Improved lightweight DL algorithm for biometric identification from EEG signal

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Abstract Biometrics is a growing field, which permits identification of individuals by means of unique physical features. Electroencephalograph (EEG)-based biometrics utilizes the small intra-personal differences and large inter-personal differences between individuals’ brainwave patterns. However, traditional EEG-based subject identification techniques frequently require a lot of electrodes, making it cumbersome and impractical for real-world applications. In this research, we suggest a method for subject identification using lightweight convolutional neural networks (CNN) while minimizing the number of electrodes. We propose a approach for subject identification in EEG that aims to minimize the number of electrodes while leveraging the power of CNNs. To achieve this, we divide the conductive electrodes of the cortex into (64, 32, 16) distinct groups. By exploiting the automatic feature extraction capabilities of CNNs, we process the EEG data from each electrode group individually. Remarkably, Electrodes (16) achieved an accuracy rate of 97.72%, 32 odd electrodes achieved an accuracy rate of 98.16%, while 32 even electrodes achieved an accuracy rate of 99.3%, and electrodes (64) achieved an accuracy rate of 95.47%. These results clearly demonstrate the robustness and efficacy of our method in accurately identifying individuals based on their EEG patterns. By decreasing the number of electrodes and capitalizing on the distinctive patterns captured by the electrode groups, our method provides a practical and efficient solution for subject identification in EEG.

Keywords: subject identification, electroencephalography (EEG), minimizing electrodes, lightweight convolutional neural networks (LCNNs)

1. Introduction

The development of biometrics brought with it the technological advancement of information systems. identification and security. Access to electronic boxes and voting machines, for example, became from the use of passwords, cards and printed documents to the use of digital ones, which offer more convenience to people by eliminating the risk of forgetting elements used for their identification (Lumini & Nanni, 2017) continue to allow the use of service by people in cases of theft, and are less likely to be forged (Obaidat et al., 2018). Biometric systems can be used to combat fraud (Bobkowska et al., 2019) and increase the level of security of health services, transport and social, among other types, used daily by a large number of people (Obaidat et al., 2018). One of the human characteristics that has been explored for the construction of biometric systems the electroencephalogram (EEG) (Carrión-Ojeda et al., 2021), which consists of recording the electrical signals present in brain activity through the positioning of electrodes on the scalp. EEG signals vary depending on the way in which an individual performs a task, whether motor or imaginary, as well as the emotional state he finds himself in (Lee & Hsieh, 2014). In order to extract the characteristics that differentiate one individual from another, and that “reside” within an EEG signal, we can use different techniques, such as calculating the Hamming distance between two encoded signals (Damaševičius et al., 2018), similarity by cosine (R. Das et al., 2017), or a type of neural network explored in the field of Deep Learning called Convolutional Neural Network (CNN) (Schons et al., 2018), which is focused on performing convolution operations. This type of architecture presents good results in experiments that have sequential data (Sherstinsky, 2020), and in addition to be used in image recognition (Jogin et al., 2018) and linguistic modeling (Lin & Tegmark, 2017). They can also be used in the construction of systems biometrics (Sun et al., 2019). The contributions of this study can be summarized as:
(i) Design Lightweight Convolutional Neural Layers Network (CNN).
(ii) Reduce the number of electrodes.

The rest of the work is organized as follows: Section 2 highlights other work related to the proposal, as well as some results and/or conclusions reported in them. The Datasets implementation is presented in Section 3. Section 4 presents the
methodology adopted. Section 5 demonstrates the results obtained in the different experiments carried out, and discussions about them. Finally, Section 6 presents the conclusions taken from the work presented.

