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MULTI-CHANNELS DEEP CONVOLUTION NEURAL NETWORK FOR EARLY CLASSIFICATION OF MULTIVARIATE TIME SERIES

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Abstract

Today, many time series forecasting approaches require data pre-processing and analysis to make accurate predictions. This study uses Deep Neural Networks to examine the performance of the most popular Time Series estimators on a variety of EEG sensing field series (DNN). All DNN models have automated hyper-parameter search. So it may be used on the EEG dataset without understanding the model. These advertisements were automatically launched using internal feature extraction and benchmarking of 61 EEG features. Deep learning-based DNN model that refined data engineering with 97.00% accuracy performed well in the research. The thesis evaluates two shallow networks, one DNN and one LSTM, to overcome this limitation and better explain DNN outcomes in time series classification. We broaden the few experimental parallels to include a baseline study of the two categorization fields for time series, where studies are scarce. We designed an extensible experiment structure and cross validated our models on three datasets to do this. Engine-operating depressives are classified. The method tested DNN and LSTM independently for each dataset and is generalizable to other neural network models for comparison research. Basic DNN performs like LSTM and trains faster. When DNN uses more workouts, we notice a balance in seconds and repeats. DNNs are better than LSTM for time series classification due to their efficiency and faster preparation.

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Introduction

Dataset forecasting is used to anticipate stock prices, exchange rates, and employment levels in corporations. Climate scientists use it to estimate wind speeds, daily minimum temperatures, and ballpark precipitation [1]. When evaluating climate data, organizations may need to plan for unexpected sales spikes or avert natural disasters. [2] uses these examples to demonstrate the response variable's predictive power. Time series forecasting, which is crucial in economics, meteorology, business, science, and industry, still involves examining the past or present to predict the future [3]. Fitting and predicting a series with one model is difficult since each signal and series has its own strengths and correlations to external factors. As noted in [4], researchers, actuaries, and economists have devised various studies and models throughout the years to boost prediction precision. Thus, several Time series models have been adopted or improved, but as noted in [5], just because there are many options does not mean they are all successful.

Sequential modeling issues have made ANN popular in recent years. CNN has becoming more popular for sequential issues, even if LSTM and GRU perform better in language processing. In order to draw comparisons with LSTM, [6] investigates the application of CNNs to time series, a domain where conventional techniques have been utilized. We seek to understand the potential application domain for time series categorization after CNN language advancements. As indicated in [7], we compare three medical, electrical, and sports applications to comparative studies that used linguistic activities as their default benchmarks. These recurring events are not temporal sequences. Time series modeling also uses field-established approaches. Common strategies use simple or complex regression analysis. Status space models, autoregressive moving averages, and autoregressive models are examples. Multivariate time series, unlike univariate ones, measure numerous phenomena or variables. We will study prediction models for time series with a single independent variable. Since there are two sorts of time series, discrete and continuous, the recording method can also be applied to differentiate between the two. According to [8], discrete time series are observations made at regular intervals (sampling). (monthly, quarterly, yearly) This temporal pattern is widespread (for example, the tracking of the unemployment rate, which is commonly monitored every quarter). Continuous time series are denser (due to the fact that they are continuous). This dissertation robustly categorizes time, a necessity for vision-based algorithms to classify natural time series. As mentioned in [9], times are key for human connection and many important everyday duties. Digital image time and distance measurement has changed science, gaming, and animation. Factory automation, virtual reality, disability care and rehabilitation, and performance evaluation have also been automated [10].

Aim of Study

Time series analysis is used to forecast the future by analyzing the past and present. This study compared LSTM and unidimensional DNN time series categorization. DNNs were tested for their ability to replace conventional methods in dynamic domains like time series. Time series neural network modeling is in its infancy. Despite the lack of comparable studies, DNN-based models have shown promise. Forecasts will employ the most accurate data capture model. Predictions will be made using a forecasting model. I. Endogenous variables—the series' previous values determined by a deep neural network—are univariate time series' two most crucial variables.

Multivariate time series forecasting requires deterministic exogenous components (explicative variables) (like calendar data).

This experiment uses no exogenous medications. The data-optimal model is used to predict the series' future values. Predictions can be made short-term or long-term. This estimating method considers Time Series granularity and frequency. This is the most unique time series forecasting solution for corporations and other organizations (using the most data that is currently available). Due to the information's granularity, our estimators should be accurate up to a sub-horizon, after which we retrain them.

1.Background

The user can attach specialist equipment to their body to inspect joints and geometry. It's unpleasant and unusual. Specialized equipment might be expensive. Vision-based apps are suggested for their usability, low cost, and natural feel.

Convolutional neural network time detection algorithms use RGB camera and picture color information. [11] predicted that RGB cameras will soon record depth data alongside RGB images to help viewers grasp object size, shape, and distance. These color and depth pictures can recognize and track an object, as anticipated in [12]. We used depth, skin color, and CNN data to develop a 3D time-tracking system to enhance digital images.

Computer mice, keyboards, and remote controls control machinery. This human-robot interface will likely improve over time. Numerous trials have modified human-machine interface techniques and components [13]. It's like programming a computer or robot. As humans connect socially, machines should too. A small improvement. Time series should help it understand commands and human behavior.

