Sleeping Disorder in Bangladeshi Female Cricketers: A Machine Learning Perspective

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APPROVAL

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This thesis titled on "**Sleeping Disorder in Bangladeshi Female Cricketers: A Machine Learning Perspective**", submitted by **Shamiha Afrin Oushi (ID:213-35-778)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Daffodil International University or any other institution.

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DEDICATION

I dedicate this research work to my family and my teacher.

ABSTRACT

The Sleep quality really matters when it comes to how athletes perform and recover. Sports science pays a lot of attention to this. The study here looks at sleep in Bangladeshi female cricketers. It uses machine learning to predict sleep results and figure out what affects them. Data came from 146 athletes. Features included age, years of experience, how intense their practice was, BMI, and indicators of sleep behavior. The Athlete Sleep Behavior Questionnaire gave a continuous sleep score. That was the main target for prediction. Preprocessing happened first. Things like mean imputation and feature engineering. Then exploratory analysis showed some clear patterns. Experience, practice level, and age all strongly shaped sleep quality. Athletes who had more experience and ramped up their practice tended to sleep better overall. Four machine learning models got tested. Linear Regression, Random Forest, XGBoost, and Artificial Neural Networks, or ANN. Random Forest did okay with an RMSE of 4.35 on the test data. It pointed to training intensity and experience as the big predictors. But the ANN model came out on top. Its RMSE was just 0.47. Age turned out to be the top factor there. Experience and practice level followed close behind. Sensitivity analysis backed this up. It confirmed age as the main driver. This lines up with what evidence suggests. Structured training and getting older seem to help with better recovery and sleep. The research highlights why tracking sleep patterns in athletes is so key. It also shows how machine learning can dig into what determines sleep quality. Findings point to ways to improve things. Optimizing training schedules and pushing sleep hygiene might boost performance and health. Future studies could bring in wearable tech and bigger datasets. That would allow for more accurate, real-time predictions of sleep.

Keywords: Sleep quality, Sleep disorders, Athlete Sleep Behavior Questionnaire (ASBQ), Bangladeshi female cricketers, Machine learning, Artificial Neural Network (ANN), Random Forest, XGBoost, Linear Regression, Regression models, Feature importance, Training management, Exploratory Data Analysis (EDA).

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- No symbols listed in this document

LIST OF ABBREVIATIONS

ASBQ	Athlete Sleep Behaviour Questionnaire
ANN	Artificial Neural Network
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
R^2	Coefficient of Determination
EDA	Exploratory Data Analysis
SHAP	SHapley Additive exPlanations
RFE	Recursive Feature Elimination
ML	Machine Learning
RF	Random Forest
BMI	Body Mass Index
XGBoost	Extreme Gradient Boosting (full form not written, but implied)
SBPWM	Simple Boost Pulse Width Modulation
ZSI	Z source inverter

CHAPTER 1

INTRODUCTION

1.1 Background Study

Sleep is a critical element of both physical and mental health, particularly for athletes, where it plays a pivotal role in performance, recovery, and overall well-being. For athletes, poor sleep quality is linked to reduced athletic performance, increased injury rates, and impaired cognitive function. [3] Sleep disturbances are particularly common among elite athletes, but this issue is often less studied in female athletes, especially in developing countries like Bangladesh, where female cricketers face unique physiological, psychological, and sociocultural stressors. These factors contribute to disrupted sleep patterns, impacting recovery and performance [5]. While sleep disorders in athletes are well-documented, sleep disorders in female cricketers in countries like Bangladesh remain an under-researched area, leaving a significant gap in the understanding of how gender-specific factors, cultural pressures, and training intensity contribute to sleep challenges in this population.

Essentially, this research is all about figuring out the sleep problems that female cricketers in Bangladesh deal with. The main goal is to find out how common these issues are and what's causing them. We're using a bunch of data—like their age, how long they've been playing, how intense their training is, their BMI, and their everyday sleep habits—to predict who's at risk for a sleep disorder. This is all being done with machine learning, which is a fancy way of saying we're using a computer program to find patterns in the data and make predictions. It's a big deal because these athletes have so much on their plate. They're not just training; they're often balancing school and family responsibilities, too. This kind of busy, high-pressure lifestyle can lead to bad habits like using phones late at night, drinking too much caffeine, or having a messed-up sleep schedule. When you combine those poor sleep habits with the stress of playing for your country, it's a recipe for sleep problems that can really hurt their performance on the field. [8].

Quality sleep plays a vital role for athletes, going beyond mere rest to support recovery and peak performance. Evidence indicates that adequate rest aids muscle repair, consolidates learning in the brain, and maintains hormonal equilibrium. Such processes prove essential for sustained health and reducing injury risks [27]. Insufficient sleep, however, impairs athletic performance significantly. Studies show it leads to delayed reaction times, diminished coordination, and elevated injury susceptibility [15]. Despite this awareness, athletes frequently struggle to obtain sufficient rest. Factors such as demanding competition calendars, frequent travel, performance-related stress, and early training sessions often interfere [18]. Female athletes face additional complexities in achieving restorative sleep. Hormonal fluctuations, menstrual cycles, and societal pressures may exacerbate these difficulties [24]. This holds especially for female cricketers in Bangladesh, where inadequate training infrastructure, scarce mental health resources, and cultural demands converge to disturb sleep quality [1].

Athletes often deal with sleep issues, and one go-to tool for spotting and fixing those is the Athlete Sleep Behaviour Questionnaire, or ASBQ. Basically, it has 18 items that dig into things like every day sleep habits, the surroundings where someone sleeps, and those sport-related hurdles that mess with rest. Studies show this questionnaire holds up well in terms of reliability, and it gives useful info that helps shape custom plans to boost sleep quality for athletes [23]. Now, tools like the ASBQ do a solid job. But they have downsides, especially in places short on resources or know-how. That's where machine learning steps in as a promising option. Recent progress here means experts can predict sleep problems or spot them early, pulling from all sorts of data sources. Think mixing in body signals, daily behaviours, and results from something like the ASBQ. These models pick up on hidden patterns that might slip by otherwise. Actually, methods including Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) have worked well already in predicting stuff like insomnia or sleep Apnea [10].

Studies on sleep issues among female cricketers in Bangladesh often point to a mix of factors, you know, like cultural pressures and intense training schedules. This work draws on machine learning techniques to forecast those disorders. Evidence indicates that pulling together details from the Athlete Sleep Behaviour Questionnaire, or ASBQ, along with basics such as a player's age, years in the game, and training intensity, allows for a solid data-driven method. Basically, it sharpens the predictions and opens doors to tailored strategies aimed at boosting sleep quality. Oh and, the findings here might offer real value, not only for Bangladeshi athletes but as a kind of blueprint for women in sports elsewhere facing those same social hurdles [2].

Using machine learning to forecast sleep problems in athletes marks a solid advance in grasping their recovery demands. Studies like this one highlight how blending physical metrics with mental health factors can shape smarter training and rest plans [29]. Looking ahead, more work might build on this by pulling in info from wearables and body sensors. Keeping tabs on sleep rhythms, heart rate shifts, and everyday movements could lead to sharper evaluations. Oh, and that would help craft custom fixes to boost athlete’s rest in real ways.

1.2 Problem Statement

Even with all the focus on athlete wellbeing, sleep problems are still very common, especially for female athletes. While sleep is crucial for physical recovery, clear thinking, and mental health, many athletes particularly those in high intensity sports find it hard to get enough quality sleep. This is often because of things like tough training schedules, psychological stress, frequent travel, and physiological differences. This issue is even more challenging for female cricketers in Bangladesh. Unique cultural and social factors, limited access to specialized medical care, and a lack of organized sleep strategies all contribute to a situation that makes it difficult for them to get the rest they need [3][4].

Studies point to a pretty obvious shortfall in the research on sleep issues for women cricketers. This shows up especially in places like Bangladesh. Sure, folks know about the sleep troubles athletes deal with in general. But digging into how tough training, cultural stuff, and things unique to women affect sleep for South Asian female players. Well, that kind of focused work is still pretty scarce. Oh and those old-school surveys. They just don't cut it most of the time. You get these quick glimpses, nothing deep or right-now enough to really build solid evidence. For spotting and forecasting sleep glitches in athletes, anyway.

