Category	ML Category	Prediction Outcome	Citation	Attribute Category	ML Method	PM	Improve Method
Engagement	Classification	Withdraw/ Not withdraw	Al-Shabandar et al. (2019)	Demographic, Behavioural	RF, FFNN, MLP, GBM, GLM	Accuracy, F1-SCORE, Sensitivity, Specificity, AUC	FS – chi-square RS – SMOTE HT – Random Search, Grid Search
Engagement	Classification	Level of Engagement	Flanagan et al. (2020)	Behaviour	SVM	Accuracy, Precision, Recall, F1-SCORE-score, AUC	-
			Ayouni et al. (2021)	Behavioural, Cognitive, Social engagement	ANN, DT, SVM	Accuracy, Precision, Recall, F1-SCORE	-
			Gorgun et al. (2022)	Discussion post	DT, RF, SVM	Accuracy, Precision, Recall, F1-SCORE	HT – Not specified
			Kurian (2023)	Behaviour	DT, CART, ANN	Accuracy, Precision, Recall, F1-SCORE, ROC	FS - Spearman correlation
			Qin et al. (2024)	Behaviour	SVM, CNN, RNN, LSTM	F1-SCORE	-
Engagement	Classification	Type of engagement	J.-Y. Wu (2021)	Demographic, engagement	RF, SVM, ANN	Accuracy, Precision, Recall, F1-SCORE, specificity	-
			Altamimi et al. (2022)	Behaviour	NN, SVM, DT, RF, kNN	MAE, MedianAE, RMSE; Accuracy, Precision, Recall, F1-SCORE	-
Engagement	Regression	Difference between deadline	Imhof et al. (2022)	Behaviour	NB, kNN, RBFN, FFNN, RT, GBM, RF, SVM	F1-SCORE, MAE, G-score, positive Precisiondicted value, TPR, Accuracy, Matthews correlation coefficient	HT - Grid search
Engagement	Clustering	Level of Engagement	Gledson et al. (2021)	Behavioural	K-Means, hierarchical clustering	Silhouette coefficient	-
			Binali et al. (2021)	Behavioural, cognitive, social, emotional engagement, metacognitive, self-regulation	K-Means	-	-
Engagement	Clustering	Level of Engagement	Quesada et al. (2022)	Behaviour, demographic	K-means, Spectral Clustering, Bisecting Kmeans, Agglomerative Clustering	Silhouette coefficient	-

Category	ML Category	Prediction Outcome	Citation	Attribute Category	ML Method	PM	Improve Method
Engagement	Clustering	Level of Engagement	Tamba et al. (2023)	Behaviour	KMeans	Silhouette coefficient	HT - Grid search
Engagement	Clustering	Level of Engagement	Kim et al. (2023)	Behaviour	K-Means	Silhouette coefficient	-
Engagement	Clustering	Engagement Consistency	Sher et al. (2020)	Engagement	Agglomerative	Silhouette coefficient	-
Engagement	Clustering& Classification	Cognitive Domain	Y. Yamasari et al. (2020)	Achievement	K-Means	Silhouette coefficient	FS – Correlation + OneR
Engagement	Clustering	Level of Engagement	Kim et al. (2023)	Behaviour	K-means, EM, farthest first	Accuracy, Precision, Recall, F-measure	-
Engagement	Clustering	Engagement Consistency	Sher et al. (2020)	Engagement	Agglomerative	Silhouette coefficient	-
Engagement	Clustering& Classification	Cognitive Domain	Y. Yamasari et al. (2020)	Achievement	K-Means K-means, EM, farthest first	Silhouette coefficient Accuracy, Precision, Recall, F-measure	FS – Correlation + OneR
Engagement	Clustering& Classification	Procrastinator/ Not procrastinator	Hooshyar et al. (2020)	Behavioural, cognitive engagement	K-Means SVM, Gaussian processes, DT, RF, NN, AdaBoost, NB	- Accuracy, Precision, Recall, F1-SCORE	-
Engagement	Clustering& Classification	Procrastinator/ Not procrastinator	H. M. Xu et al. (2021)	Time Management (cognitive engagement)	K-Means Jrip, PART, ZeroR, NB, J48	- Accuracy, Precision, Recall, F1-SCORE, kappa	-
