# Use of Machine Learning Methods in Psychiatry

## Psikiyatride Makine Öğrenmesi Yöntemlerinin Kullanımı

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**Abstract**

Machine learning methods, which are becoming more and more popular in artificial intelligence and data analysis, provide learning from data in many different fields. In the studies conducted in the field of health, these methods support healthcare professionals and physicians. Psychiatry is one of these areas. Machine learning methods provide support to problems such as diagnosis, prediction of disease course or monitoring response to a treatment. In this study, machine learning studies in the field of psychiatry are examined. The aim of the study is to examine the studies of machine learning in the field of psychiatry and especially the studies conducted using electroencephalography (EEG) data. Accordingly, studies on machine learning in the field of psychiatry in SCOPUS and Google Scholar sources were examined. In order to reveal the general situation in the literature, studies using machine learning methods in the field of psychiatry were examined. Afterwards, studies using both machine learning methods and EEG data in psychiatry were examined. It is hoped that this study will be useful to researchers in terms of the publications about machine learning in psychiatry and especially the publications using EEG data.

**Keywords:** Psychiatry, machine learning, psychiatric diseases

**Öz**

Yapay zeka ve veri analizinde gün geçtikçe daha popüler hale gelen makine öğrenmesi yöntemleri birçok farklı alanda veriden öğrenmeyi sağlamaktadır. Sağlık alanında yapılan çalışmalarda bu yöntemler sağlık çalışanlarına ve hekimlere destek sunmaktadır. Psikiyatri de bu alanlardan bir tanesidir. Hastalıkların tanı, hastalık seyrinin tahmini veya bir tedaviye verilecek yanıtın gözlemlenmesi gibi problemlere makine öğrenmesi yöntemleri destek sağlamaktadır. Bu çalışma kapsamında psikiyatri alanında yapılmış olan makine öğrenmesi çalışmaları incelenmiştir. Çalışmanın amacı, makine öğrenmesi yöntemlerinin psikiyatri alanında kullanımının araştırılmasıdır. Özellikle elektroensefalografi (EEG) verisi kullanılan araştırmalara odaklanılmıştır. Bu amaçla, psikiyatride alanında yapılan makine öğrenmesi ile ilgili olan SCOPUS ve Google Scholar Referencesındaki yayınlar incelenmiştir. Literatürdeki genel durumun ortaya konması amacıyla, psikiyatri alanında makine öğrenmesi yöntemlerinden yararlanan çalışmalara incelenmiştir. Sonrasında ise daha detaylı bir şekilde psikiyatri alanında makine öğrenmesi ve EEG verisi kullanılarak yapılan araştırmalar incelenmiştir. Bu çalışmanın psikiyatride makine öğrenmesi ile ilgili yapılan yayınlar ve özellikle EEG verisi kullanılan yayınların derlenmesi açısından araştırmacılara faydalı olabileceği umulmaktadır.

**Anahtar sözcükler:** Psikiyatri, makine öğrenmesi, psikiyatrik hastalıklar

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**ONE** of the considerably popular research and application areas of artificial intelligence and its sub-branches i.e. data mining and machine learning methods, is the field of health. The implementation of these methods in health studies ensures benefits in terms of early diagnosis and prediction of course of diseases, while basically aiming to improve the quality of life of people. Kutlu (2010) symbolized the process during which physiological signals received from the patient were collected and analyzed, as shown in Figure 1. Accordingly, in the first stage, data is collected from the patient who consults a doctor relevant to a certain complaint, the obtained data is analyzed and a decision-making process is initiated in consequence of this analysis. In the wake of the decision cocluded regarding the diagnosis or the course of the disease, the relevant steps are taken and the therapy process is initiated. It may be asserted that many concepts related to artificial intelligence, which can be referred as technology, models or methods, actually support our decision-making. When machine learning methods are mentioned as a sub-branch of artificial intelligence, it is seen that these methods are used to create models to support the decisions of doctors at the present time and these methods can actually avail in many different aspects ranging from diagnosis to treatment of diseases.
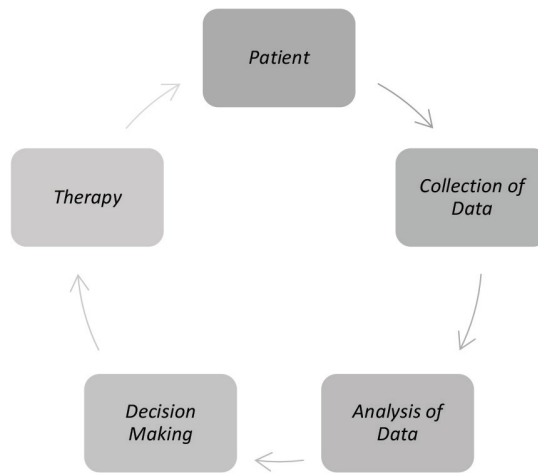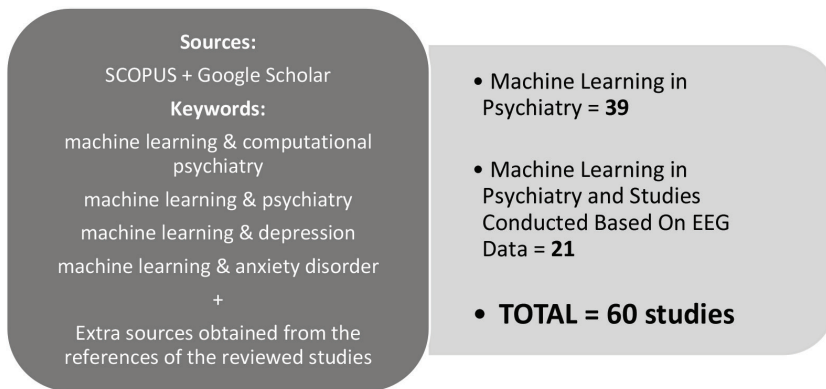


