2021 Fourteenth International Workshop on Selected Topics in Mobile and Wireless Computing

Automatic Diagnosis of Intellectual and Developmental Disorder Using Machine Learning Based on Resting-State EEG Recordings

Johannes Breitenbach
University of Bayreuth
Bayreuth, Germany
johannes.breitenbach@mail.de

Dominik Raab
Aalen University
Aalen, Germany
dominik.raab@studmail.htw-aalen.de

Eric Fezer
Aalen University
Aalen, Germany
eric.fezer@studmail.htw-aalen.de

Daniel Sauter
Aalen University
Aalen, Germany
email@danielsauter.de

Hermann Baumgartl
University of Bayreuth
Bayreuth, Germany
hbaumg@ieee.org

Ricardo Buettner
University of Bayreuth
Fraunhofer FIT
Bayreuth, Germany
ricardo.buettner@uni-bayreuth.de

***Abstract*—Intellectual and developmental disorder results in lifetime impairments in cognitive capabilities and adaptability is highly prone to developing several forms of further diseases and is associated both with high care costs. In this study, we applied a machine learning approach for differentiating healthy individuals and individuals with intellectual and developmental disorder using resting-state electroencephalography recordings. Our approach sets a new benchmark with a balanced accuracy of 91.67%. In addition, by adopting novel model interpretability methods, we highlighted the low beta sub-band in the range of 19.5–21 Hz as the most important distinctive feature. Individuals with an intellectual and developmental disorder show significantly lower beta activity.**

Keywords—E-health, electroencephalography, machine learning

I. Introduction

According to the American Association on Intellectual and Developmental Disabilities and the American Psychiatric Association, intellectual developmental disorder (IDD), also termed as intellectual disability, is characterized by intellectual and adaptive behavior deficits in intellectual, conceptual, social, and practical domains during the developmental period and originates before the age of 18 [1, 2]. IDD comprises a broad range of several forms of developmental difficulties resulting in lifetime impairments in cognitive capabilities and adaptability [3, 4], whereby the estimated prevalence rate of IDD is in the range from 0.05 to 1.55% [5]. In addition, challenging behaviors and prejudices accompany IDD [6, 7].

Caring for a child affected by an IDD is associated both with high costs and higher levels of parental stress. According to Genereaux et al. [8], the annual costs for a family treating a handicapped child range from CA$ 2,245 to 225,777. These costs are composed on the one hand of a loss of income and the cost of time spent caring for the child, and on the other hand, costs to the welfare state occur, which can be as high as CA$ 119,188. Both the parental costs and the societal costs are increased by a higher severity of IDD. Parents of a child with IDD suffer from significantly higher levels of stress compared to parents of a child without IDD [9, 10]. Moreover, individuals with IDD were found to be twice as likely to have a criminal charge against them when compared with individuals without IDD [11].

Both children and adolescents affected by IDD show a significantly higher prevalence of conduct disorder, anxiety disorder, hyperkinesis, epilepsy, mental illness, dementia, and schizophrenia [12–18]. Furthermore, adolescents with IDD are more likely to be overweight and obese [19]. Obesity is regarded as one of the world's major health problems [20, 21] and is linked with a minimized life expectancy [22]. In addition, Substance-Related and Addictive disorders pose a significant risk for adults with an IDD, as they are much more susceptible to such disorders. Substance-Related and Addictive disorders are associated with high levels of psychiatric and other comorbidities [23].

Questionnaires measuring individuals' IQ and SQ are commonly used for IDD detection, whereby it is a subjective measurement method. Conversely, physiological measurements such as magnetic resonance imaging (MRI) and electroencephalography (EEG) are more objective due to their involvement of physiological indicators and reactions of the human body. Significant MRI abnormalities have been found in subjects with IDD [24–27]. Investigations regarding the relationship of EEG and IDD are rare or are way behind and highlight an increase of the delta and theta bands of the IDD population compared to healthy individuals [28, 29]. Regarding cognitive impairment, a beta band decrease is present [30]. These interactions between IDD, other serious mental disorders, and brain activity [24–30], as well as the impacts regarding health care costs [8] and social effects [9–11], justifies the relevance of using a more novel method by analyzing patients' EEG data already at a very early stage of life in order to make a statement about the potential presence of an IDD and so counteract the spread of the disorder.

Early detection of an IDD has several advantages for the affected individuals, such as supporting the development and personality of especially younger IDD individuals and, in addition, aiding to limit the extent of IDD. Furthermore, IDD individuals' parents benefit from early detection due to the possibility of preparing mentally and learning to manage the caring for their IDD child [31]. Instead of only taking questionnaires into consideration that can lead to biases among children due to misunderstanding, EEG is a much more reliable method for data acquisition. In addition, compared to MRI, costs for EEG implementation are lower, and EEG is easier to establish.

