Detecting the Severity of Major Depressive Disorder from Speech: A Novel HARD-Training Methodology

Edward L. Campbell, Judith Dineley, Pauline Conde, Faith Matcham, Femke Lamers, Sara Siddi, Laura Docío-Fernández, Carmen García-Mateo, Nicholas Cummins, the RADAR-CNS Consortium

Abstract

Major Depressive Disorder (MDD) is a common worldwide mental health issue with high associated socioeconomic costs. The prediction and automatic detection of MDD can, therefore, make a huge impact on society. Speech, as a non-invasive, easy to collect signal, is a promising marker to aid the diagnosis and assessment of MDD. In this regard, speech samples were collected as part of the Remote Assessment of Disease and Relapse in Major Depressive Disorder (RADAR-MDD) research programme. RADAR-MDD was an observational cohort study in which speech and other digital biomarkers were collected from a cohort of individuals with a history of MDD in Spain, United Kingdom and the Netherlands. In this paper, the RADAR-MDD speech corpus was taken as an experimental framework to test the efficacy of a Sequence-to-Sequence model with a local attention mechanism in a two-class depression severity classification paradigm. Additionally, a novel training method, HARD-Training, is proposed. It is a methodology based on the selection of more ambiguous samples for the model training, and inspired by the curriculum learning paradigm. HARD-Training was found to consistently improve – with an average increment of 8.6% – the performance of our classifiers for both of two speech elicitation tasks used and each collection site of the RADAR-MDD speech corpus. With this novel methodology, our Sequence-to-Sequence model was able to effectively detect MDD severity regardless of language. Finally, recognising the need for greater awareness of potential algorithmic bias, we conduct an additional anal-
ysis of our results separately for each gender.

Keywords: RADAR-MDD, Major Depressive Disorder, Severity Classification, Sequence-to-Sequence model, Hard-Training methodology

1. Introduction

Major Depressive Disorder (MDD) is among the world’s most common mental health issues. According to an Organisation for Economic Co-operation and Development (OECD) report released in 2018, approximately 21 million people (4.5%) were living with a depressive disorder across European Region (EU) countries in 2016 [1]. MDD also results in a high number of years lived with disability (YLD) in the European region, with the World Health Organisation estimating depression contributes 859 YLD per 100,000 population [2]. With the ongoing Covid-19 pandemic, the global health situation has deteriorated, and people are even more susceptible to present symptoms related to MDD [3, 4]. Since the beginning of the pandemic, the prevalence of MDD is estimated to have increased by 28% [3].

Due to the prevalence and high associated socioeconomic costs associated with MDD, several initiatives have started to explore new ways to improve the management and treatment of MDD. Remote Assessment of Disease and Relapse in Major Depressive Disorder (RADAR-MDD) is one such initiative [5]. It is a research project developed as part of Remote Assessment of Disease and Relapse – Central Nervous System (RADAR-CNS) [6], a major EU Innovative Medicines Initiative (IMI) research programme that investigates the use of remote measurement technologies (RMT) to monitor people with depression, epilepsy and multiple sclerosis in real-world settings. RADAR-MDD is a longitudinal cohort study examining the utility of multi-parametric RMT, including speech, physical activity, sleep, heart rate, location and social interaction signals, to measure changes in symptoms and predict relapse in people with MDD [5]. The main focus of the work presented in this paper is the 2-class automatic speech-based classification of MDD severity. RADAR-MDD is unique as an experimental speech corpus; it is the first speech-health dataset that contains speech in three languages that were collected with the same tool and protocol [6] [7] [8].

Speech is uniquely placed as a health signal, containing a complex combination of cognitive, neuromuscular and physiological information. It has a pyramidal structure of information levels; running from acoustic information at the lowest level, then onto prosodic, phonetic and finally conversational at the highest level [9] [10]. The acoustic, phonetic and prosodic levels are of particular interest in speech-based depression detection. The acoustic and phonetic levels are directly influenced the physical actions of the respiratory and

\[1\]https://www.radar-cns.org/
articulatory systems, and are affected by depression through related psychomotor effects. Clinically, prosodic abnormalities associated with depression are well documented [6]. Speech affected by depression is often subjectively characterised in clinical settings by decreased verbal activity, decreased utterance length, reduced speech rate and the presence of long pauses [11] [12] [13]. There is a wide range of papers in the relevant literature that support these observations and strengthen the case for speech to be considered a valuable marker of depression. However, the complexity of speech and the natural variety of human voices make robust extraction of speech patterns associated with depression a highly non-trivial task.

A range of deep learning approaches have been explored in relation to speech-based depression detection, with Convolutional Neural Network (CNN) systems being highly prominent, e.g. [14] [15] [16] [17]. While such approaches are popular, helping to overcome the lack of specificity associated with the use of generic multivariate speech representations, they can be highly complex, raising concerns of overfitting when training data is sparse. Moreover, without the addition of recurrent layers, which add further complexity, such systems do not explicitly model temporal changes in speech patterns, which have been shown to contain important information about depression [6]. There has been less focus on Recurrent Neural Network (RNN) based approaches in speech-based depression detection despite their wider use in related tasks such as speech emotion recognition [18]. A small number of depression detection works have utilised RNNs within their speech models, e.g. [19] [20]. Of particular relevance for the work in this paper is the approach proposed in [19]. Key results from that work highlight the suitability of a Recurrent Neural Network (RNN) modelling approach using Mel Frequency Cepstral Coefficients (MFCCs) as input. Experiments on the Distress Analysis Interview Corpus (DIAC) corpus [21] [22] showed a validation accuracy of 76.27% when classifying low versus high levels of depression severity. It is not surprising that such an approach is well suited to depression detection: 1) MFCCs have shown to be suitable for capturing changes in speech motor control effects linked to depression [23] and 2) recurrent layers would help model important temporal changes in the distribution of these features.

