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Research Paper: Artificial intelligence and stochastic process-based analysis of human psychiatric disorders

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ABSTRACT

This paper contains an analysis and comparison of different classifiers on different datasets of Psychiatric Disorders- Personality Disorder, Depression, Anxiety, Schizophrenia and Alzheimer's disease. Psychiatric disorders are also referred to as mental disorders, abnormalities of the mind that result in persistent behavior which can seriously cause day to day function and life. Stochastic in AI refers to if there is any uncertainty or randomness involved in results and are used during optimization; Using this process also helps to provide precise results. The study of stochastic process in AI uses mathematical knowledge and techniques from probability, set theory, calculus, linear algebra and mathematical analysis like Fourier analysis, real analysis, and functional analysis. this technique is used to construct neural network for making artificial intelligent mode for processing and minimizing human effort. This paper contains classifiers like SVM, MLP, LR, KNN, DT, and RF. Several types of attributes are used and have been trained by Weka tool, MATLAB, and Python. The results show that the SVM classifier showed the best performance for all the attributes and disorders researched in this paper.

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1. Background

Psychiatric Disorder is a mental illness that disturbs one's thinking, moods, and behaviors. Its consequence is an increase in risk of disability, pain, death, or loss of freedom. Recently, the implementation areas of Artificial Intelligence (AI) are growing. AI and computer simulation play a vital role in domain research such as statistics, forecasting, discovery, and more. With this technology, a solution to various problems can be found accordingly. Moreover, the stochastic process is when the initial state is known; however, the next state is unpredictable. Also, it has randomness, and the patterns need to be recognized.

In this paper, diverse psychiatric disorders' datasets are analyzed for their efficacy in predicting psychiatric disorders. Furthermore, the Weka tool, MATLAB, and Python are used to perform the analyses. The selection of which classifiers to use was based on the research done in the literature survey. Depression is a constant feeling of sadness and loss of interest. A personality disorder is a mental disorder in which one has a rigid and unhealthy pattern of thinking, functioning, and behaving. Anxiety disorder is excessive fear or stress. Schizophrenia is a serious mental illness that causes irrational thoughts, abnormal actions, delusion and wandering, such as hearing loss.

Alzheimer's disease (AD) is a progressive and degenerative brain disorder that results in nerve cell death, tissue loss, and memory loss in the brain. The global rate of AD is gradually increasing, and early diagnosis of AD is essential for the patient's care to control and prevent the progression of the disease for future treatments.

2. Literature Survey

Table 1 summarizes methodology and findings of studies regarding psychiatric disorders.

3. Method

Classification is a technique to identify the classes of given data points. To classify the data, we use classifiers. Classifiers take some data as input (training data), using which they train the model and find out how the data are related according to a class. Five disorders (Depression, Personality Disorder, Anxiety, Schizophrenia, and Alzheimer's Disease) are explained in this paper. One dataset for each disorder is taken for training and analysis. We focused on features from every dataset and classifiers were applied on each of the attributes. Analysis of each dataset by selecting the most important attribute out of many and analyzing them with classifiers, is the main process of our dataset analysis. Based on research we have listed, classifiers who have achieved highest accuracy in psychiatric disorders, on reference to this, Support Vector Machine (SVM), Logistic Regression, Multi-Layer Perceptron (MLP), Decision Tree (DT), k-Nearest Neighbor (KNN) and Random Forest (RF), are chosen as shown in Figure 1.

Support Vector Machine (SVM)

A Support Vector Machine is a machine learning algorithm used mainly for classification. SVM works both for regression and classification, but nowadays it is mostly used for classification due to its precise classifying ability. In this, the data is divided into n-dimensional spaces called hyperplanes. A decision boundary is created so that the new data can be separated and put according to its features into different classes (10).

Logistic Regression (LR)

Logistic Regression is the extension of linear regression. In this, instead of straight lines or hyperplanes, data is fitted using a logistic function with only two possible outcomes, 0 and 1 (12).

Multi-Layer Perceptron (MLP)

MLP is an addition to the feed-forward neural network. In this, there are three layers- Input layer (which receives the input data to be preprocessed), output layer (which performs the classification) and hidden layer present between input and output layer, containing arbitrary layers that are true computational engines of MLP (12).

Decision Tree (DT)

A Decision Tree is a flowchart type tree-like structure whose internal nodes are the tests on attributes, each leaf node holds a class label and every branch is the outcome of the test (12).

Table 1. Literature survey on psychiatric disorders

Research Title	Methodology	Findings
Arribas et al. "A signature-based machine learning model for distinguishing bipolar disorder and borderline personality disorder" (2018). (1)	- 130 participants (BD, BDP, and healthy individuals) - Classifier: Random forest - Signature-Based Model	Mood scores accuracy: - Healthy = 89–98% - BD = 82–90% - BDP = 70–78%
Acharya et al. "Automated EEG-based Screening of Depression Using Deep Convolutional Neural Network" (2018). (2)	- 30 Participants (15 depressed and fifteen healthy individuals) - EEG signals of both left and right brain hemispheres (open and rest states 5 minutes) - 13 layered Deep CNN model - Ninety percent train, 10% test - The network was trained using the backpropagation algorithm with a batch size of five.	Left hemisphere: - Accuracy = 93.54%, - Sensitivity = 91.89%, - Specificity = 95.18%. Right hemisphere: - Accuracy = 95.49%, - Sensitivity = 94.99%, - Specificity = 96.00%.
Shrivastava et al. "A SVM-based classification approach for obsessive compulsive disorder by oxidative stress biomarkers" (2019). (3)	- OCDP and Non-OCDP participants - Blood samples - SVM with 2 variants, Random Forest, Linear Discriminant Analysis, and K-NN (base classifier) - 5 osbMarkers - Clusters: K-Means and Fuzzy C-Means	- SVMR accuracy = 97±1%. - Fuzzy C-Means better with accuracy = 76.67%
Saeedi et al. "Major depressive disorder assessment via enhanced k-nearest neighbor method and EEG signals" (2020). (4)	- 34 depressed and thirty healthy individuals - Feature selection method: Genetic Algorithm - Three Classifiers: E-KNN, SVM, and MLP - 10-Cross Validation	Accuracy were as follows: - E-KNN = 98.44% (±3.4), SVM = 92.18% (±6.9), KNN = 95.31% (±5.2), MLP = 93.75% (±6.8) - Sensitivity: E-KNN = 97.10%, SVM = 88.23%, KNN =96.80%, MLP = 90.00% - Specificity: E-KNN = 100%, SVM =96.66%, KNN =93.33% MLP =94.41%
Cremers et al. "Borderline personality disorder classification based on brain network measures during emotion regulation" (2020). (5)	- Participants: 51 BPD, 26 Cluster C Disorder, and forty-four non-patients - fMRI data (acquired and preprocessed) - Images formatted from BrainVoyager to nifti format. - Phasic and Tonic Networks - Classifier: Linear Support Vector Machine	- Tonic-Strength model highest Balanced Accuracy = 62% - BPD vs NPC = 55% (bal. acc.)

