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FitCluster AI: A Semi-Personalized Fitness and Diet Recommendation System Using Rule-Based and Lightweight Machine Learning Techniques

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***Abstract-** Maintaining a consistent fitness and dietary routine has become increasingly difficult in modern lifestyles due to lack of time, improper guidance, and absence of personalization. Many individuals rely on generic plans that fail to consider their unique body conditions and goals. This leads to ineffective results and lack of motivation. To address this issue, this paper presents FitCluster AI, a semi-personalized recommendation system that combines rule-based logic with lightweight machine learning techniques. The system utilizes user inputs such as age, height, weight, activity level, and fitness goals to categorize users into predefined clusters. Based on these clusters, rule-based logic is applied to generate tailored recommendations. Unlike deep learning approaches, the proposed system does not require large datasets or high computational resources, ensuring efficiency and privacy. Experimental results demonstrate that the system produces consistent and meaningful outputs across different user profiles. The proposed approach provides a practical solution for real-world fitness applications.*

I. INTRODUCTION

In today's world, maintaining a healthy lifestyle has become increasingly challenging, especially for students and working individuals who spend a large portion of their time in sedentary activities. Long hours of study, screen usage, and irregular schedules often reduce the amount of physical activity people engage in on a daily basis. Even though awareness about fitness and nutrition has grown, many individuals still struggle to follow a consistent routine that suits their personal needs. This gap between awareness and actual practice is one of the major reasons why people fail to achieve their fitness goals.
One of the common ways people try to improve their fitness is by following workout plans and diet charts available on the internet or through mobile applications. While these resources provide a starting point, they are usually designed for a wide audience and do not consider individual differences. Factors such as body weight, height, lifestyle, and fitness goals play an important role in determining what kind of plan is suitable for a person. When these factors are ignored, users may not see noticeable progress, even if they follow the plan regularly. Over time, this leads to frustration and loss of motivation.

Another challenge is the lack of proper guidance during the fitness journey. Many users are unsure about how to adjust their routines based on progress or how to choose between different types of exercises and diets. Without clear direction, they may either overtrain, undertrain, or follow ineffective methods. This shows that simply providing information is not enough; users need structured guidance that adapts to their situation.

To address these issues, some modern systems use machine learning techniques to generate personalized recommendations. These systems analyze user data and attempt to provide suggestions that match individual needs. Although this approach can improve accuracy, it also introduces certain difficulties. Machine learning systems require a large amount of data to function effectively, and collecting such data is not always practical. Users may also be concerned about sharing personal health information, especially when it is stored or processed continuously.

In addition to data-related concerns, complex models often lack transparency. Users receive recommendations, but they are not always able to understand how those recommendations were generated. This makes it harder for users to trust the system and follow its advice confidently. Moreover, advanced systems may require higher computational resources, which limits their usability in lightweight applications.

Considering these challenges, there is a need for a solution that is both practical and easy to use, while still providing useful recommendations. The goal is not to create a perfect system that captures every detail, but to design one that offers clear and meaningful guidance without unnecessary complexity.

FitCluster AI is developed with this idea as its foundation. Instead of relying on large datasets or complex algorithms, the system uses a small set of important user inputs such as height, weight, activity level, and fitness goal. These inputs are then used to group users into categories based on their physical condition. Once grouped, the system applies a set of predefined rules to generate recommendations that are suitable for each category.

This approach is referred to as semi-personalization. Rather than creating a completely unique plan for every individual, the system provides recommendations at a group level. This reduces complexity while still ensuring that the suggestions are relevant. It also allows the system to operate quickly and efficiently without requiring heavy computation.
Another important aspect of FitCluster AI is its transparency. Since the recommendations are generated using clear rules, users can understand the reasoning behind them. This makes the system easier to trust and encourages users to follow the suggestions more consistently. In addition, the system does not rely on continuous data collection, which helps address privacy concerns.

The design of FitCluster AI focuses on balancing simplicity, usability, and effectiveness. It aims to provide guidance that is easy to follow while still being based on logical reasoning. By avoiding unnecessary complexity, the system becomes more accessible to a wider range of users.

In summary, FitCluster AI attempts to bridge the gap between generic fitness plans and highly complex personalized systems. It provides a middle ground where users receive meaningful recommendations without the need for large datasets or advanced models. The following sections describe how the system is implemented, how it generates recommendations, and how it performs under different conditions.

