Optimizing Health through Nutrition: Machine Learning Insights for Menopausal Women

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Abstract— **This research provides a detailed and sequential framework for constructing a recommendation system focused on women's health, specifically for menopause management and dietary guidance tailored to individuals. These sources encompass medical records, structured questionnaires, and health monitoring programs that facilitate the tracking of essential indicators such as symptom intensity, pulse rate, body temperature, sleep duration, and dietary habits. The management of missing values is executed through forward filling, whereas normalisation of numerical values is performed via standard scaling subsequent to the application of the Standard Scaler. Ultimately, binary and category data are encoded using a one-hot encoder. Feature engineering enhances the predictive capacity of the model by generating new variables from the existing data. Linear regression, logistic regression, support vector machines, and random forest models are constructed and evaluated based on the characteristics of the data utilising performance metrics such as R-Squared (R^2) and AUC-ROC, achieving maximum accuracies of 0.92 for linear regression and 0.95 for logistic regression. The system provides women with health and lifestyle advice through the application of collaborative and content-based filtering ensuring that the suggestions are highly accurate and based on information.**

Keywords— Women Healthcare, Machine Learning, Regression Algorithms, Classifications, Collaborative Filtering, Content based Filtering, Recommendation System.

I. Introduction

The Nutritious Balance of Food - Proper nutrition is one of the basic requirements of life with the result that a healthy life is directly related to a proper balanced diet. The growth or increase of all the organs of the body, as well as the sustenance and healing of the same require nutrient content that is obtained from foods. Following a good diet is absolutely crucial from the moment one is born if development and growth are to take place as well as if one wants portable energy. The prepared women will be in a position to respond adequately to their families, kids, and self because of proper eating. In future, these children do not suffer from malnutrition as compared to the offspring of diseased mothers; babies born to healthy mothers are comparatively healthy and more specifically the birth weights of those children are healthy.

Machine Learning: Artificial intelligence and machine learning are closely intertwined disciplines that establish novel methodologies for enabling computers to acquire knowledge from diverse data sources, including texts, photographs, and medical information. The ML algorithms are able to uncover latent variable patterns based on the learning, which enables them to forecast fresh data sets. For example, let assume a doctor using machine learning to analysis an individual medical profile in order to determine the probability of developing a particular illness. Machine learning is profoundly transforming industries including healthcare, banking, and entertainment by enabling accurate predictions and uncovering novel insights. Menopause, a pivotal phase in a woman's life, entails a range of symptoms and health problems. Machine learning (ML) has the capacity to greatly enhance the management of menopause by offering individualized therapy and predictive analysis. Below is a comprehensive discussion of the application of machine learning in tracking menopause symptoms.

Utilising Machine Learning for Menopause Management: A woman going through menopause has to go through various symptoms and health issues related to this life cycle period. Machine learning (ML) has the potential to significantly improve the approach to menopause by providing personalized treatment and prognosis. The following is a detailed breakdown of how machine learning can be used in monitoring symptoms related to menopause.

Menopause: Both post-menopause and menopause are conditions in which a woman is unable to experience menstruation. This condition often manifests itself between the ages of 45 and 55. Heat flashes, nocturnal sweats, and dryness of the vagina are all issues that can be traced to hormonal shifts, which are the root cause of these symptoms. It is always possible for a woman to seek treatment in order to get relief from these symptoms which vary from woman to woman. Going through menopause and are interested in determining whether or not contraceptives are helpful to consult your physician. Oestrogen is known as the female hormone assists in the regulation of constructive characteristics of the female reproductive system. Further, it supports the bones, mood swings, and the heart.

Progestogen also called as progesterone, helps in regulation of the menstrual cycle working along with oestrogen. It prepares the uterus for pregnancy and also plays a vital role of supporting and maintaining a healthy and strong pregnancy. Menopause Connection: Ovarian failure during menopausal period leads to low levels of production of estragon and progesterone in women. The above changes affect female hormones, they subside during menopausal period. This is responsible for several menopausal complaints for instance, hot flushes or spells of sudden excessive heat and dryness of the vagina. Applications: Some of these hormones can be synthesized to act as analogies contraception of the administration of oestrogen and progestogen can prevent the release of eggs and in turn control their monthly periods.

