

Using Machine Learning For Sentiments And Behavioral Analysis In Digital Communication To Provide Mental Health Insight And Support

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Abstract

The goal of the review is to describe how machine learning has demonstrated exponential progress in consuming vast amounts of data and producing accurate results on par with human intelligence. It offers a glimpse of the future, when advanced data, analysis, and analytical models work together to aid countless individuals with health problems. The current use of machine learning (ML) in the healthcare industry is reviewed in this paper, along with its limitations, predictive analysis, and areas that require further investigation and are difficult to diagnose.

New Findings: We have examined thirty papers on the use of machine learning (ML) for the detection of mental stress. These papers used a variety of sources, including social networking sites, blogs, discussion forums, student records, the Questioner technique, clinical datasets, real-time data (audio, video, and driving tasks), bio-signal technology (EDG, EEG), wireless devices, and suicidal thoughts. Together, these studies demonstrate the great accuracy and promise of machine learning algorithms in mental health, as well as which ML algorithm produces the best outcomes.

Summary: Many sectors, such as traditional clinical trials, which are insufficient to gather all of a person's information, have emerged with the development of machine learning. Currently, these disorders are classified under the DSM-V stage in order to identify them early on and begin treatment before anything goes wrong. It has changed the mental health practice by cutting down on stand time, making it easier and more convenient for people to receive better healthcare whenever they need it.

Keywords: Mental stress; Sentiment analysis; SVM; Naïve Bayesian classifier; Twitter; Depression; Machine learning

1. Introduction

Advancements in technology have led to the discovery and development of innovative methods with significant potential to assist patients facing complex medical conditions. As technology progresses, patients are among the first to benefit, as it enables the identification of optimal treatment options.

Globally, healthcare organizations are increasingly adopting digital and automated systems. Machine Learning (ML) has the ability to collect and analyze vast amounts of data, generating intelligent solutions for diagnosing and treating patients with mental and emotional health conditions. The rising global population has placed immense pressure on the healthcare sector to improve treatment and service delivery.

According to McKinsey, big data and ML have the potential to generate annual revenues of \$100 billion. ML has revolutionized healthcare by making groundbreaking advancements. For example, Google has developed an ML algorithm capable of detecting cancerous tumors, while Stanford University has applied deep learning techniques to identify skin cancer.

This article provides a comprehensive review of ML techniques in mental health, their applications across various healthcare domains, a literature survey, performance metrics, a summary of relevant studies, limitations, future research directions, recommendations, and challenges in diagnosing complex health conditions.

ML in Mental Health

The term "Machine Learning" (ML) was first introduced by Arthur Samuel in 1952. Over the years, ML applications in medicine have grown significantly. It enables machines to "learn" automatically and predict outcomes without human intervention. Deep Learning (DL), a subset of ML, is widely used in healthcare, assisting both patients and medical professionals.

ML plays a crucial role in fields such as oncology, radiology, cardiology, and pathology, where complex datasets are analyzed to identify patterns, aiding clinicians in making better decisions by interpreting medical images and reports.

According to the World Health Organization (WHO), approximately 1.94 billion people worldwide suffer from mental health disorders, with anxiety being the most common condition, affecting 248 million individuals.

Depression is a severe mental health issue that can lead to suicidal tendencies, contributing to an estimated 8 million deaths annually (14.3%). Early recognition of stress symptoms, whether short-term or long-term, can prevent suicidal thoughts and improve mental health outcomes.

Similarly, the healthcare industry generates vast amounts of data. Many countries have started digitizing patient information through Electronic Health Record (EHR) software, which stores data such as medical records, prescriptions, and billing information. The WHO states that depression often leads to mental disorders, highlighting the need for intelligent systems capable of detecting early symptoms and learning from data to provide accurate and timely predictions about a person's emotional state.

ML Techniques for Big Data Analysis

Machine Learning (ML) is an integral component of Artificial Intelligence (AI) that automates predictive analytics. It is particularly effective in processing and analyzing large datasets collected from various sources. According to IDC, the volume of data is expected to grow by 50 times, reaching 5.2 ZB for analytical processing by 2025. Unlike traditional methods, which focus on interpretation, ML is prediction-driven. It enables systems to learn from data, identify patterns, and generate insights that are valuable for decision-making.

