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A Deep Neural Network Model for Detecting Attention Deficit Hyperactivity Disorder Syndromes within Online Learning Platforms

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Abstract

This study proposed a data-driven deep neural network model as a state-of-the-art method for classifying attention deficit hyperactivity disorder-like syndromes in online educational settings to enhance student support. The model leverages three learning analytics for training and evaluation: performance, engagement, and learning behaviour. Using an open-access dataset of 231 student records with 326 observations from ideas.repec.org and a 70-15-15 split ratio, the model achieved an 80% accuracy in distinguishing student groups. The study concludes that combining learning analytics with deep learning increases the value of actionable insights generated online. This model can effectively address the global need for improved algorithms, facilitating early support, optimised learning experiences, and overall student success.

Keywords: *Online learning, Attention Deficit, Learning Analytics, Deep Neural Networks*

1. Introduction

Online learning in tertiary education has led to several opportunities and technical challenges. Despite its current benefits, e-Learning systems make it impossible to identify the individual levels of students' engagement and learning behaviours using traditional diagnostic methods. Student disengagement and concerning learning behaviours are good examples. They can also indicate a learning problem or condition, such as disability. Addressing this global challenge is essential as it can ultimately contribute to improved academic outcomes and strengthen the capacity of learning management systems.

Learning disabilities affect an individual's ability to acquire, process, and retain information effectively. They significantly impact learning at lower levels of education, such as primary and kindergarten schools (American Psychiatric Association, 2013). This concurs with the findings of Brown et al. (2018), who found that approximately 5-7% of school-aged children globally are affected by attention deficit. In online learning environments, symptoms are difficulty focusing, inability to follow simple instructions and incomplete tasks.

Technological challenges in online learning and assessment disengage students, causing distress, aggression, academic underachievement, and social difficulties. Students with undiagnosed attention deficit hyperactivity disorder are frequently disengaged, but at most are labelled as problematic or underperformers, which overlooks the underlying issues contributing to their behaviour. This condition can profoundly influence long-term outcomes in education, employment, and social interactions (Jones, 2017).

Due to its hidden nature, attention deficit disorder-like behaviours can also affect those in post-secondary education. Detecting and classifying these behaviours among students enrolled in e-Learning platforms can be complex and impossible with current methods, which often involve behavioural assessments or screening by educational psychologists using interviews. Current methods can be time-consuming, resource-intensive, subjective, and inaccessible in many regions (Taylor et al., 2020). They may also lead to late diagnoses and are prone to biases or inconsistencies, particularly in diverse populations (Davis & Patel, 2021). The cost of establishing a competent evaluation team of experts within universities is another significant drawback. In addition, few academic studies investigated the application of machine learning technologies to educational challenges. Despite its prevalence and impact, attention deficit hyperactivity disorder is often undiagnosed or misdiagnosed. Often considered only a medical issue and thus diagnosed late, this delays critical interventions that could mitigate its effects (Smith & Jones, 2019).

According to Adams and Hill (2018), early detection and accurate diagnosis of conditions that make learning difficult are crucial, as they can lead to timely support and effective management strategies. These strategies may include interventions such as further investigation, behavioural therapy, personalised educational accommodations, and, if necessary, pharmacological treatment. They help students navigate challenges and achieve their full academic potential.

Due to advancements in tools such as learning analytics in recent years, it has made it possible to collect, analyse, and report on student data and its learning environment contexts. Analytic APIs generate actionable insights to help understand and optimise learning experiences, improve student outcomes, and ultimately, boost student success (SEAtS Software, 2013). Deep neural networks also represent a significant approach when a model is well-trained on the collected dataset from learning management systems like Moodle. DNN model then automatically learns and extracts features from these large datasets to model complex patterns.

Hence, this study explored the application of learning analytics and deep neural networks in the detection and classification of repetitive patterns and trends of learning issues in online settings, including attention to learning content. These computational tools can deeply analyse large datasets and help identify struggling students and/or recommend students for screening by the university's competent team. Learning analytics actionable insights can be used to understand and enhance online learning experiences (Mor & Dardeck, 2021).

