**SUPPLEMENTARY APPENDIX**

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References.…………………………………………………………………………………………………………………………………………..20**Table S1:** Reporting quality of adequate-quality papers

|  |  |  |  |
| --- | --- | --- | --- |
| **Items** | **Reported, n (%)** | **Not reported, n (%)** | **Unclear, n (%)** |
| **Methods** | | | |
| Data source | 8 (100) | 0 (0) | 0 (0) |
| Data split methods | 8 (100) | 0 (0) | 0 (0) |
| Test set eligibility criteria (evaluation set) | 8 (100) | 0 (0) | 0 (0) |
| **Results** | | | |
| Baseline characteristic | 8 (100) | 0 (0) | 0 (0) |
| Treatment outcome classification | 8 (100) | 0 (0) | 0 (0) |
| Flow diagram | 8 (100) | 0 (0) | 0 (0) |
| Disease severity score distribution | 0 (0) | 8 (100) | 0 (0) |
| Use of reporting guideline | 0 (0) | 8 (100) | 0 (0) |

**Table S2.** Frequency table of features contributing to the study

|  |  |
| --- | --- |
| **Feature** | **Frequency** |
| Neuroimaging | 35 |
| Clinical and demographic variables | 30 |
| Molecular genetic | 8 |
| Cognitive measures | 6 |
| Neuroimaging and clinical | 9 |
| Clinical and cognitive | 4 |
| Clinical and genetic | 4 |
| Neuroimaging and genetic | 1 |
| Clinical, cognitive, and neuroimaging | 1 |

**Table S3:** Frequency table of missing value imputation methods

|  |  |
| --- | --- |
| **Missing value imputation methods** | **Frequency** |
| Did not address any imputation method | 44 |
| List-wise deletion, removing features with more missing values, and exclusion of subjects for the treatment of missing values. | 12 |
| Mean and mode imputation | 2 |
| Bagged tree imputation method | 1 |

