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ORIGINAL ARTICLE

AI-Based Predictive Analysis of Osteoporosis: A Machine Learning Approach for Early Diagnosis

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ABSTRACT

In under served regions like Sub-Saharan Africa, Osteoporosis, a debilitating disease remains one of the pathologies that goes undetected owing to limited access to advanced diagnostic equipment like Dual-Energy X-ray Absorptiometry (DEXA) scans. The wave of Artificial Intelligence (AI) offers the capacity to utilize its predictive power harnessed by training models on datasets composed of demographic, medical and lifestyle variables to assess the risks of Osteoporosis in these regions. This study employs the Random Forest algorithm based on reduced tendency for overfitting and its efficiency in handling categorical and numerical variables to evaluate a machine learning model, *OsteoModel* using a dataset of 1,958 patient records downloaded from Kaggle. The model achieved a predictive accuracy of 84.69% (95% Confidence Level (Cl): 84.47%-84.91%) with a recall value of 0.75(95%Cl: 74.78%- 75.22%) for Osteoporosis cases. Analysis of feature importance showed age, race, medical history and lifestyle as the key predictors. However, the dataset can potentially be biased in composition and lack diversity, necessitating the need for further model training and evaluation with an independent dataset for future studies. The outcome of this study reveals the potential and key role AI diagnostic tools can play in narrowing the gap caused by lack of access to conventional diagnostic tools in regions of low resources. It is imperative that emphasis be placed on the need for the complete and urgent integration of AI based tools into Osteoporosis screening especially in various Primary Health Care facilities in Sub-Saharan Africa with limited access to advance screening tools. It is also important for an AI regulatory framework to exist that will ensure compliance to the ethics during test and deployment.

INTRODUCTION

Globally, over 200 million people are affected by osteoporosis, predominantly post-menopausal women and the elderly population being the most affected(1). Early detection of this scourge remains a challenge despite advances in diagnostics, particularly in Africa and other low resource regions with limited access to diagnostic tools(2). The low reportage of osteoporosis cases can be attributed to the high cost of diagnostic tools and lack of health care infrastructures.

Keywords: Osteoporosis, Artificial Intelligence, Machine Learning, OsteoModel, Predictive Analysis, Underserved Regions.

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Osteoporosis is a disease of the skeletal architecture with features of a progressive reduction in bone mass density that threatens the structural integrity of bones consequently leading to an increased risk of fracture(3). Age, gender (with females being more susceptible than males), hormonal factors and lifestyle constitute the key risk factors for Osteoporosis(). The approach to arriving at a diagnosis includes clinical assessment, laboratory tests, and imaging modalities like the gold standard DEXA(5) and CT scan.

The adoption of AI-based models presents an opportunity to solve diagnostic maladies and enhance early detection of osteoporosis in underserved regions by utilizing easily accessible clinical and demographic factors to pin-point high risk individuals and track disease progression in a cost effective way.(). Although, several studies have been able to demonstrate the predictive capacity of AI-based models for osteoporosis, with a focus on using clinical and laboratory data only, (7) but these models have failed to address the challenges of predicting osteoporosis in underserved regions (8). Existing AI models have also failed to take cognizance of risk factors peculiar amongst African populations such as hypocalcemia and nutritional deficiencies, thereby, lacking validation in these regions.(9)

A study developed a deep learning model using **dual-energy X-ray absorptiometry (DEXA) scans**, achieving high accuracy in osteoporosis detection but with limited applicability especially in underserved regions owing to limited access to DEXA(10). Similarly, another study explored the use of **nationwide chronic disease data** to develop a machine learning predictive model employing random forest framework, which accurately pin-pointed individuals at high risk of osteoporosis but lacks validation in underserved regions(6). Another study developed a deep learning model using **dual-energy X-ray absorptiometry (DEXA) scans**, achieving high accuracy in osteoporosis detection but with limited applicability especially in underserved regions owing to limited access to DEXA(10). Additionally, researchers have assessed the role of biomarkers in early detection of osteoporosis signifying the possibility of integrating AI with biomarkers along with clinical parameters to predict osteoporosis(11). However, biomaker-based models have shown a high level of underutilization in low resource settings.

