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A Machine Learning Based Physical Exercise and Meditation Recommendation System for Patients with Chronic Health Conditions

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Abstract: Chronic health conditions are long-term medical issues that degrade a person's life quality. These disorders frequently require ongoing medical care and can severely limit daily activities. Managing chronic health issues usually requires regular physical exercise, meditation, and stress-minimization technique. Previous research has focused primarily on recommending physical exercise or meditation for patients with chronic health conditions, rather than combining the two. They also did not look into proper machine learning (ML) model selection, accuracy results in improvement, dataset development, or hyperparameter tuning techniques for the physical exercise and meditation recommendation systems. To eradicate these issues, this paper delivers an ML-based physical exercise and meditation recommendation system for patients with chronic health conditions based on 9 ML classifiers. This paper created a dataset based on patient data that includes characteristics such as person's habits, alcohol consumption information, exercise information, chronic health information, stress level, anxiety symptoms, sleeping issues, exercise, and medication recommendations. Among the ML models tested, the K-nearest neighbors (KNN) model had the highest accuracy of 96% and $F1$ score of 98% for predicting appropriate physical exercise and medication recommendations. According to the important performance metric value comparison results, the proposed KNN-based prediction scheme outperforms previous works by 6.6 percent in accuracy and 5 percent in recall value. This paper brings a mobile application that initiates features like physical exercise and medication recommendations, information about physical exercise and medication, and doctor appointments. The mobile app evaluation revealed that more than 83% of reviewers provided acceptable feedback on the app's design and necessity.

Keywords: chronic health conditions, physical exercise, meditation, machine learning, prediction, KNN

1. Introduction

Nowadays, it is common to aim for a healthy lifestyle that includes both physical and mental well-being. Regular physical activity and mindfulness exercises, such as meditation, have been linked to a number of health benefits, including reduced stress, improved cardiovascular health, and improved cognitive function. Regular physical activity can play a major role to improve personal physical fitness. Physical activity can also play an important role to minimize the several chronic disease risk (e.g., diabetes). Along with physical exercise, some authors also identified meditation as a common solution for many chronic illnesses. According to New York State Department of Health [1], the authors discussed common chronic health conditions and diseases found in humans, such as hypertension, hypotension, diabetes, various types of cancer, chronic pain, osteoarthritis, and cardiovascular disease. According to Mayo Clinic [2], the authors recommended various types of exercises based on chronic health conditions, such as aerobic exercise (e.g., cycling) and flexibility exercise (e.g., yoga). According to Dubey and Muley [3], the author proposed various types of meditation based on chronic health conditions, including mindfulness meditation, loving-kindness meditation, guided meditation, transcendental meditation, and body scan meditation, among others. According to Cramer et al. [4], the authors demonstrated that yoga and meditation can be helpful to reduce blood pressure, depression, and anxiety.

Cherkin et al. [5] identified that mindfulness-based meditation technique (e.g., relaxation technique) can reduce the back pain of an adult person. Meditation has also been shown to help cancer survivors deal with emotional distress [6]. Furthermore, Acosta et al. [7] suggested that regular aerobic exercise can play a major role to reduce the hypotension of a person. The authors of Harvard Health Publishing [8] proposed that daily 45-minute body scan meditation could benefit patients suffering from chronic back pain. Cillessen et al. [9] demonstrated that mindfulness meditation can help breast cancer patients manage stress and mildly improve depressive symptoms. Furthermore, Black et al. [10] indicated that mindfulness meditation can reduce depression and provide a healthy solution for the patients with fatigue and insomnia. Lots of researcher investigated the issue regarding physical exercise and meditation recommendation. As a result, sedentary lifestyles are driving up healthcare costs. As a result, there has been a recent surge of interest in developing recommendation systems that consider a patient's specific health conditions and recommend

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physical exercise and meditation as a treatment option for chronic patients.

Several frameworks [11, 12] based on machine learning (ML) technologies have been developed to assist people in recommending physical activity or diet, but little research has been conducted on incorporating meditation practices to address mental health issues associated with chronic health conditions. Bangladesh, like many other countries, is increasingly concerned about the prevalence of chronic health conditions among its population. Sedentary lifestyles, combined with increased work-related stress, have contributed to the rise in chronic health problems such as diabetes, cardiovascular disease, cancer, hypertension, and musculoskeletal disorders. Addressing these challenges through a tailored Physical Exercise and Meditation Recommendation System offers a promising opportunity to promote healthier lifestyles and overall well-being among Bangladeshis. The existing literature on chronic health assistance systems [11–13] was plagued by a number of issues, including a lack of exercise and medication recommendations, as well as low user engagement and accuracy. The existing research did not look into both physical exercise and medication recommendations for chronic health patients. Existing works did not use proper ML model selection by examining multiple performance metrics or hyperparameter tuning techniques. They also did not create a suitable dataset for ML-based physical exercise and medication recommendations for chronic health patients. Existing work did not create a mobile app-based assistance system for chronic health patients.

To eradicate these problems, this paper dispatches a ML-based physical exercise and meditation recommendation prediction system for patients with chronic health conditions. The proposed system will evaluate nine ML models to select the best model. In addition, a mobile application will be created with interactive features such as physical and meditation recommendations, exercise lists, and meditation techniques.

The important contributions of this article are listed below:

1) This paper presented a ML-based physical exercise and meditation recommendation model for chronic health patients by assessing the patient's health profile and various classifier performances. This paper creates a dataset for recommending physical exercise and meditation to patients based on their personal habits, food consumption alcohol consumption, exercise habits, chronic disease information, stress level, anxiety symptoms, sleeping issues, exercise, and medication prescription information.
2) To find the best prediction model, the proposed scheme compared various ML techniques, including random forest (RF) classifier, gradient boost, support vector machine (SVM), K-nearest neighbors (KNN), XGBoost classifier, CatBoost classifier, logistic regression (LR), MLP classifier, and decision tree (DT) classifier. To achieve higher accuracy, the proposed ML-based prediction model employs hyperparameter tuning, scaling, and data preprocessing techniques. The appropriate ML model is chosen after considering five key performance metrics, including accuracy and $F1$ score value. This paper delivers the performance comparison between the proposed ML-based prediction scheme and existing literary works.
3) This article delivered a user-friendly mobile application that can recommend physical exercise and meditation, help users schedule doctor appointments, teach them how to meditate, and provide a variety of exercise options.