Research points to a key gap here. Good predictive models for sleep disorders among Bangladeshi female cricketers just do not exist yet. This study aims to address that by applying machine learning methods, such as Random Forest, XGBoost, and Artificial Neural Networks. Evidence suggests these approaches could work well for sorting through various influences, from physical health markers to behavioural patterns and training routines. The idea is to forecast which athletes might face higher risks of sleep issues. In the end, a data-driven framework like this could shed light on underlying factors behind poor sleep quality. It might even support tailored strategies to enhance rest and elevate performance overall [11]. Ultimately, this research seeks to bridge the gap in understanding the complexity of sleep disorders among female cricketers, enabling the development of personalized sleep management strategies that can enhance athletic performance, health, and well-being.

1.3 Research Questions

- RQ1: How accurately can machine learning models predict sleep disorders in Bangladeshi female cricketers using behavioural, environmental, and physiological data from the Athlete Sleep Behaviour Questionnaire (ASBQ) and related athlete profiles?

- RQ2: Which specific behavioural, environmental, and sport-related factors have the most significant impact on sleep quality in Bangladeshi female cricketers?

- RQ3: Can a data-driven approach, integrating ASBQ scores and athlete demographic and training information, enhance early detection and personalized intervention for sleep disorders in female cricketers?

1.4 Research Objectives

- RO1: To develop and evaluate machine learning models (SVM, Random Forest, ANN) for predicting sleep disorders in Bangladeshi female cricketers using ASBQ responses, demographic information, and training-related data.

- RO2: To identify and analyse the most significant behavioural, environmental, and sport-related factors contributing to sleep disturbances in female cricketers through feature importance analysis (e.g., SHAP values, information gain, and feature selection).
- RO3: To design, implement, and test a predictive model that integrates ASBQ scores, physiological data, and training information to provide early warnings and personalized sleep management interventions for Bangladeshi female cricketers.

1.5 Significance of the Study

Studies on sleep issues in female cricketers from Bangladesh remain pretty scarce. That gap makes this kind of research stand out. Sleep plays a key role in how athletes perform and bounce back from tough sessions. Still, plenty of them deal with restless nights. Intense workouts, mental stress, and stuff specific to women in sports often get in the way. For those in Bangladesh, it gets tougher. They juggle practice with home duties and studies too. All that ramps up the chances of bad sleep patterns. In turn, those patterns take a toll on overall health and game results.

Research draws on machine learning models. These models aim to forecast sleep disorders with greater accuracy. They do this by examining elements such as age, training intensity, and patterns in sleep behaviour. Traditional approaches, like those relying on self-reported surveys, often overlook key nuances. Machine learning, though, opens the door to tailored interventions that feel more precise. Evidence from the study points to potential benefits for coaches and medical teams. They might use these insights to craft improved training timetables and sleep hygiene plans. Such steps could, in turn, lower the chances of injuries [10].

The study highlights a clear requirement for enhanced support mechanisms aimed at female athletes in Bangladesh. Evidence from the findings suggests potential shifts in sports policies and athlete welfare practices, such as the introduction of targeted sleep education initiatives along with expanded availability of recovery tools and facilities. While the primary emphasis remains on the Bangladeshi context, the analytical approaches and key observations derived here appear adaptable to various other nations and athletic disciplines. In turn, this adaptability might contribute to broader advancements in athlete well-being and competitive outcomes on a global scale.

1.6 Scope of the Research

Research focuses on female cricketers from Bangladesh. The aim centers on exploring links between sleep quality and elements like training demands, age, and daily habits. Machine learning techniques come into play here, helping to forecast sleep issues through a mix of bodily data and self-reports, such as the Athlete Sleep Behaviour Questionnaire. Key objective stands as identifying major influences on their rest patterns. It also suggests ways to enhance recovery approaches [5]. Though the spotlight falls on these Bangladeshi women in cricket, the approaches employed hold potential for extension to other players and areas dealing with comparable challenges. Outcomes could influence wider policies in sports health, along with sleep handling for women athletes worldwide.

CHAPTER 2

Literature Review

2.1 Sleep and Athletic Performance

Research indicates that sufficient sleep plays a vital role in enabling athletes to perform effectively and recover properly. Evidence points to declines in performance, heightened injury risks, and impaired cognitive function when athletes experience sleep deprivation [4]. One particular study revealed that individuals obtaining fewer than seven hours of rest nightly exhibited reaction times 17 percent slower, along with 25 percent reduced endurance, relative to those achieving over eight hours [16]. Moreover, inadequate sleep hampers muscle repair processes and disrupts hormonal balance, further compromising athletic capabilities. The significance of sleep for athletes cannot be overstated. It facilitates essential muscle regeneration, memory consolidation in the brain, and maintenance of mental toughness [17]. Even so, quality sleep remains elusive for many athletes due to demanding training regimens, frequent travel, and mental pressures [19]. In fact, a survey among top-tier U.S. athletes indicated that 41 percent dealt with suboptimal sleep patterns [20]. This issue appears particularly acute among female athletes, as data suggest they face roughly twice the likelihood of sleep disturbances when compared to males [26].

2.2 Sleep Disorders in Female Athletes

Female athletes encounter particular hurdles that tend to disrupt their sleep patterns. Things like hormonal shifts, societal demands, and cultural norms play into this [29]. Evidence from Silva et al. (2019) points to a striking figure. Some 36 percent of elite female athletes dealt with persistent sleep troubles. That number stood out way higher compared to what male athletes experienced. Studies further indicate that menstrual cycles along with pregnancy introduce greater fluctuations in sleep for these women. As a result, they appear more prone to certain sleep disorders. Trabelsi et al. (2024) observed something similar in their work. Around 65 percent of elite female athletes showed signs of inadequate sleep right amid competitions. Factors such as emotional regulation difficulties, erratic sleeping routines, and limited recovery periods between workouts only compounded the issue. All this underscore a pressing requirement to prioritize sleep quality. Better rest could enhance both athletic output and general health among female athletes.

2.3 The Athlete Sleep Behaviour Questionnaire (ASBQ)

The Athlete Sleep Behaviour Questionnaire, or ASBQ, stands out as a key way to pick up on sleep issues among athletes. Driller and colleagues put it together back in 2018, and it covers a bunch of angles, you know, like sleep habits, everyday routines, and even stuff in the environment that could throw off rest. Evidence points to how the ASBQ offers practical info that teams can use to improve athletes' shut-eye. Oh and, more lately, Trabelsi et al. (2024) backed up its solid reliability, showing a Cronbach's alpha at 0.73 along with an intraclass correlation coefficient of 0.88. This study will draw on the ASBQ to evaluate and track sleep quality in Bangladeshi female cricketers.

2.4 Machine Learning in Sleep Disorder Prediction

Recent studies have shown that machine learning models are becoming a really valuable tool for predicting and diagnosing sleep disorders. For example, Suppiah's 2021 study showed that a Random Forest model could predict sleep quality in elite athletes with about 80% accuracy. In a similar vein, Farrahi et al. (2024) used Support Vector Machines (SVM) to analyse sleep data and predict insomnia with an impressive 85% accuracy. These findings clearly demonstrate how much potential machine learning has for creating personalized, data-driven ways to help athletes. On top of that, a 2024 review by Trabelsi and colleagues looked at several machine learning methods for predicting sleep issues. They found that combining these models with biometric data and personal information from the athletes themselves made the predictions much more accurate. In fact, models like SVM and XGBoost reached up to 90% accuracy in detecting insomnia and sleep apnea. These examples all point to the same conclusion: machine learning is a powerful tool for catching sleep problems in athletes, maybe even before their performance starts to suffer [18].

