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Systematic Observation of EEG classification using Deep Learning

Mala Malik

Assistant Professor, Department of Computer Science, Mata Ganga Khalsa College for Girls, Manji Sahib, Kottan, Ludhiana

ABSTRACT Electroencephalography is the earliest diagnostic tool in the field of neurology (EEG). Several deep machine learning architectures have recently been designed to capture the information contained in EEG signals. Classification is critical in brain computer interface (BCI) schemes. Deep learning algorithms have been successfully used in a number of newresearches to learn landscapes and classify various types of data. This study conducted a comprehensive review of EEG categorization using deep learning, resulting in the discovery of 90 studies from the Web of Science and PubMed databases. In these investigations, researchers looked at a range of criteria, including task type, EEG pre-processing techniques, input type, and learning depth. The current approaches and performance outcomes in EEG categorization using deep learning are summarised in this article. In the interests of encouraging or directing future research employing EEG datasets to apply deep learning, a collection of practical recommendations is presented.

Nonetheless, Deep Learning designs involve a large variety of hyper parameters that influence the model's performance. In this research, we offer a method for optimising Deep Learning models that takes into account not only the hyper parameters but also the structure of the model, allowing us to suggest solutions with a variety of architectures based on layer combinations. The results of the experiments show that deep architectures enhanced by our technology outperform baseline approaches and produce computationally efficient models. Furthermore, we show that optimised structures outperform baseline models in terms of energy efficiency.

Keywords: Evolutionary computing, deep learning

Introduction

The cerebral cortex, which makes up the brain, possesses tremendous and blooming spatiotemporal dynamics that are only found in humans. Seizures are a type of epilepsy that occurs when the brain's electrical system malfunctions. Epilepsy is a condition in which the brain has repeated seizures. EEG analysis provides important information on brain activities and can be used to detect brain illnesses, including epilepsy. EEG includes waveforms with various frequencies, amplitudes, and spatial dispersion. Theta waves are found between 4 and 7.5 Hz, alpha waves are found between 8 and 13 Hz, beta waves are found between 14 and 40 Hz, and gamma waves are found above 40 Hz. The EEG may show aberrant electrical discharge when a brain disease develops. Meaningful communication is possible thanks to electrode implantation in the frontal pole (Fp), frontal (F), parietal (P), temporal (T), and occipital (O) parts of the brain. Even and odd integers were employed as subscripts to separate the two hemispheres of the brain.

EEG recording (EEG) is extensivelyrummage-sale in neural engineering, neurology, and biomedical manufacturing research (eg, Brain Computer Interface, BCI) due to its great time resolution, non-invasiveness, low economic cost. I am. Sleep analysis; and seizure detection).EEG will become more generally applicable and less reliant on specialised skills as these signals are automatically classified. A typical EEG classification pipeline includes removing artefacts, identifying characteristics, and classifying them. At its most fundamental level, an EEG dataset is a two-dimensional matrices of actual values representing scalp recordings of brain-generated potentials under certain task conditions. Because of its well-organized nature, EEG data is ideal for machine learning. The EEG data was submitted to a number of traditional machine learning and pattern identification techniques.

Deep learning-based EEG signal categorization algorithms have become increasingly prominent in recent years. Because EEG data represent recordings of bio potentials across the scalp over time, researchers frequently use DL designs to collect both spatial and temporal information. A CNN cascade is usually used first, followed by an RNN, most commonly an LSTM. The nature of neural networks mandates that the preceding levels in these cascade structures function as feature extractors for the subsequent layers.

1. Methods

➢ Search Methods aimed at Identification of Studies

The PRISMA systematic appraisal and meta-analysis strategy uncovered studies and reduced the quantity of data collected to evaluate deep learning applications for EEG data classification utilising this technique. December 22nd, 2018, a search was conducted in both the Web of Science and the PubMed databases by the following keywords: ("Deep

Neural Network*" OR "Deep Learning" OR "Deep Machine Learning" OR "Deep Convolutional" OR "Boltzmann Machine*" OR "Deep Recurrent" OR "Deep LSTM") AND ("EEG" OR " (described below). The following standards were used to weed out definite studies:

- Electroencephalography alone:-To reduce erraticism in the educations, research utilisingmulti-model datasets, such as EEG study in combination with additional physiological signals or on films, was deleted.
- Human task categorization:-This research focused solely on the use of EEG data to classify human tasks.
- Deep learning - In this appraisal, deep knowledge is clear as neural networks that must at least binary hidden layers.

