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EEG-Based Machine Learning Techniques for ADHD Detection: A Review of Datasets, Feature Extraction Methods, and Classification Algorithms

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ABSTRACT

Attention-Deficit/Hyperactivity Disorder (ADHD) is a common neurodevelopmental condition that disrupts attention, impulse control and executive function, yet it is still diagnosed largely through subjective behavioral assessment. Pairing electroencephalography (EEG) with machine learning has become a popular route toward more objective markers. In this review we compare fifteen EEG-based ADHD studies published between 2020 and 2025 on three points: the datasets they used, how they pulled useful features out of the EEG signal, and which classifiers they trained to separate ADHD from control participants. Feature extraction turns out to be very varied, running from handcrafted statistical and nonlinear measures to representations learned automatically by deep networks, and the classifiers range from support vector machines to graph-based neural networks. Two structural problems stand out, though. More than half of the studies draw on one and the same public dataset, and their validation strategies differ so much that the reported accuracies, several of them above 99%, cannot be lined up fairly against each other. We set out these problems and suggest where future work should head: larger and more varied datasets, standardized subject-level validation, and closer attention to interpretability. All three are needed before EEG-based ADHD detection can be trusted in clinical practice.

Keywords: Attention-Deficit/Hyperactivity Disorder (ADHD); Electroencephalography (EEG); Machine Learning; Feature Extraction; EEG Datasets; Classification Algorithms

1. Introduction

ADHD ranks among the most frequently diagnosed neurodevelopmental disorders in childhood. Global prevalence estimates run from roughly 5% to 11%, and the symptoms often carry on into adolescence and adulthood. Diagnosis still leans on behavioral observation, parent and teacher questionnaires, and structured clinical interviews. That is a subjective process, and co-occurring conditions that mimic ADHD can muddy it further. For this reason researchers have long been interested in EEG, a non-invasive and comparatively cheap way to record objective neurophysiological differences between children with ADHD and their typically developing peers. The best-known findings involve theta and beta band activity and raised theta/beta ratios, although these have not replicated consistently across populations.

The tools available to researchers have grown a great deal in recent years. Instead of depending on a handful of manually chosen EEG markers, machine learning and deep learning can extract and combine far larger and more complex feature sets, and some models learn discriminative patterns straight from raw or lightly processed signals. The result is a fast-growing literature that is also quite fragmented. Studies differ in dataset, preprocessing pipeline, feature extraction method and classifier, so the accuracies they report, often above 90% and occasionally above 99%, are hard to compare head to head.

This review looks at fifteen studies from 2020 to 2025 that apply machine learning to EEG-based ADHD detection. We compare them along three lines: the datasets used, the feature extraction methods applied, and the classification algorithms employed. Reading the studies side by side brings out patterns that are easy to miss when each is read alone, especially the heavy dependence on a few shared datasets and the inconsistent way model performance is validated and reported.

2. Review Methodology

2.1 Literature Search Strategy

We identified studies by searching IEEE Xplore, ScienceDirect, PubMed/MEDLINE and Google Scholar. The search strings combined terms for the disorder, the signal modality and the analytical approach (for example "ADHD," "EEG," "machine learning," "deep learning" and "classification"). We also screened the reference lists of retrieved articles by hand to catch relevant studies that the database searches had missed. The search covered 2020 to 2025, the period in which EEG-based ADHD detection developed most rapidly, particularly with the move toward deep-learning-based feature extraction.

2.2 Inclusion and Exclusion Criteria

A study was included if it used EEG as its primary neurophysiological modality, applied a machine learning or deep learning classifier to separate ADHD participants from healthy or typically developing controls, reported at least one quantitative performance metric, and gave enough methodological detail for comparison. We excluded studies that relied only on non-EEG modalities, review articles and meta-analyses, papers that did not report classification performance, duplicate or preprint versions of studies already included, and work that classified ADHD subtypes or comorbidities rather than ADHD against controls.

