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A Systematic Literature Review on Implementation of Hybrid Machine Learning-Based Predictive Analysis Model for Customer Use of a Mobile Fitness Application

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Abstract: Access to health and fitness-related services is now more convenient thanks to the rising popularity of mobile fitness applications. Mobile fitness apps can employ predictive analytics to personalize user experiences to increase user engagement and retention. Hybrid machine learning models have been popular in recent years as efficient methods for predictive analysis across a range of fields. This comprehensive evaluation of the literature intends to investigate the usage of hybrid machine learning-based predictive analysis models specifically for user interaction with mobile fitness applications. We will talk about the advantages of the Hybrid Machine Learning-Based Predictive Analysis Model for Customer Use of a Mobile Fitness Application. The review summarizes the results from numerous research that were published between 2018 and 2022. In this study, 50 publications were analyzed to identify the research gaps relevant to the learning-based predictive analysis model for customer use of a Mobile Fitness Application. The findings of this review give academics and practitioners in the field of mobile fitness applications useful insights into the current state-of-the-art & future directions.

Keywords: Machine learning, Fitness applications, health, physical activity, customer usage

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INTRODUCTION

People in the modern world deal with busy, active lifestyles on a daily basis. Encouragement of people to choose or maintain healthy lifestyles to lower their chance of getting chronic diseases is thus one of society's major challenges. It is crucial to engage and motivate citizens with healthy activities that are tailored to their interests, as this will serve as a key driver in the process of safeguarding good health from a preventive point of view, aligned with the pursuit of Sustainable Development Goal, "good health and wellbeing". This is one of the causes for the recent trend in research towards health recommendation systems, notably in the areas of food and exercise. When we make regular exercise a habit, it has a significant impact on both our physical and emotional health [1]. This literature review mentioned a total of 50 papers, which suggests that there is a citation deficit in the field. In order to keep the current work up to date for the readers, a thorough search has been done in this literature review with a focus on finding related Implementation of Hybrid Machine Learning-Based Predictive Analysis Model for Customer Use of a Mobile Fitness Application papers up until 2022. This Review Paper's Contribution The contribution of this work is as follows, based on the information discovered thus far in the literature:

· The deployment of a hybrid machine learning (ML)-based predictive analysis model for customer

use of mobile fitness applications is the focus of this literature review, which spans up to the most recent studies in this subject published through 2022.

· Mobile fitness apps based on ML have first been introduced. Applications will also be addressed in order to identify the various activities.

· This survey will also discuss various machine learning approaches and how they apply to various predictive analytic models for customer use based on papers that have been published up until 2022.

· The research gap in ML-based analysis model for user use of mobile fitness applications that the authors have found, as well as their proposed research strategy.

· A statistical summary of publications on ML-based mobile applications that have been published has been provided at the conclusion. This will assist researchers in getting a sense of the potential of published research in a particular area of interest.

RESEARCH OBJECTIVES

The preliminary aim of this systematic literature review (SLR) is to present a comprehensive analysis on the mobile fitness applications and their role in influencing the users to maintain their fitness. The objectives of this SLR are as follows:

A. To conduct a systematic and in-depth review on different mobile fitness applications for improving the fitness level of the users.

B. To review different machine learning models and predictive analysis approaches used in the design of mobile fitness applications.

C. To identify the research gaps, limitations from the existing literary works and suggest future research directions.

Table 1. Challenges faced with existing fitness applications

Citation	Age & year	Application	Fitness test	Number of enrolled participants
[3] Kamboj, S., (2020)	50+	Mobile application	physical activity	40
[4] Alli, A. A., (2019)	65+	smart city applications	Walking	25
[5]Binyamin, S. S.,(2021)	70+	Mobile health application	10 mints walk test	38
[28] M. H. B. de Moraes Lopes(2020)	10-20	Smart phone application	Modern activity	50

RESEARCH QUESTIONS

RQ 1. Can this review justify the role of machine learning algorithms in enhancing the efficiency of mobile fitness applications?

RQ 2. Can this review address the problems related to the performance of mobile fitness applications in terms of accuracy?

Table 2 .Weekly goals of the challenges

Citation	Application type	No.of. Participant	Weekly goals
Goldstein, S. P.,(2018) [31]	Walking running tracker	13	90 mints of exercise and flexibility exercises
Hurst, C. ;(2019) [33]	Diet and exercise plan	20	135 mints of exercise and flexibility of exercises
S. Bian, V. F(2019) [37]	Diet and exercise plan	10	145 mints of exercise and flexibility of exercises
Depari, P. Ferrari(2019) [40]	Calorie counter	23	200 mints of exercise and flexibility of exercises

Table 3. Consumer adoption of smartphone fitness apps

Citation	Application	Follow up	Outcomes
T.-C. Kang,(2019) [27]	Mobile application	3 months	Self-reported weight and dietary intake of vegetables, sugary soft drinks.
Chen, Q., & Lee, S. (2021) [46]	Smart phone application	12 weeks	Smoking rates, physical activity, alcohol or fruit and vegetable consumption. Biochemical measures:
E. T. Luhanga, A. A. (2018) [32]	Mobile application	6 month	Weight (kg), BMI, physical activity (MET-minutes), and diet behaviours'.

