

Multi-Modal Emotion recognition on IEMOCAP Dataset using Deep Learning.

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Abstract—Emotion recognition has become an important field of research in Human Computer Interactions as we improve upon the techniques for modelling the various aspects of behaviour. With the advancement of technology our understanding of emotions are advancing, there is a growing need for automatic emotion recognition systems. One of the directions the research is heading is the use of Neural Networks which are adept at estimating complex functions that depend on a large number and diverse source of input data. In this paper we attempt to exploit this effectiveness of Neural networks to enable us to perform multimodal Emotion recognition on IEMOCAP dataset using data from Speech, Text, and Motion capture data from face expressions, rotation and hand movements. Prior research has concentrated on Emotion detection from Speech on the IEMOCAP dataset, but our approach is the first that uses the multiple modes of data offered by IEMOCAP for a more robust and accurate emotion detection.

1. Introduction

Emotions are very important in human decision handling, interaction and cognitive process [3]. With the advancement of technology our understanding of emotions are advancing, there is a growing need for automatic emotion recognition systems. However one of the new and exciting directions this research is heading is using multimodal data sources to make accurate emotion classifications. Each of the modes have been individually studied extensively, such as emotion detection using speech facial expressions and text transcripts. In this paper we combine these modes to make stronger and more robust detector for emotions. For our research we particularly explore Neural Networks and advanced machine learning techniques such as Attention and Dropout. Neural network is a machine that is designed to model the way our brain performs a particular task, where the key concepts of brain as a complex, non-linear and parallel computer are imitated [?], and possess the ability to model and estimate complex functions depending on multitude of factors. Recently the developments in machine learning using Deep Neural Networks have achieved state-of-the-art performance in Text and Sentiment Analysis [2],

Automatic Speech Recognition [4], and Image recognition [8].

In our research we perform multimodal emotion detection from the IEMOCAP dataset [12], which consists 12 hours of audio-visual data of improvisations and scripted scenarios from actors, annotated for emotions. A lot of the prior research in this field is concentrated on detecting emotions using just the speech part of the dataset. Two important papers in this field are the works of [13] and [17]. Both use RNN based architectures on extracted speech features to obtain the their best results. [13] use Markov chain over input signals to remove segments with no emotional state. [17] use Connectionist Temporal Classification loss function to allow them model states with little or no emotions in speech window. We replicate their results for speech based emotion recognition and build upon their works.

In our research we seek to detect emotions using the data from many modalities of IEMOCAP. For this we explore various deep learning based architectures to first get the best individual detection accuracy from each of the different modes. We then try combine them in an ensemble based architecture to allow for end-to-end training across the different modalities using the variations of the better individual models. Our ensemble consists of Long Short Term Memory networks, Convolution Neural Networks, Fully connected Multi-Layer Perceptrons and we complement them using techniques such as Dropout, adaptive optimizers such as Adam, pretrained word-embedding models and Attention based RNN decoders. Comparing our speech based emotion detection with [13] we achieve 62.72% accuracy compared to their 62.85%; and comparing with [17] we achieve 55.65% accuracy compared to their CTC based 54% accuracy. After combining Speech (individually 55.65% accuracy) and Text (individually 64.78% accuracy) modes we achieve an improvement to 68.40% accuracy. When we also account MoCap data (individually 51.11% accuracy) we also achieve a further improvement to 71.04%.

2. Related Works

Emotion is a psycho-physiological process that can be triggered by conscious and/or unconscious perception of objects and situations and is associated with multitude of

factors such as mood, temperament, personality, disposition, and motivation [20]. Emotions play an important role in human communication and can be expressed either verbally through emotional vocabulary or by expressing nonverbal cues such as intonation of voice, facial expressions, and gestures [15]. Emotion recognition has been studied widely using speech [13] [17] [16], text [9], facial cues [10], and EEG based brain waves [11]. One of the biggest open-sourced multimodal resources available in emotion detection is IEMOCAP dataset [12].