**Figure 1. Basic elements of a medical care system (Kutlu 2010).**

Considering the studies examined within the scope of this particular research study that utilized machine learning methods in the field of psychiatry, it was seen that the number of patients was not notably high, polycentric data collection was not performed, certain studies used solely one single type of data and more than two diseases were not ever addressed at the same time. The aim of this study is to examine the machine learning based studies in the field of psychiatry and to investigate the studies conducted exclusively using EEG data at the same time. The study was compiled by limiting the scope of the literature review conducted to form the basis for the doctoral dissertation entitled "Differentiation of Psychiatric Diseases by Machine Learning". Accordingly, machine learning studies in the field of psychiatry in

general manner were examined. Therewithal, studies using machine learning methods and EEG data in the field of psychiatry, which are furthermore the subject of the thesis, have been scrutinized by narrowing the general scope. It is expected and hoped that this study will be useful and advantageous to researchers in terms of compiling publications about machine learning in psychiatry and exclusively of those publications using EEG data.

## Method

The literature review is structured based on two different titles. Accordingly, the deductive approach has been adopted. Studies using machine learning methods in psychiatry (n=39) and studies using EEG data and machine learning methods in psychiatry (n=21) were analyzed. The scope of the studies included and approached in the study is shown in Figure 2.

Sources:
SCOPUS + Google Scholar
Keywords:
machine learning & computational psychiatry
machine learning & psychiatry
machine learning & depression
machine learning & anxiety disorder
+
Extra sources obtained from the references of the reviewed studies

• Machine Learning in Psychiatry = **39**

• Machine Learning in Psychiatry and Studies Conducted Based On EEG Data = **21**

• **TOTAL = 60 studies**

**Figure 2. The scope of research included in the study**

The resources examined and benefited from within the scope of the study were obtained in consequence of different reviews conducted on in Google Scholar and SCOPUS databases. Scanning and reviews using the keywords "machine learning" & "computational psychiatry", "machine learning" & "psychiatry", "machine learning" & "depression", "machine learning" & "anxiety disorder" were realized between October 2019 - November 2019. 60 of the obtained studies were included in the study. Afterwards, the sources used by the mentioned studies were examined and the scope of the search was expanded. Studies involving EEG data, psychiatric diseases and machine learning methods were determined and examined in detail according to the specified criteria.

## Results

The findings obtained as a result of the literature review are given under two titles in Figure 2, and the studies examined under the titles are included in the sub-sections of the titles. Once the literature is examined, it is seen that machine learning methods are used for studies

conducted related to different diseases. Studies conducted with machine learning techniques in psychiatry are involved with different diseases, different data types and different analysis methods. The studies examined in Table 1 are denominated incidental to the number of data and method they used.

## Attention deficit and hyperactivity disorder (ADHD)

Mueller et al. (2010) and Öztoprak et al. (2017) used the data and SVM to distinguish ADHD patients and healthy individuals from each other. Kuang and He (2014) used the deep learning method for comparison of ADHD patients with healthy individuals and disease subgroups.

## Depression

Nouretdinov et al. (2011) used transductive conformal predictor and SVM in their studies for the prediction of diagnostic and prognostic indicators. Suhasini et al. (2011) developed a decision support system utilizing SVM, radial basis function neural network (RBFNN) and back propagation neural network (BPNN) techniques, for detecting depression and anxiety. R. H. Perlis et al. (2012) conducted a study for the classification of treatment response to be applied as LJR and NLP for examining the long-term effects of depression treatment. Perlis (2013) developed a model based on olarak LJR, NB, RF, SVM for estimating the risk of treatment resistance on behalf of patients diagnosed with depression. Redlich et al. (2016) used Gaussian process classifier and SVM methods in predicting the treatment response to electroconvulsive therapy (ECT) treatment during the treatment of depression. Dipnall et al. (2017) used self-organized mapping, boosted regression, and multivariate LJR methods to discover the patterns underlying depression. Walss-Bass et al. (2018) used the component-wise gradient boosting algorithm to determine which inflammatory markers can be used to predict the development of depression and anxiety. Zilcha-Mano et al. (2018) used RF to predict response to placebo and drug treatment in patients with depression. Hatton et al. (2019) conducted a study for the prediction of depression in elderly individuals with the extreme gradient boosting and LJR methods. Li et al. (2017) conducted a study using Bayesian nonparametric cluster analysis method for the clustering of anxiety and depression in cancer patients.

## Schizophrenia

Yoon et al. (2012) developed a classification model with LDA in order to differentiate schizophrenia patients. Brodersen et al. (2014) utilized supervised and unsupervised machine learning methods to separate schizophrenia patients and healthy individuals from each other. SVM classification model and Gaussian mixture model clustering model has been created. Dowd et al. (2016) utilized the Q-learning algorithm, one of the reinforcement learning methods to understand anhedonia and avolition in