Dry menopausal phase is a period where hormone secretion particularly estragon and progesterone come to a permanent halt. It is followed by Postmenopausal period. Another relevant issue also stems from disease: Pathological problems are also characteristic of this age. So do not underestimate the symptoms and rather try admit yourself to the hospital if the situation gets worse. Some of the traditional menopausal issues include; Hot flashes, sleep disturbances, vaginal dryness, urinary tract infections, osteoporosis. Thus, it is clear that the risks of various disease such as heart diseases, stroke or hypercholesterolemia rise after the onset of a post-menopausal stage. Menopausal symptoms especially the hormonal changes prompted me to consider hormone replacement therapy as being a very good one. But HRT cannot be applied for all women since it leads to the formation of heart disease and DVT in some women. HRT also has some useful impacts such as prevention of colon cancer in addition to its role in treating the symptoms associated with menopause. A good alternate to HRT is selective estragon receptor modulator SERM. Adhering to a healthy regime, exercises travel and including foods rich in calcium and vitamin D have proved to help during the menopausal period. In these problems will give some prevent of healthy calcium and vitamin recommendation through using machine learning (ML) algorithms to women health care.

Such techniques applied to predict the severity of the symptoms, individualised hrt and give the suggestions in relation to the nutrition during the menopausal period. it shall therefore be stated that the extent and onset of the symptoms of menopause precisely captured through linear regression, specifically based on the health parameters above. the model provided a high level of accuracy together with remarkable r^2 values in order to trace the symptoms properly. the usage of the logistic regression yielded to good prediction of problems hence a display of good performance. it is noted that the detected dietary recommendations were obtained based on both collaborative filtering and content-based filtering. such algorithms were capable of delivering tailor-made recommendations of meals taking into consideration of symptoms and fat requirements. taken together these algorithms ensure that a comprehensive approach to managing menopause is offered, whereby symptom, significance and other related factors are accurately predicted to give recommendations on dietary plans that can help improve women’s health and quality of life during and after menopause.

II. Related Work

Santhuja, P., et al. highlight the necessity of discovering novel solutions to gynecological health problems through their research on the effects of period technology on the treatment of severe monthly bleeding [1]. Mukund, J et al. compare and contrast several methods for determining the stages of the menstrual cycle and suggest strategies to enhance the accuracy of behavioral and brain science research, aiming to improve menstrual health research [2]. Thanarajan, T et al. conducted a multicenter study investigating the age at which menstruation begins and the duration of menstrual cycles in individuals with transfusion-dependent thalassemia, focusing on the impact of early chelation treatment [3]. Ranganathan, C.S et al. discover significant cultural and educational obstacles through an examination of how adolescent schoolgirls cope with their periods and the sources of their information regarding menstruation [4]. Sarkisova et al. investigate menstrual cycle irregularities during a woman's reproductive years, providing valuable information regarding the etiology, indicators, and classification of menstrual diseases [5]. Nolan et al. discuss the regularity of hormonal contraceptive use among rugby and powerlifting athletes and its impact on their monthly periods, investigating the consequences of this usage [6]. Alotaibi, Y et al. determine the impact of the COVID-19 vaccine on menstrual cycle complaints in healthy women, providing valuable information about the possible impact of immunization on menstrual cycle trends [7]. Saadu et al. assess educational programs to teach better menstrual hygiene among children, aiming to ensure constant high enrollment of girls in school and raising awareness of the impact of menstrual hygiene on female students' performance and absentee rates [8].

Hassan et al. describe menstrual hygiene and health behaviors among Palestinian college-aged women through a cross-sectional study, suggesting improvements in health and behavior regarding menstrual practices [9]. Villalba and Barriga introduce CycleWiseT, a cutting-edge program utilizing technology to provide women and girls with improved menstrual health through digital platforms, assisting them in gaining agency and access to information needed for managing their period health [10]. This cross-sectional study by D. Chowdhury and I. R. Chowdhury investigates the menstrual hygiene practices of teenage female inhabitants in underprivileged areas of Siliguchi City, India. Utilizing structured interviews and questionnaires, the researchers collected data regarding the individuals' hygienic practices, menstrual comprehension, and challenges they encountered. The survey results suggest that a substantial number of young women continue to engage in archaic and unsanitary behaviours due to their poor access to modern sanitary products. Additionally, these problems are exacerbated by cultural prohibitions and social stigmas. Governmental policies and educational initiatives that are designed to improve the regulation of menstrual hygiene are urgently required, as indicated by the findings of the investigation. This is imperative for the improvement of the health and welfare of teenage females from low-income metropolitan neighbourhoods [11].