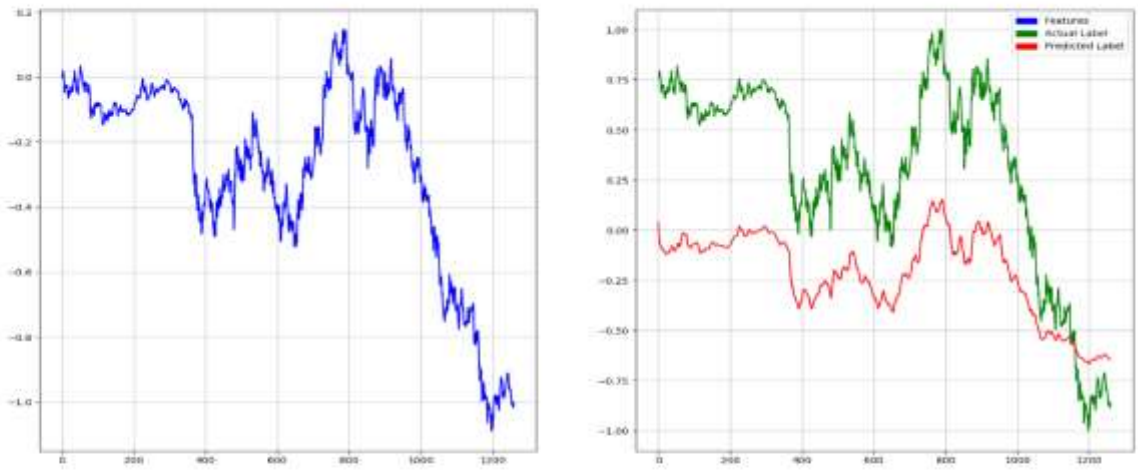


Figure 1: The close examination of the time series understands why feature values as the time series varies slightly (in value) between train and test data sets [12].

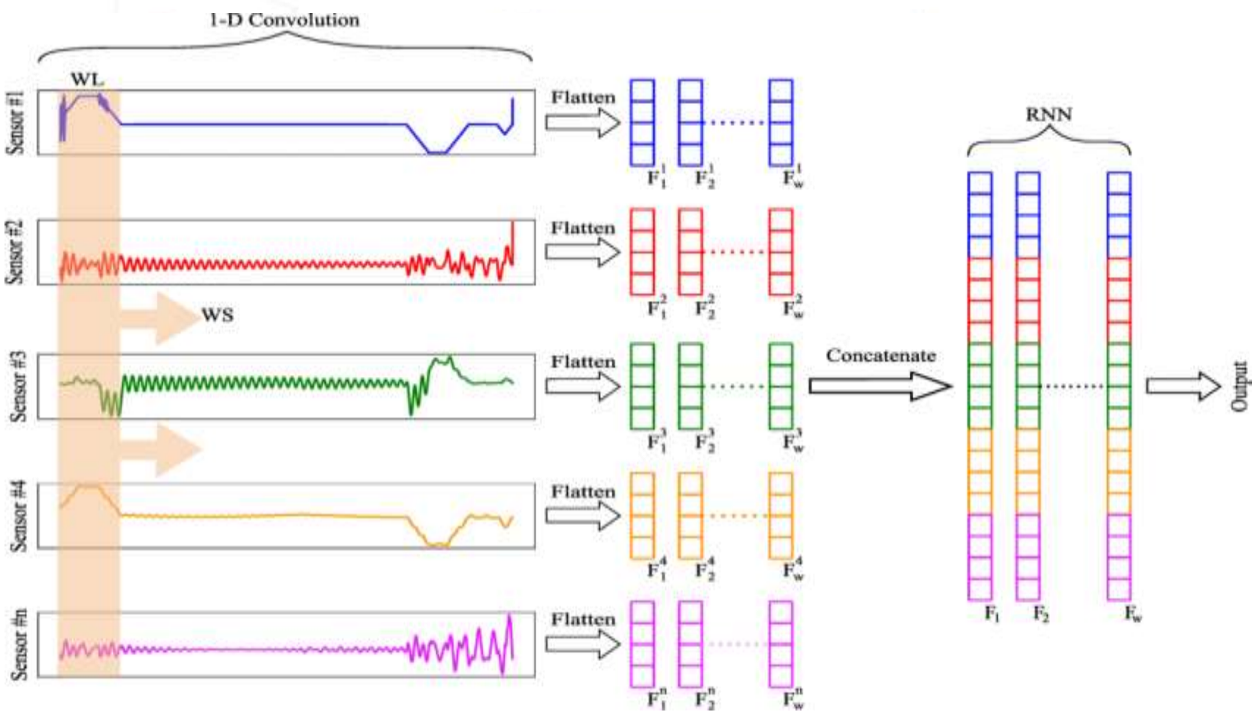


Figure 2: Time series detection using CNN since all signals in the sensors are detected, the letters on the flatten of origin sticker are found as well with concatenation [14].

According to [18], time motion tracking tracks times in 3D space one frame at a time in real time. Tracking algorithms often consider dimensions, color, and geometry. Algorithms generally miss tracking and must be re-initialized [19]. Skin masks conceal the wearer while revealing time. Without a clear skin mask, depth perception has no value for timing. Rigorous criteria reduce false detection but reduce data accessibility [20]. There must be a tradeoff between faulty skin segmentation and accurate tracking. The tracking algorithm will suffer. Misleading skin signs and noise will increase missed diagnoses if detection thresholds are too high.

With a complicated background, the skin model and assumption that the ROI is constantly in motion can be used [22]. In uncontrolled situations with fluctuating lighting, however, erroneous skin detection has been recorded. Motion segmentation can find variations between the dynamic foreground and static backdrop [23]. Basic temporal segmentation reduces skin detection errors. Tracking moving pixels uses two methods [24]. Remove frames first. The camera's noise sensitivity limits identification accuracy, although time or facial movement can reveal and conceal background elements [25].