Utilizing neuroscientific data offers the possibility to predict future individuals' states of health [32]. The dramatic upswing in the past years that IT-based healthcare has undergone depends on the combination of increased computational power and the availability of huge new datasets [33]. Machine learning (ML) in healthcare is an emerging application field enabling detection of schizophrenia [34, 35] and cognitive impairments [36] as well evaluation of working memory [37].

This study was aimed at deploying a validated supervised ML method both to classify participants affected by an IDD and to define reliable EEG frequency bands useful to distinguish individuals with a diagnosis of an IDD from non-IDD individuals. The most important contributions of this paper are:

- We developed an automatic classification method for accurate and reliable classification of IDD and non-ID individuals with a balanced accuracy of 91.67 percent.
- In our work, we have shown that using ML and EEG data is a promising, novel, and objective method for an automatic IDD diagnosis instead of a manual diagnosis utilizing questionnaires that are highly subjective and prone to misunderstanding, especially for younger individuals.
- With the help of both Random Forests' (RF) variable importance function and novel model interpretability packages LIME and SHAP, we provided novel insights by pointing out that the low beta frequency bandwidth from 19.5 Hz to 21.0 Hz is highly relevant for distinguishing IDD individuals from non-ID individuals. By extracting the relevant frequency bands, the required amount of data to be analyzed can also be reduced, enabling diagnosis on mobile and embedded computing devices with limited computational power [38].

The paper is organized as follows: First, we provide an overview of related work. Next, we detail the research methodology, including the several ML methods used, information about the dataset, and the steps to preprocess the EEG data. Afterward, we present the ML results concerning the performance indicators and the most important variables extracted. We then discuss the results. Finally, we conclude by including limitations and ideas for future research.

II. Related Work

IDD-affected individuals are prone to other disorders. Epilepsy is implicated in IDD individuals, affecting 22% of the IDD population [40], and therefore suitable for an automated detection based on ML algorithms in view of the fact that ML-based epilepsy detection using EEG recordings has been extensively studied with outstanding results of 99% accuracy [39]. Wang et al. [40] achieved a sensitivity of 63.1 – 81.3% in detecting seizures in IDD patients using a highly unbalanced dataset. Inputting metabolite markers of individuals affected by an IDD and healthy controls into a ML algorithm is also a promising approach both for predicting key markers and to differentiate between the different severities of an IDD [41].

Sareen et al. [42] observed an overall lesser brain activity of patients with an IDD compared with the typically developing controls during the executive processing of different tasks. However, an improvement in mental functioning has been detected when performing a cognitive training exercise depending on the focus of this exercise. Regarding music and resting-state EEG recordings, no significant differences exist, indicating that the preservation of the functional circuits remains intact within the participants with IDD. The detailed analysis of the brain entropy using functional MRI during resting-state by Saxe et al. showed a correlation with the subjects' intelligence. Here, a higher intelligence correlates with a higher brain entropy within parts of the left superior cerebellum and bilateral frontal areas [43]. A higher incidence of brain anomalies in individuals with IDD has been detected compared to healthy individuals [27]. People suffering from an IDD show greater regional gray matter volumes in the ventral and dorsal anterior cingulate cortex and smaller regional gray matter volumes in the left thalamus and cerebellar hemisphere, as well as greater white matter volume in the left frontoparietal region and smaller volumes in the posterior limbs [44]. Considering brain abnormalities in children with an IDD, higher occurrences in cerebral and posterior fossa are prevalent [24]. Investigations regarding the relationship of EEG and IDD are rare but highlight an increase of the delta and theta bands of the IDD population compared to healthy individuals [28, 29]. In general, cognitive impairment is associated with a decrease in the spectral power density in the beta band [30].

III. Methodology

A. Data Preprocessing

1) Independent Component Analysis

Noises generated during EEG data gathering should be removed before putting the EEG data into the ML model [45]. The circumstance that the different forms of noises are not completely avoidable leads to the relevance of a conscientious preprocessing of the EEG data. Therefore, the publishers of the dataset applied the Independent Component Analysis (ICA) algorithm [46] to correct raw EEG data.

2) Spectral Analysis and Feature Extraction

Before the EEG signals are available for use as input features for our ML methods after noise removal through ICA, they must be converted into a frequency signal [47]. This procedure is done by executing EEG spectral analysis with a Fast Fourier Transform, which is a frequently used method in neurosciences [48, 49]. The power spectrum is traditionally divided into the five frequency bands: alpha (7.5–12.5 Hz), beta (12.5–30 Hz), theta (3.5–7.5 Hz), delta (0.5–3.5 Hz), and gamma (> 30 Hz). In our work, we novate the hypothesis by Buettner et al. [39], revealing that the information value of dividing the power spectrum into finer frequency bands could be higher than the traditional division into larger frequency bandwidth. Therefore, as a feature extraction criterion, we break down the EEG power spectrum into 99 fine frequency bands in the range from 0.5 Hz to 50 Hz with an increment of 0.5 Hz.

