## Seizure Detection Based on Statistical Features and Deep Learning Classifiers

The field of seizure detection has seen significant advancements with the integration of deep learning classifiers and statistical feature extraction techniques. Traditional machine learning models such as Support Vector Machines (SVMs) and Random Forest classifiers have demonstrated reasonable success, but they often require extensive feature engineering and do not always generalize well across different datasets. In contrast, deep learning models, particularly Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and hybrid models, have shown superior performance by learning complex patterns directly from raw EEG data. This section reviews the state-of-the-art methods in seizure detection using statistical features and deep learning classifiers, analyzing the effectiveness of different approaches in terms of accuracy, interpretability, and real-time applicability.

## 1. Seizure Detection Using Statistical Features

EEG signals are highly complex, non-stationary, and exhibit significant variability in spectral and temporal domains. To extract meaningful patterns for seizure classification, various statistical feature extraction techniques have been employed. These features can be broadly categorized into four groups:

1. **Time-Domain Features**: These include mean, variance, skewness, kurtosis, zero-crossing rate, and line length, which help quantify the amplitude and distribution of EEG signals over time (Tzallas et al., 2007).

2. **Frequency-Domain Features**: Features such as power spectral density (PSD), spectral entropy, and spectral energy are derived from transformations like the Fourier Transform to capture rhythmic patterns associated with seizures (Sharmila & Geethanjali, 2019).

3. **Time-Frequency Transformations**: Techniques like Short-Time Fourier Transform (STFT), Discrete Wavelet Transform (DWT), and Empirical Mode Decomposition (EMD) are used to capture both spectral and temporal information, improving seizure onset detection accuracy (Faust et al., 2015).

4. **Non-Linear Features**: Methods such as Approximate Entropy, Sample Entropy, Fractal Dimension, and Hjorth Parameters are applied to model the complexity and randomness of EEG signals during seizure episodes (Ein Shoka et al., 2023).

These statistical features are often used as inputs to deep learning models, enhancing their classification performance by providing structured, domain-specific information.

## 2. Deep Learning-Based Seizure Detection

Deep learning models have revolutionized seizure detection by automatically extracting hierarchical features from EEG signals, eliminating the need for manual feature selection. Unlike traditional machine learning classifiers, deep learning models are capable of capturing both spatial and temporal dependencies in EEG recordings, leading to improved accuracy and generalizability.

### 2.1 Convolutional Neural Networks (CNNs)

CNNs have been widely used in seizure detection due to their ability to learn spatial patterns from EEG spectrograms or raw signals. CNN architectures apply convolutional filters to capture localized signal variations, making them effective for seizure detection. Several studies have demonstrated the effectiveness of CNNs:

- **Alhussein et al.** (2023) developed a **CNN-LSTM hybrid model**, achieving **99.02% accuracy** on the CHB-MIT dataset by integrating convolutional layers with recurrent layers to capture both spatial and temporal dependencies.

- **Mekruksavanich et al.** (2025) incorporated an **attention mechanism** into a CNN model, improving interpretability while maintaining high accuracy. The attention mechanism helps the model focus on the most relevant EEG regions during classification.

### 2.2 Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs)

Recurrent Neural Networks (RNNs) are particularly effective for sequential data analysis, making them well-suited for EEG-based seizure detection. LSTMs and their variant, BiLSTMs (Bidirectional LSTMs), are designed to capture long-term dependencies in time-series EEG data.

- **Zhao et al.** (2024) proposed a **Residual BiLSTM (ResBiLSTM) model**, which integrates residual learning with bidirectional LSTMs, achieving **95.03% accuracy** on the TUH Seizure Dataset. The residual connections helped prevent vanishing gradient issues in deep recurrent networks.

- **Cao et al.** (2025) demonstrated that a **hybrid CNN-BiLSTM model** could generalize well across datasets, achieving **100% accuracy** on the Bonn and New Delhi EEG datasets. This model leveraged CNNs for spatial feature extraction and BiLSTMs for temporal feature modeling.

### 2.3 Hybrid Deep Learning Models

Combining different deep learning architectures often leads to improved performance by leveraging the strengths of multiple models. Several hybrid approaches have been proposed:

- **CNN+Autoencoder**: This model uses an autoencoder for unsupervised feature extraction, achieving **98.79% specificity** on the Freiburg dataset (Shao et al., 2025).
- **CNN+LSTM Hybrid**: This architecture integrates CNNs for spatial pattern detection and LSTMs for capturing sequential dependencies, providing robust seizure classification (Hogan et al., 2025).
- **Residual Networks (ResNet) + LSTM**: ResNets extract localized spatial features while LSTMs model long-term temporal dependencies, leading to enhanced seizure detection (Zhao et al., 2024).

## 3. Comparative Analysis of Deep Learning Models

The table below summarizes the performance of various deep learning models on benchmark EEG datasets:

| Classifier | Features Used | Performance (%) | Dataset | Reference |
|---|---|---|---|---|
| CNN+LSTM | Time-Frequency Features | **99.02%** | CHB-MIT | Alhussein et al. (2023) |
| ResBiLSTM | Statistical + ResNet Features | **95.03%** | TUH Seizure Data | Zhao et al. (2024) |
| CNN+Autoencoder | EEG Signal Patterns | **98.79%** | Freiburg | Shao et al. (2025) |
| CNN-BiLSTM | Time-Frequency + DWT | **100%** | Bonn/New Delhi | Cao et al. (2025) |
| ANN | Time-Frequency | **High Accuracy** | EEG Dataset | Tzallas et al. (2007) |

## 4. Observations and Recommendations

1. **Hybrid deep learning models outperform standalone CNNs or LSTMs**, especially when combining spatial and temporal features. Models like CNN-BiLSTM and ResBiLSTM have demonstrated high accuracy across multiple datasets.
2. **Statistical feature selection significantly improves seizure detection accuracy** when combined with deep learning architectures. Feature extraction techniques such as wavelet transform and entropy-based methods contribute to more robust models.