Inspired by the system presented in [19], the MDD severity detection system proposed in this paper also uses MFCC’s but in a sequence-to-sequence classification model with local attention mechanisms. Given the widespread success of this paradigm in Natural Language Processing (NLP) tasks, it is not surprising that it has also been used in language-based depression models, e.g. [24] [25]. Despite strong results in related speech tasks [REFS], this approach is arguably under utilised in speech-based depression detection.

Adding to the novelty of the proposed approach is the proposed HARD-Training paradigm. This is based on the concept of Curriculum Learning, in which training instances are presented to a model in increasing levels of modeling difficulty [26]. Again, this approach has been used in related tasks such as emotion recognition; e.g. [27] [22], but to the best of the authors’ knowledge remains under explored within depression detection. During initial experimentation, we observed that when using a curriculum based training approach, only
a sub-section of training samples, those nearest the classification boundary was critical in boosting system performance. Presented results demonstrate that HARD-Training consistently improves system performance over training with all available samples. To the best of the authors’ knowledge, this is the first time such a result has been presented in the speech-health literature. Summarising, the principal paper’s contributions are as follows:

1. Introduce a new and extensive speech database (RADAR-MDD) for the analysis of MDD, containing three different languages (English, Spanish, Dutch), two speech elicitation tasks and an overall size of 59.12 effective hours. To the best of the authors’ knowledge, this is one of the few speech corpus developed for the analysis of any kind of mental disorders of such a large size and with a multilingual perspective [6, 7, 8].

2. Propose a novel approach (HARD-training) for the selection of training samples in the task of MDD binary classification. It is based on a curriculum learning paradigm, improving the generalisation capacity of the proposed classifier with an accuracy increment of 8.6%.

3. Validate the efficacy of HARD-training for MDD severity classification across three languages, and separately for each gender.

The paper structure is as follow: first, we describe the RADAR-MDD corpus, explaining the data collection procedure, study population and speech data. Then, the detection system is depicted, starting from the feature extraction process to a detailed description of the Sequence-to-Sequence classifier. Section 4 describes the basis of Curriculum learning methods, and what lead us to develop a new strategy referred in this paper as HARD-training. Section 5 shows experimental settings and results, and Section 6 comprises our conclusions.

2. RADAR-MDD Speech Corpus – Study Population

RADAR-MDD was an observational cohort study with three recruitment sites: King’s College London (KCL, London, United Kingdom); Amsterdam UMC, Vrije Universiteit (VUmc; Amsterdam, The Netherlands). The full eligibility and exclusion criteria for RADAR-MDD are published in [5]. Briefly, the core eligibility criteria were having met the DSM-5 diagnostic criteria for non-psychotic MDD within the past two years prior to enrolment and having recurrent MDD (lifetime history of at least two episodes). Exclusion criteria included having a history of bipolar disorder, schizophrenia, MDD with psychotic features, or schizoaffective disorder; having dementia; and moderate or severe drug or alcohol use in the six months prior to enrolment. All participants were aged over 18, and were able to give informed consent.

Eligible participants were identified and recruited through several channels. This included existing research cohorts who had consented to be contacted for future research opportunities, primary and secondary mental health services, or advertisements placed on mental health charity websites, circulars or Twitter
Table 1: Extracts from The North Wind and the Sun used in the scripted task

**Extract 1:** The North Wind and the Sun were disputing which was
the stronger, when a traveller came along wrapped in a warm cloak. They agreed that the one who first succeeded in making the traveller
take his cloak off should be considered stronger than the other.

**Extract 2:** Then the North Wind blew as hard as he could, but the
more he blew the more closely did the traveller fold his cloak around him;
and at last the North Wind gave up the attempt.

**Extract 3:** Then the Sun shone out warmly, and immediately the
traveller took off his cloak. And so the North Wind was obliged to
confess that the Sun was the stronger of the two

notices. At the Amsterdam collection site, participants were also partially re-
cruited through Hersenonderzoek.nl (https://hersenonderzoek.nl). All par-
ticipants provided written consent and provided detailed baseline assessments
as outlined in [5].

2.1. Service User Involvement

The RADAR-MDD protocol was co-developed with a patient advisory board
(including service users) who shared their opinions on several user-facing as-
pects of the study including the choice and frequency of survey measures, the
usability of the study app, participant facing documents, selection of optimal
participation incentives, selection and deployment of wearable device as well
as the data analysis plan. The speech task, and subsequent analysis has been
discussed specifically with the patient advisory board.

2.2. Speech Collection in RADAR-MDD

Data were collected in RADAR-MDD using three main methods. First, all pri-
mary and secondary clinical outcome measures were collected every three months
via Research Electronic Data Capture (REDCap) software. Participants
also had to install two purpose-built apps to allow remote data collection. The
first app enabled active RMT (aRMT) data collection, in which users provided
questionnaire and speech data through active user actions with the app. The
second app enabled passive RMT (pRMT) data collection in which background
signals such as Bluetooth and location data as well as activity and cardiovas-
cular parameters from the wrist-worn device were collected with minimal user
interactions. Both apps are part of the the open-source, RADAR-base m-Health
data collection system.

