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Predicting Binge Eating Disorder Using Machine Learning Methods

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Yeme Bozukluklarının Makine Öğrenmesi Yöntemleri Kullanılarak Tahmin Edilmesi

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Abstract

Eating disorders are enduring conditions characterized by elevated rates of mortality and morbidity, presenting a serious threat to life. Among these disorders, binge eating disorder is the most prevalent. Therefore, it is an important health problem that often results in obesity worldwide. This study was conducted to evaluate the eating attitudes and behaviors of university students and predict binge eating disorder using machine learning methods. The study was carried out on 306 individuals (117 males and 189 females). Individuals' personal characteristics were questioned using the questionnaire form. The Bulimic Investigatory Test Edinburgh (BITE) test was used to determine whether individuals taking part in the study had binge eating disorder. In this study, in which binge eating disorder was classified, different artificial neural network models were created by changing the basic parameters, and the optimum model was assessed accordingly. Among the models created with different layers and activation functions, the optimum results were obtained using the number of fully connected layers as 2, first and second layers' sizes as 10, and ReLU, a nonlinear activation function, in the Bilayered Neural Network structure. This study is the first trial in which binge eating disorder is predicted using machine learning methods, and we believe that machine learning is an important tool to help researchers and clinicians diagnose, prevent, and treat eating disorders at an early stage.

Keywords: *Machine learning algorithms; Binge eating disorder; Bulimic investigatory test Edinburgh (BITE); Eating disorder*

Öz

Yeme bozuklukları, yüksek ölüm ve hastalık oranlarıyla karakterize edilen ve yaşam için ciddi bir tehdit oluşturan kalıcı durumlardır. Bunlar arasında en yaygın olanı tıkanırcasına yeme bozukluğudur. Bu nedenle dünya çapında sıklıkla obeziteyle sonuçlanan önemli bir sağlık sorunudur. Bu çalışma, üniversite öğrencilerinin yeme tutum ve davranışlarının değerlendirilmesi ve tıkınırcasına yeme bozukluğunun makine öğrenmesi yöntemleri kullanılarak tahmin edilmesi amacıyla yapılmıştır. Araştırma 306 kişi (117 erkek, 189 kadın) üzerinde gerçekleştirilmiştir. Bireylerin kişisel özellikleri anket formu ile sorgulanmıştır. Çalışmaya katılan bireylerde tıkınırcasına yeme bozukluğu olup olmadığını tespit etmek amacıyla, Bulimic Investigatory Test Edinburgh (BITE) testi kullanılmıştır. Tıkınırcasına yeme bozukluğunun tahmin edildiği bu çalışmada, temel parametreler değiştirilerek farklı yapay sinir ağı modelleri oluşturulmuş ve buna göre optimum model değerlendirilmiştir. Farklı katmanlar ve aktivasyon fonksiyonları ile oluşturulan modeller arasında Çift Katmanlı Sinir Ağında katman sayısı 2, birinci ve ikinci katman boyutları 10 ve doğrusal olmayan aktivasyon fonksiyonu olan ReLU kullanılarak optimum sonuçlar elde edilmiştir. Bu çalışma, anket çalışmalarından tıkınırcasına yeme bozukluğunun makine öğrenmesi yöntemleri kullanılarak tahmin edildiği ilk çalışma olup, makine öğreniminin, araştırmacıların ve klinisyenlerin yeme bozukluklarının erken teşhisi, önlenmesi ve tedavisine yardımcı olacak önemli bir araç olduğuna inanıyoruz.

Anahtar Kelimeler: *Makine öğrenmesi algoritmaları; Tıkınırcasına yeme bozukluğu; Bulimic investigatory test Edinburgh (BITE); Yeme bozukluğu*

1. Introduction

Eating disorders are severe, potentially life-threatening conditions characterized by high rates of mortality and morbidity (Güney and Kuruoğlu 2007, Sönmez 2017). These disorders typically emerge during late adolescence or early adulthood and are linked to the social, physical, and psychological development of young adults (Badrasawi and Zidan 2019). Binge eating disorder (BED), being the most prevalent eating disorder, represents a significant global health issue linked to obesity on a widespread scale (Albertsen *et al.* 2019, Hay *et al.* 2020, Hutson *et al.* 2018, Wonderlich *et al.* 2009).

