# Speech-Based Artificial Intelligence Emotion Biomarkers in Frontotemporal Dementia

by

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## Abstract

Acoustic speech markers are well-characterized in Frontotemporal Dementia (FTD), a heterogeneous spectrum of progressive neurodegenerative diseases that can affect speech production and comprehension as well as higher-order cognition, behavior, and motor control. While profound apathy and deficits in emotion processing are also common symptoms, emotional content has yet to be explored in acoustic models of speech. We retrospectively analyze a dataset of standard elicited speech tasks from 69 FTD and 131 healthy elderly controls seen at the University of Melbourne. We develop two ResNet50 models to classify FTD vs healthy elderly controls using spectrograms of speech samples: 1) a naive model, and 2) a model that was pre-trained on an emotions speech dataset. We compare the validation accuracies of the two models on different speech tasks. The pre-trained model better classifies FTD vs. healthy elderly controls, and the behavioral variant of FTD (bvFTD) vs. healthy elderly controls with validation accuracy scores of 79% and 84% respectively in the monologue speech task, and 93% and 90% in the picture description one. When considered singularly, the 'happy' emotion best discriminates between FTD vs healthy elderly controls compared to other latent emotions. Pre-training acoustic models on latent emotion increases the classification accuracy for FTD. We demonstrate the greatest improvement in model performance on elicited speech tasks with greater emotional content. Considered more broadly, our findings suggest that inclusion of latent emotion in acoustic classification models provides a benefit in neurologic diseases that affect emotion.

Thesis Supervisor: James Glass
Title: Senior Research Scientist

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# Chapter 1

# Introduction

[1]Frontotemporal Dementia (FTD) is the most common early Neurodegenerative Disease (ND) and the behavioral variant (bvFTD) is four times more common than the other two Primary Progressive Aphasia (PPA) variants combined, the semantic variant (svPPA) and the non-fluent variant (nfvPPA) [Hogan et al., 2016]. The annual FTD per patient costs, estimated at about $120,000.00, are about double those of Alzheimer's Disease (AD), with additional household income decreases of about 50% [Galvin et al., 2017].

The current generally accepted criteria for a definite bvFTD diagnosis [Rascovsky et al., 2011] require (a) ruling out all other ND conditions, including AD, svPPA and nfvPPA, and all other psychiatric conditions, (b) behavioral/cognitive tests that can not be reliably conducted clinically [Ahmed et al., 2021], and (c) establishing either a pathogenic mutation or hitopathological evidence. As a result, current diagnosis of the onset of bvFTD often takes several years, an average of over five years since the onset of the symptoms with 50% receiving a wrongful psychiatric diagnostic beforehand [Ducharme et al., 2020], and the exact type often takes even longer to reliably establish, with diagnosis costs per patient of over $50,000.00 [Galvin et al., 2017].

Artificial intelligence (AI) could lower these diagnostic costs but the many existing examples of non-speech-based automatic classification always yield accuracies of under

[1]A substantial part of this chapter is drawn from the manuscript "Speech-Based Artificial Intelligence Emotion Biomarkers in Frontotemporal Dementia" by Fjona Parllaku, Brian Subirana, Katerina Placek, Brian Tracey, and Adam Vogel.

90% (or lower 90s at best) and have been demonstrated only in small samples. These AI methods have included using visual processing on MRI images [Poonam et al., 2021, Donnelly-Kehoe et al., 2019, Kim et al., 2019], oculomotor tracking [Lage et al., 2021], EEG [Metin et al., 2018], cortical thinning measurements [Du et al., 2007], and gray matter density maps [Möller et al., 2016]. It is possible that these methods could be drastically improved if the datasets were to increase in size. However, the example databases that these methods rely on are, in turn, also very expensive to generate, suggesting speech as an alternative, given how easy and inexpensive it is to capture sound on mobile devices. Another inexpensive technology is natural language processing (NLP); AI has already shown it can outperform humans in the longitudinal diagnosis of psychiatric conditions based on NLP. It has already been shown that speech can help discriminate different neuredegenerative conditions such as primary progressive aphasia [Fraser et al., 2014].

Building on previous work, in this thesis we introduce novel speech-based artificial intelligence emotional biomarkers that generate longitudinal metrics of ND evolution, and demonstrate their use in bvFTD discrimination. We believe bvFTD is a good candidate because of the inherent complexity of discriminating it from other conditions. To demonstrate the performance of our research, we test it on datasets containing patients with different ND conditions, including svPPA and nfvPPA. We hope that our research will help make the case for a longitudinal dataset of ND conditions, including FTD, AD and Parkinson's Disease (PD) that can help validate and further engineer our proposed framework for emotional biomarkers. We feel there is a need to generate speech-based biomarkers beyond emotion. The framework we develop also allows incorporating other modalities such as NLP, vision and EEGs. The low costs and ease of administration of speech tests for longitudinal bvFTD discrimination could have many advantages such as broad population screening, support for adaptive clinical trials and extension to other ND.

## 1.1 Background: Why Emotional Biomarkers?

We begin this section by reviewing the complexity of bvFTD discrimination in the context of all ND.

### 1.1.1 Diagnosing bvFTD versus other Medical Conditions

The boundaries between "different" neurodegenerative diseases (ND) are not always clear, and overlaps as well as co-existing conditions have been well documented (e.g. PSP-FTD [Pradhan and Tandon, 2020]), especially when taking a longitudinal view of the conditions (e.g. FTD with on-going AD pathological process [Padovani et al., 2013]). In the case of bvFTD, symptoms may be confounded or confused with completely unrelated late adulthood psychiatric disorders [Woolley et al., 2011] that may also affect dimensions including apathy, anhedonia, psychosis and lack of emotional response and empathy [Pose et al., 2013]. There is evidence of psychological symptom overlap between bvFTD and schizophrenia [Shinagawa et al., 2014]. However, often psychosis and mood disorders are not considered indicative of bvFTD [Galimberti et al., 2015] despite being common in a third of confirmed bvFTD patients [Waldö et al., 2015]. Notwithstanding all of the above, bvFTD seems to come in the last diagnostic stage, and according to the exclusion criteria [Rascovsky et al., 2011], symptoms are not to be classified as bvFTD if the "behavioral disturbance is better accounted for by a psychiatric diagnosis." Research has established differences between FTD types and AD that can help overcome this strong exclusion criteria requirement [Bozeat et al., 2000].

There are language and speech deficit overlaps between bvFTD and other dementia variants such as PPA and AD [Blair et al., 2007, Geraudie et al., 2021], and common visual facial emotion deficits between bvFTD and AD [Jiskoot et al., 2021]. Emotional apathy may have common neural basis in bvFTD and ALS [Caga et al., 2021]. Shared emotional symptoms between AD and FTD have been shown to have distinctive physiological responses [Hoefer et al., 2008]. bvFTD and Semantic Dementia (SD) also share some common emotional responses to facial expressions [Kumfor et al.,

2019]. A bvFTD diagnostic is not valid if the "pattern of deficits is better accounted for by other non-degenerative nervous system or medical disorders."

Within bvFTD, there are variants with distinctive symptoms. The characteristic bvFTD apathy shortcomings on Goal Directed Behavior have been segmented into three different types, each of which impacts its own specific areas of the brain [Massimo et al., 2015]. Nevertheless, bvFTD seems to come, once more, in the last position, even behind any other ND including svPPA and nfvPPA, as stated in the exclusion criteria [Rascovsky et al., 2011].

### 1.1.2 Emotional Biomarkers for Longitudinal Diagnosis of bvFTD

We contend focusing on Emotions is a good strategy for diagnosing bvFTD against other ND for the following four reasons:

1. **Central Role of the Frontal Lobe in Primate Emotions:** The central role of the amygdala and the orbitofrontal cortex [Lane et al., 1997, Kringelbach and Rolls, 2004] in the primate emotions and its behavioral influences [Bagozzi et al., 2000] through connections between these brain areas and others such as the hypothalamus, was established decades ago [Rolls, 1990, Rolls, 2000], even for masked tasks [Whalen et al., 1998]. More recently, there is evidence linking the degree of damage to these brain areas connected to emotions and bvFTD severity [Sokolowski et al., 2021, Xu et al., 2021, Šimić et al., 2021]. Further evidence along the same direction came in through direct and inverse reinforcement tasks, showing also a direct relationship between emotional processing and behavioral disturbances [Rolls et al., 1994]. Connections between the role of the orbitofrontal lobe in emotions and psychiatric conditions such as depression and schizophrenia have been established [Rolls, 2019] [Rolls, 2021]. The connection between the frontal lobe and emotion expression has been long established [Dawson, 1994, Heilman, 2021], and at least in the case of schizophrenia, frontal lobe differences may impact emotion expression in positive amplification tasks and not in negative amplification ones [Henry

et al., 2007]. Emotion expression has demonstrated a certain degree of invariance across some dementia types and has been linked to longitudinal dementia resilience [Magai et al., 1997, Laricchiuta et al., 2017, Cerasa, 2018].

