An Overview of the Application of Artificial Intelligence in Aging-related Healthcare

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Abstract

With the rapid global development of artificial intelligence (AI), the field of gerontechnology has garnered significant attention, emerging as a crucial focus for AI applications. This review delves into how artificial intelligence addresses the challenges posed by an aging society, with a specific focus on the widespread applications in key areas such as robotics, speech recognition, knowledge graphs, and image detection. Challenges arising from an aging society, including reduced labor supply, increased elderly care burden, pressure on medical resources, and social isolation, necessitate innovative solutions, and the rise of artificial intelligence offers new possibilities for tackling these challenges. In terms of application prospects, artificial intelligence demonstrates extensive potential in health monitoring and early warning, life care and assistance, education, and entertainment. These technologies not only enhance the quality of life for the elderly but also provide more intelligent and personalized services. In the evolution of artificial intelligence, the emergence of large-scale pre-trained models has provided new perspectives for addressing traditional issues, making AI applications in gerontechnology more robust and flexible.

1. Introduction

With the rapid advancement of technology, artificial intelligence (AI) is spearheading a global revolution, profoundly transforming various aspects of our daily lives. Amidst this sweeping wave of innovation, the field of gerontechnology has emerged as a focal point for AI applications, showcasing tremendous potential. This review aims to delve into how artificial intelligence addresses the escalating challenges posed by an aging society, focusing on its extensive applications in key areas such as robotics, speech recognition, knowledge graphs, and image detection.

1.1. Background Introduction

Population aging stands as a significant societal challenge, exerting profound impacts on diverse sectors such as the economy, society, culture, healthcare, and elderly care. According to the United Nations projections, by 2020, the global population aged 60 and above will reach one billion, constituting 13.5% of the total population. By 2050, this figure is expected to increase to 2.2 billion, representing 21.5% of the global population. China, being one of the countries with the most severe aging population, reported, based on the results of the seventh national census, that the population aged 60 and above has reached 264 million, accounting for 18.7% of the total population, with those aged 65 and above making up 13.5%. The scale, depth, and speed of aging in China pose significant pressures and challenges to socio-economic development and the well-being of the population.

In the evolution of AI, traditional machine learning models are transitioning to deep learning models, such as Convolutional Neural Networks (CNNs [15]), Recurrent Neural Networks (RNNs [27]), and Graph Neural Networks (GNNs [26]), achieving significant progress. However, challenges such as the dependency of deep learning models on massive labeled data, the time-consuming nature of data labeling, and the generalization difficulties of models with limited data remain constraints. To address these challenges, researchers have proposed Pre-trained Models (PM) based on large-scale datasets, adopting a two-stage approach: during the pre-training phase, models acquire domain knowledge from extensive unsupervised data, and in the fine-tuning phase, domain knowledge is transferred to specific tasks through minimal labeled data, enhancing the model's generalization capability.

The success of pre-trained models initially in Computer Vision (CV), where they learned visual knowledge from extensive image data and achieved outstanding performance through fine-tuning on task-specific data, extended to Natural Language Processing (NLP) with models like Transformer. This rise of new models signifies a shift towards a paradigm where "a large-scale pre-trained model is applicable to multiple downstream tasks," gradually replacing the traditional approach of "task-specific models for specific tasks."

In recent years, the emergence of Artificial Intelligence Generated Content (AIGC) has garnered widespread attention. The rapid development of large-scale pre-trained models like BERT [7], GPT-2 [23], and GPT-3 [2] has provided substantial support for the rapid advancement of AIGC technology. The scale of model parameters has swiftly grown from billions to tens of billions, and by continually expanding model parameters, researchers are exploring the potential for performance improvement.

The development of the AI field has undergone a transition from traditional machine learning models to deep learning models, marking a shift from relying on manually crafted features and statistical methods to the rise of large-scale pre-trained models. This evolution has not only achieved remarkable results in fields such as computer vision and natural language processing but also provided more robust and flexible tools for AI applications in gerontechnology. In the following sections, we will delve into the specific applications of artificial intelligence in gerontechnology, with a focus on robotics, speech recognition, knowledge graphs, and image detection, comprehensively understanding how these technologies become critical factors in addressing the challenges of an aging society.

1.2. Challenges of an Aging Society

As the aging society becomes more prevalent, we face a series of unique and complex challenges that impact not only the elderly themselves but also the entire social structure and public service systems. Key challenges include a reduction in labor supply, an increasing burden of elderly care, pressure on medical resources, and the rise of social isolation and loneliness. The rise of artificial intelligence presents new possibilities for addressing these challenges.

In an aging society, the imbalance between a relatively smaller young labor force and a larger elderly population may lead to a decline in productivity and socioeconomic instability. With the growing elderly population, the demand for pensions and healthcare escalates rapidly, imposing significant financial pressure on the social welfare system, necessitating innovative financial models and health management strategies. The sharp increase in demand for medical services places a strain on insufficient and unevenly distributed medical resources, potentially affecting the health conditions of the elderly. As individuals age, some may experience a shrinking social circle, leading to an increase in social isolation, posing a threat to mental health and overall quality of life.

In this context, there is an urgent need for innovative solutions to better adapt to the new realities of an aging society. The rise of artificial intelligence provides new possibilities for addressing these challenges by introducing intelligent and personalized services, offering the potential for positive changes in the health, social engagement, and daily lives of the elderly. The application prospects of artificial intelligence technology in gerontechnology are broad, encompassing health monitoring and early warning, life care and assistance, as well as education and entertainment. These applications not only improve the quality of life for the elderly but also provide them with more intelligent and personalized services.

