

Speech Emotion Recognition

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Abstract—Identifying emotion from speech is a non-trivial task pertaining to the ambiguous definition of emotion itself. In this work, we formalize our problem as a multi-class classification problem and compare performance of two categories of models. For both the models, we extract some hand-crafted features from a given audio signal. In the first approach the extracted features are used to train six traditional machine learning classifiers. The second approach is based on deep learning wherein a baseline Feed-forward Neural Network and an LSTM classifier are trained over the same features. In order to resolve ambiguity in communication, we also include features from the text domain. We report accuracy, f-score, precision and recall for the different experiment settings we tested our models in. Overall, we show that lighter machine learning models trained over hand-crafted features achieve comparable performance when compared to the current deep learning based state-of-the-art for emotion recognition.

Index Terms—speech emotion recognition, machine learning, deep learning

I. INTRODUCTION

Communication is the key to human existence and more often than not, we have to deal with ambiguous situations. For instance, the phrase, “This is awesome,” could be said under either happy or sad settings. Humans are able to resolve ambiguity in most of the cases because we can efficiently comprehend information from the multiple domains (henceforth, referred to as modalities), namely, speech, text and visual. With the rise of deep learning algorithms, there have been multiple attempts to solve the task as in [1] [2] [3]. However, this rise has made practitioners to rely more on the power of the deep learning models as opposed to meaningful features

originating from the concerned modality. In this work, we explore the implication of hand-crafted features for emotion recognition and compare the performance of such models with the heavily data-reliant deep learning models. Furthermore, we also combine features from the textual modality to understand the correlation between features from different modalities. More formally, we pose our task as a multi-class classification problem and employ to two classes of models to solve that. For both the approaches, we first extract hand-crafted features from the time domain of the audio signal and train the respective models.

In the first approach, we train traditional machine learning classifiers, namely, Random Forests, Gradient Boosting, Support Vector Machines, Naive-Bayes and Logistic Regression. In the second approach we build a Multi-Layer Perceptron and an LSTM [4] classifier to recognize emotion given a speech signal. The models are evaluated on the *IEMOCAP* [5] dataset under different settings, namely, *Audio-only*, *Text-only* and *Audio + Text*.

The rest of the paper is organized as follows: Section II describes existing methods in the literature for the task of speech emotion recognition; Section III gives an overview of the the dataset used in this work and the pre-processing steps applied before feature extraction. Section IV describes proposed models and implementation details; Results are reported in Section V, followed by conclusion and future scope of this work in Section VI ¹.

II. LITERATURE REVIEW

In this section, we review some of the work that has been done in the field of speech emotion recognition (SER). The task of SER is not new

¹Code for all the experiments is available at <http://tinyurl.com/y55dlc3m>

and has been studied for quite some time in literature. A majority of the early approaches ([6] [7]) used Hidden Markov Models (HMMs) [8] for identifying emotion from speech. Recent introduction of deep neural networks to the domain has also significantly improved the state-of-the-art performance. For instance, [3] use recurrent encoders and [9] use autoencoders to solve the task. Recently, methods have been suggested to efficiently combine features from multiple domains, such as, Tensor Fusion Networks [10], Low-Rank Matrix Multiplication [11], instead of trivial concatenation.

This work aims to provide a comparative study between 1) deep learning based models that are trained end-to-end and, 2) lighter machine learning based models, for which, we construct hand-crafted features. We also investigate the information residing in multiple modalities and how their combination effects the performance.

III. DATASET

In this work, we use the *IEMOCAP* [5] released in 2008 by researchers in University of Southern California (USC). It contains five recorded sessions of conversations from ten speakers and amounts to 12 hours of audio-visual information along with respective transcriptions. It is annotated with eight categorical emotion labels, namely, anger, happiness, sadness, neutral, surprise, fear, frustration and excited. It also contains dimensional labels such as values of the activation and valence from 1 to 5; however, they are not used in this work.

The dataset is split into multiple utterances for each session and we further split each of the utterance file into multiple `wav` files so that each `wav` file contains one sentence each. This was done using the start timestamp and end timestamp provided for the transcribed sentences. This results in a total of $\sim 10K$ audio files which are then used to extract features.