2. **Possible Discriminating Power of AI Detectable bvFTD Emotional Syndromic Response compared with that of other ND and Psychiatric Conditions:** There is evidence of the role of emotions in the onset of bvFTD and it has been suggested that complex self-referencing emotions such as embarrassment are the root cause of the first behavioral symptoms [Levenson and Miller, 2007, Ferenczi et al., 2020]. Emotions are related to the six diagnostic criteria for possible bvFTD with the possible exception of F2 and F3 [Ghetti et al., 2021]. Emotion processing is a differentiating characteristic of bvFTD versus other ND [Mendez, 2021a, Serrani, 2016, Garcia-Cordero et al., 2021, Manuel et al., 2020, Bono et al., 2021], and of bvFTD versus other types of FTD [Bozeat et al., 2000, Yang et al., 2021].[Brown et al., 2020] The degree of behavioral changes has been linked to the lack of visual and sound emotional perceptiveness in patients with ventral frontal lobe damage [Hornak et al., 1996, Orjuela-Rojas et al., 2021]. As the disease progresses emotional processing continues to degrade [Levenson and Miller, 2007]. FTD subtypes show distinct decreased emotional expressiveness with some having 100% prevalence of emotional loss, affecting happiness, sadness, anger, fear, disgust, and surprise while others only having a limited effect on certain emotions like fear [Snowden et al., 2001, Mendez, 2021b]. This suggests that focusing on one single emotion like happiness or apathy may be enough to distinguish between FTD subtypes. Within the discrimination criteria of bvFTD, emotion may play a role in several of them and symptoms are also confounded, to the point where the current state-of-the-art may not enable clinical-only tests to determine if criteria A-F [Rascovsky et al., 2011] are present [Ahmed et al., 2021], nor even the psychiatric exclusion criteria[Sepúlveda-Ibarra, 2020, Lanata and Miller, 2016, Ducharme et al., 2020], while AI may be able to do so. Furthermore, the neural impact

of emotion processing in bvFTD has been linked to different neural areas depending on the negative emotion affected being fear, disgust, anger or sadness [Kumfor et al., 2013], suggesting that emotion processing may not only be a good source to diagnose bvFTD against other ND but also to longitudinally track bvFTD progression and, perhaps, even to identify the particular neural areas being affected in each case.

3. **Cross-Cultural Emotional Invariance:** We are interested in developing metrics that can self-adapt to cross cultural differences. Emotional processing seems so fundamental to socializing that it may have genetic common origins across human cultures[Ekman, 1999] and to that of other species [Preston and De Waal, 2002] as is demonstrated by the fact that humans can detect subtle emotional speech cues from other species such as the type of roaring in cats [McComb et al., 2009]. Inter-species speech emotional processing is a quality that other species have, in the case of dogs even to the point of integrating multi-modal cues [Albuquerque et al., 2016]. It has been suggested that emotional similarities between dogs and people are also present in the case of dementia of either species [Cummings et al., 1996], and that perhaps contact with dogs may help preserve emotional processing capabilities in humans with dementia [Perkins et al., 2008]. We find these results, and those reviewed in the sections above, tantalizing but lacking metric biomarkers that can enable objective comparisons. The methods that we will develop may be used to standardize emotional processing metrics across human conditions and perhaps even throughout the animal kingdom.

4. **Success of Emotional Identification in Artificial Intelligence:** There has been tremendous progress in AI techniques to discriminate multiple Emotions [Saxena et al., 2020, Feng and Chaspari, 2020]. There are also examples that demonstrate the value of using emotions in contexts related to dementia discrimination [Russell et al., 2021, Linz et al., 2018]. There is not one emotion AI can not discriminate increasingly more reliably. The methods are getting better,

reaching 99+% in many cases and the number of publicly available databases is proliferating. Our hope is that speech processing may one day be able to automatically segment differences in emotional responses in parallel with how the bvFTD brain analyzes them, initially by using transfer learning from well functioning AI emotion recognition programs.

We contend apathy is a good proxy for the broader connections between bvFTD and emotions. To further elaborate why, and having established the possible importance of AI emotion recognition in bvFTD, we will now dig a bit deeper into the benefits of analyzing apathy related emotional biomarkers.

### 1.1.3 The possible role of Emotional Apathy Biomarkers in the diagnostic of bvFTD

Apathy is the most common initial symptom of bvFTD [Shinagawa et al., 2006], [Rascovsky et al., 2011] and is present to a certain degree in almost all bvFTD patients [Chow et al., 2009]. The presence of emotional apathy in bvFTD, in addition, is related to many other disease symptoms, such as decreased heart rate variability [Guo et al., 2016], and is often correlated with the severity of the disease [Ducharme et al., 2018], making apathy a natural target for precise measurement as a longitudinal biomarker for bvFTD. Apathy is connected to emotional blunting which has been used in psychiatric diagnosis for over two hundred years [Pinel, 1806][2], [Abrams and Taylor, 1978].

Apathy has been shown to be a good discriminator to identify AD [Hsieh et al., 2012, Bayard et al., 2014] and to isolate bvFTD among all NDs, including other FTD variants as we briefly discuss next. It is a good discriminator of bvFTD versus AD since it seems to evolve differently AD [Wei et al., 2020] with one distinctive aspect of bvFTD apathy versus that in AD being the prevalence of demotivation versus

[2]From pages 199-200: *But now the brilliant intellect was for ever obscured, and he sunk irrecoverably into a sort of imbecility and reverieism, bordering upon dementia. (. . . ) His taste for the fine arts, with his propensity to exertion of any kind, had for ever disappeared. Ennui, disgust with life, his gloomy melancholy and apathy made rapid progress.*

dysphoria [Derouesné et al., 2012]. Emotional apathy alone may also help distinguish bvFTD from Parkinson's disease [Ang et al., 2018]. Differences in the prevalence of apathy between FTD subtypes have been reported. [Snowden et al., 2001] In fact, apathy, when evaluated only by caregivers, can be enough to distinguish bvFTD from other FTD variants [Eslinger et al., 2012]. A direct connection between emotional blunting and FTD has been found using an emotional blunting scale [Abrams and Taylor, 1978], with high discrimination results against AD. [Mendez et al., 2006]

Several of these metrics explicitly incorporate different root causes of apathy such as behavioral, social and emotional ones, yet none have made it to generally accepted diagnostic criteria such as the DSM-V. [Starkstein and Leentjens, 2008] It has been suggested that there are three apathetic subtypes[Levy and Dubois, 2006]: Cognitive, Emotional-affective and Auto-activation. In healthy individuals there is a negative correlation between emotional and behavioral apathy subtypes according to the AMI, and a positive one between social and emotional apathy subtypes [Ang et al., 2017]. Specific apathy scales have been developed for a traget ND such as AD [Robert et al., 2009], in which, again, emotion plays a central role. A specific apathy scale to distinguish between bvFTD and svFTD has also been proposed [Lansdall et al., 2017].

Emotion may play a central role in all the syndromic spectrum of apathy, as it has been shown that FTD subjects have multimodal impairments in recognizing emotions, despite having identity recognition intact, both in facial images as well as in speech [Keane et al., 2002, Chen and Chen, 2020]. A review of previous methods concluded proposing a Multidimensional Apathy Framework, based on three dimensions one of which is centered on emotion and it includes concepts related to perception and expression such as affective flattening, indifference, emotional neutrality/blunting[Abrams and Taylor, 1978], and emotional integration impairment. [Radakovic and Abrahams, 2018] Subsequently, this framework has proven apathy measurements can distinguish among NDs, including FTD subtypes [Radakovic et al., 2021].

This lack of a clear definition may explain why of the 6 defining criteria for prob-

able bvFTD, Apathy is the least consistent when being rated by experts [LaMarre et al., 2013, Harris et al., 2013]. In AD, just the presence of Apathy also varies depending on how it is measured, and the study that one looks at, with estimates ranging from 49% to 89% [Nobis and Husain, 2018]. Only a handful of Artificial Intelligence attempts at isolating apathy have been described [Linz et al., 2018]. More recently a direct connection between computer vision analysis of facial expression and apathy has been demonstrated. [Zeghari et al., 2021]

The importance of apathy combined with the lack of objective criteria for measuring it may be the reason why when the Apathy Workroup of ISTAART's (International Society to Advance Alzheimer's Research and Treatment) NPS-PIA (Neuropsychiatric Syndromes Professional Interest Area) reviewed the latest research regarding apathy in NCDs suggested an avenue for future research was finding technological objective markers for it [Lanctôt et al., 2017]. Despite being the most common symptom of bvFTD, apathy has not been used explicitly in the discrimination of bvFTD, whether using speech or other sensors.

# Chapter 2

# FTD Classification and Prediction

In this chapter, we describe the FTD speech data and preprocessing as well as the baseline ResNet-50 model used for classification of the audio recordings of FTD and healthy patients carrying out different tasks during their clinic visits. We use the MFCC transforms of the audio recordings in the classification process. The classification experiments are made twice: using the simple 75%-25% split, as well as the 10-fold cross-validation. The results of the experiments are shown at the end of this chapter.

## 2.1 Data and Preprocessing

In this section we describe the datasets and the main steps of data pre-processing: renaming files to ease the organization of data used for the experiments, and getting spectrograms of the audio recordings for use with Neural Networks for the classification tasks.

### 2.1.1 FTD and Healthy subjects Datasets

We examined recordings collected at the University of Melbourne (consisting of healthy elderly controls [Schultz et al., 2021], and FTD subjects [Vogel et al., 2017]), with patient characteristics shown in Table 2.1. The healthy elderly subjects visited the

clinic once and performed a number of speech tasks (listed below). FTD subjects were recorded during visits to the University of Melbourne clinic for periodic check-ups (annually or less frequent), though for the large majority of subjects, only a single visit was available.

| Diagnosis | Age | Years since Diagnosis | Male | Female | Other |
|---|---|---|---|---|---|
| FTD | 65.0 (60.15 / 71.0) | 3 (2 / 5.5) | 45 | 24 | 0 |
| Controls | 63.0 (56.0 / 70.0) | - | 61 | 70 | 0 |

Table 2.1: Subject information. Age and Years since Diagnosis are listed as median (25th percentile / 75th percentile).