1.1. Related work

Many works have been proposed in the research papers on the EEG biometric methods, including both machine and deep learning methods. To use machine learning models, it is necessary to initially extract distinguishing features of the signals, and then the model can be trained on them. In these works, the choice of the feature extraction method is very effective on the accuracy of the model. Methods such as AutoRegressive Model, Support Vector Machine, k-nearest neighbors (k-NN), Power Spectral Density, and Fourier transform are some commonly used EEG feature extractor methods to name. With the advancement of deep learning methods, these methods have quickly found their place in EEG biometric and it has shown that they can achieve higher accuracy. The important advantage of these methods is that the features are not required to extract explicitly, but the model itself has the ability to recognize the features hidden in the raw data. Most of the works which have proposed a deep learning approach on EEG biometric are based on “Convolutional Neural Networks” (CNN) models. In this section, works present in the literature that are related to the proposed topic are presented. The criteria for selecting related works were those that used CNN in the construction of a biometric system based on EEG. Several studies have explored the use of CNNs for electrode selection and feature extraction in various domains. These studies have demonstrated the effectiveness of CNNs in capturing spatial information and extracting discriminative features from electrode signals. For example, In (R. Das et al., 2017), EEG signals from 50 individuals were recorded by the authors themselves using 17 electrodes. A screen showed individuals randomly selected geometric shapes, and they were instructed to concentrate only when a circle appeared, this being the target, and ignore the appearance of other geometric shapes, these being non-target. A CNN was then used to classify individuals in biometric identification mode, and 98.8% accuracy was reported in non-target vs non-target comparisons. Target (when both the EEG signal sample and the CNN output indicated that the individual was ignoring a non-target) and 80.65% accuracy in target vs target comparisons. In (Schons et al., 2018), 90% of the signals recorded in a resting state with Rest Eyes Open were used for training, the remaining 10% for validation, and the signals recorded in a resting state with Rest Eyes Closed for testing. The Equal Error Rate (EER) metric, generated through comparisons between genuine (intra-class) and impostor (inter-class) pairs of feature vectors, was used to measure efficiency of the neural network. When using a window size of 12 seconds and a bandpass filter of 30-50Hz, an EER of 0.19% was obtained. Another study (Sun et al., 2019), they proposed a new (CNN) with a global local and spatial-temporal elect named (GSLE-CNN), which works straight with the raw data of EEG, and they investigated the performance of the model on datasets of 157 volunteers. The authors (Yang et al., 2018) concluded that the more brain regions are used for training and testing the system, the greater the performance. It was also observed that training and testing data from different tasks performed by individuals do not imply a reduction in performance, and that the more training data is used, the higher the network performance will be, obeying the law of Diminishing Returns. In study (Ma et al., 2015), the authors proposed a CNN-based approach of manually designed methods for this purpose, to extract the best and most unique neurological features unique to an individual and to classify behavior using EEG datasets from Resting State with Open Eyes and Closed Eyes. In Study (Zhang et al., 2017), researchers propose the MindID approach, whereby the EEG data waveforms are analyzed and the findings reveal that in the delta pattern are the most unique information for personal identification, then the decomposed delta pattern was fed into the attention-based Recurrent Neural Networks architecture that determines the weights different channels of EEG. Whereas the study (B. B. Das et al., 2019), they proposed a dense spatio-temporal structure for EEG-based person identification, where they initially processed the raw EEG by using CNN to extract accurate and relevant spatial features because it is known to extract features automatically via the raw data, after that, by using a long short-term memory (LSTM) network to process temporal data. In study (Lai et al., 2019), the aim of this research was to discover the EEG order of CNN inputs to investigate which input order is most appropriate for EEG towards EEG-based selection performance. Most of the studies confirm that the convolutional neural network CNN doesn't require complicated pre-processing of the signal, feature extraction, and feature selection steps, and this was confirmed (Lai et al., 2022), in his published study on biometric identification, proposed a new architecture for a (CNN) model. EEG signals were used in this study for identification via biometrics, as large-scale experiments have been performed to design this deep CNN style. A new approach suggested by (Alsourami et al., 2023), the study presents a lightweight CNN model consisting of just a small number of learnable parameters that allows training and evaluation of the CNN architecture on the little amount of available EEG dataset. In the study (Bidgoly et al., 2022), the suggested method, which uses deep learning method, can capture the pattern of users' EEG waves for identification and authentication purposes.

The similarity between the studies that were mentioned previously and the subject of our research is the use of the same dataset in the research experiments, which is (Physionet), but the dissimilarity was in the number of electrodes used, as we experimented using (64,32,16) electrodes instead of (64) electrodes.

1.2. Datasets implementation

https://www.malque.pub/ojs/index.php/msj
The dataset employed in this study consisted of EEG recordings collected from a diverse group of subjects. The PhysioNet EEG dataset was obtained from a publicly available repository to ensure its accessibility and reproducibility. Physionet EEG Datasets are a popularity benchmark for biometrics using EEG in the literature and are freely available. The Physionet datasets contain recordings of EEG signals from 109 participants who completed motor movements and imagery tasks (MI). Each participant performed a series of tasks while following cues displayed on the screen. The task schedule began with two 60-second baseline tasks, one where the participant rested with their eyes open (EO) and the other where they rested with their eyes closed (EC). This was followed by three sets of four 120-second tasks involving motor movement and imagery. Sixty-four electrodes on the scalp were used to record EEG signals, and each signal was sampled at a frequency of 160 Hz. BCI2000 instrumentation system creators and PhysioNet produced and updated the dataset. For every participant, there were 14 separate acquisition sessions, and during each session, various motor/imaging activities were considered during recording.

