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Review Article

Optimistic Stratagems of Machine Based Deep Learning Employed with Automation in Psychiatry and Early Neurodevelopmental Disorders

Anita Margret A[1]* and Aishwarya S[2]

[1]*Department of Biotechnology and Bioinformatics, Bishop Heber College, Tamilnadu, India*

[2]*Department of Bioinformatics, University of Madras, Tamilnadu, India*

Abstract

Automation has become a significant module in abetting diagnosis during the contemporary era of medical field. Deep learning is a categorization of machine learning encompassing artificial intelligence. Machine based learning is renowned for its rapid detection of anomalies and has gained immense attention in recent years. The data is catalogued in an amicable manner where the results are presentable based on various images, videos, and sounds with high accuracy through a regularized mechanization using big data. The impact of neurological disorders is felt as the burden that is expanding in due course of global population both in developed and developing countries. Early developmental disabilities are an assemblage of conditions due to impairment in physical, learning, language, or behavior areas which profoundly affect the normal existence of children. The spectrum of neurological ailment is diversified irrespective of demographic parameters and entails significant diagnosis and treatment. Brain is the most complicated organ that requires extensive advances in understanding its development and behavior. Interdisciplinary developments are the becoming inevitable to enhance clinical practice and diagnosis through convolution neural networks. It is necessary to propagate innovative approaches to treat neural disorders and monitor brain development. This chapter proposes a novel framework of research involved with animal models and various detection strategies to perceive neural irregularities. Several visual approaches with biomarkers as neuroimage bestows application during various gestational ages. Conversely, the contents uplift the promise of machine learning at varied levels in neuroscience investigation to discover the working of neural network and brain functioning.

Prelude on Neurodevelopment Disorders and Its Global Prevalence

Neurodevelopment Disorders (NDDs) are mental infirmities which affects the foremost functioning of neurological system and brain. They are formed due to neurogical deformities that onset from birth and interfere with the progression of embryological development which produce impairments in the functioning of central nervous system [1]. They include varied neurological conditions that lead to intellectual disabilities and communication like disorders Autism Spectrum Disorder (ASD), Attention-Deficit/Hyperactivity Disorder (ADHD), neurodevelopmental Motor Disorders, and Specific Learning Disorders. The impact of these disorders affects the personal, social, and economic existence of an individual. Deciphering a specific causative source for these infirmities remains a challenge since the reason to decipher the specific reason for the disability is diverse [2] it includes various genetic, nutritional, infectious diseases, traumatic parameters. Globally, there is a sturdy need to devise remedy and combat this mental ailment. Though, neonatal and infant mortality are considered as, a threat to the society, the rise of neurodevelopmental disabilities is alarming and requires a significant curb, since it is considered as second leading cause of fatality [3]. There is a greater prevalence (80%) of NDD in low- and middle-income countries where the maximum global population (90%) of children prevail [4]. Understanding the impact of neurological disabilities the UN formulated sustainable development goals reduce the burden of non-communicable diseases by 2030. There is an immediate necessitate to devise stratagems and plans that would target neurological disorders which would potentially help to achieve the goals of UN.

Threats of Neurological Disorder and Its Normal Existence

Several neurological disorders confine the normal physiological existence of an individual which affects their regular functioning and activities. Neurological and psychiatric disorders are assumed to be negligent due to the few incidence of direct mortality. The assessment of GBD (The Global Burden of Disease Study) in 1990 reported that noncommunicable ailments such as neurological disorders substantially can hinder health and endure to be a burden worldwide [5]. Further it stated that neurological disabilities were the foremost cause of disrupting healthy life and its threats were underrated by considering only death rate. Hence, based on the need to update the predictions