Among the FTD-diagnosed subjects, we focused on three main FTD variants including: 'bvFTD', 'svPPA' and 'nfvPPA'. Therefore, the number of unique recordings we used from these variants of the FTD-diagnosed subjects was 506, and 900 from the unique visits of the control subjects. Each recording corresponds to different tasks, some of which are repetition tasks such as 'pataka', 'pata', and 'sustained aaah', and the others correspond to two tasks requiring a more elaborate thinking process 'picture description' and 'monologue'. As shown in Table 2.2, bvFTD is the dominant variant in our dataset reflecting it being the most common in general populations of the three investigated. The numbers of recordings per FTD-diagnosed variant and totals, and also per healthy subjects for each task are shown in Table 2.2.

| | No. of subjects | Total no. of recordings |
|---|---|---|
| All FTDs | 176 | 693 |
| 3 FTDs | 69 | 506 |
| bvFTD | 40 | 301 |
| svPPA | 11 | 77 |
| nfvPPA | 18 | 128 |
| Healthy | 131 | 900 |

Table 2.2: Total numbers of subjects for each group, and the number of their corresponding recordings.

| N per diagnosis | PTAK | PATA | AAAH | PICS | MONL | DAYS | all tasks |
|---|---|---|---|---|---|---|---|
| 3 FTDs | 87 | 72 | 166 | 26 | 74 | 45 | 506 |
| bvFTD | 53 | 42 | 105 | 14 | 44 | 26 | 301 |
| svPPA | 16 | 14 | 29 | 4 | 4 | 15 | 77 |
| nfvPPA | 18 | 16 | 32 | 8 | 7 | 15 | 128 |
| Healthy | 192 | 206 | 216 | 58 | 55 | 201 | 900 |

Table 2.3: The number of audio recordings per diagnosis (N), as well as for each corresponding task

### 2.1.2 File Naming Scheme

The first step of data pre-processing consisted in establishing a new file naming scheme which facilitated the next steps of the classification and prediction tasks. We can summarize this scheme as follows: `Filename_ID_M/F_Year_Task_Diagnosis_Visit`. `ID` represents the patient identification number which is made up of two parts: `DEM/OLD`, where `DEM` represents subjects with FTD and `OLD` represents the healthy ones, as well as a three digit number which is uniquely assigned to each subject. `Year` is in the form of `A` and a number starting from 1, indicating the first year the subject made a visit. `Task` can be one of the 6 repetition tasks we have considered in our experiments: sustained vowel repetitions, repetitions of days of the week, a monologue, repetition of 'pata', and 'pataka' and picture descriptions.

$$\texttt{Task} = \{\texttt{AAAH, DAYS, MONL, PATA, PTAK, PICT}\}$$

The last number shows which visit the recording corresponds to. It is 1 to represent the first visit of the particular year, 2 for the second visit, and so on. Table 2.4 shows a few examples of the filenames of the recordings of the same subject `DEM001` carrying out different repetition tasks throughout different years and visits, as used in the experiments.

### 2.1.3 MFCC Spectrograms of the Audio Recordings

Audio files were transformed to a MFCC (Mel Frequency Cepstral Coefficient) representation for use in machine learning, using the librosa library [McFee and Nieto,

| Filename | ID | M/F | Year | Task | Diagnosis | Visit |
|---|---|---|---|---|---|---|
| DEM001_M_A1_AAAH_bvFTD_1 | DEM001 | M | A1 | AAAH | bvFTD | 1 |
| DEM001_M_A2_COOK_bvFTD_1 | DEM001 | M | A2 | COOK | bvFTD | 1 |
| DEM001_M_A2_DAYS_bvFTD_2 | DEM001 | M | A2 | DAYS | bvFTD | 2 |
| DEM001_M_A3_MONL_bvFTD_3 | DEM001 | M | A3 | MONL | bvFTD | 3 |

Table 2.4: Illustration of File Naming Scheme.

2015]. MFCCs were computed with 40 msec overlapped windows with a new frame every 20 msec. Note that we had observed low frequency (<100 Hz) hum in some of the Melbourne recordings, but the MFCC settings above exclude this hum.

MFCC values were plotted to form images of size (432, 288), which were then normalized and resized to meet the expected image size for ResNet-50 input [Migdał, 2018]. MFCC images had a fixed duration of 5 seconds, chosen because the typical length of IEMOCAP utterances (the dataset used for emotion classification training) is close to 5 sec. Shorter utterances were zero-padded to 5 sec, while longer utterances were truncated.

## 2.2 Baseline FTD Detection Models

To test the potential value of pre-training on emotions data for separating dementia subjects from controls, we built a baseline model. A PyTorch implementation of a simple ResNet-50 model was created to classify the data with the aim of defining a reference base case to compare with subsequent approaches. The ResNet-50 model used was pretrained on ImageNet by freezing all ResNet-50's convolutional layers, and only training the last one fully connected (dense) layer, at the beginning. Then, more experiments were carried out with different numbers of frozen layers. As this classification task has only 2 classes (compared to 1000 classes of ImageNet), we had to replace the last layer. Cross-validation with 10 folds was used. The three classification tasks implemented were: 'FTDs vs. Healthy', 'bvFTDs vs. Healthy', 'bvFTD vs. svPPA vs. nfvPPA'.

Given that some repetition tasks have a limited number of recordings, we picked only the ones that have 10 or more recordings, to minimize random choices during

the classification tasks.

## 2.3 Experiments

We used the baseline ResNet-50 model for the four classification tasks: 'FTD vs. Healthy', 'bvFTD vs. Healthy', 'svPPA vs. Healthy', and 'nfvPPA vs. Healthy'. A simple 75%-25% train-test split was used for the first part of the experiment. We then used 10-fold cross-validation for the same classification tasks as the second part of the experiment.

The simple split classifier results after training are shown in Table 2.5. Table 2.6 shows the results of the 10-fold cross-validation of the same classification tasks.

Figures 2-1 and 2-2 shows the comparison graph of the accuracy scores of the ResNet-50 model with all layers frozen except the last one, with only 5 layers frozen and with 1 layer frozen.

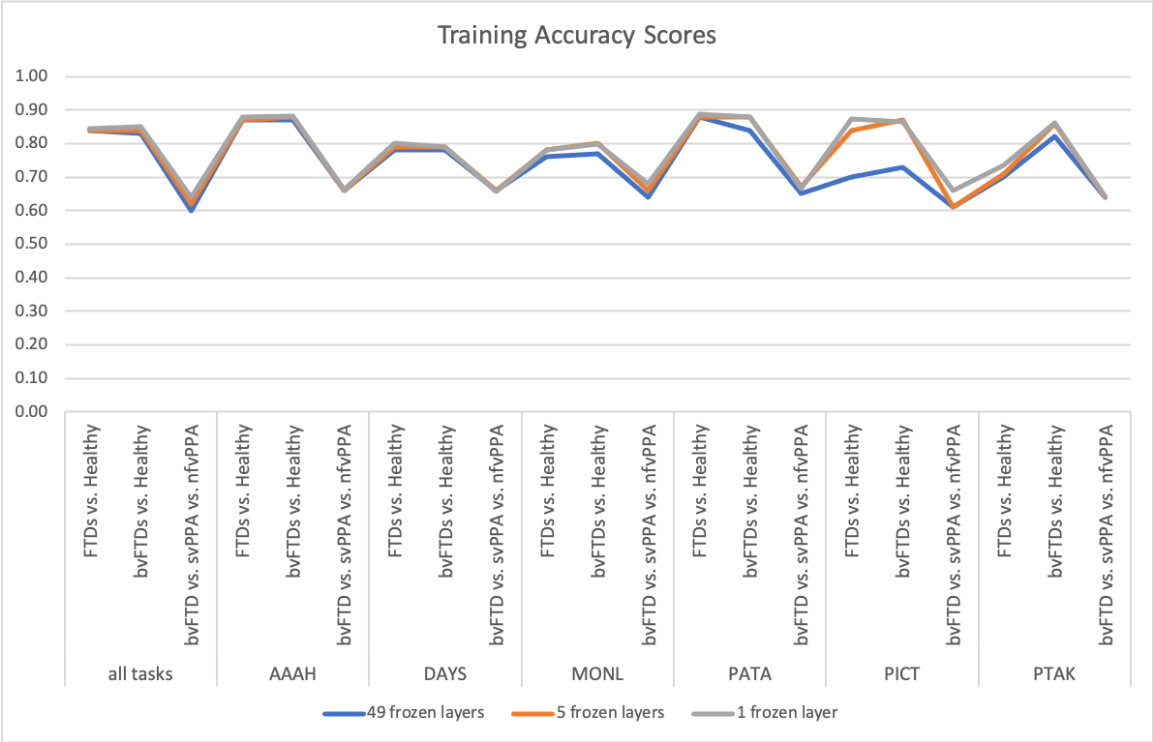


Figure 2-1: Comparison of training accuracy scores between the ResNet-50 model with all layers frozen except the last one, with only 5 layers frozen and with 1 layer frozen.

| 1 frozen layer | | ResNet-50 | | | |
|---|---|---|---|---|---|
| | | train | | validation | |
| Tasks | | loss | accuracy | loss | accuracy |
| all tasks | FTDs vs. Healthy | 0.40 | 0.84 | 0.35 | 0.87 |
| | bvFTDs vs. Healthy | 0.39 | 0.85 | 0.43 | 0.81 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.82 | 0.60 | 0.91 | 0.52 |
| AAAH | FTDs vs. Healthy | 0.31 | 0.87 | 0.25 | 0.88 |
| | bvFTDs vs. Healthy | 0.30 | 0.88 | 0.33 | 0.88 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.80 | 0.66 | 0.89 | 0.55 |
| DAYS | FTDs vs. Healthy | 0.46 | 0.79 | 0.54 | 0.79 |
| | bvFTDs vs. Healthy | 0.46 | 0.78 | 0.56 | 0.78 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.90 | 0.66 | 0.93 | 0.59 |
| MONL | FTDs vs. Healthy | 0.50 | 0.78 | 0.56 | 0.73 |
| | bvFTDs vs. Healthy | 0.51 | 0.80 | 0.58 | 0.80 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.88 | 0.64 | 0.91 | 0.52 |
| PATA | FTDs vs. Healthy | 0.32 | 0.89 | 0.35 | 0.87 |
| | bvFTDs vs. Healthy | 0.29 | 0.88 | 0.41 | 0.85 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.72 | 0.67 | 0.93 | 0.57 |
| PICT | FTDs vs. Healthy | 0.41 | 0.87 | 0.39 | 0.89 |
| | bvFTDs vs. Healthy | 0.44 | 0.87 | 0.42 | 0.86 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.87 | 0.66 | 1.16 | 0.50 |
| PTAK | FTDs vs. Healthy | 0.51 | 0.73 | 0.55 | 0.76 |
| | bvFTDs vs. Healthy | 0.32 | 0.86 | 0.37 | 0.86 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.87 | 0.64 | 1.10 | 0.50 |

