EmoInHindi: A Multi-label Emotion and Intensity Annotated Dataset in Hindi for Emotion Recognition in Dialogues

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Abstract

The long-standing goal of Artificial Intelligence (AI) has been to create human-like conversational systems. Such systems should have the ability to develop an emotional connection with the users, hence emotion recognition in dialogues is an important task. Emotion detection in dialogues is a challenging task because humans usually convey multiple emotions with varying degrees of intensities in a single utterance. Moreover, emotion in an utterance of a dialogue may be dependent on previous utterances making the task more complex. Emotion recognition has always been in great demand. However, most of the existing datasets for multi-label emotion and intensity detection in conversations are in English. To this end, we create a large conversational dataset in Hindi named EmoInHindi for multi-label emotion and intensity recognition in conversations containing 1,814 dialogues with a total of 44,247 utterances. We prepare our dataset in a Wizard-of-Oz manner for mental health and legal counselling of crime victims. Each utterance of the dialogue is annotated with one or more emotion categories from the 16 emotion classes including neutral, and their corresponding intensity values. We further propose strong contextual baselines that can detect emotion(s) and the corresponding intensity of an utterance given the conversational context.

Keywords: Multi-label Emotion and Intensity Recognition, Dialogues, Low-resource Language

1. Introduction

Emotions are fundamental human characteristics that have been researched for many years by researchers in psychology, sociology, medicine, computer science, and other domains. Ekman’s six-class categorization (Ekman, 1992) and Plutchik’s Wheel of Emotion which proposed eight basic bipolar emotions (Plutchik and Kellerman, 2013), are two notable works in understanding and categorising human emotions. Emotions play an important role in our daily life and emotion detection in text has become a longstanding goal in Natural Language Processing (NLP). Emotions are inherently conveyed by messages in human communications. With the popularity of social media platforms like Facebook Messenger, WhatsApp and conversational agents like Amazon’s Alexa, there is a growing demand for machines to interpret human emotions in real conversations for more personalized and human-like interactions.

The ability to effectively identify emotions in conversations is crucial for developing robust dialogue systems. There are two major types of dialogue systems: a task-oriented dialogue systems and a social (chit-chat) dialogue system. The former is concerned with creating a personal assistant capable of performing specific tasks, but the latter is concerned with capturing the conversation flow, which focuses more on the speaker’s feelings. In both these systems, understanding the user’s emotions is crucial for providing better user experience and maximizing the user satisfaction. Nowadays, many websites, blogs, tweets, conversational agents support Hindi language and some of them use Hindi as a primary language as well. However, most studies of emotion in conversations have focused on English language interactions (Chen et al., 2018; Yeh et al., 2019; Hazarika et al., 2018; Ghosal et al., 2019; Kim et al., 2018; He and Xia, 2018; Yu et al., 2018; Huang et al., 2019); comparatively very little attention is given to emotion detection in regional languages like Hindi. Towards this end, we propose a novel conversational dataset EmoInHindi for identifying emotions (e.g., joy, sad, angry, disgusted etc.) in textual conversations in Hindi language, where the emotion of an utterance is detected in the conversational context.

1.1. Problem Definition

Given a textual utterance of a dialogue along with the conversation history (previous few utterances in dialogue), the task is to identify the emotion category(s) of each utterance from a set of pre-defined emotion categories and their corresponding intensity values. Formally, given the input utterance $U_t$ consisting of sequence of words $U_t = \{w_1, w_2, ..., w_T\}$ and the conversation history $C$ consisting of sequence of utterances $C = \{U_1, U_2, ..., U_{t-1}\}$, the task is to predict one or more emotion label, $e = \{e_1, e_2, ..., e_L\}$ from N pre-defined set of emotions and corresponding intensity value $i = \{i_1, i_2, ..., i_L\}$, where $i_k \in \{0, 1, 2, 3\}$ of the utterance $U_t$. Fig. 1 depicts a sample dialogue from our dataset, where each utterance is labeled with one or more underlying emotions and corresponding intensity value.
1.2. Contribution
The key contributions of our work are two-fold:

- We propose EmoInHindi\footnote{https://www.iitp.ac.in/ai-nlp-ml/resources.html}, the currently largest Hindi conversational dataset labeled with multiple emotions and their corresponding intensity values.
- We setup strong baselines for utterance-level multiple emotion and intensity detection task and report their results for identifying emotion(s) and the corresponding intensity expressed in an utterance of a dialogue written in Hindi.