Research Title	Methodology	Findings
Yang et al. “Multivariate classification of drug-naive obsessive-compulsive disorder patients and healthy controls by applying an SVM to resting-state functional MRI data” (2019). (6)	- Examined fractional Amplitude Low-Frequency Fluctuation (fALFF) - Applied Support Vector Machine (SVM) to discriminate OCD patients - Values of fALFF, calculated from sixty-eight drug-naive OCD patients and sixty-eight demographically matched healthy controls (classification model)	- SVM = 72%
Khazbak et al. “MindTime: Deep Learning Approach for Borderline Personality Disorder Detection” (2021). (7)	- User adds a diary input. - Analyzed to detect if there are signs of BPD symptoms. - Investigation of different classifiers to extracts features (Naive Bayes, SVM, KNN, and finally LSTM)	- SVM = 90.1% - LSTM = 91% - CNN = 65%
Bracher-Smith et al. “Machine learning for genetic prediction of psychiatric disorders: a systematic review” (2021). (8)	- Classifiers: naive Bayes, k-Nearest Neighbors (k-NN), penalized regression, decision trees, random forests, boosting, Bayesian networks, Gaussian processes, Support Vector Machines (SVMs), and neural networks - Dataset: thirteen studies were selected for inclusion, containing seventy-seven distinct ML models - Type: psychiatric disorders from genetics alone	- Schizophrenia :0.54–0.95 AUC - Bipolar: 0.48–0.65 AUC - Autism: 0.52–0.81 AUC - Anorexia: 0.62–0.69 AUC - AUC: Area Under the ROC (Receiver Operating Characteristic) Curve
Saidi et al. “Hybrid CNN-SVM classifier for efficient depression detection system” (2021). (9)	- 189 participants (audio): 107 training set, thirty-five validation set, and forty-seven test set - DAIC-WOZ dataset is used. - Using CNN classifier for training - The fully connected layers are replaced by SVM layers. - Input map is given to CNN. - The classification is done by an SVM classifier.	Accuracy: - CNN = 58.57% - Hybrid CNN-SVM (the proposed model) = 68%
Priya et al. “Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms” (2019). (10)	- 348 participants - DT, Random Forest, Naive Bayes, SVM, and KNN. - Data from the Depression, Anxiety and Stress Scale questionnaire (DASS ‘21) - Scores labeled on the basis of severity - normal, mild, moderate, severe, and extremely severe.	For depression: - Accuracy - DT=0.778, RF=0.798, Naive Bayes= 0.855, SVM=0.803, KNN=0.721 - F1 Score - DT=0.723, RF=0.766, Naive Bayes= 0.836, SVM=0.765, KNN=0.687

Research Title	Methodology	Findings
Pan et al. "Detecting Manic State of Bipolar Disorder Based on Support Vector Machine and Gaussian Mixture Model Using Spontaneous Speech" (2018). (11)	- Two classifiers are used- SVM (Support Vector Machine) and GMM (Gaussian Mixture Model) - Data Collection: twenty-one hospitalized patients' speeches were recorded. - Features Extraction: key features pitch, MFCC, etc. extracted by software SMILE. The LIBSVM toolbox → SVM HTK tool → GMM - 3 patients for single patient test & 21 patients for multiple patients test - The manic state detection accuracies of SVM and GMM compared using student's t-test,	For single patient experiment, accuracy obtained overall: - SVM = 88.56±5.26 - GMM = 84.46±1.85 - For multiple patient experiments, accuracy overall: - SVM =60.87±18.90 - GMM = 72.27±6.90
Dabhane et al. "Depression Detection on Social Media using Machine Learning Techniques" (2021). (12)	- Logistic Regression, KNN, SVM, DT, MLP, and Naive Bayes - Data collection: diverse types of tweets from twitter API (CSV file) - Data Preprocessing: removal of duplicate entries - Exploratory Data Analysis: analyze datasets and collect key features - Training and Testing 2 steps: 1. Implementing Algorithms Individually 2. Implementing Ensemble Learners: Here, the voting classifier and Blending ensemble classifier were used for greater performance and accuracy.	- KNN = 73.29% - Logistic regression = 84.86% - SVM = 85.04% - Naive Bayes Classifier = 83.04% - Decision tree=80.53% - Multilayer perceptron (MLP) = 78.65% For ensemble implementation: - Voting Classifier = 85.35% - Blending Classifier = 87.21%
Islam et al. "Detecting Depression Using K-Nearest Neighbors (KNN) Classification Technique" (2018). (13)	- 7145 Facebook comments data was collected using NCapture and processed using the LIWC2015 tool and then paraphrases were extracted to detect emotions. - Different KNN classifiers like Fine KNN, Medium KNN, Coarse KNN, Cosine KNN, Cubic KNN, and Weighted KNN were applied and their f-measure was compared. - The experiment was done in 10-fold cross-validation on all testing datasets.	Emotional Process: - Fine KNN = 0.59, Medium KNN = 0.59, Coarse KNN = 0.71, Cosine KNN = 0.58, Cubic KNN = 0.59, Weighted KNN= 0.60 Linguistic Style: - Fine KNN = 0.58, Medium KNN = 0.57, Coarse KNN = 0.70, Cosine KNN = 0.60, Cubic KNN = 0.57, Weighted KNN= 0.62 Temporal Process: - Fine KNN = 0.58, Medium KNN = 0.57, Coarse KNN = 0.70, Cosine KNN = 0.59, Cubic KNN = 0.57, Weighted KNN= 0.58 All features: - Fine KNN = 0.58, Medium KNN = 0.56, Coarse KNN = 0.67, Cosine KNN = 0.60, Cubic KNN = 0.55, Weighted KNN= 0.61