The previous related researches are discussed in section two. Section three presents the proposed prediction scheme's methodology, including detailed working steps such as dataset collection and model construction, as well as evaluation results. Section 4 describes the developed mobile app features in great detail. Section 5 gives the mobile app examination results. Section six provides the key findings along with some limitations and future research avenues.

2. Literature Review

Several research studies have been conducted to recommend physical exercise or diet, with a focus on chronic health conditions. In the following, we have discussed them one by one.

Fan et al. [11] created a residual neural network-based physical exercise recommendation system for patients by analyzing their physical fitness test results and personal information. They compared the proposed prediction model's results to those of the CNN and SVM models. They demonstrated that their proposed system has a precision of 79.9% and a recall of 83.7%. Their work is limited to general populations rather than those with chronic diseases. They did not consider meditation suggestions for patients with chronic health conditions.

Ferretto et al. [12] designed a heuristic-based physical activity recommendation system for hypertensive patients. The methodology involved evaluating recommendations based on profile similarity, using Pearson's correlation coefficient to achieve high levels of accuracy in scenarios with multiple patient profiles. The study found that approximately 75% of the system's recommendations were approved by the specialists. They focused solely on physical activity, ignoring mental health factors like meditation and other chronic conditions. Baruah et al. [13] created a ML-based yoga exercise prescription method for chronic patients. The authors gathered health information and preferences from 100 participants. The goal is to provide users with personalized yoga practice recommendations based on their health profiles, preferences, co-morbidities, and geographical location. To generate personalized exercise recommendations, the system used content-based filtering with a Restricted Boltzmann Machine (RBM) model. They discovered that the hybrid RBM (Boltzmann machine) model performed better (RMSE 0.0012) than the other ML models tested. The study was conducted on small populations and focused solely on yoga recommendations, leaving out other physical exercises or meditation practices, limiting its applicability for overall health management. Jagatheesaperumal et al. [14] presented an ML and IoT based heath monitoring and fitness plan suggestion system for the patients. In their work, the CatBoost classifier outperforms other ML and DL classifiers for the diet plan recommendation system. The limitations of their work are that they used a small dataset and predicted only one diet plan for users. They did not look into the physical exercise and mediation recommendation systems for chronic health patients.

Bhimavarapu et al. [15] used a stacked RBM-based mechanism to develop a physical activity recommendation system. To develop a physical activity prescription for persons with respiratory diseases, the authors looked at their food intake, habits, and personal information. Their proposed model had an RMSE value of.0985. The limitation of their work is that they did not look into medication suggestions for chronic health patients.

Mahyari and Pirolli [16] proposed a dual RNN-based workout exercise recommendation system that uses health information and previous activity data. They did not compare their model's performance to previous works. Their study did not look into chronic diseases or meditation recommendations for patients. Sadhasivam et al. [17] presented a k-means clustering-based diet and exercise recommendation system for general users that considers users' food consumption, BMI, and personal information. However, the authors did not examine the accuracy results or any other metric. They also did not compare the prediction model's performance to other existing systems.

Lioner et al. [18] used a regression algorithm to recommend physical exercise programs based on a person's body fat data. They demonstrated that their proposed regression scheme achieved 73% accuracy in physical exercise recommendations. They did not, however, compare the performance of their proposed model to that of other existing works. They also did not look into meditation recommendations for chronic health patients. Abu-Issa et al. [19] created an ANN-based medication recommendation system for patients with diabetes symptoms. Their work is limited to food, physical activity, and medicine recommendations. Their proposed scheme had an accuracy of 89.5% for medication recommendations. They did not compare their work to previously published works or ML methods. VeerasekharReddy et al. [20] used a CNN model to predict diabetic disease and a healthcare prediction system for patients with diabetic symptoms. Their proposed scheme provides a validation accuracy of 89%. They did not compare the performance of their work to other Ml and DL systems. They also did not recommend any physical exercise or meditation for patients with chronic diseases. As previously discussed, existing research is limited by small datasets and specific populations, reducing the generalizability of findings. Furthermore, there is a scarcity of comprehensive systems that include both physical and mental health recommendations. They did not use appropriate feature selection, hyperparameter tuning, or scaling techniques. They also did not present a mobile app that recommended both physical exercise and meditation for chronic health patients. To minimize these factors, this article creates a ML-based physical exercise and meditation recommendation system for choric health patients that improve prediction accuracy while also examining multiple characteristics. This article also creates a mobile app to assist chronic health patients by providing suggestions for physical exercise and meditation, as well as doctor appointments.

3. Proposed Framework

Section 3 of this paper discusses in detail the ML-based physical exercise and meditation recommendation system for people with chronic health issues.

3.1. System design

Figure 1 depicts the methodology diagram of our proposed ML-based physical exercise and meditation recommendation system for chronic health patients. First, this paper gathered information about chronic disease patients from users. We have communicated with patients, doctors, and hospitals about the dataset collection. The dataset is gathered through both online and offline (paper) methods. Following the collection of chronic health patient data, we performed data preprocessing, feature selection, scaling, and normalization. To determine the best prediction model, we compared the accuracy and $F1$ score values of nine different ML classifiers.

The following ML classifiers were compared: KNN, SVM, MLP, RF, CatBoost, XGBoost, LR, DT, and gradient boost method. We divided the dataset into three parts: training, testing, and validation. To improve model performance, we used hyperparameter tuning and K cross-fold validation techniques. We collected training and testing data with the chosen model. Finally, we integrated the best ML model into the mobile app for predicting physical activity and meditation activity in chronic health patients. Figure 2 depicts the flowchart diagram for our mobile app that provides recommendations for physical exercise and meditation. This mobile app for physical exercise and meditation assistance is built with the Flask API framework and a Google Firebase-based backend framework. The developed application includes features such as sign-in, physical exercise, and meditation prediction for chronic health patients, a list of physical exercise and meditation steps, and doctor consultation, among others. In Section 4, this paper will provide a detailed discussion of the mobile app features. Next, this paper provides a discussion of all used ML and DL methods.

