure of graph networks, just like taking snapshots of the graphs [9].

3.4. Recommendation System Domain

In the field of recommendation systems, deep learning constructs deep neural network models to deeply mine and analyze user behavior data, achieving accurate user portraits and personalized recommendations and improving user experience. Recommendation systems can be divided into various types, such as content-based recommendation, collaborative filtering recommendation, hybrid recommendation systems, etc. Deep learning-based recommendation systems can effectively improve the accuracy and diversity of recommendations.

Collaborative filtering based on deep neural networks is a recommendation algorithm that combines deep learning with collaborative filtering. This algorithm constructs a deep neural network model to extract features and recognize patterns from historical behavior data of users and items, thereby calculating the similarity between users or items and achieving recommendations. Compared with traditional collaborative filtering algorithms, deep neural network-based collaborative filtering has stronger feature extraction capabilities and higher recommendation accuracy. At the same time, the algorithm can also handle sparsity and cold start problems, improving the robustness of the recommendation system.

Content recommendation based on deep learning is a recommendation algorithm that utilizes deep learning techniques to mine and match the content features of users and items. This algorithm constructs a deep neural network model to extract features and learn representations of multimedia content such as text and images, thereby calculating the similarity between users and items and achieving recommendations. Compared with traditional content-based recommendation algorithms, deep learning-based content recommendation has stronger feature extraction capabilities and higher recommendation diversity. At the same time, the algorithm can also handle multimodal data fusion problems, improving the flexibility and scalability of the recommendation system.

A hybrid recommendation system is a recommendation system that combines the advantages of multiple recommendation algorithms. The system constructs multiple sub-models and uses different recommendation algorithms to mine and match historical behavior data, content features, and other information of users and items. Then, the recommendation results of multiple sub-models are fused and optimized to obtain more accurate and diverse recommendation results. A hybrid recommendation system can select appropriate sub models and fusion strategies based on specific tasks and data characteristics to improve the performance and user experience of the recommendation system.

4. Review of Relevant Research Literature

Zhu, Wenbo, and Hu, Tiechuan used natural language processing techniques to determine and categorize opinions about covid vaccines with the highest accuracy possible[1].Hu, Tiechuan ,Zhu, Wenbo and Yan, Yuqi developed a traffic prediction model based on existing literature. By using MAE and t-test to simulate data similar to the Los Angeles County traffic data used by Yu et al. in their deep learning and traffic prediction research in extreme weather scenarios, the traffic prediction model created outperforms current methods in providing higher accuracy in traffic prediction[2].Zhu Wenbo discussed the application and scheduling of big data in distributed networks and analyzed the opportunities and challenges of data management systems. Analysis shows that big data scheduling in cloud computing environments is the most effective way to transmit and synchronize data[3]. Some scholars have conducted research on head mounted displays. Song Y and Arora P's study showed that horizontally shifting virtual images to the ears can provide good performance and comfort during different types of tasks[5]. Song Y, Arora P, Singh R and others compared the various offset distances between optical combiners and the user's primary gaze position (PPOG) towards the nose[6]. Liu Dong's research emphasizes that MT2ST is an efficient machine learning solution specifically designed to optimize word embedding training[8]. Liu D's survey aims to provide a

comprehensive overview of current advancements in model compression and their potential to make LLMs more accessible and practical for diverse applications[10]. Tan L, Liu S, Gao J, et al. propose targeted optimizations for the YOLOv10 model, incorporating the detection head structure from YOLOv8, which significantly improves product recognition accuracy. Additionally, they develop a post-processing algorithm tailored for self-checkout scenarios to further enhance the application of the system[13]. Wu Z, Chen J, Tan L, et al. present a lightweight image fusion algorithm specifically designed for merging visible light and infrared images, with an emphasis on balancing performance and efficiency. The effectiveness of the lightweight design is validated through extensive ablation studies, confirming its potential for real-time applications in complex environments[14]. Liu X, Yu Z, and Tan L's research focuses on classifying three different types of lung X-rays and testing five different pre-trained models on a lung X-ray image dataset. MobileNetV2, as the best-performing pre-trained model, will be used as the base model for further analysis.

Fine-tuning and additional attention have been made within the feature layer, resulting in a significant improvement in performance [15]. Focusing on skin lesion diagnosis, Liu X's study evaluated the implementation of deep learning methods using the HAM10000 dataset. To further improve the accuracy, integrated models were developed, where the stacked model performed the best with an accuracy of 0.83. Based on this, the SkinNet model was proposed, which combined with customized architecture and fine-tuning, achieved an accuracy of 0.867 and an AUC of 0.96. The study demonstrated the effectiveness of integrated learning in improving skin lesion classification [16]. Tan L, Liu X, Liu D, et al. propose an improved Dung Beetle optimizer (CICRDBO) based on circle mapping and longitudinal horizontal crossover strategy. The initial population diversity is increased by the circle approach and the vertical-horizontal crossover strategy improves the global search capability. Simulation results show that the improved algorithm excels in both convergence speed and optimization accuracy. The algorithm is further applied to the hyperparameter selection of the random forest classification algorithm for binary classification prediction in the retail industry, and its usefulness is demonstrated by SHapley additive expansion (SHAP) analysis [17].

