Machine Learning Techniques to Enhance the Mental Age of Down Syndrome Individuals: A Detailed Review

Irfan M. Leghari[1], Hamimah Ujir[2], SA Ali[3], Irwandi Hipiny[4]
Faculty of Computer Science and Information Technology, Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak[1, 2, 4]
Faculty of Artificial Intelligence & Mathematical Sciences, SMIU, Karachi-74000, Pakistan[3]

***Abstract*—Down syndrome individuals are known as intellectually disabled people. Their intellectual ability is classified into four categories known as mild, moderate, severe, and profound. These individuals have significant limitations in learning and adapting skills. Psychologists evaluate mental capability of such individuals using conventional intellectual quotient method instead of using any technology. The research matrix shows most of research has been carried out on analyzing neuroimaging, antenatal screening, and hearing impairment of individuals. But there is still an obvious gap of evaluating mental age using artificial intelligence. We have proposed an artificial neural network model, which supervises how software is used to obtain dataset using Knowledge Base Decision Support System. In a survey (N = 120) individuals examined by psychiatrist, medical expert, and a teacher to assess the presence of Down's syndrome by analyzing their physical and facial appearances, and communication skills. Only (N = 62) individuals declared as Down syndrome. Selected individuals invited to perform mental ability assessment using Interactive Mental Learning Software. The results of mental age of Down syndrome with a raise in IQ from severe to moderate (20% to 35%), moderate to mild (35% to 75%) severity were carried out with the help of assessing the interactive series of software opinion polls based on comparison, logic, and basic mathematical operations using initial IQ (iIQ), and enhanced IQ (eIQ) variables input and output parameters.**

Keywords*—Artificial Intelligence; Artificial Neural Network (ANN); Down Syndrome Individuals (DSI); Interactive Mental Learning Software (IMLS)

I. Introduction

The usage of artificial intelligence (AI) in biological fields is increasing, but it's usage in mental disorders is only partial [1-2]. Machine learning (ML) supports the integration of psychological, clinical, and social aspects when approaching the diagnosis of impairments [3]. Artificial intelligence-based applications have promptly been developed for psychiatric diagnosis [4-9]. Furthermore, AI has enormous potential for defining the diagnosis of mental illnesses [10-12]. The purpose of this research is to provide a smart way of learning for Down syndrome individuals (DSI). Of course, this will be helpful for them in practical and professional life, so that they can behave independently with less assistance from their parents or teachers. Until now, research has been carried out on their facial expressions, prediction of their inhibitory capacity, and prediction of mental deficiency using clinical technologies, but still, no work has been done on learning using artificial intelligence technology, which is very important and needs to be focused on. Artificial intelligence techniques provide the best solution using machine learning and artificial neural networks, this work will be explained in section 4.3.

Born with multiple challenges, Down syndrome individuals are part of every society. They are supposed to be a social and economic burden on families and society. Down syndrome is caused by the presence of an extra copy of chromosome-21. The prevalence level of DSI is approximately 1 in every 800 births [13]. These individuals may have significant cognitive impairments and have an intelligence quotient (IQ) ranging from 30 to 70 percent. In addition, mental abilities that are mostly decreased in these individuals including expressive language, memory, and fine motor skills. Such individuals also have significant limitations in learning and adapting. Adaptive abilities are linked with general mental skills measured with IQ [14]. While the quality of life for DS individuals is improving in both the educational and social domains [15].

The learning process associated with cultural and environmental factors is important for DS individuals due to their social requirements and independency [16-18]. Hence, due to the common difficulties in mental and fine-motor skills, the potential of the individual with Down syndrome as a learner might be perceived as limited [19-21]. They face several different problems in daily life activities while walking, talking, chewing, and learning [20]. The learning ability of DS individuals is classified into four categories: mild, moderate, severe, and profound (Fig. 1). These categories are classified according to their mental age. But in general practice, DS people are grouped as per their physical age. This classification depends on the range of intelligent quotient scores and symptoms [14].

Fig. 1. Level of mental impairment of Down Syndrome Individuals.

Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak.

1) Learn in homogeneous educational environments and perform social activities with the least support.

2) Individuals need partial support from parents and teachers to carry out tasks. The practitioners use rehabilitation tactics for development ranging from moderate to mild.

3) This category requires continued learning and support to carry out an activity.

4) Significant deficits in adaptive and functional skills.

The research plan demonstrates the selection criteria using a survey bifurcated into two parts, i.e., general, and technological. After seeking the research gap the research contributions propose the technical way to evaluating unidentified mental age of DS individuals. The research further discusses the implementation of software-based ANN model (Fig. 2).

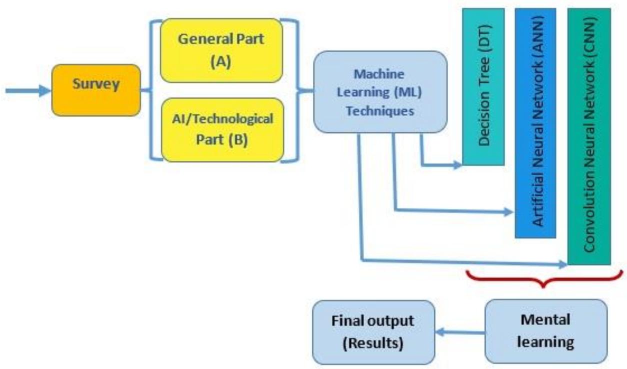

Fig. 2. Proposed research plan.

II. Literature Review

During the artificial intelligence age of the last decade (2012-2022), an essential number of studies have addressed the use of AI techniques to support people with intellectual disability. The comprehensive literature presents review of the highly illustrative research work of the past ten years i.e., 2012-2022. Furthermore, a research paper matrix is used to identify the research gap in the context of the previous decade (Table I).

Vicari et al., Rosen et al., & Hategan et al., [22-24] proposed a neuroimaging technique using machine learning (ML). Potential bio-supportive artificial intelligence models used to predict mental age are based on brain or neuroimaging data, which serve as neuroimaging data with ML techniques that provide excessive insights for developmental disabilities in Down syndrome children. Machine language models were proposed using imaging recognition features. Research carried out to present knowledge of the neurocognitive, psychopathological, and neurobiological assessment and treatment of patients with Down Syndrome, which suggested rehabilitation as sole effective method for improving cognitive and linguistic abilities.

Amanda Saksida et al., [25] highlighted the problem of cognitive and hearing impairment that happened to most DS children during early childhood. The authors evaluated the effects of hearing impartment on receptive language and hearing skills and observed main factors of cognitive decline using audiometry testing. In a survey over 41 participants aged between 3 and 10 with DS out of 150 excluding individuals with serious disorders of language, visionary, and cognitive with an IQ of 40, were referred for the audio-logical inspection process. Cognitive skills of 17 individuals of 6 years were measured.