**Table S4.** Methods for construction of the machine learning model

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Study reference** | **Predictor type** | **Max n of**  **predictors**  **used in the**  **model** | **Prediction method** | **Validation**  **method** | **Variable**  **selection** | **Additional**  **methods** | **Missing**  **data**  **imputation** | **Outcome** | **Treatment procedure** |
| (Alemi et al., 2011) | Genetics | 50 | Classification and regression trees (CART) | 10-fold cross- validation |  |  |  | Remission | Anti-depressant |
| (Al-Kaysi et al., 2017) | Demographical, clinical | 1 | Using three algorithms (support vector machine, extreme learning machine, and linear discriminant analysis) | Leave-one-out cross-validation |  |  |  | Response | Transcranial direct current stimulation (tDCS) |
| (Athreya et al., 2019) | Pharmacogenomics, clinical | 7 | Random forest | Nested cross-validation (inner 10-fold cross-validation, outer 5-fold cross-validation), external validation |  | Clustering | No missing data | Response | Anti-depressant |
| (Bailey et al., 2018) | Clinical, neuroimaging | 30 | Support vector machine (SVM) | 5-fold cross- validation |  | Morlet Wavelet Transform |  | Response | Repetitive Transcranial Magnetic Stimulation (rTMS) |
| (Bailey et al., 2019) | Clinical, neuroimaging | 54 | Support vector machine (SVM) | 5-fold cross- validation |  |  |  | Response | Repetitive Transcranial Magnetic Stimulation (rTMS) |
| (Bartlett et al., 2018) | Clinical, neuroimaging, demographical, Psychometric | 10 | Random forest | 5-fold cross-validation | Variable importance ranking |  |  | Remission | Anti-depressant |
| (Browning et al., 2019) | Emotional bias, clinical | 64 | Support vector machine (SVM) | Hold-out validation, leave-one-out cross-validation | C parameter in support vector machine (SVM) |  | Mean value | Response | Anti-depressant |
| (Cao et al., 2018) | Demographical, clinical | 16 | Linear kernel support vector regression (SVR) |  |  |  |  | Response | Electroconvulsive therapy (ECT) |
| (Carrillo et al., 2018) | Cognitive | 1 | Gaussian Naive Bayes classifier | 7-fold cross-validation |  |  |  | Response | Psilocybin |
| (Cash et al., 2019) | Neuroimaging, clinical | 4 | Support vector machine (SVM) | Leave-one-out cross-validation, 12-fold cross-validations |  | Shapiro–Wilk test, Pearson's or Spearman's analysis |  | Response | Repetitive transcranial magnetic stimulation (rTMS) |
| (Cepeda et al., 2018) | Treatment history, administrative | 10 | Decision tree | External validation, cross-validation |  |  |  | Resistance | Anti-depressant |
| (Chekroud et al., 2016) | Clinical | 25 | Gradient boosting machine | 10-fold cross-validation, external validation | Elastic net model |  | Including only patients without missing observations | Remission | Anti-depressant |
| (Corlier et al., 2019) | Neuroimaging | 783 | Elastic net regularization | 10-fold cross-validation |  | t-test |  | Response | Repetitive transcranial magnetic stimulation (rTMS) |
| (Costafreda, Khanna, Mourao-Miranda, & Fu, 2009) | Neuroimaging |  | Support vector machine (SVM) | Leave-one-out cross-validation | Principal components analysis |  |  | Remission | Cognitive-behavioral therapy |
| (Crane et al., 2017) | Clinical, neuroimaging | 5 | Logistic regression, random forest | Leave-one-out cross-validation, 5-fold leave-one-out cross- validation, external validation |  |  | Were excluded | Remission | Anti-depressant |
| (Delgadillo & Salas Duhne, 2020) | Clinical, demographical | 15 | Elastic net regularization, random forest | Cross-validation |  |  |  | Reliable and clinically significant improvement (RCSI) | Cognitive-behavioral therapy (CBT) |
| (Drysdale et al., 2017) | Neuroimaging | 258 | Support-vector machine (SVM) classifiers (using linear kernel functions) | Leave-one-out cross-validation |  | Canonical correlation analysis (Online Methods), PCA |  | Response | Repetitive Transcranial Magnetic Stimulation (rTMS) |
| (Erguzel et al., 2015) | Neuroimaging | 6 | Artificial neural network (ANN) | k-fold cross-validation (k=6, 8, 10) |  |  |  | Response | Repetitive transcranial magnetic stimulation (rTMS) |
| (Etkin et al., 2015) | Cognitive emotional biomarkers, clinical, demographical |  | Logistic regression | Leave-one-out cross-validation on bootstrap subsample, external validation |  | Linear Discriminant Analysis (LDA) | Were excluded | Remission | Anti-depressant |
| (Goldstein-Piekarski et al., 2018) | Neuroimaging | 2 | Generalized linear model (GLM) | Leave-one-out cross-validation |  |  |  | Remission | Anti-depressant |