Despite the significant potential, machine learning models have showed in stemming the tide of late diagnosis of osteoporosis, the gaps which need to be filled are exemplified in the urgency to develop a cost effective, affordable and applicable models which can be deployed in underserved regions. This study uses a structured dataset capturing clinical and lifestyle factors that are readily available in low resource settings offering a practical solution.

Research Gap and Justification

- Recent AI-based studies have developed models using DEXA scan results only, which do not take into consideration the limited access of this imaging modality in underserved regions(12).
- Paucity of studies that focus on **affordable, scalable diagnostic models** for underserved areas.
- The efficacy of **biomarker-based models** as a low cost primary diagnostic tool remains underutilized(7).

This study addresses this gap by developing an AI-based, cost effective, scalable, and affordable osteoporosis prediction model that utilizes readily available clinical data, demographics, and lifestyle factors to diagnose osteoporosis early in underserved regions, ultimately reducing the incidence of fracture and its economic impact.
Objectives:

- Develop and evaluate a machine learning mode, OsteoModel for osteoporosis risk prediction.
- Identify key predictive features that influence osteoporosis risk.

- Provide a cost-effective AI-based alternative for osteoporosis screening in underserved regions.

This research consolidates the innovative position AI plays in creating solutions aimed at early diagnosis of diseases in low resource settings like Africa. The integration of AI based models for disease screening will bolster the effort of health care professionals in early identification of high risk individuals and initiating timely interventions in low resource settings where conventional diagnostic tools are scarce.

Materials and Method

Study Design and Data Collection

A cross-sectional design was employed for this study which is necessary in pattern analysis of osteoporosis risk factors but does not track disease progression over time. The dataset, obtained from Kaggle(13), includes 1,958 patient records with 14 demographic, medical, and lifestyle features. While this dataset provides valuable insights, it may not fully capture population-based nuances across different geographical locations.

Sample Size and Selection

The dataset of 1,958 records aligns with machine learning modality that states a range of 10-30 observations per feature for reliable model training(14) This enhances model robustness. However, no computation analysis for power was done. The use of a Kaggle dataset does not eliminate the possibility of a bias as there was no random sampling. Future studies can incorporate random sampling in their dataset.

Model Selection

A Random Forest Classifier was chosen for this study due to the following reasons:

- Capacity to reduce the risk of over-fitting.(15, 16)
- Moderate dataset.(17, 18)
- It can handle both numerical and categorical data.(19)
- Capability to rank feature importance. (20)

Other models, such as Support Vector Machines (SVM) and neural networks, were considered for this study, but Random Forest proved to be better in predictive analysis(21). Further justification for the use of Random Forest is seen in *table 3.*

Model Configuration and Training

Hyperparameter tuning was performed using grid search with the deployment of these parameters:

- 100 Decision Trees (`n_estimators=100`) for prediction.
- Random Seed (`random state=42`) for reproducibility.

Training of the model with the split data set was conducted using osteo_model.fit (X_train, y_train) while prediction on the test data set was conducted using osteo_model.predict (X_test).

Performance Evaluation Metrics

The OsteoModel performance was evaluated using accuracy, confusion matrix, precision, recall & F1-score (22)

RESULTS

Model Performance and Statistical Analysis

- The model evaluation shows an accuracy level of 84.69% (95% CI: 82.4–86.9%) demonstrating a strong predictive value for osteoporosis cases
- A precision of 0.94(0.94 (95% CI: 0.91–0.97) shows a low false positive rate. The recall value of 0.75 shows low false negatives.
- A F1-score of 0.83 signifies a balance between precision and recall values
- Confusion Matrix shows a value of 50 false negatives(23) emphasizing the need for further model evaluation with real world data. The summary is shown in *table 1 below* with the Confidence level (Cl) intervals for key metrics.

