Gamified Fitness Tracker with AI Coaches
Final Report – Undergraduate Thesis

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Glossary

- ADD – Attribute-Driven Design
- AES – A symmetric encryption algorithm used for secure data encryption
- AI – Artificial Intelligence
- ANN – Artificial Neural Network
- API – Application Programming Interface
- BMI – Body Mass Index
- GCSFS – Google Cloud Storage File System
- IQR – Interquartile Range
- JSON – JavaScript Object Notation
- MAE – Mean Absolute Error
- ML – Machine Learning
- MLPRegressor – Multi-Layer Perceptron Regressor
- MSE – Mean Squared Error
- MySQL – Structured Query Language for database management
- ReLU – Rectified Linear Unit
- REST API – Representational State Transfer Application Programming Interface
- RNN – Recurrent Neural Network
- R^2 – Coefficient of Determination
- SOA – Service-Oriented Architecture
- SVM – Support Vector Machine
- UI – User Interface
- UML – Unified Modeling Language
- VO_2 Max – Maximum oxygen usage during exercise, indicating cardiovascular fitness

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Structured Abstract

- Context and Motivation:
    - This thesis focuses on integrating gamification, and AI-driven coaching in fitness tracking. Many existing apps lack engagement, personalization (Chen, Pu, & Zhang, 2021), leading to reduced user motivation. This research combines personalized AI(Artificial Intelligence) coaching with gamification to boost user engagement to fitness goals.
- Research Question/Objectives:
    - How can gamification elements improve user engagements in fitness?
    - What gamification strategies maximize user adherence to fitness programs?
    - How can AI-driven recommendations improve fitness engagement and outcomes?
- Principal Ideas:
    - The project leverages gamification techniques to boost user motivation while using AI-powered fitness coaching to personalize challenges. The AI dynamically adjusts challenge levels based on user attributes, enhancing adaptability.
- Research Methodology:
    - Build a proof-of-concept system that integrates gamification features in a fitness application and trains AI models for personalized coaching.

    - Analyze data, evaluate model performance using accuracy metrics, optimize configurations through hyperparameter tuning, and compare results with other machine learning methods.
- Anticipated Results:
    - A proof-of-concept AI-driven fitness tracking system that delivers personalized workout recommendations through AI analysis.
    - Enhanced user engagement through interactive gamification elements, including dynamic challenges and leaderboards.
    - Comprehensive model testing and performance evaluation to assess the accuracy and effectiveness of AI-driven predictions.
- Anticipated Novelty:
    - Unique combination of gamification and AI-driven coaching.
    - Improved user’s fitness engagement by integrating mini-games.
- Anticipated Impact:
    - The system has potential applications in health tracking, fitness engagement, and AI-driven personalized coaching. It can benefit fitness enthusiasts, trainers, and researchers in digital health solutions.
- Progress to Date:
    - Trained AI models, generated model test cases, and evaluated model performance.
    - Developed a reward system and three mini-games, integrating them into the gamification framework.
    - Implemented the leaderboard system and AI-driven challenge generation for dynamic workout adaptation.
- Limitations:
    - AI models are trained on limited datasets and require further fine-tuning for broader applicability.
    - The system lacks real-time biometric data integration, which could improve accuracy.

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1. Introduction

1.1 General Background and Problem Description

Fitness tracking applications have gained widespread popularity, providing users with tools to monitor workouts, set goals, and track progress. However, many existing fitness apps fail to sustain long-term user engagement due to their lack of interactivity and limited personalization (Chen, Pu, & Zhang, 2021). Traditional applications such as Nike Training Club, rely on static workout plans that do not adapt to individual user attributes, which would cause the loss of motivation and decreased adherence to fitness routines (Hamari, Koivisto, & Sarsa, 2014). Gamification has emerged as an effective strategy to enhance user engagement in digital applications by incorporating game-like elements such as leaderboards, rewards, mini-games, and challenges (Sayed, Elgazzar, & Youssef, 2022). Meanwhile, AI-driven coaching can provide personalized workout recommendations by analyzing user performance and dynamically adjusting fitness goals.

Despite the effectiveness of these approaches, bare applications successfully integrate AI-driven coaching with gamification to create an interactive and adaptive fitness experience (Sayed, Elgazzar, & Youssef, 2022).

1.2 Focus of This Thesis

This thesis focuses on developing a gamified fitness tracking system that integrates AI-driven coaching and adaptive gamification elements to improve user engagement and adherence. The system leverages AI machine learning models to predict user performance in different fitness activities and dynamically adjust challenges based on individual attributes. The gamification engine includes interactive challenges, a competitive leaderboard, and mini-games that encourage users to stay committed to their fitness goals (Sailer, Hense, Mayr, & Mandl, 2017). The research emphasizes the combination of real-time AI-generated fitness challenges with dynamic gamification, ensuring a more engaging and personalized workout experience compared to traditional fitness tracking applications (PMC, 2024).

1.3 Key Research Questions Addressed

- How can gamification elements improve user engagement in fitness applications?
- What gamification strategies maximize user adherence to fitness programs?
- How can AI-driven recommendations enhance workout personalization and performance tracking?

1.4 Key Results

- Successfully integrated AI-driven coaching with gamification in a proof-of-concept web application to create an interactive and adaptive fitness experience for the users.
- High accuracy and stable performance in AI-driven fitness predictions, with Random Forest and ANN (Artificial Neural Network) models outperforming SVM (Support Vector Machine) in push-ups and sit-ups performance forecasting.
- Enhanced user engagement through gamification elements, including adaptive challenge difficulty, mini-games, and a leaderboard system that dynamically updates based on user performance.