Falin H.E et al., [26] presented a machine learning model to predict Down syndrome in third trimester antenatal screening. The authors used the machine learning (ML) random forest model to predict Down's syndrome. In a survey, around 58,972 pregnant women underwent screening to analyze predictive efficiency. The ML model predicted ratio of 66.7% DS, with a 5% false positive rate in the data set. The model achieved a DS detection rate of 85.2%, with a 5% false positive rate. The study showed that the ML model expands the DS prediction rate with a similar false positive ratio in contrast to the laboratory risk model.

Furthermore, Jojoa-Acosta et al. [27] investigated how does a neuropsychological assessment of intellectual functioning in people with Down syndrome changes over time. The purpose of the research was to predict repressive control capacity using a novel data-driven method. A sample of n = 188; 49.47% men; and 33.6 ± 8.8 DS adult individuals having mild-moderate levels of mental retardation was taken into the process. Machine learning Random Forest model used to support vector machine and logistic regression algorithms for the prediction of inhibition capacity. The neuropsychological method was applied for data collection of assessment of memory skills, language skills, executive functions, and praxis was submitted for execution in an algorithm. The outcomes reveal that the finest interpreters for inhibition capacity were verbal memory, constructive praxis, planning, immediate memory, and written verbal comprehension.

In a research led by Children's National Hospital [28] a software device built using machine learning and deep learning technology that detects the presence of the genetic syndrome. The innovation of a software device helps children without any access to specific clinics. The designed software increases access and ML technology to predict the syndrome. The method detects the existence of genetic syndromes using facial photographs. The researchers trained data from 2,800 pediatric DS individuals from different countries.

Similarly, Aida Catic et al. [29] proposed an image processing recognition method to identify affected fetuses early in pregnancy through accurate genetic testing to provide the woman with the preference for the selective continuation of the pregnancy or termination. They intend to replace the traditional process of chromosome photographs with image processing recognition and rule-based classification algorithms. A sample of 2500 pregnant women was collected to determine the figures of maternal levels. All women underwent an ultrasound examination. After the ultrasound examination and maternal blood sample, the blood samples were analyzed using the Prisca software. Artificial Neural Network expert system parameters indicate the tested subject has one of the prenatal syndromes or is healthy.

TABLE I. RESEARCH PAPER MATRIX (IDENTIFYING RESEARCH GAP) MACHINE LEARNING TECHNIQUES TO ENHANCE THE INTELLIGENT QUOTIENT LEVEL OF DOWN SYNDROME INDIVIDUALS

Paper	Author & Year	Topic	Machine learning Techniques/Methodology		
			Decision Tree (DT)	**Artificial Neural Network (ANN)**	**Convolution Neural Network (CNN)**
The Influence of Hearing Impairment on Mental Age in Down Syndrome: Preliminary Result	Amanda Saksida et al October 2021	Analyzing whether hearing impartment has a connection with the cognitive problem of Down syndrome individuals.	X	X	X
A machine learning model for the prediction of down syndrome in second-trimester antenatal screening	Falin H.E et al October 2021	Trimester antenatal screening using Machine learning random forest model	X	✓ [1]RF	X
Executive Functioning in Adults with Down Syndrome: Machine-Learning-Based Prediction of Inhibitory Capacity	Jojoa-Acosta et al October 2021	Machine-Learning-Based Prediction of Inhibitory Capacity	X	✓ [1]RF [2]SVM [3]LRA	X
Machine learning tool detects the risk of genetic syndromes in children with diverse backgrounds	Children's National Hospital September 2021	This machine learning technology indicates the presence of a genetic syndrome from a facial photograph	X	✓ [4]DL	X
Application of Neural Networks for classification of Patau, Edwards, Down, Turner and Klinefelter Syndrome based on first-trimester maternal serum screening data, ultrasonographic findings and patient demographics	Aida Catic et al 2018	To identify affected fetuses early in pregnancy through amniocentesis with accurate genetic testing.	X	✓	X
Brain-predicted age in Down syndrome is associated with beta-amyloid deposition and cognitive decline	James H. Cole et all August 2017	Predict brain age using structural neuroimaging data in DS individuals	X	✓ [4]DL	X
Predicting Age Using Neuroimaging: Innovative Brain Ageing Biomarkers	James H.Cole December 2017	Machine learning supervised model for brain age prediction. The predicted brain age was used as a metric to statistically relate to other measured characteristics of the participants	X	✓ **[5]NI**	X
A pilot study of the use of emerging computer technologies to improve the effectiveness of reading and writing therapies in children with Down syndrome	Vanessa G. Felix et al February 2016	The tool helps to improve reading and writing abilities in Spanish, through mobile computing, multimedia design, and computer speech-recognition techniques named HATLE. During the data collection survey various assessment taken out. Participants were from 6 to 15 years old. *IQ scores were not available for any of the participants.*	X	X	X
Using Dynamic Bayesian Networks for the Prediction of Mental Deficiency in Children with Down Syndrome	Houssem Turki et al 2014	Proposed a new approach to knowledge extraction from temporal data.	X	✓ [6]DBN	X
Cognition in Down syndrome: a developmental cognitive neuroscience perspective	Jamie O. Edgin et al January 2013	The assessment of several functions of this region seems relatively less impaired than other aspects of cognition. Spatial position and implicit memory are also less affected than an object in location binding or episodic memory.			

[1]Random Forest Model [2]Support Vector Machine [3]Logistic regression algorithms [4]Deep learning[5]Neuroimaging [6]Dynamic Bayesian Networks

James H. Cole et al. [30] employed a machine learning approach to predict mental age of DS individuals using a structural neuroimaging dataset (N = 46). The chronological age subtracted from predicted age to get a different score of brain-predicted age. The research model analyzed the brain-predicted age calculation at three levels. In the first level, the similarity index of the Gaussian Processes (GP) regression model using a magnetic resonance imaging (MRI) dataset was collected. In the second level model accuracy was assessed for differentiating brain-predicted age. In the third and fourth levels, testing and brain age were predicted. The authors emphasized the need to examine trajectories of change in DS individuals to get further information about the likelihood of future neurologic decline and negative brain ageing.

Moreover, James H. Cole et al., 2017 [31] analyzed the brain diseases burden of age-associated functional decline. A supervised machine learning model proposed for brain age prediction. Neuroimaging data obtained from MRI scans using machine learning regression model. Cross-validation included 90% of participants and a predicted age of let out of 10%. The predicted mental age was compared with the chronological age of test-set participants. The brain-predicted age difference between brain age and chronological age is assumed to reflect advanced ageing and younger brains. The authors have emphasized that the technical aspects of analyzing brain age are further improved. Neuroimaging brain age measures could be used to evaluate neuroprotective impediments.

