**MiniRocket: A Very Fast (Almost) Deterministic Transform for Time Series Classification**

<https://dl.acm.org/doi/abs/10.1145/3447548.3467231>

**Raw EEG classification with Detach‑Rocket Ensemble**  
Solana et al. (2024) introduce a pruned, ensemble version of ROCKET that operates on 1–2 s windows of preprocessed EEG and MEG without any hand‑crafted spectral or time‑frequency features. They show it recovers channel relevance and matches or exceeds classic ML pipelines on both modalities [arXiv](https://arxiv.org/abs/2408.02760?utm_source=chatgpt.com).

**ROCKET‑driven vs. classic EEG features**  
Mizrahi et al. (BMC Psychology, 2024) compared features extracted by ROCKET on preprocessed scalp‑EEG (μV time series during an arrow‑flanker task) against traditional spectral/time‑domain features in an XGBoost classifier. The ROCKET features boosted true‑positive rates for “insecure” vs. “secure” attachment style classification (88.4% TPR vs. lower for classic features) [BioMed Central](https://bmcpsychology.biomedcentral.com/articles/10.1186/s40359-024-01576-1?utm_source=chatgpt.com).

**MiniRocket subject “fingerprinting” in M/EEG**  
In Frontiers Neuroscience (2023), Solana et al. applied MiniRocket to raw 1 s MEG/EEG resting‑state segments and achieved > 99% accuracy in identifying individuals—demonstrating that random convolutional kernels can pick up highly individual neural signatures without any feature engineering

**Deep 1D‑CNNs (InceptionTime / ResNet / FCN)**

* **EEG‑Inception** (Ce Zhang et al., 2021):  
  An end‑to‑end Inception‑style 1D‐CNN applied to raw EEG for four‐class motor imagery (MI) decoding. No spectral inputs—just band‑passed μV data into stacked inception modules. Achieved ~88–89 % accuracy on BCI IV datasets, with < 25 ms per trial inference [PubMed](https://pubmed.ncbi.nlm.nih.gov/33691299/?utm_source=chatgpt.com).
* **Automated MDD detection with raw EEG** (Rafiei et al., IEEE Access 2022):  
  A customized InceptionTime model on 19‑channel resting‑state EEG (eyes‑closed), end‑to‑end from raw μV. Reached 91.7 % accuracy (full channels) and 87.5 % after channel‐reduction [CoLab](https://colab.ws/articles/10.1109%2Faccess.2022.3190502?utm_source=chatgpt.com).
* **Semantic‑segmentation FCN (ResNet‑18 backbone)** for eye‑blink artefact detection in multi‑channel EEG (IET Signal Processing 2019):  
  Uses a fully‐convolutional network to segment raw EEG traces into “blink” vs. “non‑blink” regions, with > 94 % detection accuracy [IET Research Journals](https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/iet-spr.2019.0602?utm_source=chatgpt.com).

**2. CNN + RNN hybrids**

* **SeriesSleepNet** (Frontiers in Physiology 2023):  
  A two‑stage model—CNN module trained on 30 s of raw EEG per epoch → bi‑LSTM module for inter‑epoch context. Applied to sleep‐stage scoring on raw EEG; exploits end‑to‑end learning without manual feature extraction [Frontiers](https://www.frontiersin.org/journals/physiology/articles/10.3389/fphys.2023.1188678/full?utm_source=chatgpt.com).

**3. Transformer and RNN‑based models**

* **Depression Diagnosis & Drug‑Response Prediction** (Saeedi et al., arXiv 2023):  
  Compares CNN, LSTM, CNN–LSTM, and **Transformer** architectures on raw EEG for (a) MDD vs. control classification and (b) antidepressant responder vs. non‑responder. The Transformer achieved ~97 % accuracy and > 97 % recall on both tasks [arXiv](https://arxiv.org/abs/2303.06033?utm_source=chatgpt.com).

**4. DTW + k‑NN / SVM connectivity features**

* **ERP classification via DTW‑based connectivity** (Al‑Rubaye & Bayat, IEEE 2019):  
  For single‐trial Stroop ERP, computes pairwise Dynamic Time Warping distances between 16 electrodes (1 s epochs) → 120 DTW features → SVM/KNN classification of congruent vs. incongruent stimuli. Demonstrates that raw μV DTW features alone support > 90 % accuracy [biyoklinikder.org](https://biyoklinikder.org/TIPTEKNO19_Bildiriler/115.pdf?utm_source=chatgpt.com).

**Take‑home**

– **InceptionTime** (and its variants) already power state‑of‑the‑art raw‑EEG classifiers in BCI and clinical tasks.  
– **FCN/ResNet**‐style 1D‐CNNs and **CNN+RNN hybrids** (e.g., SeriesSleepNet) handle both spatial (multi‑channel) and temporal context end‑to‑end.  
– **Transformers** are now matching or exceeding CNN/RNNs on EEG classification tasks.  
– **DTW+KNN/SVM** remains a simple, interpretable baseline for single‑trial ERP decoding.

Starting with any of these off‑the‑shelf architectures (InceptionTime, FCN, CNN+LSTM, or a lightweight Transformer) on your 150 → 30 channel data should give you a strong benchmark—then you can compare against MiniRocket or your own SARIMA‑feature pipeline as needed.

Power cluster analyses:  
 **Maris & Oostenveld (2007)** introduced cluster-based permutation tests to control family-wise error in time–frequency data. [Wikipedia](https://en.wikipedia.org/wiki/Electrocorticography?utm_source=chatgpt.com)

 **Kucewicz et al. (2014)** showed that high-gamma (70–140 Hz) power in MTL and cortex predicts recognition memory success. They computed time–frequency power with Morlet wavelets, baseline-corrected to a pre-stimulus window, then compared conditions with cluster-based permutation tests [Wikipedia](https://en.wikipedia.org/wiki/High-frequency_oscillations?utm_source=chatgpt.com).

 **Voytek et al. (2015)** applied similar methods in frontal cortex, showing theta (4–8 Hz) increases during WM maintenance, and high-gamma carries item-specific information