JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Artificial Intelligence in Supporting People with Dyslexia: A Comprehensive Review

Priyanka Panghal[1]
Ph.D. Student[1]
Department of Human Development and Family Studies, CCS HAU, Hisar, Haryana
Dr. Poonam Malik[2]
Assistant Scientist
Department of Human Development and Family Studies, CCS, HAU, HISAR
Amita Verma[3]
Ph.D. Student[3]
Department of Human Development and Family Studies, CCS HAU, Hisar, Haryana

Abstract
Dyslexia, a common learning disorder characterized by difficulties in reading, writing, and spelling, affects a significant portion of the population. Traditional methods of support and intervention have had varying degrees of success, often limited by the availability of specialized educators and resources. The advent of Artificial Intelligence (AI) presents new opportunities to enhance support for individuals with dyslexia. This review paper explores the current landscape of AI applications in aiding people with dyslexia, focusing on tools for early diagnosis, personalized learning, and real-time assistance. This paper examines AI-driven diagnostic tools that leverage machine learning algorithms to identify dyslexic tendencies at an early age, enabling timely intervention. Additionally, this paper discusses AI-powered educational platforms that adapt to individual learning paces and styles, offering customized exercises to improve reading and writing skills. Real-time assistance technologies, such as speech-to-text and text-to-speech systems, are also reviewed for their effectiveness in mitigating the challenges faced by dyslexic individuals in academic and professional settings. The paper highlights key research findings, evaluates the efficacy of various AI applications, and identifies areas for future research. By integrating AI into dyslexia support strategies, the quality of life of dyslexic people can be enhanced.
Key Words: Dyslexia, Artificial Intelligence, Diagnosis, Intervention

Introduction
Dyslexia is a neurobiological, developmental, language-based learning disability that impacts an individual's ability to learn or read accurately and fluently, as well as their ability to develop spelling skills. Those with dyslexia struggle to connect spoken language with written words due to deficits in the phonological component of language. This difficulty in accuracy and fluency in decoding words can hinder reading comprehension and vocabulary growth (Snowling, 2019). Additionally, spelling challenges can affect the quality of written composition. Dyslexia can lead to poor academic performance, low self-esteem, and lack of motivation, but it is not indicative of low intelligence, laziness, or poor vision, and it affects individuals across a wide range of intellectual abilities (Denton et al, 2006). Recent studies show that up to 20% of the global population have a specific learning disability (SLD), dyslexia being the most common among them (Wagner et al, 2020). According to the Dyslexia Association of India (2022), 10–15% of Indian children are dyslexic. Other studies conducted in India report similar findings, with prevalence rates ranging from 6% to 13.67%.

As previously mentioned, dyslexia is linked to difficulties with reading, which in turn causes affected individuals to struggle with comprehension and concept memorization, as well as taking notes during lessons (Kumas et al, 2021). Therefore, it is evident that specific and effective support interventions are necessary to ensure equal opportunities for dyslexic students. In these interventions, early diagnosis of dyslexia is the first one because it has been shown that early recognition of dyslexia can significantly reduce the problems it causes (Battistuta et al, 2017).

Various strategies are employed to detect dyslexia, utilizing both conventional and advanced approaches (Al Lamki, 2012). Traditional methods often rely on teacher observations, standardized reading tests, and behavioural evaluations to identify potential indicators of dyslexia in students. While these methods are useful, they may have limitations in terms of accuracy and early detection. Advanced techniques leverage technological and scientific advancements to provide more detailed insights. For instance, researchers can examine brain activity patterns associated with dyslexia using neuroimaging techniques such as functional magnetic resonance imaging (fMRI) and magnetoencephalography. Genetic testing is also utilized to determine the increased likelihood of dyslexia due to specific genetic markers (Beneventi et al., 2010; Bowyer et al., 2010). Additionally, computer-based assessments and eye-tracking technologies help identify reading patterns and eye movements, pinpointing specific difficulties. All these techniques utilize AI which is an emerging field for the detection and designing interventions for dyslexia.

