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Research and Application Prospects Analysis of Artificial Intelligence and Machine Learning in Weight Loss

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Abstract: This paper studies the research achievements of artificial intelligence (AI) and machine learning in Weight Loss in the past decade and analyzes the impacts and application prospects of AI and machine learning on Weight Loss. Obesity has become the most significant threat to human health. It is estimated that the global number of obese people will exceed 2.16 billion in 2023. AI and machine learning can analyze a large amount of complex data (including genetic, gene expression, metabolic, gut microbiota, hormonal, dietary, behavioral, and environmental factors, etc.) more efficiently and accurately. They have opened new avenues in areas such as analyzing the causes of obesity, predicting obesity risks, diagnosing obesity and determining its subtypes, providing personalized and precise nutrition plans, and offering psychological support, making it possible to address the weight loss issues of such a large-scale population. This paper systematically analyzes the integration of relevant scientific research achievements with various links in Weight Loss, exploring the direction for the further practical and commercial transformation of scientific research achievements. At the same time, based on the urgent pain points in Weight Loss applications, it analyzes the current research gaps and deficiencies and proposes suggestions for future scientific research directions.

Keywords: Artificial Intelligence, Machine Learning, Weight Loss, Obesity Prediction, Precision Nutrition

1. Introduction

Obesity is widely recognized as a crucial determinant of human health [1]. According to the World Health Organization (WHO) [2], over 1 billion people were obese in 2022, including approximately 650 million adults, 340 million adolescents, and 39 million children. By 2030, the number of overweight people is expected to exceed 2.16 billion [3]. The increasing incidence of obesity poses serious public health risks, contributes to increased mortality, places a substantial economic burden on serious public health risks, contributes to increased mortality, and even affects the birth rate [4].

The causes of obesity are multifactorial, including genetic factors, environmental factors [5], eating habits, and physical activity [5, 6]. Diet management and physical activity are the main determinants in preventing and controlling obesity [7, 8]. However, the growing complexity of obesity's underlying factors makes it difficult to accurately predict obesity risks or personalize weight loss interventions using only traditional analysis methods [9]. There is an increasing need for solutions that can handle complex data and provide deeper insights.

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Advancements in artificial intelligence (AI) and machine learning (ML) offer powerful solutions for Weight Loss. These technologies can efficiently process and analyze complex biological and behavioral data, such as genetic, metabolic, gut microbiota, hormonal, dietary, behavioral, and environmental factors. They can identify hidden patterns, analyze the correlations between various factors, and model the complex relationships among multiple variables to achieve individual obesity risk prediction, individual body composition analysis, and a better understanding of how diet, nutrition, physical activity, and metabolic responses affect obesity risks. They can also generate prediction models [10] for early intervention and prevention, as well as personalized and precise nutrition advice. Moreover, with the help of AI-powered chat tools [11], it is possible to instill health concepts and provide psychological support to many overweight and obese people on a large scale, which will play an important role in achieving and maintaining weight loss results [12-24].

2. Health data collection for Weight Loss

2.1. Data sources

With the help of various wearable devices (such as smart bracelets and smart watches), it is possible to collect users' physical data, including heart rate, exercise, and sleep quality. Body composition data, such as weight, body fat percentage, muscle mass, and basal metabolism, can be obtained through smart body fat scales. In addition, it is also possible to collect users' body photos by using mobile phone cameras, as well as their dietary information, such as food types and intakes, and lifestyle data, such as daily routines and work intensity [25]. At the same time, CT and MRI imaging data, as well as medical-grade blood glucose, blood lipid, ketone body, gene, gene expression, gut microbiota, and metabolic information, will also become important data sources.

2.2. Data analysis

Data mining techniques in machine learning are used to analyze the large amount of collected data. For example, through association rule mining, it is possible to discover the relationships between certain food intakes and weight changes or the correlations between exercise patterns and body fat rate reduction [17]. Cluster analysis can classify users according to different physical characteristics and living habits to better understand the Weight Loss characteristics of different groups.

3. Applications of artificial intelligence in Weight Loss

AI and machine learning have transformed Weight Loss by enabling personalized solutions based on genetic, metabolic, and behavioral data. Unlike traditional one-size-fits-all methods that rely solely on BMI and calorie control, AI can tailor nutrition, and intervention plans to individual profiles. The integration of biological data—such as genes, metabolites, and gut microbiota—has advanced Weight Loss to a deeper, more lasting, and even transgenerational level.

Smart devices further enhance this process by offering real-time monitoring, reminders, and psychological support, improving adherence and long-term outcomes. Additionally, AI accelerates research by uncovering complex links between obesity factors and treatment responses, driving innovation in meal replacements, supplements, and therapeutics.

3.1. Obesity prediction and classification

3.1.1. Analysis of the causes of obesity

Early detection of obesity is crucial for reducing related health risks. Although BMI offers a quick and convenient measurement index, it fails to reflect underlying causes. Recent studies have

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developed machine-learning models using lifestyle variables instead of BMI, achieving an accuracy of 86.5%. Beyond diet frequency, socioeconomic and environmental factors can be integrated to enhance prediction. By combining advanced machine-learning techniques, such as deep learning, ensemble methods, or neural networks, the accuracy and prediction ability of the model can be further improved. Collecting data from more diverse populations and regions can make the model more robust [26].

