

Emotion Recognition Using Fusion of Audio and Video Features

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Outline

Motivation

Existing Datasets and Methods

Proposed Method

Why emotion recognition is important?

1. Interpersonal Relationships
2. Human Computer Interaction

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Applications

1. Call centers (Zoom, Hangout, Skype, etc.)
2. Business meetings
3. Tutor Agents

Applications

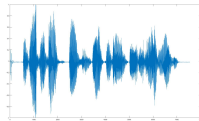
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Emotion Expression Modalities

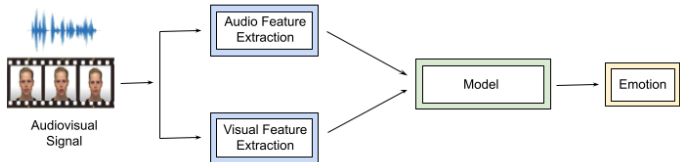
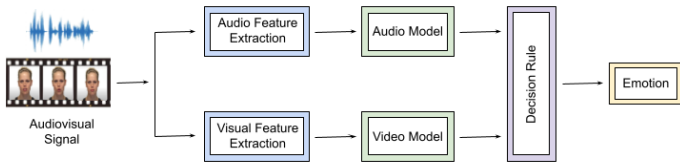
**PURE
TEXT**



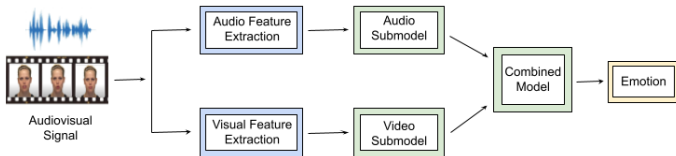
Datasets

1. RAVDESS (Livingstone and Russo, 2018)
2. SAVEE (Philip and Haq, 2014)
3. IEMOCAP (Busso et al., 2008)
4. SEMANIE (McKeown et al., 2010)
5. AFEW (Dhall et al., 2012)
6. eNTREFACE'05 (Martin et al., 2006)
7. ...

Methods



Methods



Major contributions

1. Use hybrid method for modality fusion on the raw data (e.g., audio and pictures from video) to be able to use existing whole content
2. Train and test sets separation based on the speakers (this is important as models tend to overfit to speakers and so the generalization error will be high in this cases)
3. Use mixture of different datasets with augmentation of real world noise in order to provide robustness

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Emotions and Datasets

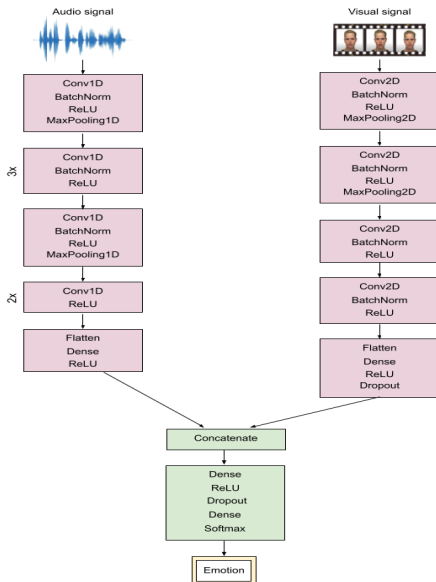
Emotions

1. Happy
2. Angry
3. Sad
4. Neutral

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Proposed Architecture

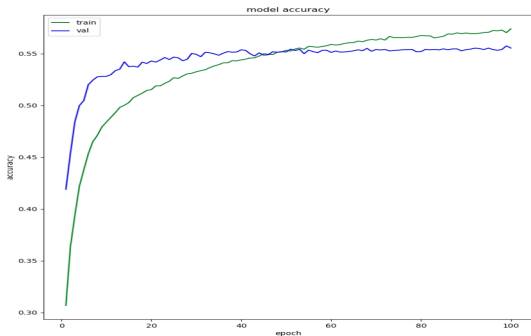


Results Random Split

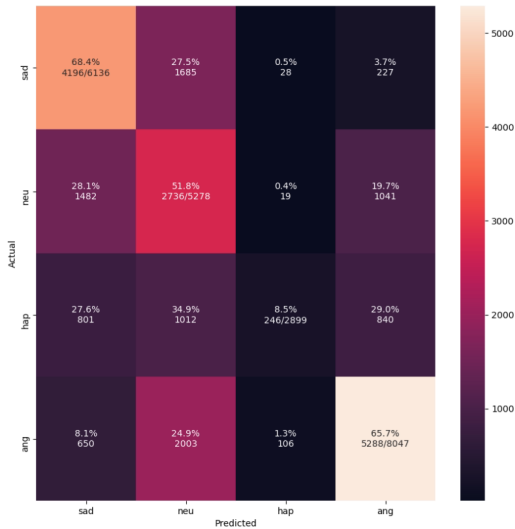
models	Accuracy random.s.	Accuracy speaker s.
Baseline	54	-
Lightgbm Audio	87.7	57.6

Results Speaker Split

models	Accuracy
Baseline	54
Audio model	54
Video model	57.7



Confusion Matrix



Demo

Videos: [▶ Link](#)

Source code: [▶ Link](#)

Thank you!

References

- Busso, C., Bulut, M., Lee, C.-C., Kazemzadeh, A., Mower Provost, E., Kim, S., Chang, J., Lee, S., and Narayanan, S. (2008). Iemocap: Interactive emotional dyadic motion capture database. *Language Resources and Evaluation*, 42:335–359.
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- Philip, J. and Haq, S. (2014). Surrey audio-visual expressed emotion (savee) database. *University of Surrey: Guildford, UK*.

Precision, Recall, F1score

-	precision	recall	f1-score	support
sad	0.60	0.68	0.63	6136
neu	0.36	0.37	0.37	5278
hap	0.40	0.22	0.28	2899
ang	0.68	0.71	0.69	8047
accuracy			0.56	22360

Features

Audio

1. ZRC
2. RMS
3. Mel Spectrogram
4. MFCC
5. Chromagram

Video

1. 20 faces of (50, 50) size