Towards Universal End-to-End Affect Recognition from Multilingual Speech by ConvNets

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Abstract—We propose an end-to-end affect recognition approach using a Convolutional Neural Network (CNN) that handles multiple languages, with applications to emotion and personality recognition from speech. We lay the foundation of a universal model that is trained on multiple languages at once. As affect is shared across all languages, we are able to leverage shared information between languages and improve the overall performance for each one. We obtained an average improvement of 12.8% on emotion and 10.1% on personality when compared with the same model trained on each language only. It is end-to-end because we directly take narrow-band raw waveforms as input. This allows us to accept as input audio recorded from any source and to avoid the overhead and information loss of feature extraction. It outperforms a similar CNN using spectrograms as input by 12.8% for emotion and 6.3% for personality, based on F-scores. Analysis of the network parameters and layers activation shows that the network learns and extracts significant features in the first layer, in particular pitch, energy and contour variations. Subsequent convolutional layers instead capture language-specific representations through the analysis of supra-segmental features. Our model represents an important step for the development of a fully universal affect recognizer, able to recognize additional descriptors, such as stress, and for the future implementation into affective interactive systems.

Index Terms—universal affect recognition, speech, emotion, personality, end-to-end

I. INTRODUCTION

RECognition of human affect is a very important aspect of human communication. We not only convey messages by their literal meaning, but also by how they are expressed and other forms of non-verbal communication. This includes cues like tone of voice, gesture, facial expression, or even more subtle elements such as body temperature and heart rate [1], [2]. Many of the main affect characteristics are universal across different languages and cultures. This motivates the creation of universal models. It is becoming increasingly important for machines to be able to recognize various forms of human affect. An affect recognition model should be universally applicable, not just in specific domains and languages. This will help us develop more advanced interactive systems [3], [4] that are able to detect and use affect, in addition to standard ASR and NLP techniques, to provide advanced services such as personality analysis, counseling, education, medical, or commercial services. We focus on affect recognition from audio and speech in this work through two universal affect characteristics retrievable from speech, namely emotion and personality.

In the field of emotion detection, there is no general agreement on the number of basic emotion descriptors [5]. It ranges from three (Anger, Happiness and Sadness, with the eventual inclusion of the Neutral class) to up to 20 for some commercial services. Each available corpus includes a different set of emotions. These emotions are often projected onto a plane formed by two main axes: Valence and Arousal [6]. This way the classification task is reduced to the prediction of these two scores and the identification of a point on the plane. This greatly simplifies the classification process and training procedure, but it is less natural for humans to understand and interpret the meaning of Valence and Arousal compared to discrete emotions labels. Furthermore, it poses difficulties and uncertainties in the annotation process. Various emotion types are usually obtained through clustering the plane. For these reasons, and to provide more detailed analysis on each emotion, we decided to perform classification on discrete emotion values in our work described in this paper.

For personality recognition a standard set of descriptors are five personality traits from the Big Five model [7]. Traits are patterns in thought and behavior. An individual scores between 0 (low) and 1 (high) for each trait. Thus, an individual’s personality is represented by a 5-dimensional vector of scores for the following traits:

- **Extraversion** refers to assertiveness and energy level. Low scorers in this trait are more reserved and calm.
- **Agreeableness** refers to cooperative and considerate behavior. Low scorers in this trait are less interested in social harmony with those around them.
- **Conscientiousness** refers to behavioral and cognitive self-control. Low scorers in this trait are typically seen as more irresponsible and disorganized.
- **Neuroticism** refers to a person’s range of emotions and his/her control over these emotions. Low scorers are often more chaotic and anxious.
- **Openness to Experience** refers to creativity and adventurousness. Low scorers in this trait are typically more conservative and less curious.

We are particularly interested in whether affect is language-dependent and whether we can build a universal affect
recognition system. Some researchers found that emotions vary only a little from one language or culture to the other [8]. The Big Five traits of personality have been demonstrated to be quite robust over different geographic locations [9]. Our previous work has shown that the manifestation of at least some affect, such as stress, is more gender-dependent than language-dependent [10]. It is interesting for us to investigate what features of speech, if any, are language independent. Finding commonality in the speech of different languages has shown to be effective for multilingual acoustic modeling, where it shares part of their phone set at the model level, the state-level, or the acoustic feature level [11], [12], [13]. Multilingual models are also beneficial with the scarcity of training data in one or multiple languages. For our task on affect recognition, there is not a huge amount of human-labeled data available in any language. We postulate that a universal end-to-end model shared between different language samples may improve the performance on each individual language.

Another objective of our work is to explore machine learning methods that can extract features automatically from raw waveforms, without explicit human design. We are motivated by the fact that the human auditory system is capable of processing audio in different languages without any morphological changes. In addition, previous work on multilingual speech recognition has shown that there are stronger responses in certain groups of the spectral frequencies to phonetic sounds in certain languages. The class of deep learning algorithms called Convolutional Neural Networks (CNN) has shown to be astute in automatic feature extractions in both the image and speech domains [14], [15]. We aim to investigate end-to-end CNN models for affect recognition. An important objective of using automatic feature extraction combined with classification is to bypass the time delay in extracting features. A system based on narrow-band raw waveforms would allow us to avoid any corpus-dependent and language-dependent feature engineering step, would be applicable to any sort of spoken input signal, such as phone calls, and would require less memory and pre-processing overhead.