*Corresponding author: Anita MA, Department of Biotechnology and Bioinformatics, Bishop Heber College, Tamilnadu, India, E-mail: anitamargret5@gmail.com

of global mortality WHO prepared a forecast to elucidate the trends for deaths and anomalous impacts of the neurological disabilities that ranges from 2005 to 2030 [6]. The Disability-Adjusted Life Years (DALYs) are a progression that deduces the complete health and expectation of life. It coordinates with the number of years expended on sickness, disability or early death that are prevalent among different countries. The data in table 1 represents the measurement of DALYs in thousands that are related with neurological ailments from 2005, 2015 till 2030 [7]. It is intimidating that the neurological disorders has raised from 2005 (92 million DALYs) to 103 million in 2030 which contributes an upsurge of nearly 12% conversely, cognitive impairment diseases such as Alzheimer and dementias are predicted to show a profound increase of 66% from 2005 to 2030.

| Cause category	2005		2015		2030	
	No. of DALYs (000)	Percentage of total DALYs	No. of DALYs (000)	Percentage of total DALYs	No. of DALYs (000)	Percentage of total DALYs
Epilepsy	7 308	0.5	7 419	0.5	7 442	0.49
Alzheimer and other dementias	11 078	0.75	13 540	0.91	18 394	1.2
Parkinson's disease	1 617	0.11	1 762	0.12	2 015	0.13
Multiple sclerosis	1 510	0.1	1 586	0.11	1 648	0.11
Migraine	7 660	0.52	7 736	0.52	7 596	0.5
Cerebrovascular disease	50 785	3.46	53 815	3.63	60 864	3.99
Poliomyelitis	115	0.01	47	0	13	0
Tetanus	6 423	0.44	4 871	0.33	3 174	0.21
Meningitis	5 337	0.36	3 528	0.24	2 039	0.13
Japanese encephalitis	561	0.04	304	0.02	150	0.01
Total	92 392	6.29	94 608	6.39	103 335	6.77

Table 1: Presents the data in percentage that projects the futuristic occurrence neurological disorders associated with DALYs (Data from Updated projections of global mortality and burden of disease, 2002-2030: data sources, methods and results Geneva, World Health Organization, 2005) [8].

The estimated reduction of DALYs in poliomyelitis, tetanus, meningitis and Japanese encephalitis **(**57%) combined console the menace during the fourth coming years [9]. The graphical representation in figure 1 illustrates the significance of death rates during 2005, 2015 and 2030 [6]. The death rate of neurological disorders is influenced by the pathogenesis of other diseases. For instance, cerebrovascular diseases are responsible for 85% of the deaths due to neurological disorders. The GBD data reveals the significance rise of neurological disorders from 2005 to 2030 [10].

The projected threats of these ailments would plan futuristic strategies to restrain and find contemporary remedies. Consequently, distinct actions to improve the mental health are required instantly otherwise the neurological burden will remain as a serious threat to public health.

Deep Learning-A Novel Strategy Involved In Monitoring and Screening of Neural Anomalies

