Human activity recognition using deep electroencephalography learning.

introduces a deep learning-based framework for classifying EEG artifacts (FCEA)

involving a Convolutional Neural Network and a Long Short-Term Memory Recurrent Neural Network.

a 3-class dataset of EEG activities was created.

ameras, accelerometers, gyroscopes and sound sensors have been used to detect the movement of users in automatic Human Activity Recognition (HAR) systems.

In HAR system design, Machine Learning (ML) algorithms have made significant progress in the extraction of human activity fea- tures from sensor data.

7% of the studies used only a combination of CNNs and RNNs, whereas, 40 % used only CNNs and 14 % used only RNNs.

whilst reading printed text, speaking out loudly and watching a TV program.

The technologies used for detecting human actions are commonly based on heterogeneous sensors placed throughout the environment, such as cameras and wearable sensors equipped with accelerometers, gyroscopes and biosensors [1–4]. Cameras provide video data in form of a 3D matrix.

The CNNs are more appropriate for learning and interpreting camera and motion-detection sensor data. The LSTM networks are not capable of classifying video data alone. They, however, attain a desirable classification performance when they are used for modeling accelerometer and gyroscope raw data, as well as the feature maps populated by a CNN [2].

Moreover, the smartphone and smartwatches which have been mostly used in HAR, are not suitable for recognizing facial activities.

Analyzing and training a neural network on EGG (Electroencephalography) data involves several steps. Here's a general guide to get you started:

1. **Understand the EGG Data:** - Familiarize yourself with the structure and characteristics of the EEG data you have. Understand the number of channels, sampling frequency, and the duration of the recordings.

2. **Preprocess the Data:** - Clean the data by removing artifacts and noise. Common preprocessing steps include filtering, artifact removal, and normalization. - Segment the data into epochs. This involves dividing the continuous EEG signal into smaller, manageable chunks, often aligned with specific events or stimuli.

3. **Feature Extraction:** - Extract relevant features from the EEG epochs. Common features include power spectral density, time-domain features, and statistical measures.

4. **Data Splitting:** - Split your data into training, validation, and test sets. This is crucial for evaluating your model's performance on unseen data.

5. **Build a Neural Network Model:** - Choose or design a neural network architecture suitable for your task. For time-series data like EEG, recurrent neural networks (RNNs) or long short-term memory networks (LSTMs) are often used. Alternatively, you can use 1D convolutional neural networks (CNNs).

6. **Model Training:** - Train your neural network on the training dataset. Use the validation set to monitor the model's performance and prevent overfit-

ting. - Experiment with different hyperparameters, architectures, and regularization techniques to improve performance.

7. **Evaluation:** - Evaluate your trained model on the test set to assess its generalization to new, unseen data. - Use appropriate metrics for your task, such as accuracy, precision, recall, or specific metrics relevant to EEG analysis.

8. **Interpretation:** - Interpret the results and gain insights into the neural network's performance. Understand which features contribute most to the model's predictions.

9. **Fine-Tuning and Optimization:** - If necessary, fine-tune your model or explore advanced techniques to improve performance, such as transfer learning or ensemble methods.

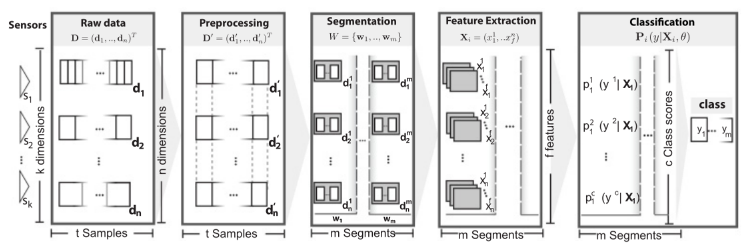
10. **Documentation and Reporting:** - Document your approach, findings, and any challenges faced during the analysis. This is crucial for reproducibility and collaboration.

Remember that the specific steps and techniques may vary based on the nature of your EEG data and the task you are trying to solve. Always adapt your approach based on the characteristics of your data and the goals of your analysis.

Paper: A Tutorial on Human Activity Recognition Using Body-Worn Inertial Sensors

Reference: (ANDREAS BULLING, Max Planck Institute for Informatics, Germany ULF BLANKE, Swiss Federal Institute of Technology (ETH) Zurich, Switzerland BERNT SCHIELE, Max Planck Institute for Informatics, Germany).

while recognizing the task of brushing one's teeth.




Raw signals ($D$) are first processed ($D'$) and split into $m$ segments ($W_i$) from which feature vectors ($X_i$) are extracted. Given features ($X_i$), a model with parameters $\theta$ scores $c$ activity classes $Y_i = \{y^1, \ldots, y^c\}$ with a confidence vector $p_i$.