A Review of the Main Factors, Computational Methods, and Databases Used in Depression Studies

Ariane C. B. da Silva[1], Renata C. Santana[1], Thiago H. N. de Lima[1], Maycoln L. M. Teodoro[2], Mark A. Song[1], Luis E. Zárate[1] and Cristiane N. Nobre[1]

[1]*Institute of Exact Sciences and Informatics, Pontifical Catholic University of Minas Gerais, Dom José Gaspar, Belo Horizonte, Brazil*

[2]*Department of Psychology, Federal University of Minas Gerais, Belo Horizonte, Brazil*

Keywords: Depression, Data Analysis, Machine Learning, Instruments.

Abstract: Depression is a mental health disorder that affects millions of people worldwide. The disorder results from a complex interaction of biological, psychological, and social factors, leading to difficulty in both prognosis and diagnosis. In this work, we performed a review on studies about depression, to identify the main computational techniques used to support the prediction (prognosis and diagnosis) of depression, and the main attributes that might influence the development of the disorder. Our results indicate that, in the last ten years, Logistic Regression, Machine Learning techniques such as Support Vector Machines and Neural Networks, and other supervised learning algorithms, have been employed more frequently for studies predicting depression and selecting features related to it. Attributes like insomnia, gender, marital state, and use of tobacco, for example, were related to the development of depression. The review indicated growing effectiveness in using machine learning methods for analyzing data related to depression.

1 INTRODUCTION

Depressive disorders are characterised by feelings of sadness, loss of interest or pleasure, feelings of guilt or low self-esteem, disturbed sleep or appetite, low energy and lack of concentration. Depression can be long lasting or recurring, substantially hindering an individual in several environments, such as work and school (Wray et al., 2018).

Depression results from a complex interaction of social, psychological and biological factors. People who have experienced adverse events in life such as unemployment, death of loved ones or psychological trauma are more likely to develop it (Suzuki et al., 2018). In addition, depression can lead to more stress and dysfunction. It worsens the life situation of the affected person and the disorder itself.

Precisely because it involves so many factors the diagnosis of depression is still challenging (Stapley et al., 2016), and there is an increasing demand for computational techniques able to provide decision support for its diagnosis. Among these techniques, we highlight the Machine Learning and statistical methods, widely used for health problems.

Recently, Machine Learning has achieved impressive results in difficult problems such as speech recognition, image and video object recognition, and natural language processing (Goodfellow et al., 2016), (Schmidhuber, 2015), (Witten et al., 2016), as well as Bioinfomatics problems such as the prognosis of diseases and disorders such as depression (Khademi and Nedialkov, 2015), (Ravì et al., 2017) . In 2017, the CLEF eRisk, an international workshop brought together works aiming at the early prediction of risks on the internet, including people with suicidal inclination or people susceptible to depression. Machine learning techniques such as Random Forest (RF), Naive Bayes (Villegas et al., 2017), Recurrent Neural Networks (RNN) (Sadeque et al., 2017), Support Vector Machine (SVM) and Ensemble methods (Trotzek et al., 2017), (Almeida et al., 2017) were used to predict as early as possible the risk of mental health issues from user-generated content in social media.

Techniques capable of predicting, with high accuracy, whether a person may develop depression are important to aid in its diagnosis and, consequently, its prognosis.

B. da Silva, A., Santana, R., N. de Lima, T., Teodoro, M., Song, M., Zárate, L. and Nobre, C.
A Review of the Main Factors, Computational Methods, and Databases Used in Depression Studies.
DOI: 10.5220/0010815800003123
In *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2022) - Volume 5: HEALTHINF*, pages 413-420
ISBN: 978-989-758-552-4; ISSN: 2184-4305

A review of studies carried out in this area could support research focused on computational techniques and methods of computer science and statistics, applicable to the problem of predicting whether a person might develop depression and characterizing its profile. This review structures relevant works that answer questions relevant to the area, assisting in the investigation and clinical treatment of this complex mental disorder.

In order to identify the main works that employed computational approaches in the diagnosis of people with depression, three research questions, presented in Section 2, guided this study. The questions focus on the following: 1) the main characteristics related to people with depression, 2) the main computational methods used in its analysis and 3) what kind of databases are being used in this context .

The following Sections describe the protocol used in this review article, and the answers we found for the research questions we proposed.

