International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2020): 7.803

Predictive Modeling for Health Score Calculation: Assessing Individual Health Risks and Providing Personalized Recommendations

Durga Prasad Amballa

Hyderabad, India
Email: *adprasad.amballa[at]gmail.com*

Abstract: ***The increasing prevalence of chronic diseases and the growing emphasis on preventive healthcare have led to the development of innovative tools for assessing individual health risks. This paper presents an AI-powered health score calculation system that utilizes user-provided information, including demographics, lifestyle, health history, habits, health conditions, and family medical history, to generate a comprehensive health score. The proposed system employs machine learning algorithms trained on large datasets to identify potential health risks, probable diagnostics, and at-risk health vitals. By comparing an individual's health score with their peers, the system aims to provide motivation for improvement and offer personalized recommendations for necessary health tests to aid in the early detection and prevention of chronic diseases. The health score is calculated using a weightage model that considers the impact of core body vitals based on user inputs and habits. This paper discusses the development, validation, and potential applications of the AI-powered health score calculation system in the context of personalized healthcare.***

Keywords: health score, AI, machine learning, personalized healthcare, risk assessment, preventive medicine

1. Introduction

The global burden of chronic diseases has been steadily increasing, with cardiovascular diseases, cancers, respiratory diseases, and diabetes being the leading causes of morbidity and mortality worldwide [1]. To address this growing concern, there has been a shift towards preventive healthcare, which emphasizes the early detection and management of risk factors to prevent the onset or progression of chronic diseases [2]. One promising approach to support preventive healthcare is the development of personalized health risk assessment tools that can provide individuals with insights into their current health status and potential risks.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have enabled the creation of sophisticated health risk assessment systems that can process large amounts of data and generate personalized recommendations [3]. These systems have the potential to empower individuals to take proactive steps towards improving their health and reducing their risk of developing chronic diseases.

This paper presents an AI-powered health score calculation system that leverages user-provided information to assess individual health risks and provide personalized recommendations. The proposed system aims to bridge the gap between population-level health risk assessment and individualized preventive care by considering a wide range of factors, including demographics, lifestyle, health history, habits, health conditions, and family medical history.

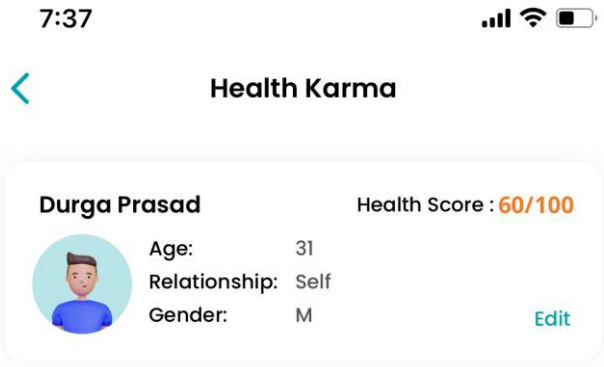

Figure 1: Health Score of user filled the questionnaire

2. Methods

1) Data Collection and Preprocessing

The health score calculation system relies on user-provided information to assess individual health risks. The following data points are collected from users:

a) Demographics: age, gender, ethnicity, occupation, education level
b) Lifestyle: physical activity, diet, sleep patterns, stress levels
c) Health history: past illnesses, surgeries, medications, allergies
d) Habits: smoking, alcohol consumption, drug use
e) Health conditions: current diagnoses, symptoms, treatment plans
f) Family medical history: chronic diseases in first-degree relatives

The collected data is preprocessed to ensure consistency and compatibility with the ML models. This includes data cleaning, normalization, and encoding of categorical variables.