To improve the communication ability Vanessa G. Felix et al. [32] developed HATLE application to provide a computer-assisted technique for DS individuals. The data was obtained through a survey of DS participants speaking Spanish aged between 6 and 15 years. IQ scores were not available for any of the participants. The average age of DS individuals was 10.4 years. During the assessment, literacy skills including letter identification, reading, handwriting, and spelling were assessed. A score of all assessments from 0 to 10 was obtained. The training with HATLE was processed group-wise using Android tablets and computers. The outcome of the research reveals that the initial recognition level was set at 0.5, which slowly increased the accuracy rate of further demanding thresholds in steps of 0.1.

Houssem Turki et al. [33] proposed a Dynamic Bayesian Network (DBN) for knowledge extraction from historical data on temporal data to develop a structured learning algorithm for predicting mental retardation in Down syndrome individuals. The experiment took place at the Medical Genetics and Child Psychiatry departments at a hospital in Tunisia. The authors obtained a heterogeneous dataset in collaboration with a team of experts. The purpose of the research is the extraction of knowledge from a great number of datasets that evolve dynamically.

Jamie O. Edgin et al. [34] analyzed a problem with late-developing neural systems in DS individuals and the function of the prefrontal cortex. The assessment of functions was observed relatively less as compared to other aspects of cognition. The results observed were that implicit memory and spatial position are less affected than an object in episodic memory. The authors recommended further study of the fractionated skills patterns in DS individuals, which may benefit developmental change of cognitive functions.

To provide similar learning opportunities for differently abled people Syed Ali [35] proposed a model for adaptation of the Heterogeneous Education System (HES) to the Homogeneous Education System (HES) proposing information technology tools of speech recognition and mathematics. The proposed model suggests that by providing the procedure of conversion and tools, equal opportunities can be provided to different disabilities in the same learning environments. The research has not particularly been done for DS individuals, but the mechanism strongly suggests for all individuals with perform differently. Hence, the research delivers importance to enhance learning and to improve communication difficulties.

In neuroimaging data retrieval, Vicari et al., [22] proposed techniques assessed, including magnetic resonance imaging (MRI), a biotechnology body and brain imaging scanning technology. Rosen et al.; Hategan et al.; Raznahan et al.; & Wintermark et al. [23-24], [36-37] proposed that magnetic imaging is the leading clinical technique to evaluate the level of mental impairment. This technique is used to analyze psychiatric abnormalities that are difficult to detect using computed tomography (CT) For example, AI multimodal learning applications and deep learning methods have been developed for brain imaging [38]. Moreover, convolutional neural networks [39] and deep neural networks [40-42] engaged in neuroimaging to explain the neural relationships of mental disorders [40] [43-46].

Heinsfeld et al., [47] proposed that electroencephalography (EEG) signals are important to understanding how the human mind works and evaluating mental impairment. In contrast to MRI and CT, electroencephalography has greater resolution [48] analysed by Grotegerd et al. In addition, EEG data graphs were evaluated using artificial intelligence models presented by Hannesdóttir et al.; Avram et al., Thibodeau et al., & Hosseinifard [49-52].

III. Research Contributions

A. Mental Age Evaluation

This research illustrated the valuable studies that tried to solve problems in evaluating and diagnosing mostly researched cognitive impairment, i.e., Down syndrome. Wherein, artificial intelligence neural network model-based techniques and software approaches are implemented to bring down syndrome analysis and seek ratio of their mental approach and to further strengthen them with software. The proposed model (Fig. 3) is divided into two portions *(A and B)*. Firstly, the model evaluates the identification of Down syndrome. Here, the model reveals three major components of cognitive psychology known as cognitive neuroscience, human psychology, and information processing through computers. As per the neuroscience perspective, thinking abilities depend on working memory. The area of cognitive psychology considers the study of mental functions in which people require knowledge to understand their experiences. The model emphasizes both artificial intelligence and biological methods. The investigation is applied to individuals diagnosed with Down syndrome.

A survey comprised over 120 individuals with DS of different age groups (>=8 & =30) was included to identify different cognitive traits (Fig. 5). The survey was based on interviews conducted by a team consisting of a psychiatrist, special education instructor and parents accompanying the DS individual. The team of psychiatrists, based on observations and professional knowledge, identified intellectual disability using facial expressions and psychological traits of DS individuals. Distinct facial features include distinctive slanting eyes, a small chin, abnormal outer ears, a flat nasal bridge, and a flattened nose. Psychological traits include talking, paying attention, and social rules. A team of special education teachers used simple mathematical problems to evaluate numerical skills, reasoning, and decision-making skills. The research contributions are further based on an artificial neural network model to evaluate the intelligent quotient of Down syndrome individuals. The intelligent algorithm reveals the criteria of the artificial neural network model. The software access repeatedly until their mental functioning improves from severe to moderate and from moderate to mild levels using variables initial IQ (iIQ), and enhanced IQ (eIQ) denoted as input and output parameters based on the practical, creative, and analytical testing. The method constructs membership functions building set of rules into the knowledge base and evaluates rules in the Inference Engine (Table II).

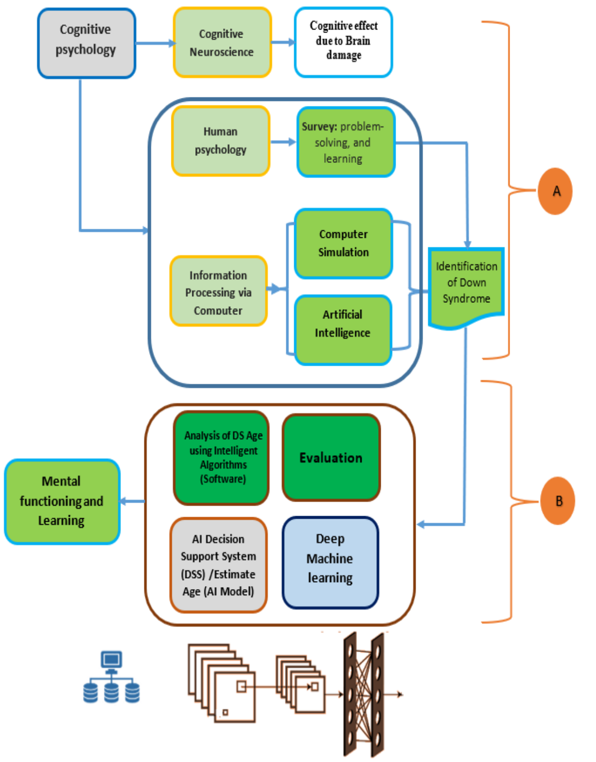

Fig. 3. A proposed model of mixed approach.