Similar to the challenge of acquiring information from time series, our purpose of classifying and detecting time series shares similar features. Time series signals' rectangle shape simplifies text interpretation. Therefore, it is essential to locate them in the image and use Optical Character Recognition (OCR) software to extract the text. [26] proposes finding and monitoring time series plates for EEG signal regulation. Maximally Stable Extremal Regions locate the time series plate in the supplied image (MSER).

2.Methodology

There are three series that can be utilized: static, dynamic, or both. Figure 3 illustrates how a static time series can transmit information not through the passage of time, but rather through a complex combination of several places and indications. Some individuals use a limited range of arm movements to imitate a trajectory. The fact that human series are meant to work in tandem with factory workers is particularly pertinent in this instance. This section will describe the primary time trajectory motions required to analyze a simple time series set.

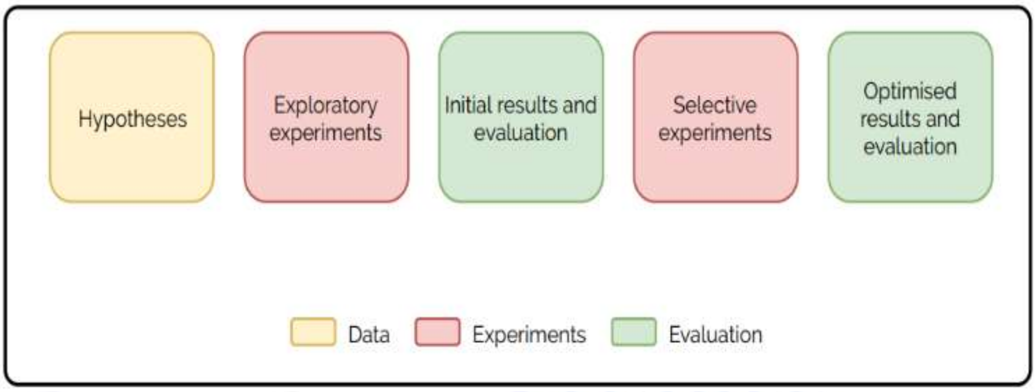


Figure 3. General level experiment design for this research.

2.1 Dataset Description

The UCI open-source repository provided the time series EEG steady-state visual evoked potential signals data set. We employ the same reasoning we used to develop the DNN model's helper function that automates the optimal parameter search. In the case of the DNN model, we constructed a series function that will serve as a helper function for determining the model's optimum parameters in a timely manner. The dataset can be downloaded from an open-source repository:https://archive.ics.uci.edu/ml/datasets/EEG+SteadyState+Visual+Evoked+Potential+Signals

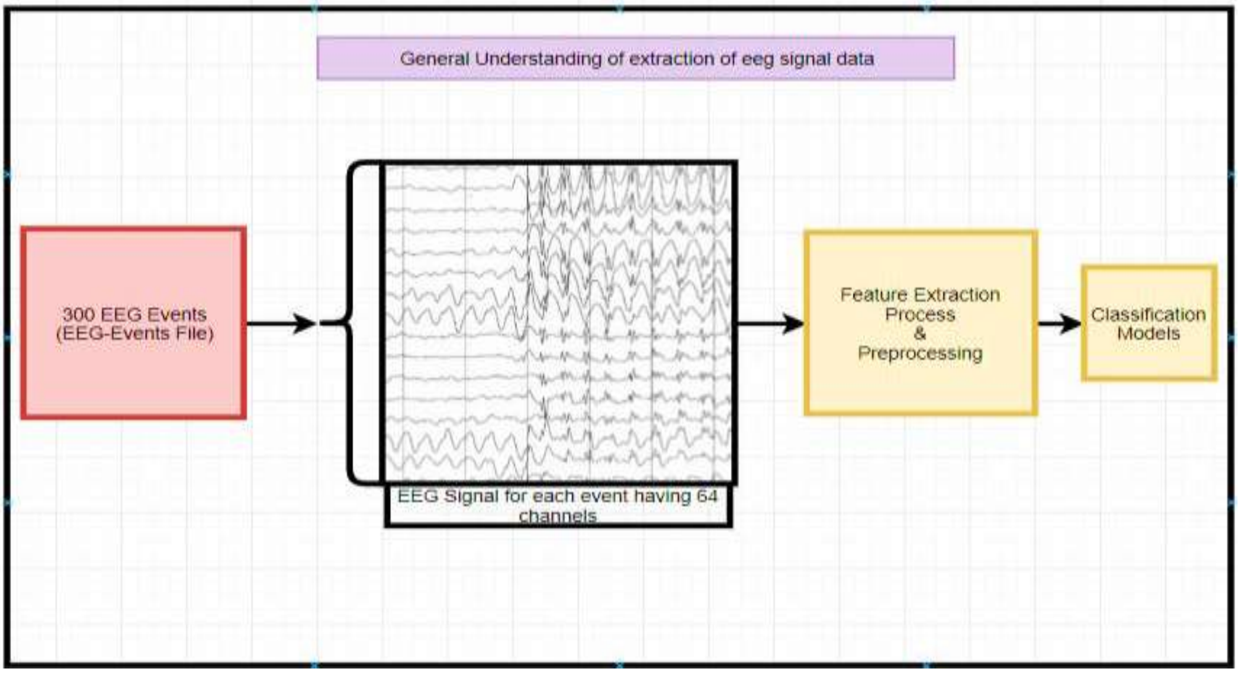


Figure 4. General description of data extraction and feature extraction for DNN model.

