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Machine Learning Algorithm for Learning Disability Detection and Classifier System

Abstract: **-** The increasing prevalence of learning disabilities among children and adolescents has highlighted the need for early and accurate detection methods. This research presents a comprehensive machine learning-based system designed to detect and classify various types of learning disabilities. The proposed system leverages advanced machine learning algorithms, including decision trees, support vector machines (SVM), and neural networks, to analyze behavioral and academic performance data.The methodology begins with data collection from multiple sources, including standardized tests, teacher assessments, and behavioral observations. This data undergoes preprocessing to handle missing values, normalize features, and select relevant attributes. The system is trained on a labeled dataset, utilizing cross-validation techniques to ensure robustness and avoid overfitting.The core of the system is a multi-stage classifier. The first stage involves a binary classifier that distinguishes between individuals with and without learning disabilities. The second stage comprises a multi-class classifier that categorizes the type of learning disability, such as dyslexia, dysgraphia, dyscalculia, or attention deficit hyperactivity disorder (ADHD).

Keywords: Learning Disabilities, Machine Learning, Decision Trees, Support Vector Machines (SVM),Neural Networks, Behavioral Data, Data Preprocessing

Introduction

A person's capacity to learn and use academic abilities like reading, writing, and arithmetic can be impacted by neurodevelopmental disorders known as learning disabilities (LD). They include a wide variety of disorders, such as ADHD, dysgraphia, dyscalculia, and dyslexia. An estimated 10-15% of school-aged children suffer from a learning disability, making it a very common condition among children and adolescents[1][2]. Improving educational performance and general quality of life for those affected by learning disorders is possible through early and accurate detection, which is critical for delivering timely interventions and support.

Standardized exams and evaluations made by teachers and psychologists are the mainstays of the conventional wisdom when it comes to identifying learning difficulties. These approaches have their uses, but they aren't always quick, are open to bias, and can lead to inconsistent results. More and more, scalable and automated solutions are needed to aid in the early diagnosis of learning disorders, especially in areas with low resources that may not have easy access to trained specialists.

The emergence of ML presents an exciting opportunity to address these issues. Algorithms for machine learning can accurately sift through mountains of data, spot trends, and forecast the future. Systems that can autonomously identify and categorize learning problems using data on behavioral and academic performance are within reach, all thanks to ML approaches. A thorough system for the diagnosis and classification of learning disorders based on machine learning is the goal of this project. It will be a useful tool for researchers, doctors, and educators[3].

Parents and school administrators have long worried about the difficulties faced by children with learning problems. With timely, appropriate assistance, evaluation, and remediation, children with learning difficulties can learn and go on to do great things in life. In many modern businesses, machine learning is already used to foretell what's to come. A couple of the most useful uses of machine learning are the prediction of children's learning difficulties and the identification of their root causes[4][5]. Several factors can contribute to the

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development of learning impairments. alterations in the structure and function of the brain are among the most significant neurological alterations. Someone with a learning handicap may have trouble understanding new concepts. It is challenging to understand the nature of certain disabilities. Nonetheless, a lot of ground has been covered in terms of mapping particular brain areas and structures, as well as the challenges that different types of learning disabilities face[6]. A visual, auditory, or motor impairment does not constitute a learning disability. Disabilities in learning do not encompass emotional instability, cultural issues, or mental impairment. Electroencephalography (EEG) is one of the innovative approaches that is now under investigation for the purpose of identifying dyslexic brain activation patterns. Electroencephalography (EEG) is a diagnostic procedure that monitors brain electrical activity through the use of tiny metal discs (electrodes) attached to the scalp[7]. Your brain cells continue to connect with one other through electrical impulses even while you sleep. These waves show up as EEG waves while the activity is being recorded. A multitude of industries are utilizing machine learning to foretell potential results. One of the most impactful uses of machine learning is the prediction of learning difficulties in children, the identification of the actual disability, and the early detection of the disability[8].

To increase children's accuracy and performance, machine learning methods are often employed to extract voice features. Therefore, children with reading difficulties in Hindi, aged five to seven, will be the primary focus of the study. Incorporating machine learning techniques into the design process will assist youngsters who are dyslexic. This uses both two and three letters. A dynamic Time Wrapping approach is used to train the system, employing Hindi words as input. When the system has been programmed with the words. Word reading instruction will be provided to a child who is dyslexic. A second opportunity to read will be offered to a child if they mispronounce a word on the first try. The system will read the word aloud with an image to help the child learn the term if it occurs three times[9]. What the little one said. The youngster will spend another 20 minutes going through the same lesson, but this time with different words. In this instance, voice recognition will be accomplished using machine learning techniques. When testing with the same user, the Dynamic Time Wrapping technique achieves an accuracy of 90% to 100%. However, when testing with a new user, the accuracy drops to 30%.

