PERSONALIZED GYM RECOMMENDATION SYSTEM USING MACHINE LEARNING

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DEDICATION

We dedicate the effort on our dissertation to our family members and friends. A special feeling of gratitude to our wonderful family and friends who constantly inspire us to accomplish our goals.

ABSTRACT

The Personal Gym Recommendation System (PGRS) is a digital platform aiming to provide tailored fitness and health advice to gym-goers, focusing on those new to the gym environment. By analyzing user-provided data such as age, height, weight, and medical conditions like hypertension and diabetes, PGRS crafts personalized fitness and dietary plans aligned with individual health profiles and goals. This study evaluates four models, revealing notable differences in their performance metrics. Particularly, the Decision Tree model for regressions achieves exceptional accuracy, scoring 100% on the training set and maintaining 99.91% on the testing set. Similarly, the Decision Tree model for classification demonstrates robust performance, though slightly lower, with a training accuracy of 99.29% and testing accuracy of 87.99%. These findings stress the significance of considering data nature and feature types when selecting appropriate models. Despite challenges in dataset collection, especially in acquiring Somali fitness data, overfitting remains a persistent issue despite preprocessing efforts.

Keywords: Gym, Recommendation, Machine Learning, Model, Accuracy, and Personalized.

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Abbreviations

PGRS = Personalized Gym Recommendation System.

RAM = Random Access Memory.

ML = Machine Learning.

KNN = K-Nearest Neighbor.

DFD = Data Flow Diagram.

FitRec = Fitness Recommendation.

BMI = Body Mass Index.

IDE = Integrated Development Environment.

HTML = HyperText Markup Language.

CSS = Cascading Style Sheets.

WSGI = Web Server Gateway Interface.

ROI = Return on Investment

IoT = Internet of Things

AI = Artificial Intelligence.

CHAPTER ONE: INTRODUCTION

1.1 Background

A gym is a facility where individuals go to engage in physical exercise to improve their fitness and overall health. It serves as a space for people to work out and achieve their fitness goals, offering a range of equipment and classes tailored to diverse needs. Members expect gyms to provide a comfortable environment with high-quality equipment and amenities, ensuring a positive and supportive atmosphere for their fitness journey. (Zhou et al., 2017).

Machine learning is a dynamic field of computational algorithms, that mimics human intelligence by adapting to its environment. Integral in the era of big data, machine learning finds successful applications across various domains. In fields like pattern recognition, computer vision, finance, and medical applications, it has proven effective. Notably, over half of cancer patients undergo radiotherapy, a crucial treatment. Machine learning can enhance radiotherapy processes, such as radiation physics quality assurance, treatment planning, and outcome prediction. Its ability to learn and adapt in real-time can significantly improve the safety and efficacy of radiotherapy, ultimately leading to better patient outcomes (El Naqa & Murphy, 2015).

Recommender systems are like personal assistants that use data about what you like and what you've done before to suggest things you might enjoy. They're used in social media, entertainment, and shopping websites to help you find what you want. These systems look at what people similar to you have liked or done before to make suggestions. They use different methods, like looking at your interests or what you've bought, to figure out what you might like. In gyms, they use similar techniques to suggest workouts based on what you've done before and what others like you have done. These systems aim to make you happier and keep you coming back by giving you recommendations that match your interests. (Sundaramurthy, 2020).

Machine learning for fitness means using computers to give health advice based on things like your weight and height. This is important because being healthy is becoming more and more important, especially with more people being overweight. The software uses a method called regression analysis to guess how much body fat you have and then gives you advice on what to eat and how to exercise. It also has different parts depending on how fit you are, like diet plans, exercise suggestions, and even talking to a doctor online. This all helps people stay healthy in a way that's just for them. (Jeyaranjani & Kapoor, 2021).

A recommendation system aims to predict customer interests and understand their perspectives. It provides users with information tailored to their needs, taking their preferences into account. For enhanced recommendation accuracy, it's crucial to conduct a more thorough analysis of the data. Exposure to extreme cold can compromise people's immune systems. Lack of physical activity can exacerbate the impact of flu, affecting immunity and respiratory health. Regular exercise boosts immune function. Individuals who are frequently exposed to colds are at higher risk of illnesses, as maintaining a normal body temperature requires more effort. This research developed a system to predict physical fitness using data on calorie burn, ethnicity, gender, preferences, and health issues. The system recommends exercises based on the user's likes, considering their comorbidities, geographical location, and patterns in physical activity and diet (Baruah et al., 2023).

The MARS-Gym framework combines recommender systems and reinforcement learning concepts for training and evaluating in dynamic marketplaces. It uses reinforcement learning to model how an agent interacts with its environment, allowing for off-policy learning and fairness considerations. Recommender systems have become crucial in online markets, improving user experience and business success by offering personalized recommendations. The framework aims to formalize recommendation systems and decision-making processes, utilizing reinforcement learning principles. Its components include data engineering, simulation, and evaluation modules to assess recommender system performance. By considering user behavior, item details, and market dynamics, the framework provides a platform to train and evaluate recommender systems, taking into account user satisfaction, visibility, and fairness. (Santana et al., 2020).

Current fitness advice systems often overlook specific factors like thyroid health, activity preferences, and calorie intake. This new approach aims to address these gaps by providing tailored exercise programs for thyroid patients. It uses theoretical knowledge about exercise's impact on thyroid function to customize workouts based on individual needs and health profiles. The system incorporates user-specific elements like calorie consumption and exercise preferences to design personalized regimens using hybrid model techniques. Factors such as gender, age, and exercise intensity are considered to create individualized recommendations. By adapting workouts based on user feedback and physiological data, the system ensures tailored fitness plans for thyroid patients, promoting better health outcomes. (Vairale & Shukla, 2020).

This research explores how combining IoT, blockchain, and machine learning can create secure fitness systems. Blockchain technology ensures data integrity and security, while IoT devices collect fitness data like activity levels and biometrics. The decentralized nature of blockchain supports safe data storage and management. Machine learning analyzes this data to provide personalized diet and workout plans. By integrating these technologies, the study aims to improve data privacy, accessibility, and insights into fitness services. This approach addresses challenges like trust and transparency in IoT networks while enhancing data responsibility and privacy. (Jamil et al., 2021).

The development of the fitness recommendations framework is built on the evolution of personalized fitness plans and the increasing role of technology in promoting physical health. It explores traditional methods of matching user preferences with workout programs and the limitations of user adjustments. The focus is on Reinforcement Learning (RL), a branch of machine learning that emphasizes decision-making through interactions with the environment. RL optimizes rewards over multiple recommendations, emphasizing long-term strategies over short-sighted approaches. Key variables include user preferences, fitness goals, session progress, and feedback, shaping both the recommendation process and user engagement. Ethical considerations and trial procedures underscore the importance of safety and ethical standards in the research. (Tragos et al., 2023).

This study highlights the shift towards holistic exercise approaches, acknowledging the health benefits of practices like yoga and meditation. These ancient Indian techniques have been scientifically proven to reduce stress, improve sleep, and strengthen the immune system, benefiting both physical and mental health. Regular exercise is known to enhance immunity and reduce the risk of chronic diseases like cancer and diabetes, as emphasized by the World Health Organization. Terms like "exercise prescription," "yoga," "meditation," and "immune system enhancement" are defined in the study. An exercise prescription is a personalized list of activities tailored to health goals, while yoga and meditation promote both physical and mental well-being by reducing stress and boosting immunity. (Balpande et al., 2023).

In recent years, the importance of maintaining a healthy lifestyle has become increasingly evident. Regular exercise offers numerous health benefits, such as reducing the risk of chronic illnesses like obesity, diabetes, and heart disease. However, with so many fitness options available, it can be challenging for individuals to find the right program. To address this challenge, scientists have proposed personalized fitness recommendation systems that use machine learning to analyze individual data and provide tailored advice. These systems consider various factors like age, gender, fitness level, and health goals to offer customized recommendations that are more likely to be effective. Research on personalized fitness recommendation systems dates back to the early 2000s, focusing on using machine learning algorithms to generate suggestions based on individual data analysis. By incorporating sequential information about past performance and fitness activities, machine learning algorithms can produce more precise and tailored recommendations, helping individuals achieve their fitness objectives more effectively. Additionally, these systems often consider factors like health goals, BMI, age, and gender to further enhance recommendation accuracy and assist users in reaching their fitness goals. (Abdulaziz et al., 2021).

1.2 Problem Statement

In the ideal situation, individuals who want to build or improve their health and fitness would be better off getting recommendations and the right type of exercise that is effective to get motivated and achieve their goals in fitness (GYM).

The current generation is increasingly concerned about health and fitness, leading to a surge in the usage of personalized fitness (GYM) recommendations. Many individuals struggle to achieve their fitness goals due to the limitations of existing personalized fitness recommendations. Current devices often lack comprehensive features tailored to individual needs, hindering users from receiving accurate and actionable insights. Additionally, gym-goers may lack real-time feedback and guidance during their workouts, hindering their ability to adapt and progress efficiently. The main problem is that everyone wants the teacher to track them or give them recommendations, which is a problem for gym teachers.

The consequence of this limitation is that users do not receive accurate or actionable insights that are specific to their personal health and fitness goals. This hinders their progress and may lead to dissatisfaction, decreased motivation, and potentially even health risks if the recommendations do not align with their individual needs. The lack of recommendation personalization in fitness technology could result in a reduced impact on the overall health and fitness levels of the population, which in turn could have broader implications for public health and wellness. If there is no proper recommendation, the person doing the fitness may be seriously injured or die from the problem.

To solve all these problems, our research promises to develop a machine-learning model that provides tailored recommendations specifically crafted for individuals new to the gym environment. It also promises to meet the needs of personalized gym recommendations.

1.3 Research Objectives

1.3.1 General Objectives

The main goal of our study is to create a system that assists people who go to the gym by providing them with a recommendation system.

1.3.2 Specific Objectives

I. To develop a gym recommendation system that takes into account the specific fitness preferences of both beginners and intermediates.

II. To recommend tailored fitness programs, including specific exercises and equipment required, based on the unique health profiles and fitness goals of individuals.

III. To design a beautiful user interface in which users can enter their information such as personal profiles or preferences.

1.4 Research Questions

I. How to develop a gym recommendation system that takes into account the specific fitness preferences of both beginners and intermediates?

II. How to recommend tailored fitness programs, including specific exercises and equipment required, based on the unique health profiles and fitness goals of individuals?

III. How to design a beautiful user interface in which users can enter their information such as personal profiles or preferences.?

1.5 Motivation of the Study

The motivation behind this research is that we saw that many young people are in long queues in fitness centers or are ready to improve their fitness, and the problems they have are that they do not have recommendations related to their fitness, and the frustration they face when they do not have the right process to succeed. that caused them to stop going to the gym.

To solve this problem, we decided to develop a gym recommendation system using machine learning algorithms that will ultimately simplify the process of fitness.

1.6 Significance of the Study

The main importance of this study is to help you control your weight, prevent diseases and illness, improve your mood, and boost energy. to get a recommendation and full details about how the individual should maintain his body, it is also important to have an individual or individuals who succeed in the fitness process.

1.7 Scope & Limitations

In our research focuses on everyone who wants to start going to the gym, regardless of whether they're newbies or already have some experience. The recommendations particularly target those who are new to the gym environment.

1.8 Organization of the Study

Chapter Two: In this chapter, a thorough review of existing literature on book recommendation systems is conducted. The focus is on understanding the various methodologies and algorithms employed in the field and assessing the strengths and limitations of current systems.

Chapter Three: The methodology chapter outlines the research approach, detailing the methods employed to collect and preprocess data. It provides insights into the selection of machine learning algorithms considered for personalized book recommendations. By explaining the processes involved in obtaining and preparing the dataset, this chapter ensures transparency in the research methodology.

Chapter Four: This chapter delves into the analysis of chosen machine-learning algorithms for book recommendations. Simultaneously, it outlines the design of the recommendation system, elucidating the architectural components and illustrating how user preferences are incorporated into the system.

Chapter Five: In this we will discuss the testing phase, elucidating how the system's functionality and performance were rigorously evaluated, and providing insights into its real-world applicability.

Chapter Six: In This, we will discuss the chapter and critically analyze the results obtained from the implementation and testing phases. It assesses the system's performance in terms of accuracy, precision, recall, and user satisfaction, comparing these results with existing benchmarks.

Chapter Seven: The concluding chapter summarizes the key findings and contributions of the study. It discusses the practical implications of the developed book recommendation system and suggests potential areas for future research and enhancements in the field of personalized book recommendations.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

The term "gym" refers to a physical fitness center where people participate in a variety of physical activities, the term "gym" refers to a place where people go to work out, get in shape, and accomplish their fitness objectives. This research focuses on examining how gender affects exercise practices and experiences in gym environments, emphasizing the role of the gym as a location where gendered norms and behaviors are manifested and possibly reinforced. The gym is viewed as a place where people embody gender ideals, navigate gender performances, and negotiate spatial relations that contribute to the gendering of physical activity. (Coen et al., 2018).

The word "gym" refers to a fitness center where people can work out and perform training exercises to enhance their general health and physical fitness. A wide range of tools and resources are usually available in gyms for cardiovascular, strength, and flexibility training. The goal of the project was to improve users' experiences at the gym by applying machine learning and artificial intelligence (AI) technology. The app under discussion in this study intends to give gym patrons access to virtual coaches, individualized training regimens, and instruments for tracking supplement consumption and exercise efficiency. The intention is to optimize exercises, increase efficiency, and improve users' entire fitness experience by bringing AI and machine learning into the gym setting. (Hasni et al., 2022).

In fitness industry has experienced a notable transition towards customization due to the acknowledgment of each person's distinct physiological and psychological attributes. The use of genetic insight gained from DNA testing, personalized fitness technologies, and the revolutionary role AI is playing in personalized fitness programming are all examples of this trend. Fitness personalization refers to customized exercise regimens, dietary planning, and lifestyle adjustments based on body composition, metabolic rate, preferred type of activity, and pre-existing medical issues. This strategy seeks to improve health and wellness objectives and maximize fitness results. (Metz, 2006).

The changes that modern gym and fitness culture has undergone historically, examining how it came to be seen as a billion-dollar worldwide phenomenon in today's world. The research attempts to get a thorough grasp of the development of this business by analyzing a wide range of studies on gym and fitness culture. It examines various approaches to fitness and muscle-building procedures within a global, historical, and sociocultural framework and emphasizes three pivotal globalization eras that have created modern fitness culture. The study highlights the transition from a national muscular culture dominated by men to a globalized, commercialized business that spreads different ideas about fitness, food, exercise, and lifestyle. Furthermore, this research shows how bodybuilding ideals have changed over time by relating early advances in physical culture to contemporary trends. Through this analysis, the report sheds light on the societal, cultural, and economic elements affecting the growth of gym and fitness culture, offering insights into the evolving landscape of this industry. (Andreasson & Johansson, 2014).

2.2 Machine Learning in Fitness

Machine learning (ML) is a field focused on training machines to achieve advanced cognitive abilities, enabling them to analyze information in a manner akin to human thought processes. Given its reliance on data-driven approaches, ML seamlessly integrates into various aspects of our daily lives, as well as complex and interdisciplinary domains. The proliferation of commercial, open-source, and user-centric ML tools has sparked an essential question when applying ML to investigate phenomena or scenarios: What defines a good ML model? In approaching this query, it is acknowledged that the definition of a good ML model depends on several factors. (Naser & Alavi, 2020).

The study aimed to explore algorithms for suggesting fitness tracker goals that enhance user commitment. Three consecutive studies were conducted, involving qualitative analysis and quantitative measures to assess transparency, trust, and goal commitment. Participants were presented with step data and goal suggestions based on a specific algorithm. Findings indicated that transparency in goal suggestions positively influenced goal commitment. Limitations included participant recruitment and cultural factors. The study highlighted the importance of transparent goal-setting algorithms in fitness trackers and suggested avenues for future research in this area.(Woźniak et al., 2020).

With many manufacturers producing a variety of wearables that communicate via Bluetooth with smartphones, the usage of these gadgets for tracking one's health and fitness has become increasingly popular. The research on wearable fitness gadgets' security and privacy flaws is presented in this paper. Supervised machine learning approaches are utilized to track individuals and forecast their fitness activities by collecting and evaluating data supplied by wearable devices during synchronization. The findings highlight privacy concerns by demonstrating how feasible it is to follow people and their actions. Based on the preliminary research findings, suggestions are made to improve wearable device security.(Reichherzer et al., 2017).

The combination of supervised machine learning algorithms and wearable sensor technology offers a viable method for correctly categorizing functional fitness routines during an ongoing activity. To classify different activities that are performed during a workout session, this study looks into the use of machine learning techniques to analyze data collected from wearable sensors. The study shows how supervised machine learning works well for real-time exercise identification, highlighting how it might improve fitness tracking and customized training regimens. The results show that wearable sensor data and machine learning can be used to accurately classify exercises, opening the door for more sophisticated fitness tracking systems. (Preatoni et al., 2020).

With several advantages like reducing chronic diseases and enhancing mental health, physical activity is essential for preserving general health and wellbeing. By using machine learning techniques, notably Linear Discriminant Analysis, to analyze data from wearable Inertial Measurement Units (IMUs), the study offers a fresh option for overseeing exercise workouts. The goal of the research is to lower the computational burden to facilitate embedded implementation compatibility. Experiments were out to assess the suggested method showed an exercise counting inaccuracy of less than 6% and an exercise detection accuracy of above 93%. The goal of the research is to improve exercise quality monitoring and encourage efficient physical activity, which will benefit users' health outcomes. (Depari et al., 2019).

