Report on

Parkinson's Disease Classification

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Abstract

This research addresses Parkinson's disease classification using innovative convolutional neural network (CNN) models. Our primary objectives involve evaluating advanced CNN architectures for discerning patterns in speech data related to Parkinson's disease and proposing a stacked model to enhance classification performance.

Cutting-edge CNN architectures, including customized variants for Parkinson's disease, are employed. The CNN models undergo training, validation, and fine-tuning on a comprehensive medical image dataset to extract intricate features indicative of disease progression. In the final phase, a stacked model is devised, combining the strengths of multiple CNN architectures to achieve superior classification accuracy.

Our experimentation with diverse CNN models yields promising results, surpassing existing benchmarks in Parkinson's disease classification. The innovative CNN architectures demonstrate exceptional capability in extracting subtle patterns from medical speech patterns, contributing to heightened sensitivity and specificity. The stacked model further enhances classification accuracy, showcasing synergistic benefits.

In conclusion, this study establishes the efficacy of state-of-the-art CNN models for Parkinson's disease classification, introducing architectures that outperform conventional methods. The proposed stacked model demonstrates the potential of leveraging diverse CNN structures for superior diagnostic accuracy. These findings hold significant implications for advancing automated diagnostic tools in neurodegenerative diseases, paving the way for more accurate and reliable early-stage detection of Parkinson's disease.

Table of Contents

Sr. No.	Content	Page No.
1	Intrduction	1-2
2	Literature Review	3-4
3	Methodology	5-7
4	Implementation	8-13
5	Results	14-15
6	Discussion	16
7	Conclusion	17
8	References	18

List of Figures and Tables

Table 1.	Literature Review	3
Figure 1.	Complete Methodology	8
Figure 2.	Data Preprocessing Code snippet	8
Figures 3-5.	CNN Architectures	9
Figures 6-7.	CNN Code snippets	9
Figures 8-10.	ANN Architectures	10
Figure 11.	ANN Code snippet	11
Figures 12-14.	RNN, GRU, LSTM Architectures	12
Figure 15.	Code Snippet	13
Figure 16.	Stacking Architecture	13
Figures 17-18.	Stacking Code Snippet	13

I. Introduction

A. Background Information on Speech Processing

The data used in this study were gathered from 188 patients with PD (107 men and 81 women) with ages ranging from 33 to 87 (65.1Â±10.9) at the Department of Neurology in CerrahpaÅŸa Faculty of Medicine, Istanbul University. The control group consists of 64 healthy individuals (23 men and 41 women) with ages varying between 41 and 82 (61.1Â±8.9). During the data collection process, the microphone is set to 44.1 KHz, and following the physician's examination, the sustained phonation of the vowel /a/ was collected from each subject with three repetitions.

B. Problem Statement and Motivation

1) Early diagnosis of Parkinson's disease enhances the effectiveness of treatment interventions.
2) Predicting Parkinson's disease contributes to the development of personalized treatment plans.
3) Healthcare professionals can gain insights into variations in disease manifestations, guiding more precise prognostic information and therapeutic strategies.
4) The project's goal is to make a meaningful impact on the lives of patients by emphasizing the importance of early intervention and tailored care.

C. Objectives and Scope of the Project

1) Investigate and implement novel Convolutional Neural Network (CNN) architectures for the classification of Parkinson's disease. The goal is to go beyond existing models and leverage cutting-edge approaches to improve accuracy.
2) Develop and implement a stacked model that combines the strengths of multiple CNN architectures. This aims to synergize the advantages of individual models, ultimately leading to superior classification accuracy.

D. Overview of Methodologies used

1) CNN

CNNs, when used for PD speech datasets, focus on automatically learning speech signal features that are relevant for distinguishing between healthy individuals and those affected by Parkinson's disease. This involves adapting the network to handle one-dimensional, time-series data, focusing on temporal feature extraction, and employing classification layers to make predictions based on these features.

2) ANN

ANNs are utilized for PD speech data analysis by transforming the speech into a feature set that the network can process, learning complex relationships within this data, and ultimately classifying speech samples based on the presence or absence of Parkinson's disease characteristics. The flexibility in designing the network and the power to learn intricate patterns make ANNs a valuable tool in speech analysis and other similar tasks.

