Introduction

Machine learning is a type of artificial intelligence that involves training computer systems to learn from data and make predictions or decisions without being explicitly programmed. In other words, machine learning algorithms can identify patterns and relationships in large datasets and use that information to make predictions or classifications about new data.

In the case of Parkinson's disease diagnosis, machine learning can be applied by training algorithms on large datasets of patient information and medical records. These algorithms can then learn to identify patterns and features that are indicative of Parkinson's disease, such as tremors, gait abnormalities, and speech changes.

For example, a machine learning algorithm could be trained on a dataset of patient information that includes details about their symptoms, medical history, and genetic information. The algorithm would then use this information to learn patterns and relationships that are associated with Parkinson's disease, such as specific combinations of symptoms or genetic markers.

Once the algorithm has been trained, it can be used to predict whether new patients are likely to have Parkinson's disease based on their symptoms and other medical information. This can be particularly useful for early diagnosis and treatment of the disease, as well as for monitoring disease progression and evaluating the effectiveness of different treatments.

Deep learning is a subfield of machine learning that focuses on training artificial neural networks to perform complex tasks. In recent years, it has become a popular approach for solving a wide range of problems in areas such as image recognition, natural language processing, and speech recognition.

The key advantage of deep learning is its ability to automatically learn features from raw data, eliminating the need for manual feature engineering. This makes it particularly useful for tasks that involve large and complex datasets, where manual feature engineering would be prohibitively time-consuming or even impossible.

[An image of Aritifical neural network architecture]

At the heart of deep learning are artificial neural networks, which are inspired by the structure and function of the human brain. Neural networks consist of layers of interconnected nodes, or "neurons," that process and transmit information. In deep learning, neural networks are typically composed of many layers, allowing them to learn increasingly complex features and representations.

One of the most popular types of neural network used in deep learning is the convolutional neural network (CNN), which is particularly well-suited to image and video analysis. Another common type is the recurrent neural network (RNN), which is often used for natural language processing and speech recognition.

Convolutional Neural Networks (CNNs): CNNs are a type of deep learning algorithm that are particularly well-suited for image classification tasks. They work by applying a series of convolutional filters to an input image, which helps to identify and extract relevant features. The output of the convolutional layers is then passed through fully connected layers for classification.

[An image of CNN architecture]

Dataset:

Before deep dive into our use case, let’s start with exploring our dataset “Parkinson’s Drawings: Distinguishing Different Stages of Parkinson’s Disease” [1].

This dataset consists of two main subdirectories: Spiral, and Wave. These images that are from different sizes, and they are divided into ‘healthy’ and ‘parkinson’ categories. The images that are found in the spiral directory are for handwritten drawings of a spiral shapes by human with and without the mentioned above disease. Similarly, the wave directory contains images of drawings of the wave shape.

In depth, the dataset, which is in total of 204 images, is divided in the following way:

* 36 training images of spiral shape (healthy)
* 36 training images of spiral shape (parkinson)
* 36 training images of wave shape (healthy)
* 36 training images of wave shape (parkinson)
* 15 testing images of spiral shape (healthy)
* 15 testing images of wave shape (parkinson)
* 15 testing images of spiral shape (healthy)
* 15 testing images of wave shape (parkinson)

[images taken from dataset]

Methodology:

As mentioned before, our data is divided into ‘spiral’ and ‘wave’ and this to ensure the diversity of shapes taken from the human drawings. Therefore, our models are going to be trained separately on both these categories and then discuss the outcomes accordingly.

To gain wider understanding of data, and to achieve better training results, four models have been developed for training, this can provide better results, and create a comparison between these models. Our models are pre-built models taken from TensorFlow library.

Model 1: DenseNet201 [2]

This is a convolutional neural network architecture that was introduced in 2017. It is a type of "dense" network, meaning that each layer is connected to every other layer in a feedforward manner. This design helps to improve the flow of information throughout the network and can lead to better performance. DenseNet201 has 201 layers, and it was trained on the ImageNet dataset, which contains over 1 million labeled images in 1,000 categories.

Model 2: MobileNetV2 [3]

This is another convolutional neural network architecture that was introduced in 2018. It is designed to be lightweight and efficient, making it well-suited for mobile devices and other applications with limited computational resources. MobileNetV2 uses a technique called "depthwise separable convolutions," which reduces the number of parameters needed for the network while maintaining high accuracy. It was also trained on the ImageNet dataset.