BED is defined by recurrent and uncontrollable episodes of excessive eating, often without compensatory actions (Gordon *et al.* 2019, Turan *et al.* 2015). Research suggests a connection between BED and social influences, depression, nutritional status, self-esteem, stress and anxiety (Badrasawi and Zidan 2019). Those with BED often experience shame regarding their behaviors and may hesitate to disclose their symptoms to both therapists and

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individuals in their social circle (Berg *et al.* 2012). Overeating is a behavior that is usually hidden and does not normally emerge if the clinician does not directly investigate eating habits (Wonderlich *et al.* 2009). The diagnostic criteria for BED include eating rapidly at least once a week for about three months, consuming food until discomfort, eating despite lack of hunger, solitary eating due to shame, followed by feelings of disgust, depression, or intense guilt, and absence of compensatory actions (Kober and Boswell 2018). According to the DSM-5, the severity of BED is determined as follows: binge eating once to three times per week on average (non-severe), binge eating four to seven times per week on average (moderate), binge eating eight to thirteen times per week on average (severe), binge eating fourteen times or more per week on average (excessive) (American Psychiatric Association 2013). Individuals diagnosed with BED face an increased likelihood of developing dyslipidemia, hypertension, type 2 diabetes, and metabolic syndrome in comparison to those without eating disorders.

Moreover, they may have more sleeping problems than people without eating disorders (Badrasawi and Zidan 2019). Obesity and related physical complications often accompany because there are no compensatory behaviors such as vomiting, excessive exercise, fasting, and the use of laxatives in individuals with BED (Gordon *et al.* 2019). Less than 50% of people with BED receive treatment (Kessler *et al.* 2013).

University students can change their eating habits to cope with the stress caused by leaving their family and the place of residence for their education and to adapt to university life, along with the effect of adolescence, which may even cause eating disorders (Türkmen and Sivrikaya 2020). From this perspective, in the study, the eating attitudes and behaviors of university students were evaluated by applying different machine learning (ML) methods, and it was estimated whether BED was experienced.

In another study using machine learning methods, risk was diagnosed and predicted in eating disorders, depression, and alcohol use disorder (Desrivières *et al.* 2024). The Random Forest-based method was used to prepare data and linear regression and logistic regression models for risk prediction.

A recent study investigated how the diagnostics of eating disorders can benefit from novel technologies such as machine learning as well as natural language processing (NLP) (Merhbene *et al.* 2024). Presented a review of the application of machine learning techniques in detecting eating disorders from text and evaluated the models used, focusing on their performance, limitations, and the potential risks associated with current methodologies.
In the literature, especially recently, many studies have been conducted to evaluate the prediction, prevention, and treatment of eating disorders using ML methods (Benítez-Andrades *et al.* 2022, Cerasa *et al.* 2015, Forrest, *et al.* 2021, Linardon *et al.* 2022, Orrù *et al.* 2021; Raab *et al.* 2020; Ren *et al.* 2022; Sadeh-Sharvit *et al.* 2020; Wang 2021).

Early identification of individuals with eating disorders is crucial as untreated symptoms often escalate in frequency, severity, and permanence. Timely diagnosis and prompt initiation of treatment are linked to favorable outcomes in the management of eating disorders (Lewinsohn *et al.* 2000). Therefore, the study aimed to evaluate the prediction model that could be used in the early diagnosis of BED using ML methods.

2. Materials and Methods

The sample of this study consists of 117 males and 189 females between the ages of 17-28 who voluntarily took part in the study. Analyses were carried out using the survey method based on the information obtained from 306 volunteers.

The questionnaire consists of 2 sections, which include general information and the BITE scale. The participants are asked to answer 12 questions in the general information section and 40 questions in the Bulimic Investigatory Test section. The answers to the questionnaire questions were used as independent variables in the analysis.

