# Detailed Comparative Analysis of EEG-Based Sleep Stage Classification Studies

| Paper / Authors | Year / Source | Objective / Research Goal | Dataset / Sample | Signal Type & Channels | Preprocessing | Feature Extraction | Model / Algorithm Used | Training Details | Evaluation Metrics / Strategy | Quantitative Results | Key Strengths / Contributions | Limitations / Open Gaps |
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| **Wang et al. – Enhancing Automatic Sleep Stage Classification with Cerebellar EEG and ML Techniques** | 2023, Neurocomputing | Investigate cerebellar EEG (ECeG) for improved sleep stage classification | ~25 subjects, simultaneous scalp EEG + cerebellar EEG | EEG + Cerebellar | Bandpass filtering, artifact rejection, epoching (30s) | Frequency features, statistical, entropy measures | SVM, Random Forest, Ensemble | N/A (classical ML) | Accuracy, F1-score, confusion matrix | ~90% avg. accuracy | Introduced cerebellar EEG as complementary input; improved stage transitions | Small dataset; possible contamination from occipital alpha and neck EMG |
| **Wara et al. – Systematic Review on AI for Sleep Stage Classification & Sleep Disorder Detection** | 2024, BSRM Journal | Survey AI methods in sleep stage classification and disorder detection | 50+ studies reviewed | EEG, EMG, EOG, ECG | Varied preprocessing per study | Manual or learned features per study | CNN, LSTM, SVM, RF, hybrid models | Varied per study | Accuracy, F1-score, Cohen's Kappa, comparison tables | Accuracy 80–97% depending on study | Comprehensive mapping of datasets, models, metrics; identifies trends | Lack of standardized evaluation; no quantitative benchmarking across studies |
| **Yousefi & Rahimi – Sleep Disorder Diagnosis Using EEG and LSTM Deep Learning** | 2024, Islamic Azad University | Develop LSTM-based model to diagnose sleep disorders | Public EEG dataset, ~197 recordings | Multi-channel EEG | Filtering, normalization, epoching | Bandpower, spectral entropy, statistical | LSTM | Adam optimizer, 50 epochs, batch size 32 | Subject-independent cross-validation | 93–95% accuracy | Strong temporal modeling; handles sequential EEG | Limited interpretability; overfitting risk; lacks external validation |

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| **Zekriyapanah & Farjamnia – EEG Sleep Stage Classification with CWT and Deep Learning** | 2025, MUST Journal | Use time-frequency CWT for deep learning-based sleep staging | Sleep-EDF, single & multi-channel EEG | Single/multi-channel EEG | Filtering, normalization, 30s epoching | Continuous Wavelet Transform images | CNN | SGD/Adam optimizer, 100 epochs | k-fold CV, subject-independent | 92–94% accuracy, Kappa ≈0.83 | Rich time-frequency representation; robust feature extraction | Computationally intensive; sensitive to CWT parameters |
| **Jiajun Zhong – Dynamic Multi-Scale Feature Fusion for Robust Sleep Stage Classification** | 2023, Southwest Minzu University | Improve single-channel EEG staging using multi-scale fusion | Sleep-EDF & MASS datasets | Single-channel EEG | Filtering, normalization, epoching | Multi-scale temporal/frequency features | Multi-branch CNN + dynamic fusion module | Adam optimizer, 60 epochs, batch 64 | Leave-one-subject-out CV | 88–91% accuracy | Robust to non-stationarity; suitable for wearable/home devices | N1 misclassification; limited cross-dataset validation |
| **Liu et al. – PicoSleepNet: Ultra Lightweight Sleep Stage Classification using Spiking Neural Network** | 2024, Neurocomputing | Develop ultra-lightweight SNN for embedded EEG devices | Public single-channel dataset | Single-channel EEG | Standard filtering, spike encoding | Time-domain spike encoding | Spiking Neural Network | Custom SNN training; low-resource hardware | Accuracy, power consumption, memory usage | 86–90% accuracy; very low energy and parameter count | Energy-efficient; suitable for embedded systems | Early-stage research; limited benchmarking |
| **Zhu et al. – Research on Sleep Stage Classification Based on CNN + LSTM** | 2024, Guangdong Medical University | Combine CNN and LSTM for improved temporal/spatial EEG features | Clinical EEG dataset (~100 subjects) | Multi-channel EEG | Filtering, epoching, normalization | CNN-extracted features + statistical | CNN + LSTM hybrid | Adam optimizer, 80 epochs | 5-fold CV, subject-independent | 92% accuracy | Captures spatial & temporal patterns; improved N2 detection | Large model size; computationally heavy |
| **Singh et al. – EASM: Efficient AttnSleep Model** | 2024, Springer Nature | Detect sleep apnea from EEG | Public apnea dataset | Single-channel EEG | Filtering, epoching | Temporal + spectral attention features | Attention-based CNN | Adam optimizer, | Accuracy, Sensitivity, | 94.8% accuracy, AUC=0.96 | Attention maps improve | Focused on apnea, not full |

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| **for Apnea Detection** | | using attention-based model | | | | | (AttnSleep variant) | 100 epochs | Specificity, AUC | | interpretability; high efficiency | sleep staging; dataset-specific |
| **Ito & Tanaka – SleepSatelightFTC: Lightweight and Interpretable Model** | 2023, IEEE Transactions | Lightweight interpretable model for single-channel EEG sleep staging | Sleep-EDF & MASS datasets | Single-channel EEG | Filtering, epoching, normalization | Combined time & frequency embeddings | Dual-branch CNN with self-attention | Adam optimizer, 60–80 epochs | Subject-independent cross-validation | 91–93% accuracy, Kappa ≈0.84 | High interpretability; efficient; real-time feasible | Requires broader validation; explainability needs clinical verification |