Acta Neurophysiologica
ISSN: 2996-7554

Academic Strive
Researcher's perception is our reality

Research Article *Volume 6 Issue 1*

Estimation of Bone-Mass in Games - Sports and Athletics Participants: A Study with Supervised Learning Classification Techniques

Raju VR[123]*

[1]CMR College of Engineering & Technology, India

[2]Nizam's Institute of Medical Sciences, NIMS Hospital, India

[3]CMR Institute of Medical Sciences, CMR Hospital, India

***Corresponding author:** Dr Venkateshwarla Rama Raju, PhD, CMR College of Engineering & Technology, Kandlakoya (V), Hyderabad, India, Email: drvenkateshwararrr@gmail.com

Received Date: December 26, 2024; **Published Date:** February 10, 2025

Abstract

Ability of ideal bone mineral density (BMD) in athletes especially within the female athletes is an worthy attribute of confirming their good health (safety) through their lives, and examining of BMD is necessary and also a prime objective to circumvent or evade fractures and bone-related injuries. Several tools for assessing bone health exist today. However, lacking the applicability needed for constant watching and also not capable for the female athletes' demographics. As a consequence of this, we explore the main goal of utilizing the machine learning`s supervised binary classifier techniques to discriminate concerning standard and low-bone-mass individuals amongst female athletes (games and sports) using feature manifestations extricated as of the given feedback form (usually questionnaire). Dataset comprised >200athletes. We evaluated five distinct models: decision-tree (DT), logistic-regression (LR), multi-layer perceptron (MLP) random-forest (RF), and XG-Boost. The data validation done through cross-validation plus significancy of the features were measured via the imperative permutation. XG-Boost showed the most balanced results in terms of sensitivity and specificity, achieving values of 0.94 and 0.63 which was also obtained an area under curve AUC) of 0.74 and an accuracy of 0.68. We examined that the duration of the current period of amenorrhea, and impact of sport, showed the highest relevance, and was coherent with preceding literature. Other features such as thinness level, number of training days in a week and age at menarche also showed high importance. The models demonstrated promising results in identifying low bone mass subjects from normal ones, indicating that the feature-manifestations based on questionnaires can be an important source for evaluating low BMD in female athletes.

Keywords: Bone Mineral Density; Low Bone Density; Fe- male Athletes; Female Health; Machine Learning

Abbreviations

BMD: Bone Mineral Density; LR: Logistic-Regression; DT: Decision Tree; MLP: Multi-Layer Perceptron; RF: Random Forest; CNNs: Convolutional Neural Networks; CT: Computational Tomography; FRAX: Fracture Risk Assessment Tool; FHA: Functional Hypothalamic Amenorrhea.

Introduction

BMD is a measure of the quantity of calcium (Ca+) and other minerals in a volume of the bone, and it is greatly correlated through the strength of such bone. BMD peaks in primitive majority post skeletal growth, but age-related bone loss affects both genders, notably accelerated in menopausal women due to hormonal shifts and estrogen deficiency [1,2]. WHO provided standardized definitions for low bone mass, initially using the T-score to categorize it for postmenopausal white women [3] with revisions made for osteoporosis classification in 2008 [4].

Ensuring optimal bone healthiness (physical condition) has been acknowledged as a critical issue for female athletes, as it directly impacts their well- being and performance throughout their lives. Yet the athletes needs to be mindful of lowly bonemass, referred to as as osteopenia, as it significantly increases the jeopardy of osteoporotic fragility fractures [5]. Given the implication of athlete's bone physical condition or fitness, it is essential to address long-term risks such as osteopenia and osteoporosis and the short-term hazard of bone injuries [6]. Though physical-exercise workouts has been widely recognized as a critical factor within the deterrence or preclusion plus treatment of osteoporosis, achieving optimal bone health requires a balance between various other factors as well, such as nutrition, vitamin D, calcium, hormones, and sports type. Imbalances, as seen in the female athlete triad, can compromise bone health and lead to bone stress injuries and early-onset osteoporosis [7].

