Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IMPACT FACTOR: 7.056

IJCSMC, Vol. 13, Issue. 10, October 2024, pg.58 – 66

Analysis and Interpretation of Physiological Social Demographic Parameter in Menopausal Women

Shubhangi D C[1]; Umme Salma[*2]

[1]Professor Department of CSE, VTU Kalaburagi, INDIA
[2]M.Tech Student Department of CSE, VTU Kalaburagi, INDIA
drshubhangipatil1972@gmail.com; umme2798@gmail.com

DOI: https://doi.org/10.47760/ijcsmc.2024.v13i10.007

Abstract*— *A woman's menopause is normal period of her life. Some females have both emotional and physical symptoms throughout menopause. Depression is one of the many difficulties that some women experience after menopause. This project aims to enhance menopausal women's quality of life by predicting the onset of depression and tackling the lack of experts, knowledge, and awareness in this field. An interesting and difficult area of artificial intelligence study is the use of machine learning to forecast when postmenopausal women may have depressive symptoms. Through the use of supervised machine learning, this study develops a system that is remarkably accurate. Return on investment (ROI), area under the curve (AUC), recall, specificity, accuracy, F-Measure, and ROC are some of the metrics used by different classification methods to evaluate classifier performance. Random Forest and DT had the greatest accuracy rate of 99.04% among the classifiers we tested. In addition to predicting a patient's likelihood of having depression, this study analyzes the menopause according to its four stages: pre-, peri, meno-, and post-menopause. As a result, ML could be used to diagnose postmenopausal women with depression for the first time.

Keywords*— *pre-menopause, peri-menopause, menopause and post-menopause, F-Measure, Receiver Operating Characteristic, Precision–Recall Curve, Area under the Curve

I. INTRODUCTION

Every woman eventually goes through menopause [1]. Menopause is characterised by the cessation of menstrual periods and the gradual loss of oestrogen and progesterone production by the ovaries [2]. Key sign of menopause is when a woman's period stops being continuous for at least 12 months [3]. This condition causes a lady to become infertile. Menopause often begins around the age of 50 in Western countries and between the ages of 45 and 55 in China. [4-6]. In contrast, women in Bangladesh typically go through menopause among ages of 40 and 50, having average mean age of 45 [7]. As a woman's longevity increases, she loses about a third of her life at menopause [8]. Every woman goes through menopause in her own unique way. Researchers in Bangladesh found that menopausal women go through three distinct stages [9]. There is a "perimenopausal premenopausal" group, a "postmenopausal" group, and a "premenopausal" group of women. Women were classified as premenopausal if their monthly menstruation was consistent throughout the last 12 months, and postmenopausal if they had no menstrual blood at all during that time [10]. "Natural menopausal women" are defined as women in their forties and fifties [7]. Women are considered to be in the premenopausal stage if they have had irregular menstrual cycles over the last twelve months or if their last menstrual period was three months ago [3].

Depressive symptoms are by product of menopause, which is itself significance of physical, social, and psychological transformation [11,12]. Commonly seen mental health problems among these people is depression, which may lead to physical sickness in the future. Mood disorders, such as depression, are a leading cause of impairment in females [13]. Almost 20% of women experience depression, which is almost double the proportion of males [14]. By 2030, major depressive disorder is projected becoming main source of illness burdens globally. Amongst females throughout globe, it is a leading cause of depression at the moment [15]. Among women experiencing menopause, the prevalence of depressive syndrome ranges from 5.9% to 23.8% [16-18]. The risk of major depressive disorder is 2-3 times high in peri-menopausal females than in premenopausal women, according to studies [19–21]. Nearly seventy-three million adult women suffer from serious depression every year [22]. Reason being that melancholy is a symptom of menopause, and melancholy causes both mental and physical health problems. For women going through menopause, it's a big deal. Mental and physical health problems go unnoticed by most males because of a lack of knowledge and education. If a woman experiencing menopause-related depression is self-aware enough to recognize the early warning signs, she may be able to treat her condition at an earlier stage. Furthermore, it is also observed that physicians, psychologists, and psychiatrists do not always know whether a patient is sad or not since certain symptoms are milder than others. Depression in postmenopausal women may therefore be more easily diagnosed with the use of a model or system. With that in mind, we set out to discover a model for the first depression diagnosis in menopausal women using machine learning.

