EMOTIONAL ILLNESS DETECTION USING DEEP LEARNING

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Abstract:
A substantial societal concern posed by the increased incidence of mental diseases has prompted research into cutting-edge technology to improve forecasting capacities and guide targeted interventions. Deep Learning (DL), a type of machine learning, has drawn a lot of attention for its potential to forecast and categorize the outcomes of mental illness using a variety of data sources. This systematic review summarizes prior work on the use of deep learning techniques to forecast the onset of mental illness. This review explains the benefits and drawbacks of current methodologies while seeing patterns and promising directions for further investigation. It does this by looking at a variety of datasets, model architectures, and evaluation criteria. In addition to underlining the necessity for standardized procedures, improved interpretability, and ethical issues when deploying these predictive models in actual healthcare settings, the synthesis of findings highlights the promising potential of deep learning in predicting mental illness. This review offers insightful guidance for the improvement and growth of deep learning-based prediction models, enabling eventually more efficient and individualized approaches to mental illness prevention and treatment as mental health interventions continue to advance.

Keywords: Depression, Anxiety, Stress, Deep Learning, PRISMA.

1. Introduction

A medically prominent disparity in an individual's intellectual, emotional control or behavioral stability is often referred to as mental disorder. It is ordinarily linked to distress or functional impairment in the crucial areas. It appears in many varieties. It has also been coined as mental health issues from time to time. The latter is more generic as it comprises of mental illness, psychological disablement and other cognitive states linked to rational distress, functional disability or endangerment of self-harm.

In 2019, 301 million people, including 58 million kids and teenagers, suffered from anxiety illness [1]. Over boarded fear, worry and behavioral anomalies are the general characteristics of anxiety disorders. Generalized anxiety disorder, panic disorder, social anxiety disorder, separation anxiety disorder, etc. are some of the classifications of anxiety disorders. There are effective and methodical cures and treatments available in conjunction with medicines that may as well be taken into consideration, depending upon the gravity and age of the victim.

There were 280 million victims with depression worldwide in 2019 [1], including 23 million children and teenagers. Depression is divergent from the usual mood swings and quickened emotional reactions to hindrances in real life. An episode of such a mental state lasts at least two weeks and is defined by depressive mood, including sad, agitated or hollow feelings or loss of happiness or interest in activities for the major half of the day. Other symptoms may include deficiency of concentration, overwhelming guilt or low self-esteem, hopelessness, suicidal tendencies, disrupted sleep and mental burnout. Suicidal risk is increasing among depressed people.

The impedance of stress, being a prototypical reciprocation of the typical stress, is unhealthy if it affects our routine. It creates modifications in our physical and mental planes, leading to poor judgement and actions. Stress causes a significant purge in the quality of life, directly contributing to the psychological and physiological disorder and diseases. It possesses a vital role on one's physical and mental well-being. Stress is a normal reaction to everyday pressures, but can become unhealthy when it upsets our day-to-day functioning. Stress involves changes affecting nearly every system of the body, influencing how people feel and behave [2].

Deep learning has become a paradigm that is revolutionizing how we analyze and understand complex data in the field of artificial intelligence (AI). Deep learning, which combines computer science, neuroscience, and machine learning, has demonstrated previously unheard-of ability in the extraction of complex patterns and representations from enormous and varied datasets. In-depth analysis of the use of deep learning approaches in the context of emotional health prediction is provided in this systematic review. An individual's psychological state, behavior, and interactions are significantly shaped by their emotional health, which is an essential aspect of total wellbeing.

Artificial neural networks with numerous layers are used in deep learning, a subset of machine learning techniques that allows models to gradually learn and extract hierarchical features from unstructured input. This method mimics the complex neuronal interconnection found in the human brain, enabling machines to learn complex representations on their own basis directly from the input. Deep learning is especially effective at detecting subtle emotional nuances that may be difficult to detect using conventional analysis techniques because of its ability to automatically learn and adapt features from the input data.

Deep learning models have shown outstanding promise in understanding and predicting emotional states across several modalities, including text, visuals, audio, physiological signs, and social interactions. This is relevant to the field of emotional health prediction. Deep learning algorithms show potential in facilitating accurate emotional health evaluations and providing fresh insights into people's mental well-being by learning patterns inherent in these varied data sources.