Research Title	Methodology	Findings
Wang et al. “Using Electronic Health Records and Machine Learning to Predict Postpartum Depression (PPD)” (2019). (14)	- Clinical assessment of PPD was used as the outcome based on Statistics Canada and International Classification of Diseases (ICD-10-CM) . - AI methods included LR, SVM, DT, NB, XGBoost, and RF.	The results suggest a potential for applying machine learning to EHR data to predict PPD and inform healthcare delivery. Best prediction performance achieved an AUC of 0.79 that it was for SVM model.
Al-ezzi et al. “Severity Assessment of Social Anxiety Disorder Using Deep Learning Models on Brain Effective Connectivity” (2021). (15)	- They recruited eighty-nine participants from 502. - Examine the SAD data and develop a task for SAD assessment to acquire EEG data. - EEG data preprocessing is done. And high and low frequency deflections. - Dataset helps to explain brain activity values. - Applied connectivity features for precision based SAD prediction based on PDC algorithm. - Different Deep learning network algorithm applied and then do analysis on the findings.	The CNN+LSTM is more accurate than the 2 layer or 3 layer CNN and LSTM with attention mechanisms. The result of CNN+LSTM: - Accuracy=93% - Sensitivity=95% - Specificity=85% - Precision=86%
Sau and Bhakta, ”Screening of anxiety and depression among seafarers using machine learning technology” (2019). (16)	- Study the variable data including the questionnaire with people such as their age, education, family, etc. - Feature selection eliminates the irrelevant features from the set of predictor values. - A final dataset with all fourteen features and one target and 470 instances were prepared for different classification. This was divided into two groups based on the period of data collection.	The classifiers and their accuracy and precision data: - CatBoost = 89.3%, 89% - Logistic regression = 87.5%, 84% - SVM = 82.1%, 80.7% - Naive Bayes = 82.1%, 76.9% - Random Forest = 78.6%, 80.7%
Jothi et al, ”Predicting generalized anxiety disorder among women using Shapley value” (2020). (17)	- The data acquisition phase, data relevant to the study were collected. - After that, Data cleaning and transformation would be performed. - The feature selection using Shapley value was conducted using the original GAD features. - selected features were used as inputs for classification prediction algorithms. - In the last phase, classification performance criteria were used to evaluate the prediction algorithm.	The performance of prediction models without feature selection is less than with the feature selection. The accuracy, sensitivity and specificity of classifier with feature selection, respectively: - Naive Bayes = 80%, 98.79%, 76.47% - Random Forest = 90.6%, 93.47%, 69.53% - J48 = 95.70%, 97.5%, 86.3%

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Gui et al. "The Impact of Emotional Music on Active ROI in Patients with Depression Based on Deep Learning: A Task-State fMRI Study" (2019). (22)	- A large convolution kernel of the same size as the correlation matrix for the feature matching of 264 ROIs. 1. 4D fMRI data are used to generate the 2D correlation matrix of one person's brain based on ROIs 2. processed by the threshold value which is selected according to the characteristics of complex network and small-world network. After that, the DLM in this paper is compared with SVM, logistic regression (LR), k-Nearest Neighbor (kNN), a common DNN, and a deep CNN for classification. 3. Calculate the matched ROIs from the intermediate results of the DLM which can help related fields further explore the pathogeny of depression patients.	Deep analysis of the brain mechanism of depressed patients is more conducive to solving the condition of depressed patients.
Wen et al. "Deep Learning Methods to Process fMRI Data and Their Application in the Diagnosis of Cognitive Impairment" (2018). (23)	- DL methods in fMRI Data Analysis: CNN (Feature Extraction, Auto-Encoder, 3D-CNN); FNN; - Development of DL Methods for fMRI Data Analysis in Cognitive Impairment.	This study reviewed the recent literature of deep learning used in fMRI data. We can make full use of the auto-extracted features to improve accuracy of deep learning methods.
Liu et al. "Classification of Alzheimer's Disease by Combination of Convolutional and Recurrent Neural Networks Using FDG-PET Images" (2018). (24)	- 3D FDG-PET image; - ADNI dataset(PET-MRI-Othertests); - MCI, NC and early AD classification. - Using deep 2D CNN network, Recurrent neural networks (RNNs); - BGRU network layer for classification	BGRU can boost the classification. This method performs better than others.
Sau and Bhakta, "Predicting anxiety and depression in elderly patients using machine learning technology" (2017). (25)	- 510 participants - Ten classifiers (BN, NB, Log, MLP, SMO, KS, RS, J48, RF, RT) were evaluated with a data set of geriatric patients. - They were tested with a 10-fold cross validation method.	The results showed that Random forest predicts anxiety and depression in elderly patients better than other classifiers also with accuracy 91% and false positive 10%, gold standard tool. - RF (AUC: 94.3, Accuracy: eighty-nine, F1: 85.1)
McGinnis et al. "Rapid Anxiety and Depression Diagnosis in Young Children Enabled by Wearable Sensors and Machine Learning" (2018). (26)	- 63 children and their primary caregivers - DSM-IV was checked to diagnose mental disorders. - Participant motion was tracked using a belt-worn IMU. - classification accuracy compared for SVM, DT, kNN, LR also for just accelerometer features (ACC), just gyro features (GYR), just angle features (ANG).	Analysis suggests that, when paired with machine learning, 20 seconds of wearable sensor data extracted from a fear induction task can be used to diagnosis internalizing disorders in young children with a high level of accuracy and at a fraction of the cost and time of existing assessment techniques and the LR model is the best performing compared to other with accuracy of 80% and AUC 0.92.