2.3 Study Selection Process

Records from the database searches were first screened by title and abstract to drop clearly irrelevant results. The remaining articles were read in full and checked against the criteria above. This left fifteen studies for detailed comparison of datasets, feature extraction methods and classification algorithms.

3. Characteristics of Reviewed Studies

The fifteen included studies were published between 2020 and 2025 and differ in dataset size, EEG recording setup and classification approach; Table 1 summarizes them. Ten of the fifteen use participants from public EEG datasets recorded during a visual attention or cognitive task, most often the widely reused dataset of 61 children with ADHD and 60 controls originally collected by Nasrabadi et al. A smaller group uses adult samples, independently collected clinical samples or multi-site data. The public-dataset studies all use 19 channels, whereas the independently collected datasets vary more, with 7 to 12 channels. Classifiers run from classical machine learning to deep architectures such as CNN, ConvLSTM and GCN, and accuracy is the metric reported most consistently.

Table 1. Summary of reviewed studies on EEG-based ADHD detection.

Author (Year)	N	ADHD/Control	Ch.	Recording Condition	Dataset	Algorithm	Main Performance
Maniruzzaman et al. (2022) [11]	121	61 / 60	19	Visual attention/counting task	Public (Nasrabadi et al.)	SVM (RBF) + LASSO	94.2% accuracy
Moghaddari et al. (2020) [12]	61	31 / 30	19	Continuous mental task	Public (Nasrabadi et al.)	13-layer CNN	98.48% (subject-based)
Dubreuil-Vall et al. (2020) [5]	40	20 / 20	7	Flanker task (adults)	Independently collected	4-layer CNN	88.0% ± 1.12%
TaghiBeyglou et al. (2022) [15]	121	61 / 60	19	Visual attention task	Public (Nasrabadi et al.)	CNN + Logistic Regression	95.83% (unseen epochs)
Karabıber Cura et al. (2024) [7]	33	15 / 18	12	Clinical EEG recordings	Independently collected	DarkNet19 + ML classifiers	96.6–99.9%

Author (Year)	N	ADHD/Control	Ch.	Recording Condition	Dataset	Algorithm	Main Performance
Bakhtyari and Mirzaie (2022) [3]	91	46 / 45	19	Task-based EEG	NBML dataset	ConvLSTM + attention	99.34% average
Latifi et al. (2024) [9]	121	61 / 60	19	Visual attention task	Public (IEEE DataPort)	Siamese CNN	99.17% accuracy
Bansal et al. (2025) [4]	121	61 / 60	19	Visual attention task	Public (IEEE DataPort)	Modified ResNet + attention	99.42% accuracy
Ahire (2025) [1]	121	61 / 60	19	Visual attention task	Public (IEEE DataPort)	Attention-fused CNN	97.60% (80/20 split)
Li et al. (2025) [10]	57; 121	29/28; 61/60	19	Task-based EEG (2 datasets)	Hospital data + public dataset	GCN + LSTM + CNN	97.29% / 96.67%
Kim and Yang (2025) [8]	168	107 / 61	19	Quantitative EEG, 30-s segments	Korean clinical dataset	XGBoost	90.81% accuracy
Sathiya et al. (2024) [13]	121	61 / 60	19	Visual attention task	Public (Nasrabadi et al.)	SVM / k-NN + Gabor features	96.4% accuracy
Alim and Imtiaz (2023) [2]	120	Not split 61/60	19	Visual attentional task	Public dataset	Gaussian SVM	93.2% / 94.2% (CV)
Sharma and Singh (2023) [14]	121	61 / 60	19	Visual attention task	Public (IEEE DataPort)	MEMD–GA–ANN	96.16% accuracy
Ekhlasi et al. (2021) [6]	121	61 / 60	19	Visual attention task	Public (Nasrabadi et al.)	ANN + GA feature selection	89.7% (theta band)

Table 1 shows a clear pattern: eight of the fifteen studies, plus part of Li et al.[10]'s two-dataset comparison, depend on some version of the same 121-child public dataset. Sections 4 and 8 return to this concentration, because it bears directly on how much real methodological diversity lies behind the field's reported accuracy gains.