The independent variables and data types in the General Information section are included in Table 1. Body mass index is a derived variable obtained using the height and weight information stated by the participant.

Table 1. Features.

Features	Data Type
Gender	Categorical
Age	Numeric
Weight	Numeric
Size	Numeric
Max weight	Numeric
Min weight	Numeric
Ideal weight	Numeric
Mother’s educational status	Categorical
Father’s educational status	Categorical
Mother’s profession	Categorical
Father’s profession	Categorical
Number of siblings	Numeric

The BED of the participants was evaluated using the Bulimic Investigatory Test, Edinburgh (BITE), developed by Henderson and Freeman (Henderson and M.Freeman 1987). The BITE is a scale consisting of 33 questions that measure the symptoms of bulimia nervosa or binge eating. It has two subscales, called the "symptom scale" and "severity scale." The highest score obtained from the test was found to be 30. All 37 main criteria and 4 sub-criteria in the Bulimic Investigatory Test are categorical data.

The BITE scores were determined by the expert according to the answers given to the questions in the questionnaire. According to the calculated BITE score, the state of BED used as a dependent variable in the study was classified as in Table 2. 113 out of 306 people in the study sample did not have BED, 168 people had abnormal eating behavior, but no BED, and 25 people had BED.

Table 2. BITE score ranges.

BITE Score Range	Situation	Frequency
0 -10	No binge eating disorder	113
11-19	Have abnormal eating behavior. No binge eating disorder	168
>20	Have a binge eating disorder	25

In the study, analyses were conducted for 306 standardized samples according to 53 features. 306 samples in the data set were randomly divided into training and test data sets. In the analysis, 215 samples were used for the system training, and 91 samples were used for system testing. The 5-fold cross-validation method was used in training.

2.1 Machine learning techniques

Machine learning methods imitate human-specific learning styles and are developed to make correct predictions by extracting patterns from previous observations through algorithms (Schapire 2003). The model created with the algorithms used is established to show the highest performance for the data set analyzed. There are many available ML methods developed for clustering, classification, prediction, or regression (Atalay and Çelik 2017).

Classification algorithms learn which data will be assigned to certain classes from the class information in the data within the training data set and then predict the correct class information of the test data accordingly (Khehra and Pharwaha 2016). In the literature, many classification algorithms support different types of data, such as K-nearest neighborhood (KNN), linear regression, logistic regression (LR), support vector machines (SVM), random trees, decision trees and Naive Bayes (Aggarwal and Zhai 2012, Ashour *et al.* 2018, Bulk *et al.* 2022, Harrell 2015). Different ML methods were applied while determining the classification method suitable for the data set analyzed in the study. To this end, the data set was analyzed using MATLAB (MATLAB is a registered trademark of The MathWorks, Inc.) programming language. The results were evaluated based on the performance metrics derived from implementing the methods (Metlek and Kayaalp 2020).

Support Vector Machines (SVM) is a learning technique originating from statistical learning theory, employed for pattern recognition and solving two or multiclass classification challenges. Initially, SVM maps the data to a higher-dimensional space for linear separation, aiming to maximize the margin between classes. The primary goal of SVM is to derive the optimal hyperplane that effectively separates classes and maximizes the distance between support vectors of distinct classes (Ayhan and Erdoğmuş 2014). While obtaining these planes, different models are formed using different core functions.

The study created different models according to the hyperplanes determined using SVM Linear, Quadratic, Cubic, and Gaussian kernel functions. In all SVM models, the box restriction level was selected as 1. Among the SVM models established, the best result was obtained with the Quadratic kernel function. For the quadratic SVM, the final model was created by selecting the Kernel scale and the Automatic and Multiclass method was selected as One-vs-One.

The K-Nearest Neighbor (KNN) algorithm is a non-parametric method and stands out as one of the most popular and widely utilized algorithms in the realm of ML techniques. A learning cluster is created for training purposes using tagged data with known class information. It is a supervised ML method in which classification is made using the proximity between the new sample and the nearest *k* samples (Bin Alam *et al.* 2021). Many different metrics are used to determine a class and calculate the distance between the samples (Affonso *et al.* 2017). The number of the nearest samples to be evaluated in the classification according to the selected metric is determined by changing the number of *k*.

