

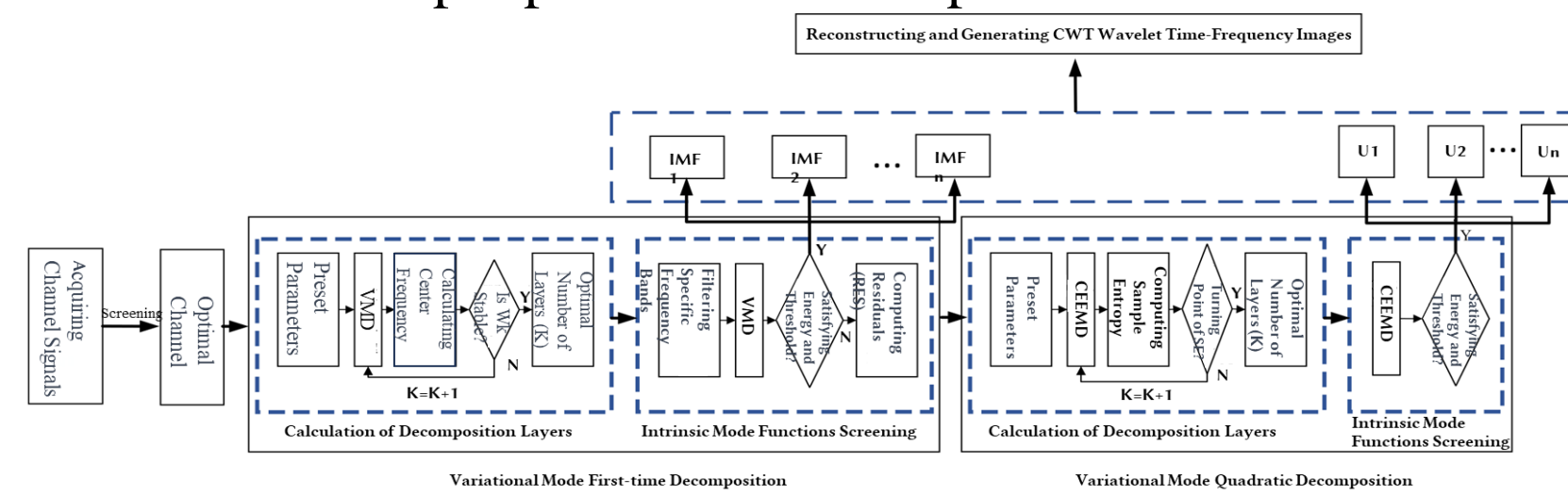
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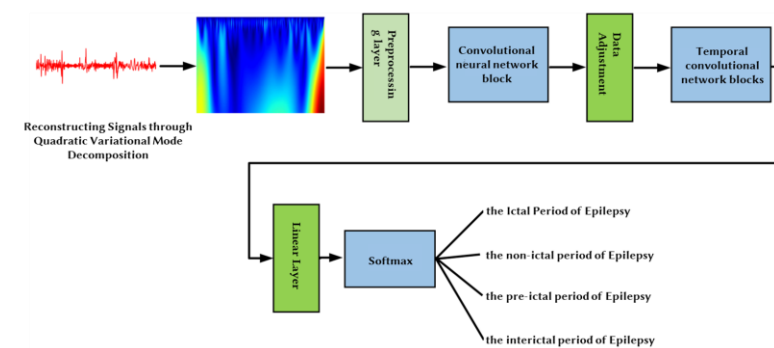
Introduction

Epilepsy involves sudden abnormal brain neuron discharges, leading to symptoms like loss of consciousness and convulsions. Diagnosis uses clinical history and EEG, which records brain electrical activity. Automatic epilepsy detection methods include neural networks and various signal analysis techniques. Traditional methods struggle with EEG artifacts. Empirical Mode Decomposition (EMD) adapts to both time and frequency domains but has limitations. Variational Mode Decomposition (VMD) is a more effective method, and Complementary Ensemble Empirical Mode Decomposition (CEEMD) addresses residual noise. The paper presents a model using Variational Mode Quadratic Decomposition (VMQD), combining VMD and CEEMD for better signal extraction. Continuous Wavelet Transform (CWT) converts signals into time-frequency images, and Convolutional Neural Networks (CNN) with Temporal Convolutional Networks (TCN) analyze these images for improved EEG signal classification.

The model preprocesses data through de-noising, power spectral density analysis, and dynamic channel selection. After preprocessing, it applies VMD on the chosen optimal channel signal for initial decomposition. The residual component is then processed with CEEMD for secondary decomposition. This dual-step approach, depicted below, addresses the nonlinearity and complexity of epileptic signals by calculating decomposition layers and selecting intrinsic mode components, facilitating the classification of epileptic EEG seizure processes.