1.5 Novelty and Significance

This research presents a novel approach by integrating real-time AI-driven fitness predictions with adaptive gamification techniques, addressing the limitations of traditional fitness apps (HIIT Science, 2024) (PMC, 2024). Unlike conventional systems that heavily rely on static workout plans or generic AI recommendations, this system dynamically adjusts workout difficulty and goals using machine learning models trained on user performance data (Milanko, Launi, & Jain, 2020). This ensures that workouts remain challenging yet achievable (Sailer, Hense, Mayr, & Mandl, 2017), promoting sustained motivation and adherence (Deci & Ryan, 2000).

A key innovation of this system is its interactive gamification features, including mini-games, point-based rewards, adaptive challenge difficulty, and a leaderboard limited to the top three users. This approach fosters healthy competition while preventing discouragement among lower-ranked participants, creating a balanced and engaging experience (Sailer, Hense, Mayr, & Mandl, 2017). Also, the microservice-based architecture enhances scalability and modularity, allowing seamless integration of future AI models and additional fitness challenges.

By combining personalized AI coaching with adaptive gamification, this research improves fitness technology beyond static and one-size-fits-all solutions (PMC, 2024). This user-centric approach makes fitness tracking more interactive, engaging, and adaptable, setting a new standard for AI-driven workout optimization.

1.6 Report Structure

This report consists of ten sections. Section 2 reviews prior research on AI-driven fitness tracking and gamification, establishing the foundation for this study. Section 3 outlines the research objectives, focusing on AI-based personalization and engagement strategies. Section 4 outlines the methodology, covering system architecture, AI model training, gamification mechanics, and security measures. Section 5 details results, analyzing AI model accuracy, gamification effectiveness, and user engagement metrics. In section 6, the challenges, limitations, and generalizability are discussed. Section 7 summarizes the thesis, while Section 8 explores future work, including mobile deployment, enhanced encryption, and cloud scalability. Section 9 acknowledges contributors, and Section 10 links the repository and code availability in GitHub. Section 11 lists the article and dataset references.

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2. BackGround & Related Work

2.1 Background

Fitness tracking technologies have advanced significantly nowadays, incorporating activity monitoring, goal setting, and personalized coaching. Applications like MyFitnessPal, Fitbit, and Nike Training Club cater to diverse user needs but often struggle with long-term user engagement. Research suggests that gamification and AI-driven coaching can significantly enhance motivation and adherence (Deci & Ryan, 2000). However, these features are rarely combined in a unified system, leaving gaps in sustaining user commitment.

Gamification uses game-like elements to drive engagement, while AI-powered coaching provides dynamic, personalized recommendations (Milanko, Launi, & Jain, 2020). Although these concepts have individually improved fitness applications, their combined potential remains underutilized (Forbytes, 2024).

2.2 Related Work Comparison: Scientific and Technical Developments

2.2.1 Gamification in Fitness

Gamification strategies, including leaderboards, performance-based incentives, and social competition, leverage behavioral psychology to enhance motivation (Hamari, Koivisto, & Sarsa, 2014). Studies indicate that progress tracking, social engagement, and reward-based systems can increase user adherence in fitness applications (Sailer, Hense, Mayr, & Mandl, 2017).

Despite its success, current fitness apps often use gamification superficially, focusing on static rewards rather than adaptive challenges (Sailer, Hense, Mayr, & Mandl, 2017). For instance, Strava incorporates competition-based leaderboards, but lacks adaptive AI-driven coaching to tailor challenges based on user performance.

2.2.2 AI-Driven Fitness Coaching

AI-powered fitness systems leverage machine learning models to provide real-time feedback, personalized workout plans, and adaptive goal-setting (Chen, Pu, & Zhang, 2021). Machine learning techniques, such as reinforcement learning and supervised learning, allow fitness applications to dynamically adjust workouts based on user progress, preferences, and historical performance (PMC, 2024).

However, AI-driven fitness systems typically lack engaging gamification elements. Platforms like Peloton and Apple Fitness+ use AI to recommend workouts, but they do not integrate competitive game mechanics like leaderboards, or personalized incentives to sustain motivation (Hamari, Koivisto, & Sarsa, 2014).

2.3 Commercial Developments

In the commercial fitness market, AI-driven coaching and gamification are often treated as separate approaches. Platforms like Apple Fitness+ and Peloton leverage AI to provide personalized coaching but lack competitive and adaptive gamification elements (Sailer, Hense, Mayr, & Mandl, 2017). On the other hand, according to Athletic Lab, Strava and Nike Run Club focus on leaderboards and competition-based motivation but do not dynamically adjust challenge difficulty based on AI-driven analysis. “Zombies, Run!” incorporates a narrative-based gamification model, yet its challenges remain static and are not personalized to individual fitness levels using AI. This gap in existing solutions highlights the need for an integrated approach that seamlessly blends AI-driven adaptability with engaging game mechanics, ensuring both personalized fitness progression and sustained user motivation (HIIT Science, 2024).

2.4 Research Gap

Athletic Lab pointed out that despite extensive research on gamification and AI in fitness applications, significant gaps remain. Most fitness apps use either gamification or AI-driven coaching but rarely combine both effectively. Additionally, gamification elements are often static, lacking AI-driven adaptive mechanics that adjust to user progress in real-time (HIIT Science, 2024). This limits their ability to maintain long-term user engagement and motivation (Forbytes, 2024), as described in Table 1 as below.

