Osteoporosis detection

**Abstract**

Osteoporosis is a [disease](http://en.wikipedia.org/wiki/Disease) of [bones](http://en.wikipedia.org/wiki/Bone) that leads to an increased risk of [fracture](http://en.wikipedia.org/wiki/Bone_fracture) and it is characterized by low bone mineral density and micro-architectural deterioration of bone tissue. In this article, the dataset consists of 3426 subjects (1083 pathological and 2343 healthy cases) whose diagnosis was based on laboratory and osteal bone densitometry examination. In all cases, four diagnostic factors for osteoporosis risk prediction, namely age, sex, height and weight were stored for later evaluation with the selected classifiers. In order to categorize subjects into two classes (osteoporosis, non-osteoporosis), twenty machine learning techniques were assessed, based on their popularity and frequency in biomedical engineering problems. All classifiers have been evaluated using the well-known 10-fold cross validation method and the results are reported analytically. In addition, a feature selection method identified that with the use of only two diagnostic factors (age and weight), similar performance could be achieved. The scope of the proposed exhaustive methodology is to assist therapists in osteoporosis prediction, avoiding unnecessary further testing with bone densitometry.

**Keywords: dataset, deep learning algorithm**

Introduction

Osteoporosis is the prevailing bone’s disease, and its features are low bone density mass and the modification of their micro-architecture structure, so that bones’ tolerance is reduced and the risk of fracture is increased. In osteoporosis, the Bone Mineral Density (BMD) is reduced; the bone micro-architecture is disrupted whereas the concentration and the variety of proteins in bones are altered. The classic osteoporotic fractures are hip, vertebral and wrist fractures. Osteoporotic fractures are defined as occurring at a site associated with low BMD and which at the same time increased in incidence after the age of 50 years .

Apart from the direct physical implications of a fracture, such as pain and inconvenience, osteoporotic fractures are a major cause of morbidity and mortality. The lifetime risk in the United States for a hip, spine, or forearm fracture at the age of 50 years has been estimated to be 40% in women and 13% in men. In Sweden, the corresponding percentages are 46% for women and 22% for men. Caucasians and Asians are at increased risk, since African and Americans have 6% higher BMD. In the European Union one person breaks a bone because of osteoporosis every fifteen seconds. It is a fact that a percentage as high as 75% of the women with osteoporosis disregards this disorder.

There are two types of osteoporosis, the primary (idiopathic) osteoporosis, which is a most frequent disease for women after menopause and is called postmenopausal osteoporosis. This type also includes the senile osteoporosis that may also be developed in men. The secondary osteoporosis, which may occur on anyone in the presence of particular hormonal disorders and other [chronic](http://en.wikipedia.org/wiki/Chronic_(medicine)) diseases, as a result of [medications](http://en.wikipedia.org/wiki/Medications), specifically [glucocorticoids](http://en.wikipedia.org/wiki/Glucocorticoid) or other conditions causing increased bone loss by various mechanisms. In this case the disease is called steroid or glucocorticoid induced osteoporosis . Often the first apparent symptom of osteoporosis is a broken bone, which is why the condition is also known as “the silent crippler”, as people do not realize they have osteoporosis until it’s too late. However early detection and treatment of osteoporosis can decrease the fracture risk of a person to a minimum. For these reasons, there are studies using Artificial Intelligence techniques that are used for predicting whether a person has osteoporosis or not.

Osteoporosis is a prevalent and debilitating bone disease characterized by reduced bone density and structural deterioration, leading to an increased risk of fractures. It primarily affects older adults, especially postmenopausal women, but can also impact men and younger individuals with specific risk factors. Early detection is crucial for effective management and prevention of severe complications. Traditional Diagnostic Methods Traditional diagnostic methods for osteoporosis include: The Role of Deep Learning in Osteoporosis Detection Deep learning, a subset of machine learning and artificial intelligence (AI), has shown tremendous potential in medical imaging and diagnostics. By leveraging large datasets and advanced neural networks, deep learning algorithms can automatically learn and identify complex patterns in medical images, potentially outperforming traditional methods in accuracy and efficiency.