**Table 1. Machine learning in psychiatry**

|  | Source | Disorder | Number of samples | Method |
|---|---|---|---|---|
| 1 | Mueller et al. (2010) | ADHD | 148<br>74 ADHD<br>74 control | SVM |
| 2 | Öztoprak et al. (2017) | ADHD | 108<br>70 ADHD<br>38 healthy | SVM |
| 3 | Kuang and He (2014) | ADHD | 545<br>450 ADHD<br>95 healthy | Deep learning |
| 4 | Nouretdinov et al. (2011) | Depression | 38<br>19 depression<br>19 healthy | Transductiand conformal predictor, SVM |
| 5 | Suhasini et al. (2011) | Depression, anxiety | 400 ADHD | BPNN, RBFNN, SVM |
| 6 | R. H. Perlis et al. (2012) | Depression | 5198 depression | LJR, NLP |
| 7 | Perlis (2013) | Depression | - | LJR, NB, RF, SVM |
| 8 | Redlich et al. (2016) | Depression | 68<br>47 depression<br>21 healthy | Gaussian process classifier, SVM |
| 9 | Dipnall et al. (2017) | Depression | 2123 depression | Self-organised mapping, boosted regression, multivariate LJR |
| 10 | Walss-Bass et al. (2018) | Depression, anxiety | 254 depression, anxiety | Component-wise gradient boosting |
| 11 | Zilcha-Mano et al. (2018) | Depression | 174 depression | RF |
| 12 | Hatton et al. (2019) | Depression | 284 depression | Extreme gradient boosting, LJR |
| 13 | Li et al. (2017) | Depression, anxiety | 321 | Bayesian nonparametric cluster analysis |
| 14 | Yoon et al. (2012) | Schizophrenia | 102<br>51 schizophrenia<br>51 healthy | LDA |
| 15 | Brodersen et al. (2014) | Schizophrenia | 41 schizophrenia<br>42 healthy | SVM, Gaussian mixture model |
| 16 | Dowd et al. (2016) | Schizophrenia | 38 schizophrenia<br>37 healthy | Q-learning |
| 17 | Cao et al. (2018) | Schizophrenia | 262<br>131 schizophrenia<br>131 healthy | MTL_NET (multi-task learning with network structure), MTL_SNET (sparse network structure), MTL_L21 (joint feature learning), MTL_EN (joint feature learning with elastic net), MTL_Trace (low-rank structure), LJR, SVM, RF |
| 18 | Viviano et al. (2018) | Schizophrenia | 188<br>113 schizophrenia<br>75 healthy | SVM |
| 19 | Barzilay et al. (2019) | Schizophrenia | 25 schizophrenia | SVM |
| 20 | Fond et al. (2019) | Schizophrenia | 549 schizophrenia | CART |
| 21 | Pinaya et al. (2019) | Schizophrenia, autism spectrum disorder | 263 patient<br>1113 healthy | Deep autoencoder, SVM |

**Table 1. Continued**

|    | Source | Disorder | Number of samples | Method |
|----|--------|----------|-------------------|--------|
| 22 | Galatzer-Levy et al. (2014) | PTSD | 957 PTSD | Linear SVM, optimized linear SVM, polynomial SVM, RF, AdaBoost, kernel ridge regression, Bayesian binary regression |
| 23 | Karstoft et al. (2015) | PTSD | 957 PTSD | SVM |
| 24 | Papini et al. (2018) | PTSD | 271 PTSD | XGBoost |
| 25 | Mwangi et al. (2016) | Bipolar | 256<br>128 bipolar<br>128 healthy | Relevance vector machine learning algorithm |
| 26 | Eugene et al. (2018) | Bipolar | 120 bipolar | DT, RF |
| 27 | Perez Arribas et al. (2018) | Bipolar, borderline personality | 130<br>48 bipolar<br>31 borderline personality disorder<br>51 healthy | RF |
| 28 | Edgcomb et al. (2019) | Bipolar | 552 bipolar | CART |
| 29 | Han et al. (2020) | Opioid | 41579 opioid | ANN, distributed RF, gradient boosting machine |
| 30 | Ellis et al. (2019) | Opioid | 716533<br>9518 opioid<br>707015 healthy | RF |
| 31 | Zhao and So (2019) | Schizophrenia, depression, anxiety | 3478 patient<br>12436 gen | DNN, SVM, RF, gradient boosted machine with trees (GBM), LJR (with elastic net regularization) |
| 32 | Mellem et al. (2020) | Schizophrenia, bipolar, ADHD | 272<br>50 schizophrenia<br>49 bipolar<br>43 ADHD<br>130 healthy | LASSO regression, elastic net regression, RF |
| 33 | Sohn et al. (2011) | other | 335 sample | C4,5 |
| 34 | Qin et al. (2014) | other | 76 sample | LNR |
| 35 | Bedi et al. (2015) | other | 34 sample<br>5 psychosis<br>29 non-psychosis | Convex hull classifier |
| 36 | Just et al. (2017) | other | 34<br>17 suicidal ideators<br>17 control | Gaussian Naive Bayes |
| 37 | Sato et al. (2018) | other | 622 sample | one-class SVM |
| 38 | Walsh et al. (2018) | other | 1470 sample | RF, LJR |
| 39 | Stamate et al. (2019) | other | 272<br>260 psychosis<br>212 healthy | RF, SVM, Gaussian Processes, LJR, ANN |

ANN: Artificial neural network, BPNN: Backpropagation neural networks, CART: Classification and regression tree, DNN: Deep neural network, DT: Decision tree, LDA: Linear discriminant analysis, LJR: Logistic regression, LNR: Linear regression, NB: Naive Bayes
NLP: Natural language processing, RBFNN: Radial basis function neural network, RF: Random forest, SVM: Support vector machine

schizophrenia according to their data. Cao et al. (2018) distinguished schizophrenia patients and healthy individuals from each other with machine learning methods using gene data. In the study, MTL_NET (multi-task learning with network structure), MTL_SNET (sparse network structure), MTL_L21 (joint feature learning), MTL_ EN (joint feature learning with elastic net), MTL_Trace (low-rank structure), LJR, SVM and RF algorithms are used. Viviano et al. (2018) applied the SVM method in their study aimed at evaluating social cognitive and neurocognitive performance and discovering biomarkers in patients with schizophrenia. Barzilay et al. (2019) developed a face recognition system for predicting schizophrenia patients and used SVM for classification. Fond et al. (2019) used the CART method from decision trees to estimate the likelihood of relapse of schizophrenia episodes and the patient's discontinuation of treatment. Pinaya et al. (2019) used the deep autoencoder and SVM method to detect brain anomalies in patients diagnosed with schizophrenia and autism spectrum disorder.

