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OSTEOPOROSIS FRACTURE ANALYSIS USING MACHINE LEARNING

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Abstract - *Osteoporosis is a disease of bones that results in an increased risk of fracture and it is distinguished by low bone mineral density and micro-architectural deterioration of bone tissue. All over the world, the risk of an osteoporotic fracture is found in 1 in 3 women and 1 in 5 men having aged more than fifty years. In every 3 seconds, an osteoporotic fracture is estimated to occur. Osteoporosis occurs and associated with the hip, spine and wrist; it is the most common fracture. With increased age in both women and men, the possibility of these fractures especially occurs at the hip and spine.*

Osteoporosis, which is simply a porous bone, is a disease in which the density and quality of bone are decreased. The risk of fracture increases as bones become more porous and fragile. Bone loss happens gradually and quietly. Until the first fracture occurs, there are often no symptoms. The suggested exhaustive methodology's scope is to assist therapists in osteoporosis prediction, preventing unnecessary further tests with bone densitometry. In our project, we will create an accurate and validated Machine Learning model to predict the risk of osteoporotic fracture based on a variety of factors such as age, gender, medical history, and so on.

Key Words**:** osteopenia, osteoporosis, machine learning, data pre-processing, data mining, evolutionary algorithms, regression, classification, deep learning

1. INTRODUCTION

Osteoporosis is the most common bone disease, characterized by low bone density mass and changes in micro-architecture structure, which reduces bone tolerance and increases the risk of fracture. Bone mineral density (BMD), which is interrupted by bone micro- architecture, is diminished during osteoporosis, while proteins in the bones are decreased in their concentration and variation. Hip, vertebral, and wrist fractures are the most common osteoporotic fractures. Osteoporotic fractures are described as those that occur at a site with low BMD and that have risen in frequency after the age of 50[1][2][3]

Aside from the general physical consequences of a fracture, such as pain and inconvenience, osteoporotic fractures are a leading cause of morbidity and death. The lifelong risk of a hip, spine, or forearm fracture in the United States is believed to be 40% for women and 13% for men in the United States at the age of 50.In Sweden, the corresponding percentages for men and women are 46 percent and 22 percent, respectively. African and American people have a 6% higher BMD than Caucasians and Asians, putting them at a greater risk. Someone breaks a bone in the European Union every 15 seconds because of osteoporosis. It is a fact that up to 75% of women with osteoporosis are completely unaware of their condition.

There are two kinds of osteoporosis: primary (idiopathic) osteoporosis and postmenopausal osteoporosis, which is the most common illness in women after menopause. This category also contains senile osteoporosis, which may affect men. Secondary osteoporosis is a type of osteoporosis that can develop in anyone with certain hormonal disorders or other chronic illnesses, as a result of drugs, particularly glucocorticoids, or other conditions that cause increased bone loss through various mechanisms. The condition is known as steroid or glucocorticoid-induced osteoporosis in this case[4]

A broken bone is often the first symptom of osteoporosis, which is why it's also known as "the quiet crippler" because people don't understand they have it until it's too late. Early detection and treatment of osteoporosis, on the other hand, can significantly reduce a person's fracture risk. For these reasons, artificial intelligence methods are being used in research to predict whether or not a person has osteoporosis.

2. LITERATURE SURVEY

SR.NO	PROJECT TITLE	AUTHORS	YEAR
1	Intelligent Osteoporosis Prediction System 28–37 in International Journal of Computer Applications, vol. 32, no. 5	Moudani, W., Shahin, A., Chakik, F. and Rajab, D.	2011
2	Machine Learning Techniques for Determining the Incidence of Osteoporosis in Postmenopausal Women 673–679 in Journal of Mathematical and Computational Modeling.	Ordonez, C., Matias, J. M., de Cos Juez, J. F. and Garcia, P. J.	2009
3	Predicting Osteoporosis Outcome Based on Genetic Factors in a Taiwanese Women Population: A Comparison of Classification Algorithms with Wrapper-Based Feature Selection 1–8 in International Journal of Endocrinology	Hseuh-Wei, C., Yu-Hsien, C., Hao-Yun, K., Cheng-Hing, Y. and Wen-Hsien, H.	2013
4	An Improved and Optimal Bone Disease Prediction Based on Risk Factors 820–823 in International Journal of Computer Science and Information Technologies.	Saranya, M. and Sarojimi, K.	2016

[1] devised a system for detecting osteoporosis in adults at an early stage. Expert physiotherapists were interviewed to determine osteoporosis risk factors, after which data was collected from 2845 patients using the FRAX tool (i.e. WHO Fracture Risk Assessment Model) for risk stratification. The FRAX tool predicted the likelihood of bone fracture over a 10-year period. The discovery of important factors revealed that age, BMI, prior fractures, alcohol, and smoking were all linked to the risk of osteoporosis. The model was created and tested using decision tree algorithms like ID3, C4.5, and Random Forest. With an accuracy of 99.9%, the results found that the random forest decision trees algorithm outperformed other decision trees algorithms.