An essential component of general health and well-being is cardiovascular fitness, which measures how well the circulatory system functions to supply oxygen to the body's tissues during physical exertion. The objective of this work is to use machine learning approaches based on non-intrusive data obtained from wearable sensors to characterize cardiovascular fitness. Volunteers with various aerobic power levels, as well as those with specific medical illnesses and risk factors for non-communicable diseases, participated in a long-term study. Wearable technology was used in the study protocol to capture physiological data, such as activity levels and vital signs. Machine learning models were created to estimate cardiovascular fitness levels using the data that was gathered.(Frade et al., 2023).

It can be difficult but crucial to predict users' commitment to physical exercise in fitness apps to increase engagement and encourage healthy habits. To predict training adherence behavior among users of a fitness app over a given period, this study investigates the application of deep learning techniques. Artificial intelligence systems use data from past training sessions to make precise predictions about user behavior. Ethical requirements were followed in the research process, and 777 participants' data were gathered via a smartphone application that provides customized exercise regimens. The effectiveness of the deep learning approach in predicting exercise adherence is demonstrated by the experimental setup's results, underscoring its potential to improve user engagement and long-term adherence in fitness apps.(Jossa-Bastidas et al., 2021).

In particular, for those pursuing physical education, physical fitness is an essential component of total health and well-being. In this work, unsupervised machine learning approaches are used to profile physical fitness among physical education majors. Physical education majors were divided into several fitness profiles by researchers based on data analysis on a variety of physical fitness indicators, such as muscular strength, flexibility, cardiovascular endurance, and body composition. Diverse clusters indicating distinct degrees of physical fitness among the subjects were identified by the results. To improve the general health and well-being of physical education majors, this approach offers insightful information on the various aspects of their physical fitness and identifies areas that require work.(Bonilla et al., 2022).

The purpose of this work is to improve our knowledge of the metabolic reactions to physical activity by investigating a machine-learning method for predicting the usage of muscle glycogen during exercise. To create predictive models for muscle glycogen utilization, the research makes use of data on exercise duration, intensity, and individual metabolic profiles. The work underscores the significance of customized modeling techniques for precise forecasts by dividing temporal domains and taking into account the distinct patterns of glycogen consumption among various muscle fiber types. Nuanced modeling methodologies are necessary, as the results indicate that muscle glycogen utilization is more variable at exercise periods longer than sixty minutes. Based on each person's unique metabolic reaction to exercise, the prediction models created in this study provide insightful information about how to maximize performance and direct dietary changes.(Jagnesakova et al., 2022).

The function of machine learning in cardiovascular medicine is well covered in this review paper. In addition to stressing the need to utilize machine learning for data analysis, risk prediction, and individualized patient care, the paper delves into the principles of AI algorithms and their possible uses in related fields. To create machine learning models that are successful for cardiovascular medicine, the review highlights the significance of meticulous model design, data integration methodologies, and validation approaches. The obstacles and restrictions of applying machine learning in this particular industry are also covered in the essay. These include the requirement for organized processes, high-quality data, and model validation. In general, the goal of this review is to advance the field's understanding of how best to apply machine learning algorithms to cardiovascular medicine to improve patient outcomes.(Shameer et al., 2018).

Monitoring people's physical states in real-life situations—such as sports, the workplace, healthcare, senior care, and everyday activities requires evaluating energy usage. Based on heart rate activity data recorded right after training sessions, this study investigates the application of many machine learning algorithms, such as support vector machines, decision trees, and linear regression, to predict physical stress levels in athletes. This research intends to improve the understanding of post-exercise energy expenditures and enable athletes to get individualized training methods by categorizing the known levels of in-exercise loads into groups based on calories. (Gang et al., 2019).

The application of machine learning algorithms to evaluate human motion during exercise was the main focus of the systematic literature review. 88 pertinent publications demonstrating advances in shallow and deep learning methodologies were found by applying the PRISMA methodology. The significance of customized tests with comprehensible results that can adjust to various motion capture systems was underlined by the study. Problems like the scarcity of publicly available data, the diversity of exercise motions, and the lack of sizable accessible datasets were emphasized. With an emphasis on real-time computation and adaptability, the results showed an increasing interest in applying machine learning for human motion evaluation. The research emphasized how machine learning can transform human motion monitoring and evaluation during exercise in a variety of fields, including sports, wellness, health, and rehabilitation.(Frangoudes et al., 2022).

Cardiopulmonary exercise testing, or CPET, is a useful diagnostic and assessment tool for a variety of cardiovascular disorders and an individual's ability to exercise. It includes monitoring an individual's heart rate, oxygen intake, and breathing in response to physical activity. Based on data from cardiopulmonary exercise testing (CPET), the study offers a novel approach for grading the severity of activity limitation. By analyzing CPET data and classifying patients into varying severity levels of cardiovascular and ventilatory constraints, the study makes use of machine learning approaches. The researchers hope to offer a more precise and individualized evaluation of exercise capability in people with cardiopulmonary disorders by creating and validating this classification model.(Inbar et al., 2023).

2.3 Gym Recommendation Systems

The world we live in now places a greater emphasis on technological growth. Technologies and automation systems like intelligent games, automobiles, environmental solutions, healthcare, etc. have all been made possible by the development of machine learning. The creation of machine learning algorithms for a successful and efficient healthcare system is the main goal of the study. A method for proposing exercise and diet regimens is developed using algorithms that are narrowly focused. Our technique involves the K-Means Clustering algorithm, which is one such algorithm. Using this method, the trained dataset is given the diet and workout schedule. Thus, the system has been built in a specialized manner thanks to our methodology. To further improve comprehension, the system's accuracy and precision are contrasted with those of other machine learning methods. (Hemaraju et al., 2023).

Our proposed system analyses and monitors health parameters and the values from the patients' newest disease-related data to improve the health of patients with various ailments by suggesting healthier diets and exercise regimens. We took into account people with diabetes, hypertension, or thyroid conditions. Doctors can utilize our system to make dietary and exercise recommendations based on their most recent findings and individual health information. Our system can be broadly divided into two modules: 1. Health surveillance; 2. Dietary and exercise advice. The system would recommend follow-up appointments in the Health Monitoring module until the reports return to normal. A decision tree is the algorithm used for categorization in the Diet and Exercise Recommendation module. More specifically, dietary and activity recommendations are made using C4.5. Using our customized datasets, a C4.5 Decision tree will assist in making recommendations and deciding whether or not to supply a specific food item and exercise to a given individual. (Mogaveera et al., 2021).

In today's advanced society, where technology plays a key role and has the potential to dictate the bulk of our daily activities, many people suffer from a wide range of different types of maladies and illnesses. It is well-accepted that keeping up a good diet and exercise program is essential to keeping the body strong and in shape, but because there are so many factors to consider, it can be difficult to prescribe a diet and exercise program quickly. Nowadays, most people are very conscious of their fitness and health, and they constantly fluctuate between wanting to gain weight, lose weight, or maintain their current level of health. Thus, depending on user inputs such as height, weight, and age used to calculate their BMI, we propose a diet and exercise recommendation system that provides a list of meals and exercise ideas. Numerous nutrients and calories are considered, in addition to other relevant data such as proteins, lipids, calcium, iron, potassium, salt, sugar, vitamin D, carbs, and fiber. There are many food items considered, including prominent vegetarian and non-vegetarian cuisines. When cooking, nutrients, lipids, and carbs are the three primary components that are taken into account. We calculate how many calories they ingest and how many they must burn to maintain their fitness with these food items, allowing us to make recommendations for future workouts.(Sadhasivam et al., 2023).

To facilitate the fitness assistance system (F AS) using artificial intelligence, this research suggests a recommender system (RS). To create these recommendations for both new and experienced users, the RS is utilized. The article's objective is to create an RS that can learn, assess, forecast, and provide these recommendations in addition to utilizing AI to converse with people. To forecast the ideal workout for every beginning, Artificial Neural Networks and Logistic Regression have been utilized. Members can also choose their workout depending on their condition thanks to the agent built with the Soar architecture's reinforcement learning capacity. Validation of the utility application's effectiveness is achieved by the experimental outcome. (Tran et al., 2018).

It's important to maintain a healthy lifestyle, which includes getting enough sleep, eating a balanced diet, and exercising frequently. The saying "Age is just a number" reminds us that being older shouldn't stop someone from leading a healthy life. An increasing number of people, particularly young people, are interested in fitness because of government and industry programs. With wearable technology and smartphone apps that track heart rate, sleep patterns, and activity levels, tracking fitness and health progress has never been simpler thanks to technology. Users have more options because of the growing popularity of fitness applications, including diet planning and workout tracking. Picking a dependable and trustworthy app is crucial, though. With its ability to forecast a user's diet and exercise regimen based on their food intake, the app places a high priority on accuracy and dependability. Based on the particular requirements and interests of each user, the app will utilize machine learning algorithms to offer personalized recommendations. Two other key functions of the app are tracking progress and keeping track of workouts. Individualized advice and insights to help users reach their fitness objectives can be obtained by tracking their workouts and tracking their progress over time. The app hopes to be a vital component of this journey, enabling users to make educated decisions about their fitness and health thanks to technology. The objective is to develop a dependable, user-friendly app that can offer tailored advice to assist users in reaching their fitness objectives. (Yadav et al., 2023).

The k-Nearest Neighbors (k-NN) algorithm, a back-propagation neural network (BPNN), the body mass index (BMI), basal metabolic rate (BMR), and a novel food recommendation system are utilized in this study to recommend a suitable daily calorie food for an overweight person to help them achieve a healthy body status. A person's BMI is used by the system to determine if they are considered overweight. A person's Daily Needed Food Calories (DNC) are determined by the system using their BMR value. The saturated value of the DNC is the test object for the k-NN algorithm, which uses it to identify a correct calorie daily food set from the food dataset. The method uses overweight and saturated DNC levels to anticipate how many days it will take a person to achieve a healthy BMI status while following the recommended diet. Lastly, the BPNN is used by the system to assess the degree of user satisfaction. The food suggestion system that has been provided may be a useful tool for raising public awareness of healthy weight. (Gopalakrishnan, 2021).

2.4 Personalization in Fitness

The goal of the research project PERFECT (Personalized Exercise Recommendation Framework and architECTure) is to create a personalized exercise recommendation system with wearable trackers and mobile health (mHealth) technology. By utilizing wearable trackers and mHealth technology, the PERFECT study presents a fresh method for personalized workout suggestions. A contextual multi-arm bandit framework is used to build smartphone and wearable applications that track, gather, and suggest exercise by gathering and evaluating users' physiological data and information about their daily activities. Twenty female college students tested the mHealth workout program as part of the study. The results showed that the amount of time spent exercising each day had significantly increased, and the walking and recommendation system components had received high satisfaction ratings.(Asgari Mehrabadi et al., 2023).

The study offers a fresh method for creating personalized workout recommendations by modeling heart rate and activity data. FitRec is an LSTM-based model that integrates context from a user's past activities and activities themselves, developed by the authors. FitRec's ability to capture personalized changes in users' heart rate profiles during exercise is evaluated on a dataset that includes workout logs and parallel sensor information. The suggested model performs better than baseline models in a range of tasks including customized recommendations. The study also provides a sizable exercise dataset that may be used in sequence modeling, heart rate data analysis, and personalization studies. This work presents comprehensive experiments on a real-world dataset and pioneers the use of sequential modeling methods for personalized fitness recommendation. (Ni et al., 2019).

This research provides a clinical review on the prescription of personalized exercise doses, with an emphasis on determining the ideal exercise intensity for each individual and quantifying the lowest and maximum levels of exercise that yield health benefits. Promoting physical activity is a crucial tactic for illness prevention, as it is acknowledged that physical inactivity poses a substantial risk for cardiovascular disease. To attain the benefits of longevity, current standards suggest engaging in a specific quantity of strenuous or moderate-intensity aerobic activity per week. Nonetheless, a sizable section of the general public continues to lead inactive lives despite the availability of information. Exercise guidelines that are more straightforward and tailored to the individual may increase motivation and physical activity participation. This review tries to provide hypothetical personalized exercise recommendations based on people's respective fitness levels by assessing the amount of activity and its effects on longevity. The results imply that even at lower than currently advised levels of physical activity, there can be notable health advantages and that high-intensity exercise may provide more cardiovascular protection than moderate-intensity exercise.(Zubin Maslov et al., 2018).

Adult health may suffer as a result of the rising use of home-based teleworking, which encourages sedentary behavior. The current exercise guidelines, which are based on broad principles, might not be appropriate or useful for fostering well-being in teleworking situations. In this work, a new viewpoint known as the Network Physiology of Exercise is presented, which redefines health as an emergent adaptive state that arises from intricate interactions at several levels. Within this framework, the development of fitness is centered on optimizing each person's functional diversity potential via customized and diverse training regimens. In addition to highlighting the use of technology in fitness evaluation and exercise prescription, the report dispels popular misconceptions about the best posture and exercises. It highlights the necessity of establishing customized work settings and giving people the freedom to actively engage in the exercise process. There are new suggestions put out regarding teleworking posture, home exercise counseling, exercise monitoring, and the functions of fitness and medical specialists. Rather than just providing exercise prescriptions, health practitioners take on the role of co-designers, helping users learn, adapt, and contextualize exercise to support somatic awareness, overall health, job satisfaction, productivity, work-life balance, and well-being. (Almarcha et al., 2021).

By recommending exercises that are in line with the teaching objectives, the goal is to enhance learning outcomes and lessen the workload for students. Through the use of cognitive diagnostic, the technique evaluates students' comprehension of knowledge points and, depending on their responses, establishes the degree of investigation for each topic. The required mastery level is shown on the labels of the exercises. By recommending exercises that closely align with the learning objectives, the technique lessens the workload for students and improves the quality of their workouts. The suggested exercise difficulty can be controlled by using a feed-forward neural network to anticipate the predicted results of the students. The method's contributions include letting students choose exercises according to their preferred level of difficulty and suggesting exercises that are in line with the syllabus. When compared to other recommendation approaches, experimental tests show a much greater prediction success rate. Overall, the method of personalized exercise prescription increases students' exercise performance while offering an efficient means of personalized learning that is in line with instructional goals. (Li Sr & Xu, 2022).

The study offers a customized food and activity recommendation system for people with Type 1 Diabetes (T1D) to help them manage their condition on their own. Enhancing glycemic management and lowering the chance of hypoglycemic episodes were the goals. To forecast blood glucose levels and identify the best courses of action, the system made use of a patient-specific model of glucose dynamics. A modified UVa/Padova simulator was used to run the simulations. Two self-management schemes—the Starter scheme and the Skilled scheme—were used to compare the recommender system's performance. The study's primary contribution was the creation and evaluation of the customized recommender system. It reduced the mean Low Blood Glucose Index by 84% and the Blood Glucose Risk Index by 49%, outperforming the Starter program. When compared to the Starter and Skilled plans, there were also fewer hypoglycemic episodes during and after exercise. Comparable to the Skilled scheme, which offered an offline optimal solution, was the recommender system's performance. (Xie & Wang, 2019).

The study suggests an automated method to improve e-learning system personalization. The aim is to suggest exercises according to the individual learning goals and requirements of the learner. The study tackles the shortcomings of current systems that offer identical materials to every learner without taking into account their unique attributes. Using a course knowledge tree, the process entails creating formal models to represent exercises, knowledge points, and their relationships. A computational approach is suggested to automatically update learning objectives as the learner progresses. Based on the learner's learning condition, which includes response preferences and knowledge point grasp, the learner's learning needs are appropriately stated. The learning purpose is one of three influencing elements taken into account when recommending an exercise. Also, the research has produced formal models, a computer technique for updating learning objectives, and a mechanism for precisely describing the demands of the learner. The paper uses a running example to show the viability and correctness of the suggested approach. The approach can accurately offer activities that match the learner's needs by taking into account the learner's grasp state, answer preferences, and the learning purpose. (Diao et al., 2018).

2.5 Challenges and Opportunities

The fitness culture offers health benefits as well as obstacles. The changing definition of fitness, which is impacted by social, political, and economic variables and results in differing interpretations, is one of the main problems. Fitness has become increasingly commercialized on a worldwide scale, which has an effect on the privatization and individualization of leisure activities and may make it more difficult to find group solutions to public health problems like obesity and inactivity. Because the commercial fitness industry frequently links exercise to consumer goods, it may make it more difficult for certain populations to benefit from its health benefits. Additionally, issues of inactivity, particularly among marginalized people, may worsen as a result of the aggregate drop in the provision of fitness facilities. Still, there are chances for development among these difficulties. Positive change can occur through recognizing the collective character of health issues and advocating for collective solutions, tackling physical education in childhood, reimagining physical activity routines, and changing cultural perspectives on health and accountability. Future health can be achieved by highlighting the value of promoting physical activity from an early age, reassessing urban land use to create surroundings that are conducive to physical exercise, and moving towards a more community-based approach to health and well-being. (Smith Maguire, 2006).