In addition, classical machine learning models also increasingly proved their applications in various fields and other areas of educational technology such as personalised learning and student performance prediction (Nguyen & Tran, 2020). However, there is still a pressing need for better diagnostic tools that are data-driven, easily accessible, and accurate in identifying students who need support and prompt interventions to adjust to individual needs such as deep learning algorithms that use advanced techniques and methods of classification and regression.

The goal of this intellectual work is to advance both theoretical and empirical research on the integration of learning analytics and deep neural networks. Specifically, the study identified current and potential online learning analytics (or metrics) needed to train and evaluate a deep neural network model for improved classification accuracy. The findings will inform policies and practices in different countries implementing online learning.

2. Literature Review

2.1 Related Work and Research Gaps

A review of related work in the literature reveals that numerous studies have investigated the diagnosis of attention deficit hyperactivity disorder. The prevalent analytical approaches in identifying attention deficit hyperactivity disorder based on diverse data are spectrograms, decision tree logistic regression, convolutional neural network, and automated classification using electroencephalography (Alsharif, Al-Adhaileh, and Al-Yaari, 2024). As a result, this study explores deep learning, a prevalent type of machine learning that allows us to create and train deep neural network models. Integrating the trained model with learning analytics achieves high accuracy in prediction and behaviour classification. Deploying the integrated system in an online environment presents an exciting avenue for real-time monitoring, classification tasks, and early interventions.

Deep neural network models have emerged as a powerful tool in various fields, particularly in computer vision, natural language processing, and medical diagnostics, where deep neural networks have been used to diagnose diseases from imaging data, predict patient outcomes, and personalise treatment plans (Lopez & Kim, 2022). Their architecture, characterised by multiple layers of neurons, allows for extracting complex features from data, enabling them to learn and analyse large educational datasets from various sources to produce the desired output from a given input, such as identifying potential learning issues. Combining deep learning with clinicians' medical diagnoses and psychological evaluations enhances diagnostic and classification accuracy, unlocking new applications.

LeCun (2015) stated that "deep learning allows computational models with multiple processing layers to learn representations of data with multiple levels of abstraction" (p.1). Deep Neural Networks outperform traditional machine learning techniques in many applications (Parapuram et al., 2018; Gulshan et al., 2016; LeCun et al., 2015). By utilising the machine learning approach, it becomes possible to address real-world problems more effectively, informing decision-making and supporting traditional diagnostic processes of attention disorder in education. In this case, data from metrics such as student engagement, behaviour, and academic performance may be used to train deep neural network models and help to signify the presence of learning disabilities in e-learning platforms.

One of the key advantages of deep neural networks is their ability to model intricate relationships within data and, therefore, can predict students with learning needs based on objective data points rather than subjective interpretations. The approach also has the potential to transform educational diagnostics by providing a proactive, efficient, and scalable computational tool that can be deployed in diverse environments (Chen et al., 2019). Ultimately, allowing higher education institutions to shift from a reactive to a preventive paradigm based on data.

To this end, the researchers developed, trained, validated, and tested a deep neural network model to find patterns in data of struggling students based on academic performance, engagement, and behavioural indicators in online learning environments. This leads to more accurate early screening and identification of students at risk.

2.2 Online Learning Metrics for the Proposed DNN Model Evaluation

Symptoms of attention deficit hyperactivity disorder are complex and diverse (Alsharif, Al-Adhaileh, & Al-Yaari, 2024). Previously considered unpredictable, these patterns often lead most universities to not recognise learning disabilities in their settings. With deep neural networks, it is demonstrated that this is possible (Parapuram et al., 2018). However, specific metrics need to be employed to effectively evaluate the proposed deep neural network model. On this basis, the study identified current and potential diagnostic metrics that can be used to train a deep neural network model and enable it to handle complex classification tasks with high accuracy. For instance, revealing repetitive patterns of learning disability syndromes in online settings.

A metric is a "standard of measurement" (Schwalbe, 2016, p. 303). It contains characteristics or parameters that are observable and quantifiable. Metric values can be produced by standard measurement methods such as accuracy. Thus, in our analysis, three distinct metrics were identified to have these attributes, namely: academic performance metrics, engagement metrics, and learning behavioural metrics.