Speech data collection in RADAR-MDD started in London in August 2019,
and in December 2019 at the other centres. Study participants were asked to
complete two speech-recording tasks every two weeks. First, the app produced
notifications each time speech recordings were scheduled. Before starting each
recording task, participants were reminded, via on screen instructions, to find
a quiet place to complete the recordings and to complete the recordings in
Table 2: Description of sociodemographic data and audio file distribution in the scripted (Scrpt) and unscripted (Uns) RADAR-MDD speech files used in this paper

|                     | London-KCL (English) | Amsterdam-VUmc (Dutch) | Barcelona-CIBER (Spanish) |
|---------------------|-----------------------|------------------------|---------------------------|
|                     | Scrpt  | Uns    | Scrpt  | Uns    | Scrpt  | Uns    |
| Participants        | 271    | 258    | 107    | 101    | 108    | 104    |
| Gender M/F          | 59/212 | 56/202 | 25/82  | 22/79  | 33/75  | 22/71  |
| Mean Age            | 45(±16) | 42(±17) | 54(±10) |
| No. Files           | 4,504  | 3,500  | 1,768  | 1,192  | 1,167  | 916    |
| Size (hours)        | 17.62  | 18.92  | 6.89   | 5.86   | 5.52   | 4.42   |

their normal voice. The first recording was a scripted speech task (ST), in which the participants read aloud an extract from Aesop’s fable, The North Wind and the Sun [28]. To help minimise potential confounding effects due to regular repetition of the text, the fable was split into three parts (Table 1). The three extracts were rotated in order such that participants recorded a different extract each time the task was scheduled. The second task was a free-response speech activity (FR) in which participants were asked to speak about what they were looking forward to in the following seven days [31]. Participants were able to re-record their extracts should they wish, and were also given the choice to skip the tasks. In addition to recording their speech, participants also completed a 8-item Patient Health Questionnaire (PHQ-8; [32]) to assess their level of depression. This was administered once every two weeks throughout the duration of follow-up.

2.3. Speech Data Overview

Once recorded, the speech data were encrypted and sent to a secure server. When on the server the collected data were separated into the respective tasks and decrypted into 16 kHz Waveform Audio File Format (WAV) files. All files that either were under five seconds in length were not considered in our analysis. The final number of participants and audio files considered in our analysis are presented in Table 2. There was a higher proportion of female than male participants. Unsurprisingly, as KCL had the largest cohort and had been collecting speech for the longest, the largest amount of speech data was collected in the UK.

During the scripted task, all participants were invited to read the same fragments of a text in the language of the country they were enrolled in. As a result, the standard deviation of audio recordings length was much less in this task than in the unscripted one. Combining this observation with the expected acoustic uniformity in the scripted data, we can consider the scripted corpus as a controlled experimental framework [33]. There are two main sources of variation: speech style and linguistic content [9, 10]. Speech style varies in both tasks, and linguistic content only varies in the unscripted task. Given this, we expect that the effects of depression will be the more dominant source of variation in the scripted data when compared to the free response speech.
The distribution of the audio recording durations in the RADAR-MDD speech corpus is given in Figure 1. The average recording length is 14.5s and 19.0s for the scripted and unscripted tasks respectively.

We assigned a level of depression severity to each file using the concurrently collected PHQ-8 scores. We divided the speech files into two classes: (i) mild and moderate depression severity (PHQ-8 < 10), herein referred to as the low class; and (ii) moderately severe and severe depression (PHQ-8 ≥ 10), herein referred to as the high class. Visualizations of the PHQ-8 distribution are given in Figure 2. Importantly when considering the interpretation of our results on a per-country basis, there are no notable differences related to the distribution of scores between the different tasks when comparing within each collection site.

In the next section, we move on to describing our Sequence-to-Sequence system for the automatic speech-based two-class detection of MDD severity.

3. Sequence-to-Sequence system for speech-based MDD detection

Speech is a useful and informative remote measurement technologies (RMT) signal, which offers additional advantages over other RMT signals. Most notably, it is rich signal that can be collected cheaply and non-invasively using a smartphone. Moreover, we only require a relatively small amount of data (e.g. a few sentences or phrases) to capture depression information [34]. However, robustly classifying this information in a machine learning pipeline is non-trivial [35]. This section explains the algorithm we propose for this task.

3.1. Feature Extraction

Our severity detection system has two main stages: feature extraction and classification. Regarding feature extraction, we converted the speech data into log Mel-filterbank energy, referred to herein as Mel-Spectra, features. This is a popular, yet highly effective speech feature based on the non-linear human ear perception of sound [36, 37]. The suitability of these features in combination
with recurrent neural networks has been established over a range of different speech processing tasks [REFs, see if there is a depression one]. Mel Spectra features captures changes at the acoustic information level of speech; however, when viewed as a sequence, they are also informative of the prosodic and phonetic levels [38]. They are a *low-level* speech descriptor, extracted from very small windows (typically 25 ms in length) of speech to ensure the captured signal has a quasi-periodic structure. Given an audio segment to be processed via short-term sliding windows, the key steps in Mel-Spectra extraction are as follows (Figure 3):

1. Split the speech signal into overlapping short-time frames
2. Apply the Fast Fourier Transformation (FFT) on each frame
3. Filtering the FFT results using a Mel filterbank
4. Compute the log energy of filterbank output

### 3.2. Sequence to Sequence modelling

The classification step of our system is achieved by a sequence-to-sequence model (Figure 4) with a local attention mechanism [39, 40]. The selection of this
model is to enable the longer-term sequential processing of the mel-spectrum features [41, 42]. Our approach is built on Recurrent Neural Network (RNN) architectures which have been shown to be effective in the processing of sequential data [43]. RNNs ability to track and store dependencies throughout a sequence has been key in tasks such as Stock Price Pattern Recognition [44, 45] and health care [46]. The use of RNN’s is further justified given that depression has been shown to alter temporal properties of speech; e.g. [47, 48].

Sequence-to-Sequence (Seq2Seq) models [39] are a powerful extension of the RNN architecture. They have been successfully applied in a range of tasks, including tasks related to depression prediction, such as speech-based emotion recognition [49, 50, 51]. Seq2Seq is a modelling paradigm that uses two sets of RNNs to convert one sequence of items in one domain into a sequence in another domain [52]. The first RNN network is known as the encoder and the second one as decoder. The encoder learns to processes each item of an input sequence and converts this information into a fixed (static) representation vector know as the context vector. The decoder then learns to converts this static representation into new sequence.