A popular statistical approach for binary classification problems is LR. It calculates the probability that an input falls into a particular class. A reliable classification model that determines the best hyperplane to divide data into distinct classes is the SVM. By maximizing the margin between the classes, this hyperplane guarantees the optimal separation. DT operates by continually dividing the input data into subsets according to the input feature values. During training, the RF ensemble learning technique generates several DTs. A random selection of characteristics and data is used to train each tree in the forest. It aggregates individual tree predictions in classification tasks to determine the most popular class label. By comparing a new data point to its K

Figure 1
ML-based methodology for physical exercise and meditation recommendation prediction system

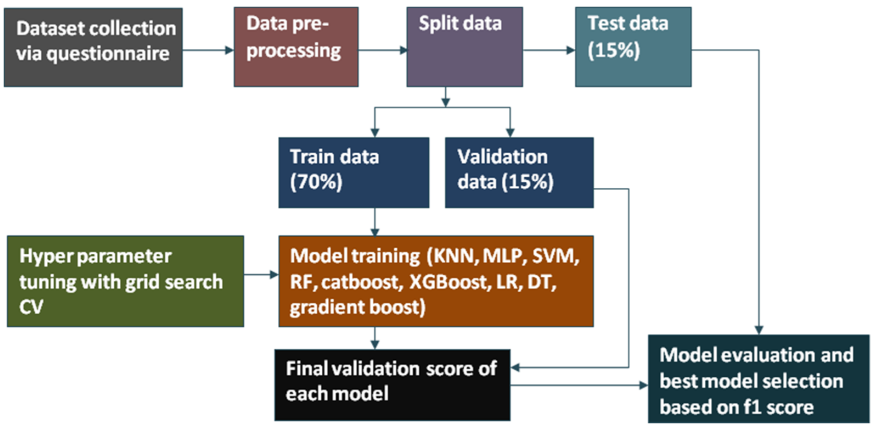
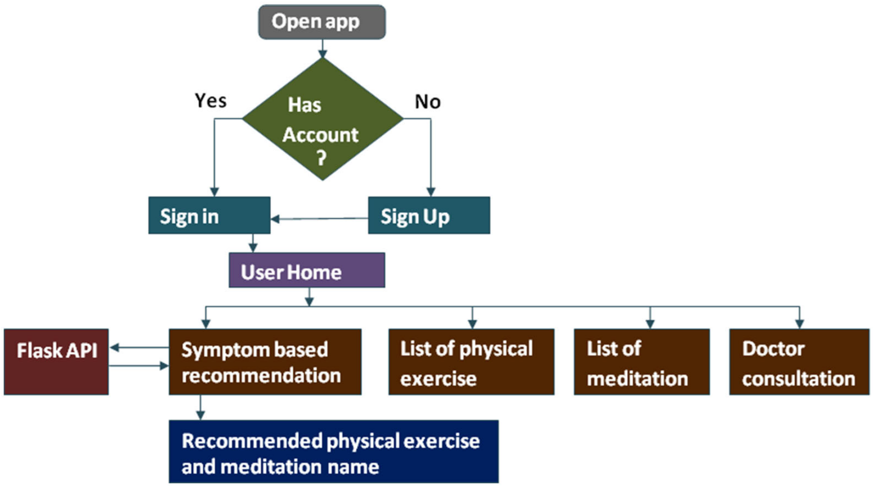


Figure 2
Flowchart diagram of our physical exercise and meditation assistance mobile application



closest neighbors in the training dataset, KNN classifies or forecasts its value. KNN uses a distance metric—typically the Euclidean distance—to assess how similar data points are. It chooses the most prevalent class label among the K neighbors for classification. An ensemble of weak learners, usually DTs, is built successively using XGBoost, with each new tree fixing mistakes caused by earlier trees. It iteratively improves predicting performance by reducing a predetermined loss function using a gradient descent technique.

In order to create a powerful predictive model, the ensemble learning technique known as gradient boosting builds a number of weak prediction models, usually DTs, one after the other. It functions by highlighting locations where earlier models performed badly and lowering the errors of those earlier models. Every model in the series improves the overall prediction by concentrating on the residual errors of the preceding model. An excellent gradient boosting approach for handling categorical data without preprocessing is called CatBoost. It makes use of an innovative technique called ordered boosting, which enhances accuracy by utilizing the inherent order of categorical data.

In order to prevent overfitting, CatBoost employs symmetric trees and automatically handles missing data. Training on huge datasets with less hyperparameter adjustment is made possible by its effective implementation. One kind of neural network intended for classification problems is the Multi-layer Perceptron classifier or MLPClassifier. It is composed of multiple node layers that are feedforward coupled to one another. Using modifying weights to reduce the discrepancy between expected and actual results, the model learns using backpropagation.

3.2. Data collection and dataset preparation

We have collected chronic patient's data by creating questionnaires using Google Forms, which were then distributed to respondents via social media or emails, as well as conducting face-to-face surveys. We asked the patients 15 questions during consultations with doctors. Respondents were asked to provide information about various health and lifestyle factors associated with chronic conditions. To ensure data quality and accuracy, responses were validated by qualified physicians. This validation process involved comparing the collected data to established medical criteria. Physicians specifically looked for complete responses, consistency in reported medical conditions, and adherence to specific health metrics. We received a total of 686 responses from respondents. Figure 3 depicts a glimpse of our dataset.

Table 1 summarizes the questionnaire and feature names from our dataset. The dataset includes questions about personal health information and habits. Personal health information includes height, weight, stress level, and anxiety symptoms, whereas habits include exercise frequency, alcohol consumption, the type of exercise prescribed, the type of meditation prescribed, and sleeping problems.

3.3. Data cleaning, visualization, and data preprocessing

Most questions in the dataset have categorical answers, but some fields, such as Name, allow for open-ended responses. Though this field is not used during model training, it is useful for dataset authentication. We removed unnecessary data from the dataset (e.g., a person's name) and discarded missing or null values to ensure proper model training. We used several Python libraries to visualize the dataset, including "Matplotlib" and "Seaborn". Figure 4(a) shows that a significant proportion of respondents are male (i.e., those who helped create the dataset).

We can also see that there are fewer female respondents than males. Figure 4(b) shows the number of respondents by age. It shows that the age range of "28–54" makes up the majority of the dataset, indicating that people in this age group are patients suffering from chronic health conditions. Figure 5(a) shows that diabetes affects between 120 and 140 people, making it the most common chronic condition reported. Following closely, hypertension affects between 100 and 120 people. Hypotension, on the other hand, affects the smallest number of respondents, ranging from 20 to 40. These findings highlight the varying prevalence of chronic conditions in the surveyed population, with diabetes being the most significant health concern among respondents.

