

Emotion Recognition from Speech using Representation Learning in Extreme Learning Machines

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Abstract: We propose the use of an Extreme Learning Machine initialised as auto-encoder for emotion recognition from speech. This method is evaluated on three different speech corpora, namely EMO-DB, eNTERFACE and SmartKom. We compare our approach against state-of-the-art recognition rates achieved by Support Vector Machines (SVMs) and a deep learning approach based on Generalised Discriminant Analysis (GerDA). We could improve the recognition rate compared to SVMs by 3%–14% on all three corpora and those compared to GerDA by 8%–13% on two of the three corpora.

1 INTRODUCTION

The *Emotion Challenge* at Interspeech 2009 (Schuller et al., 2009a) defined, for the first time, exact test-conditions on the FAU Aibo Emotion Corpus (Steidl, 2009) to compare performances from different participating groups. The challenge organisers provided a setting which introduced strict comparability and reproducibility across several research groups. Later Schuller et al., 2009b provided “the largest-to-date benchmark comparison under equal conditions on nine standard corpora in the field using the two pre-dominant paradigms: modelling on a frame-level by means of Hidden Markov Models and supra-segmental modelling by systematic feature brute-forcing.” In addition, Stuhlsatz et al. proposed a deep learning approach based on GerDA that could outperform the previous results on a simpler two class problem derived from the original multi-class problem.

While the community has established new fields in speech classification, i.e. paralinguistic analysis (Schuller et al., 2010) and speaker traits (Schuller et al., 2012), any new approach in emotion recognition should still be compared against the benchmark presented in (Schuller et al., 2009b) and (Stuhlsatz et al., 2011).

In our contribution we propose the use of Extreme Learning Machine (ELM) (Huang et al., 2012) initialised as auto-encoder (AE) (Uzair et al., 2016)

for emotion recognition from speech. The method was evaluated on three considerable different speech corpora (EMO-DB, eNTERFACE, SmartKom). We improved the recognition rates achieved by Support Vector Machine (SVM) in (Schuller et al., 2009b) by 5%/3% on EMO-DB/eNTERFACE and 14% on SmartKom.

The rest of the paper is organised as follows. Section 2 describes the emotional speech corpora that were used for our evaluation. Section 3 recapitulates the idea of the single layer (SL) ELM (Huang et al., 2012) and further describes the supervised feature learning with an ELM-based AE proposed by (Uzair et al., 2016). Our experimental setup and the results are presented in Section 4, followed by the summary and discussion in Section 5.

2 CORPORA

The chosen corpora are Berlin Emotional Speech Database (EMO-DB), eNTERFACE and SmartKom. They cover acted (EMO-DB), induced (eNTERFACE), and natural emotions (SmartKom). Further, the textual content is strictly limited (EMO-DB), with some variation (eNTERFACE), and of full variance (SmartKom), given in two languages (English, German). The speakers’ age, gender, and background as well as the recording conditions like the used mi-

crophone and room acoustics vary between the three corpora. Last but not least, the number of samples per class is balanced (eINTERFACE) and unbalanced (EMO-DB, SmartKom). In the following we shortly describe each corpus.

2.1 EMO-DB Corpus

EMO-DB (Burkhardt et al., 2005) is a popular studio recorded speech database, covering seven emotional classes, namely: *anger, boredom, disgust, fear, joy, neutral, and sadness*. Ten actors (5 female and 5 male) simulated the emotions, producing 10 German utterances (5 short and 5 longer sentences) without any relation between the emotions and the sentences' content. One of the sentences is for instance: "Das will sie am Mittwoch abgeben." ("She will hand it in on Wednesday"¹).

The corpus thus provides a high number of repeated words in diverse emotions. To ensure emotional quality and naturalness of the utterances a perception test with 20 subjects was carried out. Utterances with a recognition rate better than 80% and naturalness better than 60% were chosen for further analysis (Burkhardt et al., 2005). Table 1 shows a summary for the number of samples per class.