| (Gordon, Rush, Palmer, Braund, & Rekshan, 2015) | Cognition,  emotional cognition, clinical | 2 | Logistic regression | Cross-validation | Removing the predictor with the highest mean absolute correlations with all of the other predictors being evaluated |  | Were excluded | Remission | Anti-depressant |
| (Guilloux et al., 2015) | Molecular | 13 | Support-vector machine (SVM) | Nested leave-one-out cross-validation, external validation |  |  |  | Non-remission | Medicine plus psychotherapy |
| (Hasanzadeh, Mohebbi, & Rostami, 2019) | Neuroimaging | 4 | K-nearest neighbors (KNN) | Leave-one-out cross- validation | Minimal-redundancy-maximal-relevance (mRMR) | Multiple artifact rejection algorithm (MARA) |  | Response | Repetitive transcranial magnetic stimulation (rTMS) |
| (Iniesta et al., 2016) | Demographical and clinical | 125 | Elastic net regularized regression | 10-fold cross-validation and permutation |  |  |  | Remission | Anti-depressant |
| (Iniesta et al., 2018) | Genetics, clinical | 20 | Elastic net regularized regression | 5-fold cross-validation and holdout external replication | CAT score |  | Bagged tree nonparametric method | Remission | Anti-depressant |
| (Jaworska, De La Salle, Ibrahim, Blier, & Knott, 2019)(2019) | Demographical, clinical, neuroimaging | 169 | Random Forests | 10-fold cross-validation | Extremely randomized trees (ERT) algorithm |  | Were excluded | Response | Anti-depressant |
| (Jiang et al., 2018) | Neuroimaging | 6 | Linear regression | Nested cross-validation (inner 10-fold cross-validation, outer leave-one-out cross-validation), external validation | ReliefF voxel-wise feature selection |  |  | Remission | Electroconvulsive therapy (ECT) |
| (Kambeitz et al., 2020) | Neuropsychological, socio-demographical, clinical | 56 | XGBoost tree boosting algorithm | Nested cross-validation |  |  |  | Response | Transcranial direct current stimulation (tDCS), anti-depressant |
| (Karim et al., 2018) | Neuroimaging | 8 | Tikhonov-regularized logistic classification | 10-fold cross- validation | PCA + Least angle regression feature selection |  |  | Remission | Anti-depressant |
| (Alexander Kautzky et al., 2017) | Sociodemographical, clinical | 48 | Generalized linear model (GLM) | 10-fold cross- validation | Random forest |  | Were excluded | Resistance | Anti-depressant |
| (A. Kautzky et al., 2019) | Clinical | 7 | Elastic net regularization | 10-fold cross-validation |  | Logistic regression |  | Resistance | Anti-depressant |
| (Khodayari-Rostamabad, Reilly, Hasey, De Bruin, & MacCrimmon, 2010) | Neuroimaging | 17 | The kernel partial least squares regression  method with a Gaussian Kernel  (KPLSR) | Nested cross-validation (inner 10-fold cross-validation, outer 11-fold cross-validation) | Kullback– Leibler (KL) distance measure |  |  | Response | Anti-depressant |
| (Khodayari-Rostamabad, Reilly, Hasey, De Bruin, & MacCrimmon, 2011) | Neuroimaging | 4 | Mixture of factor analysis model (MFA) | Leave-2-out cross-validation | Minimal-redundancy-maximal-relevance criterion (mRMR) |  |  | Response | Repetitive Transcranial Magnetic Stimulation (rTMS) |
| (Khodayari-Rostamabad, Reilly, Hasey, de Bruin, & MacCrimmon, 2013) | Neuroimaging | 27 | Mixture of factor analysis model (MFA) | Leave-n-out randomized permutation cross-validation | Fisher discriminant ratio (FDR) |  |  | Response | Anti-depressant |
| (Korgaonkar et al., 2015) | Neuroimaging | 3 | Decision tree | Cross- validation, external validation |  |  |  | Non-remission | Anti-depressant |
| (Leaver et al., 2018) | Neuroimaging | 25 | Support-vector machine (SVM) | Nested cross-validation (inner and outer 5 fold cross-validation) | Recursive feature elimination (RFE) |  |  | Response, non-response | Electroconvulsive therapy (ECT) |
| (Lin et al., 2018) | Clinical, genetics | 16 | MFNN with 1 hidden layer, logistic Regression | 10-fold cross- validation | Generalized  multifactor  dimensionality  Reduction (GMDR) |  | Were excluded | Response, remission | Anti-depressant |
| (Maciukiewicz et al., 2018) | Genotype | 38 | Support-vector machine (SVM), classification and regression trees (CART) | Nested cross-validation (inner 10 fold cross-validation, outer 5 fold cross-validation) | Logistic regression, lasso regression |  | Excluded for predictors, for outcome LOCF was used | Response | Anti-depressant |
| (Moreno-Ortega et al., 2019) | Neuroimaging | 2 | Logistic regression | Leave-one-out cross-validation |  |  |  | Remission, response | Electroconvulsive therapy (ECT) |