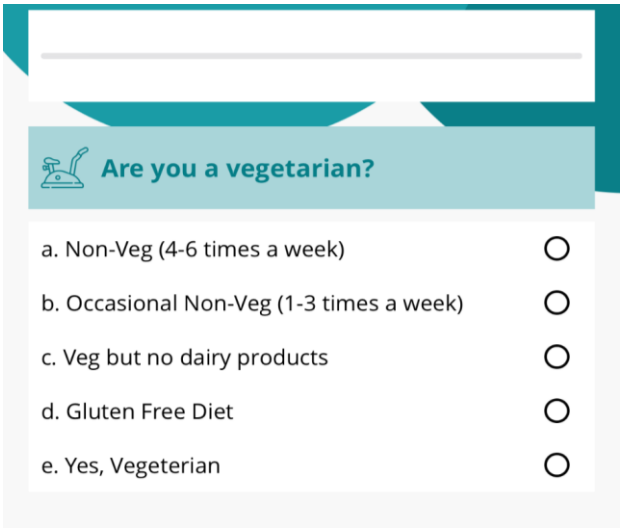

Figure 2: Series of questions to know lifestyle and health history of the user

2) Machine Learning Model Development

The core of the health score calculation system is a suite of ML models trained on large datasets to identify potential health risks and provide personalized recommendations. The models are developed using a combination of supervised and unsupervised learning techniques, depending on the specific task and available data.

3) Health Risk Identification

A supervised learning approach is employed to train models that can identify potential health risks based on user-provided information. The training data consists of anonymized electronic health records (EHRs) and associated risk factors, such as demographics, lifestyle, and health history. The models are trained to predict the likelihood of an individual developing specific chronic diseases, such as cardiovascular diseases, cancers, respiratory diseases, and diabetes [4].

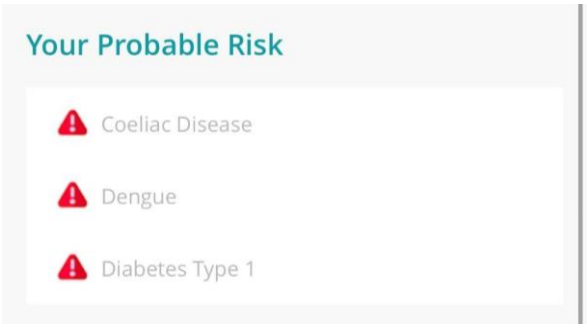

Figure 3: List of risks identified based on user inputs

4) Probable Diagnostics and At-Risk Health Vitals

Unsupervised learning techniques, such as clustering and anomaly detection, are used to identify probable diagnostics and at-risk health vitals based on patterns in user-provided data. The models are trained on large datasets of EHRs to learn the typical ranges and combinations of health parameters associated with various health conditions [5]. When presented with a user's data, the models can identify deviations from the learned patterns and suggest potential areas of concern.

5) Peer Comparison and Personalized Recommendations

To provide users with a comparative perspective on their health status, the system includes a peer comparison feature. Users are matched with a cohort of individuals with similar demographics and health profiles, and their health scores are compared to the group average. This comparison serves as a motivational tool to encourage users to adopt healthier behaviors and seek necessary medical care [6].

Based on the identified health risks, probable diagnostics, and at-risk health vitals, the system generates personalized recommendations for necessary health tests and lifestyle modifications. These recommendations are based on evidence-based guidelines and expert knowledge, tailored to the individual's specific needs and circumstances [7].

6) Health Score Calculation

The health score is calculated using a weightage model that considers the impact of core body vitals based on user inputs and habits. Each health parameter is assigned a weight based on its relative importance in determining overall health status. The weights are derived from expert knowledge and validated using statistical methods [8].

The weighted health parameters are then combined to generate a composite health score on a scale of 0 to 100, with higher scores indicating better overall health. The score is accompanied by a detailed breakdown of the individual health parameters and their contributions to the overall score.

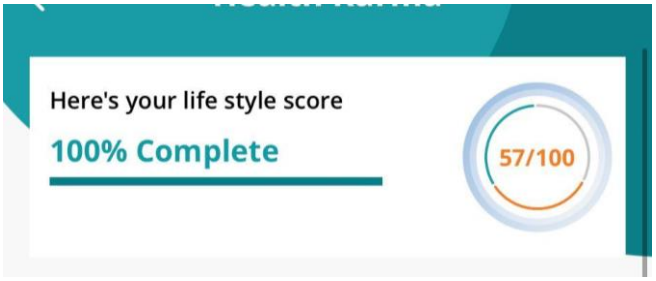

Figure 4: Score calculated based on inputs user provided out of 100.

3. Results and Discussion

The proposed AI-powered health score calculation system has the potential to revolutionize personalized healthcare by providing individuals with comprehensive insights into their health status and risks. By leveraging user-provided information and ML algorithms, the system can identify potential health risks, suggest probable diagnostics, and provide personalized recommendations for necessary health tests and lifestyle modifications.