2.2 eINTERFACE Corpus

eINTERFACE (Martin et al., 2006) is a public audiovisual emotion database. The emotional classes are *anger, disgust, fear, joy, sadness and surprise*. Recordings were taken in an office environment given five pre-defined English utterances. It is to be noticed that the speakers were recruited during a summer school. Though the recordings were done in English the majority of participants were non-native speakers. Therefore, a huge variety of accents and dialects are included in the corpus. To induce an emotional state, subjects are asked to listen carefully to a short story and to 'immerge' into the situation. Once they are ready, the subjects pronounce the five proposed utterances, which constitute five different reactions to the given situation (one at the time). An example in an anger mood is: "What??? No, no, no, listen! I need this money!". Finally, two experts decided whether the subject expressed the emotion clearly. If so, the sample was added to the database. For our purpose, we used only the audio part of the corpus. Table 1 shows the final distribution of the 1277 samples over the six classes.

¹<http://emodb.bilderbar.info/index-1280.html>

2.3 SmartKom Corpus

The SmartKom (Steininger et al., 2002) corpus is an audiovisual corpus of spontaneous speech and non-acted emotions. It consists of Wizard-Of-Oz dialogues, in German and English. As in Schuller et al., 2009b we used the German part of the corpus. Seven classes are labelled, namely: *neutral, joy, anger, helplessness, pondering, surprise and unidentifiable*. In comparison to EMO-DB and eINTERFACE it is the largest database containing 3819 samples in total. However, emotion classification on this corpus poses to be a hard challenge due to the noisy recording environment, unbalanced classes (cf. Table 1) and less pronounced, non-acted speech.

3 METHODS

In this section briefly introduce the idea and training algorithm of the ELM (Huang et al., 2012). Afterwards, we describe the supervised feature learning with an ELM-based AE that was originally used to construct deep ELMs for image set classification in (Uzair et al., 2016).

We further present the feature extraction and the experimental setup for the emotion recognition task.

3.1 Extreme Learning Machines

In general, the ELM trains a single hidden layer feed-forward neural network (SLFN) by randomly setting the weights of the input layer and calculating the weights of the output layer analytically. In contrast to a backpropagation approach, the input weights are never updated and the output weights are learned in a single step, which is basically the learning of a linear model.

A supervised learning problem is comprised of N training samples, $\{\mathbf{X}, \mathbf{T}\} = \{\mathbf{x}_j, \mathbf{t}_j\}_{j=1}^N$ where $\mathbf{x}_j \in \mathbb{R}^d$ and $\mathbf{t}_j \in \mathbb{R}^q$ are the j^{th} input and corresponding target samples, respectively. The SLFN with n_h hidden nodes fully connected to d input and q output nodes is modelled as

$$\mathbf{o}_j = \sum_{i=1}^{n_h} \beta_i f_{\text{net}}(\mathbf{w}_i^\top \mathbf{x}_j + b_i) \quad (1)$$

where, $\mathbf{w}_i \in \mathbb{R}^d$ is the weight vector connecting the i^{th} hidden node to the input nodes. $\beta_i \in \mathbb{R}^q$ is the weight vector that connects the i^{th} hidden node to the output nodes, and b_i is the bias of the i^{th} hidden node. The activation function f_{net} can be any non-linear piecewise continuous function, for instance the sigmoid function or hyperbolic tangent.

Table 1: Overview of the three selected corpora giving the language and the number of samples per class.

Corpus	Content	#/class						
		anger	boredom	disgust	fear	happiness	neutral	sadness
EMO-DB	German	anger	boredom	disgust	fear	happiness	neutral	sadness
	acted	127	79	38	55	64	78	53
eNTERFACE	English	anger	disgust	fear	happiness	sadness	surprise	-
	induced	215	215	215	207	210	215	-
SmartKom	German	anger	helplessness	joy	neutral	pondering	surprise	unidentified
	variable	220	161	284	2179	640	70	265

The training process of an ELM is comprised of random feature projection and linear parameter solving. Random feature projection is simply the random initialisation of the hidden layer parameters $\{\mathbf{w}_i, b_i\}_{i=1}^{n_h}$ resulting in the projection of the input data into a random feature space through the mapping function f_{net} . This random projection distinguishes ELM from other learning paradigms, which usually learn the feature mapping.