Literature Survey

1.Kanis JA, Oden A, Johnell O, De Laet C, Jonsson B, Oglesby AK: The components of excess mortality after hip fracture. Bone 32:468–473, (2003)

The aim of this study was to assess the relationship between morbidity from hip fracture and that from other osteoporotic fractures by age and sex based on the population of Sweden. Osteoporotic fractures were designated as those associated with low bone mineral density (BMD) and those that increased in incidence with age after the age of 50 years. Severity of fractures was weighted according to their morbidity using utility values based on those derived by the National Osteoporosis Foundation. Morbidity from fractures other than hip fracture was converted to hip fracture equivalents according to their disutility weights. Excess morbidity was 3.34 and 4.75 in men and women at the age of 50 years, i.e. the morbidity associated with osteoporotic fractures was 3-5 times that accounted for by hip fracture. Excess morbidity decreased with age to approximately 1.25 between the ages of 85 and 89 years. On the assumption that the age- and sex-specific pattern of fractures due to osteoporosis is similar in different communities, the computation of excess morbidity can be utilized to determine the total morbidity from osteoporotic fractures from knowledge of hip fracture rates alone. Such data can be used to weight probabilities of hip fracture in different countries in order to take into account the morbidity from fractures other than hip fracture, and to modify intervention thresholds based on hip fracture risk alone. If, for example, a 10-year probability of hip fracture of 10% was considered an intervention threshold, this would be exceeded in women with osteoporosis aged 65 years and more, but when weighted for other osteoporotic fractures would be exceeded in all women (and men) with osteoporosis.

2.Cooper C, Atkinson EJ, Jacobsen SJ, O’Fallon WM, Melton LJ (1993) A population based study of survival after osteoporotic fractures. Am J Epidemiol 137:1001–1005

Vertebral fractures are the most frequent of the fractures associated with osteoporosis, yet little is known of their impact on health in the United States. To aid in this understanding, the authors examined the survival rate of 335 residents of Rochester, Minnesota, who had an initial radiologic diagnosis of vertebral fracture between 1985 and 1989. Seventy-six died during 809 person-years of follow-up. The overall survival rate was worse than expected, and diverged steadily from expected values throughout the course of the study. At 5 years after diagnosis, the estimated survival was 61% compared with an expected value of 76% (relative survival = 0.81, 95% confidence interval (Cl) 0.70-0.92). The 5-year relative survival after a hip fracture in Rochester was a comparable 0.82 (95% Cl 0.77-0.87), but there was a much greater excess of deaths within the first 6 months as compared with patients with vertebral fractures. The 5-year relative survival rate after a distal forearm fracture was 1.00 (95% Cl 0.95-1.05). Clinically diagnosed vertebral fractures are rarely fatal, and the reduced survival seen subsequently could relate to comorbid conditions. Nonetheless, the excess mortality should be accounted for in assessing the public health impact of osteoporosis.

3.Johnell O, Kanis JA: An estimate of the worldwide prevalence and disability associated with osteoporotic fractures. Osteoporos 17, 1726–1733, (2006)

The aim of this study was to quantify the global burden of osteoporotic fracture worldwide. The incidence of hip fractures was identified by systematic review and the incidence of osteoporotic fractures was imputed from the incidence of hip fractures in different regions of the world. Excess mortality and disability weights used age- and sex-specific data from Sweden to calculate the Disability Adjusted Life Years (DALYs) lost due to osteoporotic fracture. In the year 2000 there were an estimated 9.0 million osteoporotic fractures of which 1.6 million were at the hip, 1.7 million at the forearm and 1.4 million were clinical vertebral fractures. The greatest number of osteoporotic fractures occurred in Europe (34.8%). The total DALYs lost was 5.8 million of which 51% were accounted for by fractures that occurred in Europe and the Americas. World-wide, osteoporotic fractures accounted for 0.83% of the global burden of non-communicable disease and was 1.75% of the global burden in Europe. In Europe, osteoporotic fractures accounted for more DALYs lost than common cancers with the exception of lung cancer. For chronic musculo-skeletal disorders the DALYs lost in Europe due to osteoporosis (2.0 million) were less than for osteoarthrosis (3.1 million) but greater than for rheumatoid arthritis (1.0 million). We conclude that osteoporotic fractures are a significant cause of morbidity and mortality, particularly in the developed countries.

