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PUNJABI EMOTIONAL TEXT DATABASE: ANNOTATIONS, STRUCTURE AND VERIFICATION

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Abstract

This paper introduces Punjabi Annotated Emotional Text Database which has been created to classify human emotions in six different categories as anger, disgust, fear, happiness, sadness and surprise. Various online resources are used to prepare this database and then various preprocessing steps are applied to normalize the data. Text containing total 354796 words is collected. Database of these words consists of each category of above discussed. This database has been verified by 150 people of an average age group from 15 years to 50 years. For this randomly 10 sentences of all the classes were given to recognize the emotion category present in the specified sentence. Results of verification are measured under various standard metrics. Finally, this annotated emotional database is used for the development of emotion detection system for Punjabi text data.

Keywords: Punjabi Text, Annotated Emotional Database, Emotion Detection, Recognition Rate

1. Introduction

Emotion detection is the way to identify a human being's emotional state or state of mind. These states of mind can be happiness, joy, anger, sadness, disgust, fear, love, abuse, hopefulness, information, forgiveness, blame, guilt, hopelessness, pride, sorrow, instructions, thankfulness, and confusion etc. In our real life emotions occupies an important role to share information between human beings. For development of emotion detection system, data can be collected from many real world events, blog posts, online websites, newspapers and surveys etc. (Bandhakavi et al., 2017; Bharti et al., 2022; Desmet and Hoste, 2013). Emotions can be extracted from speech, faces, gestures, body language and from text also (Nivetha et al., 2016; Shivhare and Saritha, 2014). Emotion, feeling, affect, opinion and sentiment are the terms which are interrelated and are used interchangeably (Saheen et al., 2014; Poria et al., 2015). These terms can be used interchangeably but it leads to confusion about features engaged in text analysis (Munezero et al., 2013; Gil et al., 2015; Tarhanicova et al., 2015). Though lots of research work has been done on Emotional Mining from text in English (Abdi et al., 2019; Kusal et al., 2021; Gao et al., 2015), Turkish, Arabian, Greek, Czech (Burget et al., 2011; Karin et al., 2017) and other languages but very little work has been done for Indian languages (Yar et al., 2016; Nandwani and Verma, 2021). Research work in this area has been done in many Indian languages such as Telgu, Bengali, Hindi and a few on Punjabi languages (Kaur and Gupta, 2014).

Emotion Monitoring is done to observe the various emotional states of human being's mind (Landowska et al., 2014; Kanjo et al., 2015; Servi and Elson, 2015). To observe this various emotional expressive features are used which helped us to find out various
emotional states. That features are as self reporting which is one of the oldest and popular way to gather emotional states. In this participants are asked to enter their state of mind manually. Though self reporting is comparatively realistic method of gathering people's emotional states, but sometimes people may not be want to share their true emotions either intentionally or unintentionally. So, this technique should only be applied when people volunteer them. Physiological signals are also being used for this purpose. In this emotions are detected by the use of various electronic devices such as wearable sensors. Speech is also widely used method for emotion detection by examining the aural features of speech and then correlates them with emotional state of the speaker. Facial expression, phone usage, mobile network data (Zualkernan et al., 2017) and social networks (Sun et al., 2018) are other emotion expressive features **(**Graterol et al., 2021; Krommyda et al., 2021). Human beings possess the capability to sense emotions. In our day to day life, people automatically reacted against emotions that happen to them. On the other hand, these emotional states also describe how people react and identify the circumstances they were passed through. So, the role of emotions in our real life should not be underestimated. That's why, it's the requirement of current market scenario to develop an automated emotion detection system that consist capability to detect and recognize and then categorize emotions of human being to make them capable to assist people in coping with their day to day emotional burden.

Sufficient work has been done on emotion detection from text documents for English and other foreign languages but till now a little work is reported for Indian languages. In Indian languages, research has been done on emotion detection from text of Hindi, Telugu, Bengali, and a few on Punjabi. Data collection is the most crucial and very first step for the development of emotion detection system. Databases for almost all other languages are available online but Punjabi emotional database is not available earlier. So, this is first time Punjabi emotional database has been created by collect the data from various online sources and then annotations are provided to all the data manually under six different labels. These labels are as anger, disgust, fear, happiness, sadness and surprise further this annotated database is used for training and after successful training this database is used for testing of the emotion detection system for Punjabi text data.

This paper consist various sections as Section 2 explains the structure of the annotated database with complete detail of data count; Section 3 provides verification process of the database and results and discussion with various performance measures; Section 4 brings to light on applicability of annotated database followed by the conclusion in the section 5.

2. Structure of Annotated Database

2.1. Design of Database

Data in Punjabi language is collected from various online sources; major portion of data is collected from Punjabi online newspapers. Data is saved in the form of various text files. This collected data is in the raw form. Various pre-processing functions are applied on it to make it usable for machine learning and classification process. These steps are required to refine the data. These steps include normalization of text data, tokenization, stop word removal, and morphological analysis etc. But before these pre-processing steps, one necessary step is to provide annotations to all the text files manually and then categorize them under six different labels as anger, disgust, fear, happiness, sadness and surprise. This annotated database consists of total 1721 text files. Further each file contains data in the form of paragraphs, sentences and words. Anger contains 340 text files, disgust consists of 293 text files, fear consists of 258 text files, happiness consists of 280 text files, sadness consists of 280 text files, and surprise consists of 270 text files. Distribution of data in the form of percentage is shown in Figure 1.

