Deep Feedforward Neural Networks for Prediction of Mental Health

Ramasamy Mariappan and Gopi Battineni

Abstract Mental health disorders or psychiatric issues such as Alzheimer's disease (AD), cognitive impairments, and depression have an impact on physical health. The early detection of patients who are at risk of a mental health crisis is of paramount importance to reduce burdens and costs that can result from. However, the high prevalence of mental health issues makes it impractical to manually review complicated patient health records to make proactive psychiatric health care decisions. Artificial intelligence (AI) techniques have recently been developed to aid mental health professionals, such as psychiatrists and psychologists, in making clinical decisions. Recently, deep learning approaches find great attention among biomedical researchers due to their unmatchable ability to use very large size datasets to predict medical results. One such tremendous application is the use of deep learning for the prediction of psychiatric disorders. However, typical deep learning (DL) approaches suffer from limitations due to their significant presumptions, which make this not suitable for medical imaging. This book chapter reviews the literature on DL algorithm applications in predictive research on psychiatric health. In particular, it gives a succinct overview of contemporary DL techniques in psychiatric health research. This chapter proposed a novel deep learning method using deep feedforward neural networks coupled with psychiatric tools, which could hasten a new way for integration into prognostic research in digital psychiatry and eventually lead to its use in clinical results. In our final section, it examined the major difficulties in applying DL algorithms and psychiatric tools to enhance the prognosis and prediction of mental health disorders and leveraging several interesting applications for DL algorithms along with physician's intelligence for enhancing mental health treatment.

Keywords Mental health · Psychiatric tools · EEG · DL · Neural networks

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1 Introduction

The digital mental health sector has experienced rapid growth over the past decade due to the proliferation of digital tools and technical advancements, increasing consumer preferences for digital health, and the impacts of COVID-19 and natural disasters on the user's ability to access face-to-face services [1]. However, despite the rapid growth of the digital mental health sector, supply and demand barriers continue to exist, impeding the effective operation of the sector [1–3]. Consumers can experience issues accessing services due to poor health or digital literacy, digital infrastructure, or pre-existing social inequalities. Some may also be hesitant to use digital mental health services due to mistrust in their efficacy or concerns about the use of their data. Poor awareness and distrust are also experienced by health professionals, in part due to an underdeveloped evidence base for how digital mental health services could be best used [4]. In particular, there is limited evidence to understand the suitability of digital interventions for low prevalence and complex mental health issues, and vulnerable or at-risk population cohorts. While health professionals understand the need to cater to the unique needs and preferences of consumers, they can find it overly complex to navigate the digital mental health ecosystem and match consumers to the right services.

Cognitive challenges are suggestive highlights of all psychological messes. High paces of mental indications, prominently tension, sorrow, self-destructive conduct, and posttraumatic stress disorder have been accounted for in the all-inclusive community following past nCoV scourges, independent of irresistible status. An investigation of 90 COVID-19 cases with a 97% reaction rate also demonstrated undeniable degrees of mental trouble with 59% determined to have mental problems furthermore [5]. The modest quantity of data accessible from creature examines and past respiratory scourges recommend not just that novel coronavirus may influence the cerebrum, but that the subsequent impact on cognitive operations might persevere for a significant stretch after recuperation. While new cases of very much described neurological problems resulting from the current pestilence might be moderately simple to distinguish, enduring sub-clinical problems, for example, mild cognitive decline, focal memory and speech loss, or intensification of previous degenerative neuropathology like vascular dementia, and Alzheimer's illness, may effectively go undetected or then again be ascribed to mental responses and social change produced by the pandemic.

The current longitudinal studies of neurological disorders should be expanded to collect data on COVID-19 openness and immune response status in addition to the psychological functioning, brain imaging, and disease biomarker data that are now collected [3]. The development of new COVID-19 mice models, which will enable the assessment of the interaction between viral pathology and neurodegeneration and contribute to the advancement of new therapies, will encourage preclinical studies aimed at determining the robotic relationship between COVID contamination and neurological illness [6]. The common barriers to cognitive assessment are listed below:

- Poor coordination of psychological evaluations with EMR frameworks makes a significant clerical work burden to archive the yield of a cognitive performance assessment.
- Moreover, the absence of an appropriate combination with the EMR framework additionally restricts the capacity to follow a person's cognitive/psychological insight over the long run.
- In certain conditions, testing apparatuses are ineffectively planned and additionally unintuitive for clients.
- Also, numerous cognitive tests have exhibited restricted worth when sent to a heterogeneous patient populace. This constraint arises due to the initial development and testing being inhomogeneous.
- Early identification of MCI is challenging because of constraints related to cognitive diseases. Symptoms or signs identified with the underlying beginning of MCI can change altogether between people, contingent upon etiology, intellectual hold, and variable requests of everyday living, among different elements.
- Alzheimer's association encourages parental care to be aware of the main indication of the presence of COVID-19 disease in people with dementia or AD.

By aiming at the above-mentioned factors, the current chapter proposes to examine the wide scope of mental health issues, neuropsychiatric ramifications, neurological issues, psychiatry issues, and neuropsychiatric issues like disarray and cognizance. Even though extreme neuropsychiatric consequences are relatively rare, a sizable number of people would be impacted globally. Since previous flu pandemics were linked to long-lasting neuropsychiatric effects, it is plausible that new viral contaminations with a wide range could also generate persistent mental gloom.