The optimum KNN model was chosen from the Fine, Medium, Coarse, Cosine, and Cubic KNN models created according to different distance metrics and nearest neighbor numbers. While Euclidean is the distance metric used to classify in Fine, Medium, and Coarse KNN models, this metric is Cosine in Cosine KNN and Minkowski in Cubic KNN. The models were formed according to the number of the nearest neighbors (1-10-100), and their performances were compared. In the selected optimum Cosine KNN model, the number of neighbors was considered 10, the Distance metric was considered Cosine, and the Distance weight was considered Equal. Artificial neural networks (ANNs) are mathematical models that imitate the biological brain with their ability to create, derive, and explore new human-specific information (Barkana *et al.* 2017). Generally, in ANNs, which consist of a series of neurons, interconnection, and learning rules, each processing element has five basic elements: input, weight, additive function, activation function, and output. These basic parameters are determined and changed according to the data and model, and artificial neural network models are formed to make a classification in many different areas, such as health, construction, and logistics.

In this study, in which BED was classified, different artificial neural network models were created by changing the basic parameters, and the optimum model was assessed accordingly. Among the models created with different layers and activation functions, the optimum results were obtained using the number of fully connected layers as 2, first and second layers' sizes as 10, and ReLU, a nonlinear activation function, in the Bilayered Neural Network structure (Vila-Blanco *et al.* 2020).

Another method employed is discriminant analysis, which is a linear technique assuming a direct relationship between a dependent variable and one or more independent variables (Alunni *et al.* 2015). Since the dependent variable used in the analyses was divided into three groups, a full linear discriminant analysis of the covariance structure was carried out using the preferred method.

Boosted trees, one of the ensemble classifiers, are used in classification and regression problems (Ashour *et al.* 2018). In the analyses, along with the AdaBoost method, the Maximum number of splits was selected as 20, learner type decision tree and rate as 0.1, and the number of learners as 30.

The Bagged (Bootstrap Aggregation) Trees method, another ensemble classifier, creates a series of models trained on random data and combines these models for prediction (Ashour *et al.* 2018). The Bagged Trees model applied to the data set was established by selecting the number of learners as 30 and the maximum number of splits as 214 for the decision tree learning type with the Bag method. The Subspace Discriminant method is also accepted as a community learning method. Its main principle is to improve the predictive performance of a single model created by training and combining multiple models. Thus, a higher accuracy rate is obtained compared to a single classifier model (Karaca *et al.* 2019). In the model established in the Subspace Discriminant method, which is preferred due to rapid classification and less memory use, analyses were performed by selecting the Ensemble method as Subspace, the Learner type as Discriminant, the Number of learners as 30, and the Subspace dimension as 27.

In the literature, different metrics are used to evaluate the process of classification using ML methods (Sokolova *et al.* 2006). The criterion of classification success is determined by the Confusion Matrix, which is comprised of samples that are correctly and incorrectly classified for each class. The number of samples classified as true positive is expressed with TP, false positive with FP, false negative with FN, and true negative with TN. The widely accepted evaluation criteria for comparing the classification performances of different algorithms using these values are accuracy, sensitivity, and recall.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

ROC-AUC curves are the performance metric for classification problems used to compare the success of different models trained on the same data set. The AUC value refers to the area under the ROC curve and assumes a value between 0 and 1 (Sokolova *et al.* 2006). Classification accuracy is measured with the AUC curve. When evaluating the model, it is supposed that the closer the AUC value to 1 is, the more successful the model is.

3. Results and Discussions

In the study, classification was made using different ML methods on the same data set. Accuracy and AUC values were used to compare the classification models obtained with different algorithms. The results obtained from the test and training data for the 7 classification methods created are presented in Table 3. When the accuracy rates of the models created using different classification methods and the AUC values obtained from ROC curves are evaluated, the classifiers by which the best predictions were made with the data set are Support Vector Machines (84.6%) and Subspace Discriminant (82.4%) methods. The confusion matrix and ROC curves of both methods created for the test data are presented below (Figure 1-2-3-4).