The output weights $\{\beta_i\}_{i=1}^{n_h}$ can be collected in a matrix $\mathbf{B} \in \mathbb{R}^{n_h \times q}$ and are learned using the regularized least squares approach. Let $\Psi(\mathbf{x}_j) = [f_{\text{net}}(\mathbf{w}_1^\top \mathbf{x}_j + b_1) \dots f_{\text{net}}(\mathbf{w}_{n_h}^\top \mathbf{x}_j + b_{n_h})] \in \mathbb{R}^{1 \times n_h}$ denote the activation vector at the hidden nodes to the input \mathbf{x}_j . The aim is to solve for \mathbf{B} , such that it minimises the sum of the squared losses of the prediction errors:

$$\min_{\mathbf{B}} = \frac{1}{2} \|\mathbf{B}\|^2 + \frac{C}{2} \sum_{j=1}^N \|\mathbf{e}_j\|^2 \quad (2)$$

$$\text{s.t. } \Psi(\mathbf{x}_j)\mathbf{B} = \mathbf{t}_j^\top - \mathbf{e}_j^\top, \quad j = 1, \dots, N$$

The first term in equation (2) is a regularizer against over-fitting, $\mathbf{e}_j \in \mathbb{R}^q$ is the error vector for the j^{th} training example $\mathbf{e}_j = \mathbf{t}_j - \mathbf{o}_j$, and C is a tradeoff coefficient.

By concatenating the hidden layer activations $\mathbf{H} = [\Psi(\mathbf{x}_1)^\top, \dots, \Psi(\mathbf{x}_N)^\top]^\top \in \mathbb{R}^{N \times n_h}$ and target vectors $\mathbf{T}[\mathbf{t}_1, \dots, \mathbf{t}_N] \in \mathbb{R}^{N \times q}$ equation (2) can be reformulated as an unconstrained optimization problem, which is widely known as ridge regression or regularized least squares

$$\min_{\mathbf{B}} = \frac{1}{2} \|\mathbf{B}\|^2 + \frac{C}{2} \|\mathbf{T} - \mathbf{HB}\|^2. \quad (3)$$

Since the problem is convex, its global solution needs to satisfy the linear system:

$$\mathbf{B} + \mathbf{CH}^\top(\mathbf{T} - \mathbf{HB}) = 0. \quad (4)$$

The solution to this system depends on the size of \mathbf{H} . If \mathbf{H} has more rows than columns ($N > n_h$), which is usually the case when the number of training patterns is larger than the number of the hidden nodes, the system is overdetermined and a closed form solution exists:

$$\mathbf{B}^* = \left(\mathbf{H}^\top \mathbf{H} + \frac{\mathbf{I}_{n_h}}{C} \right)^{-1} \mathbf{H}^\top \mathbf{T}, \quad (5)$$

where $\mathbf{I}_{n_h} \in \mathbb{R}^{n_h \times n_h}$ is the identity matrix.

If the number of training patterns is less than the number of hidden nodes ($N < n_h$) we have an underdetermined least squares problem. In this case, we can restrict \mathbf{B} to be a linear combination of the rows in \mathbf{H} : $\mathbf{B} = \mathbf{H}^\top \alpha$ where $\alpha \in \mathbb{R}^{N \times q}$. Notice that when $N < n_h$ and \mathbf{H} is of full row rank, then \mathbf{HH}^\top is invertible. Substituting $\mathbf{B} = \mathbf{H}^\top \alpha$ in equation (4), and multiplying both sides by $(\mathbf{HH}^\top)^{-1} \mathbf{H}$, we obtain

$$\alpha - \mathbf{C} \left(\mathbf{T} - \mathbf{HH}^\top \alpha \right) = 0, \quad (6)$$

hence

$$\mathbf{B}^* = \mathbf{H}^\top \alpha = \mathbf{H}^\top \left(\mathbf{HH}^\top + \frac{\mathbf{I}_N}{C} \right)^{-1} \mathbf{T}. \quad (7)$$

Therefore, in cases where the number of training samples N is larger than the number of hidden units n_h , we use (5) to compute the output weights, otherwise we use (7).