B. Classification

Taking the preprocessed data as input variables, we evaluated the RF [50], XGBoost [51], SVM [52], and C5.0 Decision Tree [53] regarding the performance for classifying whether a participant has an IDD or not, based on their individual intelligence quotient (IQ) and social quotient (SQ) provided within the dataset together with their brain activity in the form of the EEG data.

The RF classifier contains a collection of unpruned, binary decision trees. It can handle many input variables and is operable both for classification and regression tasks. Ensemble methods, as the RF are often applied due to the persuasion that a decision aggregated from various models is often superior to a decision from a single model. Here, the several decision trees vote to produce a final classification based on the majority vote [50]. XGBoost is a decision tree predictor based on the approach of gradient boosting, which means that in order to achieve a better result, a set of multiple poor predictive models is used [51], while the SVM algorithm is based on the idea of finding a hyperplane, which divides a dataset into classes [52]. The C5.0 decision tree algorithm splits the sample by the determination of fields that provide the maximum information gain. This is repeated until the sample cannot be split more. Finally, the lowest level split gets examined, and the sample splits that show no remarkable contribution to the model gets rejected [53].

Using post-hoc interpretability techniques, the decisions of the selected algorithms can be explained, allowing an identification of specific EEG frequency sub-bands being useful to distinguish individuals with a diagnosis of an IDD from non-IDD individuals [54, 55]. Deep learning methods, whose major drawback is limited interpretability, were not considered in this study [54].

C. Evaluation

In order to achieve reliable results, which represent the basis for selecting the most suitable algorithm, we make use of repeated k-fold cross-validation (CV). The average of the recorded errors of all rounds is computed [56]. For this work, we set k to 10 and repeated this procedure 20 times. In addition, we make use of novel model interpretability packages Local Interpretable Model-agnostic Explanations (LIME) [57] and SHapley Additive exPlanations (SHAP) [58] in order to further analyze the decision-making process of our classifier and uncover the most important features according to these packages.

D. Dataset

The dataset is provided by Sareen et al. [59] and is publicly available. We used an EEG dataset consisting of 14 male participants in total, including their IQ and SQ. Seven participants are rated as affected by an IDD, whereby the remaining seven participants were healthy. The IQ of the IDD participants has been evaluated based on their completion of Malin's Intelligence Scale for Indian Children (MISIC), an Indian adaptation of Wechsler's Intelligence Scale for Children (WISC). The MISIC has 12 subtests uniform separated into two categories verbal and performance, resulting in a verbal IQ, a performance IQ, and finally, a total IQ score. For SQ evaluation, the Vineland Social Maturity Scale, which measures social maturity or social competence, was used.

The raw EEG data were acquired with a sampling frequency of 128 Hz using the Emotiv Epoc+ data acquisition system, and the electrodes were placed according to the international standard 10–20 extended localization system, also known as the 10-10 system and referenced to X and Y [59]. The raw and preprocessed data includes 14-channel EEG data for two minutes of resting-state followed by two minutes of music state.

IV. Results

A. Identified Feature Subset

To identify important frequency sub-bands, the variable importance function of caret was implemented, and then the variables with the highest importance were selected. The analysis of RF's variable importance function regarding the EEG frequency bands reveals that the frequency sub-bands in the range from 19.5 to 21 Hz were highly relevant for the decision-making process. Therefore, these three sub-bands assigned to the low beta range were used to train the distinction between healthy and IDD participants.

B. Classification Results of the ML Models

As visible in Table I, our RF classifier achieves the best overall performance with a balanced accuracy of 91.67%. The other performance indicators were also in a very good range. Using SVM, we can achieve a relatively good balanced accuracy of 86.67% and the best values for specificity with 91.67% and positive predictive value with 94.25%. The C5.0 decision tree classifier has a mediocre accuracy of 72.5%, but the best sensitivity with 93.33% equally to RF. The XGBoost classifier has a balanced accuracy of 78.33%. Therefore, using our RF approach, we achieved a total lift in overall accuracy of 41.67% on the balanced dataset.

TABLE I. Performance Indicators of Used ML Methods Based on Repeated 10-Fold CV

Performance Indicator	**Random Forest**
Balanced Accuracy	**91.67%** (+/- 8.55%)
Sensitivity	**93.33%** (+/- 13.68%)
Specificity	90.00% (+/- 15.67%)
Positive Predicition Value	92.50% (+/- 11.75%)
Negative Prediciton Value	**95.00%** (+/- 10.26%)
Kappa	**0.8333** (+/- 0.171)

Table II summarizes the classification results using the final RF classifier, which showed the best results compared to the other evaluated algorithms, in the form of a confusion matrix. Based on 20 times repeated 10-fold cross-validation, our RF can assign 46.67% (2.8) of the healthy participants to the true class achieving a sensitivity of 93.33%. 45% (2.7) of IDD participants were correctly classified. 8.33% (0.5) misclassification occur.