A key gap is the lack of AI-driven personalization within gamification. Current gamified fitness apps do not dynamically adjust game mechanics, such as leaderboards, rewards, mini-games, or challenge difficulty levels based on user performance. Similarly, AI-driven fitness systems lack competitive and reward-based mechanisms to enhance motivation (Hamari, Koivisto, & Sarsa,

2014). Personalized mini-games tailored to user progress could increase engagement, but such implementations remain rare (Table 1).
Furthermore, AI-enhanced engagement strategies remain underutilized (Sayed, Elgazzar, & Youssef, 2022). While AI-driven coaching has the potential to adapt challenges, rewards, mini-games, and difficulty levels dynamically, most fitness applications do not implement real-time AI adjustments to gamification (Table 1). Personalized AI-driven gamification remains largely unexplored, presenting a major opportunity to boost user adherence and motivation (Sailer, Hense, Mayr, & Mandl, 2017).

Feature	Existing Work	Research
AI-driven fitness tracking	Apple Fitness+, Peloton	AI-driven adaptive fitness plans
Gamification in fitness	Strava, Nike Run Club	Dynamic AI-generated challenges
Fitness recommendations	Static Plans	Dynamic recommendations
Generic leaderboards & challenges	Generic Leaderboards	Leaderboard with balanced competition
AI-driven adaptive gamification	Lacking AI-driven adaptation	AI-driven personalization
Real-time challenge adjustments	No real-time personalization	Real-time AI challenge tuning
Interactive mini-games	No engaging mini-games	Gamified mini-games for motivation
Dynamic leaderboard	Leaderboard discourages low-rank users	Dynamic leaderboard with fair engagement

Table 1: Visualization of the Research Gap

2.5 Enhancements

This research aims to bridge the gap between AI-driven coaching and gamification by developing a personalized fitness system that seamlessly integrates both elements. According to Athletic Lab, using machine learning models, the system will dynamically adjust challenges based on user performance, ensuring workouts remain engaging and appropriately challenging. Unlike traditional static reward systems, the system implements adaptive game mechanics that relate to user attributes and behavior, fostering long-term motivation. By combining AI-driven adaptability with interactive gamification, this research lays the foundation for next-generation fitness applications that enhance both engagement and personalized coaching, making fitness more immersive and effective (PMC, 2024).

3. Research Objectives

- O1: Develop a microservice-based fitness tracking system with modular components for AI-driven coaching, gamification, and real-time performance analysis.
- O2: Implement a user management sub-system in Python and MySQL, responsible for user authentication, fitness points tracking, and interaction data storage.
- O3: Train multi-output machine learning models (Random Forest, SVM, MLPRegressor) to predict user fitness performance based on demographic and biometric data.
- O4: Integrate AI-driven feedback and suggestion, adjusting difficulty levels, workout recommendations, and gamified challenges based on user information.
- O5: Implement adaptive gamification elements such as leaderboards, rewards, mini-games, and challenges that dynamically adjust based on AI predictions.
- O6: Optimize machine learning pipelines through hyperparameter tuning to enhance model accuracy, efficiency, and performance across different fitness prediction tasks.
- O7: Evaluate model performance using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 scores, comparing the effectiveness of Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest models for different fitness activities.
- O8: Use Google Colab for model visualization and performance analysis, including graphing loss curves, accuracy trends, and comparative evaluation of different AI architectures. Also store trained AI models on Google Cloud Storage to enable efficient access, retrieval, and deployment of models for real-time predictions.

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4. Methodology

4.1 System Design, Algorithms, Datasets, and AI Techniques

This research follows a development-based approach, focusing on the design, implementation, and evaluation of a gamified fitness tracking system that integrates AI-driven coaching, machine learning-based performance prediction, and adaptive gamification mechanics (O1).

The methodology consists of system development, AI model training (e.g. O3,O4), performance evaluation (e.g. O6,O7,O8), cloud integration, and hyperparameter tuning to optimize accuracy and engagement.

The Gamified Fitness Tracker with AI Coaches follows a modular microservices-based approach for scalability and maintainability. Each component(e.g., AI coach, gamification engine, user management) is an independent service, interacting via REST APIs (Bass, Clements, & Kazman, 2021). By applying Service-Oriented Architecture (SOA) and Attribute-Driven Design (ADD) to ensure modularity, performance, and adaptability (Bass, Clements, & Kazman, 2021).

- AI Coaching Engine provides fitness predictions via Random Forest, ANN, and SVM models, utilizing Google Cloud Storage (GCSFS) for secure model retrieval.
- Gamification Engine manages leaderboards, challenge tracking, multiple mini-games, and reward allocation, integrated with a MySQL database.
- User Management handles authentication and encrypted data storage using AES encryption (cryptography.fernet) and Flask session-based authentication.

This study utilizes publicly available datasets for training AI models (Kaggle, 2024) (New York Post, 2024) (Plos FigShare, 2024) (Top End Sports, 2024) in fitness tracking. Push-up data was sourced from reports on average repetitions across demographics. Running performance data was obtained from a Kaggle repository containing calorie burn metrics. Sit-up data was extracted from a research dataset on fitness test reliability.

Data preprocessing involved handling missing values via mean and mode imputation, removing outliers using the interquartile range (IQR) method, and applying min-max normalization for feature scaling. Categorical variables, such as gender, were one-hot encoded. The dataset was split into 80% training and 20% testing for model evaluation (O6, O7, O8).