This work is a significant extension of our earlier attempts to detect speech emotions from narrow-band speech raw waveforms [16], [17] to include personality analysis and a multilingual approach. In this paper we significantly revise the model and experimental setup from our previous works and experiments on more datasets in different languages. We do not only limit the application to the emotion detection problem, but we also show the effectiveness on the more difficult personality detection from speech, again in a multilingual setting. We then provide more insights about what the model is actually trying to learn, and how it generalizes across languages.

II. RELATED WORK

A. Multilingual approaches for speech and language

Multilingual approaches from speech and language first appeared in the 1990s with statistical models. These models have been found to help improve the performance for those languages with limited resources, through taking advantage of the similarities among different languages and by borrowing from resource-rich languages [13]. Since we are interested in deep learning methods that can automatically extract features, we also look at recent multilingual neural models that have been proposed in speech processing, including speech recognition [18], [19], [20], [21], [22], [23], [24], [25]. Neural network architectures and training procedures were specifically designed to handle multilingual input and take advantage of multiple languages combined to improve the recognition performance on each of them.

For Automatic Speech Recognition (ASR), [18], [19] used a multi-layer DNN with an array of language-specific final layers to share the acoustic features across different languages. [20], [21] instead used a similar DNN with a single final layer fine-tuned on different languages, while [22] applied a progressive layer by layer training first from a multilingual corpus and then from specific languages. Other techniques were used to adapt the final layers such as low-rank factorization of parameter matrices [23] or bottleneck layers and extra features [24], [25].

B. Emotion recognition from speech

Previously speech emotion detection was performed through the extraction of many features from the audio sample which are then fed into a supervised classifier [26]. A standard set of features included speech features such as MFCC, psycholinguistic features [27] and other low-level audio features such as pitch, zero-crossing rate, energy and many others [20]. They were extracted from small audio frames, typically of around 25 ms, and then combined together to represent the utterance to analyze. This combination was performed either through many statistical functionals such as mean, standard deviation, skewness, kurtosis, etc. [28], or directly through the classifier [29]. The classifier choice ranged from basic supervised classifiers such as SVM [26], [30] and decision trees [31], to more complex deep learning structures such as DNN [32], CNN [33], ELM [29] or LSTM in the case of continuous emotion detection [34]. Most of the analysis was performed on the valence-arousal plane [26], often grouping multiple discrete emotions as high/low valence and high/low arousal [35], [30].

All those feature sets were often collected and provided in various shared task [35], [37], [38], and used as standard feature sets for affect recognition thereafter. Others have applied more complex feature engineering and feature selection [39], but these processes are often time consuming, add overhead latency or be database dependent. Departing from the traditional feature engineering approach [40], [41] used deep learning models to perform automatic feature extractions from the audio represented as a spectrogram. In these works the spectrograms are described as the “raw audio signal”. However, we note that the spectrogram itself, though more limited in scope, is already a feature extraction step where each audio frame is associated with its FFT coefficients, thus it is not the “raw audio signal” as purported. We are interested in investigating whether CNNs can extract features and classify them correctly directly from the time-domain raw waveform.

Extending the analysis to the field of multilingual and cross-domain emotion and personality recognition, most works applied traditional feature-engineering with eventual speaker-normalization [35], [42], [43] tried to solve the problem through
the extraction of a shared feature representation using Kernel
Canonical Correlation Analysis [44], while [45], [46] obtained
the shared feature representation training an autoencoder. [50]
managed to increase the classification accuracy over various
corpora by using unlabeled data.

With the exception of [47] and our preliminary work [16],
[17], no other work to our knowledge have ever tried to classify
paralinguistic traits using raw waveforms as input directly.
Even [47] analyzed only a very limited dataset, and only on
the valence-arousal dimensions, providing very limited insights
on the proposed network architecture.

C. Personality recognition from speech

The field of Personality Computing is quite young, but some
work has been published on recognizing Big Five personality
traits from the non-verbal part of speech [48]. Just as in emotion
detection, most of the work has focused on extracting low-
level prosodic features and statistical functions thereof, using
a standard classification algorithm such as SVM or Random
Forest to determine whether the subject scores above or below
the median for each of the five traits [49], [50], [51].

The Interspeech 2012 Speaker Trait Challenge [52] was
the first comprehensive effort to compare different approaches
to the problem, by benchmarking on the same test dataset.
Popular prosodic features are statistics of pitch, energy, first
two formants, length of voided and unvoiced segments, as well
as Mel Frequency Cepstral Coefficients (MFCC). The winner
of the competition extracted thousands of spectral features before
doing a feature selection process [53], a method that was very
common [54]. These features were then mapped to the five
traits through SVM classifiers. Classification accuracies from
this challenge are between 60 and 75 percent, depending on the
trait. Although many different approaches and machine learning
algorithms were tried, none of them clearly outperformed the
others. Also, due to the limited number of subjects, the results
from these works are often statistically unreliable and could
be heavily corpus-dependent.

Related work found that the Extraversion and Conscientious-
ness traits were easiest to classify, and Openness to Experience
the hardest [55], [51]. [60].

