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Predictive Diagnostic Model for Early Osteoporosis Detection Using Deep Learning and Multimodal Imaging Data: A Systematic Review and Meta-Analysis

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Abstract **- Osteoporosis is a common condition that weakens bones, making them more prone to fractures. Early detection is crucial for preventing fractures and improving patients' quality of life. However, traditional methods, such as Dual-Energy X-ray Absorptiometry (DXA), often struggle to accurately predict fracture risk and may overlook minor changes in bone structure. This study focuses on developing a predictive model for early osteoporosis detection using deep learning algorithms combined with various imaging techniques, including MRI, CT, and High-Resolution Peripheral Quantitative Computed Tomography (HR-pQCT). A systematic review and meta-analysis of studies published between 2014 and 2024 were conducted, examining the use of deep learning models applied to multimodal imaging data. The meta-analysis highlighted differences in the accuracy and effectiveness of various models, and their performance was measured in terms of accuracy, sensitivity, and specificity, following PRISMA guidelines. The results showed that deep learning models outperformed traditional methods in early osteoporosis detection. The use of multiple imaging techniques provided a more detailed assessment of bone health, allowing the models to identify complex patterns that are difficult for human interpretation. These models demonstrated high accuracy and significant potential for improving clinical decision-making. By integrating deep learning with multimodal imaging, this approach offers a promising solution for enhancing the early detection of osteoporosis. The models tested in this study proved to be highly effective, yielding more accurate fracture risk predictions and enabling earlier interventions. This could lead to better patient outcomes and reduced healthcare costs.**
Keywords: **Osteoporosis Detection, Deep Learning, Multimodal Imaging, Fracture Risk Prediction, Meta-Analysis**

I. INTRODUCTION

Osteoporosis is a widespread skeletal condition characterized by weak bones and an increased risk of fracture, posing a significant global health challenge [1]. The term "osteoporosis" is derived from "osteo" (related to bones) and "porosis," from the Greek term "poros," meaning "pore" or "passage." Thus, osteoporosis refers to "porous bones," indicating a state of reduced bone density and increased bone fragility [12].

This silent and progressive disease often remains undetected until a fracture occurs [17], leading to severe morbidity, increased mortality, and higher healthcare costs [2]. Early identification of individuals at risk for osteoporosis is crucial for implementing preventive measures, effective treatment strategies, and minimizing fracture-related complications. Traditional diagnostic methods, such as Dual-Energy X-ray Absorptiometry (DXA), lack the precision to detect early bone deterioration and often miss subtle changes in bone microarchitecture [3].

To overcome these limitations, there is growing interest in using advanced computational methods and multimodal imaging to develop predictive diagnostic models for early osteoporosis detection. Deep learning can help analyze intricate patterns in medical images and detect high-dimensional features that the human eye cannot discern. By combining multimodal imaging data, such as DXA, MRI, and CT scans, predictive models can provide a detailed assessment of bone health [13], supporting proactive interventions and personalized treatment plans [4].

This research aims to create a predictive diagnostic model for early osteoporosis detection using deep learning and multimodal imaging. By leveraging deep learning algorithms and integrating various imaging techniques [14], the goal is to enhance the accuracy, sensitivity, and specificity of osteoporosis diagnoses, ultimately improving patient outcomes and reducing the healthcare burden.

Through a detailed analysis of multimodal imaging data and the development of robust predictive models, this research seeks to advance our understanding of osteoporosis pathophysiology, improve clinical decision-making, and promote personalized bone health management strategies.

II. RATIONALE

The goal of this project is to systematically perform a thorough review of the relevant literature to determine how deep learning and multimodal imaging data can assist in the prediction and early detection of osteoporosis. Early detection of osteoporosis depends on the influence of the independent variables [5]. In this case, the accuracy or success of early osteoporosis detection relies on the predictive capability of the deep learning models being studied [18].

III. OBJECTIVES OF THE STUDY

The main purpose of this study is to identify and closely examine the effectiveness of creating a predictive diagnostic model for early osteoporosis detection using deep learning and multimodal imaging data. The specific objectives are as follows.

1. To conduct a thorough examination of existing articles on the development of predictive diagnostic models for early osteoporosis detection using deep learning and multimodal imaging data.
2. To identify the most effective methods for building a predictive diagnostic model for early osteoporosis detection using deep learning and multimodal imaging data.

IV. METHODOLOGY

A. Criteria for Eligibility

Criteria for this systematic review included publications from the last decade (2014-2024) in the English language that specifically utilized deep learning frameworks to classify and predict the occurrence of osteoporosis. The review addressed the following questions: What deep learning frameworks have been utilized for predictions, and what are their performance and limitations

B. Defining Criteria for Exclusion

1. Research that does not use deep learning models
2. Studies focusing on patients with bone defects other than osteoporosis
3. Research that does not report prediction model accuracy metrics
4. Non-English publications
5. Articles with inaccessible full text
6. Conference abstracts, letters, editorials, case reports, reviews, and meta-analyses were excluded.