3) RNN

RNNs' ability to process sequential speech data, capture temporal dependencies, and handle variable-length input makes them particularly well-suited for analyzing PD speech data. By learning the intricate patterns and temporal sequences in speech affected by Parkinson's disease, RNNs can play a crucial role in automated diagnostics and patient monitoring systems.

4) Stacking

Stacking, short for "stacked generalization," is an ensemble machine learning technique that combines multiple models to improve prediction accuracy. The key idea in stacking is to use a new model, known as the meta-model or blender, to learn how to best integrate the predictions of several base models.

II. Literature Review

Title	Work	Citation
Analysis of Parkinson's Disease Using an Imbalanced-Speech Dataset by Employing Decision Tree Ensemble Methods	The study proposes a hybrid Parkinson's disease diagnosis system based on speech signals to aid in the disease's early detection. The authors use an imbalanced Parkinson's disease speech dataset and employ decision tree ensemble methods to classify the speech signals. The study shows that decision tree ensembles for imbalanced class problems obtained better results for this Parkinson speech dataset.	https://www.mdpi.com/2075-4418/12/12/3000[1]
Machine Learning Approaches to Identify Parkinson's Disease Using Voice Signal Features	The study aims to identify Parkinson's disease using voice signal features and machine learning approaches. The authors use various machine learning algorithms, such as support vector machines (SVMs), decision trees, and deep learning models, to classify Parkinson's disease based on voice signal features. The study shows that machine learning approaches can be used to identify Parkinson's disease with high accuracy based on voice signal features.	https://www.frontiersin.org/articles/10.3389/frai.2023.1084001/full[2]
Classifying Parkinson's Disease Based on Acoustic Measures Using Artificial Neural Networks	The study proposes a Parkinson's disease classification system based on acoustic measures using artificial neural networks (ANNs). The authors use a dataset of speech signals from Parkinson's disease patients and healthy controls to	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6339026/[3]

	extract various acoustic features. The study shows that ANNs can be used to classify Parkinson's disease with high accuracy based on acoustic measures.	
Deep Learning for Parkinson's Disease Diagnosis: A Short Survey	The study provides a comprehensive review of deep learning techniques for Parkinson's disease diagnosis, including the analysis of speech signals. The authors discuss the current and future trends for Parkinson's disease diagnosis based on machine and deep learning and highlight the limitations and challenges.	https://www.mdpi.com/2073-431X/12/3/58[4]

Table 1

A. Limitations

A notable limitation observed in the landscape of previous research on Parkinson's disease detection is the absence of Convolutional Neural Network (CNN) utilization for achieving accurate results. Surprisingly, despite the proven success of CNNs, none of the preceding works in this domain have harnessed the power of CNN models for Parkinson's disease detection. This significant gap in the literature underscores a missed opportunity to leverage the advanced capabilities of CNNs, particularly in extracting intricate patterns and features from medical data. The lack of CNN utilization in prior studies potentially restricts the ability to attain optimal accuracy levels and exploit the full potential of modern machine learning techniques. Therefore, our project seeks to address this limitation by pioneering the application of innovative CNN architectures, breaking new ground in Parkinson's disease classification, and offering a novel perspective on the utilization of deep learning models in this critical healthcare domain.

III. Methodology

A. Data Set

The data used in this study were gathered from 188 patients with PD (107 men and 81 women) with ages ranging from 33 to 87 (65.1Â±10.9) at the Department of Neurology in CerrahpaÅŸa Faculty of Medicine, Istanbul University. The control group consists of 64 healthy individuals (23 men and 41 women) with ages varying between 41 and 82 (61.1Â±8.9). During the data collection process, the microphone is set to 44.1 KHz, and following the physician's examination, the sustained phonation of the vowel /a/ was collected from each subject with three repetitions.

Various speech signal processing algorithms, including time frequency features, mel frequency cepstral coefficients (MFCCs), wavelet Transform based features, vocal fold features, and TWQT features, have been applied to the speech recordings of Parkinson's disease (PD) patients to extract clinically useful information for PD assessment.