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Gui et al. "The Impact of Emotional Music on Active ROI in Patients with Depression Based on Deep Learning: A Task-State fMRI Study" (2019). (22)	- A large convolution kernel of the same size as the correlation matrix for the feature matching of 264 ROIs. 1. 4D fMRI data are used to generate the 2D correlation matrix of one person's brain based on ROIs 2. processed by the threshold value which is selected according to the characteristics of complex network and small-world network. After that, the DLM in this paper is compared with SVM, logistic regression (LR), k-Nearest Neighbor (kNN), a common DNN, and a deep CNN for classification. 3. Calculate the matched ROIs from the intermediate results of the DLM which can help related fields further explore the pathogeny of depression patients.	Deep analysis of the brain mechanism of depressed patients is more conducive to solving the condition of depressed patients.
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McGinnis et al. "Giving Voice to Vulnerable Children: Machine Learning Analysis of Speech Detects Anxiety and Depression in Early Childhood" (2019). (27)	- 71 children who spoke fluent English and their caregivers - Using DSM-IV to diagnosis children with internalizing. - Assessment of audio features to characterize the ability of the proposed approach for identifying children with an internalizing disorder - Classification models included LR, SVM with a linear and Gaussian kernel and RF.	The results showed that machine learning analysis of audio data from the task can be used to identify children with an internalizing disorder with 80% accuracy (54% sensitivity, 93% specificity). This new tool is shown to outperform clinical thresholds on parent-reported child symptoms, which identify children with an internalizing disorder with lower accuracy and similar specificity and sensitivity in this sample.
Nemesure et al. "Predictive modeling of depression and anxiety using electronic health records and a novel machine learning approach with artificial intelligence" (2021). (28)	- Use of Electronic Health Records (EHR) data of 4184 undergraduate students - A total of fifty-nine biomedical and demographic features from the general health survey were used. - Psychiatric diagnoses were done by a multi-stage process such as using DSM-IV - AI methods included XGBoost, RF, SVM, kNN and NN	The results indicated moderate predictive performance for the application of machine learning methods in detection of GAD and MDD based on EHR data.
Richter et al. "Using machine learning-based analysis for behavioral differentiation between anxiety and depression" (2020). (29)	- 125 participants: included HA, HD, HAD, and LAD (control) - Questionnaires to assess anxiety and depression included DASS-213, STAI-T27, BDI–II28, RRS29, and PSWQ30. - Behavioral tasks included EDPT, RTs, FAFT, WIT, WSAP, FET, and IST - AI method: DT	The prediction model for differentiating between symptomatic participants (i.e., high symptoms of depression, anxiety, or both) compared to control revealed a 71.44% prediction accuracy for the former (sensitivity) and 70.78% for the latter (specificity). 68.07% and 74.18% prediction accuracy was obtained for a two-group model with high depression/anxiety, respectively and Distinguishing between anxiety and depression by specific behavioral measures.
Chen et al. "Detecting Abnormal Brain Regions in Schizophrenia Using Structural MRI via Machine Learning" (2020). (30)	- Sample size: COBRE: Paranoid SZ=34, NC=34 - Extraction white matter and gray matter volume - Using SVM classifier	- Accuracy = 85.27% - Sensitivity = 85.87% - Specificity = 85.08%
Calhas et al. "On the use of pairwise distance learning for brain signal classification with limited observations" (2020). (31)	- A sample of eighty-four people; Feature extraction was performed using SNN architecture along with DSTFT. - After receiving the output of feature extraction the following classifiers were trained SVM, RF, XGB, NB, and KNN. This process was performed in LOOCV.	From the tested classifiers. DSTFT-SNN-XGB were found to be the most efficient. - Accuracy = 0.95±0.05% - Sensitivity = 0.98±0.02% - Specificity = 0.92±0.07%

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Fernando et al. “Neural memory plasticity for medical anomaly detection” (2020). (32)	- Recurrent ANN: LSTM layers followed by a Neural Memory Network with plasticity mechanism using EEG recordings from the auditory oddball trials.	There are no existing machine learning models that attempt the classification of schizophrenia risk using EEGs. With 93.86 ± 0.21% accuracy.
Guo et al. ”Support Vector Machine-Based Schizophrenia Classification Using Morphological Information from Amygdaloid and Hippocampal Subregions” (2020). (33)	- Sample size: COBRE: SZ=179, NC=77 - Extraction structural features (hippocampus, amygdala) - Using SVM classifier	- Accuracy = 81.75% - Sensitivity = 84.21% - Specificity = 81.16%
Phang et al. ”A Multi-Domain Connectome Convolutional Neural Network for Identifying Schizophrenia From EEGs Connectivity Patterns” (2020). (34)	- The proposed approach uses the MDC-CNN framework for classifying SZ and Healthy Control (HC) using EEG based effective brain networks. - Feature extraction was based on Time domain VAR model coefficient matrix (2D), frequency domain PDC matrix (2D), and hand crafted complex network measures (1D).	Performance of MDC-CNN on decision level - Accuracy = 91.69% - Sensitivity = 91.11% - Specificity = 92.50% - Classification time= 0.81s
Oh et al. “Identifying Schizophrenia Using Structural MRI With a Deep Learning Algorithm”, (2020). (35)	-- Sample size: BrainGluSchi COBRE, MCICShare, MorphCH, NUSDAST: SZ=443, NC=423 - Normalization - Create 3D images - Divide the brain into eight regions in each image - Using 3D CNN for classifier	Acc=97 Sen=96 Spec=96
Matsubara et al. “Deep Neural Generative Model of Functional MRI images for Psychiatric Disorder Diagnosis” (2019). (36)	- The proposed technique accepts any type of fMRI time series. It can be a 3D, 2D, k-space image, a vector of voxels, a feature vector of ROIs or a state of dynamic functional connectivity. - The DGM (deep neural generative model) approach was implemented using deep neural networks.	The accuracy of the proposed model for the following disorder are: SZ=71.3% BD=64%
Talpalaru et al. ”Identifying schizophrenia subgroups using clustering and supervised learning” (2019). (37)	- Sample size: NUSDAST: SZ=104, NC=63 - Segmentation using CIVET pipeline - Extraction means cortical thickness value from seventy-eight regions - Using agglomerative hierarchical clustering to feature reduction/selection - Using SVM, RF, Logistic regression to prediction that RF was better than others (accuracy)	Acc=75