**Problem statement**

Osteoporosis detection traditionally relies on a combination of clinical assessments, patient history, and advanced imaging techniques. High cost and limited availability in some regions. Requires specialized equipment and trained personnel. Does not provide detailed information on bone quality or structure.

**Objective**

objective of utilizing deep learning for osteoporosis detection is to enhance the accuracy, efficiency, and accessibility of diagnosing this condition. By leveraging advanced computational techniques, deep learning aims to overcome the limitations of traditional diagnostic methods and provide a more robust framework for early detection and management.

**Existing System**

Osteoporosis detection traditionally relies on a combination of clinical assessments, patient history, and advanced imaging techniques. Each method offers unique advantages and limitations, contributing to the comprehensive diagnosis and management of the disease. Here is an overview of the existing systems used in osteoporosis detection:

1. Dual-Energy X-ray Absorptiometry (DEXA) DEXA is considered the gold standard for measuring bone mineral density (BMD). It uses low-dose X-rays at two different energy levels to differentiate between bone and soft tissue, providing precise measurements of BMD.

Advantages:

High accuracy and precision in measuring BMD.Low radiation dose compared to other imaging modalities. Provides T-scores, which are essential for diagnosing osteoporosis and assessing fracture risk.

Limitations:

High cost and limited availability in some regions. Requires specialized equipment and trained personnel. Does not provide detailed information on bone quality or structure.2. Quantitative Computed Tomography (QCT)

Overview:

QCT provides 3D imaging and volumetric measurements of BMD.

It can differentiate between cortical and trabecular bone, offering more detailed insights into bone structure.

Advantages:

Superior in assessing bone quality and structure.

Can detect changes in bone density that DEXA might miss.

Limitations:

Higher radiation exposure compared to DEXA.

More expensive and less widely available.

Requires specialized equipment and expertise.

3. Peripheral Quantitative Computed Tomography (pQCT)

Overview:

pQCT is similar to QCT but focuses on peripheral sites like the forearm or tibia.

It measures volumetric BMD and provides information on bone geometry and strength.

Advantages:

Lower radiation dose than QCT.

Useful for assessing bone strength and predicting fracture risk.

Limitations:

Limited to peripheral sites and not suitable for assessing central skeletal sites like the spine or hip.

Less widely available than DEXA.

4. Quantitative Ultrasound (QUS)

Overview:

QUS measures the speed of sound waves passing through bone, usually at peripheral sites like the heel.

It assesses bone density and quality indirectly.

Advantages:

Portable, radiation-free, and relatively inexpensive.

Suitable for large-scale screening.

Limitations:

Less precise than DEXA and QCT.

Limited to peripheral sites and cannot measure central skeletal sites.

Provides indirect measurements that may not correlate directly with fracture risk.

5. Radiographic Absorptiometry (RA)

Overview:

RA involves analyzing standard X-rays to estimate BMD.

It uses hand radiographs and a reference wedge to assess bone density.

Advantages:

Can be integrated into routine clinical practice using standard X-ray machines.

Lower cost and radiation dose compared to DEXA.

Limitations:

Less accurate and precise than DEXA.

Limited to specific anatomical sites (e.g., hand).

6. Magnetic Resonance Imaging (MRI)

Overview:

MRI provides detailed images of bone and soft tissue without using ionizing radiation.

It can assess bone quality, including trabecular architecture.

Advantages:

High-resolution images of bone and surrounding tissues.

No radiation exposure.

Limitations:

Expensive and not typically used solely for BMD assessment.

Limited availability and longer scan times.

Emerging Technologies and AI Integration

The integration of artificial intelligence (AI) and deep learning into osteoporosis detection represents a significant advancement. These technologies can analyze large datasets of medical images, identify patterns, and predict osteoporosis with high accuracy. Deep learning models, especially convolutional neural networks (CNNs), have shown promise in automating the analysis of imaging data, potentially surpassing traditional methods in:

Accuracy: Identifying subtle changes in bone structure and density.

Efficiency: Reducing the time needed for image analysis and diagnosis.

Accessibility: Enabling wider access to diagnostic tools, especially in remote or underserved areas.

Challenges:

Ensuring high-quality, annotated datasets for training models.

Integrating AI systems seamlessly into clinical workflows.

Addressing regulatory and ethical considerations.