In the field of personalized health and wellness assessment, fitness data analytics offers both opportunities and obstacles. The lack of longitudinal fitness data, which makes it difficult to offer thorough insights to people individually or in communities, is one of the major obstacles. There are also several technical obstacles, like data privacy concerns and the requirement for consistent data. The advantages might be enormous, though. Workout summaries can provide valuable insights that can assist refine training regimens and identify reasons why goals are not being met. Governments can create well-informed health policies by analyzing health data from fitness applications. Analysis of longitudinal fitness data can support life course epidemiology and help forecast early health concerns. For app providers, it's also critical to develop user-friendly systems for tracking meal information and to guarantee privacy and confidentiality. Ultimately, tackling these issues is both a duty and a chance to fully utilize fitness data analytics to enhance individual health outcomes and promote healthier communities. (Bhargava & Nabi, 2020).

Encouraging physical activity at work has advantages and disadvantages. There is little scientific proof that workplace physical exercise programs are beneficial, even though they may enhance workers' productivity, well-being, and health. Prior research on intervention studies has mostly involved motivated or engaged participants, and corporate-fitness or general health education programmers have demonstrated insufficient rates of involvement and long-lasting behavioral change. Programmers that are tailored to each individual's needs and are individually based have shown greater success. To have an impact on the workforce as a whole, it is essential to incorporate modern theories of behavior modification and organizational change, highlight the connections between the workplace and outside environments, and address workplace culture. Evaluation of desired employer-related results, including less absenteeism increased productivity, and management support for behavioral changes. (Marshall, 2004).

There are obstacles and chances for body area sensor networks (BASNs) to be widely used. Size, cost, compatibility, and perceived worth are among the difficulties that need to be overcome. Comparatively speaking to standard wireless sensor networks, BASN nodes need to be noninvasive and have smaller batteries and nodes. User comfort is greatly influenced by placement and packaging. Other difficulties are related to the economy and the requirement for cooperation between technologists and subject matter specialists. Conversely, fresh applications in healthcare, fitness, entertainment, and other fields can be made possible via BASNs. Their potential to enhance people's lives and change the way they engage with technology is remarkable. In addition to enabling telehealth applications and facilitating personalized care, BASNs can offer continuous quantitative data. They can also integrate with the current IT infrastructure, improve safety in situations where life is in danger, and maintain and enhance bodily functioning. To fully utilize BASNs, stakeholder collaboration and the creation of standardized protocols and interfaces are necessary. (Hanson et al., 2009).

There were opportunities and problems associated with the creation and operation of the senior exercise park. One of the challenges was finding a suitable site for the park and making sure environmental safety issues were met. There were difficulties with logistics as well, like planning and setting up classes. It was required to alter the workout apparatus to address the unique functional deficiencies of the elderly. Due to restricted access to public transport, participant recruitment was difficult. But there were also a lot of great opportunities at the senior exercise park. With an emphasis on balance, mobility, and function, it provided an exceptional outdoor training setting designed with senior citizens' requirements in mind. By offering an enjoyable and engaging form of exercise, the park boosted the well-being of the community. The participants reported high rates of adherence and satisfaction with outdoor exercise. It may encourage elderly adults to lead more active and healthier lives if outdoor exercise equipment is available in public areas. By providing facilities, safety measures, and access for people of all ages, local and municipal authorities can improve surroundings that attract older people. In addition to promoting an inclusive and active community, senior exercise parks help older people's physical and mental well-being. (Levinger et al., 2018).

2.6 Related Works

Shah et al. (2022), developed a diet recommendation system based on different machine learners to create a system for recommending diets based on individual health goals by utilizing a variety of machine learning classifiers. The research assessed the precision, recall, accuracy, and F1-score of the suggested diet plans for weight increase, weight loss, and healthy living by contrasting the performance of classifiers such as KNN, SVM, Decision Tree, Random Forest, Navier Bayer's, and Extra tree. To construct a dataset for analysis, patient data from various sources was gathered and encoded. The study's contribution is to the field of personalized nutrition recommendations by providing insights into the efficacy of various classifiers in generating customized diet programmers. The KNN classifier demonstrated its effectiveness in recommending diet plans as seen by the results, which showed noteworthy precision, recall, accuracy, and F1-score percentages. The study also demonstrated how well the LSTM strategy performed in forecasting and diet recommendations when compared to conventional machine learning techniques.

Iwendi et al. (2020), developed a realizing and efficient IoMT-assisted patient diet recommendation system through a machine-learning model. This research focuses on applying deep learning and machine learning models to create a patient diet advice system effectively. The system analyses health-based medical databases with patient and product specifics to automatically identify appropriate meal recommendations based on age, gender, disease, and nutritional content. The recommendation process is improved by several algorithms, including logistic regression, naïve Bayes, RNN, LSTM, GRU, and MLP. The study highlights the necessity of customized dietary advice based on the requirements and medical conditions of each patient. Data reading, preprocessing, feature visualization, training, testing, and assessment are the six stages of the suggested model. Through an examination of deep learning and machine learning methods, the study emphasizes how crucial it is to take various patient conditions into account when making food recommendations. The system's ultimate objective is to become even more automated and integrated with other eHealth features so that remote patients can utilize it extensively.

KHALID et al. (2021), developed a design and implementation of a clothing fashion style recommendation system using deep learning the goal of the research was to employ deep learning technology to build and execute a system that recommends clothing styles. By examining pictures of clothes, the algorithm attempted to identify patterns, styles, and materials to generate customized suggestions. By taking user preferences and feedback into account, the model may improve its recommendations and accommodate different interests. The contribution of the method is that it provides a new way for an individual to improve their manner of dressing by enabling them to eliminate unwanted aspects from their outfit photos. To enhance performance and resilience while supporting a variety of client types, the model integrated deep learning methods with conventional recommendation systems. Even when the system was evaluated using web photos that weren't part of the dataset, the results demonstrated that it was highly accurate at capturing clothing designs and patterns. Overall, the study showed how well the system worked to provide accurate and customized clothing recommendations based on user input photographs and preferences.

Furtado & Singh. (2020), developed a movie recommendation system using machine learning the goal of this study is to create a recommendation system that makes movie recommendations to users based on their preferences and past evaluations. The system attempts to offer more individualized and varied movie suggestions by merging content-based and collaborative filtering techniques, hence minimizing the effort needed by users to select from a wide range of possibilities. To suggest films that match users' tastes, the technique examines user behavior and past viewings. While the content-based strategy depends on the past and ratings of individual users, the collaborative approach takes into account the ratings of users who share similar likes when making suggestions. The study makes a significant addition by presenting a model that, in contrast to content-based systems, improves the user experience by providing explicit outcomes, enabling viewers to consider a greater variety of movie selections. In general, the system attempts to simplify the process of choosing films, facilitating users' discovery and enjoyment of films that suit their tastes.

Roy et al. (2020), developed a machine learning-based automated resume recommendation model to develop a system that can effectively identify qualified applicants from a wide pool of applications, interpret various CV formats, and match candidate talents to job criteria. The researchers proposed to improve the resume suggestion process's accuracy and efficiency by assessing several classifiers and applying Machine Learning classification algorithms. Machine learning classifiers such as Linear SVM are used in conjunction with text transformation and feature extraction in the suggested methodology. A resume suggestion system that is automated and the discovery that Linear SVM is the best classifier are the study's two primary contributions. Based on how well resumes match job requirements, the models for classification and recommendation perform in classifying resumes and making pertinent recommendations.

According to Garg. (2021), developed a drug recommendation system based on sentiment analysis of drug reviews using machine learning. The study covers the creation of a medication recommendation system that makes use of machine learning techniques for sentiment analysis of patient feedback. The system seeks to improve the relevance and accuracy of prescription drug orders by evaluating patient feedback. Several vectorization techniques and classification algorithms are used to predict sentiment and make medication recommendations based on personal preferences. By providing a data-driven method for medication suggestion that takes patient sentiment into account, the study advances healthcare technology. The system has the potential to improve patient outcomes and provide personalized drug recommendations, as demonstrated by the high accuracy of 93% that the LinearSVC classifier with TF-IDF vectorization obtained in predicting sentiment from drug reviews. To increase the system's efficacy in practical applications, recommendations are made for additional improvements such as data balance and hyperparameter optimization.

Urdaneta-Ponte et al. (2021), developed a recommendation system for education review using collaborative filtering to improve educational outcomes and offer individualized learning experiences, recommendation systems have grown in significance in the field of education. Utilizing algorithms, these systems evaluate user data and offer suggestions for courses, learning materials, and other educational components. Finding gaps, obstacles, and chances for more study and advancement in this field can be facilitated by a thorough evaluation of recommendation systems in the educational field. The objectives of the systematic review on recommendation systems in education were to examine the many kinds of systems that are employed, pinpoint suggested learning materials, evaluate developmental strategies, find gaps in the literature, and offer suggestions for additional study. The emphasis on formal education was evident from the results, and recommendation systems heavily featured machine learning and collaborative filtering techniques.

Latha & Rao. (2023), developed a product recommendation using an enhanced convolutional neural network for an e-commerce platform. Processing client feedback is typically a challenging process that involves challenging the interpretation and analysis of the textual data. Thus, this research publication implements an efficient deep learning-based recommendation architecture. The improved CNN model further improves product sentiment analysis by using Glove as a pre-trained model with a skip-gram in the word-embedding layer to find the appropriate product ratings based on the user's experience. More specifically, the updated CNN model's embedding layer efficiently turns each word into a fixed feature vector, which contributes to lower dimensions and improved word representation. The upgraded CNN model outperformed the standard CNN, achieving a mean recall of 94.80%, precision of 93.64%, and accuracy of 96.92% on the database of Amazon product reviews.

Boughanmi & Ansari. (2021), developed a dynamic of musical success using a machine-learning approach for multimedia data fusion. These researchers created a novel multimodal machine learning framework that applies to creative product settings to combine multimedia data (such as metadata, acoustic features, and user-generated textual data) and use it to predict the performance of musical albums and playlists. A distinct data set gathered from several online sources is used by the authors to estimate the suggested model. The predictive superiority of the model over multiple benchmarks is demonstrated by the authors. The findings shed light on how musical success has changed over the previous fifty years. The researchers then employed the model's components to make marketing decisions, including predicting the reception of upcoming albums, diagnosing and adjusting records, creating playlists tailored to the tastes of various music-loving generations, and offering recommendations based on context.

Unger et al. (2020), developed context-aware recommendations based on deep-learning frameworks. In this paper, they proposed a unique deep-learning recommendation framework that combines neural collaborative filtering recommendation techniques with contextual information. Given that context is frequently represented by a dynamic, high-dimensional feature space across a variety of applications and services, they proposed modeling contextual data in a variety of ways for a variety of uses, including rating prediction, top-k recommendation generation, and user feedback classification to be more precise, they described three deep context-aware recommendation models based on the proposed framework. These models are based on explicit, unstructured, and structured latent representations of contextual data that are obtained from several contextual dimensions, such as time, place, and user action. The superiority of the suggested deep context-aware models over the most advanced context-aware techniques is validated by offline evaluation of three context-aware datasets.

Ferreira Jesus & Kayser Macieski. (2023), developed a menu recommendation system using machine learning to utilize information from food purchases made by the city or the restaurant itself to assist and influence menu planning. building a project with the help of data analysis and machine learning to help chefs and restaurants alike prepare menus that feature foods and products that entice patrons to place larger orders, return, and recommend the establishment. giving cooks the tools they need to produce food for their restaurants more accurately and with a greater chance of being requested by patrons. The primary objective of this research is to forecast consumer preferences for foods and use that information to offer products to restaurants for their next menu. Establishing a proficient system for selecting ingredients can streamline the process of creating meals and enhance patron contentment in general. The possibility of this project to assist society in addressing the enormous issue of food waste and the disparities it involves was another driving force behind the decision to pursue it.

Singh et al. (2023), developed an optimized doctor recommendation system using supervised machine learning. Over the last ten years, we have encountered a lot of patients and medical issues. As a result, individuals struggle to select physicians who are qualified for their particular condition. Based on a patient's medical history, several Machine Learning (ML) based methods already exist to predict doctors. On the other hand, based on patients' medical circumstances, it is crucial to accurately and efficiently suggest doctors to patients. Consequently, we provide a procedure that uses ML techniques to quantitatively rank (weight) every characteristic. We also present a framework that uses weight prediction to improve operational efficiency and propose doctors based on the similarity score and the doctor's skill score. Furthermore, the usefulness of the proposed framework is empirically shown on real-world datasets, where it reduces the average loss by around 34% and 3%, respectively, when compared to Convolutional Neural Network (CNN) and Support Vector Machine (SVM). Compared to cutting-edge methods, the results show that the algorithm can effectively recommend doctors to patients.

Shahbazi & Byun. (2020), developed a project that suggests symmetric articles that are relevant to e-learners from the academic platform of DBLP and the social network Twitter based on reinforcement learning. We realized that the terms in the e-learning system needed to be broadened to encompass a wide variety of concepts to match the tweet content with the local context, profile, and history. The application took advantage of the Grow-bag dataset, which creates concept graphs of extensive Computer Science themes based on the co-occurrence scores of Computer Science terms, to extend terms of the local context, profile, and history. Through this application, the necessity and effectiveness of social media-connected e-learning software that makes recommendations for the material that students are studying in an online learning environment were made clear. That said, the application as it is now is limited to the field of computer science. Future work must focus on expanding these kinds of applications to new fields.

Coelho et al. (2018), developed a personalized travel recommendation system using social media analysis to provide more individualized travel advice, this study investigates the usage of Twitter data. Travel-related tweets are identified using a machine-learning classification algorithm. Personalization of recommendations about places of interest for the user is then achieved by leveraging the travel tweets. Historical structures, parks, museums, and eateries are all considered places of interest. Moreover, friends' and followers' travel-related tweets are collected to further customize the model. In addition to ranking whatever vacation categories they preferred, volunteer Twitter users were requested to submit a survey using their handle. We assessed our model by contrasting its predictions with the survey respondents' selections. The evaluations indicate a prediction accuracy of 68%. Both an upgraded travel-tweet training dataset and an improved machine learning trip category categorization method can increase the accuracy.

Gosai et al. (2021), developed a crop recommendation system using machine learning, with the intelligent crop suggestion system to analyze important data such as temperature, humidity, rainfall, PH value, nitrogen, phosphorus, and potassium to help farmers make informed judgments about crop cultivation. The system makes precise crop suggestions based on past data by using machine learning methods like Decision Tree, Naïve Bayes, Support Vector Machine, Logistic Regression, Random Forest, and Boost. The system's goal is to provide farmers in India with customized crop recommendations that would increase agricultural production and profitability. With a 99.91% classification accuracy on average for crops and Boost being found to be the best algorithm, the system covers a large number of crops and districts and takes into account a variety of environmental conditions to provide customized suggestions.

Tsuji et al. (2014), developed book recommendations using machine learning methods based on library loan records and bibliographic information. This study examines how library lending records and bibliographic data might be analyzed to apply machine learning techniques for book suggestions. Two groups of participants are involved in the study: T University Library and Information Science majors who were invited to submit the titles of books they would like to check out from the university library. The study attempts to propose books that match users' interests by using training data from prior experiments to compute association rules, similarities between book titles, and matches between NDC categories. The performance of Amazon's recommendation system is contrasted with the outcomes of the suggested techniques. Future directions for research include investigating how training data size affects system performance and integrating university-specific data into recommendation algorithms.

Tai et al. (2021), developed a content-based recommendation using machine learning These days, user profile-based online recommender systems are popular in both the engineering and research fields. The recommendation relies heavily on users' profiles being captured accurately. A large body of research, including content-based recommendations, has recently been published on user profile extraction. In this study, a three-step profiling strategy is adopted to better capture users' profiles. (1) Logistic regression is used to predict purchase items. (2) Support vector machines (SVM) are used to forecast the purchase category, and (3) convolutional neural networks (CNN) and long short-term memory (LSTM) are used to predict the user's rating. With the user dataset that was gathered from Amazon, this study performed better than the baseline model. Consequently, the work can provide people who would like to buy with suitable recommendations. In the future, methods for video signal processing will also be considered to record users' facial expressions for more accurate recommendations.

Appadoo et al., 2020), developed a job recommendation system called Job Fit, which predicts the most suitable candidate for a job based on prior data, machine learning methods, and recommender systems. The job requirements and candidate profiles are inputted into the proposed job recommendation system, which then generates a Job Fit score that indicates each applicant's suitability for the specific job. Finally, the system gives the HR specialists a ranked list of all applicants, with the ones who are most suited for the position being suggested first. The study will enable HR to make sure that the best candidates, those suggested by the algorithm, are screened and interviewed in a limited pool while also ensuring that the better candidates are not overlooked.

According to Torres. (2023), developing a conceptual framework for pharmaceutical product recommendations and identifying pertinent product categories based on attributes and expert opinions are the goals of this endeavor. The specific goals include explaining pharmacy recommendation systems, characterizing and contrasting distance functions that can form clusters of related and clinically significant products for pharmaceutical counseling, utilizing machine learning techniques and contrasting them, and sharing the outcomes. To establish a remote function that is in line with medication counseling, an expert consultation was conducted. It was possible to determine the variables' significance in the definition of the distance function thanks to this consultation. Following that, the data was examined in Microsoft Excel, SPSS, and Python utilizing the Spyder IDE and the libraries Pandas, Natural Language Toolkit (NLTK), Unicode, Plotly, Matplotlib, NumPy, SciPy, and Scikit-learn. (Torres, 2023).

Jahanian et al. (2013), developed a recommendation system for the automatic design of magazine covers The goal of the project is to create an Automatic Design of Magazine Covers (ADoMC) system that will help users create eye-catching magazine cover designs without the need for specialized design knowledge. Users could enter text strings, images, mastheads, and preferred color schemes into the system, and it would assess them to produce customized designs. The study advanced the discipline by highlighting the quantification of subjective design principles and incorporating personalization in automatic design systems. The outcomes demonstrated the effective development of ADoMC, which could produce designs in line with user preferences and garnered favorable feedback on the system's ability to produce aesthetically pleasing designs from experts in the field.