IV. METHODOLOGY

This section describes the data pre-processing steps followed by a detailed description of the features extracted and the two models applied to the classification problem.

TABLE I: Number of examples for each emotion

| Class | Count |
|--------------|-------------|
| Angry | 860 |
| Happy | 1309 |
| Sad | 2327 |
| Fear | 1007 |
| Surprise | 949 |
| Neutral | 1385 |
| Total | 7837 |

A. Data Pre-processing

a) Audio:: A preliminary frequency analysis revealed that the dataset is not balanced. The emotions “fear” and “surprise” are under-represented. In order to alleviate the issue, we use upsampling techniques. We then combine examples from “happy” and “excited” classes as “happy” was under-represented and the two emotions closely resemble each other. In addition to that, we also discard examples classified as “others”; they corresponded to examples that were labelled ambiguous even for a human. Applying the aforementioned operations resulted in 7837 examples in total. Final sample distribution for each of the emotions is shown in Table I.

b) Text:: The available transcriptions were first normalized to lowercase and any special symbols were removed.

B. Feature Extraction:

Here, we describe the hand crafted features used for both, ML- and DL-based models.

1) Audio Features:

a) Pitch: Pitch is important because wave forms produced by our vocal cords change depending on our emotion. Many algorithms for estimating the pitch signal exist. We use the most common method based on *autocorrelation of center-clipped* frames [12]. Formally, the input signal $y[n]$ is center-clipped to give a resultant signal, $y_{clipped}[n]$:

$$y_{clipped}[n] = \begin{cases} y[n] - C_l, & \text{if } y[n] \geq C_l \\ 0, & \text{if } |y[n]| < C_l \\ y[n] + C_l, & \text{if } y[n] \leq -C_l \end{cases} \quad (1)$$

Here, C_l is nearly half of the mean of the input signal and $[\cdot]$ denotes the discrete nature of the input signal. Now, autocorrelation is calculated

for the obtained signal $y_{clipped}$, which is further normalized and the peak values associated with the pitch of the given input $y[n]$. It was found that center-clipping the input signal resulted in more distinct autocorrelation peaks.

b) Harmonics: In the emotional state of anger or for stressed speech, there are additional excitation signals other than pitch ([13], [14]). This additional excitation is apparent in the spectrum as harmonics (see Figure 1) and cross-harmonics. We calculate harmonics using a median-based filter as described in [15]. First, the median filter is created for a given window size l , given by”

$$y[n] = \text{median}x[n - k : n + k] | k = (l - 1)/2 \quad (2)$$

when l is odd. For cases when l is even, the median is obtained as the mean of two values in the middle of the sorted list. This filter is then applied to S_h , the h -th frequency slice of a given spectrogram S , to get harmonic-enhanced spectrogram frequency slice H_h as:

$$H_i = M(S_h, l_{harm}) \quad (3)$$

Here M is the median filter, i is the i -th time step and l_{harm} is the length of the harmonic filter.

c) Speech Energy: Since energy of a speech signal can be related its loudness, we can use it to detect certain emotions. Figure 2 shows the difference in energy levels of an ”angry” signal v/s that of a ”sad” signal. We use standard Root Mean Square Energy (RMSE) to calculate the signal using the equation:

$$E = \sqrt{\frac{1}{n} \sum_{i=1}^n y[i]^2} \quad (4)$$

RMSE is calculated frame by frame and we take its average and standard deviation.

d) Pause: We use this feature to represent the ”silent” portion in the audio data. This quantity is directly related to our emotions; for instance, we tend to speak very fast when excited (say, angry or happy, resulting in a low *Pause* value). The feature value is given by:

$$Pause = Pr(y[n] < t) \quad (5)$$

where t represents a carefully-chosen threshold of $\approx 0.4 * E$, E being the RMSE.

e) Central moments: Finally, we use mean and standard deviation of the amplitude of the signal to incorporate a ”summarized” information of the input.