Engagement	Clustering& Classification	Procrastinator/ Not procrastinator	Y. Yang et al. (2020b)	Behavioural engagement	K-Means, Spectral, Agglomerative	Fowlkes mallow index (FM), F-measure, element-centric	-
Engagement	Clustering& Classification	Engagement level	T. Yang et al. (2021)	Behavioural	Gaussian Mixed Model Clustering SPBi-LSTM, SVM, RF, LR	- Accuracy	
Engagement	Clustering& Classification	Engagement level	Benabbes et al. (2023)	Behavioural	K-Means, agglomerative, birch, DBSCAN DT, LR, RF, MLP, KNN, SVM	Silhouette, Calinski-Harabasz index TNR, TPR, AUC	HT – Not specified FS - PCA
Engagement	Clustering& Classification	Engagement level	Feng and Fan (2024)	Demographic, behaviour	K-Means J48, kNN, Bayes Net, RF, SVM, Logit Boost	F-measure Kappa, Accuracy, Precision, Recall, F1-SCORE, AUC, Youden index	FS - PCA

Category	ML Category	Prediction Outcome	Citation	Attribute Category	ML Method	PM	Improve Method
Engagement	Regression/ Classification	Student attitude	Guo et al. (2020)	Demographic, scores, discussion - engagement	Linear regression, polynomial regression, LASSO, SVR	RMSE	
Engagement	Regression/ Classification	Engagement Score, Engagement Level	Alshammari (2024)	Behaviour	NB, LR, SVM, RF DT	Precision, Recall, F1-SCORE Accuracy, Sensitivity, Specificity, balance Accuracy, Kappa	VIF feature selection
Engagement and Performance	Clustering	Engagement and study performance	Bucos and Dragulescu (2020)	Behaviour, Performance	K-Means	Silhouette coefficient	-
Engagement and Performance	Clustering	Engagement and study performance	H. Chen and Ward (2022)	Behaviour, Performance	K-Means, Affinity Propagation, Spectral, Hierarchical, Density-based Spatial	Adjusted rand index	-
Engagement and Performance	Classification	Engagement and Pass/Fail	López-Zambrano et al. (2022)	Behaviour	J48	ROC, AUC	-
Engagement and Performance	Classification	Engagement and performance	Wei et al. (2023)	Score	LR, SVM, MLP, RNNs, LSTM, GRU, bi-LSTM	F1-SCORE	-
Engagement and Performance	Classification	Engagement and performance	Preethi et al. (2024)	Behaviour	kNN, NBC, SVM, LOA	Accuracy, Precision, Recall, F1-SCORE, Kappa	-
Engagement and Performance	Classification	Engagement and performance	Mary.T and Rose.P. J (2023)	Demographic, Behaviour	RF, XGBoost	Accuracy, Precision, Recall, F1-SCORE	-
Engagement and Performance	Clustering & Classification	Type of engagement and grade	Xie et al. (2021)	Behaviour, Assessment Score, Final Grade	K-Means ECOC, RF	- Accuracy	FS – Genetic Algorithm
Engagement and Performance	Clustering & Classification	Procrastination, grade	Y. Yang et al. (2020a)	Behaviour	K-Means SVM, Gaussian Process, DT, RF, NN, AdaBoost, NB	- Accuracy, Precision, F1-SCORE, Kappa	-
Engagement and Performance	Clustering & Regression	Engagement level and assessment mark	Orji and Vassileva (2020)	Engagement, overall score	expectation-maximization RF	- Accuracy, RMSE	-

Category	ML Category	Prediction Outcome	Citation	Attribute Category	ML Method	PM	Improve Method
Engagement and Performance	Clustering & Regression	Engagement level and assessment mark	Subirats et al. (2023)	Behaviour, marks	K-Means, Hierarchical	-	
					MLP Regressor	MAE	
Engagement and Performance	Clustering & Regression	Engagement level and grade	R. Nand et al. (2020)	Engagement	Self-organizing map (SOM)	-	-
					NN regression	MSE, R	