1.3. The Rise of Artificial Intelligence and its Prospects

Artificial intelligence is a comprehensive field that involves the research, development, and application of computer systems designed to simulate, extend, and expand human intelligence. This discipline comprises various subfields, including machine learning, computer vision, natural language processing, knowledge representation and reasoning, robotics, and more. It possesses capabilities such as perception, reasoning, learning, and decision-making. Artificial intelligence technology has made significant progress in various application domains, providing robust support for enhancing the quality of life for the elderly, strengthening autonomy, delaying cognitive decline, promoting social participation, and increasing overall happiness. These technologies also offer more intelligent and personalized services for the elderly.

The rise of artificial intelligence can be attributed to several key factors. Firstly, the improvement in computational power plays a vital role. With the continuous development of computer hardware technology, the computational capabilities of artificial intelligence models have significantly increased, enabling them to handle more complex data and tasks. Secondly, the accumulation of data is a crucial driver for the development of artificial intelligence. The widespread use of the internet and intelligent devices has led to the accumulation of massive data, providing rich material for training artificial intelligence models. Additionally, continuous advancements in algorithms are a key factor in the success of artificial intelligence. Researchers continually innovate new algorithms, improving the performance and robustness of artificial intelligence models.

In the field of gerontechnology, artificial intelligence holds broad application prospects. In the realm of health monitoring and early warning, artificial intelligence utilizes technologies such as image detection and speech recognition to monitor the health status of the elderly, promptly detecting potential health issues and providing corresponding warnings and advice. In life care and assistance, devices such as robots and voice assistants can offer intelligent life care and assistance services for the elderly, aiding them in accomplishing daily tasks and enhancing their quality of life. In the domains of education and entertainment, artificial intelligence has already been applied to the education, gaming, and social activities of the elderly.

Although the application of artificial intelligence in gerontechnology is still in its nascent stages, some preliminary achievements have been made. For example, in the field of health monitoring, artificial intelligence technology has been applied for fall detection, heart disease monitoring, and diabetes management in the elderly. In the realm of life care, artificial intelligence robots have been successfully employed for companionship, rehabilitation, and meal delivery services for the elderly. As artificial intelligence technology continues to advance, its applications in gerontechnology will become more widespread and profound, providing more convenient, secure, and comfortable support for the lives of the elderly.

2. Application of Speech Recognition Technology in Gerontology

2.1. Overview of Speech Recognition

2.1.1 Definition of Speech Recognition

Speech recognition, also known as automatic speech recognition (ASR), computer speech recognition or speech to text (STT), refers to the computerized process of converting human speech into corresponding text. In other words, it involves the automatic extraction of textual information from vocal sound signals. The fields encompassed by speech recognition technology include signal processing, pattern recognition, probability theory, information theory, vocal production, auditory perception, artificial intelligence, etc.

2.1.2 History of Speech Recognition

In the 1950s, the Bell Labs in the United States pioneered the development of the earliest electronic computer-based speech recognition system, Audrey. By tracking resonant peaks in speech, Audrey could recognize ten English digits. From the 1950s to the 1990s, artificial neural networks were introduced to speech recognition. Linear Predictive Coding (LPC) and Dynamic Time Warping (DTW) also emerged successively, addressing issues of variable speech information length and enhancing the accuracy of speech recognition.

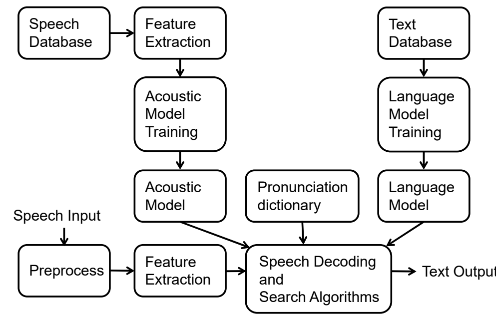

Figure 1. The flow chart of methodologies of speech recognition.

The most significant breakthrough in speech recognition technology came with the application of Hidden Markov Models (HMM). Starting with Baum's introduction of relevant mathematical reasoning and further research by Rabiner and others, in 1990, researchers, including Kaifu Lee at Carnegie Mellon University, developed the SPHINX system. This system, with the GMM-HMM (Gaussian Mixture Model-Hidden Markov Model) framework at its core, represented the first high-performance, speaker-independent, large vocabulary, continuous speech recognition system in history.

From the 21st century onward, with the rapid advancement of artificial intelligence and deep learning algorithms, hybrid recognition systems and end-to-end recognition systems based on common networks such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have achieved impressive recognition results and system stability. To date, speech recognition systems based on neural networks remain a research focal point for scholars globally. [11]

2.1.3 Methodologies of Speech Recognition

Speech recognition first processes the audio information, extracts features, and then undergoes acoustic model training to establish an acoustic model. This acoustic model, along with a pronunciation dictionary and language model, collectively predicts and outputs text based on the input speech. [11] The whole process is shown in figure 1.

2.2. The Application of Speech Recognition in Healthcare

The application of speech recognition in healthcare primarily manifests in two aspects: intelligent voice input and diagnosis of specific medical conditions.

2.2.1 The Application of Intelligent Voice Input in Hospitals

The most direct application of speech recognition in hospitals involves the computerized entry and processing of voice content for archiving and identification purposes.