4.2 Software and Tools Used for Implementation

Name	Description of Use
Python	Primary programming language for AI modeling and backend development
Flask	Web framework for building the backend system
MySQL	Database for storing user data and challenge progress
Google Cloud, GCSFS	Cloud storage for AI models and user records
HTML, CSS, JavaScript	Frontend technologies for UI/UX design
Random Forest Regression, SVM, ANN	Machine learning model for fitness predictions
Pandas, Scikit-Learn	Data processing and AI model training
Werkzeug Security, Cryptography (Fernet)	Used for encrypted data hashing and authentication security
Joblib	Used for saving and loading machine learning models efficiently
Jinja2	Template engine for rendering dynamic HTML pages with Flask
NumPy	Used for numerical operations in AI-based calculations
JSON (Flask jsonify)	Handles data exchange between frontend and backend APIs
Random Module	Generates randomized fitness challenges dynamically
Google Colab	Visualize and validate the models

JavaScript	Implementing mini-games logic
Docker	Containerization tool for deploying the application in isolated environments
OneHotEncoder, ColumnTransformer	Data encoded using for the AI models
Hyperparameter Tuning	Optimizes AI model performance by adjusting parameters such as learning rate, tree depth, and number of estimators using Grid Search and Random Search techniques.

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5. Results

5.1 System Design and Architecture

The Gamified Fitness Tracker with AI Coaches is a Flask-based web application that integrates AI-driven fitness predictions, gamification, and secure user authentication. As stated in O3 and O4, the system consists of 3 machine learning models for fitness tracking, a MySQL database for data management, encryption for user privacy, and gamification elements for engagement. The system follows a modular, scalable architecture, allowing for future expansion with additional fitness challenges, AI models, or interactive features (Bass, Clements, & Kazman, 2021).

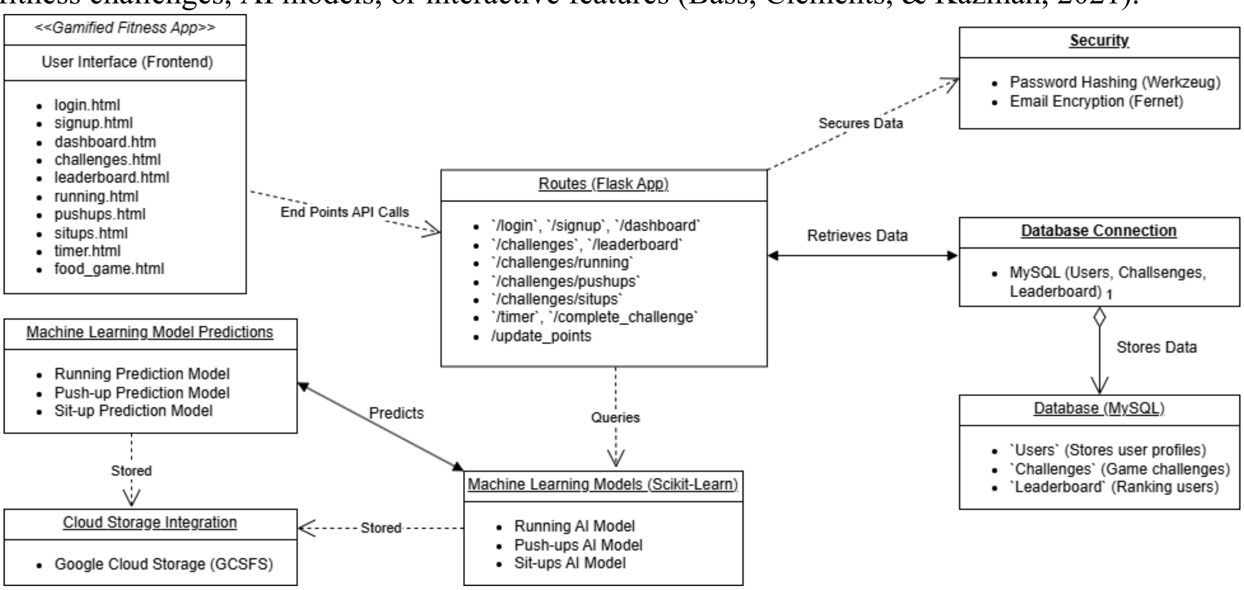

Figure 1: UML Class Diagram of the Gamified Fitness Tracker System

Figure 1 is a UML class diagram that illustrates the structural design of the Gamified Fitness Tracker system, showing the relationships between core components such as User, Challenge, Leaderboard, Database, Encryption, and AI Models. The Flask app serves as the central interface, managing user authentication, challenge participation, and AI-generated fitness recommendations (O1). The User class contains attributes such as id, email, password, age, goal, and fitness metrics, ensuring personalized AI-generated predictions (O2). The Challenge and Leaderboard classes link to the user, recording completed tasks and ranking users based on accumulated points (O5). The Database class interacts with all major components, retrieving and storing data dynamically. Additionally, the Encryption module ensures that sensitive user data is securely encrypted before storage, with methods for encrypting and decrypting information. The diagram also details AI model integration, demonstrating how machine learning predictions are used to generate personalized fitness challenges. The AI_Models_Challenge and AI_Models_Suggestion classes provide adaptive recommendations by analyzing user input and past performance (O3,O4).