C. Defining Criteria for Inclusion

For this study, the researchers utilized the PICOS framework (Participants, Interventions, Comparison, Outcomes, and Study Design) to determine the criteria for selecting articles.

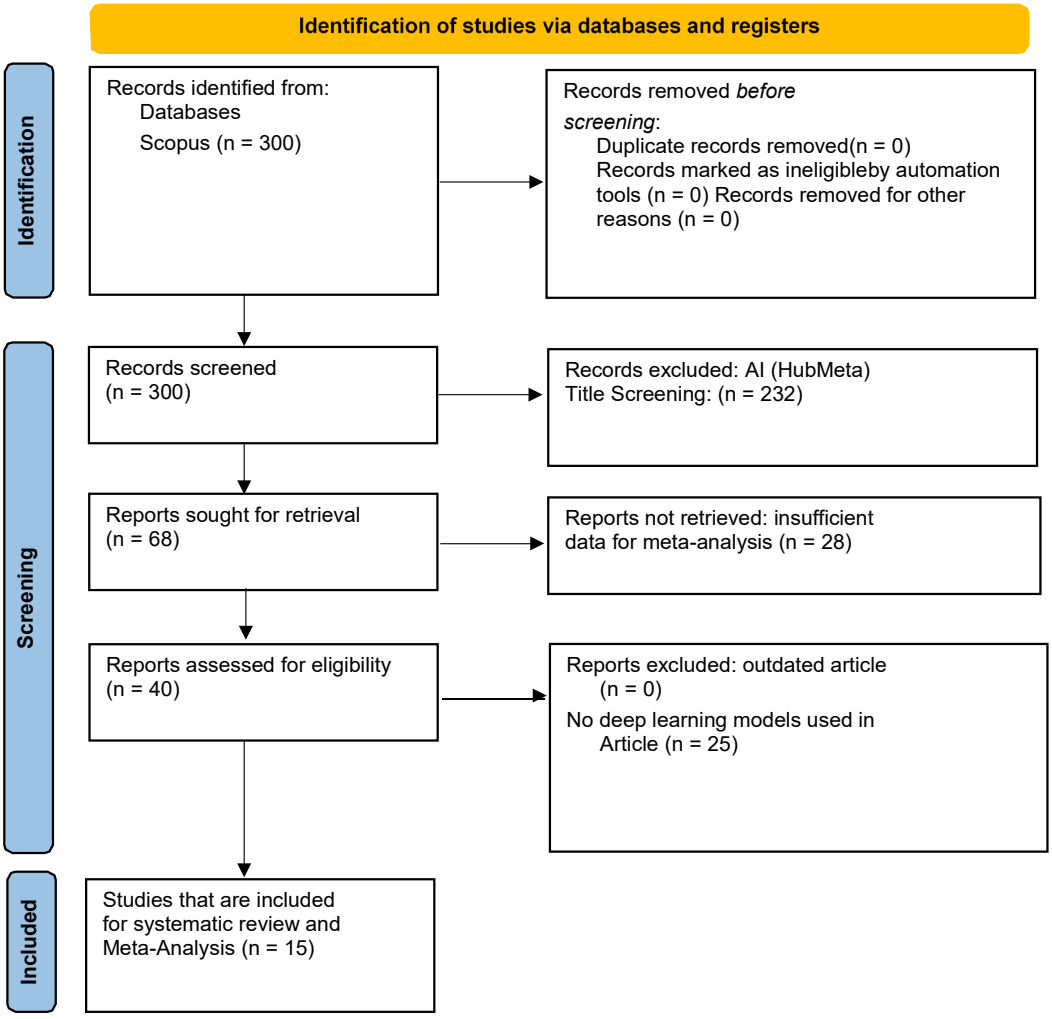

Fig. 1 The Flow diagram shows the number of studies eventually screened

V. SEARCH STRATEGY

The approach employed for this thorough examination adheres to the principles outlined in the PRISMA 2020 guidelines. Any modifications to this protocol and the rationale during the systematic review will be documented in the final report. The database used for the search strategy was Scopus, and the searches were conducted in May 2024 using a combination of keywords and advanced queries. A total of 300 articles were found using the following search query in Scopus.