The artificial neural network model presents the mechanism of the intelligent algorithm for repeating the usability of the interactive software, denoted as the middle layer of the ANN model (Fig. 4). The neural network model is supposed to judge the cognitive traits of individuals to analyze the IQ. The middle layer plays a part in the manifest of the interactive software application. The overall process is based on three layers. The input layer holds the initial data of the learning process of DS individuals (8–30 years). The intermediate hidden layer represents long-term memory, sensing, decision-making, perception, supervisory skills, thinking, logic, and learning complexities of the DS individuals. The hidden layer performs a nonlinear transformation of the inputs entering the network. The computations from the hidden layer are transformed into the output layer to reveal data to the outside world in the form of the computed mental level and capability.

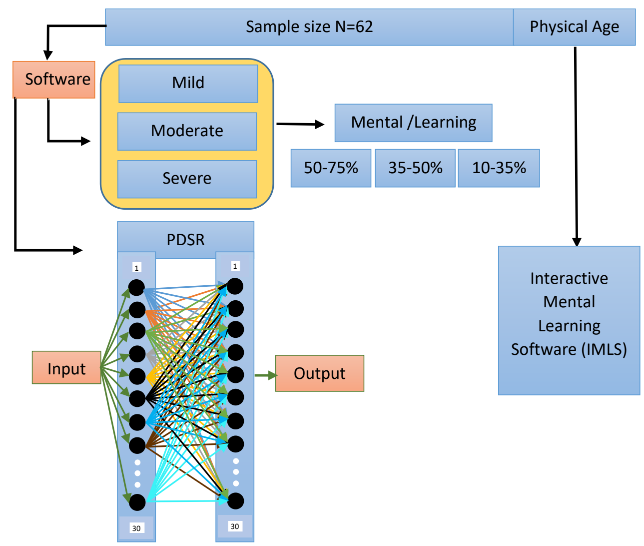

Fig. 4. Artificial neural network model.

TABLE II. INTELLIGENT ALGORITHMS OF INTERACTIVE MENTAL LEARNING SOFTWARE

Step 1 − Define variables and parameters

Variables or parameters are inputs and their outputs like parameter for IQ are,

IQ (iq) = {practical, creative, analytical}

Every member of this set is covering some level of intelligence IQ values.

Create a matrix of based on their syndrome and mental impairment. Build a set of rules into the knowledge base in the form of IF-THEN-ELSE structures.

If {level of Down Syndrome is **Mild**} then (**IQ level 50-75**) Else

If {level of Down Syndrome is **Moderate**} then (**IQ level 35-50**) Else

If {level of Down Syndrome is **Severe**} then (**IQ level 20-35**) Else

If {level of Down Syndrome is **Profound**} then (**IQ level 10-20**)

Step 2 − Construct membership functions for Step 1

Step3 – Maintained knowledge base rules

Step 4 − Evaluate rules in the rule base (Inference Engine)

End

B. Supervised Learning Algorithm

We have implemented ML algorithms to evaluate the projected mental age of the DS individuals. Individuals with Down syndrome's brain/mental age efficiency improves with practice on a software based on supervised learning algorithm. The end of the exponential research (N = 120), an efficient framework is proposed to identify and improve the mental age of Down syndrome children and young adults (Table III). For the analysis of training set sizes, bootstrapping techniques are used to estimate the reliability of the ML algorithm for different training set sizes. In the ANN technique, the resampling method is used to resample the original training set with a replacement to get a new training set of the chosen sample size. The advantage of this technique is that it allows us to judge the toughness of performance around training dataset sizes and to recognize the smallest training set sizes essential for checking the performance above the expected level.

C. Multicriteria Decision Support System (DSS)

To improve the learning abilities of DS individuals, the Knowledge Base Decision Support System (DBSS) is used in cascading fashion. The decision support system is based on four multiple criteria for DS individuals for learning and problem solving. The decision support system checks all the four criteria of Down syndrome in cascade and fixes the criteria based on the minimum criterion. The algorithm is based on decision-based criteria over an alleged cascading in descending order of the learning model on minimum criteria.

- Call at the Dataset.
- A cascading effect scenario to detect.
- Decision support algorithm is used for deciding the set accordingly to minimum criteria.
- Intelligent Quotient (IQ).

D. Interactive Mental Learning Software

The interactive graphical environment is based on 30 public opinion polls (Table IV). Software provides an interactive and simple platform to use opinion pool with the help of teacher or parents. The series of opinion polls contain questions based on comparison, logic, and basic mathematical operations. Individuals are supposed to search for the best option to increase their mental score at the end of the pool (Fig. 6).

The software is accessible through laptop, desktop, or smartphone. Input is selected using a mouse, keypad or by touchpad. Different series of questions appears showing three options to choose best one. Colorful shapes of birds, fruit, and vegetables, colors, vehicles enhance interest of individuals and reduce frustration. The comparison covers the questions of the basic shapes and figures, which helps in developing the logic of the DS individuals. Making comparisons between numbers and alphabets helps DS individuals develop their decision-making abilities. Basic mathematical operations cover only addition (+) operation. The mathematical console is comprised of the addition of birds, animals, shapes, and numbers. The assessment process is divided into three rounds (Round-I, II & III). Round-I process (N = 20) individuals (Table V). Round-II processed (N = 20) (Table VI) and Round-II processed (N = 22) individuals (Table VII).

TABLE III. ARCHITECTURE FOR MENTAL AGE (MA) OF DS INDIVIDUALS

Age assessment Module		System	Inference Engine (Decision Support System)	System Module
Mild	50-75	It stores IF-THEN rules provided by experts.	It simulates the human reasoning process by making system inference on the inputs and IF-THEN rules.	It transforms the set obtained by the inference engine into a crisp value.
Moderate	35-50			
Severe	20-35			
Profound	10-20			

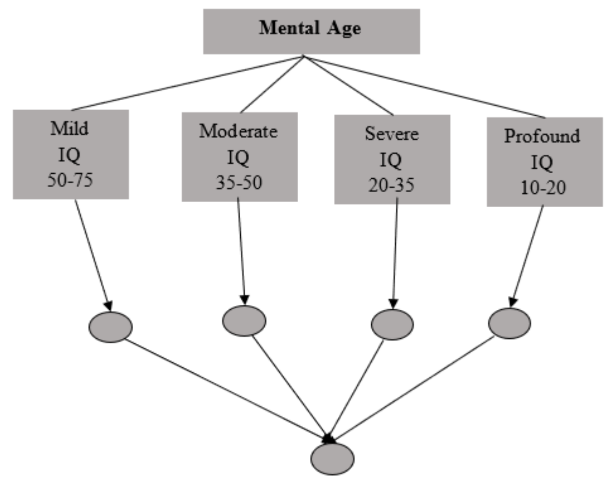

Fig. 5. Decision tree of Down Syndrome individuals.