TABLE II. CONFUSION MATRIX OF THE RF. VALUES BASED ON UNSEEN TEST DATA (N = 6) AND REPEATED 10-FOLD CV

		Reference	
		Healthy	*IDD*
Predicted	*Healthy*	**46.67% (2.8)**	5% (0.3)
	IDD	3.33% (0.2)	**45% (2.7)**

C. Detail Analysis of the Important Frequency Bands

By analyzing and comparing the spectral power density of healthy and IDD participants, significant differences in these highlighted frequency bands are prevalent. Participants affected by an IDD have a much lower spectral power density in the low beta sub-band compared to healthy participants. In terms of numbers, the mean spectral power density of participants with an IDD is decreased by 86.51% (19.5–20 Hz), by 87.86% (20–20.5 Hz) and by 86.06% (20.5–21 Hz). Furthermore, as shown in Table III, all these differences are significant expressed by the corresponding one-tailed p-values ($p<0.1$, $p<0.05$, and $p<0.01$) while the effect sizes are high (Cohen's $d > 0.5$). These statistical computations underline the importance of these frequency bands for the decision-making process of the RF highlighted by the variable importance function. These insights correspond to the general statement that the EEG power is positively correlated with IQ [60–63].

As individuals affected by an IDD are more vulnerable to developing several other disorders such as conduct disorder, anxiety disorder, hyperkinesis, epilepsy, mental illness, dementia, and schizophrenia, we strengthen our insights regarding the decreased beta spectral power density among IDD participants by pointing out the proven decreased beta spectral power density among dementia individuals [64–70] and anxiety disorder individuals [71].

TABLE III. SPECTRAL POWER AND STATISTICAL CHARACTERISTICS OF THE THREE SUB BANDS FOR HEALTHY VS. IDD

Characteristic	19.5-20 Hz	20-20.5 Hz	20.5-21 Hz
Mean healthy	82,387.73	83,121.42	75,416.06
Mean IDD	11,114.77	10,089.31	10,514.96
SD healthy	126,174	73,188.99	43,877.12
SD IDD	4,212.18	3,901.44	6,961.67
p-value	< 0.1	< 0.05	< 0.01
Cohen's d	0.7984	1.4092	2.066

In order to eliminate possible existing differences in the EEG frequency bandwidths that could be due to the prevailing age differences between healthy (mean age = 21.28 ± 1.60) and IDD participants (mean age = 28.28 ± 2.05), we selected as an additional test data exactly those four participants with the smallest age differences between the two classes with an age difference p-value >0.05. Here, the RF classified the four participants completely correctly according to their ground truth class label.

According to the LIME heatmap plot, the most important features are F3 and FC6. While low spectral power density of channel F3 in the sub-band 20.0–20.5 Hz, the uppermost feature in the plot, is highly important for classifying cases 9 and 10 as class 1 "IDD", a high spectral power density of channel F3 in the sub-band 20.0–20.5 Hz, the second uppermost feature in the plot, is highly important for classifying cases 3 and 4 as class 0 "healthy". This corresponds to our statistical computations in Table III. We also make use of SHAP [58] Force Plot enabling us to uncover how the value range of the EEG sub bands' spectral power density affecting the final decision of our RF classifier. SHAP Force Plot provides a global understanding of the model by giving the user the possibility to select every single feature within the dataset and then finally to investigate how the value range of the feature affects the final decision of the model. Here, as a feature to observe, we selected the frequency sub-band 20.0–20.5 Hz of channel O2.

The model classifies participants with low spectral power density in the frequency sub-band 20.0–20.5 Hz of channel O2 as IDD participants. But with increased power spectral density, the model tends more and more to classify the participants as healthy ones. These insights of SHAP Force Plot are reflected in our analysis regarding the much lower mean power spectral for IDD participants and, therefore, correspond with the insights generated by LIME and the computed statistical parameters.