TITLE-ABS-KEY (predict OR forecast*) AND (diagnostic* OR analy*) AND (detection OR discovery) AND (osteoporosis OR osteopenia OR osteodystrophy) AND ("Deep Learning" OR "Machine Learning" OR "Artificial intelligence") AND (ct OR "Computed Tomography" OR mri OR "Magnetic Resonance Imaging") AND (LIMIT-TO (SUBJAREA , "MEDI") OR LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "BIOC")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (OA , "all"))*

This query combines Medical Subject Headings (MeSH) terms for osteoporosis, multimodal imaging data, recurrence, and predictive analytics to narrow the search to articles specifically related to predictive diagnostic models for early detection of osteoporosis using deep learning and multimodal imaging data.

A. Selection Process

1. *Population/Patient:* Patients at risk of osteoporosis or individuals with suspected bone health issues.
2. *Intervention:* Development of a predictive diagnostic model [19] using deep learning algorithms and the integration of multimodal imaging data (including DXA, MRI, and CT scans) [15].
3. *Comparison:* Traditional diagnostic methods for osteoporosis detection, such as DXA scans, compared to the integration of deep learning techniques and multimodal imaging data [20].
4. *Outcome:* Improved accuracy, sensitivity, and specificity in the early detection of osteoporosis, leading to timely interventions and optimized treatment strategies [21], as well as reduced fracture-related complications. Other outcomes include the reported performance of the predictive diagnostic model for early detection of osteoporosis using deep learning and multimodal imaging data [22].

VI. DATA COLLECTION PROCESS

A. Data Extraction, Sorting and Selection

The researcher will use a standard data extraction method to extract data from the articles. Data extraction will be performed by the researcher, and any discrepancies will be resolved by applying the eligibility criteria, AI-assisted screening, and personal judgment. The extracted data will include study characteristics, participant details, interventions, outcomes, and results.

Regarding the screening process, a researcher conducted an exercise in which titles and abstracts of the studies were retrieved to evaluate eligibility based on predefined inclusion and exclusion criteria. Full texts will be obtained for all articles that meet the eligibility criteria. The selection process will involve three stages:

1. First, all search results will be imported into Mendeley and then transferred to the HubMeta systematic review manager to assist with the review, including the removal of duplicate articles prior to reviewing the titles and full texts.
2. Titles and abstracts will be carefully sorted by both an AI assistant and a single reviewer, strictly following the PICOS criteria.
3. Finally, the papers will be confirmed by reviewing their full texts.

B. Data Items

Study details: Title, authorship, publication year, journal title, research methodology, sample size, inclusion and exclusion criteria, and data sources.

C. Assessment of Quality

Each study will undergo a quality assessment, focusing on four primary criteria:

1. Potential selection bias,
2. Instrumentation accuracy,
3. Management of missing data, and
4. Reporting of measurement results.

D. Measures of Summary

Key summary measures include odds ratios (OR) or hazard ratios (HR) along with 95% confidence intervals (CI) to further evaluate the classification and prognostic accuracy of the predictive analytics framework [16].

E. Strategy for Data Integration and Synthesis

A flow chart following the PRISMA guidelines will be provided to document the study selection process, showing the number of papers retained at each stage. A narrative synthesis will be performed, and the findings of the included studies will be summarized and presented in a table. If enough studies are available, a meta-analysis will be conducted using a random-effects model. Homogeneity and heterogeneity will be assessed using the I^2 statistic. Since this process aims to observe the deep learning models employed for early detection of osteoporosis and the accuracy of prognosis prediction, the outcomes will be presented quantitatively. A table will be created to summarize the

studies included in the final review, highlighting key features such as datasets, deep learning models, accuracy, and study outcomes.

F. Assessment of Bias in research

The researcher examines various biases, including selection bias, performance bias, detection bias, attrition bias, and reporting bias, using specific criteria. Any discrepancies are carefully reviewed and resolved through a thorough reassessment process. Evaluating bias aids in understanding and summarizing the study results and may lead to the exclusion of studies with significant bias from the final review.

G. Study Design

This systematic review will include studies that utilize a predictive diagnostic model for the early detection of osteoporosis using deep learning and multimodal imaging data. The selection of studies will adhere to PRISMA guidelines.

VII. DATA EXTRACTION, SORTING, AND SELECTION

Information from the studies was gathered using a standardized data extraction form, and discrepancies were resolved through AI-assisted screening and judgment. The extracted data included study characteristics, participant details, interventions, outcomes, and results. The selection process reportedly involved three stages:

1. Search results were imported into Mendeley and HubMeta, with duplicate articles removed.
2. Titles and abstracts were screened by an AI assistant and a reviewer based on the PICOS criteria.
3. Full-text articles were reviewed to confirm eligibility.