4. EEG Datasets Used for ADHD Detection

4.1 Public and Private Datasets

The resource used most often among the reviewed studies is the public EEG dataset collected by Nasrabadi, Allahverdy, Samavati and Mohammadi and hosted on IEEE DataPort. It holds recordings from 61 children with ADHD and 60 age-matched controls (aged 7–12) made during a visual counting task. Eight of the fifteen studies use it directly, and one more includes it as one of two datasets in a multi-site comparison. The attraction is easy to see: it is free to download, already labeled, and large enough for supervised learning without the burden of collecting new data.

The other studies rely on independently collected institutional datasets. These tend to be smaller, but the diagnoses were confirmed more directly through clinical interview. They include the adult sample (20 ADHD, 20 control) recorded during a Flanker task by Dubreuil-Vall et al.[5], the NBML dataset (46 ADHD, 45 control) of Bakhtyari and Mirzaie[3], the independently collected sample (15 ADHD, 18 control) of Karabıber Cura et al.[7], the Korean clinical cohort (107 ADHD, 61 control) of Kim and Yang[8], and one of the two datasets used by Li et al.[10], which came from Changchun Sixth Hospital (29 ADHD, 28 control).

4.2 Dataset Characteristics and Reuse

Most of the reviewed studies focus on children aged 7–12, and the adult sample of Dubreuil-Vall et al.[5] is the main exception. Recordings are overwhelmingly task-based, usually a sustained visual attention or counting task, rather than resting-state. Nineteen-channel EEG dominates only because that is the montage of the shared public dataset; the independently collected datasets show real variation, from 7 to 12 channels. The most important pattern here is dataset reuse. More than half of the reviewed studies use the very same 121-child sample and differ only in preprocessing, feature extraction or classifier. A common benchmark makes surface-level comparison convenient, but it also means that much of the field's apparent progress may come from optimizing against one demographically narrow sample rather than from improvements that generalize. Cross-dataset validation, in which a model trained on one dataset is tested on an independent one, is still rare. Among the reviewed studies, only Li et al.[10] evaluate performance across two separate datasets.

5. Feature Extraction Methods

Feature extraction turns raw EEG signals into representations a classifier can learn from, and it is where the reviewed studies differ most. They fall broadly into two camps. In handcrafted feature engineering, researchers explicitly compute a predefined set of statistical, spectral or nonlinear measures. In automatically learned approaches, a deep network builds its own internal representation directly from the EEG signal.

5.1 Handcrafted Features

- Time-domain and morphological features: Maniruzzaman et al.[11] extracted 342 candidate morphological and time-domain descriptors and then cut them down through feature selection.
- Spectral and band-power features: Alim and Imtiaz[2] took linear features from only the first four EEG frequency sub-bands, which lowered the computational load while keeping accuracy intact.
- Filter-bank statistical features: Sathiya et al.[13] used a bank of Gabor filters to split the EEG into narrow-band signals, then computed entropy, standard deviation, skewness and kurtosis from each.
- Nonlinear and time-frequency features: Karabıber Cura et al.[7] combined Hjorth parameters, skewness and kurtosis with nonlinear measures such as the Lyapunov exponent and fractal dimensions, and assembled them into image-like EEG feature maps.
- Connectivity-based features: Ekhlasi et al.[6] computed directed phase transfer entropy between electrode pairs, which captures how information flows between brain regions instead of only describing signal amplitude.
- Decomposition-based features: Sharma and Singh[14] applied three different multivariate decomposition techniques to the EEG, derived a small set of features from each resulting oscillatory mode, and then used evolutionary and distance-based feature selection.