II. RELATED WORK

Even within the same culture, menopausal symptoms might vary greatly in both kind and frequency from one country to the next [30]. For some menopausal women, these symptoms may be so debilitating that they lead to depression. So, the purpose of this research was to look at menopausal symptoms and their correlation with socio-demographic factors in order to find out how common depression is among women going through this transition. The Tankisinuwari region in Morang District was the site of a cross-sectional research. Hormonal shifts during menstruation are associated with altered mood, according to mounting evidence [31]. Unfortunately, there is a lack of research that compares the severity of mental health issues throughout menopausal stages. That is why we set out to examine the link between menopausal symptoms, depression, and suicide ideation.

During menopause, a woman may go through menstrual cycle irregularities or even a complete cessation of menstruation, all of which may have an impact on her mental health and marital happiness [32]. Developed to examine if menopausal symptoms, depressive symptoms, and marital satisfaction are linked in newly menopausal women. [33] Depression is two to five times greater during menopause than before or after. MRS, BKMI, and the Beck depression inventory were completed by 40-year-old female volunteers to compare menopausal women's depression risk in 2006 and 2021. In 2021, there was an 8% increase for mild menopausal symptoms, a 1.9% increase for moderate symptoms, and a 3.2% increase for severe symptoms compared to 2006. In 2021, there was an uptick in the number of participants reporting menopausal symptoms, trust issues, self-blame, crying spells, mood swings, thoughts of suicide, and anxiety compared to 2006. Also, there’s reduced number of participants without depressive symptoms but an increase in those suspected of mild or severe depression. Finally, in 2021, symptoms of menopause were associated with a rise in depressed mood, as measured by the BKMI and MRS.

III. METHODOLOGY

Datase**t**: This module makes use of the internal patient dataset. According to Table 1, the dataset includes the following parameters:

Parameter	
Age	Age of the participant
menopause	Menopausal status 0-No 1-Yes
peww	Physical exercise without works 0-No 1-Yes
hf	Hot flashes 0-No 1-Yes
ost	Osteoporosis 0-No 1-Yes
diabet	Type 2diabetes
chd	Coronary heart disease 0-No 1-Yes
heartbeat	Heart beating quickly 0-No 1-Yes
tense	Tense 0-No 1-Yes
sleep	Sleep 0-No 1-Yes
excitable	Excitable 0-No 1-Yes
Concetration	Difficulty in concentrating 0-No 1-Yes
tired	Feeling tired 0-No 1-Yes
sweat	Sweat at night 0-No 1-Yes
menstruation	Physical problem during menopause 0-No 1-Yes
irritability	Irritability 0-No 1-Yes
pressurehead	Pressure 0-No 1-Yes
tingling	Tingling 0-No 1-Yes
headache	Headache 0-No 1-Yes
pain	Muscle and joint pain 0-No 1-Yes
breathe	Breathing difficulties 0-No 1-Yes
knowledge	Knowledge about menopause 0-No 1-Yes
pillknowledge	Knowledge about pill 0-No 1-Yes
agediff	Age diff from their husband 0-No 1-Yes

TABLE 1: PARAMETER TABLE

Pre-processing: Data cleaning and removal of null values

Classification: Data is being used to determine if a patient is suffering from depression or not using machine learning models like DT, RF, SVM, and NB.

SVM

Classification via SVM is based on the margin notation on both sides of the hyperplane. SVM kernels convert low-dimensional input space into high-dimensional space to separate problems. For issues involving non-linear separation, it is mostly helpful. The kernel, in its simplest version, performs a number of complicated data transformations before discovering how to partition the data according to the labels or outputs

$$\text{Specified Linear: } K(w,b)=w^{T}x+b$$

$$\text{Polynomial: } K(w,x)=(\gamma w^{T}x+b)^{N}$$

$$\text{Gaussian RBF: } K(w,x)=\exp(-\gamma||x_i-x_j||^{n}$$

$$\text{Sigmoid: } K(x_i,x_j)=\tanh(\alpha x_i^{T}x_j+b)$$

Decision Tree

DTs are a kind of supervised machine learning that use a recursive tree-structure. All directed trees (DTs) have three types of nodes: root/intermediate, path, and leaf. A deliberation of degree of unpredictability in data being managed is entropy. As entropy of data increases, it becomes more challenging to draw any conclusions. For a single attribute, mathematical description of entropy is: If we take current state S and divide it by likelihood of event i in that state or the proportion of class i in node in that state, we get pi. Reducing entropy is one example of information gain. It estimates database entropy discrepancy and average entropy after split utilizing attribute values. One such decision tree method is ID3 (Iterative Dichotomiser), which makes advantage of information gain.