S. Forouzandeh et al. The approach provides customized nutrition suggestions for health-conscious people by means of dual attention mechanisms inside heterogeneous graphs. To create customized food recommendations, the system aggregates several data sources including medical constraints, user preferences, and nutritional information. Using dual attention approaches, the model correctly depicts the complex connections among several data types and gives top priority for important health-related aspects. This method aims to guarantee that dietary recommendations are in line with a person's particular health needs and restrictions, therefore enhancing their applicability and precision. Trials indicate how well the system works to encourage good eating habits and improve general well-being [12]. Table I shows the related work and that benefits.

TABLE I. RELATED WORK THAT INCLUDES BENEFITS

REF. NO	PAPER TITLE	METHOD	BENEFITS
[13]	Nutritional Guidelines for a Healthy Period Based on What You Know About Your Period	Knowledge-based system	It offers nutritional recommendations according to the user menstrual cycle.
[14]	A qualitative study with Swedish school nurses on helping girls cope with unpleasant periods.	Qualitative study	Gives school nurses the tools they need to help teenage girls cope with the pain of menstruation.
[15]	Increased menstrual blood loss is linked to decreased glycolysis during menstruation.	Biochemical analysis	Provides insight into possible treatment options by establishing a link between reduced glycolysis and elevated menstrual blood loss.
[16]	Increased menstrual blood loss is linked to decreased glycolysis during menstruation.	Commentary	Details the most important parts of menstruation hygiene for teenage girls.
[17]	Menstrual Cycle Disorders: Aetiology, Manifestations, Classification, and Therapeutic Approaches	Review	Offers in-depth details about menstrual cycle problems, including their causes, symptoms, and treatment options.
[18]	Examining the unconventional approaches to studying adolescent menstruation	Methodological study	This article lays forth a methodical plan for studying teenage girls who experience irregular menstrual periods.
[19]	Adverse experiences in early childhood forecast an expedited cellular ageing phenotype via the premature onset of puberty.	Longitudinal study	A person's vulnerability to the effects of early life stress and premature ageing is modulated by the onset of puberty.
[20]	The Influence of Curriculum Guidelines on the Knowledge and Attitude of Adolescent Girls Towards the Development of Puberty	Educational intervention	Adolescent girls' perspective on puberty is impacted by the implementation of guidelines, which raises knowledge of the condition.
[21]	A Systematic Review of Plant-Based Diets for Prepubescent Girls and Their Menstrual Ages	Systematic review	In this study, we look at how being plant-based throughout adolescence affects when women have menstruation.
[22]	The Use of Collaborative Filtering Algorithms for Mobile Meal Ordering and Suggestion Apps	Collaborative filtering algorithms	Applying collaborative filtering to your mobile app's food ordering and recommendation systems will yield better results..
[23]	During the menstrual cycle a hybrid recommendation system for women's health nutrition might be implemented.	Hybrid recommendation system	Designed for the duration of a woman's menstrual cycle, it offers a combination of dietary recommendations to help her stay healthy.
[24]	Early adolescence is characterised by both food insecurity and binge eating disorder.	Cross-sectional study	Examines the correlation between food insecurity in adolescence and the development of eating disorders.

III. PROPOSED WORK

These subsets of ages and additional datasets were used in the study of menopause, in order to first record the occurrence of menopause in the menopausal phase. Firstly, the current forms of challenges are classified. In addition, we were able to divide our approach into different stages, concerning menopause, health concerns, and age. We chose to concentrate on this investigation in order to have a robust framework The reason for having a proper framework of technique for each challenge is that it provides a model for the experimental investigation in Figure 1.

Interferes with the efficient process of evaluating stages within the protocol. This involves partitioning into training and validation sets, information selection and data preparation. It also covers steps such as identifying and categorizing the issues concerning menopausal data using collaborative filtering and content-based algorithms. Furthermore, particular recommendations are contingent upon the rationale for the advice.