The integration of artificial intelligence (AI)-based systems, especially those utilizing deep learning techniques, has significantly advanced dyslexia diagnosis. While traditional methods depended on manual evaluations, AI development has enabled more efficient and precise detection systems (Jothi Prabha and Bhargavi, 2019). Deep learning, a branch of AI, has proven highly effective in detecting dyslexia (Poulsen et al., 2023). By employing neural networks to analyze complex patterns and data relationships, deep learning models can identify subtle differences in handwriting styles between individuals with and without dyslexia. While traditional methods aid in initial screening, it is crucial to use advanced procedures to understand how dyslexia develops in the brain. This knowledge can be vital in designing tailored interventions and providing personalized support to individuals with dyslexia at any age. This review paper is also planned to analyze these advanced procedures based on AI in supporting dyslexic people.

AI in Diagnosis of Dyslexia (Machine Learning Techniques)

Support Vector Machines (SVM) have demonstrated exceptional efficiency in accurately predicting dyslexia. As a popular classification algorithm in machine learning, SVM operates by identifying an optimal hyperplane to effectively separate different classes within the data. Specifically, SVM has shown promising results in the context of dyslexia prediction. It has been extensively used to classify fMRI (functional magnetic resonance imaging) data, distinguishing between dyslexic and non-dyslexic individuals. For instance, a study by Martin et al. (2016) utilized SVM to classify fMRI data from dyslexic and non-dyslexic children, achieving an accuracy of 87.5%. This highlights the algorithm's effectiveness in differentiating between the two groups. Similarly, research by Plante et al. (2015) applied SVM to classify fMRI data of dyslexic and non-dyslexic adults, attaining an accuracy of 80%. These findings underscore the utility of SVM in the prediction of dyslexia.

K-Nearest Neighbours (KNN) is another classification algorithm that has been investigated for its potential to predict dyslexia. KNN assigns class membership to a data point based on the classes of its neighbouring data points within the feature space. By calculating the distances between data points, KNN identifies the K closest neighbours and assigns the majority class of these neighbours to the target data point. In dyslexia prediction, KNN has shown promising outcomes. For instance, a study by Kaisar (2020) used KNN to classify linguistic and behavioural features of dyslexic and non-dyslexic individuals, achieving an accuracy of 82%. Similarly, research by Thompson et al. (2018) applied KNN to analyze neuroimaging data of dyslexic and non-dyslexic children, resulting in an accuracy of 76%. These studies highlight the effectiveness of KNN in the context of dyslexia prediction.

Artificial Neural Networks (ANN) have been used to predict dyslexia with impressive accuracy. ANN, a robust machine learning technique, is inspired by the structure and functionality of biological neural networks. It comprises interconnected nodes, or artificial neurons, organized in layers that process and transmit information. By training on data from dyslexic and non-dyslexic individuals, ANN can discern complex patterns and make precise predictions. Several studies have demonstrated the effectiveness of ANN in dyslexia prediction. For instance, Martin et al. (2016) utilized ANN to analyze linguistic and cognitive features of dyslexic and non-dyslexic individuals, achieving an accuracy of 91%. Similarly, a study by Plante et al. (2015) employed ANN to classify behavioural and genetic data of dyslexic and non-dyslexic children, resulting in an accuracy of 85%. These findings underscore the potential of ANN in accurately predicting dyslexia.

Convolutional Neural Networks (CNNs): In dyslexia research, Convolutional Neural Networks (CNNs) have been employed to classify brain scans, such as MRI or fMRI, of dyslexic and non-dyslexic individuals. CNNs utilize convolutional layers to detect local patterns and pooling layers to aggregate information, enabling the automatic learning of discriminative features that differentiate between the two groups. For example, Zahia et al (2020) used CNNs to classify brain activation patterns from fMRI data, achieving an accuracy of 88% in distinguishing dyslexic from non-dyslexic individuals. Similarly, a study by Alqahtani et al (2023) applied CNNs to analyze structural brain data, obtaining an accuracy of 82% in predicting dyslexia. CNNs' capability to automatically learn relevant features from raw input data, such as brain scans, has significantly advanced dyslexia research. Their proficiency in capturing spatial information and hierarchical representations makes them highly effective in identifying patterns associated with dyslexia.