To summarize, ELMs have two attractive properties compared to other learning schemes. Firstly, the hidden mapping function is generated randomly with any continuous probability distribution for the weight initialization. Secondly, the only parameters that are learned are the output weights, efficiently done by solving a single linear system. These properties make ELMs more flexible than SVMs and much faster to train than the feed-forward networks using backpropagation (Uzair et al., 2016).

3.2 Representation Learning in Extreme Learning Machines

In feature learning, i.e. learning a rich representation of the input data, it is crucial to achieve generalization when the input data is large and unstructured as, for instance, in image set classification. Such problems are usually solved by deep (convolutional) neural networks using an auto-encoder pre-training, where the single layers learn to map the input to itself (Bengio et al., 2013). Such deep neural networks achieve the state-of-the-art performance in many computer vision tasks but have two major drawbacks. First, they

require a large amount of training material and second, the training is very slow, hence requires a large amount of computational power.

Uzair et al. proposed the use of ELM-based AEs to construct a deep ELM. It is defined as multiple-layer neural network whose parameters are learned by training a cascade of multiple ELM-AE layers. A fully connected multi-layer network with h hidden layers is comprised of the parameters $\mathbf{L} = \{\mathbf{W}^1 \dots \mathbf{W}^{h+1}\}$, where $\mathbf{W}^i = [\mathbf{w}_1^i \dots \mathbf{w}_{n_i}^i]^\top \in \mathbb{R}^{n_{i+1} \times n_i}$. Each layer is trained as individual ELM-AE, i.e. the targets are set the same as the inputs. For example, \mathbf{W}^1 is learned using the corresponding ELM with $\mathbf{T} = \mathbf{X}$. The weight vectors are initialised orthonormal, as the orthogonalization of these random weights tends to better preserve pairwise distances in the feature space (Johnson and Lindenstrauss, 1984) compared to independent random initialisation. Next, depending on the number of hidden layer nodes and training samples, equation (5) or (7), is used to calculate \mathbf{B}^1 . These AE weights re-project the random representation of the input data back into its original space while minimizing the reconstruction error. Therefore, it is used as the weight matrix of the first layer $\mathbf{W}^1 = \mathbf{B}^{1\top}$. The weights of the following layers are learned accordingly by setting the in- and output of layer h to the representation of the previous layer \mathbf{H}_{h-1} . The computation of \mathbf{B} with equation (5) or (7) does not ensure orthogonality. However, orthogonality results in a more accurate solution since the data always lie in the same space. Therefore, \mathbf{B} is calculated as the solution to the Orthogonal Procrustes problem

$$\mathbf{B}^* = \min_{\mathbf{B}} \|\mathbf{HB} - \mathbf{T}\|^2, \quad (8)$$

s.t. $\mathbf{B}^\top \mathbf{B} = \mathbf{I}$.

The closed form solution is obtained by finding the nearest orthogonal matrix to the given matrix $\mathbf{M} = \mathbf{H}^\top \mathbf{T}$. To find the orthogonal matrix \mathbf{B}^* , the singular value decomposition $\mathbf{M} = \mathbf{U}\Sigma\mathbf{V}^\top$ is used to compute $\mathbf{B}^* = \mathbf{U}\mathbf{V}^\top$.

Figure 1 illustrates the training procedure. Note that the final layer weights are learned as standard ELM while the lower layers are initialised as ELM-AE.

3.3 Feature Extraction

The openEAR toolkit (Eyben et al., 2009) was used to extract 6552 features as 39 functionals of 56 acoustic low-level descriptors and their corresponding first and second order delta regression coefficients. We applied the feature extraction on utterance level. Thus, every utterance, i.e. time series of variable length, is represented as a single vector of 6552 elements. Details on