Abnormalities associated with nervous system are based on congenital and environmental attributes. The development of nervous system occurs both during and after birth and hence is influenced by a varied environmental issue which can lead to neural anomalies. Congenital anomalies are up surging and are common among infants. It is estimated that 2%-3% of new born are diagnosed with complicated congenital malformation which can drive towards an increase rate of morbidity and mortality [11]. There is a significant necessitate to curb and devise strategies to understand its etiologies. Digitalization of significant data and resources is the prerequisite of today's era of data science management. Machine Learning (ML) Artificial Intelligence (AI) and deep learning techniques are considered as the essential tools to decipher complications in the contemporary period. Figure 2 depicts the integrated coherence and their individual versatility to resolve intricacies in the field of neuroscience. Nearly 45% of official units are performed with automated technologies where, 80% of its features are based on the capabilities of ML capabilities [12].
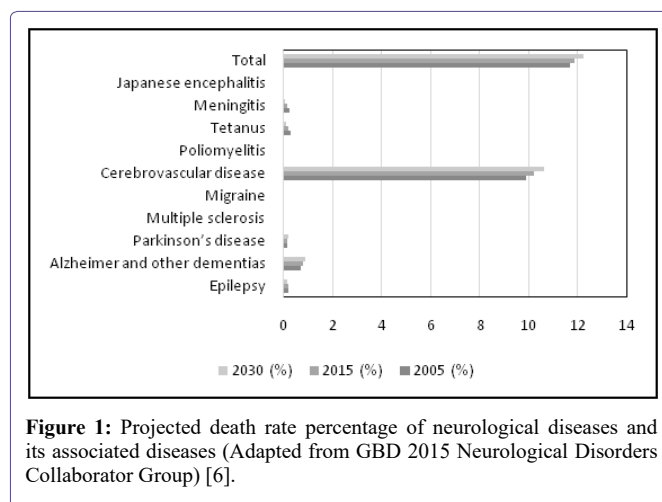
Figure 1: Projected death rate percentage of neurological diseases and its associated diseases (Adapted from GBD 2015 Neurological Disorders Collaborator Group) [6].
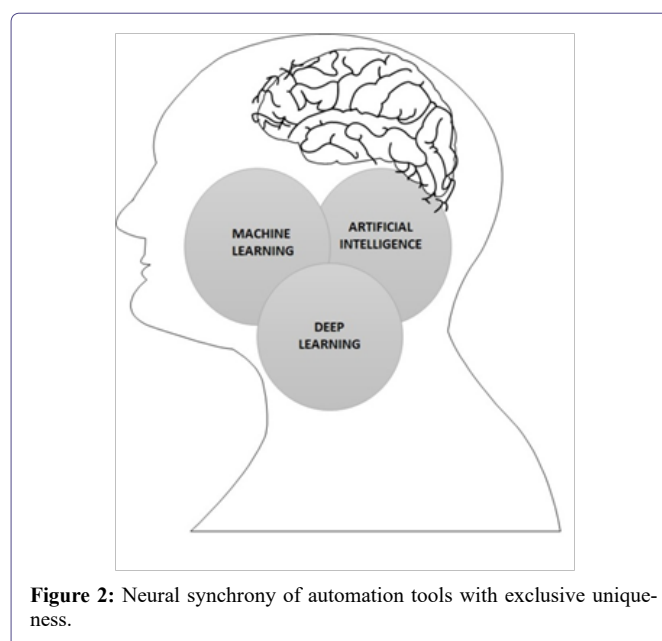
Figure 2: Neural synchrony of automation tools with exclusive uniqueness.

The optimistic ambiances of these technologies in massive scale can benefit health care and could create an economic impact by saving labor-intensive expenses widely. The estimation of the International Data Corporation states that the futuristic activities and daily schedules are dependent on AI and ML which will eventually grow to $79.2 billion by 2022. Holding a multifarious progress there is an expectation of upsurge in the annual economic growth rate of 38% from the year 2018 to 2022 [13]. Machine learning develops methodologies that are fed in the computer as mathematical models and procure significant algorithms that can solve a given problem. Deep involves the concept automation profoundly than the classical system, where the computers represent and features mechanically. It focuses on processing the raw data instinctively without feeding prior experiential data or learning inputs [14]. The enchantment in deep learning networks includes the distinguished pattern and structure involved behind the immense data. The varied computational models known as neural networks support the working mechanisms constituted in deep learning concepts.

Stages of Deep Learning

Deep learning conceptualizes distinct phases to evaluate and decipher a particular query. The initial stage requires defining the opted network and it's planning which is preceded by the compilation step. This stage constitutes is to configure the specific model and the compile the critical parameters that defines the evaluation procedure [15]. Computing and calculating are the foremost aspects of deep learning where, configuring and fitting the model plays a significant role. This function exercises the model to fix an exact set of iterations on a dataset. Another significant step of deep learning is evaluation where the model is verified for its functioning. The programmed test data, validated with a variable data through random tests can relate an augment the ideal operation of the model [16]. Once the model is created the final phase is to deploy and transmit the program widely. The choice of transmission is very important to gain publicity and can be done by creating websites and apps.