The core component of the encoder and decoder set-up is the RNN blocks. In our work, they are realised by a Gated Recurrent Unit (GRU) layers (Fig. 5). In the input, a Batch Normalization layer is applied for decreasing the training time of the model. Linear transformations is also applied for guarantee matrix compatibility between some consecutive blocks. In the decoder, we added a local attention mechanism in order to consider information relevance when processing the output. As we are actually performing a sequence-to-label task, we augment the output of the decoder with a feed-forward layer to performance binary classification.

During our initial system development phase (results not given), we observed
that the selection of training samples had a strong influence on the system performance. Based on these observations and subsequent tests, we developed a new approach, **HARD-Training**. This paradigm is inspired by curriculum learning [27, 26], explained in the next subsection.

### 4. Curriculum learning

Curriculum learning is a method designed to assist in maximising efficacy when training *Deep Neural Networks* (DNNs) [20]. It is based on how we as humans efficiently learn. We learn easy tasks that gradually become more complicated, incorporating new and more complex abstract concepts. By choosing what and when we learn, we can increase the speed at which learning can occur. The goal is to start small, learn easier aspects of the task or easier sub-tasks, and then gradually increase the difficulty level.

In many machine learning applications, the loss function follows a non-convex criterion, having several local minimums [53]. Consequently, we have to find the global minimum of a non-convex training criterion. Curriculum learning has been found beneficial in those cases, being a version of a continuation method optimisation strategy that deals with minimising non-convex criteria [26, 54]. The key idea of continuation methods is to optimise a smooth objective and then gradually consider less smoothing, with the intuition that the smooth version of the problem reveals the global picture. This training approach has been found to increase the training speed and achieve a better generalisation capacity [20]. This generalisation benefit infers that the curriculum learning concept operates similar to a regulariser [55].
Using a curriculum learning method for training, less complex samples feed the DNN with a high weight. In the case of the ambiguous samples, these feed the DNN with a low weight. This weight distribution helps to control the influence of the samples during training. However, applying such an \textit{a priori} assumes that non-ambiguous samples are more informative when updating the gradient, this is not always the case \cite{56}. Underexposure to ambiguous samples could even be detrimental when needing to minimise the variance of gradient updates \cite{56}. In this work, we introduce an alternate strategy to curriculum learning, \textbf{HARD-Training}, which is introduced in the next section.

\subsection*{4.1. HARD-Training methodology for binary classification.}

The method we proposed in this subsection is a variation of the Curriculum Learning approach explained previously. We keep the same key idea where \textit{ambiguous samples for humans are ambiguous for computers as well}. However, we take an opposite view of what samples are more relevant for the training of a binary classifier. We assume that by focusing purely on ambiguous samples will improve the generalization capacity of the network over training with all available samples. This improvement in generalization capacity of the model is translated into a better test performance.

We demonstrate the advantages of HARD-Training through a binary MDD severity detection task, i.e. the low and high classes. During training, the goal of our detection system is to find the optimal separation hyperplane that classifies the samples as high (moderately severe, and severe MDD) or low (mild and moderate MDD). The optimisation process is defined by a non-convex criterion as well. As a result, the decision boundary depicts a non-linear function. Referring ambiguous samples as hard, and non-ambiguous samples as easy, we hypothesise that hard samples are those closest to the optimal separation hyperplane (Fig. 6); it is this proximity that makes them difficult to be classified correctly. On the other side, easy samples are those far from the separation hyperplane.

Based on this assumption, we propose the following concept:

- During the training of a binary classifier, the use of hard (ambiguous) samples only is suitable for learning the optimal separation hyperplane, while easy samples would not lead to an effective approximation. The separation hyperplane defined by easy samples is more likely to follow a linear function due to the greater distance between them. This is not an appropriate function to guarantee the generalisation capacity of the classifier, making ineffective the classification of hard samples. Hard samples are closer to the optimal decision boundary because of their condition as ambiguous. Therefore, optimising the model using only hard samples help us to classify easy samples as well, and with a high accuracy. We conclude that, in training, easy samples can only make noisier the finding of the classifier’s decision boundary.

The next step is to define what samples are ambiguous or not to the model. For our classification task, we use the PHQ-8 scores to define current symptom
severity. A person meets the PHQ-8 criteria for having high depression symptom severity by obtaining a score greater or equal to 10. Moreover, a score less than 5 indicates low/no current depression symptoms, while a score greater than 15 indicates severe depression symptoms. Given this, we assume there is greater ambiguity in the presentation of depression symptoms closer to the cut of score of 10, as it is depicted in Figure 7.

We undertook a simple experiment to validate our easy-hard partition assumption. In it, we trained a smaller version of our Seq2Seq model, using 32 as the hidden size of the GRU layers, from the decoder and encoder. Firstly, we trained the model, randomly picking 128 sequences from the group of easy samples (e.g. PHQ8 ≤ 5 and PHQ8 ≥ 15). Secondly, we initialized the model again and picked another 128 training sequences but from the group of hard samples. Then, we compared the training loss of the model for the easy and hard group respectively. On both cases, the total of training epochs was 500. If our assumption is valid, the training loss should be lower when easy samples are used; this experiment was repeated several times. The Figure 8 shows a sample of what has been the behaviour of the training loss on those experiments.

Initially, both the easy and hard training loss are similar, but after approximately 200 epochs the difference between them becomes clear. It is easy to visualise how difficult it was for the model to assimilate the patterns that came from the hard samples. This was the case most of the time we performed this experiment, which validates our assumption of the intervals defined for easy and hard samples. Nevertheless, there were a few cases were the model was able to learn from easy and hard samples to a similar speed. We attribute this seldom behavior to the high variability of speech features.
5. Experimental settings and results

Our system utilises Mel-spectrum features and a Seq2Seq model as classifier. We extracted 40 dimensional mel-spectrum features using a window of 0.25 ms with a hop of 10 ms via the Librosa Python package. These features were then split into sequence of 500 vectors, representing 5 secs long. The selection of this temporal length was based on our previous experience working on the DAIC-WOZ database, where a 5 seconds length appeared to be the optimal sequence
length. The Seq2Seq model is augmented by a Batch Normalisation layer in the input, as well as unidirectional GRU layers in the encoder and decoder, each with a hidden layer size of 128. We use a local attention mechanism with a window size of 1.5 secs. The total of trainable parameters of the model was 204115. The batch size was set to 128, with 100 epochs of training. The Adam algorithm \cite{kingma2014adam} was taken as optimiser using Binary Cross Entropy as loss function. One cycle learning rate policy \cite{smith2017cyclical} was done to fast up the convergence time of the model. To avoid exploding gradient, Gradient clipping method \cite{pascanu2012understanding} was applied on the last layer of the model.