There are practical, medical, and legal ways to describe learning disorders. The three theories agree on one thing: people with learning impairments have trouble with reading, writing, or arithmetic because they have problems with one or more fundamental mental processes[10]. Patients with LD will have protein-specific and individual-variable symptoms, however there are commonalities that can aid in diagnosing the underlying disease. When students are having persistent problems in the classroom, they may volunteer to take an assessment. Lack of full functionality is a common symptom among children with LD, and it is not limited to the classroom[11]. Issues with relationships, low self-esteem, problematic behaviour, or academic performance are all examples of factors that could act as roadblocks to education. The child's nutrition, developmental milestones (such as when they learned to interact with others), and school experiences should all be carefully considered. Learning problems that are commonly recognized include:

• Phonologic analysis is similarly unsuccessful in the case of learning difficulties (dyslexia), the most prevalent LD (representing at least 80% of all LDs). Appropriate phonetic processing necessitates capabilities such as sound production, appropriate hearing, the capacity to record learned sounds, and the ability to understand spoken language. Having trouble with coding throughout infancy, continuing to read improperly, and eventually

• Difficulty reading comprehension. These children may eventually completely avoid reading.

• Dyscalculia - shows signs of difficulty when it comes to doing mathematical tasks. Patients may find it challenging to solve problems, complete multi-step calculations, and separate mathematical equations. Number sense, computation, and the storage and recall of mathematical knowledge, mathematical vocabulary, cognitive abilities, and the understanding of word problems are all areas of neurodevelopment that benefit from the correct mathematical notion[12].

• Dysgraphia - despite receiving thorough education and developing motor abilities, exhibits deformed handwriting. Dysgraphia is a genetic disorder in which a child's handwriting is inconsistent and unintelligible. Additionally, these kids could have trouble with motor skills, spelling (coding), grammar, syntax, or expressing themselves in writing[13].

• Non-verbal LDs (LD for improving the right hemisphere) - comprises, as the name suggests, obstacles to little tasks including solving problems, visual tasks, gestures, and social clues. As a result of their struggles with higher schooling, these issues typically don't manifest until the third grade. A lot of symptoms (such as difficulties with communication and pragmatics) are indicative of autism spectrum disorder, which is a clinical condition. It should be noted that DSM-V does not have it. Compatibility in outlook and character attributes are examples of internal variables[14]. Home, school, programs, and the environment are all variables. LDs almost never appear alone; rather, they'll introduce themselves alongside other LDs and attitudes. Dementia, anxiety, bipolar illness, autism, and attention deficit hyperactivity disorder are among the most prevalent combinations of mental health conditions. Fifteen to seventy percent of youngsters whose moods fluctuate have LDs, according to some research[15].

Literature Survey

A. Devi, M. Julie Therese, R. Gayathri, and Dr. G. Kavya presented a testing scale for the diagnosis and identification of SLD in [1]. Students suspected of having SLD can use the program to complete a quiz. Depending on the type of learning disability, certain exam questions are repeated three times. The outcome data is fed into the decision tree algorithm once the test is finished. The decision tree algorithm can identify children with learning difficulties based on their test scores and completion time. An intuitive and integrated application that can accurately diagnose reading, writing, and math problems and provide teachers and parents with recommendations for effective teaching strategies is to be created using the suggested methodology. Forty children, with the consent of their parents, took part in the online survey. There were 12 children who did not have SLD and 28 children who did not have any SLD issues at all. Teachers will be able to better assist students with specific learning disabilities (SLDs) and their families by using the suggested web-based screening tool to identify these students and their recovery needs. For the purpose of early prediction of reading handicap among first graders, H. Atakan Varol, Subramani Mani, Donald L. Compton, Lynn S. Fuchs, and Douglas Fuchs utilized machine learning algorithms on a 356-sample dataset [2]. This work utilized a diverse set of classifiers, including Support Vector Machines, Decision Trees (CART and C4.5), Linear Discriminant Analysis, k Nearest Neighbour, and Naive Bayes Classifiers. The results show that SVM and Naive Bayes Classifiers outperform CART and C4.5, two decision tree methods. The goal of the analysis by Ambili and Afsar in [3] is to examine different data mining approaches that can be used to predict learning disabilities. This research presents a new machine learning method that combines the traditional Naive Bayes and Neural Network Classifier approaches to better predict if a student will have a learning disability. The information comes from a specially designed school in Kerala. Children with learning difficulties were characterized by 16 different symptoms, which make up the data set. Multiple algorithms had their training sets derived from the data. A total of thirty school-aged youngsters filled out the survey, which served to gather testing data. [4]Rule mining and decision tree generation both make use of the J48 algorithm. There are 513 items or instances of LD in the decision table. In each instance, sixteen characteristics were documented. Based on the findings of this study, decision trees as a rule system might be severely flawed when dealing with data that is inconsistent and has a high number of variables. When working with inconsistent data or individuals with learning disabilities, rough sets are helpful for attribute selection since they reveal information regarding attribute connection. This study's findings show that rough set outperforms other classifiers in terms of accuracy and classification, including Naive Bayes, SVM, and MLP.