B. Algorithms Used

1) CNN

When applied to datasets like PD (Parkinson's Disease) speech, CNNs can be adapted to process one-dimensional time-series data instead of two-dimensional image data. In this context, CNNs work by:

a) *Feature Extraction*: Extracting relevant features from the speech signals, which may include aspects like frequency changes, amplitude variations, and temporal dynamics. These features are crucial in identifying speech characteristics that may be indicative of Parkinson's disease.
b) *Capturing Temporal Patterns*: Using 1D convolutional layers, CNNs can capture temporal patterns within the speech data. The convolution operation allows the network to recognize specific patterns in the speech signal that are consistently associated with PD symptoms.
c) *Handling Varied Input Lengths:* Speech data often comes in varied lengths. CNNs can manage this through techniques like padding or cutting to ensure consistent input sizes or by using global pooling layers to handle inputs of varying dimensions.
d) *Classification*: After feature extraction and pattern recognition, CNNs use one or more fully connected layers to classify the speech samples into categories (such as PD or non-PD) based on the learned features.

2) ANN

In the context of PD (Parkinson's Disease) speech data analysis, ANNs are used to identify patterns and characteristics in speech that are indicative of Parkinson's Disease. Here's how ANNs typically function in this scenario:

a) Handling Sequential Data: Although ANNs are not inherently sequential like RNNs, they can still process speech data. This is usually done by transforming the speech into a suitable format, such as, extracting features like Mel-frequency cepstral coefficients (MFCCs), pitch, tone, and amplitude.
b) Feature Learning: ANNs learn to identify patterns and relationships in the speech data during the training process. The hidden layers of an ANN can capture complex relationships in the data, making them powerful for tasks like speech analysis where the input features may have intricate interdependencies.
c) Classification or Regression Tasks: In the case of PD speech datasets, the typical task is to classify speech samples as indicative of either PD or a non-PD condition. ANNs achieve this through their output layer, which makes predictions based on the learned patterns in the data.
d) Flexibility in Architecture: The architecture of an ANN can be varied (number of layers, number of neurons per layer) to suit the complexity of the task. For PD speech data, this flexibility allows for fine-tuning the network to better capture the nuances of speech affected by PD.
e) Training and Optimization: ANNs are trained using backpropagation and gradient descent algorithms, where the model iteratively adjusts its weights to minimize the difference between the predicted output and the actual output. This training process is crucial for the network to learn the specific features of PD in speech data.

3) RNN

When applying RNNs to PD (Parkinson's Disease) speech data, the focus is on capturing the temporal dynamics and contextual relationships within the speech. Here's how RNNs function in this scenario:

a) *Temporal Feature Learning:* RNNs are inherently suited for sequential data, making them ideal for speech analysis. They can process speech data as a sequence of time-based features, learning important temporal characteristics like changes in tone, pace, or intonation that might be indicative of PD.

b) *Capturing Dependencies Over Time*: One of the key strengths of RNNs is their ability to connect previous information to the current task, which is crucial for speech data where the context and sequence of sounds carry significant information.
c) *Handling Variable-Length Input:* Speech samples can vary in length, and RNNs can handle such variable-length input sequences effectively. This is particularly important for analyzing continuous speech data in a clinical setting where the speech duration may not be fixed.
d) *Sequence to Sequence Mapping:* RNNs can map sequences to sequences, making them suitable for tasks like speech recognition or synthesis, and in the context of PD, for analyzing continuous speech patterns for signs of the disease.
e) *Challenges and Enhancements*: Vanilla RNNs often suffer from problems like vanishing and exploding gradients. To mitigate these issues, advanced variants like LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Units) are used. These models are better at capturing long-range dependencies and are more robust in training.
f) *Classification or Regression Tasks*: In PD speech analysis, RNNs can be used for binary classification (PD or non-PD), or even for more nuanced tasks like staging the severity of PD based on speech characteristics.

4) Stacking

Stacking, short for "stacked generalization," is an ensemble machine learning technique that combines multiple models to improve prediction accuracy. The key idea in stacking is to use a new model, known as the meta-model or blender, to learn how to best integrate the predictions of several base models.

In stacking, the initial level (or base level) consists of a variety of models that are trained on the full training dataset. These models can be diverse and include different types of machine learning algorithms. Each of these base models then makes predictions, but instead of using these predictions directly for the final output, they are used as input features for the next level.