TABLE I DATA EXTRACTED FROM SYSTEMATIC REVIEWED PUBLICATIONS

1. M. Tassoker, M. Ü. Öziç, and F. Yuce, "Comparison of five convolutional neural networks for predicting osteoporosis based on mandibular cortical index on panoramic radiographs," Dentomaxillofacial Radiology, vol. 51, no. 6, 2022 [6]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
C1, C2, C3	AlexNET	81.1
C1, C2	GoogleNET	88.9
C1, C3	AlexNET	98.6
C1, (C2+C3)	GoogleNET	92.8
2. S. H. Kong *et al.*, "Development of a Spine X-Ray-Based Fracture Prediction Model Using a Deep Learning Algorithm," *Endocrinology and Metabolism*, vol. 37, no. 4, pp. 674-683, 2022 [1]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
Images + Clinical Features	DeepSurv (men)	61.2
Images only	DeepSurv (women)	61.4
Clinical features only	FRAX	54.7
Clinical features only	CoxPH	59.4
3. M. Jang, M. Kim, S. J. Bae, S. H. Lee, J.-M. Koh, and N. Kim, "Opportunistic Osteoporosis Screening Using Chest Radiographs With Deep Learning: Development and External Validation With a Cohort Dataset," *Journal of Bone and Mineral Research*, vol. 37, no. 2, pp. 369-377, 2022 [2]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
Internal Test Set	OsPor-screen	91.2
External Test Set	OsPor-screen	88.0
4. Y. Chen, X. Sun, X. Sui, Y. Li, and Z. Wang, "Application of bone alkaline phosphatase and 25-oxhydryl-vitamin D in diagnosis and prediction of osteoporotic vertebral compression fractures," *J Orthop Surg Res*, vol. 18, no. 1, 2023 [7]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
B-ALP	spinal CT images	86.7
25-OH-VD	spinal CT images.	83.3
5. C.-I. Hsieh *et al.*, "Automated bone mineral density prediction and fracture risk assessment using plain radiographs via deep learning," *Nat Commun*, vol. 12, no. 1, 2021 [7]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
Hip Osteoporosis	Automated Tool	91.7
Spine Osteoporosis	Automated Tool	86.2
High 10-Year Major Fracture Risk	Automated Tool	95.0
High Hip Fracture Risk	Automated Tool	90.0

6. M. T. Löffler *et al.*, "Automatic opportunistic osteoporosis screening in routine CT: improved prediction of patients with prevalent vertebral fractures compared to DXA," *Eur Radiol*, vol. 31, no. 8, pp. 6069-6077, 2021 [8]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
Trabecular vBMD	Automated Assessment in CT	88.5
Integral vBMD	Automated Assessment in CT	86.0
Manual vBMD	Manual Assessment in CT	88.5
Areal BMD (aBMD)	Lumbar DXA	66.8
7. Y. Pan *et al.*, "Automatic opportunistic osteoporosis screening using low-dose chest computed tomography scans obtained for lung cancer screening," *Eur Radiol*, vol. 30, no. 7, pp. 4107-4116, 2020 [9]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
200 annotated LDCT scans	Automated BMD	92.7
8. S. Wang *et al.*, "Combining Deep Learning and Radiomics for Automated, Objective, Comprehensive Bone Mineral Density Assessment From Low-Dose Chest Computed Tomography," *Acad Radiol*, vol. 31, no. 3, pp. 1180-1188, 2024 [10]		
Dataset	**CNN Model**	**Accuracy (%)**
Internal Testing cohorts	VB-Net (TVCB segmentation)	93.9
External Testing cohorts	ASeg model (Radiomics for BMD prediction - first-level model)	96.5
9. C. Zhang, L. Fan, S. Zhang, J. Zhao, and Y. Gu, "Deep learning based dental implant failure prediction from periapical and panoramic films," *Quant Imaging Med Surg*, vol. 13, no. 2, pp. 935-945, 2023 [11]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
Periapical Images	CNN	78.6
Panoramic Images	CNN	78.7
Periapical + Panoramic	CNN	87.0
10. Y. Sato *et al.*, "Deep Learning for Bone Mineral Density and T-Score Prediction from Chest X-rays: A Multicenter Study," *Biomedicines*, vol. 10, no. 9, 2022 [12]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
Chest X-rays	Ensemble Learning	84.0
11. K. Yoshida *et al.*, "Feasibility of Bone Mineral Density and Bone Microarchitecture Assessment Using Deep Learning with a Convolutional Neural Network," *J Comput Assist Tomogr*, vol. 47, no. 3, pp. 467-474, 2023 [13]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
Vertebral images	ResNet50	91.5
12. J. Schilcher, A. Nilsson, O. Andlid, and A. Eklund, "Fusion of electronic health records and radiographic images for a multimodal deep learning prediction model of atypical femur fractures," *Comput Biol Med*, vol. 168, 2024 [14]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
Imaging data	CNN	79.6
Tabular data	Vision Transformers	90.3
13. Q. Dong *et al.*, "Generalizability of Deep Learning Classification of Spinal Osteoporotic Compression Fractures on Radiographs Using an Adaptation of the Modified-2 Algorithm-Based Qualitative Criteria," *Acad Radiol*, vol. 30, no. 12, pp. 2973-2987, 2023 [15]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
Local dataset	Ensemble averaging of five deep learning algorithms	77.1
MrOS Study dataset	Ensemble averaging of five deep learning algorithms	73.7
14. T. Peng *et al.*, "A study on whether deep learning models based on CT images for bone density classification and prediction can be used for opportunistic osteoporosis screening," *Osteoporosis International*, vol. 35, no. 1, pp. 117-128, 2024 [16]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
Opportunistic CT scan	VB-Net (segmentation)	81.5
15. Q. Dong *et al.*, "Deep Learning Classification of Spinal Osteoporotic Compression Fractures on Radiographs using an Adaptation of the Genant Semiquantitative Criteria," *Acad Radiol*, vol. 29, no. 12, pp. 1819-1832, 2022 [17]		
Dataset	**Deep Learning Model**	**Accuracy (%)**
radiographs	GoogLeNet	82.0

