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4. Results
This section represents an analysis of what we found from the 19 reviewed papers. We analyze the paper on the basis of some questions related to Artificial Intelligence techniques, datasets, evaluation metrics, effectiveness, challenges, and future directions in Artificial Intelligence based attention assessment.
4.1. What Artificial Intelligence techniques are commonly used for assessing attention and focus in digital environments?
From the reviewed papers, a large range of Artificial Intelligence techniques were used to assess attention and focus, advancements in machine learning, and deep learning. These methods were applied to different datasets, such as physiological signals (such as, EEG), behavioral data (such as, facial expressions, eye-tracking), and environmental factors (such as, video data from classrooms).
• Deep Learning Models: Deep learning methods, especially Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, were frequently used for attention and focus detection tasks involving sequential or image data. As an example, YOLOv3 and YOLOv5 (Papers [1], [8]) were used to analyze real-time student behavior in classrooms and e-Learning environments. These models can have significant effectiveness in detecting attention by tracking facial expressions and body movements.
• Support Vector Machines (SVM): SVM was another widely used method, especially for classification tasks involving EEG and behavioral data. SVM models were found to perform well in identifying attention-based patterns and cognitive states, especially in ADHD diagnosis and cognitive load estimation tasks (Papers [11], [12], [19]). Combining with methods like Random Forest or Deep Neural Networks (DNNs) the SVM classifiers can have high accuracy in detecting attention shifts.
• Random Forest and Ensemble Methods: Random Forest, AdaBoost, and XG-Boost were used in various studies for tasks such as classifying attention in educational factors and diagnosing ADHD. These models provided robust results by combining multiple classifiers but small sample sizes cause overfitting (Papers [2], [13], [15]).
• Behavioral and Physiological Data Integration: An important section that the integration of multiple data types, such as facial expression recognition (FER), eye-tracking, and EEG data. The integration of these features using machine learning techniques like SVM or Deep Neural Networks (DNNs) allowed for better prediction
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of attention levels (Papers [7], [16]). This combination of data types made the models stronger by balancing out the weaknesses.
Figure 2: Distribution of AI Techniques Used
Table 4: AI Subfields and Techniques Summary

AI Subfield	Techniques Used	Number of Papers	Paper Numbers
Computer Vision	YOLO v3, Deep Learning, Computer Vision	2	[1], [8]
Machine Learning (ML)	Logistic Regression, SVM, Decision Tree, KNN, AdaBoost, MLP, Extra Tree Classifier, Voting Classifier	7	[2], [3], [7], [9], [10], [12], [13]
Deep Learning	SDAE + MLP, LSTM + MLP, 1D CNN, CNN, BiLSTM, DNN	8	[3], [4], [6], [8], [11], [12], [18], [19]
Hybrid Models	Hybrid cluster-based unsupervised learning, 1D CNN	1	[4]
Natural Language Processing (NLP)	Whisper API, GPT-4	1	[6]
Feature Extraction & Recognition	DeepFace, VGG-Face, Dlib, EAR, MobileNet-SSD, MediaPipe Pose, FER	1	[6]
Data Fusion/Multimodal	Multiple ML techniques (integrated analysis across modalities)	1	[7]
Reinforcement Learning	None	0	-

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4.2. What datasets and evaluation metrics are used for Artificial Intelligence based attention assessment studies?

The datasets and evaluation metrics used in the reviewed studies varied greatly, reflecting the differences in attention-related tasks. From diagnostic assessments of different datasets and metrics were used to monitoring attention in real-time classroom factors and attention disorders like ADHD.

Datasets: A range of datasets was applied to assess attention and focus, with a focus on both behavioral data and physiological signals.

•EEG-based datasets were most commonly used in the context of cognitive load and attention deficit detection. For example, the ADHD-200 dataset gave a large collection of EEG data for ADHD classification[11], [19]. Also, EEG data from wearable devices were used in real-time attention estimation tasks (Papers [3], [4]).

•Eye-tracking datasets were also common in attention studies, especially for analyzing visual attention in e-Learning and classroom environments. The CEW dataset and OULAD dataset gave data on eye states, facial expressions and pupil movements. (Papers [7], [9]).

•SPECT brain scans were used in some studies to assess brain activity and its correlation with attention deficits (Paper [19]). These datasets used for understanding attention-related disorders in-depth.

•Facial expression datasets were generally useful in assessing attention in facial expressions were linked to students' engagement levels (Papers [1], [9]).

Evaluation Metrics: Several evaluation metrics were used to assess the effectiveness of Artificial Intelligence models in detecting attention shifts and disorders:

•Accuracy was the most common metric that is used to classifying attention levels in real-time systems (Papers [1], [3], [8]). Deep Learning and SVM models achieved high accuracy scores in various attention-related tasks.

•Precision, Recall, and F1-Score were commonly used to evaluate performance in imbalanced datasets, that in real-time applications where precision and recall are important for identifying both attention and distraction states (Papers [2], [6], [9]).

•Area Under Curve (AUC) was often used for ADHD detection and cognitive load estimation tasks. Those observed in studies with SVM (Papers [11], [12], [19]), which has High AUC values, demonstrated the ability of model that discriminates between different attention-related states effectively.

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•Homogeneity Score and Silhouette Coefficient were used in unsupervised learning models to assess the quality of clustering in attention data (Paper [4]).

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