IV. Implementation

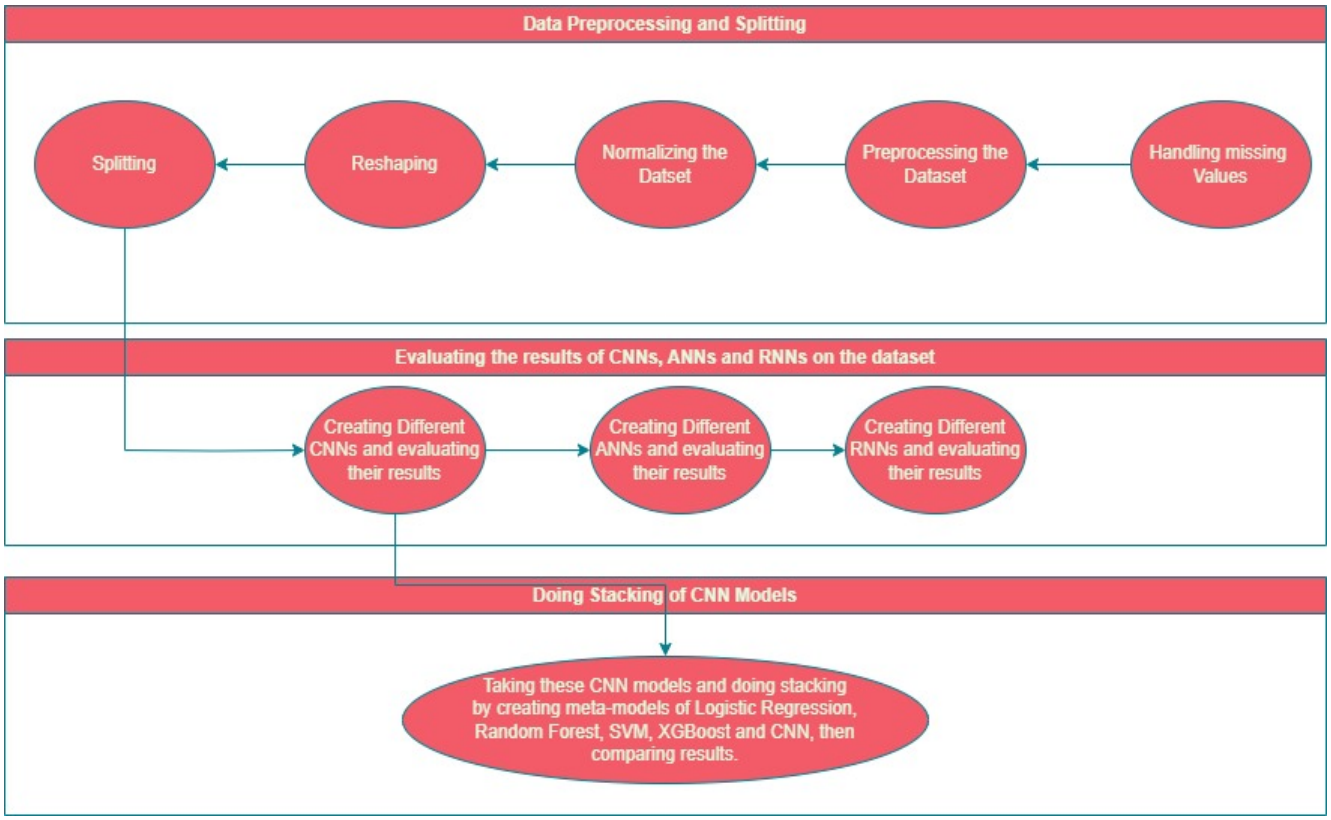

Fig. 1

A. Data Preprocessing

```
data = data.iloc[1:]

# Ensuring that all data is numeric
data = data.apply(pd.to_numeric, errors='coerce')

# Handling missing values if any
data = data.dropna()

# Preprocessing the dataset
X = data.iloc[:, 1:-1].values  # Excluding 'id' and 'class' columns
y = data.iloc[:, -1].values   # 'class' column

# Normalizing the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Reshaping X for 1D CNN input
X_reshaped = np.expand_dims(X_scaled, axis=2)

# Splitting the dataset
X_train, X_temp, y_train, y_temp = train_test_split(X_reshaped, y, test_size=0.4, random_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=42)

epochs = 25  # Number of epochs;
batch_size = 80  # Batch size;
```