ML is broadly classified into three categories: Supervised Learning, Unsupervised Learning, and Reinforcement Learning. Additionally, Deep Learning (DL) is a specialized subset of ML.

Supervised Learning (SL)

In this learning approach, a dataset acts as a guide, training the model to learn from observations. Once trained, the model can make predictions when new data is introduced. Mathematically, this process involves mapping inputs (X) to outputs (Y) using an algorithm: $Y = f(X)$.

Supervised Learning is widely applied in healthcare, where it helps recognize patterns and assist clinicians in decision-making. A common example is text classification, which analyzes text-based data to detect sentiment. In mental health diagnostics, it can classify cases of Major Depressive Disorder (MDD) by categorizing posts as depressed, non-depressed, positive, negative, or neutral.

Unsupervised Learning(USL)

Unlike Supervised Learning, Unsupervised Learning does not rely on labeled data or external supervision. It works with input variables (X) but lacks predefined output variables (Y). Instead, the algorithm identifies hidden patterns in data and organizes it into meaningful clusters.

Common techniques used in Unsupervised Learning include K-Means clustering, Hierarchical clustering, K-Nearest Neighbors (KNN), and Principal Component Analysis (PCA). In healthcare, genetic analysis uses clustering techniques to study DNA patterns, aiding in biological evolution research and cancer classification based on genetic computations.

Reinforcement Learning(RL)

Reinforcement Learning is based on a "trial-and-error" approach. The system interacts with its environment, learns from feedback, and optimizes its actions to achieve the best possible outcome.

In healthcare, Reinforcement Learning has promising applications, although its real-world implementation faces challenges. Some notable examples include its use in the treatment of lung cancer, epilepsy, and bioinformatics. By analyzing past patient data and adapting to new information, RL-based models can assist in personalized treatment planning and predicting disease progression.

Deep Learning in Healthcare

Deep Learning(DL) has significantly enhanced healthcare by assisting medical professionals and improving patient care. It can learn autonomously, processing unlabeled and unstructured data to extract meaningful insights. Deep Learning AI mimics the functioning of the human brain, enabling applications such as object recognition, speech processing, language translation, and decision-making. In the healthcare industry, DL-based solutions are used for chatbots, medical imaging analysis, cancer detection, and the identification of rare diseases.

Machine Learning in Mental Health

In specialized healthcare fields like bioinformatics, ML has made significant progress by analyzing complex datasets. Researchers are increasingly using ML techniques for diagnosing mental health disorders. The five most commonly used ML algorithms in mental health studies include:

- SupportVectorMachines(SVM)
- RandomForest (RF)
- K-NearestNeighbors(KNN)
- GradientBoostingMachine(GBM)
- NaïveBayes(NB)

According to Cho et al. (2019), SVM, GBM, RF, and NB have been widely applied in mental health research. The primary purpose of ML techniques is to analyze large datasets and extract valuable insights for better decision-making.

The healthcare sector primarily utilizes Supervised and Unsupervised Learning for medical data analysis. Additionally, Reinforcement Learning (RL) is also used for predictive modeling and complex data-driven decision-making in healthcare applications.

2. Background

Social Media and Mental Health Prediction

In their 2017 study, Aldarwish and Ahmad explored the use of user-generated content (UGC) from social networking platforms like Facebook, Twitter, and Instagram to predict mental health conditions. Researchers believe that analyzing social media posts can help identify individuals experiencing mood fluctuations, stress, anxiety, and loss of hope, including those who have not been formally diagnosed.

According to the World Health Organization (WHO), suicide is one of the leading causes of death among individuals aged 15 to 29 worldwide.

Machine Learning in Mental Health and Sentiment Analysis

Machine Learning (ML) has widespread applications in medical diagnosis, speech recognition, image processing, and Natural Language Processing (NLP). It enables researchers to extract valuable insights from large datasets and develop intelligent systems for mental health assessment.

Diagnostic questionnaires such as the Beck Depression Inventory (BDI) and the Center for Epidemiologic Studies Depression Scale (CESD-R) (Hussain et al., 2015) are commonly used for assessing patients' mental health conditions.