This complete investigation of the application of deep learning methods for emotional health prediction is the goal of this systematic review.

2. Methodology

In order to provide a comprehensive picture of the developments in research on the diagnosis of emotional health, numerous concepts and topics were taken into account for this study throughout the selection, extraction, and analysis of previous studies. The following issues have all been taken into consideration: "How to predict stress, anxiety, and depression," "How deep learning is used for the mental illness prediction," and "What are the different deep learning algorithms used for prediction." Google Scholar, Elsevier ScienceDirect, EBSCO, and IEEE Xplore were among the databases that were searched. The terms "mental illness prediction", "deep learning for mental illness diagnosis", "artificial intelligence for emotional health", "depression prediction", "stress prediction", and "anxiety prediction" were carefully searched in these four well-known electronic databases. Additionally, the above phrases' combinations were considered.

A. The Choice of Documents

When evaluating the papers, their applicability to the aforementioned topics was taken into account. To evaluate if they were relevant to our field of interest, we looked at the titles, abstracts, and keywords. After that, the papers were divided into two groups based on the inclusion and exclusion criteria listed below.

E1: Publications that don't directly address the prediction of stress, anxiety, and depression using DL methods.
E2: Articles that hardly mention the subjects being discussed
E3: Content that doesn’t contain any of the keywords
E4: Identical documents
I1 Full-text articles
I2 Only English-language papers
I3 Publications between 2018 and 2023.

B. PRISMA

The Preferred reporting items for systematic review and meta-analysis (PRISMA) methodology, which outlines how to conduct a systematic review, was used in the study [3]. 76 documents in total were initially obtained from all web sources. Overlap was discovered through the Google Scholar search and eliminated, leaving only 58 papers. 35 papers were subsequently eliminated after each title and abstract were carefully examined. The best 23 papers were chosen after careful consideration, and they are all listed in this review. Figure 1 depicts the screening procedure.