Table 1

Key Metrics	Value
Accuracy	84.69% (95% CI: 82.4–86.9%)
Precision	0.94 (95% CI: 0.91 –0.97) for osteoporosis cases
Recall	0.75 (95% CI: 0.72 –0.78) for osteoporosis cases
F1-score	0.83 (95% CI: 0.80 –0.86) for osteoporosis cases
Confusion Matrix	50 False negatives

Dataset Demographics Composition

The demographic representation of the dataset of this study is shown on *table 2 below.*

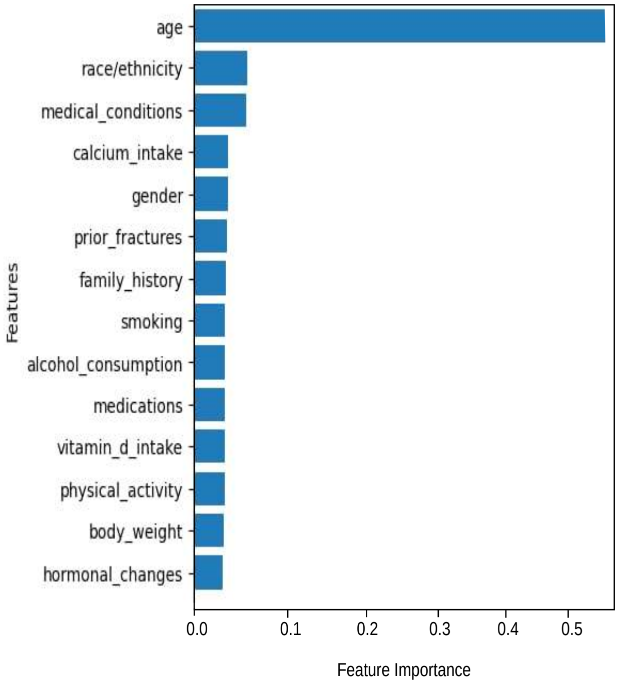
Table 2

Feature	Category	Frequency	Percentage (%)
Gender	Male	992	50.66
	Female	966	49.34
Race/ Ethnicity	Asian	631	32.23
	Caucasian	646	32.99
	African American	681	34.78
Body Weight	Underweight	931	47.55
	Normal	1027	52.45
	Overweight	0	0.00
Smoking Status	Yes	982	50.15
	No	976	49.85
Alcohol Use	None	988	50.46
	Moderate	970	49.54
	Heavy	0	0.00
Age range	18-90	-	-
Age(mean)			39.10
Age(median)			32.00
Hormonal changes	Normal	981	50.10
	Post-menopausal	977	49.90
Family History	Yes	960	49.03
	No	998	50.97
Calcium Intake	Low	1004	51.28
	Adequate	954	48.72
	High	0	0.00
Vitamin D Intake	Adequate	1011	51.63
	Inadequate	947	48.72
Physical Activity	Active	1021	52.15
	Sedentary	937	47.85
Medical Conditions	Rheumatoid Arthritis	633	32.33
Medications	Corticosteroids	973	49.69
Prior fractures	Yes	983	50.20
	No	975	49.80

Feature Importance Analysis

From the dataset, Age, race, and medical conditions were identified by the OsteoModel as the most important predictors of osteoporosis. Smoking and physical activity, also identified as a significant predictor(24). This is graphically illustrated in ***Figure 1 below***