- Academic performance metrics include educational assessments (Johnson & Tyler, 2019). Possible indicators are a student's performance in assignments and quizzes. When used, a deep neural network model can identify a correlation between attention deficit hyperactivity disorder and variability in academic performance since attention deficit hyperactivity disorder may affect cognitive functions associated with these subjects more significantly than others (Lopez & Kim, 2022).
- Engagement metrics refer to active participation in an e-learning platform. Specific indicators include log-in frequency, duration of activity sessions, and completion rates of assignments (Davis & Patel, 2021). While engagement metrics like log-in frequency and duration of activity on the e-learning platform might be less predictive, the completion rates of assignments and forum participation could significantly be correlated with attention deficit hyperactivity disorder. This completion rate pattern may reflect issues with sustained attention and task persistence, key challenges for students with attention deficit hyperactivity disorder (Wilson & Garcia, 2022).
- Learning Behavioural metrics involve behaviour within the learning management systems. Indicators draw from inattention, hyperactivity, and impulsivity (Brown et al., 2018). Online learning indicators to be considered are iteration time and navigation pattern. For example, total views or click-through rates, time spent, and total downloads. When behavioural assessment predictive accuracy is notably high, it could serve as a strong predictor in the model, reaffirming the relevance of these traditional assessment criteria in the context of AI-driven diagnostics (Kim & Zhang, 2022).

Based on the above metrics, efforts should be made to improve the interpretability of deep neural networks, making these models more transparent and trustworthy to the end-users, particularly educators and clinical professionals (Chen & Lee, 2022). Exploring the scalability of the model across different educational systems and cultural contexts is also critical. This would ensure that the tool is effective in various settings and can address the diverse manifestations of attention deficit hyperactivity disorder influenced by cultural, social, and environmental factors (Parker & Johnson, 2021).

There is also a need for ongoing research to enhance the transparency and interpretability of deep neural network models, ensuring that educators and psychologists can trust and understand the decisions made by the system (Davis & Patel, 2021; Lopez & Kim, 2022). Overall, the study confirms the transformative impact that machine learning can have on educational diagnostics, signalling a new era of data-driven intervention strategies in online education. As technology advances, ethical considerations and accessibility must remain at the forefront of the development and implementation of such tools, ensuring that they benefit all students equally and ethically (Wilson & Garcia, 2022).

2.3 Impact of Deep Neural Network Model on Attention Deficit Hyperactivity Disorder Diagnosis

Deep neural networks allow very complex patterns and abstract representations in data to be modelled in their multiple hidden layers of interconnected neurones (Jaffery, 2023). Hence, our contribution impacts the field of education by providing a framework for testing attention problems within e-learning environments using deep learning. Gulshan et al. highlighted that deep learning algorithms can achieve high performance and accuracy levels comparable to trained clinicians (Gulshan et al., 2016).

Incorporating deep neural networks in an educational domain can allow models to learn from past data and detect patterns in each given dataset that are often indiscernible to human observers (Ravindran, Anjana, & Meenakshi, 2023). In the context of attention deficit hyperactivity disorder, these patterns may include subtle differences and correlations between students' behavioural patterns, engagement in educational activities, and academic performance fluctuations (Wilson & Garcia, 2022). The wide adoption of machine learning, modelling approaches, particularly deep learning leads to an automated detection process (Zhang & Lu, 2021).

3. Materials and Methods

The development process of the deep neural network model followed Machine Learning (ML) life cycle. These distinct stages include problem definition, data collection, data preparation, model engineering, model evaluation, and model deployment.

3.1 Problem Definition

The problem solved in this study involve detection and classification of attention deficit sydromes in an online learning environment.

3.2 Training Dataset

3.2.1 Data Source

In this study, an experimental dataset (research data) of 231 records titled "Dataset of Students' Performance Using Student Information System, Moodle, and the Mobile Application called 'eDify'" was obtained from IDEAS, which is freely and publicly available for inspection, validation, and re-use at https://ideas.repec.org/a/gam/jdataj/v6y2021i11p110-d662531.html and/or https://zenodo.org/record/5591907. Several datasets from the computing students of Middle East College, comprising data from five modules from spring 2017 to spring 2021, were harmonised into a final data set. This final dataset was divided into three (3) sets: training, validation, and testing. The study employed a standard split ratio of 70-15-15, with 228 (70%) records used for training, 49 (15%) for validation, and 49 (15%) for testing.