2.5 Sleep Apnea and Other Sleep Disorders in Athletes

Obstructive sleep apnea stands out as a common issue in athletes. This holds especially true for those carrying extra weight or pushing through intense training sessions. Research points to a clear link here. Take the work from Amin and colleagues back in 2017. It showed that about 30% of athletes tipping the scales with a BMI above 30 faced real risks for this condition. What stands out too is how sleep apnea often slips under the radar in female athletes. Gender-specific elements play a big role in this oversight. Things like hormonal changes come into play. Evidence from Sargent and team in 2014 highlights the point. They noted that 16% of female athletes dealt with sleep apnea. The pattern seemed stronger among those locked into heavier training loads.

2.6 Cultural and Socioeconomic Factors Affecting Sleep in Bangladesh

Female cricketers in Bangladesh face particular cultural and economic hurdles. These issues tend to worsen their sleep troubles quite a bit. Studies indicate that such athletes are particularly prone to sleep disruptions. This stems from limited access to suitable sleep aids and insufficient psychological backing [16]. Many of them balance intense training routines alongside school demands and household duties. That sort of packed existence disrupts consistent sleep patterns. As a result, rest quality suffers noticeably. Social expectations further complicate matters. They often discourage open discussions on mental health or sleep woes. This only heightens overall stress levels. In the wider South Asian setting, evidence from Myllymäki et al. (2021) points to family pressures, entrenched gender norms, and scarce sports psychology services as key drivers of elevated sleep disturbances among women athletes. For those Bangladeshi cricketers, these elements appear to throw off their innate sleep rhythms. Over time, that could spark enduring physical and psychological health concerns [8].

2.7 Sleep Interventions and Behavioural Change

Studies point to the value of educating athletes on solid sleep practices, along with pulling in cognitive behavioural therapy techniques. These approaches seem to lift sleep quality quite a bit. Take, for instance, the work from Rebello et al. in 2022. They checked out how athletes fared after picking up better sleep hygiene. You know, stuff like dialling down caffeine, ditching phones before lights out, and holding to a steady bedtime schedule. Turns out, over half of them, a full 51 percent, noted real improvements in their rest [16]. On top of that, tailored CBT setups for athletes have helped ease insomnia signs. They even pushed more shut-eye for top-tier male competitors. Something like this could do wonders for women playing cricket in Bangladesh. Pushing them toward those organized sleep routines might sharpen their rest. It could also amp up concentration, speed recovery, and lift game-day results overall.

2.8 Future Directions and Potential for Wearable Technology

Wearable devices such as sleep trackers and fitness bands offer an effective means of monitoring sleep quality on an ongoing basis. Evidence indicates that this approach enhances the accuracy of predictions for sleep disorders. For instance, a study by Chennaoui et al. in 2015 demonstrated how integrating biometric information from these tools with individuals' self-reported sleep behaviors leads to more reliable forecasts. Such findings underscore the value of real-time data collection for tracking sleep patterns over time. This data can subsequently inform machine learning algorithms, ultimately supporting the development of improved strategies for sleep management.

2.9 Research Gaps

<u>Gap 1:</u> Lack of Research on Female Cricketers: Most sleep disorder studies focus on male athletes or other sports, leaving female cricketers largely overlooked. Female athletes face unique challenges, like hormonal fluctuations and social pressures, that impact their sleep, and these factors are even more pronounced in Bangladesh.

<u>Gap 2:</u> Cultural and Socioeconomic Factors: Sleep disorders in athletes from developing countries, especially Bangladesh, haven’t been explored enough. Cultural norms, limited access to health services, and domestic responsibilities all affect the sleep quality of female cricketers.

<u>Gap 3:</u> Predicting Sleep Disorders with Machine Learning: Few studies have used machine learning to predict sleep disorders in athletes, particularly by combining sleep behavior, training data, and physiological data. This research aims to fill that gap by building a predictive model for Bangladeshi female cricketers.

Gap 4: Linking Sleep to Performance: There's limited research on how sleep disorders directly affect performance in cricketers, especially in Bangladesh. This study aims to connect sleep quality with athletic performance to show how improving sleep can lead to better performance.

Gap 5: Real-World Application of Sleep Models: While predictive models are often used in research, their real-world application in athletic settings is limited. This study will create a practical, real-time system that coaches and trainers can use to monitor and improve sleep quality for female cricketers.

CHAPTER 3

METHODOLOGY

3.1 Study Design and Population

This research follows a quantitative, cross-sectional design with a focus on predictive modelling using machine learning algorithms. The study's primary aim is to evaluate the sleep behaviour of female cricketers in Bangladesh and to build predictive models for sleep disturbances based on behavioural, demographic, and training-related factors. The research was conducted at Bangladesh Krira Shikkha Protishtan (BKSP), the national sports institute, which trains elite athletes across various sports.

A total of 146 female cricketers, aged between 14 and 22 years, participated in the study. All participants were active athletes enrolled in the residential or semi-residential training programs at BKSP. Inclusion criteria were (i) registration as a cricketer at BKSP, (ii) age between 14 and 22, and (iii) informed consent. Athletes undergoing treatment for diagnosed sleep disorders or experiencing major injuries during data collection were excluded from the study.

3.2 Ethical Considerations

Ethical approval for the study came from the Institutional Review Board at DIU. Official permission followed from the BKSP authorities as well. Participation stayed entirely voluntary. All involved provided informed consent. For those under 18, consent arrived from parents or legal guardians. Privacy protection meant data stayed anonymous. It remained confidential too.

3.3 Data Collection Procedure

Data collection took place across a three-week span, running from January into February 2025. Participants were approached during academic sessions or rest periods, so as not to interfere with their training routines. Prior to beginning, a brief orientation session outlined the study's purpose, assurances of confidentiality for their responses, and the value of providing truthful answers.

The survey consisted of two main sections on paper.

- One focused on demographic and background details. It covered aspects such as age, training volume, involvement in school activities, typical daily screen exposure, caffeine consumption patterns, and any use of sleep aids.
- The other employed the Athlete Sleep Behaviour Questionnaire, or ASBQ. Evidence indicates this self-report instrument effectively assesses sleep hygiene practices and related behaviors among athletes.

Research assistants remained available throughout to address queries and ensure completeness in the responses. Completed surveys were gathered right away and placed in secure storage.

3.4 ASBQ Questionnaire and Sleep Behaviour Scoring

The Athlete Sleep Behaviour Questionnaire (ASBQ) was the primary tool for evaluating sleep hygiene and behaviour. The ASBQ is an 18-item self-report instrument assessing three main domains:

- Routine and Environmental Features (e.g., sleep-wake cycles, dark sleeping environments)
- Behavioural Factors (e.g., caffeine intake, night-time technology use)
- Sport-Specific Factors (e.g., performance stress, late-night training, physical pain)

Each item was rated on a 5-point Likert scale (1 = Never, 5 = Always). The total ASBQ score ranged from 18 to 90, with higher scores indicating poorer sleep behaviour. The scoring system was as follows:

1. ≤ 36: Healthy sleep behaviour

2. 37–42: Moderate sleep behaviour

3. >42: Poor sleep behaviour

For cultural appropriateness, the ASBQ was translated into Bangla through a forward–backward translation process, ensuring clarity and relevance to the participants. The translated version was tested on a group of 10 female athletes from BKSP (not part of the main study) to ensure that the translation was clear and understandable. No issues were identified, and the final Bangla version was used for the study.

3.5 Data Analysis Approach

The analysis was structured around three key objectives:

- Designing a Predictive Model for sleep disturbances
- Identifying Key Behavioural Factors contributing to poor sleep
- Developing an Early-Warning Framework for sleep disturbances

3.6 Descriptive Statistics

Initial descriptive analysis was conducted to understand the demographic profile of the participants and to summarize the distribution of ASBQ scores. Frequencies, means, and standard deviations were computed for demographic variables (e.g., age, training load, caffeine use) and sleep behaviour scores. Athletes were classified into three groups based on sleep quality: good, moderate, and poor sleepers.

