

CHAPTER I

INTRODUCTION

1.1. Introduction

Body transformation and overall health concerns remain a significant global health issue. A study by N. L. binti Ramzee and colleagues, which analyzed global health trends, indicates that an unhealthy diet and a sedentary lifestyle contribute to premature death from non-communicable diseases, which accounts for roughly 71% of all deaths globally, every year. [1]. For individuals seeking improvements for their physical well-being, this combination of inadequate diet and exercise practices presents many challenges.

The development of effective diet and exercise recommendation systems faces significant implementation challenges that limit their practicality. Many existing fitness applications rely on overly simplistic algorithms or lack scientific validation, resulting in generic recommendations that fail to account for user-specific goals and characteristics [2]. Traditional recommendation approaches, often relying on rule-based systems, frequently fail to account for individual preferences, fitness levels, or health conditions, leading to suboptimal outcomes. For instance, these systems cannot effectively differentiate between distinct fitness objectives such as fat loss, muscle gain, or maintenance phases. This oversight can be detrimental, as users aiming for weight loss may inadvertently be recommended exercises better suited for muscle gain, increasing their risk of injury and delaying progress [3].

Many commercial fitness recommendation applications lack a robust evidence-based foundation, often relying on marketing-driven content rather than peer-reviewed scientific literature. The scientific validity and reliability of these applications are difficult to determine due to a limited number of studies, and the quality of commercial apps has been found to be low-to-moderate [4]. The few systems that attempt algorithmic recommendations typically use simple linear models or basic decision trees [3]. The difficulty in assessing the accuracy and reliability of fitness recommendation systems is compounded by a lack of research into what drives autonomous and persistent fitness behaviors [5].

Machine learning approaches offer promising solutions for implementing

robust recommendation systems. XGBoost has demonstrated superior performance in classification tasks across various domains due to its ability to handle complex features and provide interpretable results [6]. However, its application to fitness recommendation systems remains underexplored, particularly for classifying users into evidence-based diet and exercise templates based on their individual characteristics.

This thesis addresses the critical implementation challenges in diet and physical exercise recommendation systems by developing a scientifically grounded XGBoost-based classification framework. The research systematically compiles evidence-based physical exercise and diet templates from peer-reviewed sources and authoritative health organizations, then implements an optimized XGBoost classifier to assign users appropriate templates based on their individual characteristics and stated goals. By focusing on classification performance optimization and systematic validation against established benchmarks, this approach provides a foundation for reliable, scientifically grounded fitness recommendation systems that can be effectively deployed in real-world applications.

1.2. Problem Statement

Based on the research background that has been presented, this research identifies several main problems that need to be studied further. Current fitness recommendation systems face several critical limitations that this research aims to address:

- 1 What evidence-based parameters define optimal physical exercise and diet templates for fat loss, muscle gain, and maintenance goals?
- 2 How do classification performance metrics for XGBoost compare to other machine learning models and baseline methods when assigning fitness templates?
- 3 How can the effectiveness and user-friendliness of a fitness recommendation website application be evaluated?

1.3. Objectives

This study aims to accomplish the following objectives:

- 1 To identify and compile evidence-based parameters that define optimal physical exercise and diet templates for fat loss, muscle gain, and maintenance goals through systematic review of authoritative literature sources.
- 2 To evaluate and compare the classification performance of XGBoost against other relevant machine learning models and baseline methods, using appropriate metrics.
- 3 To evaluate the effectiveness and user-friendliness of the fitness recommendation website application through collection of user satisfaction data and assessment of user engagement.

1.4. Scope and Limitations

The research will focus on a few points such as:

- 1 The system classifies users into pre-designed templates (rather than generating dynamic or fully customized plans), based on fitness goals, activity levels, and BMI categories, therefore the model relies on template classification, not continuous output prediction or real-time personalization. The template database is compiled from evidence-based sources and scientific literature, ensuring that recommendations align with current best practices in exercise and diet science.
- 2 The system is intended for an average healthy adult (19 - 65 years of age) and will be limited to the three specified fitness goals without addressing specialized needs and diets (for example, chronic illnesses, sport-specific training, and specificity for vegetarian meals).
- 3 The current system is not intended for clinical or professional use, however can be developed as such.
- 4 The model's performance may be limited by the size and demographic diversity of the training data.

1.5. Research Methods

This research employs systematic, multi-phase methodology incorporating:

1. Literature Review Phase: Comprehensive systematic review of fitness science, sports nutrition research, and AI recommendation systems, focusing on evidence-based parameter identification and template development from authoritative sources.
2. Algorithm Development Phase: Implementation and optimization of XGBoost classification models, including hyperparameter tuning, feature engineering, and comparative analysis against baseline methods and alternative machine learning approaches.
3. Validation and Evaluation Phase: Systematic performance evaluation using cross-validation, holdout testing, and user experience assessment through controlled testing protocols and user satisfaction surveys.
4. Implementation Phase: Development of web-based application interface and systematic evaluation of system effectiveness, user engagement, and recommendation accuracy in real-world deployment scenarios.