The ChaLearn 2016 shared task challenge released a large
corpus of 10,000 extracts from YouTube video blogs [57].
each clip was labeled with continuous Big Five labels. Each
of the participants of the shared task used audio as well as
video, and it is not possible to directly look at recognition
performance from just audio. This workshop is still interesting
for two reasons. The corpus provided is, to our knowledge,
the biggest open-domain personality corpus, and the best
performing teams used neural network techniques. However,
although teams inserted video directly into a neural network,
they still extracted traditional audio features (zero crossing
rate, energy, spectral features, MFCCs) that were then fed into
the neural network [58], [59], [60]. A deep neural network
should however be able to extract such features itself (if
relevant for the task). An exception was [61], but they used a
neural network specialized for image processing and computer
vision, and did not adapt it to audio input. The team with the
best performance in the challenge extracted openSMILE [26]
acoustic features as used in the INTERSPEECH 2013 challenge
baseline set [38], which they linearly mapped to the Big Five
traits. They did not publish their work. The challenge was
aimed at the computer vision community (many only used facial
features), thus although many teams analyzed their approaches
to vision, not many looked into detail what their deep learning
network was learning regarding audio input.

III. METHODOLOGY

In this paper, we propose a method for automatically
recognizing emotion and personality from speech in different
languages, without the need for feature extraction upfront. We
propose to achieve this with a multi-layer Convolutional Neural
Network (CNN) framework, trained end-to-end from raw
waveforms. We train models in monolingual and multilingual
settings. We compare our model with a similar CNN model
that takes spectrogram representations as input.

A. Preprocessing

We are interested in recognizing affect from a given input
audio sample. The very first processing step is to downscale
the input sample to a uniform sampling rate. We choose narrowband
speech at 8kHz for our work. There are two main reasons
for this choice. The first is to analyze how the system would
work under the worst possible conditions, for example to detect
emotion over a phone call. The second one is to reduce the
eventual transmission time and memory requirements when
the speech has to be sent over internet or has to be stored and
processed in an embedded system, it also reduces the number
of network parameters.

An aspect often overlooked while designing models for
affect recognition is the input volume. Features such as relative
energy within or across frames are important components of
affect, as sudden changes may signal high arousal emotions
like anger. However absolute energy over the entire sample
is not useful, as it mainly depends on the volume the sample
was recorded at. The absolute energy level may cause severe
overfitting to the model. This is often evident with emotions
like anger or sadness, where sometimes the model only learns
to distinguish the classes through the amplitude level ignoring
the rest of the features. Different language corpora, especially
when consisting of spontaneous speech, may contain samples
recorded at varying input volumes. The position of the speaker
with respect of the microphone may also differ each time.
All these aspects cannot be determined a priori. Volume
normalization techniques, such as peak or RMS normalization,
can be applied but they are not fully suitable for our task
for the following reasons: 1) Peak normalization would suffer
from isolated peaks which are often not representative of the
whole sample; 2) RMS normalization instead would be sensibly
different depending on the amount of silence in the audio
sample, which is not always related to affect (potentially due
either to a low speaking rate, pauses in the recording or the
microphone kept open).

Starting from the assumption that affect does not change
depending on the recording volume, during the training phase,
but not during the evaluation, we randomized uniformly the amplitude (volume) of the input audio sample through an exponential random coefficient $\alpha$ at each training iteration, where $\alpha$ is equal to

$$\alpha = 10^{U(-a,a)}$$

where $U(-a,a)$ is a uniform random variable, and $a$ a hyperparameter. We applied this pre-processing instead of normalizing the volume to a fixed value in order to increase the robustness of the system. A uniform random variable over a wide range of value (compared to a normal distribution) not only as said before helps reducing the overfitting related to the energy component, but also strongly augments the training set size.

C. CNN model description

Our CNN consists of a stack of convolutional layers of different sizes. It is followed by a global average pooling operation on the output of each layer, a weighted average combination of all these vectors, a fully connected layer and final activation layer (softmax for emotion and sigmoid for personality). The specific role of each layer will be described in detail in Section VI. A model diagram is shown in Figure 1.

The CNN receives as input a raw sample waveform $x$ of narrow-band speech, sampled at 8 kHz, of arbitrary length. We split the input signal into two feature channels as input for the CNN. The first one is the raw waveform as-is, the second one is the signal with squared amplitude. The second channel is aimed at capturing the energy component of the signal and learn an implicit normalization.

The two input signal components are then directly fed into a first convolutional layer:

$$x_i^{(1)} = f(W^{(1)}x_{[i,i+v]} + b^{(1)})$$

where $v$ is the convolution window size and $f$ a non-linear function. In this first layer we use a window size of 200, which at 8 kHz sampling rate corresponds to 25 ms, and a stride of 100, which corresponds to around 12 ms. The output size dim($x_i^{(1)}$) (the number of filters trained) from each window is set to 512. This first layer acts as a low-level feature extractor, or a customized filterbank learnt over the corpus during training. It ideally replaces the discrete features extraction step or the FFT computation of the spectrogram window. The window length of 25 ms is a common choice for the feature extraction step, as shown in previous works using feature-based or spectrogram based CNNs [36], [33].