VIII. META-ANALYSIS

To analyze the heterogeneity of the accuracy of each deep learning model reported in the included articles, a statistical tool (GraphPad Prism) will be used with repeated measures ANOVA (Analysis of Variance). Repeated measures ANOVA is suitable since multiple measurements are taken on the same subjects over time.

A. How Meta-Analysis was Performed Using Repeated Measures ANOVA in GraphPad Prism

1. *Data Entry:* The data entry process involved inputting data into GraphPad Prism, typically organized with columns representing different deep learning models and rows representing the accuracy of each model.
2. *Select Analysis:* To select the analysis, one must navigate to the "Analyze" menu in GraphPad Prism and choose "Descriptive Statistics" from the list of analyses.
3. *Input Data:* Data input involved selecting the data table and specifying the columns containing the accuracy of the predictive diagnostic models as dependent variables. The independent variable representing the deep learning models used was specified, along with the indication of the repeated measures structure, including occurrence (or number of cases).
4. *Adjust Settings:* Settings in GraphPad Prism could be adjusted for the analysis, including the ANOVA model type (e.g., within-subject's factors only, mixed model with between-subjects factors), handling of missing data, and adjustment for sphericity.
5. *Interpret Results:* The interpretation of results involved paying attention to the accuracy of the predictive diagnostic models, as well as any interactions between them, provided by GraphPad Prism after running the repeated measures ANOVA. Significance levels had to be considered to determine the clinical relevance of the findings.
6. *Post-Hoc Tests:* If significant effects were indicated by the repeated measures ANOVA, post-hoc tests could be conducted to examine specific pairwise comparisons between the accuracies of the predictive diagnostic models. GraphPad Prism offered various post-hoc tests, such as Tukey's multiple comparisons test or Bonferroni correction.

TABLE II DESCRIPTIVE STATISTICS

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
	AlexNET	oogleNET	pSurv (m	Surv (wo	FRAX	CoxPH	sPor-scre	nal CT imag	tomated Tr	nated Asse	AL ASSES	Lumbar DXA	tomated BM	VB-Net	seg Mode	CNN MODEL	Ensemble Learning	ResNet50	on Transforr
1	Number of values	1	2	1	1	1	1	1	1	1	1	1	1	1	2	1	1	2	1	1
2																				
3	Minimum	81.14	82.00	61.20	61.40	54.70	59.40	91.20	86.70	91.70	88.50	86.00	66.80	92.70	81.50	96.50	87.00	77.10	91.50	90.30
4	25% Percentile	81.14	82.00	61.20	61.40	54.70	59.40	91.20	86.70	91.70	88.50	86.00	66.80	92.70	81.50	96.50	87.00	77.10	91.50	90.30
5	Median	81.14	85.47	61.20	61.40	54.70	59.40	91.20	86.70	91.70	88.50	86.00	66.80	92.70	87.70	96.50	87.00	80.55	91.50	90.30
6	75% Percentile	81.14	88.94	61.20	61.40	54.70	59.40	91.20	86.70	91.70	88.50	86.00	66.80	92.70	93.90	96.50	87.00	84.00	91.50	90.30
7	Maximum	81.14	88.94	61.20	61.40	54.70	59.40	91.20	86.70	91.70	88.50	86.00	66.80	92.70	93.90	96.50	87.00	84.00	91.50	90.30
8																				
9	Mean	81.14	85.47	61.20	61.40	54.70	59.40	91.20	86.70	91.70	88.50	86.00	66.80	92.70	87.70	96.50	87.00	80.55	91.50	90.30
10	Std. Deviation	0.000	4.907	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	8.768	0.000	0.000	4.879	0.000	0.000
11	Std. Error of Mean	0.000	3.470	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	6.200	0.000	0.000	3.450	0.000	0.000
12																				
13	Lower 95% CI		41.38												8.922			36.71		
14	Upper 95% CI		129.6												166.5			124.4		