II. LITERATURE SURVEY

A. General Fitness Planning Methods

Before digital tools became common, most fitness advice came from trainers, books, or standard plans shared by health organizations. These plans were designed for large groups of people and followed general guidelines such as daily exercise routines and balanced diets. While this approach worked as a starting point, it did not take into account how different each individual can be in terms of body type, metabolism, and lifestyle.

Many beginners still rely on these kinds of plans because they are easy to access and simple to follow. However, problems start appearing when users try to achieve specific goals such as weight loss or muscle gain. Since the plans are not customized, users often do not see expected results, even after putting in effort. This creates confusion and reduces motivation over time.

Another issue is that users are expected to adjust these plans on their own based on their progress. This requires a certain level of knowledge about fitness and nutrition, which most people do not have. Without proper understanding, users may either overtrain, undertrain, or follow incorrect diet patterns.

In addition, these methods do not provide any feedback mechanism. There is no system to track progress or suggest improvements. Users are left to figure things out themselves, which makes the process less effective.

Overall, while traditional fitness planning methods are simple and widely used, they lack flexibility and fail to adapt to individual needs. This limitation highlights the need for systems that can offer more personalized guidance.

B. Systems Based on User Tracking

To improve on static plans, several systems introduced tracking features where users can record their daily

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activities. These systems allow users to log steps, calories consumed, workout duration, and other health-related metrics. Based on this data, users can monitor their progress and make adjustments.

This approach adds a level of interaction that was missing in traditional systems. Users can see patterns in their behavior and understand how their actions affect their fitness outcomes. It also encourages awareness, which is an important part of maintaining a healthy routine.

However, the effectiveness of these systems depends heavily on user consistency. Users are required to regularly input data, sometimes multiple times a day. Over time, this process becomes repetitive and tiring, especially for users who are not highly disciplined.

Another problem is data accuracy. If users forget to log activities or enter incorrect values, the system may generate misleading feedback. This can result in poor decisions and slow progress.

Moreover, tracking systems usually provide only basic in- sights rather than complete recommendations. They show what the user has done but do not always guide what the user should do next in a structured way. Because of these limitations, tracking-based systems im- prove awareness but still fall short in delivering fully guided and personalized fitness solutions.

C. Machine Learning-Based Approaches

With advancements in artificial intelligence, machine learning has been applied to fitness recommendation systems to improve personalization. These systems analyze user data to identify patterns and generate suggestions based on previous behavior and similar user profiles.

The main advantage of this approach is its ability to learn over time. As more data is collected, the system can refine its recommendations and become more accurate. This allows users to receive advice that is better suited to their needs compared to traditional or tracking-based systems.

However, machine learning approaches introduce several practical challenges. One major issue is the requirement for large amounts of data. Without sufficient data, the models may not perform well or may produce unreliable recommendations. Another concern is privacy. Users may not feel comfortable sharing detailed health and lifestyle data, especially when it is stored and processed continuously. This limits the availability of high-quality data needed for these systems.

In addition, machine learning systems often lack transparency. Users receive recommendations, but they are not always able to understand how those recommendations were generated. This reduces trust and makes it harder for users to follow the advice confidently.

Therefore, while machine learning improves personalization, it also introduces complexity, data dependency, and trust- related issues.

D. Deep Learning and Advanced Models

Deep learning represents a more advanced form of machine learning and has been used in some fitness applications to capture complex relationships between user inputs. These models can process multiple factors at once and produce highly detailed recommendations. In theory, deep learning systems can provide very accurate and personalized outputs. They are capable of handling non- linear patterns and can adapt to different types of user data. This makes them powerful tools in many domains.

However, their application in fitness systems comes with significant drawbacks. First, deep learning models require very large datasets to function effectively. Collecting such data in the fitness domain is difficult due to privacy concerns and inconsistent user participation.

Second, these models require high computational power, including GPUs and optimized environments. This makes them less suitable for lightweight applications or systems intended for general users.

Another major issue is interpretability. Deep learning models often act as black boxes, meaning that users cannot easily understand how decisions are made. In health-related applications, this lack of clarity can be a serious drawback.

Due to these challenges, deep learning-based systems are powerful but not always practical for simple and user-friendly fitness applications.

E. Need for a Simpler Alternative

From the discussion of existing methods, it is clear that there is a trade-off between simplicity and personalization. Traditional systems are easy to use but do not adapt, while advanced systems provide better recommendations but require more data and resources.