2.2 Deep Neural Network Architecture

Time series forecasting with Deep Neural Networks (DNN) is growing, especially for large datasets. DNN mimics complex non-linear models and adapts to data. Since DNNs are general-purpose estimators, we must take extra steps to make sure our network meets the needs of the many learning tasks we plan to use it for. Our experimental methodology is described here. We will just present a high-level overview of the useful units and architecture for this study, assuming the reader is familiar with deep learning approaches. We used mean, standard deviation, variance, kurtosis, and skewness. Deep learning model evaluation requires a large moving window. We tried several techniques. Because the window size was fixed, the initial model automation technique was simple. Because of their core nature, DNNs may employ data ordering to process time series better than other data types. We offer a method to build and optimize a deep learning DNN model using a dataset. Our exploratory heuristics yielded the best results. Our DNN models used only two of the numerous DNN units analyzed. Our research used the Sequence to Sequence with Dense Layer framework, which takes a sliding window and outputs a series. Online schooling allows a predetermined set of rules to guide behavior throughout a state shift. This will let the algorithm adapt to novel dynamic circumstances. Control, gaming, information, and AI have investigated this technique. Figure 3.2 contrasts the three common methods. Sparse coding with hierarchical matching pursuit is an exciting study. Language and series models characterize an object. Robots learn by seeing people grasp for specific-sized and-colored items. Sparse coding extracts an input signal from large data without labeling. Thus, datasets can extract higher-level properties without costly feature set construction. Dictionary learning (DNN) uses sparse linear code words to represent data.

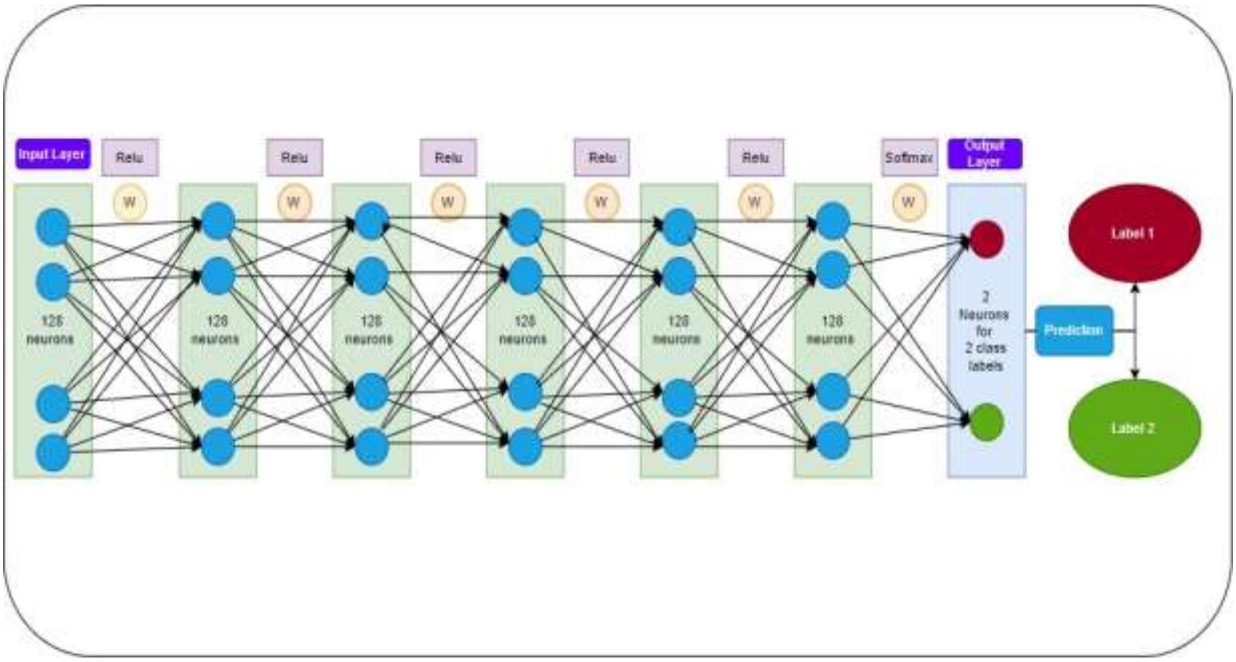


Figure 5. The deep neural network architecture.

This paradigm enables us to create long-term value projections (predict points). As we are interested in the model's capacity to predict the future, we chose this method so that we would not introduce any additional mistake by using previous projected values as input for subsequent predictions. In our benchmarking method, we subjected four notable models to rigorous testing. Using heuristics, all parameters are automatically determined.