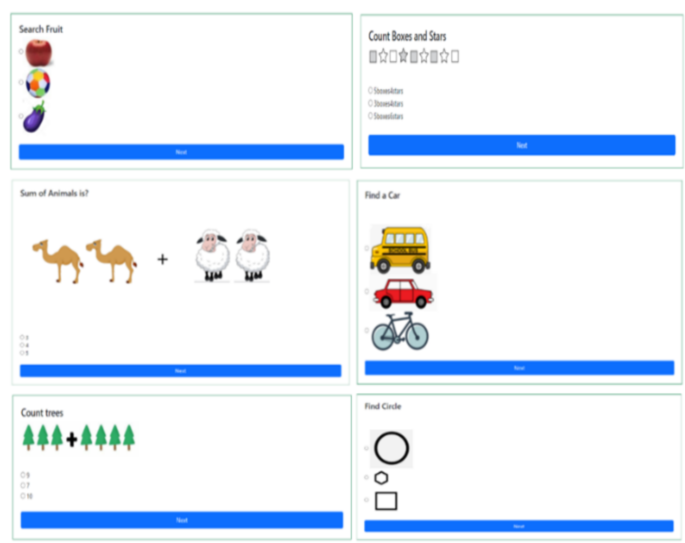

Fig. 6. Interactive Mental Leaning Software (IMLS).

TABLE IV. INTERACTIVE MENTAL LEARNING (IML) SOFTWARE CRITERIA

Q #	Question (Pictorial/Text)	Options given in pictorial / text form
Q1	Search Fruit (images)	(a) Fruit (b) Ball (c) Vegetable
Q2	Click Red Color (Colors)	(a) Aqua (b) Red (c) Yellow
Q3	Find a number (5)	(a) 5 (b) M (c) A
Q4	Find a Car (images)	(a) Bus (b) Car (c) Bicycle
Q5	Search greater number	(a) 10 (b) 5 (c) 0
Q6	Search 3 Birds (images)	(a) 3 birds (b) 2 birds (c) 1 bird
Q7	Find a Sheep (images)	(a) Camel (b) Sheep (c) Goat
Q8	Count Donuts (images: 8)	(a) 6 (b) 7 (c) 8
Q9	Sum of Animals is (images: 2 Camel and 2 sheep)	(a) 3 (b) 4 (c) 5
Q10	M for:	(a) Jeep (b) Car (c) Mobile
Q11	A for:	(a) Apple (b) Banana (c) Cat
Q12	1 + 1	(a) 3 (b) 2 (c) 4
Q13	Which Bird is Flying? (images)	(a) 1 Nonflying bird (b) 2 NFB (c) 1 Flying Bird
Q14	We go to school by. (images)	(a) Car (b) Bus (c) Bicycle
Q15	Rabbit lives in? (images)	(a) Human House (b) Tree (c) Burrows
Q16	Rabbit eats? (images)	(a) Donut (b) Muffin (c) Carrot
Q17	Cat run after? (images)	(a) Bird (b) Dog (c) Rat
Q18	Goat gives? (images)	(a) Eggs (b) Milk (c) Fish
Q19	Aisha is a female?	(a) Yes (b) No
Q20	We fly in. (images)	(a) Car (b) Ship (c) Aeroplane
Q21	Count small circles?	(a) 8 (b) 9 (c) 7
Q22	Count Stars? (x + xx)	(a) 4 (b) 2 (c) 3
Q23	Count Circles? (images)	(a) 2 (b) 3 (c) 4
Q24	Count Boxes & Stars	(a) 5boxes4stars (b) 3boxes4stars
Q25	We talk on. (images)	(a) Mobile (b) Watch (c) Laptop
Q26	Count trees? (image)	(a) 9 (b) 7 (c) 10
Q27	Count clouds? (image)	(a) 10 (b) 11 (c) 12
Q28	Find a Circle? (images)	(a) Circle (b) Hexagon (c) Square
Q29	Find a Square? (images)	(a) Square (b) Hexagon (c) Circle
Q30	Which circle is big? (images)	(a) Small circle (b) Big circle

TABLE V. SOFTWARE DRIVEN AGE ROUND-I SAMPLE SIZE N=20 MILD (50-75%) MODERATE (35-50%) SEVERE (20-35%) MODERATE (10-20%)

S.No	Participants	Physical Age (Years)	Processed Mental level	Improved traits
1.	Participant-1 (Male)	12	45%	Perception (40%), attention (45%)
2.	Participant-2 (Female)	13	50%	Sensing (50%), Reasoning (45%)
3.	Participant-3 (Male)	15	25%	Sensing (25%), memory (20%)
4.	Participant-4 (Female)	15	45%	Responsive (40%), attention (45%)
5.	Participant-5 (Male)	14	50%	Decision making (50%), Reasoning (50%)
6.	Participant-6 (Female)	8	45%	Perception (40%), attention (45%)
7.	Participant-7 (Male)	17	65%	Sensing (65%), memory (65%)
8.	Participant-8 (Female)	8	60%	Sensing (60%), Logic (55%)
9.	Participant-9 (Female)	13	65%	Perception (65%), memory (55%)
10.	Participant-10 (Male)	10	55%	Logic (50%), attention (55%)
11.	Participant-11 (Male)	12.6	45%	Responsive (45%), memory (40%)
12.	Participant-12 (Male)	8	30%	Responsive (30%), attention (35%)
13.	Participant-13 (Male)	9	35%	Attention (35%), DM (35%)
14.	Participant-14 (Male)	18	70%	Reasoning (65%), Memory (70%)
15.	Participant-15 (Male)	15	55%	Social (50%), attention (55%)
16.	Participant-16 (Female)	18	55%	Logic (50%), attention (55%)

17.	Participant-17 (Male)	9	45%	Sensing (45%), FM Skills (45%)
18.	Participant-18 (Male)	16	65%	Reasoning (60%), attention (65%)
19.	Participant-19 (Female)	9	55%	Sensing (50%), Responsive (55%)
20.	Participant-20 (Female)	11	35%	Logic (30%), Memory (35%)

TABLE VI. SOFTWARE DRIVEN AGE ROUND-II SAMPLE SIZE N=20 MILD (50-75%) MODERATE (35-50%) SEVERE (20-35%) MODERATE (10-20%)

