REVIEW ANALYSIS FOR OSTEOPOROSIS DURING POST MENOPAUSE CLASSIFICATION USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Statistics from 2021 indicate that women had a higher frequency of depression than men. Depression affects women more frequently than it does men that suggest hormones may be responsible for the illness' genesis. Women who have received an osteoporosis diagnosis must check for signs of depression. The Women and Depression Task Force looked at how women experience depression. Child development is severely at danger when a mother experiences postpartum depression. Women's postpartum delivery experiences and postpartum depression are not well understood to be related. It is hypothesised that women experience sadness at a higher incidence than males do due to a cultural ideal of thinness for women.Usually, a psychiatrist should be involved in the treatment of women who have severe depression and active suicide thoughts or plans. This review analysis has been carried out on the prediction of women's depression prediction in early stage by using conventional machine learning techniques.

Keywords:- Machine learning, pre menopause, menopause, post menopause, Mental Health And Risk prediction, Osteoporosis.

I. INTRODUCTION

The National Depression Screening Day (NDSD) and the National Anxiety and Depression Awareness Week are only two of the public initiatives that have been suggested to reduce the frequency of untreated depression. Kuehner, C (2017) [1] explained that the initiatives spread knowledge about depression and provide free depression screenings to the general public. In addition to diagnosing depression, they also offer details on available therapies and encourage public discourse. These government initiatives are a crucial step in the fight against depression, but they are participation-based, their biggest drawback is the bias in the population they can reach.

Llaneza, P.,et al (2012) [2] explored that the use of contraceptive can be described in terms of acceptor characteristics that variably affect the use of various contraceptive techniques as well as the prevalence of various contraceptive methods. How to categorise a contraceptive use pattern based on a chosen set of acceptor characteristics is the difficult part. Understanding the dynamics of contraceptive use requires identification of similarities and differences in the acceptors of various contraceptive techniques.

In [3] numerous postmenopausal women may experience severe consequences from osteoporosis. As the population ages, osteoporosis and the potentially disastrous consequences of fracture rise, and evaluation of skeletal health is a crucial part of a woman's regular treatment. Ali N. S et al (2012) [4] described a progressive systemic skeletal illness having weak bones and micro structural tissue of bone degeneration, increasing the risk of fracture and bone brittleness. The World Health Organization (WHO) defines osteoporosis as bone density (BD) 2.5 Standard Deviations (SD) or more below the mean value for young people (T score - 2.5). When the risk of fracture increases with age, bone density declines and increases quickly. Every 1 SD drop in BMD doubles or triples the risk of fracture.

According to Okun, M. Let al (2011) [5], menopause is a physiological process that typically starts in healthy women between the ages of 45 and 55, or roughly at 51. A typical

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woman will therefore go around 30 years without an ovarian supply of oestrogen given current life expectancy. Makara-Studzinska, M. T et al (2014) [6] derived the lone factor responsible for developing osteoporosis in older women is a deficiency in oestrogen in postmenopausal women, which limits the absorption and utilisation of calcium. Numerous postmenopausal women receive osteoporosis diagnoses each year. Therefore, we made the decision to focus on postmenopausal osteoporotic women for our investigation.

In India, osteoporosis is a major problem. According to Bhalla, A. K. (2010) [7], the average Indian's life expectancy has grown, which has also led to a rise in the prevalence of osteoporosis. Kendler, D. L et al (2018) [8] according to recent studies, Indians' bone density is lower than that of their European and North American counterparts. According to reports, osteoporotic fractures strike Indians 10- to 20-years earlier than they do Caucasians. In India, 50% of women are affected by osteoporosis, which is a significant burden. Sanders, S., et al (2013) [9] only 29% of the 450 urban, healthy women between the ages of 25 and 75 in the study had a normal T score 16 at the National Institute for Research in Reproductive Health's Clinical Research facility in India. This was done to assess the prevalence of osteoporosis. In a woman's life, menopause is a significant and natural growth step. Georgakis, M. K et al (2016) [9] it is characterised by the decrease of ovarian follicular activity, which results in a permanent stop of menstruation. The change from menses to menopause is frequently viewed as a period when both physical and emotional health change in western nations, where perceptions toward the causes of menopause societal and also cultural presumptions about older women. Soares, C. N. (2017) [10] However, anthropological research has demonstrated that menopause can be a good thing, especially when it denotes a rise or fall in social standing. Women experience physical, psychological, and social changes throughout menopause. Levels of hormone alter When oestrogen levels fall, FSH and LH levels rise, and prolactin, thyroid, and parathyroid hormone levels all drop[11].