Table 2.5: The training and validation accuracy scores for each classification task using the baseline ResNet-50 model, for tasks which have at least 10 recordings, as per Table 2.3.

| 10-fold CV | | ResNet-50 | | | |
|---|---|---|---|---|---|
| | | train | | validation | |
| Tasks | | loss | accuracy | loss | accuracy |
| all tasks | FTDs vs. Healthy | 0.39 | 0.88 | 0.38 | 0.84 |
| | bvFTDs vs. Healthy | 0.39 | 0.84 | 0.41 | 0.83 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.83 | 0.65 | 0.87 | 0.63 |
| AAAH | FTDs vs. Healthy | 0.34 | 0.87 | 0.33 | 0.86 |
| | bvFTDs vs. Healthy | 0.34 | 0.89 | 0.29 | 0.86 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.83 | 0.64 | 0.87 | 0.64 |
| DAYS | FTDs vs. Healthy | 0.40 | 0.88 | 0.45 | 0.86 |
| | bvFTDs vs. Healthy | 0.34 | 0.87 | 0.35 | 0.86 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.83 | 0.64 | 0.86 | 0.63 |
| MONL | FTDs vs. Healthy | 0.53 | 0.76 | 0.55 | 0.74 |
| | bvFTDs vs. Healthy | 0.55 | 0.77 | 0.58 | 0.76 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.79 | 0.67 | 0.83 | 0.64 |
| PATA | FTDs vs. Healthy | 0.46 | 0.88 | 0.48 | 0.88 |
| | bvFTDs vs. Healthy | 0.42 | 0.84 | 0.43 | 0.81 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.85 | 0.65 | 0.89 | 0.63 |
| PICT | FTDs vs. Healthy | 0.54 | 0.75 | 0.59 | 0.70 |
| | bvFTDs vs. Healthy | 0.50 | 0.76 | 0.53 | 0.73 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.90 | 0.61 | 0.96 | 0.60 |
| PTAK | FTDs vs. Healthy | 0.46 | 0.82 | 0.52 | 0.80 |
| | bvFTDs vs. Healthy | 0.44 | 0.83 | 0.48 | 0.82 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.85 | 0.64 | 0.86 | 0.62 |

Table 2.6: The training and validation accuracy scores for each classification task using the baseline ResNet-50 model, with 10-fold cross validation.

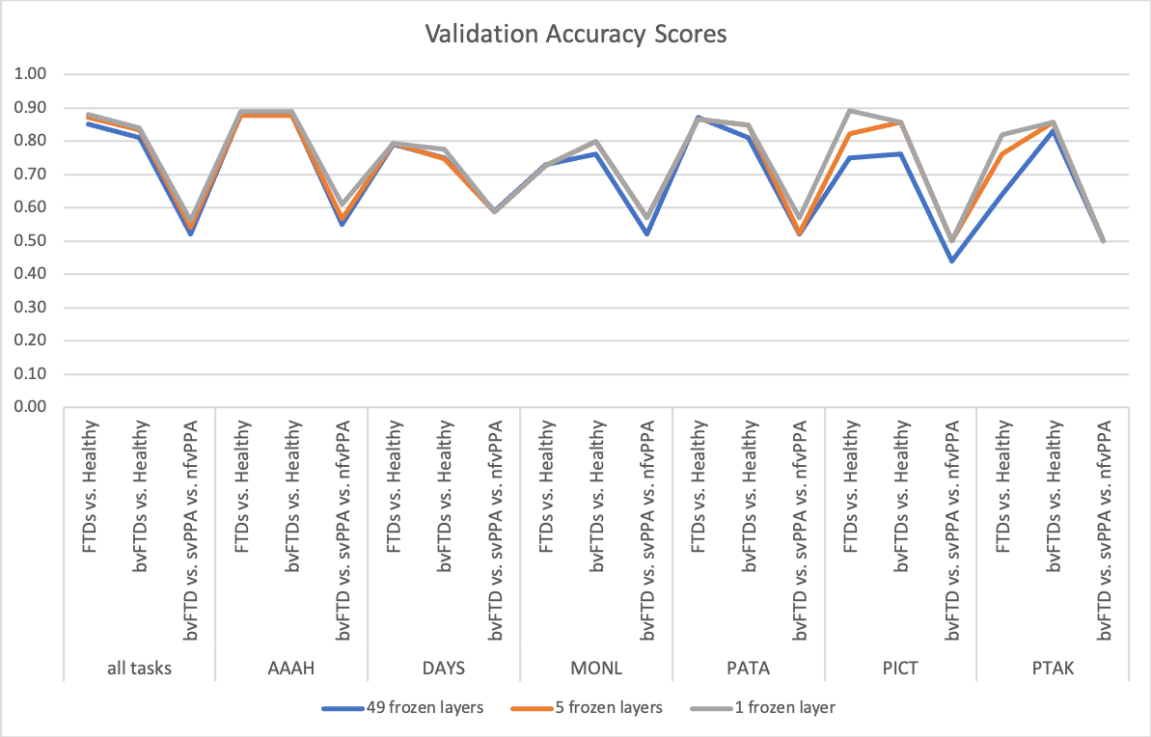


Figure 2-2: Comparison of validation accuracy scores between the ResNet-50 model with all layers frozen except the last one, with only 5 layers frozen and with 1 layer frozen.

In addition to computing classification accuracy scores, the Area-Under-the-Curve (AUC) of the Receiver Operator Characteristic (ROC) plot (plotting true positive rates vs false positive rates) has been calculated and plotted for each classification task. The values ranged between 0.7 and 0.9, indicating an overall good performance of our baseline model. The AUCs for each classification task corresponding to the combination of all repetition tasks are shown in Figure 2-3. The AUCs for the 3FTDs vs. Healthy classification task corresponding to each repetition task are shown in Figure 2-4.

## 2.4 Chapter Summary

The baseline ResNet-50 model seems to do a particularly good job in classifying subjects into FTDs vs. Healthy, as well as bvFTDs vs. Healthy with accuracy scores in the range $75\% - 90\%$ for both training and validation sets. The accuracy scores for

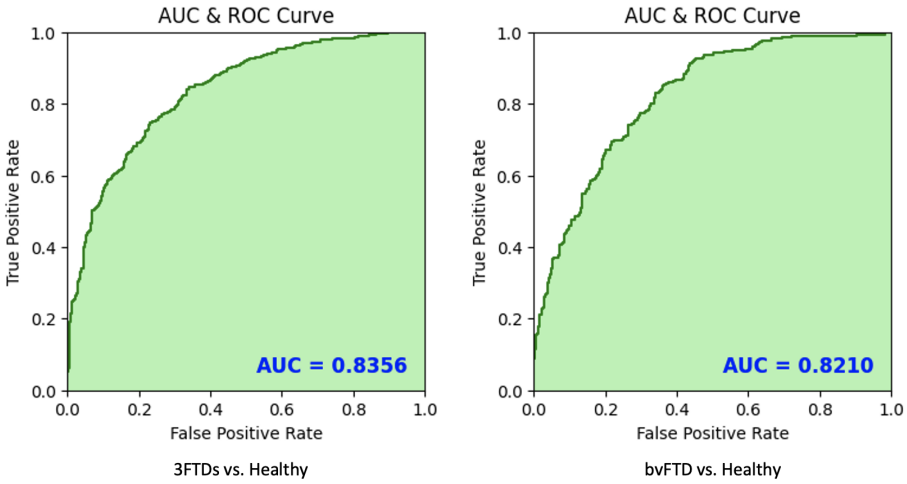


Figure 2-3: The AUCs for the 3FTDs vs. Healthy and the bvFTD vs. Healthy classification tasks corresponding to the combination of all repetition tasks.