3.1.2. Obesity prediction, identification, degree subtype judgment, and risk threshold judgment

AI can achieve the analysis of the causes of obesity [27], obesity prediction and identification[28-30], degree judgment [31], and subtype judgment [32, 33]. The emergence of machine-learning models enables the processing of massive datasets and the detection of complex relationships and interactions between obesity predictors [34]. Machine learning can achieve more accurate predictions and continuously adjust over time, promoting the transformation towards personalized and preventive healthcare. These methods can not only reduce the medical burden caused by obesity but also emphasize the importance of early detection and prevention. Early identification enables timely intervention, easing healthcare burdens and guiding precision nutrition plans tailored to obesity subtype and metabolic abnormalities [35, 36].

3.1.3. Body composition analysis

Body composition, including the measurement of muscle and fat mass in the body, is of great significance for determining obesity subtypes and predicting risks. Traditional methods for estimating body composition, such as anthropometric measurement, dual energy X-ray absorptiometry, and bioelectrical impedance analysis, have limitations in application. Cross-sectional imaging is achieved through the segmentation of computer tomography and magnetic resonance imaging studies. AI and deep learning have overcome the problems of manual image segmentation by professional readers, which is time-consuming and labor-intensive and limits the application in large-scale research and routine clinical practice, through automated methods in tissue segmentation. The emergence of neural network architectures for pixel-level image segmentation provides an opportunity to create body composition analysis tools [37]. The effectiveness of using machine-learning and deep-learning algorithms to automatically segment abdominal adipose tissue in CT and MRI scans has been demonstrated [33]. Additionally, machine-learning models using smartphone-based 2D imaging can estimate fat mass. A smartphone camera trained by machine learning and automatically processing 2D standing lateral digital images can quickly and cost-effectively identify adult obesity phenotypes in practice [38].

3.2. Personalized precision nutrition plans

3.2.1. Food image recognition in nutritional intake assessment

Dietary assessment is a key step in personalized nutrition plans. An individual's ability to track food intake plays an important role in self-monitoring, which is a crucial link in behavior change [39]. However, using traditional methods to assess dietary intake places a considerable cost and burden on individuals and is prone to errors because they usually rely on self-reporting [40].

Food image recognition is a promising strategy. Since most people own smartphones with cameras, the entry threshold is low, and it can cover many people. In 2014, deep learning was first used to identify food images. Deep neural networks, which consist of multiple processing layers, can learn relevant image features by training on a set of input images. A new deep-learning architecture for

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food image recognition has been proposed, with an increased image size and an additional convolutional layer at the beginning of the neural network [41, 42]. A fully convolutional network variant (a fully convolutional network that can segment images at the finest granularity) has been proposed [43], with an accuracy rate of 92.18%. In the future, this technology can be used to improve dietary assessment in clinical trials. Consumer health applications can also apply this solution in the future to improve personal dietary assessment and promote self-monitoring for positive behavior change.

3.2.2. Personalized and precision nutrition

AI-assisted platforms can optimize calorie intake and macronutrient distribution according to users' metabolic and hormonal status to address individual adaptive responses, such as metabolic slowdown during calorie restriction. For example, machine-learning algorithms can identify specific macronutrient ratios that minimize hunger while maximizing fat oxidation and muscle preservation, enhancing the effectiveness of precision nutrition strategies. These algorithms can also incorporate factors such as circadian rhythms, physical activity levels, and psychological stress to further refine the recommendations.

AI models show significant potential in predicting the metabolic responses (such as blood glucose and insulin fluctuations) of specific foods. AI can integrate multiple factors, including genes, gene expressions [23], metabolic markers [21], gut microbiome composition [19, 22], and dietary patterns, to develop personalized and precise nutrition advice. These models go beyond traditional macronutrient and calorie calculations, considering hormone levels, metabolic flexibility, and energy distribution, which is crucial for addressing challenges such as adaptive thermogenesis and hormonal disorders during the weight-loss process.

AI can provide continuous tracking and real-time feedback through wearable devices, home IoT devices, mobile applications, and big-data-based connected health platforms. By analyzing biological features such as heart rate variability, blood glucose levels, and calorie consumption, and regularly performing body composition analysis to obtain real-time physiological data, advanced biomarkers, including metabolomics and proteomics profiles, can provide a deeper understanding of the metabolic state. AI can integrate these data streams to improve prediction models, enabling a dynamic and iterative weight-management approach. This allows users to immediately adjust their dietary intake, physical activity, sleep, etc. For example, an AI application may recommend a protein-rich snack after detecting a post-exercise blood glucose drop to ensure continuous energy levels and muscle recovery. AI can also adjust mealtimes and dietary structures according to detected metabolic rate or hormonal fluctuations, develop a universal assessment chart for nutritional biomarkers, and study how to best predict body mass index and discover dietary patterns by deploying neural networks [21].