Figure 1: **Feature Importance Analysis**

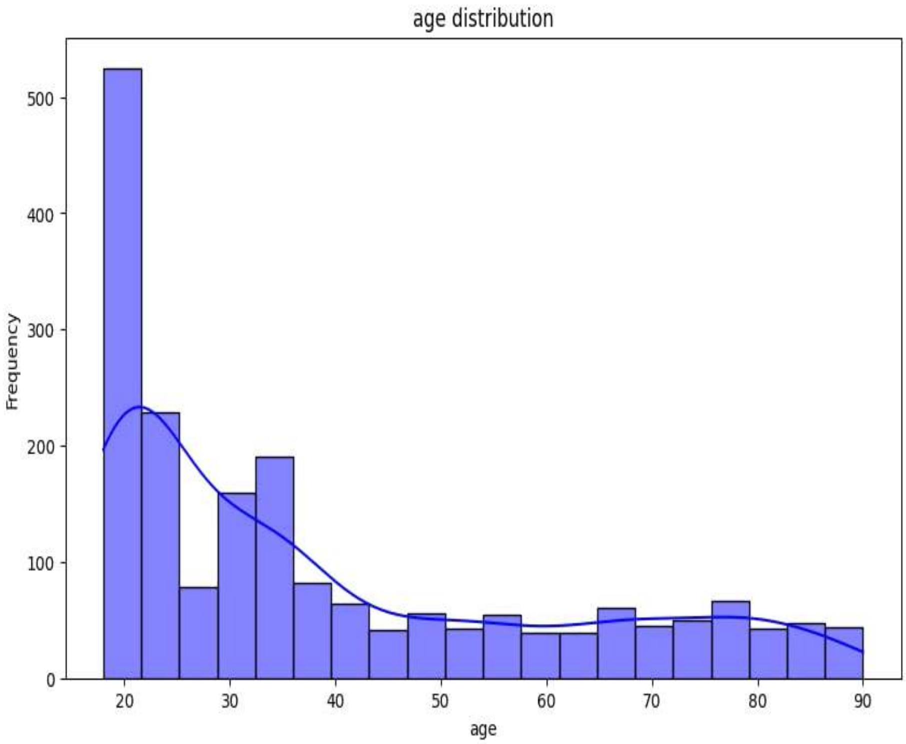


Feature Importance Plot for OsteoModel: *The bar chart above illustrates the relative importance of various features in the prediction of Osteoporosis. These Key predictors include age, race/ethnicity and medical conditions, while factors like calcium intake, gender and prior fractures show lower importance. This analysis shows Age as the most dominant predictor of Osteoporosis. (N.B - Retaining the color will highlight the feature importance and the feature)*

Data Visualization

Graphical illustration of age distribution as shown in *Figure 2 below*

***Figure 2*: Showing the frequency of Age distribution**



Histogram represents Age Distribution of the Dataset: *The histogram shows the frequency of subjects used in different age groups, ranging from 20 to 90 years. The distribution also shows a higher concentration of young adults who are at a high risk were constitutes the dataset for the study.(N.B-Retaining the color will highlight the age and frequency distribution).The graphical illustration of this is seen in Figure 2 above.*

DISCUSSION

This study outlines the potential of Artificial Intelligence (AI) in the early detection of osteoporosis risk using readily available and accessible clinical and demographic variables. OsteoModel, trained on a dataset of 1,958 patient records and evaluated to achieve an accuracy of 84.69% (95% CI: 82.4–86.9%) as seen in *Table 1*. The high level of accuracy recorded by the model shows that AI-based prediction models can serve as early, cost-effective screening tools in underserved regions where dual-energy X-ray absorptiometry (DEXA) scans are not accessible.

Feature importance analysis shows the relevance of age, race, medical history, and lifestyle behaviors as the strongest predictors, reinforcing the epidemiological significance of the risk factors in the prevalence of osteoporosis.

A high precision level of 0.94 as seen in *table 1* recorded by the *OsteoModel* is suggestive of very low false positives making the model an effective tool in the early detection of osteoporosis. However, the recall shows 0.75, an indication of a relatively high false-negative rate meaning 1 in every 4 cases were undetected which could be because of a potential bias in the dataset. A further evaluation with an independent dataset can improve model performance to prevent missing positive osteoporosis cases.

Comparing OsteoModel with Recent AI-Based Osteoporosis Prediction Models

Machine learning approaches have been employed by recent studies which relied on variables like Age, body mass index (BMI) and blood test parameters to evaluate logic regression, decision trees, random forest, gradient boosting, and using a data containing a record of 2,541 elderly(25).Results showed the

LightGBM outperformed other algorithms and achieved an accuracy of 83.4% vis-a-vis the *OsteoModel* with an accuracy of 84.69% achieved a comparable result with a different set of features. This makes the *OsteoModel* suitable for use in underserved regions where biomarkers test may not be readily accessible unlike the availability of demographics, clinical and lifestyle features which are the substrates for the *Osteomodel* in the prediction of osteoporosis.