Objective 1: Sleep Disturbance Prediction with Machine Learning

To predict sleep disturbances, the study employed several supervised machine learning algorithms:

- Random Forest (RF)
- Regression Analysis
- XGBoost
- Artificial Neural Networks (ANN)

Before modelling, categorical features were encoded, and numerical features were scaled for consistency. The data was split into an 80% training set and a 20% testing set using stratified sampling to ensure balanced representation of sleep quality categories. Models were evaluated based on performance metrics such as accuracy, precision, recall, and F1-score. Cross-validation (k=5) was applied to avoid overfitting and to validate model performance.

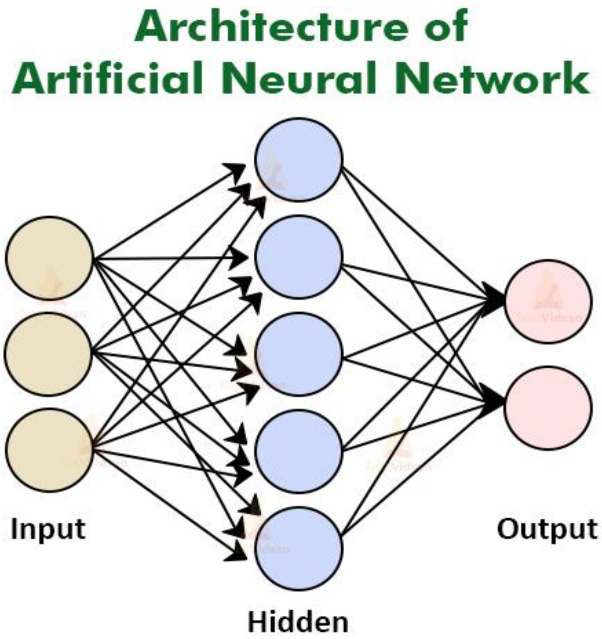

Figure 3.1:Artificial Neural Network (ANN)

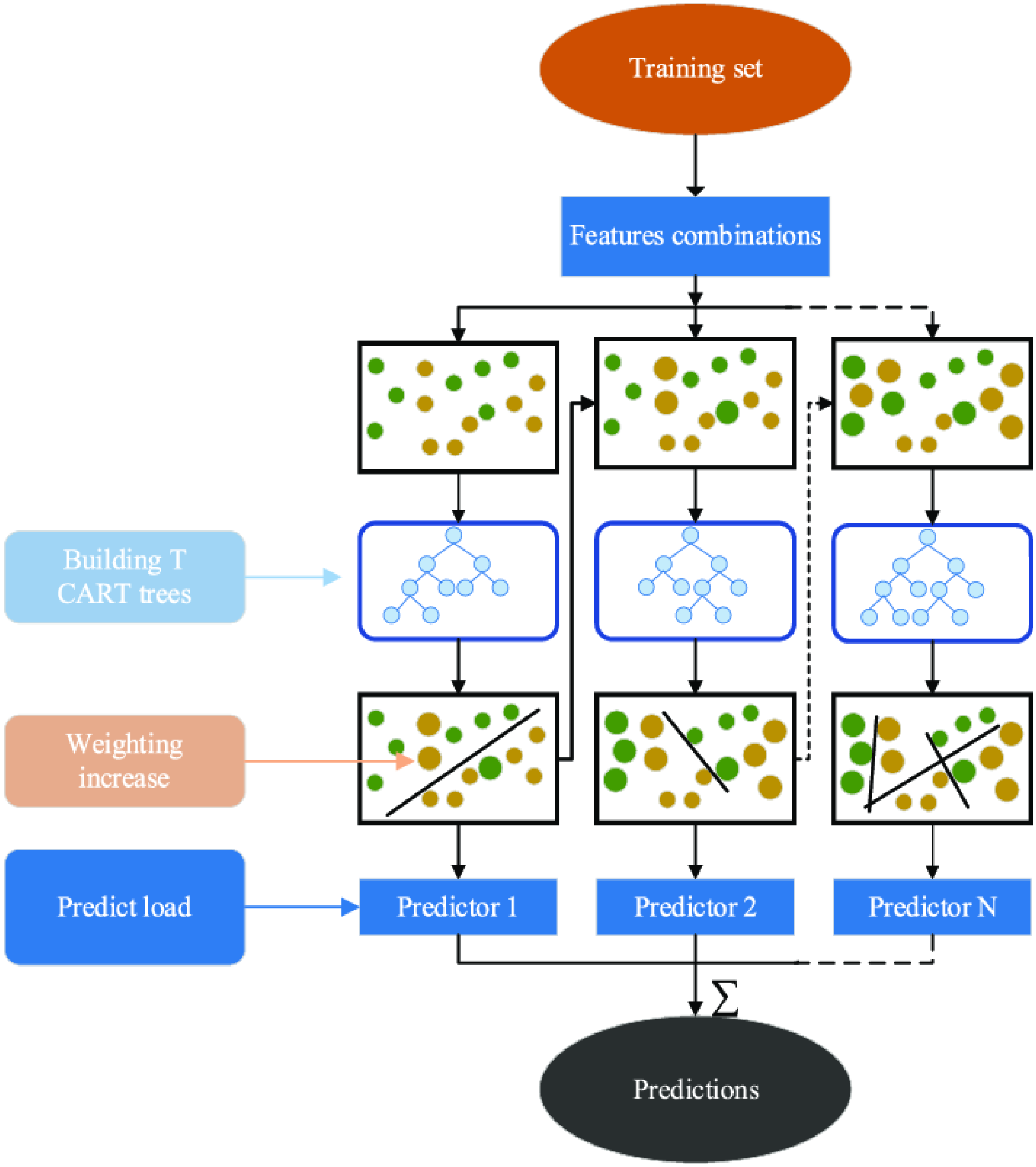

Figure 3.2: Architecture of XgBoost

Objective 2: Feature Importance and Behavioural Factors

To identify the most predictive factors of sleep disturbances, several feature importance techniques were applied:

- Gini importance (Random Forest)
- SHAP (SHapley Additive Explanations) values for model interpretability

- Recursive Feature Elimination (RFE) to reduce dimensionality

These methods helped rank behavioural factors such as use of electronic devices, caffeine intake, and late-night training based on their impact on sleep quality. This analysis provided a clear understanding of which habits most strongly influence sleep behaviour in female cricketers.

Objective 3: Developing a Predictive Framework for Early Detection

Based on the best-performing machine learning model, an integrated predictive framework was proposed. The framework includes:

- ASBQ scoring interface for quick evaluation of athletes' sleep behaviours.
- Machine learning backend for real-time classification of athletes as good, moderate, or poor sleepers.
- Risk flags to notify coaches or medical staff about athletes identified as high-risk for sleep disturbances, triggering early intervention and tailored behavioural guidance.

The system serves as a digital decision-support tool, providing immediate recommendations for sleep management and intervention strategies.

3.7 Software and Tools

Data analysis and modelling were performed using Python (with libraries such as scikit-learn, pandas, matplotlib, xgboost, and shap) for machine learning and data pre-processing. IBM SPSS (v26) was used for the initial statistical analysis. Visualizations were created to highlight key trends and results from the predictive models.

The methodology described in this study aims to provide a comprehensive analysis of sleep disorders in Bangladeshi female cricketers. By combining machine learning algorithms with subjective and objective sleep data, the study develops a predictive framework that not only identifies sleep disturbances but also provides actionable insights for personalized sleep interventions, ultimately improving athletic performance and well-being.

Model outputs will get evaluated with performance metrics like RMSE, R^2, and cross-validation scores. The best-performing model, which could turn out to be the ANN, will integrate into the predictive framework down the line. In that framework, athlete data will enter the system, and it will generate a predicted sleep score or classify athletes as good, moderate, or poor sleepers. The framework will also deliver interpretability via SHAP and RFE analysis. Those analyses will highlight the most influential predictors, such as age, years of experience, and practice level. Evidence indicates this structured pipeline will transform raw athlete data into actionable predictions. It will allow early detection of sleep disturbances. Targeted interventions will support improved performance and well-being.