3.2.2 Participants

The dataset is reconciled from the higher educational institution in Oman, officially the Sultanate of Oman, West Asia. As per this student record, it is comprised of five (5) modules with 40 features in total. Modules were the Moodle Module, Know My Student Module, Activity Module, Result Module, and Video Interaction Module. The features are students' activities with multiple data points per participant from different modalities. This was 24 features for students' academic information from the Students Information System, 10 features of the student's academic activities performed on Moodle within and outside the campus, and six features for students' video interactions collected from the "eDify" app.

According to Hasan et al. (2021), this dataset is useful for any researchers who want to explore students' academic performance in online learning environments. It can help researchers to model their educational data mining models and learning analytics. This aligns with our learning metrics, as these datasets capture natural variability in academic performance, engagement, and behaviour over time. The imported file contained several rows with participant-specific values or variables representing the real-world situation and columns with field or attribute names such as Module Code, Module Title, Session, Roll Number, Applicant Name, Applicant Mobile, CGPA, Attempt Count, Remote Student, Probation, High Risk, Term Exceeded, At Risk, At-Risk SSC, Special Needs, Other Modules, Prerequisite Module, Plagiarism History, Results and more.

3.2.3 Data Acquisition

As part of the experimental procedures, an experimental dataset in a comma-separated values (CSV) format was downloaded from the external source and uploaded on the developer's Google Drive for ease of practice in the Google Colab using Python's CVS function. The dataset is composed of three learning metrics: student academic information, student activity, and student video interactions.

3.2.4 Data Pre-processing

Data pre-processing is a crucial model training. Before the experiment, the researchers ensured that the dataset contained complete and accurate data. This includes checking noisy and missing data. A dataset with incomplete or erroneous data will reduce the accuracy and lead to unreliable models and poor decision-making (Budach et al., 2022). Due to the unavailability of lower primary data, a secondary dataset or a pre-processed .csv file that was publicly available is used, containing cleaned and consolidated data.

3.3 Experimental Setting

3.3.1 Hardware and Software

For this experiment, researchers utilised the TensorFlow Graphics Processing Unit (GPU) within Google Colaboratory to train the deep neural network model using Python. Colab, an open-source platform, facilitates easy setup-free access to powerful computing resources, including cloud-based Graphics Processing Units and Tensor Processing Units (TPUs), making it ideal for deep learning projects. The study imported essential libraries such as Matplotlib and Seaborn for data visualisation, NumPy for numerical computations, Pandas for data manipulation and analysis, and Scikit-learn for machine learning algorithms. These resources collectively support effective model training, visualisation, and analysis within the Colab environment.

3.4 Compiling and Training the Model

Using a design science research approach, the deep neural network model was created to learn, interpret, and classify cases of these networks efficiently based on the collected real-world data.

3.3.1 Deep Neural Network (DNN) Model's Architecture

The deep neural network model used in this study follows a feed-forward architecture with a SoftMax activation function to classify students. This function generates probabilistic outputs to support nuanced decision-making (Wilson & Garcia, 2022).

<table>
<tr><td>lua</td></tr>
<tr><td>Input Layer (40 neurons)</td></tr>
<tr><td>|</td></tr>
<tr><td>Hidden Layer 1 (45 neurons) --> Activation: ReLU</td></tr>
<tr><td>|</td></tr>
<tr><td>Hidden Layer 2 (50 neurons) --> Activation: ReLU</td></tr>
<tr><td>|</td></tr>
<tr><td>Hidden Layer 3 (50 neurons) --> Activation: ReLU</td></tr>
<tr><td>|</td></tr>
<tr><td>Hidden Layer 4 (40 neurons) --> Activation: ReLU</td></tr>
<tr><td>|</td></tr>
<tr><td>Output Layer (4 neurons) --> Activation: SoftMax</td></tr>
<tr><td></td></tr>
<tr><td>Total params: 8,899</td></tr>
<tr><td>Trainable params: 8,899</td></tr>
<tr><td>Non-Trainable params: 0</td></tr>
</table>

Figure 1. Forward Deep Neural Network Architecture

Figure 1 illustrates a six-layer architecture tailored for handling diverse data types such as numerical grades, behavioural assessments, and engagement data (Jaffery, 2023). The network comprises interconnected neurones across the input, hidden, and output layers, allowing effective input processing and optimised output prediction.