Emotion Artificial Intelligence and Text Analysis

Deshpande and Rao (2017) highlighted that Emotion Artificial Intelligence is an evolving field focused on text analysis. With the rapid expansion of digital media, both text and image-based datasets are now used for sentiment analysis. Researchers classify social media posts, such as tweets, as negative, neutral, or positive, which helps in detecting depression.

Today, people frequently express their thoughts, emotions, and opinions through social networking sites, making text-based communication one of the most widely used forms of interaction. In Emotion AI, textual data is leveraged for sentiment detection using various ML techniques.

Impact of Mental Health Disorders

Stress is often associated with negative life experiences and is considered a form of mental distress. According to global statistics, mental health disorders

have severe consequences on the body, leading to conditions such as panic attacks, anxiety, fear, depression, substance use disorders, schizophrenia, eating disorders, and post-traumatic stress disorder (PTSD).

Reports indicate that around 13% of the global population suffers from mental health and substance use disorders. While occasional feelings of sadness are normal, persistent negative emotions may indicate mental illness or depression, requiring timely intervention.

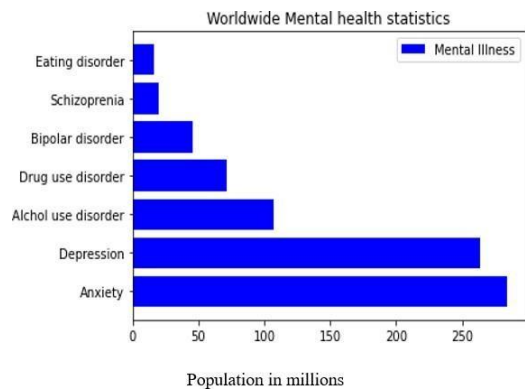


Figure.1 Worldwide Statistics of Mental Health and Substance use disorder (in millions)

3. Methods: Study Selection and Performance Measures

Review of Research on Mental Illness Detection Using Machine Learning

A comprehensive review of research papers focusing on the detection of mental illness using various Machine Learning (ML) techniques has been conducted. The research papers were sourced from PubMed, Google Scholar, ScienceDirect, conference proceedings, and academic journals. The selection process involved using relevant keywords such as mental illness diagnosis, sentiment analysis, depression detection, and machine learning.

Data Sources for Stress Detection

The studies reviewed primarily focus on stress detection using social media posts from platforms like Twitter and Facebook, as well as clinical records and biometric sensor data (e.g., Heart Rate Variability (HRV), Electrocardiography (ECG), and Electroencephalography (EEG)).

Table 1 presents details of 30 studies, summarizing key aspects such as study objectives, datasets used, accuracy levels, methodologies, and ML algorithms applied in the field of mental health prediction.

Popular Mental Health Hashtags and ML Advancements

Social media users often express their mental health struggles through widely used hashtags such as #depression, #anxiety, and #sadness, which are analyzed for sentiment analysis (Fig. 2). Over the years, ML has significantly contributed to healthcare by improving diagnosis, treatment, medical data analysis, and decision-making in clinical settings.

Growth of Research in Mental Health Detection Using ML

The number of publications on mental illness detection using ML techniques has steadily increased between 2011 and 2020 (Fig. 3). Different ML algorithms have been applied to various datasets to detect mental stress, with accuracy varying based on the dataset size and sample composition.

Comparison of ML Algorithm Performance

A comparative analysis (Fig. 4) highlights the accuracy levels of Support Vector Machines (SVM) and Naïve Bayes across different datasets, including:

- SocialMediaPosts(Facebook,Twitter)
- SentimentAnalysisonTwitterandFacebookPosts
- UniversityStudentRecords
- BiosensorData(EEG)

These findings demonstrate the effectiveness of Machine Learning in mental health analysis, paving the way for further advancements in stress and depression detection.