It is then followed by several higher convolutional layers, of the same number of filters. Their convolution window size and stride is set to capture increasingly larger time spans. The subsequent convolutions are aimed at combining the features and capturing information at the suprasegmental level, such as phonemes, syllables and words, as well as looking at the difference between contiguous frames.
Since our intent is to capture globally expressed emotion and personality characteristics from the entire audio frame, the contributions of the convolutional layer outputs must be combined together. This is done by a global average pooling operation over the output vectors:

$$x_{i,j}^{\text{AP}} = \frac{\sum_l(x_{i,j}^l)}{L_i}$$

(3)

where $i$ is the window index, $L_i$ the number of output windows from the convolution layer, and $j$ the feature vector index within each convolution window. The average pooling is performed over the output vectors of each layer instead of just the final one. This would combine the contributions of both the segmental and suprasegmental features at different temporal granularities for the final emotion and personality decision. The output average-pooling vectors for each layer are then combined through a weighted-average layer where the weights are parameters of the model:

$$x_{i,j}^{\text{OUT}} = f \left( \sum_l W_{i,j}^{\text{OUT}} x_{i,j}^{\text{AP}} + b_{\text{OUT}} \right)$$

(4)

where $l$ is the layer index, and $f$ again the non-linear function.

We decided to use average pooling instead of the more common max-pooling. This choice yielded higher results on the development sets. It is also meaningful as the objective of our work is to detect the overall affect of an entire utterance or a speech passage. The global average pooling can be seen as merging together all the intermediate affect results [1]. It sums and accumulates the contributions among all the speech segments considered, instead of just selecting a few salient instances. We empirically noticed that applying max-pooling, even side-by-side with average pooling, makes the network overfit the training data more easily.

After obtaining the audio-frame overall vector $x_{i,j}^{\text{OUT}}$ by weighted-average of each convolutional layer output (Eq. 4), we then feed it through a fully connected layer, followed by a weighted-average of each convolution layer output (Eq. 4), where the weights are parameters of the model:

$$x_{i,j}^{\text{AP}} = \frac{\sum_l(x_{i,j}^l)}{L_i}$$

(3)

where $i$ is the window index, $L_i$ the number of output windows from the convolution layer, and $j$ the feature vector index within each convolution window. The average pooling is performed over the output vectors of each layer instead of just the final one. This would combine the contributions of both the segmental and suprasegmental features at different temporal granularities for the final emotion and personality decision. The output average-pooling vectors for each layer are then combined through a weighted-average layer where the weights are parameters of the model:

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After obtaining the audio-frame overall vector $x_{i,j}^{\text{OUT}}$ by weighted-average of each convolutional layer output (Eq. 4), we then feed it through a fully connected layer, followed by a final softmax/sigmoid layer. This last layer performs the final classification/regression operation and outputs the probability of the sample to belong to each emotion class analyzed as well as the personality trait scores.

In each of the intermediate layers the exponential linear activation function is used as non-linearity [63], as it performed better on the development set compared to other popular choices such as the hyperbolic tangent (tanh) or the rectified linear function (ReLU).

### D. Multilingual adaptation

Our CNN is already designed to handle a multilingual setting taking advantage of data in different languages. The duty of the first layer is to learn and extract low-level features common across all languages, such as filterbank features, pitch and energy. More data can improve this step’s performance. The subsequent layers are instead delegated to supra-segmental features, some of which are specific to languages or groups of languages. The application of a large layer size, 512 in our architecture, also allows the network to better learn these language-specific features and language acoustic models.

Although the model is already adequate to learn affect from multiple languages, further language-specific adaptation is desirable. After the initial training on the full dataset, we retrain the final layers after the average pooling on a single language data. This adaptation, or fine-tuning step, operates by weighting differently the extracted features of each layer, in order to adapt to each specific language analyzed. It is here where different affect states are communicated that can be dependent on language.

### E. Spectrogram CNN

Until recently the idea of using the raw representation of a signal often refers to a spectrogram presented as an image to a CNN [40], [41]. As a comparison baseline, we propose a similar CNN that takes the spectrogram representation as input.

The spectrogram CNN is very similar to the one used for raw waveforms. A spectrogram representation is first extracted from a raw input waveform, again sampled at 8 kHz. This is done through a Tukey window of 25 ms, with an FFT-size of 256, and yields a series of 129 power spectral features for each window. This operation replaces the feature extraction done by the first convolution layer of the raw waveform network. The subsequent layers are the same as in the raw waveform network, including several convolutional layers, global average pooling for each layer, weighted-average, fully connected and activation layers.

### IV. EMOTION RECOGNITION EXPERIMENTS

#### A. Corpora

In our experiments we make use of two set of corpora: a multi-domain English corpus with crowdsourced labels, and a set of smaller corpora of acted emotions in various languages. A summary of the number of utterances of each corpus is shown in Table I.

The English corpus is made of data we collected and annotated in multiple phases over time [16], [69]. We collected thousands of utterances and short speeches from different sources including monologues (TED talks, YouTube vloggers) and dialogues (TV shows, debates). In the case of TV shows, individual utterances were segmented from the audio track using the subtitles timestamps as references. The monologues instead were cut into segments of around 10 – 15 s, using silences as references. We then labeled them with several emotion descriptors, using student helpers and through Amazon Mechanical Turk. Each audio clip was annotated by a minimum of one annotator (in the case of the student helpers, previously instructed on the task) to a maximum of five annotators. We took the label selected by the majority of the annotators, discarding the sample in case of disagreement. In this work we only consider the subset of utterances classified as anger, sadness, happiness and anxiety. We also annotated the data with other emotions labels. However, some of them were not present in all languages. Others contained a number of samples too limited for training.