## Post-traumatic stress disorder (PTSD)

Galatzer-Levy et al. (2014) conducted a study utiling different SVM methods (linear SVM, optimized linear SVM, polynomial SVM), RF, AdaBoost, kernel ridge regression, Bayesian binary regression methods to predict the chronic PTSD situation that may occur after a traumatic event. Karstoft et al. (2015) used SVM to predict PTSD risk. Papini et al. (2018) used the XGBoost method for the prediction of PTSD occurence and development.

## Bipolar disorder

Mwangi et al. (2016) utilized the relevance vector machine learning algorithm to distinguish individuals diagnosed with bipolar disorder from healthy individuals. Eugene et al. (2018) used RF and DT methods relying on gene data to predict the response to lithium treatment in bipolar patients. Perez Arribas et al. (2018) developed a model with RF for differentiating bipolar and borderline personality disorder patients. Edgcomb et al. (2019) developed a model using the CART to determine the factors for psychiatric reapplication in individuals diagnosed with bipolar disorder and another medical disease at the same time.

## Opioid addiction

Han et al. (2020) used ANN, distributed RF, and gradient boosting machine methods to predict opiate abuse in adults. Ellis et al. (2019) developed a model using RF to predict opiate addiction by analyzing electronic health data.

## Mixed (Handling More than one Disease)

Zhao and So (2019), in their study on drugs and medication prescribed in schizophrenia,

depression, anxiety disorder utilised DNN, SVM, RF, gradient boosted machine (with trees) and LJR (with elastic net regularization) methods. Mellem et al. (2020) conducted their study using LASSO regression, elastic net regression, RF methods for patients diagnosed with schizophrenia, bipolar disorder and ADHD in order to predict irregular mood, anxiety and anhedonia states.

## Other disorders

Sohn et al. (2011) used the C4,5 algorithm to predict the side effects of drugs and medication used in psychiatry and psychology. Qin et al. (2014) used LNR to predict childhood anxiety disorders. Bedi et al. (2015) conducted a study to estimate the psychosis risk of individuals by using the convex hull classifier method based on voice and speech analysis data. Just et al. (2017) developed a model for evaluating suicide risk using the gaussian naive Bayes method. Sato et al. (2018) used brain connectivity data to predict one-class SVM psychopathology which is a type of SVM method. Walsh et al. (2018) used RF and LJR to predict suicide risk in adults. Stamate et al. (2019) performed a study using RF, SVM, Gaussian Processes, LJR, ANN to distinguish between psychosis spectrum disorder patients and healthy individuals.

## Machine learning in psychiatry and studies conducted based on EEG data

At this stage of the literature review, studies conducted using EEG data and machine learning methods in the field of psychiatry, which is the subject of this study, were examined. Thus, it was made possible to compare the studies in the literature on the basis of the disease, data type and methods used. For this purpose, studies in both national and international literature were examined. National and international studies conducted with machine learning techniques in the field of psychiatry using EEG data are given in Table 2.

The concept of machine learning, which nowadays confronts researchers in different fields, is one of the sub-branches of artificial intelligence. These methods offer algorithms to draw meaningful results from data in research in different fields. Machine learning is defined as "calculation methods using experience to improve performance or make accurate predictions" (Mohri et al., 2012). Flach (2012) stated that machine learning is "about using the right features to create the right models that perform the right tasks". The reason for examining which methods are used in the studies included in this study is that different factors affect the performance of machine learning algorithms. Balaban and Kartal (2018) state the factors that affect the performance of machine learning methods as follows:

**Table 2. Machine Learning in Psychiatry and Studies Conducted Based on EEG Data.**

| | Source | Disorder | Data set source/ethics committee / Supporting Organization | Data type | Number of samples | Method | Language/program | Validation | Performance |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Khodayari-Rostamabad et al. (2010a) | Schizophrenia | St. Joseph's Hospital, Centre for Mountain Health Services, Hamilton, Ontario | QEEG | 37 schizophrenia 23 (R=12, NR=11) 14 (R=7, NR=7)) | PLSR | MATLAB | LOOCV | specificity, sensitivity average 87.12% sensitivity 83.33%, specificity 90.91% specificity, sensitivity average 89.7% sensitivity 85.7%, specificity 93.75% specificity, sensitivity average 85.7% sensitivity 85.7%, specificity 85.7% |
| 2 | Khodayari-Rostamabad et al. (2010b) | Depression | Natural Sciences and Engineering Research Council of Canada (NSERC) | EEG | 22 depression (R=8, NR=14) | PLSR | - | nested 11-fold cross-validation | specificity, sensitivity average 86.6% specificity 85.7% sensitivity 87.5% |
| 3 | Khodayari-Rostamabad et al. (2011) | Depression | Natural Sciences and Engineering Research Council of Canada (NSERC), Etherden Fellowship at St Joseph's Healthcare Foundation | EEG | 27 depression (R=9, NR=9) | Mixture of factor analysis technique | - | leave-2-out (L2O) cross-validation | specificity, sensitivity average 80% specificity 83.3% sensitivity 77% |
| 4 | Ahmadlou et al. (2012) | ADHD | Atieh Comprehensive Center for Psych and Nerve Disorders, Tahran, Iran | EEG | 30 ADHD (15 positive response, 15 negative response) | LDA | - | (%60 train %40 test) * 100 | accuracy 84.2% specificity 80.6% sensitivity 88% |
| 5 | Hosseinifard et al. (2013) | Depression | Psychiatry Centre Atieh, Tehran, Iran | EEG | 90 45 depression 45 healthy | KNN, LDA, LJR | MATLAB | 2/3 train 1/3 test | accuracy 73.3% (KNN) accuracy 76.6% (LDA) accuracy 76.6% (LJR) |
| 6 | Khodayari-Rostamabad et al. (2013) | Depression | St. Joseph's Health Care, Hamilton, Ontario, Canada | EEG | 113 22 depression (R=7, NR=15) 91 healthy | Mixture of factor analysis technique | - | leave-2-out (L2O) cross-validation * 100 | specificity, sensitivity average 87.9% specificity 80.9% sensitivity 94.9% |