Big Data and Artificial Intelligence in Analyzing Neural Data and Brain Networks

The human brain is a complex organ interconnected with conceptualized hierarchical network, where abundant of neurons are specifically organized into networks which process and transmit information. Brain network are hubs where information are processed from precise patterns through neurons, which brain associate the functioning of brain [17]. This network has a structural, functional progression which is instigated during the early pattern of development and proceeds into adulthood followed by senescence. These biological events are administered by involuntary events and the experiential history of an individual.

Artificial Intelligence and Brain Networks

The application of artificial intelligence reflects profoundly in neuroscience with wide benefits in fields like neuroanatomy, neuro-development, electrophysiology, functional brain imaging, and neural basis of cognition [18]. Brain network comparison and characterizations related to anomalies or disorders among a population can be performed using various interface of artificial intelligence like graph theoretical analyses, Magneto Encephalographic (MEG) and neuro-imaging studies [19]. There is a tremendous change in the clinical diagnosis among hospitals along with health care systems. They have improved widely to produce data from nervous system in terms of as Medical Imaging which would monitor developmental anomalies and neural deformities.

Neuroimaging Deep Learning Strategies in Psychiatry

Medical experts and neurologist customize these visual imaging technologies to treat brain pathologies, as well as identifying risks and adverse reactions pertaining to therapies. Hence these techniques pave the way for understanding, envisaging diseases and treating, through vital diseases managing techniques. Conversely, the recent developments in neuroimaging are cost-effective and beneficial economically. There are various techniques like Computed Tomography (CT), Positron Emission Tomography (PET), and Magnetic Resonance Imaging (MRI) which are readily amicable with low risk analysis [20]. These imaging techniques revolutionize the study of central nervous system and brain which was earlier very much complicated. It allows the medical professionals to evaluate the structural aspects of brain without damaging it and detect neural abnormalities.

Behavioural and Visual Data Interpretation Using Convolutional Neural Networks (CNNS) As Models

Convolutional Neural Networks (CNNs) are validated models related with the visualization biotic samples and is known as the study of biological vision. They are considered as integrative tools and have accomplished to create of state of art models depicting both the neural activity and behavioral aspects. Convolutional neural networks functions with the principle of automation that links the concepts of artificial intelligence with neuroscience [21]. The progression and activity of a brain can be captured with contemporary tools originated from the fields of computer science and engineering. The foremost resurgence in the field of neuroscience has happened due to the recapitulation of neuronal networks of ventral stream whose, activities are represented through visual information [22]. The finest aspect of CNNs it can predict the visualization of an organism. The observation of an animal can be validated through artificial units and can be forecasted as the activities performed by its real neurons [23]. Figure 3 illustrates a comparative model which represents the neuronal activities between a real and artificial system. The behavioral assessment of humans and animals remains as a challenge. But CNNs outperforms the classical models and relates more with the existing -world image. Hence, can establish itself as a virtuous interface to relate human behavior with its contiguous animal species. A fine study [24] interrelated the behavioral patterns of human and monkeys and by using several features CNN architectures a comparable match score elucidated the relationships between both the species [25].

Automation Techniques Involved In Various Neurological Ailments

Neurological disorders are caused due to the deformities that occur in the peripheral and central nervous systems. The lack of neural coordination will lead several distortions like poor coordination, muscle weakness with pain, paralysis, seizures and loss of consciousness [27]. These symptoms are associated with more than 600 different types of mental ailments where some like brain tumor, Parkinson's Disease (PD), Alzheimer's Disease (AD), Multiple Sclerosis (MS), epilepsy, dementia, headache disorders, neuroinfectious, stroke, and traumatic brain injuries are frustrating and requires immediate remedy.
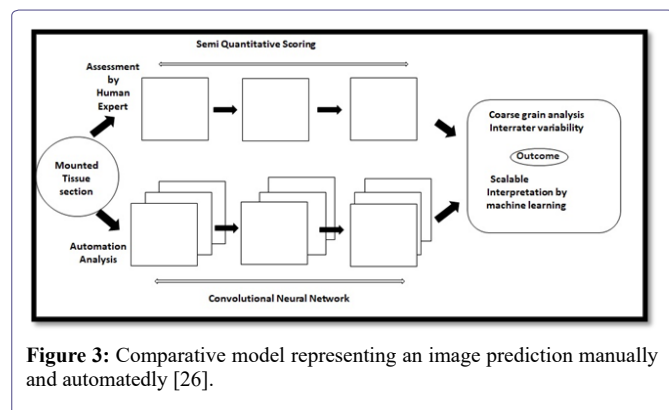
Figure 3: Comparative model representing an image prediction manually and automatedly [26].