To train a universal multilingual model and evaluate the performance of our classifier on different languages, we used
TABLE I
NUMBER OF UTTERANCES OF EACH CLASS, AND TOTAL NUMBER, IN THE EMOTION CORPORA CONSIDERED. IN PARENTHESIS THE DIVISION AMONG TRAINING AND TEST SET.

| Language   | English | Estonian | German | Spanish | Italian | Serbian |
|------------|---------|----------|--------|---------|---------|---------|
| Anger      | 1202 (1092/110) | 1246 (1115/131) | 2128 (1933/195) | 952 (865/87) | 5528 |
| Sadness    | 306 (275/31)  | 249 (224/25)  | 271 (243/28)  | 826 |
| Happiness  | 127 (102/25) | 62 (54/8)  | 68 (62/6)  | 328 |
| Anxiety    | 725 (652/73) | 731 (657/74) | 732 (658/74) | 735 (661/74) | 2923 |
| English     | 84 (56/28)  | 84 (56/28)  | 84 (56/28)  | 84 (56/28) | 336 |
| Total       | 366 (244/122) | 366 (244/122) | 366 (244/122) | 366 (244/122) | 1464 |

TABLE II
RESULTS (PERCENTAGE) ON MULTILINGUAL TASK FOR THE FOUR EMOTIONS ANALYZED (ANGER, SADNESS, HAPPINESS, ANXIETY). P STANDS FOR PRECISION, R FOR RECALL, AND F1 FOR F-SCORE (OR F1 MEASURE).

| Method               | P   | R   | F1  | P   | R   | F1  |
|----------------------|-----|-----|-----|-----|-----|-----|
| Single lang. spec    | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Multilingual spec    | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Single lang. raw      | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Multilingual raw      | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Fine-tuned raw        | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Single lang. spec     | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 |
| Multilingual spec     | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 |
| Single lang. raw      | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 |
| Multilingual raw      | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 |
| Fine-tuned raw        | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 | 4.0 |

several corpora listed below. Compared to the English database, they contain a limited number of speakers who were actors that generated each emotion in a studio setting. Source sampling rate was usually 16 kHz or higher.

- **Estonian - Estonian Emotional Speech Corpus [64]**: the corpus consists of 1234 Estonian utterances. They are generated by a single actress in four emotions: Anger, Joy, Sadness and Neutral.

- **German - Berlin EmoDB [65]**: this database consists of 535 German utterances. A total of 5 short and 5 long utterances were generated by 5 actors and 5 actresses in 7 emotions: Anger, Neutral, Fear, Boredom, Happiness, Sadness and Disgust (not all the actors read all the sentences for each emotion).

- **Spanish - INTERFACE Emotional Speech Syntesis Database [66]**: this database includes around 150 items (phonemes, words, short, long sentences and a longer 30 s passage) in Spanish language. Each item is spoken by a male and a female actors in several emotions: Anger, Sadness, Joy, Surprise, Disgust, Fear and Neutral. For the purpose of our work we discarded the phonemes and the individual words.

- **Italian - EMOVO [67]**: emotion corpus in Italian. It includes 6 actors (3 males and 3 females), each acting 14 sentences into 7 different emotions: Anger, Neutral, Disgust, Joy, Fear, Surprise, Sadness.

- **Serbian - Serbian Emotional Speech Database [68]**: made of 3 actors and 3 actresses and a total of 2694 utterances, including one longer passage but excluding the isolated word part of the database. It includes five emotions: anger, happiness, fear, sadness and neutral.

In our work we analyze a subset of emotion labels common to most of the corpora: namely anger, sadness, happiness and anxiety. As each database is made of slightly different emotions or denominations, we take fear as anxiety and joy as happiness.

B. Experimental setup

To build the test sets, for the corpora which included different speakers of different genders. For the German, Italian and Serbian corpora one speaker of each gender was used as the test set. For the other three corpora we could not apply speaker separation. In the Spanish and Estonian corpora contained too few speakers for each gender: one male and female the former,
The volume randomization hyperparameter was set to 1.5.

Each audio sample was transformed into a wav format at 16 bits and downsampled to 8 kHz with sox. To keep the input range of every sample small and avoid parameter overfitting during training, a constant value of $k = 5 \cdot 10^{-4}$ was multiplied to every input audio sample. The $k$ value was chosen in order to approximately normalize the overall standard deviation to 1. The volume randomization hyperparameter $a$ (see Eq. 1) was set to 1.5.

We apply four convolutional layers after the first feature extraction layer, the first layer with a kernel size of 8 and a stride of 2, and each subsequent ones with a kernel size of 4 and a stride of 2. This means that each layer from the first to the last analyzes increasingly larger time spans starting from 25 ms. To train our CNN we applied standard backpropagation with the Adam optimizer [70]. The initial learning rate was set to $10^{-4}$, and halved once after the first 25 epochs and subsequently after another 15 epochs. We stopped training when the error on the development set began to increase. During the global multiclass training a minibatch size of 2 was used, while in the single class and fine-tuning we used a minibatch size of 1.