For physicians, the application scenarios for hospital information input are diverse, encompassing the input of outpatient medical records, reports from examinations such as ultrasound and X-rays, prescription formulation, and medical record entries. In traditional hospital settings, doctors typically complete reports by handwriting or typing. With the aid of speech recognition systems, physicians articulate reports verbally, effectively reducing workload, enhancing efficiency, and significantly reducing operational costs in hospitals. In some countries like the United States, the usage of speech recognition input in clinical settings has surpassed 20%. [14] Companies like Nuance, Royal Philips Electronics, and Siemens Healthineers have introduced speech recognition systems developed specifically for medical systems, effectively reducing time and economic costs. In a smart speech recognition system applied at The Affiliated Hospital of Qingdao University [14], the system team constructed a medical domain language model tailored to hospital application scenarios. Employing a self-learning mechanism supported by distributed computing for high performance, it achieved commendable results. Feedback from ward doctors indicated that recording electronic medical records through voice input improved efficiency by nearly threefold compared to keyboard input, effectively saving doctors' time in writing medical records, enhancing their work efficiency, and allowing them more time to serve patients.

For patients, speech recognition applications are observed in intelligent guidance and patient self-service scenarios. For individuals with lower level of education, speech recognition effectively resolves issues related to typing, providing more humane services to patients.

In specific hospital scenarios such as pre-hospital emergency dispatching, speech recognition also plays a crucial role. According to a research conducted in Nanjing [3], in the actual acceptance and dispatching tasks of dispatchers, situations often arise where the caller cannot speak Mandarin, the address provided is unfamiliar or difficult to record, or the caller speaks too rapidly. These instances necessitate dispatchers to repeatedly inquire and verify information, significantly diminishing their efficiency and prolonging dispatching times. Integrating speech recognition into emergency dispatch systems enables voice input, dialect recognition, and reversed dialect playback functionalities. Faced with scenarios where the caller speaks a dialect, a foreign language, or speaks too rapidly, dispatchers can swiftly retrieve information using speech recognition systems to enhance emergency response efficiency.

2.2.2 Diagnosis of Specific Diseases Using Speech Recognition

Speech recognition can also be applied in the diagnosis of specific diseases. Some neurological disorders possess characteristics of early-stage detection and diagnosis difficulties, yet subtle indications can manifest in language expression. Utilizing speech recognition and machine learning for early diagnosis and intervention can reduce the risk of contracting such diseases. The most common conditions include Alzheimer's disease (AD) and Parkinson's syndrome.

Alzheimer's disease (AD) is a progressively degenerative neurological condition with insidious onset. Clinically, it is characterized by comprehensive dementia symptoms such as memory impairment, aphasia, personality, and behavioral changes. Language-related symptoms account for 60-80% of total patients. Speech, as a biological marker, offers rapid, convenient, accurate, and non-invasive diagnosis and clinical screening for AD compared to brain imaging, cognitive testing, and mini-mental state examination (MMSE). Speech recognition analysis uses acoustic features extracted from speech audio and Natural Language Processing (NLP) techniques to extract language features from written or spoken text, aiding in dementia classification. Efficient diagnosis of AD can be achieved using large language models. A study published in 2022 [1] revealed that text embeddings generated by GPT-3 can reliably detect Alzheimer's disease. Furthermore, text embeddings outperformed traditional acoustic-based methods and even competed with fine-tuned models, exhibiting significant prospects for early dementia diagnosis.

Parkinson's disease (PD), another common neurodegenerative disorder, remains incurable in modern medicine. Unlike AD, early PD symptoms often manifest in resting tremors, muscular rigidity, bradykinesia, and later may include memory decline. Research [5] has found that vocal cord damage, an early symptom, appears in about 90% of PD patients. Acoustic analysis mainly reveals high-amplitude perturbation, high fundamental frequency perturbation, low harmonic-to-noise ratio, and low fundamental frequency. Hence, early detection of PD can be accomplished through extracting acoustic features from speech signals. Currently, domestic and international researchers primarily employ traditional feature extraction methods combined with machine learning algorithms to achieve PD recognition. Max and others collected continuous vowel phonation 'a' to form the first speech database in 2009, utilizing support vector machine classifiers for diagnosis, demonstrating that vowels suffice for PD detection. [30] Subsequently, different researchers developed tools such as artificial neural networks, AlexNet models, residual neural networks [10], etc., for early PD detection. In 2021, Zhang Tao and researchers published a method [28] based on time-frequency hybrid domain local statistics achieving an accuracy of over 97%, providing a robust tool for early Parkinson's diagnosis.

Moreover, speech detection methods are applicable to diseases such as stuttering in pediatric patients. [38] This involves constructing corpora and utilizing tools such as Hidden Markov Models (HMMs) and Support Vector Machines (SVMs) for data processing and assessment. In recent years, with advancements in computing power and the development of deep learning technologies such as Automatic Speech Recognition (ASR) and Natural Language Processing (NLP), the accuracy of speech recognition diagnosis for diseases presenting symptoms in speech has significantly increased, becoming an efficient and widely applicable detection tool.

2.3. Speech Recognition and Aging

In the seventh national census, China's population aged 60 and above accounted for 18.7% of the total population, with those aged 65 and above representing 13.5%. By 2035, it is projected that China's population aged 60 and above will surpass 400 million, accounting for over 30% of the total population, entering a stage of severe aging. Consequently, China faces significant challenges in population aging with limited medical resources. Improving medical visit efficiency and enhancing the medical experience for the elderly are urgent. With the development of artificial intelligence, the continuous improvement in speech recognition accuracy provides new possibilities for the healthcare system in an aging society.

