Cognitive IoT and Computational Intelligence for Mental Wellbeing

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Abstract: In the current world of competition and tremendous struggle, mental wellbeing is one of the most important things that need to be taken care of. With hundreds of millions of people suffering from mental disorders like depression, Alzheimer's disease, schizophrenia, etc. each year, there have to be intelligent systems that can diagnose, track, and manage the mental wellbeing of a person. Computers have been widely used in various clinical applications like clinical text analysis and medical image analysis. Computers have found their use in various use cases in medical domains like cancer diagnosis, tumor analysis, etc. Computational intelligence has been used in building smart predictive models that can be phenomenal for diseases that require early clinical intervention. Depression, Alzheimer's disease, etc. are mental disorders that worsen with time when they are not taken care of. Thus, there should be systems to early identify mental disorders. In this chapter, we will discuss various ways in which mental wellbeing can be taken care of using computational intelligence.

1. Introduction

In a world full of opportunities and competition, mental wellbeing has always been a topic that has been overlooked. People tend to underestimate the influence that a healthy mind can have on daily activities. Mental wellbeing is about the ability to bring positivity in thoughts and feelings our mind processes every second. Mental wellbeing is also about how well we tackle with day-to-day problems, handle stresses and move forward in life. With good mental wellbeing, people can realize their value, importance, and responsibilities. The interpersonal skills and the connections people can make depends upon how well their mental health is. Only a healthy mind can make people reach their fullest potential through which they can make their contribution towards family, community, nation, and humanity as a whole. Thus, mental wellbeing is a topic that should have been treated with much importance and scrutiny.

Today, the minds of the people are extremely occupied with thoughts of competition, incompleteness, and a lot of negative thoughts to add to mental illnesses. With technology invading human lives, social interactions have become very less and schedule has become very hectic. Due to this, the problems of depression, anxiety, personality disorders, etc. have become very common.

Mental disorder has been seen comparatively more in older age population but the fact that younger population is also susceptible to mental disorders shouldn't be neglected. According to the World Health Organization report in 2015, suicide is the second most common cause of death in the population group of age 15 to 29 years globally [1]. The most common cause of suicide is depression. Depression is one of the largest causes of global illness with an estimated 300 million or nearly 5% of the world population affected by it [1]. Depression is a very common yet serious medical condition that affects how a person feels, thinks, acts, and perceives things around him. Apart from depression, there are other serious illnesses that can bring deadly consequences. Luckily, through which these conditions can be treated effectively by pharmacotherapy or psychotherapy [2].

Computers and sensors have been around us for so long. Since the inception of the age of electronics, researchers have always tried to find out the ways through which computers and sensors can be used for the benefit of humankind. From industrial applications to important healthcare applications, computers and sensors have their applications in a wide range of areas. The rapid disruptions in the field of electronics, especially the advancements in sensors, happened after the tremendous improvements in radar technologies leading to wireless systems in the 1970s [3]. In the last forty years or so, with the increasing advancements in the infrastructures, wireless communication systems have been evolving rapidly [4].

Lately, with the advent of modern tools and technologies, there has been a paradigm shift in how patients with mental illnesses are treated. The incorporation of Artificial Intelligence (AI) and the Internet of Things (IoT) in human lives have made researchers to come up with innovative ways of tackling mental illnesses. Traditional healthcare relies on simple questionnaires and physical examination for assessing the mental wellbeing of the patients. This usually becomes ineffective at times when there are a lot of factors like patient's background, education, unreliable autobiographical memory, and a lot more to add to [5]. Thus, there was a much-needed transition on ways to cure mental illnesses. Lately, there has been increased usage of AI, IoT, and intelligent systems for assessing mental wellbeing and curing it. Internet of Things, commonly known as IoT, is an interconnected network of sensors that continuously collect various data. The data collected through the sensors are integrated to build more informative data. The analysis is then done on the available data to infer valuable information which can later be used for various purposes. For example, a heartbeat sensor can calculate the heartbeats of a person. The sensor continuously collects the heartbeat data and if there is any abnormal heartbeat rate, the sensors can be programmed to display the information of abnormality. This information provided by sensors can be used by the person to make informed medical decisions like visiting the doctor or calling emergency helplines in case of high abnormality. Further, the same sensor can be made to automatically call the emergency helpline in case of abrupt and fatal abnormal heartbeat rates. With that being said, cognitive computing can be defined as expert systems which have reasoning abilities and can infer insights from data like human beings [6]. Cognitive computing is a subset of artificial intelligence that can assist human beings in taking decisions.

Scientists have always been interested in how human brains work and have been working on finding ways to mimic the human brain. With unprecedented development in the field of natural language processing, computer vision, etc. there has been a spike in the development of deep learning as a field [7]. Earlier, there were a lot of barriers to deep learning. The main barrier was the processing power required for deep learning as the algorithms required heavy mathematical operations. With increasing research in the field of parallel computation and computer architecture, deep learning has developed by multiple folds in just the past few decades. The processing infrastructure has become so portable that they can even be fit into small chips. This has given rise to an increasingly high variety of sensors and IoT devices. The devices have the power of cognition or in other words, the power to decipher information from the data provided. The insights that sensors can derive from the given information have been becoming more and more accurate which adds a lot of value to big data analytics.

Cognitive IoT, thus, is an extended version of IoT where IoT devices are given the power of cognition giving them learning and reasoning abilities through which they can derive insightful information. Cognitive IoT blends the physical world we live in with the world of the internet, data, and machine intelligence [8]. In the world we live in, billions of bytes of data are processed every second and is estimated to increase by multiple folds in the coming days. This ubiquitous data can be leveraged for social good and general wellbeing of ours [9]. These days, data has been used in each and every sector and there is not a sector where big data hasn't been used. Artificial Intelligence (AI) and Big Data are thus called the fourth industrial revolution because of their ability to change everything [10]. As the development in big data continues, some impacts are being brought along which can influence our lives directly in many ways.