**Table 2. Continued**

| | Source | Disorder | Data set source/ethics committee / Supporting Organization | Data type | Number of samples | Method | Language/ program | Validation | Performance |
|---|---|---|---|---|---|---|---|---|---|
| 7 | Zhang et al. (2013) | Depression | National Basic Research Pro-gram of China, National Natural Science Foundation of China, EU's Seventh Framework Programme OPTIMI, Fundamental Research Funds for the Central Universities | EEG | 15 13 depression 2 healthy | BPNN, KNN | SPSS | 2/3 train, 1/3 test + 3-fold CV | mean classification rate 94.2% (BPNN) mean classification rate 92.9 (KNN) |
| 8 | Tenev et al. (2014) | ADHD | ADHD = ADHD Project of EU-Cost Action B27, healthy = professional colleagues and community organization from Skopje, Macedonia | QEEG | 117 67 ADHD 50 healthy | SVM | - | 10-fold CV | accuracy 82.3% |
| 9 | Ergüzel et al. (2015a) | Depression | İstanbul Nöropsikiyatri Hastanesi | QEEG cordance | 55 depression (R=30, NR=25) | ANN | MATLAB | 6,8,10-fold CV | accuracy 89.09% (k=6), 85.45% (k=8) 87.27% (k=10) |
| 10 | Ergüzel et al. (2015b) | Trichotilomani-obsessive compulsive disorder | NP İstanbul Hospital | QEEG cordance | 79 39 TTM, 40 OKB | ANN, SVM, KNN, NB | MATLAB | 6, 10-fold CV | accuracy 63.29% ANND accuracy 67.08% SVM accuracy 59.96% KNN accuracy 56.96% NB accuracy 81.04% feature selection + SVM |
| 11 | Ergüzel et al. (2015c) | Depression-bipolar | İstanbul Nöropsikiyatri Hastanesi | QEEG cordance | 101 46 bipolar 55 depression | SVM (linear kernel, polynomial kernel, RBF kernel) | MATLAB | 6-fold CV(outer), 5-fold CV (inner) | accuracy 62.37% (no feature selection) accuracy SVM + PSO (73.26%) accuracy SVM + GA (75.24%) accuracy SVM + ACO (78.21%) accuracy SVM + IACO (80.19%) |
| 12 | Mohammadi et al. (2015) | Depression | Royal Ottawa HealthCare Group, the University of Ottawa Social Sciences and Humanities Research Ethics Boards | QEEG | 98 53 depression 43 healthy | C4,5 | MATLAB, IBM SPSS Modeler | % 70 train, % 30 test | accuracy 80% |

**Table 2. Continued**

| | Source | Disorder | Data set source/ethics committee / Supporting Organization | Data type | Number of samples | Method | Language/ program | Validation | Performance |
|---|---|---|---|---|---|---|---|---|---|
| 13 | Al-Kaysi et al. (2016) | Depression | Black Dog Institute, Human Research Ethics Committee of the University of New South Wales | EEG | 10 depression | SVM, LDA, ELM | - | LOOCV | error rate 0.2167 |
| 14 | Johannesen et al. (2016) | Schizophrenia | VA Connecticut Healthcare (VACHS) Human Studies Subcommittee, Yale University Human Investigation Committee | EEG | 40 schizophrenia 12 healthy | SVM | - | 3-fold CV | accuracy 87%, sensitivity 90%, specifility 77% |
| 15 | Ramyead et al. (2016) | Psychosis | FePsy Clinic at University Psychiatric Clinics Basel, University Psychiatric Outpatient Department of Basel or a psychiatrist's private practice | EEG | 53 ARMS-NT=35, ARMS-N=18 | LASSO (least absolute shrinkage and selection operator) | R | 10-fol CV *10 | balanced accuracy 57% (LPS), sensitivity 4%, specifility 67% balanced accuracy 69% (CSD), sensitivity 63%, specifility 76% balanced accuracy 70% (stacked), sensitivity 58%, specifility 83% |
| 16 | Mumtaz et al. (2017a) | Depression | Outpatient Clinic of Hospital Universiti Sains Malaysia (HUSM), Malaysia | EEG | 63 33 depression 30 healthy | LJR, NB, SVM | - | 10-fold CV *100 | accuracy 97.6%, sensitivity 96.66%, specifility 98.5% (LJR) accuracy 96.8%, sensitivity 96.6%, specifility 97.02% (NB) accuracy 98.4%, sensitivity 96.66%, specifility 100% (SVM) |
| 17 | Mumtaz et al. (2017b) | Depression | Hospital Universiti Sains Malaysia (HUSM), Kelantan, Malaysia | EEG | 74 30 healthy 34 hasta (R =16, NR =18) | LJR | MATLAB | 10-fold CV *100 | accuracy 87.5%, 95% sensitivity, specifility 80% |

