

# Depression Prediction using Machine Learning: A Review

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## ABSTRACT

Predicting depression can mitigate tragedies. Numerous works have been proposed so far using machine learning algorithms. This paper reviews publications from online electronic databases from 2016 to 2020 that use machine learning techniques to predict depression. The aim of this study is to identify important variables used in depression prediction, recent depression screening tools adopted, and the latest machine learning algorithms used. This understanding provides researchers with the fundamental components essential to predict depression. Fifteen articles were found relevant. We based our review on the Systematic Mapping Study (SMS) method. Three research questions were answered through this review. We discovered that sixteen variables were deemed important by the literature. Not all of the reviewed literature utilizes depression screening tools in the prediction process. Nevertheless, from the five screening tools discovered, the most frequently used were Hospital Anxiety and Depression Scale (HADS) and Hamilton Depression Rating Scale (HDRS) for general population, while for literature targeting older population Geriatric Depression Scale GDS was often employed. A total of twenty-two machine learning algorithms were identified employed to predict depression and Random Forest was found to be the most reliable algorithm across the publications.

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## 1. INTRODUCTION

As the coronavirus (COVID-19) pandemic spread across the globe, it is causing a significant degree of fear and concern in the public. In terms of public mental health, elevated depression rates are the most significant psychological effect to date. Younger adults had higher mental health rates, while adults enduring serious health issues had more mental health problems [1]. The analysis showed that mental health problems decreased by 5% with every year's rise in age [2]. Children from lower socio-economic classes who were exposed to experiences of mental health problems early in their lives, be it due to both or either parent, were more likely to become mentally ill later in life. Mood disorders and suicide-related findings have soared over the past decade [3], [4]. According to the Institute for Public Health, mental health disorders among adults have increasingly become worrying from 10.7% in 1996 to 29.2% in 2015 [5].

Depression, the most common type of mental illness, is a psychological condition that happens to anyone at various ages due to specific reasons such as loss of self-esteem and social environment. The symptoms faced by depressed individuals may have a severe effect on their capability to deal with any

condition in everyday life, which significantly varies from the usual mood variations. Depression affects not only physical but also psychological well-being [6]. It is associated with diabetes, hypertension, and back pain [7]. Besides that, a mental disease is often a burden in the form of tension, marriage breakdown, or homelessness for families, friends, caregivers, and other relationships [8]. Therefore, an initiative and commitment to prevention and treatment for depression are necessary.

Depression is one of the leading mental illnesses that is least diagnosed, considering the incidence and seriousness. The diagnosis and evaluation of signs of depression rely almost exclusively on data provided by patients, family members, friends, or caregivers [9]. This type of article, however, is inaccurate because it relies on the reporter's total integrity. Depression-related self-perceived shame is widespread in societies worldwide and is associated with unwillingness to seek professional assistance [10]. Patients are also hesitant to express their depressive feelings with physicians, so a discussion of depression often relies heavily on a general practitioner's willingness to engage with the patient. The prevalence of depression in Malaysia is considerably higher than in the United States and most other Western countries [11]. Depression is a severe mental illness and a significant public health issue that has a massive effect on society. In the worst case, depression can lead to suicide. Even though it is a severe psychological issue, fewer than half of people with this emotional problem have received mental health services [6]. It may be attributed to various reasons, including lack of knowledge of the disease. Additionally, researchers discovered that embarrassment and self-stigmatization tend to pose as more significant factors for not obtaining medical attention than others' actual prejudice and adverse reactions [12].

The capability to predict depression using machine learning algorithms before conditions worsen is essential. Therefore, in this paper, we conducted a systematic review of literature from 2016 to 2021 (time of writing) to help researchers better understand this area. This review aims to firstly, identify variables relevant to the prediction of depression using machine learning techniques, secondly, identify the latest and most frequent screening types used in detecting depression and finally, popular state-of-the-art techniques in machine learning to predict depression based on chosen metrics and values of performance.