Tools for Dyslexia Diagnosis

DysLexML, a screening tool for dyslexia based on machine learning techniques, aims to provide an automated and objective assessment of dyslexia through a series of language-related tasks. In the study, data was collected from 44 dyslexic and 44 non-dyslexic participants who performed various language-related tasks. This data was then used to train several machine learning algorithms, including decision trees, support vector machines, and random forests, to classify participants as dyslexic or non-dyslexic. DysLexML demonstrated an accuracy of 89.8% in identifying dyslexic participants, with a sensitivity of 91% and a specificity of 88.6%. The authors suggest that DysLexML could serve as a screening tool for dyslexia in clinical and educational settings, offering an objective and efficient method for identifying individuals who may need further evaluation and support. The study underscores the potential of machine learning techniques for the early detection and diagnosis of dyslexia and highlights the importance of developing automated and objective screening tools for this condition (Asvestopoulou et al, 2019).

Rello et al. (2018) introduced a novel method for screening dyslexia in English using **human-computer interaction (HCI)** measures combined with machine learning. The study included 24 dyslexic and 23 non-dyslexic participants who were tasked with reading a set of texts and performing various HCI tasks. The collected data were then analysed using different machine learning algorithms to identify potential features for dyslexia screening. The results demonstrated that a combination of HCI measures, such as reading speed, fixation duration, and saccade amplitude, could effectively classify dyslexic and non-dyslexic individuals. This method offers a fast, cost-effective, and reliable way to screen for dyslexia in English, potentially improving early detection and intervention for the disorder.

Rello et al. (2016) introduced a screening tool for dyslexia called **Dytective**, which uses a game-based approach to evaluate reading skills. The game collects data on various linguistic features, including phonology, orthography, and semantics, and employs machine learning algorithms to predict the risk of dyslexia. The study indicates that this game-based method is engaging and effective in identifying individuals at risk of dyslexia, with an accuracy rate of 90%.

Khan et al (2018) proposed a **diagnostic and classification system (DCS)** for identifying dyslexia in children using machine learning techniques. The system combines auditory and visual stimuli to assess a child's reading ability and analyses the data using feature selection and classification algorithms to determine the presence and severity of dyslexia. The authors report that their system is highly accurate and provides an objective and efficient means of diagnosing dyslexia, potentially leading to earlier intervention and improved outcomes for affected children.

AI-Based Assistive Technologies for Personalized Learning of Dyslexic People

The use of AI assistive tools has shown significant potential in enhancing the educational experience for students with dyslexia. Various technologies have been developed over the years, employing different algorithms and methodologies to support learning. For instance, in 2013 (Ndombo and Osunmakinde), an intelligent dyslexic system utilizing machine learning and visualization concepts was introduced to improve reading and writing skills by helping students understand the alphabets and letters. A year later, the Agent DYSL adaptive reading system incorporated machine learning algorithms and audio processing techniques to personalize the reading environment for students, resulting in improved reading pace and accuracy (Athanaselis et al, 2014).

In 2015 (Hamid et al), a computer-based learning model explored the effectiveness of machine learning methods in the learning process. By 2017, a range of applications, such as Learning Ally and Natural Reader, were developed using deep convolutional text-to-speech models to assist students with reading and writing, boosting their confidence and independence. In 2018 (Sood et al), digital applications like DIMMAND and CapturaTalk employed chatbots to provide tailored interventions for literacy difficulties, although detailed information on their effectiveness was limited.