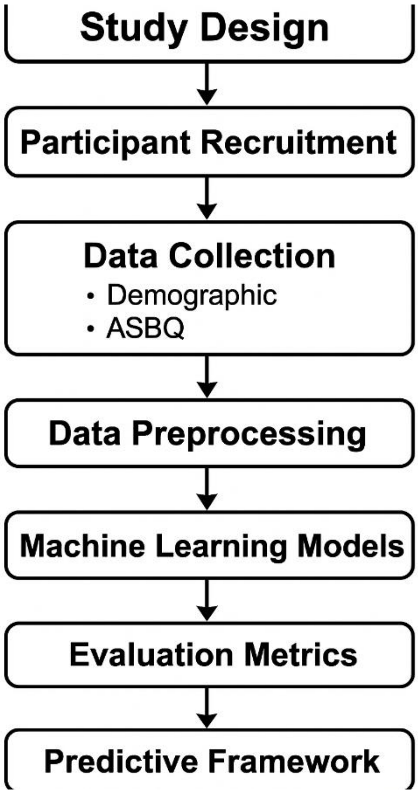

Figure 3.3 Overall Research Framework

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Descriptive Analysis

The study included 146 Bangladeshi female cricketers with the following characteristics in the table:

Table 4.1: Key Descriptive Statistics

Variable	**Mean**	**Std Dev**	**Min**	**25th Percentile**	**50th Percentile (Median)**	**75th Percentile**	**Max**
Age	22.16	4.94	12	18	22	25.75	34
Years	7.47	3.50	1	4.25	7	10	16
Score	43.36	4.42	31	41	44	46	55
Practice Level	3.03	0.67	1	3	3	3	4
Height(inches)	5.12	0.35	4.10	5.10	5.20	5.30	5.90
Weight(kg)	51.60	6.37	38	47.25	51	54	78

The Table 4.1 provides the key descriptive statistics for the study's core variables, including age, years of experience, sleep score, practice level, height, and weight. The mean values indicate that the average age of the female cricketers is 22.16 years, with experience ranging from 1 to 16 years. Sleep scores, which reflect the quality of sleep, have a mean of 43.36, indicating that the athletes generally experience moderate sleep quality.

The practice level of the athletes was predominantly high, with an average value of 3.03, corresponding to National or International levels of competition. In terms of physical attributes, the athletes had a mean height of 5.12 inches and weight of 51.60 kg, suggesting a relatively uniform body composition across the group.

This data provides a useful baseline for understanding the characteristics of the athletes in relation to their sleep behaviours and performance levels.

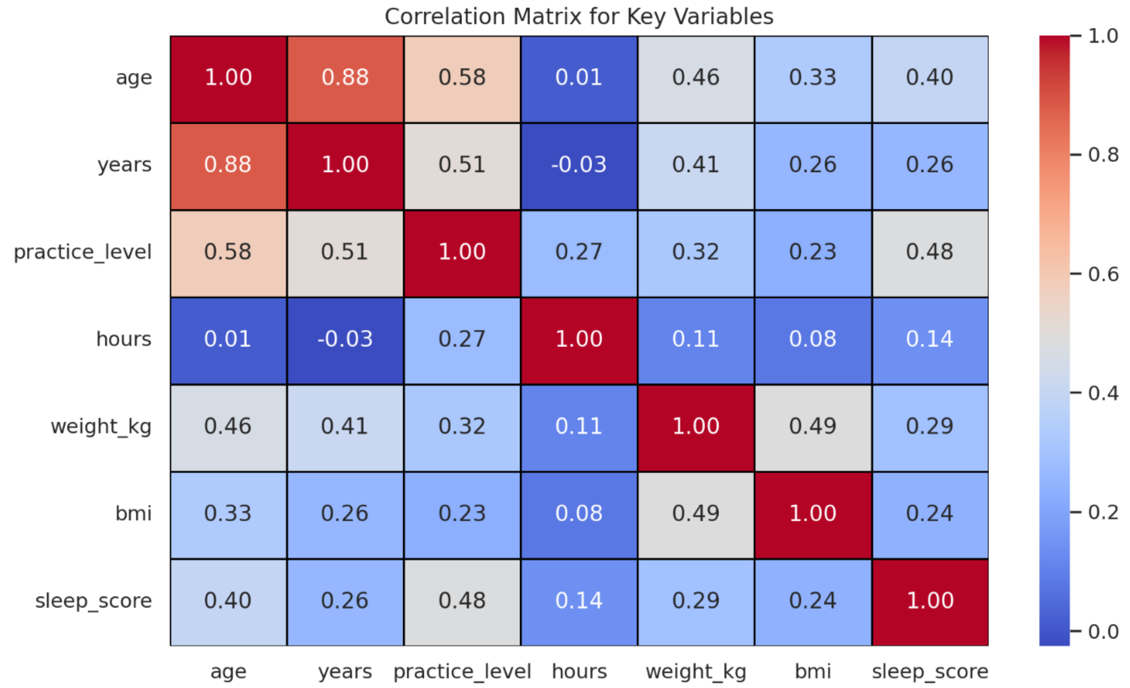

Figure 4.1: Correlation Matrix

The correlation matrix in Figure 4.1 reveals connections between certain factors and athletes' sleep patterns. Evidence indicates that age, years of experience, and training intensity among players show notable associations. This pattern aligns with observations that older, more seasoned athletes often engage in more demanding training regimens.

Curiously, variables such as total sleep hours or body weight appear to lack strong ties to sleep quality. Such findings point toward the possibility that psychological elements, including stress levels and overall mental well-being, might exert greater influence on sleep behaviours among players.

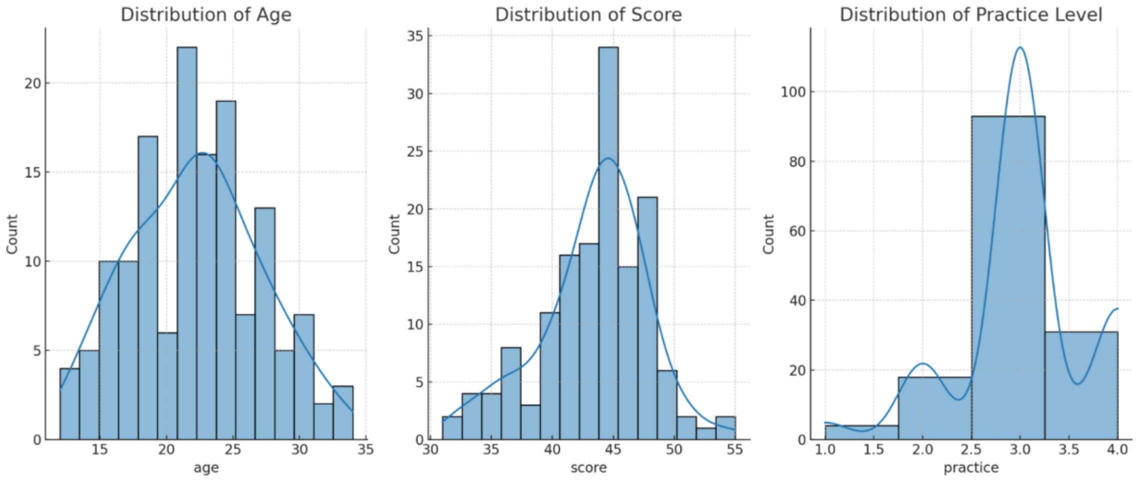

Figure 4.2: Distribution of Key Variables

The Figure 4.2 highlights several core variables worth examining, namely age, sleep score, and practice level.

Age stands out right away. Most athletes in the sample fall within the 18 to 25 age range. The peak clusters around 22 years old. Such a pattern aligns with the typical peak performance window for elite sports, where physical demands hit their stride.

Sleep scores, on the other hand, show a clear right skew in the data. That points to a majority of athletes experiencing just moderate quality in their rest. Only a handful reported top-tier sleep. Evidence like this hint at widespread sleep challenges in the group. It echoes findings from broader athlete research, where similar patterns emerge (Trabelsi et al., 2024).