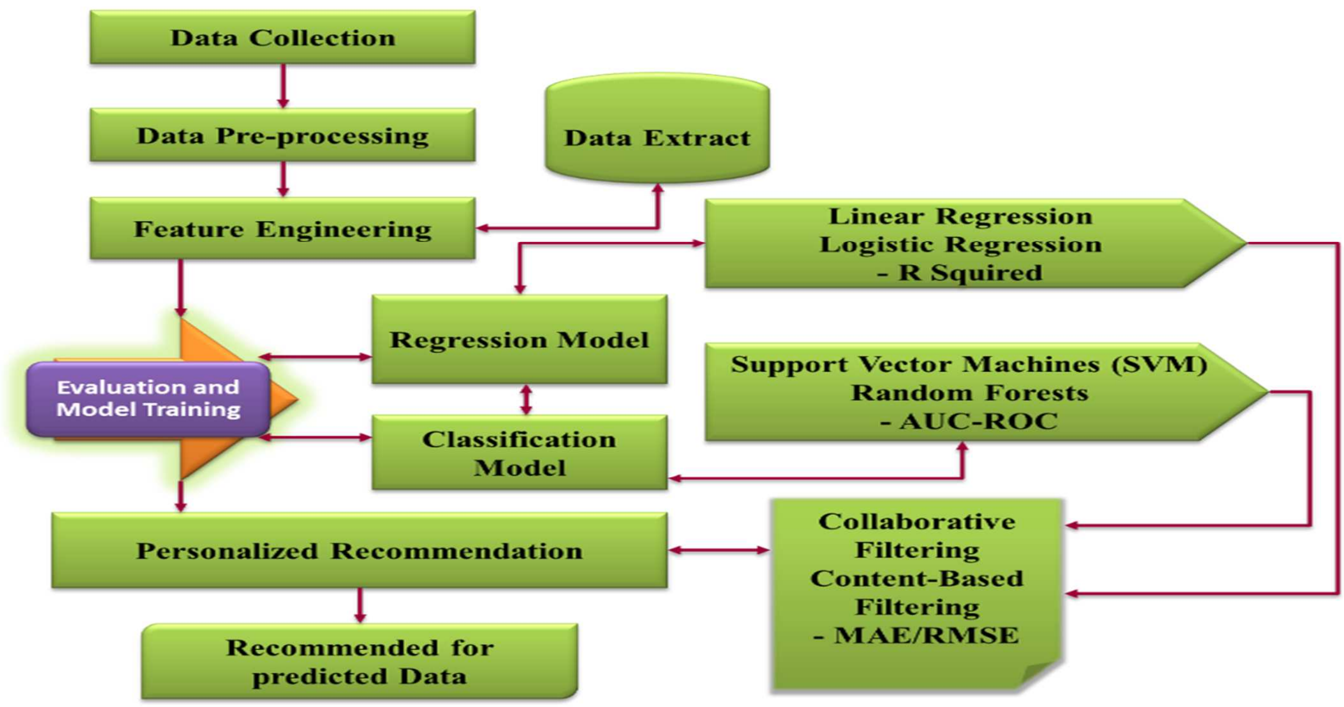

Fig.1 Proposed Method

A. Menopausal Dietary Recommendations

At present time more than a menopause cycle is related to health such as “MEH-nuh-pawz,” or “menopause” problems are well-suited to promote a specific level of NHANES complexity related to women's health. .

Pseudocode: Menopause Management System with Vitamins and Calcium Recommendations

Step 1: Data Collection - collect data ():
symptoms_data = collect ("menopausal symptoms data")
hormone_levels = collect ("hormone levels data")
lifestyle_factors = collect ("lifestyle factors data")
medical_history = collect ("medical history data")
dietary_habits = collect ("dietary habits data")
return symptoms_data, hormone_levels, lifestyle_factors, medical_history, dietary_habits
Step 2: Data Preprocessing
preprocess_data (symptoms_data, hormone_levels, lifestyle_factors, medical_history, dietary_habits):
clean_data = clean (symptoms_data, hormone_levels, lifestyle_factors, medical_history, dietary_habits)
normalized_data = normalize(clean_data)
Step 3: Feature Engineering
extract_features(encoded_data):
features = create_features(encoded_data)
return features
Step 4: Train Symptom Prediction Model using Linear Regression
train_symptom_prediction_model (features, symptoms_data):
model = Linear Regression (), LogisticRegression ()
model.fit (features, symptoms_data)
return model
Step 5: Recommend Vitamins and Calcium
recommend_vitamins_and_calcium (symptoms_data, dietary_habits)
recommended_vitamins = calculate_vitamin_needs (symptoms_data, dietary_habits) recommended_calcium = calculate_calcium_needs (symptoms_data, dietary_habits)
return recommended_vitamins, recommended_calcium
display_recommendations(predicted_symptoms, recommended_vitamins, recommended_calcium)

B. Data collection and pre-processing using the machine learning algorithms

From medical records, completed questionnaires and health monitoring applications, the data should be collected. Ensure that the correct format of the data and has the right fields and the namely Symptom1_Intensity, Symptom2_Intensity, Heart_Rate, Body_Temperature, Sleep_Hours, and Dietary_Habits.