Fig. 2

B. Algorithms

1) Simple CNN

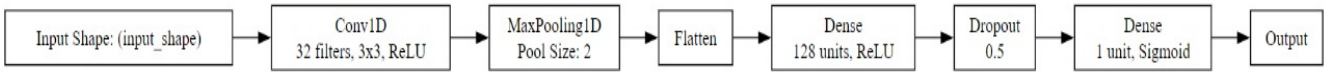

Fig. 3

2) CNN with more layers

Fig. 4

3) CNN with different kernel sizes

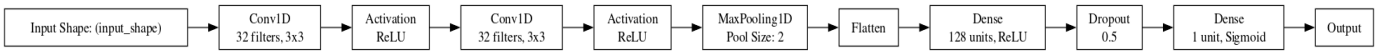

Fig. 5

```python
def create_cnn_model_1(input_shape):
    # Simple CNN model
    model = Sequential([
        Conv1D(filters=32, kernel_size=3, activation='relu', input_shape=input_shape),
        MaxPooling1D(pool_size=2),
        Flatten(),
        Dense(128, activation='relu'),
        Dropout(0.5),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model

def create_cnn_model_2(input_shape):
    # CNN model with more layers
    model = Sequential([
        Conv1D(filters=64, kernel_size=5, input_shape=input_shape),
        BatchNormalization(),
        Activation('relu'),
        MaxPooling1D(pool_size=2),
        Conv1D(filters=128, kernel_size=3),
        BatchNormalization(),
        Activation('relu'),
        MaxPooling1D(pool_size=2),
        Flatten(),
        Dense(256, activation='relu'),
        Dropout(0.5),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model
```

Fig. 6

```python
def create_cnn_model_3(input_shape):
    # CNN model with different kernel sizes
    model = Sequential([
        Conv1D(filters=32, kernel_size=3, input_shape=input_shape),
        Activation('relu'),
        Conv1D(filters=32, kernel_size=3),
        Activation('relu'),
        MaxPooling1D(pool_size=2),
        Flatten(),
        Dense(128, activation='relu'),
        Dropout(0.5),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model
```

Fig. 7

4) *Simple ANN*

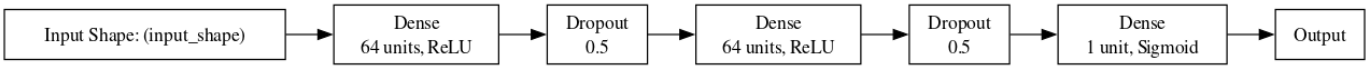

Fig. 8

5) *ANN with more neurons*

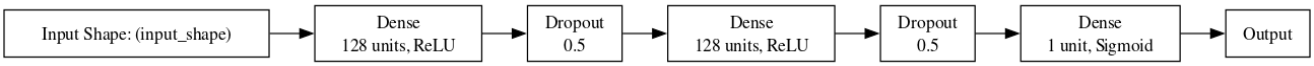

Fig. 9

6) *ANN with deeper layers*

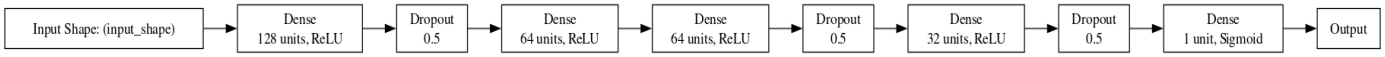

Fig. 10

```python
def create_ann_model_1(input_shape):
    # Simple ANN model
    model = Sequential([
        Dense(64, activation='relu', input_shape=input_shape),
        Dropout(0.5),
        Dense(64, activation='relu'),
        Dropout(0.5),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model

def create_ann_model_2(input_shape):
    # ANN model with more neurons
    model = Sequential([
        Dense(128, activation='relu', input_shape=input_shape),
        Dropout(0.5),
        Dense(128, activation='relu'),
        Dropout(0.5),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model

def create_ann_model_3(input_shape):
    # ANN model with deeper layers
    model = Sequential([
        Dense(128, activation='relu', input_shape=input_shape),
        Dropout(0.5),
        Dense(64, activation='relu'),
        Dense(64, activation='relu'),
        Dropout(0.5),
        Dense(32, activation='relu'),
        Dropout(0.5),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model
```