The dataset consists of approximately 12 hours of audio-visual data, including facial recordings, speech and text transcriptions. The dataset is an acted and has multispeaker recordings, and has been an important dataset for emotion based research. However most of the research on this has concentrated specifically in emotion detection using Speech based data. One of the early important papers on this dataset is "Speech Emotion Recognition Using Deep Neural Network and Extreme Learning Machine" [18] which beat state of the art by 20% over techniques that used HMMs, SVMs and other shallow learning methods. They perform segment level feature extraction, feed those features to a MLP based architecture, where the input is 750 dimensional feature vector, followed by 3 hidden layer of 256 neurons each with rectilinear units as non-linearity. This feeds to an utterance level classifier which predicts the final emotion.

"High-level Feature Representation using Recurrent Neural Network for Speech Emotion Recognition" [13] follows the previous research [18]. They trained long short-term memory (LSTM) based recurrent neural network and achieved about 60 % accuracy on IEMOCAP dataset. First they divide each utterance into small segments with voiced region, then assume that the label sequences of each segment follows a Markov chain. They extract we extract 32 features for every frame: F0 (pitch), voice probability, zero-crossing rate, 12-dimensional Mel-frequency cepstral coefficients (MFCC) with log energy, and their first time derivatives. The network contains 2 hidden layers with 128 BLSTM cells (64 forward nodes and 64 backward nodes). They achieve 62.85 % accuracy with this technique.

Another research we closely follow is "Emotion Recognition From Speech With Recurrent Neural Networks" [17]. Where they use CTC loss function to improve upon RNN based Emotion prediction. They use 34 features including 12 MFCC, chromagram-based and spectrum properties like flux and roll-off. For all speech intervals they calculate features in 0.2 second window and moving it with 0.1 second step. The use of CTC loss helps as often almost the whole utterance has no emotion, but emotionality is contained only in a few words or phonemes in an utterance which the CTC loss handles well. Unlike [13], Chernykh et. al. use all the session data for the emotion classification. Another important research on Speech based Emotion recognition is the work of [14] which uses transfer learning to improve on Neural Models for emotion detection. Their model uses 1D convolutions and GRU layers to initialize a neural model for Automatic Speech Recognition inspired by Deep Speech. They use many datasets for ASR based training on CTC

loss, and then fine-tune this model on IEMOCAP. Using only IEMOCAP as the baseline model, they achieve 55% accuracy, and with the help of fine-tuning on top of the pretrained ASR model they achieve 61% accuracy.

3. Experimental Setup

We use The Interactive Emotional Dyadic Motion Capture (IEMOCAP) database for the task of multi-modal emotion recognition. It consists of about 12 hours of audio-visual data from 10 actors. The recordings follow dialogues between a male and a female actor in both scripted or improvised topics. After the audio-visual data has been collected it is divided into small utterances of length between 3 to 15 seconds which are then labelled by evaluators. Each utterance is evaluated by 3-4 assessors. The evaluation form contained 10 options (neutral, happiness, sadness, anger, surprise, fear, disgust frustration, excited, other). We consider only 4 of them anger, excitement (happiness), neutral and sadness so as to remain consistent with the prior research. We consider emotions where atleast 2 experts were consistent with their decision, which is more than 70 % of the dataset, again consistent with prior research.

Along with the .wav file for the dialogue we also have available the transcript each the utterance. For each session one actor wears the Motion Capture (MoCap) camera data which records the facial expression, head and hand movements of the actor. The Mocap data contains column tuples, for facial expressions the tuples are contained in 165 dimensions, 18 for hand positions and 6 for head rotations. As this Mocap data is very extensive we use it instead of the video recording in the dataset. These three modes (Speech, Text, Mocap) of data form the basis of our multi-modal emotion detection pipeline.

Next we preprocess the IEMOCAP data for these modes. For the speech data our preprocessing follows the work of [17]. We use the Fourier frequencies and energy-based features Mel-frequency cepstral coefficients (MFCC) for a total of 34 features They include 12 MFCC, chromagram-based and spectrum properties like flux and roll-off. We calculate features in 0.2 second window and moving it with 0.1 second step and with 16 kHz sample rate. We keep a maximum of 100 frames or approximately for 10 seconds of the input, and zero pad the extra signal and end up with (100,34) feature vector for each utterance. For the text transcript of each of the utterance we use pretrained Glove embeddings [19] of dimension 300, along with the maximum sequence length of 500 to obtain a (500,300) vector for each utterance. For the Mocap data, for each different mode such as face, hand, head rotation we sample all the feature values between the start and finish time values and split hem into 200 chronological arrays. We then average each of the 200 arrays along the columns (165 for faces, 18 for hands, and 6 for rotation), and finally concatenate all of them to obtain (200,189) dimension vector for each utterance. We can now proceed to feed our model these processed input modal vectors.