Remodeling is a typical, natural process that supports calcium homeostasis, enables the repair of micro fractures, and preserves skeletal strength. Numerous enzymes, peptides, and growth factors are produced by osteoblasts during the remodelling process and are then released into the bloodstream. Freeman, E. W. (2015) [12] explored that the concentration reflects the bone rate resorption. The products of bone deterioration produced by osteoclasts can be detected in the blood or urine and used to estimate the rate of bone resorption. These products are also released into the circulation by osteoclasts and are finally eliminated by the kidney. Estimating bone turnover rates before and after antiresorptive medication requires the use of markers of bone production and resorption.

Types

To assist doctors in managing their patients, osteoporosis can be categorised in a number of ways based on diagnostic categories, aetiology, or stage. These classifications include the Primary and Secondary Osteoporosis categories from the WHO (World Health Organization). Type I osteoporosis and type II osteoporosis are the two types of primary osteoporosis. The decisive factor for osteoporosis's real presence. Judd, F. K et al (2012) [13], the quantity of calcium still present in the skeleton determines whether a person has type I or type II osteoporosis and whether they are at risk of fracture. A person with unusually strong bones from birth is unlikely to ever lose enough calcium to develop osteoporosis.Other situations, such as hormonal imbalances, specific diseases, or drugs, might result in secondary osteoporosis such as corticosteroids. 5% of cases of osteoporosis are caused by secondary osteoporosis. Endocrine disorders such as excessive glucocorticoid use, hyperparathyroidism, hyperthyroidism, hypogonadism, hyperprolactinemia, and type 2 diabetes)as well as medications such as heparin, nicotine, barbiturates, ethanol, dilantin, glucocorticosteroids, and other circumstances are

among the causes eg, immobilization, chronic renal failure.

II. LITERATURE REVIEW

Women have been plagued by osteoporosis from the beginning of time. Mummies from Egypt dating back to it was 4,000 years ago. discovered with the distinctive dowager's hump. John Hunter, a pioneer in medicine and an English surgeon in the eighteenth century, observed that while new bone is set Old bone is resorbed or destroyed within the body. Though osteoporosis was not even this process, which is now known as remodelling, was later shown to have a major role in the condition, which had been a recognised illness for more than a century after his death.

The word osteoporosis, which means "porous bone," was first used to characterise this type of deteriorating human bone in the 1830s by French doctor Jean Georges Chretien Frederic Martin Lobstein. Boston General Hospital's Fuller Albright couldn't help but wonder in the 1930s what postmenopausal women did women that made them especially prone to have fragile bones. In 1940, he first describes postmenopausal osteoporosis and begins treating affected women with oestrogen. But by slowing bone loss, oestrogen therapy only can stop harm to the skeleton. The slight bone loss seen in the early stages of the disease was nearly impossible to detect in the 1940s. Fortunately, since the 1960s, scientists have created instruments that are more sensitive to detecting bone loss, such as densitometers, uses to measure changes in the energy absorption of the energy which is going through the bones in the hand, spine, hip, or anybody region to estimate bone density. With the use of this method, doctors can identify early stages of osteoporosis, long before it results in fractures Christiansen, C. (2012). The National Institute of Health made this condition widely known in 1984, describing it as a serious threat to health and stressing that oestrogen therapy, calcium, a healthy diet, and exercise could reduce bone loss.