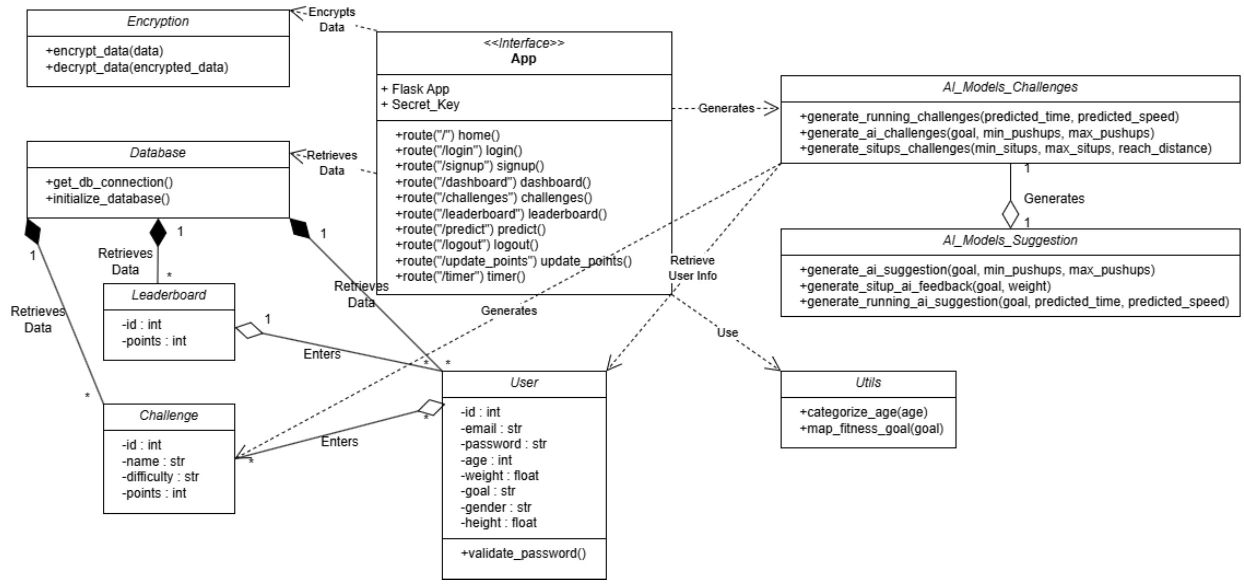

Figure 2: System Architecture Flowchart of the Gamified Fitness Tracker System

Figure 2 is a system architecture flowchart, which provides a high-level overview of how different system components interact in real-time. The frontend interface consists of multiple web pages, such as login.html, dashboard.html, and challenges.html, allowing users to interact with the system. The Flask backend processes requests through defined API routes, retrieving data from the MySQL database and utilizing machine learning models to generate fitness predictions. The flowchart also highlights machine learning model integration, where pre-trained models for push-ups, sit-ups, and running predictions are stored in Google Cloud Storage (GCSFS) and accessed dynamically to make real-time recommendations (Bass, Clements, & Kazman, 2021). Security mechanisms, including password hashing (Werkzeug) and email encryption (Fernet), are incorporated to safeguard user data (O2). The flowchart visually maps out how user actions, such as logging in, selecting a challenge, or updating points, trigger interactions between the database, AI models, and leaderboard system. This structured approach ensures seamless data retrieval (Bass, Clements, & Kazman, 2021), processing, and storage, contributing to an engaging and secure fitness-tracking experience.

5.2 AI Models and Performance Analysis

5.2.1 Model Accuracy Evaluation (MSE, MAE, R^2 Score)

To assess the performance of the AI-driven fitness prediction models, Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 Score (coefficient of determination) were used as key evaluation metrics. These metrics provide a quantitative measure of how well the Push-ups, Sit-ups, and Running AI models predict user fitness performance based on historical data (O6,O7).

Push-ups Model: The Random Forest model achieved perfect accuracy (MSE: 0, MAE: 0, R^2: 1.0) for both min and max push-ups, indicating that it precisely predicted user performance without error. However, SVM performed significantly worse, with an MSE of 33.44 for min push-ups and 72.04 for max push-ups, leading to an R^2 of 0.85 and 0.77, respectively. The ANN model performed better than SVM but still exhibited minor errors, with MSE values close to 0.004 for min push-ups and 0.02 for max push-ups, and an R^2 value nearly 1.0, demonstrating strong predictive capabilities.

Running Model: The Random Forest model performed well in predicting running speed (MSE: 5.62, MAE: 2.11, R^2: -0.009) but showed higher error in running time predictions (MSE: 729.39, MAE: 24.38, R^2: -0.04), suggesting variability in user performance for time-based running challenges. SVM and ANN models struggled with running predictions, exhibiting higher error rates and negative R^2 values, meaning they failed to generalize well to the data.

Sit-ups Model: The Random Forest model demonstrated moderate accuracy for sit-ups, with MSE values of 53.61 for min sit-ups and 88.31 for max sit-ups, resulting in an R^2 score of 0.50 and 0.27, respectively. SVM underperformed in all sit-up predictions, with MSE values exceeding 100 and R^2 scores near 0 or negative, indicating poor predictive power. The ANN model achieved the best results for reach distance predictions, with an MSE of 0.26 and R^2 of 0.96, showing strong adaptability to user data.