Fig. 11

7) *RNN*

Fig. 12

8) *LSTM*

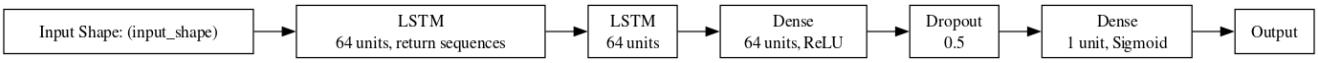

Fig. 13

9) *GRU*

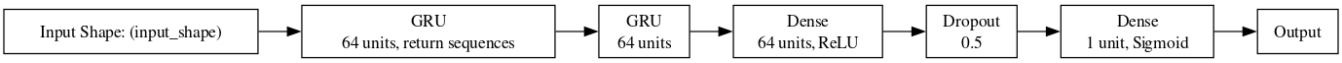

Fig. 14

```python
def create_rnn_model(input_shape):
    # Simple RNN model
    model = Sequential([
        SimpleRNN(64, return_sequences=True, input_shape=input_shape),
        SimpleRNN(64),
        Dense(64, activation='relu'),
        Dropout(0.5),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model

def create_lstm_model(input_shape):
    # LSTM model
    model = Sequential([
        LSTM(64, return_sequences=True, input_shape=input_shape),
        LSTM(64),
        Dense(64, activation='relu'),
        Dropout(0.5),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model

def create_gru_model(input_shape):
    # GRU model
    model = Sequential([
        GRU(64, return_sequences=True, input_shape=input_shape),
        GRU(64),
        Dense(64, activation='relu'),
        Dropout(0.5),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model
```