Neuro Developmental Disorders

Attention Deficit Hyperactive Disorder (ADHD) and Autism Spectrum Disorder (ASD) are impulsive developmental neuro disabilities which affect the cognitive progress of an individual. Though both the disorders have some common symptoms they differ in terms of neurological pattern. ASD relates with the learning aspect of the patient along with his communication, language and social behavior. Whereas, ADHD influences the growth patterns of brain and its development that can lead to extreme impulsive hyperactive behavior [28]. The diagnosis and treatment to these disorders depends on the behavioral symptoms, which can be variable and thus uncertain. Hence there is an immense need to comprehend the structural and physiological activities of neurological system to reinforce behavioral patterns of an individual that would elucidate the ambiguity related to the disorder.

Applications of deep learning has enhanced the cognitive skill management and therapy through neuro imaging which overcomes the risk assessment of classical radiology methods. The diagnostic history of ADHD has incorporated Machine learning concepts in neuroimaging which reveals abnormalities in the regions of brain [29]. Later there was a profound transformation in the degree of automation and emerged an ethiological model of ADHD which primarily focused on the pathophysiology toward dysfunctional interactions within and between distributed networks [30]. Currently, there is a huge advancement in the deep learning skills of automation where the entire brain network is connected and its differential patterns are correlated in terms of low-frequency and spontaneous Blood Oxygenation Level Dependent (BOLD) activity. The functional architecture of the brain is characterized intensely along with its essential neural activities which are evaluated and stated as resting-state functional connectivity (rs-fc) [31]. The advantage of deep learning techniques is intensely used in the prenatal and early diagnosis which relates the functional and structural region of brain. Thus it can improve social skills and resolve the communication problems among ASD affected children. Certain automated tools like Functional Magnetic Resonance Imaging (FMRI) which studies the structure of brain [32] and the Autism Brain Imaging Data Exchange (ABIDE) that deciphers specific biomarker expertise in detecting and treating ASD [33,34] The ASD biomarkers are conceived with multi-channel convolutional neural networks based on a patch-level data-expanding method that involves in early diagnosis and treatment in prenatal phase [35,36] Further, Variational Autoencoder (VAE) intensifies the functional connectivity pattern and Stereotypical Motor Movements (SMM) which facilitates body rocking and complex hand movements in autism patients.

Neural Disability Leading to Impairment of Memory and Cognitive Function

Alzheimer's is a progressive neural disease that gradually leads to loss of memory and cognitive function. Dementia is the foremost ailment in Alzheimer's disease where 60-80% of patients suffer with memory loss. Hence both are twinned with each other and require immediate antidote since the prevalence of these ailments is increasing. As per the data of World Alzheimer Report [37], about 50 million people were affected with this mental deformity in 2018, which is forecasted to upsurge thrice by 2050. There is significant need to restrain this condition and deep learning concepts significantly assist to promote mental health. The initial transformation of Mild Cognitive Impairment (MCI), among Alzheimer's patients is monitored by Magnetic Resonance Images (MRI) which are actively coordinated by open source databases like ADNI (adni.loni.usc.edu), AIBL (aibl.csiro.au), OASIS (www.oasis-brains.org) and software's like Statistical Parametric Mapping (SPM) [38]. Machine learning techniques consisting of artificial network and interface like Support Vector Machine (SVM), Artificial Neural Network (ANN), and deep learning [39,40] classifies Alzheimer's and its various stages. The destructive features of brain leading to memory loss is predicted by several dementia representations like neuropsychological based models, health-based models, multifactorial models and genetic risk scores [41]. The synchronization of multiplex neural networks with the Magnetic Resonance Imaging (MRI), segregates healthy brains from those affected with memory loss. Atrophy of brain leads to progressive Mild Cognitive Impairment (pMCI) which is regularly monitored by Positron Emission Tomography (PET) scans and contemporary machine learning algorithms [42]. Alzheimer's based dementia diagnosis is enabled [43], by machine learning methodology which has devised novel biomarkers based on Extreme Gradient Boosting XGBoost, Random Forest and Deep Learning concepts that assesses the metabolites in the blood e Cerebrospinal Fluid (CSF).