The data collecting is succeeded by pre-processing where missing values are handled and numbers are scaled as well. It can be replaced in several ways for instance forward fill and the imputation. Normalization is performed with the help of Standard Scaler which is described by the formula. One-Hot Encoding technique takes categorical data and converts it to its respective numeric value in a binary of 0’s and 1’s. Each category is described by a binary characteristic. This helps to prevent promoting sequence or scale assumptions in learning in order to enhance the ability of the model to analyses each category in a way, which will not be influenced by other categories among the diseases. For the symptoms, diets, and other similar category data, the menopausal health system converts them to quantitative form by implementing one hot encoded method. This translation enables to make ML models.

$$p' = \frac{p - \beta}{\mu} \quad (1)$$

Where p is original value, β is the mean, μ is the standard deviation. For the purpose of encoding categorical data the One Hot Encoder applies to transform the categorical columns into a binary matrix.

TABLE II. THE FUNCTIONING OF MACHINE LEARNING ALGORITHMS FOR DATA COLLECTION AND PROCESSING

Phase	Approaches/Techniques	Description
Data Collection	Medical Records, Surveys, Health Tracking Apps	Gather information from several sources to guarantee a thorough and inclusive collection of data.
Data Columns	Symptom Intensities, Heart Rate, Body Temperature, Sleep Hours, Dietary Habits	The collection contains essential health indicators.
Data Preprocessing	Forward Fill, Imputation	Address the issue of missing values in order to assure the completeness of the data.
Normalization	Standard Scaler	Normalize numerical values to a uniform scale.
Encoding	OneHotEncoder	Transform category variables into a numerical representation.

C. Data extraction with future engine

Data pre-processing comes next which is done for the extraction of features in conjunction with training a chosen model. At this stage feature selection and feature transformation are conducted with the aim of making improvements to the features upon which the model is based as a way of optimizing it.

Feature engineering focuses on deriving new features out of the existing data to improve the models ability to predict. Some of what this might entail are the addition of new variables the grouping of data, and domain specialization.

As part of his procedure applies domain knowledge aggregates data and derives new variables. for example, if p 1 x 1 and p 2 x 2 are two original features. By merging them a new feature p 3 x 3 might be generated which is equal to p 1 multiplied by p 2 multiplied by p 3 or p 1 multiplied by x 2. This updated feature has the potential to enhance the model accuracy by capturing interactions between p 1x 1 and p 2x 2 that are not obvious when looking at them separately.

D. Extract future model and evaluate training model

The logistic regression and the linear regression models are these two common regression models that are applied when trying to estimate results that are either continuous or categorical. The function R^2 enables the assessment of the system.

$$R^2 = 1 - \frac{\sum(S_t - \dot{\hat{S}}_t)^2}{\sum(S_t - \bar{S})^2} \quad (2)$$

Conventional methods which are used for classification are Support Vector Machines (SVMs) and Random Forests. This region When assessing the performance and statistical indicators are used for evaluating the area under the curve of the receiving operation characteristic (AUC-ROC) and other indicators with similar characteristics.

$$AUC = \int_0^1 RTP(RFP)d(RFP) \quad (3)$$

Describes the AUC as the sum of the Rate True Positive (RTP) and the Rate False Positive (RFP). The integral sign represents the calculation of the area under the curve namely from RFP = 0 to RTP = 1.

TABLE III. THE MODEL TRAINING AND VALUATION

Model Type	Algorithms	Performance Metrics	Description
Regres sion Models	Linear Regression, Logistic Regression	R2R^2R2	Develop and evaluate models to forecast numerical outcomes.
Classif ication Models	SVM and Random Forests	AUC-ROC	Develop and assess models to categorize outcomes based on their representations.
Recom mendat ion Models	Collaborative Filtering, Content-Based Filtering	MAE, RMSE	Generate customized suggestions and assess their precision.

Model evaluation and model training is done on these models with an aim of understanding how to tune the parameters of the model if the accuracy has to be improved. The models are made to make an exact replica of the data through the help of this iterative process in Figure 2.