Figure 5(b) shows that diabetes has the highest median weight, indicating that patients with diabetes tend to weigh more than those with other chronic conditions. Figure 6 depicts the relationship between exercise frequency and the types of physical activity undertaken by individuals. Aerobic exercise is the most popular type of exercise in all frequency categories, particularly among

Figure 3
Sample values from dataset

(a)

Your name	Your age	Your gender	Your height (cm)	Your weight (kg)	Do you smoke?
Rita	51	F	169	68	No
Rahim	35	M	158	64	No
Karim	56	M	169	57	No

(b)

Do you consume alcohol?	How often do you engage physical exercise per week	What types of chronic medical conditions or diseases do you have?	How would you rate your stress level (scale 1-10)	Do you Experi-ence symp-toms of anxiety or depression?	Do you have troubled sleeping?
No	Occasionally (3-4 times per week)	Diabetes	Moderately high (6-8)	Yes	Yes
No	Never	Cardiovascular	Moderate (5)	Yes	Yes
No	Regularly (5-6 times per week)	Hypertension	Moderately high (6-8)	No	No

Table 1
Dataset questions with feature name

Questions	Shortened feature name
Your Name?	Name
Your age?	Age
Your gender?	Gender
What is your height (cm)?	Height
What is your weight (kg)?	Weight
Do you smoke?	Smoking
Do you consume alcohol?	Alcohol consumption
How often do you engage in physical exercise each week?	Exercise frequency
What types of chronic medical conditions or diseases do you have?	Chronic conditions
On a scale of 1–10, how would you rate your current stress levels?	Stress level
Do you experience symptoms of anxiety or depression?	Anxiety symptoms
Do you have trouble sleeping?	Trouble sleeping
If Yes, please specify the type of exercise:	Type of exercise
If yes, please specify the type of meditation:	Type of meditation

those who "never" exercise. Flexibility exercises are recommended for those who exercise frequently (5–6 times per week). Strength training is more common among people who exercise occasionally (3–4 times) or infrequently (1–2 times).

Figure 7 depicts the BMI distribution of individuals based on the type of physical activity prescribed to them. The median BMI for the recommended aerobic exercises is around 24, with one

Figure 4
Gender and age distribution visualization

(a)

Gender	Count
Male (M)	550
Female (F)	150

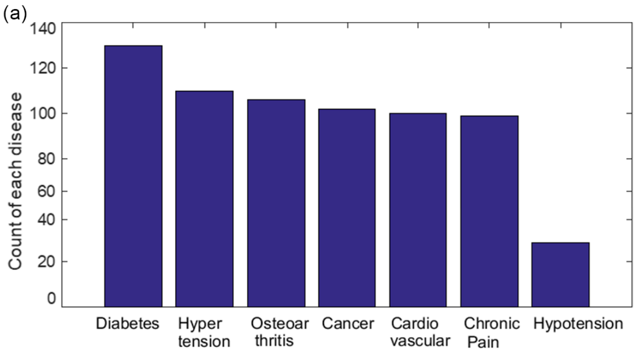
(b)

Age distribution	Chronic health patient percentages	Age distribution	Chronic health patient percentages
43	6.6%	22	2.9%
38	6.1%	37	2.8%
27	5.4%	42	2.8%
48	4.5%	52	2.6%
26	4.5%	44	2.5%
32	4.4%	23	2.3%
41	4.4%	36	2%
28	4.2%	39	1.9%
34	4.2%	29	1.9%

(c)

Age distribution	Chronic health patient percentages	Age distribution	Chronic health patient percentages
30	3.9%	53	1.9%
33	3.5%	56	1.2%
25	3.4%	21	1.2%
46	3.4%	49	1.2%
45	3.4%	31	1.2%
35	3.4%	54	1.2%
24	3.1%	47	0.9%
40	0.6%	48	0.6%

Figure 5
Chronic disease data count and weight distribution



(b)

Disease name	Weight range
Cancer	58-65
Cardiovascular	62-68
Chronic pain	59-63
Diabetes	64-74
Hypertension	59-64
Hypotension	57-64
Osteoarthritis	60-68

Figure 6
Relationship between exercise frequency and types of physical exercise

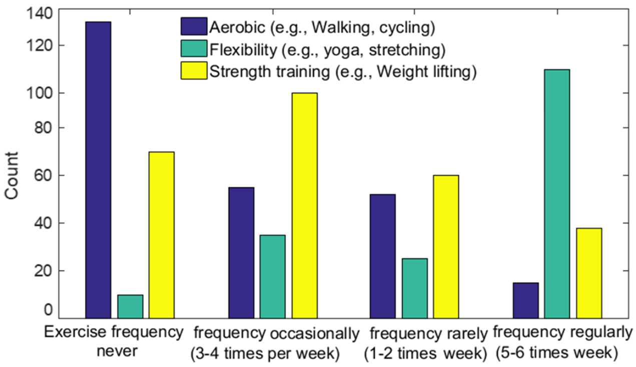


Figure 7
BMI distribution by type of physical exercise

Exercise name	BMI distribution by exercise
Aerobic exercise (e.g., walking, cycling)	21-24
Flexibility exercise (e.g., Stretching, yoga)	20-23
Strength training (e.g., Weight lifting)	23-27

notable outlier at a lower BMI of about 18. Individuals advised to engage in flexibility exercises have a slightly lower median BMI of around 22, with a narrower range, indicating a more consistent BMI distribution in this group. In contrast, the median BMI for individuals prescribed strength training exercises is around 26, with a wider range, indicating greater BMI variability among this group.

Following the data cleaning operation, we ran preprocessing, encoding, normalization, and scaling operations. To preprocess the data, we first removed the Bangla language text from the dataset and then examined the dataset to see if there were any null fields. Because there were no optional questions, the dataset contained no fields with null values. We then addressed the categorical features by converting them to a format suitable for ML models. We chose one-hot encoding for a variety of reasons. One-hot encoding generates a new binary column for each possible category value.

This method is particularly useful for our dataset because it handles nominal data, is compatible with most algorithms, and reduces high dimensionality. We used the pd.get_dummies function from the panda's library. Figure 8 depicts the sample values after applying one-hot encoding to the dataset. The correlation matrix in Figure 9 shows the linear relationships between the dataset's numerical variables: age, height, weight, and BMI. Age has weak positive correlations with height, weight, and BMI, indicating that these metrics increase slightly with age. Height is moderately positively correlated with weight and moderately negatively correlated with BMI, indicating that taller people weigh more but have lower BMI. Weight has a strong positive correlation with BMI, which means that heavier people have higher BMIs.

To remove outlier data, we first calculated the body mass index (BMI) value by using both the height values and weight values and then removed the original columns. Next, we detected and removed outliers from the numeric columns, specifically age and BMI. Using the interquartile range method, we identified and removed any data points that fell significantly outside of the typical range, resulting in a cleaner and more reliable dataset for analysis. Figure 10 shows a two-step process for calculating BMI and removing outliers from a dataset. To prepare the data for training, we used standard scaling to normalize the feature values.