METHODOLOGY FOR CONDUCTING SLR

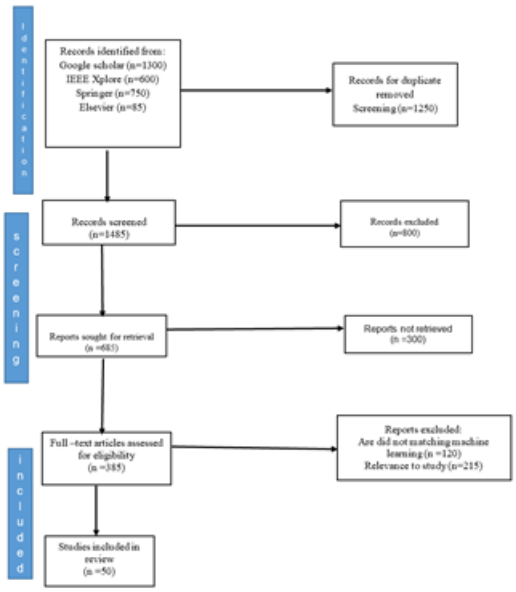

Figure 1. Prisma Model

By looking up the pertinent articles. The PRISMA Model for the SLR is shown in figure 1.

Firstly, articles are sourced using electronic Databases such as IEEE, Springer, and Elsevier. Next, articles are sourced using online search engines such as Google Scholar also has been considered. Secondly, the articles are filtered based on the relevance of the articles to the study. Thirdly, the articles are filtered based on the keywords of the study that exclude articles if the keywords are not present in the title. Filter articles based on the abstract that exclude articles if the keywords and search strings are not present in the abstract. Further, read full text articles based on the relevance to the topic of the research and objectives that exclude articles if the content of the paper is not relevant to the finalized keywords. Further, the articles included in the qualitative and quantitative analysis are considered in the study. Finally, articles those are not older than 2019 are considered for analysis.

REVIEW

Customer fitness applications have been significantly impacted by the development of machine learning (ML) and deep learning (DL) techniques [25]. Numerous studies [26–28] have used ML approaches to improve various elements of fitness applications.

Table 4: Systematic Review

Citation Reference number	Year	Findings/Observation	Identified Research Gaps

[30]	2018	mSTAR study: Personalized step goals intervention group had significant daily step increase.	Investigate the impact of different goal setting sources. Explore the impact of different dynamic goal setting algorithms.
[32]	2018	Participants desired informational and emotional support, and daily challenges with their support network	Validation with larger sample, long-term effects, and facilitation of emotional support
[39]	2019	The proposed deep learning methods can accurately predict physical activity and functional fitness levels using smartphone acceleration signals recorded during the 6MWT	validating the proposed methods with larger and more diverse datasets, exploring their applicability in real-world clinical settings, and assessing their long-term predictive capabilities
[42]	2019	Current consumer market problems: irrational consumer structure, weak fitness and leisure industry, privacy concerns with fitness apps, inactive consumer demand, and inadequate sports venue supply.	Lack of comprehensive studies on the long-term effectiveness and impact of mHealth applications on user health outcomes
[44]	2020	Perceived aesthetics, technology readiness, and mobile usefulness significantly influence behavioral intention to use wearable payment	Mobile ease of use does not have a significant impact on behavioral intention
[46]	2021	Random forest achieved better discrimination verification power compared to other models	improving real identity privacy information and other aspects of the platform
[47]	2021	An ensemble approach using regression models and clustering achieved 87% accuracy and 85% F1_score in predicting user adherence	variables related to engagement, motivation, and longer longitudinal periods for more accurate predictions

The application of two deep learning-based algorithms demonstrates their great accuracy in predicting levels of physical activity and functional fitness. Future mobile health systems may use the suggested method, which would enhance clinical evaluation and lower the price of healthcare services. [40] Proposes