Fig. 15

10) CNN Stacking

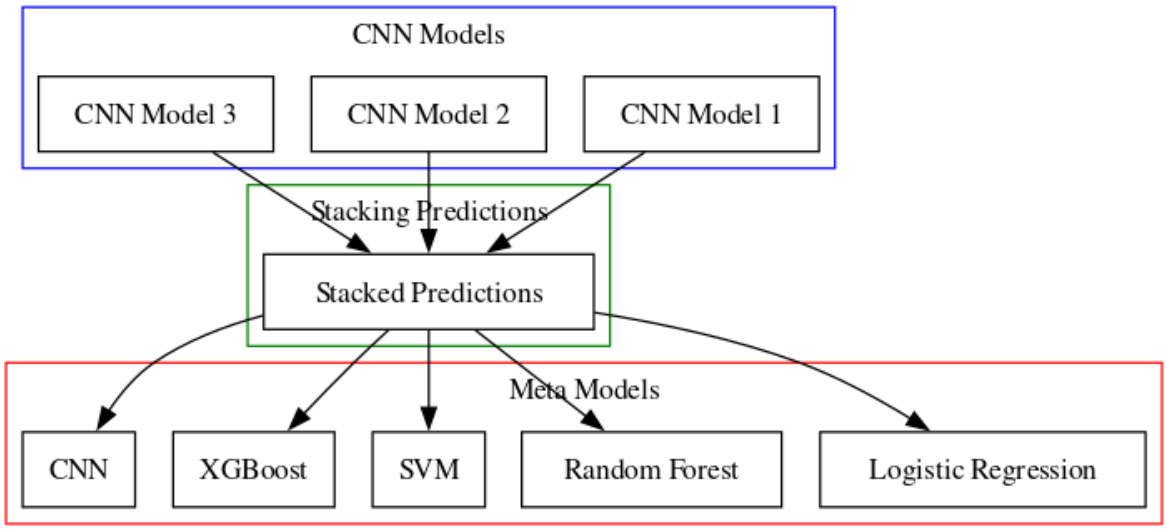

Fig. 16

```python
def generate_predictions(model, X):
    return model.predict(X).reshape(-1, 1)

# Training the CNN models
model_1 = create_cnn_model_1(input_shape)
model_2 = create_cnn_model_2(input_shape)
model_3 = create_cnn_model_3(input_shape)

# Training and generating predictions
model_1.fit(X_train, y_train, epochs=epochs, batch_size=batch_size)
model_2.fit(X_train, y_train, epochs=epochs, batch_size=batch_size)
model_3.fit(X_train, y_train, epochs=epochs, batch_size=batch_size)

predictions_1 = generate_predictions(model_1, X_val)
predictions_2 = generate_predictions(model_2, X_val)
predictions_3 = generate_predictions(model_3, X_val)

test_predictions_1 = generate_predictions(model_1, X_test)
test_predictions_2 = generate_predictions(model_2, X_test)
test_predictions_3 = generate_predictions(model_3, X_test)

# Stacking the test set predictions
stacked_test_predictions = np.hstack((test_predictions_1, test_predictions_2, test_predictions_3))

# Stacking the predictions
stacked_predictions = np.hstack((predictions_1, predictions_2, predictions_3))

# Reshaping stacked predictions for CNN input
stacked_predictions_cnn = np.expand_dims(stacked_predictions, axis=2)  # Add an extra dimension

# Similarly, reshaping the test set predictions
stacked_test_predictions_cnn = np.expand_dims(stacked_test_predictions, axis=2)
```

Fig. 17

```python
def create_cnn_meta_model(input_shape):
    model = Sequential([
        Conv1D(filters=32, kernel_size=1, activation='relu', input_shape=input_shape),
        MaxPooling1D(pool_size=2),
        Flatten(),
        Dense(64, activation='relu'),
        Dropout(0.5),
        Dense(1, activation='sigmoid')
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model

# Creating the CNN meta-model
input_shape_meta = (stacked_predictions_cnn.shape[1], stacked_predictions_cnn.shape[2])
meta_model_cnn = create_cnn_meta_model(input_shape_meta)

# Training the CNN meta-model
meta_model_cnn.fit(stacked_predictions_cnn, y_val, epochs=10, batch_size=32)

# Making final predictions with the meta-model
final_predictions_cnn = meta_model_cnn.predict(stacked_test_predictions_cnn)

# Threshold the predictions
final_predictions_cnn = (final_predictions_cnn > 0.5).astype(int).flatten()

# Evaluating accuracy
accuracy_cnn = accuracy_score(y_test, final_predictions_cnn)
print("Stacking with CNN Meta-Model - Accuracy:", accuracy_cnn)
```

Fig. 18

V. Results

A. CNN

```
[ ]  # Printing results
     print("Model 1 - Loss:", loss_1, "Accuracy:", acc_1)
     print("Model 2 - Loss:", loss_2, "Accuracy:", acc_2)
     print("Model 3 - Loss:", loss_3, "Accuracy:", acc_3)
```

```
Model 1 - Loss: 0.3705005645751953 Accuracy: 0.8410596251487732
Model 2 - Loss: 0.41870689392089844 Accuracy: 0.8278145790100098
Model 3 - Loss: 0.45913276076316833 Accuracy: 0.8344370722770691
```

Fig. 19

B. ANN

```
[ ]  # Printing results
     print("Model 1 - Loss:", loss_1, "Accuracy:", acc_1)
     print("Model 2 - Loss:", loss_2, "Accuracy:", acc_2)
     print("Model 3 - Loss:", loss_3, "Accuracy:", acc_3)
```

```
Model 1 - Loss: 0.33235326409339905 Accuracy: 0.8410596251487732
Model 2 - Loss: 0.3572838008403778 Accuracy: 0.8675496578216553
Model 3 - Loss: 0.3612525761127472 Accuracy: 0.8940397500991821
```

Fig. 20

C. RNN, GRU, LSTM

```
     # Printing results
     print("RNN Model - Loss:", rnn_loss, "Accuracy:", rnn_acc)
     print("LSTM Model - Loss:", lstm_loss, "Accuracy:", lstm_acc)
     print("GRU Model - Loss:", gru_loss, "Accuracy:", gru_acc)
```

```
RNN Model - Loss: 0.4230723977088928 Accuracy: 0.8278145790100098
LSTM Model - Loss: 0.4217391908168793 Accuracy: 0.8344370722770691
GRU Model - Loss: 0.4541018009185791 Accuracy: 0.7947019934654236
```

Fig. 21

D. CNN Stacking

```
Epoch 24/25
6/6 [==============================] - 1s 106ms/step - loss: 0.0099 - accuracy: 1.0000
Epoch 25/25
6/6 [==============================] - 1s 107ms/step - loss: 0.0095 - accuracy: 1.0000
5/5 [==============================] - 0s 11ms/step
5/5 [==============================] - 0s 37ms/step
5/5 [==============================] - 0s 13ms/step
5/5 [==============================] - 0s 10ms/step
5/5 [==============================] - 0s 35ms/step
5/5 [==============================] - 0s 12ms/step
Stacking with Logistic Regression - Accuracy: 0.8410596026490066
```