The majority of psychiatric studies, which have used machine learning, have been on categorization or diagnosis. However, researchers have pointed out that the existing methods underperform due to a lack of understanding of the constraints of the various machine learning techniques or psychiatric issues and their associated procedures and highlighting the challenge in developing and validating such models. Previous studies have shown that the analysis of neuroimages using deep learning (DL) techniques can offer evidence of mental health issues, which can be applied in clinical settings and aid in the identification of mental illnesses [7]. However, to accomplish this goal, numerous issues must be resolved.

- Because the DL architectures often need large data samples to train the models, the analysis of neuroimaging data may be difficult due to the absence of such data.
- The imaging data typically occupy a high-dimensional space; for instance, a 64 2D neuroimage can yield 4096 characteristics [8]. As a result, there is a chance that the DL models will overfit.
- One potential solution to this problem is to use feature engineering to make the data less dimensional before supplying it to the DL models.

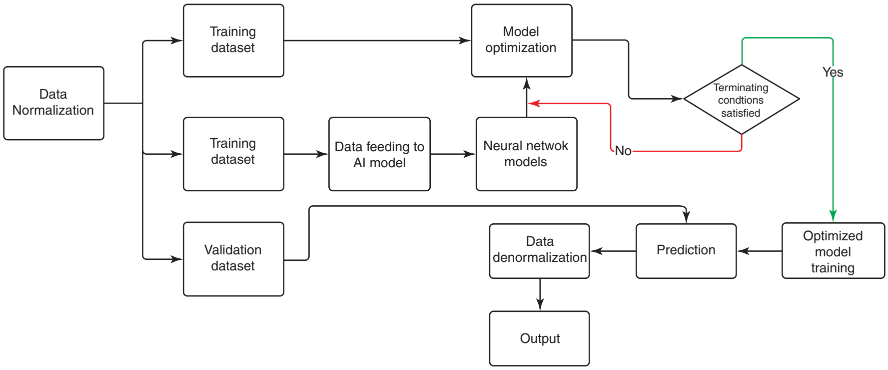

Fig. 1 Deep learning architecture

The DL models have been proven to perform better than the conventional ML models in the prediction of several disorders, including depression, and schizophrenia [9, 10]. These models can profit from feature engineering techniques. However, because these techniques extract features based on past knowledge, they might leave out some details that are important for mental outcome study. Using convolutional neural networks (CNN) to automatically extract information from the raw data is an alternate method [11, 12]. Figure 1 presents the architecture of DL model, and it is indicated that neural networks are effective in processing unprocessed neuroimage data.

One of the simplest and most often used neurological symptom diagnostics in the literature is electroencephalography (EEG) [13, 14]. The EEG data are typically categorized as high-density, continuous streaming data. There are several difficulties despite the early success of using DL algorithms to evaluate EEG data for researching various mental health issues.

- One significant issue is the amount of inaccurate, noisy, and redundant information present in raw EEG data obtained from sensors due to depleted batteries, errors in sensor readings, and sporadic communication failure in wireless sensor networks.
- The raw EEG signal must first undergo several preprocessing stages (such as data denoising, data interpolation, data transformation, and data segmentation) before being fed to the DL models.
- The analysis of the EEG streaming data is computationally due to the dense properties of the raw EEG data, which presents a challenge for the model architecture choice. One solution is to use a dimensionality reduction technique using feature engineering.
- On the one hand, using feature selection/extraction techniques, several types of features can be gleaned from the raw data.
- The ability of DL to learn relevant features from "all" available data is one of its intuitive qualities, hence feature selection procedures are less frequently used in DL application scenarios.

- One option is to pre-train a deep neural network using a sizable source dataset using Google Inception v3 model is fully connected layers on top of the network, and then use traditional backpropagation to fine-tune the network using the small target dataset.

Some of the major mental health issues are addressed and listed below:

- Schizophrenia is a severe mental illness that causes aberrant reality interpretation.
- An extreme mental health disease called bipolar disorder, also known as manic depression, generates emotional highs (mania or hypomania) and lows (depression).
- Attention Deficit Hyperactivity Disorder (ADHD): A brain disorder that impairs your ability to focus, remain still, and maintain behavioral control (common in children) [15].
- Anxiety is a state of unease, anxiety, or dread. Extreme mood swings, such as emotional highs and lows, are a sign of bipolar disorder.
- Depression is a common and serious medical disorder that negatively affects a person's feelings, thoughts, and behavior.
- After experiencing a traumatic, frightening, or hazardous event, some people develop.
- Post Traumatic Stress Disorder (PTSD): A disorder, which affects people who suffered from a traumatic, frightening, or dangerous incident.

The methods and classification modes presented in Table 1 majorly highlighted and used in the current literature to predict and classify psychiatric issues.

A new method for the proactive prediction of mental health or psychiatric issues using digital psychiatric tools and a feedforward deep convolution neural network (FFDCNN) was discussed in this work. The rest of the manuscript is organized as

Table 1 List of classification and prediction models

Prediction models	Classification
Bayesian network model	Gaussian classification
Naive Bayes algorithm	Logistic regression algorithm
Logistic regression algorithm	Neural networks model
Multilayer perceptron model	Random forest algorithm
Sequential minimal optimization	Support vector machine
K-star model	XGBoost algorithm
Random subspace model	K-nearest neighbors model
J48 algorithm	
Random forest algorithm	
Random tree	
LASSO model	
Linear regression algorithm	
SVM classifier	
CatBoost algorithm	
XGBoost algorithm	
KNN classifier	

follows. Section 2 explores the psychiatric tools and their biomarkers. Section 3 provides brief introduction on FFDNN, followed by a discussion, and a few future challenges ahead in Sect. 4. Section 5 concludes the chapter with possible future works ahead for further work.