A 10-Fold speaker-stratified cross-validation strategy was used for the system test on the London and Amsterdam corpus respectively. In the case of Barcelona corpus, a 5-Folds were used because of the smaller total recording length of this corpus. When performing HARD-Training, we removed the easy samples from the training group; however both easy and hard samples were present in the test fold.

Figure 9 compares the results using the classic and HARD-Training approaches. We refer as classic approach to the training process where is not applied a curriculum learning strategy; therefore, every sample (hard and easy) feeds the model during training. The HARD-Training method consistently outperforms the classic approach for every collection place. The biggest difference of performance between them is around 10% of accuracy and the smallest one is around 5%. This means that despite of the training loss is higher for the HARD method in the same amount of epochs, it achieve a better generalisation capacity during test. This was the basis of our hypothesis to follow this training strategy. In addition, we can conclude that the benefits of HARD-Training are steady through different languages.

![Figure 9: Comparison of the Seq2Seq performance when using classic and HARD-Training methods on the scripted and unscripted tasks](image)

The Table 3 depicts the final results of the Seq2Seq model using the proposed HARD-Training method. The results are quite stables with an accuracy from 75.12% to 81.70 throughout the three collection places. Area Under Curve (AUC) values are in most of the cases over 80%, which means a good class separation ability through different decision thresholds. The lowest performance was in the unscripted task of the Barcelona corpus, which is at the same time the smallest corpus. The standard deviation of the accuracy is higher for the unscripted task than for the scripted one in every collection place. We expected
Table 3: Results of the Seq2Seq model using The HARD-Training method

| Collection place (Language) | Task   | Accuracy | AUC     |
|----------------------------|--------|----------|---------|
| London-KCL (English)       | scripted | 76.76 ±- 1.28 | 81.58 ±- 2.34 |
|                            | unscripted | 78.63 ±- 3.71 | 80.67 ±- 4.22 |
| Amsterdam-VUmc (Dutch)     | scripted | 81.70 ±- 4.68 | 83.91 ±- 6.16 |
|                            | unscripted | 77.33 ±- 6.39 | 77.94 ±- 9.15 |
| Barcelona-CIBER (Spanish)  | scripted | 79.15 ±- 2.31 | 81.97 ±- 3.84 |
|                            | unscripted | 75.12 ±- 4.28 | 73.39 ±- 4.61 |

Figure 10: Comparison of the Seq2Seq accuracy for male/female participants

this behaviour because of the open setting condition of the unscripted task.

Finally, to contribute to wider discussion regarding bias and fairness in Artificial Intelligence and machine learning research, we conduct a gender independent analysis of our results. We split the results from Table 3 into male/female participants, as it is showed on Figure 10. As a general trend, the system performs stronger on male participants from KCL and VUmc, however there is not a noticeable drop-off in performance for the female participants when compared to the gender independent results for these sites. This stronger performance for males is surprising given the gender imbalance of the corpus and will investigate further in future research. For the CIBER site, the system performs stronger for females, which is more in line with expectation based purely on weighted gender distributions.

6. Conclusions

The Remote Assessment of Disease and Relapse – Major Depressive Disorder (RADAR-MDD) speech corpus is a new longitudinal dataset containing approximately 60 hours of speech collected from almost 500 participants over an 18 month period. Matching the three collection sites, London, Amsterdam and Barcelona, the data collected is in English, Dutch and Spanish. To the best of
Utilising this dataset, we designed and implemented a Sequence-to-Sequence model with local attention mechanism for a 2-class depression severity detection task. The novel aspect of this model was the proposed HARD-Training paradigm. HARD-Training is based on a Curriculum Learning approach, however, it utilises a different selection criteria in relation to which samples are more relevant for the model training. Consistent results were demonstrated across the three language groups and two different speech tasks with the RADAR-MDD speech corpora. On average, hard training improved the model’s accuracy by 8.6% and achieved an Area Under Curve over 80% in almost every case tested. Finally, a gender-independent analysis was carried out to validate the Sequence-to-Sequence performance according to the gender of the participant. Results were strong for female and male participant’s samples, but the best results were mostly achieved processing samples from male participants. Future work efforts will focus on verifying the benefits of HARD-Training in other scenarios, namely different speech-health tasks and different signals from remote measurement technologies.

7. Acknowledgments

This work has received financial support from Axudas propias para a mobilidade de Personal Investigador da Universidade de Vigo 2021, the Xunta de Galicia (Centro singular de investigación de Galicia accreditation 2019-2022), Consellería de Cultura (Educación e Ordenación Universitaria; ayudas para a consolidación e estruturación de unidades de investigación competitivas do Sistema Universitario de Galicia -ED431B 2021/24), and the European Union (European Regional Development Fund - ERDF).

Funding The RADAR-CNS project has received funding from the Innovative Medicines Initiative 2 Joint Undertaking under grant agreement No 115902. This Joint Undertaking receives support from the European Union’s Horizon 2020 research and innovation programme and EFPIA (www.imi.europa.eu). This communication reflects the views of the RADAR-CNS consortium and neither IMI nor the European Union and EFPIA are liable for any use that may be made of the information contained herein. The funding body have not been involved in the design of the study, the collection or analysis of data, or the interpretation of data.