In this chapter, we primarily provide a detailed overview of how cognitive IoT and sensors, along with the power of computational intelligence, can be used to tackle with problems of mental illnesses. The chapter will discuss in detail how IoT and computational intelligence can be used in healthcare applications specifically for mental wellbeing. Computer vision (CV) and Natural Language Processing (NLP) being the most prominent fields used in tackling mental disorders, the chapter emphasizes exploring the applications of CV and NLP for mental wellbeing. With more concrete examples of use cases in neurodegenerative diseases like Alzheimer's disease (AD), Parkinson's disease (PD), etc. and other mental illnesses like depression, schizophrenia, dementia, etc., the chapter will also explore the possibilities where computational intelligence can be used in conjunction with the expert insights from medical practitioners. The chapter also focuses on the advantages and disadvantages of automated systems over trivial clinical practices and presents the ways through which intelligent mental diagnostic systems can be made more robust.

2. Cognitive IoT and Computational Intelligence in Healthcare

Computational systems are currently being used extensively in the diagnosis of various diseases as well as in the cure of various diseases that plague mankind. Computational intelligence has also been successfully used to tackle the current COVID-19 pandemic [11]. Artificial intelligence and machine learning have been successfully used to diagnose diseases like the swine flu, common cold, influenza, hepatitis, Alzheimer’s, Parkinson's, and even various types of cancer. Apart from the diagnosis of the diseases, the various dimensions of health monitoring like heartbeat calculation, calorie burn calculations, etc. are being done by cognitive IoT. Those devices have the power to give intelligent outputs based on the basic inputs taken from IoT devices, mostly wearables [72].

Amrane et al. [12] have done a study on using machine learning models for the diagnosis of breast cancer. The dataset they used was taken from the Wisconsin Breast Cancer Database. Nine characteristics were used in the study. The study compared the accuracy of different machine learning models namely, k nearest neighbors and Naive Bayes classifier. The highest accuracy was given by the Naive Bayes Classifier with an accuracy of 97.51%. Esteva et al. [13] have proposed a deep convolutional neural network that diagnoses skin cancer with dermatologist level accuracy. The system they developed is as good as a real-life medical practitioner in diagnosing skin cancer from images of lesions. The dataset they used consisted of 129, 450 images. The highest accuracy of the CNN model in 3-way classification was 72.1 ± 0.9%. The highest accuracy obtained by using a real-life dermatologist in the same experiment was 66.0%. This study shows that computations images are much better than real life dermatologists in diagnosing skin cancer using images.

Machine learning and computational intelligence can also be used to diagnose a disease like swine flu using the data of the patients. Bhatt et al [14] have successfully used machine learning techniques like support vector machines, linear discriminant analysis, and neural networks for the diagnosis of swine flu. In their study, neural networks gave the highest accuracy. Banerjee et al. [15] have used machine learning techniques like random forest classifier to diagnose COVID-19 in patients using full blood count.

These are just a few examples in which computational intelligence has been used to diagnose different diseases. In the subsequent sections, we explore in detail different types of technologies that have been used to diagnose mental disorders.

3. Computer Vision for early diagnosis of mental disorders using MRI

Computer Vision has been vastly used in today’s world to solve various real-world problems. Computer Vision also finds applications in the medical industry, particularly in diagnosis by making use of medical imagery like MRI, CT scan, and X-ray. Computer Vision as we know the subject today mainly consists of image processing and deep learning techniques for extracting relevant data out of images or video feed which is a sequence of images. Today, convolutional neural networks (CNN) can be considered as the backbone of computer vision as it has been shown to be highly accurate among a range of different computational problems.

Magnetic Resonance Imagery is a technique that is used to generate imagery of the human physiological system. It makes use of strong magnetic fields, magnetic field gradients, and radio waves to generate imagery of different human body parts. MRI is considered to be safe and it finds myriads of uses in today's healthcare industry. Different computer vision techniques have been applied to MRI images for the automatic diagnosis of numerous diseases. MRI images can be taken of different parts of the body from the brain to the liver and gastrointestinal systems. In this section we discuss applications of artificial intelligence and computer vision for the diagnosis of mental disorders such as Alzheimer's, using MRI images [16].

MRI has been extensively used for the diagnosis of Alzheimer's as it is a brain disease and the physical effect of Alzheimer's is clearly seen in the brain tissues. Farooq et al. [17] have proposed a system that diagnoses a patient with Alzheimer's using MRI images as shown in fig. 1. Along with the diagnosis of Alzheimer's, it also does the diagnosis of mild cognitive impairment and late mild cognitive impairment. Patients with these symptoms are more likely to develop Alzheimer's in the near future and hence their system can be considered as an early diagnosis of Alzheimer's disease. Their system is a multi-class classifier and the classes are Alzheimer's, Mild cognitive impairment, late mild cognitive impairment, and healthy persons. Their system incorporates deep convolutional neural networks. The system's architecture pipeline mainly consists of two parts. The first part which converts MRI volume to 2D slices, namely the data preprocessing step. The second part classifies the image into a 4-class label, namely the classification part. Since MRI scans are provided in 3D volume form it is necessary to convert them into 2D slices so as the CNN can work on them. In the data preprocessing part of the system, gray matter segmentation and skull stripping are carried out through spatial normalization, bias corrections, and modulation using the SPM-8 tool. Using python nibabel package gray matter volume is converted into JPEG slices. Using these slices different convolutional neural network models are trained. They used standard CNN models such as GoogLeNet, ResNet-18, and ResNet-152. In their experiment, GoogLeNet