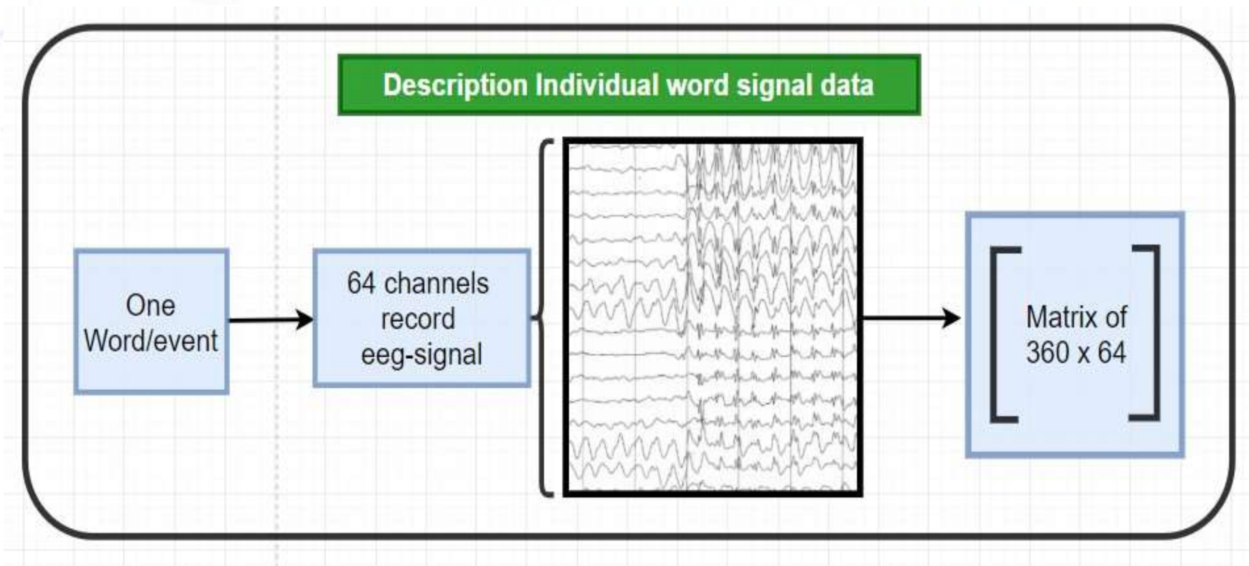


Figure 6. Processing the individual EEG signal extraction with 64 record channels in DNN.

3. RESULTS

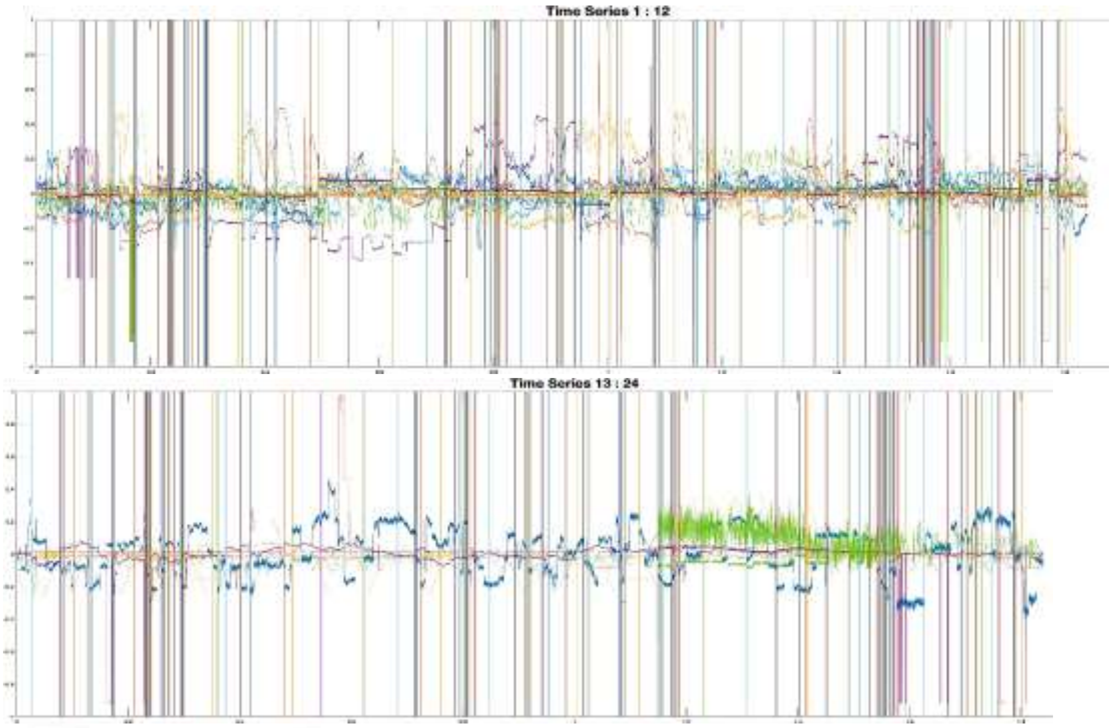
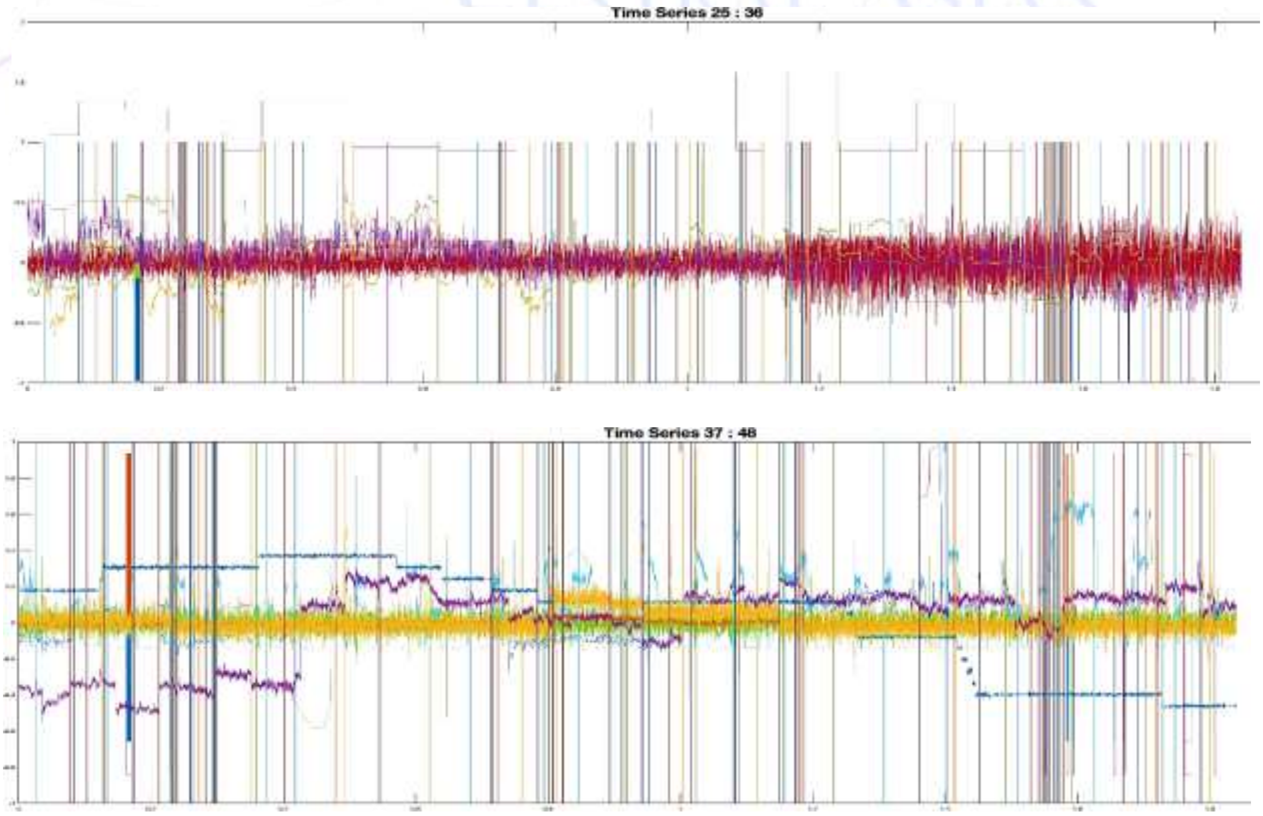