Participant recruitment in Amsterdam was partially accomplished through Hersenonderzoek.nl, a Dutch online registry that facilitates participant recruitment for neuroscience studies (https://hersenonderzoek.nl/). Hersenonderzoek.nl is funded by ZonMw-Memorabel (project no 73305095003), a project in the context of the Dutch Deltaplan Dementie, Gieskes-Strijbis Foundation, the Alzheimer’s Society in the Netherlands and Brain Foundation Netherlands.

Participants in Spain were recruited through the following institutions: Parc Sanitari Sant Joan de Déu network of mental health services (Barcelona); In-
Institut Català de la Salut primary care services (Barcelona); Institut Pere Mata-Mental Health Care (Tarrassa); Hospital Clínic San Carlos (Madrid). This paper represents independent research part funded by the National Institute for Health Research (NIHR) Maudsley Biomedical Research Centre at South London and Maudsley NHS Foundation Trust and King’s College London. The views expressed are those of the author(s) and not necessarily those of the NHS, the NIHR or the Department of Health and Social Care.

We thank all the members of the RADAR-CNS patient advisory board for their contribution to the device selection procedures, and their invaluable advice throughout the study protocol design. This research was reviewed by a team with experience of mental health problems and their carers who have been specially trained to advise on research proposals and documentation through the Feasibility and Acceptability Support Team for Researchers (FAST-R): a free, confidential service in England provided by the National Institute for Health Research Maudsley Biomedical Research Centre via King’s College London and South London and Maudsley NHS Foundation Trust.

We thank all GLAD Study volunteers for their participation, and gratefully acknowledge the NIHR BioResource, NIHR BioResource centres, NHS Trusts and staff for their contribution. We also acknowledge NIHR BRC, King’s College London, South London and Maudsley NHS Trust and King’s Health Partners. We thank the National Institute for Health Research, NHS Blood and Transplant, and Health Data Research UK as part of the Digital Innovation Hub Programme.

We thank our colleagues both within the RADAR-CNS consortium and across all involved institutions for their contribution to the development of this protocol. We thank all the members of the RADAR-CNS patient advisory board for their contribution to the device selection procedures, and their invaluable advice throughout the study protocol design. In particular we thank Grace Lavelle, Daniel Leightley, Maria Teresa Peñarrubia-María, Gemma Riquelme Acid, Katie M. White, Alina Ivan, Carolin Oetzmann, Sara Simblett, Yatharth Ranjan, Zulqarmain Rashid, Amos A. Folarin, Josep Maria Haro, Srinivasan Vairavan, Til Wykes, Richard Dobson, Vaibhav A. Narayan and Matthew Hotopf.

References

[1] OECD and European Union, Promoting mental health in europe: Why and how, OECD iLibrary (2018).

[2] World Health Organization, Depression and other common mental disorders: Global health estimates, [https://bit.ly/3aTX7LN](https://bit.ly/3aTX7LN) (2017).

[3] D. F. Santomauro, A. M. M. Herrera, J. Shadid, P. Zheng, C. Ashbaugh, D. M. Pigott, C. Abbafati, C. Adolph, J. O. Amlag, A. Y. Aravkin, et al., Global prevalence and burden of depressive and anxiety disorders in 204 countries and territories in 2020 due to the COVID-19 pandemic, The Lancet 398 (10312) (2021) 1700–1712.
[4] R. H. Han, M. N. Schmidt, W. M. Waits, A. K. Bell, T. L. Miller, Planning for mental health needs during COVID-19, Current psychiatry reports 22 (12) (2020) 1–10.

[5] F. Matcham, C. Barattieri di San Pietro, V. Bulgari, G. De Girolamo, R. Dobson, H. Eriksson, A. Folarin, J. M. Haro, M. Kerz, F. Lamers, et al., Remote assessment of disease and relapse in major depressive disorder (RADAR-MDD): a multi-centre prospective cohort study protocol, BMC psychiatry 19 (1) (2019) 1–11.

[6] N. Cummins, S. Scherer, J. Krajewski, S. Schnieder, J. Epps, T. F. Quatieri, A review of depression and suicide risk assessment using speech analysis, Speech Communication 71 (2015) 10–49.

[7] Y. Li, Y. Lin, H. Ding, C. Li, Speech databases for mental disorders: A systematic review, General Psychiatry 32 (3) (2019) e100022.

[8] D. M. Low, K. H. Bentley, S. S. Ghosh, Automated assessment of psychiatric disorders using speech: A systematic review, Laryngoscope Investigative Otolaryngology 5 (1) (2020) 96–116.

[9] D. Reynolds, W. Andrews, J. Campbell, J. Navratil, B. Peskin, A. Adami, Q. Jin, D. Khusacek, J. Abramson, R. Mihaescu, et al., The supersid project: Exploiting high-level information for high-accuracy speaker recognition, in: IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), IEEE, Hong Kong, China, 2003, pp. 784–785.

[10] D. Reynolds, J. Campbell, B. Campbell, B. Dunn, T. Gleason, D. Jones, T. Quatieri, C. Quillen, D. Sturim, P. Torres-Carrasquillo, Beyond cepstra: exploiting high-level information in speaker recognition, in: Workshop on Multimodal User Authentication, IEEE, Santa Barbara, CA, USA, 2003, pp. 223–229.

[11] M. JH Balsters, E. J Krahmer, M. GJ Swerts, A. JJM Vingerhoets, Verbal and nonverbal correlates for depression: a review, Current Psychiatry Reviews 8 (3) (2012) 227–234.

[12] J. A. Hall, J. A. Harrigan, R. Rosenthal, Nonverbal behavior in clinician—patient interaction, Applied and preventive psychology 4 (1) (1995) 21–37.

[13] C. Sobin, H. A. Sackeim, Psychomotor symptoms of depression, American Journal of Psychiatry 154 (1) (1997) 4–17.