### C. Results

Results of our experiments on multilingual emotion detection are shown in Table III. They are represented in terms of precision, recall and F-score over each emotion and language. We obtained an average F-score of 67.7% (68.5% after fine-tuning the last layer) across all the languages using our raw waveform CNN trained on multiple languages. We obtained an average of 55.2% with the same model trained on a single language, 58.2% from the multilingual spectrogram baseline and 60% from the same baseline trained on single languages. Overall, this yields a relative improvement of 12.8% of the

| Method                  | MAE | A    | P    | R    | F1 | MAE | A    | P    | R    | F1 | MAE | A    | P    | R    | F1 |
|------------------------|-----|------|------|------|----|-----|------|------|------|----|-----|------|------|------|----|
| Single lang. spec      | .1194 | 63.7 | 67.6 | 62.0 | .0427 | 61.6 | 65.0 | 60.0 | 37.7 | .0352 | .951 | 59.2 | 62.5 | 38.9 | .0629 | 68.1 |
| Single lang. raw       | .1248 | 74.0 | 64.0 | 56.4 | .0421 | 68.5 | 71.4 | 69.2 | 70.3 | .0398 | 65.0 | 74.0 | 67.9 | 65.4 | .0722 | 67.5 |
| Multilingual spec      | .1194 | 63.7 | 67.6 | 62.0 | .0427 | 61.6 | 65.0 | 60.0 | 37.7 | .0352 | .951 | 59.2 | 62.5 | 38.9 | .0629 | 68.1 |
| Multilingual raw       | .1077 | 64.8 | 67.9 | 62.8 | .0513 | 51.7 | 56.1 | 54.2 | 52.5 | .0807 | 60.0 | 58.1 | 75.3 | 65.6 | .0731 | 72.5 |
| Fine-tuned raw         | .1087 | 64.1 | 61.1 | 83.7 | .0182 | 56.6 | 57.6 | 54.6 | 50.4 | .0418 | 66.2 | 61.4 | 69.0 | 60.5 | .0701 | 67.6 |

and only one female speaker the latter. In the English dataset instead most of the samples did not include any information about the speaker identity. In any case the overall number of speakers and samples in this language was much greater than the other language corpora, since it includes data from a large number of sources. For these three datasets around 10% of samples of each emotion class were taken as test set. The detailed division among training and test set is reported in Table III. The test set was kept the same during the multiclass and fine-tuning training phases, as well as with various network configurations. In order to tune the network structure and hyperparameters, and determine the early stopping condition, a subset of the training set of 10% was each time randomly taken as the development set.

Each audio sample was transformed into a wav format at 16 bits and downsampled to 8 kHz with sox. To keep the input range of every sample small and avoid parameter overfitting during training, a constant value of $k = 5 \cdot 10^{-4}$ was multiplied to every input audio sample. The $k$ value was chosen in order to approximately normalize the overall standard deviation to 1. The volume randomization hyperparameter $a$ (see Eq. 1) was set to 1.5.
multilingual raw waveform CNN over the second best model, the spectrogram CNN trained on individual languages.

V. PERSONALITY RECOGNITION EXPERIMENTS

A. Corpora

For the personality recognition task we use three different languages datasets: a bigger one in English and two smaller ones in Mandarin and French. Each sample from each dataset is annotated with five continuous scores between 0 and 1 (for the Big Five personality traits). Each dataset is recorded at a sampling rate of at least 8 kHz. The datasets are:

- **English** - ChaLearn Looking at People 2016 Apparent Personality Analysis (APA) Dataset [57]: consists of 8,000 clips of around 15 seconds, taken from YouTube blogs with diverse conversational content. The videos are labeled by Amazon Mechanical Turk workers. Audio clips are extracted from the videos.

- **Mandarin Chinese** - Beijing Social Personality Corpus (BSPC) [56]: consists of 258 male and 240 female clips taken from 70 Chinese talk shows. Clip length varies from 9 to 13 seconds. The utterances are labeled by three student workers each by filling in a standard NEO-PI-R personality inventory for the speakers.

- **French** - SSPNet Speaker Personality Challenge [71]: consists of 640 clips taken from French radio shows. Each clip is labeled by 11 unique judges. Final scores are taken as the average of the scores of these judges.

It’s important to note that the distributions (means and standard deviations) of trait scores differ per dataset. Especially the spread in scores for the Chinese dataset is very small. To combine all data for training, the labels thus need to be normalized.

For the English dataset we use the pre-defined ChaLearn Validation Set (2,000 samples) as test set. For Mandarin, we take 60 samples each from male and female speakers, which results in 120 samples in total. For French, we take out 160 random samples to serve as test set. As the development set we used 10% samples from each corpus.

B. Experimental setup

For the personality recognition experiments we used four convolutional layers in the CNN. Everything else is identical to the architecture used for the emotion recognition experiments. We pre-processed the input samples and trained the network mostly in the same way, and with the same single and multi-lingual experiments, as described for emotion in the previous section. However, an important exception is represented by the labels. Due to the difference in label distributions (mean and spread), across the three datasets we rescaled all training labels to have the same mean and standard deviation before training. We assumed the labels distribution for each personality trait as a Gaussian random variable. At evaluation time, the output predictions were inversely converted back to the original distribution for each individual language. We trained the model with a regression cost function by minimizing the Mean Squared Error between model prediction and ground truth:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (p_i - g_i)^2$$  \hspace{1cm} (5)

where $p_i$ is the vector of the five trait predictions for a given sample $i$ and $g_i$ is the vector of the five ground truth trait values for that sample. Another difference is the higher learning rate of $2 \cdot 10^{-4}$.