In hospital settings, considering the low Mandarin proficiency and lower educational levels among the elderly population, speech recognition effectively establishes a communication channel between hospitals and patients, improving medical visit efficiency. In emergency scenarios, speech recognition notably accelerates information retrieval, saving time for rescuing patients.

Regarding the diagnosis of specific diseases in the elderly population, Alzheimer's disease, Parkinson's disease, and other neurodegenerative diseases are prevalent. The application of speech recognition and machine learning algorithms for early diagnosis of such diseases facilitates convenient and accurate determination of affected individuals through text and speech analysis, enabling interventions.

3. Application of Robots in Gerontology

3.1. Overview of Robots in Gerontology

In the highly regarded field of aging-friendly technology, the application of artificial intelligence robots in aging has garnered widespread research interest and societal attention.

Intelligent robots demonstrate significant potential in areas such as elderly care, medical services, and social companionship. By integrating advanced sensing technologies, natural language processing, and machine learning algorithms, AI robots can better understand and respond to the needs of the elderly, providing them with more personalized and comprehensive services.

3.2. Home-assistant Robots

With the aging of society, a significant issue arises as an increasing amount of household chores falls on the shoulders of one individual. This places a considerable burden on the caregiver, leading to heightened life stress and a higher likelihood of family disputes.

Home assistance robots aim to enhance the convenience of domestic life. For those working diligently outside the home, these robots can carry out household tasks in the domestic environment when individuals are away. Equipped with an integrated software system, these robots include modeling, recognition, and operational skills, as well as software-based motion generation methods. [35]

3.3. Health and Life Caring Robots

With the increasing elderly population, the number of individuals in need of healthcare continues to rise, and there is a growing population of bedridden elderly individuals requiring lifestyle care. To address this issue, it is necessary to develop robots for health and lifestyle care, primarily targeting the elderly who, due to declining physiological functions, are unable or find it inconvenient to perform certain tasks related to clothing, food, housing, and transportation. This aims to alleviate their physical strain and provide convenience in their daily lives, allowing them to maintain their independence and quality of life.

For instance, in 2017, Toyota introduced its first autonomous assistant, the Human Support Robot (HSR), which has been deployed in homes in the United States to assist individuals with disabilities in automating daily tasks such as opening doors or retrieving food and water from cabinets. It is also used in Japanese hospitals to aid in caring for the increasingly aging population in Japan. [17]

3.4. Safety-caring Robots

In China and Japan, a significant proportion of the elderly prefer to age in place [18]. It can be anticipated that with the development of an aging society, there will be an increasing number of empty-nest elderly individuals, and the safety issues associated with living alone become an urgent matter to address. Safety service robots are employed to create a secure home environment for the elderly, providing early warnings of potential environmental risks and timely feedback on possible accidents to enhance risk prevention and management mechanisms.

For instance, Cobalt Robotics has designed a robot specifically for indoor security patrol tasks. The company has developed a 1.5-meter-tall Cobalt robot equipped with a conical touch screen and LEDs. These robots come with integrated access control functions, allowing them to wirelessly communicate with access card readers within authorized enclosed areas. While patrolling designated work areas, they can use artificial intelligence systems to detect suspicious intrusions, such as abnormal door openings and potential safety issues, seeking human assistance when necessary. These robots can also selectively scan documents, act as mobile broadcasting systems and alarms, and recharge when their battery levels are low.

Puppy Bingo is another robot designed for home health scenarios. It can monitor, record, and manage users' health indicators, including body temperature, blood pressure, blood oxygen, and fetal heart rate. A health management center facilitates the management of health indicators for all family members, enabling users to stay informed about their own and their family members' health conditions in real-time. Additionally, Puppy Bingo features a smart medication box on top, allowing users to organize medications and set reminder times. In the unfortunate event of a family member falling, fainting, or experiencing other emergencies, Puppy Bingo can identify the situation promptly and remotely call family members, buying precious time for medical assistance. [17]

3.5. Elderly Entertainment Robots

Facing the super-aging society, the shortage of nursing care and social isolation of the older people have become major issues in many countries, especially during the pandemic. Social isolation has been shown to increase the risk of death by about 0.3 and to hasten the progression of dementia. To organize recreational activities is, on the other hand, difficult for the facility staff to implement for a variety of reasons. To alleviate the burden of the staff, robots could be introduced in the recreation, which is called robot assisted recreation(RAR) [13].

For instance, given that interaction with animals heal human mind and showed positive effects for elder peoples' health, but elder peoples are afraid of negative effects of animals such as allergy, infection, bite, and scratch. Scientists made animal type robots as examples of artificial emotional creatures. The animal type robots have physical bodies and behave actively while generating goals and motivations by themselves. They interact with human beings physically. When elder people engage physically with an animal type robot, it stimulates their affection. When we applied this kind of robot in the nursing home, the result is promising: The robots improved the moods of the elderly and brought vitality to their lives. Moreover, nursing staff's mental poverty decreased because the elderly people spent their time by themselves with the robots. [12] [33]

3.6. Elderly Self-realization Robots

Self-Realization Robots for Elderly Service robots are employed to assist the elderly in re-education and reemployment activities, providing them with multidimensional learning and employment growth opportunities and helping them rediscover their value by leveraging their abilities, skills, and experiences.