5.2 Automatically Learned Representations

- Image-based CNN features: Moghaddari et al.[12] converted frequency-band activity into RGB images that a 13-layer CNN learned from directly.
- Spectrogram-based CNN features: Dubreuil-Vall et al.[5] fed wavelet-based spectrograms of event-related EEG activity into a CNN, so no spectral features had to be picked by hand.
- Raw-signal CNN features: TaghiBeyglou et al.[15] passed raw EEG straight into a CNN without any prior transformation, and later reused the learned feature maps in classical classifiers.
- Spatiotemporal connectivity features: Bakhtyari and Mirzaie[3] used a ConvLSTM to learn dynamic inter-channel connectivity patterns over time, without specifying connectivity measures manually.
- Autoencoder-based latent features: Bansal et al.[4] combined autoencoder-derived latent representations with statistical and spectral descriptors

inside a modified ResNet architecture.

In chronological order, the 2020–2022 studies lean more on handcrafted features with classical classifiers, while work from 2023 onward increasingly favors deep, automatically learned representations. This shift can hide a practical advantage of handcrafted features: they stay directly interpretable. In a clinical setting that matters, since a prediction that cannot be traced to a specific, physiologically meaningful property of the signal is of limited use.

6. Machine Learning and Classification Algorithms

6.1 Traditional Machine Learning

Support Vector Machines (SVM) are the classical algorithm used most often in the reviewed literature. They are typically paired with handcrafted features and often use a radial basis function kernel to separate non-linearly distributed classes. Maniruzzaman et al.[11], Alim and Imtiaz[2] and Sathiya et al.[13] all report strong results with SVM variants. k-Nearest Neighbors (k-NN) and Decision Trees mostly appear as comparison baselines and generally do worse than SVM on the same feature sets. TaghiBeyglou et al.[15] use Logistic Regression, a linear probabilistic classifier, as a lightweight final stage after CNN-based feature extraction. Random Forest, an ensemble of decision trees, shows up as a comparison classifier in several of the broader evaluation sets. Kim and Yang[8] use XGBoost, a regularized gradient-boosting method well suited to structured feature data, on quantitative band-power features and pair it with a SHAP-based interpretability analysis.

6.2 Neural Network and Deep Learning Methods

Artificial Neural Networks (ANN) and Multilayer Perceptrons (MLP) appear both as standalone classifiers and as parts of feature-selection pipelines. Ekhlasi et al.[6] and Sharma and Singh[14] both get their best results from an ANN combined with evolutionary feature selection. Among deep learning architectures, Convolutional Neural Networks (CNN) are the most common overall. They have been applied to image-like frequency-band representations (Moghaddari et al.[12]), to spectrograms (Dubreuil-Vall et al.[5]) and to raw EEG (TaghiBeyglou et al.[15]). More specialized architectures go further. ConvLSTM combines convolutional and recurrent processing to model spatial and temporal dependencies together, and it reaches the highest average accuracy in this review (Bakhtyari and Mirzaie[3]). Graph Convolutional Networks (GCN) treat EEG electrodes as nodes in a graph linked by functional relationships; Li et al.[10] use them alongside LSTM and CNN components across two independent datasets. Siamese networks (Latifi et al.[9]) learn similarity relationships between EEG samples instead of classifying them directly. Hybrid approaches try to combine the representational strength of deep networks with a lighter final classifier. One example is Karabıber Cura et al.[7], who use a pretrained DarkNet19 network purely as a feature extractor and then apply classical machine learning for classification.