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Liang et al, "Classification of First-Episode Schizophrenia Using Multimodal Brain Features: A Combined Structural and Diffusion Imaging Study" (2019). (38)	- This paper discussed identifying schizophrenia and multimodal multivariate neuroimaging features. - Multiple brain measures including regional Gray Matter (GM) volume, cortical thickness, gyrification, Fractional Anisotropy (FA), and Mean Diffusivity (MD) were extracted using fully automated procedures. - Gradient Boosting Decision Tree was then applied on the structural MRI data.	- 75.05% Accuracy was achieved from fused structural and diffusion tensor imaging metrics. - Average accuracy derived from combined features selected from cortical thickness, gyrification, FA, and MD was 76.54%. - 63.50% for GMV, 66.47% for cortical thickness, and 66.00% for MD. In another dataset, average accuracy was 54.70% for GMV, 60.94% for cortical thickness, and 67.43% for MD.
Chatterjee et al, "Identification of brain regions associated with working memory deficit in schizophrenia" (2019). (39)	- Preprocessing of functional MRI data. - Group ICA is applied to the Time series fMRI data. - Segment ICs with AAL atlas. Then extracting statistical features for each segment. - Applying FDR for feature ranking and classification using the feature subsets for each IC in LOOCV (leave-one-out cross validation) and SVM, and k-nearest neighbors.	Ninety-four percent (SVM) Ninety-six percent (1-NN)
Kalmady et al. "Towards artificial intelligence in mental health by improving schizophrenia prediction with multiple brain parcellation ensemble-learning" (2019). (40)	-Firstly, image acquisition of MRI data was done. Then image pre-processing was performed, in which pre-processing and feature extraction was done using MATLAB. After that each functional image was smoothed using a 4mm FWHM Gaussian kernel. Lastly, prediction and evaluation framework. "L2-regularized Logistic regression" AI technique was used.	The Accuracy of the L2 regularized logistic regression technique is 87%.
Qureshi et al. "3D-CNN based discrimination of Schizophrenia using resting-state fMRI" (2019). (41)	Structural data acquisition, functional data acquisition, pre-processing of functional MRI data, independent component analysis using MELODIC, classification using 3D-CNN deep learning framework.	Acc=98.01% Sen=97.49% Spec=98.62%
Yu et al. "Magnetic resonance imaging study of gray matter in schizophrenia based on XGBoost" (2018). (42)	- Sample size: Clinical: SZ=100, NC=100 - Extraction GLCM features - Using XGBoost classifier	Acc=72
Manohar and Ganesan. "Diagnosis of Schizophrenia Disorder in MR Brain Images Using Multi-objective BPSO Based Feature Selection with Fuzzy SVM" (2018). (43)	- Sample size: NAMIC: 60 Images from 20 people (SZ+NC) - Extraction hu moments, GLCM, zernike moments, and structure tensor - Using BPSO based on fuzzy SVM classifier	Acc=90 Sen=92.86 Spec=87.5

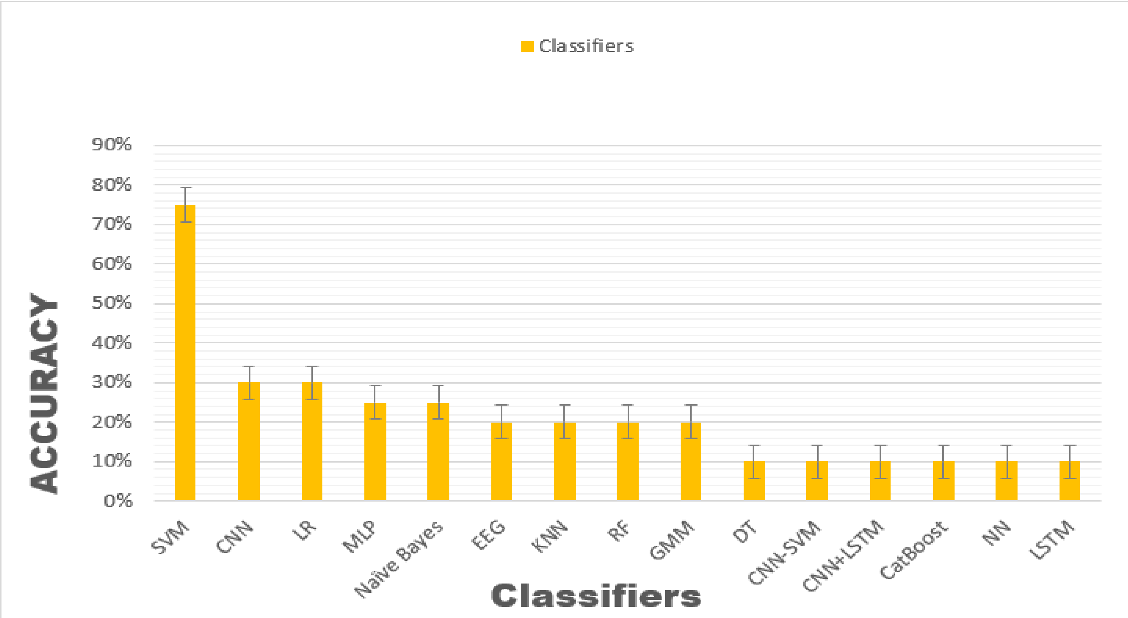

Figure 1. Comparison of classifiers used in literature

Random Forest (RF)