This creates a gap where users need a system that is both practical and somewhat personalized, without being overly complex. Such a system should work with minimal input, avoid heavy computation, and still provide useful guidance.

FitCluster AI is designed to address this gap. Instead of relying entirely on data-driven models, it uses a combination of simple grouping and rule-based logic. Users are categorized based on basic parameters, and recommendations are generated using clear and understandable rules.

This approach reduces dependency on large datasets and avoids the complexity of advanced models. At the same time, it provides better guidance than generic plans by considering important user characteristics.

By focusing on simplicity, clarity, and efficiency, FitCluster AI offers a balanced solution that fits real-world usage scenarios.

III. METHODOLOGY

The design of FitCluster AI focuses on keeping the system simple while still producing useful and relevant fitness recommendations. Instead of relying on large datasets or complex learning models, the system works by taking a small set of user inputs and processing them through a structured sequence of steps. The idea is to reduce unnecessary complexity and still provide guidance that makes practical sense for the user.

The overall flow of the system starts with collecting basic information, followed by processing that data, grouping users based on their physical condition, and finally generating recommendations using predefined rules. Each stage is designed to be lightweight so that the system can respond quickly and remain easy to maintain.

A. User Input Collection

The first step involves gathering a few important details from the user. These include age, height, weight, activity level, and fitness goal. These inputs are chosen because they directly influence how a person should approach fitness and diet planning.

One important design choice here is keeping the input minimal. Many systems ask for too much information, which can make users lose interest. In contrast, FitCluster AI only asks for what is necessary. This makes the system easier to use and increases the chances that users will actually interact with it.

Basic checks can also be applied to ensure that the values entered by the user are realistic. For example, extremely low or high values for height or weight can be filtered. This helps avoid incorrect calculations later in the process.

B. Data Preparation

Once the inputs are collected, they are prepared for further processing. This mainly involves converting all values into a consistent format. For example, height is handled in meters and weight in kilograms to ensure that calculations are accurate.

If any input is missing, the system can still proceed by using simple assumptions or default values. This allows the system to remain functional even when the user does not provide complete information.

This step may seem simple, but it plays an important role in ensuring that the rest of the system works smoothly without unexpected errors.

C. Deriving Key Indicators

After preparing the data, the system calculates key indica- tors that help in understanding the user's physical condition. The most important among these is the Body Mass Index (BMI), which is calculated using height and weight.

BMI provides a quick way to estimate whether a person is underweight, normal, overweight, or obese. While it is not a perfect measure, it is widely used and gives a reasonable starting point for making decisions.

In addition to BMI, the system also considers the user's activity level and fitness goal. These factors help refine the recommendations. For example, two users with the same BMI may still require different plans depending on whether they want to lose weight or build muscle.

D. User Grouping Approach

Instead of treating every user completely differently, the system groups users into categories based on their BMI and related factors. This approach simplifies the recommendation process while still keeping it relevant.

Users in the same category are assumed to have similar needs. For example, users who fall into the overweight cate- gory and have a weight loss goal will receive similar types of recommendations.

This grouping method avoids the need for complex clustering algorithms. It keeps the system fast and predictable, which is important for real-time applications.

E. Rule-Based Recommendation Logic

Once the user is grouped, the system applies a set of predefined rules to generate recommendations. These rules are based on basic fitness principles.

For example, if a user is overweight and wants to lose weight, the system suggests a combination of calorie control and cardio exercises. On the other hand, if a user is under- weight, the system focuses on increasing calorie intake and strength training.

The advantage of this approach is that it is easy to under- stand. Each recommendation is linked to a clear condition, so the user can see why a particular suggestion was made. This makes the system more transparent compared to complex AI models.

F. Generating Final Recommendations

In the final step, the system combines all the information and presents it in a clear format. The output includes workout suggestions, basic diet guidance, and general advice.

The recommendations are kept simple so that users can actually follow them. Instead of overwhelming the user with too much detail, the system focuses on practical suggestions that can be applied in daily life.
Users can also change their inputs later and receive updated recommendations. This makes the system flexible and adapt- able without needing continuous data tracking.

G. Why This Approach Works

The main strength of this methodology is its balance be- tween simplicity and usefulness. By avoiding heavy computation and large datasets, the system remains efficient and easy to use.

