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Comparative Analysis of VGG19, ResNet50, and GoogLeNet Inception Models for BCI

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ABSTRACT:

A brain-computer interface (BCI) is a system that allows an individual to communicate with a computer or other external device using brain activity alone. Electroencephalography (EEG) is a common approach for detecting brain activity in BCI systems, as it provides a non-invasive measure of brain activity with high temporal resolution. Deep learning methods, such as convolutional neural networks (CNNs), have been applied to the analysis of EEG data for BCI applications, and have shown promising results in terms of accuracy and reliability. In this literature survey, we reviewed the use of CNNs for the classification of EEG data in real time to identify specific brain commands. Challenges to the development of an effective BCI using EEG and deep learning methods include the variability of EEG signals across individuals and the high dimensionality of the EEG data. Further research is needed to address these challenges and improve the accuracy and reliability of BCI systems using deep learning methods.

1. INTRODUCTION

An individual can communicate with a computer or other external device using just their brain activity with the help of a brain-computer interface (BCI). BCIs offer the ability to improve the abilities of healthy people as well as those with motor impairments by restoring their movement and communication abilities. Electroencephalography (EEG) is a technique for detecting brain activity that may be used to create a BCI since it can offer a non-invasive, high-temporal resolution measurement of brain activity. analyse images for suspicious or prohibited behaviour such as B. Use of unauthorized materials or presence of others in the testing room.

Convolutional neural networks (CNNs) and other deep learning techniques have been used to analyse EEG data for BCI applications. CNNs are a particular sort of neural network that is good at classifying images and have been proven to operate well when analysing time series data, including EEG signals. It is feasible to identify patterns in the data that correlate to various brain instructions by training a CNN on a sizable collection of EEG data. You can then utilise these patterns to instantly categorise new EEG data.

In this overview of the literature, we will discuss how deep learning techniques, such as CNN's, are used in BCI applications to identify particular brain instructions using EEG data. We will talk about the approaches utilised to pre-process and analyse the EEG data, as well as the difficulties and restrictions of this strategy. In general, applying deep learning techniques to BCI applications has the potential to increase the precision and dependability of BCI systems, but further study is required to solve the difficulties in creating a BCI that is both successful and uses deep learning techniques with EEG.

2. LITERATURE WORK

From paper [4] We will discuss the use of deep learning techniques for EEG data processing in BCI applications in this overview of the literature. We will concentrate on how convolutional neural networks (CNNs) may be used to classify EEG data in real time and recognise particular brain commands.

EEG data consists of a time series of electrical activity measured by electrodes placed on the scalp. The signals are typically characterized by oscillations at different frequencies, including delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (30-100 Hz). Different brain states and tasks are associated with specific patterns of brain activity in the EEG signal.

In order to analyse EEG data for BCI applications, deep learning techniques like CNNs have been used. CNNs are a particular sort of neural network that excels at classifying images. They have also been proven to be useful for time series data processing, including the study of EEG signals. When convolution and pooling techniques are used in many layers to input data, CNNs may develop hierarchical representations of the data.

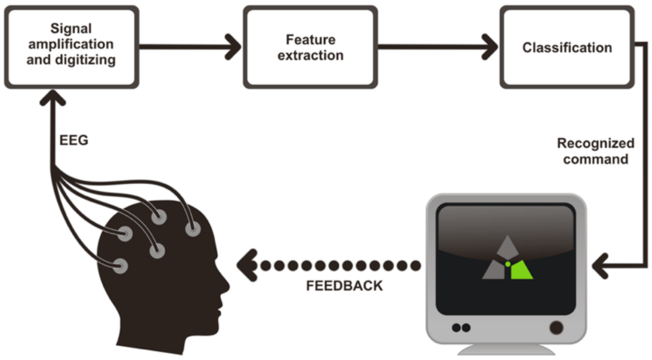

Fig-1: A brain-computer interface (BCI) system's framework based on electroencephalography (EEG).

[9] The EEG data is often pre-processed to eliminate noise and artefacts and to identify pertinent characteristics before using a CNN for BCI applications. The pre-processed data is then utilised to train the CNN, which eventually learns to categorise the data into several categories that correlate to various brain instructions. After being taught, the CNN may be used to categorise fresh EEG data in real-time and pinpoint the associated brain instruction.