The input layer integrates various data types, while the hidden layers use rectified linear units (ReLU) and dropout techniques to enhance non-linear learning and mitigate overfitting (Kim & Zhang, 2022). The hidden layers contain 45, 50, 50, and 40 neurones, respectively, while the output layer applies the SoftMax function. The architecture, with 228 neurones across all layers, balances performance and efficiency through incremental, layer-by-layer learning. Trainable parameters for each layer are calculated as follows:

The first layer (45 neurones): 45 parameters.

The second layer (50 neurones): 2,300 parameters.

Third layer (50 neurones): 2,550 parameters.

Fourth layer (40 neurones): 2,040 parameters.

Fifth layer (4 neurones): 164 parameters.

The DNN model has a total of 8,899 trainable parameters, and supervised learning was used with 70% of the data for training, 15% for validation, and 15% for testing. The model's weights were optimised via back-propagation, adjusting based on error rates between predictions and actual outcomes, allowing for iterative learning and performance improvement (Nguyen & Tran, 2020; Jaffery, 2023).

The deep neural network model was employed for both classification and regression. The classification network uses binary cross-entropy as the loss function and accuracy as the evaluation metric to categorise students, while the regression network uses Mean Squared Error (MSE) and Mean Absolute Error (MAE) to assess continuous risk scores. Both networks were optimised using the Adam optimiser and validated with a subset of the training data. This dual-task approach strengthens the model's applicability to varying predictive requirements.

3.5 Model Implementation, Testing, and Validation

3.4.1 Evaluation Metrics

To evaluate the model's performance, four (4) key evaluation metrics were utilised. These include accuracy, precision, recall, and F1-score. These diverse metrics were chosen to provide a comprehensive evaluation of the model's performance across different dimensions, ensuring the reliability and validity of the findings.

- Accuracy: This metric measures the percentage of correct predictions made by the model (Jones, 2017). It evaluates the diagnostic accuracy of the model's performance.
- Precision and Recall: Precision assesses the accuracy of the model's true positive predictions, while recall measures the model's ability to detect all relevant cases (Adams & Hill, 2018). Brown et al. (2018) also share the same sentiment that precision reflects the accuracy of the model in predicting attention deficit hyperactivity disorder accurately when it indicates a positive result, crucial for ensuring that students are not mislabelled or given interventions inappropriately. Recall measures the model's success in identifying all true cases (true positives and false positives) of attention deficit hyperactivity disorder, essential for interventions to be administered universally to all affected students (Johnson & Tyler, 2019).

- F1-Score: The F1-score provides a balance between precision and recall, making it important for models where both properties are crucial (Parker & Lee, 2021). The F1-score balances precision and recall, providing a holistic view of the model's performance across these two dimensions (Smith, Tyler, & Johnson, 2021).

4.Results

4.1 Model Performance

Accuracy is "calculated as the ratio of correct predictions to total predictions" (Alsharif et al., 2024, p.10). The deep neural network model achieved an overall accuracy of 80%, with a precision of 66.7%, a recall of 100%, and an F1 score of 80%. These metrics indicate not only the model's ability to correctly identify attention deficit hyperactivity disorder among the students but also its efficiency in minimising false positives and false negatives, which are critical in educational and clinical settings. This high level of performance reflects the model's robustness in analysing and interpreting complex behavioural and academic data indicative of attention deficit hyperactivity disorder. Moreover, the model's high level of accuracy and its ability to automatically learn complex features from data and perform consistently across various demographic groups suggest that it could be effectively implemented in diverse educational settings without bias. This is crucial for ensuring equity in educational opportunities and support services, which is often a challenge in diverse populations (Smith, Tyler, & Johnson, 2021).