These robots can support the elderly in various ways. (a) Education and Skills Training, service robots can offer education and training courses, aiding the elderly in acquiring new skills or updating existing ones to adapt to the ever-changing demands of the job market. (b) Employment Resources and Information, they can provide access to employment resources, occupational information, and job opportunities, helping the elderly understand and engage in suitable job positions or projects. (c) Personalized Support, these robots can offer personalized support based on the interests, abilities, and needs of the elderly, assisting them in finding reemployment opportunities or activities that suit them. (d) Social Interaction and Psychological Support, they can provide social interaction and psychological support, reducing elder peoples' sense of loneliness and encouraging them to actively participate in the community and work environment [17].

The application of such robots provides more opportunities and resources for the elderly, enabling them to reintegrate into society, unleash their potential, and contribute to society. This is conducive to enhancing the sense of self-efficacy [34].

For instance, Elli.Q, a social companion robot, uses human-like body language, voice and other dimensions to interact more comfortably and naturally with users. Elli.Q can also use artificial intelligence technology to actively learn users' hobbies, behaviors, and personalities, and recommend appropriate activities for users based on their characteristics. Elli.Q can also help older adults who are not sensitive to new technologies use social media and teach them to play simple online games and monitor their physical health and home environment.

4. Application of Knowledge Graphs in Gerontology

4.1. Overview of Knowledge Graph

Knowledge Graph, proposed by Google in 2012, is a novel way of describing information, utilizing the concept of semantic networks to establish explicit models of relationships between knowledge elements. It encompasses knowledge definitions, instance data, as well as standards, technologies, and tools required for constructing, managing, and applying, forming a comprehensive ecosystem. Among these, the most crucial techniques involve knowledge extraction, knowledge embedding, and knowledge reasoning.

Knowledge extraction in a knowledge graph refers to the automatic retrieval of information from various texts and data sources, converting it into structured representations of knowledge to enrich the content of the knowledge graph. These techniques aim to identify, extract, and represent entities, relationships, and attributes from unstructured or semi-structured data.

Knowledge embedding in knowledge graphs is a technique that maps entities and relationships into a low-dimensional continuous vector space. This method is employed to represent and learn the entities, relationships, and their semantic associations within a knowledge graph. The goal of this technique is to transform symbolic information in the graph into continuous vector representations, facilitating processing and inference by machine learning models.

Knowledge reasoning is a crucial function of knowledge graphs, inferring unknown information based on graph facts. Methods encompass logical rule-based reasoning, distributed representation learning, and neural networks.

Logical rule-based reasoning derives highly precise inferences using symbolic and simple rules, divided into first-order predicate logic and description logic. Statistical reasoning employs machine learning to extract rules from graphs, categorized as inductive logic programming and association rule mining. On the other hand, graph-based reasoning leverages graph structures as features, ensuring efficiency and interpretability.

Distributed representation learning inference maps entities and relationships into vector spaces through projection, involving tensor decomposition, distance models, semantic matching, and multi-source information. Tensor decomposition represents graphs as tensors, computing scores through decomposition for inference. Distance models infer latent relationships via offsets. Semantic matching models address the semantic diversity of entities and relationships. Multi-source information synthesizes various data to enhance model performance.

Neural network inference tackles reasoning tasks through feature capture and nonlinear transformations. This includes convolutional neural networks for image processing, recurrent neural networks for sequential data, and reinforcement learning for sequential decision-making problems. These methods address the lack of interpretability in models or provide limited interpretability, enabling more comprehensive and efficient knowledge reasoning.

4.2. Application of Knowledge Graphs

The application of knowledge graphs in the field of gerontology is often associated with expert systems. An expert system is a computer system based on artificial intelligence that aims to simulate the knowledge and decision-making processes of domain experts, particularly in the realm of healthcare. These systems utilize stored rules and information within a knowledge base, employing a reasoning engine to conduct inference and provide diagnostic suggestions or treatment plans for medical practitioners. Their functioning involves knowledge acquisition, reasoning mechanisms, and learning for improvement. In healthcare, expert systems assist in diagnosing illnesses and proposing treatment strategies, offering potential value in aiding decision-making and handling complex scenarios. However, while these systems can deliver professional-grade advice and solutions, their limitations lie in challenges related to knowledge acquisition and representation, as well as potential constraints and limitations in handling uncertainties when facing novel situations.

Expert systems rely on structured knowledge within their repositories for reasoning and decision-making, while knowledge graphs offer a powerful means of representing and integrating diverse knowledge sources into a unified structure. In healthcare applications, this symbiosis becomes evident as expert systems utilize the rich knowledge representations provided by knowledge graphs to enhance their reasoning capabilities. Knowledge graphs contribute by consolidating medical information from various sources, enabling expert systems to access comprehensive and interconnected medical knowledge for more informed decision-making. Additionally, the continuous updating and enrichment of knowledge graphs facilitate the evolution of expert systems by incorporating the latest medical findings and insights. This collaboration between expert systems and knowledge graphs significantly enhances the depth and breadth of medical expertise available for diagnosis, treatment planning, and healthcare decision support.

4.2.1 Auxiliary Diagnosis

Diagnosis plays an incredibly crucial role as the foundation of medical practice. Employing an appropriate knowledge graph to aid in diagnosis can significantly enhance the efficiency of doctors and drastically reduce the rate of misdiagnosis.

Diagnosis, in essence, involves combining knowledge and experience to assess new existing conditions. A single doctor can only rely on their own experiences for judgment. However, a knowledge graph integrates a vast amount of knowledge and real clinical cases into its system, enabling diagnoses to incorporate a broader spectrum of medical experiences, thereby improving diagnostic accuracy and efficiency. In the process of auxiliary diagnosis, a more reliable approach involves using the knowledge graph to provide multiple possible diagnostic outcomes, thus minimizing the occurrence of missed diagnoses or misdiagnoses. The knowledge graph augments the connections between different pieces of information, rendering the entire diagnostic process more interpretable. Incorporating reinforcement learning methods continuously updates the knowledge graph, enhancing its performance in auxiliary diagnosis. Zhang et al . [37] introduced weighted averages into the knowledge graph, enhancing diagnostic reliability by weighting the degree of sharing among various traditional Chinese medical treatment methods.