At the same time, it still provides more relevant guidance than generic fitness plans. The use of grouping and rule-based logic ensures that recommendations are not random, but based on clear reasoning.

This makes FitCluster AI a practical solution for users who want guidance without dealing with complicated systems.

IV. RESULTS AND DISCUSSION

To understand how well FitCluster AI performs, the system was tested using multiple sample user profiles that represent different real-world scenarios. Since the system is not dependent on large datasets, these test cases were created to cover a variety of combinations such as different body types, activity levels, and fitness goals. This allowed us to observe how the system behaves under different conditions without relying on external data sources.

The first observation from testing was that the system consistently produces outputs that match the input conditions. For example, users with higher BMI values and a goal of weight loss were always given recommendations focused on calorie reduction and cardio-based exercises. Similarly, users with lower BMI values received suggestions that included increased calorie intake and strength-based workouts.

This shows that the rule-based logic is working as intended and is aligned with basic fitness principles.

Another important point is the consistency of results. When similar inputs were provided multiple times, the system produced the same recommendations. This is expected since the system does not rely on randomness or probabilistic models. While this may seem simple, it is actually an advantage because it ensures predictable behavior. Users can trust that the system will respond in a stable and reliable way.

The response time of the system was also observed to be very fast. Since there is no heavy computation or model training involved, recommendations are generated almost instantly. This makes the system suitable for real-time applications such as web platforms or mobile apps, where users expect immediate feedback.

In terms of usability, the recommendations generated by the system are easy to understand and follow. Instead of providing overly complex plans, the system focuses on practical suggestions that users can apply in their daily routine. This increases the chances that users will actually follow the recommendations, which is an important factor in achieving fitness goals.

When compared with traditional fitness plans, FitCluster AI offers better adaptability. Traditional plans remain fixed regardless of the user, while this system adjusts recommendations based on input values. At the same time, when compared with machine learning-based systems, FitCluster AI avoids the need for large datasets and complex computations. However, the system is not without limitations. Since it is based on predefined rules, it may not handle highly unique or complex user cases. For example, users with medical conditions or very specific requirements may need more specialized recommendations. Also, users within the same category receive similar outputs, which may not fully capture small individual differences.

Despite these limitations, the system achieves its main goal of providing simple and useful recommendations. It strikes a balance between personalization and practicality, making it suitable for users who want guidance without dealing with complicated systems.

Overall, the results show that FitCluster AI performs reliably, efficiently, and in a way that aligns with real-world fitness needs. The system may not be perfect, but it provides a strong foundation for building lightweight and user-friendly fitness recommendation tools.

V. CONCLUSION

This project was built around a simple idea: fitness guidance should be easy to understand and practical to follow, without depending on complicated systems or large amounts of data. Instead of trying to create a highly complex model, FitCluster AI focuses on using a few meaningful inputs and turning them into useful suggestions through a clear and structured process. During development and testing, it became clear that even a basic grouping approach can produce sensible outcomes when it is combined with well-defined rules. By using BMI along with activity level and user goals, the system is able to separate users into categories and provide recommendations that match general fitness logic. This shows that full personalization is not always necessary to achieve helpful results.

One thing that stands out in this system is how easy it is to understand. Every output can be linked back to a specific condition, which makes the behavior of the system predictable. This is important because users are more likely to follow advice when they know why it is being given. In many modern systems, this clarity is missing.

The system also performs well in terms of speed and simplicity. Since there is no training process or heavy computation, the results are generated immediately after input is given. This makes it suitable for applications where quick interaction is expected. At the same time, the system avoids collecting large amounts of personal data, which helps reduce privacy concerns.

At the same time, the simplicity of the system brings certain limitations. The recommendations are based on pre- defined rules, so they may not fully adjust to uncommon or highly specific cases. Also, users within the same category receive similar outputs, even though their situations may differ slightly. These are

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acceptable trade-offs considering the goal of keeping the system lightweight and easy to use.

There is clear scope to build on this work. Adding a feedback system where recommendations change based on user progress would make the system more adaptive. Another possible improvement is connecting the system with wearable devices to get real-time activity data. This would help refine suggestions without making the system overly complex.

In the end, FitCluster AI shows that a straightforward approach can still be effective. By focusing on clarity, efficiency, and usability, the system provides a practical solution for users who need guidance without dealing with complicated tools. It serves as a solid base for future improvements in simple and accessible fitness recommendation systems.

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