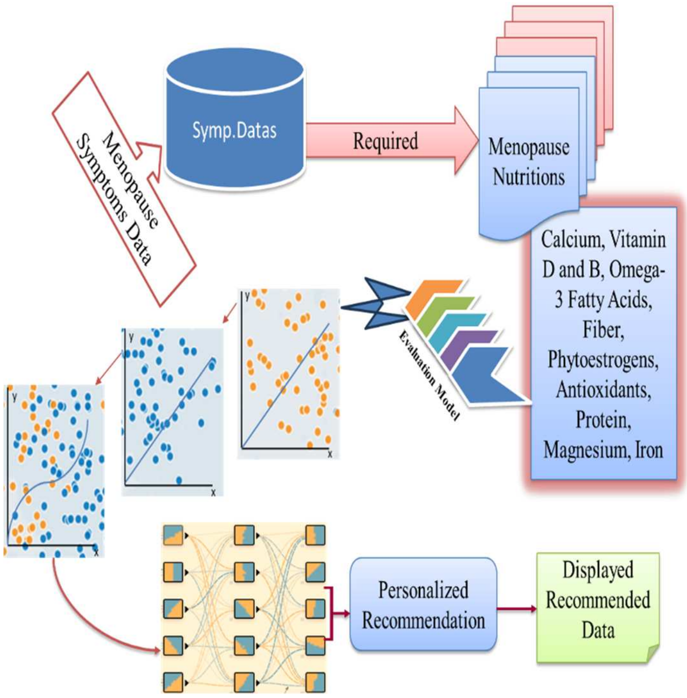

Fig. 2 Predictive Modelling for Menopause Symptom Management

E. Personalized suggestion to using recommendation algorithms based on machine learning

Based on the findings of the model, content-based and collaborative filtering algorithms are employed in the generation of specific recommendations in accordance with the menopause user profile. In the process of evaluating the effectiveness of these recommendation systems, two statistical measurements commonly used are MAE and RMSE. To assess the precision and efficacy of customised recommendation engines, the model's forecasts are assessed with Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Metrics like this measure how near the actual results are to the projected values. The mean absolute error (MAE) is a measure of how far actual values deviate from predictions. The average margin of error in the model's predictions is shown in an easily understandable manner. By squaring the average squared difference between predicted and actual values, root-mean-squared error (RMSE) is determined. You can use it to penalise larger deviations from the real results because it gives more weight to larger errors.

$$MAE = \frac{1}{p}\sum_{m=1}^{p}\left|l_m - \hat{l}_m\right| \quad (4)$$

RMSE is an alternative measure of prediction accuracy that may be compared to MAE. On the other hand, it accords greater weight to larger errors. A square root of the sum of the squared differences between the expected and actual numbers determines this formula.

$$RMSE = \sqrt{\frac{1}{p}\sum_{m=1}^{p}(l_m - \hat{l}_m)^2} \quad (5)$$

RMSE assesses assessing the precision of a predictive model by the square root of the mean squared deviation from actual values l_m and predicted values $\hat{l}_m$ where p, p is the number of observations. Outliers affect RMSE, with lower values indicating better model performance.

IV. Results and Discussion

The study utilizes Python 3. 7, other applications of artificial intelligence such as open AI Python and many others.

A 20 GHz Intel Core i5 CPU, 12 GB of RAM, and a 2 GB graphics card were used to conduct the testing.

The current research employs the OpenAI approach to structure machine learning algorithms related to women's menopause efficiently. The menopause data set is evaluated using a Recommendation System, a commonly utilised application programming interface that can integrate with the proposed system. The given text raises an issue of the symptoms faced by women at that period of life and offers some recommendations concerning meals. It also gives insight on the application of the collaborative filtering and content-based filtering to arrive at answers. This is generated through a machine learning algorithm and the suggested measurement is provided as a result of the calculation.