We evaluate the model both from a regression point of view, evaluating the Mean Absolute Error (MAE) between the prediction and the ground truth for each trait, and from a classification point of view by turning the predictions and corresponding labels into binary classes using the average of each trait as the boundary between the two classes. In this setting we compute classification accuracy, precision, recall and F-score.

C. Results

Results on each corpus, including the average over each trait for each language, are shown in Table [IV-A]. The fine-tuned multilingual model performs best on the test sets in terms of F-score. For the multilingual model using raw waveforms, we obtained an average F-score over the three languages of 62.4%. Training this same model on each language individually resulted in an average F-score over the languages of 56.7%. Using a spectrogram instead of raw waveforms gives an average F-score of 58.8%. Thus, our multilingual efforts show a relative improvement of 6.3% over the spectrogram approach and 10.1% over the single language approach.

VI. DISCUSSION

A. Affect recognition performance

Results obtained for both emotion and personality recognition show that in all cases the multilingual training with raw waveforms input outperforms both the spectrogram input and the single language training. In some cases, like the German or Serbian emotion corpora, and the Chinese personality dataset, the improvement is particularly significant. Another evident result, in particular on the emotion experiments, is that using raw waveforms improves the performance of the multilingual training, while on the other hand the spectrogram input is better on the single language case. Fine-tuning of the last layers helps in most cases achieving an improvement, although in a minority of cases it is not that beneficial. It seems less useful when the datasets are larger than average (the two English datasets) or very small (the emotion German corpus).

Regarding the emotion recognition task, there is no particular emotion that is easier or more difficult across all the languages. Some emotions in specific languages are sometimes mistaken, for example in the English dataset _sadness_ or German _happiness_ is often classified as _anger_. These misclassifications are often related to the specific corpus characteristics.
These features include energy, pitch, contour variations and also frequency for emotion recognition by the CNN.

Fig. 3. Frequency response of each of the 512 filters (horizontal axis) of the first-layer of the CNN for emotion recognition. Above are shown the filters applied to the raw signal, below those applied to the squared signal. It is evident how energy (left) and pitch (middle) are the main features extracted for emotion recognition by the CNN.

B. Low-level feature selection layer

The first layer of our CNN has the role of extracting low-level features from the raw waveforms. It is important to visualize and understand which kind of features are extracted, how much these features correspond with those used in traditional feature-based approaches [35], and whether something new or unusual is extracted.

To visualize the first layer we follow a similar procedure as used in [62], [17]. We consider each row of the parameter matrix \( W^c \), which represents a filtering function applied to each convolution window and whose output is then summed together before the application of the non-linearity. We transform each filter to the frequency domain, taking the absolute values of the FFT:

\[
F(W_{i,f}^{(1)}) = |\text{FFT}(W_{i,f}^{(1)})|
\]

where \( i \) is the filter index. Each FFT coefficient represent the activation of the filter to each frequency. We do this for both the raw waveform channel and the squared signal channel. The activation values have been converted to logarithmic scale with the following function:

\[
a(i,f) = 20 \log_{10}(F(W_{i,f}^{(1)}))
\]

To better show the filter contributions we sorted them according to the frequency with the highest activation, in ascending order. Figures 3 and 4 show the filter activation pattern respectively for the emotion recognition and personality recognition experiments.

In the emotion recognition experiments, three kinds of features are evident from the plots. Approximately one-third of the filters applied to the raw waveform, and more than half of those applied to the squared value have their peak at 0 Hz. This first set of filters is likely capturing the signal energy. A second set of filters in reverse proportion over raw signal and squared signal channels has instead its peak over a narrow range of low frequency values, between 0 and 250 Hz. Those filters act as pitch detectors, and this is compatible with the

Fig. 4. Frequency response of each of the 512 filters (horizontal axis) of the first-layer of the CNN for personality recognition. Above are shown the filters applied to the raw signal, below those applied to the squared signal. In this case the network extracts a wider feature set than in the emotion detection case. These features include energy, pitch, contour variations and also frequency components between 500 and 1000 Hz.
fact that the average human pitch frequency lies below 250 Hz for both males and females [72].

It is interesting to note what happens for frequencies above 250 Hz. In the original waveform signal input channel, very few filters have their central frequency between 250 Hz and 500 Hz, and the higher frequencies in the spectrum are almost ignored. This may be due to an amount of emotion data available too small to capture effectively further information at higher frequency, or might suggest the hypothesis that high frequency components do not carry useful information for emotion detection. If the latter hypothesis is confirmed, there would be no need to use wide-band audio to improve the performance on emotion detection. However, in the squared signal input channel, a small number of filters extend above 500 Hz. These filters may capture the local amplitude variations of the signal, particularly frequent in angry speech. They may also learn an amplitude normalization function to apply to the signal, to remove the effect of variable amplitude levels at input (often due to non-uniform recording volume across samples). This hypothesis is supported by the observation that most filter activate dominantly on 0 Hz.