Random forest (RF) models are machine learning models that make output predictions by combining outcomes from a sequence of regression decision trees (60). It creates many classification trees and a bootstrap sample technique is used to train each tree from the set of training data. This method only searches for a random subset of variables in order to obtain a split at each node. For the classification, the input vector is fed to each tree in the RF, and each tree votes for a class. Finally, the RF chooses the class with the highest number of votes (61).

k-Nearest Neighbor (KNN)

KNN assumes that similar things exist nearby. KNN classifies the new data into most related categories. It collects and stores all the available data and then classifies a new category based on similarities between data (12).

3.1. Proposed Method

3.1.1. Weka Tool Approach

Weka tool is a collection of data mining tasks with machine learning algorithms. Data prepossessing, regression, visualization, classification, clustering, and association rules are predefined tools in the Weka tool. In this paper, for depression, personality disorder, anxiety, and schizophrenia, we have used the weka tool to apply three classifiers; SVM, Logistic, and MLP. In this approach, dataset analysis is done by Preprocessing and Classifying the dataset attributes. A flowchart of this approach is shown in Figure 2.

Raw dataset is taken as input in the weka tool. Instances store all values (nominal, numeric) in floating point numbers, if the attribute is nominal then the value is stored at the corresponding value in attributes definition. Every dataset had different instances. In Weka tool the first step is to preprocess the dataset and then classify it to obtain results.

1. Preprocessing

Attributes are the fields of data. They are also called features of the data. Attributes in the dataset can have data types such as: numeric (contains a floating-point number), nominal (represents a fixed set of nominal values), string (represents a dynamically expanding set of nominal values), date (represents a date), and relational (contain other attributes) is used for representing Multi-Instance data. In preprocessing, firstly nominal attributes are normalized after discretization is applied to the same. Secondly, numeric attributes are standardized for setting up the standard deviation to one.

a. Normalization

This method allows the transformation of any element from an equivalence class of any shape transforms into a specific one. It helps to eliminate the gross influences. Dataset was raw before normalizing, after normalizing all the nominal attributes of the dataset, the minimum and maximum values were set to 0 and 1 respectively. The scale is set to 1.0. The value of distinct was forty-four. This is how attribute values are brought to alignment using normalization.

b. Discretization

This filter allows converting a real-valued attribute into an ordinal attribute. It is a process of dividing the geometry of a dataset into finite elements to prepare for analysis. Dataset was normalized before applying discretization to attributes. After applying discretization to all nominal attributes, the value of count and weight became the same. The labels were divided into ten parts having a bin range precision of six. The desired weight of instances per interval was 1.0. Value of distinct became ten from forty-four after discretization.

c. Standardization

This filter is a scaling technique where the values are centered around the mean with a unit standard deviation. Unique standard deviation is obtained by standardization. Before applying standardization the standard deviation, mean, maximum and minimum can be any float value. After applying this method, the value of standard deviation becomes 1.0 for every numeric attribute in the dataset. Minimum and maximum values can be any negative/positive float value while the mean will be set to 0. Preprocessing is complete and the dataset is ready to classify.

2. Classification

This method includes classifier, attribute selection, and test options. Test options are used to set the percentage split value or cross-validation (folds). Only one attribute can be chosen at a time to obtain specific results for that attribute. Folds in machine learning means the distribution of data into equivalent parts like threefold, four-fold, etc.

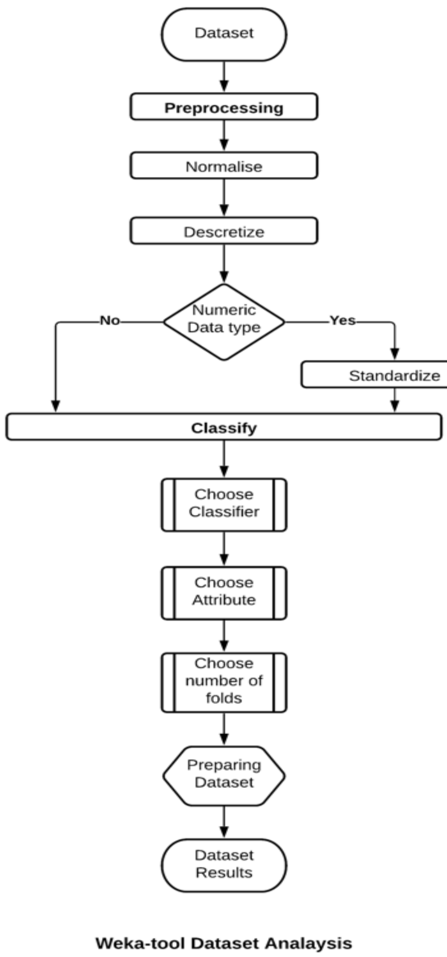

Figure 2. Weka Tool Dataset Analysis

Number of folds can be the same as the number of instances but to obtain accuracy folds should be between 5 to 20, not more than that. If folds are set to 10, then 1 fold is taken for training and the remaining 9 are taken for testing in the weka tool. Classifiers, attributes, and folds are predefined tools in the weka tool. Machine learning uses some specific mathematical methods to train datasets which are known as classifiers. In the Weka tool, firstly an attribute is selected then folds are set to 10, 12, or 8 (as per wish), then a classifier is selected, and finally after some preparation time, we obtain the results for that particular attribute and classifier. One after one attribute is trained and tested to observe which attributes obtain the highest accuracy among all attributes.