Though further advancements in knowledge graphs are required to achieve more refined diagnoses, they prove particularly effective in the realm of assisting traditional Chinese medicine diagnoses. For instance, clinical doctors in non-nephrology departments lacking knowledge about chronic kidney disease (CKD) might seldom recognize abnormal kidney function data, leading to delayed CKD management. Doctors can access longitudinal records; however, without appropriate attention or sufficient knowledge advantage, this valuable information remains buried in the data, resulting in wastage. Additionally, due to heavy workloads and limited time, extensive long-term clinical data is unsuitable for comprehensive review by clinical doctors. Introducing an interpretable artificial intelligence knowledge graph can effectively integrate various information, aiding doctors in specific diagnosis of medical conditions. Shang et al. [25] established an electronic medical record-oriented knowledge graph, utilizing semantic reasoning and graphical explanations of significant findings to assist clinical doctors in identifying crucial clinical information often overlooked in practice.

4.2.2 Personalized Recommendations

Elderly individuals, as a vulnerable group in society, have greater medical needs. Due to physical reasons, even when facing the same medical condition, different elderly individuals may exhibit varying symptoms. This necessitates a sufficient level of personalization in medical care.

Knowledge graphs are now capable of providing personalized recommendations in various aspects, including medication suggestions, daily exercise, and dietary plans, to maintain the user's physical well-being. By establishing a profile for each patient and understanding their past treatments and personal habits, recommendations become more humanized and rational. Knowledge graph AI based on machine learning, reinforcement learning, and similar methods can achieve personalization through continuous fine-tuning. For instance, in the case of diabetes, a knowledge graph can provide personalized health management advice based on the patient's blood sugar control, dietary habits, exercise routines, and other relevant information. This advice encompasses medication treatment plans, dietary suggestions, exercise routines, aiding patients in better disease management and reducing the risk of complications.

The entity extraction algorithm based on BiLSTM-CRF proposed by Wang et al. [32] and the Traditional Chinese Medicine (TCM) medical recommendation model using KNN can better analyze contextual statements, understand user needs, and validate recommendations using clinical data from TCM. This validation process renders the recommendations more reasonable and aligned with the user's requirements.

4.2.3 Intelligent Forecasting

Intelligent medical forecasting holds significant potential for development and application. Leveraging various learning methods such as neural networks reinforces predictions related to diseases, clinical outcomes, and even cancer mortality rates. Its applications in clinical practice are extensive. For instance, by analyzing patients' clinical data and medical images, intelligent medical forecasting aids in predicting potential complications, enabling early intervention and treatment to prevent the worsening of conditions. Moreover, it can forecast the development trends of chronic diseases, assisting patients and doctors in devising more scientific treatment plans to improve treatment outcomes.

In the realm of cancer, intelligent medical forecasting plays a pivotal role. By analyzing patients' genetic information, clinical data, and pathological characteristics, it helps doctors more accurately predict cancer development trends and metastasis risks, offering crucial references for personalized treatment plans. OpenAI, for example, developed an AI model for predicting potential kidney damage, enabling patients to anticipate kidney-related diseases earlier for timely treatment. Chu et al. [4] created a knowledge-aware multi-center clinical dataset applicable for models predicting various clinical outcomes, integrating learning models into knowledge graphs to facilitate clinical outcome forecasting across diverse clinical environments in multiple centers.

Elderly individuals, as a distinct group, often experience multiple chronic diseases, frequent visits to multiple specialists, and the use of multiple medications, leading to a higher susceptibility to adverse drug reactions. Due to differences in the professional levels of medical personnel across various healthcare institutions, expecting most doctors to rely solely on their professional knowledge for PIM (Potentially Inappropriate Medication) judgment when prescribing medications is not practical. By incorporating more drug and patient information into knowledge graphs, labeling this information, and calculating the influence of conditional nodes on risk factors, the prediction of potential inappropriate medication behaviors can be anticipated. [19]

5. Application of Image Detection Technology and IoT

With the increasingly significant global trend of aging populations, the health status of the elderly has become a focal point of societal concern [22]. Artificial intelligence has provided unprecedented opportunities for technological innovation in the field of elderly health. Advances in technologies such as image processing, machine learning, and deep learning offer robust support for achieving real-time monitoring, precise diagnosis, and personalized treatment. The continuous optimization of intelligent algorithms makes health management for the elderly population more feasible. This section aims to delve into the comprehensive review of computer vision and image processing technologies in several major directions of artificial intelligence for aging applications, including health monitoring and identification, fall detection, medical diagnosis, and assistance in daily life.

5.1. Health Monitoring and Recognition

The rapid development of wearable and mobile devices has facilitated the application of Internet of Things (IoT) technology in the healthcare sector [39] [6]. Real-time monitoring of human activities, especially the Activities of Daily Living (ADL) of the elderly, is a significant concern in smart healthcare. The use of wearable and mobile sensors can significantly enhance medical rehabilitation and elderly care. Therefore, Human Activity Recognition (HAR) in ubiquitous computing environments has become a hot topic to better understand people's daily behaviors and interactions with their living environments, widely researched in the domain of Healthcare Internet of Things (IoHT) [29]. HAR can be considered as an artificial intelligence technology that automatically analyzes and identifies human activities and behavior patterns through the observation of data from wearable devices.