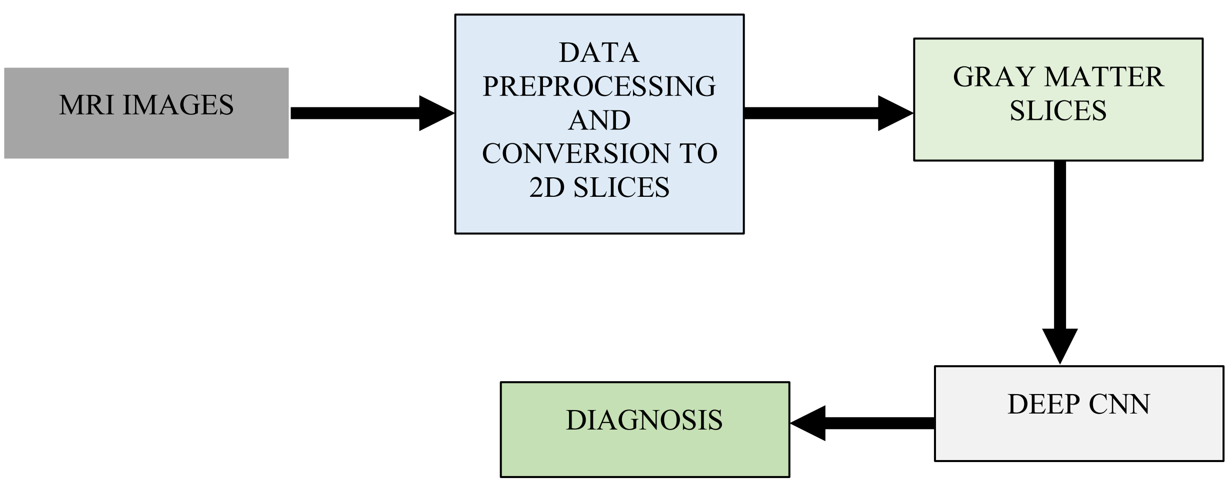

Fig. 1. A high-level overview of the flow of steps in the diagnosis of AD

performed the best with an accuracy of 98.88%. The dataset that they used to perform their experiment was the dataset obtained from ADNI. The data set consisted of a total of 355 patients and hence 355 MRI volumes out of which 137 are healthy persons, 73 are patients with Alzheimer's, 61 are patients with late mild cognitive impairment, and 84 are patients with mild cognitive impairment. Their paper has one of the highest recorded accuracies for Alzheimer’s detection in this particular dataset.

MRI of the brain is also used for the diagnosis of Parkinson's disease as it is also a disease in which the physical pointers or effects are found in the brain. There have been studies that show that Parkinson’s can be diagnosed using MRI with the help of computer vision techniques. Here we have discussed one such relevant paper. Esmaeilzadeh et al. [18] have used 3D convolutional neural networks for the accurate diagnosis of Parkinson’s disease. In their study, they have used images from the PPMI database which is a standard dataset for diagnosis of Parkinson's. Each image is a 3D image and consists of about 4 million pixels. In their system, first data preprocessing is performed and further data augmentation is done so as to increase the cardinality of the dataset. After that, the training and testing are done using a 3D CNN model. In the data preprocessing step standard skull stripping algorithm is used so as to remove non-cerebral tissues in the image. The algorithm is named as Brain Extraction Technique (BET). After this process, the image consists of around 800,000 pixels. In the data augmentation step, a new augmented image is formed by switching the left and right hemispheres of the brain. A 3D CNN model is used for the classification of the dataset. In this model, a leaky relu activation function is used. Exponential learning rate decay is used for the optimizer. The accuracy of their model on the data set was 100% which is staggeringly high and shows that their model is very effective. Using their model, they also created a heat map of the brain so as to determine which parts of the brain have more weightage in the diagnosis of Parkinson’s disease. The parts of the brain that they found to be more important in the diagnosis had been confirmed by medical doctors in earlier research. They also found that a particular part of the brain that medical practitioners had neglected in the diagnosis of Parkinson's, was also very important. With this research, we can see that computation systems are not just effective at automated diagnosis but can also be used to derive important facts and knowledge about the human physiological system.

MRI also finds its use cases in the automated diagnosis of schizophrenia. This is possibly because schizophrenia directly affects the various parts of the physical brain. Hu et al. [19] have proposed a 3D CNN system that is able to diagnose schizophrenia using MRI images with relatively high accuracy. IN their study they compare the accuracy of CNN models with hand-crafted featured engineered machine learning models and show that CNNs are the better option in this particular problem of schizophrenia diagnosis using MRI. They used two independent datasets so as to determine the cross-dataset testing accuracy of the model. They tested various different CNN models among which a hybrid of inception and ResNet model gave the best accuracy. The testing accuracy was 79.27%. The accuracy, when tested on a different dataset than with which it was trained, came out to be 70.98%. IN the current literature the accuracy of their paper is one of the highest ever recorded, and yet it could be considered quite low as it is even less than 80% and hence much research is yet to be done in the field of schizophrenia diagnosis using artificial intelligence and soft computing techniques.

Computer vision and CNN models have also been used in the diagnosis of attention deficit hyperactivity disorder (ADHD) using MRI. Zou et al. [20] have proposed a 3D CNN model that diagnoses ADHD using structural MRI (3D) and functional MRI(4D). They performed their experiment on the ADHD-200 data set and achieved a state-of-the-art accuracy of 69.15%. IN this research they did feature extraction first instead of directly plugging the data into the CNN model. This enabled their model to give higher accuracy.

CNN models have also been used to automatically diagnose depression and epilepsy in patients using MRI. Pominova et al. [16] have compared the effectiveness of different CNN models as well as models with CNN and RNN(recurrent neural networks), in diagnosing epilepsy and depression using structural MRI and functional MRI. They have achieved a ROC-AUC score of 0.73 when diagnosing depression against a control group. They also created a heat map of the brain using their trained models to show which parts of the brain gave more importance in the diagnosis of epilepsy and depression.