We used the Standard Scalar function to ensure that each feature had a mean of zero and a standard deviation (SD) of one. This step improves the performance of ML models by ensuring that all features contribute equally. To ensure scaling consistency, the scalar was fitted to the training data before being applied to the validation and test sets. Figure 11 depicts a code snippet that uses the scikit-learn library's Standard Scaler to standardize features in the dataset. Figure 11 confirms that the Standard Scaler successfully transformed our data to have a mean of approximately 0 and a SD of 1 for each feature.

3.4. Model selection, hyperparameter tuning, training, and testing results

To test the model after training, we divided the overall dataset into testing (fifteen percent), training (seventy percent), and validation data (fifteen percent). This split ensures that the evaluation is conducted on testing data that was not seen during the training phase, resulting in an unbiased assessment of model performance. We have used training data regarding construction and tuning of the models, whereas we have used validation data to calculate the validation score. Table 2 depicts the distribution of datasets used for training and testing activities. To train both datasets, we tested nine ML models (e.g., RF, SVM, KNN, MLP, DT, Gradient Boosting, CatBoost, XGBoost, and LR).

To handle our multi-class classification problem, we initialize each model and wrap it in a "MultiOutputClassifier". Figure 12 shows that a Grid Search CV with K-fold cross-validation is performed for each model using the predefined hyperparameter

Figure 8
Samples of the dataset after encoding

(a)

User no	Age	Height	Weight	Gender (F)	Gender (M)	Smo king (No)	Smo king (Yes)	Exercise frequency never	Exercise frequency occasionally
0	25	162	63	False	True	True	False	False	False
1	20	167	49	True	False	True	False	True	False
2	30	163.6	68	False	True	False	True	True	False
3	35	172	67	False	True	False	True	False	False
4	38	164	59	False	True	True	False	True	False

(b)

Exercise frequency rarely	Aerobic exercise	Flexibility exercise	Strength training	Body Scan Medi tation	Guided Medi tation	Loving Kind ness Medi tation	Mindful Ness Medi tation
True	True	False	False	False	False	False	True
False	True	False	False	False	False	False	True
False	True	False	False	False	False	False	False
True	True	False	False	False	False	False	True
False	True	False	False	False	False	True	False

Figure 9
Correlation matrix between different numerical variables

	Age	Height	Weight	BMI
Age	1	.23	.25	.11
Height	.23	1	.3	-.28
Weight	.25	.3	1	.83
BMI	.11	-.28	.83	1

Figure 10
Code snippet for outlier detection and removal

```
#1. Calculate BMI
df ["BMI"] =df ["Weight"]/ (df ["Height"]/100)**2
df.drop(columns=["Weight","Height"], inplace=true
#2. Outlier detection and removal
Numeric_cols= ["Age","BMI"]
Q1=df[Numeric_cols ].quantile (0.25)
Q3=df[Numeric_cols ].quantile (0.75)
IQR=Q3-Q1
df=df[((df[Numeric_cols]<(Q1- 1.5*IQR))|(df[Numeric_cols]>(Q3+1.5*IQR))).any(axis=1) ]
```

grids. Then, we fit each model to the training data, and the optimal hyperparameter for each model is identified. Tables 3, 4, 5, and 6 provide a description of each model and its hyperparameter setup. In the LR method, c can be termed as the inverse of regularization strength. Larger values of c reduce the penalty coefficient.

The "Lbfgs" solver is used for optimization and is efficient on medium to large datasets. The solver employs quasi-Newton methods. The KNN method's "n_neighbors" parameter dispatches the neighbors' number. It can be used to make predictions regarding a new data point. A lower n neighbor value results in more complex models that may over fit the training data, whereas a higher value produces a smoother decision boundary but may underfit. Uniform weight indicates that all neighbors contribute equally to the prediction. Following the selection of optimal

Figure 11
Feature scaling operation and results

```
#standardize features
scaler=StandardScaler ()
x_train_scaled=scaler.fit_transform (x_train)
x_val_scaled=scaler.transform (x_val)
x_test_scaled=scaler.transform (x_test)
After scaling:
Scaled training data mean:
[2.44e-16   1.78e-15   9.54e-17   -9.54e-17
-2.59e-17   2.59e-17   -3.7e-17   -4.07e-17
6.3e-17    -8.9e-17    -1.2e-17    3.7e-17
7.7e-17     -7.04e-17  8.15e-17    4.35e-17
-7.41e-18   -3.8e-17    -5.28e-17  3.33e-17
-6.67e-17    1.03e-17   -1.29e-16  -4.07e-17
6.30e-17     -6.30e-17   -6.11e-17  -1.01e-16]
```

Table 2
Dataset split size

Split	Dataset size
Total	686
Train	482
Validation	102
Test	102

hyperparameters, we evaluated the model's accuracy value, precision value, *F*1 score value, and RMSE (root mean square error). We chose the best prediction model based on these metrics. In this context, accuracy refers to the frequency of accurate predictions made by a model. The precision of a model is the proportion of accurately detected positive predictions among all cases that the model anticipated to be positive. The percentage of

Figure 12
Hyperparameter optimization

```
for model_name, model in models.item ();
multi_output_model=MultiOutputClassifier (model)
grid_search=GridSearchCV (multi_output_model, param_grids[models_name],
cv=kf, scoring="accuracy",n_jobs=1)
grid_search.fit(x_train, y_train)
best_params=grid_search.best_params_
best_model=grid_search.best_estimator_
val_score=accuracy_score(y_val, best_model.predict (x_val))
```

Table 3
Hyperparameter settings for logistic regression and SVM

Model name	Hyperparameters	Values
Logistic regression	predefined	C: [0.01, 0.1, 1, 10, 100], penalty: [l2], solver: [lbfgs, saga]
Logistic regression	optimal	C: 100, penalty: l2, solver: lbfgs
SVM	predefined	C: [0.1, 1, 10], kernel: [linear, rbf]
SVM	optimal	C: 10, kernel: rbf

Table 4
Hyperparameter settings for decision tree and random forest

Model name	Hyperparameters	Values
Decision tree	predefined	max_depth: [None, 10, 20, 30], min_samples_split: [2,5,10], min_samples_leaf: [1,2,4]
Decision tree	optimal	max_depth: None, min_samples_split: 2, min_samples_leaf: 1
Random forest	predefined	n_estimators: [100,200], max_depth: [10, 20, None], min_samples_split: [2,5,10]
Random forest	optimal	n_estimators: 100, max_depth: 20, min_samples_split: 2, learning_rate: 0.2, subsample: 0.9

accurate forecasts to all actual positive cases is known as recall. $F1$ is a trustworthy statistic, particularly in cases where the dataset is unbalanced. It is the precision and recall harmonic mean. RMSE calculates the mean size of the discrepancies between expected and actual values.