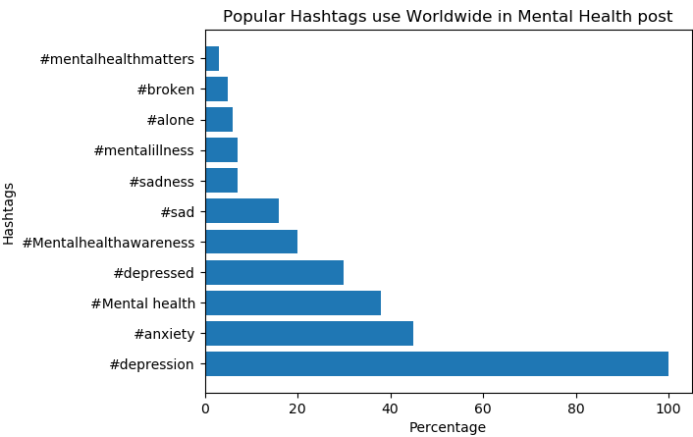


Figure.2TopHashtagsusedindepressiononInstagram,Twitter,
and Facebook

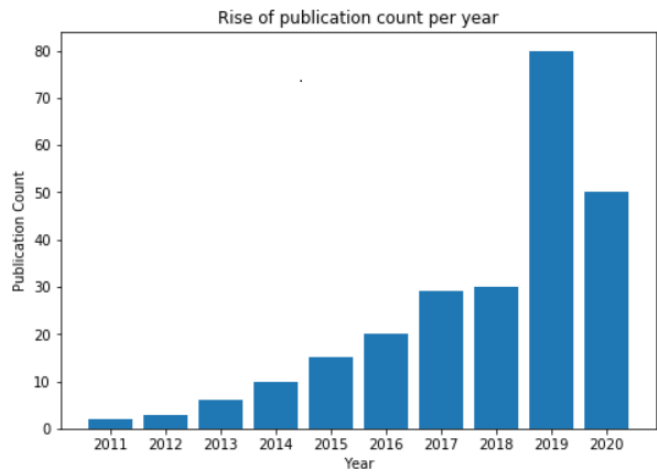


Figure.3Publicationcountincreasesfrom(2011-2020)inmentalhealthusingML

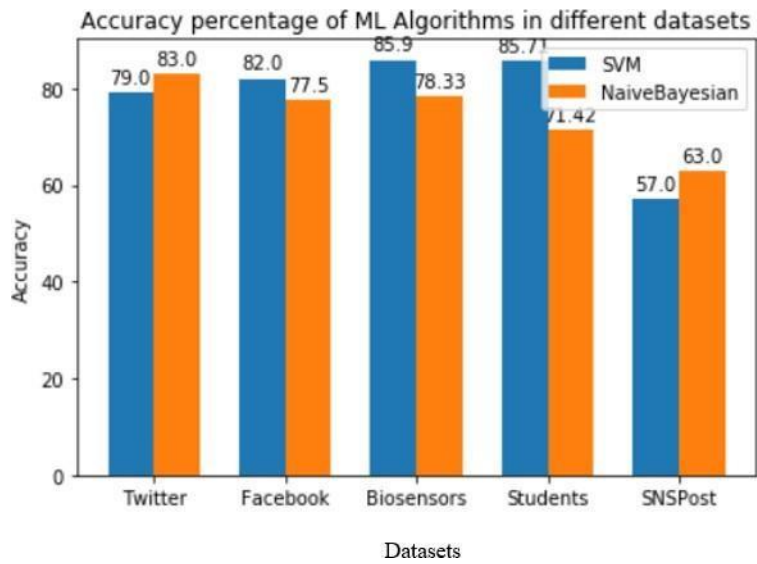


Figure.4AccuracypercentageofSVMandNaïveBayesianclassifierondifferentdataset

Table 1 Summary of ML Techniques used to detect Mental Stress, Dataset, Method and