2 METHOD

First, the research questions were specified, followed by the development and validation of a research protocol including the inclusion/exclusion criteria for the selection of documents. After that, the relevant articles were selected based on the criteria adopted in the previous phase, and have their qualities assessed, and results summarised. Finally, in the last phase, the results of the review were analysed and made into a report that is then validated.

Subsections 2.1 and 2.2 better detail the process adopted.

2.1 Research Questions

Considering that the formulation of research questions should be guided by their significance and importance for professionals and researchers in the field, three research questions (RQs) were formulated for this study:

RQ 1. What are the main factors related to depression that are cited in the literature?

RQ 2. Which computational methods, related to machine learning and statistics, are used in depression studies?

RQ 3. What are the databases available for depression analyses?

2.2 Considered Repositories

Our choice of data sources included the main repositories of computer science articles, such as the Association for Computing Machinery (ACM), the Institute of Electrical and Electronics Engineers (IEEE), ScienceDirect, and repositories related to health studies, such as PubMed. These repositories were chosen for their scope, as they involve areas related to health (biology, psychology, and specialised medicine topics) and computing. It is relevant to highlight that, at least, one of the terms "depression" or "depressive disorder" needed to be present in the title or abstract of the document and one of the terms "machine learning", "logistic regression", "data mining" or "statistical analysis" could be present anywhere in the text.

The process of eliminating articles was applied with the following criteria: 1) Articles written in languages other than English and those that were not directly related to at least two of the research questions were excluded; 2) Articles reporting on the same study were considered equivalent, and the most recent version was kept; 3) Books, tutorials, editorials, posters, panels, transcripts of lectures, workshops and demonstration materials have been disregarded; 4) Articles dealing with pharmacological treatment and analysis of its effects were disregarded, as they are not in the scope of this review.

Table 1 presents the searched digital repositories and the number of articles kept in each selection phase. Each article returned by the searches was reviewed individually by the authors of this paper, and the decision to keep or discard a subset of an article was made based on a majority vote.

Table 1: Number of articles kept after each of the three filtering phases of the review.

Datasets	Initial Filter	Filter by title	Filter by abstract	Filter by reading
ACM	39	25	23	12
IEEE	17	14	12	11
PubMed	493	233	68	26
ScienceDirect	232	83	33	7
Total	781	355	136	56

There were 56 articles[1], identified with the letter "A" followed by a number from 1 to 56, and then an indication of the repository from where the article was obtained and its publication year.

[1] Data from the all articles selected after the entire selection/exclusion phase can be accessed at https://drive.google.com/file/d/1G7EVcdiVqpgoghW1Go3E314lmuIaYOXg/view?usp=sharing.

3 DISCUSSION

The research questions presented in subsection 2.1 are discussed in this Section and related to data and information covered in the selected articles of this review.

3.1 What Are the Main Factors Related to Depression Cited in the Literature?

Depression is a common illness that negatively affects people's quality of life. Its diagnosis is difficult as depression is caused by the interaction of varied factors such as biological, psychological, and social (Patel et al., 2007), among others, making it easy to be misdiagnosed as different disorders, or not at all.

In order to identify these main causes, we propose a taxonomy of relevant factors related to depression that was obtained by integral reading the articles selected in this review.

The taxonomy is presented in Figure 1, and consists of four broad dimensions: 1) Comorbidities, 2) Risk factors, 3) Identified phases of depression, and 4) Main symptoms. In addition, each of these four broad dimensions was subdivided into more specific aspects at different levels of granularity.

Observing Figure 1, the complexity of the interaction between the factors that characterize depression is clear, either by the number of factors or by the subdivisions that cover distinct but related areas: behavioral, neurobiological or health-related, geographical, socioeconomic and demographic factors. Apparently unrelated factors such as smoking, number of people in the family, and place of residence may, together or not, trigger the process leading to depression. The taxonomy highlights the difficulty inherent in the task of diagnosing and predicting depression.

There is a connection between risk factors, comorbidities, major symptoms, and age/physiological phases, concerning depression (Figure 1). We also noted a prevalence of research on adults and people with chronic diseases, to the detriment of other age groups.

Risk factors can be subdivided into six main subgroups: behavioral, psychological, demographic, geographic, socioeconomic, neurobiological, and general health. Regarding demographic and socioeconomic questions, there is a predominance of questions regarding age, sex and education. Such factors may directly influence the diagnosis of the disorder since, for example, it is known that women tend to be diagnosed with depression more often than men (Beck and Alford, 2011) (Silva et al., 2014).

