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The Advantages of Health Recommending System with Wearable Devices

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Abstract:

The health recommendation system is one of the critical application scenarios of machine learning technology. With the advantages of wearable and mobile devices to collect rich user health monitoring data, machine learning algorithms can accurately advise users' health status and corresponding living habits. However, some technical and regulatory challenges still need to be solved at this stage. Specifically, to ensure real-time recommendation results, the health recommendation system needs to adopt the method of training computational learning algorithms on wearable devices. However, due to wearable devices' limited computing resources and storage space, it is often difficult to obtain satisfactory results by changing the strategy. In addition, the issue of data privacy deserves attention because wearable devices collect a lot of user privacy information, but the data manager is often not the user himself. Finally, Bluetooth protocol usually connects wearable devices, making them vulnerable to intentional attacks. This paper investigates the above problems and expounds on the solutions to related problems.

Keywords: Health recommendation system; Wearable Devices; Machine learning; Deep learning.

1. Introduction

In today's digital age, where information is abundant and lifestyles are increasingly diverse, dietary recommendation systems have become paramount in helping individuals navigate the complex landscape of nutrition. These systems leverage technology to provide personalized advice, enhancing health outcomes and culinary experiences. Modern dietary recommendation systems utilize algorithms that analyze vast datasets encompassing nutritional science, individual health profiles, dietary preferences, and genetic information. Initially, these systems focused on essential caloric intake and macronutrient distribution. Over time, they have evolved to consider micronutrient needs, dietary restrictions (such as allergies or intolerances), cultural dietary practices, and individual health goals (weight management, athletic performance, chronic disease prevention). At the core of these systems lie sophisticated algorithms that process user-inputted data or data retrieved from wearable devices (like fitness trackers) and health records. Machine learning models, including neural networks and decision trees, then analyze this data to generate personalized recommendations [1].

In the health recommendation system, the Key factors considered include: 1) Nutritional Requirements: Calculated based on age, sex, weight, activity level, and health status. 2) Food Preferences: Derived from user-provided information or previous dietary patterns. 3) Health Goals: Whether it's weight loss, muscle gain, managing chronic conditions, or improving overall well-being. 4) Cultural and Lifestyle Factors: Considering dietary habits influenced by cultural background or religious beliefs. These systems continuously learn and adapt based on user feedback and updated scientific research, ensuring recommendations remain relevant and effective [2].

Recently, advancements in artificial intelligence and wearable technology have refined these systems. Integration with real-time health monitoring devices and genetic profiling may unlock even more personalized dietary insights. Today's smart watches can measure heart rate, sleep mode, blood oxygen and water equality. The development of wearable technology, such as dynamic electrocardiogram monitors, makes it possible to continuously monitor patients remotely and improves preventive health care. The popularity and use of wearable technology have increased dramatically in the past few years, and many new products are introduced yearly. Smartwatches, fitness trackers and virtual reality headphones are some of the most popular wearable technology products. These devices are designed to provide users with various functions and benefits, such as tracking physical activity, monitoring health and enhancing entertainment.

Wearable and mobile devices, including smartphones, smartwatches and smart glasses, have become a part of daily life. Collecting users' health status through wearable devices and recommending reasonable life plans have become the focus of researchers' attention and show excellent application potential. Wearable health monitors cover a wide range of technologies worn near or embedded in human skin to systematically collect physiological and background information. Contemporary consumer wearable devices such as smart watches or fitness belts capture detailed real-time data about activity patterns, heart rhythm, sleep stages, gait indicators and stress biomarkers by constantly sensing and processing signals from peripheral nerves, tissues and organs. In essence, these devices collect valuable quantitative digital biomarkers, which can guide positive health behaviours or timely medical intervention at the individual and collective levels. At the personal level, wearable devices enhance people's awareness of personal health choices by providing detailed quantitative feedback on exercise, sleep, nutrition and stress. For nursing providers, accessing the time biological signal data set is helpful in finely characterizing the health trajectory so that the treatment can meet subtle personal needs [3].