Song et al. (2016), developed a machine learning-based software process model recommendation method. The goal of the project is to use historical project data analysis to create a machine learning-based approach for software process model recommendations for new projects. The process entails testing classification algorithms, identifying significant project attributes automatically, and examining how process models and project factors relate to one another. A methodical approach to selecting process models, taking into account different project and team elements, and assessing how process models affect project success indicators are all part of the contribution. As demonstrated by the results, the approach was successful in suggesting appropriate process models, underscoring the significance of taking team and project features into account when making decisions.

Hernández-Nieves et al. (2021), developed a recommendation system for investments based on the extraction of buy/sell signals from technical analysis and forecast outcomes using machine learning. Various methods for data extraction and analysis have been examined as part of this study. The development process is demonstrated, along with the data extraction and machine learning prediction methods that were employed. Included is the technical analysis metrics computation. A visualization platform has been suggested to facilitate high-level user-recommendation system interaction. As a result, a platform with a user interface for data analysis, prediction, visualization, and financial advice is produced. Beyond being user-friendly and intuitive, the platform aims to allow anyone, regardless of experience level in the stock market, to draw inferences from the data and assess the information the system has analyzed.

2.7 Research Gap

Even though machine learning has come a long way in personalized fitness recommendations, there are still several holes in the literature that need more investigation and study.

Although this is the first time that this has been done in Somalia, we want to establish a system of personal gym recommendations for beginners in Somalia. Most of the current gym recommendation systems target a broad audience and pay little attention to novices. This study fills a major vacuum in the literature by focusing on customized machine-learning strategies that help people who are new to fitness activities before they enroll or attend. Algorithms that take into account the special difficulties and needs of novices are needed, taking into account their differing levels of fitness, personal preferences, and early resistance to strenuous exercise regimens.

2.8 Summary

In this chapter, we conducted a comprehensive review of the existing literature on the intersection of machine learning and fitness, focusing on personalized gym recommendations for beginners. We explored the application of machine learning in fitness contexts, evaluated current gym recommendation systems, and examined the importance of personalization in fitness programs. Challenges and opportunities were identified, and related technologies were considered. The research gap section highlighted critical areas where current literature falls short, providing the foundation for our proposed Personal Gym Recommendation System for Beginners Using Machine Learning. Chapter 3 will delve into the methodology that guides our approach to address these research gaps.

CHAPTER THREE: METHODOLOGY

3.1 Introduction

Personalized Gym Recommendations are highly significant as they offer individuals tailored fitness plans based on their unique characteristics, preferences, and goals to new gym goers. This customization increases motivation by aligning exercises with individual interests, optimizing workout efficiency, and promoting adherence to routines. With the integration of adaptive algorithms and progress tracking, these systems evolve with users' changing fitness levels, ensuring ongoing effectiveness and reducing the risk of injury. The personalized approach, combined with technology integration and additional support features, contributes to a holistic and enjoyable fitness experience, ultimately leading to better results and improved overall well-being.

This chapter outlines developing a Personalized Gym Recommendation System to leverage a comprehensive dataset, including user demographics, health conditions, physical metrics, and fitness goals. The system uses machine learning algorithms to analyze this data and generate personalized gym and exercise recommendations. The objective is to facilitate users in finding the most suitable gym options and fitness plans, thus supporting them in achieving their fitness goals effectively.

3.2 System Description

The Personal Gym Recommendation System (PGRS) is a comprehensive digital platform designed to offer personalized fitness and health recommendations to individuals seeking to improve their physical well-being. Utilizing user-provided data, PGRS evaluates various health indicators, including age, height, weight, and medical conditions such as hypertension and diabetes, to tailor fitness and dietary recommendations that align with the user's unique health profile and fitness goals.

The Personalized Gym Recommendation System represents a significant advancement in the use of technology within the fitness industry. By providing users with personalized, data-driven gym recommendations, the system not only enhances the user experience but supports individuals in achieving their fitness goals more effectively. This system sets a new standard for personalized fitness solutions, leveraging machine learning to deliver customized recommendations that cater to the unique needs of each user.

3.3 System Architecture

In this section, we will explain the structure of our system and how it will work This system consists of data collection that is sent to the model by verifying the extracted data and then displaying recommendation information to showcase the personalized gym recommendations generated by the system using the Python flask.

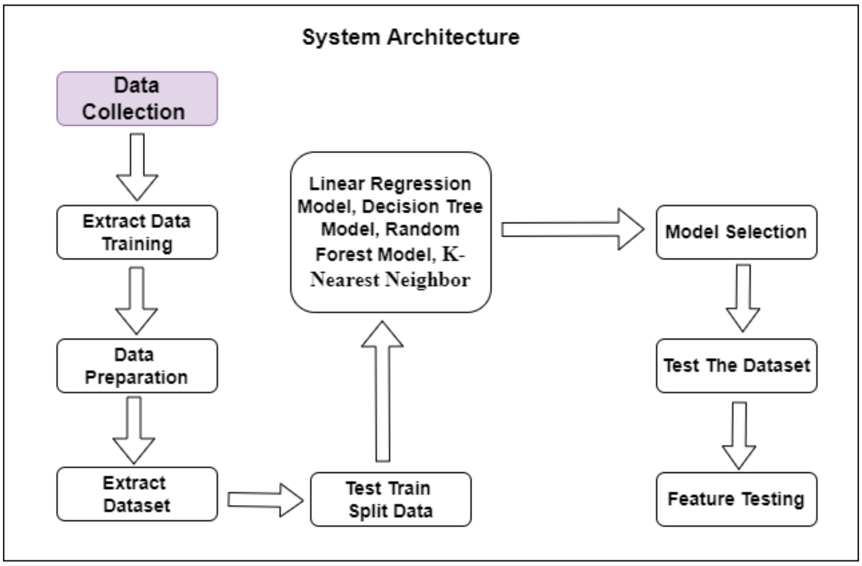


Figure 3.1 System Architecture

3.4 System Features

In addition to the features mentioned in the system description, some other features that could be included in the Personalized Gym Recommendation System using machine learning are:

3.4.1. Personalized Fitness Plans

Based on the user's Body Mass Index (BMI), existing health conditions, and fitness objectives, PGRS crafts customized workout routines that encompass exercises, fitness types, and required equipment.

3.4.2. Dietary Recommendations

Alongside physical activity suggestions, the system provides dietary guidance tailored to support the user's health and fitness targets, considering their specific nutritional needs.

3.4.3. Health Tracking

Users can input their physical health data to receive updated recommendations as their health status evolves, ensuring that the guidance remains relevant and effective.

3.4.4. Goal-Oriented Recommendations

Whether the aim is weight loss or weight gain. PGRS adjusts its recommendations to align with the user's aspirations, offering advice on exercises, and dietary habits.

3.4.5. Print Recommendation Information

This functionality allows users to effortlessly print out the details of their gym recommendations. This feature is particularly useful for users who prefer having a physical copy of the recommendation for reference or to discuss with friends, family, or personal trainers.

3.4.6. Export to Excel file

This functionality allows users to export data or reports generated by the system into Excel format for further analysis, sharing, or storage.

3.5 System Methodology

This section details the comprehensive methodology employed in the development of the Personalized Gym Recommendation System, focusing on the dataset's lifecycle from collection and preparation through to the model selection, training, evaluation, and the final implementation, including both frontend and backend components.

3.5.1. Dataset

The first step involves gathering comprehensive data, which includes user demographics, health metrics, fitness goals, and user preferences. This data forms the foundation for training machine learning models.

The success of any machine learning-based system relies heavily on the quality and quantity of the data used for training. For this study, we get a dataset from Kaggle, comprising information on gym-goers' preferences, historical workout data, and user demographics. Data sources include user surveys, gym databases, and publicly available datasets related to fitness and health. To ensure privacy and compliance with ethical standards, all personally identifiable information is anonymized and secured. The dataset used in this study that we get from Kaggle contains **14589** records and **18** columns.

The foundation of our system is a robust dataset, meticulously collected to include a wide range of variables crucial for personalized recommendations. This dataset comprises user demographics (age, sex, height, weight), health metrics (BMI, presence of conditions such as hypertension or diabetes), fitness goals (e.g., weight loss, weight gain), and preferences (fitness type, preferred workouts, and equipment needs).

3.5.2. Data Preparation

Data preparation, also known as data preprocessing, is the process of cleaning, organizing, and transforming raw data into a format suitable for analysis or training machine learning models. It is a crucial step in the data analysis and machine learning pipeline, as the quality of the input data significantly impacts the performance and effectiveness of the models.

The main goals of our data preparation include:

I. **Handling Missing Data**: Identifying and addressing missing values in the dataset. This can involve removing rows with missing values, imputing missing values based on statistical measures, or using advanced techniques to predict missing values.

II. **Encoding Categorical Variables**: Converting categorical variables (non-numeric) into a numerical format that machine learning models can understand. Common methods include one-hot encoding, label encoding, or using embeddings for more complex categorical data.

III. **Data Splitting:** Dividing the dataset into training, validation, and testing sets. The training set is used to train the model, the validation set is used for fine-tuning and hyperparameter tuning, and the testing set is used to evaluate the model's performance on unseen data.

IV. **Handling Data Duplicates**: Identifying and handling duplicate records in the dataset to avoid biases in model training and evaluation.

3.5.3. Model Selection

For the Personalized Gym Recommendation System as outlined, the model selection process involves evaluating several machine learning algorithms to determine which is best suited for predicting personalized gym recommendations based on the collected dataset. The selected models include:

I. **Linear Regression:** Typically used for predicting a continuous variable, but in this context, it might be explored for its simplicity and interpretability, potentially to predict numerical target variables for gyms based on user preferences.

II. **Decision Trees:** A model that uses a tree-like graph of decisions and their possible consequences. It’s effective for classification and regression tasks and provides clear logic for decision-making, making it suitable for understanding how various factors influence gym recommendations.

III. **Random Forest:** An ensemble learning method that operates by constructing multiple decision trees during training time and outputting the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random forests correct for decision trees' habit of overfitting to their training set, offering more robust and accurate predictions.

IV. **K-Nearest Neighbors (KNN):** The inclusion of K-Nearest Neighbors (KNN) into the data preparation process for the Personalized Gym Recommendation System introduces a model that emphasizes similarity between data points for making predictions. KNN is a straightforward, instance-based learning algorithm where the prediction for a new instance is determined based on the most similar data points in the training set.

3.5.4. Training

The training model process for the Personalized Gym Recommendation System involves preparing the selected machine learning algorithms using the dataset we've collected, to accurately predict personalized gym recommendations. Given the selection of models outlined earlier (Linear Regression, Decision Tree, and Random Forest), the training process is as follows:

Training Process Overview:

I. **Splitting the Dataset**: Initially, the dataset is divided into training and testing sets, a common practice to evaluate the performance of machine learning models on unseen data. Typically, the split might be 80% for training and 20% for testing, though these proportions can vary based on the dataset size and specific requirements.

II. **Feature Selection** Before training, relevant features (variables) that are likely to influence gym recommendations are identified based on the dataset. This could include user demographics, fitness goals, preferences, and gym attributes. Features might be selected based on domain knowledge, statistical analysis, or feature importance scores derived from preliminary model runs.

3.5.5. Implementation

The implementation of the Personalized Gym Recommendation System is the process where the system is built, deployed, and made operational for end-users. It involves integrating the trained machine learning models into a functional application that users can interact with to receive personalized gym recommendations. The implementation is broadly divided into two main components: the front end and the back end.

3.5.6.1 Frontend

The front end is the user interface through which users interact with the recommendation system. It is developed using web technologies such as HTML, CSS, Bootstrap, Taliwandcss, and JavaScript, providing a responsive and intuitive design that works across devices. Key features of the frontend include:

I. **User Input Forms**: Where users can enter their demographics (age, sex, height, weight), and health metrics conditions such as hypertension or diabetes).

II. **Recommendation Display**: A section to showcase the personalized gym recommendations generated by the system.

3.5.6.2. Backend

The backend, built with Flask in Python, handles data processing, model training, and recommendation generation. Flask routes manage requests from the front end, executing the machine learning models and returning personalized gym suggestions to users.

3.6 System Development Environment

In this study, we will need to develop an environment tool that will assist us in proposing this system, as well as a set of processes and programming tools that will provide an interface and a convenient view of the development process, which will include writing code, testing it, and packaging the build for deployment.

The Development Environment includes:

- **I.** Python flask.
- **II.** PyCharm Community Edition 2023.2.2
- **III.** XAMPP for Windows 8.2.12 (PHP 8.2.12)

Flask is a lightweight and flexible web framework for Python. It is designed to be simple and easy to use, making it an excellent choice for developing small to medium-sized web applications and APIs. Flask provides the essential tools to build web applications, and it follows the WSGI (Web Server Gateway Interface) standard.

PyCharm Community Edition is a free, open-source version of the PyCharm IDE (Integrated Development Environment) developed by JetBrains. It is designed to provide essential tools and features for Python development, making it accessible to developers without requiring a paid subscription.

XAMPP for Windows is a software package that combines several key tools needed for web development into one easy-to-use package. The name XAMPP stands for Cross-Platform (X), Apache (A), MySQL (M), PHP (P), and Perl (P). Apache is a popular web server, MySQL is a database management system, PHP is a programming language for creating dynamic web pages, and Perl is another programming language often used for web development. Together, these components provide a platform for building and testing websites and web applications on a local computer before they are uploaded to a live server.

To register the users of our gym recommendation system, we can use XAMPP to set up a local web server environment on our Windows computer. With XAMPP, we can create a website or web application where users can sign up for the gym recommendation service. We can use PHP to handle user registration forms and store user information in a MySQL database. Apache will serve the web pages to users' browsers, allowing them to access the registration functionality seamlessly. This way, we can develop and test the registration system locally before deploying it to a live server for public use.

3.7 System Requirement

The Hardware and Software Requirements for building the project of Personalized Gym Recommendation using machine learning vary depending on your operation system and the digital platform for which you are developing this system there are some requirements. These are the hardware and software requirements, respectively, and they should be available when developing this project. Although these requirements depend on how complex the system is even the least complex one also has some requirements for you to develop that particular software.

3.7.1 Hardware Requirements

A computer system is made up of units that are put together to work as one to achieve a common goal. The hardware device requirements for the implementation of Personalized Gym Recommendations using machine learning are:

Table 3.1 Hardware Requirement

Components	Specification	Purpose
Processor	Quad-core 2.5 GHz or higher	To efficiently run complex machine learning algorithms and handle large datasets
RAM	8 GB or higher	To support simultaneous processing and analysis of large amounts of data
Hard Drive	500 GB SSD	For fast data access and storage of large datasets
Graphics Card	Dedicated GPU with at least 4GB VRAM	To accelerate machine learning tasks, especially if using deep learning models
Network Interface Card	Gigabit Ethernet or better	For fast data transfer and connectivity within a network

3.7.2. Software Requirements

This section explains the minimum software requirements for using our program, as shown in the table below.

Table 3.2 Software Requirement

Software Tool	Version	Purpose
Python (Flask)	3.8 or higher	Web framework for processing model's data
MySQL	3.3 or higher	Relational database management system
XAMPP Server	3.3.0	Local server environment for hosting the application
Windows OS 8+	8 or higher	Operating system for running the software

Table 3.3: Required Libraries

Library	Purpose
scikit-learn	Machine learning library for predictive modeling
NumPy	Numerical computing library for efficient data handling
Pickle	Serialization library for saving and loading Python objects
Joblib	Library for efficient persistence of Python objects
matplotlib	For data visualization library for creating plots and charts

Table 3.4: Integrated Development Environment

IDE	Description
Visual Studio	Integrated development environment for Our Web Application Frontend Part
Jupiter Notebook	Interactive coding environment for Python
Pycharm	Integrated development environment Specific for Python, Web Application Server Side Flask Part

CHAPTER FOUR: ANALYSIS AND DESIGN

4.1. Introduction

This chapter provides a system for analyzing and designing a system that separates personalized fitness/gym recommendation systems. In this section, we will discuss the current system, the problem it solves, how it will perform, and why we're using it. The requirements of the system can be two main parts Functional and Non-Functional Requirements the functional requirements explain the necessary non-functional requirements and describe how the system works, while functional requirements describe what the system should do. The system design is the essential phase of this chapter and it will be proven in the form of a Graphical representation by the usage of a Data Flow Diagram (DFD) to recognize how the prediction works logically.

4.2. System analysis

System analysis involves the study of machine learning methods of recommending to the users and the most important face factor is to collect a dataset based on Somalia gyms after we get the dataset from Kaggle and teach the models by removing any Data cleaning as mentioned in Chapter three after those models have been tested. Any data cleaning will be done, the interface will be streamlined for users to use this system.

4.3. Existing Approaches

The existing gym recommendation systems predominantly rely on basic filters such as location, price, and available facilities. These systems often overlook the personal preferences and fitness goals of users, leading to generic and less satisfactory recommendations. Moreover, many of these systems do not employ advanced algorithms to analyze user data for more tailored suggestions. The lack of personalization and foresight in these systems results in a gap between user expectations and the recommendations provided.