a method for fitness workout supervision utilizing wearable IMUs and machine learning algorithms. To increase exercise correctness and inspire users, the strategy focuses on activity classification and counting. The experimental tests show high exercise detection accuracy of over 93% and low exercise counting error of less than 6%. The suggested method is computationally effective, making it appropriate for use in low-cost wearable's with limited resources. The approach's performance is on par with that of more sophisticated methods described in the literature. By creating a model that combines the fuzzy Technique for Order of P by Similarity to Ideal Solution (TOPSIS) and analytical Hierarchy Process (AHP) approaches, [41] intends to close the research gap in selecting mHealth apps. A framework for assessing and ranking mHealth applications based on user happiness, functionality, usability, and information quality is provided by the suggested model. [42] Presents an analysis of Chinese consumer demand for leisure and physical activity in the context of big data. The report emphasizes the growing and changing consumer demand in this industry as well as the substantial contribution of mobile Internet. In order to solve current issues in the consumer fitness and leisure industry, the study suggests concrete approaches. [43] Offers a framework for workload computation in applications related to fitness and health at work. The technology uses wearable sensors to assess heart rate and recognize human activities. The activity classifier performs well in both real-time testing (92% accuracy) and validation (97.5%). The system's ability to monitor physical workload and identify bodily adaptation to training regimens is demonstrated by a case study. In order to forecast physical effort and improve injury prevention in physically demanding occupations and workplaces, future study can investigate the relationship between physical workload and activities. [44] Investigates the variables affecting wearable payment uptake. The study uses deep learning analysis to determine whether wearable payment acceptance is high. The results show that users' behavioral intention to utilize wearable payment is highly influenced by perceptions of aesthetics, technology readiness, and mobile usefulness. The influence of mobile usability is not found to be considerable, nevertheless. To enhance the comprehension and uptake of wearable payment, the study recommends examining actual usage behavior, introducing more components, exploring moderating factors, and contrasting various deep learning architectures. [45] Examines how fitness applications affect people's perceptions of and comprehension of health and fitness. To explore the relationship between humans and technology in fitness app designs, the study employs a post phenomenological viewpoint and combines design analysis and interviews. The results imply that deliberate design features, promoting accomplishments and self-improvement, impact users' perceptions of health and fitness. The versatility of technological mediation, however, enables reinterpretation and alternate interpretations. Further investigation into individualized health technologies and their social ramifications is stressed by the study. [46] Suggests using machine learning to evaluate user activities on a platform for at-home workouts. To anticipate continued usage, the study uses data from Keep users and a random forest model. The algorithm successfully predicts continued usage 88% of the time, with Keep certification being the key factor. The report emphasizes the need for platform upgrades in terms of privacy and other areas. [47] Addresses the prediction of user adherence to fitness app training. The study offers a system that classifies users and forecasts their adherence behavior using machine learning methods and clustering algorithms. The outcomes show the potential of cutting-edge strategies to increase user engagement in fitness apps and decrease app churn. The expanded Technology Readiness and Acceptance Model (TRAM) is used in the study in [48] to analyze why people choose to use health and fitness apps. The results demonstrate the impact of both positive and negative technological preparedness on perceived use, utility, and enjoyment. The study highlights the need for

additional research to address its flaws, which include sample bias, a lack of generalizability, and erratic results on the impact of technological preparedness on cognitive aspects. A tailored physical activity suggestion system employing fitness tracker data is the main topic of [49]. The system groups users based on their physical and physiological characteristics and previous activity patterns using clustering techniques. The model creates customized activity schedules and makes suggestions to users depending on their goals and adherence. In addition, [50] suggests a deep reinforcement learning (DRL)-based adaptive approach for individualized physical activity recommendations in mobile health (mHealth) information services. Personal behavioral aspects are taken into account by the DRL-based recommender system, which dynamically modifies the physical activity recommendation policy depending on real-time implementation behavior. The experimental findings show that this method for adaptive learning enhances recommendation performance by more than 4.13%. The study highlights the need for additional research on the effects of rewards and penalties in increasing physical activity participation, but it also recognizes the restriction of not evaluating parameter values for mHealth interventions.

CONCLUSION

The studied research shows that hybrid machine learning-based predictive analytic models have a major impact on how customers utilize mobile fitness applications. It has been demonstrated that these models enhance user interaction, behavior modification, and general user experience. Mobile fitness apps can offer tailored suggestions, precise activity tracking, and improved social support by combining machine learning techniques like reinforcement learning, deep learning, and clustering. The literatures reported research gaps show the need for additional study in a number of areas. The study of non-linear correlations between fitness and host use, the validation of approaches using field data, and comparative research across various ecosystems are all necessary in the subject of herbivore-plant interactions. Future research in the area of fitness apps should concentrate on examining the effects of various goal-setting sources and design elements, resolving the problem of missing data in lapse prediction models, and confirming findings using bigger sample sizes. In addition, it is important to investigate the long-term impacts of social support in group fitness apps, improve algorithms for sports data analysis, and enhance training methods and exercise modes. The literature also highlights how crucial it is to handle privacy issues, enhance usability, and assess the long-term efficacy and impact of health applications. In order to improve the precision of forecasting user adherence in fitness applications, future study should also take engagement, motivation, and longitudinal period characteristics into consideration. Important research directions include examining the factors impacting wearable payment uptake, comprehending user behavior patterns, and optimizing platforms for improved privacy and usability. The hybrid machine learning-based predictive analytic approach has the potential to completely change the landscape of mobile fitness applications, as shown by the results of the literature review. These applications can offer personalized and adaptable recommendations, improve user engagement and adherence, and enhance overall health and fitness outcomes by utilizing the power of machine learning algorithms. In conclusion, the literature study offers insightful information about the state-of-the-art in hybrid machine learning-based predictive analysis models for user use of mobile fitness applications. The results emphasize the potential advantages of these models and point up significant areas for future investigation. We can open up new doors for individualized and efficient health and fitness management by filling in these gaps and exploring the potential of machine learning in the realm of fitness applications.

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