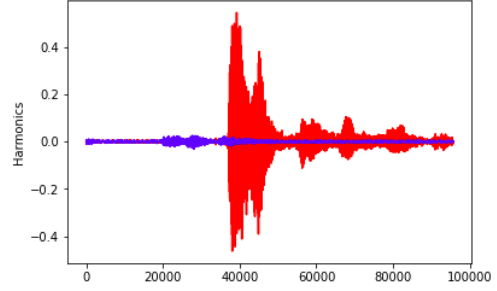


Fig. 1: Harmonics of angry (red) and sad (blue) audio signals

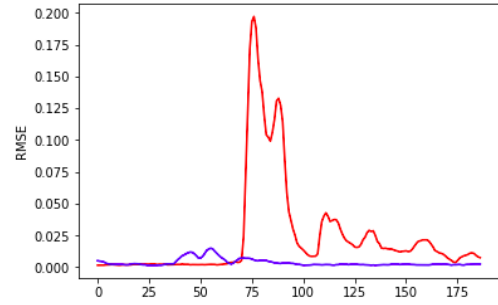


Fig. 2: RMSE plots of angry (red) and sad (blue) audio signals

2) Text Features::

a) Term Frequency-Inverse Document Frequency (TFIDF): TFIDF is a numerical statistic that shows the correlation between a word and a document in a collection or corpus. It consists of two parts:

- *Term Frequency:* It denotes how many times a word/token occurs in a document. The simplest choice is to use *raw count* of a token in a document (sentences, in our case).
- *Inverse Document Frequency:* This term is introduced to lessen the bias due to frequently occurring words in language such

“the”, “a” and “an”. Usually, idf for a term t and a document D is defined as:

$$idf(t, D) = \log \frac{N}{|d \in D : t \in d|} \quad (6)$$

The denominator shows the frequency of documents containing term t

Finally TFIDF value for a term is calculated by taking the product of TF and IDF values.

C. Machine Learning Models:

This section describes the various ML-based classifiers considered in this work, namely, Random Forests, Gradient Boosting, Support Vector Machines, Naive-Bayes and Logistic Regression

a) Random Forest (RF): Random forests are an ensemble learners that operate by constructing multiple decision trees at training time and outputting the class that is the mode of the classes (classification) of the individual trees. It has two base working principles:

- Each decision tree predicts using a random subset of features [16]
- Each decision tree is trained with only a subset of training samples. This is known as bootstrap aggregating [17]

Finally, a majority vote of all the decision trees is taken to predict the class of a given input.

b) Gradient Boosting (XGB): XGB refers to eXtreme Gradient Boosting. It is an implementation of boosting that supports training the model in a fast and parallelized way. Boosting is another ensemble classifier combining a number of weak learners, typically decision trees. They are trained in a sequential manner, unlike RFs, using forward stage-wise additive modelling. During the early iterations, the decision trees learnt are simple. As training progresses, the classifier become more powerful because it is made to focus on the instances where the previous learners made errors. At the end of training, the final prediction is a weighted linear combination of the output from the individual learners [18].

c) Support Vector Machines (SVMs): SVMs are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. An SVM training algorithm essentially builds a non-probabilistic binary linear classifier (although

methods such as Platt scaling exist to use SVM in a probabilistic classification setting). It represents each training example as a point in space, mapped such that the examples of the separate categories are divided by a clear gap that is as wide as possible (this is usually achieved by minimizing the hinge loss). New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall. SVMs were originally introduced to perform linear classification; however, they can efficiently perform a non-linear classification using the kernel trick [19], implicitly mapping their inputs into high-dimensional feature spaces.

d) Multinomial Naive Bayes (MNB): Naive Bayes classifiers are a family of simple “probabilistic classifiers” based on applying Bayes’ theorem with strong (naive) independence assumptions between the features. Under multinomial setting, the feature vectors represent the frequencies with which certain events have been generated by a multinomial (p_1, \dots, p_n) where p_i is the probability that event i occurs. MNB is very popular for document classification task in text [20] which too essentially is a multi-class classification problem.

e) Logistic Regression (LR): LR is typically used for binary classification problems [21], that is, when we have only two labels. In this work, the LR is implemented in a one-vs-rest manner; six classifiers have been trained for each class and finally, we consider the class that is predicted with the highest probability.