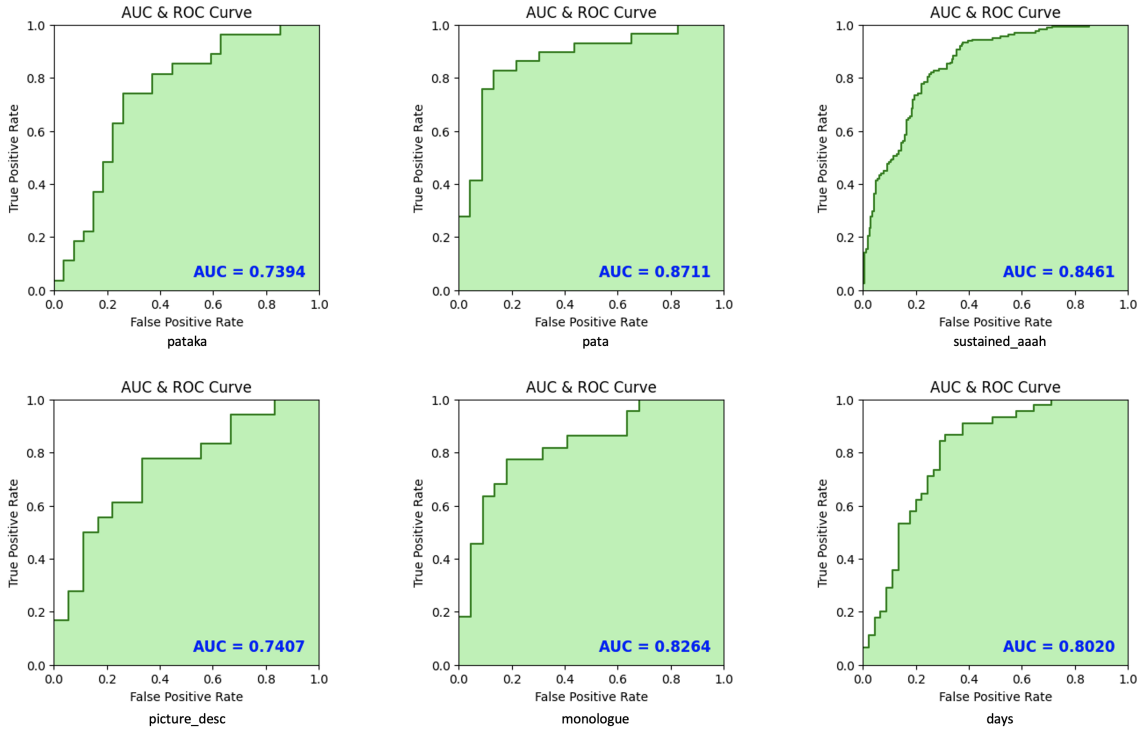


Figure 2-4: The AUCs for each classification task corresponding to the combination of all repetition tasks.

the bvFTD vs. svPPA vs. nfvPPA are lower, in the $50\% - 70\%$, but still good overall. The AUCs also confirm an overall good performance of the baseline model. Moreover, we observe similar accuracy scores when freezing different numbers of layers in the

ResNet-50 model, as per Figures 2-1 and 2-2, with 1 frozen layer giving slightly better accuracy scores throughout all the tasks. Therefore, we chose to continue the rest of the experiments using only 1 frozen layer, for better accuracy scores, given that the time needed to train this model wasn't significantly more when only 1 layer was frozen, compared to only the last one frozen.

# Chapter 3

# Emotion Classification and Prediction

In this chapter we describe similar classification tasks to the ones described in Chapter 2, where the Resnet50 model is used again, but this time it is pretrained on the IEMOCAP emotions dataset first, which we also describe in this section. The same datasets of FTD and healthy subjects, and the same MFCC transforms are used as described in Section 2.1. We then make predictions using the Resnet50 model trained on the emotions dataset, on the recordings of the bvFTD patients doing the MONL (monologue) task. We compare the trends of the 'happy' emotion among the healthy and the bvFTD patients and make a generalization about the convexity of these trends.

## 3.1 IEMOCAP Emotion Dataset

For re-training the ResNet classifier to recognize emotions, we used the widely-used IEMOCAP dataset [Busso et al., 2008]. This dataset consists of professional actors expressing a variety of different emotions, which were then classified by listeners into 9 emotion categories ('angry,' 'happy,' 'fear,' 'frustrated,' 'excited,' 'neutral," "sad,' 'surprised,' and 'others'). Labeled IEMOCAP audio clips vary in duration but are typically in the 3-5 second range.

The IEMOCAP dataset comprises of audio recordings, and the number of recordings for each emotion is as shown in Table 3.1.

| angry | excited | frustrated | happy | neutral | sad | other | surprised | fearful |
|---|---|---|---|---|---|---|---|---|
| 229 | 143 | 280 | 136 | 384 | 194 | 415 | 126 | 113 |

Table 3.1: The number of recordings per each emotion in the IEMOCAP dataset, used in the experiments.

The same preprocessing steps as the ones described in section 2.1.2 were followed for the IEMOCAP dataset.

## 3.2 Emotion Recognition Pre-training

To extract emotion scores from audio, we re-trained a PyTorch implementation of a ResNet-50 model [Migdał, 2018] which was pretrained on ImageNet. As the emotion classification task for IEMOCAP has only 9 classes (compared to 1000 classes of ImageNet), we replaced the last layer. A simple 75%-25% train-test split was used. We re-trained the model, freezing only the first layer, for 10 epochs. Visual inspection showed that the training loss was approaching an asymptotic limit after epochs 6-7. The accuracy of the predicted emotions was then assessed as described below.

## 3.3 Incorporating Emotion into FTD Models

At first, we carried out the experiments using all the emotions from the IEMOCAP dataset, and then we experiment with models trained on only 2-class classifiers, e.g.: 'happy' vs. 'other emotions' where 'other emotions' includes the other 8 emotions in the IEMOCAP dataset.

### 3.3.1 All-emotions model:

For this model, ResNet50 was first retrained to recognize emotions, as described above. This model was then retrained a second time to recognize dementia type (with the final fully connected layer replaced, for binary classification rather than the 9 emotions output classes) for the same tasks described above. Cross-validation with 10 folds was again used.

### 3.3.2 Single-emotion models:

A series of 9 single-emotion models were trained to determine whether pre-training on certain emotions is more useful preparation for dementia vs. healthy classification. In each of the 9 models, ResNet50 was first retrained to recognize a single emotion vs all others (rather than to putout scores for the 9 emotions classes). This model was then retrained a second time to recognize dementia type for the same tasks described above. Cross-validation with 10 folds was again used.

## 3.4 Experiments

For this part we used the same ResNet-50 model as before, pre-trained on ImageNet, but also trained on the IEMOCAP dataset [Carlos Busso and Narayanan, 2008]. The weights from training the model on the emotions dataset were saved, and then used for the same three classification tasks, similarly to the simple ResNet-50 model. The training and testing accuracy scores were compared for the simple ResNet-50 model and the one including the sentiment biomarker. The results of the ResNet-50 model including the sentiment biomarker are shown in Table 3.2.

We carried out the same experiments on the emotions dataset as in the initial classification tasks described in Section 2.3. The training and validation accuracy scores for the classification of the IEMOCAP dataset were 54% and 51% respectively.

Table 3.3 highlights the increase in accuracy scores for the model trained on the emotions dataset as described in Section 3.3.1 compared to the baseline Resnet50 model described in Section 2.2.

## 3.5 Emotions Predictions

After having obtained the results from the classification tasks, the average values of each predicted emotion for all the recordings, were calculated. The results were compared between FTD-diagnosed and healthy subjects, as well as between bvFTD-diagnosed and healthy subjects. These results are shown in the bar plots in Figure

| 1 frozen layer | | ResNet-50 + emotions | | | |
|---|---|---|---|---|---|
| | | train | | validation | |
| Tasks | | loss | accuracy | loss | accuracy |
| all tasks | FTDs vs. Healthy | 0.41 | 0.83 | 0.37 | 0.86 |
| | bvFTDs vs. Healthy | 0.38 | 0.86 | 0.43 | 0.83 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.80 | 0.66 | 0.94 | 0.55 |
| AAAH | FTDs vs. Healthy | 0.29 | 0.87 | 0.28 | 0.89 |
| | bvFTDs vs. Healthy | 0.32 | 0.88 | 0.31 | 0.89 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.82 | 0.67 | 0.89 | 0.57 |
| DAYS | FTDs vs. Healthy | 0.47 | 0.80 | 0.48 | 0.82 |
| | bvFTDs vs. Healthy | 0.47 | 0.81 | 0.64 | 0.79 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.81 | 0.70 | 0.88 | 0.62 |
| MONL | FTDs vs. Healthy | 0.44 | 0.79 | 0.38 | 0.79 |
| | bvFTDs vs. Healthy | 0.54 | 0.85 | 0.51 | 0.84 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.88 | 0.69 | 0.90 | 0.57 |
| PATA | FTDs vs. Healthy | 0.30 | 0.90 | 0.28 | 0.88 |
| | bvFTDs vs. Healthy | 0.28 | 0.89 | 0.48 | 0.85 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.72 | 0.69 | 0.97 | 0.62 |
| PICT | FTDs vs. Healthy | 0.36 | 0.90 | 0.29 | 0.93 |
| | bvFTDs vs. Healthy | 0.36 | 0.90 | 0.31 | 0.90 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.88 | 0.66 | 1.08 | 0.51 |
| PTAK | FTDs vs. Healthy | 0.41 | 0.79 | 0.40 | 0.79 |
| | bvFTDs vs. Healthy | 0.33 | 0.88 | 0.82 | 0.86 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.89 | 0.66 | 0.92 | 0.61 |

Table 3.2: The training and validation accuracy scores for each classification task using the baseline ResNet-50 model, trained on the IEMOCAP dataset.

| 1 frozen layer | | % increase in accuracy | |
|---|---|---|---|
| Tasks | | train | validation |
| all tasks | FTDs vs. Healthy | -1.59 | -0.62 |
| | bvFTDs vs. Healthy | 1.11 | 2.34 |
| | bvFTD vs. svPPA vs. nfvPPA | 9.83 | 4.83 |
| AAAH | FTDs vs. Healthy | 0.00 | 1.18 |
| | bvFTDs vs. Healthy | 0.00 | 1.41 |
| | bvFTD vs. svPPA vs. nfvPPA | 1.24 | 4.16 |
| DAYS | FTDs vs. Healthy | 1.13 | 3.45 |
| | bvFTDs vs. Healthy | 2.61 | 1.92 |
| | bvFTD vs. svPPA vs. nfvPPA | 6.82 | 5.89 |
| MONL | FTDs vs. Healthy | 1.34 | 8.33 |
| | bvFTDs vs. Healthy | 6.79 | 5.00 |
| | bvFTD vs. svPPA vs. nfvPPA | 6.98 | 9.09 |
| PATA | FTDs vs. Healthy | 1.06 | 1.72 |
| | bvFTDs vs. Healthy | 1.21 | 0.00 |
| | bvFTD vs. svPPA vs. nfvPPA | 2.94 | 8.33 |
| PICT | FTDs vs. Healthy | 2.63 | 4.00 |
| | bvFTDs vs. Healthy | 3.44 | 5.57 |
| | bvFTD vs. svPPA vs. nfvPPA | 0.00 | 2.50 |
| PTAK | FTDs vs. Healthy | 7.85 | 4.00 |
| | bvFTDs vs. Healthy | 2.70 | 0.00 |
| | bvFTD vs. svPPA vs. nfvPPA | 2.21 | 21.42 |

Table 3.3: The percentage increase in the accuracy scores for both training and validation calculated as: percentage increase = increase $\div$ original number $\times$ 100.