Regarding the most frequent symptoms in depression, sleep disorders, depressed mood, and fatigue were the most recurrent in the studies evaluated. Such symptoms can be easily stigmatized, that is, people who live with a depressed individual can mistake their symptoms with laziness and lack of interest and, consequently, blame the patient. This kind of stigma has its roots in the very construction of the definition of the term "depression" - which, for centuries, was not understood as a disorder that depended on the proper care of medicine, but rather as something related to spirituality (Quevedo et al., 2018).

Knowing and understanding the broad interconnected aspects presented by this taxonomy helps in holistically understanding depression. Treatments that disregard the scope of the disorder may be doomed to fail. Therefore, the challenge is to act on different levels to enhance the quality of life of people with depression.

3.2 Which Computational Methods, Related to Statistics and Machine Learning, Are Used in Depression Studies?

Most of the works analyzed in this study used either Logistic Regression, Neural Networks or Support Vector Machines (SVM).

Patel et al. (2016) present a research from previous work that focuses on the study of depression and uses features related to magnetic resonance imaging to generate prediction models for depression. Fourteen papers, of the fifteen selected by the authors, used Support Vector Machines (SVM).

Galiatsatos et al. (2015) employed Bayesian Networks to create an optimised model of psychological factors that lead study patients to have thoughts of death or suicide in order to more quickly achieve appropriate treatment. According to the authors, the results of these experiments ratify the opinion of some experts that the most significant factors affecting mentally depressed patients, who have thoughts of death or suicide, are mood swings, loss of interest or pleasure, feelings of indignity/guilt, living in urban areas and low focus.

Yang et al. (2016) used decision tree algorithms to classify people with depression. The decision tree was built according to the PHQ-8 score (Kroenke et al., 2009) and other characteristics of the participants, obtained through the analysis of transcription files from their consultations. Their model obtained results, reaching a F1-score of 0.571 for the depressed class and 0.877 for the non-depressed class.