**Table 2. Continued**

| | Source | Disorder | Data set source/ethics committee / Supporting Organization | Data type | Number of samples | Method | Language/ program | Validation | Performance |
|---|---|---|---|---|---|---|---|---|---|
| 18 | S. Zhao et al. (2017) | Depression | Beijing Anding Hospital Affiliated to Capital University of Medical Sciences | EEG | 170 81 depression, 89 healthy | Local classification(KNN + NB), SVM (RBF Kernel), Xgboost (Gbtree + LJR) | - | %75 train, %25 test 10-fold CV | local classification(KNN + NB) 78.4%, SVM (RBF Kernel) 77.8%, Xgboost (Gbtree + LJR) 75.8% |
| 19 | Bailey et al. (2018) | Depression | Monash Alfred Psychiatry Research Centre | EEG | 39 depression (R=10, NR=29) 20 healthy | SVM | - | 200,000 * 5-fold CV | balanced accuracy 91% sensitivity 90% specificity 92% |
| 20 | Ergüzel and Tarhan (2018) | Depression | Neuropsychiatry Istanbul | qEEG | 147 depression (R=90, NR=57) | ANN, SVM, DT | | 10-fold CV | accuracy 82.9%, specificity 88.9% (ANN) accuracy 86.4%, specificity 95.6% (SVM) accuracy 78.3% specificity 85.6% (DT) |
| 21 | Ergüzel et al. (2019) | Opioid | Neuropsychiatry Istanbul Hospital Department of Psychiatric Outpatient Clinics | qEEG | 134 75 opioid 59 healthy | LJR, ANN | MATLAB | 8-fold CV | accuracy 84.3% (LJR) accuracy (overall accuracy) 94.89% (ANN) |

Method
- ANN = artificial neural network
- DT = decision tree
- ELM = extreme learning machine
- KNN = k-nearest neighbor
- LDA = lineer discriminant analysis
- LJR = lojistik regression
- NB = naïve Bayes
- PLSR = partial least squares regression
- RF = random forest
- SVM = support vector machine

Validation
- CV = cross validation
- LOOCV = leave-one-out-cross validation

Number of Samples
- ARMS-NT = at-risk mental state patients did not made a transition to psychosis
- ARMS-T = at-risk mental state patients made a transition to psychosis
- R = responder
- NR = non-responder

* In some of the studies, more than one result was obtained with more than one parameter or algorithm. Since it is not possible to add all the results to the table, the best result or the results highlighted by the authors of the study are presented. Original sources can be examined to reach all results.

Data set: Since the data set is included in the algorithm for the purpose of "learning", it is called an experience. Excessive experience and data on different situations affect the performance positively.

- Existence of variables affecting the result: The existence of an attribute/variable (column) suitable for the problem under investigation affects the result.

- The chosen learning: Choosing the appropriate learning strategy for the problem under investigation or the structure of the data set affects the results.

- The algorithm used and parameters belonging to the algorithm, if available: Choosing the appropriate algorithm and, if any, parameters suitable for the structure of the data set and the chosen learning strategy can affect the performance.

Flach (2012) shows the logic of applying machine learning as in Figure 3. A data set consisting of examples (rows) and variables (columns) is used to perform a specific task. In accordance with the chosen learning strategy, part or all of the data set is used for the learning of the algorithm and the model is obtained by applying the selected algorithm to the training data. Different criteria are calculated according to the outputs of the model and performance evaluation is made. The learning strategy varies according to the structure of the current data set, while the learning strategy is called controlled or supervised in cases where the class values in the data set are certain, the learning strategy is called uncontrolled or unsupervised when the class values are not known (Mohri et al. 2012). To put it more clearly, in the supervised learning approach in the data set, the category / label that each sample belongs to is clear and analysis is made based on these values. In unsupervised learning, these values are not clear. In the supervised learning approach, it is aimed to make future inferences with methods such as classification and regression, while in the unsupervised learning approach, it is aimed to discover the features in the data by methods such as clustering (Bishop 2006).

The column given in the table as "Method" in Table 2 refers to the algorithms used. Different classification algorithms or statistical methods working according to the supervised learning approach were used in all studies. In the column referred to as "Application language/Program", the programming language used for the implementation of machine learning algorithms and the platform where this language was written is expressed. In the column that expresses "Validation", ie model performance evaluation methods, it is stated that the method according to which the training data set was selected while applying the classification algorithms was stated. In the classification methods, the data set is divided into two as training and testing; While the model is created with the training data set, the performance of the model is tested with the test data set. Bootstrap where the desired number of samples were randomly selected (Efron and Tibshirani 1993), hold-out where the data set was divided into training and test according to the
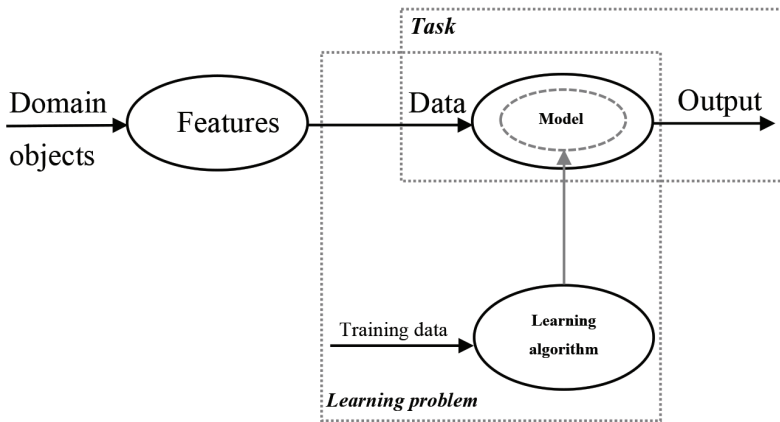
**Figure 3. An overview of how machine learning is used to address a given task (Flach 2012)**

determined ratio (Kohavi 1995), and cross validation method where one piece at a time was assigned as training and test by dividing the data set into equal numbers (Mosteller and Tukey 1968, Stone 1974) are frequently used among these methods. In the "Performance" column, which expresses the model performance evaluation criteria, it is stated according to which calculation value the performances of the created models are evaluated. Accuracy, error rate, sensitivity, recall, specificity, positive predictive value, negative predictive value, F-score of classification algorithms based on the values in Figure 4 (Han et al. 2012) are calculated and the evaluation of the model is completed accordingly.