6.3 Model Evaluation Methods

Studies report performance with a mix of standard classification metrics. Accuracy, the proportion of correctly classified samples, is the figure reported most consistently across all fifteen studies, although it can mislead on imbalanced datasets. Precision describes how reliable positive predictions are, and recall (sensitivity) describes how well the model finds actual ADHD cases. Both matter clinically, because false positives and false negatives have different practical consequences. Roughly half of the studies report the F1-score, the harmonic mean of precision and recall. Specificity, the correct identification of control cases, is reported less consistently than sensitivity. The cross-validation strategies used to estimate generalization also vary considerably, including Leave-One-Out, k-fold, Leave-One-Subject-Out and simple holdout splits (Table 2). This inconsistency, discussed further in Section 8, is one of the main obstacles to comparing reported performance fairly across studies.

Table 2. Validation strategies used across the reviewed studies.

Validation Approach	Studies Using It
Leave-One-Out CV (LOOCV)	Maniruzzaman et al.[11]
k-fold cross-validation	Moghaddari et al.[12]; Bakhtyari and Mirzaie[3]; Li et al.[10]
Leave-One-Subject-Out (LOSO)	Karabıber Cura et al.[7]; Kim and Yang[8]
Holdout train/test split	Bansal et al.[4]; Alim and Imtiaz[2] (also 10-fold CV)

Validation Approach	Studies Using It
Not clearly specified	Latifi et al.[9]; Sharma and Singh[14]

7. Comparative Analysis of Reviewed Studies

Comparing the fifteen studies directly, instead of describing them one by one, shows which methodological choices tend to go together and where performance differences are better explained by dataset or validation choice than by the algorithm itself. Table 1 shows that ten of the fifteen studies use the shared public dataset (or a near-identical version), while five rely on independently collected private samples. The private-dataset studies are smaller but benefit from direct clinical confirmation of diagnosis. The public-dataset studies amount, in effect, to repeated re-analysis of one underlying sample rather than independent tests of the field's core hypothesis.

Preprocessing pipelines differ more in rigor than in basic approach. Most studies apply band-pass and notch filtering plus fixed-length segmentation, but they diverge sharply on artifact handling: some use formal ICA-based artifact removal, while others feed raw EEG into a CNN on the assumption that the network can learn to absorb the noise. The feature and classifier choices show the same chronological drift toward automatically learned representations described in Sections 5 and 6. Validation strategy (Table 2) differs enough between studies that reported accuracies are not directly comparable even when the dataset is identical.

It would be a mistake to read Table 1 and conclude that the study with the single highest accuracy, Bansal et al.[4] at 99.42%, has the "best" method in this review. Three factors complicate that conclusion. First, validation strategies differ in strictness. Leave-One-Subject-Out validation, used by Karabıber Cura et al.[7] and Kim and Yang[8], stops any one subject's data from appearing in both the training and test sets, which makes it a more conservative and arguably more trustworthy estimate of real-world performance than a simple holdout split. Second, small datasets inflate variance, as the 96.6–99.9% accuracy range that Karabıber Cura et al.[7] report across just 33 subjects shows. Third, eight studies share the same underlying dataset, so differences in their accuracy more plausibly show how aggressively each pipeline was tuned to that one sample than a real, generalizable gain in diagnostic capability. The more defensible reading of this comparison is that the most trustworthy evidence comes from studies that combine an independent dataset, subject-wise validation and transparent reporting of both segment- and subject-level performance, such as Moghaddari et al.[12] and Li et al.[10], even where their raw accuracy is not the highest reported.

8. Discussion and Research Gaps

8.1 Dataset Overlap and Small Sample Sizes

The most important pattern in this review is that eight of the fifteen studies rely, wholly or partly, on the same 121-child public dataset. On the surface this convergence looks reassuring, as if the field had independently confirmed that EEG-based machine learning can detect ADHD reliably. In reality it mostly reflects repeated optimization against one relatively small, single-site sample with a narrow age range, not independent replication. Sample sizes across the review, from 33 to 168 participants, are modest by machine learning standards, and samples this small inflate the variance of reported performance, as the wide accuracy range in Karabıber Cura et al.[7] shows directly.