2. Related Work
With the development in Artificial Intelligence (AI), emotion classification has become a significant task because of its importance in many downstream tasks like response generation for conversational agents, customer behavior modeling, multimodal interactions and many more. Recently, Kim et al. (2018)\cite{kim2018investigated} investigated multi-label emotion classification for textual data. Kim et al. (2018)\footnote{https://www.iitp.ac.in/ai-nlp-ml/resources.html} performed multi-label emotion classification on twitter data using multiple Convolution Neural Network (CNN) networks along with self-attention and Huang et al. (2019)\cite{huang2019employed} employed sequence-to-sequence framework for multi-label emotion classification. Yu et al. (2018)\cite{yu2018improved} improved the performance of multi-label emotion classification on twitter data by using transfer learning. Our present study differs from the previous multi-label emotion classification research in that we categorise emotions of utterances of conversations, which require contextual knowledge from previous utterances, making the task more difficult and intriguing.

Recently, emotion recognition in conversations has been in demand. Li et al. (2017)\cite{li2017developed} developed a high-quality multi-turn dialogue dataset, DailyDialog labelled with emotion information. Chen et al. (2018)\cite{chen2018proposed} proposed a corpus named EmotionLines for detecting emotions in dialogues gathered from Friends TV scripts and private Facebook messenger dialogues. EmoContext \cite{chatterjee2019another} is the another publicly available conversational dataset for emotion detection. All these datasets mostly focus on chit-chat dialogues. Lately, Feng et al. (2021)\cite{feng2021introduced} introduced EmoWOZ, a large-scale manually emotion-annotated corpus of task-oriented dialogues.

Most of the existing methods and resources developed for emotion analysis are available in English \cite{yadollahi2017lately}. Lately, there has been work on developing resources for detecting emotions from Hindi text. For instance, Vijay et al. (2018)\cite{vijay2018created} created a corpus, consisting of sentences from Hindi-English code switched language used in social media for predicting emotions. Likewise, Koolagudi et al. (2011)\cite{koolagudi2011proposed} proposed a Hindi corpus consisting of sentences taken from auditory speech signals for emotion analysis task. Another Hindi dataset consisting of sentences from news documents of disaster domain for emotion detection was proposed by Ahmad et al. (2020)\cite{ahmad2020presented}. Kumar et al. (2019)\cite{kumar2019presented} presented a largest annotated corpus in Hindi comprising of sentences taken from various short stories in which each sentence is annotated with relevant emotion categories given the context of a sentence. However, all of these works are focused on non-conversational settings. The long-term goal of our present work is to build a dialogue system capable of having a conversation with the user in Hindi. Such a system should not only be able to respond in Hindi according to the user’s intent, but its utterances should also be aligned with the user’s emotional state. As opposed to existing works on emotion detection from textual data in Hindi language, our present work provides a multi-label emotion and intensity annotated conversational dataset in Hindi.
3. Dataset

In this section, we describe the complete details of our EmoInHindi dataset.

3.1. Dataset Preparation

The dataset that we prepared for our experiment comprises of dialogues focused on mental health counselling and legal assistance for women and children who have been victims of various types of crimes ranging from domestic violence, workplace harassment, matrimonial fraud, to cybercrimes like cyber stalking, online harassment, masquerading and trolling. We construct the dataset in Hindi in Wizard-of-Oz (Kelley, 1984) style. Every dialogue in the dataset starts with a basic description of the victim, after which the victim is asked about the problem and accordingly provided with the required assistance. The crime victims need emotional comfort and support for expressing their feelings freely, hence the dialogue systems should interact with the users empathetically. Such conversational agents that comprehend human emotions assist in enhancing the user’s communication with the system, thereby strengthening the communication in a positive direction (Martinovsky and Traum, 2006; Prendinger and Ishizuka, 2005). We have annotated every utterance in a dialogue with multiple appropriate emotion categories and their corresponding intensity.