Table II presents descriptive statistics that shed light on how different models perform in detecting osteoporosis using deep learning and multimodal imaging. Key statistics such as mean, standard deviation, and confidence intervals (CIs) help evaluate each model's accuracy and reliability.

For AlexNet, the data shows consistent performance, with a mean of 81.14 and no variation in percentiles or spread measures (standard deviation = 0, CI = 41.38-129.6). This uniformity may suggest that AlexNet struggles to capture the nuances in the data.

GoogleNet has more variability, with a mean of 85.47 and a standard deviation of 4.907. Its confidence interval (CI = 41.38-129.6) indicates a broader range of uncertainty, implying that its performance may vary more than that of AlexNet.

The Ensemble Learning approach shows a mean of 80.55 and a standard deviation of 4.879, with a CI ranging from 36.71 to 124.4. This suggests that Ensemble Learning is a solid method, displaying reliable performance across different samples.

VB-Net stands out with a higher mean of 87.70 and a lower standard deviation of 6.200. This indicates that VB-Net may be better at identifying subtle patterns in imaging data for predicting osteoporosis.

Other models, such as ResNet50 and CNN models, show similar performance levels, with means of 91.50 and 87.00, respectively. Both have low variability, suggesting they are dependable for the early detection of osteoporosis through multimodal imaging.

Overall, these statistics indicate that while some models, such as VB-Net and CNN models, provide higher accuracy and reliability, others, like AlexNet and GoogleNet, may have limitations in variability and consistency. This information can help in choosing the right models for developing predictive diagnostics in osteoporosis detection using deep learning and multimodal imaging.

IX. VISUALIZATION OF DATA

Visualizations of the data in Fig. 2 include a bar chart created in GraphPad Prism to illustrate trends in the accuracy of each deep learning model. These visualizations aided in the interpretation and presentation of findings.

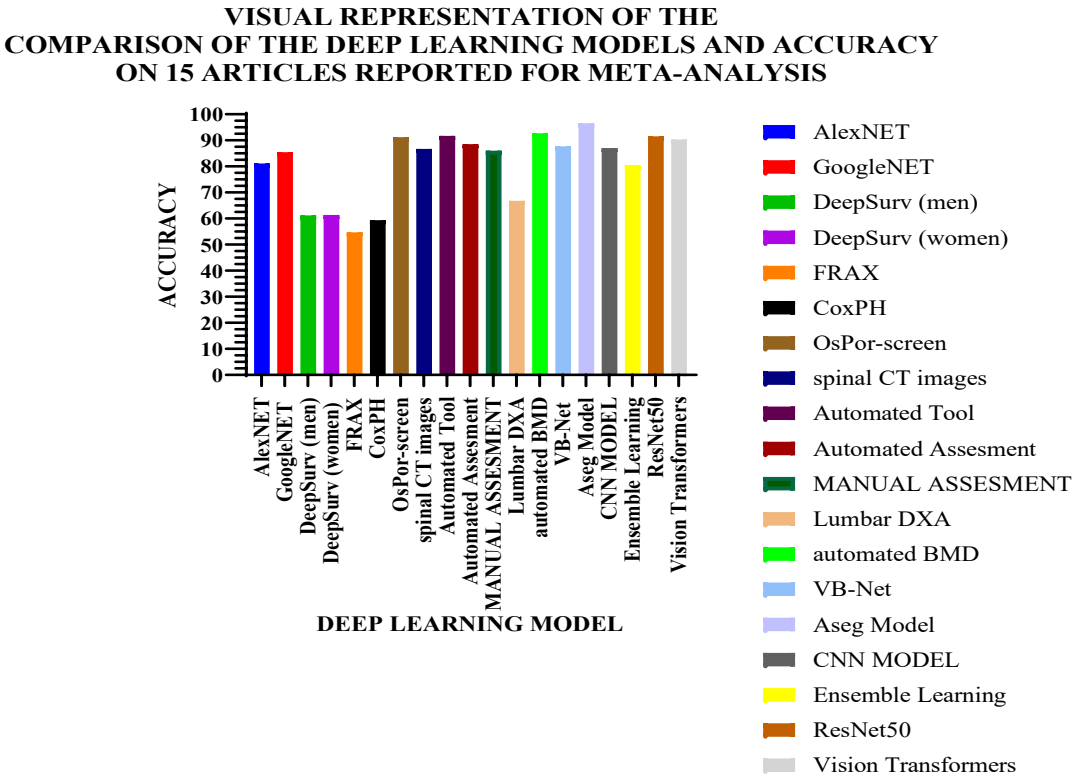

Fig. 2 The Visualized data showing the heterogeneity between accuracies of each deep learning model