S.No	Participants	Physical Age (Years)	Processed Mental level	Response toward activities
1.	Participant-21 (Female)	10	30%	Attention - memory (30%)
2.	Participant-22 (Female)	12	55%	Sensing (55%), DM (50%)
3.	Participant-23 (Female)	14	45%	Perception (45%), memory (40%)
4.	Participant-24 (Male)	11	55%	Sensing - attention (55%)
5.	Participant-25 (Female)	15	55%	Logic (50%), DM (55%)
6.	Participant-26 (Female)	13	45%	VM (45%), attention (40%)
7.	Participant-27 (Female)	14	35%	Sensing – Logic (30%)
8.	Participant-28 (Male)	10	25%	Reasoning (30%), Memory (25%)
9.	Participant-29 (Male)	18	50%	Reasoning - attention (55%)
10.	Participant-30 (Female)	16	45%	Logic - attention (45%)
11.	Participant-31 (Female)	8	35%	Sensing - FM Skills (35%)
12.	Participant-32 (Male)	13	55%	Reasoning - attention (55%)
13.	Participant-33 (Female)	12	40%	Sensing (40%), Responsive (45%)
14.	Participant-34 (Male)	10	55%	Logic - Responsive (55%)
15.	Participant-35 (Male)	16	35%	Sensing - memory (30%)
16.	Participant-36 (Female)	8	40%	Sensing (40%), memory (35%)
17.	Participant-37 (Female)	14	65%	Reasoning - memory (65%)
18.	Participant-38 (Female)	9	40%	Sensing (40%), memory (45%)
19.	Participant-39 (Male)	10	55%	Decision making-responsive (50%)
20.	Participant-40 (Female)	15	45%	Sensing (45%), memory (50%)

TABLE VII. SOFTWARE DRIVEN AGE ROUND-III SAMPLE SIZE N=22 MILD (50-75%) MODERATE (35-50%) SEVERE (20-35%) MODERATE (10-20%)

S.No	Participants	Physical Age (Years)	Processed Mental level	Improvements in cognitive traits
1.	Participant-41 (Male)	15	45%	Social – Decision making (40%)
2.	Participant-42 (Male)	25	60%	Reasoning (60%), DM (55%)
3.	Participant-43 (Male)	30	65%	Logic (50%), Memory (65%)
4.	Participant-44 (Female)	20	60%	Sensing – Decision making (55%)
5.	Participant-45 (Female)	22	40%	Attentive (40%), Memory (45%)
6.	Participant-46 (Male)	15	35%	Sensing – Logic (35%)
7.	Participant-47 (Male)	23	55%	Sensing (55%), Memory (60%)
8.	Participant-48 (Male)	27	70%	Social (70%), Sensing (65%)
9.	Participant-49 (Male)	25	45%	Attention (40%), Sensing (45%)
10.	Participant-50 (Female)	30	50%	Memory (50%), Attention (45%)
11.	Participant-51 (Male)	22	60%	Social (70%), Sensing (65%)
12.	Participant-52 (Male)	25	55%	DM (55%), FM Skills (50%)
13.	Participant-53 (Male)	28	45%	Social (40%), Memory (45%)
14.	Participant-54 (Male)	27	60%	Reasoning – Attention (60%)
15.	Participant-55 (Female)	22	45%	DM (45%), Sensing (40%)
16.	Participant-56 (Female)	20	50%	Memory (50%), DM (45%)
17.	Participant-57 (Male)	30	45%	Attention (40%), Sensing (45%)
18.	Participant-58 (Female)	19	50%	Social – Decision making (55%)
19.	Participant-59 (Male)	17	60%	Sensing (60%), Memory (65%)
20.	Participant-60 (Female)	17	45%	Responsive (45%), Sensing (40%)
21.	Participant-61 (Female)	30	50%	Logic (50%), Sensing (45%)
22.	Participant-62 (Female)	25	50%	Logic (50%), Memory (45%)

IV. Discussion and Future Work

The research carried out to investigate the mental age of DS individuals. The literature matrix identified the research gap of assessing actual mental age using AI-ANN model. The technology claims to enhance mental age of DS individuals having least IQ level. The interactive and simplest platform of software increase usability interest and reduce frustration. The different question of logical, mathematical, and analytical reasoning boosts the thinking ability, perception, reasoning, logic, and memory of the individuals. Such traits result change in IQ from severe to moderate (IQ>20% to 35%), moderate to mild (IQ>35% to 75%). Research outcomes also show the comparison and authenticity between software-based IQ assessment and traditional methods. The variation in the mental age is identified with yellow line of the graphical illustration (Fig.7, 8 and 9).

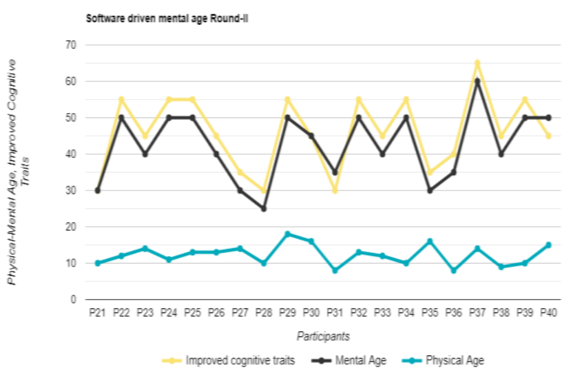

Fig. 7. Graph - software driven mental age round-I.

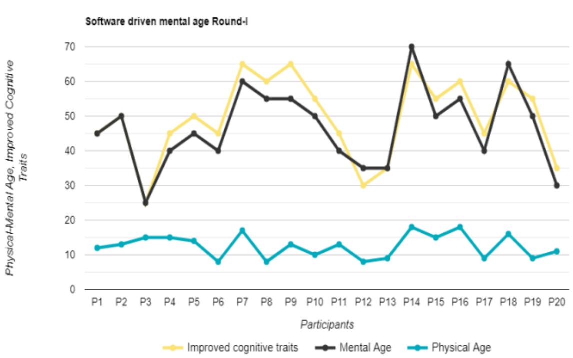

Fig. 8. Graph - software driven mental age round-II.

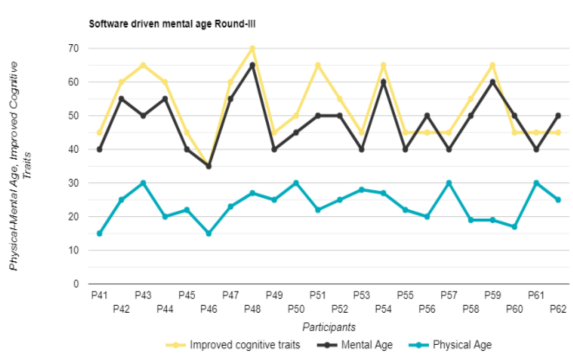

Fig. 9. Graph - software driven mental age round-III.

