

LONG SHORT-TERM MEMORY MODEL WITH THE EXTERNAL TREND AND INTERNAL COMPONENTS ANALYSIS

O. Inkin, V. Belozyorov

¹*Oles Honchar Dnipro National University, postgraduate student, Ukraine*

²*Oles Honchar Dnipro National University, Doctor of Physical and Mathematical
Sciences, Professor, Ukraine*

Abstract. *This paper presents a modification of a recurrent neural network with long-term and short-term memory for modeling electroencephalogram signals and highlights its potential in predicting pathological conditions. The demonstrated interpretation includes a method for decomposing the external trend and internal components that most characteristically determine the parameters of the input signal. The obtained segmented data, after pre-processing by this method, are further processed by a neural network, which is trained on them with more efficient calibration. As a result, the trained network can reproduce the data on which it was trained and predict the further trend of brain activity. The results show the potential of this approach for both basic neuroscience research and clinical applications in the diagnosis and modeling of neuropathologies.*

Keywords: *EEG, LSTM, ETICA, neural network, modeling, trend decomposition.*

The development of automated electroencephalogram (EEG) analysis systems has become essential for timely medical decision-making, particularly when managing brain-related pathologies where rapid assessment can significantly impact patient outcomes. Medical professionals require sophisticated tools that can provide initial analysis and guidance regarding illness severity or the potential approach of critical periods. Within the complex patterns of EEG signals, the ability to predict future developments holds tremendous clinical value for intervention planning. Recent computational advances have positioned neural signal prediction as a primary focus in cutting-edge research, with recurrent neural networks (RNNs) demonstrating remarkable effectiveness across multiple domains. Long short-term memory (LSTM) networks, an advanced RNN variant, have proven particularly valuable by addressing the vanishing gradient problem through the implementation of memory cells in place of standard hidden layer units, thereby enhancing predictive capabilities [1, 2, 3]. Predictive accuracy can be further enhanced through hybrid or ensemble modeling approaches. Despite these technological advances,

certain EEG time series remain challenging to analyze due to their inherent instability and chaotic nature. The External Trend and Internal Components Analysis (ETICA) decomposition method effectively addresses this limitation by systematically dividing highly fluctuating data into more manageable lower-frequency components, creating a robust foundation for subsequent analysis and prediction tasks [4, 5, 6].

The integration of LSTM networks with outer-trend decomposition and inner-component analysis presents a sophisticated framework for modeling EEG signals that addresses the inherent problems of non-stationarity and complex temporal dependencies in neural data. This methodological approach begins with a thorough preprocessing of EEG signals using bandpass filtering, artifact removal, and segmentation, followed by an ETICA decomposition step that separates the signal into physiologically relevant components - outer trends that capture low-frequency drift, rhythmic components that correspond to neural oscillations in different frequency bands, and transient components that represent event-related potentials. These decomposed elements serve as the basis for further parameter extraction, from which statistical, frequency, and connectivity characteristics are extracted and normalized before being fed into an architecturally optimized LSTM network designed with multiple recurrent layers, carefully calibrated regularization dropouts, and output layers. The network's ventilation mechanism, consisting of forgetting gates, entry gates, and exit gates, allows it to selectively retain relevant historical information while discarding noise, thus modeling both short-term and long-term dependencies characterizing cognitive processes, seizure dynamics, sleep architecture, and various neurological states (Fig. 1).

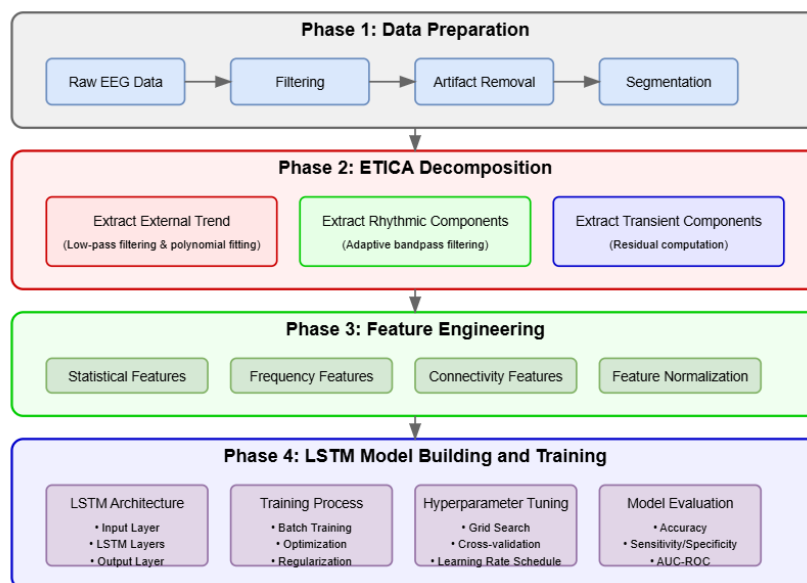


Figure 1 – Architecture LSTM-ETICA model

This synergistic combination demonstrates high performance in creating an interface between the brain and the computer and has the potential to be further adapted to detect abnormal EEG patterns. To demonstrate the results of processing with the described tool, a MATLAB script was developed and some EEG signals with abnormal areas were simulated (Fig. 2).