Mathematical representation of IG is:

$$\text{Information Gain } (T, X) = \text{Entropy}(T) - \text{Entropy } (T, X)$$

Gini Index

When analyzing dataset splits, Gini index may be thought of as a cost function. To get it, add up all squared probabilities of the classes and then deduct one from that total. Contrasted with information gain, which prefers smaller divisions with different values, it is easier to implement and supports bigger partitions.

Evaluation metrics

Accuracy, False Positive Rate, Precision, Recall, and other performance measures are used in Machine Learning to assess the efficacy of ML-based intrusion detection systems. To be sure, when it comes to binary classification challenges, the Accuracy (AC) score is where it's at. The following equation may be used to define it:

$$AC=(TP+TN)/(TP+TN+FP+FN)$$

wherein TP signifies number of True Positive results and TN stands for number of True Negative results. Number of assault events that were accurately identified is called the True Positive rate. The number of accurately identified normal cases is called True Negative. Conversely, the amount of valid traffic that is incorrectly marked as an attack is known as False Positive (FP). A False Negative (FN) is the sum of all the attack cases that are mistakenly thought to be normal. Since FN is more dangerous than FP, its use is often reduced while trying to identify incursion. Nevertheless, along from the Accuracy measure, 4 other metrics—FPR, Precision, Recall, and F1 score—are taken into account for unbalanced class data, particularly in cases when the goal is to effectively identify incursion (positive occurrences).

Rate of False Positives (FPR) is deliberated by dividing number of false negative events (FP) with total number of true negative events. One way to say it is as follows:

$$FalsePositiveRate(FPR)=FP(FP+FN)$$

Precision: with which a model correctly predicts an instance is called its precision, and it is a measure of the model's overall performance. This may be represented mathematically by the following equation:

$$Precision=TP(TP+FP)$$

Recall/ Detection Rate (DR) It is metric by which the ML model's True Positive detection accuracy is evaluated. Additionally, Recall evaluates the precision with which model extracts useful information. For this reason, it goes under many names, including Sensitivity and True Positive Rate. This is one way to represent mathematical expression:

$$Recall/DR=TP(TP+FN)$$

4.*F1 Score* To get ML model's total accuracy, one must consider Recall and Precision tradeoff, which accounts for both FP and FN. The following equation may be used to express the F1 score:

$$F1score=(2*Recall*Precision)(Recall+Precision)$$

IV. SYSTEM ARCHITECTURE

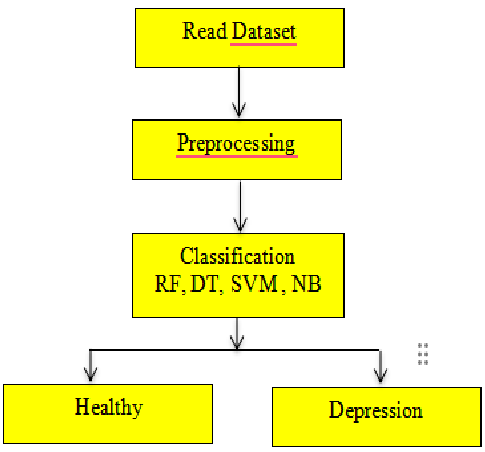


Fig-1: System Architecture

Architecture Description

- Retrieves and loads the dataset (self-generated)
- Splits data into two sets: test and train.
- Deletes empty records
- Utilizing RF, DT, NB, and SVM, among other classification models
- Determining if the patient is suffering from depression
- Findings and Analysis