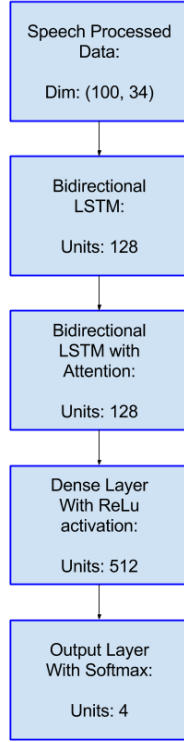


Figure 1: Neural Model for Speech based Emotion detection

4. Models and Results

In this section we present the different Neural Network based models we attempted over each of the modes as well as our final combined model, while also comparing with prior research. We begin with the speech based emotion detection model detection.

4.1. Speech Based Emotion Detection

Our first model (Model1) consists of three layered Fully Connected model with 1024,512,256 hidden neural units with 'Relu' as activation and 4 output neurons with Softmax. The model takes the flattened speech vectors as input and trains using cross entropy loss with Adadelata as the optimizer. Model2 uses two stacked LSTM layers with 512 and 256 units followed by a Dense layer with 512 units and Relu Activation. Model3 finally uses 2 LSTM layers with 128 units each but the second LSTM layer has Attention implementation as well, followed by 512 units of Dense layer with ReLu activation. Model4 improves both the encoding LSTM and Attention based decoding LSTM by making them bi-directional. All these last 3 models use Adadelata as the optimizer. We divide our dataset with a randomly chosen 20 PC validation split and report our accuracies based this set. As we can see the final Attention based LSTM model performs the best. We also try many variations

TABLE 1: Speech emotion detection models and accuracy

Model	Accuracy
Model1	50.6%
Model2	51.32%
Model3	54.15%
Model4	55.65%

TABLE 2: Comparison between our Speech emotion detection models and previous research

Model	Accuracy
Lee and Tashev [13]	62.85%
Ours (improv only)	62.72%
Chernykh [17]	54%
Neumann [16]	56.10%
Lakomkin [14]	56%
Ours (all)	55.65%
Ours (all, Speech + text + Mocap)	71.04%

of the speech data including using MelSpectrogram, smaller window (0.08s) with longer context (200 timestamps) as well as combining these approaches into one big network but did not achieve improvements.

To compare our results with prior research we use our best model (Model4) and evaluate it in the manner similar to various conditions of the previous researches. We train using Session1-4 and use Session5 as our test set. Like [13] we use only the improvisation session for both Training and Testing and achieve similar results. To compare with [17] [16] [14] who use the both scripted and Improvisation sessions we achieve again achieve similar results. One important insight of our results is with minimal preprocessing and no complex loss functions or noise injection into the training, we can easily match prior research's performance using Attention based Bidirectional LSTMS.

4.2. Text based Emotion Recognition

For our next task of performing emotion detection using only the text transcripts of our data resembles that of sentiment analysis, a very common and highly researched task of Natural Language Processing. For this approach we again try similar models as before. Here we try two approaches Model1 which uses 1D convolutions of kernel size 3 each, with 256,128,64 and 32 filters using Relu as Activation and Dropout of 0.2 probability, followed by 256 dimension Fully Connected layer and Relu, feeding to 4 output neurons with Softmax. Model2 uses two stacked LSTM layers with 512 and 256 units followed by a Dense layer with 512 units and Relu Activation. Both these models are initialized with Glove Embeddings based word-vectors. We also try Randomized initialization with 128 dimensions in Model3 and obtain similar performance as Model2. The LSTM based models use Adadelata and Convolution based models use Adam as optimizers.