| (Mumtaz, Xia, Yasin, Ali, & Malik, 2017) | Neuroimaging | 15 | Logistic regression | 10-fold cross-validation |  | Wavelet and STFT based technique for decomposition of EEG data |  | Response | Anti-depressant |
| (Nie, Vairavan, Narayan, Ye, & Li, 2018) | Clinical and sociodemographical | 700 | Random forest, Gradient boosting decision tree, XGBoost, l2 penalized logistic regression, elastic net | 10-fold cross-validation, external validation | k-means clustering followed by test, elastic net |  |  | Resistance | Anti-depressant |
| (Nouretdinov et al., 2011) | Clinical, neuroimaging |  | Support vector machine (SVM) | Cross-validation | t-test |  |  | Diagnostic, Prognostic | Anti-depressant |
| (Patel et al., 2015) | Demographical, cognitive ability, imaging | 11 | Alternating decision tree | Nested cross-validation (inner and outer leave-one-out cross-validation) |  |  | Participants with missing data were omitted | Diagnostic, response | Anti-depressant |
| (Pei et al., 2020) | Neuroimaging, genetics | 90 | Support vector machine (SVM) | Leave-one-out cross-validation (LOOCV) | SVM-RFE (recursive feature elimination), Minimum redundancy maximum relevance (mRMR) algorithm | Fisher’s z-score, logistic regression |  | Early-response | Anti-depressant |
| (Perlis, 2013) | Clinical, sociodemographical | 15 | Logistic regression, random forest, Naive Bayes classifier, support vector machine (SVM) | 10-fold cross-validation, external validation | Cross-validation in the logistic regression model |  | Mean and mode imputation | Resistance | Anti-depressant |
| (Redlich et al., 2016) | Neuroimaging |  | Support vector machine (SVM), Gaussian process classifier | Leave-one-subject-out cross-validation | No feature selection |  | Excluded | Response | Exercise |
| (Rethorst, South, Rush, Greer, & Trivedi, 2017) | Clinical | 4 | Logistic regression | 10-fold cross-validation | Lasso, random forest | Bootstrap during variable selection |  | Remission, non-response | Anti-depressant |
| (Siegle et al., 2012) | Neuroimaging, clinical | 5 | Random forest | External validation |  | B-spline regression |  | Response, remission | Cognitive therapy |
| (Sikora et al., 2016) | Neuroimaging | 24 | Multivariate Relevance Vector Regression (RVR) Analysis | Leave-one-out cross-validation |  | Independent component analysis (ICA) |  | Response | Anti-depressant |
| (Sun et al., 2020) | Neuroimaging | 280 | Connectome-based predictive modeling (CPM) | 10-fold cross-validation |  |  |  | Remission | Electroconvulsive therapy (ECT) |
| (Tian et al., 2020) | Neuroimaging | 37 | Linear soft-threshold support vector machine | Leave-one-out cross-validation | Minimum redundancy maximum relevance (mRMR) | Multivariate pattern analysis (MVPA) |  | Response | Anti-depressant |
| (van Breda et al., 2018) | Clinical | 538 | Random forest, k-nearest neighbors, general linear model (GLMB) | 10-fold cross-validation | Feature similarity analysis (FS) |  | Removed features with 80% or more missing data. Other features with missing values were imputed with zero | Therapy success | Treatment as usual (TAU), Blended treatment (BT) |
| (Wade et al., 2016) | Neuroimaging | 28,760 | Support vector machine (SVM) | Leave-one-out cross-validation |  |  |  | Response | Electroconvulsive therapy (ECT) |
| (Wang et al., 2018) | Neuroimaging | 4 | Linear support vector machine (SVM) | Leave-one-out cross-validation |  |  |  | Response | Electroconvulsive therapy (ECT) |
| (Williams et al., 2015) | Neuroimaging, clinical | 2 | Discriminant analysis classifier | Leave-one-out cross-validation |  | Blocked randomization procedure |  | Response | Anti-depressant |
| (Wu et al., 2020) | Neuroimaging |  | Linear regression | 10-fold cross-validation, leave-one-site cross-validation, hold-out validation |  | Band power feature extraction |  |  |  |
| (Zandvakili et al., 2019) | Neuroimaging | 28 | LASSO regression, support vector machine (SVM) | Leave-one-out cross-validation, leave-two-out cross-validation |  |  |  | Response | Repetitive transcranial magnetic stimulation (rTMS) |
| (Zhang et al., 2020) | Clinical, sociodemographical, treatment history, genetics | 13 | Support vector machine (SVM) | k-fold cross-validation |  | t-test or rank-sum test and the chi-square  (c2) |  | Resistance | Anti-depressant |
| (Zhdanov et al., 2020) | Neuroimaging | 185 | Support vector machine (SVM) | Leave-one-site-out cross-validation, 10-fold cross-validation | Unpaired 2-tailed t-test |  |  | Response | Anti-depressant |