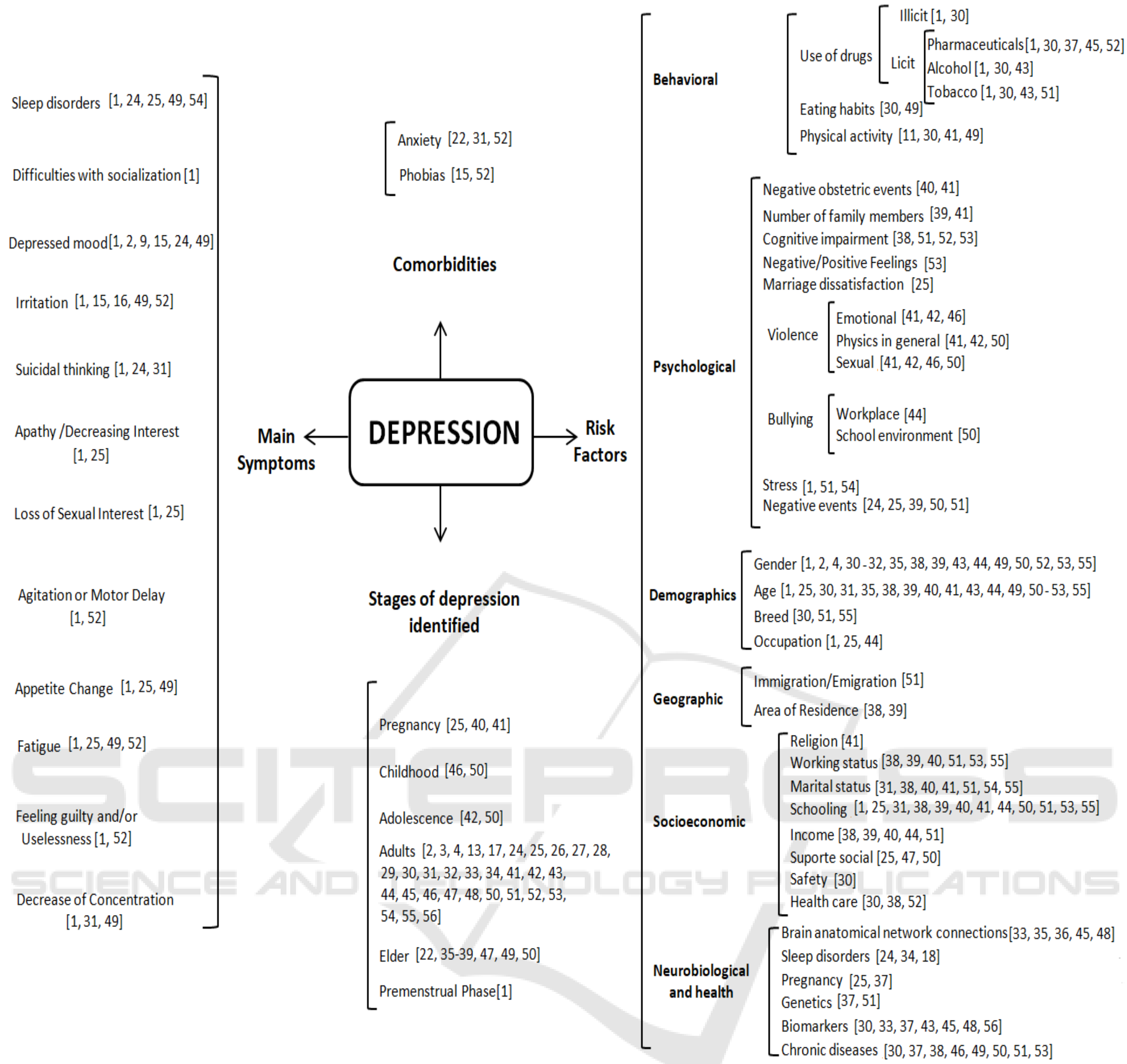

Figure 1: Factors related to depression.

Patel et al. (2015) used various machine learning methods with multimodal image input to create prediction models for the diagnosis of depression in the elderly or late depression and treatment response. Their demographic and cognitive ability data were recorded, and brain characteristics were acquired using multimodal magnetic resonance imaging pre-treatment. Linear and nonlinear learning methods were tested, and decision trees obtained the most accurate prediction models for the diagnosis of late depression (87.27% accuracy) and treatment response (89.47% accuracy). The diagnostic model included age measures, mental state examination scores and structural imaging. The authors conclude that combinations of images and measurements might help to better predict a diagnosis of late depression and treatment response. They further add that these findings may help better understanding of late depression and identify preliminary steps for personalised treatment of late depression.

Tung and Lu (2016) and Chen et al. (2020) used statistical models applied to text mining to analyze and predict signs or terms of depression in web posts. The authors propose their own extraction method to automatically detect negative event terms. The first article proposed model gets a recall and F-measure of 0.668 and 0.624, respectively and the authors conclude that the developed model can help doctors more effectively diagnose and even track the depression of web post authors.

Tadesse et al. (2019) also investigated texts posted on social media combining machine learning and Natural Language Processing (NLP) techniques, seeking to identify a set of more common terms in posts from users with depression. The authors concluded that with the use of an especific NLP technique, the classifier with the best performance is the SVM with 80% accuracy and 0.80 F1 scores, comparing to combined NLP techniques associated to Multilayer Perceptron (MLP) neural network that reached 91% accuracy and 0.93 F1 scores.

Yanikkerem et al. (2013) employed the Chi-squared test and Fisher's test to identify the relationship between social and demographic variables related to pregnant women and their average scores of a self-evaluation questionnaire that determines the severity of depression. The authors identified that low schooling levels, unplanned pregnancies, lack of social support, and pregnancy-related physical symptoms were the most important risk factors for determining prenatal depression.

Sengupta and Benjamin (2015) constructed a logistic regression model to estimate the prevalence of depression and identify risk factors associated with depression on the elderly population. The authors identified that residing in urban areas, being female, old age, living alone, poverty and functional and cognitive impairment are strong predictors for depression.

Some recent studies have been using the combination of classifiers in order to further improve the prediction performance of their models. Yang and Bath (2019) proposed a system framework, to predict depression in older age and assess a large number of factors from different domain areas associated with it, combining Gradient Boosting Machine (GBM), Keras-based Convolutional Neural Network (KNN), Regularized Greedy Forest (RGF) and Logistic Regression. Through the proposed model, the authors identified and separated the factors related to depression by domain area, aiming at the development of appropriate help strategies.