Having trained the above classifiers, we take ensemble of the best performing classifiers and use it for comparison with the current state-of-the-art for emotion recognition on the IEMOCAP dataset.

D. Deep Learning Models

In this section, we describe the deep learning models used. Typically, Deep Neural Networks (DNNs) are trained in an end-to-end fashion and they are expected to “figure out” features completely on their own. However, training such a model can take a lot of time as well as computational resources. In order to minimize the computational overhead, we directly feed the handcrafted features as input to these models and

compare their performance with the traditional end-to-end trained counterparts. In this work, we implement two types of models:

a) *Multi Layer Perceptron (MLP)*: MLP belongs to a class of feedforward neural network. It consists of at least three nodes: an input, a hidden and an output layer. All the nodes are interleaved with a non-linear activation function to stabilize the network during training time. Their expressive power increases as we increase the number of hidden layers upto a certain extent. Their non-linear nature allows them to distinguish data that is not linearly separable.

b) *Long Short Term Memory (LSTM)*: LSTMs [4] were introduced for long-range context capturing in sequences. Unlike MLP, it has feedback connections that allow it to decide what information is important and what is not. It consists of a gating mechanism and there are three types of gates: input, forget and output. Their equations are mentioned below:

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \quad (7)$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \quad (8)$$

$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \quad (9)$$

$$c_t = f \cdot c_{t-1} + i_t \cdot \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \quad (10)$$

$$h_t = o_t \cdot \sigma_h(c_t) \quad (11)$$

where initial values are $c_0 = 0$ and $h_0 = 0$ and \cdot denotes the element-wise product, t denotes the time step (each element in a sequence belongs to one time step), x_t refers to the input vector to the LSTM unit, f_t is the forget gate's activation vector, i_t refers to the input gate's activation vector, o_t refers to the output gate's activation vector, h_t is the hidden state vector (which is typically used to map a vector from the feature space to a lower-dimensional latent space,) c_t is the cell state vector and W, U and b are weight and bias matrices which need to be learned during training. From figure 3, we see that an LSTM cell

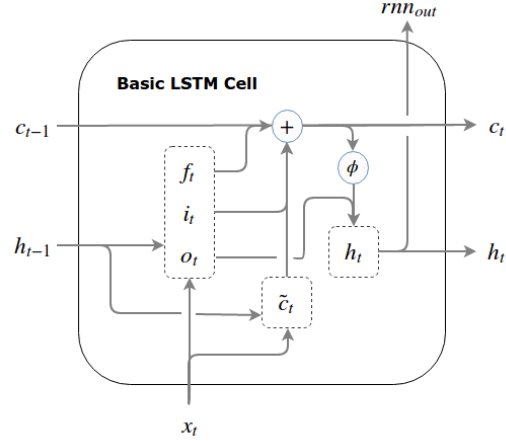


Fig. 3: Visualization of an LSTM cell

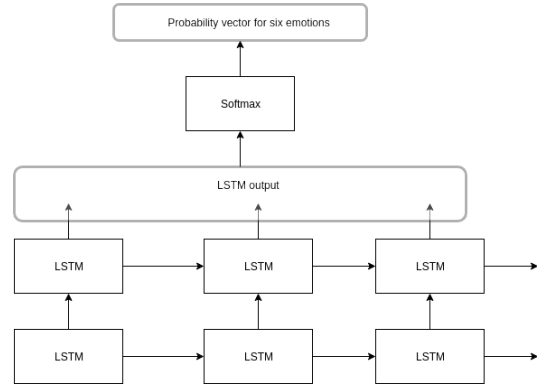


Fig. 4: LSTM classifier

is able to keep track of hidden states at all time steps through the feedback mechanism.

Figure 4 shows the network implemented in this work. We feed the feature vectors as input to the network and finally pass the output of the LSTM network through a softmax layer to get probability scores for each of the six emotions classes. Since we are using feature vectors as input, we do not need another decoder network to transform it back from hidden to output space thereby reducing network size.