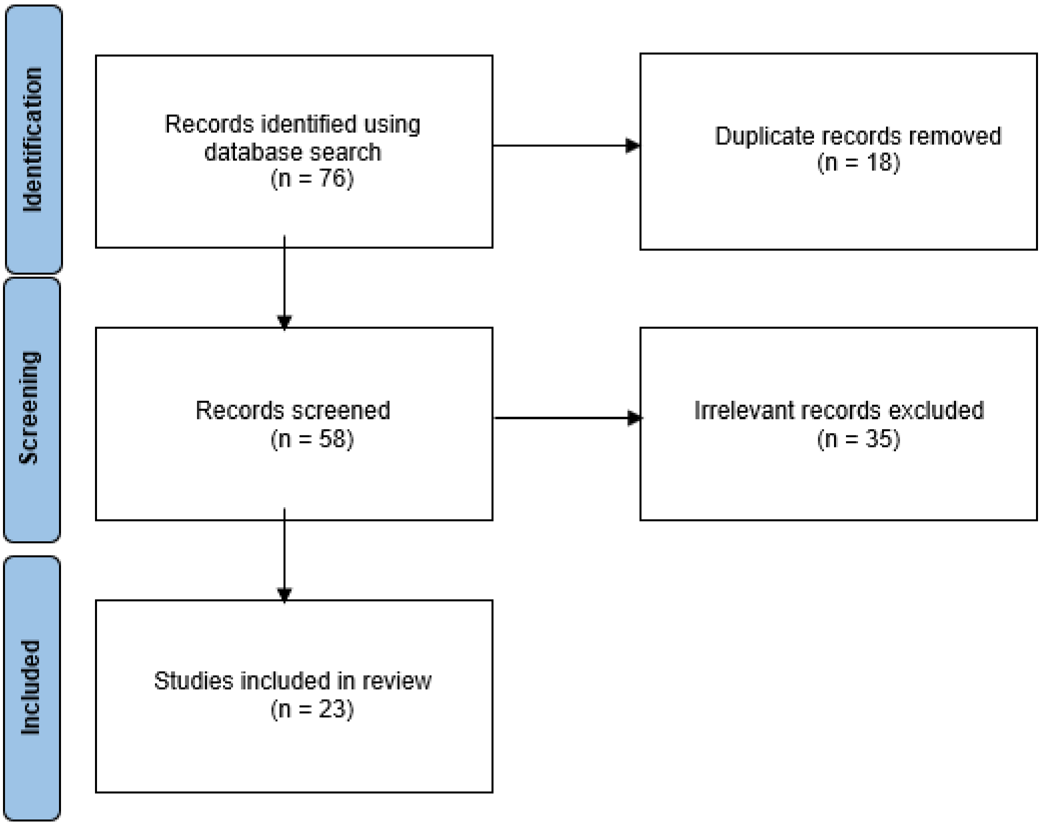

Figure 1. PRISMA Methodology

3. Literature Review Findings

Pandit et al. [4] developed a deep neural network model that outperforms all other classifiers by around 40% accuracy. The DNN replaces all machine learning classifiers and ANN by around 30%, according to the harmonic mean, which also suggests that the DNN is better at predicting anxiety and sadness. For anxiety and depression, respectively, the tabular DNN can predict properly 9 out of 10 times and nearly 10 out of 10 times.

Using BERT, Zeberga et al. [5] proposed a unique framework to quickly and accurately identify postings linked to depression and anxiety while preserving the contextual and semantic meaning of the words used throughout the whole corpus. In order to improve performance and accuracy, they also suggest the knowledge distillation methodology, a more modern method for transferring knowledge from a big pretrained model (BERT) to a smaller model. The authors used details from Twitter and Reddit, the two most popular social media platforms. They used word2vec, BERT, and Bi-LSTM to efficiently examine and find symptoms of anxiety and depression in social media posts. Utilizing the information, it outperformed similar cutting-edge techniques and achieves an accuracy of 98%.

In order to forecast elderly population depression throughout the pandemic time based on social characteristics, Nguyen and Byeon [6] looked at a deep neural network (DNN) model. The 2020 Community Health Survey of the Republic of Korea, provided study with a wealth of data. The training was with the details of 36,258 participants and 22 variables after the data had been cleaned. They combined the DNN model with a LIME-based explainable model. The study found that the model could predict events with an accuracy of 89.92. The F1-score (92), precision (93.55), and recall (97.32) results further demonstrated efficacy of the suggested strategy. The pandemic era has a significant impact on the older population's risk of developing depression in later life. This understandable DNN model can assist in identifying patients so that early therapy can be begun.

The study by Ameer et al. [7] categorized PTSD, ADHD, bipolar disorder, and depression using unstructured user data from the Reddit platform. The authors developed multi-class machine learning models for classical machine learning, deep learning, and transfer learning. The Reddit post dataset was created to identify mental diseases and classify them into one of five categories. Machine learning employed the linearSVC, LR, NB, and RF algorithms, with linearSVC demonstrating the best accuracy (0:79 F1- Score 0:80) and linearr (0:79 F1- Score 0:80). Deep Learning employed GRU, Bi-GRU, CNN, LSTM, and Bi-LSTM; Bi-LSTM fared well (Accuracy 0.78 and F1 - Score 0.71). BERT, XLNet, and RoBERTa were employed in transfer learning, with RoBERTa performing best (Accuracy 0.83, F1 Score 0.83).

Uddin et al. [8] provided an effective method for locating texts representing one's own self-reported depressive symptoms using a recurrent neural network (RNN) based on long short-term memory (LSTM). The method is used on a sizable dataset taken from a public Norwegian youth information website. The features outperform more traditional methods that primarily rely on word rather than symptoms. The time-sequential characteristics are then trained to distinguish texts describing depression symptoms from those without such descriptions (non-depression posts) using a deep learning approach (i.e., RNN). Finally, depressive posts are automatically predicted using the trained RNN. The system's performance is compared to that of conventional techniques, where it outperformed them all. By producing superior grouping than other conventional features, the linear discriminant space amply demonstrates the robustness of the features. Additionally, because the characteristics are based on potential depressive symptoms, the system may produce insightful justifications for the choice utilizing the explainable Artificial Intelligence (XAI) technique known as Local Interpretable Model-Agnostic Explanations (LIME).