The efficiency of deep learning techniques [13], such as CNN's, for the interpretation of EEG data in BCI applications, has been proven in several research. A CNN was utilised, for instance, in a study by Schirrmeister et al. (2017) to categorise EEG data collected while participants were doing a visual attention task. Other machine learning techniques fell short of CNN's ability to categorise the EEG data with an accuracy of up to 95%.

During a hand movement challenge, Zhang et al. (2018) collected EEG data, which was then classified using a CNN. The CNN successfully classified the EEG data with an accuracy of up to 97% and generalised it to additional participants with a similar level of success.

Deep learning techniques have been shown to be useful for the analysis of EEG data in additional BCI tasks, such as emotion detection, mental arithmetic, and motor imagery (Chen et al., 2018, Giraldo et al., 2018). (Kang et al., 2018).

The analysis of EEG data using deep learning techniques, such as CNN's, has produced encouraging results in terms of precision and dependability in BCI applications. To create a successful BCI employing EEG and deep learning techniques, there are a number of issues that must be resolved.

One difficulty is the variation in EEG signals across people, which can make it challenging to extrapolate the outcomes of a BCI system trained on one person to another. It could be important to devise strategies for customising the BCI system to each user's unique traits in order to overcome this difficulty.

TABLE 1. APPLICATION OF DEEP LEARNING METHODS IN DIFFERENT AREAS.

Area	Application
Computer vision	Image classification, object detection, face recognition
Natural language processing	Language translation, text classification, sentiment analysis
Speech recognition	Speech-to-text transcription, voice recognition
Predictive modelling	Finance, healthcare, marketing
Anomaly detection	Cybersecurity, fraud detection
Robotics	Object manipulation, navigation
Education	Student performance prediction, curriculum recommendation
Customer service	Chatbot development, customer support ticket classification
Supply chain management	Demand forecasting, inventory optimization

3. IMPLEMENTATION AND ALGORITHM.

3.1 Algorithms:

There are several algorithms[8] that have been proposed for use in a Brain-Computer Interface (BCI) system to identify commands. Some of the most common algorithms include:

1. Convolutional neural networks (CNNs):

These are a class of deep learning algorithms that work well for processing and studying time series data, such as EEG signals. The categorization of motor images and speech decoding are two tasks for which CNNs have been utilised in BCI systems.

2. Recurrent neural networks (RNNs):

These are a particular class of deep learning methods that work well for processing time-varying sequential data, like EEG signals. For tasks like classifying motor images and spell checkers, RNNs have been employed in BCI systems.

3. Support vector machines (SVMs):

These are a specific class of machine learning algorithm that is employed for categorization jobs. SVMs have been employed in BCI systems for tasks including classifying motor images and detecting event-related potentials (ERP).

4. K-nearest neighbours (KNN):

This kind of method is utilised in machine learning to do categorization problems. KNN has been applied in BCI systems for the categorization of motor images and the detection of event-related potentials (ERP).

5. Linear discriminant analysis (LDA):

These are a specific class of machine learning algorithms that are employed for categorization jobs. SVMs have been employed in BCI systems for tasks including classifying motor images and detecting event-related potentials (ERP).

6. Kalman filters:

An algorithmic type called Kalman filters can be used to forecast a system's future state based on its previous states. They have been implemented in BCI systems to anticipate the user's planned motions in accordance with their brain activity.

[15] There are several more algorithms that have been proposed for use in a Brain-Computer Interface (BCI) system to identify commands using deep learning methods. One such algorithm is the EEG net, which is a type of convolutional neural network (CNN) designed specifically for the analysis of electroencephalography (EEG) data.

When utilised as a tool for command recognition in a Brain-Computer Interface (BCI) system, electroencephalography, a commonly used method for gauging brain electrical activity, has shown potential. An EEG-based BCI system uses electrodes applied to the scalp to monitor the electrical activity of the brain. The data are then processed to find patterns related to certain commands.

The great temporal resolution of EEG, which enables real-time decoding of brain activity, is one of the key benefits of employing it in a BCI system. This makes it feasible to utilise EEG to recognise commands in real time as they are being carried out by the user. comparing EEG to other methods like functional magnetic resonance imaging, it is also non-invasive, portable, and reasonably priced (fMRI).