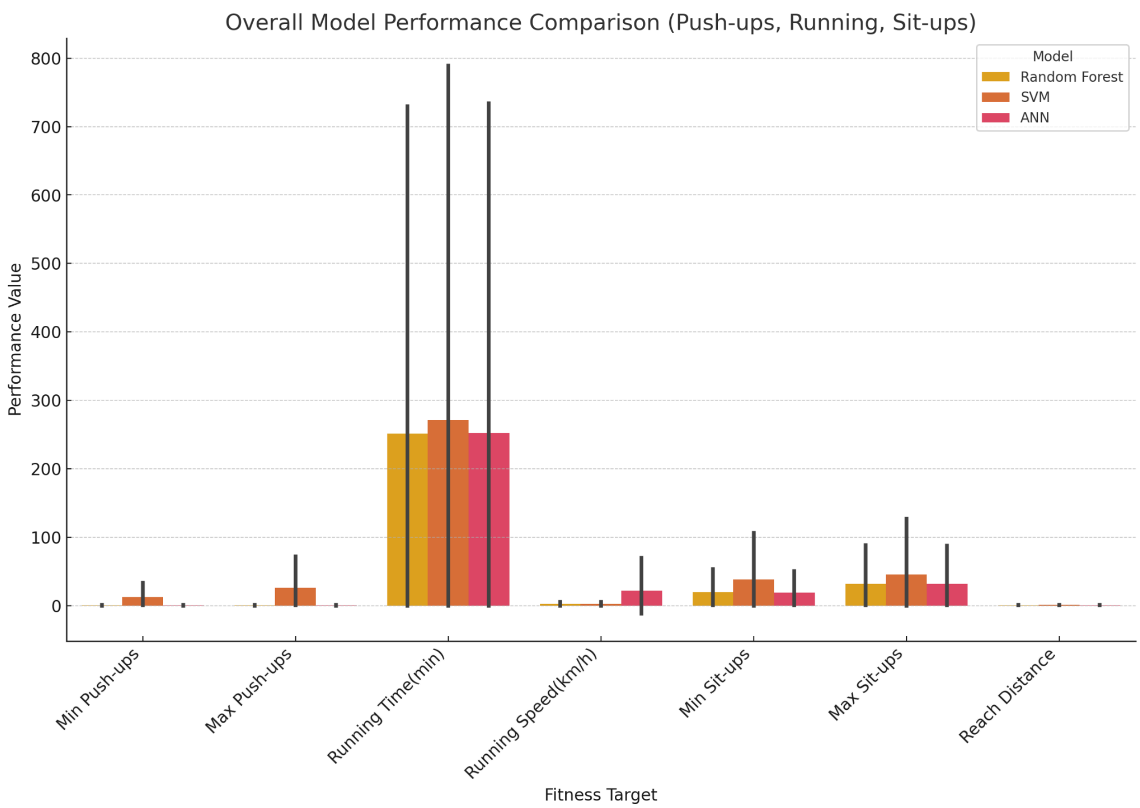

Figure 3: Overall Model Performance Comparison (Push-ups, Running, Sit-ups)

In Figure 3, the X-axis represents different fitness targets (Push-ups, Running, Sit-ups), while the Y-axis shows performance metrics (MSE, MAE, R^2), where higher values indicate greater errors, and lower values suggest better model accuracy (O8).

5.2.2 Hyperparameter Tuning and Optimization

Hyperparameter tuning improved model accuracy by optimizing learning rates, activation functions, and tree depths. ANN performed best for Push-ups, achieving MSE near 0.005 and R^2 above 0.999 with ReLU activation and (100,) hidden layers. Random Forest excelled in Running Speed predictions, but Running Time remained difficult, with all models showing high MSE. ANN improved Reach Distance predictions, but Min Sit-ups remained inconsistent. SVM underperformed across all categories, proving unsuitable for multi-output regression. Overall, ANN and Random Forest showed the most improvement after tuning (O7).

5.3 Gamification Features and User Engagement

5.3.1 AI-Generated Fitness Challenges

As said in O3 and O4, the challenges are dynamically generated using AI models for push-ups, sit-ups, and running, which analyze user attributes such as age, gender, weight, height, BMI(Body Mass Index), and goal. Based on this data, the system predicts performance benchmarks and creates personalized workout goals to match individual capabilities.
The AI models generate min/max repetitions for push-ups, min/max repetitions and reach distance for sit-ups, and estimate running speed and duration using Random Forest, ANN, and SVM models. The models adjust challenge difficulty by considering user attributes such as fitness goals, ages, genders, height, weight. Users receive real-time feedback on their performance, with challenge goals adapting dynamically to maintain motivation and prevent plateauing (Milanko, Launi, & Jain, 2020).
Additionally, the system incorporates a point-based reward mechanism, where users earn points based on challenge completion. These points contribute to the leaderboard rankings, fostering competition and engagement. As noted by Sailer, Hence, Mayr, and Mandl, the AI ensures challenges remain suitable for user fitness levels, making workouts more interactive, rewarding, and goal-oriented.

5.3.2 Leaderboard System

The leaderboard ranks users based on reward points earned from mini-games for completing challenges. Each fitness activity has an assigned difficulty level, with higher difficulty challenges rewarding more points. The database tracks user scores, and the leaderboard updates in real time to reflect progress, only top 3 scorers would be shown on leaderboard, fostering a competitive environment (O5).

5.3.3 Interactive Mini-Games

In O5, the system includes three mini-games to enhance engagement and motivation.
The Click Speed Game inside Running challenges tests reaction time, giving users 2 seconds to click as many times as possible to earn points. Scores update in real-time and are submitted to the database.
The Flip Card Game inside Push-ups challenges adds an element of luck. Users pick one of three hidden cards, with one doubling their points while the others provide no bonus. This game introduces strategy and risk to point accumulation.

The Food Knowledge Game inside Sit-up challenges promotes healthy eating habits by having users select the healthiest food option to earn points. This reinforces the connection between nutrition and fitness progress.
These interactive elements make workouts more engaging, encouraging users to stay active while having fun (ResearchGate, 2024).