Recent developments in 2020 (Dystech, UNESCO, Rello et al and Shukla et al) saw the introduction of various digital applications, such as Voice Dream Reader and DytectiveU. Voice Dream Reader and similar tools used voice-bots to improve reading skills, demonstrating that e-readers could enhance reading speed and comprehension compared to traditional paper reading. DytectiveU, using support vector machine algorithms, offered personalized game-based exercises to enhance cognitive skills related to dyslexia. Additionally, generative adversarial networks were applied to convert natural language text into images, aiding students in their learning process. More recent tools like Lexia and others are literacy programs designed to cater to the unique needs of students with dyslexia. It offers personalized reading materials and exercises that align with each student's reading level and progress, ensuring tailored support for their learning journey. Overall, these advancements highlight the continuous improvement and growing impact of AI assistive tools in supporting dyslexic students' educational journeys.

Limitations and Challenges of AI Applications in Dyslexia

While machine learning (ML) and AI techniques have shown significant potential in predicting dyslexia, there are several limitations and challenges to consider:

Data Availability: A major challenge is the scarcity of large, diverse datasets. Many studies rely on small datasets, which may not adequately represent the broader population.

Generalization: ML and AI models for dyslexia prediction and treatment may perform well on the training data but struggle with new, unseen data, a problem known as overfitting. This can result in poor real-world performance.

Algorithm Complexity: Some ML and AI algorithms are complex and hard to interpret, making it difficult to understand how a particular prediction was made. This lack of transparency can be a significant drawback in clinical settings where clear explanations are essential.

Class Imbalance: Dyslexia prediction and treatment often suffer from class imbalance, where there are far fewer dyslexic samples compared to non-dyslexic ones. This can lead to biased models with poor accuracy.

Feature Selection: Identifying relevant features is crucial for accurate prediction models, but it can be challenging and often requires expert knowledge of dyslexia.

Preprocessing: The choice of preprocessing techniques, such as data cleaning, normalization, and feature extraction, greatly impacts the performance of ML and AI models.

Ethical Concerns: There are ethical issues associated with using ML and AI for dyslexia prediction and treatment, such as the potential for stigmatizing individuals or limiting their opportunities based on the predictions.

Ethical Considerations to apply AI tools in Dyslexia

When using sensitive personal data for dyslexia prediction, ethical considerations are paramount to address concerns around privacy and potential stigmatization. The use of eye-tracking and other behavioural data introduces privacy issues that require researchers to obtain informed consent from participants and ensure data protection through secure storage and proper sharing policies. Additionally, machine learning algorithms used for dyslexia prediction can inherit biases from the training data. Researchers must actively work to prevent their models from reinforcing existing biases or stereotypes. Importantly, dyslexia prediction should not be used to exclude or discriminate against individuals with dyslexia. Instead, the focus should be on leveraging the predictions to provide early intervention and support without labelling or stigmatizing individuals (Chakraborty & Sundaram, 2020; Kariyawasam et al., 2019; Rello et al., 2016).

Future Direction to Use AI in Dyslexia

AI Machine learning holds great promise for early identification and intervention in dyslexia, but there are several key areas where further research and improvements are needed:

Larger Datasets: A major challenge in dyslexia prediction and intervention using AI machine learning is the limited availability of large and diverse datasets. Future research should prioritize collecting and sharing extensive datasets that encompass various populations, languages, and cultures.

Enhanced Feature Engineering: Feature engineering involves selecting and extracting relevant data features for machine learning. Future work should aim to develop improved methods for feature engineering, focusing on capturing significant features related to cognitive processes and linguistic attributes.

Model Interpretability: For machine learning models to be useful in dyslexia prediction, they must be interpretable, allowing clinicians and educators to understand how predictions are made. Future research should focus on creating more interpretable and transparent models.

Validation and Replication: Dyslexia prediction and intervention models need to be validated on independent datasets to ensure robustness and generalizability. Future studies should concentrate on replicating existing models on different datasets and comparing their performance to determine the most effective approaches.

Integration with Clinical Practice: To be beneficial in real-world settings, dyslexia prediction and intervention models must be integrated into clinical practice. Future research should focus on developing user-friendly interfaces for these models and testing their practical effectiveness in clinical environments.

By addressing these areas for improvement, researchers can enhance the accuracy, reliability, and clinical utility of machine learning models for dyslexia prediction and intervention, ultimately benefiting early identification and intervention efforts for children with dyslexia (Velmurugan, 2023).