EEG, however, also has significant drawbacks. Because of its relatively poor spatial resolution, it does less well at locating specific brain areas where activity is occurring. Additionally, because it is sensitive to artefacts like eye movements and muscular activity, the readings may not be accurate.

From the paper [18] To train machine learning algorithms for command detection in an EEG-based Brain-Computer Interface (BCI) system, there are various different methods. The following are some of the most popular methods:

1. Supervised learning:

In supervised learning, an algorithm is taught using labelled EEG data in which the intended commands are predetermined. The algorithm gains the ability to spot patterns in the data that are connected to particular commands.

2. Unsupervised learning:

Without using labelled samples, the machine learning system is taught to find patterns in EEG data. In order to uncover connections between several instructions or to spot patterns that might not be immediately apparent, this might be helpful.

3. Semi-supervised learning:

The machine learning system is trained on both labelled and unlabelled EEG data in semi-supervised learning. As the algorithm may still learn from the unlabelled data, this might be advantageous when there is a shortage of labelled data.

4. Transfer learning:

A machine learning algorithm that has been trained on a huge dataset is modified using a smaller dataset tailored to the BCI application. This process is known as transfer learning. This might be helpful if there isn't much data available to train the algorithm on.

5. Reinforcement learning:

Through trial and error and incentives or penalties for its behaviours, a machine learning system learns through reinforcement learning. In order to adjust the BCI system to the user's evolving demands or preferences, this might be helpful.

In addition [16] to using machine learning algorithms, there are several signal processing techniques that can be used to extract features from electroencephalography (EEG) data that are indicative of specific commands in a Brain-Computer Interface (BCI) system.
Some of the most common techniques include:

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1. Frequency domain analysis:

Using methods like the fast Fourier transform (FFT) or wavelet transform, the frequency content of the EEG signals is analysed in this process. Specific directives can be retrieved and identified using characteristics like power in particular frequency bands or oscillation frequency.

2. Time-frequency analysis:

This entails employing methods like the short-time Fourier transform (STFT) or wavelet transform to examine the time-varying frequency content of the EEG signals. Specific directives can be recognised using features like the time-frequency distribution of the signals or the frequency modulation of oscillations.

3. Temporal features:

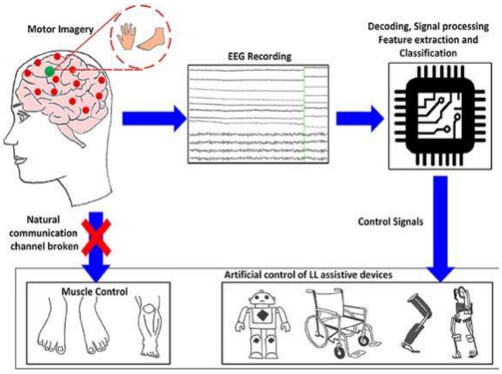
In order to achieve this, information from the EEG signals' temporal domain must be extracted, such as the latency or length of particular episodes. Specific instructions can be recognised using these features.

4. Spatial features:

The process of doing this entails taking specifics from the spatial distribution of the EEG data, such as the position or distribution of activity across several electrodes. To distinguish between different instructions, utilise these characteristics.

5. Nonlinear features:

This includes taking characteristics of the EEG signals, such as their complexity or entropy, from their nonlinear dynamics. Specific instructions can be recognised using these features.



3.2 Implementation:

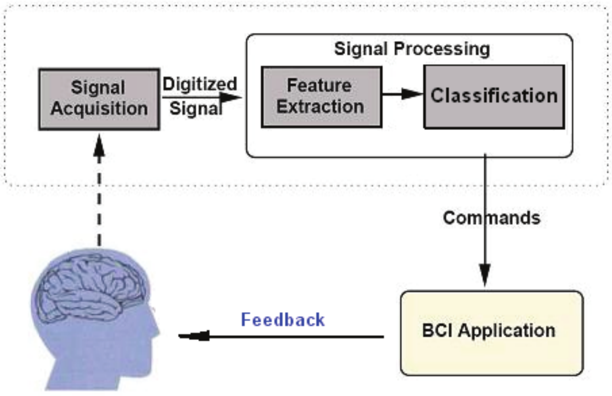


Fig -3: The block diagram of a BCI system

From the paper [32] The implementation of a Brain-Computer Interface (BCI) system to identify commands using an EEG net (a type of convolutional neural network designed for the analysis of electroencephalography (EEG) data) involves several steps. Some of the main steps include:

1. Data collection:

Electrodes are positioned on the scalp to record electroencephalography (EEG) data for a Brain-Computer Interface (BCI) system, which measures the electrical activity of the brain.