V. RESULTS AND DISCUSSIONS

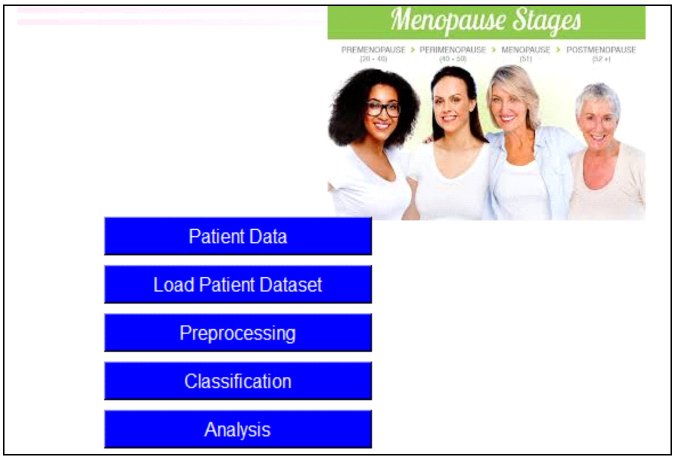


Figure 2: Menu

A menu appears here. This is where the main program begins. Options like "patient data," "load dataset," "classification," and "analysis" are available from menu.

Patient Name	Age	Hf	Os	Db
48	43	1	0	0
47	35	1	1	0
46	54	1	1	1
45	43	0	0	0
44	45	1	1	1
43	45	1	1	1
42	43	1	0	0
41	35	1	1	0
40	54	1	1	1
39	43	0	0	0
38	45	1	1	1
37	45	1	1	1
36	43	1	0	0
35	35	1	1	0
34	54	1	1	1

Fig-3: Load Patient Data

Retrieves the patient database. This agitates and shows the patient's daily activity.

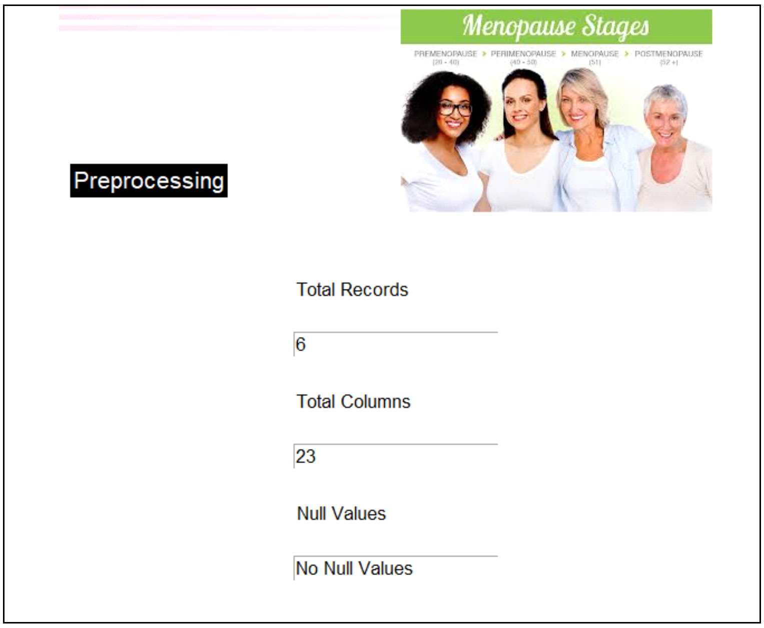


Figure 4: Preprocessing

Its primary function is to eliminate blanks and tidy up data sets.

To train ML models, raw data must first undergo data preparation. Accuracy and performance of the model are directly affected by this stage, making it an essential part of the ML workflow.

	Model	Training Accuracy %	Testing Accuracy %
0	Logistic Regression	87.878788	73.333333
1	Support Vector Machine	69.696970	46.666667
2	Decision Tree Classifier	100.000000	60.000000
3	Random Forest Classifier	100.000000	60.000000
4	Naive Bays	87.878788	73.333333

Fig-5: Classification Accuracy

Classification with the use of LR, SVM, DT, RF, and NB.

Machine learning method that is supervised and can predict a continuous numerical value. A model is a representation of connection amongst a dependent variable and an independent variable or variables. Market trend forecasting, experience-based compensation prediction, and cause-and-effect connection analysis are common applications of linear regression. Commonly employed in machine learning, random forest method aggregates the results of several decision trees. Its versatility and user-friendliness have contributed to its widespread usage, especially as it can manage both classification and regression issues. Data miners often use decision tree learning. Building a model that can take several inputs and use them to forecast a target variable's value is the objective.