Brain tumor also causes mental disorders in patients ranging from forgetfulness to loss of motor coordination. Much research has been done on the detection of brain tumours using computational resources. Shahzadi et al. [21] have proposed a CNN + LSTM hybrid network that can be used for brain tumor classification using MRI. In their system VGC-16, a standard convolutional neural network was used for feature extraction, and then LSTM was used for the classification of brain tumors. The accuracy of the system was found out to be 84%.

4. Feature Selection Techniques and Optimization Techniques Used

Different machine learning techniques have been used for the diagnosis of diseases in computational healthcare. Apart from computer vision and deep learning, simple machine learning algorithms in conjunction with intelligent feature engineering, feature selection, and feature extraction methods have been successfully used for the diagnosis of many mental disorders from statistical data as well as medical imagery data. In this section, we discuss some of the more recent and state-of-the-art machine learning and feature selection techniques used for the diagnosis of mental disorders.

Forouzannezhad et al. [22] have used support vector machines with radial basis function for the diagnosis of Alzheimer's. The schema of the pipeline is shown in fig. 2. In their study, the input data consisted of three parts, the PET (positron emission transmission) images, MRI (magnetic resonance imagery), and standard neuropsychological test scores. In their study, a total of 896 participants from the Alzheimer's Disease Neuroimaging Initiative (ADNI) was considered. This is a standard dataset for Alzheimer's disease diagnosis. They used standard softwares for feature extraction of MRI and PET. In the feature selection process firstly ANOVA (analysis of variance) with a P value of 0.01 was used and further random forest based on "Gini" importance was applied. After that classification was done using SVM with radial basis function. Their study classified patients into 4 classes, namely normal control (CN), early mild cognitive impairment (EMCI), late mild cognitive impairment (LMCI), and Alzheimer's (AD). The classification is done binarily, i.e., CN vs EMCI, CN vs LMCI, and CN vs AD is performed. Their proposed approach gave an accuracy of 81.1% in classifying CN vs EMCI, an accuracy of 91.9% in classifying CN vs LMCI, an accuracy of 96.2% in classifying CN vs AD. This accuracy is expected because the physical effects of AD are much more pronounced in the brain compared to the physical effects of EMCI.

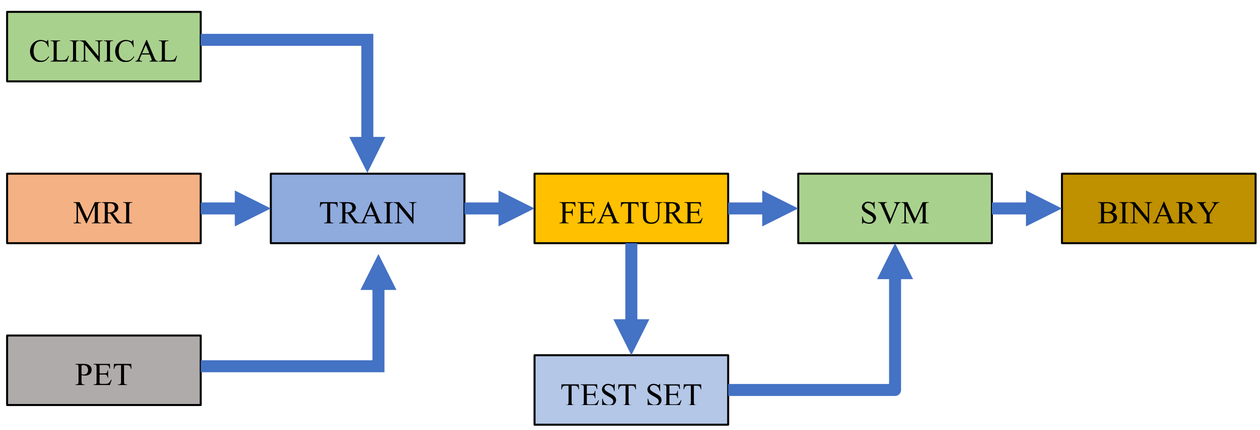

Fig. 2. Schematic Pipeline of the system for diagnosis of AD with SVM

Various machine learning algorithms have also been successfully used to diagnose Parkinson's. Ali et al. [23] have proposed a machine learning model that uses the voice of patients to diagnose Parkinson's among them. The dataset they used consists of 40 patients and from each patient 20 samples of voice recording were taken.

Their proposed feature selection algorithm ranks the various features using a statistical model known as the chi-square test and then further searches the optimal subset of the features that are ranked and then selects the samples iteratively. The classifier they used was Neural Networks and it was shown that their system gave an accuracy of 97.5% which is staggeringly huge. Avuclu et al. [24] did a comparative evaluation of various machine learning algorithms and compared them on their accuracy of the diagnosis of Parkinson's based on voice-based features. The dataset they used consisted of 31 people among which 23 people had Parkinson's. A total of 195 samples were collected from each subject. They compared four different machine learning methods, namely k nearest neighbor, random forest, Naive Bayes and support vector machine.

An electroencephalogram (EEG) is a test that detects electrical activity in the brain using miniature electrodes attached to the scalp. EEG signals have been extensively used for analyzing the brain. EEG signals have also been used for the diagnosis of various mental disorders. We discuss one such use case of EEG in the diagnosis of depression. Hosseinifard et al. [25] have used machine learning and non-learning features extracted from EEG signals to classify depressive patients from normal subjects. The dataset they used consisted of 45 normal subjects and 45 depression patients. They have experimented with different feature extraction algorithms such as Higuchi, Detrended fluctuation analysis, Correlation dimension, and Lyapunov exponent to extract features from the EEG signals. For optimal feature selection, they use genetic algorithms with an initial population of 50, crossover rate of 80%, and a mutation rate of 4%. The machine learning algorithms that were used in their experiments were k nearest neighbors, linear discriminant analysis, and linear regression. The highest classification accuracy of 83.3% was achieved when the feature extraction technique used was correlation dimension and the machine learning model used was the linear regression model. Using all the nonlinear features extracted by all of the different feature extraction methods the accuracy of the system went up to 90% when the linear regression model was used.