Engagement and Performance	Clustering & Regression	Engagement level and grade	Rodriguez et al. (2021)	Engagement	K-Means	-	-
					Simple Regression	R-squared, Residual Std Error, f-statistic	
Performance	Classification	Grade	L. Q. Chen et al. (2021)	Behaviour, demographic, academic	SVM, LR, Bayes, TBCGA-ECOC, RF, XGB	Accuracy	FS – Genetic Algorithm
Performance	Classification	Grade	Hooshyar and Yang (2021)	Behavioural, social engagement	NN, L-SVM, R-SVM, GP, DT, RF, AB, NB	Accuracy, Precision, Recall, F1-SCORE, JAccuracyard, Fbeta	-
Performance	Classification	Grade	Altaf et al. (2019)	Behaviour, Grade	Multilayer FFNN	Accuracy, Recall, MSE	-
Performance	Classification	Grade	Predić et al. (2018)	Social engagement, score	NB, hidden NB, J48, RF	Accuracy, Precision	-
Performance	Classification	Grade	Sathe and Adamuthe (2021)	Demographic, score, behaviour	C5.0, J48, NB, RF, kNN, SVM, CART	Accuracy, Precision, Recall, TPR, FPR	FS - Pearson correlation
Performance	Classification	Grade	Ravneil Nand et al. (2021)	Demographic, Behaviour	ANN, DT, Decision Table, NB	Accuracy, TPR	RS - RUS FS - Pearson Correlation
Performance	Classification	Grade	Chandra et al. (2021)	Academic Background, score, behaviour	ANN, DT, SVM, NB, LR	Accuracy, Precision, Recall, F1-SCORE-	FS - Correlation
Performance	Classification	Grade	Nayak et al. (2023)	Demographic, Grade	J48, NB, RF, MLP	Accuracy, Precision, Recall, RMSE, ROC	FS - IG, GR, Pearson correlation
Performance	Classification	CGPA	Nachouki and Abou Naaj (2022)	Grade	RF	RMSE	-
Performance	Classification	Risk	Pongpaichet et al. (2020)	Behaviour, Grade	DT, RF, NB, stochastic Gradient Descent, LR, SVM, NN	Accuracy, Precision, Recall	RS – ROS
Performance	Classification	Risk	H. Wan et al. (2019)	Behaviour	gradient boosting, DT, TrAdaBoost	AUROC	-
Performance	Classification	Risk	Ramaswami et al. (2020)	Behaviour	RF, NB, LR, KNN	Precision, Recall, F1-SCORE	FS - Embedded
Performance	Classification	Risk	Macarini et al. (2019)	Behaviour	NB, RF, AdaBoost, MLP, KNN, DT	AUC	RS - SMOTE

Category	ML Category	Prediction Outcome	Citation	Attribute Category	ML Method	PM	Improve Method
Performance	Classification	Risk	Kumar Veerasamy et al. (2020)	Assessment performance	RF	Accuracy, AUC	-
Performance	Classification	Risk	Albreiki et al. (2023)	Demographic, Score	XGB, lightGBM, SVM, ExtraTree, RF, MLP	AUC, Sensitivity, Specificity, Accuracy	-
Performance	Classification	Risk	H.-C. Chen et al. (2022)	Demographic, Interaction	CNN, LSTM, CNN+LSTM	Accuracy, Pr, Recall, F1-SCORE	RS - SMOTE+RUS
Performance	Classification	Risk	Shoukath (2023)	Score	SVM	Accuracy, Precision, Recall, F1-SCORE	RS - SMOTE
Performance	Classification	Risk	Bañeres et al. (2023)	Demographic, Behaviour	DT	TNR, ACCURACY, TPR, F1-SCORE.5	-
Performance	Classification	Risk	Kurniadi et al. (2023b)	Behaviour	LR	Accuracy, Precision, Recall, F1-SCORE	Lasso and ridge regularization
Performance	Classification	Risk	Kurniadi et al. (2023a)	Behaviour	DT, RF	Accuracy, Precision, Recall, F1-SCORE-	-
Performance	Classification	Risk	Osborne and Lang (2023)	Behaviour	LR, RF, kNN, NN, Generalized Linear Model (GLM)	Accuracy, Sensitivity, Specificity, Precisionc allision, AUC	-
Performance	Classification	Risk	Altaf et al. (2023)	Behaviour, Demographic	CNN, LSTM, CNN+LSTM	Accuracy, Precision, Recall, F1-SCORE	RS- SMOTE FS - CNN