2 Psychiatry Tools

There are numerous neurological complications, psychological complications, and mental health complications. The following neuropsychological complications are observed among psychiatric patients, as shown in Table 2. In the current literature, there are numerous analog psychiatry tools such as anxiety scales, anxiety inventory, PTSD inventory, depression inventory, cardiac anxiety questionnaires, ICD questionnaires, etc.

2.1 Electroencephalogram (EEG)

EEG is one of the easiest and most important neurological analytical tests that can alter clinical decisions. Determining whether a patient has neurological entanglements is beneficial. Scientists found that around 33% of COVID patients who were given an EEG had unusual neuroimaging restricted in the frontal flap of the mind [16]. A portion of the EEG adjustments found in COVID-19 patients may show harm to the brain that probably won't have the option to be fixed in the wake of recuperating from the sickness. EEG stays vital in the assessment of the patient with impeded cognizance, especially with the end goal of barring non-convulsive seizures and status epilepticus. It may not generally be the infection acting straightforwardly on the cerebrum causing the strange EEG readings, it is very well may be the

Table 2 Neurological/psychological/mental health complications

Neurological complications	Psychological complications	Mental health complications
• Developmental dyslexia • Encephalopathy • Encephalitis • Epilepsy • Hereditary ataxia • Huntington's disease • Juvenile myoclonic epilepsy • Myelitis • Parkinson's disease • Progressive supranuclear palsy • Stroke	• Attention deficit hyperactivity disorder (ADHD) • Anorexia nervosa • Autism • Anxiety • Asperger syndrome • Addiction • Bipolar affective disorder • Depression • Obsessive-compulsive disorder (OCD) • Panic disorder • Post traumatic stress	• Dementia in Alzheimer's disease • Dementia in Parkinson's • Frontotemporal dementia • Cognitive decline • Mild cognitive decline (MCD) • Memory loss

oxygen admission, heart issues identified with COVID-19, or another kind of result, which is the reason he says that exhaustive patient consideration ought to incorporate more imaging of the cerebrum or EEG testing as important. Specifically, EEG can be utilized to survey encephalopathy, epileptogenicity, also, any central anomalies in patients with COVID-19 [17]. Previous studies have proven that the EEG is a vital tool that shows the neurological complications, mental health issues, etc. associated with various diseases. Hence, this research paper proposes to investigate mental health issues and psychiatric issues, especially those affected with neurocognitive impairments.

Measurement of EEG to diagnose psychiatric disorders using a novel methodology was proposed. It will also investigate the effect of COVID on mental health and psychological complications including stress, depression, cognitive deficits, motor palsies, sensory deficits, cranial nerve deficits, and cerebella affection such as ataxia or nystagmus, etc. by monitoring brain waves through brain–computer interface (BCI) [18]. In this work, it can be evaluating the EEG parameters of patients encountering shifting levels of encephalopathy concerning an essential COVID-19 ailment. This will help us to get sufficient details on variations in mental health and neuropsychiatric parameters due to the COVID attack. A multi-channel brain wave EEG equipment will be used to record the brain waves of the COVID patient who is affected or who has recovered. Theta waves are obtained during the COVID attack by filtering the brain waves acquired by the BCI mind-wave kit. Theta wave power levels are then compared before and after the COVID-19 attack using the BCI Graphical User Interface (GUI) software tool. The following neuropsychological complications will be analyzed. At the patient's bedside, an experienced neurophysiologist will record the patient's EEG. The EEG data will be recorded using a minimum of 9 silver/silver chloride recording electrodes, arranged according to the 10–20 international standard, with the extra ground and reference electrodes. The EEGs will be acquired during a 20–30-min period by a BCI-based EEG system (Refer to Fig. 2). Filters with low and high frequencies of 0.53 Hz and 70 Hz, respectively, were applied to the EEG channels at a 3 dB level. A single-channel ECG was concurrently recorded. The variations in frequency bands across a range of psychiatric diseases are described in Table 3 in the resting state condition.

The brain waves alpha, beta, and theta can be visualized using an EEG device and its associated eSense meter, as shown in Fig. 3. The EEG Lab brainwave visualizer uses a signal processing method using MATLAB, applying FIR filter and wavelet transform to extract the brain wave frequencies, respectively, alpha 1, alpha 2, and delta signals.