➢ **Extraction and Presentation of Data**

a. The subsequent types of information were gathered:
   - Task info
   - Task sort
   - Number of topics
b. Artifact elimination strategy
   - Manual
   - Automatic
   - Removal
c. Frequency variety used for study
d. Preparation of Input
   - Signal topographies of EEG
   - Channel assortment methods

2. Result and Discussion

This section begins with an overview of the study's pre-processing processes. The next sections look at general categories of activities, input formulations, and architectural trends. The findings part closes with a circumstance study based on a publicly available dataset, which lets for comparisons of different deep learning design options.

➢ **Has deep learning been used to investigate EEG classification tasks?**

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Emotion recognition (17 percent), motor imagery (20 percent), mental workload (15 percent), seizure detection (15 percent), and additional studies (14 percent), which included Alzheimer's organization, bullying directories detection, despair, and gait panning, were among the tasks presented in these studies. The following sections cover the general procedures for various jobs.

Tasks for Recognizing Emotions:-People who are working on emotion recognition jobs are frequently required to watch videos that have already been pre-assigned by experts with specific moods. An EEG was recorded as well as an assessment of one's own emotions as a result of these viewings. It was chosen to use the original emotion class and self-assessment to adopt a widely accepted approach of describing emotions. Emotion recognition research helps computers better grasp the user's current emotional state in general.

Tasks Requiring Mental Workload:-The patient's EEG was recorded while he was engaged in a variety of mental tasks of varying difficulty. Driving simulation studies, true pilot studies, and responsibility assignments, among other things, have been used to measure the mental workload levels of drivers and pilots. Mental effort was classified using statistics like as reaction time and path deviation in driver and pilot experiments. The workload classification approach utilised in responsibility studies was based on an individual's increasing number of acts. This exam can be used in one of two ways to track cognitive stress or BMI performance.

Tasks for Detecting Seizures: The EEG signals of epileptic patients are chronicledthroughout and after episodes for seizure detection research. For some datasets, there was also a control group of non-epileptic patients' EEG signals collected. The purpose of these research efforts was to detect impending seizures and inform the epileptic patient ahead of time.

Tasks for Assessing Sleep Stages: Individuals' EEG data are collected nightly in Sleep stage scoring remained the job with the fewest studies. The signs were divided into four categories for classification: sleep stages 1, 2, 3, 4, and rapid eye movement (REM). The ultimate goal of this study is to reduce the reliance on medical professionals for sleep stage analysis and comprehension.

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Tasks Related to the Event: Participant EEGs are regularly recorded in surveys to identify and classify event-related potentials with simultaneous visual representation. In these tasks, one examines a rapid sequence of images or text to draw attention to a particular marker. EEG data shows a stereotyped response, usually in the procedure of a P300 response, when a particular character or image is displayed. These activities are useful for research because of the comparatively clean sign (minimizing artefacts) the high signal-to-noise ratio not normally found in EEG data. The development of better nonverbal communication systems is supported by EEG research on event-related potential tasks.

- **Methods of Pre-Processing**

Because EEG devices pick up external electrical physiological signals such eye blinks and neck muscles' electromyograms, EEG data is inherently noisy. When the subject moves, there are also worries regarding motion artefacts caused by cable movement and electrode displacement. The detection and elimination of EEG artefacts has been widely researched in the past literature, and this review will not go over that ground again. The artefact removal procedure was approached in one of three ways (shown in Figure below), with the exception of the 40.9% of research that did not address any specific artefact removal process. 1) human removal (28.8%) 2) automatic removal (8.2%), and 3) no cleaning or removal (22.1percent).

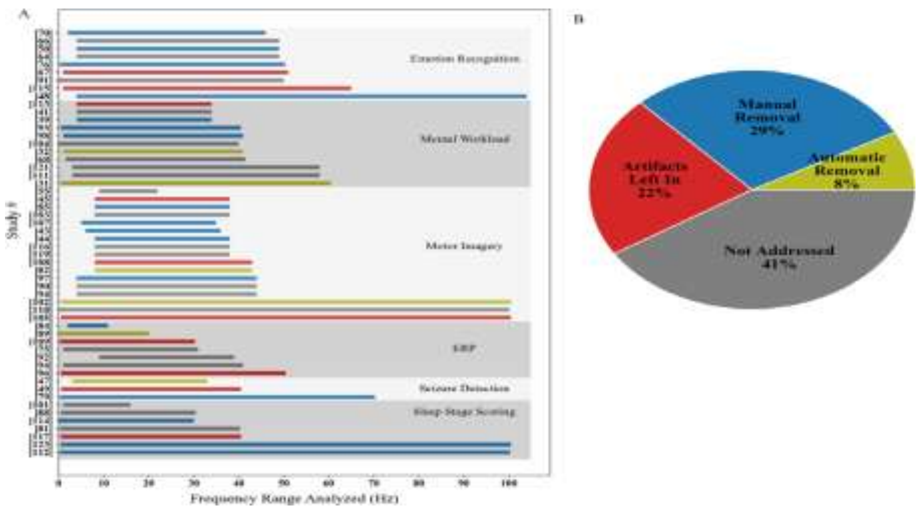

Fig.1: Filtering and artefact removal techniques. A) In the EEG analysis, the frequency range is grouped by task type.B) The varied colours of the bars represent

