Sno	Author	Title	Methodology	Scope	Dataset	Evaluation Parameters	Links
1.	Hatoon S. ALSAGRI), and Mourad YKHLEF.	Machine Learning-Based Approach for Depression Detection in Twitter Using Content and Activity Features	Using SVM classifier they have taken two approaches	This study aims to detect whether the user is depressed, from the nature of his\ her tweets and activity in the network.This study exploits data collected from 111 user profiles and more than 300,000 tweets.	Private dataset	Accuracy reaching 82.5 and F-measure reaching 0.79.	_pdf (jst.go.jp)
2.	Faisal Muhammad Shah, Farzad Ahmed, Sajib Kumar Saha Joy, Samir Sadek, Sifat Ahmed, Rimon Shil, Md. Hasanul Kabir	Early Depression Detection from Social Network Using Deep Learning Techniques	The workflow methodology was divided into 2 parts A. Feature extraction in which TrainavleEmbed Features, GloveEmbed Features, Metadata Features, FastextEmbed Features were combined for achieving better result. Embedded features were fed into Bidirectional Long Short Term Memory(BiLSTM), it had information about the past and future that helped the model to predict more accurately	Limitation is that though the users are correctly classified, it takes too long time to detect them as depressed. Further work can be done to solve this problem	Reddit(post) Dataset	F1 score, $P_{latency}$,$F_{latency}$, Early Risk Detection Error (ERDE)	https://www.researchgate.net/profile/Faisal-Shah-8/publication/342243792_Early_Depression_Detection_from_Social_Network_Using_Deep_Learning_Techniques/links/5f3ec5bea6fdcccc43db7d61/Early-Depression-Detection-from-Social-Network-Using-Deep-Learning-Techniques.pdf

3	Galen Chin-Lun Hung, Pei-Ching Yang, Chen-Yi Wang,Jung-Hsien Chiang*	A Smartphone-Based Personalized Activity Recommender System for Patients with Depression	Davies–Bouldin index (DB index) is used to evaluate cluster validity in the recommendation algorithm. The Davies–Bouldin indexis the ratio of the sum of the within cluster scatter to the between cluster separation.	they would like to make our system capable of communicating with the electronic health record, which would further the detection of clinically notable emotional alteration. We plan to make our results publicly available so mobile systems developers targeting depressed patients can use our findings as the stepping stone to facilitate their works, which is crucial in improving the conditions of public mental health.	EmoRecorder module	rScore,Mean Absolute Error(MAE), Mean Average Position (MAP)	https://dl.acm.org/doi/pdf/10.4108/eai.14-10-2015.2261655
4.	A. T. BECK, M.D. C. H. WARD, M.D. M. MENDELSON, M.D. J. MOCK, M.D. AND J. ERBAUGH, M.D. PHILADELPHIA	An Inventory for Measuring Depression	A. Construction of the Inventory.—The items in this inventory were primarily clinically derived. B. Administration of the Inventory.—The inventory was administered by a clinical psychologist and a sociologist C.Description of Patient Population.—The patients were drawn from the routine admissions to the psychiatric outpatient department of	The inventory was able to discriminate effectively among groups of patients with varying degrees of depression. It also was able to reflect changes in the intensity of depression after an interval of time.	Not Provided	Correlation Coefficient: 0.65 Standard Error: 0.068 P: <0.01	An Inventory for Measuring Depression (eular.org)

			Hospital of the University of Pennsylvania.				
5.	Janet B.W. Williamsa,c, Kenneth A. Kobakc , Per Bechg , Nina Engelhardtc , Ken Evansf , Joshua Lipsitza,c, Jason Olinb , Jay Pearsond and Amir Kalalie	The GRID-HAMD: standardization of the Hamilton Depression Rating Scale	The GRID-HAMD separates the frequency of the symptom from its intensity for most items, refines several problematic anchors, and integrates both a structured interview guide and consensus-derived conventions for all items. Usability was established in a small three-site sample of convenience, evaluating 29 outpatients, with most evaluators finding the scale easy to use.	This report describes the GRID-Hamilton Depression Rating Scale (GRID-HAMD), an improved version of the Hamilton Depression Rating Scale that was developed through a broad-based international consensus process.	Not Provided		[untitled (researchgate.net)]()
6.	Matthias J. Mu¨ller*, Hubertus Himmerich, Barbara Kienzle, Armin Szegedi	Differentiating moderate and severe depression using the Montgomery–A˚ sberg depression rating scale (MADRS)	At the time of inclusion, the patients were interviewed according to the DSM-IV SCID-I module for where the criteria of the DSM-IV manual were Rating Scale Self-Affective (CPRS-S-A) and Montgomery Asberg Depression Rating Scale Self ˚ used.	A gradation of moderate and severe depression using the MADRS and based on a comparison with the HAMD17 to replicate and expand these findings, depressive symptoms were assessed in hospitalized patients with major depression using the MADRS, the HAMD17, and the CGI.	Not Provided	HAMD17 and MADRS	[doi:10.1016/S0165-0327(02)00120-9 (researchgate.net)]()

7.	Abigail Orlando, Keenan Venuti, and Matthew Tesfalul	Collaborative Filtering Recommender System for Treatment of Depression	The recommender system,For our user-user implementation we first cluster all users with a k-means clustering algorithm based on user demographic and behavioral data.For our item-item implementation, treatment rating predictions for unrated treatments are determined using traditional item-item CF.	document and analyze user demographic data by creating a more comprehensive survey and reporting system. This report would also include how often a patient misses a treatment and account for time specificity of treatment to behavioral symptoms.	Private Dataset	Accuracy and confidence ratings	Collaborative Filtering Recommender System for Treatment of Depression.pdf (keenanvenuti.com)
8.	Silvia PuglisiJavier Parra-ArnauJordi FornéDavid Rebollo-Monedero	On content-based recommendation and user privacy in social-tagging systems	Information filtering systems that have been developed to predict users' preferences, and eventually use the resulting predictions for different services, depend on users revealing their personal preferences by annotating items that are relevant to them. At the same time, by re-vealing their preferences online users are exposed to possible privacy attacks and all sorts of profiling activities by legitimate and less legiti-mate entities.	As future research lines, we shall investigate how other information filtering models are affected by the application of certain PET. Specifical-ly we shall consider researching how different aspects of users' activities are categorised and profiled by information filtering systems, and what content-measures can be taken to protest user privasy	Dataset(Delicious)	Privacy Risk assessment.	On content-based recommendation and user privacy in social-tagging systems | Elsevier Enhanced Reader