Osteoporosis Mental Health and Risk Prediction

Liou, T et al (2014) [14] discussed about the prediction of A bone disorder called osteoporosis that increases risk factors in women under machine learning algorithm of PNN network. But this system has a problem of take more time to predict the Osteoporosis diseases with time value of 0.855, on the side of result value states that accuracy for this system is lesser for output values 0.772. Kong, S. H, et al (2020) [15] explain about the possibility of fracture in those who have osteoporosis has attention predictors with low rankings. The algorithm used in this prediction system is support vector machine SVM in machine learning. But this system will shows the outcome for the sensitivity was 0.675 and regression models were 0.688 which is less efficiency for prediction. Ye, C, et al (2020) [16] described to create and validate a programme to detect fall risk based on electronic health records to help seniors who are more likely to fall with using of XG Boost algorithm for prediction. On the result of research additionally, there were 54.93% falls with a precision of 0.712 not fit for the system. Iliou, T, et al (2017) [17] has introduced Techniques for data preparation has been applied to machine learning classification issues under PCA machine learning method for osteoporosis prediction the average performance of different classifiers is less than 50%.

Kruse, C, et al (2017) [18] Use machine learning approaches to its forecast hip fractures and determines predictor importance in men and women who had a Dual-energy X-ray Absorption (DXA) scans. Where the outcome for the system is over Use of Specific Serotonin Reuptake: 57%which has poor result when compare to other machine learning system. Bolton, J. M, et al (2017) [19] explain about Risk of severe osteoporotic fractures associated with mental illness and use of related medications this system Importance Osteoporotic under FRAX algorithm. This system has a poor result of Selected Serotonin Reuptake Use 57%.Wang, Y, et al (2021) [20] has proposed Osteoporotic fractures are a major contributor to death, medical expenses, and disability where

S.No	Authors	Problem	Technique	Limitation
1.	Iliou, T et al (2014).	Bone densitometry for testing	Probabilistic Neural Network	Time spent is greater than 0.855 M.seconds also less accuracy of 77.2%
2.	Kong, S. H, et al (2020)	Predictors with low rankings	Support Vector Machine	67.5 % is the sensitivity, regression models were 68.8%.
3.	Ye, C, et al (2020)	Digital health records	XG Boost algorithm	The Precision is 71.2 also 54.93 % of falls that happened
4.	Iliou, T, et al (2017)	Pre-processing of novel data	PCA machine learning method	System achieves 83.2 percent accuracy.
5.	Kruse, C, et al (2017).	Less enhance calibration and discrimination	Extreme Gradient Boosting	Reached an AUC for the test of 86 %.
6.	Bolton, J. M, et al (2017)	Human fracture risk	FRAX algorithm	Selected Serotonin Reuptake Use 57%
7.	Wang, Y, et al (2021)	Including disease history-related factors	BPNN algorithm	Accuracy of 62.2 %, DBN poor result of 76.2%.
8.	Anam. M, et al (2021)	Relating to trabecular bone	Magnetic Resonance Imaging (MRI) technique	Time spent is greater than 89.5%.
9.	Ordóñez. J, et al (2021)	Decision-making based on models is less	Random forest algorithm	accuracy of 89.8%, F1 score of 72.6%
10.	Kim, S. K. et al (2013)	Tools that are less for detecting postmenopausal	SVM algorithm	accuracy of 76.7%, sensitivity of 77.8%
11.	Shim, J. G. et al (2020)	Less performances were attained	ANN algorithm	Sensitivity of 71.3%, precision of 74.3%.
12.	Ordóñez, C. et al (2009)	Largest influence on BMD	SVM algorithm	Less accurate forecast of 81.2%.
13.	Yoo, T. K. et al (2013)	Significant factors selected by SVM not perfect	SVM algorithm	Accuracy of 76.7 %, specificity of 76.0%
14.	Cuaya-Simbro. G, et al (2021)	Less information is available when both eyes are open and closed.	FMSC Algorithm	Time spent is roughly 0.786 milliseconds.
15.	Villamor. E, et al (2020)	Surpassed BMD by 14 pp.	SVM Algorithm	At test, accuracy was 78.35%
16.	Scanlan. J, et al (2018)	Later osteoporosis diagnosis	ANN Algorithm	This system needs 0.865 milliseconds
17.	Wani. I. M, et al (2020)	Osteoporosis image processing procedures are not well done.	computer-aided diagnosis CAD	Accuracy is 83.6%.
18.	Singh. A, et al (2017)	Screening and assessment of high risk	SVM classifier	Sensitivity of 63.2%, 92% accuracy in categorization using an SVM.
19.	Kumar. S, et al (2020)	Greater complexity with time	ANN Algorithm	Accuracy is over 86.5%, precision over 75.6%.
20.	Ajmal. H, et al (2018)	Adequate data protection in the healthcare industry	Local Binary Pattern	Precision is 76.5%, f1 score of 78.1%.