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different artefact removal procedures. Artefacts were intentionally left in studies with red bars to function as contaminants, but studies with dark grey bars did not take any steps to remove them from their results. The studies are categorised according to the type of application they are being used for.

Surprisingly, manual approaches were utilised to remove artefacts in more than a quarter of the studies (26 out of 90). When data are lost or severe EMG artefacts are present, a sudden outlier is easy to spot visually. In multi-channel recordings, however, finding persistent noisy channels might be problematic. Because manual data processing is very subjective, other researchers will have a difficult time reproducing the techniques. 22 percent of the studies that did not take any steps to eliminate EEG artefacts did so in a systematic manner. ICA and Discrete Wavelet Transformation were the primary artifact-removal techniques in the remaining 80% of the studies examined (DWT). To keep the signal's bandwidth in check, frequency domain filters were often used in EEG investigations. If only a small fraction of the spectrum is of interest, the rest can be safely ignored. A low pass filter was utilised in around half of the attempts to maintain the signal in the low gamma band or lower. A figure 1 show that, in adding to limiting the incidence ranges they studied, most research applied an artefact removal strategy.

- **Trends in Deep Learning Architecture**

Design Options for Architecture: This segment of the evaluation focuses on recognising patterns that have been generated in deep knowledge architectures such as the key typical and end classifier. This info has been gathered and is depicted in the diagram below.

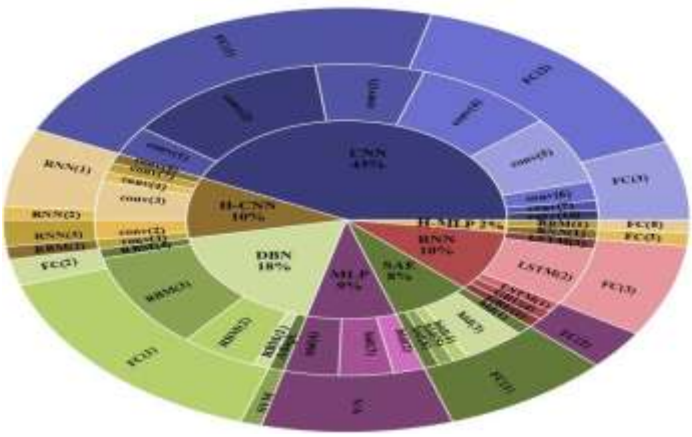

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Fig.2: Architectures of Deep learning in all researches The central circle in Figure represents a basic deep learning technique, whereas the middle and outer circles represent the primary design elements of a specific deep learning approach. Flexibility is the key to success. DBN stands for Deep Belief Network, and CNN is for Convolutional Neural Network. NFC stands for "number of fully connected layers," whereas Nhid is for "number of hidden levels." The acronyms H-CNN and H-MLP stand for Hybrid Convolutional Neural Network and Hybrid Multi-Layer Perceptron, respectively. Boltzmann Machines with Restrictions (#): the total number of such machines. RNN, RNN(#), and StackedAutoEncoders are all acronyms for Recurrent Neural Network.

The architectural design strategy (43%) used by CNN includes alternating pooling of convolutional layers (usually the largest pooling layer). The integer of convolutional layers in the classifier and the type of end of classification were two of CNN's most important design features. DBN was the second most popular option with 18% of the votes cast. A DBN consists of a series of constrained Boltzmann machines stacked on top of each other, followed by a final classifier, usually consisting of a series of fully connected layers. Hybrid architectures, which make up 12% of all studies, fall into two categories: hybrid CNNs and hybrid MLPs, as shown in Fig. 2. The hybrid CNN adds multiple repeating layers or constrained Boltzmann machines inadding to the convolutional plus pooling layers. Hybrid MLP is a combination of many thick layers and a deep learning approach. An RNN (10%) consisting of a series of repeat layers was shadowed by a series of fully linked layers as a fraction of the entire number of studies. The amount of hidden layer, a key design factor, was the only feature second evaluated by MLPNN.

