

M2H2: A Multimodal Multiparty Hindi Dataset For Humor Recognition in Conversations

Dushyant Singh Chauhan[†], Gopendra Vikram Singh[†], Navonil Majumder⁺, Amir Zadeh[‡], Asif Ekbal[†], Pushpak Bhattacharyya[†], Louis-philippe Morency[‡], and Soujanya Poria⁺

[†] Department of Computer Science & Engineering
Indian Institute of Technology Patna, India

{1821CS17, gopendra_1921CS15, asif, pb}@iitp.ac.in

[‡] Language Technology Institute, Carnegie Mellon University, Pittsburgh, USA

{abagherz, morency}@cs.cmu.edu

⁺ ISTD, Singapore University of Technology and Design, Singapore

{navonil_majumder, sporia}@sutd.edu.sg

ABSTRACT

Humor recognition in conversations is a challenging task that has recently gained popularity due to its importance in dialogue understanding, including in multimodal settings (i.e., text, acoustics, and visual). The few existing datasets for humor are mostly in English. However, due to the tremendous growth in multilingual content, there is a great demand to build models and systems that support multilingual information access. To this end, we propose a dataset for *Multimodal Multiparty Hindi Humor* (M2H2) recognition in conversations containing 6,191 utterances from 13 episodes of a very popular TV series "*Shrimaan Shrimati Phir Se*". Each utterance is annotated with humor/non-humor labels and encompasses acoustic, visual, and textual modalities. We propose several strong multimodal baselines and show the importance of contextual and multimodal information for humor recognition in conversations. The empirical results on M2H2 dataset demonstrate that multimodal information complements unimodal information for humor recognition. The dataset and the baselines are available at <http://www.iitp.ac.in/~ai-nlp-ml/resources.html> and <https://github.com/declare-lab/M2H2-dataset>.

CCS CONCEPTS

• Computing methodologies; • Machine learning; • Machine learning approaches; • Neural networks;

KEYWORDS

Deep learning, Humor, Hindi dataset, Multimodal multiparty dataset

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1 INTRODUCTION

Humor [28] is defined as the nature of experiences to induce laughter and provide amusement. It can be implicit as well as explicit. Implicit humor may be expressed with neutral facial expressions and a polite tone, while explicit humor can be conveyed with laughter or funny facial expressions. Explicit humor may be easy to detect in comparison to implicit humor because of laughter or facial expression. So, while text [1–3, 5, 9, 10, 14, 22, 23, 29, 34] alone may not always be enough to understand humor but if the utterance is multimodal in nature [7, 11, 16, 17, 19–21, 25–27, 31] and is accompanied with a video of the facial expressions and tone of the speaker, it can be easily understood that the utterance contains humor.

Humor recognition is especially challenging in many Indian languages because of the following reasons: unavailability of resources and tools; morphological richness; free word order etc. In our current work, we focus on Hindi, one of the most popularly spoken languages in India. In terms of the number of speakers, Hindi ranks third¹ all over in the world. In comparison to English, Hindi is much richer in terms of morphology. In Hindi, all the nouns and adjectives have genders, and the verb agrees in number and gender with them. While, English is free of that confounding factor of the gender of a common noun, and is also free of the further complication that the verb has to agree with the gender of the noun or pronoun governing it. These challenges motivated us to do some qualitative research work for Humor detection in Hindi.

In Hindi, there is no available dataset for humour detection (neither unimodal nor multimodal). In our work, we introduce a new dataset, named as M2H2, which includes not only textual dialogues but also their corresponding visual and audio counterparts. The main contributions of our proposed research are as follows:

- We propose a dataset for *Multimodal Multi-party Hindi Humor* recognition in conversations. There are 6,191 utterances in the M2H2 dataset;

¹<https://currentaffairs.adda247.com/hindi-ranks-3rd-most-spoken-language-in-the-world/>

- We set up two strong baselines, *viz.*, DialogueRNN [15] and bcLSTM [18] with MISA [12] for multimodal fusion. Both DialogueRNN and bcLSTM are contextual models.
- Empirical results on the *M2H2* dataset show the efficacy of multimodal information over only textual information for humor detection.

2 DATASET

We gathered samples from a famous TV show "*Shrimaan Shrimati Phir Se*"² and annotated them manually. We make groups of these samples (utterances) based on their context into scenes. Each utterance in each scene consists of a label indicating humor of that utterance *i.e.*, humor³ or non-humor. Besides, each utterance is also annotated with its speaker and listener information. In multiparty conversation, listener identification poses a great challenge. In our dataset, we define the listener as the party in the conversation to whom the speaker is replying. Each utterance in each scene is coupled with its context utterances, which are preceding turns by the speakers participating in the conversation. It also contains multiparty conversations that are more challenging to classify than dyadic variants. We show the dataset statistics in Table 1.