Performance	Classification	Risk	Saidani et al. (2024)	Behaviour	RF, LR, GNB, ETC, SGD, SVM, kNN, DT, GBM	Accuracy, Precision, Recall, F1-score	FS - CNN;
Performance	Classification	Performance	Hassan et al. (2021)	Academic background, demographic, economic, behaviour	DT, KNN, NN, NB, SVM, AB, Bagging, RF, GR, XGB	Precision, Recall, F1-SCORE	RS - SMOTE, ROS, ADS, RUS, NM, CNN, ENN, TL, SMOTEENN, SMOTETL FS- 3 filter, 3 wrappers HT – grid search
Performance	Classification	Performance	Hassan et al. (2019)	Academic background, demographic, economic, behaviour	DT, ANN, SVM	Accuracy, Precision, Recall, F1-SCORE, AUC	FS – RF Regressor HT – Grid Search
Performance	Classification	Performance	Hassan et al. (2020)	Academic background, demographic, economic, behaviour	DT, RF, Bagging, Boosting, AdaBoost, Gradient Boosting, XGBoost	Accuracy, Precision, Recall, F1-SCORE	RS – SMOTE, ROS, ADASYN, RUS, ENN, TL, SMOTE-ENN, SMOTE-TL, SMOTEBoost, RUSBoost
Performance	Classification	Performance	Saleem et al. (2021)	Academic background, demographic, behaviour	DT, RF, Gradient Boosting Trees, NB, KNN	Precision, Recall, F1-SCORE	-

Category	ML Category	Prediction Outcome	Citation	Attribute Category	ML Method	PM	Improve Method
Performance	Classification	Performance	Lee and Kurniawan (2019)	Behaviour, performance, score	Linear Regression	Precision, Recall	FS – Recallursive Feature Elimination
Performance	Classification	Performance	Evangelista (2021)	Behaviour, Score	NB, DT, RF, kNN, OneRule, J48, SVM, NN, Jrip	Accuracy, Precisionn, Recall, F1-SCORE	FS - Correlation RS - SMOTE
Performance	Classification	Performance	Prasertisirikul et al. (2022)	Demographic, behaviour, score	LR, NB, kNN, SVM, DT, RF, XGBoost	Accuracy, Precision, Recall	FS - XGBoost Importance RS - SMOTE
Performance	Classification	Performance	Gaftandzhieva et al. (2022)	Behaviour	RF, XGB, kNN, SVM	Accuracy, Precision, Recall, F1-SCORE	RS- Single-point crossover FS - Chi-square
Performance	Classification	Performance	Smirani et al. (2022)	Behaviour	Light Gradient Boosting Machine, XGB, RF	Accuracy, Precision, Recall, F1-SCORE	-
Performance	Classification	Performance	H. Ma et al. (2023)	Behaviour	LSTM, lSVM, rbfSVM, LR, DT, RF	Kappa coefficient, Precision, Recall, F1-SCORE	FS - CNN
Performance	Classification	Performance	Sabri et al. (2023)	Demographic, Behaviour, Grade	SVM	Accuracy, Precision, Recall, F1-SCORE	-
Performance	Classification	Dropout or Not Dropout	J. Chen et al. (2019)	Behaviour	Logistic Regression, SVM, DT, back propagation NN, entropy net, LSTM, GA-ELM, DT-ELM	Accuracy, Precision, Recall, F1-SCORE-, AUC, training time	FS – IG
Performance	Classification	Dropout or Not Dropout	Zheng et al. (2020)	Behaviour	FWTS-CNN, LR, NB, RF, SVM, DT	Accuracy, Precision, Recall, F1-SCORE-	-
Performance	Classification	Dropout or Not Dropout	Yu et al. (2021)	Demographic, score, grade	LR, GBT	Accuracy, Recall, TNR	HT - Grid search
Performance	Classification	Dropout or Not Dropout	Niyogisubizo et al. (2022)	Grade	RF, XGB, GB, Feed-forward NN	Accuracy, Precision, Recall, F1-SCORE, AUC	FS - Correlation HT – Not specified
Performance	Classification	Dropout or Not Dropout	Pecuchova and Drlik (2023)	Behaviour, Score	LR, RF, DT, kNN, SVM, AdaBoost, XGBoost	Accuracy, Precision, Recall, F1-SCORE	RS - SMOTE HT - Grid Search