4.4. The Proposed System

This System aims to revolutionize the way individuals know and select gyms by leveraging advanced data analytics and personalization algorithms. At its core, this system will use a user's preferences (sex, age, height, weight), and health data (hypertension and diabetes), to recommend personal information (BMI, Standard weight, and body fat percentage), workouts that the user can do, available equipment, dietitian needs such as vegetables, proteins are taken, and juice, and membership plans to tailor recommendations. Furthermore, the system will adapt over time, learning from user interactions to refine its suggestions, ensuring that recommendations remain relevant and highly personalized. This adaptive approach will be supported by a robust, user-friendly interface that encourages engagement and simplifies the decision-making process. By addressing the limitations of existing gym recommendation platforms, the proposed system is designed to offer a more intuitive, efficient, and customized gym selection experience.

4.5. System Requirements

A requirement is a statement in writing of a quality that a new system must possess. Researchers talk about the specifications for the fitness recommendation as a general, Recommendation System in this section. The requirement is divided into functional requirements and non-functional requirements using machine learning.

4.5.1. Functional Requirements

A functional requirement specifies how an action or activity should be carried out.

The following are the functional criteria that the proposed system must meet:

- **User:** A user is a person who utilizes something, and it is nearly usually used in connection to that object.
- **Input as Data**: Input refers to any data that is delivered to a computer or software application. The process of delivering information to the computer is also known as data entry since the information delivered is also considered data.
- **Data preprocessing**: which is part of data preparation, refers to any sort of processing done on raw data to prepare it for further processing.
- **Data extraction:** is the process of gathering or obtaining various sorts of data from several sources, many of which are unstructured or poorly organized.
- **Data segmentation:** the act of splitting and grouping comparable data based on predetermined parameters so that it may be used more effectively in marketing and operations.
- **Classification model:** takes some data and produces an output that categorizes it into one of many categories

4.5.2. Non-Functional Requirements

The requirements of non-functionally are:

- **Security:** the system should have security to ensure the secureness of information.
- **Accessibility:** the system is available on the Internet and can be accessed at any time from any place through an Internet connection.
- **Privacy:** The system can only be used by administrators and authorized users.
- **User Friendly:** The system is simple and interesting.

4.6. Feasibility Study

The feasibility of developing a Personalized Gym Recommendation System involves evaluating various aspects to determine whether the project is viable and worth pursuing. This analysis covers technical, economic, operational, and schedule feasibility to ensure that the project can be implemented successfully and effectively meet its goals.

4.6.1. Technical Feasibility

The technical feasibility assesses whether the current technology is capable of supporting the proposed system. This includes evaluating software and hardware requirements, the availability of technology to handle personalized data analysis, and the integration capabilities with existing systems. Given the advancements in machine learning algorithms, developing a Personalized Gym Recommendation System is technically feasible. The main technical considerations would involve selecting appropriate algorithms for personalization, ensuring data privacy and security, and designing an intuitive user interface.

4.6.2. Economic Feasibility

Economic feasibility evaluates the cost-effectiveness of the project, considering the initial development costs, operational expenses, and the expected return on investment (ROI). The development of a Personalized Gym Recommendation System requires investment in software development, data acquisition, and marketing. A detailed cost-benefit analysis would be necessary to ensure that the project's potential revenues justify the investment.

4.6.3. Operational Feasibility

Operational feasibility involves determining whether the project can be implemented within the existing operational framework of potential users and stakeholders. This includes assessing whether users are likely to accept and use the system and whether gyms are willing to participate. User acceptance testing and stakeholder interviews can provide insights into the system's potential adoption and identify any operational hurdles that need to be addressed.

4.6.4. Schedule Feasibility

Schedule feasibility assesses whether the project can be completed within a reasonable time frame. This involves considering the availability of developers, resources, and the integration of feedback loops for testing and refinement. Setting realistic timelines that allow for the development, testing, and deployment of the system is crucial for its success.

4.7. System Design

In this part, we'll go through machine learning model system design. System design is the process of defining pieces of a system, such as modules, architecture, components, and their interfaces, as well as data, depending on the requirements. Design architecture, Design interface, and Design databases are all phases in the system design process.

4.7.1. Data Flow Diagrams (DFD)

A Data Flow Diagram (DFD) is a graphical representation of the flow of data through an information system. It models a system's process aspects, depicting how data moves from input to processing modules, and finally to output. DFDs are used for the visualization of data processing in software engineering and are crucial for understanding complex systems by breaking down their processes into simpler, more manageable components. Here's an explanation of the components and processes involved in the DFD:

I. **Input Data:** Input data refers to the raw data collected or fed into the system before any processing occurs. In the context of a Personalized Gym Recommendation System, input data could include user preferences (like sex, age, height, weight), and health conditions (like hypertension and diabetes),. This data is crucial as it forms the foundation upon which personalized recommendations are made.

II. **Pre-processing:** Pre-processing involves cleaning and preparing the input data for further analysis or processing. This step might include handling missing values, normalizing data, encoding categorical variables, and removing outliers. For a gym recommendation system, pre-processing ensures that the data fed into the feature extraction and machine learning models is clean, consistent, and ready for analysis.

III. **Features Extraction:** Feature extraction involves transforming raw data into a set of features that can be used to train a model. This process is critical in machine learning as it helps in identifying the most relevant attributes that contribute to the outcome. In the context of gym recommendations, feature extraction might involve identifying key attributes from user profiles and gym data, such as user fitness goals, preferred gym amenities, location preferences, and historical gym usage patterns.

IV. **Training Dataset:** The training dataset is a subset of the pre-processed data used to train machine learning models. It includes both the features (extracted in the previous step) and the target variable (e.g., user satisfaction with a gym recommendation). The model learns from this dataset to understand patterns and relationships between the features and the target outcome.

V. **Prediction:** Prediction involves using the trained model to forecast the outcome for new, unseen data. Once the model is trained, it can predict the likelihood of a user preferring a specific gym based on their profile and preferences. This step is crucial for making personalized gym recommendations to users.

VI. **Testing Dataset:** The testing dataset is another subset of the pre-processed data, separate from the training dataset, used to evaluate the performance of the trained model. It helps in understanding how well the model generalizes to new data. The testing dataset is crucial for identifying overfitting, where the model performs well on the training data but poorly on unseen data.

VII. **Results:** Results refer to the output generated after applying the trained model to the testing dataset. and the actual recommendations made to users. Analyzing the results helps in understanding the effectiveness of the model in making personalized gym recommendations and identifying areas for improvement.

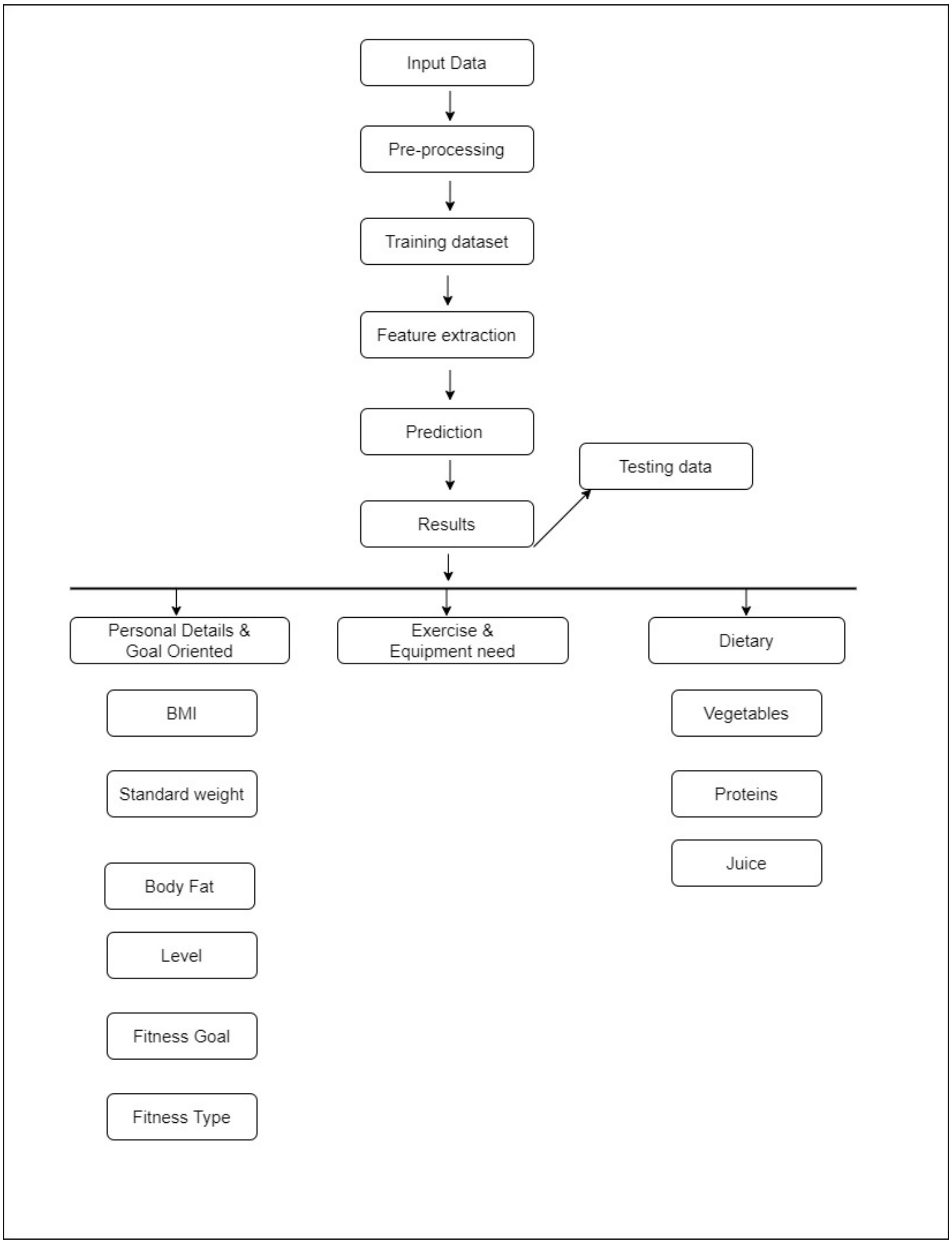
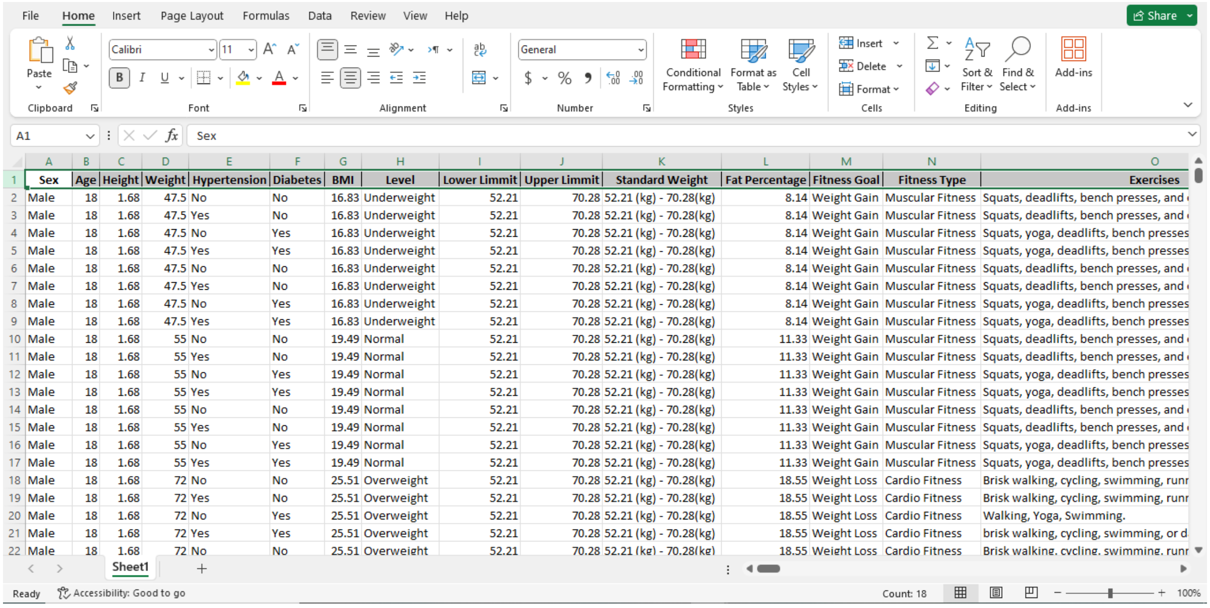


Figure 4.1 Data Flow Diagram of PGR

4.8. Dataset Design



	Sex	Age	Height	Weight	Hypertension	Diabetes	BMI	Level	Lower Limmit	Upper Limmit	Standard Weight	Fat Percentage	Fitness Goal	Fitness Type	Exercises
2	Male	18	1.68	47.5	No	No	16.83	Underweight	52.21	70.28	52.21 (kg) - 70.28(kg)	8.14	Weight Gain	Muscular Fitness	Squats, deadlifts, bench presses, and
3	Male	18	1.68	47.5	Yes	No	16.83	Underweight	52.21	70.28	52.21 (kg) - 70.28(kg)	8.14	Weight Gain	Muscular Fitness	Squats, deadlifts, bench presses, and
4	Male	18	1.68	47.5	No	Yes	16.83	Underweight	52.21	70.28	52.21 (kg) - 70.28(kg)	8.14	Weight Gain	Muscular Fitness	Squats, yoga, deadlifts, bench presses
5	Male	18	1.68	47.5	Yes	Yes	16.83	Underweight	52.21	70.28	52.21 (kg) - 70.28(kg)	8.14	Weight Gain	Muscular Fitness	Squats, yoga, deadlifts, bench presses
6	Male	18	1.68	47.5	No	No	16.83	Underweight	52.21	70.28	52.21 (kg) - 70.28(kg)	8.14	Weight Gain	Muscular Fitness	Squats, deadlifts, bench presses, and
7	Male	18	1.68	47.5	Yes	No	16.83	Underweight	52.21	70.28	52.21 (kg) - 70.28(kg)	8.14	Weight Gain	Muscular Fitness	Squats, deadlifts, bench presses, and
8	Male	18	1.68	47.5	No	Yes	16.83	Underweight	52.21	70.28	52.21 (kg) - 70.28(kg)	8.14	Weight Gain	Muscular Fitness	Squats, yoga, deadlifts, bench presses
9	Male	18	1.68	47.5	Yes	Yes	16.83	Underweight	52.21	70.28	52.21 (kg) - 70.28(kg)	8.14	Weight Gain	Muscular Fitness	Squats, yoga, deadlifts, bench presses
10	Male	18	1.68	55	No	No	19.49	Normal	52.21	70.28	52.21 (kg) - 70.28(kg)	11.33	Weight Gain	Muscular Fitness	Squats, deadlifts, bench presses, and
11	Male	18	1.68	55	Yes	No	19.49	Normal	52.21	70.28	52.21 (kg) - 70.28(kg)	11.33	Weight Gain	Muscular Fitness	Squats, deadlifts, bench presses, and
12	Male	18	1.68	55	No	Yes	19.49	Normal	52.21	70.28	52.21 (kg) - 70.28(kg)	11.33	Weight Gain	Muscular Fitness	Squats, yoga, deadlifts, bench presses
13	Male	18	1.68	55	Yes	Yes	19.49	Normal	52.21	70.28	52.21 (kg) - 70.28(kg)	11.33	Weight Gain	Muscular Fitness	Squats, yoga, deadlifts, bench presses
14	Male	18	1.68	55	No	No	19.49	Normal	52.21	70.28	52.21 (kg) - 70.28(kg)	11.33	Weight Gain	Muscular Fitness	Squats, deadlifts, bench presses, and
15	Male	18	1.68	55	Yes	No	19.49	Normal	52.21	70.28	52.21 (kg) - 70.28(kg)	11.33	Weight Gain	Muscular Fitness	Squats, deadlifts, bench presses, and
16	Male	18	1.68	55	No	Yes	19.49	Normal	52.21	70.28	52.21 (kg) - 70.28(kg)	11.33	Weight Gain	Muscular Fitness	Squats, yoga, deadlifts, bench presses
17	Male	18	1.68	55	Yes	Yes	19.49	Normal	52.21	70.28	52.21 (kg) - 70.28(kg)	11.33	Weight Gain	Muscular Fitness	Squats, yoga, deadlifts, bench presses
18	Male	18	1.68	72	No	No	25.51	Overweight	52.21	70.28	52.21 (kg) - 70.28(kg)	18.55	Weight Loss	Cardio Fitness	Brisk walking, cycling, swimming, runr
19	Male	18	1.68	72	Yes	No	25.51	Overweight	52.21	70.28	52.21 (kg) - 70.28(kg)	18.55	Weight Loss	Cardio Fitness	Brisk walking, cycling, swimming, runr
20	Male	18	1.68	72	No	Yes	25.51	Overweight	52.21	70.28	52.21 (kg) - 70.28(kg)	18.55	Weight Loss	Cardio Fitness	Walking, Yoga, Swimming.
21	Male	18	1.68	72	Yes	Yes	25.51	Overweight	52.21	70.28	52.21 (kg) - 70.28(kg)	18.55	Weight Loss	Cardio Fitness	brisk walking, cycling, swimming, or d
22	Male	18	1.68	72	No	No	25.51	Overweight	52.21	70.28	52.21 (kg) - 70.28(kg)	18.55	Weight Loss	Cardio Fitness	Brisk walking, cycling, swimming, runr

Figure 4.2 Dataset Design

A dataset is a group of cells on an Excel worksheet that contain data that can be analyzed. To make the Analysis process work with your data, you must apply a few simple guidelines when structuring data on an Excel worksheet. For a dataset design tailored for analysis or machine learning purposes, such as for a Kaggle competition or data science project, we distinguish between features (independent variables) and target variables (dependent variables) as follows:

4.8.1. Features (Independent Variables):

1. **Sex**: Gender of the individual (Male/Female). This is a categorical variable that might affect fitness recommendations, diet, and exercise regimens.
2. **Age:** Age of the individual. Age can significantly influence fitness goals, types of recommended exercises, and dietary needs.
3. **Height:** Height in meters. This physical characteristic can be used to calculate BMI and determine appropriate weight ranges.