However, the development of technology has brought many new challenges. For example, how can users' data privacy be protected, and how can a health recommendation system be run on mobile devices and wearable devices with limited computing power and storage capacity?

This paper systematically expounds on the main problems that wearable and mobile devices face related to health recommendation systems and the existing solutions. The content of this paper can provide a valuable reference for researchers in related fields.

2. Model Compression

Mobile and wearable devices have various sensing applications: health, exercise, happiness, emotion/stress recognition, activity recognition, mobile tracking, identity verification, positioning, rehabilitation, elderly care, sleep monitoring, augmented reality and virtual reality, and occupational safety. It is challenging and sometimes impossible to train machine learning algorithms, profound learning algorithms, on mobile and wearable devices with limited resources because computing power, storage space and, most importantly, battery is limited. However, to ensure the algorithm's response time, reduce the communication overhead and ensure reliability, it is necessary to train the machine learning algorithm on the mobile device. A popular method is to optimize (that is, compress and accelerate) the network after training. In this case, the model can be trained and optimized on external devices by reducing the model size, and then it can be transplanted to devices with limited resources. Another method is considering resource constraints in the training process to optimize the network. Similarly, external equipment can be used for training, or if there are enough resources, the model can be trained on a mobile device [4].

Low-rank factorization: The parameters of the neural networks may be redundant, which may lead to slower training speed. As shown in Figure 1, low-rank factorization can be applied to avoid parameter redundancy [5]. The low-order factorization algorithm combines linear correlation vectors and gradually reduces the size of parameters. One of the ways to make mobile machine learning possible is quantization. It compresses the model's overall size by representing numbers with low precision. For example, parameters with low precision, such as 8-bit-wide fixed-point value, can be used instead of representing data with 32-bit-wide precision without reducing the model's success rate.

Fig. 1 Low rank factorization

2) Optimal pruning of resource-constrained model is a common technique which compresses the network by eliminating unimportant parameters. Unstructured pruning can be done at the weight, layer or block level. For example, amplitude-based weight pruning can identify the parameters that have negligible influence on model prediction, prune synapses and neurons to eliminate redundant connections and reduce the model size with minimum accuracy reduction [6].

3) Modify the optimization routine: When training the model, the emphasis is on minimizing the error rate, but we can also consider the computational complexity, memory occupation, computational speed and power consumption. For example, Stamoulis et al. proposed the

hyperparametric optimization problem using Bayesian optimization technology to minimize error rate and energy [7]. They show that this method reduces the energy consumption of image classification on mobile devices by six times when tested on commercial Nvidia mobile SoC. The hardware-aware neural architecture search (NAS) method is helpful for running DNN models efficiently on devices with different hardware and tasks.

3. Data Privacy and Security

Continuous personal health monitoring has been realized with the increasing popularity of wearable health devices such as fitness trackers and smartwatches. However, serious privacy issues have also arisen due to the real-time collection of sensitive data. Profit-driven motivation leads to the sale of user data, which exposes individuals to various risks. Collecting sensitive health information, such as biometrics and medical history, and then selling it to third parties, including pharmaceutical and insurance companies, raises serious privacy issues. Advertisers and marketers use these data for targeted advertising, which can influence employment, insurance and credit decisions. Unintentional data exposure, violation and malicious abuse pose a severe threat. A significant problem is the lack of informed consent in collecting and sharing personal health data. Many users may need to realize that their data is being collected and may be sold, or they may not fully understand the potential consequences. Companies sometimes hide these data collection details in their privacy policies, making it difficult for users to grasp the whole situation of their data. This lack of transparency is a severe violation of privacy.