Orabi et al. [9] presented a system that analyses social media posts to identify people who may be at risk for depression. In order to achieve this, authors present an effective neural network architecture that enhances and optimizes word embeddings. On the CLPsych 2015 shared task and the Bell Let's Talk datasets, the optimized embeddings produced by the architecture were compared to three widely used word embeddings, random trainable, skip-gram, and CBOW. Compared a few chosen CNN- and RNN-based models to find the most effective ones and parameters for detecting depression in various scenarios.

Establishing deep learning models that can identify responders from non-responders and forecast potential antidepressant treatment results in major depressive disorder (MDD) were the main objectives of the study by Lin et al. [10]. They used SNP dataset.Then, using a multilayer feedforward neural network (MFNN) with one to three hidden layers, logistic regression models were compared to MFNN models. The best predictive model for predicting remission was the MFNN model with three hidden layers (AUC = 0.8060 0.0722; sensitivity = 0.7732 0.0583; specificity = 0.6623 0.0853).

Uyulan et al. [11] used a deep convolutional neural network (CNN) approach and sophisticated computational neuroscience methodology to construct an electroencephalography (EEG)-based diagnosis model for MDD. To distinguish between MDD patients and healthy controls, three different deep CNN structures - ResNet-50, MobileNet, and Inception-v3 - were modelled using EEG recordings. By gathering data from 19 electrodes, EEG data are gathered for the four primary frequency bands (D, q, a, and b), accompanying spatial resolution with position information. Models built using location data and the MobileNet architecture produced classification accuracy of 89.33% and 92.66%, respectively. In terms of frequency bands, the delta frequency band fared best for ResNet-50 architecture, outperforming other bands with a 90.22% prediction accuracy and an area under the curve (AUC) value of 0.9. The study's key contribution is the identification of specific spatial and temporal variables that can be used to differentiate between 46 people with MDD and 46 people without the disorder using different DL designs. The primary goal of this study is to investigate translational biomarkers of mood disorders from a DL perspective, and although it is difficult, computational methods are highly valuable for the diagnosis process because they are faster and more accurate than conventional methods while also having the potential to advance understanding of psychiatric disorders.

Amanat et al. [12] implemented a LSTM model, which consists of two hidden layers, large bias, and RNN with two dense layers on textual data, is implemented in this paper. This model can be useful in preventing people from mental illnesses and suicidal thoughts. The suggested model achieved 99.0% accuracy. Regarding the suggested model's mean accuracy, they also contrast it with other models.

The automatic detection of MDD utilizing EEG data and deep neural network architecture was the main goal of the study by Rafiei et al. [13]. First, a customized Inception Time model is used for this purpose to identify MDD sufferers using 19-channel unprocessed EEG inputs. Then, in order to eliminate redundant channels, a channel-selection method that consists of three channel-selection processes is used. Their method achieved 87.5% accuracy after channel reduction and 91.67% with the entire set of channels.

In their research, Kim et al. [14] created an approach to increase the precision of multi-channel electroencephalogram (EEG) data used to identify emotional stress. The technique creates a 3D gated self-attention CNN by fusing a 3D CNN with an attention mechanism. To retrieve EEG spatiotemporal information, the EEG data is first divided into four frequency bands. Each frequency band is then subjected to a 3D CNN block. Then, by using a gated self-attention mechanism to collect salient information from each frequency band.

With the help of manually created features and deeply learned features from the spectrogram, a convolutional neural network is proposed by Kapoor and Kumar [15] for the identification of stress and rage. In order to get more noticeable characteristics and improve recognition accuracy, a combined feature set combines information from two alternative representations of speech signals. Comparatively to other methods of emotion assessment, the one being offered is more computationally efficient. The TESS, RAVDESS, and EMO-DB datasets were used.