Liu X, Du R, Tan L, et al. show a real-time helmet detection solution based on YOLO, utilizing the SHEL5K dataset. The proposed CIB-SE-YOLOv8 model combines the SE attention mechanism and the improved C2f block to improve detection accuracy and efficiency. The model provides a more effective solution for construction site safety compliance and helps to reduce injury accidents [18]. Tan L, Liu D, Liu X, et al. proposed an efficient Grey Wolf Optimizer (EGWO) aimed at overcoming the limitations of standard Grey Wolf Optimization (GWO) by enhancing population diversity through sine mapping, balancing exploration and mining with a horizontal vertical crossover strategy, and improving search efficiency and accuracy while maintaining lightweight computation. The experiment shows that EGWO performs excellently in convergence speed, solution accuracy, and robustness and has been validated in the hyperparameter adjustment of the random forest model in the housing price dataset [19]. Wang C, Sui M, Sun D, et al. delve into meta reinforcement learning (Meta RL), define generalization limits, ensure convergence, and propose an innovative theoretical framework to evaluate the performance of Meta RL algorithms. The analysis revealed the relationship between algorithm design and task complexity, established convergence guarantees, and comprehensively understood the long-term performance drivers of Meta RL [20]. Liu H, Li I, Liang Y, et al. optimized convolutional neural networks for pneumonia recognition, selected AlexNet and InceptionV3, combined medical image features, and used knowledge extraction techniques to improve computational efficiency. The results show that the AlexNet model has significantly improved predictive performance and reduced computational costs [21].

The research by Sun D, Liang Y, Yang Y, et al. is based on attention mechanisms and multimodal data for image representation. It integrates semantic and hidden layers and improves the robustness of the feature evaluation model through Word2Vec and convolutional neural network evaluation. The simulation results validate the effectiveness of the new method [22]. Wang C, Yang Y, Li R, et al. proposed the SoftPromptComp framework, which utilizes summarization, soft prompt compression, and enhanced utility preservation mechanisms to optimize the context processing of Large Language

Models (LLMs), significantly reducing computational overhead, improving efficiency, and maintaining content quality. This provides direction for the universality and practicality of LLMs in practical applications [23]. Zhan Q, Ma Y, Gao E, et al. propose a combination of CNN and BLSTM architecture for clinical text temporal expression recognition, enhancing understanding of complex medical terms, comprehending temporal expression context, addressing the limitations of independent prediction labels, and experimentally verifying the effectiveness of the model, which is significantly better than traditional methods [24]. Ma Y, Sun D, Gao E, et al. explore the relationship between optimization theory and deep learning, emphasizing the universality of optimization problems in deep learning. Research on the gradient descent algorithm and its variants, introduce the SGD optimizer enhancement method to improve interpretability and accuracy, and experimentally confirm the effectiveness of the improved algorithm [25].

Zheng Z, Cang Y, Yang W, et al. explored the role of Named Entity Recognition (NER) in enhancing medical resource utilization and clinical decision-making intelligence and proposed a new model, RoBERTa FGM MHA CRF, which significantly improves the accuracy and generalization ability of medical NER by integrating multiple technologies. At the same time, medical image processing technology faces problems of noise and artifacts [28]. Sun D, Sui M, Liang Y, et al. proposed a medical image denoising and segmentation algorithm that combines transfer learning and attention mechanisms and designed an integrated medical image-assisted diagnosis system [29]. Regarding the existing problems in health queries, Cang Y, Yang W, Sun D, et al. proposed an advanced medical text classification method using an ALBERT pre-trained language model, which significantly improved classification accuracy [30]. Sun D, Zhang T, and Chen L proposed an image super-resolution reconstruction algorithm based on compressive sensing and depth sensing neural networks, and experiments showed that its performance was superior to some state-of-the-art algorithms. These studies demonstrate the enormous potential of deep learning technology in medical text processing and image processing, providing strong support for the future development of digital healthcare services [31]. Liang Y, Gao E, Ma Y, et al. found that the semantic feature extraction algorithm (A-ELMO), which combines semantic feature-oriented vocabulary vector representation with an attention mechanism, has significant advantages in improving the sensitivity and detection ability of sensors [34].

5. Raining and Optimization Techniques

The optimization of deep learning algorithms is the key to improving model performance and generalization ability. Common optimization methods include the gradient descent algorithm, stochastic gradient descent algorithm, Adam optimization algorithm, etc. In addition, regularization techniques such as L1 regularization and L2 regularization, as well as dropout methods, are also important means to improve the model's generalization ability. In practical applications, researchers also need to choose appropriate optimization methods and parameter settings based on specific tasks and data characteristics to achieve optimal model performance.

From the research of the above literature, it can be found that compared to a single deep learning method, integrating other methods or multiple methods often leads to higher accuracy. Therefore, the integration of deep learning methods with other methods has certain research significance.

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