These conditions seen can result in significant morbidity and time lost from training and competition, emphasizing the importance of early recognition and appropriate treatment. Because of this, easy to apply or employ tools which are efficient of continuously assessing and monitoring bone health in female athletes are essential for the athlete's well-being. Through this, the study targets to implement models for the prediction of bone condition, shape, etc. in female athletes, while also exploring the consequence or significancy of features related to body mass and the menstrual cycle. The models here are trained to classify whether the subjects have minimal bonemass or normal bone mass. Following the [8] diagnostic criteria ad FDA (food and drug administration) low-slung bonemass is defined in this enquiry as an athlete whose z-score of bone density at the lumbar vertebrae is less than -1 [8].

Several methods are projected to estimate the risk of low bone mass. For naivety, separated them into two categories: imaging based classification and questionnaire based classification. For automatic imaging based predictions, deep learning is by far the main approaches used, with Convolutional Neural Networks (CNNs) being the go to model. Some notable studies include the use of a CNN to identify fractures, predict BMD, and assess fracture risk using plain radiographs [9], a deep-learning frame work to predict the density of a bone-mineral as of a single axial cut of the L1 bone on computational tomography (CT) [10] and a deep learning model to predict bone mineral density and T-scores using chest X-rays [11]. Despite the successful outcomes achieved in these studies, the reliance on clinical imaging may pose challenges in terms of accessibility and continuous monitoring.

Aims and Objectives

On the other hand we have questionnaire based classifiers. The most notorious of these is the Fracture Risk Assessment Tool (FRAX) [12] that predicts fracture probabilities for the next 10 years. However, it overlooks certain known fracture risk variables and lacks dose-response relationships. As it relies on age-related rates for fractures and deaths, calibration with population-specific data is also required [13]. Notably, as it was obtained by applying the data as of an older population, younger female athletes might not be properly evaluated due to its minimum age limit of 40, far exceeding the average age of most elite athletes. Therefore, there's a need for a new model tailored specifically for female athletes.

Methods

Clinical Demographics and Data

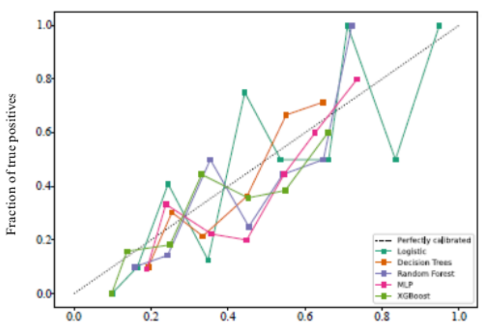
The dataset consists of >212 athletes and almost all of them are gender (women) subjects and their age ranging as of >12 to <=49 years. Data consists of their oldness like age and age at the menarche, time-duration of current amenorrhea, their height and weight, their sport event, presence of secondary amenorrhea during the teens, history of fractures and number of training days in a week. The BMD was done by restrained through dual energy X - ray absorption-metry (DXA) on their vertebra`s lumbar-spine:L1–L4 and the outcome value was determined as 1 for subjects(patients) with Z-scores < -1 and 0 for the others. This analysis thus considered low BMD as the positive case. There were 79 subjects classified with low BMD.

Circa few novel feature-manifestations were led to replace some of the original ones by applying the technological feature-engineering. Their heights and weights were employed to process BMI, as of that the thinness level was derived with the cut-offs presented in [14]. The sports were replaced by their exercise load (the impact they cause on the bones), with the four categories being: no impact, low impact, multi-directional impact and high impact. The last model-paradigms were accomplished then by employing the amenorrhea duration, sport impact, age at menarche, thinness score, training days in a week, secondary amenorrhea and fracture history as features.

For missing values, 24 subjects had missing values on the training time due to interrupted practices because of injuries or other reasons, so these values were filled as 0. There was also 1 subject missing age at menarche as it hasn't yet ensured its first menstruation, plus that`s filled by using k-NN imputation with 3 neighbors.