Bharti et al. [16] devised a ML, DL, and a hybrid model approach to emotion categorization on a multitext dataset made up of sentences, tweets, and dialogues. These experiments employed three datasets: ISEAR, WASSA, and emotion-stimulus. The pipeline first received the text as an input, and it then transformed the text into a vector. The ML Classifier was trained using these vectors. Second, the pretrained word vector was used to extract the features, and the embedding matrix (18210, 300) served as the DL model's input layer. The DL model was used to train the padded vector. The latent vector from the combined model is given as an input vector for SVM model for training.

In their study, Liu et al. [17] classified the acquired emotional EEG data using a deep neural network (DNN), and the emotional state of college students is determined using the classification outcomes. Different EEG characteristics are initially extracted in order to convey the original EEG data information as completely as possible, keeping in mind that different features can reflect different information of the original data. Second, the autosklearn model integration technique is used to combine numerous characteristics. Third, the DNN receives the combined characteristics and produces the final classification outcome. The experimental findings demonstrate the method's benefits in publicly available datasets, and the accuracy of emotion recognition is greater than 88%. This demonstrates that the technique for recognizing emotions may be employed in practical settings.

Nasrullah and A. Jalali [18] gathered the dataset from Reddit. Two recurrent (bidirectional LSTM) and one convolutional neural network are employed in their study to perform the classification. The dataset is preprocessed in the first stage, after which the preprocessed data are run through many deep learning models, including RNN andCNN.

The brain-computer interface (BCI) described in the study by Shah et al. [19] used multi-channel electroencephalograms (EEG) to analyze human emotions and brain complexity utilizing a novel framework for emotion recognition. They used two datasets in their research: dataset for emotion analysis using EEG, physiological, and video signals (DEAP) for LSTM model implementation, and database for emotion recognition through EEG and ECG signals from wireless low-cost off-the-shelf devices (DREAMER) for LSTM model validation. The framework consists of an emotion timing model and a linear model for EEG signal mixing. After being exposed to external stimuli, stress-bins were developed for each user to help them gauge their state of tension or calm. The DEAP dataset was used with the LSTM framework for emotion detection, and the mean recognition accuracy using the area under the curve as the evaluation matrix for valence and arousal, respectively, was 82.02% and 76.52%, supporting the framework's competency. Their work is novel in that it has increased feature extraction skills, uses context correlations to increase accuracy, and incorporates spatiotemporal information into the proposed model framework.

4. Results and Discussion

Table 1 lists the DL methodologies employed by various researchers, along with related mental diseases and their results. Some researchers have looked at stress, anxiety, and depression all at once, whereas others have just looked at one of these. Numerous methods, such as DNN, ANN, CNN, DRNN, and LSTM, have been used by them.

Table 1. Performance Comparison

Paper	Year	Mental Illness	Dataset	Algorithms	Model Performance
[4]	2023	Anxiety, Depression	Covid – 19 impact survey	ANN	Anxiety: ANN - 62 (A); 71 (F1); 71 (P); 71 (RC) and DNN - 91 (A); 91 (F1); 91 (P); 91(RC) Depression: ANN - 63 (A); 66 (F1); 67 (P); 66 (RC) and DNN - 96 (A); 96 (F1); 96 (P); 96 (RC)
[5]	2022	Depression and Anxiety related posts	Reddit and Twitter	Proposed KD distilled_BERT method	98 (A)
[6]	2022	Depression	2020 Community Health Survey	DNN	89.92 (A) 93.55 (P) 97.32 (RC)