Machine learning methods were used by Ordonez et al. [2] to determine the prevalence of osteoporosis in postmenopausal women. The researchers constructed a non-linear model using the regression support vector machines technique to determine the relationship between BMD, diet, and lifestyle behaviors for a sample of 305 postmenopausal women. In addition, an initial preliminary estimate of BMD in the study women (based on a questionnaire with questions primarily about dietary habits) was used to ascertain whether they required densitometry tests. SVMs were used to create a mathematical model that determined the relationship, and regression trees were used to identify the parameters with the most weight in the relationship. Extra calcium intake, a sufficient level of sun exposure, weight control, frequent physical activity, and an adequate calorie intake were found to be the most important factors in preventing bone mass loss in postmenopausal women.

Hsueh-Wei et al. [3] compared classification algorithms for predicting osteoporosis using wrapper- based feature selection. Multilayer feed-forward neural network (MFNN), Nave Bayes, and logistic regression were used as classification algorithms. A feature selection technique based on wrappers was also used to determine a subset of main SNPs.The MFNN model with the wrapper- based approach was found to be the better predictive model for inferring disease susceptibility in Taiwanese women based on the complicated relationship between osteoporosis and SNPs. Patients and physicians will use the suggested tool to improve decision-making based on clinical variables like SNP genotyping data, according to the results.

Based on recognized risk factors, Saranya and Sarojimi [4] constructed an improved and optimum prediction model for bone disease. Pre-training and fine tuning were used to ascertain the initial risk factors for determining the onset of bone diseases. In the pre-training phase, the most significant risk factors are combined with model parameters to calculate contrastive divergence, which reduces the size of the records. In the fine-tuning phase, the results obtained in the earlier phase with the ground truth value g1 were compared to the results obtained in the fine-tuning phase with the ground truth value g2, where g1was referred to as osteoporosis and g2 was referred to as a bone loss rate. The Deep Belief Network (DBN) was used to create the model, and it was compared to models created before and after applicable feature identification. The study's findings revealed that using appropriate features increased the predictive model's performance.

3. PROPOSED METHODOLOGY

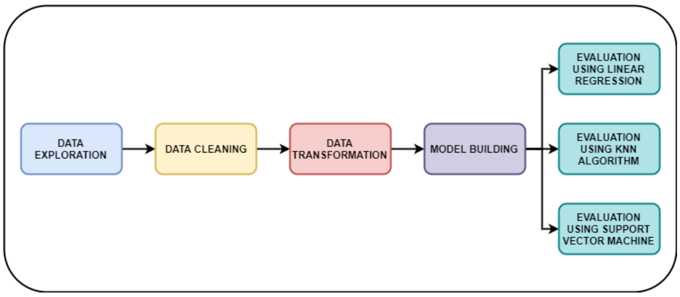

Fig 1. High Level Design

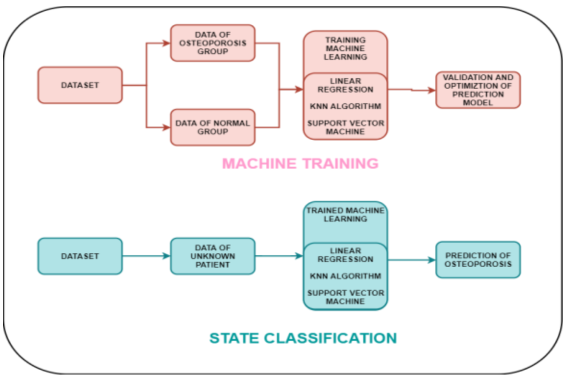

Fig. System Architecture

1. The work is divided into three phases: the initial, middle, and final stages.

2. Data Exploration, Data Cleaning, and Data Transformation are all part of the initial stage.

3. Modeling of data takes centre stage.

4. Data analysis is performed in the final stage using three models: KNN Algorithm, Linear Regression, and SVM.

5.Instead of using conventional data management systems, data exploration is akin to initial data analysis, visual exploration to understand what is in a dataset and the attributes of the data.

6. Data cleaning refers to finding incomplete, erroneous, inaccurate, or irrelevant components of the data and then replacing, updating, or deleting the dirty or coarse data.

7. Data transformation is the process of converting data from one format to another, usually from a source system's format to a destination system's requested format.

8.We move on to data modelling after the first stage is completed.The process of creating a descriptive diagram of relationships between different kinds of information to be stored in a database is known as data modelling.One of the aims of data modelling is to come up with the most effective way of storing data while still allowing full access and reporting.

9. The data is then processed with algorithms [KNN Algorithm, Linear Regression, SVM Algorithm,] to produce results.

10. The test results produced by training the models on the train dataset are shown here.

11. After the dataset has been processed, we can use the raw data to predict osteoporosis.

4. EXPECTED OUTCOMES

The following characteristics will be included in our osteoporotic fracture analysis system: The most recent dataset would be used for interpretation, and various parameters that influence osteoporosis prediction would be used. For forecast, the system employs a variety of prediction algorithms/models. The system's efficiency will be significantly improved. When the system receives patient data or an unpredicted dataset, it begins to analyse the information and predict the patient's condition based on the information provided.

5. CONCLUSION AND FUTURE SCOPE

To conclude this project, it should be observed that since a single source of data is used for analysis and different models are used to analyze the same data source, it is possible to compare the recognition accuracies of this research to find the best prediction model. In any case, the small feature set used in this work appears to be sufficient for further investigation.

The model with the greatest forecast precision or confidence value is the best prediction model. Future work may include testing more models, most likely with an exhaustive search for the best classification parameters, as well as expanding the dataset size and number of osteoporosis-related parameters. In addition, we will develop a custom prediction software or web app.

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