Chronic Neurodegenerative and Muscular Disorder

Epilepsy is a distressing neurological disease that is characterized by frequent seizures [44]. The sudden change in the functioning of the brain and its connectivity among the neural networks causes varied behaviors like irregular erratic movements, loss of consciousness temporary that affects memory. The intensity of epilepsy and seizure is monitored by Electroencephalography (EEG) which is considered as a significant clinical tool [45]. Computer based models analyses the EEG signals effectively through algorithms which are distinct and classify the EEG signals based on the series of wavelet and its entropy [46]. Exclusive set of neural network and interface like Support Vector Machine (SVM), k-Nearest Neighbour (kNN) and Radial Basis Function Neural Network (RBFNN), Artificial Neural Network (ANN) are used to categorize the signals of EEG [47-49]. Multiple genetic variations play a crucial role in developing neurodegenerative disorder like Cerebellar Ataxia (CA) which mainly affects cerebellum [50]. The dysfuntioning of cerebellum impairs the control and coordination of whole body movements, eye rotation (nystagmus), and affect speech (dysarthria). The single or multimodal imaging is associated with deep learning concepts can link the distinct genetic integrity by producing specific biomarkers. Similarly muscular dystrophy is a inherited disease characterized by muscle weakness and muscular atrophy, which leads to cardiopulmonary failure and eventually can be fatal. Magnetic Resonance Imaging (MRI) has is a noninvasive and expedient technique which can detect a discrete pattern of fatty

infiltration [51-54] .The interpretation MRI data is very important and solely depends on the medical expert and incase misdiagnosis it can lead to deleterious effect. In order to avoid these deep learning skills appears to be an ideal option. The Convolutional Neural Networks (CNNs) serves as a comparative media which can interpret informative features based on specific patterns and thus can avoid misinterpretations [55,56].

Research Stratagems Implicated in Deep Learning

Research in neuroscience has established advance stratagems to confine alterations and restrain neurological disabilities. Considering the efficacy of biomolecules and its interference in the nervous system large amount of data in can be produced by using machine learning techniques .The integrity of research findings with machine learning builds up strategies to develop diagnostics and treat mental ailments.

Identifying Biomarkers as Signatures to Construe Neurological Ailments

Many neurological disabilities are categorized as heterogeneous disorder which can imitate other forms of neurological conditions [57]. Certain circumstances can misinterpret the clinical features of neurological ailments and creates a challenge by worsening the condition. [58-60]. Biological components present in blood, neurotransmitters and Cerebrospinal Fluid (CSF) serves as neurological biomarkers. Alzheimer's disease has clinically significant biomarkers like Amyloid-beta (Aβ), tau phosphorylated (p-tau), and total-tau (t-tau) which are profoundly, applied in clinical research, and drug trials [61,62]. Conversely, there are many neurological ailments like Dementia with Lewy Bodies (DLB) or Frontotemporal Dementia (FTD), which share common symptoms with Alzheimer's disease and requires specific identification [63,64]. Immunological techniques like Enzyme-Linked Immunosorbent Assay (ELISA) has been associated with CSF AD biomarkers but is widely hindered by the variation in measurement of its analytes and chances of misinterpretations [65,66]. Hence automation techniques holds hands with the neurological ailments to capture the structural and functional changes of central nervous system by using advanced neuroimaging techniques, such as Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET). These dynamic techniques have been developed with deep learning concepts to identify AD-related structural and molecular biomarkers. Computer-aided machine learning approaches can rapidly integrate the biomarkers and finely distinguishes the various neurological ailments.