Deep Learning Trends based on a Task: In the emotion credit, and slumber stage scoring tests, there was no consensus on which deep learning algorithms to utilise. In comparison to other tasks, seizure detection research was virtually evenly split between CNNs and RNNs, with RNNs accounting for the majority of the study. Only one study employed an SAE or MLPNN to identify seizures, and none used DBNs. When comparing research utilising CNNs to research using hybrid formulations, research using CNNs comes out on top. Sleep stage scoring tasks had the most hybrid formulations, with an equal amount of each. CNN came out on top, according to ERP research. Fig. 3 depicts the many deep learning strategies that can be employed depending on the circumstances.

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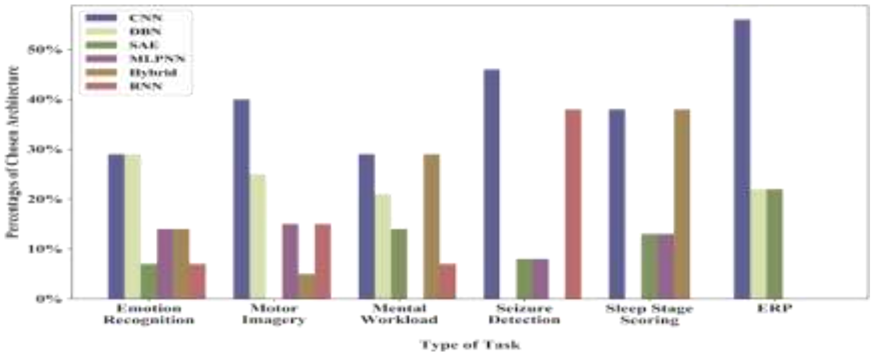

Fig.3: Deep learning architecture dimensions on the basis of different tasks.

3. Optimization Framework

Each dataset contains 178 training and 179 testing patterns, with each pattern labelled with the associated BCI class (imagined left hand movement, imagined right hand movement, or imagined foot movement), as shown in Table 1. Three participants, coded 104, 107, and 110, were chosen because they had the best results in prior EEG-BCI signal classification studies [7,20]. As a result, our goal was to apply the optimization framework to better the best outcomes acquired by other methods previously.

Number of examples for the different movements of each subject.

Subject	Left Hand		Right Hand		Feet		Total	
	Train	Test	Train	Test	Train	Test	Train	Test
104	60	56	66	65	52	58	178	179
107	56	58	57	58	65	63	178	179
110	58	59	60	60	60	60	178	179

Multi-Objective Optimization: In today's environment, multi-objective optimization problems are common. Analytical or traditional numerical methods can be used to solve these problems. To solve these issues, numerous types of heuristic search algorithms have been proposed. Optimization algorithms are divided into four categories, each of which is motivated by biology, physics, geography, and social culture. Biologically inspired algorithms attempt to emulate natural evolutionary processes or behaviors.EAs are motivated by the natural selection process, which results in the improvement of individuals in a population over successive generations: the best individuals are selected and reproduced with each other, producing offspring for the next generation, while the worst individuals are withdrawn from the population.This work's optimization technique is based on a multi-objective optimization procedure that tries to identify the vector x=[x1,x2,...,xn]

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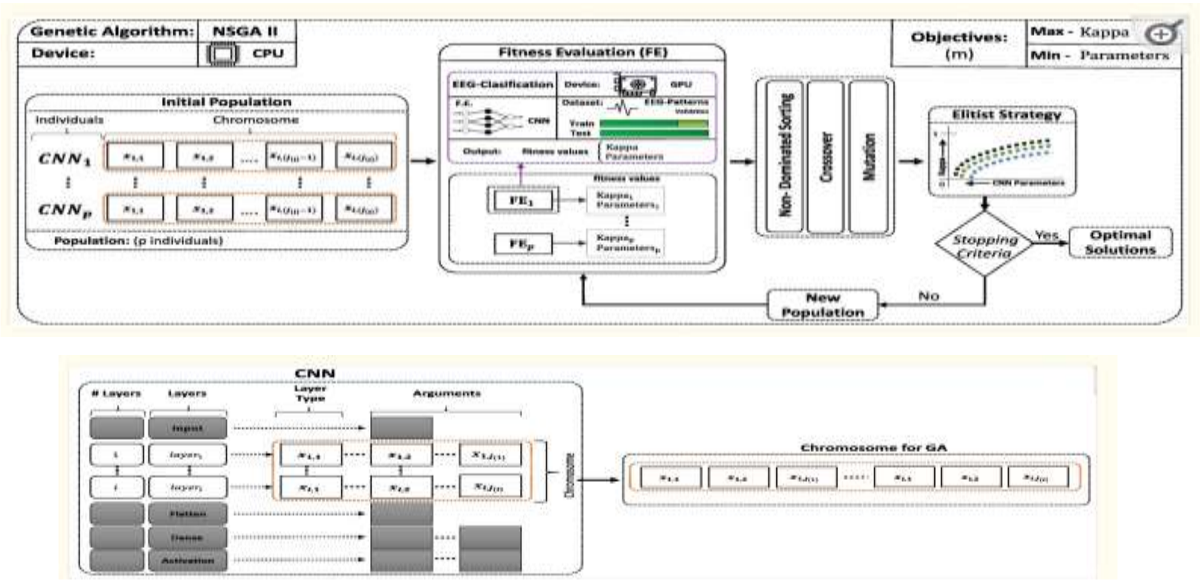
that optimises a function vector f(x), whose components (f1(x),f2(x),...,fm(x)) indicate the objectives to optimise. When all of the objectives are assessed in a Pareto front, every possible solution is equally efficient. As a result, the best practical option for a specific case might be selected.