HAR typically involves three levels: motion recognition, action recognition, and activity recognition, corresponding to low-level, mid-level, and high-level vision. Researchers continually explore solutions to HAR problems through machine learning and deep learning methods. Currently, research is mainly focused on two directions: methods based on environmental sensors and those based on wearable sensors. Environmental sensor-based methods typically use monitoring cameras, sound, temperature, and other sensors to capture context signals related to the environment, applicable in scenarios such as smart homes and rehabilitation centers. In contrast, methods based on wearable sensors are more convenient, as they do not require users to wear multiple devices, making them more socially acceptable.

A complete HAR system consists of three essential components: video frame segmentation, action representation, and the learning process. However, HAR still faces challenges such as lighting variations, changes in perspectives, and occlusions, requiring the construction of comprehensive, robust, and flexible HAR systems under various conditions and environments. Additionally, dataset limitations are a critical issue, as many studies rely on self-recorded data, lacking large benchmark datasets for testing novel applications. Therefore, in the evolution of HAR, it is essential to continue addressing these challenges to achieve broader applicability and reliability.

5.2. Fall detection

Fall Detection Technology and Applications

Globally, falls among the elderly pose a significant public health concern. Needless to say, injuries resulting from falls among the elderly not only have numerous consequences for their families but also impact the healthcare system and society at large [31].

The development of fall detection technology provides the possibility for real-time monitoring and emergency response, becoming increasingly crucial in addressing the health challenges faced by the elderly. This section will focus on introducing fall detection technology and its applications in computer vision and real-time feedback. The application of computer vision technology in fall detection involves various aspects:

Video Analysis and Image Recognition: Computer vision technology, through the analysis of video streams, can real-time monitor users' postures, movements, and behaviors. This is crucial for detecting fall events, abnormal postures, or unusual activities. Leveraging image recognition algorithms, the system can identify specific human body forms, postures, or movements, allowing it to assess the risk of falls. Deep learning technology has significantly improved the accuracy of image recognition in this context.

3D Spatial Perception Technology: Utilizing depth cameras such as Microsoft Kinect, the system can acquire precise location and posture information of users in three-dimensional space. This provides more detailed and comprehensive data for fall detection, aiding in accurately determining the user's status. Additionally, 3D perception technologies like LiDAR (Light Detection and Ranging) are introduced to provide high-resolution depth information. Li-

DAR can generate precise 3D maps in various environmental conditions, offering more reliable data for fall detection.

Real-Time Feedback and Emergency Response: Based on the results of fall detection, the system can trigger alerts, issuing warnings to users through sound, light, or vibration. The design of alert systems needs to consider reliability and timeliness to ensure users receive timely reminders when a fall occurs. Moreover, when the system detects a fall event, it can automatically trigger the call for emergency services, such as summoning an ambulance or notifying emergency contacts. Applications integrating emergency services can swiftly provide assistance in critical situations, minimizing the injuries caused by falls.

The application and integration of these computer vision technologies enable fall detection systems to comprehensively and accurately monitor user behavior, providing real-time feedback and emergency responses, effectively reducing the risks associated with falls.

In the early stages of fall detection research, sensors were commonly used as detection media, as shown in the studies by Li et al. 2009 [16], which explored the fusion of gyroscope and accelerometer data for fall and non-fall classification. However, vision-based sensors (such as surveillance cameras) and environmental sensors have become attractive alternatives. Rougier et al. [24] proposed a shape-matching technique that tracked the contour of a person through video sequences. They quantified the deformation of the human body shape from the contour using shape analysis methods. Finally, a Gaussian mixture model was used to classify falls from normal activities. Following surveillance cameras, depth cameras also gained widespread attention in this field. The earliest application of Time-of-Flight (ToF) depth cameras was by Diraco et al. [8]. They proposed a novel vision sensor-based method that did not require landmarks, calibration patterns, or user intervention. However, ToF cameras are expensive and have low image resolution. Subsequently, Rougier et al. [24]used the Kinect depth camera for the first time in 2011. They extracted two features from depth information: body center height and body velocity. They applied threshold-based algorithms to detect falls, achieving an overall success rate of 98.7

Regarding fusion technologies based on visual sensors, some studies have adopted traditional machine learning or deep learning methods to enhance the accuracy of fall detection. The methods used can be roughly categorized into two types: 1. 2D CNN (Convolutional Neural Network) technology and 2. Deep Reinforcement Learning (DRL). Espinosa et al. (2019) [9] proposed an approach based on the fusion of multiple visual sensors, studying it using publicly available datasets. They trained a classifier based on 2D CNN for identifying and classifying fall events in daily life activities. This method, by integrating information from different sensors, improved sensitivity and accuracy in detecting falls. Another approach is Reinforcement Learning (RL), an evolving branch of machine learning that is gaining popularity in fall detection. Deep Reinforcement Learning (DRL), combining the advantages of deep learning and reinforcement learning, has shown promise in fall prevention (Namba and Yamada, 2018a [20], [b] [21] and fall detection by Yang, 2018 [36]). Namba and Yamada [20] proposed a method for preventing fall risks in elderly people living independently with the assistance of robots. They collected images and videos with accident location information. However, most traditional machine learning and deep learning methods face challenges when the operating environment changes. This is because their data-driven nature makes them powerful in learning in the same environment where they were trained.

