AI in Personalized Health Management: Practices and Challenges

Zhanxu Jiang[a]
Institute of Artificial Intelligence, Beihang University, Beijing, 100191, China

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Abstract: With the improvement of medical and technological level, people are no longer satisfied with the traditional one-size-fits all inefficient medical model, but seek more consideration of individual differences and user uniqueness of a new medical model called personalized health care. Artificial intelligence, especially deep learning, has been used to analyze large amounts of medical data, and its potential in the health care field has attracted much attention. In this article, the implement of artificial intelligence in personalized healthcare are outlined, including health data analysis, genetic risk assessment, and diet and exercise intervention. Specifically, this article first classifies health data analysis into two categories from the perspective of technology, and then introduces two methods to deal with genetic risk: genetic risk prediction and drug development, and then introduces how artificial intelligence can intervene in patients' daily life from two aspects: diet intervention and exercise intervention. Finally, the article discusses the current problems encountered in the development of artificial intelligence technology in the field of personalized health, and provides a perspective on the prospects and solutions of artificial intelligence for doctors, healthcare institutions, and governments in society. It is hoped that this article can provide theoretical support and practical suggestions for doctors, health care institutions and government to cooperate to build a more intelligent and personalized health care system.

1 INTRODUCTION

Personalized health management is a revolutionary healthcare model, which analyzes users' medical data from different sources, predicts and gives targeted recommendations. Traditional healthcare models, which tend to adopt standardized treatment regimens, often do not well account for the diversity of individuals in terms of health status, genetic susceptibility, lifestyle choices, and environmental influences (Goetz & Schork, 2018). The emergence of personalized health management through customized interventions and precision medicine strategies to meet the individual needs of users while ensuring their health status. Through the use of a large number of health data analysis, prediction, recommendation and other algorithms, this healthcare model helps everyone to understand the possible health risks and gives suggestions to help patients actively participate in their own health management. However, there are several challenges to implementing this healthcare model. A major challenge is the integration and analysis of a large number of heterogeneous healthcare data sources, including Electronic Health Records (EHRs), genomic data, wearable data, and patient reports. As Artificial Intelligence (AI) technology has advanced, AI algorithms have shown outstanding performance in identifying and discovering connections among vast volumes of data. Through in-depth mining and analysis of each patient's unique multi-dimensional health data, machine learning, especially deep learning, can detect probable health trends and risk factors, thereby improving the accuracy of disease prediction and providing scientific basis for personal choices and medical decisions.

The first and most important step in most personalized health processing processes is data collection. EHRs, which hold personal health data (such as diagnostic pictures, clinical notes, and past medical histories), sensors in wearable devices that capture physiological and biochemical indexes in real-time (Pinto et al., 2017), microphones and cameras for audio and video (Kim & Chung, 2015), and social media rhetoric (Ahmed et al., 2020;

[a] https://orcid.org/0009-0003-5363-0305

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Alotaibi et al., 2020; Sekulić & Strube, 2020) are some of the most popular data resources. Much of the current research focuses on disease prediction, where researchers combine big data processing and Internet of Things (IoT) techniques to process health information, intending to predict whether a user has a specific disease, such as diabetes (Krishnamoorthi et al., 2022), chronic kidney disease (Abdel-Fattah et al., 2022), Cardiovascular Disease (CVD) (Zhang et al., 2023), cancer (Trivizakis et al., 2020; Cheerla & Gevaert, 2017), and some chronic diseases (Tiwari & Agarwal, 2023). In addition to processing the data of electronic medical records, conducting personalized health management based on real-time monitoring also received much attention. A new online prediction system using the Spark streaming framework was proposed to predict health status (Hassan et al., 2020). An exercise app that uses a reinforcement learning agent, was introduced to provide motion reminders at appropriate times based on calendar information and the user's instantaneous time (Wang et al., 2021). Some researchers applied machine learning algorithms on real-time data to find relationships between blood pressure and lifestyle factors and to provide precise advice for mitigating blood pressure risks (Chiang et al., 2021).

After predicting possible health hazards, personalized health management will also give corresponding suggestions or reminders to guide people to improve their personal health plans (Zhang et al., 2023). Some work uses recommendation systems to provide reference options for patients. In 2019, Subramaniyaswamy et al. introduced a recommendation system, called ProTrip, which supports travelers with long-term medical conditions and users who need a strict diet to suggest food availability is proposed by considering personal preferences, the nutritional value of food, and climate attributes (Subramaniyaswamy et al., 2019). Moreover, an application using machine learning algorithms is introduced to help patients with both diabetes and depression by creating customized messages with varying time and content based on patients' daily data (Aguilera et al., 2020). As mentioned above, there have been a lot of AI-related works in the field of personalized health management, and this field is developing very fast at present, so it is necessary to make a comprehensive review of them.