8.2 Inconsistent Validation and the Segment-versus-Subject Problem

The reviewed studies use at least five distinct validation schemes, often without clear justification. A closely related issue compounds this: whether a model is evaluated on whole subjects or on individual EEG segments. A single subject can contribute many overlapping segments, so a model can reach inflated segment-level accuracy by learning subject-specific signal characteristics instead of genuine ADHD-related patterns, particularly when segments from the same subject land in both training and test sets. Moghaddari et al.[12] report both subject-based accuracy (98.48%) and segmented-sample accuracy (99.06%), which is one of the few explicit illustrations of this effect in the reviewed literature. Most other studies do not report both figures, so readers cannot tell how much of a given accuracy would survive stricter subject-level testing.

8.3 Limited External Validation and Narrow Generalizability

Among the reviewed studies, only Li et al.[10] validate their model across two genuinely independent datasets. Without external validation, and given that nearly all studies focus narrowly on children aged 7–12 doing a visual attention task on 19-channel EEG, it is still largely untested how these models would generalize to adults, to resting-state recordings, to other task paradigms, or to children with common ADHD comorbidities.

8.4 Interpretability

Across the reviewed literature there is a visible trade-off between predictive performance and interpretability. Classical approaches built on handcrafted features let predictions be traced back to a specific, physiologically meaningful signal property, whereas deep learning models generally deliver strong raw performance but act largely as black boxes. Only Kim and Yang[8] make a deliberate effort at interpretability, using SHAP values to explain feature importance in an XGBoost model. Clinical adoption of a diagnostic tool typically requires some degree of explainability, so this is an area where the field's technical sophistication has run ahead of its practical readiness.

9. Future Directions

- Larger EEG datasets: collecting and publishing samples well beyond the current 121-subject benchmark would cut the performance variance seen in smaller studies and allow more statistically reliable comparisons.
- Multi-center datasets: pooling data across sites, recording systems and demographic groups would better reflect the diversity a clinical tool will eventually have to handle.
- Cross-dataset validation: routinely testing models trained on one dataset against at least one independent dataset, as Li et al.[10] do, is a more meaningful test of real diagnostic capability than repeated within-dataset validation.
- Standardized preprocessing: a shared, well-documented pipeline would make it easier to separate the effect of feature extraction and classifier choice from the effect of signal cleaning.
- Subject-independent evaluation: Leave-One-Subject-Out or equivalent subject-wise validation should become the default reporting standard, with subject- and segment-level accuracy reported side by side where relevant.
- Explainable and interpretable machine learning: wider use of techniques such as SHAP, attention-weight visualization or saliency mapping would help close the gap between high-performing deep learning models and their practical clinical usefulness.
- Combining EEG with other information: none of the fifteen studies uses non-EEG data, such as behavioral questionnaires or cognitive task performance, alongside EEG. A multimodal approach could plausibly improve both accuracy and interpretability.
- More robust deep-learning approaches: future work should prioritize architectures and training procedures designed to resist overfitting on small datasets, such as transfer learning, EEG-appropriate data augmentation, or lighter architectures less prone to memorizing subject-specific artifacts.

10. Conclusion

This review examined fifteen studies from 2020 to 2025 that apply machine learning to EEG-based detection of ADHD, concentrating on their datasets, feature extraction methods and classification algorithms. The evidence shows that EEG, combined with classical or deep learning approaches, can separate ADHD from control participants with reported accuracies that often exceed 90%, and that feature extraction has moved from handcrafted statistical and nonlinear measures toward automatically learned deep representations. At the same time, our comparison shows that raw accuracy is a poor basis for judging real progress. More than half of the studies share one dataset, validation strategies are inconsistent, and the persistent mixing of segment-level and subject-level evaluation probably inflates several of the higher figures. None of this takes away from the real promise of EEG-based machine learning for ADHD detection. It does clarify what the field needs next: larger and more diverse datasets, subject-independent and cross-dataset validation as standard practice, and a stronger parallel investment in interpretability alongside raw predictive performance.

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