Author	Method	Purpose of Study	Dataset	ML Techniques	Accuracy
Social Network Sites					
Maryam et al., (2017)	Quantitative	Predicting stress from UGC-User Generated Content in Social media sites (Facebook, Twitter, LiveJournal) classify on basis of mood and negativity and BDI-questionnaire.	6773 post, 2073 depressed, 4700 non-depressed post (textual)	SVM Naïve-Bayesian	57% 63%
Gyeongcheol et al., (2018)	Qualitatively	Analysis of ML Algorithms helps Diagnosing mental illness, properties and their limitations and how algorithms implemented	Not reported	SVM, GBM, KNN, Naïve Bayesian, K Nearest, Random Forest	75% (highest accuracy reported by SVM classifier due to its data sparsity)
Reshma et al., (2019)	Quantitative	Detecting sentiment analysis on twitter using Tensi Strength framework from social media text. Lexicon approach to detect stress and relaxation	Large datasets divided into 100 record (textual)	SVM NB WSD and n-gram	65% (Precision True Positives over sum of TP and FP) 67% (Recall True Positive over the sum of TP and FN)
Jamil et al., (2015)	Quantitative	Automatically classifies the MDD diagnosis from individuals Facebook profile in addition questionnaire technique BDI and CESD-R.	Facebook post	SVM KNN	Sadness-53.66% Late night activity-13.33% Confused-26.66%
Mandaret al., (2017)	Quantitative	Detect depression using emotional analysis on Twitter feeds using NLP based on curated word-list (negative or neutral)	10,000 Tweet Using Twitter API	SVM F-1 Score Naïve Bayes NLP	79% (linear and non-linear) 83% (text classification)
Moha. et al., (2018)	Mixed	Comparative analysis of different ML techniques and deep learning, and develop a hybrid model for sentiment analysis	1,048,588 tweets (positive and negative classification)	Naive Bayes Random Forest Decision Tree CNN Hybrid Model	77.5% 73.8% 72.5% 79.6% (word to vector 83.6%)

Author	Method	Purpose of Study	Dataset	ML Techniques	Accuracy
Social Network Sites					
Chawre et al., (2020)	Qualitative	Facebook posts used as a token. Feature extraction from social interaction and classified as positive and negative.	Not reported	TSVM SVM Naïve Bayes Random forest Decision Tree AdaBoosted D-Tree	84% (extract post) 82% (classified post) 77.5% 73.8% 72.5% 67%
Megha et al., (2018)	Mixed	Analyze existing Sentiment analysis Techniques and to Improve the overall accuracy using hybrid sentiment classification model for tweets.	1,600,000 tweet, 1000 positive and 1000 Negative review 7086 sentences	SVM AdaBoosted D-Tree Decision Tree	82% 67% 84%

Clinical Datasets					
Ravinder et al., (2019)	Quantitative	Calculate stress of University students one week before their exams and usage of internet using ML technique	Record of 206 students (Jaypee Institute of Information Technology)	SVM Random Forest Naïve Bayes KNN PSS	85.71% 83.33% 71.42% 55.55%
Christ et al., (2018)	Quantitative	Predicting persistent symptoms of depression in age more than 65	Data of (284 patients) based on demographic and psychometric for continuous 12 months	LR GB	69% 74%
Hugo et al., (2017)	Quantitative	By evaluate the behavior (depression, stress, self-esteem) of an adolescent and detect the suicidal tendency. Propose a desktop tool.	Dataset of adolescent with suicidal tendency in Peru 10000 Instances 800 real record (suicide attempts)	JRIP algorithm C4.5 (decision tree family) Naïve Bayes	97.4% 98.4% 98.65%
Ashley et al., (2020)	Quantitative	Predicting mental illness in adolescent	7,638 twins from child and adolescent Twin study	Random forest SVM	75% 75%

PhysiologicalSensors					
Chandrasekhar <i>etal.</i> ,(2018)	Quantitative	Asystemtodetectstress using biosensors EEG integrated with mobile development(iosdevice) usingMLtechniques	Electroencephalogra phy(EEG)	SVM KNN Mobile Application	Not reported
Adnan <i>etal.</i> ,(2015)	Quantitative	Machine Learning- based SignalProcessingUsing PhysiologicalSignalsfor StressDetection	K-nearest neighbour(KNN),a nd support vector machine (SVM)	Respiration, GSRHand, GSR Foot, Heart Rate andEMG	92.06% 98.41%

LimitationofML andMentalHealthStudies

LimitationsofMachineLearninginClinicalDataandSocialMedia Validation

The studies reviewed highlight several limitations ofMachine Learning (ML) when applied to clinical datasets and social media validation. One of the primary challenges is ensuring accuracy and reliability when dealing with small datasets. To enhance model performance, 10-fold cross-validation is applied, particularly when working with limited data. The iterative k-fold cross-validationtechnique isemployedto minimizeerrors,asdemonstratedby Ahuja et al. (2019).