2.2 QEEG

The Quantitative Electro Encephalo Gram (QEEG), more commonly known as a brain map, is a very powerful tool, which is used to get very important objective information about the brain [19]. The computerized EEG spectral analysis of a

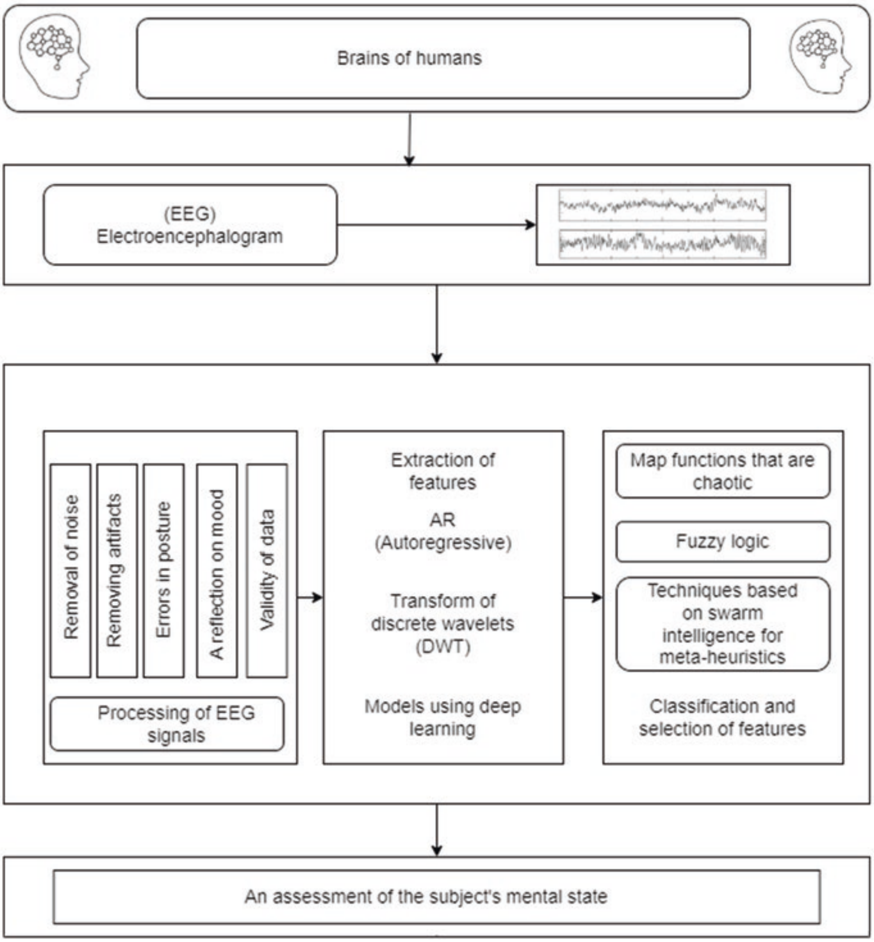

Fig. 2 EEG based on neuropsychological/mental health monitoring

Table 3 Features of EEG and qEEG

EEG features	qEEG features
Linear features: • Low-frequency power • Decay from lower to higher frequencies • Alpha -power, frequency, dispersion • A baseline of the entire frequency spectrum *Non-linear features:* • Sample-Entropy, Approx Entropy (ApEn) • Correlation dimension (CD) • Lyapunov exponent (LLE), Hurst exp (H)	• Power in α1 ,α2 ,β1 ,β2 , δ ,θ • Relative strength in the specified frequency spectrum • Relative strength in the specified frequency spectrum • Relative strength in the band of frequencies 1 • Relative strength in the band of frequencies 1 • Relative strength in the band of frequencies 2 • Relative strength in the specified frequency spectrum • The EEG power spectrum's overall strength • Beta Ratio, Theta (TBR) • Alpha to Theta ratio (TAR)

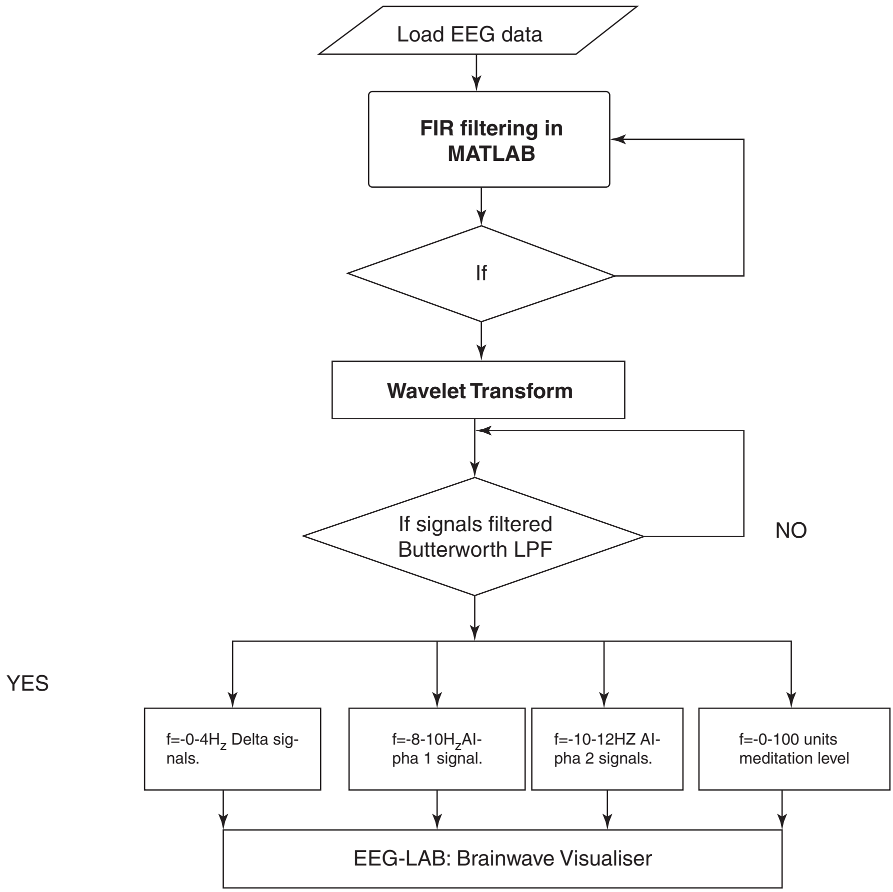

Fig. 3 Visualizing brain waves with eSense meter

neuro-cognitive impaired person provides more quantitative data than visual analysis of EEG.