Traditional machine learning methods have achieved certain results in fall detection and activity recognition, especially in applications with wearable sensors, where their results are significantly better than threshold-based methods. However, with the rise of deep learning, especially in the field involving visual sensors and sensor fusion, deep learning methods are gradually becoming state-of-the-art technology. Deep learning, by simulating artificial neural networks, better captures the complex relationships in data, improving performance in fall detection and activity recognition tasks.

As an emerging research direction in fall detection, Deep Reinforcement Learning combines the advantages of deep learning and reinforcement learning. It draws inspiration from the concepts of human psychological neuroscience, enabling the system to adapt and optimize decisions in a constantly changing environment. Deep Reinforcement Learning, while providing high adaptability, does not sacrifice accuracy and robustness, offering a promising alternative for fall detection in this field.

A significant challenge is the scarcity of real fall data. Currently, there is no convincing publicly available dataset providing sufficient real fall data as a gold standard. Most datasets are primarily based on simulated data rather than observations from the real lives of elderly people. This makes models trained on data collected from young and healthy subjects controversial when applied to the elderly. To better adapt to real-world scenarios, there is an urgent need to create benchmark datasets containing data from multiple sensors to ensure that models can accurately identify fall events in more realistic environments.

6. Challenges and Future Outlook

This paper presents a comprehensive overview of artificial intelligence (AI) applications in medical aging and its current development status. The applications can be categorized into three main aspects:

Recognition Systems Based on CNN, RNN, and Com-

mon Networks: These systems preprocess language information and undergo training to enable intelligent question-and-answer interactions related to medical care. This significantly enhances diagnostic efficiency, reduces doctors' time spent on writing medical records, improves overall doctor efficiency, allowing them to dedicate more time to patient care.

Utilizing AI Knowledge Graph Information Description: AI knowledge graphs define specific knowledge elements as entity classes and establish interrelations between different entities through relationship classes. Knowledge reasoning is achieved through methods such as tensor decomposition, semantic matching, and neural networks. The incorporation of deep learning, three-dimensional space perception technology using depth cameras, and computer vision enhances health monitoring and fall detection for the elderly. This integration provides timely feedback and emergency responses, effectively minimizing the risk of falls.

Artificial Intelligence Technology for Enhancing Intelligent Robots: AI contributes to the development of various types of robots—such as home assistance robots, life care robots, and safety service robots—to deliver comprehensive care for the elderly.

Challenges of Artificial Intelligence Technology in Health Monitoring and Fall Detection In the realm of health monitoring and recognition, the development of computer vision and mobile devices has propelled the application of Internet of Things (IoT) technology in healthcare. The advancement of fall detection technology, in particular, has opened up possibilities for real-time monitoring and emergency response for the elderly. The application of computer vision technology in video analysis, image recognition, and 3D spatial perception enhances the comprehensiveness and accuracy of fall detection systems. Simultaneously, the design of real-time feedback and emergency response improves the reliability of the system. However, the scarcity of authentic fall data remains a challenge, necessitating the establishment of benchmark datasets containing multiple sensor data to ensure the accurate identification of fall events in more realistic environments.

This paper explores the multifaceted role of AI in addressing medical aging, spanning from intelligent interactions to health monitoring and robot-assisted care, underscoring its potential in enhancing elderly care services.

However, numerous challenges persist in the application of artificial intelligence (AI) in medical aging. Imperfect model training often leads to some functions failing to achieve anticipated goals, resulting in instances of both missed and incorrect judgments. Moreover, the scarcity of precise and reliable data poses a significant hurdle, especially when measuring elderly-specific data that cannot be feasibly derived from artificial experiments but must be acquired from real-life scenarios, presenting added complexities.

Privacy and data security represent pivotal concerns. The widespread integration of AI technology in the medical realm involves an increasing volume of personal health data. Safeguarding this private data has emerged as an urgent issue necessitating resolution. Additionally, addressing technology accessibility and ethical concerns requires deeper contemplation and resolution throughout the developmental process.

Therefore, optimizing the model structure and enhancing its accuracy stand as fundamental methods to propel AI applications in medical aging. Collaborating with hospitals, clinics, or other elderly service institutions facilitates the acquisition of more accurate data for model training and validation. Addressing data privacy entails establishing more comprehensive regulations and regulatory mechanisms to uphold users' legitimate rights and privacy.

Ensuring technology accessibility involves catering to users of varying ages and abilities, ensuring inclusivity and user-friendliness for all. Ethical considerations encompass the fairness and justice of technology and its long-term societal impact, necessitating interdisciplinary research and extensive deliberation for appropriate resolution.

7. Conclusion

In conclusion, artificial intelligence demonstrates immense potential and extensive exploration opportunities within the domain of medical aging. Beyond the aforementioned four aspects, numerous other areas harbor significant potential for further development. Through persistent technological innovation, ethical considerations, and enhanced user experiences, we anticipate witnessing scientific and technological advancements that tangibly enhance the lives of older individuals in the coming years.

Simultaneously, collective efforts across all sectors of society are imperative to establish a healthier and more user-friendly science and technology ecosystem. This will enable artificial intelligence in aging to genuinely emerge as a pivotal force propelling social progress. With collaboration and innovation, we hold the confidence to craft a superior and more intelligent future for the elderly.

In this ongoing process, it's crucial to fortify interdisciplinary collaborations, integrating medical, scientific, technological, sociological, and other resources. By collectively advancing the field of aging, we aim to offer more comprehensive and compassionate care and services to the elderly, further enriching their lives.

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