Using machine learning techniques for the prediction of medical conditions is not new. Recent publications show applications in hepatitis [13], autism [14] and cancer [15]. Nevertheless, it is not without weaknesses. The primary weakness of any prediction pipeline involving machine learning techniques is the substantial dependence on correctly annotated data. If a dataset size is small, manually annotating each data point is feasible, however, in this big data era manual annotation of data has become impractical. Since machine learning techniques are trained on these annotations, a dataset with low-quality labels can result in unreliable predictions. Another weakness is the risk of overfitting. In the pursuit of achieving higher prediction performance, these techniques can develop a tendency to induce a model fitted to specific unique data points which do not represent a large portion of the population. Thus, rendering the models useless.

Our contribution via this study is a systematic review covering key aspects in predicting depression. Significant variables in previous works are identified, depression screening tools used are investigated and popular machine learning algorithms based on classical as well as new measurements of performance are highlighted.

The paper is outlined as follows. In section 2, the systematic literature review methodology is explained. Our proposed methodology and research questions are detailed in section 3. Then, the results of our review are presented in section 4. Finally, in section 5 we conclude this paper.

## 2. SYSTEMATIC MAPPING STUDY (SMS) METHOD

SMS method organises published research and their results into structured categories by systematically perusing its primary contents, methodology and results with the aim of mitigating bias and concluding using statistical meta-analysis supported by evidence [16]. Although originally introduced for medical research, SMS method has been adapted for computing. Figure 1 shows the primary three phases of the SMS method used in our study. Each phase produces an outcome which in turn triggers the next phase.

The SMS method begins with the formulation of research questions so that the coverage of existing literature can be framed. Once the scope of the review has been determined, a search of the literature is conducted involving the definition of information sources from various academic online databases, digital libraries and search engines. Exploration of these sources is performed using search terms constructed to encompass the earlier formulated research questions using Boolean operators. From all the papers extracted, screening based on keywords, abstract, introduction and conclusion sections are carried out to identify only relevant papers that can provide answers to the previous questions.

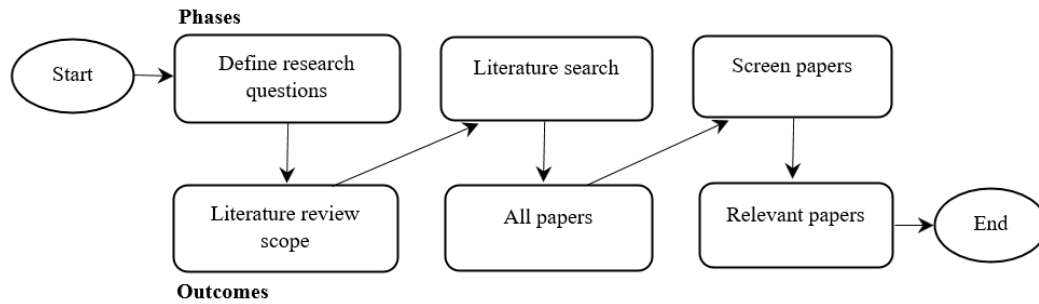


Figure 1. Phases of the Systematic Mapping Study (SMS) Method.

### 3. RESEARCH METHODOLOGY

We applied the Systematic Mapping Study (SMS) method to review existing literature from 2016 till 2020 (time of writing). Details of the application processes are explained in the following subsections.

#### 3.1. Define research questions

At this phase, research questions were formed to seek literature within the scope of predicting depression using machine learning methods. The first question is concerned with what variables were used by recent proposals for the prediction process. This answer allows researchers to identify relevant variables. A good selection of variables helps to produce good prediction performance. The second question is which depression screening tools were adopted. This question provides an understanding of a particular screening tool that has been continuously used by researchers and how many of the proposals are not utilizing any screening tools. From the answer to this question, researchers can decide the necessity of adopting specific screening tools into their work. The final question is what machine learning techniques were proposed by existing research? This question helps direct researchers to state-of-the-art machine learning techniques applied to depression prediction. Table 1 lists the constructed research questions and the motivations behind them.