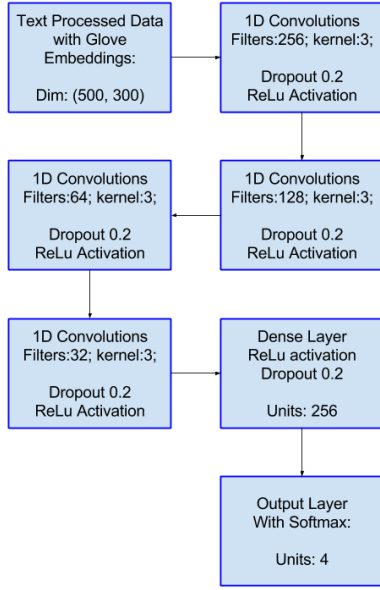


Figure 2: Neural Model for Text based Emotion detection

TABLE 3: Text emotion detection models and accuracy

Model	Accuracy
Model1	62.55%
Model2	64.68%
Model3	64.78%

4.3. MoCap based Emotion Detection

For the Mocap based emotion detection we use try LSTM and Convolution based models. For emotion detection using only the head rotation we try 2 models, first one (Model1) uses LSTM with 256 units followed by Dense layer and Relu activation, while the second model (Model2) uses just 256 hidden unit based Dense Layer with Relu and achieves better performance. We use the two models again for Hand movement based emotion detection and Dense Layer achieves better performance. For the facial expression based Mocap data, we use two stacked LSTM layers with 512 and 256 units followed by a Dense layer with 512 units and Relu Activation as Model1. Model2 on Face Mocap uses 5 2D Convolutions each with kernel size 3, Stride 2 and 32,64,64,128,128 filters, along with Relu activation and 0.2 Dropout. These layers are then followed by a Dense Layer with 256 neurons and Relu followed by 4 output neurons and Softmax. We also try Model3 which is a slight variation of Model2 where we replace the last Convolution layer with a Dense layer of 1024 units. We finally use Model3 based architecture for the concatenated MoCap data architecture with 189 input feature length. The LSTM based models use Adadelata and Convolution and Fully Connected based models use Adam as optimizers.

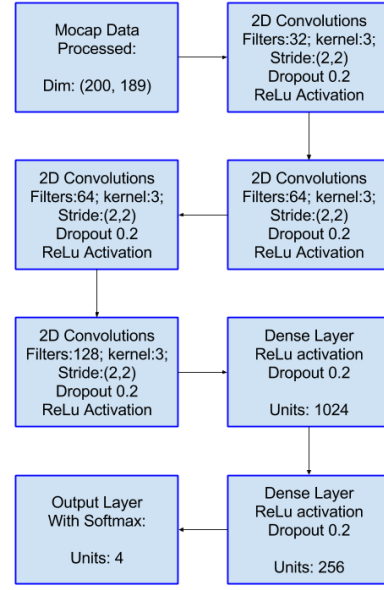


Figure 3: Neural Model for MoCap based Emotion detection

TABLE 4: MoCap based emotion detection models and accuracy

Model	Accuracy
MoCap-head Model1	37.75%
MoCap-head Model2	40.28%
MoCap-hand Model1	33.70%
MoCap-hand Model2	36.94%
MoCap-face Model1	48.99%
MoCap-face Model2	48.58%
MoCap-face Model3	49.39%
MoCap-combined Model3	51.11%

TABLE 5: Combined Multi-Modal emotion detection models and accuracy

Model	Accuracy
Text + Speech Model1	65.38%
Text + Speech Model2	67.41%
Text + Speech Model3	69.74%
Text + Speech + Mocap Model4	67.94%
Text + Speech + Mocap Model5	68.58%
Text + Speech + Mocap Model5	71.04%

4.4. Combined Multi-modal Emotion Detection

For the final part of our experiment we train models using all the three modes discussed above. We first use the text transcript and speech based vectors for one model. We try architectures which use Model1 for text processing and Model1 of speech processing architectures, both without the output neurons, their final hidden layers concatenated to 512 dimension hidden layer feeding into 4 output neurons. This