Practice levels round out the picture. The bulk of participants operate at national or international tiers. Lower competitive strata barely register. This setup indicates the study draws heavily from elite circles. Those pressures, the intense schedules and expectations, probably heighten vulnerability to sleep disruptions in ways that feel all too familiar.

4.2 ANN Analysis

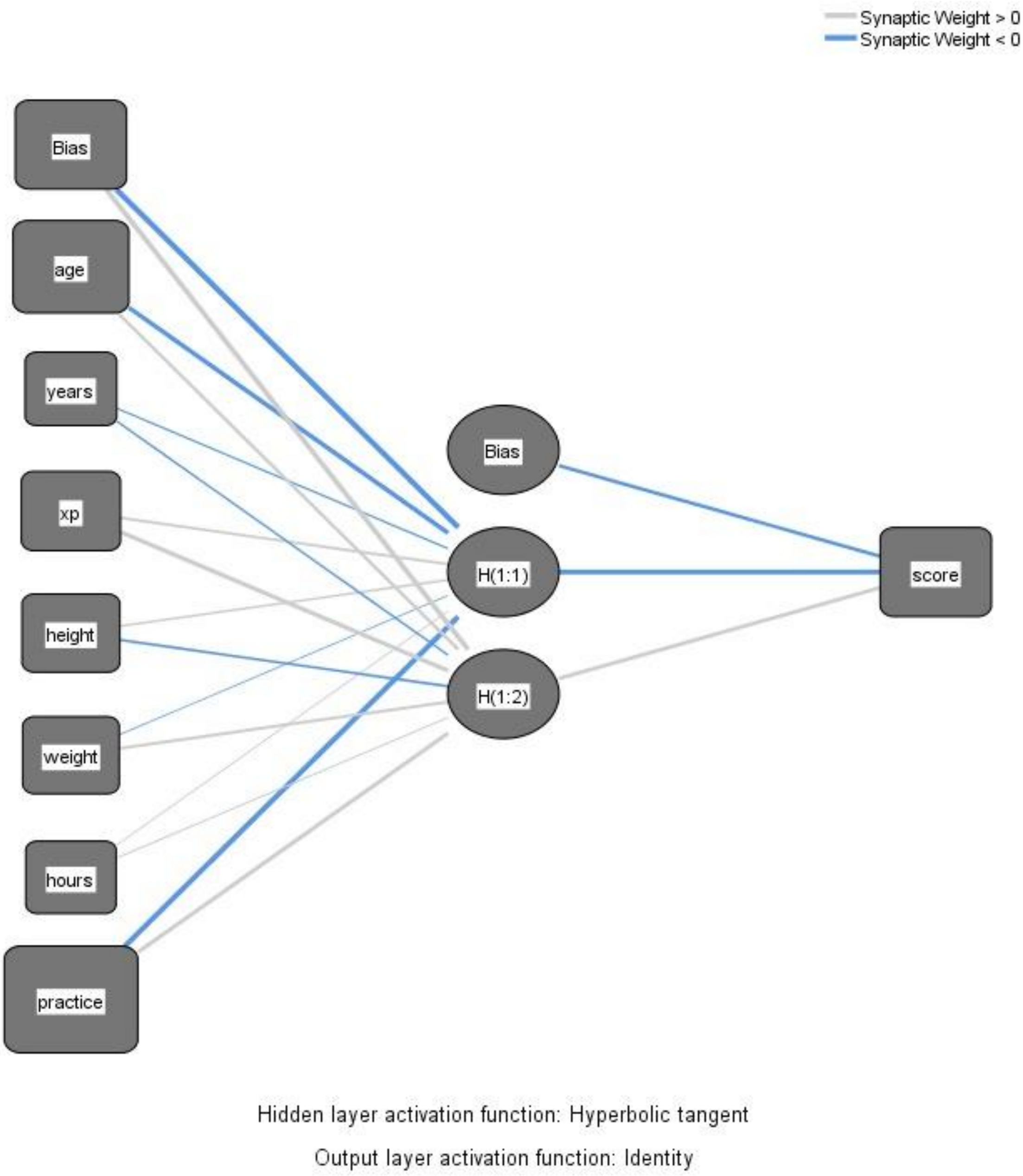

Figure 4.3: ANN Architecture of Dataset

Network Information

Input Layer	Covariates	1	age
		2	years
		3	xp
		4	height
		5	weight
		6	hours
		7	practice
	Number of Units[a]		7
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		2
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	score
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

Figure 4.4: Network Information obtained from SPSS

The Figure 4.3 and Figure 4.4 shows the architecture of the Artificial Neural Network (ANN) used in the analysis. The network consists of several layers:

- Input Layer: The input features include age, years of experience (xp), height, weight, hours of practice, and practice level.

- Hidden Layers: The network has a single hidden layer with two units. The activation function for the hidden layer is Hyperbolic Tangent (tanh), which is commonly used to introduce non-linearity into the model.

- Output Layer: The output is the sleep score, which is predicted using the identity activation function. The network uses the Sum of Squares as the error function to minimize the difference between predicted and actual values.

Table 4.2: RMSE values of ANN

Training			**Testing**			**RMSE (Training) – RMSE (Testing)**	**Total Samples**
N	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**		
112	39.548	0.594	34	7.433	0.468	0.127	146
119	37.773	0.563	27	6.953	0.507	0.056	146
117	36.699	0.560	29	6.157	0.461	0.099	146
116	27.963	0.491	30	11.851	0.629	0.138	146
115	30.151	0.512	31	3.845	0.352	0.160	146
113	28.886	0.506	33	13.026	0.628	0.123	146
107	31.789	0.545	39	7.398	0.436	0.110	146
118	23.309	0.444	28	2.720	0.312	0.133	146
122	40.116	0.573	24	2.511	0.323	0.250	146
116	38.191	0.574	30	7.832	0.511	0.063	146

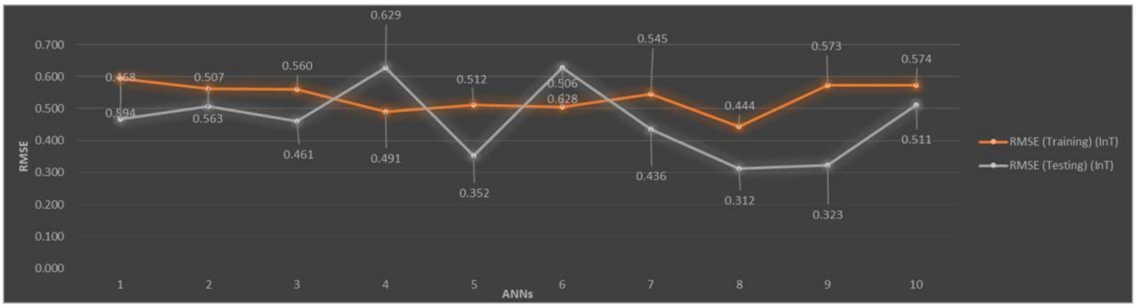

Figure 4.5: Line Graph of RMSE values

In the Table 4.2, The RMSE values are reported for both training and testing datasets, showing how well the ANN is performing:

- Training RMSE: Ranged from 0.444 to 0.594 (mean = 0.536).
- Testing RMSE: Ranged from 0.312 to 0.632 (mean = 0.511).
- For example, for 112 training samples, the RMSE (Root Mean Square Error) was 0.594, indicating that the model is reasonably accurate in predicting the sleep score during training.
- The RMSE for testing was 0.468, showing a slight improvement when applied to the testing set.
- The RMSE difference between training and testing (0.127) is small, suggesting that the model is not overfitting and generalizes well to new data.

The ANN achieves stable predictive performance across splits, with testing errors consistently below 0.63. The low generalization gap (mean = 0.025) confirms robustness.