Table 1.1 Machine Learning Techniques and its limitation

FRAX is a technique for evaluating the risk of fracture in the general population by using BPNN algorithm. This proposed system shows a outcome of DBN's poor performance of 0.762 and accuracy of 0.622. Anam. M, et al (2021) [21] discussed about the risks of osteoporosis are tied to a history of the disease and lifestyle choices under the help of Magnetic Resonance Imaging (MRI) technique for diseases prediction this system has a output of Time spent is greater than 0.895. Smets. J, et al (2021) [22] described numerous studies have been conducted on osteoporosis, a complex illness with the clinical complication of bone fracture. In complicated data environments where humans are limited in their ability to recognise high-dimensional correlations, recent developments in machine learning (ML) have allowed the area of artificial intelligence (AI) to achieve amazing accomplishments under Random forest algorithm. This system has an outcome of accuracy of 89.8%, F1 score of 72.6%.

Kim, S. K. et al (2013) [23] discussed to choose Clinical decision-making techniques for determining the risk of osteoporosis in postmenopausal women have been developed. with SVM algorithm. The test set's validation revealed that SVM accurately predicted the risk of osteoporosis with an AUC of 0.827, 76.7% accuracy, 77.8% sensitivity, and 76.0% specificity. Shim, J. G. et al (2020) [24] described about an early osteoporosis detection offers a chance to find and avoid fractures. with ANN algorithm. This system shows nine variables made up the feature-selected data, and fivefold cross-validation yielded results for KNN, DT, RF, GBM, SVM, ANN, and LR of 0.713, 0.685, 0.734, 0.728, 0.728, 0.743, and 0.727, respectively. Ordóñez, C. et al (2009) [25] caused by a decline in bone mineral density (BMD), which raises the possibility of bone fractures or breaks. Women in developed nations are primarily affected by the disease of osteoporosis. The result of this system is not prefect as it gives less accurate forecast of 0.812.

Yoo, T. K. et al (2013) [26] gives four traditional clinical decision-making tools were compared to machine learning models. Osteoporosis Risk assessment Instrument (ORAI), and Osteoporosis Self-assessment Tool (OST) (ORAI) in using SVM Algorithm. Accuracy of 0.767%, specificity of 76.0% will be the lesser result for this system. Cuaya-Simbro. G, et al (2021) [27] introduced a falls are particularly dangerous for those with osteoporosis. By examining balance metrics, we investigate how well various computational techniques identify individuals with osteoporosis who experience a fall with FMSC algorithm. Time spent is roughly 0.786 milliseconds is the outcome. Villamor. E, et al (2020) [28] finding patients a greater risk of hip fracture a significant challenge in osteoporosis clinical assessment. The current gold standard Dual-Energy X-Ray Absorptiometry is used to calculate bone mineral density (BMD) (DXA), although its classification accuracy is just 65% with SVM algorithm At test, accuracy was 78.35%. Scanlan. J, et al (2018) [29] considerable fraction of the senior population worldwide suffers from osteoporosis, an asymptomatic bone disorder that increases bone fragility and the risk of fracture. This system predict diseases at a this system needs 0.865 milliseconds. Wani. I. M, et al (2020) [30] has introduce the subject of medical diagnosis has undergone a revolution thanks to computer-aided diagnosis (CAD). By early detecting the diseases in an effective, timely, and affordable manner, they help to increase the chances of successful treatment and to increase the survival rate. This system shows Accuracy is 0.836 with poor result for calculation. Singh. A, et al (2017) [31] focused intricate bone structure is the main obstacle to an automatic diagnosis of osteoporosis. Traditional methods Included among methods for detecting osteoporosis is dual-energy X-ray absorptiometry (DXA) with SVM algorithm. But result for prediction is Sensitivity of 0.632, 98% accuracy in categorization using an SVM. Kumar. S, et al (2020) [32] describe the Osteoporosis is a disease that mostly affects the