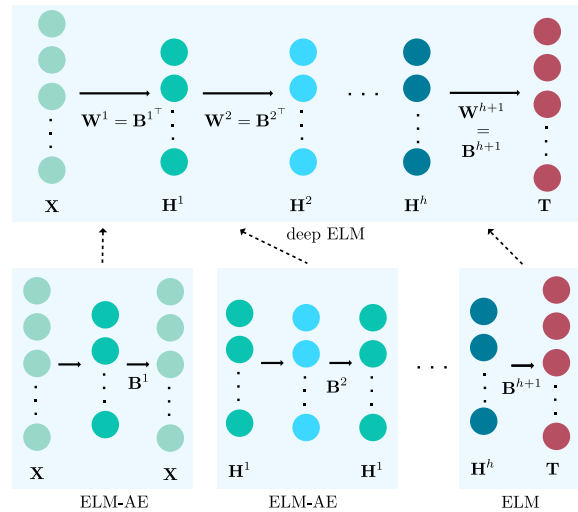


Figure 1: Representation learning in deep ELM using ELM-AE to learn the lower layer weights \mathbf{W}^1 to \mathbf{W}^h . The final layer is trained on the actual target data as standard ELM.

the functionals and acoustic low-level descriptors are given in (Schuller et al., 2009b). Further, speaker normalisation was carried out by subtraction of the mean and division by the standard deviation for every feature and every speaker.

3.4 Experimental Setup

To ensure speaker independence of the classifier the experiments are carried out in a Leave-One-Speaker-Out (LOSO) manner. That is, one speaker is left out for testing, while the remaining speakers are used for training. This is repeated until every speaker was used for testing once. The final classification results are computed as the mean over all runs.

As classes are unbalanced (cf. Table 1), classifiers are evaluated according to the unweighted average (UA), and weighted average (WA) of class wise accuracy (Schuller et al., 2009a).

For each database we used single ELM classifiers to distinguish the six or seven classes. Several hyperparameter had to be set, i.e. number of layers h , number of hidden units n_h per layer, transfer function f_{net} and the tradeoff coefficient C . The experiments to fix the hyper-parameters were carried out on EMO-DB. It is the smallest database and requires the least amount of time for training.

4 RESULTS

4.1 EMO-DB

Starting with an ELM, where the input weights are trained as auto-encoder (SL ELM-AE), we tested different configurations for the activation function $f_{\text{net}}(x) \in \{\text{sig}(x), \text{tanh}(x)\}$ and tradeoff coefficient $C = \{10, 100, \dots, 10^6\}$ with $n_h = \{50, 100, \dots, 3000\}$. To check the stability of the classifier each LOSO experiment was repeated 10 times for each parameter configuration. The reported accuracies are the mean of these 10 runs.

In general, the performance increases with increasing number of hidden nodes, however for all configurations we observed a performance drop in the range of $n_h = 250$ to 800. For larger n_h the performance saturated around $\text{WA} \approx 84\%$ in most cases. Figure 2 shows the results for $f_{\text{net}}(x) \in \{\text{sig}(x), \text{tanh}(x)\}$ and $C = 100$. Besides the drop at small n_h one can see, that the interval mean \pm standard deviation gets smaller for larger n_h . The combination $f_{\text{net}}(x) = \text{tanh}(x)$ with $C = 100$ performed best and did not saturate at $n_h = 3000$ with 89.6% WA. With further increase of n_h we found the best performing combination with $f_{\text{net}}(x) = \text{tanh}(x)$, $C = 100$ and $n_h = 4100$ resulting in 90% WA.

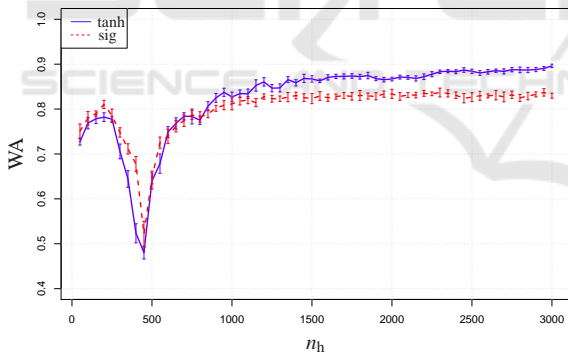


Figure 2: Weighted average (WA) of class wise accuracy of SL ELM-AE with $C = 100$, $f_{\text{net}}(x) \in \{\text{sig}(x), \text{tanh}(x)\}$ and increasing number of hidden nodes n_h on EMO-DB corpus.