3.1.2. MATLAB Python Approach

MATLAB is a high-level language and interactive environment for numerical computation, visualization, and programming which is especially useful for medical images processing. Also, Python is an interpreted high-level general-purpose programming language. Its amazing libraries and tools help in achieving the task of image processing very efficiently. In this paper, for Alzheimer's disease diagnosis, we have used MATLAB for preprocessing, segmentation, and feature extraction, and used Python to apply SVM, KNN, DT, RF and MLP classifiers on the feature matrix. In this approach, dataset analysis is done by Preprocessing, Segmentation, Feature extraction, and classifying the dataset attributes. A flowchart of this approach is shown in Figure 3.

For the Alzheimer's disease study, we obtained data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu). The ADNI was launched in 2003 by the National Institute on Aging (NIA), the Food and Drug Administration (FDA), the National Institute of Biomedical Imaging and Bioengineering (NIBIB), non-profit private pharmaceutical companies, and other organizations, with funding of $60 million for the five-year private-public partnership (62). In this study, 50 MRI images data were collected from healthy people (Mean of age ± STD = 77.92 ± 5.17 and Mean of weight ± STD = 78.62 ± 21.32) and people with Alzheimer's disease (Mean of age ± STD = 74.4 ± 9.82 and Mean of weight ± STD = 79.14 ± 12.26).

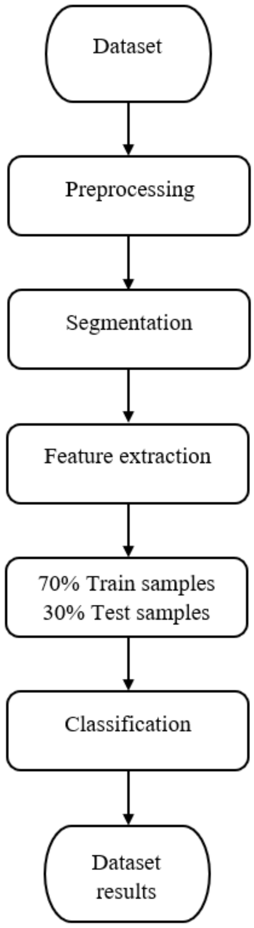

Figure 3. General steps to diagnosis of Alzheimer's disease based on MRI images using MATLAB and Python

All the participants in this study were scanned with GE Medical Systems or SIEMENS or Philips Medical Systems MRI scanner with 1.5 or 3 Tesla field strength. The T1-weighted MRI scans were captured with a coronal acquisition plane.

1. Preprocessing

In the analyzing process, at the first, pre-processing is performed to increase the quality of images. So the median filter was used to remove the noise in the images. The median filter is the filtering technique used for noise removal from images and signals. Median filter is very crucial in the image processing field as it is well known for the preservation of edges during noise removal (63).

2. Segmentation

Image segmentation is the process of partitioning an image into multiple segments (64). Image segmentation is typically used to locate objects and extract regions of interest in an image. In this paper, for the diagnosis of Alzheimer's disease, the lateral ventricles regions, hippocampus, and some areas of brain tissue are considered so that after their segmentation, features can be extracted from these areas.

Table 2. Accuracy of Personality Disorder, Depression, Anxiety and Schizophrenia for different classifiers

Classifier	Disorder	Attributes and Their Accuracy
		Elapse - 99.99%
	Personality Disorder	Gender - 58.86%
		Score - 99.55%
		Age - 37.30%
SVM	Depression	Married - 80.05%
		Incoming Salary - 82.01%
		Gender - 45.45%
	Anxiety	Student - 75.75% (12 folds)
		Age - 74.24%
		Subject - 24.54%
	Schizophrenia	Onset - 80.90%
		Disorder - 70%
		Elapse - 99.99%
	Personality Disorder	Gender - 63.70%
		Score - 21.86%
		Age - 37.57%
Logistic	Depression	Married - 81.17%
		Incoming Salary - 79.71%
		Gender - 42.42%
	Anxiety	Student - 60.60% (12 folds)
		Age - 72.72%
		Subject - 19.54% (12 folds)
	Schizophrenia	Onset - 79.09% (12 folds)
		Disorder- 66.18% (12 folds)
		Elapse - 99.99%
	Personality Disorder	Gender - 57.40%
		Score - 21.06%
		Age - 33.17%
MLP	Depression	Married - 81.24%
		Incoming Salary - 77.32%
		Gender - 42.42% (12 folds)
	Anxiety	Student - 68.18%
		Age - 74.24% (12 folds)
		Subject - 16.36% (12 folds)
	Schizophrenia	Onset - 71.36% (8 folds)
		Disorder - 60.45%

The lateral ventricles regions were extracted by Otsu's thresholding method and the hippocampus region was extracted by rectangular drawing method. Also, a skull stripping algorithm is used for segmentation of brain tissues from the surrounding region, and the Gray Matter (GM), White Matter (WM), Cerebral Spinal Fluid (CSF) were extracted using different methods of segmentation and thresholding.

3. Feature extraction

After the segmentation step, the area of each regions; lateral ventricles, hippocampus and brain tissues was calculated as a feature (Since the images are two-dimensional, the volume is equal to the area). Also, according to the changes in the intensity of the hippocampus, the statistical features such as mean and standard deviation from this region as well as texture features such as Gray Level Co-occurrence Matrix (GLCM), which includes correlation, contrast, and entropy, were extracted from this region as features. From ADNI, the scores of persons in the Mini-Mental State Examination (MMSE) and their age were also obtained to form the feature matrix. Therefore, a total of twelve features were extracted for each individual.