**Figure 4. Confusion matrix (Han et al. 2012)**

| Confusion Matrix | | Predicted | | |
|---|---|---|---|---|
| | | **Positive** | **Negative** | **Total** |
| **Actual** | Positive | **TP**<br>**true positive** | **FN**<br>**false negative** | P |
| | Negative | **FP**<br>**false positive** | **TN**<br>**true negative** | N |
| | Total | P′ | N′ | P+N |

**P:** Number of samples actually belonging to the positive class
**N:** Number of samples actually belonging to the negative class
**P′:** The number of samples predicted to be in positive class
**N′:** The number of samples estimated to be in the negative class

Khodayari-Rostamabad et al. (2010a) conducted a study to predict the response to clozapine therapy in schizophrenia patients and used the partial least squares regression method. The performance of the model was calculated as 87.12% and 89.7% by averaging the specificity and sensitivity values, and the performance of the model was calculated as 85.7% as a result of the test performed with another group of patients.

Khodayari-Rostamabad et al. (2010b) used the partial least squares regression method

to estimate the effectiveness of an antidepressant used in the treatment of depression. For the evaluation of the model, the values of specificity (85.7%) and sensitivity (87.5%) were averaged and this value was calculated as 86.6%.

Khodayari-Rostamabad et al. (2011) used the mixture of factor analysis technique to estimate the response to repetitive transcranial magnetic stimulation therapy - rTMS treatment. To evaluate the model, specificity (83.3%) and sensitivity (77.8%) values were averaged and this value was calculated as 80%.

Ahmadlou et al. (2012) conducted a study to predict the response of ADHD patients to neurofeedback treatment. For the prediction, the model was created by linear discriminant analysis, and the accuracy was obtained as 84.2%, specificity as 80.6%, sensitivity as 88.2%.

Hosseinifard et al. (2013) made a classification study in which EEG frequency bands and nonlinear features were also included, and they differentiated between depressed patients and healthy individuals. KNN, LDA, LJR were used as classifiers. Different models were obtained, including feature selection and nonlinear features. Accuracy values were obtained as 73.3% (KNN), 76.6% (LDA) and 76.6% (LJR) in relation to the classification models made according to the EEG frequency bands.

Khodayari-Rostamabad et al. (2013) used mixture of factor analysis (MFA) in their study to estimate the effect of SSRI (selective serotonin reuptake inhibitor) antidepressant treatment on patients diagnosed with depression. For the evaluation of the model, specificity values equaled to 80.9% and sensitivity values equaled to 94.4% were averaged, and this value was calculated as 87.9%.

Zhang et al. (2013), using back propagation neural network (BPNN) and KNN (k=1) obtained accuracy values equaled to 94.2% and 92%, respectively, to distinguish between patients diagnosed with depression and healthy groups.

Tenev et al. (2014) differentiated ADHD and control groups with SVM in their study. More than one classification model was created in the study. The accuracy of the model established to distinguish between diagnosed patient and healthy groups among these was achieved as 82.3%.

Ergüzel et al. (2015a) estimated with ANN to predict whether repetitive transcranial magnetic stimulation - rTMS treatment would be beneficial in patients diagnosed with depression. The highest accuracy value was obtained as 89.09% in models with different parameters.

Ergüzel et al. (2015b), in the study they conducted to classify patients with trichotillomania (TTM) and obsessive-compulsive disorder (OCD), they obtained different accuracy values in the models they built by feature selection with ANN, SVM, KNN, NB methods. The highest accuracy value was obtained as 81.04% by using feature selection with its improved version with ant colony optimization algorithm and applying SVM.

Ergüzel et al. (2015c) used a SVM as a classifier in their study to differentiate between

depression and bipolar disorder patients and obtained different performance evaluation criteria from the SVM models they created with different feature selection methods. Among these, the highest accuracy value was obtained as 80.19%.

Mohammadi et al. (2015) used the C4,5 decision tree algorithm in their study to distinguish between patients diagnosed with depression and healthy individuals, and established models using different features and methods. Accordingly, the highest accuracy value in the model was obtained as 80%.

Al-Kaysi et al. (2016) used SVM, LDA, extreme learning machine (ELM) methods to predict the response to transcranial direct current stimulation (tDCS) treatment in patients diagnosed with depression, error rate value was given to evaluate the classification. This value was obtained as the average of the three models corresponding to 0.2167.

Johannesen et al. (2016), in their study conducted on schizophrenia, developed a model that can distinguish between patients diagnosed with schizophrenia and healthy individuals obtaining an accuracy rate ewual to 87% with the SVM classifier.

Ramyead et al. (2016) used the LASSO (least absolute shrinkage and selection operator) algorithm with CSD (gamma current-source density) and LPS (lagged phase synchronization) values calculated based on EEG values in their study to predict the clinical outcomes of patients at risk of psychosis. Accordingly, the area under the ROC curve was used to evaluate the model and balanced accuracy was obtained from different models as 0.57% (LPS), 0.69% (CSD) and 0.70% (LPS-CSD combination stacked).

Mumtaz et al. (2017a) obtained different results using varied models in the study to distinguish between patients diagnosed with depression and healthy individuals. According to the interhemispheric alpha asymmetry values, the obtained accuracy values were 97.6% with LJR, 96.8% with NB and 98.4% with SVM.

Mumtaz et al. (2017b) conducted a study to predict the response of patients diagnosed with depression to antidepressant treatment. Although different model performance criteria are obtained from LJR models established by using different feature extraction and feature selection methods, the highest accuracy value obtained is 87.5%.