- qEEG provides absolute and relative power of brain waves
- Z-transform of qEEG indicates deviation from the mean value
- Z-scores were summed to yield an accordance value for each electrode in each frequency band.

All the more explicitly, qEEG estimates profoundly coordinated large-scale level neurophysiological marvels in the cerebrum, which catch the activities of enormous scope cortical organizations of neuronal gatherings and which are astoundingly related to perception, and psychological well-being. The salient spectral features of EEG as well as qEEG are listed in Table 3.

The main cognitive and psychological factors that influence COVID's effect will be quantified by the qEEG experiment. COVID generates a qEEG profile that depicts

Table 4 Biomarkers for qEEG

Spatial biomarkers	Temporal biomarkers	Spectral biomarkers
Spearman correlations of the amplitude Envelope across channels	Analysis of detrended fluctuations Widest multifractal spectrum Duration of oscillation bursts Duration of stable phase bursts Stable frequency; standard deviation Inter-quartile range of the central frequency, maximum wavelet frequency, and phase values Oscillations per window number Kurtosis, skewness, inter-quartile range, median, range, and variance are amplitude envelope metrics	Power, both absolute and relative middle frequency Central frequency power spectral edge and bandwidth Activity, complexity, and mobility of Hjorth Strength, global frequency, and spatial complexity of the Wackerman Global Field Amplitude, frequency, and spectral purity of Barlow Peak frequency and width for alpha The baseline for alpha peak power corrected for 1/f peak frequency and width for beta Beta peak power with baseline correction for 1/f

the patient's physiological condition. An accessible technique to comprehend quantitative parameters for otherwise complex neuro-physiological entities is provided by the qEEG metrics and associated scales. The z-score will then be determined and compared to the normative individual. The difference between the value of the COVID-attacked person and the mean of the population divided by the population's standard deviation (SD) is known as the *Z*-score, which is a great statistic to use.

$$Z = \frac{x_i - \overline{X}}{SD}$$

where the *z*-score indicates how much variation of the measured value from the standard optimal value. The qEEG experimental profile reveals the following biomarkers as shown in Table 4.

Neuro-feedback is the "blueprint" for changing the electrical activity of the central nervous system using feedback from the brain. It can be done using a brain–computer interface such as a mind-wave kit/sensors/electrodes placed on the scalp and ears. The BCI is then connected to the specialized neuro-feedback computer, where the software tool detects, measures, and stores brain activities. Before applying the neuro-feedback approach, QEEG is used to objectively analyze the physiological state and brain activity as shown in Fig. 4.

The psychiatric data is analyzed using psychiatric tools and the DL model. The acquired EEG data is fed into data normalization, followed by segmentation and optimal allocation of samples for getting feature selection. Then, the data size is reduced to the optimal one by using dimensionality reduction techniques with linear discriminant analysis (LDA), followed by the least square support vector (LS-SVM)

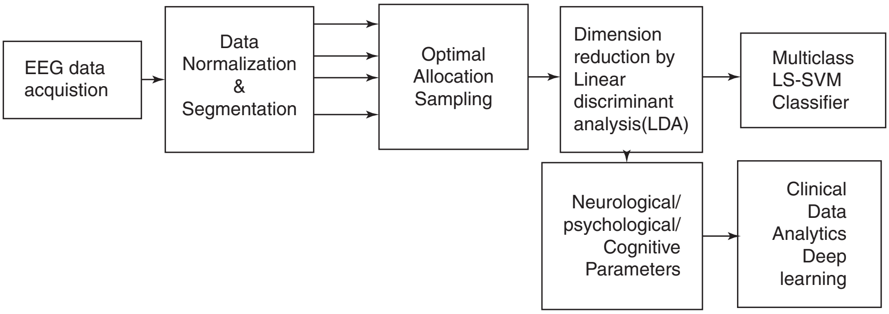

Fig. 4 Neuropsychiatric data analytics using deep learning

based classifier [20]. From the LDA analysis, the neurological/psychological parameters are finally passed into clinical data analytics using the DL model.

The multi-channel BCI kit interfaced with the EEG lab tool and Montreal Cognitive Assessment (MOCA) tool for evaluating the EEG and cognitive parameters including cognitive index (CI) is as follows.