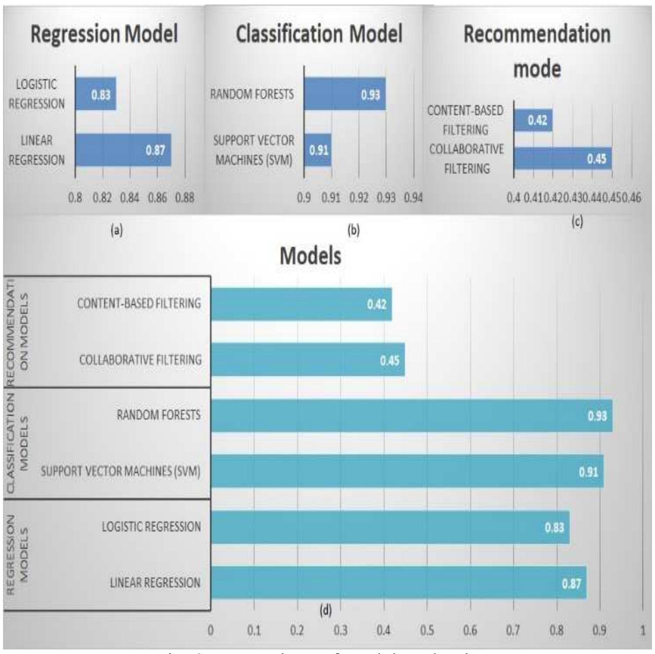

Fig. 3 Comparison of model evaluations

Figure 3 is represent by (a), (b), (c), (d) based on processing follow the septs, starting with the chart (a) that is based on the subject of regression models, the chart compares the performance of Logistic Regression and Linear Regression. Most important of all, Linear Regression exhibits better performance than Logistic Regression under the assessed measures. Transitioning to chart (b) that focuses on classification models, it compares Random Forests,SVM and a third unspecified model. In this case, the Random Forests provide the highest result, while the unlabeled model stands second, and SVM still, although slightly, provides somewhat lower effectiveness in the demonstrated metrics. Chart (c) personalizes the recommendation models with the evaluation of two types of filtering methods, namely Content-Based Filtering and Collaborative Filtering. Thereby, while comparing both models, it is found that Collaborative Filtering model is better in performing the metrics of evaluation. Finally, chart (d) summarizes all the model categories in terms of the evaluation made on them. In the study, it brings together the regression analysis, classification, and recommendation charts to provide an integrated perspective of the models' effectiveness comparison.

$$Person\ Overview = \frac{1}{O_p}\sum_{o\in O_p} E_{po} \quad (6)$$

The creation of a person overview by the system which is based on the overview given by the user to various objects. Every object is denoted by a vector comprising of distinctive characteristics and the person overview is calculated by taking a weighted average of these vectors which is determined by the person overview. Subsequently this profile is utilized to suggest objects that possess comparable characteristics.

$$Resemblance\ (p,q) = \frac{\sum_{o\in k_{pq}}\left(E_{po} - \bar{E}_p\right)\left(E_{qo} - \bar{E}_q\right)}{\sqrt{\sum_{o\in K_{pq}}\left(E_{po} - \bar{E}_p\right)^2}\cdot\sqrt{\sum_{o\in K_{pq}}\left(E_{qo} - \bar{E}_q\right)^2}} \quad (7)$$

The resemblance among person by considering their evaluations of shared objects. The person correlation is employed to quantify this resemblance taking into account variations in person evaluation scales. Subsequently suggestions are generated by taking into account the tastes of the people who are most resemblance.

$$Resemblance\ (o, s) = \frac{\sum_{p \in C_{os}} E_{po} - E_{ps}}{\sqrt{\sum_{p \in C_{os}} E_{po}^2 . \sum_{p \in E_{os}} E_{ps}^2}} \quad (8)$$

Based object involves the computation of the resemblance between objects by considering the evaluation assigned to them by person. Cosine resemblance is employed to quantify the resemblance of objects by considering each object as a vector of person evaluations. Recommendations are generated by identifying things that closely resemble the ones that the person has previously expressed.