5. Natural Language Processing based diagnostic system

NLP-based diagnostic systems can be phenomenal in making screening tests accessible. For example, the speech transcripts of the patients will Alzheimer's disease can be analyzed to get an overview of how speech deterioration occurs as the disease progresses.

The ability of a human being to listen, speak and communicate with others has undoubtedly been the greatest blessing to humankind. The ability to communicate with each other has unraveled endless opportunities for the civilization and advancement of humanity. Over the course of time, early humans discovered scripts, alphabets, and letters which again proved to be very phenomenal human discovery as it helped in the management of records, historical events, and effective communication among a larger group of people [26]. In the modern day, the scripts, alphabets, linguistics, and other aspects of language have evolved highly. There is a lot of text data generated every fraction of a second in social networks, search engines, microblogging platforms, etc. With the power of natural language processing (NLP), the text data can be processed to gain valuable insights from the data. The inception of Natural Language Processing started in the 1950s as an intersection of Artificial Intelligence and linguistics [27]. In the modern-day, it has applications in hundreds of fields like customer service, business analytics, intelligent healthcare systems, etc.

The text we generate has its own features. Deep learning models these days can classify between the speech or text produced by a healthy individual and an individual with mental illness. Thus, it can be used for designing diagnostic systems for screening mental illnesses. For example, a patient with Alzheimer's disease (AD) can be diagnosed with Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Computed Tomography Scan (CT-Scan), and other conventional scanning measures [9]. These techniques however need to be intervened by medical practitioners in each and every stage. On the other hand, the cognitive impairments in AD patients can also be evidenced by aphasia or the inability to understand and produce speech in daily activities [28]. Such anomalies in speech can be leveraged for building diagnostic systems for the early diagnosis of AD. NLP and deep learning can thus be used to build models that are able to automatically diagnose the disease. The application is however not just limited to AD and can be used in the diagnosis of any illnesses which can be characterized by cognitive impairments reflected in speech. Apart from the ease in applications, the NLP-based models can be much powerful than conventional screening tests like Mini-Mental State Examination (MMSE) [29], the Rowland Universal Dementia Assessment Scale (RUDAS) [30], etc. because the information in spontaneous speech can gain more insights than the questionnaires given for assessment. The assessments done using questionnaires are also influenced by backgrounds like education, culture experienced, and a lot of factors. Thus, the assessment techniques are not always accurate and hence the patients who are diagnosed with mental illnesses using one assessment tool may be diagnosed as control normal (CN) with another assessment tool [31]. Similarly, ethics over the collection of personal information in neuropsychological assessment is also a problem to be looked upon [32]. In this context, NLP can be used to detect anomalies in the speech narratives of the patients.

Different researchers in the past have used different modalities and algorithms to diagnose patients with different mental illnesses like Alzheimer's disease (AD), Parkinson's disease (PD), etc. Fraser et al. [33] used the speech narratives of healthy individuals and patients diagnosed with AD to build a diagnostic system based on a logistic regression algorithm. For their study, they used the corpus named DementiaBank. DementiaBank is a widely used corpus that has the speech narratives of patients with AD along with that of the healthy control normal individuals [34]. The DementiaBank has both speech (audio) and text transcripts corresponding to that audio. The algorithm used on English speech transcripts gave an accuracy of 81.93%. The model used hand-picked features with machine learning algorithms. Hand-picked features are often highly dependent upon the one who is preparing the data and can lead to high variability. Thus, lately, there has been a shift towards using deep learning-based models on the diagnosis of Alzheimer's disease. Karlekar et al. [35] with a motive to overcome the hindrances due to hand-picked features used different deep learning models to build the diagnostic system using speech narratives from DementiaBank. Out of the different deep learning models used, the CNN-LSTM model performed the best with an accuracy of 91.1%. The authors furthermore do the analysis of what AD-related features of language the deep learning models are learning.

Apart from the speech narratives in the English language, work has been done in a lot of other regional languages as well. Vincze et al. [36] used the speech narratives of patients in the Hungarian language. A total of 84 patients with 48 patients relating to mild cognitive impairment (MCI) and 36 patients having AD participated in the experiment. A rich feature sets that contained various linguistic features based on language morphology, sentiment, spontaneity in speech, and demography of participants were used for feeding the model. Such hand-picked features when used with Support Vector Machines (SVM) gave an accuracy of 75% at its best case when only more significant features were chosen. Apart from this, Thapa et al. [37] also presented an architecture for diagnosing patients with AD using Nepali speech transcripts. The baselines were established using various machine learning classifiers and later, deep learning models were also used. Among various deep learning architectures used, Kim's CNN architecture [38] performed the best with an accuracy of 0.96. Their study also uses data from the DementiaBank which was translated into the Nepali language by native language speakers for the purpose of the experiment. Furthermore, a lot of work has been done in other languages like Turkish [39], Portuguese [40], etc. However, the works done in regional languages are very limited. The unavailability of prerequisites for natural language processing like word embeddings, language models, etc. creates a barrier when regional languages are dealt with [41].

Apart from Alzheimer's disease, efforts have been made to build models for the diagnosis of Parkinson's disease (PD) as well. It is a disease similar to AD and can be diagnosed using speech or text-based features. Toro et al. [42] proposed an SVM model for the diagnosis of PD from healthy control (HC) subjects. For their study, they used the speech narratives of 50 PD and 50 HC subjects. The speech was manually transcribed and later on, NLP was used for building the models. The model which was built for the Spanish language had an accuracy of 72%. Similarly, Thapa et al. [43] used a twin SVM-based algorithm for diagnosis of PD using speech features. Using a feature selection algorithm, a total of 13 features were selected out of 23 features. With the feature selection-based twin SVM, the accuracy of 93.9% was achieved.

The research has been mainly concentrated on these two diseases viz. PD and AD because of their worldwide prevalence and the growing number of patients. The research continues to find applications of language modality in building diagnostic systems for mental illnesses other than AD and PD. Some of the works done in the domain of diagnosis of mental illnesses can be found in table 1.