- Encephalopathy: Glasgow Coma Scale (GCS)
- Level and the grade of hepatic encephalopathy (HE): "p" or class of liver cirrhosis
- EEG parameters: Alpha, Beta, Gamma, and theta
- Cognition parameters: Cognitive Index (CI), Cognitive Symptom Index (CSI), Emotional Symptom Index (ESI), MOCA score, etc.
- Mild cognitive decline (MCI) with Glasgow Coma Scale <13 or "severe Cognitive decline (SGD)" (GCS > 13) and reduced consciousness were only noted when patients were off sedation
- Performance Parameters: Classification accuracy, correlation coefficient, and Confidence Interval (CI).

where cross-correlation *(rxy) = Cov (X,Y)/SDx, SDy*

Generalized configuration score (GCS) = classification accuracy + correlation coefficient

Classification accuracy = No. of cases correctly classified/Total no. of cases

3 Feedforward Neural Networks

With the help of past and current data, predictive modeling is a statistical technique that uses machine learning and data mining to anticipate and forecast likely future outcomes. It functions by looking at both recent and historical data, then applying what it discovers to a model created to predict future outcomes. Nowadays, DL models are used to acquire or predict specific types of information. Data science, which also encompasses statistics and predictive modeling, contains deep learning as a key component. The artificial neural network (ANN) is working based on the

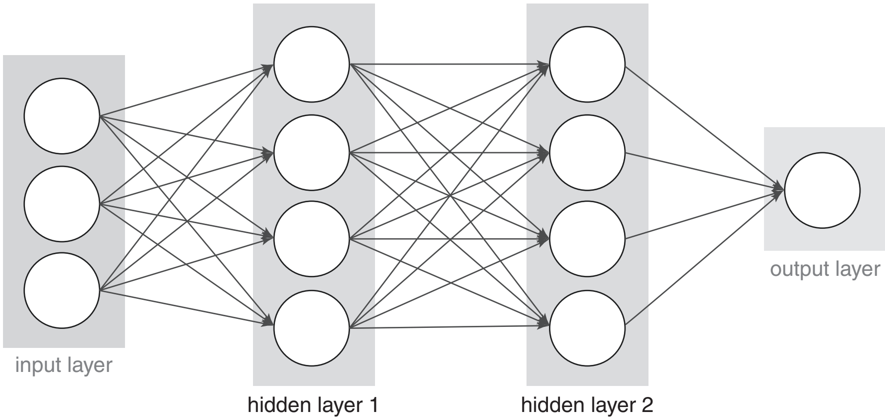

Fig. 5 Feedforward DNN with multiple hidden layers [22]

neuron relations between input and output functions through certain weights [21]. The weights and input/output functions assigned to the unit determine how the ANN will behave. For the output of each unit in this case, we will utilize the Sigmoid function. Linear and threshold are some additional functions. In comparison to the threshold and linear functions, the sigmoid function is more closely related to real neurons. We must carefully select the connections and appropriately weigh the connections for a neural network to learn.

As shown in Fig. 5, in the feedforward neural network, each connection has a weight Θ j. There are three hidden layers, namely hidden layers 2, 3, and 4. The jth layer is connected to the j + 1th layer through the weighted connection. Weight (θ) and activation value together find the activation value of the next layer. Data fed into the network is represented by input layer activity. The weights between the layers and the activity of the preceding levels define the activity of each buried layer. The weight between the previous layer's activity and that of the output layer determines the activity of the latter.

In the above network, we have two layers. Given input vectors are

$X = [x_0, x_1, x_2]$ where $x_0 = 1$ and $a_0 = 1$ are biased terms

We calculate $z_j^l = \sum_i a_i^l \theta_{ij}^l$ $\textit{where}\, a_j^l = g(z) = \dfrac{1}{1+e^{-z}}$; g is the sigmoid function,

where a_i^l is the activity of ith unit in the l–1th layer and θ_{ij}^l is the weight of the connection between the ith and jth unit.

The back propagation neural network algorithm is also known as backpropagation of errors since it transfers faults from output nodes to input nodes. A popular algorithm for training feedforward neural networks is backpropagation [23]. It calculates the loss function's gradient about the network weights. It is far more effective than simply computing the gradient for each weight directly. Gradient methods, including variations like gradient descent or stochastic gradient descent, are frequently used to train multilayer networks and update weights to reduce loss due to this efficiency. Using the chain rule and computing the gradient layer by layer, the backpropagation method calculates the gradient of the loss function concerning each weight. The back propagation neural network algorithm is defined in Algorithm 1.

Algorithm 1 Backpropagation Neural Network Algorithm

Step 1: Inputs X, arrives through the pre-connected path.

Step 2: The input is modeled using true weights W. Weights are usually chosen randomly.

Step 3: Calculate the output of each neuron from the input layer to the hidden layer to the output layer.

Step 4: Calculate the error in the outputs

Backpropagation Error = Actual Output − Desired Output

Step 5: From the output layer, go back to the hidden layer to adjust the weights to reduce the error.

Step 6: Repeat the process until the desired output is achieved.

4 Discussion

This book chapter has reviewed the existing literature on the prediction of psychiatric disorders with the application of internet and communication technologies (ICT) tools such as ML and DL algorithms. The prediction of psychiatric issues such as multiple conditions like depression, schizophrenia, and ADHD is analyzed with the help of EEG as a psychiatric tool, applied with a feedforward deep learning neural network. However, there are future challenges ahead to investigate the following issues.

Table 5 presents the different psychological issues combined with biomarkers. Cognitive, emotional, and behavioral impairments can be caused by mental illnesses. Psychiatric disorders can interfere with children's learning abilities. Mental illness can also cause inconvenience for adults, especially in their families, workplaces, and communities. Schizophrenia, depression, bipolar disorder, and anxiety are just some of the mental illnesses that exist.