[14] A. Othmani, D. Kadoch, K. Bentounes, E. Rejaibi, R. Alfred, A. Hadid, Towards robust deep neural networks for affect and depression recognition from speech, in: Pattern Recognition, ICPR International Workshops and Challenges, Springer International Publishing, Virtual Event, 2021, pp. 5–19.
[15] E. Rejaibi, D. Kadoch, K. Bentoumes, R. Alfred, M. Daoudi, A. Hadid, A. Othmani, Clinical depression and affect recognition with emoaudionet, https://arxiv.org/abs/1911.00310 (2019).

[16] M. Muzammel, H. Salam, Y. Hoffmann, M. Chetouani, A. Othmani, Aud-VowelConsNet: A phoneme-level based deep CNN architecture for clinical depression diagnosis, Machine Learning with Applications 2 (2020) 100005.

[17] Z. Zhao, Z. Bao, Z. Zhang, J. Deng, N. Cummins, H. Wang, J. Tao, B. Schuller, Automatic assessment of depression from speech via a hierarchical attention transfer network and attention autoencoders, IEEE Journal of Selected Topics in Signal Processing 14 (2) (2019) 423–434.

[18] S. P. Yadav, S. Zaïdi, A. Mishra, V. Yadav, Survey on Machine Learning in Speech Emotion Recognition and Vision Systems Using a Recurrent Neural Network (RNN), Archives of Computational Methods in Engineering (2021) 1–18.

[19] E. Rejaibi, A. Komaty, F. Meriaudeau, S. Agrebi, A. Othmani, Mfcc-based recurrent neural network for automatic clinical depression recognition and assessment from speech, Biomedical Signal Processing and Control 71 (2022) 103107.

[20] Z. Zhao, Q. Li, N. Cummins, B. Liu, H. Wang, J. Tao, B. W. Schuller, Hybrid network feature extraction for depression assessment from speech., in: INTERSPEECH, ISCA, Shanghai, China, 2020, pp. 4956–4960.

[21] F. Ringeval, B. Schuller, M. Valstar, J. Gratch, R. Cowie, S. Scherer, S. Mozgai, N. Cummins, M. Schmitt, M. Pantic, AVEC 2017: Real-life depression, and affect recognition workshop and challenge, in: Proceedings of the 7th Annual Workshop on Audio/Visual Emotion Challenge, ACM, Mountain View, CA, USA, 2017, pp. 3–9.

[22] F. Ringeval, B. Schuller, M. Valstar, N. Cummins, R. Cowie, L. Tavabi, M. Schmitt, S. Alisamir, S. Amiriparian, E.-M. Messner, S. Song, S. Liu, Z. Zhao, A. Mallol-Ragolta, Z. Ren, M. Soleymani, M. Pantic, Avec 2019 workshop and challenge: State-of-mind, detecting depression with ai, and cross-cultural affect recognition, in: Proceedings of the 9th International on Audio/Visual Emotion Challenge and Workshop, ACM, Nice, France, 2019, pp. 3–12.

[23] N. Cummins, V. Sethu, J. Epps, S. Schnieder, J. Krajewski, Analysis of acoustic space variability in speech affected by depression, Speech Communication 75 (2015) 27–49.

[24] A. Harati, E. Shriberg, T. Rutowski, P. Chlebek, Y. Lu, R. Oliveira, Speech-based depression prediction using encoder-weight-only transfer learning and a large corpus, in: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, Toronto, Canada, 2021, pp. 7273–7277.
[25] H. Zogan, I. Razzak, S. Jameel, G. Xu, Depressionnet: learning multimodalities with user post summarization for depression detection on social media, in: Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval, ACM, Virtual Event, 2021, pp. 133–142.

[26] Y. Bengio, J. Louradour, R. Collobert, J. Weston, Curriculum learning, in: Proceedings of the 26th Annual International Conference on Machine Learning, ACM, Montreal, Canada, 2009, pp. 41–48.

[27] R. Lotfian, C. Busso, Curriculum learning for speech emotion recognition from crowdsourced labels, IEEE/ACM Transactions on Audio, Speech, and Language Processing 27 (4) (2019) 815–826.

[28] International Phonetic Association, Handbook of the International Phonetic Association, Cambridge University Press, 1999.

[29] P. A. Harris, R. Taylor, B. L. Minor, V. Elliott, M. Fernandez, L. O’Neal, L. McLeod, G. Delacqua, F. Delacqua, J. Kirby, et al., The REDCap consortium: Building an international community of software platform partners, Journal of Biomedical Informatics 95 (2019) 103208.

[30] Y. Ranjan, Z. Rashid, C. Stewart, P. Conde, M. Begale, D. Verbeeck, S. Boettcher, R. Dobson, A. Folarin, R.-C. Consortium, et al., RADAR-base: open source mobile health platform for collecting, monitoring, and analyzing data using sensors, wearables, and mobile devices, JMIR mHealth and uHealth 7 (8) (2019) e11734.

[31] J. C. Mundt, P. J. Snyder, M. S. Cannizzaro, K. Chappie, D. S. Gerlats, Voice acoustic measures of depression severity and treatment response collected via interactive voice response (IVR) technology, Journal of Neurolinguistics 20 (1) (2007) 50–64.

[32] K. Kroenke, T. W. Strine, R. L. Spitzer, J. B. Williams, J. T. Berry, A. H. Mokdad, The PHQ-8 as a measure of current depression in the general population, Journal of Affective Disorders 114 (1-3) (2009) 163–173.

[33] P. Langley, Machine learning as an experimental science, Machine Learning 3 (1) (1988) 5–8.

[34] S. Alghowinem, R. Goecke, M. Wagner, J. Epps, M. Breakspear, G. Parker, Detecting depression: A comparison between spontaneous and read speech, in: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP, IEEE, Vancouver, Canada, 2013, pp. 7547–7551.