Table 1. Diagnosis of mental illnesses with text and speech modality

Authors	Year	Dataset	Language	Use-case	Modality	Algorithms	ACC	Pre	Recall	F-score
Vincze et al. [36]	2016	48 MCI 36 CN (Private)	Hungarian	Mild Cognitive Impairment	Text	SVM	75	75.8	75	75.1

Karlekar et al. [35]	2018	Dementia Bank	English	Alzheimer's Disease	Text	CNN-LSTM	91.1	-	-	-
Aluísio et al. [40]	2016	20 CN 20 MCI 20 AD (NILC Dataset)	Portuguese	CN vs MCI vs AD	Text	Naive Bayes	-	-	-	0.82
				CN vs MCI		J48 Algorithm	-	-	-	0.90
Thapa et al. [37]	2020	Dementia Bank	Nepali	CN vs AD	Text	Kim's CNN	0.96	0.97	0.96	0.96
Toro et al. [42]	2019	PC-GITA 50 PD, 50 HC	Spanish	Parkinson's Disease	Text	SVM	0.72	-	0.92	-
Thapa et al. [43]	2020	Little et al. [44]	English	Parkinson's Disease	Speech	Twin SVM	0.932	0.93	0.93	0.93
Khodabakhsh et al. [39]	2014	20 AD 20 CN (Private)	Turkish	CN vs AD	Speech	SVM	0.9	-	-	-
Fraser et al. [33]	2016	Dementia Bank	English	Alzheimer's Disease	Text	Logistic Regression	81.93	-	-	-
Fritsch et al. [45]	2016	Dementia Bank	English	Alzheimer's Disease	Text	LSTM	85.6	-	-	-
Chen et al. [46]	2019	Dementia Bank	English	Alzheimer's Disease	Text	Att-CNN+Att-BiGRU	97.42	-	-	-

Apart from diagnosis of mental illnesses from speech narratives, the clinical texts can also be used to extract the symptoms of mental illnesses (2017 Jackson). Furthermore, discourse analysis should be done to analyze how linguistic features of the speech are correlated with conversational outcomes [47].

6. Harnessing the Power of NLP for Analysis of Social Media Content for Depression Detection

With the availability of the internet and mobile phones to a very large number of people in the world, a lot of things are going on in the internet sphere every second. Social Networking Sites like Facebook, LinkedIn, etc., and microblogging sites like Twitter have given people the freedom to express their opinions, beliefs, personal experiences, feelings, etc. People tend to express a lot of things with friends and family in their network through which inferences can be made about their mental state [26].

Depression has become a very common disease nowadays. So, this has to be dealt with measures that are readily available and accessible. Thus, computer-based diagnostic measures can prove to be very effective because of their easy availability and accessibility. The diagnostic systems based on computational intelligence rely on readily available data. Most of the past works use text data from readily available sources like Reddit, Twitter, Facebook, etc.

Tadesse et al. [48] used the posts of Reddit users for building the analytical model for depression detection from Reddit posts. With 1293 posts pertaining to the depressed category and 548 posts relating to the non-depressed category, an accuracy of 91% was achieved with multi-layer perceptron. Similarly, Aldarwish et al. [49] took the posts from multiple social networking sites to build their datasets. The data was taken from various social networking sites like LiveJournal, Twitter, Facebook, etc. for building the model. The naïve Bayes classifier gave a perfect precision of 100 but performed badly in terms of other performance measures like accuracy and recall. The accuracy and recall for the model were reported to be 63 and 58 on a scale of 100 respectively. A lot of works has been done in the English language. Apart from the English language, the works are very few. However, researchers are building diagnostic systems for other languages as well.

Katchapakirin et al. [50] built a system using Facebook posts of Thai users. Facebook being the most used social network in Thailand is the platform where most of the users express their feelings freely. With 1105 posts taken from Facebook, a Deep Neural Network was used to classify the users as depressed or non-depressed. With the activity of users in Facebook like the length of posts, the time the user posts, etc. the model was able to classify with an accuracy of 85%.

Apart from the tweets, spontaneous speeches can also be used to build the model for the detection of depression. Huang et al. [51] used the audio recordings taken from smartphones to detect depression. The characteristic vocal features like pauses, differences in pronunciations were leveraged by the LDA bigram model to diagnose the subjects with an accuracy of 78.70%. The smartphone-based techniques can be useful and can be easily available. Further, spontaneous speech can be rich in features and hence can help in accurate diagnosis.

7. Computational intelligence and cognitive IoT in Suicide Prevention

Suicide has been one of the most serious issues in modern society. The competition in society, high expectations from oneself, and limited social interaction has been the factors that contribute to suicide. Every year, nearly a million people around the globe die of suicide [52]. The number is staggeringly high and suicide accounts for even higher deaths than that by war, homicide, or wide prevalent diseases like malaria. The figures might be even higher as thousands of cases go unreported. Suicide not only takes the lives of our beloved, it also keeps the lives of the ones behind in deep agony and pain. A lot of examples of relatives and families left in financial and emotional burden can be seen around us. Thus, suicide is a problem that just not kills individuals but also leaves the relatives in deep pain. Hence, there is a need to identify the risks of suicide as early as possible [53]. This can help the psychiatrists, social activists, and concerned stakeholders to step in for carrying out the preventive measures.