2. Materials and Methods

2.1. Channel selection

In our proposed method for subject identification using a reduced number of electrodes, we introduced a new approach to divide the conductive electrodes of the cortex into two distinct groups: odd and even. This division was based on the spatial arrangement and number of electrodes. Specifically, the conductive electrodes on the cortex were numbered consecutively, starting from the first electrode and continuing until the last electrode. Each group included 32 electrodes, ensuring a balanced distribution of electrode channels between odd and even groups. A series of tests were conducted with 16, 32 odd, 32 even, and 64 channels, respectively, in order to assess the spatial information included in the EEG channels. (Figure 1) displays the channels that were chosen for these tests highlighted in colors.

Figure 1 Electrode placements on the scalp and the corresponding channels (colored channels represent channels that have been empirically chosen, while white channels represent unused channels).
2.2. Dataset splitting

One of the important steps in deep learning was data splitting. This included splitting the datasets into separate groups for use with training and testing the models. The typical method for splitting the datasets when applied for EEG signals with DL was (70%, 80%, and 90%) for training sets and (10%, 20% and 30%) for testing sets. As shown in Figure 2.

![Figure 2 An illustration of the EEG Dataset splitting.](image)

The training set contains the largest size of the total dataset and is used to train and update the model's parameters during training process. The testing set typically contains the smallest size of the total dataset. It serves as independent data, that never seen from the proposed model during training process.

2.3. The architecture of Lightweight CNN model (LCNN)

In this section, we present the architecture of the proposed model (LCNN), offering a comprehensive explanation of the layer structure and operations. The LCNN model is devised to effectively process input raw data through a sequence of layers, utilizing 2Dconv layers, normalization layers, activation functions, pooling operation, and a fully connected layer. The model is carefully constructed to extract features hierarchically and culminates in a classification output. Each layer's role, parameters, and transformational steps are elucidated, providing valuable insights into the inner workings of this specialized neural network architecture tailored for accurate classification tasks. Figure (3) shows the proposed LCNN model.

![Figure 3 Shows the proposed LCNN model.](image)

Input Layer: Within the network architecture, the EEG signal's multi-channel data is harnessed as a 2D-formed input for the network. The configuration of our input data is contingent on the data organization and preparation methods. Given the provided details:

- Number of users: 109
- Number of session: 14
- Sampling rate: 160 Hz
- Number of channels: N, where N is (16, 32even, 32odd and 64, No. of channel)

Assuming data segmentation has been executed for each user and task, the structure of the input data shape can be denoted as: (Total number of samples, number of channels, number of time steps). Where:

1. Number of samples: This value corresponds to the collective count of EEG signal samples amassed across all users and tasks. If uniform sample quantities exist for each user and task, the calculation involves multiplying the number of users by the number of tasks and then by the samples per task (denoted as M). Assuming M samples per task per user, the total number of samples would be 109×14×M.
2. Number of channels: The EEG data encompasses N channels.
3. Number of time steps: This factor hinges on the duration of the recorded EEG signals. Given a sampling rate of 160 Hz, the number of time steps can be ascertained by multiplying the signal's duration in seconds by the sampling rate.

The determination of the total count of samples is define in equation (1) within the training dataset involves the
multiplication of these values while considering the split ratio.

\[ K = N \times n \times A \]  \hspace{1cm} (1)

Where: \( K \) is Total number of samples, \( N \) is Number of users, \( n \) is Number of tasks and \( A \) is Average samples per user-task combination. For example, if each user-task combination has an average of 114 samples: Total number of samples = Number of users \( \times \) Number of tasks \( \times \) Average samples per user-task combination = \( 109 \times 14 \times 114 = 173,964 \). When considering 90% of this value for the training set: 173,964 \( \times \) 90% = 156,567, and 10% for the testing set: 173,964 \( \times \) 10% = 17,396

Then the input shape for training set: (156,567, 32, 160), and testing set: (17,396, 32, 160)

Layer 1: Conv2D: This layer performs a 2D convolution on the input raw data. It has 64 filters and a kernel size determined by (109) (number of channels) and 1 (height).

Padding: The padding is set to “valid,” meaning no padding is added to the input. This results in an output feature map with smaller dimensions compared to the input.

BatchNormalization: This layer normalizes the activations of the previous layer along the channel axis. This helps in improving the training stability and speeding up the convergence.

Activation: For nonlinearity, element-wise, the ReLU was utilized in the network.

Layer 2: Conv2D: utilized in this layer 128 filters and (64) as a kernel size.