Performance	Classification	Dropout or Not Dropout	Park and Yoo (2021)	Demographic, behaviour	DT, RF, SVM, DNN	Accuracy, Precision, Recall, F1-score, ROC	RS - ROS
Performance	Classification	Dropout or Not Dropout	Anh et al. (2023)	Progress, Demographic	CNN, graph CNN-based model, tabular learning model, LR, SVM, light gradient boosting	Accuracy, Precision-macro, Recallall-macro, F1-SCORE-macro	-

Category	ML Category	Prediction Outcome	Citation	Attribute Category	ML Method	PM	Improve Method
Performance	Classification	Dropout or Not Dropout	Kaensar and Wongnin (2023b)	Academic Background, academic	DT, LR, MLP, NB, RF, SVM	Accuracy, Precision, Recall, F1-SCORE	SMOTE
Performance	Classification	Dropout or Not Dropout	Vaarma and Li (2024)	Demographic, academic background, Behaviour	LR, RF, SVM, LDA, kNN, NB, NN, XGB, CatBoost, lightgbm	Precision, Recall, F1-SCORE	Permutation importance feature selection
Performance	Classification	Pass or Fail	Sukhbaatar et al. (2019)	Behaviour, academic	NN	Accuracy, Precision, Sensitivity, F1-SCORE	-
Performance	Classification	Pass or Fail	Almeda et al. (2018)	Behaviour	J48	Kappa, AUC ROC	-
Performance	Classification	Pass or Fail	Leite et al. (2021)	Behaviour	LR, DT, SVM, NB, RBFSVM, GPC, MLP, Ridge, RF, AdaBoost, GBC, ET, LightGBM, CatBoost	Accuracy, F1-SCORE-, AUC	-
Performance	Classification	Pass or Fail	Raga and Raga (2019)	Engagement	NN	Accuracy, AUC-ROC	-
Performance	Classification	Pass or Fail	Y. Chen et al. (2020)	Demographic, behaviour	RF, J48, LR, Bagging	Precision, Recall, F1-SCORE	RS – SMOTE
Performance	Classification	Pass or Fail	Tomasevic et al. (2020)	Precisionvious performance, demographic, engagement	KNN, SVM, ANN, DT, LR, NB, Bayesian Linear regression	Accuracy, RMSE	-
Performance	Classification	Pass or Fail	Helal et al. (2018)	Demographic, behaviour, academic	NB, SMO, J48, Jrip	Precision, Recall, F1-score, kappa, AUC	-
Performance	Classification	Pass or Fail	Chango et al. (2019)	Behaviour, academic	J48, RepTree, RandomTree, JRip, Nnge, PART	Accuracy, F1-SCORE, ROC	-
Performance	Classification	Pass or Fail	Bernacki et al. (2020)	Behavioural	LRn, J48, Jrip, NB	Accuracy, Precision, Recall, kappa	FS – forward selection
Performance	Classification	Pass or Fail	Cagliero et al. (2021)	Demographic, engagement, academic	Association rules; C4.5 (DT), MLP, SVM, NB, KNN, RF	balanced Accuracy, Precision, Recall, F1-score	-
Performance	Classification	Pass or Fail	Qu et al. (2019)	Behavioural	MLP, LSTM, M-F-LSTM, NOSEP	Accuracyuracy, Recallall	-
Performance	Classification	Pass or Fail	Hasan et al. (2020)	Academic behaviour	Classification Tree, RF, KNN, SVM, LR, NB, NN, CN2 Rule Induction.	Accuracy, sensitivity, specificity, F1-score	FS – IG, GR, Gini, Genetic Algorithm, PCA
Performance	Classification	Pass or Fail	Martínez et al. (2019)	Academic, behaviour	NB, NN, DT (GBT, RF), SVM	Classification error, sensitivity, specificity, AUC	
Performance	Classification	Pass or Fail	Bretana et al. (2020)	Demographic, academic	SVM	Accuracy, Precision, sensitivity, specificity	FS – Variance inflation factor

Category	ML Category	Prediction Outcome	Citation	Attribute Category	ML Method	PM	Improve Method