3.2. Guidelines for Dataset Preparation

We contacted an expert in mental health counselling from our institute health department to understand the flow of dialogues in victims’ situations to create the conversations. At first, we tried to find out the problems of the victims and assessed their psychological needs. While counselling the victims, we make sure to be patient and kind towards them. The victims were provided a non-judgemental environment to share as much information they are comfortable to and if the victims decide to report the assault, seek medical attention, or contact organizations that can help them, then we assist them accordingly by providing the relevant legal, medical and organization information. Eventually, this was created to help the victims identify ways in which the victims can re-establish their sense of physical and emotional safety and provided a few basic safety suggestions to them so that they are aware of the crimes and can prevent such events in the future.

3.3. Annotation

The utterances in every dialogue of our proposed Hindi dataset is annotated with one or more appropriate emotion categories and their corresponding intensity. For annotating the dataset, we consider 15 emotions, namely Anticipation, Confident, Hopeful, Anger, Sad, Joy, Compassion, Fear, Disgusted, Annoyed, Grateful, Impressed, Apprehensive, Surprised, Guilty as emotion labels for the utterances in a dialogue. The emotion annotation list has been extended to incorporate one more label, namely Neutral. The “Neutral” label is designated to utterances having no-emotion. While annotating the dataset, every utterance in a given dialogue is labeled with one or more emotions. Every emotion label is accompanied with an intensity value ranging from 1-3, with 1 indicating the lower intensity and 3 the highest. The Neutral label has intensity value of 0.

For annotating the utterances in our dataset, we employ three annotators highly proficient in Hindi and have prior experience in labelling emotions in conversational settings. The guidelines for annotation along with some examples were explained to the annotators before starting the annotation process. The annotators were asked to label each utterance of every dialogue with emotion(s) and corresponding intensity value. We achieve the overall Fleiss’ (Fleiss, 1971) kappa score of 0.84 for the emotions, 0.88 for intensity, which can be considered reliable. To determine the final label of the utterances, we use majority vote.

3.4. Challenges

Generic Challenges:

Counselling the victim and providing relevant assistance to them is a challenging task. If the intelligent agent does not seem supportive and understanding, the victim feels even more frightened and alone. Consequently, we came across various challenges while creating our conversational dataset which are as follows:

- Counselling the victims according to their needs and mental state was a difficult assignment because of distinct mental state and need of every single individual.
- Difficult to recognize and customize empathetic messages for different individuals as each individual has different emotional state. Depending upon the situation, one individual may show few emotions with lower intensity while the other may express his/her emotions intensely. Hence, responding empathetically according to the user’s state is crucial for creating an amicable environment for them. For example, consider the following few utterances of two different
dialogues from our dataset with emotion(s) and corresponding intensity shown in parentheses in Table 1 which shows different empathetic responses of the agent depending upon situation and emotional state of different users.

- Providing relevant and appropriate legal information to the victims.
- Providing step-by-step guidelines to victims for reporting the assault to the law enforcement agencies.
- Helping the victim in re-establishing their sense of physical and emotional safety by being empathetic towards them.

| Metrics                          | Dataset |
|----------------------------------|---------|
| # Dialogues                      | 1814    |
| # Utterances                     | 44247   |
| Avg. utterances per dialogue     | 24.39   |
| Avg. # of emotions per dialogue  | 1.41    |
| Avg. # of emotions per utterance | 1.43    |
| # of unique tokens               | 7036    |
| Avg. # of tokens per utterance   | 18.67   |

Table 2: Dataset statistics

Annotation Challenges: The system needs to capture the correct emotion and accordingly handle the user by replying empathetically. Annotating the data with appropriate emotion and corresponding intensity is sometimes challenging. Apart from generic challenges mentioned in the previous section, we came across a few challenges while annotating the emotions which are as follows:

- Identification of implicit emotions: It is not always the case that emotions are communicated explicitly. We asked our annotators to identify both explicit as well as implicit emotions in the utterances. An example of explicitly expressed emotion would be Example 1 in which the speaker is clearly expressing that she is sad through the words नक्ष(hell), बुरा(bad) and तक(tired) because her husband tortures her.