The identification of suicidal behavior is a great challenge for psychiatrists and computational intelligence scientists. The diagnosis becomes hard because there is not a single symptom that can screen the risks. There are many social and relationship factors that need to be analyzed in greater detail. Despite a lot of complications posed by various factors, there have been efforts to find out risks and identify suicide ideation of people. There are some of the high-risk factor groups like patients with terminal illnesses and no psychiatric counseling, people with a high financial burden, and so on [54]. Factors like that can be reflected through electromedical health records, demographic information, etc. Such useful information is leveraged by machine learning algorithms to find out the probability of suicide and take proactive measures accordingly. Also, lately, social media contents are being used for the analysis by machine learning algorithms. With the high availability of mobile phones and intelligent sensors, they are also being incorporated to assess the risks of suicide and prevent them. While assessing the risks, it is more likely that the patients will convey their information to smartphone-based data collection modalities. The data can be collected through online forms, voice recordings, call logs, etc. which can be leveraged to do further analysis [55]. Cognitive IoT can also be used in such case. Such cognitive IoT devices can assess the risks at real time and let the emergency helplines communicate with the victims. In this way, cognitive IoT devices especially wearables can play a high role.

Sawhney et al. [56] built a model for the prediction of suicide ideation using various machine learning and evolutionary algorithms. The data were collected from Twitter for suicide and non-suicide labels using Twitter API. The tweets that showed a tendency of self-harm or suicide were labeled as suicidal tweets whereas the tweets that didn't show any such tendencies were labeled as non-suicidal tweets. Various machine learning and deep learning models were then tried out to evaluate the performance. Out of various deep learning and machine learning models some of which were used in conjunction with evolutionary algorithms, the random forest algorithm with binary firefly algorithm performed the best. The model Random Forest + Binary Firefly Algorithm showed the best performance in terms of accuracy, precision, and recall. The model had an accuracy of 88.82% with a precision and recall of 87.12 and 84.73 respectively on a scale of 100.

The depressed patients might have a varying degree of suicide susceptibility. Cheng et al. [57] used posts from Weibo, a popular social media in China, to curate the datasets and build the models for the assessment of suicide risks. The authors did a detailed study to assess suicide risks along with the probabilistic suicidal possibility and levels of anxiety, depression, and stress. For the respondents who earlier had suicidal communications, the recall of 70 (on a scale of 100) was obtained for classifying respondents with severe anxiety. Similarly, those with severe depression and high suicide risks were classified with a sensitivity of 65% for each.

Similarly, Fodeh et al. [58] built a K-Nearest Neighbor (KNN)-based algorithm to identify the patients who were at risk and the patients who were at high risk. The dataset of 280 tweets of class “High Risk” and 1614 tweets of class “At Risk” were taken for the study. Using the down sampling technique, the data was down-sampled to form a balanced dataset of 280 tweets of class “High Risk” and 285 tweets of class “At-Risk”. The KNN-based classifier was able to classify the two classes with a precision of 0.853 and a sensitivity of 0.933. Classification of the tweets in such a hierarchy would help the rescuers to prioritize the cases according to the degrees of severity. Lin et al. [59] also proposed the models for the prediction of suicide ideation in military personnel. The work used six machine learning models by taking six important psychological stress domains as the features. Two classification problems were defined, one with any suicide ideation and another with serious suicide ideation. For any suicide ideation, the performance measures for normal and suicidal subjects were 100% for accuracy, precision, and f-score with Multilayer Perceptron (MLP) model. Similarly, for serious suicide ideation, the accuracy of 99.9% was achieved with the MLP model.

Table 2. Use cases of Natural Language Processing in Depression Diagnosis and Suicide Prevention

Authors	Year	Language	Dataset	Use-cases	Algorithm	Acc	Pre	Rec	f-score	AUC
Sawhney et al. [56]	2019	English	Tweets	Suicidal Ideation Detection	Random Forest + Binary Firefly Algorithm	88.82	87.12	84.73	85.91	
Walsh et al. [60]	2017	English	Health Records	Predicting Risk of Suicide Attempts	Random Forest	-	0.79	0.95	-	0.84
Braithwaite et al. [61]	2016	English	Tweets	Prediction of Suicide	Decision Trees	91.9	-	-	-	-
Cheng et al. [57]	2017	Chinese	Weibo Posts	Suicide Risk and Emotional Distress	SVM	-	-	0.70 (Severe Anxiety)	-	0.75
Fodeh et al. [58]	2019	English	Tweets	Detection of Suicide Risk	KNN	-	0.853	0.933	-	0.885
Lin et al. [59]	2020	English	psychopathological observations	Detection of Suicide Ideation	Multilayer Perceptron	100	100	100	100	100
Zheng et al. [62]	2020	English	Electronic Health Records (EHR)	Suicide Attempt	Deep Neural Network	-	-	-	-	0.792
Katchapakirin et al. [50]	2018	Thai	Facebook Posts	Depression Detection	Deep Neural Network	85	80	100	88.9	-
Huang et al. [51]	2019	English	Smartphone audio recording	Depression Detection	LDA-Bigram	78.70%	-	-	0.549	-
Orabi et al. [63]	2018	English	Tweets	Depression Detection	CNN-based model	87.96	87.44	87.03	86.97	0.95
Tadesse et al. [48]	2019	English	Reddit Posts	Depression Detection	Multilayer Perceptron	91	-		0.93	-
Choudhury et al. [64]	2013	English	Tweets and Questionnaires	Depression Detection	SVM	72.34	0.74	0.629	-	-
Aldarwish et al. [49]	2017	English	Multiple Social Networking Sites	Depression Detection	Naive Bayes	63	100	58	-	-
Deshpande et al. [65]	2017	English	Tweets	Depression Detection	Naive Bayes	83	0.836	0.83	0.833	-

Despite the easy classification, there are many problems associated with machine learning models. The main problem comes from the data availability. Twitter which is the main source of data in most of the earlier works sometimes becomes unreliable. Sawhney et al. [56] point out the complications in analysis using tweets by doing detailed error analysis. The authors find out high fluctuation in the meaning that words in tweets want to convey. Most of the time, the algorithms misclassify the tweets as the tweets with suicide ideation when they had characteristics words like “kill me”, “I am done”, etc. Some tweets containing such words might actually be suicidal tweets but not always. Sometimes, people express humor or sarcasm with such words. Machine learning models fail to identify such things.