People suffering from mental illness undoubtedly experience emotional problems, cognitive difficulties, and social difficulties. In light of these issues, it can be concluded that mental illness has serious consequences for societies across the world. In addition, new strategies are necessary to prevent and treat it. For these goals to be achieved, it is crucial to detect mental illness early. Predictive analytics will revolutionize healthcare. Self-reports of mental illness, which include questionnaires that analyze patterns of feelings and social interactions, are used to diagnose mental illness. When the right treatment and care are provided, many people can recover from mental illness or emotional disorders.

Table 5 Psychiatric disorders and associated biomarkers

Psychiatric disorders	Psychiatric tools	Psychiatric biomarkers
AD	Brain imaging	Complete brain atrophy
		Increased CSF level
Bipolar disorder	Brain imaging	Reduction in hippocampus
		Brain-derived neurotrophic factor and pro-inflammatory biomarkers
		Brain proteins
		Retinal binding protein-4
		Growth differentiation factor-15
		Hemopexin, hepsin, matrix metalloproteinase- 7
	Neurotrophic method	Decreased serum BDNF level
Depression	PHQ-9 Electrophysiological	Determination of MDD score Variation in EEG frequencies at rest EEG—α and θ waves Variation in O and P activity of EEG PTEN gene C-reactive protein, interleukin-6, tumor necrosis factor-a
ADHD	SNAP25 gene	SNAP-25 gene Ddel and Mull-polymorphisms
Major psychiatric disorders	Inflammatory	Pro-inflammatory biomarkers
	Gut microbiota	Bacterial translocation via chronic stress, leaky gut
Major depressive disorder		Long non-coding RNAs (lncRNAs)
		a-1 anti-trypsin, brain-derived neurotrophic factor, Epo-lipo-protein C3, epidermal growth factor, cortisol, resistin, prolactin, myeloperoxidase, tumor necrosis factor-a receptor type-II
Schizophrenia	Inflammatory	Increased CRP
		Up-regulation of mRNA
	Neurotransmitter	Increased synaptic dopamine concentration
		Decreased plasma level of GABA
		DISC1-gene
		Protein phosphorylation patterns

It is now possible to model mental health and understand health outcomes using social media. A variety of psychological disorders are now being predicted quantitatively, including depression, anxiety, and suicidality. Using this research can help monitor mental health statuses, diagnose problems, and design interventions for these conditions. The research and methodology used in these studies are not standardized, so it is impossible to evaluate their validity. Data collected during regular medical examinations, such as wearable data, blood samples, and urine samples, can also be used as biomarkers. Researchers have found that tryptophan concentration is particularly useful for classifying people with depression based on multiple blood metabolites [24].

In addition to providing relevant data to complement clinical care, computational approaches to mental health could also identify risky behaviors, provide timely interventions, or reach populations that traditional clinical approaches are unable to reach. Because this field is still nascent, identifying trends in research modes and practices is vital for identifying gaps before they emerge systemically. In addition to reflecting scholarly research quality, these issues also demonstrate the impact clinical care and social media predictions can have on the mental health of individuals.

Machine learning is believed to have originated from machine learning. As an example, supervised learning and unsupervised learning are two of the most commonly used machine learning approaches. An approach called supervised learning predicts outcomes based on labeled input data. Classification and regression problems are excellent candidates for supervised learning. Data is being analyzed to specific measurements to make sense of the data. Unlike supervised learning, unsupervised learning aims to make sense of data on its own. Measurements and guidelines are not present in unsupervised learning. As well as being a strategy to solve a particular problem, ensemble learning strategically combines multiple classifiers. In ensemble learning, models are improved, or a reduced chance of selecting poorly performing models is reduced.

To make mental healthcare more effective and tailored, it seems essential to predict the outcomes of individual participants. Machine learning-based predictions have, however, received surprisingly little attention in digital mental health interventions. In machine learning, advanced statistical and probabilistic techniques are applied to construct systems that can learn from experience and improve over time. Mental health prediction can be greatly enhanced by using this tool. Research can be acquired from the data, personalized experiences can be provided, and intelligent algorithms can be developed. Support vector machines, random forests, and artificial neural networks are widely used algorithms in the field of machine learning for predicting and categorizing future events.

The opportunities with machine learning involve the extent of neurological conditions connected to COVID-19 and its intellectual symptoms. The fundamental connection between the pathophysiology of infection and the dissemination of viruses and their associated pro-inflammatory modifications can be studied. The challenges involve the duration and intensity of neurological and psychosocial alterations that occur after an acute viral illness. Short-term and long-term memory capacity can be affected by viral illness severity and psychological effects.

The possible future research contributions are developing suitable deep learning algorithms, which can handle high-dimensional data space with the aid of feature engineering. More research work is needed to extract appropriate psychiatric biomarkers, which are fed as input to the DL-based training model. Moreover, the development of web applications or mobile applications equipped with digital psychiatric tools as well as DL models can be easily accessible by psychiatric patients to know about the impact of psychiatric issues on their mental health.

5 Conclusions

This book chapter reviews the literature on deep learning techniques and their applications in predictive research on psychiatric health. This chapter proposed a novel deep learning method using deep feedforward neural networks coupled with psychiatric tools, which could hasten a new way for the integration into prognostic research in digital psychiatry and eventually lead to its use in clinical results. Our final section explores the challenges ahead for the prediction of mental health disorders and leveraging some interesting applications for DL algorithms along with physicians' intelligence for enhancing mental health treatment.

Conflicts of Interest No author has any conflicts of interest.