Table 1. Research Questions and Motivation

Research Questions	Motivation
RQ1: What variables were used by recent proposals in predicting depression?	The answer to this question allows researchers to identify variables relevant to the prediction of depression.
RQ2: Which depression screening tools were adopted?	The answer to this question identifies the latest and most frequent screening types used in detecting depression.
RQ3: What machine learning techniques were proposed by existing research?	The answer to this question provides researchers with popular state-of-the-art techniques in machine learning to predict depression based on chosen metrics and values of performance.

#### 3.2. Literature search

A thorough search was conducted on four prominent electronic databases utilizing the following keywords: “*depression prediction*”, “*mental health prediction*”, and “*anxiety, depression, and stress prediction*”. The keywords were combined using Boolean AND expression and OR expression. The databases searched were:

- a) IEEE Xplore (<http://ieeexplore.ieee.org>)
- b) ACM Digital Library (<http://www.portal.acm.org/dl.cfm>)
- c) Elsevier ScienceDirect (<http://www.sciencedirect.com>)
- d) Google Scholar (<http://scholar.google.com>)

#### 3.3. Screening papers

The papers were examined based on their relevance to our constructed research questions. We analyzed the title, abstracts, and keywords to ascertain they lie within our focus of interest. Then, the papers were classified into two categories based on the following inclusion (*I*) and exclusion (*E*) criteria:

- I1: Paper should directly relate to depression prediction using machine learning techniques.*
- I2: Papers should provide answers to the research questions.*
- I3: Papers should contain at least one of the search keywords.*

*E1: Posters, panels, abstracts, presentations and article summaries.*

*E2: Duplicates*

*E3: Papers without full text*

The initial collection of papers from all electronic databases yielded 73 papers. Since there exists an overlap due to the search on Google Scholar, duplicates were removed with a remaining of 50 papers. Next, 32 irrelevant papers were excluded after the title and abstract of each paper were perused. The resulting 18 papers were then fully read through and resulted in 3 found irrelevant whereas the rest of the 15 papers were included in this review. Figure 2 shows the screening process.