Zhao et al. (2017) developed a wearable system to diagnose depression. In the study where local classification (KNN + NB), SVM (RBF Kernel), Xgboost (Gbtree + LJR) classifiers were used, the separation of individuals within the patient and control groups was obtained as 78.4%, 77.8%, 75.8%, respectively.

Bailey et al. (2018) established a classification model with a linear SVM to predict the response to repetitive transcranial magnetic stimulation - rTMS in patients diagnosed with depression, and the accuracy value was obtained as 91%.

Ergüzel and Tarhan (2018) used ANN, SVM and DT in order to predict the patients who may and may not respond to repetitive transcranial magnetic stimulation - rTMS treatment and obtained the accuracy values of 82.9%, 86.4%, and 78.3%, respectively.

Ergüzel et al. (2019) established a model with linear regression and ANN classification between opioid-addicted patients and control individuals and compared their performance. More than one result was obtained separately by using absolute power, relative power and cordance values for each frequency band. The highest accuracy values were obtained for each model in the table. From the LJR model, the highest accuracy value was obtained as 84.3% with beta frequency band and absolute power values, and the average overall accuracy was obtained as 94.89% with absolute power values in the theta frequency band from the ANN model.

## Discussion

Within the scope of this study, studies conducted in the field of psychiatry were examined. Machine learning studies in the field of psychiatry and the current situation of studies using EEG data and machine learning in the field of psychiatry were tried to be put forth. Examples from the field of psychiatry regarding the general use of machine learning methods were examined, but it was aimed to approach the studies using EEG data in detail.

Considering the studies conducted with machine learning methods in psychiatry, it was seen that support vector machine (SVM) and random forest (RF) methods stand out among the studies examined. The performance of the methods used varies according to the preferred parameters. In some studies, the best result was tried to be obtained by comparing the models established with different methods, while in some studies it was ensured that the model was established in different modalities with the same method. It was seen that the number of samples varied from study to study. In studies conducted based on data other than EEG data, different types of data such as MRI, sociodemographic data, clinical data, genetic data were typically used. In the 39 studies examined, it was observed that generally a single disease was addressed and a distinction was made between the patient and the healthy individual(s), but within the scope of certain studies more than one disease was addressed.

In all of the existing studies using machine learning and EEG, it was observed that the tools used in data analysis (programming language, platform, program) were not specified. Some studies state the tools, while others do not. Some studies indicate which programs or languages are used for both EEG and data analysis purposes, while others mention a single tool. In this case, it remains unclear which tool was used at which stage of the study. However, in case it was stated that a program was used at one stage of the study, it was assumed that it was continued with this tool in the later stages. It may be beneficial for other researchers to indicate the tools used for the studies. While examining the studies in which the tools were specified, it was observed that the MATLAB program was used extensively. Although MATLAB is a program which is frequently used in many different fields, R and Python languages are frequently preferred by data science researchers. It is thought that this program was used more frequently among studies,

as the studies examined were mostly conducted by researchers working in the fields of psychiatry or medicine. The gathering of researchers working in the field of data science with researchers from different fields such as psychiatry will encourage interdisciplinary studies and disseminate the use of many current concepts and methods such as artificial intelligence, machine learning, and data mining.

When the data sets used in the studies are examined in terms of sample numbers, it is seen that the numbers vary between 10 and 170. While the number of data in many areas is much higher, number of data is within normal range with respect to health studies, especially in the field of psychiatry. The differentiation made in the studies was structured in order to classify individuals as patients, healthy individuals or as R = responders and NR = non-responders according to the response given to a treatment. A comprehensive study has not been found in terms of the type of diseases that examines whether individuals are diagnosed with more than one disease, such as ADHD, schizophrenia, depression, or bipolar. Except for two studies that differentiate depression-bipolar, OCD-TTM, other studies were structured as response to a treatment or patient-healthy individual decomposition. In cases where more than two diseases are considered and addressed together, it has been observed that more comprehensive data sets were not utilised and studied on in terms of differentiation. The reason for this situation may be due to the nature of the psychiatry branch per se.

Within the scope of the reviewed studies, some of the model performance evaluation metrics were used to evaluate the models. Not using the same metrics in every study makes it difficult to compare models in diversified studies. Whereas solely accuracy value is set forth in some studies, in other studies additional metrics such as sensitivity and precision are also given. It is not possible to reveal and demonstrate the results of the studies that share all metrics within the limits of this study, and not being able to share the same metrics in each study makes it impossible to compare models on the same basis.

## Conclusion

It is considered that machine learning methods can be applied in the field of psychiatry and can generate results that support the decision-making mechanisms of field experts. Specialist physicians make symptom-based diagnoses within the framework of both internationally accepted references such as DSM-V and ICD and their own experiences. The symptom-based diagnostic approach, supported by existing artificial intelligence technologies, can be beneficial in the field of psychiatry in many ways, such as diagnosis, treatment, adjustment of medication dose, estimation of disease or recovery durations, identification of individuals in the risk group, predicting diseases or capturing details that may be missed by the human eye. In addition, these methods can be used to provide solutions to diseases with a holistic approach from a much broader perspective by evaluating the environmental, genetic and biological factors of individuals all together. Moreover, studies to be conducted with large data sets combining different types of data such as image data i.e. EEG, MRI (magnetic resonance imaging), clinical data, genetic data, and biological

data can increase the reliability of research in this field. Considering different diseases con-comitantlt within the scope of studies may enable a comprehensive differentiation among diseases. By collecting patient and control groups from different institutions and not from a single institution, the scope of the studies can be expanded nationally and, if possible, internationally in order to generalize the results obtained from the studies. As explicitly demonstrated in this study, it is significant to conduct the studies based on interdisciplinary approach by using methods that serve data science other than and in addition to statistical methods. It is considered that the improvement of prospective studies using such and similar modalities in future will contribute to the broadening of the scope of studies in the field of psychiatry.

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