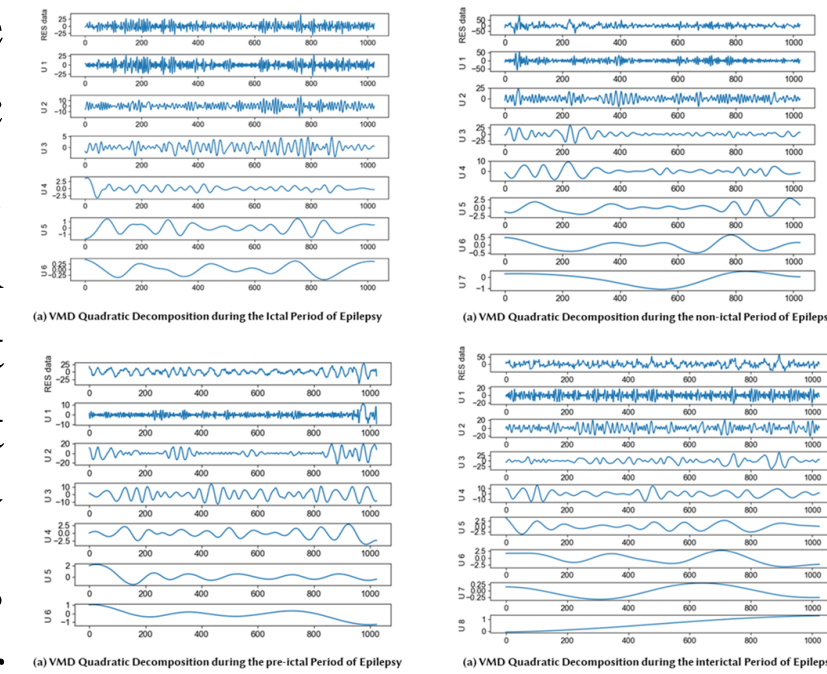
The feature learning module combines a TCN and a CNN to classify EEG signals from epileptic patients. After data variational mode quadratic decomposition, signals are converted into continuous wavelet transform time-frequency images. TCN captures dynamic changes in time series data, while CNN extracts spatial features from the images. This integration enables detailed analysis across temporal and spatial dimensions, enhancing epilepsy classification accuracy and efficiency. As shown in the figure below.



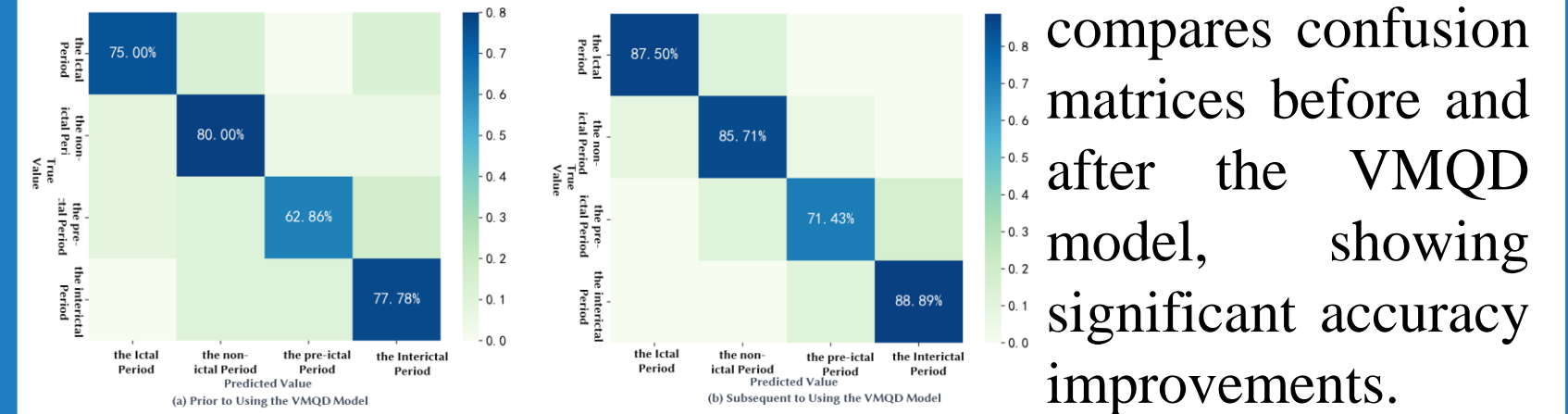
Experiments

This study used the CHB-MIT pediatric epilepsy EEG dataset from Boston Children's Hospital, acquired with the 10-20 international standard lead system. The classification periods of epileptic EEG signals include the ictal period, the non-ictal period, the pre-ictal period, and the interictal period.

The right figure shows the decomposition of epileptic EEG signals into modes (U1, U2, U3, etc.), each representing different frequencies. Significant amplitude and frequency changes during seizures reveal subtle shifts crucial for analysis.



The left figure compares confusion matrices before and after the VMQD model, showing significant accuracy improvements.



The VMQD model outperforms others in classifying epileptic seizures, with Accuracy up 3.0%, Precision 9.38%, Recall 7.2%, and F1-Score 7.6%. This shows the residual term in EEG signals during seizures contains valuable data, and secondary decomposition boosts accuracy.

Evaluation Metrics	Accuracy	Precision	Recall	F1-Score
CNN	82.0%	79.4%	75.2%	76.1
CNN-TCN	82.3%	79.8%	77.5%	74.3
VMD-CNN-TCN	84.0%	80.0%	79.0%	78.5
CEEMD-CNN-TCN	84.5%	82.0%	79.5%	81.9
VMQD-CNN-TCN	85.0%	88.8%	82.4%	83.7

Conclusion

This paper introduces VMQD, an epilepsy classification model combining VMD, CEEMD, and CNN-TCN. It accurately distinguishes EEG signal stages, including ictal, pre-ictal, interictal, and non-ictal periods, with high precision. VMQD enhances time-frequency feature quality, effectively capturing spatial and temporal patterns. It outperforms traditional models, offering robustness and reliability. Future research will expand datasets, refine algorithms, and explore clinical applications, advancing AI in epilepsy research.

Method

The VMQD model consists of two modules: 1) data processing and 2) feature learning. As shown in the figure below.

In the data processing module, the optimal channel is selected from 23 EEG channels. The chosen signals are split into sub-frames for initial variational mode decomposition, and the residual signal is further decomposed. These signals are then reconstructed into time-frequency images using continuous wavelet transform. The feature learning module uses a CNN to extract spatial features and a TCN to capture temporal features from the time-frequency images. This dual approach enhances feature representation and boosts classification accuracy.