Mahendran et al. (2020) proposed a stacking based ensemble learning model to improve the prediction accuracy of major depressive disorder in adults. This model uses KNN for preprocessing, Random Forest for feature selection, MLP, SVM and Random Forest as low-level learners. The authors confirmed that the prediction accuracy of the combined model is 98.16% against 96.9% in the best result of an isolated classifier.

3.3 What Are the Datasets Available for Depression Analyses?

Regarding the databases used in the studies, several articles use in their experiments data obtained from medical records of patients in clinics and hospitals (Matza et al., 2011), (Koleva et al., 2011), (Min et al., 2012), (Yanikkerem et al., 2013), (Hosseinifard et al., 2013), (Zeng et al., 2014), (de Moraes et al., 2016), (Xing et al., 2019), (Wan et al., 2020), (Mahendran et al., 2020), however none of this data is publicly available.

Wang et al. (2019) used the Japanese Female Facial Expression Database (JAFFE), an image dataset developed at Kyushu University, Japan. It consists of 10 Japanese female expressers, 7 posed facial expressions (6 basic facial expressions + 1 neutral) being several images of each expression for each expresser, totaling 213 images. Each image has averaged semantic ratings on 6 facial expressions by 60 Japanese viewers with resolution 256x256 pixels and 8-bit grayscale. The JAFFE images may be used for all kinds of non-commercial scientific research.

In (Sunmoo et al., 2014), the dataset used was The Behavioral Risk Factor Surveillance System (BRFSS), a US health research system with data collected via telephone calls. The purpose of the BRFSS is to collect specific data on health risk behaviors, diseases and chronic conditions, access to health services, and use of preventive health services related to the leading causes of death and disability in the United States. The latest BRFSS data, from 2017, contains 450,016 records and 358 attributes. Factors assessed by the BRFSS in 2017 included health status, healthy days, quality of life, access to health services, physical exercise, inadequate sleep, chronic health conditions, oral health, smoking, electronic cigarettes, alcohol consumption, immunization, falls, seat-belt use, knowledge about HIV/AIDS, among others.

In (Yang et al., 2016), the authors utilised data from the Distress Analysis Interview Corpus - Wizard of Oz (DAIC-WOZ) database, where clinical interviews are published to be used to support the diagnosis of psychological disorders such as anxiety and depression. Collected data includes audio and video recordings and questionnaire responses in which a variety of verbal and nonverbal characteristics were transcribed and recorded. The database includes 189 interaction sessions ranging from 7-33 minutes (averaging 16 minutes). Each session includes the transcript of the interaction, participant audio files and facial features.

Dipnall et al. (2016) used data from the Na-

Table 2: Addresses for accessing the datasets.

Abbreviation	Location	Sample Size	Base Year	URL
JAFFE	Japan	213	1998	https://zenodo.org/record/3451524#.YVt8DDHMKiM
BRFSS	United States	450016	2017	https://www.cdc.gov/brfss/data_documentation/index.htm
DAIC-WOZ	United States	189	2017	http://dcapswoz.ict.usc.edu
NHANES	United States	9544	2015-2016	https://www.cdc.gov/nchs/nhanes/index.htm
KNHANES	South Korea	8518	2011	https://knhanes.cdc.go.kr/knhanes/intro.html
NPHS	Canada	17276	2010-2011	https://www.statcan.gc.ca/eng/survey/household/3225

tional Health and Nutrition Examination Survey (NHANES), a cross-sectional study program that combines interviews and physical examinations to assess the health and nutritional status of adults and children in the United States. In the article, the authors identified three bio-markers associated with depression, from an initial set of 67: 1) red blood cell distribution, 2) serum glucose, and 3) total bilirubin. The association between depression and the three bio-markers is widely cited in the literature (Maes et al., 2011) (Miller et al., 2009) (Stewart et al., 2009) (Winokur et al., 1988).

In (Chung et al., 2014), the authors used a Korean version of the same study, the Korea National Health and Nutrition Examination Survey (KNHANES). KNHANES is a cross-sectional study conducted by South Korea's National Health and Welfare Division and is made up of three different sections: 1) a health interview, 2) a health check and 3) a nutrition survey. Psychological health data were obtained from a self-reported mental health questionnaire under the supervision of an investigator.