References

1. Hossain MM, et al. Epidemiology of mental health problems in COVID-19: a review. F1000Res. 2020;9:636. https://doi.org/10.12688/f1000research.24457.1.
2. Pandey K, et al. Mental health issues during and after COVID-19 vaccine era. Brain Res Bull. 2021;176:161–73. https://doi.org/10.1016/j.brainresbull.2021.08.012.
3. Jones EAK, Mitra AK, Bhuiyan AR. Impact of covid-19 on mental health in adolescents: a systematic review. Int J Environ Res Public Health. 2021;18(5):1–9. https://doi.org/10.3390/ijerph18052470.
4. The Lancet Psychiatry. COVID-19 and mental health. Lancet Psychiatry. 2021;8(2):87. https://doi.org/10.1016/S2215-0366(21)00005-5.
5. Talevi D, et al. Mental health outcomes of the CoViD-19 pandemic. Riv Psichiatr. 2020;55(3):137–44. https://doi.org/10.1708/3382.33569.
6. Park JG, Pino PA, Akhter A, Alvarez X, Torrelles JB, Martinez-Sobrido L. Animal models of COVID-19: transgenic mouse model. Methods Mol Biol. 2022;2452:259–89. https://doi.org/10.1007/978-1-0716-2111-0_16.
7. Lin E, Lin CH, Lane HY. Deep learning with neuroimaging and genomics in Alzheimer's disease. Int J Mol Sci. 2021;22(15):7911. https://doi.org/10.3390/IJMS22157911.
8. Awate SP, Yushkevich PA, Song Z, Licht DJ, Gee JC. Cerebral cortical folding analysis with multivariate modeling and testing: studies on gender differences and neonatal development. Neuroimage. 2010;53(2):450–9. https://doi.org/10.1016/J.NEUROIMAGE.2010.06.072.
9. Richards BA, et al. A deep learning framework for neuroscience. Nat Neurosci. 2019;22(11):1761–70. https://doi.org/10.1038/S41593-019-0520-2.
10. Zaharchuk G, Gong E, Wintermark M, Rubin D, Langlotz CP. Deep learning in neuroradiology. Am J Neuroradiol. 2018;39(10):1776–84. https://doi.org/10.3174/AJNR.A5543.
11. Gong Y, Liu L, Yang M, Bourdev L. Compressing deep convolutional networks using vector quantization. 2014.
12. Gu J, et al. Recent advances in convolutional neural networks. Pattern Recogn. 2018;77:354–77. https://doi.org/10.1016/J.PATCOG.2017.10.013.
13. Romagnoli S, Franchi F, Ricci Z. Processed EEG monitoring for anesthesia and intensive care practice. Minerva Anestesiol. 2019;85(11):1219–30. https://doi.org/10.23736/S0375-9393.19.13478-5.
14. Fung FW, Abend NS. EEG monitoring after convulsive status epilepticus. J Clin Neurophysiol. 2020;37(5):406–10. https://doi.org/10.1097/WNP.0000000000000664.

15. Thapar A, Cooper M. Attention deficit hyperactivity disorder. Lancet. 2016;387(10024):1240–50. https://doi.org/10.1016/S0140-6736(15)00238-X.
16. Cecchetti G, et al. Cognitive, EEG, and MRI features of COVID-19 survivors: a 10-month study. J Neurol. 2022;269(7):3400–12. https://doi.org/10.1007/S00415-022-11047-5.
17. Kubota T, Gajera PK, Kuroda N. Meta-analysis of EEG findings in patients with COVID-19. Epilepsy Behav. 2021;115:107682. https://doi.org/10.1016/j.yebeh.2020.107682.
18. Nijboer F, et al. An auditory brain–computer interface (BCI). J Neurosci Methods. 2008;167(1):43–50. https://doi.org/10.1016/J.JNEUMETH.2007.02.009.
19. Duffy FH, Hughes JR, Miranda F, Bernad P, Cook P. Status of quantitative EEG (QEEG) in clinical practice. Clin EEG Neurosci. 1994;25(4):vi–xxii. https://doi.org/10.1177/155005949402500403/ASSET/155005949402500403.FP.PNG_V03.
20. Pham QB, Yang TC, Kuo CM, Tseng HW, Yu PS. Combing random forest and least square support vector regression for improving extreme rainfall downscaling. Water. 2019;11(3):451. https://doi.org/10.3390/W11030451.
21. Jain AK, Mao J, Mohiuddin KM. Artificial neural networks: a tutorial. Computer (Long Beach). 1996;29(3):31–44. https://doi.org/10.1109/2.485891.
22. Brunel N, Hakim V, Richardson MJE. Single neuron dynamics and computation. Curr Opin Neurobiol. 2014;25:149–55. https://doi.org/10.1016/j.conb.2014.01.005.
23. Rajput N, Verma SK. Back propagation feed forward neural network approach for speech recognition. In: Proc. 2014 3rd Int. Conf. Reliab. Infocom Technol. Optim. Trends Futur. Dir. ICRITO 2014, 2015. https://doi.org/10.1109/ICRITO.2014.7014712.
24. Setoyama D, et al. Plasma metabolites predict severity of depression and suicidal ideation in psychiatric patients-a multicenter pilot analysis. PLoS One. 2016;11(12):e0165267. https://doi.org/10.1371/JOURNAL.PONE.0165267.