Description	Statistic
#Scenes	136
#Utterances	6191
Min #Utterances per Scene	8
Max #Utterances per Scene	155
#Utterances per Scene	45.52
#Words	34472
#Unique words	5454
#Humor class	2089
#Non-humor class	4102
#Speakers	41
Total duration	4.46 Hours

Table 1: Dataset statistics.

2.1 Challenges

We crawled the video file and transcription file using *YouTube* for the TV show "*Shrimaan Shrimati Phir Se*". The downloaded Hindi transcription file had some errors. So, we hired transcribers, who were experts in the Hindi language. They wrote Hindi utterances based on the audio files.

As the context is based on the scenes, we divide the whole dataset into scenes based on its context. Each utterance in each scene consists of a humor label (*i.e.*, humor or non-humor) and speaker and listener information.

2.2 Annotation Guidelines

We employ three Ph.D. students with high proficiency in Hindi and with prior experience in labeling *Humor* and *Non-humor* in conversational settings.

The guidelines for annotation, along with some examples (c.f. Figure 1), were explained to the annotators before starting the annotation process. The annotators were asked to annotate every utterance with humor/non-humor and corresponding speaker and listener information. We also annotated 20 annotations by ourselves and set it as a quality checker to evaluate the quality of the annotators. A majority voting scheme was used for selecting the final humor/non-humor. We achieve an overall Fleiss' [8] kappa score of 0.84, which is considered to be reliable.

3 BASELINE METHODS

In this section, we provide strong benchmarks for *M2H2* dataset. We employ three strong baselines frameworks for humor detection.

3.1 Strong Baseline for Multimodal Fusion: MISA

MISA (Modality-Invariant and-Specific Representations for Multimodal Sentiment Analysis) [12] has two main stages: modality representation learning and modality fusion. It divides each modality into two sub-spaces. The first subspace is modality-invariant, in which representations from different modalities learn to share similarities and minimize the distance between them. The second subspace is modality-specific, which is unique to every modality and contains its distinguishing characteristics. These representations give a comprehensive perspective of multimodal data, which is utilized for fusion and task prediction. The model shows the state-of-the-art (SOTA) for MOSI [33] and MOSEI [32] datasets.

3.2 Strong Conversation Classification Baseline

#1: DialogueRNN

DialogueRNN [15] is a multi-party framework tailored for modelling emotions and sentiments in conversations. In DialogueRNN, they explained a novel recurrent neural network-based system that tracks of each party state during a discussion and uses this knowledge to classify emotions. It employs three levels of gated recurrent units (GRU) to represent the conversational context in order to accurately recognize emotions, intensity, and attitudes in a discussion. They showed the SOTA performance on two different datasets *i.e.*, IEMOCAP [4] and AVEC [24].

3.3 Strong Conversation Classification Baseline

#2: bcLSTM

bcLstm [18] is a bidirectional contextual LSTM. Bi-directional LSTMs are formed by stacking two uni-directional LSTMs with opposing directions. As a result, an utterance can learn from utterances that come before and after it in the video which is of course context.

Leveraging the above three strong baselines, we formulate two setups, *viz.* MISA with DialogueRNN (MISA+DialogueRNN) and MISA with bcLSTM (MISA+bcLSTM). Here, MISA acts as a fusion model while DialogueRNN and bcLSTM are contextual models for conversation classification. DialogueRNN and bcLSTM have shown excellent performance in different conversation classification tasks such as Emotion Recognition Conversation. For MISA+DialogueRNN, we first pass multimodal inputs through MISA and obtain the fused features. These fused features are then

²Total of 4.46 hours in length

³There are 1/3rd utterances which are humorous.