**Table S5**. Description summary of the selected papers for review

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Study reference** | **Outcome** | **Outcome variable** | **Treatment duration** | **Internal** | | | | **External** | | | |
| **Accuracy** | **Balanced accuracy** | **AUC** | **Max n of subjects** | **Accuracy** | **Balanced accuracy** | **AUC** | **Max n of subjects** |
| (Alemi et al., 2011) | Remission | QIDS |  | 0.87 | 0.86 |  | 762 |  |  |  |  |
| (Al-Kaysi et al., 2017) | Response | MADRS | 6 weeks | 0.79 |  |  | 10 |  |  |  |  |
| (Athreya et al., 2019) | Response | QIDS-C, HDRS | 8 weeks | 0.8 | 0.81 | 0.83 | 254 | 0.72 | 0.71 |  | 285 |
| (Athreya et al., 2019) | Remission | QIDS-C, HDRS | 8 weeks | 0.78 | 0.78 | 0.86 | 144 | 0.75 | 0.74 |  | 182 |
| (Bailey et al., 2018) | Response | HAM-D | 8 weeks |  | 0.91 |  | 39 |  |  |  |  |
| (Bailey et al., 2019) | Response | HAM-D | 8 weeks |  | 0.87 |  | 42 |  |  |  |  |
| (Bartlett et al., 2018) | Remission | HDRS-17 | 8 weeks | 0.62 | 0.52 | 0.62 | 184 |  |  |  |  |
| (Browning et al., 2019) | Remission | QIDS-SR 16 | 8 weeks |  |  |  | 57 | 0.59 | 0.57 |  | 239 |
| (Cao et al., 2018) | Response | HAM-D |  |  | 0.84 | 0.9 | 39 |  |  |  |  |
| (Carrillo et al., 2018) | Response | QIDS | 5 weeks | 0.85 | 0.83 |  | 35 |  |  |  |  |
| (Cash et al., 2019) | Response |  | 8 weeks | 0.89 | 0.87 | 0.92 | 76 |  |  |  |  |
| (Cepeda et al., 2018) | Resistance |  |  |  | 0.79 | 0.81 | 36902 |  |  | 0.79 | 9069 |
| (Chekroud et al., 2016) | Remission | QIDS-SR16 | 12 weeks | 0.65 | 0.65 |  | 1949 | 0.57 | 0.57 |  | 151 |
| (Corlier et al., 2019) | Response | IDS-30  SR |  | 0.78 | 0.77 | 0.76 | 109 |  |  |  |  |
| (Costafreda et al., 2009) | Remission | HRSD | 16 weeks |  | 0.64 |  | 16 |  |  |  |  |
| (Crane et al., 2017) | Remission | HDRS | 10 weeks | 0.83 | 0.82 |  | 29 |  | 0.74 |  |  |
| (Delgadillo & Salas Duhne, 2020) | Reliable and clinically significant improvement (RCSI) | PHQ-9 | 7.12 months |  |  | 0.60 | 1104 |  |  |  |  |
| (Drysdale et al., 2017) | Response | HAMD | 5 weeks | 0.89 |  |  | 711 |  |  |  |  |
| (Erguzel et al., 2015) | Response | HAMD-17 | 6 weeks | 0.87 | 0.87 | 0.89 | 55 |  |  |  |  |
| (Etkin et al., 2015) | Remission | HRSD, QIDS-SR16 | 8 weeks | 0.54 | 0.54 |  | 175 | 0.5 |  |  |  |
| (Etkin et al., 2015) | Response | HRSD, QIDS-SR16 | 8 weeks | 0.54 | 0.53 |  | 175 | 0.55 |  |  |  |
| (Goldstein-Piekarski et al., 2018) | Remission | HRSD-17 | 8 weeks | 0.69 | 0.69 |  | 96 |  |  |  |  |
| (Gordon et al., 2015) | Remission | QIDS-SRS16 | 8 weeks |  | 0.70 | 0.66 | 179 |  |  |  |  |
| (Guilloux et al., 2015) | Non-Remission | HRSD-17 | 12 weeks | 0.79 | 0.78 |  | 34 |  | 0.78 |  | 63 |