E. Experiments

Here, we describe the three different settings under which we conduct our experiments in:

- *Audio-only*: In this setting, we train all the classifiers using only the audio feature vectors described earlier.
- *Text-only*: In this setting, we train all the classifiers using only the text feature vectors (TF-IDF vectors)
- *Audio+Text*: In this setting, we fuse the feature vectors from the two modalities. There have been some methods proposed to fuse vectors efficiently from multiple modalities but we simply concatenate the feature vectors from audio and text to obtain the combined feature vectors. Through this experiment, we would be able to infer how much information is contained in each of the modalities and how does fusion influence the model's performance.

F. Implementation Details

In this section, we describe the implementation details adopted in this work.

- We use `librosa` [22], a Python library, to process the audio files and extract features from them.
- We use `scikit-learn` and `xgboost` [23] [24], the machine learning libraries for Python, to implement all the ML classifiers (RF, XGB, SVM, MNB, and LR) and the MLP.
- We use `PyTorch` [25] to implement the LSTM classifiers described earlier.
- In order to regularize the hidden space of the LSTM classifiers, we use a *shut-off* mechanism, called dropout [26], where a fraction of neurons are not used for final prediction. This is shown to increase the robustness of the network and prevent overfitting.

We randomly split our dataset into train (80%) and test (20%) set. The same split is used for all the experiments to ensure a fair comparison. The LSTM classifiers were trained on an NVIDIA Titan X GPU for faster processing. We stop the training when we do not see any improvement in validation performance for >10 epochs. Here, one epoch refers to one iteration over all the training samples. Different batch sizes were used for different models.

G. Evaluation Metrics:

In this section, we first describe the various evaluation metrics used and report results for the three experiment settings.

a) *Accuracy*: This refers to the percentage of test samples that are classified correctly.

b) *Precision*: This measure tells us out of all predictions, how many are actually present in the ground truth (a.k.a. labels). It is calculated using the formula:

$$Precision = \frac{tp}{tp + fp} \quad (12)$$

c) *Recall*: This measure tells us how many correct labels are present in the predicted output. It is calculated using the formula:

$$Precision = \frac{tp}{tp + fn} \quad (13)$$

Here, tp stands for true positive, fp stands for false positive and fn stands for false negatives. We can compute these values from the respective confusion matrix.

d) *F-score*: F-score is defined as the harmonic mean of precision and recall. This measure was included as accuracy is not a complete measure of a model's predictive power but F-score is since it is more normalized.

We compare our best performing models with the current state-of-the-art as mentioned in [3]. They employ three types of recurrent encoders, namely, ARE, TRE and MDRE. They denote Audio-, Text- and Multimodal Dual- Recurrent Encoders respectively. It is important to mention that [3] only consider four emotions for classification, namely, anger, happy, sad and neutral as opposed to six in our case. In order to present a fair comparison of our method with theirs, we also run the experiments for the four classes (models with code 4-class denote such models).

V. RESULTS

In this section, we discuss the performance of models described in Section IV.

From Figure 6, we can see that our simpler and lighter ML models either outperform or are comparable to the much heavier current state-of-the-art on this dataset. A more details analysis follows:

a) *Audio-only results:* Results are especially interesting for this setting. Performance of LSTM and ARE reveals that deep models indeed need a lot of information in order to learn features as the LSTM classifier trained on eight-dimensional features achieves very low accuracy as compared to the end-to-end trained ARE. However, neither of them are able to beat the lighter E1 model which was trained on the eight-dimensional audio feature vectors. A look at the confusion matrix (Fig. 7a) reveals that detecting “neutral” or distinguishing closely related emotions such as “happy” and “surprise” is still difficult for the model.

b) *Text-only results:* We observe that performance of all the models is almost similar. We see from the confusion matrix (Fig. 7b) that text-based models are able to distinguish the six emotions fairly well. That could be attributed to the rich TF-IDF vectors that are known to capture word-sentence correlation.

c) *Audio+Text results:* We see that combining audio and text features gives us a boost of $\sim 14\%$ for all the metrics. This is a clear evidence of the strong correlation between text and speech features. Also, this is the only case when the recurrent encoders seem to perform slightly better in terms of accuracy but at the cost of precision. The lower performance of E1 maybe be attributed to the trivial fusion method (concatenation) we use as simple concatenation for an ML model would still contain a lot of modality-specific connections instead of the desired inter-modal connections. The promising result here is that combining text features indeed helped the speech based model to resolve the ambiguity between different emotion classes as shown in Fig. 7c

Overall, we can conclude that our simple ML methods are very robust to have achieved comparable performance even though they are modelled to predict six-classes as opposed to four in previous works.