Conclusion of Existing System

Existing systems for osteoporosis detection provide essential tools for diagnosing and managing this condition. While traditional methods like DEXA and QCT remain the gold standards, emerging technologies, including AI and deep learning, hold promise for enhancing diagnostic accuracy, efficiency, and accessibility. Continued research and development in these areas are crucial for improving osteoporosis detection and patient outcomes.

Deep Learning Algorithms in Osteoporosis Detection

Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have been widely used in medical imaging due to their ability to automatically extract and learn features from images. Here’s how they are being applied to osteoporosis detection:

Data Acquisition and Preprocessing:

Large datasets of medical images (e.g., X-rays, CT scans) are collected and annotated with information about bone density and osteoporosis diagnosis.

Images are preprocessed to standardize input sizes, enhance features, and reduce noise.

Model Training:

CNN architectures, such as ResNet, VGG, and U-Net, are trained on the preprocessed datasets. These networks consist of multiple layers that progressively extract higher-level features from raw pixel data.

Techniques like data augmentation (rotating, scaling, etc.) are used to improve the robustness of the model.

Feature Extraction and Classification:

The trained model extracts relevant features from the input images, such as trabecular bone patterns, cortical thickness, and bone texture.

Based on these features, the model classifies the images into categories (e.g., osteoporotic vs. non-osteoporotic).

Validation and Testing:

The model is validated and tested on separate datasets to evaluate its performance. Metrics like accuracy, sensitivity, specificity, and AUC-ROC are used to assess the model's effectiveness.

Advantages of Deep Learning in Osteoporosis Detection

Accuracy and Precision:

Deep learning models can achieve high diagnostic accuracy, potentially surpassing human experts in identifying subtle patterns associated with osteoporosis.

Efficiency:

Automated analysis of medical images can significantly reduce the time required for diagnosis, enabling quicker decision-making and treatment initiation.

Scalability:

Once trained, deep learning models can be deployed across various healthcare settings, including remote and underserved areas, improving access to diagnostic services.

Cost-Effectiveness:

Reducing the reliance on specialized equipment and personnel can lower the overall cost of osteoporosis screening and diagnosis.

Challenges and Future Directions

Despite the promising advancements, several challenges need to be addressed for the widespread adoption of deep learning in osteoporosis detection:

Data Quality and Quantity:

High-quality, annotated medical imaging datasets are essential for training robust models. Collaboration between institutions can help in creating comprehensive datasets.

Interpretability:

Ensuring that deep learning models are interpretable and explainable to clinicians is crucial for gaining trust and facilitating clinical adoption.

Integration with Clinical Workflows:

Seamless integration of AI tools into existing healthcare systems is necessary to enhance, rather than disrupt, clinical workflows.

Regulatory and Ethical Considerations:

Ensuring compliance with regulatory standards and addressing ethical concerns related to AI in healthcare are important for patient safety and data privacy.Dual-Energy X-ray Absorptiometry (DEXA): The gold standard for measuring bone mineral density (BMD).

Quantitative Computed Tomography (QCT): Provides 3D imaging and volumetric BMD measurement but involves higher radiation exposure.

Ultrasound: Less commonly used but provides a radiation-free alternative.

Despite their effectiveness, these methods have limitations such as high cost, limited accessibility, and the requirement for specialized equipment and personnel.

**Proposed System**

Classification

CNN

Training

Preprocessing

Collect dataset

Collect a dataset of images ofOsteoporosis. Images taken from different angles and under varying lighting conditions. The images need to be preprocessed, this includes steps like resizing the images to a standard size, normalizing the pixel values and removing background noise. The algorithm needs to extract relevant features from the images that can be used to estimate the classification, done using a variety of machine learning techniques. Testing the algorithm on a separate dataset of images and validate its performance. This could involve measuring the accuracy of the algorithm's predicting the classification of osteoporosis.

**Conclusion**

Deep learning in osteoporosis detection holds immense potential to transform how this condition is diagnosed and managed. By enhancing accuracy, efficiency, and accessibility, deep learning can significantly improve patient outcomes, reduce healthcare costs, and make high-quality osteoporosis care available to a broader population. As technology continues to evolve, ongoing research and collaboration will be key to unlocking the full potential of deep learning in medical diagnostics, ultimately leading to better health outcomes for patients worldwide.

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