V. DISCUSSION AND CONCLUSION

As IDD results in lifetime impairments in cognitive capabilities and adaptability, in high caring costs, and in a correlation with the occurring of several other disorders, a reliable, objective method is necessary in order to facilitate IDD detection in its early stages, counteracting the spread of the disorder and early initiate treatment methods. To date no relevant approaches have addressed developing a ML-based automatic detection of an IDD using EEG recordings. For this reason, we developed and compared several ML approaches suitable for an automatic IDD detection using resting-state EEG data. Hence, our RF classifier achieves the best overall results with a balanced accuracy of 91.67% based on 20 times repeated 10-fold cross-validation, setting a new benchmark. First, we applied RF variable importance function, highlighting the frequency bands 19.5–20 Hz, 20–21.5 Hz, and 21.5–22 Hz according to the low beta band as the most informative. Using statistical computations in order to compare the respective spectral power density of healthy participants and IDD participants makes the results of our RF classifier traceable. Participants with an IDD show significantly lower beta activity in each of the three fine frequency bands corresponding to the general statement that cognitive impairment is associated with a decrease of the spectral power density in the beta band. In order to strengthen our contribution, although we used a dataset containing a small study size, we make use of four different ML classifiers, all achieving better results than a baseline model. Furthermore, we identified a highly informative feature subset and computed significant statistical parameters.

A. Limitations

The internal validity of the classifier is very high due to the implementation of repeated k-fold cross-validation as an evaluation procedure, but the external validity is not yet given, which is another limitation of our work. We also must mention that in the used dataset, the IDD was assessed using questionnaires, whereby a questioning bias could exist as in any type of survey. It is known that medication and personality [71, 72] can influence EEG data and, as a result, classifiers.

B. Future Work

By using additional datasets for training or by establishing our IDD detection algorithm as a medical application in a clinical environment in order to get more participants, the external validity can be further improved. To validate our given insights, in future investigations on the EEG data of individuals suffering from an IDD, investigating the decreased beta activity in a focused way should be considered. In addition, we are seeking to investigate the impact and importance of specific EEG Channels for accurate classification, as we deliberately avoid a preselection of certain electrodes in this study due to the small study size.

References

[1] American Psychiatric Association, *Diagnostic and statistical manual of mental disorders: DSM-5,* 5th ed. Washington, D.C.: American Psychiatric Publishing, 2013.

[2] R. L. Schalock, *Intellectual disability: Definition, classification, and systems of supports,* 11th ed. Washington, DC: American Association on Intellectual and Developmental Disabilities, 2010.

[3] L. S. Carulla, G. M. Reed, L. M. Vaez-Azizi, S.-A. Cooper, R. M. Leal, and M. Bertelli et al., “Intellectual developmental disorders: towards a new name, definition and framework for “mental retardation/intellectual disability” in ICD-11,” *World Psychiatry*, vol. 10, no. 3, pp. 175–180, 2011.

[4] C. D. M. van Karnebeek, M. Shevell, J. Zschocke, J. B. Moeschler, and S. Stockler, “The metabolic evaluation of the child with an intellectual developmental disorder: Diagnostic algorithm for identification of treatable causes and new digital resource,” *Molecular Genetics and Metabolism*, vol. 111, no. 4, pp. 428–438, 2014.

[5] K. McKenzie, M. Milton, G. Smith, and H. Ouellette-Kuntz, “Systematic Review of the Prevalence and Incidence of Intellectual Disabilities: Current Trends and Issues,” *Current Developmental Disorders Reports*, vol. 3, no. 2, pp. 104–115, 2016.

[6] L.-C. Lee, R. A. Harrington, J. J. Chang, and S. L. Connors, “Increased risk of injury in children with developmental disabilities,” *Research in Developmental Disabilities*, vol. 29, no. 3, pp. 247–255, 2008.

[7] J. L. Matson, M. Hamilton, D. Duncan, J. Bamburg, B. B. Smiroldo, and S. Anderson et al., “Characteristics of stereotypic movement disorder and self-injurious behavior assessed with the Diagnostic Assessment for the Severely Handicapped (DASH-II),” *Research in Developmental Disabilities*, vol. 18, no. 6, pp. 457–469, 1997.

[8] D. Genereaux, C. D. M. van Karnebeek, and P. H. Birch, “Costs of caring for children with an intellectual developmental disorder,” *Disability and Health Journal*, vol. 8, no. 4, pp. 646–651, 2015.

[9] J. R. Rodrigue, S. B. Morgan, and G. Geffken, “Families of Autistic Children: Psychological Functioning of Mothers,” *Journal of Clinical Child Psychology*, vol. 19, no. 4, pp. 371–379, 1990.

[10] M. A. Roach, G. I. Orsmond, and M. S. Barratt, “Mothers and Fathers of Children With Down Syndrome: Parental Stress and Involvement in Childcare,” *American Journal on Mental Retardation*, vol. 104, no. 5, pp. 422–436, 1999.

[11] M. Nixon, S. D. M. Thomas, M. Daffern, and J. R. P. Ogloff, “Estimating the risk of crime and victimisation in people with intellectual disability: a data-linkage study,” *Social Psychiatry and Psychiatric Epidemiology*, vol. 52, no. 5, pp. 617–626, 2017.

[12] E. Emerson, “Prevalence of psychiatric disorders in children and adolescents with and without intellectual disability,” *Journal of Intellectual Disability Research*, vol. 47, no. 1, pp. 51–58, 2003.