Performance	Classification	Pass or Fail	Karalar et al. (2021)	Demographic, behaviour	gradient boosting, quadratic DA (QDA), DT, RF, ET, LR, ANN	Accuracy, Precision, sensitivity (Recallall), specificity, balanced Accuracy, F1-SCORE	FS – SelectKBest HT – Grid Search
Performance	Classification	Pass or Fail	Damuluri et al. (2019)	Behaviour	SVM, NB, KNN, LDA	Accuracy, specificity, AUC	-
Performance	Classification	Pass or Fail	Qi et al. (2018)	Behaviour	LSTM, RNN, LR, SVM	AUC	HT – grid search
Performance	Classification	Pass or Fail	Kabathova and Drlik (2021)	Interaction	LR, DT, NB, SVM, RF, NN	Accuracy, Recall, Precision, F1-score, classificati on error	HT – grid search
Performance	Classification	Pass or Fail	X. Ma et al. (2018)	Demographic, behaviour	DT, SVM, DNN	Precision, Recall, F1-SCORE	GS –UG HT – Grid Search
Performance	Classification	Pass or Fail	Hidalgo et al. (2021)	Behaviour, Performance	greedy NN, bayesian NN	Accuracy	FS – ANOVA, RFECV HT – tree-structured
Performance	Classification	Pass or Fail	Huang et al. (2021)	Behaviour	LSTM	AUC	-
Performance	Classification	Pass or Fail	Zou et al. (2020)	Behaviour	LG, NB, SVM, K-Mean, ANN	Accuracy	-
Performance	Classification	Pass or Fail	Chytas et al. (2020)	Behaviour	NN, SV, DT, kNN	Accuracy, Precision, Recall, F1-SCORE	-
Performance	Classification	Pass or Fail	Galici et al. (2023)	Behaviour	BiLSTM	Accuracyu racy	-
Performance	Classification	Pass or Fail	Deeva et al. (2022)	Behaviour	SVM, LR, RF, NB	Accuracy, AUC, top decile lift	RS - ROS
Performance	Classification	Pass or Fail	Parkavi and Karthikeyan (2023)	Behaviour	Adaptive Neuro Fuzzy Inference System, NB, kNN, SVM, DT, DA	Accuracy, Precision, Recall, F1-SCORE	FS - Factor Analysis
Performance	Classification	Pass or Fail	Hu (2022)	Behaviour	CNN	Accuracy, Sensitivity, Specificity, Precision, F1-SCORE	-
Performance	Classification	Pass or Fail	Domladovac (2021)	Behaviour	NN, gradient boosted tree, RF, LR, SVM	FNR, Recall, Accuracy	FS - Pearson Correlation HT - Grid Search
Performance	Classification	Pass or Fail	Uliyan et al. (2021)	Grade	BiLSTM, CRF	Precision, Recall, F-score	-
Performance	Classification	Pass or Fail	Alalawi et al. (2021)	Scores	RF, SVM, DT, kNN, NB	Accuracy, Precision, Recall, F1-SCORE	FS - Correlation HT - Grid Search
Performance	Classification	Pass or Fail	Cazarez (2022)	Scores	Probabilistic NN, SVM, DA	Accuracy, Re, Sensitivity, Specificity, F1-SCORE	-

Category	ML Category	Prediction Outcome	Citation	Attribute Category	ML Method	PM	Improve Method
Performance	Classification	Pass or Fail	Kustitskaya et al. (2022)	Behaviour, Score	kNN, Linear DA, Bayesian Network.	weighted F1-SCORE	-
Performance	Classification	Pass or Fail	Bertolini et al. (2021)	Demographic, behaviour, academic background	LR, elastic net regression, RF, XGBoost	AUC	FS - Correlation Attribute Evaluation, Fisher Score, IG, Relief RS - SMOTE
Performance	Classification	Pass or Fail	Karalar et al. (2021)	Demographic, Behaviour, quiz score	Gradient Boosting, Quadratic DA, DT, RF, ET, LR, ANN	Accuracy, Precision, Recall, Specificity, Balanced Accuracy, F1-SCORE	FS - Univariate statistical HT – Not specified
Performance	Classification	Pass or Fail	Bertolini et al. (2022)	Demographic, Behaviour	LR, elastic net regression, RF, XGBoost, NN	AUC	
Performance	Classification	Pass or Fail	Bertović et al. (2022)	Score	SVM, LinearSVM, MLP, RF, LR, kNN, NB, DT	AUC, Cohen Kappa, Accuracy	-