Figure 8. Visualization of processed EGG classified data from feature 1-24 using DNN.



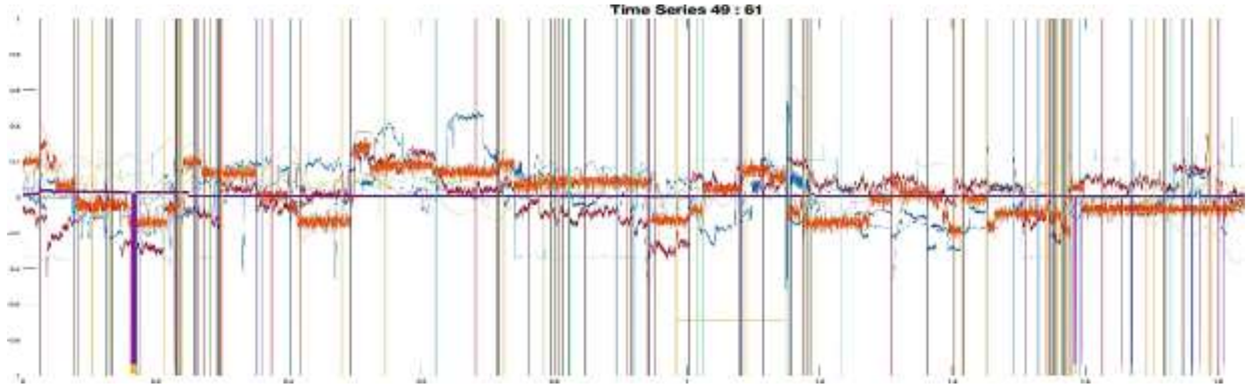


Figure 9. Visualization of processed EGG classified data from feature 25-61 using DNN.

