Research Progress in Artificial Intelligence on Organ Biological Age

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Abstract: Biological age is a standard for evaluating the degree of aging of human organs through a series of age-related markers, and it is affected by factors such as genetics, environment and lifestyle. The prediction of organ biological age aims to assess organ aging, reflecting health and predicting age-related diseases. Various machine learning models have demonstrated strong performance in predicting organ biological age, highlighting their broad clinical application prospects. This article focuses on the applications of AI in biological age prediction and related research areas.

***Keywords*:** artificial intelligence, aging, biological age, neural networks

1. Introduction

In recent years, the field of artificial intelligence (AI) has advanced at an incredible rate. Its application in medicine mostly involves an area of computer science that analyzes complex medical data and has the ability to perceive, reason, induce, summarize, and make decisions. Biological age (BA) is a standard for indirectly assessing human aging through biological markers, which can be used to stratify the population to predict certain age-related chronic diseases. The mismatch between cellular and organ ages and chronological age may lead to the early onset of age-related diseases such as Alzheimer's disease, cancer, and cardiovascular diseases. Studying human biological age and further research and judgment on human organ aging are of great significance for predicting the occurrence of organ diseases and related prognoses.

2. Technical Overview of Organ Biological Age Prediction Models

2.1 Machine Learning

Machine learning trains models on massive data to uncover patterns, enabling accurate classification and prediction of new data. It's crucial for AI in healthcare, covering supervised, unsupervised learning, reinforcement learning, and deep learning. Deep learning and neural networks excel in handling multi-dimensional, complex data. In the field of biological age prediction, common modeling methods include linear regression, support vector machines (SVM), and random forests.

2.2 Deepl Learning

Deep learning automatically extracts high-level features from data by constructing multi-layered neural network models. Unlike traditional machine learning, deep learning requires massive datasets to mitigate overfitting and demonstrates significantly superior performance to traditional ML models in handling large-scale, complex problems. When faced with complex and heterogeneous clinical data, deep learning demonstrates robust capabilities in data processing and analysis.

3. Research Progress of AI in the Prediction and Application of Organ Biological Age

Brain: Early assessment of brain age is crucial for predicting biological age and allows timely intervention for age-related neurological symptoms and other diseases. Traditional methods rely on a single type of biological marker in a single time period, and some indicators are difficult to reflect the real situation of the brain due to the existence of the blood-brain barrier. Chenzhong Yin et al. [1] developed a 3D-CNN - based AI model. By analyzing brain MRI scan changes from over a thousand adults at two time points, it calculates brain biological age (brain age) to predict aging speed and has been tested in Alzheimer's patients with high accuracy. Jinzhuo Wang et al. built a multimodal Transformer architecture. Cole, J H et al. [2] proposed a 'brain-predicted age' biomarker. Using machine learning, they combined DNA methylation - predicted age and neuroimaging - predicted age to calculate biological age.These AI models add neuroimaging and other marker - combined aging biomarkers for assessing the brain's true health and predicting neurodegenerative diseases.

Heart and Vasculature: Supported by AI, research findings [3]indicate that ECG age, derived from big ECG data analysis, can assess cardiovascular risk factors, determine heart / biological age, and predict cardiovascular outcomes and mortality. Compared with predicting biological age via DNA methylation age (DNAm PhenoAge), ECG - based heart rate variability

(HRV) analysis offers the most accurate biological age estimation. Mitchell et al. [4] developed the AI - VascularAge CNN model. It predicts vascular age via 20 - second normalized carotid, brachial, or radial artery pressure waveforms and shows clinical relevance to cardiovascular events in community samples. This offers a simple tool for quick bedside assessment of vascular age and cardiovascular risk.

Facial and Ocular Regions: According to anatomy, the retina is regarded as an extension of the central nervous system, and the optic nerve contains axons that originate from the central nervous system. Wenyi Hu et al. [5] used a deep - learning (DL) model to train on 11,052 fundus images of 19,200 participants without chronic diseases and found that the retinal age gap was related to a high risk of Parkinson's disease. This provides a new method of clinical screening. It also provides new research ideas for other age-related neurological diseases in the elderly. Reconstruct average facial contours every ten years to quantify age-related facial phenotypes. This generates the first comprehensive atlas of aging human facial phenotypes, enabling a relatively accurate age predictor. It can quantitatively predict biological age from facial phenotypes, assess risks of age-related diseases, and inform personalized treatment.

Respiratory System: Emerging AI technology is making a big difference in chest examination. Researchers have applied AI to chest X-rays to screen for pulmonary hypertension. Lee et al. [6] externally tested the artificial intelligence model established by Raghu et al. in asymptomatic Asian individuals between the ages of 50 and 80. The results indicated that CXR - Age based on deep learning was related to survival rate and disease incidence, and also showed that it is universal and accurate among different ethnic groups. CT, as an indispensable examination for patients with lung diseases, is also often used to access biological age.