[13] J. L. Matson and J. W. Bamburg, “Reliability of the Assessment of Dual Diagnosis (ADD),” *Research in Developmental Disabilities*, vol. 19, no. 1, pp. 89–95, 1998.

[14] J. L. Matson and B. B. Smiroldo, “Validity of the mania subscale of the Diagnostic Assessment for the Severely Handicapped-II (DASH-II),” *Research in Developmental Disabilities*, vol. 18, no. 3, pp. 221–225, 1997.

[15] J. L. Matson, B. B. Smiroldo, M. Hamilton, and C. S. Baglio, “Do anxiety disorders exist in persons with severe and profound mental retardation?,” *Research in Developmental Disabilities*, vol. 18, no. 1, pp. 39–44, 1997.

[16] B. Holden and J. P. Gitlesen, “The relationship between psychiatric symptomatology and motivation of challenging behaviour: A preliminary study,” *Research in Developmental Disabilities*, vol. 29, no. 5, pp. 408–413, 2008.

[17] K. E. Cherry, J. L. Matson, and T. R. Paclawskyj, “Psychopathology in older adults with severe and profound mental retardation,” *American Journal on Mental Retardation*, vol. 101, no. 5, pp. 445–458, 1997.

[18] J. A. McGillivray, M. P. McCabe, and M. M. Kershaw, “Depression in people with intellectual disability: An evaluation of a staff-administered treatment program,” *Research in Developmental Disabilities*, vol. 29, no. 6, pp. 524–536, 2008.

[19] S. Krause, R. Ware, L. McPherson, N. Lennox, and M. O’Callaghan, “Obesity in adolescents with intellectual disability: Prevalence and associated characteristics,” *Obesity Research & Clinical Practice*, vol. 10, no. 5, pp. 520–530, 2016.

[20] J. B. Dixon, “The effect of obesity on health outcomes,” *Molecular and Cellular Endocrinology*, vol. 316, no. 2, pp. 104–108, 2010.

[21] G. Stevens, M. Mascarenhas, and C. Mathers, “Global health risks: progress and challenges,” *Bulletin of the World Health Organization*, vol. 87, p. 646, 2009.

[22] H. M. Orpana, J.-M. Berthelot, M. S. Kaplan, D. H. Feeny, B. McFarland, and N. A. Ross, “BMI and Mortality: Results From a National Longitudinal Study of Canadian Adults,” *Obesity*, vol. 18, no. 1, pp. 214–218, 2010.

[23] E. Lin, R. Balogh, C. McGarry, A. Selick, K. Dobranowski, and A. S. Wilton et al., “Substance-related and addictive disorders among adults with intellectual and developmental disabilities (IDD): an Ontario population cohort study,” *BMJ Open*, vol. 6, no. 9, Paper e011638, 2016.

[24] G. Soto-Ares, B. Joyes, M.-P. Lemaître, L. Vallée, and J.-P. Pruvo, “MRI in children with mental retardation,” *Pediatric Radiology*, vol. 33, no. 5, pp. 334–345, 2003.

[25] F. Decobert, S. Grabar, V. Merzoug, G. Kalifa, G. Ponsot, and C. Adamsbaum et al., “Unexplained mental retardation: is brain MRI useful?,” *Pediatric Radiology*, vol. 35, no. 6, pp. 587–596, 2005.

[26] E. Widjaja, D. Nilsson, S. Blaser, and C. Raybaud, “White matter abnormalities in children with idiopathic developmental delay,” *Acta Radiologica*, vol. 49, no. 5, pp. 589–595, 2008.

[27] M. D. Spencer, R. J. Gibson, T. W. J. Moorhead, P. M. Keston, P. Hoare, and J. J. Best et al., “Qualitative Assessment of Brain Anomalies in Adolescents with Mental Retardation,” *American Journal of Neuroradiology*, vol. 26, no. 10, pp. 2691–2697, 2005.

[28] T. Gasser, J. Möcks, H. G. Lenard, P. Bächer, and R. Verleger, “The EEG of mildly retarded children: Developmental, classificatory, and topographic aspects,” *Electroencephalography and Clinical Neurophysiology*, vol. 55, no. 2, pp. 131–144, 1983.

[29] D. M. Psatta, R. Goldstein, and M. Matei, “EEG mapping in mentally retarded children by synthetic arginine vasotocin administration,” *Romanian Journal of Neurology and Psychiatry*, vol. 29, no. 1-2, pp. 9–16, 1991.

[30] J. S. Barlow, *The electroencephalogram: Its patterns and origins*. Cambridge, Mass., London: MIT, 1993.

[31] A. J. Persha, “Early identification and prevention of mental retardation,” *ICCW news bulletin*, vol. 40, no. 1, pp. 9–12, 1992.