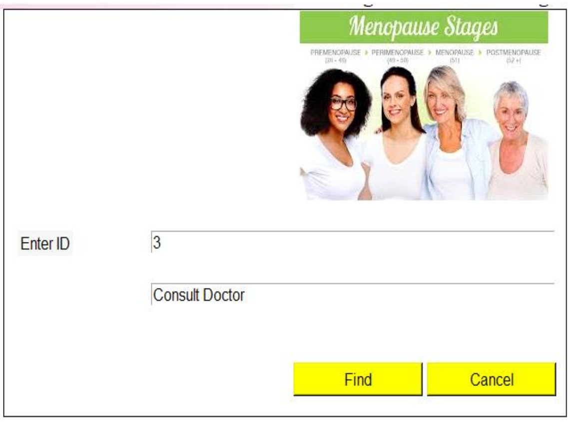
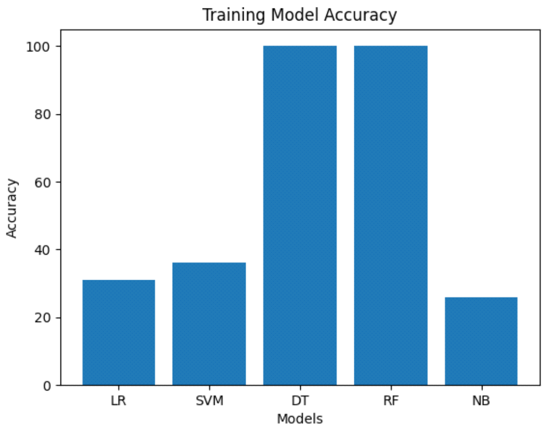


Fig-6: Finding Depressed or not

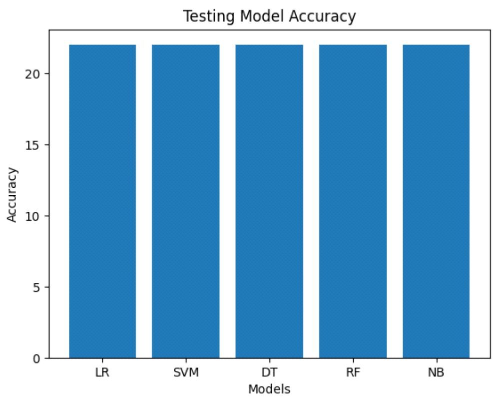
This module determines if a patient is depressed or not when user inputs their ID.



Graph 1:Training Model Accuracy

The accuracy of the training model is shown below.

Accuracy training is a method for evaluating a machine learning model's performance.



Graph2:Testing Model Accuracy

The correctness of the testing model is shown below. A machine learning model's accuracy may be evaluated via testing

VI. CONCLUSIONS

We gathered a menopause dataset for the purpose of studying depression. Following data collection, datasets underwent any necessary pre-processing. To have a better grasp of the dataset, we used EDA and statistical data analysis. For the model's construction, our group agreed on four ML techniques: support vector machine (SVM) classifier, decision tree, random forest, and NB classifier. We used measures like recall, sensitivity, specificity, accuracy, F1 score, MCC, ROC, and PRC to compare the algorithms' performance after we ran them on the changed dataset. There was further testing of the models utilising Precision-Recall and ROC curves. Following that, we isolated fourteen separate risk factors associated with each algorithm that was eventually used.