3.3. Behavioral intervention and weight-loss psychology

AI platforms can also integrate behavioral psychology principles, track compliance trends, and identify factors causing deviations. They can predict challenges such as lack of motivation or excessive stress, the impact of temporary weight plateaus on perseverance, and the loss of confidence caused by weight-loss failures and rebounds and provide proactive intervention measures to maintain consistency. This real-time adaptability helps to improve the long-term success rate and compliance of personalized weight-management plans and rebuild confidence.

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4. Advantages and limitations

4.1. Advantages

The biggest difference between Weight Loss under AI and machine learning and traditional weight-loss plan-giving methods is that the former incorporates deeper-level influencing factors in the biological field into algorithms and training, providing users with personalized and targeted precision plans [20]. Therefore, it can be called a biologically upgraded weight-loss plan. These biological factors include genes, gene expressions, heredity, epigenetics, gut microbiota-induced enterotypes, and metabolic characteristics. The era of one-size-fits-all traditional weight-loss plans based on calorie deficits and blood glucose-insulin fluctuations is about to be replaced.

In addition, AI-based methods have greatly improved in prediction ability, algorithm accuracy, user compliance, and result maintenance.

4.2. Limitations of AI and data mining

The main limitations of the current applications of AI and data mining in the field of Weight Loss include insufficient data quality and quantity, model interpretability, and ethical issues. The body composition, biological data (including genes, gene expressions, metabolism, and gut microbiota), and daily dietary, nutritional, and exercise data of most weight-loss people have not been detected and recorded for a long time with high quality. Therefore, there are deficiencies in both data quality and quantity.

Regarding model interpretability, it is very important for clinical decision-making support, patient education, and compliance in Weight Loss, as well as in ethical and legal aspects. The effectiveness of AI-based weight-management systems must be strictly verified through large-scale randomized clinical trials. The model needs to be optimized, and the system needs to be trained with the continuous accumulation of sample data. Transparency, informed consent, privacy, and reducing bias are all included in the ethical framework. Ethical issues related to data privacy and accessibility must be addressed to ensure fair adoption among different populations. The progress of explainable artificial intelligence (XAI) will also play a key role in improving transparency, building trust, and promoting the wide-scale clinical application of AI-driven solutions.

4.3. Research gaps

The results of weight-loss processes vary greatly depending on the plans adopted. Extreme weight-loss methods such as dieting and liquid fasting lead to a large proportion of muscle loss while losing weight, which further negatively impacts the health of obese people. Further research is needed on how to use AI and machine-learning modeling to personally define the advantages and disadvantages of weight-loss plans.

With the rapid development of self-media platforms and the widespread dissemination of self-media content, as well as the extensive application of content-push services, problems such as uneven content quality and information cocoons have become prominent. Many overweight and obese people are easily trapped in extreme weight-loss plan traps, resulting in physical and economic damage and a further blow to their confidence. There is a research gap in how to use AI and machine learning to detect weight-loss methods that cause physical damage and intervene.

In the past 20 years, the rapid development of biology has enabled people to have a broader and deeper understanding of the causes of obesity. There are numerous research achievements related to Weight Loss in fields such as genomics, genetics, epigenetics, metabolomics, gut microbiota, and nutrition. However, currently, there are not many solutions for life intervention that are combined with these achievements. It is of great significance for solving the global problem of obesity and

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overweight to use AI and machine learning to screen and identify the research achievements that can be applied to life intervention and precision nutrition and provide commercial transformation suggestions to accelerate the transformation of scientific research into practice and business.

5. Future outlook

Based on the retrieval, screening, and research of academic papers on AI and machine learning in the field of Weight Loss in the past decade, it can be predicted that relevant achievements can give rise to various independent products for weight loss, such as weight-loss meal replacements, nutritional supplements, measuring devices, or apps, service apps, and comprehensive system platforms [44], and even end-to-end product + service comprehensive solutions. Facing more than 1 billion overweight and obese users globally, these applications will greatly improve the efficiency and coverage of Weight Loss, have a revolutionary impact on solving the global obesity problem, and create inestimable social and economic value.

6. Conclusions

This study comprehensively retrieved and analyzed relevant papers from the past decade, classified and sorted out related scientific research achievements, and systematically analyzed their integration with various links in the practice of Weight Loss, forming a comprehensive practical closed loop for end-to-end weight-management solutions and exploring the direction for the further practical and commercial transformation of scientific research achievements.

At the same time, based on the urgent pain points in weight - management applications, it analyzed the current research gaps and deficiencies, including how to deal with the spread of wrong weight - loss concepts and their negative impacts in the information - cocoon environment where self - media networks occupy a lot of people's time; how to scientifically and quantitatively judge the advantages and disadvantages of weight - loss results to prevent excessive loss of precious muscle; and the lack of a systematic branch of weight - loss psychology in the field of psychology and how to effectively use AI and machine learning to support the psychological problems of more than 1 billion obese people globally.

In the era of rapid biological development, researchers have a rich and in-depth understanding of the deep-layer mechanisms of obesity. In the future, it is worth exploring how to use AI and machine learning to quickly transform these scientific research achievements into practical and commercial implementation plans.

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