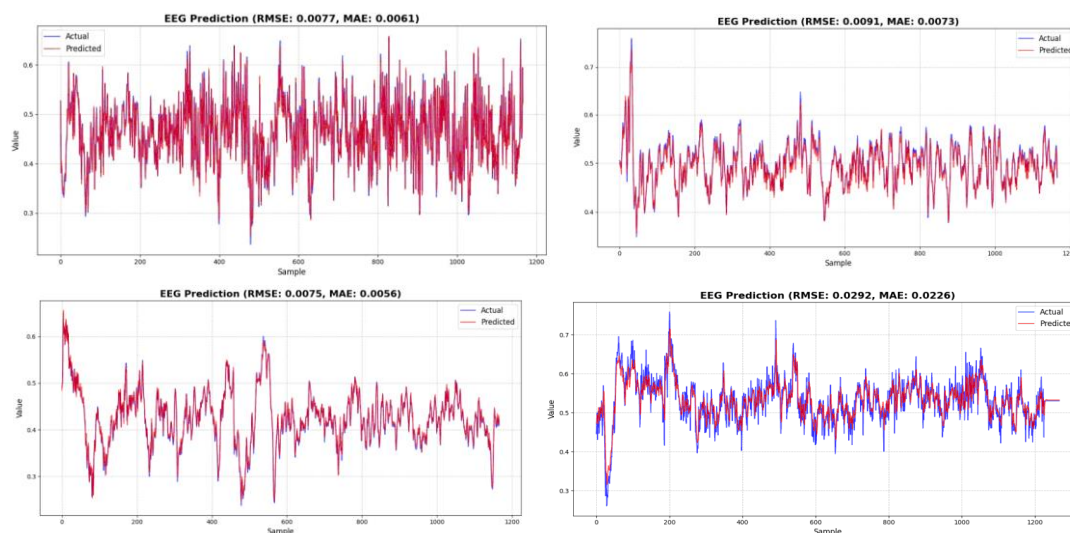


Figure 2 – Result of modeling EEG signals

As a result, the model demonstrated 95% matching accuracy and high data processing performance. However, the forecasting did not yield such encouraging results, but some of the main trends persist (Fig. 3).

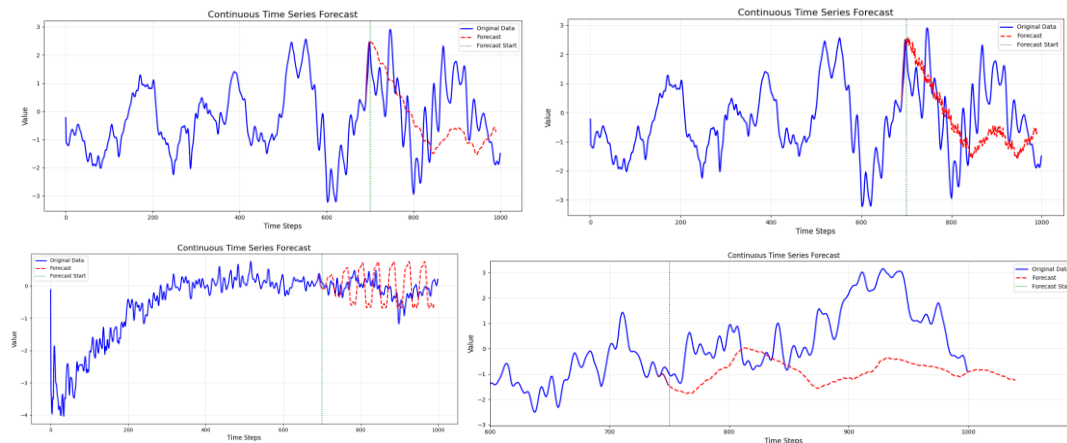


Figure 3 – Result of forecasting EEG signals

Conclusion. The proposed model, which is described in detail in the previous section, is a unique hybrid method that combines LSTM and ETICA decomposition. The ETICA method is first used to decompose the time series into internal components and external trends, which are then predicted separately by the LSTM model. The accuracy of the model's forecast is evaluated using the RMSE and MAE metrics to compare the predicted values with the initial values. In most of the experiments conducted, the average RMSE ranged from 0.007-0.009, and the MAE from 0.005-0.0075. These results indicate that ETICA-ISTM is well suited for EEG modeling and prediction, as it minimizes both the root mean square error and the mean absolute error, providing more accurate and consistent prediction.

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МОДЕЛЬ ДОВГОСТРОКОВОЇ КОРОТКОСТРОКОВОЇ ПАМ'ЯТІ З ВРАХУВАННЯМ ЗОВНІШНЬОГО ТЕНДЕНЦІЙНОГО ТА ВНУТРІШНЬОГО КОМПОНЕНТНОГО АНАЛІЗУ

Інкін О. А., Білозьоров В. Є.

Анотація: У даній роботі представлено модифікацію рекурентної нейронної мережі з довгостроковою та короткостроковою пам'яттю для моделювання сигналів електроенцефалограми та виділено її потенціал в прогнозуванні патологічних станів. Продемонстрована інтерпретація включає метод декомпозиції зовнішнього тренду та внутрішніх компонент, які найбільш характерно визначають параметри вхідного сигналу. Отримані сегментовані дані після попередньої обробки зазначеним методом в подальшому обробляються нейронною мережею, яка на них навчається з більш ефективним калібруванням. В результаті, навчена мережа може відтворювати дані, на яких вона була навчалась та спрогнозувати подальшу тенденцію мозкової активності. Отримані результати свідчать про потенціал цього підходу як для фундаментальних нейронаукових досліджень, так і для клінічного застосування в діагностиці та моделюванні нейропатологій.

Ключові слова: EEG, LSTM, ETICA, нейронна мережа, моделювання, декомпозиція тренду.

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