Reflection of Automation Techniques Using Animal Models

Animals are used as neuro models to develop novel antidotes and identify new therapeutic target against neurological ailments. These models help to evaluate its behavioral, emotional, biochemical and social aspects in association to causative agents and device ideal remedy. Various animal models have been established to mimic human disorders associated with biochemical profiling and behavioral patterns [67] *In vivo* studies in neuro science uses several animal models for the purpose to augment the functioning and mechanisms of the brain in association with behaviour [68]. Further the clinical trials endorse the detection of potential targets which outcomes to produce neuroprotective and cognition enhancing compounds [69]. Animals such as mice and zebra fish (*Danio rerio*) are considered as vivacious developmental models. The non-invasive characterization of disease can lead to phenotypical variations in mouse models which associate with disease identification, characterization and progression and eventually will evaluate the criteria for devising effective therapeutic interventions. Live animal imaging is possible with advanced techniques like Positron Emission Tomography (*PET*)-Magnetic Resonance (*MR*) and Single Photon Emission Computed Tomography (*SPECT*)-*MR* hybrid imaging. The neuro images and motion videos are compared with condition of human being and strategized to combat the ailment [70]. Zebrafish is emerging as an increasingly successful model for translational research on human neurological disorders. It is extremely validated as a powerful vertebrate model for investigating human neurodegenerative diseases [71]. The neuroanatomic and neurochemical pathways of zebrafish brain exhibit a profound resemblance with the human brain. Physiological, emotional and social behavioural pattern similarities between them have also been well established. Fascinatingly, zebrafish models have been used successfully to assess the pathology of Alzheimer's Disease (AD) as well as Tauopathy. Their relatively simple nervous system and the optical transparency of the embryos permit real-time neurological imaging.

Automated Modelling of Cognitive Behavioral Patterns *in vivo* Studies

Behavioral patterns of individuals are distinct and based on their categorizations the abnormal functioning of brain can be detected. Detection of neurological disorders is assisted by preclinical animal studies which are further simplified by automation. Behavioral analysis is a significant tool to understand and relate the brain-behavior relationship. The foremost challenge in neuroscience research is to understand and interpret the behavior with fuction and activity of neurons [72]. The development of behavioral analysis requires coordinal neuronal activity which requires precise monitoring and mechanism [73]. Automation tools simplifies the task of interpretating the behavioral patterns effectively. Deep learning skills presents advance techniques to promote automated analysis of images [74]. Comparative image analysis is adapted with various Convolutional Neural Networks (CNN) architecture which results with accurate upshots [75]. Resulting in faster and more accurate outcomes. Implementation of the CNNs has assessed behavioral patterns which analysis the imaging data that focus on body posture among animals [76]. Identification of specific behaviors in association with body positions, are interpretated by algorithms which coordinates body parts. Moreover specific algorithms are devised to analyse the clinical motor function based on subjective scoring of a behavioural activity [77]. The post treated analysis of patients is evaluated by the Kinematic analysis which reveals the specific timing and its related typical movements which differentiates the level recovery [73]. Three Dimensional (3D), marker-less kinematic analysis is contemporary deep learning techniques which assesses the comparative social behavioral interaction between two animals.

Conclusion

Neuroscientists are acclimatizing to the automation tools that are reliable and interpret the characteristic features of central nervous system. Machine learning, artificial intelligence and deep learning are unique with their specific attributes to combat neurological disorders. Understanding the neurological progression and its association with behavioural conditions can devise remedy to several neurological disabilities. Hence application of deep learning concepts enhances the quality of diagnosis and can instigate effective antidote against mental ailment.

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