			of the Republic of Korea		92 (F1)
[7]	2022	ADHA, Anxiety, Bipolar, Depression, PTSD	Reddit	RoBERTa	ADHD: 85 (P); 83 (RC); 84 (F1) Anxiety: 73 (P); 78 (P); 76 (F1) Bipolar: 83 (P); 76 (RC); 80 (F1) Depression: 76 (P); 83 (RC); 70 (F1) PTSD: 90 (P); 87 (RC); 88 (F1) None: 99 (P); 96 (RC); 98 (F1)
[8]	2021	Depression	Norwegian Dataset	LSTM based RNN	Depression: 98 (P); 97 (RC); 97 (F1); 182 (S) Non-depression: 99 (P); 100 (RC); 99 (F1); 998 (S)
[9]	2018	Depression	CLPsych 2015 dataset e Bell Let's Talk dataset	CNNWithMax (Optimized) MultiChannelCNN (Optimized)	87.957 (A); 86.967 (F1); 0.951 (AUC); 87.435 (P); 87.029 (RC) 83.117 (A); 82.252 (F1); 0.923 (AUC); 81.626 (P); 84.439 (RC)
[10]	2018	Depression	SNP Dataset	Multilayer Feed forward Network	0.8060 ± 0.0722 (AUC); 0.7732 ± 0.0583 (SE); 0.6623 ± 0.0853 (SP)
[11]	2020	Depression	EEG Dataset	Mobile Net	Hemisphere classification accuracy: 89.33 (Left); 92.66 (Right)
[12]	2022	Depression	Tweets-Scraped dataset	RNN – LSTM approach	99 (P); 98 (RC); 99 (F1); 998 (S)
[13]	2022	Depression	19 channel EEG Data	DNN	91 (A); 94.9 (SE); 88.2 (SP)
[14]	2022	Stress	DEAP dataset.	3DCGSA	96.68 (A); 96.77 (P); 96.39 (F1)

			VRE dataset EDESC dataset.		95.64 (A); 95.57 (P); 94.96 (F1) 91.52 (A); 93.20 (P); 92.82 (F1)
[15]	2022	Stress	TESS EMO-DB RAVDESS	CNN with fused features	93.7 (AT); 95.6 (AV) 97.5 (AT); 95.6 (AV) 96.7 (AT); 96.7 (AV)
[16]	2022	Emotion	ISEAR, WASSA, and Emotion-stimulus	Hybrid model CNN+ Bi-GRU +SVM	82.39 (P); 80.40 (RC); 81.27 (F1); 80.11 (A)
[17]	2022	Emotion	DEAP Dataset	DNN	Valence: 90.78 (A); 90.02 (P); 88.65 (F1) Arousal: 89.26 (A); 88.41 (P); 86.77 (F1) Liking: 89.03 (A); 87.82 (P); 85.59 (F1)
[18]	2022	Anxiety, Bipolar, Dementia, Psychotic	Reddit	Ensemble Deep Learning model	Anxiety: 80.13 (A) Bipolar: 92.14 (A) Dementia: 80.45 (A) Psychotic: 78.85 (A)
[19]	2023	Valance and arousal	DREAMER AND DEAP	LSTM	Valance: 82.02 (A) Arousal: 76.52 (A)

Note: A - Accuracy; F1 – F1 Score; P – Precision; RC – Recall; S – Support; SE – Sensitivity; SP – Specificity; AT – Test Accuracy; AV – Validation Accuracy

5. Conclusion

In conclusion, this review paper has investigated the fascinating environment of deep learning-based mental health prediction. It has become clear from the analysis that the combination of cutting-edge computational techniques and mental health prediction holds enormous promise for revolutionizing the industry. Using a combination of large datasets, novel feature extraction, and powerful deep learning architectures, it is now possible to identify and forecast mental health illnesses with surprising accuracy.

But it's important to recognize the difficulties and constraints that are already present. When implementing these models in practical applications, ethical issues like privacy and bias continue to be important factors to take into account. To ensure clinical utility and acceptance among mental health practitioners, the interpretability of sophisticated deep learning models also requires consideration. Additionally, the lack of diverse and consistent datasets

Fostering interdisciplinary cooperation between data scientists, mental health professionals, and politicians will be essential as we move forward. To fully utilize deep learning for mental health prediction, it will be essential to strike a balance between technological advancement and moral responsibility. To create models that are not only accurate but also transparent, equitable, and adaptable to many cultural and demographic contexts, more study is required.

In conclusion, there is no denying that DL has made significant advancements in mental health prediction. This review paper highlights the importance of addressing the complex problems that lie ahead while also emphasizing the positive effects that these developments may have on people who suffer from mental health illnesses. We can create a future where early intervention and assistance for mental well-being are more widely available and efficient than ever before by fostering a synergistic interaction between cutting-edge technology and human compassion.

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