Digestive System: Accurate assessment of the age of abdominal organs is crucial to the evaluation of age-related diseases and the prediction of abdominal malignancy and can effectively prevent and treat these diseases. Le [7] collected data to predict abdominal age and constructed an abdominal age predictor (AbdAge) by training a convolutional neural network. Compared with traditional aging - prediction methods, AI models can quickly analyze the impact of other clinical factors on aging, which is offering new research and prevention insights.

4. Common data sources for AI in organ biological age prediction.

Imaging: Kerber B [8] et al. proposed a deep - learning model for automatic age estimation of chest and abdominal CT scans obtained in clinical work. This model was tested and validated using public test data sets and demonstrated good reliability. MRI is also an excellent predictor of heart and brain age. Researchers collected a large number of nuclear magnetic resonance images in the database to develop models, and the results showed good prediction performance. The value of imaging data lies not only in their ability to visually display surface features of aging but also in their potential to reveal deeper mechanisms of aging. AI technology is the key to decoding the aging process.

Biological Markers: In the past few decades, various biomarkers have been used to estimate biological age - telomere length, DNA methylation, proteomics, metabolomics, and clinical biomarkers in blood. Bortz J [9] et al. developed an elastic-net-derived Cox mode. They showed us that circulating biomarkers could serve as the foundation for a straightforward, accurate, and affordable biological age measurement with the aid of artificial intelligence. They also demonstrated a practical and economical way to estimate the accurate biological age measurement method of the general population.

Multimodal Fusion Data: Single imaging modality or biological marker struggles to reflect the complex multi - system process of aging. Therefore, multimodal fusion data is the inevitable choice for AI to predict biological age. A research team from Qinghua University used CNN to extract features related to kidney function, immune status, etc., from retinal images, and developed a senescence marker called "RetiPhenoAge". This marker can predict disease risk better than traditional biomarkers like telomere length [10]. These findings suggest that while single - type data offers a window into the aging process, multimodal fusion data is necessary to fully open the door to exploring aging.

5. Summary

The development of AI, aided by numerous big-data platforms, has produced a number of more accurate and practical prediction models. Naturally, this is also inextricably linked to the ongoing development and improvement of computer algorithms. Many studies suggest that these artificial intelligence models to predict biological age, which have been validated by a substantial amount of external data, are feasible in clinical application and have great potential and market.

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References

[1] Yin, C, Imms, P, Chowdhury, NF, et al. Deep learning to quantify the pace of brain aging in relation to neurocognitive changes. P NATL ACAD SCI USA. 2023; 122 (10): e2413442122. doi: 10.1073/pnas.2413442122

[2] Cole, JH, Ritchie, SJ, Bastin, ME, et al. Brain age predicts mortality. MOL PSYCHIATR. 2018; 23 MOL PSYCHIATR. doi: 10.1038/mp.2017.62

[3] Hirota, N, Suzuki, S, Motogi, J, et al. Cardiovascular events and artificial intelligence-predicted age using 12-lead electrocardiograms. Int J Cardiol Heart Vasc. 2023; 44 101172. doi: 10.1016/j.ijcha.2023.101172

[4] Mitchell, GF, Rong, J, Larson, MG, et al. Vascular Age Assessed From an Uncalibrated, Noninvasive Pressure Waveform by Using a Deep Learning Approach: The AI-VascularAge Model. HYPERTENSION. 2023; 81 (1): 193-201. doi: 10.1161/HYPERTENSIONAHA.123.21638

[5] Hu, W, Wang, W, Wang, Y, et al. Retinal age gap as a predictive biomarker of future risk of Parkinson's disease. AGE AGEING. 2022; 51 (3): doi: 10.1093/ageing/afac062

[6] Lee JH, Lee D, Lu MT, Raghu VK, Goo JM, Choi Y, Choi SH, Kim H. External Testing of a Deep Learning Model to Estimate Biologic Age Using Chest Radiographs. Radiol Artif Intell. 2024 Sep;6(5):e230433. doi: 10.1148/ryai.230433. PMID: 39046324.

[7] Le Goallec A, Diai S, Collin S, Prost JB, Vincent T, Patel CJ. Using deep learning to predict abdominal age from liver and pancreas magnetic resonance images. Nat Commun. 2022 Apr 13;13(1):1979. doi: 10.1038/s41467-022-29525-9. PMID: 35418184; PMCID: PMC9007982.

[8] Kerber, B, Hepp, T, Küstner, T, et al. Deep learning-based age estimation from clinical Computed Tomography image data of the thorax and abdomen in the adult population. PLoS One. 2023; 18 (11): e0292993. doi: 10.1371/journal.pone.0292993

[9] Bortz, J, Guariglia, A, Klaric, L, et al. Biological age estimation using circulating blood biomarkers. Commun Biol. 2023; 6 (1): 1089. doi: 10.1038/s42003-023-05456-z

[10] Li, R, Chen, W, Li, M, et al. LensAge index as a deep learning-based biological age for self-monitoring the risks of age-related diseases and mortality. Nat Commun. 2023; 14 (1): 7126. doi: 10.1038/s41467-023-42934-8