The structure of the paper is as follows. First, Section 2 sheds some light on the different parts of the personalized health management process and explains the role of artificial intelligence in personalized health management. Then, current challenges and limitations are summarized in Section 3. Finally, Section 4 makes a conclusion and an outlook based on the previous discussion.

2 METHODS

2.1 Health Data Analysis and Prediction

2.1.1 Classical Machine Learning-Based Model

Chiang and Dey used exercise, sleep, and historical Back Propagation (BP) measurements collected from wearable devices and home BP monitors to predict daily BP levels and estimate the influence of individual health behaviors on BP (Chiang & Dey, 2018). They introduced a Random Forest (RF) with feature selection (RFFS) model to filter out unnecessary features and improve prediction accuracy, aiming to provide personalized recommendations for improving BP through sleep and exercise. The proposed RFFS model has Mean Square Error (MSE) and Mean Absolute Error (MAE) of 47.33 and 5.18 for systolic blood pressure, 37.45 and 4.30 for diastolic blood pressure, respectively. These values were lower compared to the results of other deep learning models, providing better performance in predicting blood pressure levels.

Lu et al. proposed a patient network and machine learning based risk prediction model for Type 2 Diabetes Mellitus (T2DM) (Lu et al., 2022). A real-world administrative claims dataset was used to extract medical data from T2DM patients and non-T2DM patients to construct a patient network. Using patient network analysis and machine learning algorithms, researchers extracted potential patient characteristics, such as centrality measures, that effectively predicted T2DM risk. Seven traditional machine learning models were used for the prediction. The centrality measure of the patient network and the patient's age were the most significant features in the random forest model, which performed the best out of all the models, according to the results data, which showed an accuracy of 83.98%.

2.1.2 Deep Learning-Based Model

A model named DeepRisk, based on attention mechanisms and deep neural networks, was proposed to automatically and efficiently select suitable features from longitudinal and heterogeneous electronic medical records from electronic medical records, obtain accurate and robust patient representations, and eventually estimate the patients' risk of developing cardiovascular disease (An et al., 2019). The approximate working flow of the model is as follows: Input data characteristics include age, gender, patient type (inpatient, outpatient, and emergency), number of visits, and surgical history. These data are loaded respectively into their embedding parts, producing independent embedding vectors. For each input data, a deep neural network based on the attention mechanism, or a plain deep neural network is trained to generate a representation vector of the patient. These representation vectors are concatenated and then inserted into the softmax layer to forecast patients at high risk. In comparison to current methods, DeepRisk can greatly enhance the accuracy of high-risk prediction of cardiovascular disease, according to the findings of experiments conducted on real medical datasets.

2.2 Genomic Analysis and Risk Assessment

2.2.1 Genomic Data Processing and Prediction

Dai et al. performed exon sequencing and gene loading testing in 245 preterm infants (gestational age, 32 weeks) to identify two collections of risk genes that are overexpressed in patients with Bronchopulmonary Dysplasia (BPD) and severe BPD (sBPD), named BPD-RGS and SBPD-RGS, respectively (Dai et al., 2021). In the data analysis phase, the authors used multiple tests to assess the distribution of the data, followed by Ward agglomeration method to cluster clinical characteristics. Multivariate Logistic Regression Analysis was then employed to evaluate the independent association between clinical characteristics and BPD or sBPD in 245 infants. The prediction model was created using the Least Absolute Shrinkage and Selection Operator Regression (Lasso) technique. A new method for accurate risk stratification of BPD in preterm infants has been provided by the experimental results, which demonstrated that prediction models combining BPD-RG or sBPD-RGS with basic clinical risk factors outperformed the models containing only these factors in the independent test datasets.

2.2.2 Drug Development

The application of graph convolutional networks in computational personalized medicine for medication response prediction has attracted much attention. Nguyen et al. discussed the limitations of existing methods, namely representing drugs as strings, failing to capture the native molecular structure, and lacking an in-depth explanation of genetic mutations that influence drug responses (Nguyen et al., 2021). The suggested approach GraphDRP directly depicts cell lines as binary vectors of genetic mutations and pharmaceuticals as molecular graphs. By learning features of drugs and cell lines through convolutional layers and predicting response values of drug-cell line pairs using fully connected neural networks, GraphDRP outperformed tCNNS in all experiments. Responses to drug-cell line pairs missing from the GDSC dataset were predicted and analyzed. In addition, using the saliency map, the authors identified the ten most important genomic abnormalities for the three cell lines with lower IC50 values for the corresponding drugs and their contribution to drug sensitivity.