4. **Weight:** Weight in kilograms. Weight, in conjunction with height (to calculate BMI), plays a crucial role in determining the fitness level and recommendations.
5. **Hypertension:** Indicates whether the individual has hypertension (Yes/No). This is a health condition that may restrict or influence certain types of physical activities and dietary choices.
6. **Diabetes:** Indicates whether the individual has diabetes (Yes/No). Like hypertension, diabetes is a critical health condition that affects exercise and diet recommendations.

4.8.2. Target Variables (Dependent Variables)

7. BMI: Body Mass Index. While BMI can be derived from height and weight (features), in this context, it's treated as a target variable for analysis or prediction based on the listed features

8. Level: Categorization of BMI (e.g., Underweight, Normal Weight, Overweight, Obese). This categorization provides a direct insight into the individual's health status related to their weight.

9. Lower Limit and Upper Limit: These define the healthy weight range, which could be targeted for weight management recommendations.

10. Standard Weight: A specific range indicating the healthy weight for the individual, directly tied to BMI levels and health status.

11. Fat Percentage: Body fat percentage. This is an essential measure for assessing fitness and health beyond just BMI.

12. Fitness Goal: The specific fitness goal recommended (e.g., Weight Gain, Weight Loss), which would be a direct outcome of analyzing the features.

13. Fitness Type: The type of fitness activity recommended (e.g., Muscular Fitness, Cardio Fitness), influenced by individual health metrics and conditions.

14. Exercises: Specific exercises recommended, which would vary based on the individual's fitness goal, type, and health status.

15. Equipment Required: Equipment necessary for the recommended exercises, potentially varying with the exercise regimen.

16. Diet: Recommended dietary guidelines or specifics, highly individualized based on health conditions, fitness goals, and nutritional needs.

17. Conclusion Recommendation: General advice and recommendations, summarizing the action plan for achieving fitness goals considering health conditions and personal metrics.

CHAPTER FIVE: IMPLEMENTATION & TESTING

5.1 Introduction

In this chapter, we delve into the practical aspects of implementing the solution proposed in Chapter Four. Implementation involves translating the design and architecture into functioning software or system components. Testing, conversely, ensures that the implemented solution meets the specified requirements and functions correctly under various conditions. This chapter outlines the guidelines for executing the implementation and testing phases effectively.

This chapter focuses on implementing and testing the personalized gym recommendation system using machine learning techniques. It presents the project's practical aspects, including the system's development and the evaluation of its performance through comprehensive testing.

5.2 Overview of the implementation environment

The main objective of this study is to build a system that helps gym-goers get a recommendation system to make their exercises easy.

Our system for implementing machine learning and webserver. The graphical user interface software component is the Python flask at the front end. We also use Python so that the Models of Data Collection program must be implemented Dataset as the back-end.

5.3 Training and Testing Evaluations

After training and evaluating four different models on our dataset, we found notable variations in their performance metrics. Among these models, the Decision Tree for regressions exhibited exceptional accuracy, achieving a perfect score of 100% on the training set and maintaining an impressive 99.91% accuracy on the testing set. Conversely, the Decision Tree model trained on classification variables displayed slightly lower but still robust performance, achieving a training accuracy of 99.29% and a testing accuracy of 87.99%. These results underscore the importance of considering the nature of the data when selecting a suitable model, as well as the potential impact of feature types on predictive performance. Despite the slightly lower testing accuracy of the categorical Decision Tree model, its performance remains commendable and may still offer valuable insights for classification tasks involving categorical variables. Overall, the decision tree models demonstrate the effectiveness of this approach in capturing complex relationships within the data, showcasing its versatility across different types of target variables.

Building a RandomForestClassifier model for Categorical Variables

```
In [93]: # Separate features (X) and target variable (y)
#display values, of dependant variable and independ
X = df[['sex','Age','Height', 'Weight','hypertension','diabetes']].values
y = df[['Level','Fitness Goal', 'Fitness Type', 'Exercises', 'Equipment Required', 'Diet','Conclusion Recommendation']].values

In [94]: # Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)

In [95]: # Create a RandomFores tree model
#random_forest_model = RandomForestRegressor()
random_forest_model =  MultiOutputClassifier(RandomForestClassifier(n_estimators=7,random_state=100))

In [96]: # Fit the model on the training data
random_forest_model.fit(X_train, y_train)

Out[96]:
▸ MultiOutputClassifier
▸ estimator: RandomForestClassifier
  ▸ RandomForestClassifier

In [97]: print("Random Forest Training Accuracy: ", round(random_forest_model.score(X_train,y_train)*100,2))
x_pred = random_forest_model.predict(X_test)
y_pred = random_forest_model.predict(X_train)
print("Random Forest Testing Accuracy: ", round(random_forest_model.score(X_test, y_test)*100,2))

Random Forest Training Accuracy:  98.1
Random Forest Testing Accuracy:  85.73
```

Figure 5.1 Random Forest for Classification Training

```
In [98]: # Features
feature__random_forest_test = np.array([[1,18, 1.68,47.5,0,0]])
result_random_forest = random_forest_model.predict(feature__random_forest_test)

print(result_random_forest)
print()
print("=========================================================")

[['Underweight' 'Weight Gain' 'Muscular Fitness'
  'Squats, deadlifts, bench presses, and overhead presses'
  'Dumbbells and barbells'
  'Vegetables: (Carrots, Sweet Potato, and Lettuce); Protein Intake: (Red meats, poultry, fish, eggs, dairy products, legumes,
and nuts); Juice: (Fruit juice, watermelon juice, carrot juice, apple juice and mango juice)'
  "Follow a regular exercise schedule. Adhere to the exercise and diet plan to get better results. It is important to approach
weight gain in a healthy and balanced way, focusing on both exercise and nutrition. Keep in mind that weight gain should be gra
dual and focused on building lean muscle rather than increasing fat. Additionally, it's always a good idea to consult with a he
alth care professional or registered dietitian before making any significant changes to your exercise or diet plan. Here are so
me important tips:- Stay hydrated by drinking enough water throughout the day. Monitor your progress and adjust your diet and e
xercise routine accordingly. Get adequate sleep to support muscle recovery and overall health. Always monitor your situation, a
nd consult your personal doctor or a professional counselor."]]
```

Figure 5.2 Random Forest for Classification Testing

Building a DecisionTreeClassifier model for Categorical Variables

```
In [99]:  # Separate features (X) and target variable (y)
          #display values, of dependant variable and independ
          X = df[['sex','Age','Height', 'Weight','hypertension','diabetes']].values
          y = df[['Level','Fitness Goal', 'Fitness Type', 'Exercises', 'Equipment Required', 'Diet','Conclusion Recommendation']].values

In [100]: # Split the data into training and testing sets
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)

In [101]: dtree = MultiOutputClassifier(DecisionTreeClassifier(random_state=42))

In [102]: dtree.fit(X_train,y_train)

Out[102]: MultiOutputClassifier
          estimator: DecisionTreeClassifier
          DecisionTreeClassifier

In [103]: print("The Decision Tree Model Accurency For Training:- ", round(dtree.score(X_train, y_train)*100,2))
          print("The Decision Tree Model Accurency For Testing:- ", round(dtree.score(X_test, y_test)*100, 2))

          The Decision Tree Model Accurency For Training:-  99.4
          The Decision Tree Model Accurency For Testing:-  86.4
```

Figure 5.3 Decision Tree for Classification Training

Model Selection

We selected a decision tree model for both numerical and categorical data

```
In [110]: # Separate features (X_lin) and target variable (y_lin)
          X_dtree_num = df[['sex','Age','Height', 'Weight','hypertension','diabetes']].values
          y_dtree_num = df[['BMI','Lower Limmit','Upper Limmit', 'Fat Percentage']].values

          # Separate features (X_ran) and target variable (y_ran)
          X_dtree_cat = df[['sex','Age','Height', 'Weight','hypertension','diabetes']].values
          y_dtree_cat = df[['Level','Fitness Goal', 'Fitness Type', 'Exercises', 'Equipment Required', 'Diet','Conclusion Recommendation']]

          # Split the data into training and testing sets
          X_train_dtree_num, X_test_dtree_num, y_train_dtree_num, y_test_dtree_num = train_test_split(X_dtree_num, y_dtree_num, test_size=
          X_train_dtree_cat, X_test_dtree_cat, y_train_dtree_cat, y_test_dtree_cat = train_test_split(X_dtree_cat, y_dtree_cat, test_size=

          dtree_numeric_var = DecisionTreeRegressor()
          dtree_numeric_var.fit(X_train_dtree_num,y_train_dtree_num)

          dtree_categorical_var = MultiOutputClassifier(DecisionTreeClassifier(random_state=42))
          dtree_categorical_var.fit(X_train_dtree_cat, y_train_dtree_cat)

Out[113]: MultiOutputClassifier
          estimator: DecisionTreeClassifier
          DecisionTreeClassifier

In [114]: print("The decision Tree (Numerical var) Accurency For Training:- ", round(dtree_numeric_var.score(X_train_dtree_num, y_train_dtr
          print("The decision Tree (Numerical var) Accurency For Testing:- ", round(dtree_numeric_var.score(X_test_dtree_num, y_test_dtree_
          print("The decision tree (Categorical var) Accurency For Training: ", round(dtree_categorical_var.score(X_train_dtree_cat, y_trai
          print("The decision tree (Categorical var) Accurency For Testing: ", round(dtree_categorical_var.score(X_test_dtree_cat, y_test_c

          The decision Tree (Numerical var) Accurency For Training:-  100.0
          The decision Tree (Numerical var) Accurency For Testing:-  99.93
          The decision tree (Categorical var) Accurency For Training:  99.29
          The decision tree (Categorical var) Accurency For Testing:  87.99
```

Figure 5.4 Model Selection

Brief Description

We selected the decision tree model to recommend or predict the personalization of fitness. The Decision Tree model for personalized fitness recommendations can enhance user engagement, and satisfaction, and ultimately, improve the effectiveness of fitness programs by providing tailored guidance that aligns with individual preferences and goals.

```
============================================================
Your BMI is:  29.94

Your Lower Limmit is: - 59.94

Your Upper Limmit is:- 80.68

The Standard weight:- 59.94 (kg) - 80.68 (kg)

Average Fat in Your Body is: 26.17%

Your Level is:- Overweight

Your Fitness Goal:- Weight Loss

Your Fitness Type is:- Cardio Fitness

Excercise Recommendation:- Brisk walking, cycling, swimming, running , or dancing.

Equipment Required:- Ellipticals, Indoor Rowers,Treadmills, and Rowing machine

Diet Recommendation:- Vegetables: (Broccoli, Carrots, Spinach, Lettuce, Onion); Protein Intake: (Cheese, Cattoge cheese, Skim M
ilk, Law fat Milk, and Baru Nuts); Juice: (Fruit Juice, Aloe vera juice, Cold-pressed juice, and Watermelon juice)

Conclusion Recommendation:- Follow a regular exercise schedule. Adhere to the exercise and diet plan to get better results. It
is important to approach weight loss in a healthy and balanced way, focusing on exercise and nutrition. Keep in mind that weigh
t loss should be gradual and focused on building lean muscle rather than increasing fat. Additionally, it's always a good idea
to consult with a healthcare professional or registered dietitian before making any significant changes to your exercise or die
t plan. Here are some important tips:- Stay hydrated by drinking enough water throughout the day. Monitor your progress and adj
ust your diet and exercise routine accordingly. Get adequate sleep to support muscle recovery and overall health. Always monito
r your situation, and consult your doctor or a professional counselor. Consistency: Establish a consistent eating and exercise
routine. Consistency is key when it comes to long-term weight management. NOTICE: Opt for whole grains over refined grains for
added fiber.Limit added sugars and opt for natural sources like honey or fruits.
```

Figure 5.5 Testing Decision Tree

Using SMOTEENN To Improve Decision Tree accuracy

```
In [118]: sm = SMOTEENN()
X_dt = df[['sex', 'Age', 'Height', 'Weight', 'hypertension', 'diabetes']].values
y_dt = df[['Level', 'Fitness Goal', 'Fitness Type', 'Exercises', 'Equipment Required', 'Diet', 'Conclusion Recommendation']].valu

# Splitting dataset
xdt_train, xdt_test, ydt_train, ydt_test = train_test_split(X_dt, y_dt, test_size=0.2, random_state=100)

# Setting up and training the MultiOutputClassifier with RandomForest
model_dt_smote = MultiOutputClassifier(DecisionTreeClassifier(random_state=42))
model_dt_smote.fit(xdt_train, ydt_train)

# Prediction
ydt_predict = model_dt_smote.predict(xdt_test)

# Evaluation
model_score_training = model_dt_smote.score(xdt_train, ydt_train)
model_score_testing = model_dt_smote.score(xdt_test, ydt_test)
print("After Model Improved the train is: ", round(model_score_training *100,2))
print("After Model Improved the test is: ", round(model_score_testing *100, 2))
# print(classification_report(yr_test, yr_predict))

After Model Improved the train is:  99.17
After Model Improved the test is:  88.07
```

Figure 5.6 Improving the accuracy of the model we selected by using SMOTEENN

```
# Create the MultiOutputClassifier with DecisionTreeClassifier and use GridSearchCV
grid_search = GridSearchCV(MultiOutputClassifier(DecisionTreeClassifier(random_state=42)),
                           param_grid, cv=5, verbose=1, n_jobs=-1)

# Fit the grid search to the data
grid_search.fit(X_train, y_train)

# Print the best parameters found by the grid search
print("Best Parameters:", grid_search.best_params_)

# Get the best estimator from the grid search
best_dtree = grid_search.best_estimator_

# Evaluate the accuracy on the training and testing sets using the best estimator
print("The Decision Tree Model Accuracy For Training:", round(best_dtree.score(X_train, y_train)*100,2))
print("The Decision Tree Model Accuracy For Testing:", round(best_dtree.score(X_test, y_test)*100,2))
```