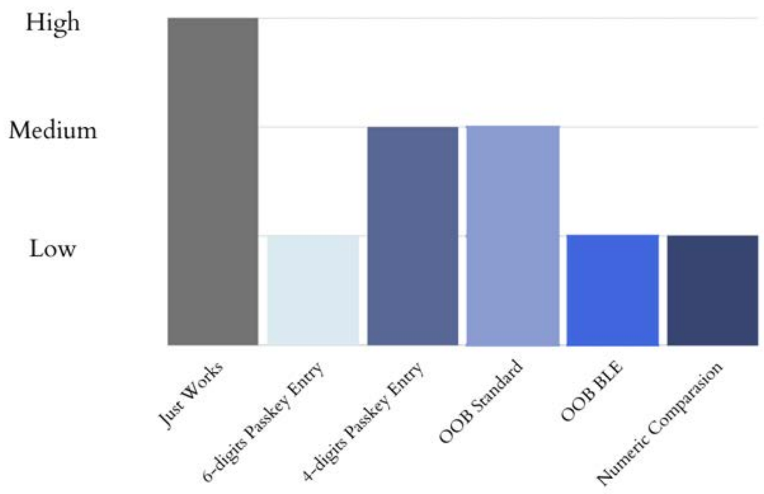

Fig. 2. Risk level on pairing methods [8]

In addition, a more critical issue is the risk of active attack, as shown in Figure 2 [8]. All smartwatches have vulnerabilities, and attackers can use these vulnerabilities to carry out different types of attacks. The chance of attack is passive sniffing, which involves intercepting packets during communication between two devices. Attackers can collect this information to take advantage of the weak pairing protocol of devices. When attacking devices with low-security pairing protocols, passive sniffing may succeed, such as using the Just Works association model. However, even if two devices have been paired, attackers can use other technologies to achieve successful passive sniffing, such as device cloning, interference and injection-free technology. The working principle of these methods is to force two devices to cancel pairing, which leads to the renegotiation of their keys. This allows an attacker to sniff the communication channel to obtain information.

4. Discussion

With the continuous integration of cutting-edge technologies such as artificial intelligence, the Internet of Things, and big data, wearable devices' accuracy and intelligence level in health detection have significantly improved. For example, AI algorithms can deeply analyze users' physiological data, provide personalized health advice, and even realize disease prevention and early warning. However, wearable devices still face many technical problems in health detection. For example, improving the accuracy and stability of monitoring data and achieving a breakthrough in non-invasive health monitoring technology are urgent problems that must be solved. In the medical field, a significant research problem is to evaluate the weight between wearable detection equipment and medical instruments based on machine learning. Wearable devices can be carried around because of their compactness and portability, which can realize real-time monitoring of users' physiological indexes, incomparable to traditional medical instruments. Therefore, the health advice given by wearable devices is more likely to affect the user's estimation of self-health. However, after strict calibration and verification, medical instruments can provide high-precision and high-accuracy measurement results, which is difficult for wearable devices to achieve. In medical diagnosis and treatment, high-precision measurement results are significant. However, its high cost reduces its frequency and influence in daily life. This paper holds that wearable devices and medical instruments are more likely to form a complementary relationship in the future rather than completely replace them. Wearable devices are used for daily health monitoring and early warning, while medical instruments are used for accurate diagnosis and treatment. In addition, with the continuous progress of technology, the boundary between wearable devices and medical instruments may gradually blur. For example, some high-end wearable devices may incorporate more medical-grade sensors and algorithms to improve their measurement accuracy and application scope. Some medical instruments may also learn from the design concept of wearable devices to achieve a more portable and humanized operation mode. The health recommendation system based on wearable devices will further affect all aspects of human life and improve the quality of human life and health.

5. Conclusion

This paper expounds on the challenges and solutions of machine learning methods in model design and data privacy in health recommendation systems based on wearable devices. Firstly, this paper introduces some technologies, such as model compression, to ensure the training effect of machine learning algorithms on wearable devices. It also introduces the problems of data privacy and the potential risks that wearable devices may have when facing specific attacks. Finally, this paper also discusses the different roles of wearable and precision medical devices in protecting users' health and looks forward to their future development prospects.

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