The method of gathering data generally involves the following steps:

Electrode placement:

To assess the electrical activity of various brain areas, electrodes are positioned on the scalp in a particular arrangement, such as the 10-20 system. Usually, a wire or cable is used to link the electrodes to EEG equipment.

Sampling rate:

To record the temporal properties of the brain activity, the EEG machine samples the amplified signals at a set rate, generally between 100 and 1000 Hz.

Signal filtering:

In order to reduce noise and artefacts like those brought on by eye movements or muscle activity, the recorded signals are often filtered. Techniques like Independent Component Analysis (ICA) and Artifact Subspace Reconstruction can be used for this (ASR).

Signal amplification:

The EEG machine amplifies the electrical impulses coming from the electrodes so they are simpler to measure. Usually, the signal-to-noise ratio is optimised by adjusting the amplification factor.

Data storage:

For subsequent examination, the filtered signals are often saved on a computer or other storage system.

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2. Data reprocessing:

From the paper [21] Data preparation is the process of preparing electroencephalography (EEG) for use in a Brain-Computer Interface (BCI) system by performing a number of operations on the raw EEG data to improve its suitability for analysis and command recognition.

The particular processes required for data preparation will vary depending on the kind of data and the needs of the BCI application.

Data preparation frequently involves the following steps:

Artifact removal:

The accuracy of the EEG readings can be affected by artefacts, such as those brought on by eye movements or muscular activity. To enhance the quality of the data, these artefacts are often removed during data preparation.

Denoising:

The accuracy of the EEG readings can also be affected by noise, including electrical interference and ambient noise. Wavelet denoising or independent component analysis (ICA) are two approaches that may be used in data preparation to get rid of noise from the data.

Feature extraction:

[22] Then, from the pre-processed EEG data, pertinent characteristics that are indicative of the user's orders should be retrieved. Frequency domain analysis and time-frequency analysis are two examples of signal-processing techniques that may be used for this.

Data segmentations:

To make the pre-processed data better suited for analysis and command detection, it may be divided into smaller time frames or epochs.

Data normalization:

The data may be normalized to remove differences in the magnitude or scale of the signals across different subjects or sessions.

3. Model training:

The next step is to use the retrieved characteristics to train the EEG net (or other machine learning algorithms) to look for patterns connected to certain instructions. Techniques for supervised, unsupervised, or semi-supervised learning can be used to do this.

4. Model evaluation:

From the paper [2] Electroencephalography (EEG) model evaluation for a Brain-Computer Interface (BCI) system entails evaluating how well a machine learning model performs in recognising patterns of brain activity connected to certain instructions. The particular assessment technique will rely on the type of data and the particular specifications of the BCI application.

Typical assessment techniques include:

Cross-validation:

In cross-validation, the data are split into two sets: a training set for the model's training and a validation set for the model's evaluation. The training set is used to develop the model, while the validation set is used to assess it. To obtain an average performance, this procedure is done several times using various data splits.

Holdout validation:

While the data is divided into a training set and a validation set, like in cross-validation, the model is only trained and tested once in holdout validation.

Online evaluation:

Online assessment entails assessing the model as it is being used by the user in the present. By contrasting the model's predictions with the user's actual orders while they are being carried out, this may be accomplished.

Offline evaluation:

Offline evaluation involves evaluating the model on pre-recorded data after it has been trained and deployed in the BCI system.

5. BCI system integration:

[24] The trained model must be integrated into the BCI system before being tested on a user to make sure it can recognise the necessary instructions precisely.

Overall, data collection, pre-processing, feature extraction, model training, and system integration are combined to develop a BCI system to detect instructions using an EEG net.

4. CRITICAL ANALYSIS

The Visual Geometry Group's VGG19 is renowned for its consistent architecture and ease of use. Small 3x3 convolutional filters are placed on top of each other over its 19 layers. ResNet50, which stands for Residual Network, on the other hand, provides skip connections or residual blocks that allow the network to pick up residual functions. Google's GoogLeNet Inception, which it created, has many parallel convolutional layers with various kernel sizes that enable it to collect a variety of characteristics. Its inception modules lighten the computational load while expanding the network's depth.