Example 1: मेरी जिन्दगी नक्ष का गुट्टा है। मैं अपने पति और उसकी यादनाओ से भक्ति कुपल हूँ। (My life has become hell, I feel too bad nowadays. I am tired of my husband and his tortures.)

Identification of implicit emotions are sometimes confusing for the annotators due to lack of explicit emotion pointer. For instance, in Example 2 in which a user is saying that her friend started laughing (in Utterance 3). In the absence of contextual information, this will be perceived as Joy. However, by looking at the context of the utterance, this will be annotated with Surprised, Sad as emotion labels.

Example 2: Utterance 1: मेरे दोस्त को नक्ष का गुट्टा है। (My friend needs help because she is in trauma)

Table 3: Emotion Distribution
Table 4: Comparison of different datasets and our proposed EmoInHindi dataset

| Dataset                          | # of sentences | # of emotions | Emotion Intensity | Annotation | Language    | Conversational | Multi-label |
|----------------------------------|----------------|---------------|-------------------|------------|-------------|----------------|-------------|
| (Vijay et al., 2018)             | 2866           | 6             | No                | Hindi-English code-mixed | No | No |
| (Koolagudi et al., 2011)         | 12000          | 8             | No                | Hindi      | No | No |
| (Harikrishna and Rao, 2016)      | 780            | 5             | No                | Hindi      | No | No |
| (Kumar et al., 2019)             | 20304          | 5             | No                | Hindi      | No | No |
| (Ahmad et al., 2020)             | 2668           | 9             | No                | Hindi      | No | No |
| EmoInHindi                       | 44247          | 16            | Yes               | Hindi      | Yes | Yes |

3.5. Dataset Statistics
In Table 5 we provide the important statistics of the dataset followed by the overall emotion distribution of our dataset in Table 4.

3.6. Comparison with the related datasets
The available datasets for emotion detection are mostly in English. Towards the task of emotion detection from Hindi text, previous attempts have been made in creating corpus containing 2,866 sentences for predicting emotions from Hindi-English code switched language used in social media (Vijay et al., 2018). A Hindi dataset, IITKGP-SEHSC consisting of 12,000 sentences collected from auditory speech signals was proposed by (Koolagudi et al., 2011). Another dataset with 780 Hindi sentences collected from children stories belonging to three genres, namely fable, folk-tale and legend and annotated with five different emotion categories: happy, sad, anger, fear and neutral was introduced in (Harikrishna and Rao, 2016). Lately, the authors in (Kumar et al., 2019) introduced the first largest annotated Hindi corpus named BHAAV for emotion detection consisting of 20,304 sentences from 230 popular Hindi short stories spanning across frequently used 18 genres, viz. historical, mystery, patriotic to name a few. The authors in (Ahmad et al., 2020) proposed Hindi corpus, Emo-Dis-HI consisting of 2,668 sentences from news documents of disaster domain, where each sentence is labeled with one of the emotion categories viz., sadness, sympathy/pensiveness, optimism, fear/anxiety, joy, disgust, anger, surprise and no-emotion. When it comes to the task of analyzing emotions from Hindi text in conversational setting, there are no conversational dataset available in Hindi. Our proposed dataset is different from the existing datasets for emotion detection from Hindi. The dataset that we present here is the first large-scale goal-oriented conversational dataset comprising of 1814 dialogues with each utterance in dialogues annotated for multi-label emotion and corresponding intensity value. Comparisons between the existing datasets and our proposed dataset, EmoInHindi are given in Table 4.

Table 5: Hyper-parameters for our experiments where.

