Unveiling the Power of EEG Signals: Parkinson's Disease Identification via Yet Another Mobile Network (YAMNet)

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Abstract: Parkinson's disease is a neurodegenerative disorder with a progressively debilitating impact on patients' movement in terms of cognitive and motor aspects. Early detection is crucial for effective disease management and better patient outcomes. There are many techniques to detect this disease, but one of the most interesting methods to achieve early detection of Parkinson’s disease is electroencephalography, which is a non-invasive and cost-effective diagnostic tool to measure brain activity. Recent studies have shown that deep learning networks can handle complex data to analyse it and extract features. One of these neural networks is called Yet Another Mobile Network (YAMNet), which was originally proposed to analyse speech signals using time-frequency information. In this research, a novel approach using YAMNet is presented for the detection of Parkinson's disease patients using electroencephalogram brain signals, as the frequency information seems very relevant for Parkinson's disease detection. The proposed approach was evaluated with an open access dataset available on the Internet, composed of electroencephalogram recordings from Parkinson's disease patients and healthy control people, obtaining an accuracy rate of 98.9%. The results suggest that YAMNet could be an encouraging tool for the initial, non-invasive detection of Parkinson's disease. This may improve patient treatments and stimulate future research in the field.

1 INTRODUCTION

Parkinson's disease (PD) is a gradually progressive neurodegenerative condition caused by the loss of dopamine-producing cells in the brain, which leads to motor and cognitive impairment (Zaman et al., 2021). A diagnosis of Parkinson's disease ordinarily involves an extensive assessment of the patient's medical history, family history, and physical examination. Bradykinesia, tremor, and rigidity are common clinical manifestations in patients, and these are the most prominent presenting symptoms (Balestrino & Schapira, 2020). Furthermore, Parkinson's disease has spread worldwide over time, increasing 2.4-fold between 1990 and 2016 (Müller-Nedebock et al., 2023).

On the other hand, the aetiology of the disease has remained unknown until these days. Parkinson's disease may present itself in diverse forms and cases, each associated with distinct prognoses and disease progressions (Lang & Espay, 2018). Moreover, a malignant subtype is observed, and it represents a small percentage of about 9% to 16% of patients. It is characterized by swift disease advancement and by the existence of both motor and non-motor symptoms. On the contrary, a high rate of around 49% to 53% of patients suffer from mild motor-dominant Parkinson's, which progresses slowly and can be effectively treated, reducing symptoms with dopaminergic medications (Sabahi et al., 2021).

Research focused on early detection and classification of the different subtypes is necessary to determine the best treatment that can be offered to patients. Researchers have investigated various alternative diagnostic methods, such as handwriting analysis, electroencephalography (EEG) signals

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analysis, magnetic resonance imaging (MRI), voice analysis, and movement tests, in order to obtain an early diagnosis and detect PD (Tăuţan et al., 2021).

It is worth noting, for example, the approach of using human gait movement patterns to neurodegenerative diseases classification, by using the kinematic theory of rapid human movements (Dentamaro et al., 2020).

The same research group has also addressed the problem of Alzheimer’s and Parkinson’s diseases detection and classification, by the analysis of handwritten trials from a pattern recognition perspective, including data acquisition, feature extraction, data analysis, and classification (Impedovo & Pirlo, 2018).

The most important kinetic features and the most significant tasks for neurodegenerative disease assessment through handwritten have been identified in (Dentamaro, Impedovo, et al., 2021), working with the novel HAND-UNIBA dataset.

Regarding the application of machine learning for neurogenerative diseases detection or classification, it is worth mentioning that this group have addressed the application of different machine learning tools, including shallow learning techniques, and deep learning with transfer learning, for neurodegenerative disease assessment through handwriting (Gattulli et al., 2022) (Dentamaro, Giglio, et al., 2021), demonstrating that this approach based on handwriting analysis combined with artificial intelligence techniques, is useful for early detection of neurodegenerative diseases.

Although there are many signals that can be used for early detection of Parkinson’s disease, EEG signals have gained much attention in recent times due to their convenience of acquisition, cost-effectiveness and high level of accuracy. In general, EEG signals present energy in the band between 0 and 100 Hz, which can be divided into five sub bands: delta, theta, alpha, beta and gamma (Khosla et al., 2020). Traditionally, EEG signals are processed using spectral analysis techniques, so the implementation of automatic diagnostic systems is based on the extraction of relevant features in the frequency domain. The extracted features are used to feed classifiers that perform the task of classification between healthy and sick people, or between different degrees of the disease, depending on what the objective is.

Convolutional neural network (CNN) models have been successfully applied as tools for feature extraction from EEG signals and the subsequent diagnosis, providing advantages over other types of systems, such as automatic feature extraction, improved accuracy, robustness, and real-time analysis (Maitin et al., 2022). This paper proposes the use of deep learning models fed by information of EEG signals in the frequency domain and demonstrates its suitability to detect Parkinson’s disease.