The performance metrics calculation formulas are presented by:

$$Accuracy = \frac{number\ of\ correct\ prediction}{total\ number\ of\ prediction} \tag{1}$$

$$Precision = \frac{true\ positive}{true\ positive + false\ positive} \tag{2}$$

$$Recall = \frac{true\ positive}{true\ positive + false\ negative} \tag{3}$$

$$f1\ score = 2 * \frac{precision * recall}{precision + recall} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{f}\sum_{i=1}^{f}(a_i - b_i)^2} \tag{5}$$

where a, b, and f are the actual, predicted values, and observation number, respectively.

Table 7 depicts the comparison results of various ML classifiers. Table 7 shows that the KNN model outperformed all other ML classifiers in terms of key performance metrics. KNN had the highest precision value of 0.9815 and recall value of 0.9805, indicating that it correctly identified a large number of relevant instances. With an $F1$ score of 0.9803, KNN delivers a balance regarding precision value and recall values. The KNN model achieves the highest accuracy value of 96%. The KNN model outperforms other ML models due to its simplicity, sensitivity to data distribution, normalization and scaling, handling of multiple output targets, and improved hyperparameter tuning.

Table 7 also shows that the MLP model has the second-best accuracy and RMSE values. Based on the best accuracy and $F1$ score value results, as well as the RMSE error value results, we chose the KNN model for predicting physical exercise and meditation recommendations for chronic health patients.

Confusion matrix analysis is critical for determining the effectiveness of proposed frameworks in categorizing different classes. Figure 13 depicts the confusion matrix of the KNN model for aerobic exercise class prediction. The figure shows that the KNN model produces no false positives, which is good. There is one false negative, which means the model failed to predict one actual aerobic exercise instance. The actual positive value for this class is 38. Figure 14(a) depicts the confusion matrix of the KNN model for predicting flexibility exercise classes. The figure illustrates that the KNN model has excellent precision and no

Table 5
Hyperparameter settings for KNN, XGBoost, and gradient boosting

Model name	Hyperparameters	Values
KNN	predefined	n_neighbors: [3,5,7,9], weights: [“uniform”, “distance”]
KNN	optimal	n_neighbors: 3, weights: distance
XGBoost	predefined	n_estimators: [100,200], max_depth: [3,5,7], learning_rate: [0.01, 0.1, 0.2], “subsample”: [0.7, 0.8, 0.9]
XGBoost	optimal	n_estimators: 200, max_depth: 3, learning_rate: 0.2, subsample: 0.9
Gradient boosting	predefined	n_estimators: [100,200], learning_rate: [0.01, 0.1, 0.2], max_depth: [3,5,7]
Gradient boosting	optimal	n_estimators: 100, learning_rate: 0.1, max_depth: 5

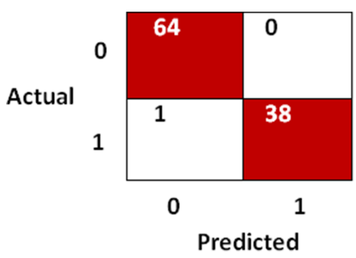
Table 6
Hyperparameter settings for MLP classifier and CatBoost

Model name	Hyperparameters	Values
MLP classifier	predefined	hidden_layer_sizes: [(50), (100), (50, 50)], activation: [tanh, relu], solver: [adam, sgd]
MLP classifier	optimal	hidden_layer_sizes: (50, 50), activation: tanh, solver: adam
CatBoost	predefined	depth: [6,8,10], learning_rate: [0.01, 0.1, 0.2], iterations: [500,1000]
CatBoost	optimal	depth: 6, learning_rate: 0.01, iterations: 1000

Table 7
Performance comparison of different ML models

Model name	Precision	Recall	*F*1 score	Accuracy	Avg. RMSE
KNN	0.9815	0.9805	0.9803	0.9611	0.063
Random forest	0.9600	0.9590	0.9595	0.920	0.072
SVM	0.9550	0.9540	0.9545	0.920	0.073
MLP	0.9705	0.9695	0.9700	0.930	0.068
Decision tree	0.8800	0.8790	0.8795	0.850	0.088
Gradient boosting	0.9410	0.9400	0.9405	0.900	0.077
CatBoost	0.9605	0.9595	0.9600	0.920	0.071
XG Boost	0.8410	0.8400	0.8405	0.840	0.092
Logistic regression	0.6230	0.6120	0.6250	0.600	0.152

Figure 13
Confusion matrix of KNN model for predicting aerobic exercise class



false positives. However, there is one false negative, indicating that the model failed to predict one actual flexibility exercise instance.

Figure 14(b) depicts the confusion matrix of a KNN model for strength training class prediction. Figure 14(b) shows that the KNN model performs well, with only two instances incorrectly predicted as not strength training (FP). There are no false negatives, implying that all actual strength training instances are correctly identified. As a result, the model performs admirably in this class, making few mistakes. Figures 15(a) and (b) show the confusion matrix of a KNN model for guided imagery meditation and body scan meditation class prediction, respectively. Figure 15(a) demonstrates that the KNN model predicts guided imagery meditation class with 100% accuracy and no false positives or false negatives. Figure 15(b) displays that the KNN model accurately predicts body scan meditation, with no false positives or false negatives.

This indicates perfect precision and recall, demonstrating the model's ability to predict this meditation type. Figure 16(a) and (b) show the confusion matrix of the KNN model for kindness meditation and mindfulness meditation class prediction, respectively. Figure 16(a) shows that the KNN model accurately predicts loving-kindness meditation, with no false positives or negatives. Figure 16(b) shows that the KNN model correctly predicts mindfulness meditation classes, with only two false positives and no false negatives. This indicates higher precision and recall values, emphasizing the model's superior performance for this type of meditation.

3.5. Comparison with existing schemes

In this subsection, we will compare the prediction accuracy value, precision value, and recall values of our proposed KNN-based model to three recent works by Fan et al. [11], Lioner et al.