In a follow-up experiment, we used a multi-layer (ML) ELM, also trained as ELM-AE (cf. Sec. 3.2). We kept $C = 100$, $f_{\text{net}}(x) = \text{tanh}(x)$ and varied $n_h^1, n_h^2 = \{1000, 1100, \dots, 5000\}$. The performance did not exceed 84% WA for any of the combinations, which leads to the conclusion that an additional layer of abstraction did not support the actual separation task of different emotional classes.

Finally, we tested a standard ELM with random input weights and fixed $C = 100$, $f_{\text{net}}(x) = \text{tanh}(x)$. Weights were initialised uniformly distributed in the

range $(-0.5, 0.5)$. The number of hidden nodes was increases starting at $n_h = 500$ up to 70000 before the performance saturated at 87.6% WA. Table 2 shows the best performing configurations for the three tested approaches, i.e. single-layer (SL) ELM-AE, multi-layer (ML) ELM-AE, and standard ELM with random input weights.

Table 2: EMO-DB classification performance of different ELM approaches with $C = 100$ and $f_{\text{net}}(x) = \text{tanh}(x)$. We show mean \pm standard deviation of unweighted average (UA), and weighted average (WA) of class wise accuracy of 10 runs.

Classifier	n_h	WA	UA
SL ELM-AE	4100	90.0 \pm 0.4	87.2 \pm 0.6
ML ELM-AE	4000, 4000	84.0 \pm 0.8	82.0 \pm 1.1
ELM	70000	87.6 \pm 0.6	87.0 \pm 0.8

4.2 eINTERFACE

Based on the results on EMO-DB (cf. Table 2), we kept $C = 100$, $f_{\text{net}}(x) = \text{tanh}(x)$ fix and varied only $n_h = \{1000, 1250, \dots, 3000\}$ to evaluate the SL ELM-AE performance on the eINTERFACE corpus. The results are shown in Figure 3. Again, we observed a drop at lower numbers of hidden units $n_h = 1250$ and a saturation starting at $n_h = 2750$. For the sake of training time and computational resources we used only a single LOSO trail for this evaluation. However, as this database contains much more utterances and 43 speakers the variation between different LOSO trails is small compared to EMO-DB. The best performance was observed at $n_h = 2750$ with 74.4% WA and 74.4% UA.

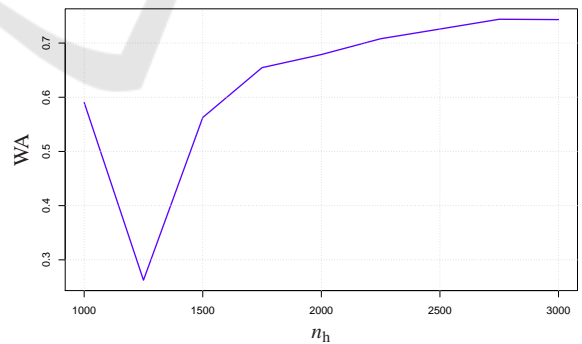


Figure 3: Weighted average (WA) of class wise accuracy of a SL ELM-AE with $C = 100$, $f_{\text{net}}(x) = \text{tanh}(x)$ and increasing number of hidden nodes n_h on the eINTERFACE corpus.

4.3 SmartKom

For the SmartKom corpus we evaluated the SL ELM-AE with $C = 100$, $f_{\text{net}}(x) = \text{tanh}(x)$ and varied the

number of hidden units n_h in the range from 50 to 7000². The results are shown in Figure 4. This time the best performance was observed at a rather low number of hidden units $n_h = 350$ with 53.6% WA and 33.4% UA.

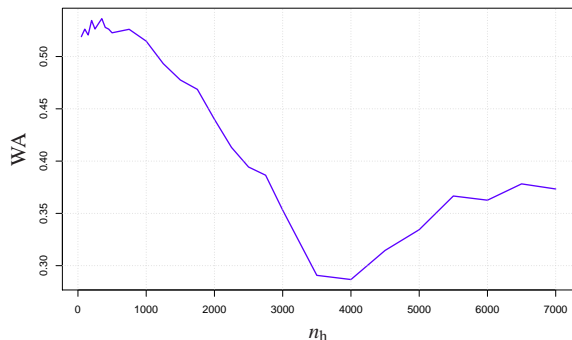


Figure 4: Weighted average (WA) of class wise accuracy of a SL ELM-AE with $C = 100$, $f_{\text{net}}(x) = \tanh(x)$ and increasing number of hidden nodes n_h on the SmartKom corpus.