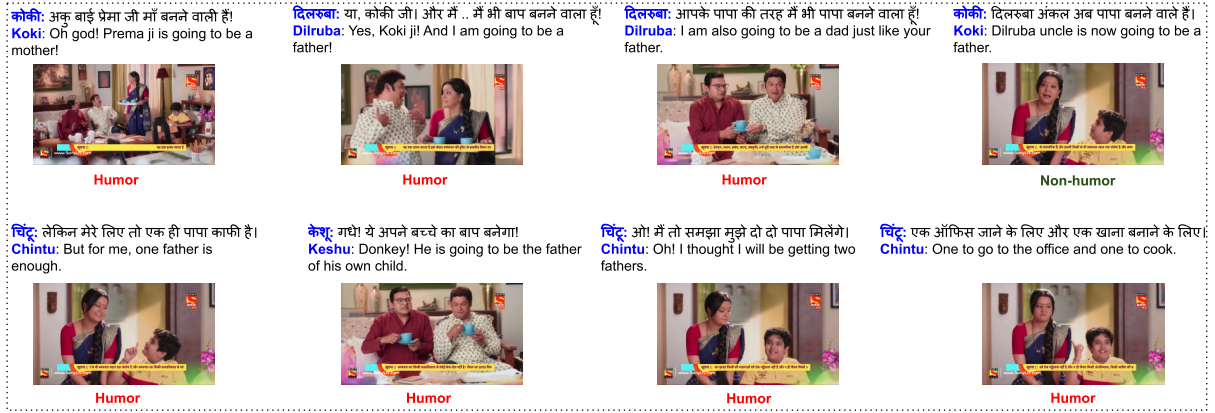


Figure 1: Some samples from dataset.

passed through DialogueRNN for humor classification. Similarly, for MISA+bcLSTM, We first pass multimodal inputs through MISA and obtain the fused features. Then, these fused features are passed through bcLSTM for humor classification.

3.4 Feature Extraction

For textual features, we take the pre-trained 300-dimensional Hindi *fastText* embeddings [13]. For visual feature extraction, we use 3D-ResNeXt-101⁴ [30] which is pre-trained on Kinetics at a rate of 1.5 features per second and a resolution of 112. While, we use openSMILE [6] for acoustic feature extraction. openSMILE⁵ can extract Low-Level Descriptors (LLD) and change them using different filters, functions, and transformations. We use a tonal low-level features group of openSMILE to extract the features.

4 EXPERIMENTS AND ANALYSIS

4.1 Experimental Setup

We evaluate our proposed model on the M2H2 dataset. We perform five-fold cross-validation for experiments. Empirically, We take five⁶ utterances as context for a particular utterance.

We implement our proposed model on the Python-based PyTorch⁷ deep learning library. As the evaluation metric, we employ precision (P), recall (R), and F1-score (F1) for humor recognition. We use Adam as an optimizer, Softmax as a classifier for humor detection, and the categorical cross-entropy as a loss function.

4.2 Results and Analysis

We evaluate our proposed architecture with all the possible input combinations (c.f. Table 2) i.e. unimodal (T , A , V), bimodal ($T+A$, $A+V$) and trimodal ($T+V+A$).

For MISA+DialogueRNN, trimodal achieves the best precision of 71.21% (16.05⁸ points \uparrow and 9.51⁹ points \uparrow), recall of 72.11% (14.79

Labels	MISA+DialogueRNN			MISA+bcLSTM		
	P	R	F1	P	R	F1
T	67.11	68.21	67.65	66.27	66.51	66.38
A	57.91	59.10	58.52	57.51	58.92	58.21
V	55.16	57.32	56.74	53.13	55.21	54.19
$T+V$	70.03	70.61	70.31	67.74	68.89	68.31
$T+A$	69.70	69.90	69.63	67.41	68.12	67.75
$A+V$	61.70	63.21	62.44	59.61	61.23	60.40
$T+V+A$	71.21	72.11	71.67	69.04	69.83	69.43

Table 2: Experiment results for MISA+DialogueRNN and MISA+bcLSTM.

points \uparrow and 8.9 points \uparrow) and F1-score of 71.67% (14.93 points \uparrow and 9.23 points \uparrow). We observe that trimodal performs better than the unimodal and bimodal. We show the results in Table 2.

Similarly, for MISA+bcLSTM, trimodal achieves the best precision of 69.04% (15.91¹⁰ points \uparrow and 9.43¹¹ points \uparrow), recall of 69.83% (14.62 points \uparrow and 8.6 points \uparrow) and F1-score of 69.43% (15.24 points \uparrow and 9.03 points \uparrow). We observe that trimodal performs better than the unimodal and bimodal.

4.3 Ablation Study

We also perform an ablation study (c.f. Table 4) to show the efficacy of contextual models. We perform experiments on MISA (i.e., without contextual information). As per the result, we can see when MISA is used with contextual models (bcLSTM or DialogueRNN) it shows significant improvement rather than when it uses alone.

4.4 Error Analysis

In this section, we perform error analysis for our baseline system i.e. MISA+DialogueRNN. We take some samples which are correctly and incorrectly predicted by the baseline model to analyze the model's strengths and weaknesses.

⁴<https://github.com/kaiqiangh/extracting-video-features-ResNeXt>

⁵<https://github.com/audeerling/opensmile>

⁶Baseline models give the best result at five.