References

[1]. L. Al-Mehaisen, O. Al-kuran, Impact of menopause on quality of life: A cross sectional study in menopausal females in the north of Jordan, Med. Sci. Discov.5 (6) (2018) 234–238.
[2]. F. Jafari, M.H. Hadizadeh, R. Zabihi, K. Ganji, Comparison of depression,anxiety, quality of life, vitality and mental health between premenopausal and postmenopausal women, Climacteric 17 (6) (2014) 660–665.
[3]. M.I. Bashar, K. Ahmed, M.S. Uddin, F. Ahmed, A.A. Emran, A. Chakraborty,Depression and quality of life among postmenopausal women in Bangladesh: A cross-sectional study, J. Menopausal Med. 23 (3) (2017) 172–181.
[4]. World Health Organization, Research on the Menopause in the 1990s: Report of a WHO Scientific Group, 1996.
[5]. W. Rössler, V. Ajdacic-Gross, A. Riecher-Rössler, J. Angst, M.P. Hengartner, Does menopausal transition really influence mental health? Findings from the prospective long-term Zurich study, World Psychiatry 15 (2) (2016) 146–154.
[6]. N. Chuni, C.T. Sreeramareddy, Frequency of symptoms, determinants of severe symptoms, validity of and cut-off score for Menopause Rating Scale (MRS) as a screening tool: a cross-sectional survey among midlife Nepalese women, BMC Women's Health 11 (1) (2011) 30.
[7]. K. Ahmed, P. Jahan, I. Nadia, F. Ahmed, Assessment of menopausal symptoms among early and late menopausal midlife Bangladeshi women and their impact on the quality of life, J. Menopausal Med. 22 (1) (2016) 39–46.
[8]. S. Sharma, V.R. Tandon, A. Mahajan, Menopausal symptoms in urban women, Alcohol 4 (2007) 3–41.
[9]. S. Jesmin, A.S. Islam, S. Akter, M.M. Islam, S.N. Sultana, N. Yamaguchi, O.Okazaki, M. Moroi, M. Hiroe, S. Kimura, T. Watanabe, Metabolic syndrome among pre-and post-menopausal rural women in Bangladesh: result from a population-based study, BMC Res. Notes 6 (1) (2013) 157.
[10]. M.R. Soules, S. Sherman, E. Parrott, R. Rebar, N. Santoro, W. Utian, N. Woods, Executive summary: stages of reproductive aging workshop (STRAW), Climacteric 4 (4) (2001) 267–272.
[11]. M.H. Cheng, S.J. Lee, S.J. Wang, P.H. Wang, J.L. Fuh, Does menopausal transition affect the quality of life? A longitudinal study of middle-aged women in Kinmen, Menopause 14 (5) (2007) 885–890.
[12]. J.L. Fuh, S.J. Wang, S.J. Lee, S.R. Lu, K.D. Juang, Quality of life and menopausal transition for middle-aged women on Kinmen island, Qual. Life Res. 12 (1) (2003) 53–61.
[13]. Y. Zheng, Y. Zhou, J. Hu, J. Zhu, Q. Hua, M. Tao, Prediction of risk of depressive symptoms in menopausal women based on hot flash and sweating symptoms: a multicentre study, Clin. Interv. Aging 12 (2017) 1993.
[14]. M. Hickey, D.A. Schoenaker, H. Joffe, G.D. Mishra, Depressive symptoms across the menopause transition: findings from a large population-based cohort study, Menopause 23 (12) (2016) 1287–1293.
[15]. P.R. Albert, Why is depression more prevalent in women? J. Psychiatry Neurosci.: JPN 40 (4) (2015) 219.
[16]. N. Santoro, C.N. Epperson, S.B. Mathews, Menopausal symptoms and their management, Endocrinol. Metab. Clin. 44 (3) (2015) 497–515.
[17]. K.E. Campbell, L. Dennerstein, S. Finch, C.E. Szoeke, Impact of menopausal status on negative mood and depressive symptoms in a longitudinal sample spanning 20 years, Menopause 24 (5) (2017) 490–496.
[18]. M. de Kruif, A.T. Spijker, M.L. Molendijk, Depression during the perimenopause: A meta-analysis, J. Affect. Disord. 206 (2016) 174–180.
[19]. L.S. Cohen, C.N. Soares, A.F. Vitonis, M.W. Otto, B.L. Harlow, Risk for new onset of depression during the menopausal transition: the Harvard study of moods and cycles, Arch. Gen. Psychiatry 63 (4) (2006) 385–390.
[20]. J.T. Bromberger, K.A. Matthews, L.L. Schott, S. Brockwell, N.E. Avis, H.M. Kravitz, S.A. Everson-Rose, E.B. Gold, M. Sowers, J.F. Randolph Jr., Depressive symptoms during the menopausal transition: The Study of Women's Health Across the Nation (SWAN), J. Affect. Disord. 103 (1–3) (2007) 267–272.
[21]. J.T. Bromberger, H.M. Kravitz, Mood and menopause: findings from the Study of Women's Health Across the Nation (SWAN) over 10 years, Obstet. Gynecol. Clin. 38 (3) (2011) 609–625.
[22]. C.N. Soares, Mood disorders in midlife women: understanding the critical window and its clinical implications, Menopause 21 (2) (2014) 198–206.
[23]. S.A. Rahman, S.R. Zainudin, V.L. Mun, Assessment of menopausal symptoms using modified Menopause Rating Scale (MRS) among middle age women in Kuching, Sarawak, Malaysia, Asia Pac. Fam. Med. 9 (2010) 5.
[24]. X. Li, F. Chen, D. Sun, M. Tao, Predicting menopausal symptoms with artificial neural network, Expert Syst. Appl. 42 (22) (2015) 8698–8706.
[25]. N. Chuni, C.T. Sreeramareddy, Frequency of symptoms, determinants of severe symptoms, validity of and cut-off score for Menopause Rating Scale (MRS) as a screening tool: a cross-sectional survey among midlife Nepalese women, BMC Women's Health 11 (1) (2011) 30.
[26]. J.T. Bromberger, L. Schott, H.M. Kravitz, H. Joffe, Risk factors for major depression during midlife among a community sample of women with and without prior major depression: are they the same or different? Psychol. Med. 45 (8) (2015) 1653–1664.
[27]. K.D. Juang, S.J. Wang, S.R. Lu, S.J. Lee, J.L. Fuh, Hot flashes are associated with psychological symptoms of anxiety and depression in peri-and post-but not premenopausal women, Maturitas 52 (2) (2005) 119–126.
[28]. E.P. Handing, C. Strobl, Y. Jiao, L. Feliciano, S. Aichele, Predictors of depression among middle-aged and older men and women in Europe: A machine learning approach, Lancet Reg. Health-Eur. 18 (2022) 100391.