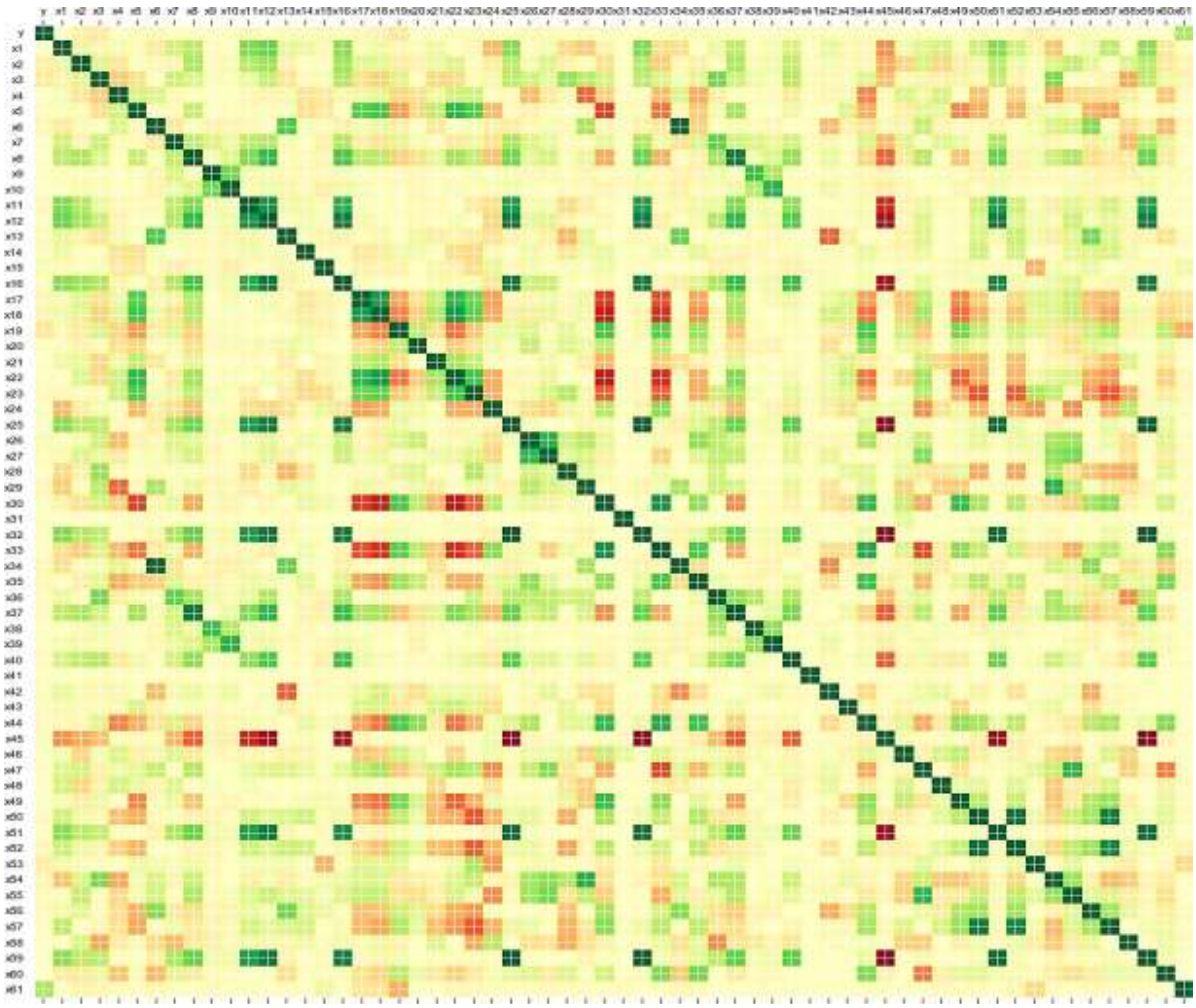


Figure 10. The Heatmap of EEG time series classification by correlation of X variables with y for all features 1-61.

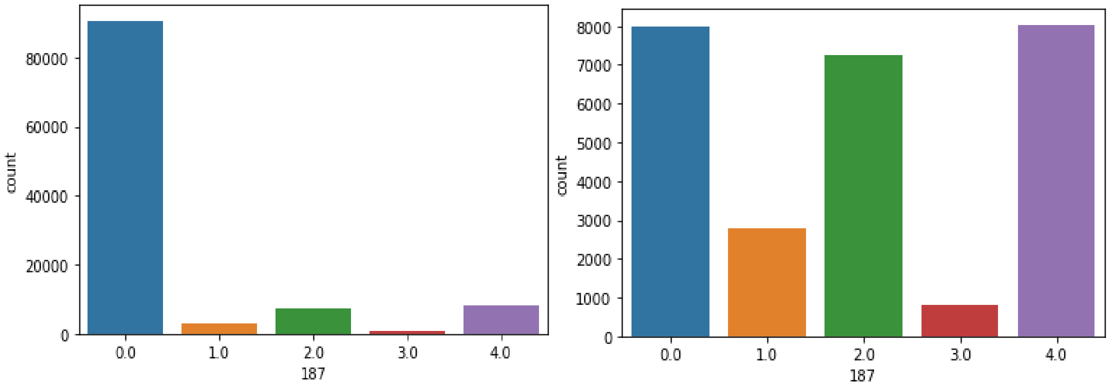


Figure 11. The overall data representation and scaling for neural network.

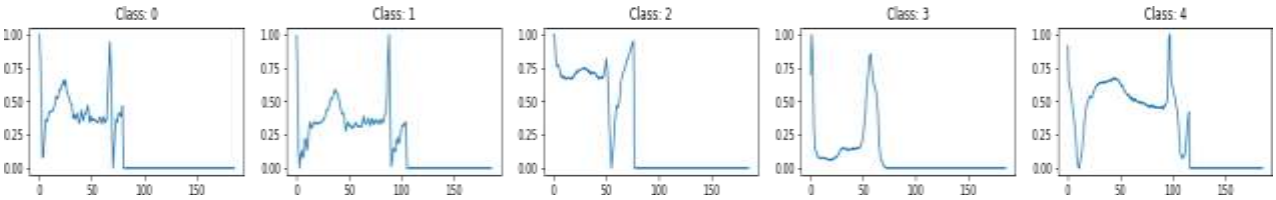


Figure 12. We Plots the Classification of classes as seen named Form Class-0 to Class-4.