| (Hasanzadeh et al., 2019) | Response | HRSD, BDI-II | 7 weeks | 0.83 | 0.83 |  | 46 |  |  |  |  |
| (Iniesta et al., 2016) | Remission | HRSD | 12 weeks |  | 0.70 | 0.69 | 793 |  |  |  |  |
| (Iniesta et al., 2018) | Remission | HRSD | 12 weeks |  | 0.70 | 0.82 | 143 |  | 0.74 | 0.77 | 150 |
| (Jaworska et al., 2019) | Response | MADRS | 12 weeks |  |  | 0.74 | 51 |  |  |  |  |
| (Jiang et al., 2018) | Remission | HDRS |  | 0.88 | 0.89 |  | 38 |  |  |  |  |
| (Kambeitz et al., 2020) | Response to anti-depressant | HDRS-17 | 10 weeks |  | 0.49 |  | 94 |  |  |  |  |
| (Kambeitz et al., 2020) | Response to tDCS | HDRS-17 | 10 weeks |  | 0.55 |  | 94 |  |  |  |  |
| (Karim et al., 2018) | Remission | MADRS | 12 weeks |  | 0.70 | 0.77 | 49 |  |  |  |  |
| (Alexander Kautzky et al., 2017) | Resistance | HRSD |  | 0.65 | 0.63 |  | 480 |  |  |  |  |
| (Alexander Kautzky et al., 2017) | Remission | HRSD |  | 0.77 | 0.68 |  | 480 |  |  |  |  |
| (A. Kautzky et al., 2019) | Resistance | HRSD |  |  |  |  | 916 |  | 0.87 |  | 702 |
| (Khodayari-Rostamabad et al., 2010) | Response | HDRS | 6 weeks | 0.87 | 0.86 |  | 22 |  |  |  |  |
| (Khodayari-Rostamabad et al., 2011) | Response | HDRS | 6 weeks |  | 0.81 |  | 27 |  |  |  |  |
| (Khodayari-Rostamabad et al., 2013) | Response | HAMD-17 | 6 weeks | 0.9 | 0.88 |  | 22 |  |  |  |  |
| (Korgaonkar et al., 2015) | Non-remission | HRSD | 8 weeks | 0.9 |  |  | 74 | 0.78 |  |  | 83 |
| (Leaver et al., 2018) | Non-remission | HAM-17,  MADRS,  QIDS-SR, | 4 weeks | 0.88 |  |  | 74 | 0.78 |  |  | 83 |
| (Leaver et al., 2018) | Response | HAM-17,  MADRS,  QIDS-SR, | 4 weeks | 0.64 | 0.68 |  | 37 |  |  |  | 9 |
| (Leaver et al., 2018) | Non-response | HAM-17,  MADRS,  QIDS-SR, | 4 weeks | 0.74 |  |  | 37 |  |  |  | 9 |
| (Lin et al., 2018) | Remission | HRSD | 8 weeks |  | 0.61 | 0.70 | 421 |  |  |  |  |
| (Lin et al., 2018) | Response | HRSD | 8 weeks |  | 0.61 | 0.69 | 421 |  |  |  |  |
| (Maciukiewicz et al., 2018) | Response | MADRS | 8 weeks | 0.61 | 0.46 |  |  |  |  |  |  |
| (Maciukiewicz et al., 2018) | Remission | MADRS | 8 weeks | 0.50 | 0.50 |  | 149 |  |  |  | 37 |
| (Moreno-Ortega et al., 2019) | Remission | HDRS-24 |  | 1 |  |  | 18 |  |  |  |  |
| (Moreno-Ortega et al., 2019) | Response | HDRS-24 |  | 0.85 |  | 0.88 | 18 |  |  |  |  |
| (Mumtaz et al., 2017) | Response | BDI-II, HADS | 6 weeks | 0.77 | 0.77 |  | 64 |  |  |  |  |
| (Nie et al., 2018) | Resistance | QIDS-C16 | 6-24 weeks |  |  |  | 1964 | 0.71 | 0.68 | 0.74 | 490 |
| (Nouretdinov et al., 2011) | Diagnosis |  | 8 weeks |  | 0.80 |  | 38 |  |  |  |  |
| (Nouretdinov et al., 2011) | Prognosis |  | 8 weeks |  | 0.83 |  | 38 |  |  |  |  |
| (Patel et al., 2015) | Diagnosis | HAM-D | 12 weeks | 0.87 | 0.87 |  | 55 |  |  |  |  |
| (Patel et al., 2015) | Response | HAM-D | 12 weeks | 0.89 | 0.89 |  | 24 |  |  |  |  |