2.3 Nutrition and Exercise Management

2.3.1 Individualized Nutrition Suggestion

Wang et al. investigated the application of machine learning algorithms to assist in the early assessment of Enteral Nutrition (EN) for patients in the Intensive Care Unit (ICU) (Wang et al., 2023). The article stated that malnutrition in intensive care patients may lead to complications and poor outcomes; however, the initiation of enteral nutrition often relies on the awareness of the physician, resulting in poor feeding proportions. The purpose of this study was to create and verify a predictive model for enteral nutrition initiation in intensive care unit patients using data from the Critical Care IV database. This study compared different machine learning models, and found that XGBoost had the best prediction performance. The model determined that the three most significant parameters determining the beginning of enteral feeding were acute kidney injury, the score on the sequential organ function assessment, and sepsis. This model was intended to help identify those high-risk patients who may benefit from early enteral nutrition, guide clinician decision making, and enhance outcome outcomes for intensive care patients.

2.3.2 Individualized Exercise Intervention

Determining the appropriate timing of intervention is important for the effectiveness of exercise recommendations. A reinforcement learn-based mobile exercise application was introduced with the aim of sending customized reminders to promote user participation in physical activity based on the user's temporary contextual information (Wang et al., 2021). Participants used the other functions in this application for three weeks during the study period. Every participant received no more than 14 reminders from this app requesting physical exercise during the fourth week, which was designated as the intervention week. The collected data were analyzed using questionnaires and one-on-one interviews. The results showed that when sent at the right time, 83.3% of users responded within 50 minutes and 66.7% of users participated in physical activity within 5 hours. In addition, the behavior of reminders could be traced to detailed information, including the time stamp when the reminder was sent, the notification click, and the start of the campaign. In conclusion, by building and testing intelligent reminder models, this research investigated the viability of using reinforcement learning models to send reminders in smartphone sports applications. Based on the lessons discovered, the timing of delivering reminders might be further optimized.

3 DISCUSSIONS

Although existing works have achieved superior performance in tasks such as prediction, they are often trained, validated and tested on specific datasets, which is not sufficient to accurately judge whether the model has overfitting. This question can be better addressed by validating the generalization ability of the model on other datasets. In the case of lack of medical data, transfer learning can also be used to learn the common feature representations in the existing datasets and transfer these feature representations to the target task.

In addition, the widely-used deep learning algorithms often lack interpretability. Due to the complexity and privacy of medical data, the lack of interpretability often makes healthcare workers and users reluctant to trust these emerging artificial intelligence tools. Some novel interpretable AI techniques, model-interpretable methods, and visualization tools are being developed to allow healthcare professionals and patients to understand the principles of how AI technologies work in more detail (Stiglic et al., 2020).

How to translate the research results into applications in real industrial products is also a challenging problem. For example, some intelligent medical platforms based on EHRs may face inconsistencies in data heterogeneity and operating standards caused by multiple data sources in practical applications (Si et al., 2021). This may require hospitals, healthcare companies, governments, and many other institutes to work together to develop standards. More interdisciplinary collaboration may be needed in the future to cultivate talents who understand both healthcare and artificial intelligence in order to better manage data and use AI to aid medical decision making (Qiu et al., 2022).

Personalized health management involves the collection and processing of a large amount of personal health data, so data privacy and security become an important challenge. Although there are some information encryption technologies (Suneetha et al., 2020; López Martínez et al., 2023) that can protect personal privacy to a certain extent, there are still risks of data leakage and abuse. Federated learning may be one answer to this problem, which can help multiple agencies to collaborate on AI while meeting the requirements of privacy protection, data security, laws and regulations.

Large language models (LLMs), which have recently become popular, are increasingly becoming the channel through which people get information, and conversational chatbots have great potential to become a personalized health assistant. LLMs have shown strong power in helping people understand medical knowledge, monitoring vital signs, complying with prescription requirements, and even assisting with individualized medical decision making (Abbasian et al., 2023; Benary et al., 2023). However, not many projects have been actually applied due to the possible problems of false output and illusion, which can be caused by a bias in the training data or insufficient predictive power of the model in large language models (Xu et al., 2024). As a result, most of the existing LLMs applications in the medical field focus on instruction fine-tuning and dataset construction. One of the future directions that large language models can be used in healthcare field is to construct knowledge graphs. Through the analysis and collation of massive medical literature, as well as the extraction of the knowledge and experience of medical experts, the big model can build a complete and accurate medical knowledge graph, and provide more comprehensive and reliable medical knowledge support for the medical inquiry intelligent assistant.