Algorithm 1

Algorithm 1: Pseudo-code of the Multi-objective Optimization Procedure for Deep Convolutional Architectures using NSGA-II

```
Generation of a random initial population;
Fitness evaluation;
Non-dominated sorting population;
while not met the stopping criterion do
    Parents selection;
    Crossover;
    Mutation;
    Fitness evaluation;
    Non-dominated sorting population;
    Elitist strategy;
    New population;
end
Final population;
Result: Final optimal solutions;
```

Proposed Optimization Outline and Submission to EEG Signal Organization: The major purpose of the optimization technique given in this paper is to create low-complexity neural network topologies with excellent classification accuracy. The suggested optimization framework does this by incorporating the following essential components. Figure 4 depicts the framework's components and how they interact during the optimization process as a block diagram.



Optimization Process

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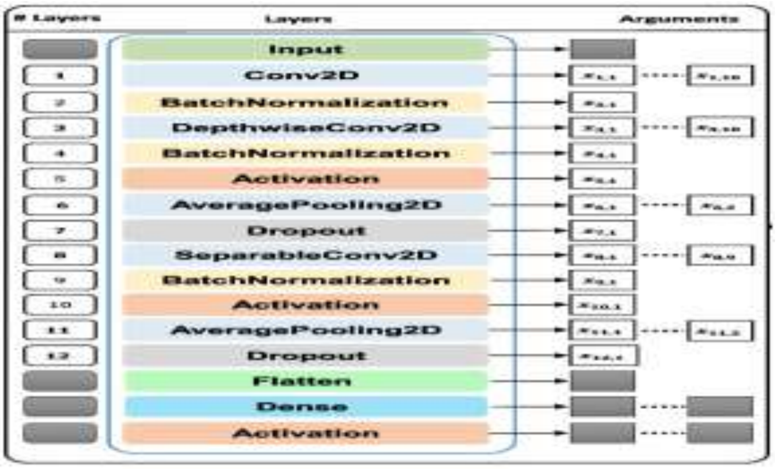

Power Efficacy of Optimized Solutions: The power consumption of the various networks employed in this study is examined in this section. This tries to compare the power efficiency of the optimised network to the baseline networks. The optimised option significantly reduces instantaneous power consumption and, as a result, the average power consumption of the various assessed models, with the optimised model requiring less power consumption throughout training.

Conclusion: This research attempted to compile a list of papers that employed a deep learning approach to classify EEG signals. Many EEG tasks, such as movement imaging and seizure detection, have been successfully completed using deep learning classification. Deep learning categorization has also been used to successfully incorporate mental burden. The input formulation and network configuration had a significant impact on the design of these deep network studies. Because of the vast number of research that looked at multiple public datasets, we were able to evaluate classification performance amongst datasets. CNNs, RNNs, and DBNs outperform other deep network types like SAEs and MLPNNs in general. When signal values or (spectrogram) images were used as inputs, CNNs outperformed DBNs, but DBNs outperformed CNNs as well when signal values or computed features were used. Later, we talked about deep network recommendations that were suited to each task's specific needs.It is envisaged that this map may also useful resource destiny deep getting to know studies the usage of EEG datasets. When as compared to conventional designs, convolutional layers with recurrent layers, in addition to restrained Boltzmann machines, confirmed promise in category accuracy and switch getting to know. It`s really well worth searching into the quantity and configuration of various layers, including RBMs, recurrent layers, convolutional layers, and absolutely connected layers. For the time being, community layout is much less essential than understanding how deep networks study uncooked as opposed to denoised EEG.

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