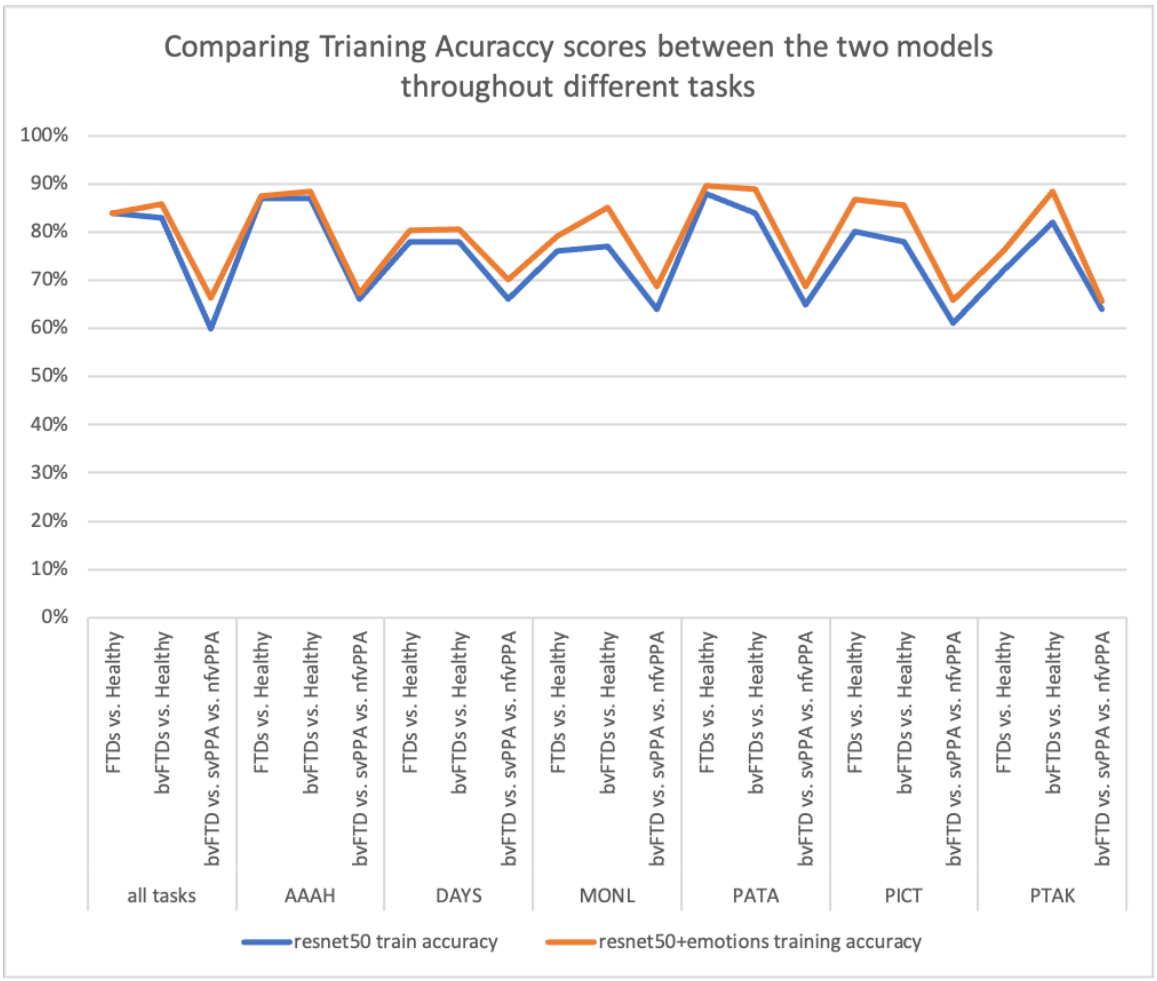


Figure 3-1: Comparison of training accuracy scores between the simple ResNet-50 model and the one with the sentiment biomarker.

3-4, together with their respective error bars.

There is a decrease in the predicted value of the 'happy' emotion in FTD subjects compared to healthy subjects, as seen in Figure 3-4. We also notice an increase in 'sad' emotion in FTD subjects. Because of this finding, we are able to use the 'happy' emotion as a discriminator for our classification tasks, which means that the ResNet50 model is trained on the same IEMOCAP dataset, which is now split into happy vs. other emotions. We find that the 'happy' emotion alone can improve classification of bvFTD, as well as the 3 FTD variants from healthy controls. The graphs in Figures 3-5 and 3-6 shows the increase in the accuracy scores for both training and validation in the 3FTDs vs. Healthy and bvFTD vs. Healthy classification tasks, throughout all

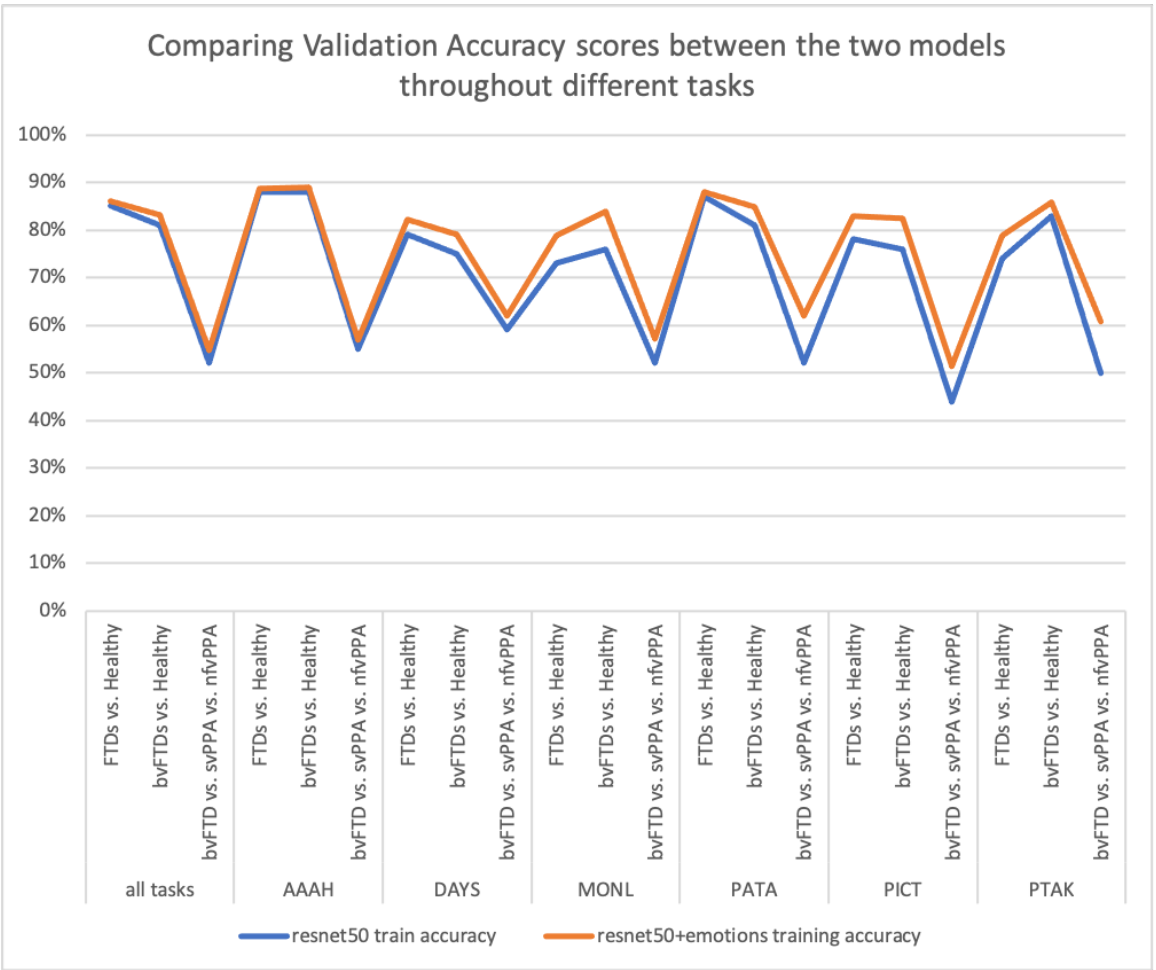


Figure 3-2: Comparison of validation accuracy scores between the simple ResNet-50 model and the one with the sentiment biomarker.