4 CONCLUSIONS

This study investigates AI's potential for assisting personalized healthcare, with a focus on how AI can be used for personalized diagnosis of various diseases, risk prediction, and intervention in health planning at all stages of personalized healthcare management. This article also discusses the challenges and opportunities, such as data quality, interpretability, privacy issues, collaboration across disciplines, and recent advances in LLMs. At present, AI cannot replace professional medical staff, but the assistance of AI can bring great convenience to medical staff and users. AI can provide significant benefits for personalized healthcare management, but it also requires careful evaluation and implementation. In the era of rapid technological development, it is also time to think about the safety and ethics problems of artificial intelligence technology. In any case, there is still much potential for the further development and application of artificial intelligence in personalized healthcare management, and future results are expected to better improve medical outcomes and patient experience.

REFERENCES

Abbasian, M., Azimi, I., Rahmani, A. M., & Jain, R. 2023. Conversational health agents: A personalized llm-powered agent framework. *arXiv preprint arXiv:2310.02374*.

Abdel-Fattah, M. A., Othman, N. A., & Goher, N. 2022. Predicting Chronic Kidney Disease Using Hybrid Machine Learning Based on Apache Spark. *Computational Intelligence and Neuroscience*, *2022*, 1‑12.

Aguilera, A., Figueroa, C. A., Hernandez-Ramos, R., Sarkar, U., Cemballi, A., Gomez-Pathak, L., Miramontes, J., Yom-Tov, E., Chakraborty, B., Yan, X., Xu, J., Modiri, A., Aggarwal, J., Jay Williams, J., & Lyles, C. R. 2020. mHealth app using machine learning to increase physical activity in diabetes and depression: clinical trial protocol for the DIAMANTE Study. *BMJ Open*, *10*(8), e034723.

Ahmed, H., Younis, E. M. G., Hendawi, A., & Ali, A. A. 2019. Heart disease identification from patients ’ social posts, machine learning solution on Spark. *Future Generation Computer Systems*, *111*.

Alotaibi, S., Mehmood, R., Katib, I., Rana, O., & Albeshri, A. 2020. Sehaa: A Big Data Analytics Tool for Healthcare Symptoms and Diseases Detection Using Twitter, Apache Spark, and Machine Learning. *Applied Sciences*, *10*(4), 1398.

An, Y., Huang, N., Chen, X., Wu, F., & Wang, J. 2019. High-risk prediction of cardiovascular diseases via attention-based deep neural networks. *IEEE/ACM transactions on computational biology and bioinformatics*, *18*(3), 1093-1105.

Benary, M., Wang, X. D., Schmidt, M., Soll, D., Hilfenhaus, G., Nassir, M., ... & Rieke, D. T. 2023. Leveraging large language models for decision support in personalized oncology. *JAMA Network Open*, *6*(11), e2343689-e2343689.

Cheerla, N., & Gevaert, O. 2017. MicroRNA based Pan-Cancer Diagnosis and Treatment Recommendation. *BMC Bioinformatics*, *18*(1).

Chiang, P.-H., & Dey, S. 2018. Personalized Effect of Health Behavior on Blood Pressure: Machine Learning Based Prediction and Recommendation. *2018 IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom)* (pp. 1-6). IEEE.

Chiang, P.-H., Wong, M., & Dey, S. 2021. Using Wearables and Machine Learning to Enable Personalized Lifestyle Recommendations to Improve Blood Pressure. *IEEE Journal of Translational Engineering in Health and Medicine*, *9*, 1‑13.

Dai, D., Chen, H., Dong, X., Chen, J., Mei, M., Lu, Y., ... & Zhou, W. 2021. Bronchopulmonary dysplasia predicted by developing a machine learning model of genetic and clinical information. *Frontiers in Genetics*, *12*, 689071.

Goetz, L. H., & Schork, N. J. 2018. Personalized medicine: motivation, challenges, and progress. *Fertility and Sterility*, *109(6)*, 952‑963.

Hassan, F., E., M., & Sahal, R. 2020. Real-Time Healthcare Monitoring System using Online Machine Learning and Spark Streaming. *International Journal of Advanced Computer Science and Applications*, *11*(9).