Wang et al. (2013) performed analyzes based on data provided by the National Population Health Survey (NPHS). The NPHS is a longitudinal survey conducted every two years in Canada since 1994/1995. The first three research cycles (1994/1995, 1996/1997 and 1998/1999) were cross-sectional and longitudinal. Starting on cycle 4 (2000/2001), it became strictly longitudinal, that is, collecting health information and factors that may influence it from the same individuals in each cycle (Catlin and Will, 1992). The NPHS longitudinal sample consists of 17,276 people and it was not renewed over time.

Table 2 presents information that characterizes the mentioned datasets, including the web address of each database, for more information. Each data set is identified in the Table by its acronym.

4 CONCLUSIONS

In this work, we sought to answer three research questions through a review of the literature. We created a taxonomy of factors related to depression, relating to the first question. The taxonomy connects the risk factors, comorbidities, main symptoms and age/physiological phases investigated in relation to depression. There is a prevalence of research on adults and/or people with chronic diseases. Regarding demographic and socioeconomic questions, there is a predominance of questions regarding age, sex and education. Six subgroups of risk factors were identified: behavioral, psychological, demographic, geographic, socioeconomic, neurobiological and health.

Analysis of the most recent studies of machine learning techniques in the context of depression has signaled a tendency to combine several classifiers to improve the performance of the model, and ensemble methods have been increasingly used.

Regarding the databases available for depression investigation, it was observed that few studies made the datasets they used publicly available, which does not encourage further studies. We also note that the NPHS longitudinal database signals an interest of the scientific community to evaluate users over time.

It is necessary to consider the limitation of the used method, as such established questions and protocols are affected by the subjectivity of the researcher(s) who perform it. The researchers need to make article/content selections to facilitate the research in a timely manner throughout the review process. In our study, the evaluation of the articles had the participation of all authors, who together decided whether or not the article should remain in the review. This helped to reduce the subjectivity in the data selection phase.

We also considered that if the searches had been performed in other database repositories with different strings, we could have found references to other computational methods and techniques, such as deep learning. For this reason, we understand that this is also a limitation since the terms and journals chosen to mark the search space and, consequently, the returned articles. Although this limitation exists, clarity about this is necessary to detect possible failures and also further work in the future.

In this article, we show a compilation of the main contributions of research analyzing the depression disorder, and show how this mental disorder has been investigated from a computing perspective. In this context, statistical methods can be applied in conjunction with different machine learning techniques at different stages of knowledge discovery processes in order to produce increasingly assertive models in the selection of relevant characteristics and in the final prediction of depression and related disorders.

ACKNOWLEDGEMENTS

The authors thank the National Council for Scientific and Technological Development of Brazil (CNPq), the Coordination for the Improvement of Higher Education Personnel - Brazil (CAPES), the Foundation for Research Support of Minas Gerais State (FAPEMIG) and Pontifical Catholic University of Minas Gerais (PUC Minas).

REFERENCES

Almeida, H., Briand, A., and Meurs, M.-J. (2017). Detecting early risk of depression from social media user-generated content. In *CLEF (Working Notes)*.

Beck, A. T. and Alford, B. A. (2011). *Depressão: causas e tratamento*. Artmed Editora, Porto Alegre, 2 edition.

Catlin, G. and Will, P. (1992). The national population health survey: highlights of initial developments. *Health Reports*, 4(3):313–319.

Chen, L., Magdy, W., Whalley, H., and Wolters, M. K. (2020). Examining the role of mood patterns in predicting self-reported depressive symptoms. In *12th ACM Conference on Web Science*, pages 164–173.

Chung, H.-K., Cho, Y., Choi, S., and Shin, M.-J. (2014). The association between serum 25-hydroxyvitamin D concentrations and depressive symptoms in Korean adults: findings from the fifth Korea National Health and Nutrition Examination Survey 2010. *PloS one*, 9(6):e99185.

de Moraes, E. V., Campos, R. N., and Avelino, M. M. (2016). Sintomas depressivos na gestação: Influência dos aspectos social, comportamental, psicológico e obstétrico. *Revista Brasileira de Ginecologia e Obstetricia*, 38(6):293–300.

Dipnall, J. F., Pasco, J. A., Berk, M., Williams, L. J., Dodd, S., Jacka, F. N., and Meyer, D. (2016). Fusing data mining, machine learning and traditional statistics to detect biomarkers associated with depression. *PLoS ONE*, 11(2):e0148195.