[32] C. J. Lowe, A. C. Reichelt, and P. A. Hall, “The Prefrontal Cortex and Obesity: A Health Neuroscience Perspective,” *Trends in Cognitive Sciences*, vol. 23, no. 4, pp. 349–361, 2019.

[33] K. K. F. Tsoi, S. K. Poon, and P. Hung, “Minitrack for Big-Data on Healthcare Application,” in *HICSS-51 Proc.*, p. 2777, 2018.

[34] R. Buettner, M. Hirschmiller, K. Schlosser, M. Rössle, M. Fernandes, and I. J. Timm, “High-performance exclusion of schizophrenia using a novel

machine learning method on EEG data," in *IEEE HealthCom 2019 Proc.*, pp. 1–6, 2019.

[35] R. Buettner, D. Beil, S. Scholtz, and A. Djemai, "Development of a machine learning based algorithm to accurately detect schizophrenia based on one-minute EEG recordings," in *HICSS-53 Proc.*, pp. 3216–3225, 2020.

[36] J Gross, N Groiss, T Rieg, H Baumgartl, and R Buettner, "High-Performance Detection of Mild Cognitive Impairment Using Resting-State EEG Signals Located in Broca's Area: A Machine Learning Approach," in *AMCIS 2021 Proc.*, in press.

[37] J Breitenbach, A Uzun, T Rieg, H Baumgartl, and R. Buettner, "A Novel Machine Learning Approach to Working Memory Evaluation Using Resting-State EEG Data," in *PACIS 2021 Proc.*, pp. 1–12, 2021.

[38] M. Magno, L. Benini, C. Spagnol and E. Popovici, "Wearable Low Power Dry Surface Wireless Sensor Node for Healthcare Monitoring Application," in *WiMob 2013 Proc.*, pp. 189–195, 2013.

[39] R. Buettner, J. Frick, and T. Rieg, "High-performance detection of epilepsy in seizure-free EEG recordings: A novel machine learning approach using very specific epileptic EEG sub-bands," in *ICIS 2019 Proc.*, Paper 2536, 2019.

[40] L. Wang, X. Long, R. M. Aarts, J. P. van Dijk, and J. B. A. M. Arends, "EEG-based seizure detection in patients with intellectual disability: Which EEG and clinical factors are important?," *Biomedical Signal Processing and Control*, vol. 49, pp. 404–418, 2019.

[41] V. Nikam, S. Ranade, N. S. Mohammad, and M. Kulkarni, "A pilot study on machine learning approach to delineate metabolic signatures in intellectual disability," *International Journal of Developmental Disabilities*, pp. 1–7, 2019.

[42] E. Sareen, A. Gupta, R. Verma, G. K. Achary, and B. Varkey, "Studying functional brain networks from dry electrode EEG set during music and resting states in neurodevelopment disorder," *bioRxiv*, Paper 759738, 2019.

[43] G. N. Saxe, D. Calderone, and L. J. Morales, "Brain entropy and human intelligence: A resting-state fMRI study," *PLOS ONE*, vol. 13, no. 2, pp. 1–21, Paper e0191582, 2018.

[44] M. K. Mannerkoski, H. J. Heiskala, K. van Leemput, L. E. Åberg, R. Raininko, and J. Hämäläinen et al., "Subjects With Intellectual Disability and Familial Need for Full-Time Special Education Show Regional Brain Alterations: A Voxel-Based Morphometry Study," *Pediatric Research*, vol. 66, no. 3, pp. 306–311, 2009.

[45] S. P. Fitzgibbon, D. M. W. Powers, K. J. Pope, and C. R. Clark, "Removal of EEG Noise and Artifact Using Blind Source Separation," *Journal of Clinical Neurophysiology*, vol. 24, no. 3, pp. 232–243, 2007.

[46] A. J. Bell and T. J. Sejnowski, "An Information-Maximization Approach to Blind Separation and Blind Deconvolution," *Neural Computation*, vol. 7, no. 6, pp. 1129–1159, 1995.

[47] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *Journal of Neuroscience Methods*, vol. 134, no. 1, pp. 9–21, 2004.

[48] M. K. van Vugt, P. B. Sederberg, and M. J. Kahana, "Comparison of spectral analysis methods for characterizing brain oscillations," *Journal of Neuroscience Methods*, vol. 162, no. 1, pp. 49–63, 2007.

[49] M. K. Ahirwal and N. D. londhe, "Power Spectrum Analysis of EEG Signals for Estimating Visual Attention," *International Journal of Computer Applications*, vol. 42, no. 15, pp. 22–25, 2012.

[50] L. Breiman, "Random Forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[51] . T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in *ACM SIGKDD '16 Proc.*, pp. 785–794, 2016.

[52] S. Abe, *Support Vector Machines for Pattern Classification,* 1st ed. Guildford, Surrey: Springer London, 2010.