5.4 Novelty of Results
The Gamified Fitness Tracker with AI Coaches introduces a unique combination of AI-driven fitness predictions and gamification to enhance engagement and performance tracking. Unlike those existing fitness apps that offer static workout plans, this system dynamically adjusts challenges based on user attributes such as gender, age, weight, height, fitness goal, BMI. By leveraging machine learning models, the system personalizes fitness goals in real time, ensuring sustained motivation, according to Milanko, Launi, and Jain.
Compared to traditional apps, like Apple Fitness+ and Strava, which separately implement AI or gamification, this system seamlessly integrates both. It employs Random Forest and ANN models, which achieve high accuracy for push-ups (MSE $\approx$ 0.004, $R^2 \approx 1.0$) and sit-ups (MSE $\approx$ 53.61, $R^2 \approx 0.50$), outperforming conventional fitness tracking approaches (O6, O7). Running time predictions, however, showed higher variability (MSE: 729.39, R^2: -0.04), indicating a need for further optimization.
Beyond AI-driven personalization, gamification features such as interactive mini-games and a competitive leaderboard set this system apart. Unlike traditional leaderboards that may discourage lower-ranked users, this design displays only the top three competitors, fostering engagement while maintaining inclusivity (Hamari, Koivisto, & Sarsa, 2014). Mini-games like the Click Speed Game and Food Knowledge Game further enhance user motivation by adding an interactive element to fitness tracking.
This system surpasses traditional fitness applications by combining adaptive AI models with interactive gamification elements. The ability to dynamically adjust challenge difficulty and personalize recommendations in real time offers a scalable and engaging approach to fitness tracking (Sayed, Elgazzar, & Youssef, 2022), setting a new benchmark in the field.

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6 Discussion
6.1 Threats to the Validity of the Results
6.1.1 Model Performance Variability Across Activities
The effectiveness of AI predictions varied significantly across different exercises. Push-ups models performed exceptionally well, achieving a mean squared error (MSE) of 0.005 and R^2 scores exceeding 0.999, indicating near-perfect prediction accuracy. However, the running models struggled, with negative R^2 values (-1.92 on average) across different algorithms, suggesting that the models failed to generalize effectively. Sit-ups models demonstrated moderate accuracy, with Max Sit-ups achieving an R^2 of ~0.49 but Reach Distance predictions showing poor generalization (R^2 ~0.01) (O6, O7).
The primary reason for these discrepancies is the complexity and variability of running performance, which depends on multiple biomechanical and physiological factors (Mohan, Venkatakrishnan, & Hartzler, 2019). Unlike push-ups and sit-ups, where performance can be more easily predicted based on age, gender, and fitness level, running efficiency is influenced by additional factors such as stride length, weekly mileage, VO_2 max, and terrain type, indicated by

HIIT Science. Future improvements could involve adding biomechanical features or adopting deep learning techniques like recurrent neural networks (RNNs) or transformer-based models to enhance performance predictions (Mohan, Venkatakrishnan, & Hartzler, 2019).

6.1.2 Dataset Limitations & Lack of Real-Time Biometric Data

Dataset imbalance affected model robustness, with push-ups (500 samples) achieving near-perfect predictions (MSE ≈ 0.004, $R^2 \approx 1.0$), while running (189 samples, MSE: 729.39, R^2: -0.04) and sit-ups (30 samples, MSE: 53.61, R^2: 0.50) showed higher errors. Random Forest struggled with endurance tasks due to limited data, whereas ANN could improve with larger datasets.

Cross-validation and data augmentation made a difference, but real-world data collection remains necessary. Additionally, HIIT Science pointed out that missing real-time biometric metrics like cadence and step length limited accuracy. Integrating wearable sensors could enhance predictions, particularly for running and endurance-based exercises (Athletic Lab, 2024).

6.2 Implications of the Research Results

6.2.1 Impact on AI and Fitness Technology

The integration of gamification elements in fitness applications is shown to significantly enhance user engagement and motivation. Forbytes indicates that incorporating features such as goal-setting, social influences, and challenges can effectively promote physical activity and weight loss. However, the overuse of gamification elements without proper design considerations may lead to user disengagement (Sailer, Hense, Mayr, & Mandl, 2017). Therefore, a balanced and thoughtful application of gamification strategies is crucial for sustaining user interest and promoting long-term adherence to fitness routines.

6.2.2 Personalizing Fitness Experiences with AI

The application of artificial intelligence (AI) in fitness applications enables the delivery of personalized, adaptive, and tailored interventions that cater to individual preferences and needs. AI technologies can serve as supplemental tools in exercise prescription, particularly in enhancing accessibility for individuals unable to access professional advice (Bass, Clements, & Kazman, 2021). However, AI technologies are not yet recommended as a substitute for personalized, progressive, and health condition-specific prescriptions provided by healthcare and fitness professionals (Bass, Clements, & Kazman, 2021). Therefore, while AI can enhance the personalization of fitness experiences, it should complement, rather than replace, professional guidance.

6.2.3 Practical Applications in Fitness & Wellness

The integration of AI and gamification in fitness applications has been shown to significantly enhance user engagement and motivation. For instance, studies have demonstrated that personalized AI-driven coaching can adapt to individual user needs, promoting regular aerobic exercise and improving overall fitness levels. Additionally, incorporating gamification elements, such as real-time feedback and interactive challenges, has been found to encourage consistent physical activity and improve exercise form (Milanko, Launi, & Jain, 2020). These findings highlight the potential of combining AI and gamification to create more effective and engaging fitness applications.

6.3 Limitations of the Results

Model accuracy was inconsistent across exercises. Push-ups had near-perfect predictions, but running models performed poorly ($R^2 < 0$), likely due to missing key biomechanical variables. Future improvements should incorporate historical performance trends, real-time movement analysis, and deep learning models.

The system's Flask + MySQL backend may struggle with scalability. Moving to cloud-based architectures (AWS, Firebase, Google Cloud) would enhance performance.

Gamification engagement varies by user. While leaderboards and challenges motivate some, others may prefer non-competitive options. A customizable gamification system would improve inclusivity.