In future work, more feature added system for enhancement of severe level of mental retardation may be suggested for academic purpose to help different intellectual disabilities in special education and job oriented technical training to make them independent.

Acknowledgment

The authors fully acknowledged Universiti Malaysia Sarawak for all the support which makes this important research viable and effective. The acknowledgement is also extended to all participants who were voluntary involved in the dataset collection.

References

[1] Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J., “Artificial intelligence in radiology”, in Nature Reviews Cancer, 2018, 18(8), pp. 500-510.

[2] Ray, A., Bhardwaj, A., Malik, Y. K., Singh, S., & Gupta, R., “Artificial intelligence and Psychiatry: An overview”, in Asian Journal of Psychiatry, 2022, 103021.

[3] Graham, S. A., Lee, E. E., Jeste, D. V., Van Patten, R., Twamley, E. W., Nebeker, C., ... & Depp, C. A., “Artificial intelligence approaches to predicting and detecting cognitive decline in older adults: A conceptual review”, in Psychiatry research, 2020, 284, 112732.

[4] Liu, G. D., Li, Y. C., Zhang, W., & Zhang, L., “A brief review of artificial intelligence applications and algorithms for psychiatric disorders”, in *Engineering*, 2020, *6*(4), pp. 462-467.

[5] Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., ... & Dean, J., “A guide to deep learning in healthcare”, in Nature medicine, 2019, 25(1), pp. 24-29.

[6] Dwyer, D. B., Falkai, P., & Koutsouleris, N., “Machine learning approaches for clinical psychology and psychiatry”, in Annual review of clinical psychology, 2018, 14, pp. 91-118.

[7] Sarma, G. P., Hay, N. J., & Safron, A., “AI safety and reproducibility: establishing robust foundations for the neuropsychology of human values”, in International Conference on Computer Safety, Reliability, and Security, Springer, Cham, 2018, pp. 507-512..

[8] Stead, W. W., “Clinical implications and challenges of artificial intelligence and deep learning”, in Jama, 2018, 320(11), pp. 1107-1108.

[9] Gao, H., Yin, Z., Cao, Z., & Zhang, L., “Developing an agent-based drug model to investigate the synergistic effects of drug combinations”, in Molecules, 2017, 22(12), 2209.

[10] Xia, Y., Yang, C., Hu, N., Yang, Z., He, X., Li, T., & Zhang, L., “Exploring the key genes and signaling transduction pathways related to the survival time of glioblastoma multiforme patients by a novel survival analysis model”, in BMC genomics, 2017, 18(1), pp.1-11.

[11] Zhang, L., Xiao, M., Zhou, J., & Yu, J., “Lineage-associated underrepresented permutations (LAUPs) of mammalian genomic sequences based on a Jellyfish-based LAUPs analysis application (JBLA)”, in Bioinformatics, 2018, 34(21), pp. 3624-3630.

[12] Graham, S., Depp, C., Lee, E. E., Nebeker, C., Tu, X., Kim, H. C., & Jeste, D. V., “Artificial intelligence for mental health and mental illnesses: an overview”, in *Current psychiatry reports*, 2019, *21*(11), pp. 1-18.

[13] Jamshidnezhad, A., Hosseini, S. M., Mohammadi-Asl, J., & Mahmudi, M., “An intelligent prenatal screening system for the prediction of Trisomy-21”, in Informatics in Medicine Unlocked, 2021, 24, 100625.

[14] Hamburg, S., Lowe, B., Startin, C. M., Padilla, C., Coppus, A., Silverman, W., ... & Strydom, A., “Assessing general cognitive and adaptive abilities in adults with Down syndrome: a systematic review”, in Journal of neurodevelopmental disorders, 2019, 11(1), pp. 1-16.

[15] Baburamani, A. A., Patkee, P. A., Arichi, T., & Rutherford, M. A. “New approaches to studying early brain development in Down syndrome”, in Developmental medicine & child neurology, 2019, 61(8), pp. 867-879.

[16] Barbosa, R. T. D. A., de Oliveira, A. S. B., de Lima Antão, J. Y. F., Crocetta, T. B., Guarnieri, R., Antunes, T. P. C., ... & de Abreu, L. C. "Augmentative and alternative communication in children with Down's syndrome: a systematic review", in BMC pediatrics, 2018, 18(1), pp. 1-16.

[17] Luna-Garcia, H., Mendoza-González, A., Mendoza-Gonzalez, R., Gamboa-Rosales, H., Galván-Tejada, J. I., Celaya-Padilla, J. M., ... & Lopez-Veyna, J. "Analyzing typical mobile gestures in mHealth applications for users with Down syndrome", in Mobile Information Systems, 2018.

[18] Kamoun, P. "Mental retardation in Down syndrome: a hydrogen sulfide hypothesis", in medical hypotheses, 2001, 57(3), pp. 389-392.

[19] Marques, L. S., Alcântara, C. E. P., Pereira, L. J., & Ramos-Jorge, M. L. "Down syndrome: a risk factor for malocclusion severity?", in Brazilian oral research, 2015, 29(1), pp. 1-7.

[20] Jan Blacher, AAMR, "Families and Mental Retardation", in A collection of Notable AAMR Journal Articles across the 20th century, 2002.

[21] Smith, P., & Smith, L. "Artificial intelligence and disability: too much promise, yet too little substance?", in *AI and Ethics*, 2021, *1*(1), pp. 81-86.

[22] Vicari, S., Pontillo, M., & Armando, M. "Neurodevelopmental and psychiatric issues in Down's syndrome: assessment and intervention", in Psychiatric genetics, 2013, 23(3), pp. 95-107.

[23] Rosen BR, Huang SY, Stufflebeam SM. "Pushing the limits of human neuroimaging", in JAMA, 2015, 314(10): pp. 993–4.

[24] Hategan A, Bourgeois JA, Cheng T, Young J. "Neuropsychology and neuroimaging in clinical geriatric psychiatry", in Geriatric psychiatry study guide. Cham: Springer, 2018, pp. 23–38.

[25] Saksida, A., Brotto, D., Pizzamiglio, G., Bianco, E., Bressan, S., Feresin, A., ... & Orzan, E. "The Influence of Hearing Impairment on Mental Age in Down Syndrome: Preliminary Results", in Frontiers in Pediatrics, 2021, 9.

[26] He, F., Lin, B., Mou, K., Jin, L., & Liu, J. "A machine learning model for the prediction of down syndrome in second trimester antenatal screening", in *Clinica Chimica Acta*, 2021, *521*, pp. 206-211.