The system's ability to compare an individual's health score with their peers serves as a powerful motivational tool, encouraging users to take proactive steps towards improving their health. The personalized recommendations generated by the system can help users prioritize their health concerns and seek timely medical care, potentially reducing the burden of chronic diseases.

However, the development and implementation of such a system present several challenges. Ensuring the privacy and

security of user-provided health information is of utmost importance, and robust data protection measures must be in place [9]. The ML models must be regularly updated and validated to ensure their accuracy and reliability in light of new medical knowledge and changing population health trends.

Moreover, the system's effectiveness in promoting behavior change and improving health outcomes must be rigorously evaluated through clinical trials and long-term studies [10]. The integration of the health score calculation system with existing healthcare infrastructure and workflows also requires careful consideration and collaboration with healthcare providers and policymakers.

4. Conclusion

The AI-powered health score calculation system presented in this paper represents a promising approach to personalized health risk assessment and preventive healthcare. By leveraging user-provided information and ML algorithms, the system can provide individuals with comprehensive insights into their health status and risks, motivate them to adopt healthier behaviors, and guide them towards necessary medical care.

While challenges remain in the development and implementation of such systems, the potential benefits for individual and population health are significant. As AI and ML technologies continue to advance, health score calculation systems are likely to play an increasingly important role in the future of personalized healthcare.

Further research is needed to refine the system's ML models, validate its performance in diverse populations, and assess its impact on health outcomes and healthcare costs. Collaboration among researchers, healthcare providers, policymakers, and patients will be essential to realize the full potential of AI-powered health score calculation systems in promoting preventive healthcare and reducing the burden of chronic diseases.

Acknowledgment
The authors would like to thank the participants in the user testing for their valuable feedback and contributions to this research.

References

[1] World Health Organization. (2018). Noncommunicable diseases. https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases
[2] Katz, D. L., Frates, E. P., Bonnet, J. P., Gupta, S. K., Vartiainen, E., & Carmona, R. H. (2018). Lifestyle as medicine: The case for a true health initiative. American Journal of Health Promotion, 32(6), 1452-1458. https://doi.org/10.1177/0890117117705949
[3] Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. New England Journal of Medicine, 380(14), 1347-1358. https://doi.org/10.1056/NEJMra1814259
[4] Weng, S. F., Reps, J., Kai, J., Garibaldi, J. M., & Qureshi, N. (2017). Can machine-learning improve cardiovascular risk prediction using routine clinical data?. PLoS ONE, 12(4), e0174944. https://doi.org/10.1371/journal.pone.0174944
[5] Miotto, R., Li, L., Kidd, B. A., & Dudley, J. T. (2016). Deep patient: An unsupervised representation to predict the future of patients from the electronic health records. Scientific Reports, 6(1), 26094. https://doi.org/10.1038/srep26094
[6] Suls, J., & Wheeler, L. (2017). On the relative effectiveness of social comparison as a tactic for promoting healthy behavior. Health Psychology Review, 11(3), 259-265. https://doi.org/10.1080/17437199.2017.1328624
[7] Dorsey, E. R., & Topol, E. J. (2016). State of telehealth. New England Journal of Medicine, 375(2), 154-161. https://doi.org/10.1056/NEJMra1601705
[8] Tyrovolas, S., Polychronopoulos, E., Morena, M., Mariolis, A., Piscopo, S., Valacchi, G., ... & Panagiotakos, D. B. (2015). The role of a healthy lifestyle index in relation to healthy ageing in Europe. The journal of nutrition, health & aging, 19(5), 532-537. https://doi.org/10.1007/s12603-014-0549-6
[9] Vayena, E., Blasimme, A., & Cohen, I. G. (2018). Machine learning in medicine: Addressing ethical challenges. PLoS Medicine, 15(11), e1002689. https://doi.org/10.1371/journal.pmed.1002689
[10] Michie, S., Yardley, L., West, R., Patrick, K., & Greaves, F. (2017). Developing and evaluating digital interventions to promote behavior change in health and health care: Recommendations resulting from an international workshop. Journal of Medical Internet Research, 19(6), e232. https://doi.org/10.2196/jmir.7126