Both classical machine learning and deep learning techniques offer the possibility of early identification of Parkinson's disease by analysing huge amounts of EEG data (Maitín et al., 2020). However, deep learning algorithms can identify minor variations in brain activity that may not be detectable with conventional diagnostic techniques. This allows earlier diagnosis, creating more effective treatment options. In addition, deep learning models can solve problems such as noise, distortion and variation in EEG signals due to various factors, such as electrode placement, motion or magnetic interference. In addition, these models can learn complex features independently, thus reducing the need for manual interference, which decreases reliance on subject expertise and self-interpretation (Khan et al., 2021).

Research into EEG techniques is advancing, with the aim of improving the accuracy and capabilities of Parkinson's disease detection and monitoring. Finally, the emergence of innovative approaches in EEG analysis through deep learning shows substantial potential for the diagnosis and management of Parkinson's disease. These advances have the potential to improve early detection, establish superior treatment options, and consequently improve outcomes for patients and their families.

In this paper, a deep neural network proposed for audio processing is applied to the detection of PD using EEG signals. The neural network is known as Yet Another Mobile Network (YAMNet) (Plakal, M. & Ellis, 2020), and it is a pre-trained deep neural network that can predict audio events from 521 classes. Audio and EEG signals share the characteristic that the information is mainly in the frequency domain, and we wonder if this pre-trained network for audio classification could be fitted to solve the problem of PD diagnosis, using the internally extracted features for audio classification. This is the hypothesis underlying the research in this paper.

The paper is organised as follows. Section 1 contains the introduction to the problem the paper deals with. Section 2 reviews the main related works. Section 3 describes the materials and methods used in the research. The results are presented and discussed in Section 4. Finally, Section 5 contains the conclusions.

2 RELATED WORKS

Various studies have been conducted to detect Parkinson's disease (PD) by analysing patients' EEG signals with deep learning techniques. For instance, Zhang et al (Zhang et al., 2022) employed the tuneable Q-factor wavelet transform (TQWT), wavelet packet transform (WPT), and deep residual shrinkage network (DRSN) to attain high classification accuracy. TQWT achieved 99.67% accuracy with features Permutation Entropy (PE) and Order Index (OI), whereas WPT produced 99.83% accuracy with energy features, and DRSN exhibited 99.87% accuracy.

In another study, Lee et al (Lee et al., 2021) were able to differentiate Parkinson's disease (PD) from healthy controls with high accuracy (99.2%), precision (98.9%), and recall (99.4%) using convolutional-recurrent neural networks (CRNN). They achieved this by extracting spatial and temporal features in multi-channel EEG signals. However, it was acknowledged that the model had certain limitations, including sensitivity to medication effects, a small sample size, and issues related to model interpretability.

On the other hand, Xu et al. (Xu et al., 2020) used a pooling-based deep recurrent neural network (PDRNN), resulting in a precision of 88.31%, a sensitivity of 84.84%, and a specificity of 91.81%. Despite these results, there were cases of misclassification, which involved 11.28% of healthy patients being classified as Parkinson's sufferers and 11.49% of Parkinson's cases being incorrectly identified as healthy. The research was also restricted by a small number of participants and potentially high computing costs when compared to conventional machine-learning methods.

The chaos theory has been applied by Shah et al. (Shah et al., 2020) to analyse variations in the EEG patterns of Parkinson's disease (PD) patients with a view to discovering a biomarker for PD classification. For classification tasks, they used the CNN Dynamical System Generated Hybrid Network (DGHNet) and Long Short-Term Memory (LSTM) units with the EEGLAB toolbox. Their study achieved a remarkable 99.2% accuracy in the classification of PD cases, even with limited computational resources. However, it was observed that additional research is required to address gaps in inter-patient classification due to the complex and patient-specific nature of EEG data.

Additionally, Oh et al. (Oh et al., 2020) constructed a thirteen-layer CNN model for detecting Parkinson's disease, attaining an accuracy rate of 88.25%, a sensitivity rate of 84.71%, and a specificity rate of 91.77%. This study was restricted by the sample size and the computational cost of the CNN configuration.

Shi et al. (Shi et al., 2019), in another study, utilized hybrid models composed of two conventional deep learning models (CNN and RNN) to categorize PD and normal EEG signals. The hybrid models performed better than the conventional models; however, the authors suspected that some data included in the database might be mislabelled. In addition, the amount of data from the PD and HC groups was small, so the five-fold technique was used to estimate the mean accuracy, obtaining the following results: 3D- CNN-RNN 82.89%, 2D-CNN-RNN 81.13%, CNN 80.89%, and RNN 76.00%.