4. Baselines
We use the following baseline models:
Baseline #1: bcLSTM: The bidirectional contextual LSTM bcLstm(Poria et al., 2017) is a bidirectional contextual LSTM. Two uni-directional LSTMs with
opposite directions are stacked to create bi-directional LSTMs. As a result, an utterance may learn from utterances in the video that occur before and after it, which is, of course, context.

**Baseline #2: bcLSTM+Attention:**
At each timestamp, an attention module is added to the output of c-LSTM in this bcLSTM with attention (Poria et al., 2017) model.

**Baseline #3: Conversational Memory Network (CMN):** Using two different GRUs for two speakers, CMN (Hazarika et al., 2018) models utterance context from dialogue history. Finally, utterance representation is obtained by querying two separate memory networks for both speakers with the current utterance. However, this model can only model two-person conversations.

**4.1. Proposed: C-Attention-Trans and C-Fourier-Trans**

We use the transformer encoder suggested by (Vaswani et al., 2017) for Context-Attention-Transformer. A C-A-Transformer is proposed to capture the deep contextual relationship with input utterance. We use a Transformer-based method to capture the flow of informative triggers across utterances. The Context-Attention-Transformer receives the input embedding and captures the input utterance’s deep contextual relationship.

We employ the Fourier transform instead of self-attention, as suggested by F-Net (Lee-Thorp et al., 2021) for Context-Fourier-Transformer. 1D Fourier Transforms are used to transform both the sequences and hidden dimensions. Instead self-attention, this trick proved to be effective.

**Working method of the model**

Suppose text features have dimension $d$, then each utterance is represented by $u_{i,x} \in \mathbb{R}^d$ where $x$ represents $x^{th}$ utterance of the conversation $i$. To get $U_i$, we collect a number of utterance in a conversation $U_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,c_i}] \in \mathbb{R}^{c_i,d}$, where $c_i$ represents the number of utterances we consider as a context in a conversation. This $U_i$ is given to both C-A-Trans and C-F-Trans for the output. We show our model in Fig 3.

The output of the C-A-Transformer and C-F-
Transformer is fed to the FC Layer, which then passes it on to the Softmax Layer for emotion and intensity prediction.

**Loss function:** The emotion intensity classifier is trained by minimizing the negative log-likelihood

\[
\mathcal{L}_{\text{Emo}} = - \sum_{em=1}^{N} y_{em} \log \tilde{y}_{em}
\]

For multilabel emotion, we use MultiLabelSoftMarginLoss, where \( y_{em} \) is the true emotion labels and \( \tilde{y}_{em} \) is the predicted emotion label. For Emotion Intensity, we use MSE (Mean Squared Error) as the loss function.

Our loss function’s primary goal is to instruct the model on how to weight the task-specific losses. For this, we use a principled approach to multi-task deep learning that takes into account the homoscedastic uncertainty (task dependent or homoscedastic uncertainty is aleatoric uncertainty that is not depending on the input data). Homoscedastic is a number that remains constant throughout all input data and changes between jobs. Task-dependent uncertainty is the effect of this, while weighting multiple loss functions (Kendall et al., 2018) of each task.

\[
\mathcal{L} = \sum_{i} W_{i} \mathcal{L}_{i}
\]

Where \( i \) defines different tasks (emotion classification and intensity).

## 5. Results and Analysis

### 5.1. Feature Extraction and Data Distribution for Experiment

For textual features, we take the pre-trained 300-dimensional Hindi fastText embedding (Joulin et al., 2016). We obtain the training and testing set using 80:20 split of the dataset. Further, the 20% of the training set is used as validation set during training to keep track of model training progress. Empirically, we take five utterances as context for a particular utterance.

### 5.2. Experimental Setup

We implement our proposed model in PyTorch, a Python-based deep learning library. We perform grid search to find the optimal hyper-parameters in Table 5. We use Adam as an optimizer. We use Softmax as a classifier for emotion. We use Transformer Encoder with two layers. The embedding size is set to 300, and the learning rate is set to 0.003. We use negative log-likelihood loss for emotion prediction. Our model converges with 30 epochs and we use 32 batch size.