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
Best Parameters: {'estimator__criterion': 'gini', 'estimator__max_depth': None, 'estimator__min_samples_leaf': 1, 'estimator__m
in_samples_split': 2}
The Decision Tree Model Accuracy For Training: 99.2
The Decision Tree Model Accuracy For Testing: 89.49
```

Figure 5.7 Improving the accuracy of the selected by using Hyper Parameter Tunning

Brief Description

After employing Hyperparameter Tuning with GridSearchCV, our selected model achieved notable improvements, boasting a training accuracy of 99.2%. On the testing set, the model demonstrated strong generalization with an accuracy of 89.49%, highlighting its enhanced predictive capability and reliability. This underscores the effectiveness of systematic hyperparameter optimization in maximizing model performance and ensuring robustness across unseen data.

5.4 Snapshots of the system

This system has three major components: forntend, backend, and data visualization for each section we will explain it separately and include her pictures

5.4.1 Front-end

The area of web development that focuses on what users view on their end is known as front-end development. It requires transferring the code created by back-end developers into a graphical interface and ensuring that the data is displayed understandably. All you'd see on a website or web application without Front End Development are unreadable scripts. People without coding experience, on the other hand, may quickly understand and use web applications and webpages due to Front-End developers. Everything you see on Google Apps, Canva, Facebook, and other web services is the result of collaboration between back-end and front-end engineers.

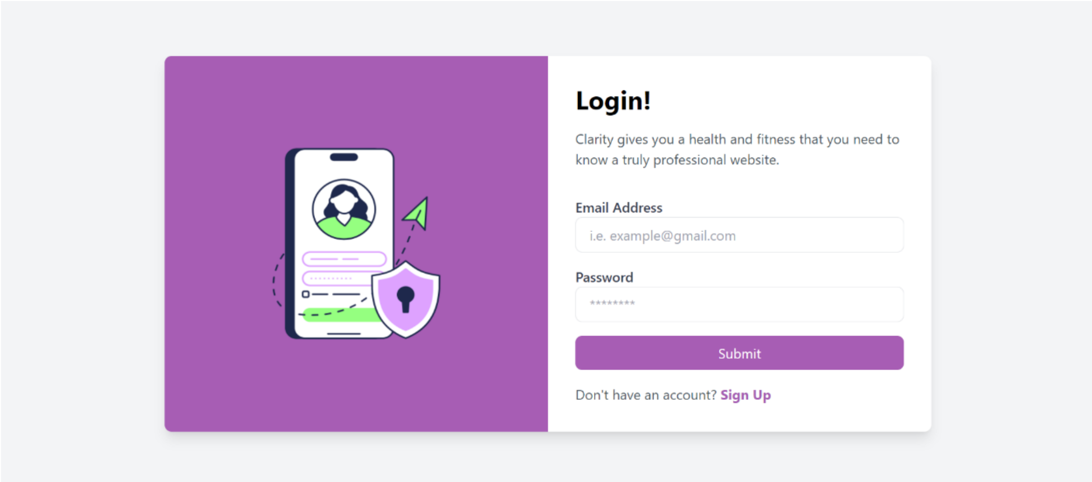


Figure 5.8 Login Page

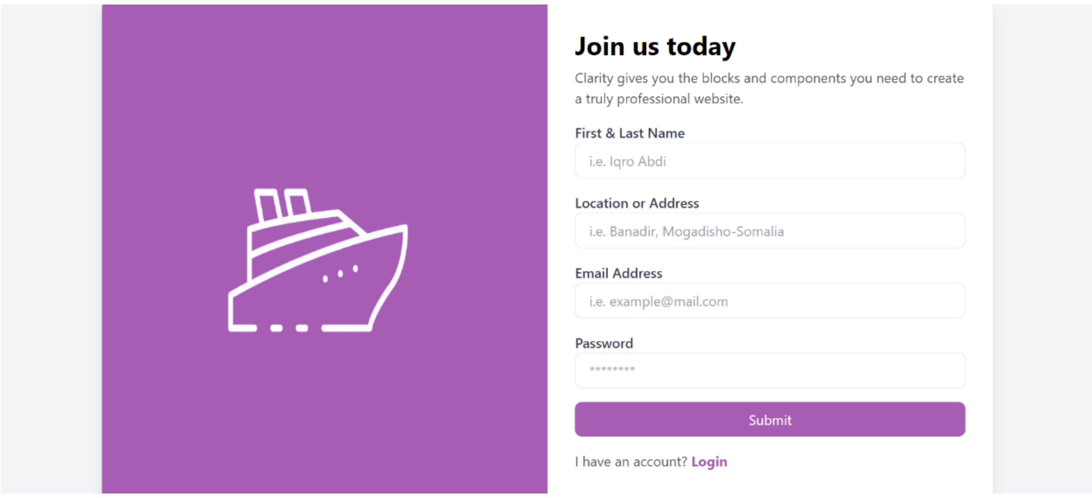


Figure 5.9 Signup Page

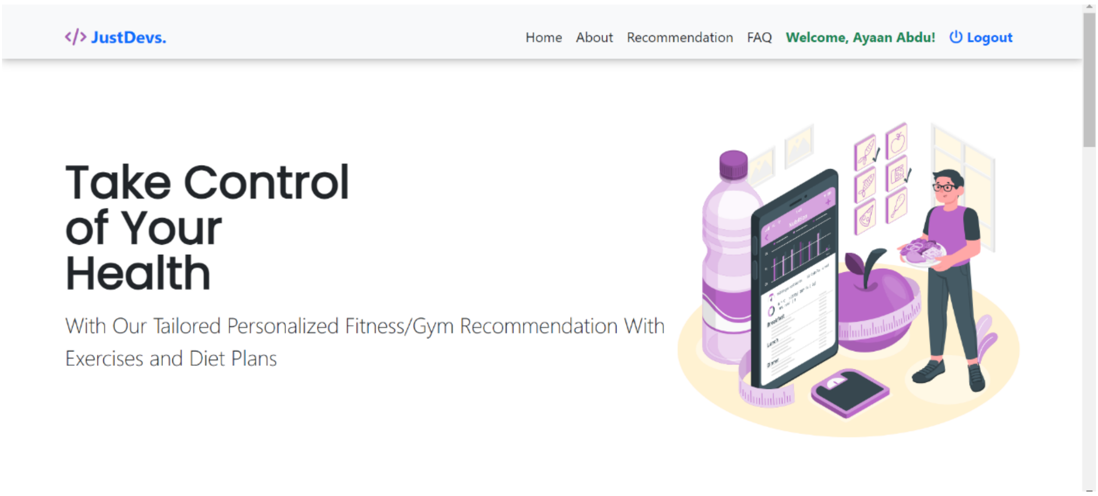


Figure 5.10 Home Page

Brief Description

A home page is the main or initial webpage of a website. It serves as the starting point for visitors to navigate through the site's content. Typically, the home page contains an overview of what the website offers, navigation links to other pages within the site, and possibly some featured or important content. It's often designed to provide easy access to the most relevant information or services offered by the website. Home pages are usually the first page users see when they visit a website, and they often set the tone and provide an impression of the site's purpose and content.

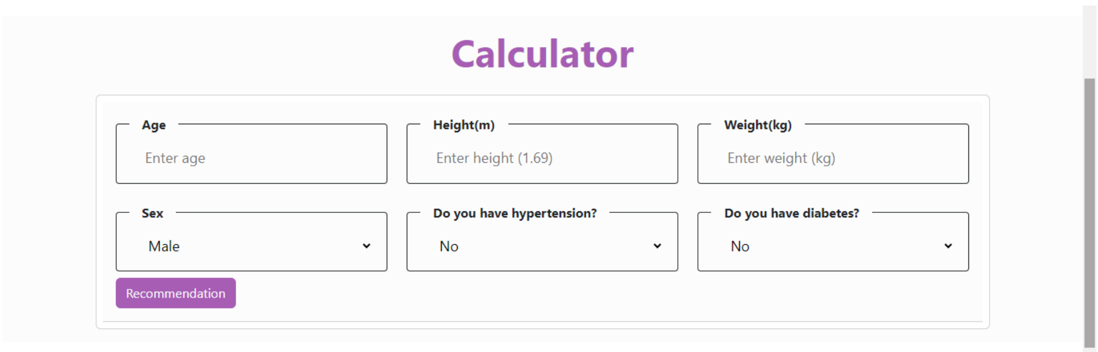


Figure 5.11 User input on Webpage

Brief Description

This figure shows a user interface. This calculator is likely designed for health-related calculations, as it has input fields for age, height (in meters), and weight (in kilograms). Additionally, it includes dropdown menus for selecting sex (with "Male" currently selected), and options to indicate whether the user has hypertension or diabetes, both currently set to "No". There is a "Recommendation" button below these fields, suggesting that the calculator might provide health recommendations based on the inputted data.

Figure 5.12 Recommendation section

Brief Description

This Figure displays results from the user preferences (user inputs) and offers tailored fitness advice. It displays the current name that logged they system, address, and email. It also shows or displays user preferences, and then displays recommendations or predictions. For example, the user's BMI is 17.30, within a normal weight range and body fat percentage. Their goal is weight gain through muscular fitness, with a suggested routine including squats, deadlifts, and presses, using dumbbells and barbells. The recommended diet emphasizes a variety of vegetables, lean proteins, and specific juice concoctions for optimal nutrition. The conclusion advises a balanced focus on both exercise and nutrition for gradual muscle growth and recommends consulting health professionals before making significant lifestyle changes. Options to print or export this information are also available.

5.4.2 Back-end

The back end refers to the sections of the code that allow it to perform but are not visible to the user. The back end of a computer system stores and accesses the majority of data and operational procedures. One or more programming languages are usually used in the code. The back end, often known as the data access layer of software or hardware, contains any functionality that requires digital access and control.

Import Necessary Libraries

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.multioutput import MultiOutputClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.metrics import classification_report
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import mean_squared_error
from sklearn.metrics import accuracy_score
from imblearn.combine import SMOTEENN
```

Figure 5.13 System Imports

Brief Description

This part is the imports section and it is done to import what it needs system. which is used to import necessary libraries and modules into the Python script.

In this Python script, we'll explore various machine learning models for both classification and regression tasks using the scikit-learn library along with some additional tools for data preprocessing and evaluation. We'll utilize techniques such as random forest, decision trees, k-nearest neighbors, and SMOTEENN for handling imbalanced data.

5.4.3 Data Visualization

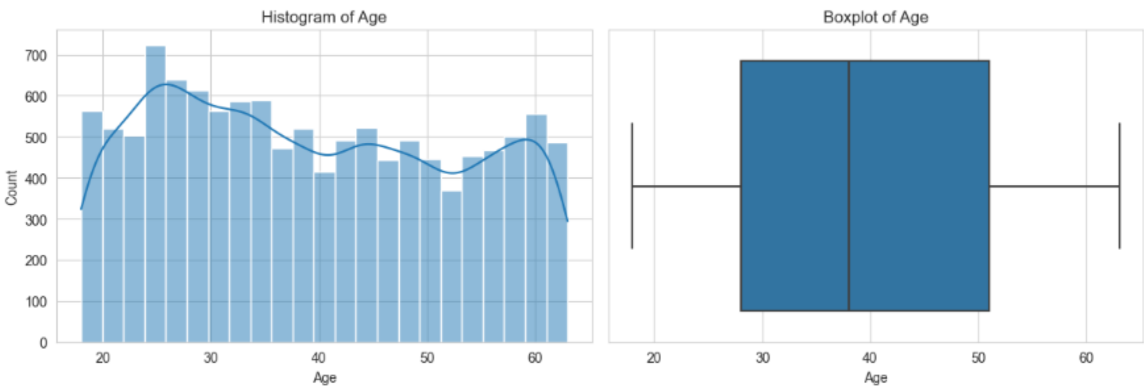


Figure 5.14 Age Distribution

Brief Description

The image contains a Histogram and a Boxplot, both depicting the age distribution in a dataset. The histogram shows a bell-shaped age frequency, suggesting a roughly normal distribution, while the boxplot indicates the median age and the spread of the data without any visible outliers. Both graphs use the same age scale for a consistent comparison of the data.

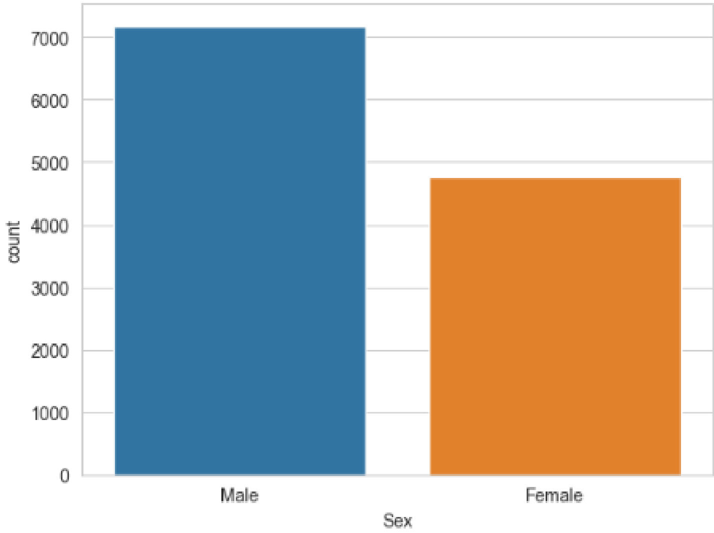


Figure 5.15 Gender Visualization

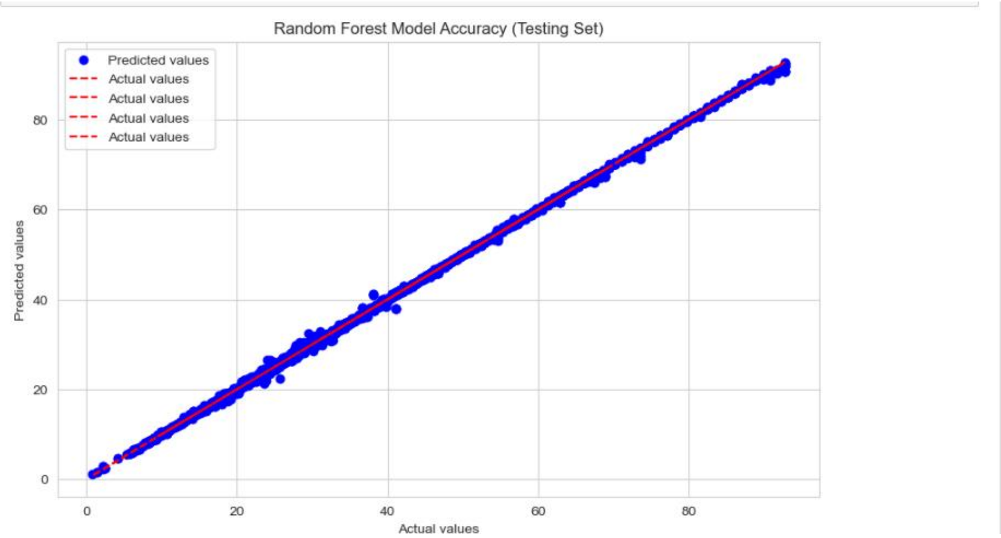


Figure 5.16 Random Forest Model Accuracy

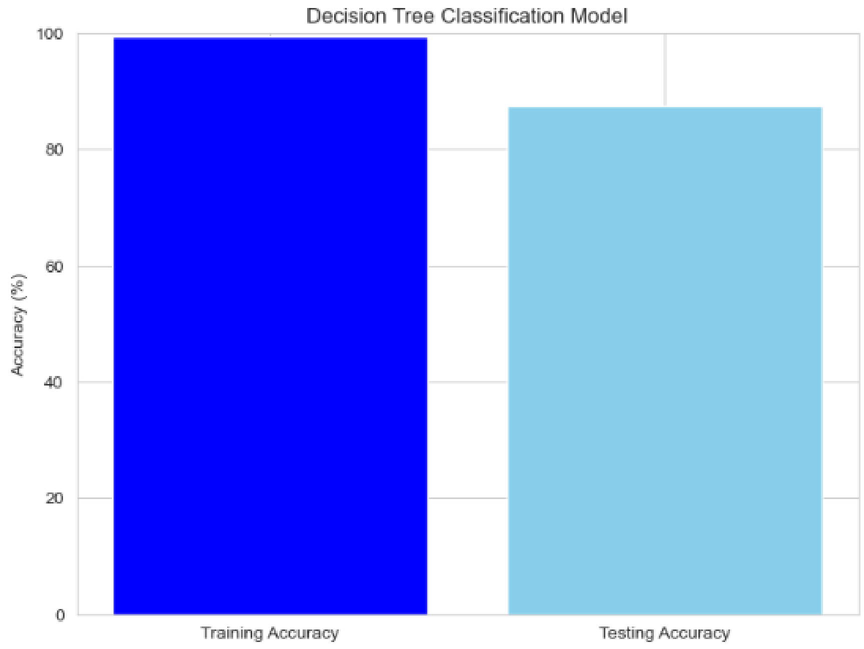


Figure 5.17 Decision tree classification model

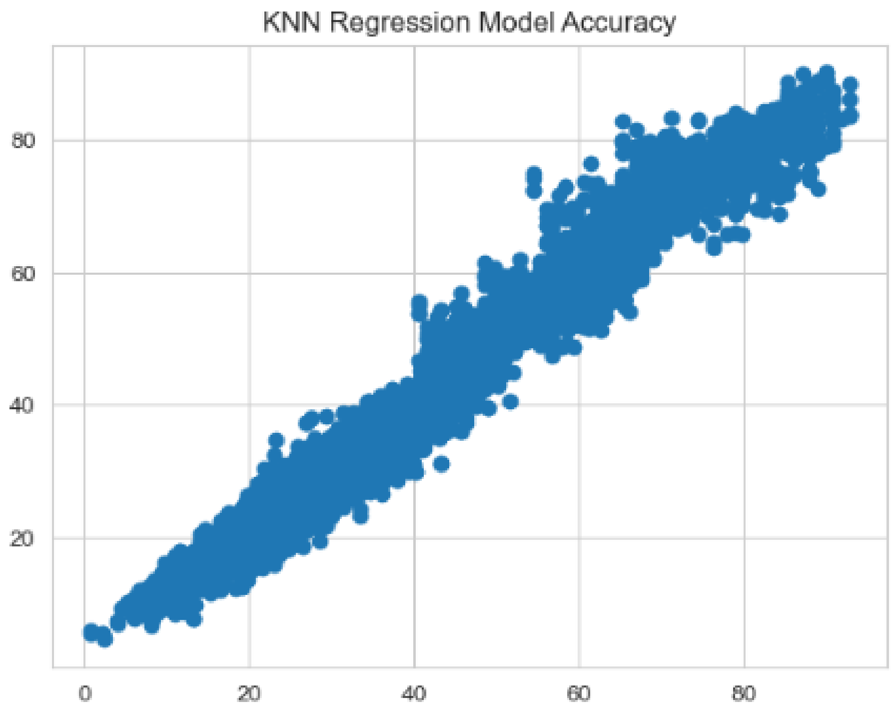


Figure 5.18 KNN regression model

Chapter Six: Discussion & Results

6.1 Discussion

The primary goal of our research is to create an innovative gym recommendation system designed to simplify workout routines by providing tailored fitness programs that cater to the unique needs and fitness levels of both beginners and intermediates. This system will leverage individual health profiles and specific fitness goals to recommend personalized exercise regimens and the necessary equipment, ensuring an optimal training experience. Furthermore, we aim to develop an intuitive and visually appealing user interface, allowing users to seamlessly input their personal information, preferences, and objectives, thus facilitating a more engaging and effective fitness journey.

We have learned from this study that fitness can be recommended using machine learning. We have learned a lot about how the machine works and the algorithms of the machine. One of the main challenges we faced was the collection of the dataset, which we had a lot of trouble with because there was no data to find Somali fitness. The main issue we're facing is that our data seems to be overfitting, even after we remove any outliers and duplicate values.

We have learned a lot about building and doing a project that no one has done before like our language, being the first researcher to do this project, we also achieved the goal we mentioned in the research objectives and related work.

6.2 Key Findings

We achieved our goal of making a system that helps people in the gym by creating a special program. This system is smart because it learns what each person's profile is and what their health conditions are, whether they're just starting or have been going to the gym for a while. It looks at each person's health information and what they want to achieve, and then it suggests the best exercises and the equipment they should use. This way, everyone gets advice that's just right for them, making their time at the gym more effective and more fun.