Techniques

For the classification, 5 different types of models were compared: logistic regression, Decision Tree (DT), Random Forest (RF), Multi-Layer Perceptron (MLP) and XG-Boost (Figure 1).



Mean Predicted Probability

Figure 1: Calibration curves for the model: Calibration curves for each of the models. As can be seen, all models presented satisfactory calibrations, with Random Forest and XG-Boost being the best calibrated while Logistic Regression was the worst.

All the models were implemented in Python 3.10.12, with the first four using the Scikit-Learn package [15] (version 1.2.2), and XG-Boost using the specific wrapper for the language [16]. The models used mostly the standard hyper-parameters defined by the library, with a few exceptions that were chosen after a cross-validation analysis within data which operated. Further, it`s important to note that, because the dataset was slightly unbalanced (with the majority class corresponding to around 67% of the subjects), balancing features in the models (such as scale_pos_weight in the XG-Boost case) were used to mitigate the biases this might have led to in the final predictions. To evaluate the model the AUC, the accuracy, the specificity and the sensitivity was employed as the main metrics. Cross-validation using 5 folds was applied to the training and evaluation of the models.

Results

Performance

Table I shows the performing outcomes intended for 5-fold cross- validation. From it, it becomes clear that all models had problems in miss-classifying the majority class (incorrectly classifying normal BMD subjects as low BMD ones), with XG-Boost actuality maximum balanced out of them in standings of specificity x sensitivity trade-off.

Model	Accuracy	Specificity	Sensitivity	AUC
Logistic Regression (LR)	0.75±0.02	0.44±0.20	0.91±0.08	0.77±0.06
Decision-Tree(DT)	0.70±0.02	0.33±0.20	0.89±0.08	0.70±0.07
Random-Forest(RF)	0.74±0.02	0.49±0.10	0.85±0.08	0.74±0.06
Multi-Layer Perceptron (MLP)	0.73±0.04	0.37±0.23	0.86±0.10	0.68±0.08
XG-Boost	0.68±0.04	0.62±0.23	0.93±0.07	0.73±0.05

Table 1: Results for 5 fold cross validation using KNN similarity as imputation method.

The calibrations of the models were assessed by training them on 2/3 of the data and calibrating on the remaining 1/3, and the results can be seen in 1. This assesses how well the probabilistic predictions of a binary classifier are calibrated, with a straight line being the ideal performance.

Significancy of the feature

From the algebra, the feature 'permutation' significancy was used to assess feature importance due to it being model-agnostic and allowing for multiple computations with different permutations, enhancing its flexibility and applicability across various models [17]. In that respect, it is crucial to make certain that features within our dataset are not correlated, as it might undermine the true significance of their importance. Through the inferences deduced, the pairwise spearman c o r r e l a t i o n amongst the features, which was possible to view that they aren`t particularly correlated, apart from secondary amenorrhea and the current amenorrhea duration, which are slightly correlated. Consequently, the dataset was used with all the features.

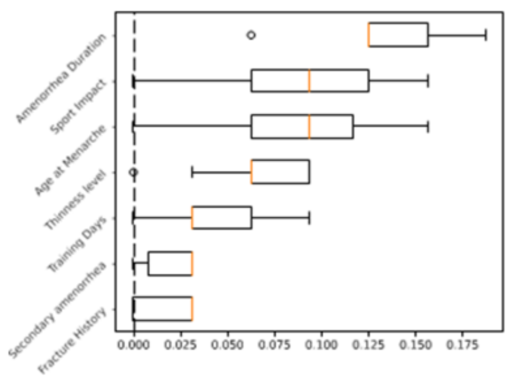


Figure 1: Permutation importance of the features. The plot shows the percentile loss in performance of the model when a feature is permuted. The impact of the sport-events plus period of current amenorrhea was the most imperative features identified, although the others also had slight importance.

Because the XG-Boost model was the one with the greatest concert in specificity (which is the focus here, as the goal is predicting correctly as many positive cases as possible), the feature importance analysis presented in Figure 1 was performed on it. And the pairwise feature significance was also measured by estimating the cumulative gain from features that occur in sequence in the tree structures of the XG-Boost model and illustrated in figure.