BatchNormalization: Similar to Layer 1.

Activation: ReLU were applied.

MaxPooling2D: These operations are performed similarly to those in layer1.

Layer 3: Conv2D: This layer had 256 filters and a kernel size of (128).

BatchNormalization: Similar to the previous layers.

Activation: ReLU activation functions were applied.

MaxPooling2D: These operations are performed in a manner similar to that in the previous layers.

Flatten: In this layer, the output of the previous layer (Layer 3) was converted into a 1D vector. It transforms 2D feature maps into a 1D representation that can be fed into a dense layer.

Dropout: This applies dropout regularization to the output of the previous layer. Dropout randomly sets a portion of the input units to zero (0) at each update during the training steps, which helps reduce the overfitting problem.

Dense: A fully connected (dense) layer is added to the (109) num-class neurons. The number of neurons in this layer corresponds to the number of output classes for classification.

Activation: The Softmax activation function is applied to the output layer to obtain the class probabilities. Softmax ensures that the predicted class probabilities sum up to 1.

Next, we set up the following training parameters as in Table 1.

<table>
<thead>
<tr>
<th>The parameters</th>
<th>The value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Epochs</td>
<td>25</td>
</tr>
<tr>
<td>Batch size</td>
<td>128</td>
</tr>
<tr>
<td>Optimizer</td>
<td>Adadelta, RMSprop, SGD, Adam</td>
</tr>
<tr>
<td>Learning rate</td>
<td>0.01, 0.001, 0.0001</td>
</tr>
<tr>
<td>Training set</td>
<td>70%, 80%, 90%</td>
</tr>
</tbody>
</table>

### 3. Result and discussion

In this section, A Comprehensive analysis is presented, evaluating the efficacy of the proposed model in accurately identifying individuals through their distinct EEG patterns. The simulation design results collected during the training process of the models and the testing results of the trained models will be presented. The accuracies and losses for the training and testing sets during the training process will be shown, as well as a discussion of the obtained results.

As demonstrated in Table 2, the testing accuracy of using the 64 channels is less than other selection channels 95.47% when used with the LCNN model, and the accuracy of using the 32-even channels is higher than other selection channels 98.54%. Figure 4 shows the model’s behavior in terms of testing accuracy.

<table>
<thead>
<tr>
<th>Channels</th>
<th>Testing accuracy</th>
<th>FAR</th>
<th>FRR</th>
</tr>
</thead>
<tbody>
<tr>
<td>16</td>
<td>97.72</td>
<td>0.0084</td>
<td>0.0108</td>
</tr>
<tr>
<td>32odd</td>
<td>98.16</td>
<td>0.0058</td>
<td>0.0088</td>
</tr>
<tr>
<td>32even</td>
<td>98.54</td>
<td>0.0044</td>
<td>0.0058</td>
</tr>
<tr>
<td>64</td>
<td>95.47</td>
<td>0.0140</td>
<td>0.0214</td>
</tr>
</tbody>
</table>
The observation that the testing accuracy of the 32-even channel configuration is higher than that of the 64-channel configuration could be influenced by several factors, and it's important to consider the following possibilities:

1. Channel Relevance: It's possible that the specific subset of 32-even channels you selected contains electrodes that are particularly informative for the identification task, while the additional channels in the 64-channel configuration may introduce noise or redundancy.

2. Data Quality: The quality of data recorded from EEG electrodes can vary across different channels.

3. Dimensionality Reduction: The reduction from 64 to 32 channels could serve as a form of dimensionality reduction, helping the model focus on the most critical EEG signals.

Three values of learning rates were experimentd with proposed 32 even channels using the parameters shown in Table 1 previously. The testing accuracies for three values of learning rate are shown in Table 3.

Table 3 Shows the results of the Testing accuracy for proposed LCNN model with 3 values of learning rate.

<table>
<thead>
<tr>
<th>Learning rate</th>
<th>0.01</th>
<th>0.001</th>
<th>0.0001</th>
</tr>
</thead>
<tbody>
<tr>
<td>Testing accuracy</td>
<td>96.22</td>
<td>98.54</td>
<td>87.55</td>
</tr>
</tbody>
</table>

As indicated in Table 3, the choice of learning rate significantly impacts the training process of the deep learning model. A learning rate that is too small can lead to slow convergence, while one that is too large can cause training instability. In this specific case, a learning rate of 0.001 appears to be the most effective, resulting in the highest accuracy among the three options, Figure 5 shows the model's behavior in terms of testing accuracy.