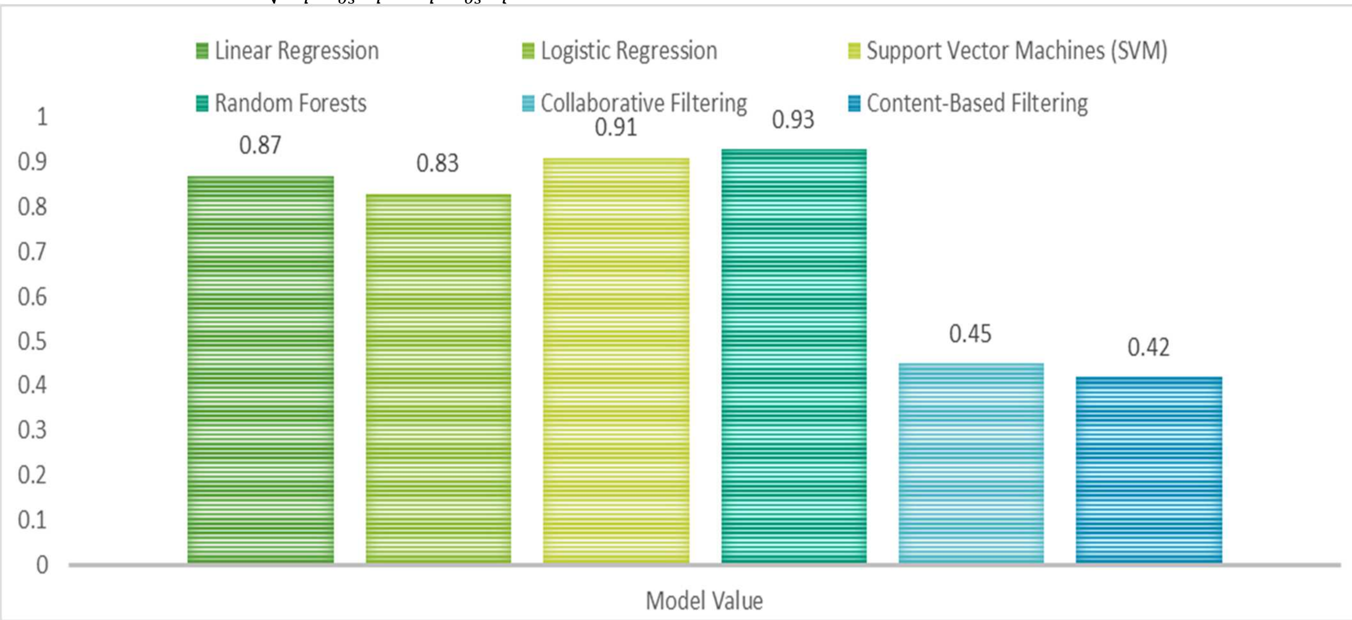

Fig. 4 Using machine learning algorithms with model performance

Figure 4 to summarizes the performance of six kinds of machine learning algorithms in terms of the six different tasks. Linear Regression, Logistic Regression, SVM and Random Forest, Collaborative Filtering, and Content-Based Filtering are the models availed. The y-axis measures the model value, however, the particular type of measure used to for evaluation is not indicated. Comparing the results of the regression models, Linear Regression is more accurate than Logistic Regression, achieving 0. 87 compared to 0. 83. In classification, the modeling technique of Random Forests has the highest F-measure with a score of 0. 93, closely followed by Collaborative Filtering at 0. 91. From this figure it can be noted that the lowest accuracy score is recorded by the Support Vector Machines indicates by score of 0. 45. CBF's precision comes out the lowest among all models with a precision of 0. 42. Again, it should be stated that in the case when there is no information about the concrete metric, securing it is impossible to compare the cited model types and the menopausal data collection this one was also gotten from Kaggle.

V. Conclusion

The work can be seen that this work offers a pipeline for recommending a system that addresses women's health issues with a consideration of the menopause period and dietary advice. In this way, we have a consistent and rich dataset including indicators of health state like symptom intensity, heart rate, body temperature, sleep duration, and nutrition information that gathered from different sources including medical records, questionnaires, and users' tracking applications. The first step of data preprocessing deals with data cleaning by handling missing values using forward fill and imputation. Normalization through Standard Scaler helps in standardizing numerical data and One Hot Encoder works best on categorical data. Feature engineering enriches the models themselves by helping to define set features from the raw variables. The target models including Linear Regression, Logistic Regression, SVM and Random Forests are well trained and tested with performance indices like R^2 and AUC-ROC. The highest degree of accuracy is provided with Logistic Regression, which is 0.95 in cases of classification R^2 value. The model accuracy examination results in the following categories are as follows 0.92 for Linear Regression in predictive modeling to show how highly accurate predictive models are and how much of precision they contain. The main feature of the considered pipeline is the combination of both collaborative filtering and content-based filtering approaches for generating the list of recommendations with high accuracy determined by the MAE and RMSE criteria. Thus, Technological support enables users to make the right choices regarding their health and well-being a breakthrough in health care and guarantees benefits for users in standings of their health and quality of life.

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