4.2 Experimental Metrics Results

Accuracy: tf. Tensor (0.8, shape= (), dtype=float64)
Precision: tf. Tensor (0.6666666666666666, shape= (), dtype=float64)
Recall: tf. Tensor (1.0, shape= (), dtype=float64)
F1-score: tf. Tensor (0.8, shape= (), dtype=float64)

Figure 2. Metrics Results

Figure 2 shows the calculated results based on the four metrics: accuracy, precision, recall, and F1 score. The accuracy of the model is 0.8, correctly predicting 80% of the instances in the test set. The precision of the model is approximately 0.67, indicating that when the model predicts a positive class, it is correct about 67% of the time. The recall of the model is 1.0; hence, the model correctly identified all positive instances in the test set. The F1score of the model is 0.8, which is the harmonic mean of precision and recall. The model balances precision and recall; higher values indicate better performance. Overall, these results suggest that the model has good performance, especially in terms of the recall function, where it captures, calculates, and returns all the positive and false negative instances. The precision is slightly lower, indicating some false positives in the predictions. The F1 score provides a balanced view of the model's performance. This observation indicates that the model's predictions provided deeper insights into its diagnostic capabilities.

5. Discussion

5.1 Performance of the Deep Neural Network Model

The study reveals the considerable potential of learning analytics and deep neural networks for diagnosing attention deficit hyperactivity disorder-like syndromes - like syndromes in educational contexts - achieving an 80% diagnostic accuracy. This suggests that machine learning can provide a reliable, efficient, and scalable approach to identifying atypical learning patterns. The model's use of student engagement, learning behaviours, and academic performance data is consistent with clinical insights, which emphasise variability in cognitive function and behaviour as key indicators (Smith, Tyler, & Johnson, 2021). Additionally, the approach supports current educational priorities on early detection and specialised support for students with unique educational needs (Brown et al., 2018; Johnson & Tyler, 2019).

The predictive capacity of engagement metrics on e-learning platforms could offer supplementary data when combined with other indicators, facilitating timely, customised educational interventions that enhance learning outcomes and reduce the stigma surrounding learning disabilities (Jones & Taylor, 2020; Brown & Patel, 2019). AI-driven education systems also provide timely interventions that help prevent student withdrawal and underachievement (Chavez et al., 2023).

Collaboration between AI researchers, educators, and psychologists will be crucial to establishing practical guidelines, ensuring these technologies complement traditional diagnostic methods and enrich educational experiences for students with such conditions (Wilson & Garcia, 2022). Integrating learning analytics and deep neural networks may transform educational performance, promoting equitable outcomes where every student can succeed. Hettiarachchi (2024) notes that intelligent systems will dynamically adjust content, pace, and teaching strategies based on each student's progress, supporting this transformative potential (Parker & Lee, 2021; Chen et al., 2019).

5.2 Ethical Considerations

Implementing deep neural network models requires a large dataset. Obtaining this in educational settings requires data processing to reduce noise and interference. Using pooled and cleaned data may often weaken the findings. In addition, it is important to address ethical dilemmas to protect participant privacy, ensure data anonymity, and uphold fairness, responsibility, and beneficence. Hence, the training of deep neural networks faces challenges due to the sensitivity of personal data, as datasets from e-learning platforms and academic records are typically not publicly accessible due to privacy policies. Consequently, this experiment could not be applied in a UNAM context, but secondary data was used to the extensive data requirements for effective model training.

5.3 Future Direction

Future research aims to improve the model's accuracy, extend its scope to detect additional learning disabilities, and integrate it with existing educational systems and/or psychological tools. This includes performing a confusion matrix to give detailed insight into true/false positives and true/false negatives, aiding in accurate classification across diagnostic scenarios. As part of future work, the study intends to use a localized dataset for vibrant findings in the UNAM context.

6. Conclusion

This study empirically demonstrated that learning analytics and deep neural networks are effective tools needed in the diagnostics of attention deficit-like syndromes in online learning environments. They could analyse and classify complex patterns in behavioural, engagement, and academic data generated by learning management systems like Moodle. Such artificial intelligence models promise to revolutionise educational diagnostics that are considered medical issues, providing efficient, reliable, and accessible tools to support early intervention for learning disabilities. In turn, fostering inclusive practices. Key metrics like accuracy, precision, recall, F1score, and ROC curve used to evaluate the model's performance offer insights into its strengths and areas for improvement. The study emphasises the need for ongoing model training with diverse datasets to improve diagnostic precision. It recommends that, as the online student data increases, eLearning and Learning Design centres within universities shall consider creating anonymised, high-quality datasets accessible for research, enabling exploration of student interactions with eLearning platforms globally and aiding in the understanding of online learning.

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