Performance	Classification	Pass or Fail	Kaensar and Wongnin (2023a)	Behaviour	NN, RF, DT, LR, Linear Regression, SVM	Accuracy, Precision, Recall, F1-SCORE	-
Performance	Classification	Pass or Fail	Han Wan et al. (2023)	Behaviour	BiLSTM	ROC-AUC, F2-measure	HT - Hill-climbing
Performance	Classification	Pass or Fail	Liz-Domínguez et al. (2023)	Academic Background, Behaviour, Academic	RF, NB, kNN	Accuracy, Precision, Recall, F1-SCORE, AUC	-
Performance	Classification	Pass or Fail	Fahd and Miah (2023)	Behaviour	DL(MLP, SM, LSTM)	Accuracy, Precision, Recall, F1-SCORE	RS - Distribution-based algorithm, SMOTE FS - Pearson coefficient
Performance	Classification	Pass or Fail	Michira et al. (2023)	Grade, Score, Behaviour	MLP, NN	Accuracy, Precision, Recall, F1-SCORE	HT - Grasshopper Optimization Algorithm
Performance	Classification	Pass or Fail	Holicza and Kiss (2023)	Demographic, Behaviour	SVM, kNN, DT, RF	Accuracy, Precision, Recall, CM, F1-SCORE, ROC_AUC	-
Performance	Classification	Pass or Fail	Al-Sulami et al. (2023)	Behaviour	RNN, LSTM, GRU, MLP	Accuracy, Recall, Precision, F1-SCORE	RS - SMOTE
Performance	Classification	Pass or Fail	Venkatachalam and Sivanraju (2023)	Academic, Demographic, Psychological	LSTM, DCNN, MLP, LightGBM, GBRT, RF, SVM, DNN	Accuracy, Precision, Recall, F1-SCORE, RMSE	FS - LDA
Performance	Classification	Pass or Fail	Abuzinadah et al. (2023)	Academic Background, Behaviour	Stochastic gradient descent, gradient boosting machine, RF, LR, extra tree, NB	Accuracy, Precision, Recall, F1-SCORE	FS - CNN RS - SMOTE

Category	ML Category	Prediction Outcome	Citation	Attribute Category	ML Method	PM	Improve Method
Performance	Classification	Pass or Fail	Liu et al. (2023)	Behaviour	NB, libSVM, MLP, SMO, J48, J48graft, optimized forest, RF, multi objective evolutionary fuzzy classifier, AdaBoostM1, Bagging, Voting	Accuracy, Precision, Recall, F1-SCORE, MCC, AUC	FS – pearson correlation, IG, GR, ReliefF, BestFirst and greedy stepwise
Performance	Classification	Pass or Fail	Rahman et al. (2024)	Demographic, Academic	DT, kNN, NB	Accuracy, Precision, Recall, F1-SCORE, AUC	-
Performance	Classification	Pass or Fail	Vanitha S (2024)	Demographic, Behaviour	MLP-LSTM, MLP-GRU, MLP-BiGRU, LR, SVM, DT, RF, kNN, NB	Accuracy, Precision, Recall, F1-score	RS - SMOTE
Performance	Classification	Pass or Fail	Parkavi and Karthikeyan (2023)	Demographic, Behaviour	kNN, DT, NB, LDA, LDA, QDA, SVM	Accuracy, Precision, Recall, F1-SCORE	
Performance	Regression	Assignment Grade	Gkontzis et al. (2018)	Interaction	RF, Linear Regression, NN, AdaBoost, SVM, KNN	MAE	-
Performance	Regression	Final Scores	Mi (2019)	Demographic, assessment score, participation	RBF Neural Network	RMSE	-
Performance	Regression	Final Scores	Le et al. (2020)	Behaviour	Linear regression, SVR, KNN-Regression, Bayesian Ridge	MSE, MAE, R2_loss	-
Performance	Regression	Final Scores	Maraza-Quispe et al. (2021)	Behaviour, Demographic, questionnaire	Simple Regression Tree	R squared, MAE, percentage of absolute error	-
Performance	Regression	Final Scores	Suresh et al. (2021)	Demographic	SVM	MSE, RMSE, MAE, R2	-
Performance	Regression	Final Scores	Yuni Yamasari et al. (2021)	Scores	Linear Regression	MSE, RMSE, MAE, R2	FS - Lasso, Ridge, Elastic net regularization
Performance	Regression	Final Scores	Alboaneen et al. (2022)	Score, Demographic	SVM, RF, kNN, ANN, LR	MAPE	-