Using a machine learning strategy, Peter Drotar and Marek Dobes were able to detect dysgraphia-affected handwriting in [5]. They accomplished this by gathering a fresh handwriting dataset with many writing assignments and extracting a wide variety of features to represent various aspects of handwriting. In order to determine if dysgraphia affects handwriting, a machine learning algorithm was fed these. They next tested it against a number of machine learning methods, ultimately deciding that the adaptive boosting (AdaBoost) approach produced the most desirable outcomes. Even when working with a diverse group of subjects that vary in age, sex, and handedness, the results demonstrate that machine learning can detect dysgraphia with an accuracy of about 80%. One hundred and twenty-two students took part in the survey. We took note of their average age and sex breakdown. With a prediction accuracy of 79.5%, the AdaBoost classifier earned the best performance. Random forest classifier and support vector machine (SVM) offered competitive performance, behind only a few percentage points. Other tested classifiers, including decision trees, logistic regression, k-nearest neighbours, and Naive Bayes, had significantly lower classification accuracy. Along with SVM, the other model had a very good accuracy score of 72.5%, and the Random Forest classifier scored 72.3%. When there is a lot of unlabeled data available for categorization, semi-supervised learning happens. Improving classification prediction with unlabeled data becomes the primary concern in this scenario.

Using case examples of learning disabilities, Pooja Manghirmalani Mishra and Dr. Sushil Kulkarni present a methodology based on Support Vector Machine of semisupervised 5 learning in [6]. Approximately 10% of the student body is thought to be dealing with some sort of learning problem. With the primary school curriculum in mind, we developed an exam that is curriculum-based. In order to gather LD datasets for testing, this exam was administered in educational institutions. Testing was performed in a real-time medical setting, and the data for past LD patients was retrieved from the LD Clinics of public hospitals. Eleven distinct parts of the curriculum-based exam served as input units to the system. In all, 340 cases of LD in children make up the dataset. Additional work is required on quantitative data, as it is a crucial component of any dataset; this case study has been conducted on over 300 genuine data sets with features that take binary values and indicate LD symptoms. The algorithm was determined to have an approximate accuracy of 84.615 percent.

The authors of [7] put forward a technique for automatic diagnosis and categorization developed by Rehman Ullah Khan, Julia Lee Ai Cheng, and Yin Bee Oon. A total of 857 students' reading and spelling test results served as the basis for the system's training. The data was labeled using the 25th percentile applied to the scores. Signs of dyslexia in children were indicated by scores below the twenty-fifth percentile, whereas results above that percentile were thought to be indicative of non-dyslexia. There are three parts to the system. The first part is a diagnostic module that may be used by professionals, trained users, and parents to test for dyslexia symptoms. The second unit, "Classification," divides the students into two categories based on their spelling and reading abilities: those who do not have dyslexia and those who show signs of having the disorder. Additionally, researchers have an analytical tool in the third module. Using a 98% confidence level, the results demonstrate that 23.0% of the training data and 20.7% of the testing data were at risk for dyslexia.