[35] N. Cummins, A. Baird, B. W. Schuller, Speech analysis for health: Current state-of-the-art and the increasing impact of deep learning, Methods 151 (2018) 41–54.
[36] Z. Tychtl, J. Psutka, Speech Production Based on the Mel-Frequency Cepstral Coefficients, in: Eurospeech, ISCA, Budapest, Hungary, 1999, pp. 2335–2338.

[37] S. Imai, Cepstral analysis synthesis on the mel frequency scale, in: ICASSP ’83. IEEE International Conference on Acoustics, Speech, and Signal Processing, Vol. 8, 1983, pp. 93–96. doi:10.1109/ICASSP.1983.1172250.

[38] K. S. Ahmad, A. S. Thosar, J. H. Nirmal, V. S. Pande, A unique approach in text independent speaker recognition using MFCC feature sets and probabilistic neural network, in: International Conference on Advances in Pattern Recognition (ICAPR), IEEE, 2015, pp. 1–6.

[39] C.-C. Chiu, T. N. Sainath, Y. Wu, R. Prabhavalkar, P. Nguyen, Z. Chen, A. Kannan, R. J. Weiss, K. Rao, E. Gonina, et al., State-of-the-art speech recognition with sequence-to-sequence models, in: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, Calgary, Canada, 2018, pp. 4774–4778.

[40] Z. Niu, G. Zhong, H. Yu, A review on the attention mechanism of deep learning, Neurocomputing 452 (2021) 48–62.

[41] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural computation 9 (8) (1997) 1735–1780.

[42] M. C. Mozer, Induction of multiscale temporal structure, in: Advances in neural information processing systems, 1992, pp. 275–282.

[43] Y. Yu, X. Si, C. Hu, J. Zhang, A Review of Recurrent Neural Networks: LSTM Cells and Network Architectures, Neural Computation 31 (7) (2019) 1235–1270.

[44] K.-i. Kamijo, T. Tanigawa, Stock price pattern recognition: A recurrent neural network approach, in: International Joint Conference on Neural Networks (IJCNN), IEEE, San Diego, CA, USA, 1990, pp. 215–221.

[45] A. Samarawickrama, T. Fernando, A recurrent neural network approach in predicting daily stock prices an application to the sri lankan stock market, in: 2017 IEEE International Conference on Industrial and Information Systems (ICIIIS), IEEE, 2017, pp. 1–6.

[46] Y. Luo, Recurrent neural networks for classifying relations in clinical notes, Journal of Biomedical Informatics 72 (2017) 85–95.

[47] A. C. Trevino, T. F. Quatieri, N. Malyska, Phonologically-based biomarkers for major depressive disorder, EURASIP Journal on Advances in Signal Processing 2011 (1) (2011) 1–18.
[48] M. Yamamoto, A. Takamiya, K. Sawada, M. Yoshimura, M. Kitazawa, K.-c. Liang, T. Fujita, M. Mimura, T. Kishimoto, Using speech recognition technology to investigate the association between timing-related speech features and depression severity, PloS one 15 (9) (2020) e0238726.

[49] X. Chen, W. Han, H. Ruan, J. Liu, H. Li, D. Jiang, Sequence-to-sequence modelling for categorical speech emotion recognition using recurrent neural network, in: Asian Conference on Affective Computing and Intelligent Interaction (ACII Asia), IEEE, Beijing, China, 2018, pp. 1–6.

[50] W.-C. Lin, C. Busso, Chunk-level speech emotion recognition: A general framework of sequence-to-one dynamic temporal modeling, IEEE Transactions on Affective Computing Early Access.

[51] Z. Zhao, Q. Li, Z. Zhang, N. Cummins, H. Wang, J. Tao, B. W. Schuller, Combining a parallel 2D CNN with a self-attention dilated residual network for CTC-based discrete speech emotion recognition, Neural Networks 141 (2021) 52–60.

[52] I. Sutskever, O. Vinyals, Q. V. Le, Sequence to sequence learning with neural networks, in: Advances in Neural Information Processing Systems, Curran Associates, Inc., Montreal, Canada, 2014, pp. 1–9.

[53] P. Jain, P. Kar, Non-convex Optimization for Machine Learning, Foundations and Trends in Machine Learning 10 (3-4) (2017) 142–363.

[54] L. Jiang, D. Meng, S.-I. Yu, Z. Lan, S. Shan, A. Hauptmann, Self-paced learning with diversity, in: Z. Ghahramani, M. Welling, C. Cortes, N. Lawrence, K. Weinberger (Eds.), Advances in Neural Information Processing Systems, Vol. 27, Curran Associates, Inc., Montreal, Canada, 2014, pp. 1–9.

[55] C. Li, M. Zhang, Y. He, Curriculum Learning: A Regularization Method for Efficient and Stable Billion-Scale GPT Model Pre-Training, https://arxiv.org/abs/2108.06084 (2021).

[56] H.-S. Chang, E. Learned-Miller, A. McCallum, Active Bias: Training More Accurate Neural Networks by Emphasizing High Variance Samples, in: Advances in Neural Information Processing Systems, Vol. 30, Curran Associates, Inc., Long Beach, CA, USA, 2017, pp. 1–11.

[57] B. McFee, C. Raffel, D. Liang, D. P. Ellis, M. McVicar, E. Battenberg, O. Nieto, librosa: Audio and music signal analysis in python, in: Proceedings of the 14th Python in Science Conference, Vol. 8, SciPy, Austin, TX, USA, 2015, pp. 18–25.

[58] D. P. Kingma, J. Ba, Adam: A Method for Stochastic Optimization, https://arxiv.org/abs/1412.6980 (2017).
[59] L. N. Smith, N. Topin, Super-convergence: Very fast training of residual networks using large learning rates, \texttt{http://arxiv.org/abs/1708.07120} (2017).

[60] R. Pascanu, T. Mikolov, Y. Bengio, On the difficulty of training recurrent neural networks, in: International Conference on Machine Learning, PMLR, Atlanta, GA, USA, 2013, pp. 1310–1318.