Galiatsatos, D., Konstantopoulou, G., Anastassopoulos, G., Nerantzaki, M., Assimakopoulos, K., and Lymberopoulos, D. (2015). Classification of the most Significant Psychological Symptoms in Mental Patients with Depression using Bayesian Network.

Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep Learning*. MIT Press. http://www.deeplearningbook.org.

Hosseinifard, B., Moradi, M. H., and Rostami, R. (2013). Classifying depression patients and normal subjects using machine learning techniques and nonlinear features from EEG signal. *Computer Methods and Programs in Biomedicine*, 109(3):339–345.

Khademi, M. and Nedialkov, N. S. (2015). Probabilistic graphical models and deep belief networks for prognosis of breast cancer. In *Machine Learning and Applications (ICMLA), 2015 IEEE 14th International Conference on*, pages 727–732. IEEE.

Koleva, H., Stuart, S., O'Hara, M. W., and Bowman-Reif, J. (2011). Risk factors for depressive symptoms during pregnancy. *Archives of Women's Mental Health*, 14(2):99–105.

Kroenke, K., Strine, T. W., Spitzer, R. L., Williams, J. B., Berry, J. T., and Mokdad, A. H. (2009). The phq-8 as a measure of current depression in the general population. *Journal of Affective Disorders*, 114(1):163 – 173.

Maes, M., Galecki, P., Chang, Y. S., and Berk, M. (2011). A review on the oxidative and nitrosative stress (o&ns) pathways in major depression and their possible contribution to the (neuro) degenerative processes in that illness. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, 35(3):676–692.

Mahendran, N., Vincent, P. D. R., Srinivasan, K., Sharma, V., and Jayakody, D. K. (2020). Realizing a stacking generalization model to improve the prediction accuracy of major depressive disorder in adults. *IEEE Access*, 8:49509–49522.

Matza, L. S., Phillips, G. A., Revicki, D. A., Murray, L., and Malley, K. G. (2011). Development and validation of a patient-report measure of fatigue associated with depression. *Journal of Affective Disorders*, 134(1-3):294–303.

Miller, A. H., Maletic, V., and Raison, C. L. (2009). Inflammation and its discontents: the role of cytokines in the pathophysiology of major depression. *Biological psychiatry*, 65(9):732–741.

Min, J. A., Lee, S. H., Lee, S. Y., Chae, J. H., Lee, C. U., Park, Y. M., and Bae, S. M. (2012). Clinical characteristics associated with different strengths of loudness dependence of auditory evoked potentials (LDAEP) in major depressive disorder. *Psychiatry Research*, 200(2-3):374–381.

Patel, M. J., Andreescu, C., Price, J. C., Edelman, K. L., Reynolds, C. F., and Aizenstein, H. J. (2015). Machine learning approaches for integrating clinical and imaging features in late-life depression classification and response prediction. *International Journal of Geriatric Psychiatry*, 30(10):1056–1067.

Patel, M. J., Khalaf, A., and Aizenstein, H. J. (2016). Studying depression using imaging and machine learning methods. *NeuroImage: Clinical*, 10:115–123.

Patel, V., Flisher, A. J., Hetrick, S., and McGorry, P. (2007). Mental health of young people: a global public-health challenge. *The Lancet*, 369(9569):1302–1313.

Quevedo, J., Nardi, A. E., and da Silva, A. G. (2018). *Depressão-: Teoria e Clínica*. Artmed Editora.

Ravì, D., Wong, C., Deligianni, F., Berthelot, M., Andreu-Perez, J., Lo, B., and Yang, G.-Z. (2017). Deep learning for health informatics. *IEEE journal of biomedical and health informatics*, 21(1):4–21.

Sadeque, F., Xu, D., and Bethard, S. (2017). Uarizona at the clef erisk 2017 pilot task: linear and recurrent models for early depression detection. In *CEUR workshop proceedings*, volume 1866. NIH Public Access.

Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *CoRR*, abs/1404.7828.

Sengupta, P. and Benjamin, A. (2015). Prevalence of depression and associated risk factors among the elderly in urban and rural field practice areas of a tertiary care institution in Ludhiana. *Indian Journal of Public Health*, 59(1):3.

Silva, M. T., Galvao, T. F., Martins, S. S., and Pereira, M. G. (2014). Prevalence of depression morbidity among brazilian adults: a systematic review and meta-analysis. *Revista Brasileira de Psiquiatria*, 36(3):262–270.