Toreduceambiguityinpredictions, WordSenseDisambiguation(WSD) has been integrated with Support Vector Machines (SVM), improving overall accuracy (Reshma & Kinariwala, 2019). However, supervised learning methodsused forstresspredictionfromtextualdata face inherent limitations and struggle to achieve accuracy comparable to human assessment.

ChallengesinDiagnosingMentalHealthDisorderswithML

Medicalprofessionals oftenclassifydisorders basedon diagnostic uniformity, such as Major Depressive Disorder (MDD), characterized by symptoms like insomnia,confusion,depression,andfatigue.However,MLmodels mustnow evolve to identify new subtypes of psychological conditions, including substance abuse, alcoholism, and illness trajectories (Hussain et al., 2015).

A critical issue in ML-based medical applications is that the size of the dataset significantly impacts algorithmic performance. ML models have shown weaker accuracy in larger samples compared to smaller datasets. Proper implementation of cross-validation techniques helps mitigate overestimation and variability, improving the robustness of predictive models.

4. Discussion: Future Research and Recommendation

Machine Learning in Mental Stress Detection and Healthcare

This study aims to explore the role of ML algorithms in detecting mental stress and their specific applications in different domains. The analysis focuses on stress detection through data collected from social media posts, clinical records, blogs, student datasets, and biosignals such as EEG, ECG, and HRV. The study determines which ML algorithm performs best on particular datasets. However, the accuracy of predictions depends largely on the volume of data used for training the model. Clinical datasets, gathered over a specific period, help in generating insights and triggering early warnings for potential health abnormalities.

Effectiveness of Machine Learning in Health Applications

Among various ML techniques, Support Vector Machines (SVM) are widely applied in the health sector, while Naïve Bayes is particularly effective for sentiment analysis on Facebook statuses. Comparative analyses indicate that hybrid classifiers yield higher accuracy and improve overall performance compared to traditional classification methods.

ML has significantly improved healthcare outcomes by leveraging large volumes of medical data. One of the key challenges in healthcare is effectively collecting, managing, and analyzing this data for prediction and treatment. ML assists health professionals in decision-making by identifying patterns, fostering medical innovation, and enhancing the efficiency of clinical trials. Real-time data from sources like lab test results, blood pressure readings, and family medical history, when combined with historical health records, helps develop predictive models for disease forecasting.

According to the Framingham study, ML achieved 56% accuracy in predicting long-term cardiovascular disease risks. Additionally, ML is being explored in clinical trials for drug discovery and substance abuse detection. Studies

indicatethataround 90%ofdrugsfailin trials, but automateddrugdiscovery can reduce costs by nearly 70%, as reported byCarnegie Mellon University.

ML-BasedElectronicHealthRecords(EHR)andEpidemicPrediction

Machine Learning-based Electronic Health Records (EHR) enable the application of predictive models across various healthcare systems. These systems integrate structured and unstructured data, including medical images, audio recordings, text-based reports, and diagnostic scans. Advanced technologies like optical character recognition (OCR), image processing (radiology, pathology, dermatology), and natural language processing (NLP) helpconvertcomplexmedicaldataintostructuredformatsforfurtheranalysis.

AcollaborationbetweenGoogleandUniversityCollegeLondonHospital led to the development of an ML algorithm that distinguishes cancerous and healthy tissues, significantly improving radiotherapy treatments. ML is also extensively utilized for predicting and monitoring epidemic outbreaks by analyzing data from social media, web sources, and satellite imaging.

Conclusion

Ultimately, Machine Learning plays a critical role in extracting insights from complex health datasets for disease prediction, treatment recommendations, and medical analysis. However, it is essential to evaluate whether these ML-driveninsightscanbeeffectivelyinterpretedandapplied inclinicalsettings for improved healthcare outcomes.

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