To make sure everyone could use our system easily, we also made a really simple and nice-looking website where users could tell the system about themselves. This part was made to be super easy for anyone to use, no matter how much they know about technology. So, with our system, people can quickly get into their workouts with exercises that are perfect for them, and they don't have to worry about figuring out all the tech stuff. We're really happy because we managed to do everything, we set out to do, making going to the gym a better experience for everyone.

6.3 Results

In our research, we developed a personalized gym recommendation system using machine learning techniques, evaluating four models including linear regression, random forest, decision tree, and KNN. Among these, the decision tree model for regressions stood out with exceptional accuracy, achieving a perfect score of 100% on the training set and maintaining an impressive 99.91% accuracy on the testing set. Conversely, the decision tree model for categorical variables or text data performed slightly lower but still robustly, with a training accuracy of 99.29% and testing accuracy of 87.99%. These results highlight the significance of considering data nature and feature types in model selection, showcasing the decision tree's effectiveness in capturing complex relationships within the data.

Further optimization through hyperparameter tuning using GridSearchCV led to significant enhancements in our selected model's performance. With a training accuracy of 99.2%, the model exhibited strong generalization on the testing set, achieving an accuracy of 89.49%. This emphasizes the efficacy of systematic hyperparameter optimization in maximizing predictive capability and ensuring reliability across unseen data. Overall, our research underscores the importance of both model selection and optimization techniques in developing robust and accurate machine-learning systems for personalized gym recommendations in today's digital age.

Chapter Seven: Conclusion, Recommendation & Future Work

7.1 Introduction

This section clarifies the research's conclusion after six months of exploration; it describes key points such as the research's conclusion, the achievement of the research objectives that were previously mentioned in chapter one of the research, guidelines, and future work for those who plan to conduct similar work.

7.2 Recommendation

Based on our experience, we suggest further exploration into personalized gym recommendation systems. Our study has focused on leveraging modern technology to provide tailored fitness guidance for individuals. We recommend this as a starting point for future research in the field. In transitioning to this new focus, we recommend two key points for future researchers to consider:

I. The machine learning that we have described above can be updated at any time in the algorithms that we have used. Maybe a lot of algorithms will become more accurate and better in terms of predictions than the ones we used before, so we recommend that if new algorithms are available, they should be used by future researchers.

II. Although this is the first time that this research has been done in Somalia, we suggest that researchers behind us who want to contribute to this research have to create or build a system that tracks gym clients and collects many types of data because fitness data does not exist in our country.

7.3 Future Work

The following directions for further research are suggested for researchers who are interested in conducting out research similar studies:

1. **Personalized Gym Recommendation Systems (PGRS):** Future research will focus on developing personalized gym recommendation systems that enhance fitness advice tailored to individual needs. This will involve integrating machine learning, the Internet of Things (IoT), artificial intelligence (AI), and software engineering.
2. **Integration of Diverse Data Sources:** A key area of future research will be the creation of intelligent systems capable of understanding each person's unique workout requirements. This will involve analyzing a wide range of information, including health metrics, daily habits, and environmental factors.
3. **Real-Time Data Collection:** Research will prioritize connecting additional devices, such as fitness trackers, to facilitate real-time data collection. This data will be leveraged to provide instant workout suggestions, thereby improving the responsiveness and personalization of fitness recommendations.
4. **Natural User Interaction:** Future work will explore the development of systems that interact more naturally with users, offering personalized guidance that emulates human coaching. This research aims to enhance user experience and engagement.
5. **Societal Impact:** Finally, research will examine the broader societal impact of these systems, including their potential to enhance public health. The ultimate goal is to develop gym recommendation systems that are not only personalized and responsive but also ethical and socially beneficial.

7.4 Conclusion

In conclusion, our research aimed to create an innovative gym recommendation system using machine learning, focusing on providing personalized fitness programs for both beginners and intermediates. We encountered challenges, particularly in data collection due to the scarcity of fitness data in Somalia, and faced issues of overfitting despite data preprocessing efforts. However, our study demonstrated the efficacy of decision tree models in achieving high accuracy for personalized gym recommendations. We recommend future exploration into personalized gym recommendation systems, emphasizing the need for updating algorithms and developing systems to collect diverse fitness data. Moving forward, we propose integrating machine learning, IoT, AI, and software engineering to build smarter systems that offer tailored workout suggestions based on individual health, habits, and environment, while prioritizing user privacy and ethical considerations. Ultimately, our goal is to develop gym recommendation systems that are not only personalized and responsive but also ethical and socially beneficial.

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Appendix SERVER

```
from flask import Flask, render_template, request, jsonify, session, redirect, url_for

from joblib import load

import mysql.connector

import re

app = Flask(__name__)

# Load your models

decision_tree_regression_model = load('models/decision_tree_regressor.joblib')

decision_tree_classification_model = load('models/decision_tree_classifier.joblib')

app = Flask(__name__)

app.secret_key = "xtay6UY&"


# MySQL configurations

mysql_config = {

    'host': 'localhost',

    'user': 'root',

    'password': '',

    'database': 'gym_recommendation'

}


@app.route('/')

def index():

    if 'username' in session:

        return render_template('index.html')
```

```
    return redirect(url_for('login'))


@app.route('/login', methods=['GET', 'POST'])
def login():
    if request.method == 'POST':
        email = request.form['email']
        password = request.form['password']

        conn = mysql.connector.connect(**mysql_config)
        cursor = conn.cursor(dictionary=True)
        cursor.execute("SELECT * FROM users WHERE email = %s AND password =
%s", (email, password))
        user = cursor.fetchone()
        cursor.close()
        conn.close()

        if user:
            session['username'] = user['fullName']
            session['email'] = user['email']
            session['address'] = user['address']
            return redirect(url_for('index'))
        else:
            return render_template('login.html', error='Sorry Invalid email or password')
```

```
    return render_template('login.html')


@app.route('/signup', methods=['GET', 'POST'])
def signup():
    if request.method == 'POST':
        name = request.form['fullName']
        address = request.form['address']
        email = request.form['email']
        password = request.form['password']

        # Check if the name is valid
        if not is_valid_name(name):
            return render_template('signup.html', error='Invalid name. Please enter a valid
name.')

        # Check if email already exists
        conn = mysql.connector.connect(**mysql_config)
        cursor = conn.cursor()
        cursor.execute("SELECT * FROM users WHERE email = %s", (email,))
        user = cursor.fetchone()
        if user:
            cursor.close()
            conn.close()
            return render_template('signup.html', error='Sorry!. his email already exists')
```

```
        # Insert user into database
        cursor.execute("INSERT INTO users (fullName, address, email, password)
VALUES (%s, %s, %s, %s)", (name, address,email, password))
        conn.commit()
        cursor.close()
        conn.close()

        # session['username'] = name
        return redirect(url_for('login'))
    return render_template('signup.html')

def is_valid_name(name):
    # Add your validation logic here, for example:
    # Name should contain only alphabets and spaces
    return bool(re.match("^[a-zA-Z ]+$", name))

@app.route('/logout')
def logout():
    session.pop('username', None)
    return redirect(url_for('login'))

@app.route('/predict', methods=['POST'])
def predict():
```

```
    if 'username' not in session:
        return redirect(url_for('login'))
    # Get input values from the form
    features = [float(request.form[feature]) for feature in ['sex', 'Age', 'Height', 'Weight',
'hypertension', 'diabetes']]


    # Make predictions using the models
    bmi_prediction = decision_tree_regression_model.predict([features])[0]
    fitness_recommendation = decision_tree_classification_model.predict([features])[0]
    # Convert NumPy arrays to Python lists
    bmi_prediction_list = bmi_prediction.tolist()
    fitness_recommendation_list = fitness_recommendation.tolist()
    # Check if prediction exists
    if bmi_prediction_list is not None and fitness_recommendation_list is not None:
        # Return prediction results as JSON data
        return jsonify(username = session['username'], email = session['email'], address=
session['address'], bmi_prediction=bmi_prediction_list,
fitness_recommendation=fitness_recommendation_list)
    else:
        # Return error if prediction failed
        return jsonify(error="Prediction failed"), 500
if __name__ == '__main__':
    app.run(debug=True)
```

Appendix B: HOME PAGE

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta http-equiv="X-UA-Compatible" content="IE=edge">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/6.5.1/css/all.min.css">
    <link rel="stylesheet" href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.2/dist/css/bootstrap.min.css">
    <link rel="stylesheet" type="text/css" href="{{ url_for('static',filename='/css/style.css') }}">
    <link href="https://fonts.googleapis.com/css?family=Poppins" rel="stylesheet">
    <title>Personalized Gym Recommendation</title>
    <style>
        details {
            margin-bottom: 1.2em;
            font-size: 20px;
        }
        summary {
            font-weight: bold;
            font-size: 1.2rem;
            cursor: pointer;
        }
```

```
        details[open] summary ~ * {
            animation: fadeIn 0.5s ease-in-out;
        }
        @keyframes fadeIn {
            from { opacity: 0; }
            to { opacity: 1; }
        }
    </style>
</head>

<body>
    <header class="bg-light shadow-md py-3">
        <div class="container">
            <nav class="navbar navbar-expand-lg navbar-dark">
                <div>
                    <a href="#" class="navbar-brand text-primary fw-bold"><i class="fa fa-code"></i> JustDevs<span class="dot">.</span></a>
                </div>
                <button class="navbar-toggler" type="button" data-bs-toggle="collapse" data-bs-target="#navbarNav" aria-controls="navbarNav" aria-expanded="false" aria-label="Toggle navigation">
                    <span class="navbar-toggler-icon p-3 bg-secondary rounded text-light"></span>
                </button>
                <div class="collapse navbar-collapse" id="navbarNav">
```

```
<ul class="navbar-nav ms-auto">
    <li class="nav-item">
        <a class="nav-link text-dark" href="#home">Home</a>
    </li>
    <li class="nav-item">
        <a class="nav-link text-dark" href="#about">About</a>
    </li>
    <li class="nav-item">
        <a class="nav-link text-dark" href="#Calculator">Recommendation</a>
    </li>


     <li class="nav-item">
        <a class="nav-link text-dark" href="#FAQ">FAQ</a>
    </li>
    {% if 'username' in session %}
        <li class="nav-item">
            <a class="nav-link text-success fw-bold" href="#">Welcome, {{ session['username'][0:10] }}!</a>
        </li>
        <li class="nav-item">
            <a class="nav-link text-primary fw-bold" href="{{ url_for('logout') }}"><i class="fa fa-power-off"></i> Logout</a>
        </li>
    {% else %}
```

```
                        <li class="nav-item">
                            <a class="nav-link" href="{{ url_for('login') }}">Login</a>
                        </li>
                    {% endif %}
                </ul>
            </div>
        </nav>
    </div>
</header>


<section id="home">
    <div class="container">
        <div id="home-content">
            <div class="left">
                <h1 class="fw-bold">Take Control of Your Health</h1>
                <p>With Our Tailored Personalized Fitness/Gym Recommendation With
Exercises and Diet Plans</p>
            </div>
            <div class="right">
                <img src="{{ url_for('static', filename='images/img1.svg') }}" alt="">
            </div>
        </div>
    </div>
</section>
```

<section id="about" class="py-5" style="background-color: #FDF8FD;">

<div class="container">

<h2 class="fw-bold p-3 display-6 text-center" style="color: #A75DB4">About Us</h2>

<ul class="fs-5 text-muted">

<li class="mb-4">

Our system, Personalized Gym Recommendation System (PGRS), is a digital platform designed to help people who are new to the gym. By collecting information such as age, height, weight, and any medical conditions like high blood pressure or diabetes, PGRS creates fitness and dietary plans that fit each user's needs. This way, everyone can get advice that matches their personal health and goals.

<li class="mb-4">

We trained four different models to ensure the best recommendations, and we chose the Decision Tree model for both regression and classification tasks. This model helps us analyze user data effectively, providing accurate and personalized fitness plans. With PGRS, newcomers to the gym can feel confident and supported as they start their fitness journey.

<li class="mb-4">

Our team consists of four dedicated members who are passionate about health and fitness. Each of us brings a unique set of skills to the table, including expertise in data analysis, machine learning, and other skills. Together, we work hard to make sure PGRS provides the best possible recommendations for our users. Our combined efforts ensure that everyone can achieve their fitness goals in a safe and effective manner.


```
            </ul>
        </div>
    </section>

    <section id="Calculator">
        <div class="container-fluid" style="background-color: #fcfcfc;">
            <div class="container">
                <h2 class="fw-bold p-3 display-6 text-center" style="color: #A75DB4">Calculator</h2>
                <div class="row">
                    <div class="col-12">
                        <div class="card p-2 mb-3">
                            <div class="card-header" style="background-color: #fcfcfc;">
                                <form id="form">
                                    <div class="row">
                                        <div class="col-sm-4 mt-2">
                                            <fieldset class="border border-1 border-dark rounded-1 px-3 py-2">
                                                <legend class="float-none w-auto px-3 text-dark fw-bold fs-6">Age</legend>
                                                <input type="number" name="Age" id="age" placeholder="Enter age">
                                            </fieldset>
                                        </div>
                                        <div class="col-sm-4 mt-2">
```

```
<fieldset class="border border-1 border-dark rounded-1 px-3 py-2">
    <legend class="float-none w-auto px-3 text-dark fw-bold fs-6">Height(m)</legend>
    <input type="number" name="Height" step="any" id="height" placeholder="Enter height (1.69)">
</fieldset>
</div>
<div class="col-sm-4 mt-2">
<fieldset class="border border-1 border-dark rounded-1 px-3 py-2">
    <legend class="float-none w-auto px-3 text-dark fw-bold fs-6">Weight(kg)</legend>
    <input type="number" name="Weight" step="any" id="weight" placeholder="Enter weight (kg)">
</fieldset>
</div>
<div class="col-sm-4 mt-4">
<fieldset class="border border-1 border-dark rounded-1 px-3 py-2">
    <legend class="float-none w-auto px-3 text-dark fw-bold fs-6">Sex</legend>
    <select name="sex" id="sex">
        <option value="1">Male</option>
        <option value="0">Female</option>
    </select>
```

```
          </fieldset>
        </div>
        <div class="col-sm-4 mt-4">
          <fieldset class="border border-1 border-dark rounded-1 px-3
py-2">
            <legend class="float-none w-auto px-3 text-dark fw-bold
fs-6">Do you have hypertension?</legend>
            <select name="hypertension" id="hypertension">
              <option value="0">No</option>
              <option value="1">Yes</option>
            </select>
          </fieldset>
        </div>
        <div class="col-sm-4 mt-4">
          <fieldset class="border border-1 border-dark rounded-1 px-3
py-2">
            <legend class="float-none w-auto px-3 text-dark fw-bold
fs-6">Do you have diabetes?</legend>
            <select name="diabetes" id="diabetes">
              <option value="0">No</option>
              <option value="1">Yes</option>
            </select>
          </fieldset>
        </div>
        <div class="mt-2 mb-2">
```

```
                                        <button class="btn text-light" type="submit" id="btnRecommend" style="background-color: #A75DB4">Recommendation</button>
                                    </div>
                                </div>
                            </form>
                        </div>
                    </div>
                </div>
            </div>
        </div>
    </div>
</section>
 <section id="result" class="mt-4 text-2xl font-bold">
</section>


<section id="FAQ" class="py-5">
    <div class="container">
        <h2 class="fw-bold p-3 display-6 text-center" style="color: #A75DB4">Frequently Asked Questions</h2>
        <div id="faqAccordion">
            <details>
                <summary>What is Personalized Gym Recommendation System (PGRS)?</summary>
```

<p>PGRS is a digital platform designed to provide personalized fitness and dietary plans based on individual user data such as age, height, weight, and medical conditions.</p>

</details>

<details>

<summary>How does PGRS collect user data?</summary>

<p>PGRS collects user data through a form where users input their age, height, weight, sex, and any medical conditions such as hypertension or diabetes.</p>

</details>

<details>

<summary>How does PGRS use the collected data?</summary>

<p>PGRS uses the collected data to create tailored fitness and dietary plans. The Decision Tree model is used for analyzing the data to provide accurate and personalized recommendations.</p>

</details>

<details>

<summary>Who can benefit from PGRS?</summary>

<p>PGRS is designed for people who are new to the gym and need personalized advice on fitness and diet plans based on their health data and goals.</p>

</details>

<details>

<summary>Is my data secure with PGRS?</summary>

<p>Yes, PGRS takes user privacy seriously and implements robust security measures to ensure that all collected data is kept secure and confidential.</p>

</details>

</div>

```
        </div>
    </section>
  <script src="https://code.jquery.com/jquery-3.7.1.min.js" integrity="sha256-/JqT3SQfawRcv/BIHPThkBvs0OEvtFFmqPF/lYI/Cxo=" crossorigin="anonymous"></script>
    <script src="https://cdn.jsdelivr.net/npm/sweetalert2@11"></script>
    <script src= {{ url_for("static",filename="js/main.js") }} ></script>
    <script>
        document.addEventListener("DOMContentLoaded", function() {
            const details = document.querySelectorAll("details");
            details.forEach(detail => {
                detail.addEventListener("click", () => {
                    details.forEach(d => {
                        if (d !== detail) {
                            d.removeAttribute("open");
                        }
                    });
                });
            });
        });
    </script>
</body>
</html>
```