A. Most Important Features:

In this section, we investigate which features contribute the most during prediction in this classification task. We chose the XGB model for this study and rank the eight audio features. We see that *Harmonic*, which is directly related to

the excitation in signals, contributes the most. It is interesting to see that “silence” attributing to *Pause*, is almost as significant as standard deviation of the autocorrelated signal (related to pitch). The low contribution of central moments is expected as a signal is very diverse and an overall feature would be unable to identify the nuances present in it.

VI. CONCLUSION AND FUTURE WORK

In this work, we tackle the task of speech emotion recognition and study the contribution of different modalities towards ambiguity resolution on the IEMOCAP dataset. We compare, both, ML- and DL-based models and show that even lighter and more interpretable ML models can achieve performance close to DL-based models. We show that ensembling multiple ML models also lead to some improvement in the performance.

In this work, we only extract a handful time-domain features from audio signals. The features could be made even richer if we could include some frequency-domain features too such as Mel-Frequency Cepstral Coefficients (MFCC) [27], Spectral Roll-off and additional time-domain features such as Zero Crossing Rate (ZCR) [28]. Also, better fusion methods such as TFN [10] and LMF [11] could be employed for combining speech and text vectors more effectively.

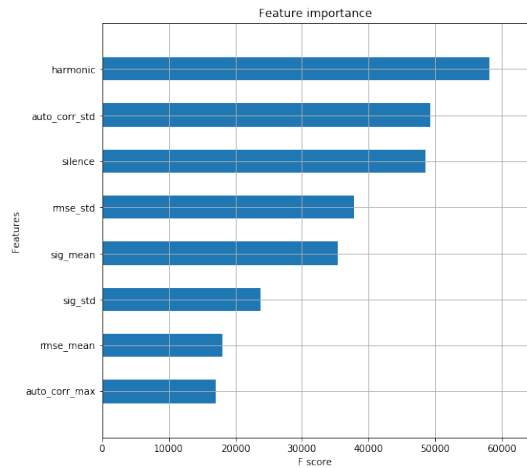


Fig. 5: Contribution of Audio features

| Models | Accuracy | F1 | Precision | Recall |
|---------------|-------------|-------------|-------------|-------------|
| RF | 56.0 | 56.0 | 57.2 | 57.3 |
| XGB | 55.6 | 56.0 | 56.9 | 56.8 |
| SVM | 33.7 | 15.2 | 17.4 | 21.5 |
| MNB | 31.3 | 9.1 | 19.6 | 17.2 |
| LR | 33.4 | 14.9 | 17.8 | 20.9 |
| MLP | 41.0 | 36.5 | 42.2 | 35.9 |
| LSTM | 43.6 | 43.4 | 53.2 | 40.6 |
| ARE (4-class) | 56.3 | - | 54.6 | - |
| E1 (4-class) | 56.2 | 45.9 | 67.6 | 48.9 |
| E1 | 56.6 | 55.7 | 57.3 | 57.3 |