Lee et al. (Lee et al., 2019), presented a framework that combines a convolutional neural network (CNN) and a recurrent neural network (RNN) with LSTM cells. The proposed model achieved remarkable outcomes, as it achieved an accuracy of 96.9%, precision of 100%, and recall of 93.4%. Consequently, the framework readily distinguishes PD from healthy controls. The researchers suggest refining the model with a larger dataset could make the CRNN framework a valuable diagnostic tool for monitoring diseases.

In a different study by Loh et al. (Loh et al., 2021), the authors investigated a deep-learning model for PD analysis. By using the Gabor transform to convert EEG recordings into spectrograms, they attained a 99.46% accuracy when training their 2D-CNN model. Additionally, the authors stressed the significance of broadening the model's capacity by integrating information on other brain irregularities, such as sleep disorders, depression, and autism, for multiple brain disorder identification as opposed to exclusively targeting one ailment.

An analysis of the literature revealed advantages and disadvantages in using deep learning techniques and algorithms with EEG brain signals to diagnose Parkinson's disease in patients.

Additionally, the studies discussed had some limitations, such as small sample sizes, expensive computing requirements, and limited interpretability of the proposed models, despite simulation studies being conducted for their assessment. Additionally, certain models require further enhancements to ensure compatibility with cloud systems and detect multiple ailments. Thus, it is imperative to conduct more research to attain accurate identification of Parkinson's disease from EEG signals using deep-learning methodologies.

The main conclusion drawn from the literature review is that EEG signals are useful for distinguishing healthy people from patients with Parkinson's disease, but that there is at the same time a major problem related to the amount of data available for deep network training.

To circumvent the problem of limited available data, several techniques have been explored, among which data augmentation and transfer learning are worth mentioning. While the use of techniques to synthetically augment the data set is problematic in healthcare applications, transfer learning techniques look promising.

Sufficiently large databases of EEG signals, even if related to other problems, are not available to train deep networks and then use the trained network to adjust it for the problem at hand, which is PD detection. For this reason, in this paper we explore a new line of research, which is the use of a pre-trained network for another very different problem, which is tuned a posteriori to solve the PD detection problem. We have chosen the YAMNet network, pre-trained for audio event classification, to solve our problem, since both audio classification and EEG processing for PD detection are performed in the frequency domain.

3 MATERIALS AND METHODS

3.1 Material

This study on Parkinson's disease used a dataset that was sourced from the Open-Neuro website, which is accessible to the public (Rockhill et al., 2020). Two sets of data make up the dataset: 15 PD patients' EEG recordings make up the first group, known as the PD dataset, while sixteen healthy controls who were taking dopaminergic medications both ON and OFF make up the second group. On their first usage, technical terms will be defined. The data was split into training (80% of the total) and validation (the remaining 20% chosen randomly), following the previously mentioned procedures.

So as to process the signals, a deep-neural network known as Yet Another Mobile Network (YamNet) has been used. This kind of deep convolutional neural network (CNN), has been proposed for audio classification. YamNet extracts relevant acoustic features from audio waveforms to classify sound events, and can predict 521 classes of audio events, after being trained on the AudioSet-Youtube corpus using the depth wise-separable convolution architecture Movilenet_v1. The architecture of YamNet was specially selected for the application of audio classification. This deep neural network is composed of 86 layers (Mohammed et al., 2023):

- 27 layers for convolutional operations, which play a key role in extracting meaningful features from the input audio waveforms.

- 27 layers for batch normalization, to ensure that the data is properly normalized, avoiding training challenges and improving learning speed.

- A ReLU activation function is incorporated after normalization, thus controlling the computational complexity of the network.

- The structure is completed with one average pooling layer, one fully connected layer, one softmax layer, and a final classification layer. These layers consolidate the information from previous layers.

YamNet exploits the transfer learning paradigm. After being trained for audio classification with the aforementioned dataset, it can be adapted with different data to other problems.

The model has learned patterns and characteristics associated with different sound events through training on a diverse set of labelled audio data. The audio signals are transformed to obtain Mel-spectrograms, that are applied as images to the network. Because of that, the input EEG signals are stored in *.wav files, considering the sampling rate is 16kHz, which is common in audio signals.

Moreover, the Yamnet network was built using Matlab 2022b software on a PC equipped with two Intel Xeon 3.10 GHz (E5-2687W) processors, 128 GB of RAM, and a 6 GB graphics card. The EEG data file from the dataset with the (.bdf) extension was read with an EEG tool in Matlab. Upon reading the file, the tool automatically converted the file format to (.mat) to be used in Matlab. The data underwent multiple processing stages.

3.2 Methods

The Yamnet process segments the wave audio into small overlapped windows, and transforms each one into a 96x64x1 Mel-spectrogram image to extract features. The images were then categorized, labelled and stored into two folders, one for the health control group and another one for Parkinson's disease patients without medication. Each folder contained a total of 840,000 images.