3. **Artifact removal techniques (ICA, PCA, wavelet transform) enhance classification accuracy** by filtering noise and improving signal quality before training deep learning models.

4. **IoT-based real-time monitoring systems**, integrating deep learning models, have improved seizure detection and remote healthcare applications. Wearable EEG sensors combined with cloud-based AI models have enabled real-time seizure prediction and intervention (Ein Shoka et al., 2023).

5. **Future research should focus on explainable AI models**, making seizure detection more interpretable for clinicians. Techniques such as attention mechanisms and deconvolutional networks may help visualize the model's decision-making process.

## 5. Conclusion

Deep learning classifiers, particularly CNNs, LSTMs, and hybrid models, have transformed seizure detection by achieving high accuracy and generalizability. The combination of statistical feature extraction and deep learning architectures has enhanced performance, making real-time and automated seizure monitoring feasible for clinical applications. Future studies should explore **more interpretable AI models, real-time processing frameworks, and personalized seizure detection algorithms** to further improve seizure prediction and intervention strategies.


1. **1.Tzallas, A. T., Tsipouras, M. G., Fotiadis, D. I., Automatic Seizure Detection Based on Time-Frequency Analysis and Artificial Neural Networks, *Computational Intelligence and Neuroscience*, 2007, 080510, 13 pages, 2007. https://doi.org/10.1155/2007/80510**
2. **Ein Shoka, A.A., Dessouky, M.M., El-Sayed, A. *et al.* EEG seizure detection: concepts, techniques, challenges, and future trends. *Multimed Tools Appl* 82, 42021–42051 (2023). https://doi.org/10.1007/s11042-023-15052-2**
3. **Hogan, R., Mathieson, S.R., Luca, A. *et al.* Scaling convolutional neural networks achieves expert level seizure detection in neonatal EEG. *npj Digit. Med.* 8, 17 (2025). https://doi.org/10.1038/s41746-024-01416-x**
4. **Zhao, Wei, Wen-Feng Wang, Lalit Mohan Patnaik, Bao-Can Zhang, Su-Jun Weng, Shi-Xiao Xiao, De-Zhi Wei, and Hai-Feng Zhou. "Residual and bidirectional LSTM for epileptic seizure detection." Frontiers in Computational Neuroscience 18 (2024): 1415967.**

5. **Cao, Xiaoshuai, Shaojie Zheng, Jincan Zhang, Wenna Chen, and Ganqin Du. "A hybrid CNN-Bi-LSTM model with feature fusion for accurate epilepsy seizure detection." BMC Medical Informatics and Decision Making 25, no. 1 (2025): 6.**
6. **Shao, Sihao, Yu Zhou, Ruiheng Wu, Aiping Yang, and Qiang Li. "Application of deconvolutional networks for feature interpretability in epilepsy detection." Frontiers in Neuroscience 18 (2025): 1539580.**
7. M. A. Sayeed, S. P. Mohanty, E. Kougianos and H. P. Zaveri, "Neuro-Detect: A Machine Learning-Based Fast and Accurate Seizure Detection System in the IoMT," in IEEE Transactions on Consumer Electronics, vol. 65, no. 3, pp. 359-368, Aug. 2019, doi: 10.1109/TCE.2019.2917895.
8. Ein Shoka, A.A., Dessouky, M.M., El-Sayed, A. *et al.* EEG seizure detection: concepts, techniques, challenges, and future trends. *Multimed Tools Appl* **82**, 42021–42051 (2023)
9. Ein Shoka, A.A., Dessouky, M.M., El-Sayed, A. *et al.* EEG seizure detection: concepts, techniques, challenges, and future trends. *Multimed Tools Appl* **82**.
10. **Chakrabarti, S., Swetapadma, A., Ranjan, A., & Pattnaik, P. K. (2020).** ***Time domain implementation of pediatric epileptic seizure detection system for enhancing the performance of detection and easy monitoring of pediatric patients. Biomedical Signal Processing and Control, 59, 101930.*** **doi:10.1016/j.bspc.2020.101930**
11. Sharmila, Ashok and Geethanjali, Purusothaman. "A review on the pattern detection methods for epilepsy seizure detection from EEG signals" *Biomedical Engineering / Biomedizinische Technik*, vol. 64, no. 5,
12. Oliver Faust, U. Rajendra Acharya, Hojjat Adeli, Amir Adeli, Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis, Seizure, Volume 26, 2015, Pages 56-64, ISSN 1059-1311
13. Ein Shoka, A.A., Dessouky, M.M., El-Sayed, A. *et al.* EEG seizure detection: concepts, techniques, challenges, and future trends. *Multimed Tools Appl* **82**.
14. Li, Wen, Guangming Wang, Xiyuan Lei, Duozheng Sheng, Tao Yu, and Gang Wang. "Seizure detection based on wearable devices: a review of device, mechanism, and algorithm." Acta Neurologica Scandinavica 146, no. 6 (2022): 723-731.

15. L. S. Vidyaratne and K. M. Iftekharuddin, "Real-Time Epileptic Seizure Detection Using EEG," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 25, no. 11, pp. 2146-2156, Nov. 2017, doi: 10.1109/TNSRE.2017.2697920.