For personality recognition, a similar observation can be made about energy (activations at 0 Hz) and pitch (activations between 0 and 250 Hz). On the other hand, a third of the filters activate between 500 and 1000 Hz, higher than the cutoff frequency for emotion. These higher activation frequencies also result in about a third of the filters for the squared signal input channel activating strongest at higher frequencies. Since the squared signal is likely used for internal normalization, this may indicate a more complex normalization for higher

Fig. 5. t-SNE projection of outputs from average pooling after the first and fifth convolutional layers, and the last fully connected layer of the emotion recognition CNN. The left column shows the sample points with the languages highlighted in different colors. The right column shows the same projection with emotion labels highlighted in different colors. Higher convolutional layers tend to cluster samples according to the language compared to the first layer. The last fully connected layer shows stronger emotion clustering instead. Some languages, in particular Spanish, Serbian, German and some English samples, seem to be clustered together according to the emotion, thus interacting with each other to build the final predictions.
frequency components in the signal.

C. Intermediate convolutional layers

As mentioned in section [III], the second to last convolutional layers are aimed at combining features at supra-segmental level and, among others, selecting the most salient phonetic units that may carry the emotion or the personality information.

To visualize the contribution of these layers over a few examples, we estimate from the average pooling vectors a weighing factor $w_t$ to each time window taking the RMS value of the difference between the average pooling values and the element-wise average, in the following way:

$$w_t = \sqrt{\frac{\sum_i (x_{ti} - \bar{x}_i)^2}{N}}$$

where $i$ is the vector element index, $N$ the vector length (512 in the emotion detection experiments) and $\bar{x}_i$ the element-wise average among all time instants. A high $w_t$ means that some of the filters have a different value than the average for that specific time-frame, and are more likely to contribute to the final classification.

Figure 2 shows the activation of the intermediate convolutional layers over speech segments randomly taken from the corpus respectively for emotion and personality. For emotion, the uniform low activation pattern over the silence regions shows these do not usually carry any emotion-related information. For personality, filters do activate over silence, indicating these regions are correlated with personality. The intermediate layers activate strongly over voiced regions, especially when there is a prosodic change, such as energy or pitch variations. The activation pattern is often similar among the layers, but it is slightly more sparse toward the upper layers. This signals that upper layers tend to select the most important features extracted by the lower layers.

The behavior of each layer after the average pooling operation, and the final fully-connected layer, is also worth noticing. We projected the output of each intermediate layer into a two-dimensional space through a t-SNE transformation [73]. The output for the intermediate layers of the emotion and personality detection networks are respectively shown in Figures 5 and 6, highlighting the language of each sample. The figures illustrate that later convolutional layers are grouping each source language into its own cluster, with more defined cluster boundaries going upwards in the layers hierarchy. It seems that, through suprasegmental feature analysis, the network is automatically learning a specific affect model for each single input language. In the emotion recognition experiments (Fig. 5, first and second rows) this pattern is very clearly shown by the t-SNE for all languages, except German due to the low amount of samples in that language. This pattern is also shown in the personality recognition experiments (Fig. 6). We also note that the Mandarin Chinese cluster is clearly distinct from the English and French clusters, which can be explained by the different cultural factors between Europe
and China which may affect personality and its perception by annotators. Another factor contributing to this might be that English and French are much more similar phonetically than they are to Mandarin Chinese. In the emotion recognition case instead, Spanish seems to have a more distinct cluster. This dataset also yields the best average performance, which could be because it is acted and emotions are very clearly expressed.

Overall, these figures show that, as we expected from previous multilingual acoustic modeling [13], [11], languages do share common features in the low, signal processing level, while they tend to have distinct characteristics at the higher, perhaps phonetic level. All these components are sent to the final classification layers, allowing the network to use both the common and different characteristics of the languages and use them to improve the final predictions. This is evident in the t-SNE representation of the emotion recognition last layer (Fig. 5 last row). Some groups of languages, in particular Serbian, Spanish, German and some English and Italian samples share emotion clusters. This could indicate that emotions from different languages have similar representations inside the network, thus explaining why adding data from other languages improves the model’s performance. The exception to this is Estonian, which has a very different root from the other languages. We do not show these projections for personality recognition, as the regression nature of this task prevents clear clusters to form.

VII. CONCLUSION

In this paper, we proposed a universal end-to-end affect recognition model using convolutional neural networks. It is able to automatically extract features from narrow-band raw waveforms and detects emotions and personality traits regardless of the input language, whose characteristics are automatically learned and distinguished. We have obtained significant improvements both over a spectrogram baseline (+12.8% for emotion and +6.3% for personality), and training it with a multilingual setting as opposed as each single input language (+12.8% for emotion and +10.1% for personality). That is, we have shown that using raw waveforms yields higher performance than using spectrograms as input, and that training on multiple languages increases evaluation performance on each individual one in comparison to training separate models for each language. We have furthermore shown how the first convolutional layer in the model extracts low level features from the audio sample, while higher layers activate on prosodic changes and learn language-specific representations.

We have shown that universal affect recognition has the potential to take advantage of each language to improve the performance of other languages, as the affect descriptors studied share features among languages. Furthermore, end-to-end deep learning architectures are able to recognize different affect classes, emotion and personality, automatically learning and processing the most relevant speech features.

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