X. DISCUSSION

The review examines how osteoporosis can be predicted early using deep learning models and various types of imaging data. It demonstrates that utilizing these programs with advanced scanning methods helps detect osteoporosis sooner and more accurately. However, because studies are conducted differently and include various types of data, comparing the results is challenging. Additionally, there are not enough large studies to ensure the reliability of the results. More research is needed to enhance the effectiveness of these prediction programs and integrate them into standard healthcare practices.

1. *Predictive Diagnostics Framework Specifics:* Dataset, deep learning model category, algorithmic approach, feature subset selection, data preprocessing techniques, model validation methods, performance evaluation criteria, and other constraints.
2. *Osteoporosis Prediction:* Accuracy of identification, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV).
3. *Prognostic Prediction:* Overall survival rate, osteoporosis survival duration, time to osteoporosis progression, response rate, and progression-free survival period.
4. *Research Findings:* Performance assessment of the predictive analytics framework in osteoporosis identification and prognostic prediction, along with identified limitations and future avenues for investigation.
5. *Funding:* No funding body provided formal funding for this review.

6. *Conflicts of Interest:* Conflicts of interest: Any conflicts of interest related to the authors, funders, or institutions involved in the study.
7. *Availability of Data and Materials:* All data and materials mentioned in this research are from the articles extracted from the Scopus database.
8. *Results:* The outcomes of this systematic review will be made available through publication in a peer-reviewed journal. They will also be shared with a wider audience by presenting them at international conferences and academic workshops organized by various institutions.

XI. CONCLUSION

Despite advancements in screening techniques and therapeutic interventions, predictive diagnosis of osteoporosis at an early stage remains elusive, leading to poor prognosis and limited treatment options for affected individuals. However, the advent of deep learning predictive models offers a promising avenue for revolutionizing osteoporosis diagnosis by enabling the prediction of recurrent patterns in multimodal imaging indicative of disease recurrence.

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REFERENCES

[1] S. H. Kong *et al.*, "Development of a spine X-ray-based fracture prediction model using a deep learning algorithm," *Endocrinol. Metab.*, vol. 37, no. 4, pp. 674-683, 2022, doi: 10.3803/EnM.2022.1461.

[2] M. Jang, M. Kim, S. J. Bae, S. H. Lee, J.-M. Koh, and N. Kim, "Opportunistic osteoporosis screening using chest radiographs with deep learning: Development and external validation with a cohort dataset," *J. Bone Miner. Res.*, vol. 37, no. 2, pp. 369-377, 2022, doi: 10.1002/jbmr.4477.

[3] C.-I. Hsieh *et al.*, "Automated bone mineral density prediction and fracture risk assessment using plain radiographs via deep learning," *Nature Communications*, vol. 12, no. 1, 2021, doi: 10.1038/s41467-021-25779-x.

[4] J. Schilcher, A. Nilsson, O. Andlid, and A. Eklund, "Fusion of electronic health records and radiographic images for a multimodal deep learning prediction model of atypical femur fractures," *Comput. Biol. Med.*, vol. 168, 2024, doi: 10.1016/j.compbiomed.2023.107704.

[5] E. Villamor, C. Monserrat, L. Del Río, J. A. Romero-Martín, and M. J. Rupérez, "Prediction of osteoporotic hip fracture in postmenopausal women through patient-specific FE analyses and machine learning," *Comput. Methods Programs Biomed.*, vol. 193, 2020, doi: 10.1016/j.cmpb.2020.105484.

[6] M. Tassoker, M. Ü. Öziç, and F. Yuce, "Comparison of five convolutional neural networks for predicting osteoporosis based on mandibular cortical index on panoramic radiographs," *Dentomaxillofacial Radiol.*, vol. 51, no. 6, 2022, doi: 10.1259/DMFR.20220108.

[7] Y. Chen, X. Sun, X. Sui, Y. Li, and Z. Wang, "Application of bone alkaline phosphatase and 25-oxhydryl-vitamin D in diagnosis and prediction of osteoporotic vertebral compression fractures," *J. Orthop. Surg. Res.*, vol. 18, no. 1, 2023, doi: 10.1186/s13018-023-04144-2.