Performance	Regression	Final Scores	Pacheco-Mendoza et al. (2023)	Demographic, Behaviour	Multiple Linear Regression;	RMSE, MAE, Mean percentage error, MAPE	-
Performance	Regression	Final Scores	Abdullah et al. (2023)	Behaviour	RF, BR, AdaBoost, XGBoost	RMSE, MAE, R squared	-
Performance	Regression	Final Scores	Jin and Jin (2023)	Academic background, Behaviour	BR, NN	error, RMSE	FS - Pearson correlation

Category	ML Category	Prediction Outcome	Citation	Attribute Category	ML Method	PM	Improve Method
Performance	Regression	Grade	Nachouki et al. (2023)	Academic background, demographic, grade	RF	RMSE	-
Performance	Regression	Grade	Z. Xu et al. (2020)	Behaviour, grade	Variance Inflation Factor, Multiple Linear Regression	R squared, Adjusted R squared	FS - Pearson correlation
Performance	Regression	CGPA	Arifin et al. (2023)	Behaviour	Gradient Boosting Regression Tree, DL, SVM, RF, generalizec linear model, DT	RMSE, MSE, MAE	HT - Grid search
Performance	Clustering	Performance	Luo and Wang (2020)	Behaviour, scores	K-Means	Sum of squared error, Silhouette coefficient	-
Performance	Clustering and Classification	Performance	Sheik Abdullah et al. (2021)	Demographic, behaviour, psychological	K-Means FFNN	- Accuracy, Precision, Recall, RMS error, correlation	FS – Genetic Algorithm
Performance	Clustering and Classification	Performance	Riestra-González et al. (2021)	Behaviour	K-Means CART-DT, NB, LR, MLP, SVM	- Accuracy, F1-SCORE, AUC	FS – Recallursive feature elimination HT – RandomizedSearchCV
Performance	Clustering and Classification	Performance	Hussain et al. (2018)	Behaviour, grades	K-Means fuzzy unordered rule induction algo (FURIA), Artificial Immune Recallognition System (AIRS), RF	- Accuracy	-
Performance	Clustering and Classification	At-risk	Li et al. (2020)	Behaviour, Internet Access	Ward's hierarchical SPDN, BLSTM_MA, LR, NB, RF, DT	- Accuracy, Precision, Recall, F1-SCORE, AUC, training time	-
Performance	Clustering and Classification	Grade	M. Wu et al. (2020)	Demographic, Score	K-Means RF, ADB, GB, XGB	- Accuracy, Precision, Recall, F1-score	FS – Random Forest
Performance	Clustering and Classification	Grade	Nuankaew and Nuankaew (2023)	Scores	K-Means NB, DT, kNN	- Accuracy, Precision, Recall, F1-SCORE	-
Performance	Clustering and Classification	Pass or Fail	Cock et al. (2023)	Demographic, Behaviour	Multi-step clustering BiLSTM	- Accuracy, FNR	SMOTE

Category	ML Category	Prediction Outcome	Citation	Attribute Category	ML Method	PM	Improve Method
Performance	Clustering and Classification	Pass or Fail	Alshabandar et al. (2020)	Demographic, academic background	K-Means CNN	- Accuracy Precision, Recall, Cohen Kappa	HT - Grid Search
Performance	Clustering and Regression	Grade	Nguyen et al. (2018)	Behaviour	k-mean, birch, agglomerative clustering Logistic Regression	Silhouette Coefficient RSquare, MSE, MAE	-
Performance	Classification and Regression	Fail/ Pass Dropout/ Not Grade	Tsiakmaki et al. (2020)	Behaviour Grade	NB, RF, Bagging, PART, SMO, Ibk-5NN, Auto WEKA	Accuracy, ROC area	FS – ExtraTreesClassifier, ExtraTreeRegressor
Performance	Classification and Regression	Good/Bad Final Grade	Elrahman et al. (2022)	Behaviour	LR, DT, RF, kNN, SVM	Accuracy, Recall, Precision, F1-SCORE-score	FS - RF

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