Conclusion

AI has the potential to revolutionize dyslexia support by enhancing early diagnosis, personalized learning, and real-time assistance. Machine learning algorithms like SVM, KNN, ANN, and CNN offer more accurate screening, while AI-powered educational platforms provide tailored exercises and real-time help. Despite challenges such as data scarcity, algorithm complexity, and ethical concerns, ongoing research and development can improve AI tools' effectiveness and integration into clinical practice, ultimately enhancing the educational and personal outcomes for individuals with dyslexia.

References

Velmurugan, S. (2023). Predicting dyslexia with machine learning: a comprehensive review of feature selection, algorithms, and evaluation metrics. *Journal of Behavioural Data Science,* 3(1), 70-83.

Kariyawasam, R., Nadeeshani, M., Hamid, T., Subasinghe, I., & Ratnayake, P. (2019, December). A gamified approach for screening and intervention of dyslexia, dysgraphia and dyscalculia. In 2019 *international conference on advancements in computing (icac)* (pp. 156-161). IEEE.

Chakraborty, V., & Sundaram, M. (2020). Machine learning algorithms for prediction of dyslexia using eye movement. In *Journal of physics: Conference series* (Vol. 1427, No. 1, p. 012012). IOP Publishing.

World's First App Screens for Dyslexia in Minutes Using Artificial Intelligence. 2020. [(accessed on 24 June 2024)]. Available online: https://dystech.com.au/education/worlds-first-app-screens-for-dyslexia-in-minutes-using-artificial-intelligence/

UNESCO; 2020. [(accessed on 25 June 2024)]. Spanish Application Using AI to Overcome Dyslexia Wins 2019 UNESCO ICT Prize. Available online: https://en.unesco.org/news/spanish-application-using-ai-help-overcome-dyslexia-wins-2019-unesco-ict-prize

Rello, L., Williams, K., Ali, A., White, N. C., & Bigham, J. P. (2016, April). Dytective: towards detecting dyslexia across languages using an online game. In *Proceedings of the 13th International Web for All Conference* (pp. 1-4).

Shukla R., Bhattacharyya B., Nadu T., Agarwal R., Nadu T. A Comprehensive Study of Audio-Visual Aids for Dyslexic Children. *Int J Electr Eng Technol (IJEET),* 2020; 11:211–218.

Sood, M. R., Toornstra, A., Sereno, M. I., Boland, M., Filaretti, D., & Sood, A. (2018). A digital app to aid detection, monitoring, and management of dyslexia in young children (DIMMAND): protocol for a digital health and education solution. *JMIR research protocols*, *7*(5), 9583-92.

Athanaselis, T., Bakamidis, S., Dologlou, I., Argyriou, E. N., & Symvonis, A. (2014). Making assistive reading tools user friendly: A new platform for Greek dyslexic students empowered by automatic speech recognition. *Multimedia tools and applications*, *68*, 681-699.

Hamid, S. S. A., Admodisastro, N., & Kamaruddin, A. (2015, December). A study of computer-based learning model for students with dyslexia. In *2015 9th Malaysian Software Engineering Conference (MySEC)* (pp. 284-289). IEEE.

Mpia Ndombo, D., Ojo, S., & O. Osunmakinde, I. (2013). An intelligent integrative assistive system for dyslexic learners. *Journal of Assistive Technologies*, *7*(3), 172-187.

Rello, L., Ballesteros, M., Ali, A. X., Serra, M., Sánchez, D. A., & Bigham, J. P. (2016, May). Dytective: diagnosing risk of dyslexia with a game. In *Pervasive Health* (pp. 89-96).

Khan, R. U., Cheng, J. L. A., & Bee, O. Y. (2018). Machine learning and Dyslexia: Diagnostic and classification system (DCS) for kids with learning disabilities. *International Journal of Engineering & Technology*, *7*(3.18), 97-100.

Rello, L., Romero, E., Rauschenberger, M., Ali, A., Williams, K., Bigham, J. P., & White, N. C. (2018, April). Screening dyslexia for English using HCI measures and machine learning. In *Proceedings of the 2018 international conference on digital health* (pp. 80-84).