Model 3: ResNet50 [4]

This is a convolutional neural network architecture that was introduced in 2015. It stands for "Residual Network," which refers to its use of "residual connections" to help mitigate the problem of vanishing gradients. ResNet50 has 50 layers, and it was also trained on the ImageNet dataset.

Model 4: VGG16 [5]

This is a convolutional neural network architecture that was introduced in 2014. It is named after the Visual Geometry Group at the University of Oxford, where it was developed. VGG16 has 16 layers and uses small 3x3 filters throughout the network. It was also trained on the ImageNet dataset and was one of the first models to achieve high accuracy on the ImageNet challenge.

All these pre-trained models are commonly used in computer vision tasks and can be fine-tuned for specific applications.

Due to the classification task that we are dealing with, we added some additional layers at the end of each model, where the first layer is a Dense Layer with 128 neurons, with ReLU activation function [6], in addition to another Dense Layer of 2 neurons that is responsible for the final probability output of the specified categories healthy and Parkinson. The activation function at this stage is a softmax [7] that is used for classification tasks.

Later on, these model are compiled to perform backpropagation using Adam Optimizer [8] and the categorical cross entropy loss function [9].

The models have been fitted successfully with batch size of 32 and to study the performance of these models the graphs below represent the results of the behavior of models during training process on both sub-datasets.

[images of performance of accuracy and loss plotted using matplotlib for each model]

Referring to the graphs, we can see that our models learned effectively, and since our aim is to choose the best model that perform the best predictions on unseen data. We ran a script that lets each model to perform a prediction on all unseen data (testing data) and we computed the ratio of correct predictions.  
The results are in the table below:

|  |  |  |
| --- | --- | --- |
| Model 1 | 0.83% | 50 out of 60 |
| Model 2 | 0.82% | 49 out of 60 |
| Model 3 | 0.52% | 31 out of 60 |
| Model 4 | 0.72% | 43 out of 60 |

These results lead to say that Model 1 and Model 2 were the best selections for this use case and a combination of their architectural networks could lead to higher accuracy, which can be a future work to improve predictions and analysis.

Introduction

Machine learning is a sort of artificial intelligence in which computer systems are trained to learn from data and make predictions or judgments without being explicitly programmed. In other words, machine learning algorithms can detect patterns and relationships in vast datasets and use that information to create predictions or categorize fresh data.

Machine learning can be used to diagnose Parkinson's disease by training algorithms on big datasets of patient information and medical records. These algorithms can then be trained to recognize patterns and traits associated with Parkinson's disease, such as tremors, gait problems, and speech alterations.

Training algorithms on big datasets of patient information and medical records can be used to apply machine learning. These algorithms can then be trained to recognize patterns and traits associated with Parkinson's disease, such as tremors, gait problems, and speech alterations.

A machine learning algorithm, for example, may be trained using a dataset of patient data that contains details about their symptoms, medical history, and genetic information. This data would then be used by the computer to discover patterns and associations related to Parkinson's disease, such as certain combinations of symptoms or genetic markers.

Once trained, the algorithm can be used to predict whether new patients are likely to have Parkinson's disease based on their symptoms and other medical data. This is especially beneficial for early disease diagnosis and therapy, as well as monitoring disease progression and evaluating the efficacy of various treatments.

Deep learning is a machine learning subject that focuses on training artificial neural networks to perform complex tasks. It has recently gained popularity as a method for handling a wide range of issues in domains such as image identification, natural language processing, and audio recognition.

The capacity of deep learning to automatically learn features from raw data eliminates the need for manual feature engineering. This makes it especially effective for applications involving big and complicated datasets, where manual feature engineering would be excessively time intensive, if not impossible.

[A diagram of the architecture of an artificial neural network]

Artificial neural networks, which are inspired by the structure and function of the human brain, are at the center of deep learning. Layers of interconnected nodes, or "neurons," process and transmit information in neural networks. Neural networks are often constructed of multiple layers in deep learning, allowing them to learn increasingly complicated aspects and representations.