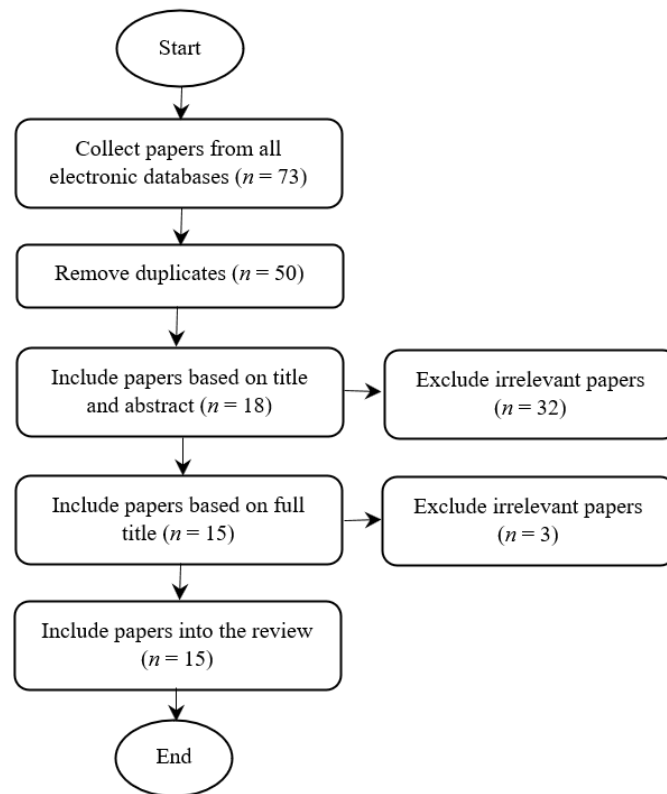


Figure 2. Paper Screening Process

#### 4. RESULTS AND DISCUSSION

The 15 relevant papers included in this review is listed in Table 2 by year, source, the scope of prediction and number of citations. The list suggests that studies on depression prediction were actively conducted in 2020 (31%) and 2016 (25%). The former is most likely due to the COVID-19 pandemic whereas for the latter no prominent event could be linked. In relation to the number of citations, sources based on computing and technology received a large number of citations since they lead to the introduction of new techniques, whereas medical-centred sources are lesser cited, owing to their more general application of these new techniques. IEEE, a widely known online database, recorded the highest number of cited sources (ICHI and KDE).

Table 2. List of Relevant Literatures

Paper ID	Year	Reference	Source	Scope of prediction	Number of citations
P1	2016	[17]	Biomedical Signal Processing and Control	Depression	18
P2	2016	[18]	International Journal of Computer Applications	Depression	21
P3	2017	[19]	Healthcare Technology Letters	Anxiety and depression	34
P4	2017	[20]	Proceedings - 2017 IEEE International Conference on Healthcare Informatics, ICHI 2017	Depression	7
P5	2017	[21]	Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence	Depression	109
P6	2018	[22]	CEUR Workshop Proceedings	Depression and anorexia	16

P7	2019	[23]	Informatics in Medicine Unlocked	Anxiety and depression	32
P8	2019	[24]	Journal of medical Internet research	Depression	41
P9	2019	[25]	International Conference on Human Centered Computing	Depression	NA
P10	2019	[26]	International Conference on Advances in Engineering Science Management & Technology (ICAESMT)-2019	Anxiety, depression, and stress	16
P11	2020	[27]	IEEE Transactions on Knowledge and Data Engineering	Depression	85
P12	2020	[28]	Procedia Computer Science	Depression	20
P13	2020	[29]	Doctoral dissertation, École de technologie supérieure	Depression	1
P14	2020	[30]	Healthcare	Depression	1
P15	2020	[31]	Journal of Affective Disorders	Anxiety, depression, and stress	2

#### 4.1. RQ1: What variables were used by recent proposals in predicting depression?

To predict depression, the researchers use several types of datasets. Some of them predict depression using demographics and clinical attributes, some use social media to collect information by using text analytics, hence, benefits from textual features instead of attributes. The various common variables in depression prediction found in 6 of the relevant papers are presented in this section. Table 3 shows the demographics and clinical variables that had been used in past research. Based on previous studies, it is found that the most used variable is *age* and *marital status*, followed by *gender*, *educational status* and *socio-economic status*. For clinical variables, *diabetes* has been used twice in previous studies, while others have only been used once and most of them in P3.

Table 3. Variables used by recent proposals

Variable	P2	P3	P4	P7	P14	P15
1. Age	✓	✓	✓	✓	✓	✓
2. Gender	✓	✓	✓		✓	✓
3. Residence status		✓	✓			
4. Educational status	✓		✓	✓		✓
5. Marital status	✓	✓	✓	✓	✓	✓
6. Income	✓		✓		✓	
7. Employment status		✓		✓	✓	✓
8. Socio-economic status		✓	✓			
9. Smoking Status			✓		✓	✓
10. Drinking					✓	✓
11. Diabetes		✓			✓	
12. Hearing problem		✓				
13. Visual impairment		✓				
14. Mobility impairment		✓				
15. Insomnia		✓				
16. Stroke					✓	