Kim, S.-H., & Chung, K. 2015. Emergency situation monitoring service using context motion tracking of chronic disease patients. *Cluster Computing*, *18(2)*, 747‑759.

Krishnamoorthi, R., Joshi, S., Almarzouki, H. Z., Shukla, P. K., Rizwan, A., Kalpana, C., & Tiwari, B. 2022. A Novel Diabetes Healthcare Disease Prediction Framework Using Machine Learning Techniques. *Journal of Healthcare Engineering*, *2022*, 1‑10.

Pinto, S., Cabral, J., & Gomes, T. 2017. We-care: An IoT-based health care system for elderly people. *2017 IEEE International Conference on Industrial Technology (ICIT)*.

López Martínez, A., Gil Pérez, M., & Ruiz-Martínez, A. 2023. A comprehensive review of the state-of-the-art on security and privacy issues in healthcare. *ACM Computing Surveys*, *55*(12), 1-38.

Lu, H., Uddin, S., Hajati, F., Moni, M. A., & Khushi, M. 2021. A patient network-based machine learning model for disease prediction: The case of type 2 diabetes mellitus. *Applied Intelligence*, *52*(3), 2411-2422.

Nguyen, T., Nguyen, G. T., Nguyen, T., & Le, D. H. 2021. Graph convolutional networks for drug response prediction. *IEEE/ACM transactions on computational biology and bioinformatics*, *19*(1), 146-154.

Qiu, Y., Wang, J., Jin, Z., Chen, H., Zhang, M., & Guo, L. 2022. Pose-guided matching based on deep learning for assessing quality of action on rehabilitation training. *Biomedical Signal Processing and Control*, *72*, 103323.

Sekulić, I., & Strube, M. 2019. Adapting Deep Learning Methods for Mental Health Prediction on Social Media. *Proceedings of the 5th Workshop on Noisy User-Generated Text (W-NUT 2019)*, 322‑327.

Si, Y., Du, J., Li, Z., Jiang, X., Miller, T., Wang, F., ... & Roberts, K. 2021. Deep representation learning of patient data from Electronic Health Records (EHR): A systematic review. *Journal of biomedical informatics*, *115*, 103671.

Stiglic, G., Kocbek, P., Fijacko, N., Zitnik, M., Verbert, K., & Cilar, L. 2020. Interpretability of machine learning‐based prediction models in healthcare. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *10*(5), e1379.

Subramaniyaswamy, V., Manogaran, G., Logesh, R., Vijayakumar, V., Chilamkurti, N., Malathi, D., & Senthilselvan, N. 2018. An ontology-driven personalized food recommendation in IoT-based healthcare system. *The Journal of Supercomputing*, *75*(6), 3184‑3216.

Suneetha, V., Suresh, S., & Jhananie, V. 2020. A novel framework using apache spark for privacy preservation of healthcare big data. In *2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)* (pp. 743-749). IEEE.

Tiwari, S., & Agarwal, S. 2023. Empirical analysis of chronic disease dataset for multiclass classification using optimal feature selection based hybrid model with spark streaming. *Future Generation Computer Systems*, *139*, 87‑99.

Trivizakis, E., Papadakis, G., Souglakos, I., Papanikolaou, N., Koumakis, L., Spandidos, D., Tsatsakis, A., Karantanas, A., & Marias, K. 2020. Artificial intelligence radiogenomics for advancing precision and effectiveness in oncologic care (Review). *International Journal of Oncology*, *57*(1), 43‑53.

Wang, S., Sporrel, K., van Hoof, H., Simons, M., de Boer, R. D. D., Ettema, D., Nibbeling, N., Deutekom, M., & Kröse, B. 2021. Reinforcement Learning to Send Reminders at Right Moments in Smartphone Exercise Application: A Feasibility Study. *International Journal of Environmental Research and Public Health*, *18*(11), 6059.

Wang, Y. X., Li, X. L., Zhang, L. H., Li, H. N., Liu, X. M., Song, W., & Pang, X. F. 2023. Machine learning algorithms assist early evaluation of enteral nutrition in ICU patients. *Frontiers in nutrition*, *10*, 1060398.

Xu, Z., Jain, S., & Kankanhalli, M. 2024. Hallucination is inevitable: An innate limitation of large language models. *arXiv preprint arXiv:2401.11817*.

Zhang, D., Liu, X., Xia, J., Gao, Z., Zhang, H., & de Albuquerque, V. H. C. 2023. A Physics-guided Deep Learning Approach For Functional Assessment of Cardiovascular Disease in IoT-based Smart Health. *IEEE Internet of Things Journal*, 1–1.