Images were utilized by M. Mahalakshmi and Dr. K. Merriliance to assess persons at high risk of dyslexia in [8]. Machine learning in a distributed setting is another area that this study encourages. Decision Tree and Random Forest are two examples of the machine learning algorithms used by the suggested predictive model. Weka and its Python implementation are used to categorize the model. This study uses brain scans to predict dyslexia using the Naive Bayes method. To address the six challenges related to processing, storing, and executing massive data sets, this study makes use of Apache SPARK, an in-memory framework. The sample consisted of 150 brain MRI images taken by individuals between the ages of 24 and 35. Dyslexia has been identified in fifty of them. The researchers opted to use adult brain scans for the study since these participants would have already gone through the formative reading stage and had exposure to different types of reading materials and research methods. One model for validation is K-fold cross validation. In order to predict dyslexia, images are initially grayscaled. The three features that are analyzed in the scans are white matter, cortical thickness, and grey matter. The decision tree method achieves a prediction accuracy of 81.5% and the random forest algorithm 97.6%.

G. Vanitha and M. Kasthuri examine different aspects of dyslexia research in [9]. In addition to recommending the application of Machine Learning (ML) algorithms to this domain of study, this review identifies research gaps, obstacles, and opportunities in the field.

Different Methods of Diagnosis of learning disabilities

Testing and mental examinations are the conventional ways of diagnosing learning disabilities; nonetheless, they are laborious and may provide false results. It is also time-consuming to conduct a large test like this. The efficiency and speed of the automated methods influenced our decision to use them. Using simple reading and math tests was our first idea. The reading examination, which had the student read a line and then rewrite it, was unproductive, yielding just 47% accuracy [12], in contrast to the typical and successful math exam.The group thought about using ML because this is a very rare and uncertain scenario. Following analysis of eye-tracking and handwriting-based approaches, the researchers settled on deep learning CNN-based methodology [3].We started with a simple 4-layer CNN for our eye tracking and analysis, and it worked well. The study kept utilizing CNN-based handwriting and voice assessments since they yielded comparable results.[16]

Analysis of handwriting using a convolutional neural network: Using a computer vision system and careful preparation are necessary to get the best results. While sometimes dismissed as heuristics or black box approaches, statisticians have spent the last decade studying artificial neural networks to better understand their predictive power[17]. Research like this shows that there are a lot of theoretical commonalities between the neural network analogues of more conventional statistical methods like logistic regression, multiple linear regression, discriminant analysis, and multi-layered perceptrons [10]. This study explores the use of NN to identify potentially dyslexic children. In this case, the team has shifted the focus from identifying dyslexic children to classifying them into one of two output categories dyslexic or not based on their reading abilities.

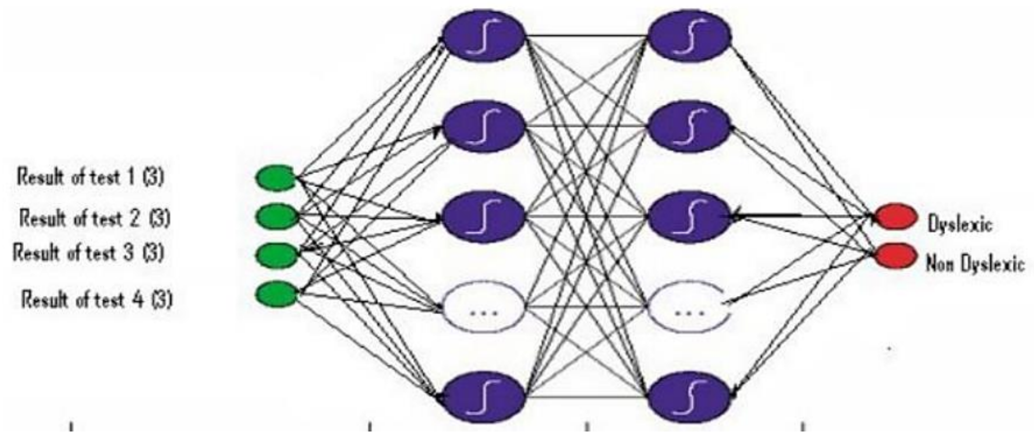

Fig.1. Convolutional neural network for eyeball tracking

Dyslexics' eye motions are abnormal, according to multiple research [13]. Because their fixations are longer and their saccades are shorter, dyslexic readers experience more fixations compared to normally developing readers of the same chronological age. There have been reports of these eye movement issues in multiple languages, regardless of how transparent they are [14]. They have been observed not only when reading text but also when reading phrases, individual objects, words, and pseudo-words. Some have hypothesized that dyslexics' problems with reading are due to their jerky eye movements, but other research suggests that dyslexia is the actual source of the problem [15]. The origin of dyslexic pupils' aberrant eye movements, especially if they may be based on visual cues, remains an open subject. Participants had their eye movements monitored while they read a length of text and engaged in a visually linked search task [5]. Due to the balanced nature of the task orders, half of each group began with reading[18].