#### 4.2. RQ2: Which depression screening tools were adopted?

Our review discovered 5 screening tools popularly used by past studies in depression prediction: Geriatric Depression Scale (GDS), Hospital Anxiety and Depression Scale (HADS), Patient Health Questionnaire (PHQ), Hamilton Depression Rating Scale (HDRS) and Depression Anxiety Stress Scale 21 (DASS-21). Refer to Table 4. We discovered that proposals predicting depression utilise screening tools when their methodology require the self-construction of a dataset. The motivation driving this construction is mainly because of the absence of an available dataset necessary to accomplish a research's unique objective of filling up a specific gap in the knowledge. For example, the use of GDS is targeted at screening depression in elders. These tools allow patients to assess themselves and ratings are based on this assessment. These self-assessment tools are not meant to replace a psychiatrist's diagnosis but instead function as a signpost to the presence of symptoms or to reinforce an earlier diagnosis that a psychiatrist may be considering. Our result shows that both HADS and HDRS were adopted by more research as compared to PHQ and DASS-21 in relation to the general population. GDS, however, was adopted when the older population is the subject of interest.

Table 4. Screening tools adopted

Paper ID	Screening tools
P1	GDS
P2	GDS
P3	HADS
P4	None
P5	None
P6	None
P7	HADS
P8	None
P9	PHQ
P10	None
P11	None
P12	DASS-21
P13	HDRS
P14	None
P15	HDRS

#### 1) Geriatric Depression Scale (GDS)

GDS [32],[33] consists of 30 questions targeted at the older population of 65 years and more who are medically ill. Although other depression screening tools are available, GDS has become the popular tool for this category of people. GDS simply requires a yes or no answer of how an elder feels in the past week. Because of its high sensitivity of 92% and specificity of 89%, GDS is viewed to be a valid and reliable tool. Table 5 shows the severity ratings produced by GDS.

Table 5. GDS Severity Ratings

Severity	Depression
Normal	0-4
Mild	5-8
Moderate	9-11
Severe	12-15

#### 2) Hospital Anxiety and Depression Scale (HADS)

HADS [34],[35] measures the severity of not only depression but also anxiety. Since its introduction in 1983, HADS has become a popular screening tool for these two mental conditions. Comprising of 7 questions for anxiety and 7 questions for depression, HADS can be easily completed within a few minutes. The validity of HADS has been proven and is now on the recommendation list of the National Institute for Health and Care Excellence (NICE) to diagnose depression and anxiety. Table 6 displays HADS' severity ratings.

Table 6. HADS Severity Ratings

Severity	Depression
Mild	8-10
Moderate	11-14
Severe	15-21

#### 3) Patient Health Questionnaire (PHQ)

The PHQ [36],[37] is a multipurpose method for screening, tracking, diagnosing, and measuring depression severity. It is a self-administered instrument with two distinct types, the PHQ-2 containing two items and the PHQ-9 containing nine items. PHQ-2 assesses the frequency of depressive episodes and anhedonia for the last two weeks, while PHQ-9 presents a clinical diagnosis of depression and measures the severity of symptoms. Table 7 shows the PHQ severity rating.

Table 7. PHQ Severity Ratings

Severity	Depression
Mild	0-5
Moderate	6-10
Moderately severe	11-15
Severe	16-20

#### 4) Depression Anxiety Stress Scale 21 (DASS-21)

DASS-21 is a compilation of three scales of self-report by a patient that determines the patient's depression, anxiety, and emotional stress states. The underlying notion is these states tend to be correlated where anxiety and depression were discovered to be comorbid illnesses [38] and depression is a stress-related mental disorder [39]. Each state is measured by answering 7 questions relating to how a patient feels over the past week. DASS was designed to calculate the level of negative emotions to assist both researchers and clinicians to observe a patient's condition over time with the aim of determining the course of treatment. Table 8 shows the DASS-21 severity ratings.

Table 8. DASS-21 Severity Ratings

Severity	Depression	Anxiety	Stress
Normal	0-9	0-7	0-14
Mild	10-13	8-9	15-18
Moderate	14-20	10-14	19-25
Severe	21-27	15-19	26-33
Extremely Severe	28+	20+	34+

#### 5) Hamilton Depression Rating Scale (HDRS)

HDRS [40],[37] is specialized in assessing the severity of depression and has also been proven useful before, during, and after therapy to assess a patient's level of depression. It is widely perceived as an effective treatment for hospitalized patients. 21 items are listed in the HDRS form. The scoring basis is on the first 17 items, with 18 to 21 items used to qualify depression further. Table 9 shows the HDRS severity rating.