### 5.3. Results

C-F-Trans, achieves the best precision of 65.98% (2.22 points ↑ in comparison of C-A-Trans and 2.85 points ↑) in comparison of bc-LSTM, 5.44 points ↑ in comparison of bc-LSTM+att, 6.26 points ↑ in comparison of bc-LSTM, recall of 66.52% (1.70 points ↑ in comparison of C-A-Trans and 2.84 points ↑) in comparison of CMN, 4.7 points ↑ in comparison of bc-LSTM+att, 6.8 points ↑ in comparison of bc-LSTM,) and F1-score of 66.24% (1.98 points ↑ in comparison of C-A-Trans and 2.87 points ↑) in comparison of CMN, 5.06 points ↑ in comparison of bc-LSTM+att, 6.82 points ↑ in comparison of bc-LSTM,). Accuracy of 67.14% (1.52 points ↑ in comparison of C-A-Trans and 3.63 points ↑) in comparison of CMN, 5.23 points ↑ in comparison of bc-LSTM+att, 6.19 points ↑ in comparison of bc-LSTM,). We observe that C-F-Trans performs better than the C-A-Trans. We show the results in Table 6 for single label emotion and intensity. For Multi-label emotion C-F-Trans, achieves the best JI of 0.055% (0.04 points ↓ in comparison of C-A-Trans, 0.018 points ↓, and 0.020 points ↓ in comparison of bc-LSTM+ATT) and C-F-Trans, achieves the best JJ of 0.055% (0.03 points ↑ in comparison of C-A-Trans, 0.08 points ↑, and 0.09 points ↑ in comparison of bc-LSTM+ATT). We show the results in Table 5.

### 5.4. Error Analysis

We show a few sample predictions (c.f. Table 7) which are correctly predicted by our proposed model (C-F-Trans). For example, as shown in Table 7, "कुक्कु यूरी सहिष्णुता करे। (Rakshak my landlord is try to harass me. Please help me.) have label Sad,Annoyed and intensity 3.1 correctly predicted by our model (C-F-Trans). But our model also confused some situations as for example, "मैं आयोज में छा लिख सकता हूँ? मुझे ग्राफ मन कराएगा। (What can I write in the application? Don’t call me dear) have label Anticipation, Annoyed but our model predicted Joy due to word ग्राफ (dear) which is maximum used with emotion Joy. So our model predicted Joy emotion and Grateful as it is come with Joy most of the time.

## 6. Conclusion and Future Direction

In this paper, we have introduced a large-scale Hindi conversational dataset, EmoInHindi prepared in Wizard-of-Oz fashion for multi-label emotion

\[\text{Table 8: Result Analysis For Single label Emotion with Intensity}\]

| Methods                     | Accuracy | Precision | Recall | F1    |
|-----------------------------|----------|-----------|--------|-------|
| bc-LSTM (Ponsa et al., 2017)| 60.95    | 59.13     | 59.72  | 59.42 |
| bc-LSTM+Attn (Ponsa et al., 2017) | 61.91 | 60.54     | 61.82  | 61.18 |
| CMN (Hazarika et al., 2018) | 65.51    | 63.13     | 64.68  | 63.35 |
| C-Attention-Trans (Ours)   | 65.62    | 63.76     | 64.82  | 64.20 |
| C-Fourier-Trans (Ours)     | 67.14    | 65.98     | 66.52  | 66.24 |

\[\text{For the global audience, we also translate these Hindi utterances into English.}\]
classification and intensity prediction in dialogues. We have evaluated our proposed EmoInHindi dataset and reported the results using strong baselines for both tasks of emotion recognition and intensity prediction. We believe that this dataset can be employed in the future for for making emotion-aware conversational agents capable of conversing with the users in Hindi. Furthermore, we would like to extend this work for more low-resource languages like Bengali, Marathi etc. so that it can be used to create emotionally-aware conversational systems that can interact with the users in their regional language thereby creating a more user-friendly environment for them.

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