Table 3. Accuracy values of classification methods.

Machine Learning Techniques		Accuracy Rates		AUC	
		Results of Train	**Results of Test**	**Results of Train**	**Results of Test**
Support Vector Machines		86.0%	84.6%	0.97	0.97
K-Nearest Neighbors		72.6%	79.1%	0.90	0.91
Neural Network		76.3%	79.1%	0.85	0.85
Discriminant Analysis		84.2%	82.4%	0.94	0.94
Ensemble Classifiers	Boosted Trees	77.2%	82.4%	0.90	0.90
	Bagged Trees	76.3%	84.6%	0.89	0.93
	Subspace Discriminant	83.3%	82.4%	0.96	0.98

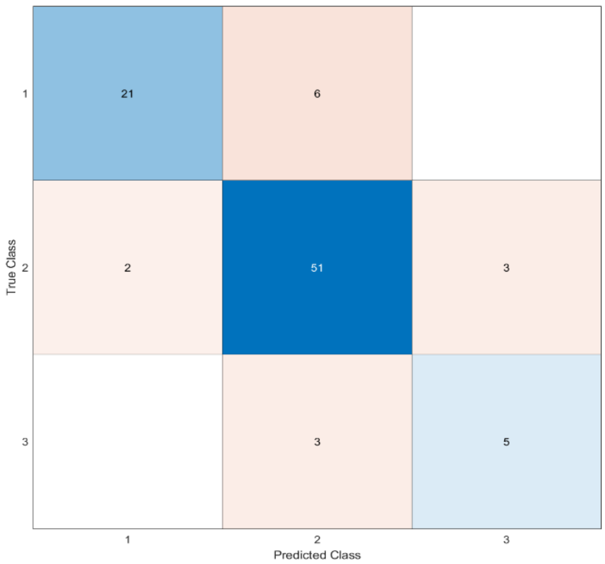

Figure 1. Confusion matrix for SVM.