In order to extract more features, the images were converted from double-valued images to the image domain of 256 colours and then converted into a grayscale matrix. The subsequent stage involved commencing the training process on the data.

Table 1 presents the initial values provided for the primary training hyperparameters. No layers were altered during the training process, just the last layer in full connection to be compatible with the classification of output.

The deep neural networks were trained with the ADAM optimizer, which significantly reduces training time while achieving remarkable results. The neural network was trained on the given dataset for fifty epochs. In order to avoid suboptimal results or an excessively extended training process, it is paramount that the learning rate be carefully calibrated and not set too high or too low. In this work, a learning rate of 1e-5 was deemed optimal.

Ultimately, the YAMNet neural network classified the data into two categories: health control and Parkinson's disease without medication, as shown in Figure 1, through its model architecture and general process steps.

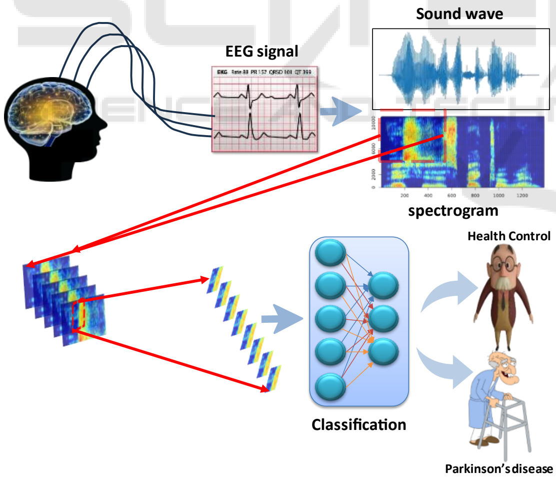

Figure 1: Model architecture.

Table 1: Hyperparameters used during the training phase.

Hyperparameter	value
Optimizer	Adam
Initial Learning Rate	0.00001
Mini batch size	10
Max epochs	50
F1 Score	Validation frequency

4 RESULTS AND DISCUSSION

The YAMNET model has been applied for the first time to the detection of Parkinson's disease through EEG signals, with the aforementioned database containing 31 files. All the signals in the files were segmented, and Mel-spectrograms were obtained. For training and validation, the dataset was split into a subgroup with 80% of images for training, and the remaining 20% for validation. With this strategy, the model achieved a remarkable accuracy of 98.97%. The model's performance was assessed, obtaining the confusion matrix that is shown in Table 2, and the results that appeared are shown in Table 2.

Table 2: Results of the confusion matrix.

		Predicted Class	
True Class	**Healthy control**	249198	2802
	PD	2362	249638
		Healthy control	**PD**

Table 3: Results.

Evaluation Metrics	Value
Accuracy	**98.97%**
Recall	**99.06%**
Precision	**98.89%**
Specificity	**98.89%**
F1 Score	**98.93%**

The study yielded encouraging results, as the confusion matrix showed the recognized samples correctly highlighted with dark boxes. The training process took 29,181 minutes and 28 seconds, requiring 50 epochs and 5,880,000 rounds of iterations.

5 CONCLUSIONS

In this work, we suggest an EEG-based approach to detect Parkinson's disease (PD) at an early stage. We process the EEG signals using YAMNet as input sound waves. The results show that the EEG signals of the two groups under study (PD and HC) can be classified with a high diagnostic accuracy, reaching up to 98.97% accuracy. These results are comparable to the best published in the literature but have been obtained using a model pre-trained to solve a very different problem, using transfer learning to tune the model for the problem at hand, that is PD detection.

This confirm that transfer learning is useful, even with networks trained for a very different problem, opening a new strategy to overcome the problem of the lack of samples for training in heath related applications.

Detecting PD in its early stages is one of the challenges facing the world, as it is essential for successful treatment and improving patients' quality of life, and we must race against time to find ways to treat this dangerous disease. The YAMNet-based method offers an affordable and non-invasive solution for the detection of Parkinson's disease, thus reducing examination time and workload in hospitals and healthcare centres. In addition, it can be used in real time, allowing PD patients to be continuously monitored using wearable technology, and to diagnose the patient earlier to offer tailored treatment options. It should be noted that the study had limitations, including the small sample size, which made training and testing more complicated and required the use of the k-fold technique, and the fact that the database belonged to a restricted age group.

Moreover, in order to enhance diagnostic precision and formulate a model for identifying and categorizing other diseases that are also related to analysing brain signals, it is crucial to verify the efficacy of our technique with a wider range of population samples and a larger dataset and variety. Additionally, the implementation of this approach on wearable devices to enable continuous monitoring of PD patients poses several challenges that call for further research.

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