Apart from suicide prevention, machine learning can be used to analyze the data of the past suicides and come up with proactive measures to nullify the effects of suicide. Various organizations have been using the past data for modeling and analyzing the effects of various plans and policies for suicide prevention. Also, various chatbots and conversational bots have been developed recently to aid in suicide prevention [66]. Suicide prevention using computational intelligence is undoubtedly one of the most useful applications of machine learning and is promising because of the early detection and high accuracy exhibited by various algorithms. Though the measures have good outcomes, various ethical issues should also be looked upon. Ethical issues while collection and processing of the data should be taken into consideration while building the models based on computational intelligence [67]. A lot of things go hand in hand with suicide prevention and because of this, computational scientists along with other stakeholders must show a coordinated effort [68].

8. Wearables and IoT Devices for Mental Wellbeing

One of the key challenges of mild mental wellbeing disorders such as mild level depression is that people may not even realize it unless it's too late. It has been reported that depression is a particularly hard thing to diagnose in the traditional way. Doctors usually diagnose depression using the traditional way of questions and answers. Since the autobiographical memory of people is not 100% accurate and also the answers of the patients can be highly mood dependent, it is more likely that depression goes undiagnosed even with the help of professional medical practitioners. There has been a rise of mental health monitoring apps for smartphones in the market today. There are many apps that act as a diary for the user to put on details about their mental health. Recently chatbots have been created using NLP that are able to chat with the user and determine their emotional states. State-of-the-art chatbots also try to uplift the user's mood using linguistic tricks. Wysa and Woebot are two such applications that are available that users have reported to be mood uplifting. The market for such applications has also been on the rise. An application called calm has been valued at a billion dollars even though no research backs up its claim of improving mental health. Similarly, there are other applications such as Calm Harm which is designed to prevent self-harm and also prevent suicide [5].

Gjoreski et al [69] have created a system that is able to do real-time detection of stress in people. Stress is relatively harmless but prolonged and continuous stress can cause irreversible damage to the human system; thus, it is very important to detect and manage stress. Their system consists of a wrist device that captures physiological data primarily photoplethysmogram (PPG). Using the data, the person is classified as having stress or not in that particular instance of time using machine learning. The machine-learning algorithm was trained in the laboratory by getting data from subjects by inducing them into stressful situations.

Being in good physical health is a prerequisite for mental well-being because a person who is sick or has a disease is not able to be in complete mental ease. Thus, it is important to monitor the physical health of people. Nowadays IoT systems have been developed that constantly monitor subjects in a non-intrusive manner and report any abnormalities in the physical system using different computational techniques. Saha et al. [70] have proposed a system that can do real-time tracking of a person's pulse rate, eco rate of heart, pressure levels, temperature as well as blood glucose levels using suitable sensors. These sensors send data to the phone that the person carries and then the smartphone further sends the data to the cloud for further analysis. Casaccia et al. [71] have proposed a system that determines the wellbeing of elderly patients through domotic sensors and machine learning algorithms. The domotic sensor consists of three parts. The first is the light status detector that detects whether the light is on or off. The second is a thermostat which monitors and controls their temperature and the third is passive infrared sensors which monitors the presence of users. For the first two months a survey was taken at regular intervals and then using that survey and data the machine learning algorithm was trained. The accuracy and effectiveness of the system at determining and regulating well-being of senior citizens was found to be effective.

9. Future Scope of Computational Intelligence in mental wellbeing

As we all know that artificial intelligence and computational systems are practically driving today's world and it finds application in many different areas. One such area is the sector of healthcare. Many computational technologies have already been developed for the accurate diagnosis of many diseases and disorders using various features from images, voices, blood samples, and so on. There can be many advances in the field of technological healthcare systems in the future. Some perspectives of the author as to what could happen in the future are discussed below.

One of the major advances would probably be in the field of diagnosis of mental disorders. There are systems that can automatically diagnose certain mental disorders such as Alzheimer's disease, Parkinson's disease, etc. with 100% accuracy using various data like MRI, PET, medical records. The entire process of diagnosis could be done without the involvement of any human beings. The entire process could be done by computational systems. Artificial intelligence systems that could potentially determine if a person would likely develop the mental disorder as fast as 50 years in the future could be developed. These systems could scan the genetic makeup of a child and determine if the child would develop certain mental disorders in the future. There could be computational systems that could also determine what kind of environment is more likely to cause mental disorders in individuals and suggest the kind of environment for optimal mental wellbeing to a certain individual based on his/her personal history and physiological makeup.

There could even be certain computational technologies which could prevent and treat a mental disease that would show up years in the future in certain individuals. Perhaps machines that can change the genetic makeup of individuals so as to cure diseases such as cancer would be made in the future. These machines could very well remove the certain genes that cause mental disorders. It could also potentially add genes to the DNA of an individual. Genes that could potentially prevent any sort of mental disorder from happening. But we probably won't see these sorts of technologies in the near future, but as human civilization progresses these kinds of systems could possibly be made.

10. Conclusion

This chapter has discussed how computational intelligence and intelligent sensors can be used for mental wellbeing. Mental wellbeing being one of the most important aspects of life should be given more emphasis and focus should be laid on making diagnostic systems as cheap and accessible as possible. Thus, more research needs to be done to aid people in living a happy life. Computational intelligence has developed immensely and, in the future, even doctors might be replaced with artificial intelligent machines. The clinical diagnosis could be done using intelligent expert chatbots that could correctly determine what disease a particular person has and automatically suggest tests and diagnosis methods that would confirm. Surgeries would probably happen automatically. Infact, robots that are capable of performing neurosurgery have already been developed in the current era, however, they still need some level of human intervention. Perhaps in the near future these robots could successfully operate without any human intervention. The future of computational technologies is only limited by human imaginations and creativity. Anything that we could think of could be done using computational technologies and artificial intelligence. The future is bright if we use these systems ethically and for the benefit of humanity.

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