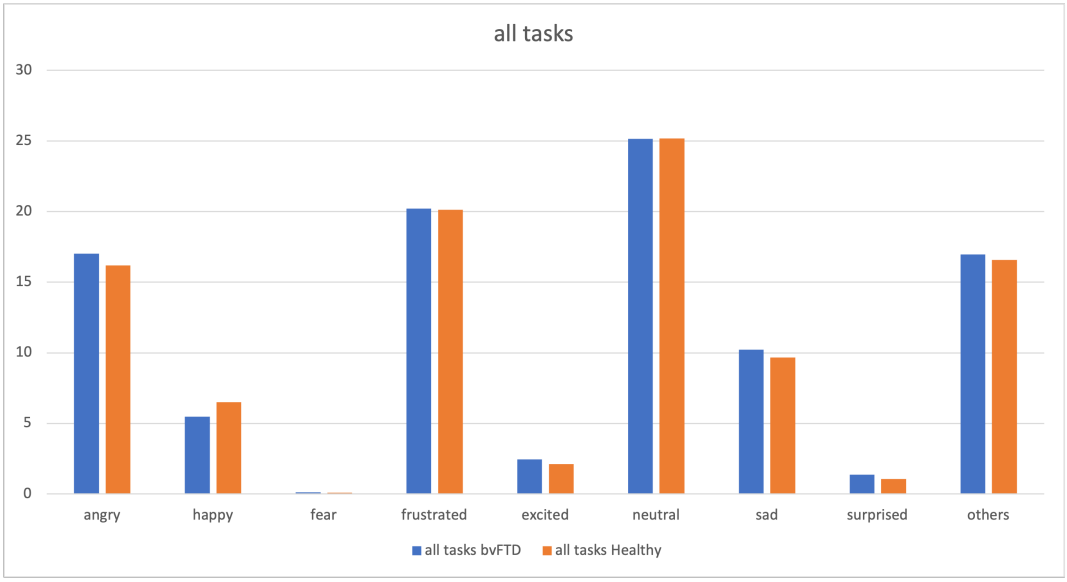


Figure 3-3: Comparison plots of the predicted percentage values of each emotion between bvFTD and healthy for all repetition tasks.

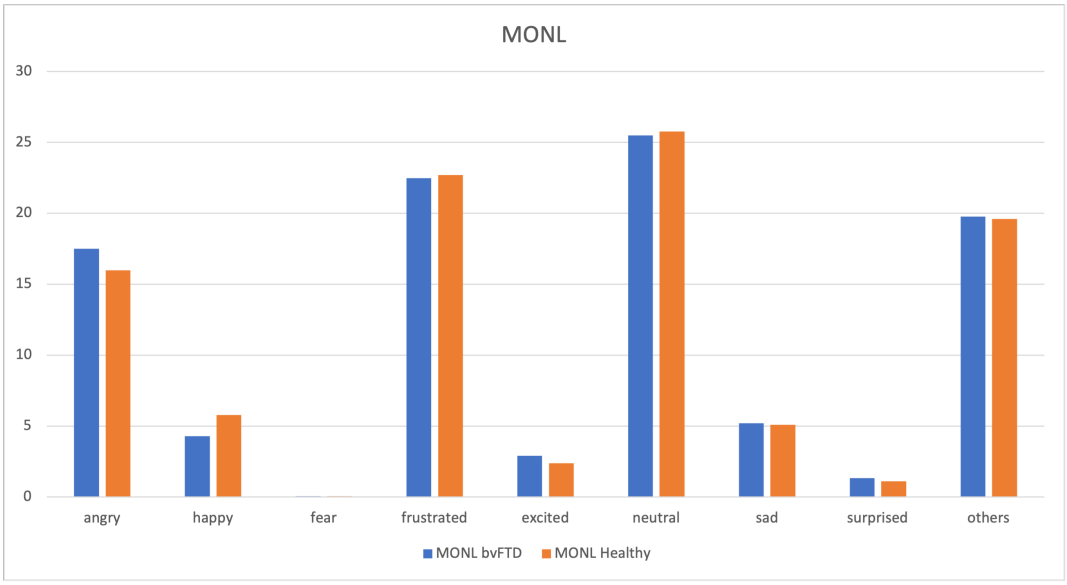


Figure 3-4: Comparison plots of the predicted percentage values of each emotion between bvFTD and healthy for the monologue task.

the speech tasks, with the greatest increase observed in the 'monologue' and 'picture description' tasks.

### 3.5.1 Analyzing the time course of sentiment

We examined the trend of the percentage values of each predicted emotion fluctuating within the same audio recording of each healthy or FTD patient, for different tasks, by looking at a window of 5 seconds, every 100 milliseconds. A scheme depicting how these values are calculated is shown in Figure 3-7. After each point is calculated, we use polyfit to find the second order polynomial that best fits these predicted values.

### 3.5.2 Second Moment of Emotion Prediction

The overall trends among bvFTD patients when compared to the control ones in terms of the predicted percentage values of the happy emotion for each 5 seconds window, is shown in Figure 3-8 for the first 40 windows. We can clearly notice a similar trend for each of the 5 patients in the group of bvFTD patients, as well as another trend similar among the control patients. Moreover, we observe the predicted percentage values to go up to a range of 14%-17.5% for the control subjects, while the maximum predicted value for the bvFTD subjects is 12.5%.

## 3.6 Chapter Summary

Incorporating emotions helped increase both training and validation accuracy scores. The improvement was the biggest in the 'picture description' and 'monologue' tasks, as shown in Figures 3-1 and 3-2, as well as Table 3.3, which is a result we would hope to obtain, considering the emotion-involved nature of those two tasks, differing from the other repetition tasks. Moreover, even using the 'happy' emotion alone helped improve the accuracy scores throughout all the speech tasks, and especially the two emotion-involved speech tasks: 'picture description' and 'monologue', as shown in the graphs in Figures 3-5 and 3-6.

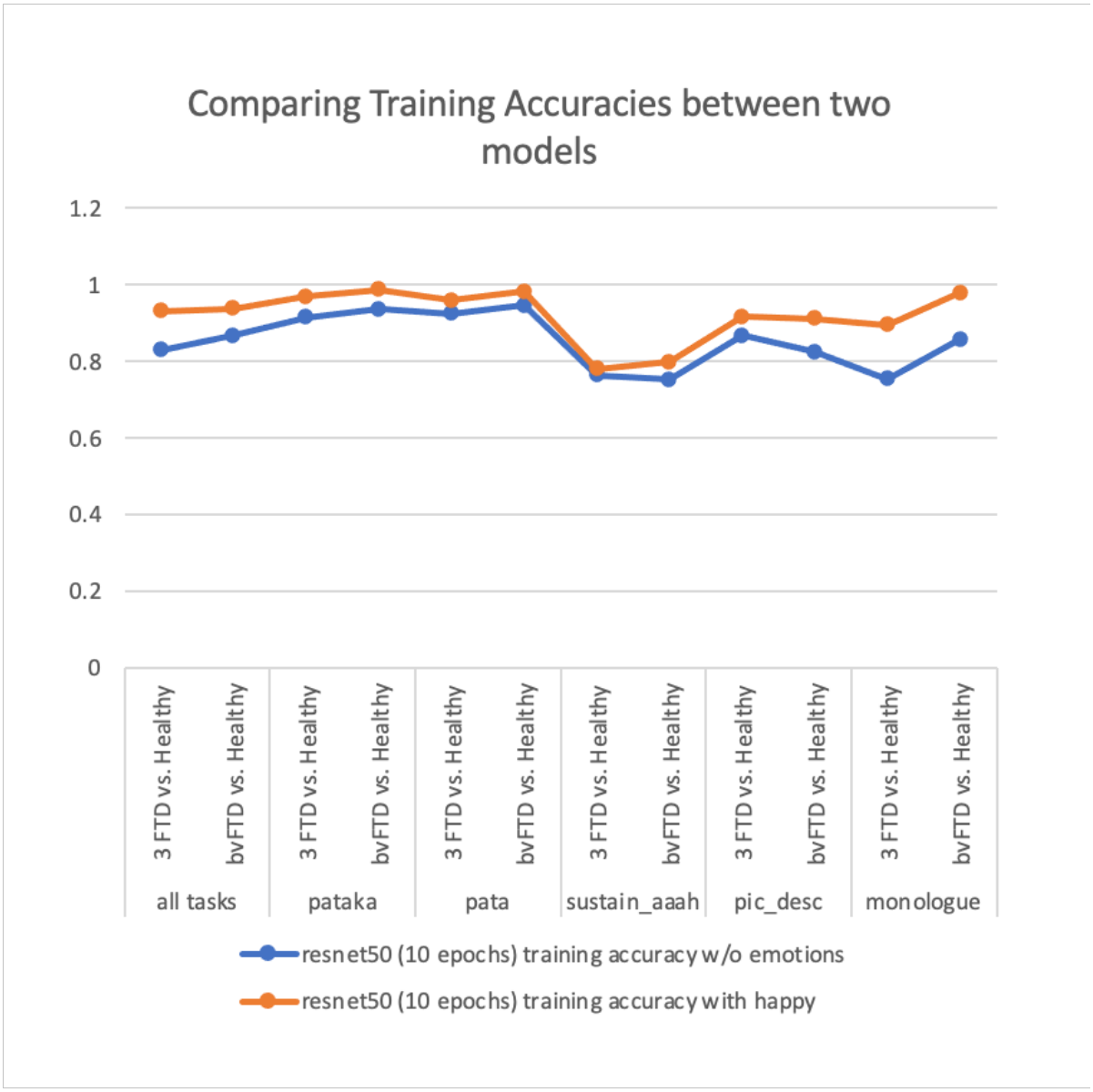


Figure 3-5: Comparison plots of the training accuracy scores of the simple ResNet-50 model and the one trained on 'happy' emotions only.