[53] J. R. Quinlan, "Induction of decision trees," *Machine Learning*, vol. 1, no. 1, pp. 81–106, 1986.

[54] A. B. Arrieta, N. Díaz-Rodríguez, J. Del Ser, A. Bennetot, S. Tabik, and A. Barbado et al. "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI," Information Fusion, vol. 58, pp. 82–115, 2020.

[55] T. Rieg, J. Frick, H. Baumgartl, and R. Buettner, "Demonstration of the potential of white-box machine learning approaches to gain insights from cardiovascular disease electrocardiograms," *PLOS ONE*, vol. 15, no. 12, Paper e0243615, 2020.

[56] R. Kohavi, "A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection," in *IJCAI'95 Proc.*, pp. 1137–1143, 1995.

[57] M. T. Ribeiro, S. Singh, and C. Ernesto, ""Why Should I Trust You?": Explaining the Predictions of Any Classifier," in *ACM SIGKDD '16 Proc.*, pp. 1135–1144, 2016.

[58] S. M. Lundberg and S.-I. Lee, "A Unified Approach to Interpreting Model Predictions," in *NIPS'17 Proc.*, pp. 4768–4777, 2017.

[59] E. Sareen, L. Singh, B. Varkey, G. K. Achary, and A. Gupta, "EEG dataset of individuals with intellectual and developmental disorder and healthy controls under rest and music stimuli," *Data in Brief*, vol. 30, Paper 105488, 2020.

[60] E. Marosi, H. Rodrìguez, T. Harmony, G. Yantez, M. Rodrìguez, and J. Bernal et al., "Broad Band Spectral Eeg Parameters Correlated with Different IQ Measurements," *International Journal of Neuroscience*, vol. 97, no. 1-2, pp. 17–27, 1999.

[61] R. G. Schmid, W. S. Tirsch, and H. Scherb, "Correlation between spectral EEG parameters and intelligence test variables in school-age children," *Clinical Neurophysiology*, vol. 113, no. 10, pp. 1647–1656, 2002.

[62] N. Jaušovec and K. Jaušovec, "Differences in EEG current density related to intelligence," *Cognitive Brain Research*, vol. 12, no. 1, pp. 55–60, 2001.

[63] R. W. Thatcher, D. North, and C. Biver, "EEG and intelligence: Relations between EEG coherence, EEG phase delay and power," *Clinical Neurophysiology*, vol. 116, no. 9, pp. 2129–2141, 2005.

[64] T. Dierks, V. Jelic, R. D. Pascual-Marqui, L.-O. Wahlund, P. Julin, and D. E. J. Linden et al., "Spatial pattern of cerebral glucose metabolism (PET) correlates with localization of intracerebral EEG-generators in Alzheimer's disease," *Clinical Neurophysiology*, vol. 111, no. 10, pp. 1817–1824, 2000.

[65] C. Babiloni, G. Binetti, E. Cassetta, D. Cerboneschi, G. D. Forno, and C. Del Percio et al., "Mapping distributed sources of cortical rhythms in mild Alzheimer's disease. A multicentric EEG study," *NeuroImage*, vol. 22, no. 1, pp. 57–67, 2004.

[66] C. Huang, L.-O. Wahlund, T. Dierks, P. Julin, B. Winblad, and V. Jelic, "Discrimination of Alzheimer's disease and mild cognitive impairment by equivalent EEG sources: a cross-sectional and longitudinal study," *Clinical Neurophysiology*, vol. 111, no. 11, pp. 1961–1967, 2000.

[67] N. V. Ponomareva, N. D. Selesneva, and G. A. Jarikov, "EEG Alterations in Subjects at High Familial Risk for Alzheimer's Disease," *Neuropsychobiology*, vol. 48, no. 3, pp. 152–159, 2003.

[68] J. Jeong, "EEG dynamics in patients with Alzheimer's disease," *Clinical Neurophysiology*, vol. 115, no. 7, pp. 1490–1505, 2004.

[69] L. S. Prichep, "Use of Normative Databases and Statistical Methods in Demonstrating Clinical Utility of QEEG: Importance and Cautions," *Clinical EEG and Neuroscience*, vol. 36, no. 2, pp. 82–87, 2005.

[70] M. Lehtovirta, J. Partanen, M. Könönen, J. Hiltunen, S. Helisalmi, and P. Hartikainen et al., "A Longitudinal Quantitative EEG Study of Alzheimer's Disease: Relation to Apolipoprotein E Polymorphism," *Dementia and Geriatric Cognitive Disorders*, vol. 11, no. 1, pp. 29–35, 2000.

[71] A. Demerdzieva, "EEG Characteristics of Generalized Anxiety Disorder in Childhood," *Acta Informatica Medica*, vol. 19, no. 1, pp. 9–15, Paper 9, 2011.