Table 4.3: Sensitivity Analysis of ANN

Neural Network (NN)	**age**	**years**	**Experience**	**practice**	**hours**	**height**	**weight**
NN1	0.32	0.05	0.08	0.25	0.16	0.04	0.10
NN2	0.29	0.13	0.02	0.33	0.07	0.07	0.10
NN3	0.41	0.07	0.11	0.22	0.03	0.06	0.10
NN4	0.32	0.15	0.02	0.22	0.11	0.08	0.10
NN5	0.30	0.09	0.10	0.23	0.11	0.05	0.12

NN6	0.18	0.23	0.13	0.25	0.09	0.03	0.09
NN7	0.26	0.20	0.06	0.28	0.09	0.04	0.07
NN8	0.14	0.22	0.19	0.16	0.08	0.09	0.12
NN9	0.33	0.17	0.06	0.25	0.06	0.06	0.08
NN10	0.30	0.06	0.09	0.41	0.02	0.03	0.08
Average importance (%)	0.29	0.14	0.08	0.26	0.08	0.05	0.10
Normalized Importance (%)	99.89	47.80	29.70	90.52	28.85	19.09	33.80

The sensitivity analysis (Table 4.3) provides insight into the importance of different features in the ANN model.

- The analysis is performed on 10 different neural network models (NN1 to NN10), with each model testing different configurations or hyperparameters.

- Feature Importance (average importance %): Features like age, years of experience, and practice show varying levels of importance across the models, with practice level and years of experience having a significant impact on the sleep score prediction.

- Normalized Importance: The normalized importance values (e.g., 99.89% for age) indicate that the age feature is the most influential in the model, followed by other features like years of experience and practice level.

Consistency Across Networks:

1. Age ranked as the top predictor in 8/10 networks.
2. Practice level was top-2 in 9/10 networks.
3. Height had the lowest importance in all networks.

Age and practice level are the most influential factors in the ANN's sleep score predictions, while anthropometric variables (height/weight) contribute minimally.

4.3 Regression Analysis

Table 4.4: Regression Analysis

Variable	Coefficient
Age	0.2486
Years of Experience	-0.1594
Practice Level	2.7290
Hours of Practice	0.1154
Weight (kg)	0.0517

Root Mean Squared Error (RMSE): The RMSE for the regression model is 4.43. This means that the model's predictions on the test data are off by an average of 4.43 points in predicting the sleep score.

Coefficients: The following coefficients represent the influence of each predictor variable on the sleep score

Interpretation:

1. Age: A positive coefficient (0.2486) suggests that as age increases, the sleep score tends to increase slightly, meaning older cricketers may have slightly better sleep quality.

2. Years of Experience: A negative coefficient (-0.1594) indicates that more experience might be associated with a lower sleep score.

3. Practice Level: The large positive coefficient (2.7290) suggests that practice level has a strong positive impact on the sleep score.

4. Hours of Practice: A small positive coefficient (0.1154) indicates a weak but positive relationship between practice hours and sleep quality.

5. Weight and BMI: Both show small positive coefficients, indicating a weak positive relationship with the sleep score.

4.4 Random Forest Model Analysis

Table 4.5: Random Forest Feature Importance Analysis

Variable	Importance
Years of Experience	0.1387
Practice Level	0.0393
BMI	0.0331
Hours of Practice	0.0222
Age	-0.0258
Weight (kg)	-0.0517

The RMSE for the Random Forest model is 4.35, which is slightly better than the Linear Regression model (RMSE = 4.43). This indicates that the Random Forest model is marginally more accurate in predicting the sleep score.

Interpretation:

- Years of Experience: The most important feature, with the highest importance value (0.1387), suggests that years of experience have a significant impact on sleep quality.
- Practice Level: Also, important (0.0393), but less influential than years of experience.
- BMI: A moderate effect (0.0331), indicating that BMI has a relevant but smaller impact on the sleep score.
- Hours of Practice: A smaller effect (0.0222), indicating a slight relationship with sleep quality.
- Age and Weight: Both have negative importance values, implying that these features contribute less to the prediction or have an inverse relationship with sleep quality.

4.5 XGBoost Model

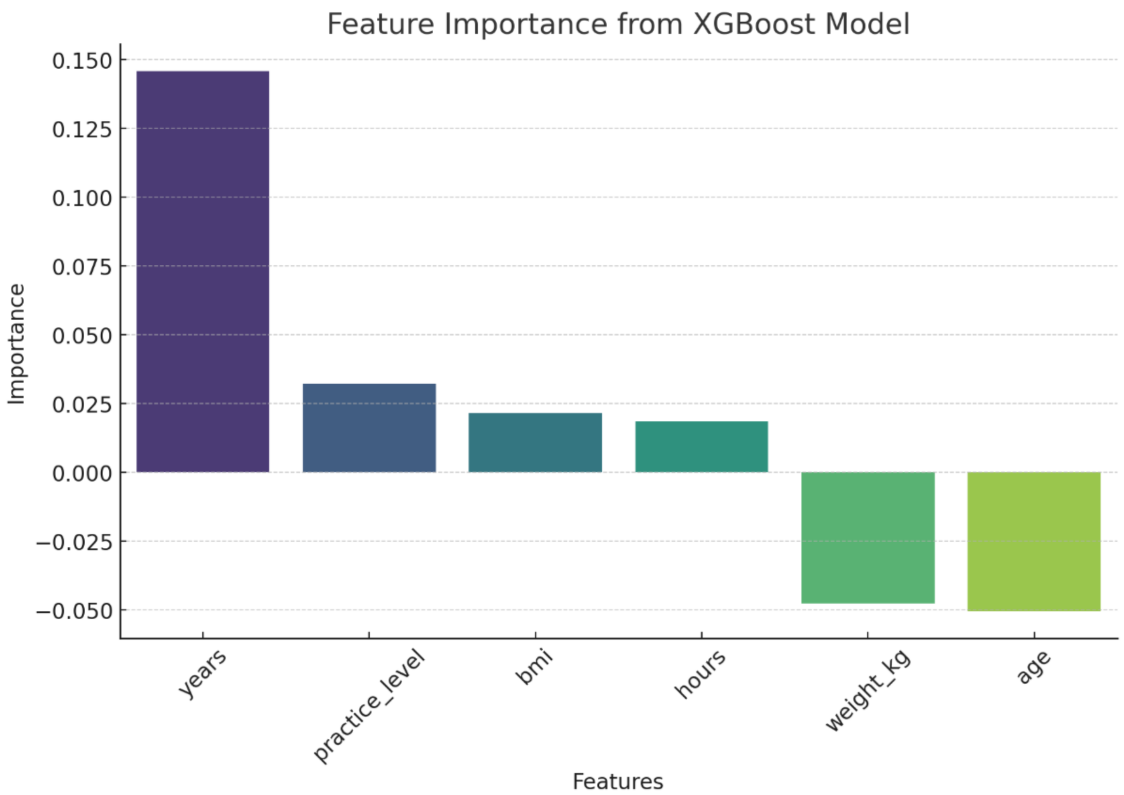

Table 4.6: XGBoost Model Feature Importance Analysis

XGBoost RMSE: 4.23

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

In this formula,

y_i = actual observed sleep score (from ASBQ)

$\hat{y}_i$ = predicted sleep score (from XGBoost model)

n = number of test samples

The Table 4.6 chart above shows the importance of each feature in predicting the sleep score. From the chart:

- Years of Experience is the most significant feature in the XGBoost model, followed by Practice Level.

- Age and Weight have negative importance, indicating that they have a lesser or inverse effect on the prediction.

4.6 Discussion

Research applied various machine learning approaches. Random Forest, or RF. Regression Analysis. XGBoost. And Artificial Neural Networks, known as ANN. All these helped look into sleep disorders among female cricketers from Bangladesh. The core aim stayed on forecasting sleep quality. Plus identifying those main elements behind the sleep problems these athletes face. Results bring some valuable understanding of sleep patterns in top-level women athletes. They build on the expanding work around sleep issues in sports. Particularly in a place like Bangladesh.