(a) Audio-only setting

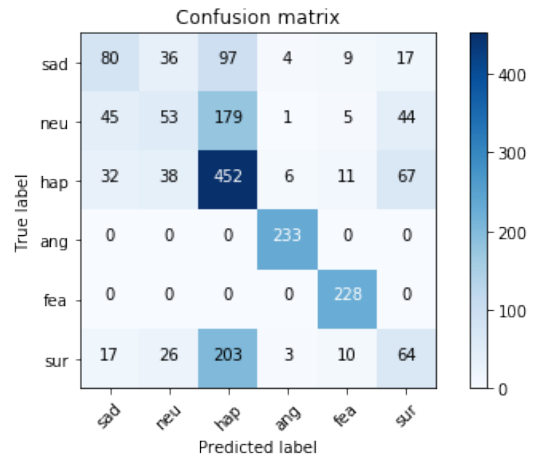
| Models | Accuracy | F1 | Precision | Recall |
|---------------|-------------|-------------|-------------|-------------|
| RF | 62.2 | 60.8 | 65.0 | 62.0 |
| XGB | 56.9 | 55.0 | 70.3 | 51.8 |
| SVM | 62.1 | 61.7 | 62.5 | 63.5 |
| MNB | 61.9 | 62.1 | 71.8 | 58.6 |
| LR | 64.2 | 64.3 | 69.5 | 62.3 |
| MLP | 60.6 | 61.5 | 62.4 | 63.0 |
| LSTM | 63.1 | 62.5 | 65.3 | 62.8 |
| TRE (4-class) | 65.5 | - | 63.5 | - |
| E1 (4-class) | 63.1 | 61.4 | 67.7 | 59.0 |
| E2 | 64.9 | 66.0 | 71.4 | 63.2 |

(b) Text-only setting

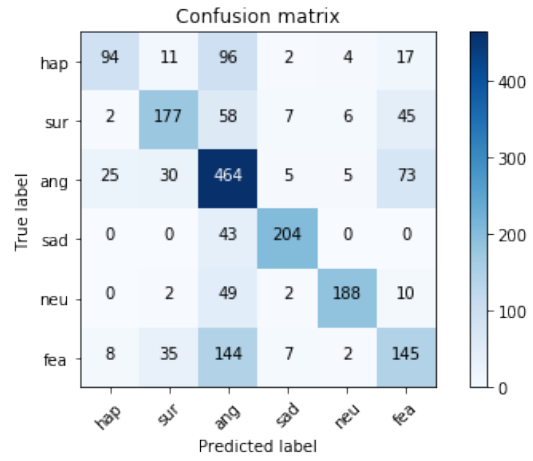
| Models | Accuracy | F1 | Precision | Recall |
|----------------|-------------|-------------|-------------|-------------|
| RF | 65.3 | 65.8 | 69.3 | 65.5 |
| XGB | 62.2 | 63.1 | 67.9 | 61.7 |
| SVM | 63.4 | 63.8 | 63.1 | 65.6 |
| MNB | 60.5 | 60.3 | 70.3 | 57.1 |
| MLP | 66.1 | 68.1 | 68.0 | 69.6 |
| LR | 63.2 | 63.7 | 66.9 | 62.3 |
| LSTM | 64.2 | 64.7 | 66.1 | 65.0 |
| MDRE (4-class) | 75.3 | - | 71.8 | - |
| E1 (4-class) | 70.3 | 67.5 | 73.2 | 65.5 |
| E2 | 70.1 | 71.8 | 72.9 | 71.5 |

(c) Audio+Text setting

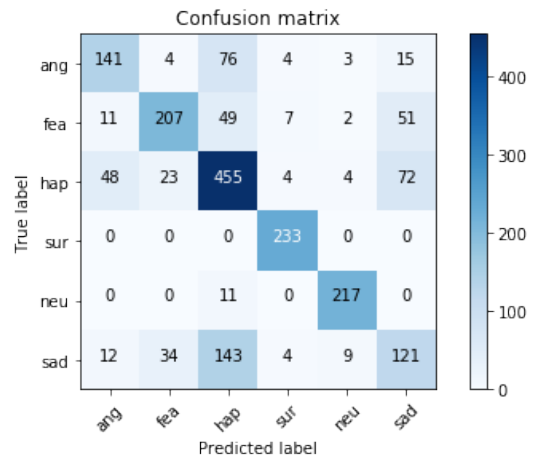
Fig. 6: Performance of different models; E1: Ensemble (RF + XGB + MLP); E2: Ensemble (RF + XGB + MLP + MNB + LR)



(a) E1, Audio-only setting



(b) E2, Text-only setting



(c) E2, Audio+Text setting

Fig. 7: Confusion Matrices of the our ensemble models; E1: Ensemble (RF + XGB + MLP); E2: Ensemble (RF + XGB + MLP + MNB + LR)

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