Results and Discussion

By applying supervised-learning-based classification algorithms we classified subjects between low BMD and normal ones. The best performing approach in terms of the specificity vs sensitivity trade-off was XG-Boost.

Our findings are reliable and unswerving through the preceding researchers work that showed the relation between amenorrhea and osteoporosis and low bone health risks [18,19]. In [20], a reduction in the BMD within the body vertebra in particular the 'lumbar-spine L1–L4 was examined for the subjects (patients) through amenorrhea, with the reduction being related to the duration of the case. Although the effects of estrogen [21] on bones might seem like a good explanation for this relation, it might not be the full story.

Functional hypothalamic amenorrhea (FHA) emerges from numerous situations for instance, eating disorders, overtraining (and imparting training overly), psychological, physical and physiological stress and strain. While these conditions have distinct features, a shared trigger is relative energy deficiency, which leads to metabolic and hormonal disturbances contributing to bone loss. Still, amenorrhea is not the only factor impacting bone loss, as reduced bone mass can be observed even in individuals with a preserved menstrual cycle [22] and other features in this study showed relevance as well.

The impact of the activity was also determined as an important factor. Athletes experiencing amenorrhea show a higher risk of low BMD when engaged in low-impact or non-impact sports compared to those in multidirectional or high-impact sports [23,24], that corresponds not just through the importance given to the impact feature, but also corroborates its strong interaction with amenorrhea duration observed here.

Premature menarche was too connected through the higher BMD and is described yet linked through the peak bone mass [25]. On the other hand, energy expenditure and periods of low energy convenience which could find as of having many training days within sports can result in reduction of bone mass [26]. The strong interaction amongst the oldness such as age at the menarche plus number of training days might indicate that subjects with older ages at menarche can have a tendency to be more affected by longer training periods, as the reduction in bone mass would have a bigger impact when peak bone mass is already lower.

Conclusions and Future Extensions

In this study, models for classifying between low and normal BMD were implemented. The models here presented still need to be validated with more data to properly assess their performances, as the existing data set was comparatively scanty and contained mainly highly specialized individuals (top-level female athletes). The dataset was also slightly imbalanced towards negative classifications. While the distribution was not highly disproportional, the final classifiers might help with further vital techniques of data balancing. Finally, few features had relatively underrepresented values compared to others, which might also bias the results and underestimate the true importance of said features.

For further steps, a longitudinal analysis of vicissitudes in bone density can be done over the duration. This would allow a well empathetic of the mechanisms that result in low scale denseness and improve the models prediction capabilities plus risk assessment.

The final models managed to achieve satisfactory performances, with XG-Boost achieving an accuracy of 0.69, a specificity of 0.63, a sensitivity of 0.94 and an AUC of 0.74. All the other trained models also obtained similar performances, with the main difference being in the specificity, where XG-Boost exceeded the alternatives. By performing permutation feature importance, it was observed which the effect of sports events plus extent of current amenorrhea were the most important features, with the others also showing importance to a lower degree which is dependable through preceding results in the literature, indicating that the models managed to extract useful information from the data. Although, performance here was not particularly high, the outcome demonstrates that the structural features at the structural level extracted as of questionnaires have the potential chosen accustomed to assist in the diagnosing of low BMD in female athletes. Still, more data is required for more concrete results.