Figure 14
Confusion matrix of KNN model for (a) flexibility exercises and (b) strength training

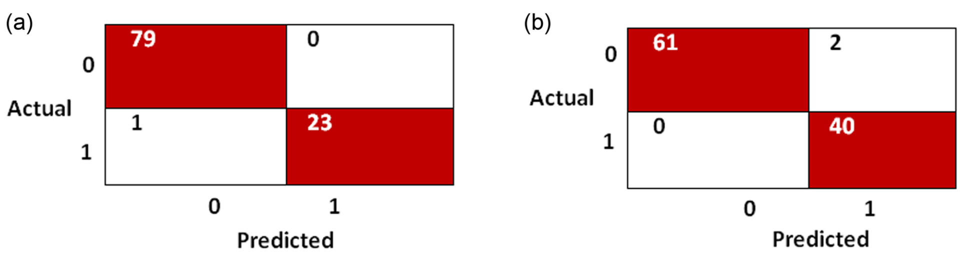


Figure 15
Confusion matrix of KNN model for (a) guided imagery meditation and (b) body scan meditation

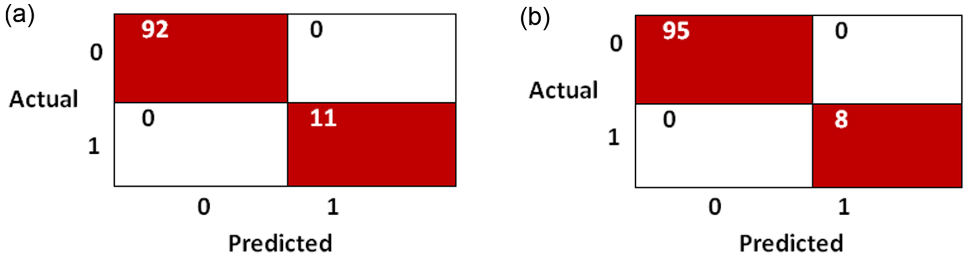


Figure 16
Confusion matrix of KNN model for (a) kindness meditation and (b) mindfulness meditation

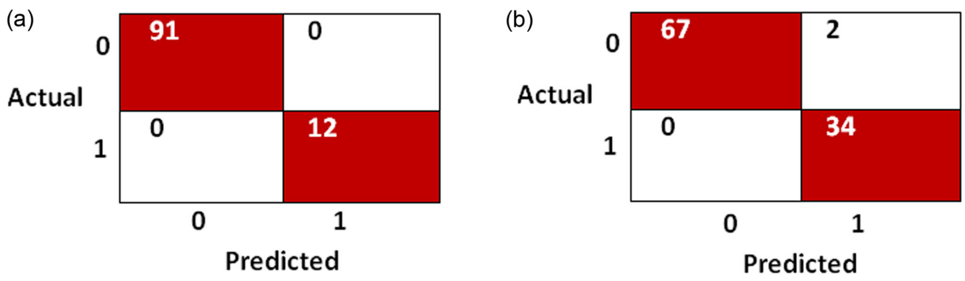


Table 8
Comparison with existing works

Method	Accuracy	Precision	Recall	Classifier	Year
Fan et al. [11]	78%	79.98	83.73	Residual network	2023
Lioner et al. [18]	73.43%	75.6%	77.3%	LASSO regression	2022
Abu-Issa et al. [19]	89.5%	91.3%	93%	ANN	2023
Our proposed scheme (KNN)	96.11%	98.15%	98.05	KNN	2024

[18] and Abu-Issa et al. [19]. The comparison results are delivered in Table 8. The tabular results hinted that our proposed KNN-based physical exercise and medication prediction model for chronic health patients achieve at least 6.6 percent higher accuracy, 6.75 percent higher precision, and 5 percent higher recall than previous works. According to the results in Table 8, Abu-Issa et al. [19] achieve the second-best accuracy value among the others. Fan et al. [11] and Lioner et al. [18] ranked third and fourth, respectively.

4. Mobile Application Development

In this section, we will talk about the physical exercise and meditation assistance mobile app features for chronic health patients. Our mobile app enables users to sign-up, sign-in, reset passwords, and log out. To improve the user experience, the screens feature a simple interface and vibrant colors. The mobile app is built using the Flask API and Google Firebase platforms. Figure 17(a) illustrates how a chronic patient can access their accounts by entering their email address and password value. If you forget your password, you can reset it, and new users can access the sign-up page via a link. Figure 17(b) shows how new users can create an account by providing a unique username, email address, and password value. Users can reset their passwords by entering their email address, as illustrated in Figure 17(c). An email with reset instructions will be sent to the provided email address. Figure 18(a) shows the home screen, which serves as the application's central navigation hub. It gives users quick access to the app's main features via clearly labeled buttons such as get recommendation, list of physical exercises, list of meditations, and doctor contact info. Figure 18(b) shows our application's physical exercise and meditation recommendation screen.

Figure 18(b) shows that users can receive tailored recommendations based on their age, height, weight, gender, smoking habits, exercise frequency, chronic conditions, stress level, alcohol consumption, anxiety symptoms, and trouble sleeping. After answering the question, the user can receive recommendations for physical exercise and meditation using our KNN-based prediction model. The form fields are translated into Bangla to accommodate local users. Figure 19(a) shows a list of physical exercises organized by health condition, including hypertension, hypotension, osteoarthritis, and chronic pain. Each category contains exercises

Figure 17
Mobile app screen for login, sign-up, and reset password

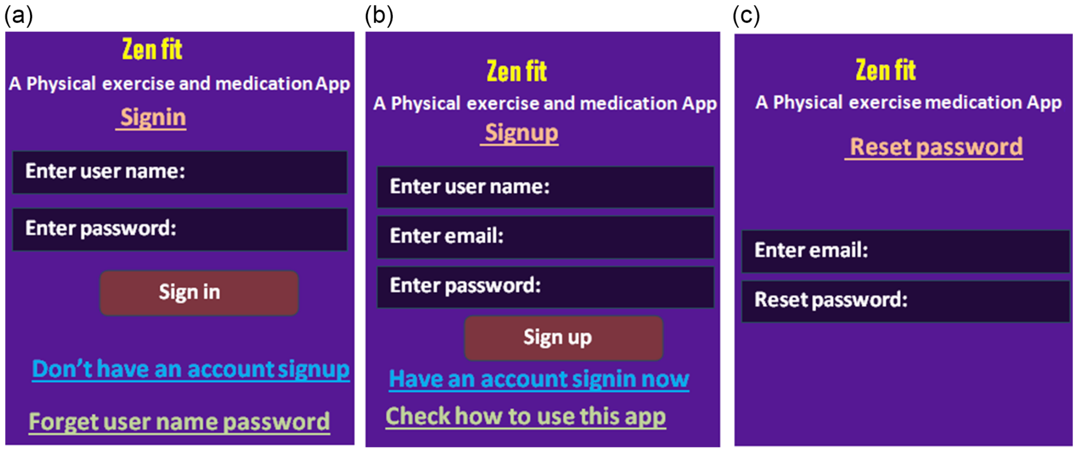
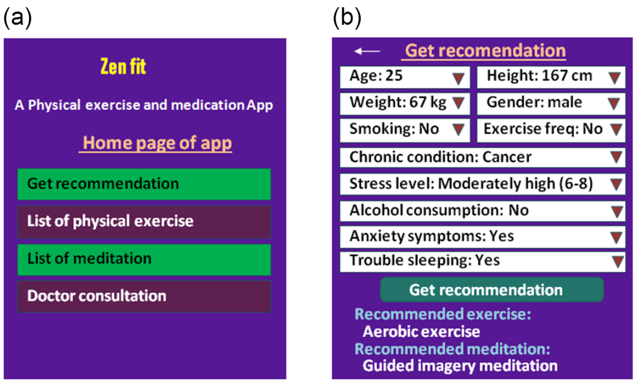