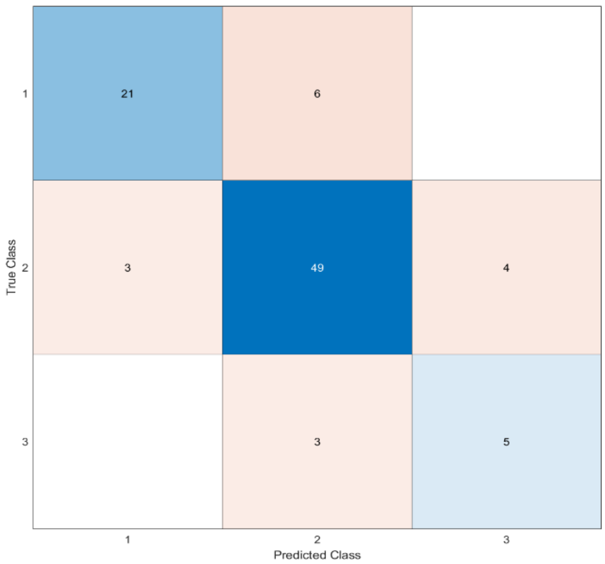

Figure 3. Confusion matrix for subspace discriminant

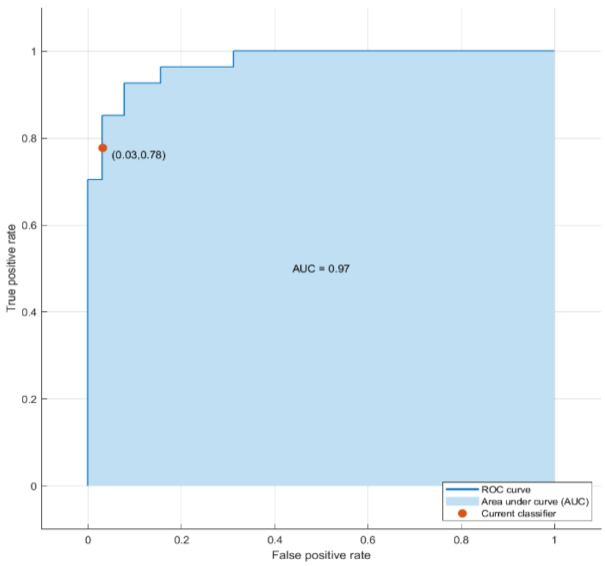

Figure 2. ROC curve for SVM

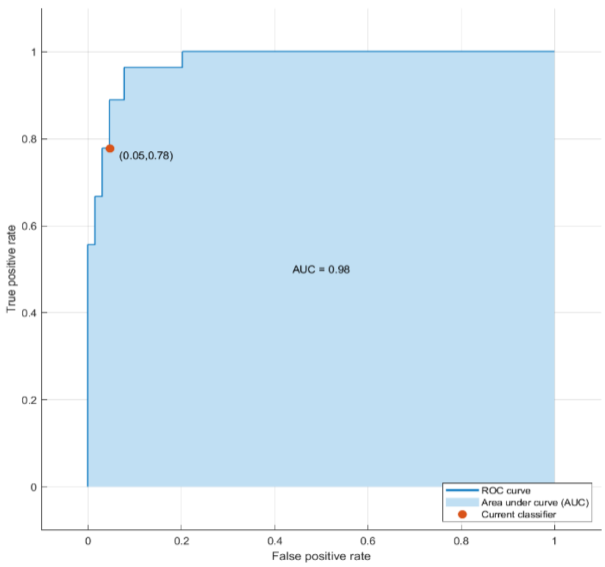

Figure 4. ROC curve for subspace discriminant

Feature selection was made using ML methods (Naïve Bayes, LR, SVM, Random Forest) according to the survey results and clinical evaluations in revealing the effective characteristics of eating disorders (Orrù *et al.* 2021).

A similar study used decision tree classification analysis, a machine learning technique, to identify the primary risk factors influencing the manifestation of eating disorders in 830 young women from China. The findings indicated that factors such as psychological distress, body image inflexibility, and body dissatisfaction significantly increased the risk of developing eating disorders (Ren *et al.* 2022).

The use of social media has increased, and it is used to obtain information about mental health from people's electronic footprints and inform/guide them about the need for treatment or the available treatment (Benítez-Andrades *et al.* 2022). In the study by Yan et al. (2019), a total of 6000 social media posts were tagged and analyzed by two clinical psychologists (Yan *et al.* 2019). In the study, social media posts were evaluated using five different ML methods in the natural language processing process, users who needed intervention were determined, and the posts were used in the early diagnosis of eating disorders. In a similar study, Twitter topics on eating disorders, which have an important position in public health research, were determined by ML methods (Zhou *et al.* 2020). One hundred twenty-three thousand nine hundred seventy-seven tweets were reviewed, and the best-performing classifier was identified to determine the tweets related to eating disorders with various supervised ML methods. Moreover, a study aimed to predict the eating disorders of users by using internet activities (Sadeh-Sharvit *et al.* 2020). The internet activities of 936 participants were analyzed with LR, decision trees, and SVM, among the ML methods, and the diagnosis of eating disorders or conditions requiring urgent intervention were predicted.

Among the studies using image processing methods to diagnose eating disorders, Cerasa et al. (2015) analyzed brain structural magnetic resonance images using the SVM method to identify the biomarkers to diagnose eating disorders (Cerasa *et al.* 2015). ML methods were employed in the study, and the effects of BED, one of the most common eating disorders, on the human brain, were analyzed using electroencephalography (EEG) data (Raab *et al.* 2020). The established model classifies individuals affected by BED and healthy individuals with an accuracy of 81.25% through theta activities in the range of 4.5 – 6 Hz. Another study on BED analyzed the data of 1,341 participants with the decision tree classification method to identify the effective eating patterns in the recurrence of BED (Linardon *et al.* 2020). About 70% of the participants were correctly classified, and it was expressed that intuitive eating was the most important parameter in recurrent BED.