Stapley, E., Midgley, N., and Target, M. (2016). The experience of being the parent of an adolescent with a diagnosis of depression. *Journal of Child and Family Studies*, 25(2):618–630.

Stewart, J. C., Rand, K. L., Muldoon, M. F., and Kamarck, T. W. (2009). A prospective evaluation of the directionality of the depression–inflammation relationship. *Brain, behavior, and immunity*, 23(7):936–944.

Sunmoo, Y., Basirah, T., et al. (2014). Using a data mining approach to discover behavior correlates of chronic disease: a case study of depression. *Studies in health technology and informatics*, 201:71.

Suzuki, M., Furihata, R., Konno, C., Kaneita, Y., Ohida, T., and Uchiyama, M. (2018). Stressful events and coping strategies associated with symptoms of depression: A japanese general population survey. *Journal of affective disorders*, 238:482–488.

Tadesse, M. M., Lin, H., Xu, B., and Yang, L. (2019). Detection of depression-related posts in reddit social media forum. *IEEE Access*, 7:44883–44893.

Trotzek, M., Koitka, S., and Friedrich, C. M. (2017). Linguistic metadata augmented classifiers at the clef 2017 task for early detection of depression. In *CLEF (Working Notes)*.

Tung, C. and Lu, W. (2016). Analyzing depression tendency of web posts using an event-driven depression tendency warning model. *Artificial Intelligence in Medicine*, 66:53–62.

Villegas, M. P., Funez, D. G., Ucelay, M. J. G., Cagnina, L. C., and Errecalde, M. L. (2017). Lidic-unsl's participation at erisk 2017: Pilot task on early detection of depression. In *CLEF (Working Notes)*.

Wan, Z., Huang, J., Zhang, H., Zhou, H., Yang, J., and Zhong, N. (2020). Hybrideegnet: A convolutional neural network for eeg feature learning and depression discrimination. *IEEE Access*, 8:30332–30342.

Wang, H., Zhou, Y., Yu, F., Zhao, L., Wang, C., and Ren, Y. (2019). Fusional recognition for depressive tendency with multi-modal feature. *IEEE Access*, 7:38702–38713.

Wang, J., Manuel, D., Williams, J., Schmitz, N., Gilmour, H., Patten, S., MacQueen, G., and Birney, A. (2013). Development and validation of prediction algorithms for major depressive episode in the general population. *Journal of Affective Disorders*, 151(1):39–45.

Winokur, A., Maislin, G., Phillips, J. L., and Amsterdam, J. D. (1988). Insulin resistance after oral glucose tolerance testing in patients with major depression. *Am J Psychiatry*, 145(3):325–330.

Witten, I. H., Frank, E., Hall, M. A., and Pal, C. J. (2016). *Data Mining: practical machine learning tools and techniques with Java implementations*. Morgan Kaufmann, 4 edition.

Wray, N. R., Ripke, S., Mattheisen, M., Trzaskowski, M., Byrne, E. M., Abdellaoui, A., Adams, M. J., Agerbo, E., Air, T. M., Andlauer, T. M., et al. (2018). Genome-wide association analyses identify 44 risk variants and refine the genetic architecture of major depression. *Nature genetics*, 50(5):668.

Xing, Y., Rao, N., Miao, M., Li, Q., Li, Q., Chen, X., Zhang, Q., and Wu, J. (2019). Task-state heart rate variability parameter-based depression detection model and effect of therapy on the parameters. *IEEE Access*, 7:105701–105709.

Yang, H. and Bath, P. A. (2019). Automatic prediction of depression in older age. In *Proceedings of the third International Conference on Medical and Health Informatics 2019*, pages 36–44.

Yang, L., Jiang, D., He, L., Pei, E., Oveneke, M. C., and Sahli, H. (2016). Decision Tree Based Depression Classification from Audio Video and Language Information. In *Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge - AVEC '16*, AVEC '16, pages 89–96, New York, NY, USA. ACM.

Yanikkerem, E., Ay, S., Mutlu, S., and Goker, A. (2013). Antenatal depression: Prevalence and risk factors in a hospital based Turkish sample. *Journal of the Pakistan Medical Association*, 63(4):472–477.

Zeng, L. L., Shen, H., Liu, L., and Hu, D. (2014). Unsupervised classification of major depression using functional connectivity MRI. *Human Brain Mapping*, 35(4):1630–1641.