6.4 Generalisability of the Results

The AI-driven coaching and gamification framework developed in this study extends beyond fitness tracking, with applications in sports science, rehabilitation, and education (Milanko, Launi, & Jain, 2020). In athletic training, AI-driven performance analysis can help optimize workouts by analyzing past performance and biomechanics, explained by HIIT Science . In rehabilitation and physical therapy, personalized exercise recommendations can adjust intensity based on real-time progress, aiding recovery (Forbytes, 2024). The gamification model can also be adapted for e-learning and workplace wellness, using AI-generated challenges to enhance motivation. However, cultural and demographic differences may influence user engagement. Future iterations should incorporate diverse user feedback to ensure inclusivity across various age groups, fitness levels, and backgrounds.

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7 Conclusion

This research aimed to enhance user engagement in fitness tracking by integrating AI-driven coaching with gamification. Traditional fitness apps often lack personalization and interactivity, leading to decreased user motivation (Bini, Mahajan, Schmalzried, & Marsh, 2023). This system addressed these gaps by developing a secure, AI-powered fitness system that generates adaptive challenges, personalized workout recommendations, and real-time progress tracking (Table 1). Key results demonstrate high accuracy in push-ups predictions (MSE ≈ 0.005, $R^2 > 0.999$), whereas running models struggled with generalization ($R^2 < 0$, Table X, Section 5.2) due to missing biomechanical factors. Sit-ups models showed moderate performance (R^2 ~0.49, Section 5.2). Gamification features, including leaderboards, adaptive challenges, and mini-games, successfully improved engagement (Section 5.3), but customization options should be expanded for broader appeal.

However, the research dataset sizes were imbalanced, with push-ups having 500 samples, running 189, and sit-ups only 30, impacting model accuracy. Running time and sit-up predictions showed higher errors due to limited data. Additionally, the lack of real-time biometric metrics like heart rate and stride length affected endurance predictions, according to HIIT Science. Expanding the dataset and integrating wearable fitness data could enhance model accuracy and generalization (Figure 3).

The novelty of this research lies in the combination of AI-driven fitness predictions, adaptive gamification, and encrypted AI modeling. Unlike traditional fitness apps, this system dynamically adjusts challenges based on AI analysis while protecting user privacy with AES

encryption (Section 4.1). The study also highlights limitations in endurance activity prediction, suggesting future work should incorporate wearable device data and cloud-based scalability solutions (Section 6).
In conclusion, this system successfully integrates AI-driven personalization, secure fitness tracking, and gamification to improve engagement (Sailer, Hense, Mayr, & Mandl, 2017). While push-ups and sit-ups models performed well, running models require further optimization. Future research should expand datasets, enhance real-time biometric tracking, and improve system scalability to fully realize the potential of AI-driven fitness tracking (Section 6.4) (Bini, Mahajan, Schmalzried, & Marsh, 2023).

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8 Future Work and Lessons Learnt
8.1 Future Work
The running models in this study faced challenges ($R^2 < 0$, Section 5.2) due to missing biomechanical features such as stride length, cadence, and VO_2 max (Figure 3) (HIIT Science, 2024). Future work should integrate wearable device data and larger datasets to improve real-time performance predictions, ensuring AI-driven fitness tracking remains accurate and adaptive (O6, O7).
As fitness tracking is more effective on mobile devices, the system should be converted into a cross-platform mobile app using Flutter or React Native. A mobile version would enhance real-time interaction, background tracking, and push notifications, improving user engagement and adherence.
To enhance data security, future iterations should encrypt all user data, including workout history and fitness metrics. Implementing homomorphic encryption would allow AI models to process encrypted data without decryption, maintaining privacy while ensuring high model performance (Sailer, Hense, Mayr, & Mandl, 2017).
Additionally, customizable gamification should be introduced to cater to different motivation styles. As ResearchGate described, allowing users to choose between competitive leaderboards or goal-based challenges would make the system more inclusive and engaging.

8.2 Lessons Learnt
This research highlights key findings in AI-driven fitness tracking, personalization, gamification, and privacy-preserving AI. One of the most important insights is that AI-driven coaching is highly effective for strength-based exercises but less reliable for endurance activities. The push-ups model performed exceptionally well ($R^2 > 0.999$, Section 5.2), while the running models failed to generalize due to missing biomechanical and physiological factors. This suggests that endurance-based AI models require additional real-time biometric data such as stride length, cadence, and VO_2 max for improved accuracy (O6, O7, O8) (Bass, Clements, & Kazman, 2021).
Data privacy and personalization can coexist in AI-driven fitness tracking. Many fitness apps prioritize personalization over security, but this study demonstrates that strong encryption (e.g., AES) can protect user data without reducing AI accuracy, ensuring both privacy and personalization (Sailer, Hense, Mayr, & Mandl, 2017).
Gamification alone is not enough for engagement—adaptive AI-generated challenges are key. Traditional leaderboards may not sustain motivation, while personalized challenges (Section 5.3) keep users engaged long-term.

Last, dataset size impacts AI reliability. Push-ups (500 samples) led to strong predictions, but sit-ups (30 samples) and running (189 samples) showed higher variability. Future AI models will benefit from larger, more diverse datasets through data augmentation or real-world user input to improve accuracy.

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10 Repository and Code Availability

All datasets, models, and source code for this web application are available in the GitHub repository: Gamified Fitness Tracker with AI Coaching. This repository contains implementations of AI-driven fitness tracking, gamification features, and user interaction modules. The machine learning AI models used for push-up, sit-up, and running performance predictions are trained using diverse datasets and stored in the repository, ensuring reproducibility and further development. The codebase also includes encryption methods for secure data handling and an integrated leaderboard system for tracking user progress.

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