Figure 18
Home page and get recommendation interface



that are beneficial to the specific condition. Figure 19(b) shows a list of meditation activities and suggestions.

The meditation list includes a variety of meditation techniques such as Body Scan Meditation, Guided Imagery Meditation, Loving-kindness Meditation, Mindfulness Meditation, and Transcendental Meditation. Each practice is briefly described to help users understand the meditation steps. Figure 19(c) depicts the doctor's contact information for physician exercise and meditation activities. Figure 19(c) depicts each doctor's profile, which includes their qualifications, specializations, and appointment contact information.

5. Evaluation Results

To determine the performance of the developed mobile application, we conducted an online evaluation. We collected 60 participants' app experience through a Google survey. The findings provide insight into how users interact with the app's various features. Table 9 depicts a detailed breakdown of the physical exercise and meditation recommendation app feature evaluation results. The evaluators examined several features. We divided them into three groups. The first group includes the login, sign-up, and password reset features. The second group includes a feature that recommends physical exercise and meditation. The third and fourth groups contain a list of physical exercise and meditation information features, respectively. The fifth group includes a doctor consultation feature.

Table 9 depicts that for all mobile app features, the recommender with excellent comment, good comment, average comment, not good

Figure 19
List of exercise, list of meditation, and doctor

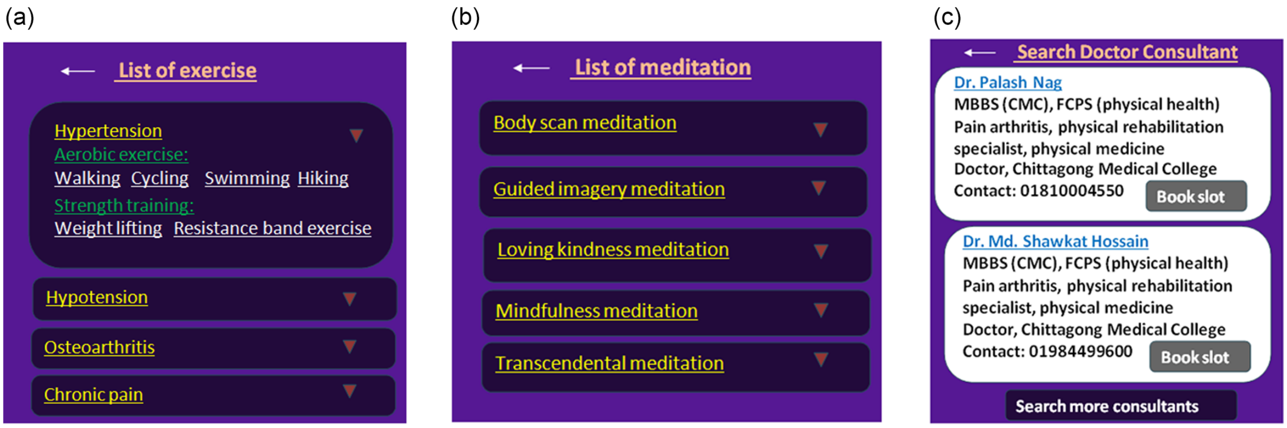


Table 9
Mobile app features evaluation results

Features	Excellent	Good	Average	Not good at all	No comment
Login, sign-up	32	18	6	3	1
Get recommendation	28	22	5	3	2
Physical exercise list	28	22	3	4	3
List of meditation	30	25	3	1	1
Doctor consultation	33	20	5	1	1

at all, and no comment ranged between 28–33, 18–25, 3–6, and 1–3. As a result, we can conclude that more than 83 percent of users provided praiseworthy comments about the mobile app features.

6. Conclusion

This article described a ML-based physical exercise and meditation recommendation framework for chronic health patients that select the best prediction model after examining 9 ML classifiers. This article creates a comprehensive dataset for predicting physical exercise and meditation activity using 686 responses and 14 key features. To improve accuracy, we performed dataset cleaning, preprocessing, feature extraction, scaling, hyperparameter tuning, training, validation, and appropriate ML model selection steps. The performance comparison results showed that the KNN model outperforms other ML classifiers, with a higher accuracy value of 96%, a higher recall value of 98%, and a lower RMSE of 6%.

The evaluation results also showed that the proposed KNN-based physical exercise and meditation prediction model outperforms existing models by at least 6.6 percent in accuracy, 6.75 percent in precision, and 5 percent in recall. This article also shows a mobile app-based assistance system for chronic health patients that include features such as login, physical exercise and meditation recommendations based on ML models, physical exercise and meditation lists with working steps, and doctor information, among others. The mobile app evaluation results showed that more than 83 percent of recommenders provided positive feedback about the usefulness of the developed app features.

Future extensions of this work may include IoT and deep learning-based real-time physical health status prediction, increased data privacy through block chain adaptation, and real-time doctor's prescription generation using generative AI and ML technology. Other future research topics could include using AI and deep learning technologies to recommend gyms based on location and cost for physical exercise, as well as developing personalized assistance systems for physical injuries and mental healthcare.

Recommendation

The results indicated that KNN techniques are most suitable for physical exercise and meditation recommendation for chronic health patients.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The dataset used in this paper was collected using Google Forms and is available from the corresponding author upon reasonable request.

Author Contribution Statement

Rakib Uddin Chowdhury: Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation. **Mahfuzulhoq Chowdhury:** Conceptualization, Methodology, Validation, Resources, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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