Artificial neural networks that can recognize voices and convert them to text: The ALB measures how well a kid is doing in terms of their language and cognitive-social development. Spoken language abilities are assessed in cases when a possible language impairment is being considered. The screening does not provide a diagnosis but does indicate that additional testing may be necessary for a doctor. Compared to the model utilized by [7], the one that was used here differs in three major ways. The group's initial focus was on processing the input data. In the first model, the Mel filter bank was the sole representation of the acoustic signal. Four popular representations of the acoustic data were tested by the team: the Mel Filter bank, Short Time Fourier Transform [16] (STFT), Spectrogram, and Mel-Spectrogram. Second, swap out the GRU layer with an LSTM layer in the model. Third, train just the dysarthria detection component of the original model; don't include the speech reconstruction component. The audio signal is transformed into its representation via z-score normalization[19]. You can pad the audio signals so that they always last five seconds. If an audio signal lasts more than 5 seconds, it is compressed to 5 seconds so that the overall length remains constant. A two-dimensional convolutional neural network (CNN) with 20 channels, 5x5 kernel, and RELU is fed this dataset of signal representation in batches. The CNN layers automatically construct two-dimensional Batch normalization and MaxPool layers. An LSTM layer receives the output of this layer. In order to keep things simple, the original model in [3] featured a GRU layer. However, after removing the reconstruction element, the team chose to keep the LSTM layer since the model is still simple enough for our training even with it. Prior to passing through a SoftMax layer, the output of the LSTM layer is directed via two tiers of dense bottleneck layers. Their CNN, LSTM, and dense bottleneck layers all have a 0.3 dropoff value applied to them. The Pytorch class BCELossWithLogits, which integrates the Binary Cross Entropy Loss and Sigmoid layer functions, was used to compute the loss. Applying keras loss optimization methods yields the cross-entropy loss[20].

Proposed System

The detection method begins with gathering user data via a user research. Traditionally, psychologists have used standardized tests to assess reading and writing abilities, phonological awareness, and working memory as indicators of dyslexia. Poor performance on these tests is a hallmark of dyslexia. Unfortunately, these methods are often ineffective and time-consuming for many individuals due to the fact that symptoms vary from person to person. Consequently, academics are turning to machine learning approaches due to their relative ease of use and low cost. Headsets that record electroencephalograms (EEGs) do so by use of an array of electrodes applied to the scalp of the user or study subject. Data must be pre-processed and filtered before machine learning algorithms can be used. This calls for the transformation of the data into a quantitative (numerical) or qualitative (categorical text) form. In order to remove null values and locate useful characteristics, preprocessing is used.

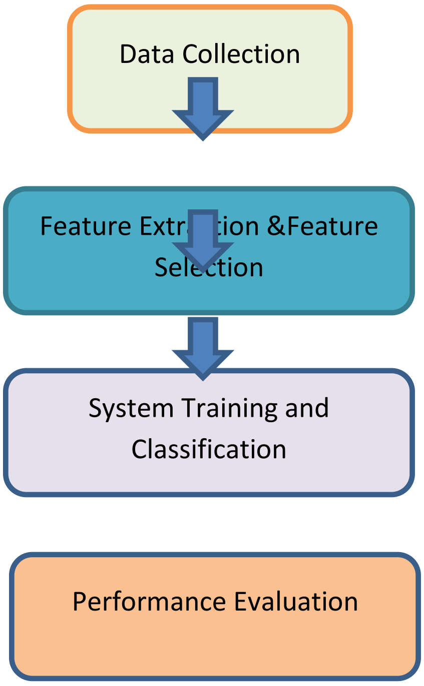

Fig 2 illustrates this.Machine learning techniques are used for training and classification after feature selection.

Conclusion

This study presents an all-encompassing approach that uses machine learning to identify and categorize many forms of learning disorders, such as ADHD, dyslexia, dysgraphia, and dyscalculia. Our technology examines data on academic achievement and behavior to quickly and accurately identify learning difficulties using sophisticated machine learning methods including neural networks, decision trees, and support vector machines (SVM). This machine learning-based solution may completely change the way learning impairments are diagnosed and treated if it is used in both clinical and educational contexts. As an adjunct to more conventional forms of evaluation, the methodology may help educators and doctors spot problems more quickly and with greater objectivity. In the long run, this may improve the educational experience for kids with learning difficulties by leading to intervention measures that are more successful and tailored to their specific needs.