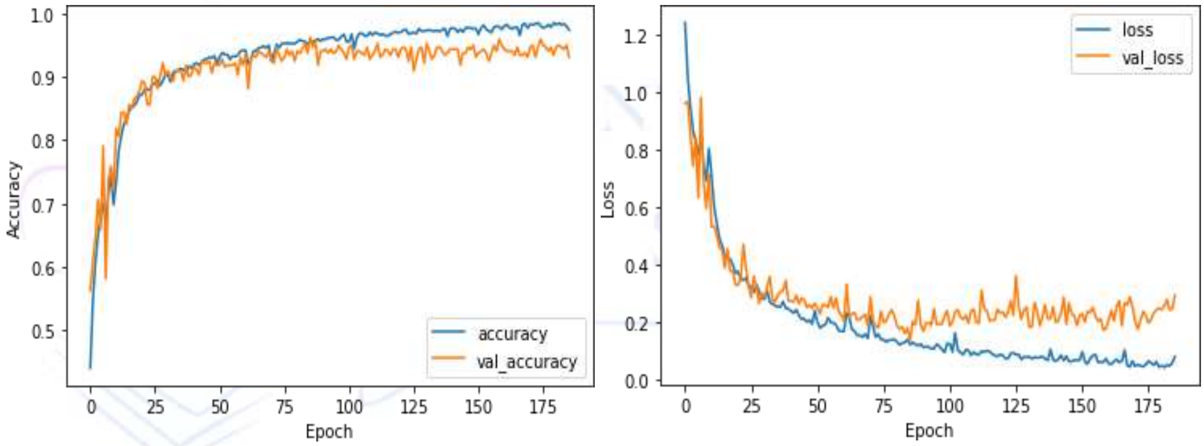


Figure 13. We plot the model Accuracy and Val_ Accuracy along with Loss and Val Loss.

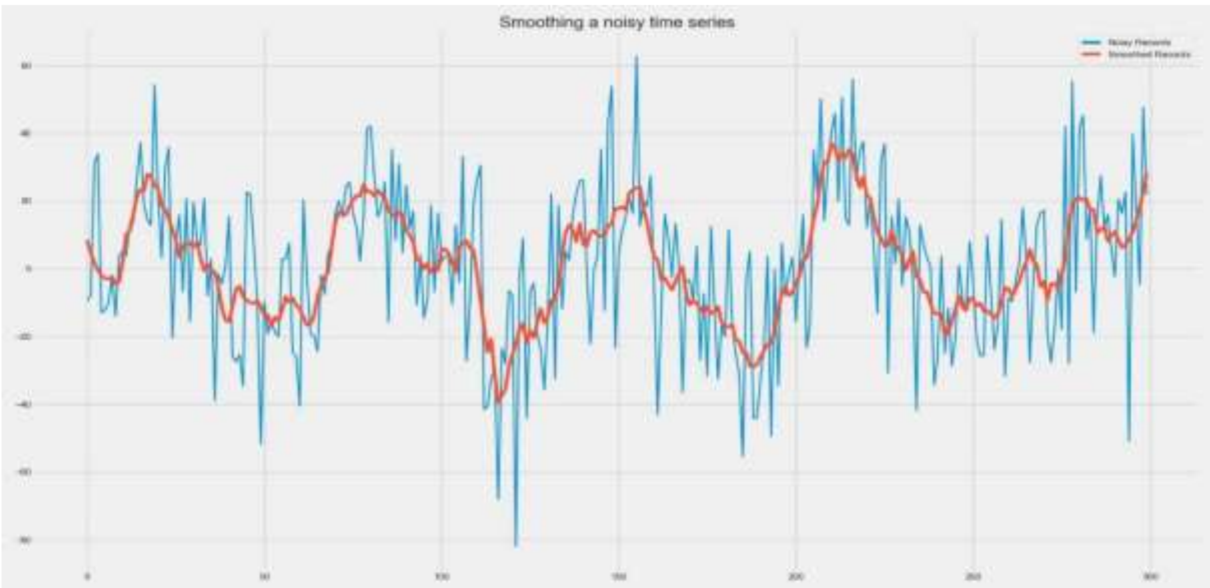


Figure 14: Smoothing a EEG time series classification using DNN model.

Table 2: The comparison of DNN accuracy with existing techniques.

Article	Technique	Accuracy
[23]	Long Term Short Memory (LTSM)	96.30%
[24]	Convolutional Neural Network (CNN)	95.98%
Proposed	Deep Neural Network (DNN)	97.00%

4.Conclusion

This study categorizes time data using deep neural networks (DNN). This study used EEG datasets of varied sizes and topics. According to data analysis, DNN performs best among time series classification rivals. However, this investigation found certain weaknesses and suggested solutions. This study used internal feature extraction and benchmarking of EEG signals of 61 different features to automatically launch these campaigns, allowing a full comparison of models across EEG datasets. Deep learning-based DNN model that refined data engineering with 97.00% accuracy performed well in the research. We performed multiple tests in three applications to better understand CNN's effect on time-series classification and to compare LSTM. First, we identified depressive individuals using engine operation and outcomes that increased baselines for both versions. Second, we forecast EV energy demand and found significant improvement potential. Our findings provide potential research grounds. Third, a multi-label grouping problem estimated preparation. Positive results showed statistical algorithms might use contextual factors to understand preparation. As training samples rise, augmentation influence decreases. Having more time sequences in a larger training set may explain this. Synthetic samples are tougher to give fresh information. The classifier also avoids overfitting. Training examples increase time pose visual quality. More samples per class would increase visual distinctions between action category sequences. Synthetic samples, which appear high-quality to humans and so have a higher inception score, should have a greater impact on data augmentation. DNNs need a lot of training data to produce samples that look like the originals. More training samples lower the beneficial enhancement effect. This project found no association between the aesthetic look of generated sequences and categorization accuracy. Initially counterintuitive. The thesis achieved its key goals. Implemented architecture improved data augmentation. Additionally, the DNN was evaluated and compared to several alternatives using appropriate metrics.

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