[29]. M.B. Waqar, S. Noreen, B. Rizwan, A. Khan, I. Bashir, R. Tanveer, T. Akram, M. Tariq, I. Khalid, M. Asif, Knowledge, attitude, and practices regarding menopause among elderly women attending tertiary health care centers in Lahore, Pakistan: Menopause among elderly women, Pak. J. Health Sci. 1 (2023) 2–17.

[30]. B. Shakya, P.K. Pokharel, B.K. Yadav, P.M. Shyangwa, I.S. Paudel, H.P. Pokharel, Prevalence of depression among menopausal women in a rural community of Morang, Nepal, Nepal Med. Coll. J. 24 (1) (2022) 30–39.

[31]. S.Y. An, Y. Kim, R. Kwon, G.Y. Lim, H.R. Choi, S. Namgoung, S.W. Jeon, Y. Chang, S. Ryu, Depressive symptoms and suicidality by menopausal stages among middle-aged Korean women, Epidemiol. Psychiatr. Sci. 31 (2022) e60.

[32]. F. Saeed Elsayed, F. Mohammed Ahmed, S. Saad Moustafa, F. Abdallah Shams Eldin, Correlation between menopausal symptoms, depressive symptoms and marital satisfaction among menopausal women, Int. Egypt. J. Nurs. Sci. Res.3 (2) (2023) 419–437.

[33]. A. Kułak-Bejda, K. Krajewska-Ferishah, A. Szyszko-Perłowska, N. Waszkiewicz, Risk assessment of depression amongst women during menopause before and during the COVID-19 pandemic, Int. J. Environ. Res. Public Health 20 (1) (2022) 596.

[34]. S. Álvarez-Pardo, J.A. de Paz, E.M. Romero-Pérez, J.M. Tánori-Tapia, P.A.Rendón-Delcid, J.J. González-Bernal, J. Fernández-Solana, L. Simón-Vicente, J.Mielgo-Ayuso, J. González-Santos, Related factors with depression and anxiety in mastectomized women breast cancer survivors, Int. J. Environ. Res. Public Health 20 (4) (2023) 2881.

[35]. Y. Liu, X. Yang, Y. Xu, Y. Wu, Y. Zhong, S. Yang, Cognitive function and depressive symptoms among Chinese adults aged 40 years and above: The mediating roles of IADL disability and life satisfaction, Int. J. Environ. Res. Public Health 20 (5) (2023) 4445.