4. Classification

After obtaining the feature matrix for all individuals, we used the Training/Testing method to separate 70% of the data for training algorithms and 30% of the data for testing algorithms. Finally, five classifications (KNN, SVM, DT, RF, and MLP) were used to distinguish between healthy people and people with Alzheimer's. Then, Accuracy, sensitivity, and specificity were used to evaluate each of the classifiers. The results for each of the classifiers are shown in Table 3.

4. Results and Discussion

The proposed system trains and tests the model for classifying the data using certain classifiers. The application of all the classifiers- SVM, KNN, Logistic, MLP, DT, and RF- are shown in Figure 5,

Table 3. Results of average accuracy, sensitivity and specificity in 10 trials obtained from classifiers for Alzheimer's Disease (Rounded, and Mean ± SD)

	KNN	SVM	DT	RF	MLP
	0.90 ± 0.08	0.94 ± 0.05	0.91 ± 0.03	0.94 ± 0.07	0.92 ± 0.06
Sensitivity	0.89 ± 0.10	0.94 ± 0.08	0.90 ± 0.11	0.96 ± 0.09	0.92 ± 0.13
Specificity	0.93 ± 0.15	0.93 ± 0.08	0.92 ± 0.09	0.93 ± 0.08	0.93 ± 0.08

Table 4. The Spearman correlation and Pearson correlation for each extracted features for AD diagnosis

	Spearman correlation	Pearson correlation
Lateral ventricle (LV) size	0.419	0.338
Hippocampus (HP) size	-0.836	-0.611
Mean of intensity	-0.143	0.068
STD of intensity	0.387	0.276
Contrast of intensity	-0.090	-0.070
Correlation of intensity	-0.373	-0.411
Entropy of intensity	-0.050	0.030
White matter size	-0.164	-0.219
Gray matter size	-0.137	-0.224
Cerebral spinal fluid size	0.215	-0.088
MMSE	-0.850	-0.820
Age	-0.181	-0.223

Table 2, and Table 3.

The tables below contain attributes selected for classification and their corresponding accuracies, and in case of AD, their corresponding sensitivity and specificity is also given. The attributes were selected according to their effect on the data provided in the dataset. For personality disorder, depression, anxiety, and schizophrenia, three attributes have been selected from the datasets. From the table given below we can observe that for Personality Disorder, Depression, Anxiety, and Schizophrenia, SVM performs the best and MLP showed the least overall performance. For AD, SVM and RF gave the best accuracy.

For the Alzheimer's disease study, the Spearman correlation, Pearson correlation and Mutual Information were calculated to evaluate each of the extracted features in the diagnosis of Alzheimer's disease. The results are shown in Table 4 and Figure 4.

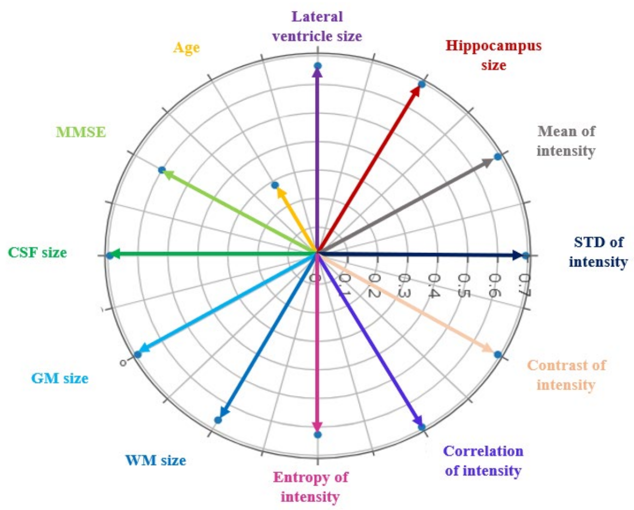

Figure 4. Impact of each feature on Alzheimer's diagnosis based on Mutual Information

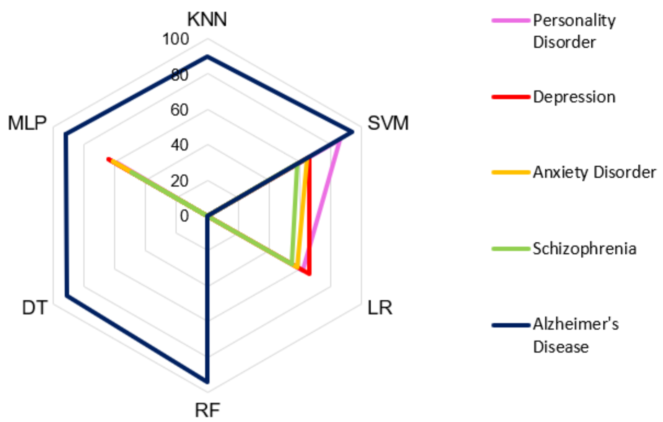

Figure 5. Results of each classifier in each psychiatric disorder

The above spider graph is plotted using data of table 2 and table 3. It shows the average accuracy for each disorder according to the classifiers.

5. Conclusion

In this research paper, SVM was better in comparison to the other two techniques. AI in psychiatric disorders uses computerized techniques as well as algorithms for diagnosis, prevention, and treatment of mental disorders. Such techniques will help society by diagnosing the disorder effectively and finding out the proper medication and treatment. Moreover, psychiatrists will be able to understand and easily find out the disorder.

In the Alzheimer's disease study, based on the Spearman correlation, Pearson correlation, and Mutual information, the extracted features were suitable features for Alzheimer's diagnosis. According to the study of papers, despite Alzheimer's disease, the lateral ventricles regions become larger and the hippocampus region becomes smaller, which in this study also follows these changes. Also, in the classification step, we tested several classifiers to find appropriate classifiers. Overall, the proposed model with the RF and SVM achieved the best performance and the accuracy of these classifiers using the proposed method are 94%.

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