Asvestopoulou, T., Manousaki, V., Psistakis, A., Smyrnakis, I., Andreadakis, V., Aslanides, I. M., & Papadopouli, M. (2019). Dyslexml: Screening tool for dyslexia using machine learning. *arXiv preprint arXiv:1903.06274*.

Zahia, S., Garcia-Zapirain, B., Saralegui, I., & Fernandez-Ruanova, B. (2020). Dyslexia detection using 3D convolutional neural networks and functional magnetic resonance imaging. *Computer methods and programs in biomedicine*, *197*, 105726.

Alqahtani, N. D., Alzahrani, B., & Ramzan, M. S. (2023). Deep learning applications for dyslexia prediction. *Applied Sciences*, *13*(5), 2804.

Martin, A., Kronbichler, M., & Richlan, F. (2016). Dyslexic brain activation abnormalities in deep and shallow orthographies: A meta-analysis of 28 functional neuroimaging studies. *Human brain mapping*, *37*(7), 2676-2699.

Plante, E., Patterson, D., Gomez, R., Almryde, K. R., White, M. G., & Asbjørnsen, A. E. (2015). The nature of the language input affects brain activation during learning from a natural language. *Journal of Neurolinguistics,* 36, 17–34.

Snowling, M. J. (2019). Dyslexia: A very short introduction. Oxford, UK: Oxford University Press.

Denton, C. A., Fletcher, J. M., Anthony, J. L., & Francis, D. J. (2006). An evaluation of intensive intervention for students with persistent reading difficulties. *Journal of learning disabilities*, *39*(5), 447-466.

Wagner, R. K., Zirps, F. A., Edwards, A. A., Wood, S. G., Joyner, R. E., Becker, B. J., ... & Beal, B. (2020). The prevalence of dyslexia: A new approach to its estimation. *Journal of learning disabilities*, *53*(5), 354-365.

Dyslexia Association of India. Available from: https://www.dyslexiaindia.org.in/Role-of-a-teacher.html. [Last accessed on 2022 Oct 05].

Kumar, J., & Suman, S. (2017). Identification and prevalence of learning-disabled students. *Int J Sci Res Publ*, *7*, 317-9.

Kumas, Ö. A., Dodur, H. M. S., & Yazicioglu, T. (2021). Teachers' Knowledge about Dyslexia and Reading Models. *International Journal of Curriculum and Instruction*, *13*(3), 3096-3121.

Battistutta, L., Commissaire, E., & Steffgen, G. (2018). Impact of the time of diagnosis on the perceived competence of adolescents with dyslexia. *Learning Disability Quarterly*, *41*(3), 170-178.

Al-Lamki, L. (2012). Dyslexia: Its impact on the individual, parents and society. *Sultan Qaboos University Medical Journal*, *12*(3), 269.

Beneventi, H., Tønnessen, F. E., Ersland, L., & Hugdahl, K. (2010). Executive working memory processes in dyslexia: behavioral and fMRI evidence. *Scandinavian Journal of Psychology*, *51*(3), 192-202.

Bowyer, S. M., Pawluk, L., Olszewski, A., Gallaway, M. L., Mansour, A., Jacobson, D., ... & Lajiness-O'Neill, R. (2010). MEG detection of attention and memory processes in individuals with dyslexia. In *17th International Conference on Biomagnetism Advances in Biomagnetism–Biomag2010: March 28–April 1, 2010 Dubrovnik, Croatia* (pp. 346-349). Springer Berlin Heidelberg.

Jothi Prabha, A., & Bhargavi, R. (2019). Prediction of dyslexia using machine learning—a research travelogue. In *Proceedings of the Third International Conference on Microelectronics, Computing and Communication Systems: MCCS 2018* (pp. 23-34). Springer Singapore.

Poulsen, M., Juul, H., & Elbro, C. (2023). A national test of dyslexia. *Annals of Dyslexia*, *73*(3), 337-355.