The success of these models depends on their performance. Even though VGG19 is straightforward, it frequently has a lot of parameters, which might cause overfitting on short datasets. ResNet50 handles the disappearing gradient with its skip connections.a challenge and makes it possible to train incredibly deep networks. On a number of image classification benchmarks, this architecture has demonstrated impressive performance advantages. On the other hand, Google Inception strikes a compromise between depth and computational effectiveness, making it suitable for real-time applications.

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Generalisation: When assessing these models, generalization—or the capacity to perform well on untested data—is a crucial consideration. Despite its simplicity, VGG19 has a good tendency to generalise when given enough training data. Skip connections and residual blocks in ResNet50 improve its generalizability and reduce its propensity for overfitting. The inception modules of Google Net Inception allow it to collect a variety of characteristics, which can help with improved generalisation on datasets with various levels of complexity.

Real-world applications require resource efficiency. Considering all of its parameters, VGG19 can be computationally costly, reducing its suitability for areas with limited resources. Despite being deeper, ResNet50 is renowned for its effective inference and training, in part because it makes use of skip connections. Google Net Inception is a great option for applications with limited resources since it achieves a balance between depth and computational effectiveness.

5.EXPERIMENTAL RESULTS

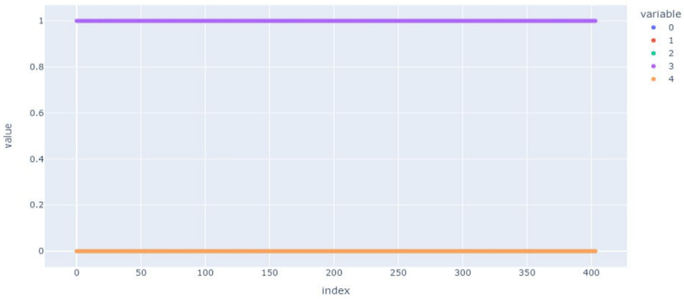

Fig-4: Vowel recognition accuracy from the imagined speech is compared between pre-trained networks as VGG19 and Resnet50.

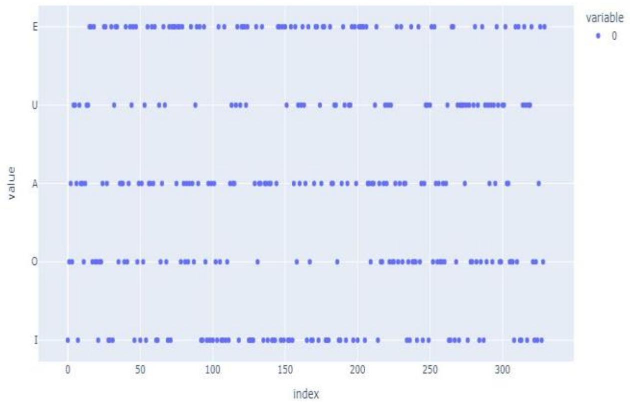

Fig-5: Vowel recognition accuracy from the imagined speech is compared between pre-trained networks as Resnet50 and GoogleNet.(Proposed network).

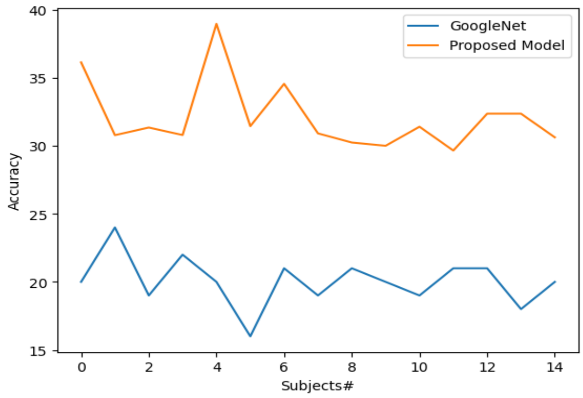

Fig-6: Vowel recognition accuracy (in%) from the imagined speech is compared between the pre-trained network GoogleNet and the proposed.