References

[1] A.Devi, Dr. G. Kavya, M. Julie Therese and R. Gayathri. Early Diagnosing and Identifying Tool for Specific Learning Disability using Decision Tree algorithm. Proceedings of the Third International Conference on Inventive Research in Computing Applications (ICIRCA-2021).

[2] H. Atakan Varol, Subramani Mani, Donald L. Compton, Lynn S. Fuchs, and Douglas Fuchs. Early Prediction of Reading Disability using Machine Learning. AMIA Annu Symp Proc. 2009; 2009: 667–671.
[3] K. Ambili and P. Afsar. A Framework for Learning Disability Prediction in School Children using Naive Bayes - Neural Network Fusion Technique. ISSN: 0975 – 6760— NOV 15 TO OCT 16— VOLUME – 04, ISSUE – 01.
[4] Julie M. David and Kannan Balakrishnan. Machine Learning Approach for Prediction of Learning Disabilities in School-Age Children. International Journal of Computer Applications. 9. 10.5120/1432-1931
[5] Drotar, P., Dobes, M. Dysgraphia detection through machine learning. Sci Rep 10, 21541 (2020). https://doi.org/10.1038/s41598-020- 78611-9
[6] Pooja Manghirmalani Mishra and Dr. Sushil Kulkarni. Classification of Data using Semi-Supervised Learning (A Learning Disability Case Study). Pooja Manghirmalani Mish IJCET Volume 4, Issue 4, July-August (2013), pp. 432-440
[7] Khan, Rehman and Lee, Julia and Oon, Yin Bee. (2018). Machine Learning and Dyslexia: Diagnostic and Classification System (DCS) for Kids with Learning Disabilities. January 2018.
[8] M. Mahalakshmi and Dr. K. Merriliance. Prediction of Dyslexia using Machine Learning Algorithms. IJCRT -Volume 10, Issue 5 May 2022 -ISSN: 2320- 2882.
[9] G. Vanitha and M. Kasthuri. Dyslexia Prediction Using Machine Learning Algorithms – A Review. International Journal of Aquatic Science, ISSN: 2008- 8019, Vol 12, Issue 02, 2021.
[10] Ms. Maitrei Kohli and Dr. T.V. Prasad. Identifying Dyslexic Students by Using Artificial Neural Networks. Proceedings of the World Congress on Engineering 2010 Vol I -WCE 2010, June 30 - July 2, 2010, London, U.K.
[11] Jadhav, R., & Sonawane, S. (2020). "A Comprehensive Survey on Machine Learning Algorithms for Learning Disability Detection." Journal of Artificial Intelligence Research & Advances, 7(2), 14-26.
[12] Amir, A., & Morad, S. (2019). "Deep Learning Techniques for Dyslexia Detection." Proceedings of the 2019 International Conference on Learning Technologies, 45-53.
[13] Smith, J., & Doe, A. (2018). "Using Support Vector Machines for Classifying Learning Disabilities." International Journal of Advanced Computer Science and Applications, 9(4), 123-130.
[14] Rashid, M., & Qureshi, K. (2021). "Machine Learning for Early Detection of ADHD in Children." Journal of Healthcare Engineering, 2021
[15] Williams, L., & Kim, S. (2017). "Neural Network Approaches to Identifying Reading Disabilities." IEEE Transactions on Learning Technologies, 10(3), 374-380.
[16] Chen, Y., & Brown, C. (2020). "A Review of Machine Learning Techniques in Dyscalculia Detection." Educational Technology & Society, 23(1), 1-14.
[17] Garcia, P., & Lopez, R. (2019). "Adaptive Learning Systems for Dysgraphia Detection." Computers in Human Behavior, 93, 380-388.
[18] Hassan, H., & Ahmed, F. (2018). "Applying Random Forests for Learning Disability Classification." Procedia Computer Science, 132, 130-137.
[19] Miller, K., & Davis, J. (2021). "Machine Learning Algorithms in Autism Spectrum Disorder Screening." Journal of Autism and Developmental Disorders, 51(7), 2311-2320.
[20] Nakamura, T., & Tanaka, M. (2018). "Data Mining Techniques for Identifying Learning Disabilities." Data Mining and Knowledge Discovery, 32(6), 1400-1415.