ML methods are used not only for detecting BED but also for predicting treatment outcomes (Forrest *et al.* 2021). The 6-month treatment status and basic clinical and demographic information of 191 patients, who had been diagnosed with BED, were assessed. Predictions were made with flexible network regression and random forests, which are logistic/linear regression and ML models known as conventional methods.

In our study, among the 7 different ML methods applied, SVM (84.6%) and Subspace Discriminant (82.4%) methods were observed to classify binge eating disorders more accurately.

4. Conclusions

ML methods are used in many fields, and their use and importance in the field of health increase every day (Veranyurt *et al.* 2020). There are many areas of application in terms of early diagnosis, treatment and planning of operational processes in health services and management using ML methods. Expanding the area of use of ML algorithms, particularly in the classification and early diagnosis of diseases, enables optimization in terms of quality and cost in the delivery of health services.

Applying machine learning techniques in eating disorders research is a relatively new and burgeoning area of investigation. While the potential benefits of leveraging advanced computational methods for the diagnosis, treatment, and understanding of these complex mental health conditions are substantial, the literature in this domain remains limited.

Recent studies have begun to explore the use of machine learning algorithms in analyzing various data sources, such as EEG recordings, to identify patterns or markers associated with specific eating disorders, including binge eating disorders (Linardon *et al.* 2022, Raab *et al.* 2020). These exploratory efforts aim to enhance diagnostic accuracy, predict responsiveness to interventions, and optimize treatment outcomes for individuals affected by eating disorders.

However, the field is still in its early stages, and further research is necessary to establish the reliability, validity, and clinical utility of machine learning approaches in the context of eating disorders. Larger-scale studies, standardized methodologies, and interdisciplinary collaborations between clinicians, researchers, and data scientists will be crucial in advancing this emerging area of inquiry (Linardon *et al.* 2020).

Unhealthy nutrition causes many diseases. These diseases are also important because of their economic burden on individuals and society. Individuals' eating attitudes and behaviors are seen to differ in coping with stress and overcoming the responsibilities of modern life. Since delays in the diagnosis and treatment process of BED, which is the most common eating disorder in adults, cause symptoms to become more frequent, severe, and permanent over time, it is extremely important to diagnose individuals with BED early and take therapeutic measures. Regarding these measures, it is recommended to increase the number of studies on the connection between BED and nutrition and cooperate with parents, dieticians, psychologists, and psychiatrists (Turan *et al.* 2015).

This is the first study in which BED is predicted by ML methods using the answers given to the questionnaire. In the study, the answers of the volunteer participants to the questions in the questionnaire and the BITE score variables calculated according to these answers were analyzed using different ML methods, and the state of BED was classified. Among the 7 different ML methods applied, SVM (84.6%) and Subspace Discriminant (82.4%) methods were observed to classify BED more accurately. According to the results, ML can be considered an important tool to help researchers and clinicians work on the early diagnosis, prevention, and treatment of eating disorders.

In future studies, it is aimed to create a model by determining the features with the highest contribution to classification performance among the features used in the analysis. Accordingly, participants can be ensured that they give an idea about BED by answering fewer questions. It is aimed to accelerate the prediction process with fewer questions, especially in organizations serving in the field of public health. It is also aimed at developing a decision support system to be used in binge eating disorder diagnosis and treatment processes with different machine learning algorithms.

As the field progresses, it is anticipated that the integration of machine learning into eating disorders research will lead to more personalized, data-driven approaches to prevention, diagnosis, and treatment, ultimately improving the quality of life for those affected by these serious mental health conditions.

Declaration of Ethical Standards

The authors declare that they comply with all ethical standards.

For this study, "Ethics Committee Approval", numbered 18698 and dated 30.11.2018, was received from Artvin Çoruh University Scientific Research and Ethics Committee. A written consent form was obtained from the participants stating that they voluntarily participated in the study.

Credit Authorship Contribution Statement

Author-1: Investigation, Methodology, Analysis, Writing

Author-2: Writing, Investigation, Questionnaire

Declaration of Competing Interest

The authors have no conflicts of interest to declare regarding the content of this article.

Data Availability Statement

All data generated or analyzed during this study are included in this published paper.

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