| (Pei et al., 2020) | Early-response | HDRS-6 | 2 weeks | 0.70 | 0.7 |  |  |  |  |  |  |
| (Perlis, 2013) | Resistance | QIDS-SR | 24 weeks | 0.69 |  | 0.71 | 1571 | 0.67 | 0.61 | 0.7 | 523 |
| (Redlich et al., 2016) | Response | DSM-IV | 6 weeks | 0.76 | 0.73 |  | 67 |  |  |  |  |
| (Rethorst et al., 2017) | Non-response | IDS-C | 12 weeks |  |  | 0.71 | 122 |  |  |  |  |
| (Rethorst et al., 2017) | Remission | IDS-C | 12 weeks |  |  | 0.79 | 122 |  |  |  |  |
| (Siegle et al., 2012) | Remission | BDI, HRSD | 16 weeks |  |  |  |  | 0.61 | 0.63 | 0.67 | 32 |
| (Siegle et al., 2012) | Response | BDI, HRSD | 16 weeks | 0.79 | 0.76 |  | 49 |  |  |  |  |
| (Sikora et al., 2016) | Response | QIDS | 10 weeks |  |  |  | 29 |  |  |  |  |
| (Sun et al., 2020) | Remission | HDRS |  | 0.69 | 0.63 | 0.63 | 122 |  |  |  |  |
| (Tian et al., 2020) | Response | HRSD | 8 weeks | 0.79 | 0.85 |  | 215 | 0.71 |  |  |  |
| (van Breda et al., 2018) | Therapy success | PHQ-9 | 3 months |  |  | 0.71 | 276 |  |  |  |  |
| (Wade et al., 2016) | Response | QIDS, HAMD, QIDS |  | 0.89 |  | 0.70 | 86 |  |  |  |  |
| (Wang et al., 2018) | Response | HRSD |  | 0.73 | 0.73 |  | 48 |  |  |  |  |
| (Williams et al., 2015) | Response | HDRS-17 | 8 weeks | 0.78 | 0.77 |  | 114 |  |  |  |  |
| (Wu et al., 2020) | Response | HAMD17 | 8 weeks |  |  |  | 309 |  |  |  | 152 |
| (Zandvakili et al., 2019) | Response | IDS-SR |  |  | 0.68 | 0.76 | 29 |  |  |  |  |
| (Zhang et al., 2020) | Resistance | HDRS-24 | 8 weeks | 0.71 | 0.73 |  | 606 |  |  |  |  |
| (Zhdanov et al., 2020) | Response | MADRS | 8 weeks |  | 0.76 |  | 122 |  |  |  |  |

**Figure S1.** Accuracy and AUC of validation methods versus the number of predictors before feature selection

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**Figure S2**. Accuracy and AUC of validation method versus the number of predictors used in the model

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**Figure S3**. Accuracy and AUC of validation method versus the number of subjects

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**Figure S4**. Accuracy in external validation versus the number of internal subjects

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**Figure S5.** Frequency of feature selection/extraction methods

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**Figure S6.** Frequency of types of machine learning methods used in this study

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**Figure S7**. Prevalence of various machine learning methods used in this study

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F**igure S8.** Frequency of validation methods used in this study

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