The convolutional neural network (CNN), which is particularly well-suited to image and video processing, is one of the most prominent forms of neural network used in deep learning. The recurrent neural network (RNN) is another popular form that is frequently used for natural language processing and speech recognition.

Convolutional Neural Networks (CNNs): CNNs are a form of deep learning algorithm that excels at picture classification. They function by applying a set of convolutional filters to an input image, which aids in the identification and extraction of key features. The output of the convolutional layers is subsequently classified using fully connected layers.

[An illustration of CNN architecture]

Before delving into our use case, let's first look at our dataset "Parkinson's Drawings: Distinguishing Different Stages of Parkinson's Disease" [1].

This dataset is divided into two sections: Spiral and Wave. These photos come in a variety of sizes and are classified into 'healthy' and 'parkinson' categories. The photographs in the spiral directory are of handwritten spiral shapes drawn by humans with and without the aforementioned condition. Similarly, the wave directory contains photos of wave shape designs.

In depth, the dataset, which contains 204 photos, is segmented as follows:

- 36 training images of spiral shape (healthy)

- 36 training images of spiral shape (parkinson)

- 36 training images of wave shape (healthy)

- 36 training images of wave shape (parkinson)

- 15 testing images of spiral shape (healthy)

- 15 testing images of wave shape (parkinson)

- 15 testing images of spiral shape (healthy)

- 15 testing images of wave shape (parkinson)

[images taken from dataset]

Methodology: As previously stated, our data is separated into'spiral' and 'wave' categories to assure the diversity of shapes derived from human drawings. As a result, we will train our models independently on both of these categories and then discuss the results.

Four models for training have been established to acquire a better understanding of data and generate better training results. This can provide better results and create a comparison between these models. Our models are ready-made models from the TensorFlow library.

DenseNet201 [2] is the first model.

In 2017, a convolutional neural network architecture was introduced. It is a "dense" network in the sense that each layer is connected to every other layer in a feedforward fashion. This architecture aids in the flow of information throughout the network, which can lead to improved performance. DenseNet201 is a 201-layer neural network that was trained using the ImageNet dataset, which contains over 1 million classified images in 1,000 categories.

MobileNetV2 [3] is the second model.

Another convolutional neural network architecture that was introduced in 2018 is this one. It is lightweight and efficient, making it ideal for mobile devices and other applications that have limited processing resources. MobileNetV2 employs a technique known as "depthwise separable convolutions," which minimizes the amount of network parameters while retaining excellent accuracy. It was trained on the ImageNet dataset as well.

ResNet50 [4] is the third model.

In 2015, a convolutional neural network architecture was introduced. It is an abbreviation for "Residual Network," which refers to how it uses "residual connections" to assist offset the problem of vanishing gradients. ResNet50 includes 50 layers and was trained on the ImageNet dataset as well.

VGG16 [5] model

In 2014, a convolutional neural network architecture was introduced. It is called after the University of Oxford's Visual Geometry Group, where it was created. The VGG16 network has 16 layers and employs small 3x3 filters throughout. It was trained on the ImageNet dataset as well, and it was one of the first models to achieve high accuracy on the ImageNet challenge.

We added some additional layers at the end of each model due to the classification task that we are dealing with, where the first layer is a Dense Layer with 128 neurons, with ReLU activation function [6], in addition to another Dense Layer of 2 neurons that is responsible for the final probability output of the specified categories healthy and Parkinson. At this step, the activation function is a softmax [7], which is utilized for classification tasks.

These models are afterwards built for backpropagation using the Adam Optimizer [8] and the categorical cross entropy loss function [9].

The models were successfully fitted with a batch size of 32, and the graphs below illustrate the outcomes of the models' behavior during the training process on both sub-datasets.

[Images showing accuracy and loss performance plotted using matplotlib for each model]

According to the graphs, our models learnt effectively, and our goal is to select the best model that performs the best predictions on unknown data. We ran a script that allowed each model to make a prediction on all unseen data (testing data), and we calculated the right prediction ratio.

The outcomes are shown in the table below:

Model 1 0.83% 50 out of 60

Model 2 0.82% 49 out of 60

Model 3 0.52% 31 out of 60

Model 4 0.72% 43 out of 60

These findings suggest that Models 1 and 2 were the best choices for this use case, and that combining their architectural networks could result in improved accuracy, which could be a future effort to improve predictions and analysis.