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4.3. How effective are machine learning models in detecting shifts in attention?
The machine learning models demonstrated varying levels of effectiveness depending on the dataset used and the context of the task:
•Real-Time Attention Monitoring: It is used for monitoring attention in classroom and e-Learning environments, Deep Learning models such as YOLOv3 and YOLOv5 work brilliantly in real-time performance, detecting attention shifts with high accuracy (Paper [8]). These models were capable of processing video data to assess facial expressions and body movements, which are the main indicators of attention in educational settings.
•EEG and Cognitive Load Estimation: Deep learning models like SDAE + MLP and LSTM + MLP achieved accuracies of up to 85.42% for detecting shifts in cognitive load and attention using EEG (Paper [3]). These models were effective in detecting subtle shifts in attention during tasks of varying difficulty and also highlighting their potential in cognitive workload management.
•ADHD Detection: ADHD-200 and SPECT brain scans were highly effec-tive in detecting attention deficits associated with ADHD that achieving accuracies of up to 99.58% (Papers [11], [19]). All of these models used a combination of SVM, Random For-est, and CNN architectures to classify ADHD based on neuroimaging and physiological data.
•Facial Expression and Eye-Tracking Models: Models analyzing facial expres-sions and eye-tracking data in classroom settings demonstrated high performance that accuracies ranging from 85% to 93.1% (Papers [7], [8]). These models were especially effective at detecting attention shifts which is related to student engagement in educational contexts.
4.4. What challenges and limitations exist in Artificial Intelligence powered attention assessment?
Several challenges and limitations were identified across the reviewed studies:
•Data-Related Issues: Many studies suffered from small sample sizes (Papers [3], [13]). Also, data imbalance was a significant issue in datasets involving attention states, where low-attention states were often ignored (Papers [9], [19]).
•Overfitting: Overfitting was a common issue in models trained on small or highly specific datasets. Overfitting led to reduced performance on unseen data (Papers [4], [15]).
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•Privacy and Ethical Concerns: Privacy and Ethical Concerns: The use of biometric data, including facial expressions, EEG, and physiological measurements, raised concerns about privacy and ethical associations, especially when working with children (Papers [6], [15]).
•Hardware Constraints: Hardware Constraints: Many models required spe-cialized equipment, such as EEG headsets and eye-trackers, which creates an issue in

scalability in real-world applications. Developing models that are less reliant on expensive hardware was a key challenge (Papers [8], [14]).

Table 5: Key Limitations Identified in Reviewed Papers

Key Limitation	No. of Papers Addressing This Limitation	Papers
Small sample size	8 Papers	[2], [3], [4], [7], [10], [12], [14], [15]
Data imbalance	3 Papers	[9], [11], [13]
Subject variability	1 Paper	[3]
Privacy concerns	2 Papers	[6], [8]
Overfitting risk	1 Paper	[13]
Comorbidities and diagnosis accuracy	2 Papers	[5], [15]
Limited feature sets (e.g., blink frequency, eye states)	2 Papers	[7], [8]
Lack of ecological validity (real-world applicability)	1 Paper	[16]
No control for confounding factors (e.g., comorbidities)	1 Paper	[15]

4.5. What are the future research directions for Artificial Intelligence based attention analysis?

The studies identify several important future directions for advancing Artificial Intelligence based attention assessment:

•Multimodal Approaches: Combining multiple data types, such as EEG, facial expressions, and eye-tracking, was highlighted as a great direction for improving attention detection accuracy. Multimodal systems can reduce limitations of individual data types and create more robust models (Papers [1], [7], [8]).

•Real-Time Systems and Scalability: Future research should focus on developing real-time attention monitoring systems that can be used in dynamic environments such

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as classrooms or workplaces. Improving the scalability of Artificial Intelligence models for large usage, especially in large, diverse populations that can strengthen models (Papers [6], [16]).

•Explainability and Transparency: In modern days, Artificial Intelligence models become more integrated into clinical and educational settings so there is a growing need for explainable Artificial Intelligence that ensure the decision-making processes are transparent and understandable. This would be especially important in contexts like ADHD diagnosis, where require clarity about model predictions (Papers [10], [19]).

•Larger Datasets and Personalized Approaches: Expanding datasets to include a wide range of individuals and environmental contexts would help improve model generalization. Also, using personalized methods that adjust to how each person thinks and processes information could make attention monitoring systems work much better and smoother (Papers [5], [9]).

•Integration with Educational Tools: Real-time feedback could be provided to learners and instructors by Integrating Artificial Intelligence based attention monitoring systems with e-Learning platforms and virtual reality tools. This could help create personalized support that helps student engagement and improves learning results (Papers [8], [7]).

Figure 3: Future Directions Suggested by Papers

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Table 6: Future Research Directions Identified in Reviewed Papers

Future Direction Suggested No. of Papers Ad-
dressing This Sug-
gestion
Papers
Real-time systems and processing 4 Papers [1], [3], [4],
[18]
Multimodal data integration 5 Papers [2], [5], [8],
[11], [15]
Larger, more diverse datasets 4 Papers [2], [3], [5],
[11]
Personalized models 3 Papers [2], [5], [3]
Improved accuracy and robustness of models 4 Papers [5], [6], [9],
[17]
Use of new technologies (e.g., VR, AI, Explainable
AI)
4 Papers [1], [6], [16],
[5]
Integration with educational tools or real-life tasks 3 Papers [1], [7], [6]
Addressing privacy concerns 2 Papers [6], [8]

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In this study, we proposed a novel deep learning framework, SC-CNN-attention, to classify ADHD and HCs on large and multi-sites' resting-state fMRI data, based�...Missing: est, | Show results with:

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Jul 15, 2024 � Multimodal AI refers to AI systems capable of processing and integrating information from multiple modalities or types of data.

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3. Real-time computing is equivalent to fast computing. 4. Real-time programming is assembly coding, priority interrupt programming, and writing.

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