5.1 ACCURACY TABLES

Speaker	Confusion Matrix	Accuracy
S1	[[37 9 15 16 7] [19 23 14 14 10] [15 7 32 13 13] [16 16 5 30 13] [22 10 13 11 24]]	0.3613861386138614
S2	[[17 15 11 14 9] [13 20 17 10 6] [16 16 21 3 10] [18 13 9 18 8] [6 12 13 16 19]]	0.2878787878787879
S3	[[17 15 12 11 8] [8 25 15 10 8] [15 14 21 6 10] [17 11 12 17 9] [14 14 14 6 15]]	0.2932098765432099
S4	[[12 21 13 10 6] [9 22 13 13 8] [10 19 18 9 9] [5 12 15 24 6] [11 19 11 6 15]]	0.2879746835443038
S5	[[52 0 0 0 0] [21 15 6 4 6] [21 2 11 7 12] [21 4 6 13 6] [25 7 5 5 10]]	0.38996138996138996
S6	[[23 13 5 8 16] [12 27 6 9 11] [14 13 8 7 15] [14 12 7 14 18] [9 14 3 12 28]]	0.31446540880503143
S7	[[26 11 9 7 13] [15 18 6 3 14] [19 10 10 8 10] [12 10 9 19 9] [13 5 10 4 31]]	0.34551495016611294
S8	[[19 15 19 5 8] [16 16 18 5 7] [12 13 25 9 7] [13 17 10 19 6] [18 7 23 11 9]]	0.2691131498470948
[illegible]	[illegible]	[illegible]

Table-1:GoogleNet-feature extractor_Imagined speech classification

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Speaker	Confusion Matrix	Accuracy
S1	[[3 0 0 0 81] [2 0 0 0 78] [4 0 0 0 76] [2 0 0 0 78] [1 0 0 0 79]]	0.20
S2	[[11 0 40 15 0] [6 0 34 26 0] [7 0 44 15 0] [5 0 37 24 0] [5 0 40 21 0]]	0.24
S3	I[[5 0 0 58 0] [8 0 0 58 0] [9 0 1 56 0] [11 0 0 55 0] [6 0 0 57 0]]	0.19
S4	[[3 5 35 0 19] [2 5 39 1 18] [3 6 40 0 16] [2 2 42 0 16] [2 2 38 0 20]]	0.22
S5	[[34 0 0 0 18] [33 0 0 0 19] [36 0 0 0 17] [38 0 0 0 12] [35 0 0 0 17]]	0.20
S6	[[1 0 59 0 5] [4 0 52 0 9] [2 0 47 0 8] [5 0 51 0 9] [5 0 57 0 4]]	0.16
S7	[[38 0 23 5 0] [37 0 15 4 0] [30 0 22 5 0] [36 0 19 4 0] [38 0 20 5 0]]	0.21
S8	[[9 0 0 0 57] [6 1 0 0 55] [4 0 0 0 62] [8 1 0 0 56] [15 0 0 0 53]]	0.19

Table-2:Google-net in imagined speech classification

6. CONCLUSION

In conclusion, the application of deep learning techniques, such as the EEG net, in a Brain-Computer Interface (BCI) system has demonstrated promising results in precisely detecting commands through the study of brain signals. The use of these techniques has made it possible to decode brain activity in real-time and has the potential to greatly enhance BCI system performance.

The potential of deep learning algorithms to enhance the robustness and generalizability of the system is one of the main benefits of applying them in BCI systems. As a result, the system is more trustworthy and usable by a variety of users and settings. Additionally, the application of deep learning methodologies can result in the creation of more sophisticated BCI systems that are capable of carrying out a variety of activities and recognising a greater variety of instructions.

To utilise deep learning in BCI systems, there are, however, drawbacks and restrictions. The requirement for huge quantities of labelled training data, which can be challenging to get in reality, is one of the key obstacles. Furthermore, the interpretability of these complicated models may be constrained, making it challenging to comprehend the decision-making process.

Overall, applying deep learning techniques to BCI systems has the potential to revolutionise the field of brain-computer interface and has a wide range of uses in industries including healthcare, education, and entertainment. To make the best use of these techniques and to determine whether they have any other potential uses, more study is required.

In terms of design, speed, generalisation, and resource efficiency, the VGG19, ResNet50, and GoogLeNet Inception models each provide certain benefits and trade-offs. The model used will rely on the particular specifications of the current picture categorization task. When choosing a model for their applications, researchers and practitioners should carefully analyse these distinctions since doing so can have a big influence on how well their computer vision projects turn out.

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