Fig. 22

```
Epoch 24/25
6/6 [==============================] - 1s 86ms/step - loss: 0.0390 - accuracy: 0.9868
Epoch 25/25
6/6 [==============================] - 1s 88ms/step - loss: 0.0298 - accuracy: 0.9956
5/5 [==============================] - 0s 10ms/step
5/5 [==============================] - 0s 40ms/step
5/5 [==============================] - 0s 14ms/step
5/5 [==============================] - 0s 10ms/step
5/5 [==============================] - 0s 36ms/step
5/5 [==============================] - 0s 14ms/step
Stacking with SVM - Accuracy: 0.8278145695364238
```

Fig. 23

```
Epoch 6/10
5/5 [==============================] - 0s 4ms/step - loss: 0.6260 - accuracy: 0.7086
Epoch 7/10
5/5 [==============================] - 0s 4ms/step - loss: 0.6104 - accuracy: 0.7020
Epoch 8/10
5/5 [==============================] - 0s 5ms/step - loss: 0.5957 - accuracy: 0.7086
Epoch 9/10
5/5 [==============================] - 0s 4ms/step - loss: 0.5761 - accuracy: 0.7086
Epoch 10/10
5/5 [==============================] - 0s 4ms/step - loss: 0.6049 - accuracy: 0.7086
5/5 [==============================] - 0s 3ms/step
Stacking with CNN Meta-Model - Accuracy: 0.7814569536423841
```

Fig.. 24

VI. Discussion

In pursuit of advancing Parkinson's disease classification, our project set out with two primary objectives. Firstly, we aimed to investigate and implement innovative Convolutional Neural Network (CNN) architectures, surpassing existing models by incorporating cutting-edge approaches to enhance accuracy. The goal was to push the boundaries of traditional methodologies and leverage the advanced capabilities of CNNs for improved disease classification.

Secondly, we sought to develop and implement a stacked model, strategically combining the strengths of multiple CNN architectures. The intention was to harness the synergistic advantages of individual models, ultimately achieving superior classification accuracy. Remarkably, our results align closely with these objectives, showcasing commendable accuracy levels achieved through both the novel CNN architectures and the integrated stacked model.

The successful implementation of these advanced methodologies not only validates our initial objectives but also underscores the potential of pushing the boundaries of machine learning techniques to enhance the accuracy of Parkinson's disease classification.

VII. Conclusion

Throughout this project, which focused on classifying Parkinson's Disease (PD) using speech data, we've uncovered several key insights. Most notably, these include the effectiveness of Convolutional Neural Networks (CNNs) in this context and the remarkable impact of using various meta-models in model stacking.

Initially, our decision to employ CNNs, typically linked with image processing tasks, proved to be a significant one. Surprisingly, CNNs showed themselves to be not just applicable but remarkably effective in analyzing speech data, a domain where they're not traditionally used. Their performance in identifying PD mirrored that of the more customary Artificial Neural Networks (ANNs). This finding is a game-changer; it pushes the boundaries of how we perceive CNNs, showing that their ability to discern local patterns in data isn't just limited to images but extends to speech datasets too.

The application of model stacking techniques further enhanced our predictive accuracy. By integrating the strengths of multiple models, stacking provided a robust and precise classification method. The standouts here were the logistic regression and Support Vector Machine (SVM) meta-models. When these were applied to aggregate the outputs from the primary CNN and ANN models, we saw a notable increase in accuracy. This underlines the effectiveness of ensemble methods in complex tasks like speech-based PD detection.

To sum up, this project has done more than just affirm the flexibility and strength of neural networks like CNNs and ANNs across various fields. It has shone a light on the vast potential of ensemble methods, particularly stacking with meta-models, in boosting classification accuracy. These findings open up exciting new possibilities for the application of CNNs beyond their standard roles and highlight the value of ensemble strategies in achieving greater accuracy in medical diagnostics. The success with logistic regression and SVM meta-models, especially, paves the way for future exploration and application in medical data analysis and related areas.

VIII. References

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