[27] Jojoa-Acosta, M. F., Signo-Miguel, S., Garcia-Zapirain, M. B., Gimeno-Santos, M., Méndez-Zorrilla, A., Vaidya, C. J., ... & Bruna-Rabassa, O. "Executive Functioning in Adults with Down Syndrome: Machine-Learning-Based Prediction of Inhibitory Capacity", in *International Journal of Environmental Research and Public Health*, 2021, *18*(20), 10785.

[28] Children's National Hospital, "Machine learning tool detects the risk of genetic syndromes in children with diverse backgrounds: The technology can potentially reduce health inequality in under-resourced areas worldwide", in *ScienceDaily*. Retrieved February 17, 2022, from *www.sciencedaily.com/releases/2021/09/210901191416.htm*.

[29] Catic, A., Gurbeta, L., Kurtovic-Kozaric, A., Mehmedbasic, S., & Badnjevic, A. "Application of Neural Networks for classification of Patau, Edwards, Down, Turner and Klinefelter Syndrome based on first trimester maternal serum screening data, ultrasonographic findings and patient demographics", in *BMC medical genomics*, 2018, *11*(1), pp. 1-12.

[30] Cole, J. H., Annus, T., Wilson, L. R., Remtulla, R., Hong, Y. T., Fryer, T. D., ... & Holland, A. J., "Brain-predicted age in Down syndrome is associated with beta amyloid deposition and cognitive decline", in *Neurobiology of aging*, 2017, *56*, pp. 41-49.

[31] Cole, J. H., & Franke, K. "Predicting age using neuroimaging: innovative brain ageing biomarkers", in *Trends in neurosciences*, 2017, *40*(12), pp. 681-690.

[32] Felix, V. G., Mena, L. J., Ostos, R., & Maestre, G. E. "A pilot study of the use of emerging computer technologies to improve the effectiveness of reading and writing therapies in children with Down syndrome", in *British Journal of Educational Technology*, 2017, *48*(2), pp. 611-624.

[33] Turki, H., Ayed, M. B., & Alimi, A. M. "Using dynamic Bayesian networks for the prediction of mental deficiency in children with down syndrome", In *2014 6th International Conference of Soft Computing and Pattern Recognition (SoCPaR)*, 2014, pp. 163-167, IEEE.

[34] Edgin, J. O. "Cognition in Down syndrome: a developmental cognitive neuroscience perspective", in *Wiley Interdisciplinary Reviews: Cognitive Science*, 2013, *4*(3), pp. 307-317.

[35] Ali, S. A., & Burney, S. A. "Conversion of heterogeneous education system (HOES) into homogeneous education system (HOES) for ease of disabled persons using information technology", in 2010 International Conference on Computer Design and Applications, 2010, (Vol. 2, pp. V2-298). IEEE.

[36] Park MTM, Raznahan A, Shaw P, Gogtay N, Lerch JP, Chakravarty MM. "Neuroanatomical phenotypes in mental illness: identifying convergent and divergent cortical phenotypes across autism", in ADHD and schizophrenia. JPsychiatry Neurosci, 2018, 43(3), pp. 201–12.

[37] Wintermark M, Colen R, Whitlow CT, Zaharchuk G. "The vast potential and bright future of neuroimaging", in Br J Radiol, 2018, 91(1087), 20170505.

[38] Webb S. "Deep learning for biology", in Nature, 2018, 554(7693), pp. 555–7.

[39] Wolfers T, Buitelaar JK, Beckmann CF, Franke B, Marquand AF. "From estimating activation locality to predicting disorder: a review of pattern recognition for neuroimaging-based psychiatric diagnostics", in Neurosci Biobehav Rev, 2015, 57, pp. 328–49.

[40] Arbabshirani MR, Plis S, Sui J, Calhoun VD. "Single subject prediction of brain disorders in neuroimaging: promises and pitfalls", in Neuroimage, 2017, 145(PtB), pp. 137–65.

[41] Vieira S, Pinaya WHL, Mechelli A. "Using deep learning to investigate the neuroimaging correlates of psychiatric and neurological disorders: methods and applications", in Neurosci Biobehav Rev, 2017, 74(Pt A), pp. 58–75.

[42] Bengio Y. "Learning deep architectures for AI. Hanover", in Now Publishers Inc., 2009.

[43] LeCun Y, Bengio Y, Hinton G. "Deep learning", in Nature, 2015, 521(7553), pp. 436–44.

[44] Plis SM, Hjelm DR, Salakhutdinov R, Allen EA, Bockholt HJ, Long JD, "Deep learning for neuroimaging: a validation study", in Front Neuroscience, 2014, 8:229.

[45] Payan A, Montana G. "Predicting Alzheimer's disease: a neuroimaging study with 3D convolutional neural networks", in arXiv, 2015, 1502.02506.

[46] Hosseini-Asl E, Ghazal M, Mahmoud A, Aslantas A, Shalaby AM, Casanova MF, et al. "Alzheimer's disease diagnostics by a 3D deeply supervised adaptable convolutional network", in Front Biosci, 2018, 23, pp. 584–96.

[47] Heinsfeld AS, Franco AR, Craddock RC, Buchweitz A, Meneguzzi F. "Identification of autism spectrum disorder using deep learning and the ABIDE dataset", in Neuroimage Clin, 2018, Vol. 17, pp. 16–23.

[48] Grotegerd D, Suslow T, Bauer J, Ohrmann P, Arolt V, Stuhrmann A, et al. "Discriminating unipolar and bipolar depression by means of fMRI and pattern classification: a pilot study", in Eur Arch Psychiatry Clin Neuroscience, 2013, 263 (2), pp. 119–31.

[49] Hannesdóttir DK, Doxie J, Bell MA, Ollendick TH, Wolfe CD. "A longitudinal study of emotion regulation and anxiety in middle childhood: associations with frontal EEG asymmetry in early childhood", in Dev Psychobiol, 2010, 52 (2): pp. 197–204.

[50] Avram J, Baltes FR, Miclea M, Miu AC. "Frontal EEG activation asymmetry reflects cognitive biases in anxiety: evidence from an emotional face Stroop task", in Appl Psychophysiol Biofeedback, 2010, 35(4), pp. 285–92.

[51] Thibodeau R, Jorgensen RS, Kim S. "Depression, anxiety, and resting frontal EEG asymmetry: a meta-analytic review", in J Abnorm Psychol, 2006, 115 (4), pp. 715–29.

[52] Hosseinifard B, Moradi MH, Rostami R. "Classifying depression patients and normal subjects using machine learning techniques and nonlinear features from EEG signal", in Computer Methods Programs Biomed, 2013, 109(3), pp. 339–45.