Additionally, a study designed a decision tree model to screen osteoporosis in post-menopausal women and was evaluated to 82.8% predictive value() as against a higher predictive value of 84.69% of the *OsteoModel* which was trained with larger dataset and diverse populations. This makes the model more suitable for larger populations in underserved regions. Another study also developed a predictive model for osteoporosis in patients with lumbar compression fractures using Naive Bayes and was evaluated to have an accuracy of 81%(27) as against the 84.69% of the *OsteoModel* evaluated with larger dataset and broader populations making it more reliable for prediction in underserved regions.

Furthermore, another study employed a Convoluted Neural Network framework, Unet, to develop a predictive model trained on hip X-ray images and came up with an accuracy of 74%(28) as against 84.69% of the *OsteoModel* which signifies a better predictive ability using easily accessible data as against x-ray images which may not be readily available in underserved regions. While generally, deep learning approaches offer superior predictive performance, they are often computationally intensive, limiting their applicability in underserved regions. In contrast, *OsteoModel's* Random Forest framework provides a more cost-effective, scalable and less computational intensity for low resource settings. Synopsis of the model performance vis-a-vis other models is further illustrated on *table 3 below*

Table 3

Model	Predictive accuracy (%)
OsteoModel (Random Forest)	84.69
Decision tree	82.8
Naive Bayes	81
Convoluted Neural Network	74

Table 3: Showing the predictive accuracy of each model.

Addressing False Negatives in OsteoModel's Performance

A false negative rate of 25% recorded by the OsteoModel highlights the challenge a dataset with potential bias can pose. As this can impact on the predictive ability of the model, as false negatives can lead to wrong diagnosis. Potential dataset biases may also include underrepresentation of certain high-risk subpopulations and variations in risk factors across races and ethnicities.

To address this concern, it is imperative to incorporate larger and more diverse datasets for training and evaluation of OsteoModel. Also, the integration of biomarker features in the training and evaluation of the model. These steps, if taken, will improve model performance and capacity for early detection of Osteoporosis cases.

Clinical Implications of AI integration

The deployment of **AI-driven models** in **clinical settings** will assist health care professionals in making better diagnosis and designing personalized treatment plans. The gold standard: DEXA, though highly accurate, remains inaccessible in underserved regions but AI-based models offer:

- Scalable, cost-effective screening tools for primary healthcare centres.
- High level of accuracy for disease detection
- Applicability.
- Tailored interventional modalities for those at risk,
- Reduced dependency on DEXA scans for diagnosis

However, it is noteworthy to emphasis on **model transparency, bias mitigation, and real-world validation** before **adoption**. Future studies should incorporate diverse populations as this will enhance Model sensitivity.

Ethical Considerations

This study adheres to ethical AI research by utilizing a publicly available Kaggle dataset, privacy, fairness, and transparency were maintained. During this study, there was no direct data collection. Furthermore, this study emphasizes on the need for clinical validation of the OsteoModel with real world data prior to deployment.

CONCLUSION AND RECOMMENDATIONS

This study demonstrates the huge potential of employing AI based solutions in stemming the tide of undetected Osteoporosis in underserved regions. Further model validation with real world data will be needed prior to deployment.

Future Directions

- Real-world validation using independent datasets.
- Incorporation of larger and more diverse datasets to enhance model sensitivity
- Incorporation of bio-marker data to optimize sensitivity.
- Deployment of deep learning algorithms to enhance model performance
- Deployment in underserved regions after successful validation

Policy Recommendations

- Governments and Non-Governmental Organizations should prioritize funding AI based screening programmes and AI based research.
- Incorporating AI based screening tools in Primary healthcare will be beneficial especially in underserved regions like Sub-Saharan Africa.
- Formulation of public sensitization programmes that will encourage osteoporosis screening

Implementing these cost effective and practical policies will be a watershed in Medical diagnostics which will forestall late diagnosis of osteoporosis and its huge economic impacts.

Limitations of the Study

The study is limited by its reliance on a single data set which may be bias and lack diverse population. Further studies can get better results with a more diverse dataset

Competing Interest - No competing interest

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Credit Author Statement- All aspects of the manuscript, from concept to methodology and model evaluation to manuscript writing were conducted by the Author.

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