⁷<https://pytorch.org/>

⁸maximum improvement over unimodal (V)

⁹maximum improvement over bimodal ($A+V$)

¹⁰maximum improvement over unimodal (V)

¹¹maximum improvement over bimodal ($A+V$)

Correct Prediction					
Hindi Utterances	English Utterances	Actual	Predicted		
			Unimodal (T)	Multimodal (T+V+A)	
1 अरे बुढ़ापे में मैं तुम्हें खुद ले के जाता।	Oh in old age I would have taken you myself.	humor	non-humor	humor	
2 ये दिलरुबा कहता है ना कि पिछले जन्म में वो छोटूमल मोटूमल करोड़पति का एकलौता बेटा था, राइट?	This Dilruba says that he was the only son of Chhotumal Motumal Crorepati in his previous life, right?	non-humor	humor	non-humor	
3 स्टाफ वालों! मेरा मतलब	Staff guys! I mean	humor	non-humor	humor	
4 कुछ याद आया? कुछ याद आया?	Remember anything? remember something?	non-humor	humor	non-humor	
5 जाते वक्त ऐसी अशुभ बातें नहीं करते।	Do not do such inauspicious things while leaving.	humor	non-humor	humor	
Incorrect Prediction					
1 ये लोग मुझे बहुत मार रहे हैं।	These guys are beating me hard	humor	non-humor	non-humor	
2 हाय, टोटा!	hey, Toto!	non-humor	non-humor	humor	
3 ये पिंकी लाई।	Pinky brought this	humor	humor	non-humor	
4 अरे भाई, मेरी असली वाली गन यहीं छुट गैड।	Hey brother, my original gun is left here	non-humor	humor	humor	
5 कौन सी असली है कौन सी नकली है।	which is real which is fake	non-humor	non-humor	humor	

Table 3: Error analysis: Some correct and incorrect predicted samples.

Setup	P	R	F1
MISA+DialogueRNN	71.21	72.11	71.67
MISA+bcLSTM	69.04	69.83	69.43
MISA	67.61	70.26	68.90

Table 4: Ablation study

We show a few samples¹² (c.f. Table 3) which are correctly predicted by the multimodal setup, but incorrectly predicted by the unimodal setup. For example, second utterance of the corrected prediction in Table 3, ये दिलरुबा कहता है ना कि पिछले जन्म में वो छोटूमल मोटूमल करोड़पति का एकलौता बेटा था, राइट? (This Dilruba says that he was the only son of Chhotumal Motumal Crorepati in his previous life, right?) Gokhale is giving idea to Keshav with a polite tone and neutral facial expression. The actual label is non-humor but the unimodal model (text) predicts it as humorous instance while the multimodal model predicts the label correctly because it is clear from the acoustic and visual features that there were no humorous punches but only normal talk. We show some visual frames in Figure 2 which clearly show the neutral facial expression.

गोखले: ये दिलरुबा कहता है ना कि पिछले जन्म में वो छोटूमल मोटूमल करोड़पति का एकलौता बेटा था, राइट?
Gokhale: This Dilruba says that he was the only son of Chhotumal Motumal Crorepati in his previous life, right?



Figure 2: Some visual frames of second utterance of correct prediction in Table 3.

On the other hand, we also show some samples, where the multimodal model fails to predict the correct label. For example, first utterance of incorrect prediction in Table 3, ये लोग मुझे बहुत मार रहे हैं। (these guys are beating me hard) has the actual label as humor. But, the multimodal fails to predict the correct label because of the sad tone and the sad visual expression of Dilruba (दिलरुबा). We

show some visual frames in Figure 3 which clearly shows the sad facial expression of Dilruba.

दिलरुबा: ये लोग मुझे बहुत मार रहे हैं
Dilruba: These guys are beating me hard

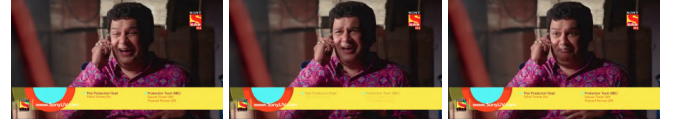


Figure 3: Some visual frames of first utterance of incorrect prediction in Table 3.

5 CONCLUSION

In this paper, we have presented a novel *Multimodal Multi-party Hindi Humor* (M2H2) recognition dataset for conversations (4.46 hours in length). We employed two strong baseline setups, viz. MISA with DialogueRNN and MISA with bcLSTM. MISA is a fusion model while DialogueRNN and bcLSTM are contextual models. We believe this dataset will also be useful as a useful resource for both conversational humor recognition and multimodal artificial intelligence. Empirical results on the M2H2 dataset demonstrate that the multimodal baselines yield better performance over the unimodal framework.

In the future, we would like to extend our work towards the multi-party dialogue generation in Hindi with the help of humor and speaker information.

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¹²For the global audience, we also translate these Hindi utterances into English.

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