Table 9. HDRS Severity Ratings

Severity	Depression
Normal	0-7
Mild	8-13
Moderate	14-18
Severe	19-22
Very severe	23+

### 4.3. RQ3: What machine learning techniques were proposed by existing research?

Table 10 shows a list of the proposed machine learning techniques that were used in past research. For papers that compare the performance of the techniques, the highest scored technique is also listed in the table. Figure 3 summarizes in a treemap the number of papers using the proposed technique. Most papers experimented on Random Forest (RF), Support Vector Machine (SVM), Random Tree (RT), Naïve Bayes (NB), Logistic Regression (LR) and Decision Tree (DT). While this indicates the popularity of a specific machine learning technique among researchers, it is more importantly to know which of these techniques consistently scores the best performance when applied over different datasets. Out of the 15 papers reviewed, 12 papers conducted a comparison of performance. Therefore, from Figure 4, the graph shows RF returning the best performance in 4 instances of the comparison. RF prevails across different performance metrics in terms of achieving the best performance against other machine learning techniques. This is not only true for classical performance metrics e.g. accuracy, precision and recall, but also newer forms of performance metrics such as ERDE. It is noteworthy of publications proposing newer machine learning techniques i.e. Sons & Spouses algorithm (SS) superseding RF on traditional measurements of performances specifically accuracy, f-measure, precision, recall and area under the receiver curve. A particularly new performance metric is ERDE (Early Risk Detection Error) formulated specifically for detecting mental illness early.

Table 10. Proposed machine learning techniques

Paper ID	Machine learning techniques used	Best technique	Performance metrics	Best performance
P1	RF, RT, MLP, and SVM	RF	Accuracy Mean absolute error Root mean squared error Relative absolute error Root relative squared error	95.45 0.12 0.22 24.30 44.79
P2	BN, LR, MLP, SMO, and Decision Table	BN	Accuracy Precision ROC area Root mean squared error	91.67 0.92 0.98 0.25
P3	BN, LR, MLP, NB, RF, RT, DT, random optimization, sequential,	RF	Accuracy True positive rate	89 89

*Paper's should be the fewest possible that accurately describe ... (First Author)*

Paper ID	Machine learning techniques used	Best technique	Performance metrics	Best performance
	random sub-space, and K star		False positive rate	10.9
			Precision/positive prediction value	89.1
			F-measures	89
			Area under the receiver curve	94.3
P4	Stacking of LR DT, NBN, NN, SVM	LR (base-level learner) with DT, NBN, NN, SVM (meta-level learner)	Mean area under the receiver curve	75
			Mean accuracy	86
P5	NB, MSNL, WDL and MDL	MDL	Precision	84
			Recall	85
			F1-measure	84
			Accuracy	84
P6	CNN with TF-IDF information	Not compared	ERDE <sub>5</sub>	10.81
			ERDE <sub>50</sub>	9.22
			F-score	37
P7	CatBoost, LR, NB, RF, and SVM	CatBoost	Accuracy	89
			Precision	84
P8	DT, RT, and RF	RF	ERDE <sub>5</sub>	18.51
			ERDE <sub>50</sub>	15.20
			F-measure	20
			Precision	12
			Recall	0
P9	BN, SVM, SMO, RT, and DT	BN	Accuracy	77.8
P10	NB, RF, GB, and Ensemble Vote Classifier	Ensemble Vote Classifier	Accuracy	85
			F-score	76.9
P11	CNN	Not compared	ERDE <sub>20</sub>	9.46
			ERDE <sub>20</sub>	7.47
			F <sub>latency</sub>	0.45
P12	NB, RF, DT, SVM, and KNN	RF	Accuracy	79.8
			Error rate	0.20
			Precision	88.1
			Recall	67.8
			Specificity	91.0
			F1 score	76.6
P13	SVM, RT, and RF	RT	Accuracy	91.3
			Recall	91.2
			Precision	91.3
P14	SS, TAN, LR, DT, NN, SVM, ADA, BA, RF, RSS	SS	F measure	91.8
			Accuracy	93.0
			Area under the receiver curve	76.9
			Precision	93.1
			Recall	90.6