[8] M. T. Löffler *et al.*, "Automatic opportunistic osteoporosis screening in routine CT: improved prediction of patients with prevalent vertebral fractures compared to DXA," *Eur. Radiol.*, vol. 31, no. 8, pp. 6069-6077, 2021, doi: 10.1007/s00330-020-07655-2.

[9] Y. Pan *et al.*, "Automatic opportunistic osteoporosis screening using low-dose chest computed tomography scans obtained for lung cancer screening," *Eur. Radiol.*, vol. 30, no. 7, pp. 4107-4116, 2020, doi: 10.1007/s00330-020-06679-y.

[10] S. Wang *et al.*, "Combining deep learning and radiomics for automated, objective, comprehensive bone mineral density assessment from low-dose chest computed tomography," *Acad. Radiol.*, vol. 31, no. 3, pp. 1180-1188, 2024, doi: 10.1016/j.acra.2023.08.030.

[11] C. Zhang, L. Fan, S. Zhang, J. Zhao, and Y. Gu, "Deep learning based dental implant failure prediction from periapical and panoramic films," *Quant. Imaging Med. Surg.*, vol. 13, no. 2, pp. 935-945, 2023, doi: 10.21037/qims-22-457.

[12] Y. Sato *et al.*, "Deep learning for bone mineral density and T-score prediction from chest X-rays: A multicenter study," *Biomedicines*, vol. 10, no. 9, 2022, doi: 10.3390/biomedicines10092323.

[13] K. Yoshida *et al.*, "Feasibility of bone mineral density and bone microarchitecture assessment using deep learning with a convolutional neural network," *J. Comput. Assist. Tomogr.*, vol. 47, no. 3, pp. 467-474, 2023, doi: 10.1097/RCT.0000000000001437.

[14] Q. Dong *et al.*, "Generalizability of deep learning classification of spinal osteoporotic compression fractures on radiographs using an adaptation of the modified-2 algorithm-based qualitative criteria," *Acad. Radiol.*, vol. 30, no. 12, pp. 2973-2987, 2023, doi: 10.1016/j.acra.2023.04.023.

[15] T. Peng *et al.*, "A study on whether deep learning models based on CT images for bone density classification and prediction can be used for opportunistic osteoporosis screening," *Osteoporos. Int.*, vol. 35, no. 1, pp. 117-128, 2024, doi: 10.1007/s00198-023-06900-w.

[16] Q. Dong *et al.*, "Deep learning classification of spinal osteoporotic compression fractures on radiographs using an adaptation of the Genant semiquantitative criteria," *Acad. Radiol.*, vol. 29, no. 12, pp. 1819-1832, 2022, doi: 10.1016/j.acra.2022.02.020.

[17] P. Krishnamoorthy and G. Madhurasree, "Feature extraction based machine learning approach for bone cancer detection," *Asian Journal of Engineering. and Applied Technology*, vol. 12, no. 2, pp. 1-6, Nov. 2023, doi: 10.51983/ajeat-2023.12.2.3787.

[18] E. E. Onuiri and O. J. Adeniyi, "Evaluating machine learning models for predicting prostate cancer progression using lifestyle factors: A systematic review and meta-analysis," *Asian Journal of Engineering. and Applied Technology*, vol. 13, no. 1, pp. 44-56, Apr. 2024, doi: 10.70112/ajeat-2024.13.1. 4241.

[19] V. Pushpalatha, "A novel framework for detection of cervical cancer," *Asian Journal of Engineering. and Applied Technology*, vol. 7, no. 2, pp. 26-30, Nov. 2018, doi: 10.51983/ajeat-2018.7.2.1016.

[20] Arokiyamary Delphina, M. Kamarasan, and S. Sathiamoorthy, "Self-organization map based segmentation of breast cancer," *Asian Journal of Engineering. and Applied Technology*, vol. 7, no. 2, pp. 31-36, Nov. 2018, doi: 10.51983/ajeat-2018.7.2.1015.

[21] O. Olosunde and E. E. Onuiri, "Deep learning models for early detection of ovarian cancer: A systematic review of ultrasound-based diagnostic tools," *Asian Journal of Engineering. and Applied Technology*, vol. 13, no. 2, pp. 15-21, Oct. 2024, doi: 10.70112/ajeat-2024.13.2.4246.

[22] S. T. Hsu, Y. J. Su, C. H. Hung, M. J. Chen, C. H. Lu, and C. E. Kuo, "Automatic ovarian tumors recognition system based on ensemble convolutional neural network with ultrasound imaging," *BMC Med. Inform. Decis. Mak.*, vol. 22, no. 1, Dec. 2022, doi: 10.1186/S12911-022-02047-6.