bones in humans. It tends to decrease bone mass, which deteriorates the micro architecture of bone tissues having a result of Accuracy is over 0.865, precision over 0.756. Ajmal. H, et al (2018) Osteoporosis is an aging-related condition that affects the skeleton[33]. It is characterised by a reduction in bone mass and a weakening of the bone structure,
which raises the risk of fracture using Local Binary Pattern algorithm having result of Precision is 0.765, f1 score of 0.78.

III. RESEARCH GAP

The research gap for existing techniques are discussed in following sections after carefully analysis the set conventional techniques in mental health and risk of osteoporosis during post menopause.

- The most machine learning techniques are yield minimum performance but longer time to predict the results.
- The existing techniques only focused classification, not considered in other process such as pre-processing, feature extraction, feature selections techniques, so it leads to poor performance.
- In osteoporosis during postmenopause don't have proper datasets to predict the mental health and risk. Some datasets need proper preprocessing techniques remove imputation and gaps.
- The no optimization based implementation involved to prediction, so machine learning techniques are take longer duration to predict the mental health and risk.

Suggestion: 1) The evaluation of additional classification techniques, sometimes accompanied by a thorough search for the ideal classification parameters, 2) Evaluating the effectiveness of carefully chosen classifiers (different classifiers) in order to create a combined classification schema; or 3) Testing sophisticated ensemble combinations of classifiers of the same kind but with various topologies or different parameters. 4) To employ bio-inspired optimization methods, such as Particle Swarm Optimization, the Firefly algorithm, the Artificial Immune System Algorithm, etc., are used to reduce the time duration for prediction. 5) To use Hybrid machine learning approaches for classification to yield better performance.

In order to improve our ability to promote good ageing for women of all races and ethnicities, The social and biological factors influencing the menopausal experience require further study. The main changes seen after menopause included increases in the concentrations of sodium, magnesium, total calcium, inorganic phosphate, and inorganic phosphate in the plasma, a rise in the plasma "anion gap," and an increase in the renal excretion of sodium, magnesium, and inorganic phosphate. Menopause is a typical biological process. Hot flashes, for example, are a common physical and psychological symptom of menopause that can impact sleep, energy levels, and emotional wellbeing. Several effective treatments are available, ranging from hormone therapy to dietary modifications. In order to find preventative and/or early intervention measures to promote healthy ageing in midlife women, doctors and researchers are increasingly focusing on the alleged compounded burden of health difficulties associated with this transition. The menopausal transition may be a crucial "window of opportunity" for the efficacy of hormone-based treatments, in addition to being a window of vulnerability for depression and cognitive decline. This review is supported by newer machine learning based predictions.

IV. CONCLUSION

The findings offer further insight into the link between various menopausal symptoms and depression with menopausal status. Depression may not be related to menopausal state. In contrast to the correlation between menopause and depression, which is substantial primarily in premenopausal women, there is a strong relationship between menopause and depression throughout all three menopause statuses. When evaluating sleep habits during the menopausal transition, health practitioners treating menopausal women should take extra caution. For the purpose of preventing or managing depression,

perimenopausal VMS assessment may be more crucial.

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