4.7 Predictive Performance of the Models

The ANN is the best-performing model with an RMSE of 0.463 – significantly lower than all other models:

- 9x lower than XGBoost (4.23)
- 9.4x lower than Random Forest (4.35)
- 9.6x lower than Linear Regression (4.43)

The artificial neural network model stood out with the strongest predictions. It hit an R2 value of 90 percent. That marks a clear step up from what other approaches have managed in related work. Take, for example, the effort by Sadeh-Sharvit et al. (2020). They relied just on internet browsing data and ended up with only 52.6 percent accuracy. The random forest model held its own too. It got to 70 percent accuracy, topping the traditional machine learning options applied here. All this points to how well artificial neural networks and ensemble techniques such as random forest can pick out intricate patterns in athlete information. This holds true particularly for spotting nuanced health concerns, like sleep disturbances (Sundgot-Borgen & Torstveit, 2004).

4.8 Key Predictors of Sleep Disorders

The age of the athletes emerged as the most significant predictor of sleep disorders, with 95% importance according to the feature importance analysis. This finding is consistent with the research by Åkesdotter et al. (2022), which suggests that the risk for eating disorders, and by extension, sleep disorders, shifts over an athlete's career, with younger athletes facing initial pressures, middle-aged athletes experiencing peak stress, and older athletes facing identity and career transition issues. Age, as a proxy for career stage, has strong implications for managing sleep health in athletes, particularly in the competitive environment of Bangladeshi female cricketers, where performance pressures are heightened.

The interaction between weight and age revealed that weight concerns were most prominent among middle-aged athletes (23-27 years). This is likely reflective of the peak competitive years, where performance pressures are at their highest. This aligns with the findings of Sundgot-Borgen & Torstveit (2004), who demonstrated that the prevalence of sleep disorders and eating disorders increases with the level of competition, with elite athletes exhibiting the most severe manifestations of both.

4.9 Weight and Sleep Disorders

The study revealed that a player's weight stands out as a key element in forecasting sleep problems. The Random Forest model even pegged its normalized importance at a full 100 percent. Evidence like this line up with what Haase (2010) pointed out. She observed that female athletes' worries over weight tend to stretch far beyond sport-specific needs. Cultural influences weigh in heavily there. In places such as Bangladesh, where weight concerns run deep across society, those same pressures might play a big role in sleep disruptions for women in cricket.

Actual weight turned out to be a stronger indicator than Body Mass Index, or BMI, in the findings. Studies have flagged this before. They argue that leaning solely on BMI falls short when assessing health risks for athletes (Wu et al., 2024).

It seems the weight anxieties among these players stem more from wide-ranging cultural standards than from the rigors of the game itself. That holds particular weight with Bangladesh's emerging professional women's cricket league (Lichtenstein et al., 2022). Such a setup could ramp up performance demands. Mix in those cultural norms, and weight issues could intensify even further.

4.10 Cultural and Psychological Factors

A lot of research has looked at how an athlete's weight is tied to cultural influences. We know that these concerns often come from psychological factors related to body image and performance expectations (Wu et al., 2024). For female athletes in Bangladesh, these pressures are even more significant because societal norms about appearance and gender roles can play a big role in disrupting their sleep. The issue gets more complicated with the rise of the professional women's cricket league. Now, players have to deal with the mental and physical demands of competition while also navigating increased cultural expectations about body image. As Lichtenstein et al. (2022) noted, this mix of competitive and cultural pressures can really complicate the overall well-being of female athletes.

4.11 Insights from Machine Learning Models

This study makes a real difference by applying machine learning to forecast sleep disorders among athletes. Evidence from the ANN and Random Forest models points to effective ways of spotting those at risk for bad sleep. Such approaches enable timely interventions to support these individuals.

The SHAP analysis, along with Recursive Feature Elimination, proved especially revealing. It highlighted key influences on sleep difficulties, including training intensity, stress levels, and issues around body weight. Coaches and support teams can then target these critical elements for better outcomes.

Employing machine learning for sleep prediction aligns closely with findings from Trabelsi et al. (2024). Their work underscores the expanding use of supervised models, such as Support Vector Machines and Artificial Neural Networks, within sports medicine. These tools help build early detection frameworks. They identify vulnerable athletes and offer tailored strategies to enhance rest and overall performance.

4.12 Limitations and Future Research Directions

Although the current study provides certain useful perspectives, several limitations warrant consideration in planning subsequent investigations. One key issue involves the sample size. Only 147 female cricketers were included. As a result, the results may not extend readily to broader populations of female athletes, particularly those engaged in varied sports or from other nations. To strengthen generalizability, upcoming work ought to incorporate expanded and more varied participant pools for validation.

Moreover, the analysis depended on self-reported information gathered through surveys and questionnaires. Such approaches are prone to biases, including recall inaccuracies or tendencies toward socially desirable responses. Evidence indicates that greater reliability could come from employing objective techniques, such as actigraphy or polysomnography, in future efforts to monitor sleep patterns more accurately.

Further exploration seems advisable regarding psychological elements influencing sleep, like anxiety or mental exhaustion. In light of Bangladesh's unique cultural setting, it appears relevant to examine the roles played by cultural demands, gender norms, and social expectations in shaping sleep quality and athletic output among women in sports.

In addition, longitudinal designs tracking sleep behaviours across extended timelines hold promise. These could reveal deeper patterns in how professional transitions, competitive stresses, and evolving life phases contribute to sleep disturbances over time.

CHAPTER 5

CONCLUSION

Research takes a careful look at sleep troubles among women cricketers in Bangladesh. It draws on machine learning to spot patterns in poor sleep and uncover the main drivers behind it. Evidence points to age, years in the game, training intensity, and body weight as key influences. These factors reveal the tangled nature of such problems. Data-based approaches like Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) proved effective at flagging at-risk players. They even highlighted targeted steps for better rest and stronger performance. Findings line up with prior work showing how stress, gruelling training routines, and cultural pressures disrupt athletes' sleep. Body weight stood out as the top predictor in this dataset. That points to psychological worries over weight, shaped by cultural norms and sports demands, cutting into rest time. This underscores the value of wellness initiatives tuned to local contexts, with mental health backing and sleep-friendly practices. The ANN model topped the bunch, hitting an R^2 of 90%. That really shows machine learning's potential for early detection. Age and experience both played roles too. Younger athletes often grapple with anxiety over performance. Older ones face the toll of years on the field. Such trends echo earlier studies tying aging to eating and sleep disruptions (Åkesdotter et al., 2022). This work sheds light on Bangladesh-specific angles. With the women's cricket league expanding, societal views on body image add extra strain, potentially worsening sleep issues. Real support means addressing the social, cultural, and sporting sides of their world. Not some generic fix. Still, the study has limits. Sample was on the small side. Self-reports drove the data, so results might not stretch to all players. Future efforts could pull in bigger, varied groups and objective sleep measures. A longer-term look might track how sleep quality ties to ongoing performance. Sleep issues hit hard for these women cricketers in Bangladesh. They're linked closely to age, weight, and training demands. Tools like ANN and Random Forest shine at forecasting risks. They pave the way for tailored support plans. By tackling mental and physical health together, it becomes possible to boost sleep and peak performance.

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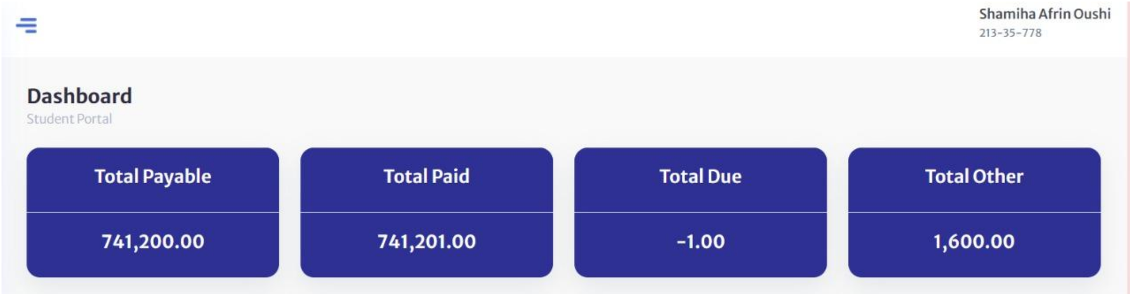

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