Four types of optimization algorithms were experimented with proposed 32 even channels using the parameters shown in Table 1. The testing accuracies for four types of optimization algorithms are shown in Table 4.
Table 4 Shows the results of the Testing accuracy for proposed LCNN model with 4 types of the Optimization algorithm.

<table>
<thead>
<tr>
<th>Optimization algorithm</th>
<th>Adam</th>
<th>RMSprop</th>
<th>SGD</th>
<th>Adam</th>
</tr>
</thead>
<tbody>
<tr>
<td>Testing accuracy</td>
<td>75.42%</td>
<td>97.96%</td>
<td>74.84%</td>
<td>98.54%</td>
</tr>
</tbody>
</table>

As shown in Table 4, the choice of optimization algorithm plays a crucial role in the training of the deep learning models. The results indicate that both Adam and RMSprop are effective choices for this EEG-based biometric identification task, with Adam achieving the highest accuracy. Conversely, SGD and Adadelta seem to perform less effectively in this context. Figure 6 shows the model’s behavior in terms of accuracy.

Three types of training sets were experimented with the proposed 32 even channels using parameters of Table 1. Table 5 presents testing accuracies for the experimentd training sets.

Table 5 Shows the results of the Testing accuracy for proposed LCNN model with 3 values of training sets.

<table>
<thead>
<tr>
<th>Training sets</th>
<th>70%</th>
<th>80%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Testing accuracy</td>
<td>96.01%</td>
<td>98.63%</td>
<td>99.30%</td>
</tr>
</tbody>
</table>

As shown in Table 5, the testing accuracy of the system is evaluated based on the proportion of the training dataset used (90%, 80%, and 70%). As the proportion of the training dataset decreases, there is a slight reduction in accuracy, indicating the importance of a sufficient training dataset for achieving high accuracy in the system. Figure 7 shows the model’s behavior in terms of testing accuracy.

The results obtained compared to the results of previous studies are considered very good because the number of electrodes used was reduced according to a specific division (64, 32odd, 32 even, and 16) channels, and a high accuracy (99.3) was obtained compared to the highest result in previous studies. This indicates the strength and efficiency of the proposed model in this study. Table 6 shows the results compared to related works.
The table demonstrates the performance of the proposed lightweight CNN model as compared to existing approaches. The proposed method achieves accuracies ranging from 95.47% to 99.3% with various electrode configurations, showing its effectiveness in biometric identification using EEG signals. In comparison to latest studies, the proposed method is outperforming. As it achieves accuracies comparable to or higher than existing models and hence those based on CNNs and CNN-LSTM combinations. The results also proved that with less number of electrodes accuracy can be enhanced, as seen in the higher accuracy achieved with 32 and 16 electrodes compared to 64 electrodes. However, it’s worth mentioning that while the proposed method shows acceptable results, there may still be limitations or areas for improvement. Further experimentation and validation with possibly including comparisons and additional datasets and even real-world testing could support a more comprehensive assessment of the proposed approach’s performance and practical applicability.

There is a list of suspected sources of error in EEG-based biometric identification studies that can be concluded in the points below:
1. Redundant EEG signals or artefacts and noise
2. Electrode placement or variable signal acquisition techniques can affect different channels.
3. Imbalanced dataset or small number of samples
4. EEG patterns changes and sensitivity to individual subjects
5. Influence of other variables or environment

By addressing the aforementioned limitations and explaining their implications, which can provide valuable insights for future research in the field of EEG-based biometric identification.

4. Conclusions

This study highlights two branches: the first is building a lightweight model, and the second is reducing the number of electrodes used. It examines the effect of electrode reduce on subject identification rates and provides valuable insights into optimizing electrode configurations. Electrodes (16) achieved an accuracy rate of 97.72%, 32 odd electrodes achieved an accuracy rate of 98.16%, while 32 even electrodes achieved an accuracy rate of 99.3%, and electrodes (64) achieved an accuracy rate of 95.47%. These results clearly demonstrate the power and effectiveness of our method to accurately identify individuals based on their EEG patterns. Most importantly, the proposed scheme represents a novel contribution to the field by reducing the number of electrodes and taking advantage of the distinct patterns captured by the paired electrodes. These notable performance improvements are important because they demonstrate the potential for more accurate and reliable subject identification using electroretinogram data. By improving the accuracy of subject identification algorithms, the risk of errors such as false acceptance or false rejection can be reduced, leading to increased security and reliability of biometric authentication systems. Gives the researchers to work towards achieving real-time EEG-based identification and authentication systems that can process EEG data in near real-time. This is especially crucial for applications that require quick and seamless user authentication.

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Not applicable

Conflict of Interest
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