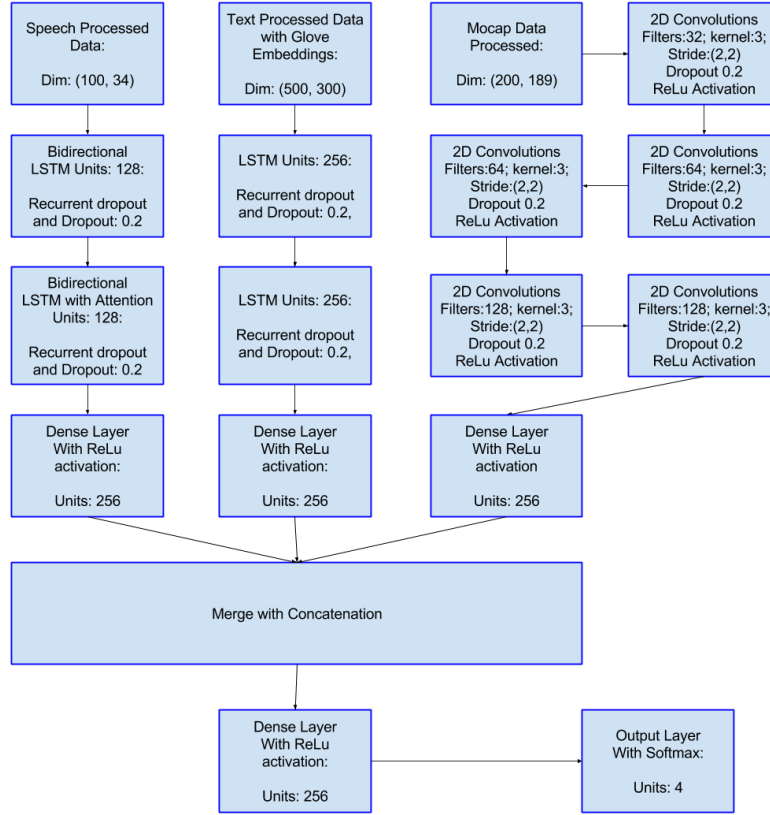


Figure 4: Simulation results for the network.

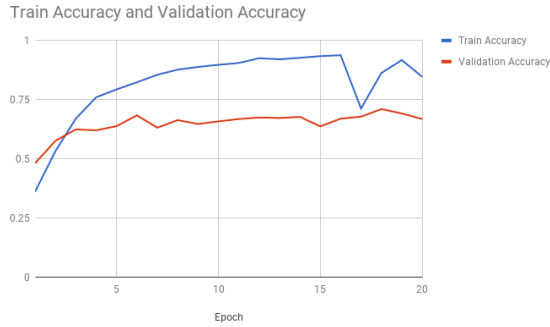


Figure 5: Accuracy graph of our Final Model

architecture doesnot yield good results. We then try a new model (Model1) which uses 3 Dense layers (1024,512,256) neurons each for both text and speech features concatenated followed by another Dense layer with 256 neurons using Relu and Dropout of 0.2 and 4 output softmax neurons. Our Model2 uses 256 units of 2 stacked LSTMS followed by a Dense layer with 256 neurons for text data; 2 Dense layers with 1024 and 256 neurons for speech data; concatenated followed by another Dense layer with 256 neurons using Relu and Dropout of 0.2 and 4 output softmax neurons.

Both model1 and Model 2 use random initializations of 128 dimensional embeddings. For Model3 we replace Model2 with Glove embeddings. We then proceed to also include MoCap data as well into one complete model. For Model4 we combine the previous Model3 with MoCap based Model 2 and concatenate all three 256 layer final outputs. For Model5 we combine the previous Model3 with MoCap based Model1 and concatenate all three 256 layer final outputs. For Model6 we replace the Dense Layers in Speech mode part of previous Model4 with Attention based LSTM architectures. All the code is available in an Open source manner in case the model descriptions aren't very clear.

5. Conclusion and Future Work

As we can see using multimodal data sources for a complete end-end Deep Learning bsaed model can significantly improve accuracy than using just one mode such as text, speech or facial change data. However which individual architectures we choose for each mode and how we combine them have a profound effect in our accuracy. Some more interesting approaches for future work could involve more permutations of architectures to obtain better end-to-end learning. We could use Transfer learning from ASR model and fine-tune it for emotion detection. Also Mocap data

is averaged over time periods to obtain 200 dimensional feature vectors is could be made more robust. We release the code publicly and it could be good starting point for future research.

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