ADA–AdaBoost, BA–Bagging, BN–BayesNet, CNN–Convolutional Neural Networks, DT– Decision Tree, GB–Gradient Boosting, KNN–K-Nearest Neighbour, LR–Logistic Regression, MDL–Multimodal Depressive Dictionary Learning, MLP–Multi-Layer Perceptron, MSNL–Multiple Social Networking Learning, NB–Naïve Bayes, NN–Neural Network, RF–Random Forest, RT–Random Tree, RSS–Random Subspace, SMO–Sequential Minimal Optimization, SS–Sons & Spouses, SVM–Support Vector Machine, WDL–Wasserstein Dictionary Learning.

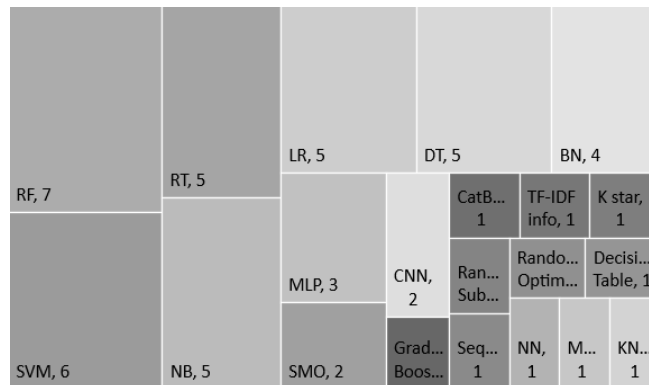


Figure 3. The number of papers using the proposed technique.



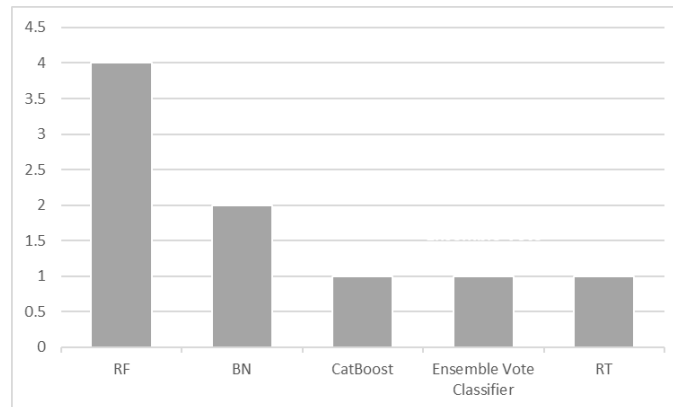


Figure 4. Techniques with consistently high performance

## 5. CONCLUSION

In this timely paper, we have reviewed depression prediction literature from 2016 to 2020 that used machine learning techniques. We employed the Systematic Mapping Study (SMS) method and the result is a total of 15 works were found relevant to the research questions constructed. The research questions focus on three important aspects of predicting depression using machine learning; they are the variables used in the literature to predict, the screening tools adopted, the machine learning techniques experimented, the metrics employed to measure each techniques' performance and the highest values achieved by the top-performing techniques. Our review has led us to conclude that information on age, marital status, gender, educational status and socio-economic status are repeatedly used across the proposals. In addition, most of the works which made use of depression screening tools relied on self-reporting types. Furthermore, Random Forest was not only the most popular machine learning algorithm among researchers but also returns the best performance in a majority of the time inclusive of newer performance metrics e.g. ERDE. It is expected that this survey will enlighten researchers on the latest machine learning techniques, performance measurements and variables used in predicting depression.

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