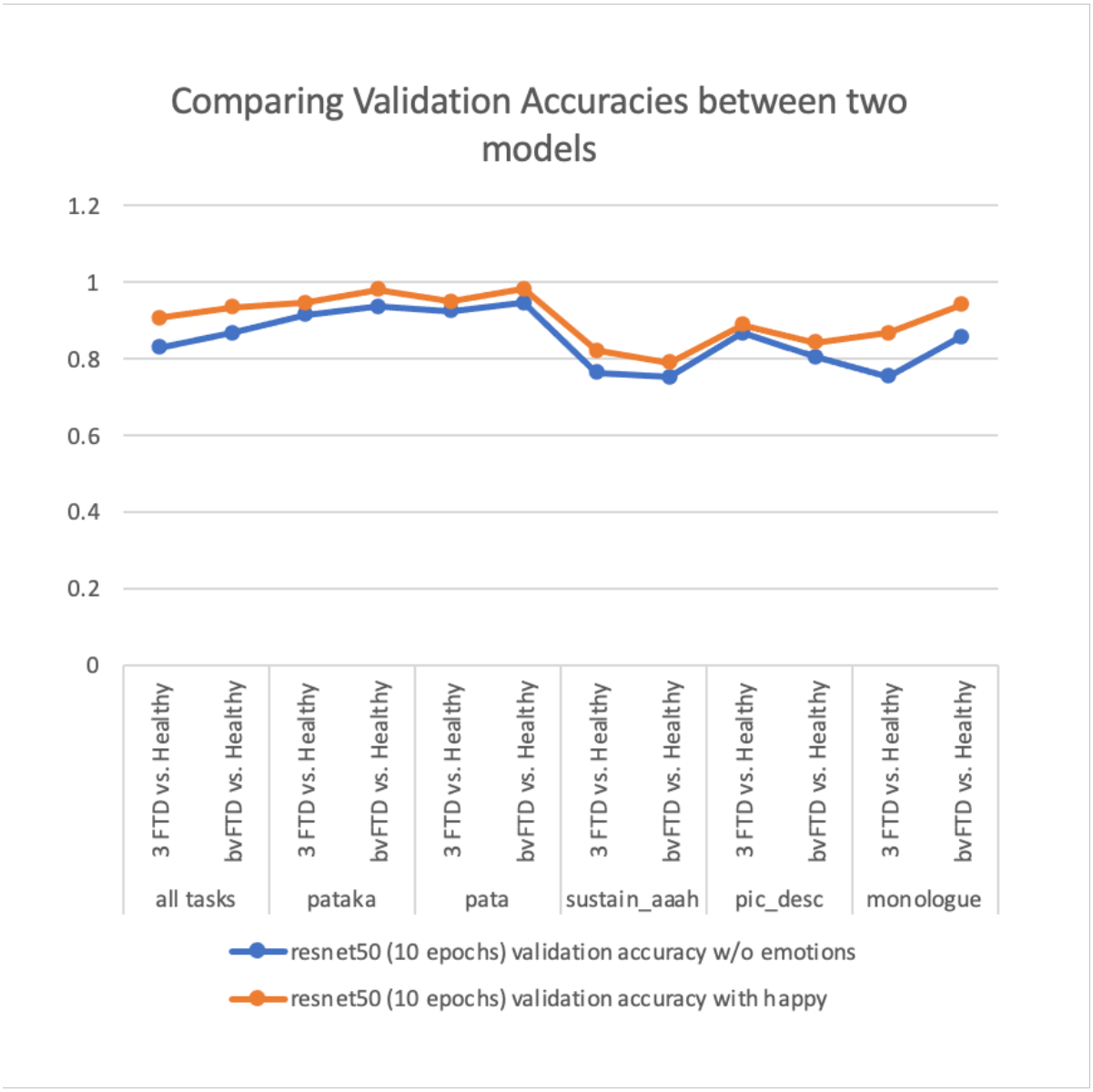


Figure 3-6: Comparison plots of the validation accuracy scores of the simple ResNet-50 model and the one trained on 'happy' emotions only.

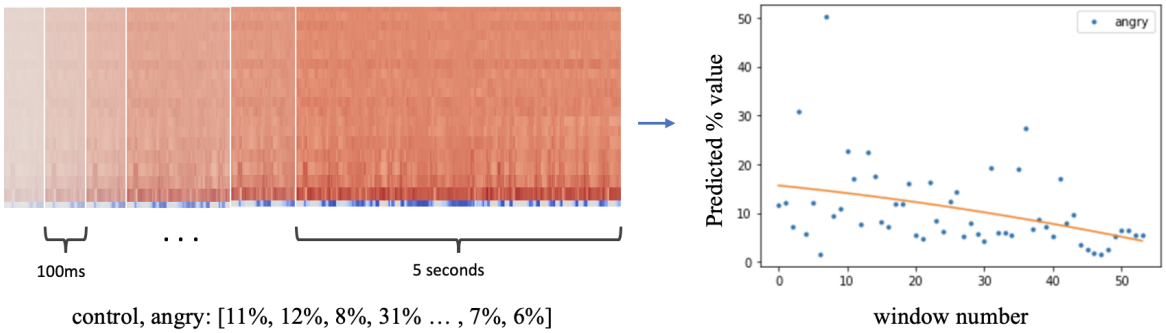


Figure 3-7: A predicted value for each emotion being considered is obtained from each 5 seconds window, every 100 milliseconds. We observe the trend with the polyfit graph or order 2.

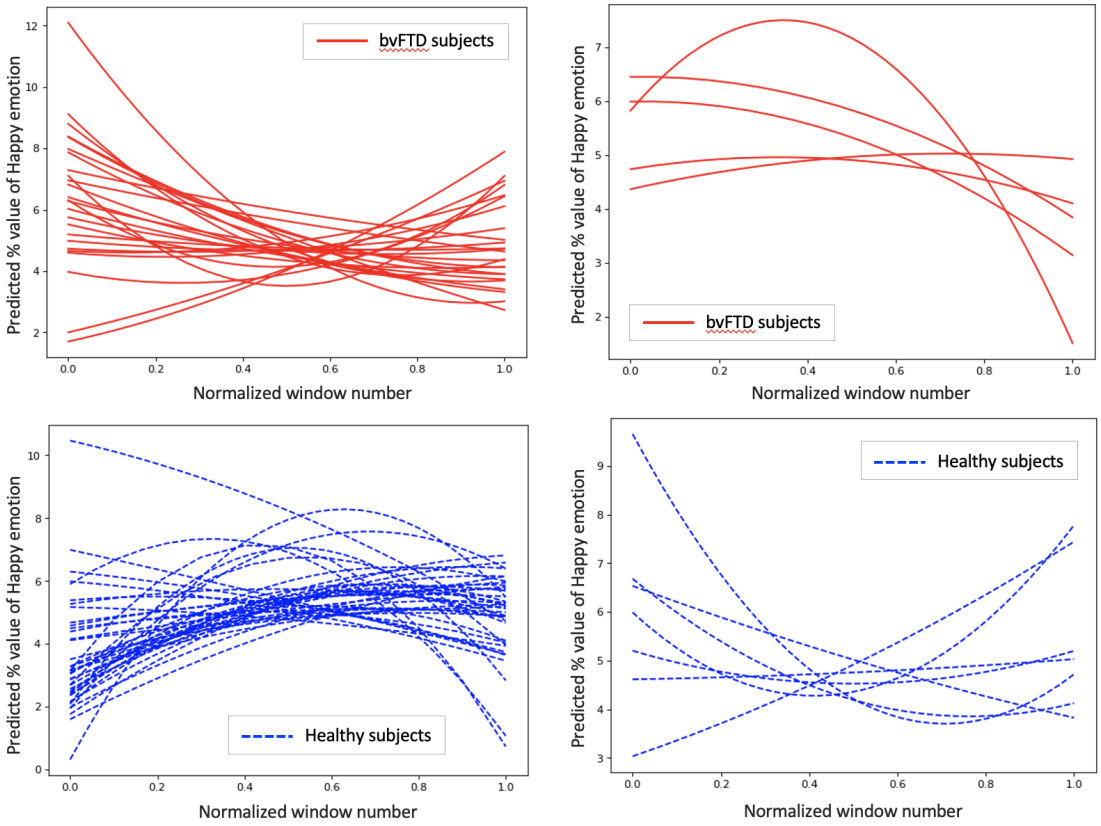


Figure 3-8: Separate graphs of trends of the predicted percentage values of the happy emotions for all the bvFTD subjects vs. Healthy ones from the **'monologue'** task with normalized x-axis values which correspond to different time windows. On the left, the predicted trends with the absolute value of the second derivative $> 0.01$ are shown for bvFTD (above) and Healthy subjects (below) are shown, and on the right the predicted trends with the absolute value of the second derivative $< 0.01$, are shown.

# Chapter 4

# Conclusion

The baseline Resnet50 model does a good job in classifying the MFCC transforms of the audio recordings of patients of different FTD variants, as well as healthy subjects. There is, however, an evident increase in both the training and validation accuracy scores of the same classification tasks, when the sentiment biomarker is introduced. This indicates that emotions play an important role in differentiating between FTD and healthy subjects, as well as among patients of different FTD variants. Moreover, as expected from the previous research done in the field, described in the related works in the introduction, apathy and difficulties in perceiving emotions are good indicators of a patient showing signs of behavioral FTD.

## 4.1 Future Work

As part of our future work, we hope to carry out more detailed statistical analysis of the current results, and come up with more sophisticated patterns in the predicted emotions of patients of all FTD variants, compared to the healthy ones, and across more repetitions tasks during different visits. Moreover, we hope to develop more advanced representations of the predicted percentage values of each emotion for looking at the trends, such as vectors of emotions corresponding to each window as described in Section 3.5.1. We also hope to look into a 2D representation of emotions, such as valence-arousal, where emotional valence describes the extent to which an emotion

is positive or negative, whereas arousal refers to its intensity, i.e., the strength of the associated emotional state. These next steps would hopefully help us to better understand the nature of the FTD variant in every patient and give more insights in the way this information would contribute in the patients treatment.

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