References

1. Sambrook P, Kelly P, Eisman J (1993) Bone mass and ageing. Baillieres Clinical Rheumatology 7(3): 445-457.
2. Sirola J, Kroger H (2011) Similarities in acquired factors related to postmenopausal osteoporosis and sarcopenia. Journal of osteoporosis 20(11): 1-28.
3. Kanis JA (1994) Assessment of fracture risk and its application to screening for postmenopausal osteoporosis: synopsis of a WHO report. WHO study group. Osteoporos Int 4(6): 368-381.
4. Padilla C, Molina-Vicenty I, Frontera-Rodrıguez M, Garcıa-Ferre A, Rivera B, et al. (2018) Muscle and bone mass loss in the elderly population: Advances in diagnosis and treatment. Journal of Biomedicine 3:40-49.
5. Miller PD, McClung M (1996) Prediction of fracture risk i: Bone density. The American Journal of the Medical Sciences 312(6): 257-259.
6. Sale C, Elliott-Sale KJ (2019) Nutrition and athlete bone health. Sports Med 49(Suppl 2): 139-151.
7. Goolsby MA, Boniquit N (2016) Bone health in athletes. Sports Health 9(2): 108-117.
8. Nattiv A, Loucks AB, Manore MM, Sanborn CF, Sundgot BJ, et al. (2007) The female athlete triad. Med Sci Sports Exerc 39(10): 1867-1882.
9. Hsieh CI, Zheng K, Lin C, Mei L, Lu L, et al. (2021) Automated bone mineral density prediction and fracture risk assessment using plain radiographs via deep learning. Nature Communications 12: 5472.
10. Kang JW, Park C, Lee DE, Yoo JH, Kim M (2023) Prediction of bone mineral density in ct using deep learning with explainability. Frontiers in Physiology 13.
11. Sato YN, Yamamoto N, Inagaki Y, Iesaki T, Asamoto T, et al. (2022) Deep learning for bone mineral density and T-Score prediction from chest x-rays: A multicenter study. Biomedicines 10(9).
12. Kanis JA, Johnell O, Oden A, Johansson H, McCloskey E (2008) FRAX and the assessment of fracture probability in men and women from the UK. Osteoporos Int 19(4): 385-397.
13. McCloskey EV, Harvey NC, Johansson H, Lorentzon M, Liu E, et al. (2022) Fracture risk assessment by the frax model. Climacteric 25(1): 22-28.
14. Cole T, Flegal K, Nicholls D, Jackson A (2007) Body mass index cut offs to define thinness in children and adolescents: International survey. BMJ 335: 194.
15. Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, et al. (2011) Scikit-learn: Machine learning in Python. Journal of Machine Learning Research 12: 2825-2830.
16. Chen T, Guestrin C (2016) XG-Boost, in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM.
17. Breiman L (2001) Random forests. Machine Learning 45: 5-32.
18. Gordon CM, Nelson LM (2003) Amenorrhea and bone health in adolescents and young women. Curr Opin Obstet Gynecol 15(5): 377-384.
19. Miller KK, Klibanski A (1999) Amenorrheic Bone Loss. The Journal of Clinical Endocrinology Metabolism 84(6): 1775-1783.
20. Davies MC, Hall ML, Jacobs HS (1990) Bone mineral loss in young women with amenorrhoea. BMJ 30(6755): 790-793.
21. Khosla S, Oursler MJ, Monroe DG (2012) Estrogen and the skeleton. Trends Endocrinol Metab 23(11): 576-581.
22. Indirli R, Lanzi V, Mantovani G, Arosio M, Ferrante E (2022) Bone health in functional hypothalamic amenorrhea: What the endocrinologist needs to know. Frontiers in Endocrinology 13.
23. Nose-Ogura S, Yoshino O, Kinoshita S, Nakamura H, Harada M, et al. (2023) Differences of bone mineral density by characteristics of sports in amenorrheic athletes. International Journal of Sports Medicine.
24. Tenforde A, Carlson J, Sainani K, Chang A, Kim J, et al. (2018) Sport and triad risk factors influence bone mineral density in collegiate athletes. Medicine Science in Sports Exercise 50: 1.

25. Ito M, Yamada M, Hayashi K, Ohki M, Uetani M, et al. (1995) Relation of early menarche to high bone mineral density. Calcif Tissue Int 57(1): 11-14.

26. Hutson MJ, O'Donnell E, Brooke-Wavell K, Sale C (2021) Effects of low energy availability on bone health in endurance athletes and High-Impact exercise as a potential countermeasure: A narrative review. Sports Med 51(3): 391-403.