5 DISCUSSION

We applied the representation learning approach in ELMs as presented in (Uzair et al., 2016) to speech emotion recognition. To fix the hyper-parameter like transfer function f_{net} and tradeoff coefficient C , several experiments were run on the smallest database EMO-DB. Table 2 summarises these experiments. Two interesting outcomes could be observed: (i) an additional layer of abstraction does not support the actual task to separate the different emotion classes; (ii) a standard ELM with random input weights performs remarkable well, given a large number of hidden nodes. We think these observations show that the extracted features (cf. Sec. 3.3) already capture a lot of information for the multi-class problem considered in this paper. Hence, an extra layer of feature learning is neither necessary nor helpful.

For the ELM and SL ELM-AE we saw both classifier to perform very well. While the SL ELM-AE needed 4100 hidden units, the randomly initialised ELM reached a comparable high performance with 70000 hidden units (cf. Table 2). Thus, it might be possible to compensate the drawback of a random weight initialisation with a sufficiently large amount of dimensions (hidden units) in the random feature space.

Given the SL ELM-AE with the highest performance on EMO-DB, we evaluated this setting on the more challenging corpora eNTERFACE and SmartKom. As discussed in Section 2, SmartKom

² $n_h = \{50, 100, \dots, 500, 750, \dots, 3000, 3500, \dots, 7000\}$

poses the hardest challenge due to its noisy recording environment, unbalanced classes and less pronounced, non-acted speech. We cannot pinpoint the reason for the high performance with a small number of hidden units $n_h = 350$ (cf. Fig. 4) compared to EMO-DB ($n_h = 4100$) and eNTERFACE ($n_h = 2750$) (cf. Figs. 2 and 3).

To rank our results we compare them against the yet best³ published results given in (Schuller et al., 2009b) and (Stuhlsatz et al., 2011). Stuhlsatz et al. learned discriminative features with Generalized Discriminant Analysis (GerDA) based on deep neural networks. The GerDA features were used for classification with a Mahalanobis minimum-distance classifier. Schuller et al. used SVMs with polynomial Kernel and pairwise multi-class discrimination based on Sequential Minimal Optimisation on the same features that we used. Table 3 shows the results side by side.

Table 3: Weighted average (WA) and unweighted average (UA) class wise accuracy of SVM, GerDA and SL ELM-AE on acoustic emotion recognition in three different speech corpora. The best results for each corpus and evaluation measure are highlighted. SVM and GerDA accuracies were published in (Stuhlsatz et al., 2011)).

Corpus	Classifier	WA	UA
EMO-DB	SL ELM-AE	90.0 ± 0.4	87.2 ± 0.6
	ELM	87.6 ± 0.4	87.0 ± 0.8
	SVM	85.6	84.6
	GerDA	81.9	79.1
eNTERFACE	SL ELM-AE	74.4	74.4
	SVM	72.4	72.5
	GerDA	61.1	61.1
SmartKom	SL ELM-AE	53.6	33.4
	SVM	39.0	23.5
	GerDA	59.5	25.0

The SL ELM-AE outperformed the SVM on all three corpora according to WA and UA. Concerning the GerDA approach, SL ELM-AE yielded the highest performance on EMO-DB and eNTERFACE but only achieved 53.6% compared to 59.5% WA (GerDA) on the SmartKom database.

As GerDA is a data-driven feature learning approach it benefits from the comparable high amount of training data in the SmartKom corpus, which supports the learning of highly compact and discriminative features (Stuhlsatz et al., 2011). This explains also the rather weak performance of GerDA on EMO-DB and eNTERFACE.

In summary our ELM-based approach shows promising results on all three considerably different emotional speech databases. It remains to be seen whether this high performance is stable throughout

³To our knowledge

other corpora. However, given the simplicity of the method and the variety of the already tested corpora we are confident that the ELM/ELM-AE can achieve, at least, comparable results to the SVM on other databases as well.

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