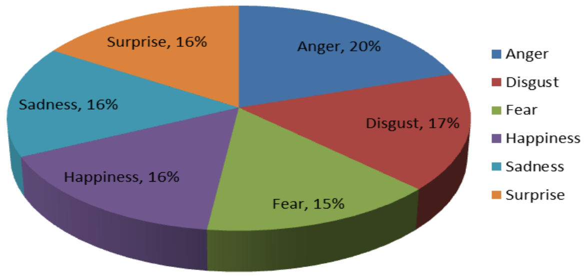

Figure 1: Distribution of data in database for various emotional classes

Figure 2 below provides a description of the text files needed to prepare database in terms of file count and size of files in KB.

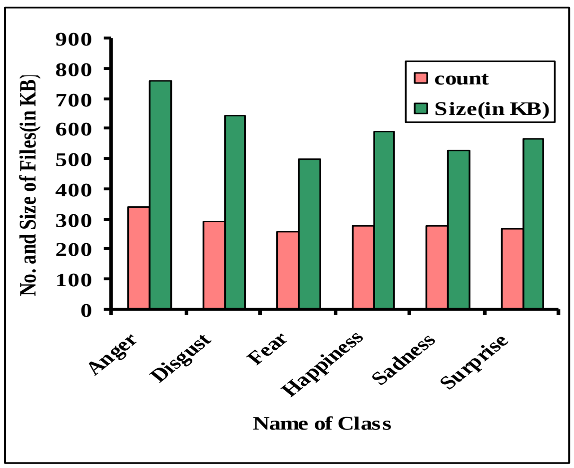

Figure2: Description of text files in database for all classes

Further, Table 1 states file counts, word counts and sentence counts contains by database for all the six classes.

Table1. Detailed description of data in all classes

Class Name	Number of Files	Number of Words	Number of Sentences
Anger	340	75058	2309
Disgust	293	64570	2016
Fear	258	50578	1714
Happiness	280	56286	1928
Sadness	280	52915	1848
Surprise	270	55389	1692

2.2. Sentences for Reading

For the subjective evaluation process and verification of database total 10 sentences were chosen randomly from database. All the sentences were free from bias and represented emotional classes very well. Following are the sentences as:

1. ਲੋਕ ਡਰ ਕਾਰਨ ਘਰਾਂ 'ਚੋਂ ਬਾਹਰ ਆ ਗਏ। (Lōka ḍara kārana gharāṁ'cōṁ bāhara ā ga'ē)
2. ਦੇਰ ਸ਼ਾਮ ਨੂੰ ਮੌਸਮ ਖ਼ਰਾਬ ਹੋਣ ਨਾਲ ਕਈ ਕਿਸਾਨਾਂ ਦੀ ਵੀ ਚਿੰਤਾ ਵੱਧ ਗਈ ਸੀ। (Dēra śāma nū mausama k̲h̲arāba hōṇa nāla ka'ī kisānāṁ dī vī citā vadha ga'ī sī)
3. ਟਰੱਕ ਤੇ ਮੋਟਰਸਾਈਕਲ ਦੀ ਟੱਕਰ 'ਚ ਇਕ ਨੌਜਵਾਨ ਦੀ ਮੌਤ ਹੋ ਗਈ ਹੈ। (Ṭaraka tē mōṭarasā'īkala dī ṭakara'ca ika naujavāna dī mauta hō ga'ī hai)
4. ਸੈਲਾਨੀਆਂ ਨਾਲ ਭਰੀ ਯਾਤਰੀ ਬੱਸ ਹਾਦਸਾਗ੍ਰਸਤ ਹੋ ਗਈ। (Sailānī'āṁ nāla bharī yātarī basa hādasā grasata hō ga'ī)
5. ਰੇਲ ਗੱਡੀ ਦੀ ਲਪੇਟ 'ਚ ਆਉਣ ਕਾਰਨ ਵਿਅਕਤੀ ਦੀ ਮੌਤ ਹੋ ਗਈ। (Rēla gaḍī dī lapēṭa'ca ā'uṇa kārana vi'akatī dī mauta hō ga'ī)
6. ਝਗੜੇ ਦੌਰਾਨ ਪਤੀ ਤੇਜ਼ਧਾਰ ਚਾਕੂ ਲੱਗਣ ਕਾਰਨ ਜ਼ਖ਼ਮੀ ਹੋ ਗਿਆ। (Jhagaṛē daurāna patī tēzadhāra cākū lagaṇa kārana zak̲h̲amī hō gi'ā)
7. ਹਾਂਡਾ ਵਲੋਂ 'ਐਕਟਿਵਾ ਇੰਡੀਆ' ਦੀ ਸ਼ੁਰੂਆਤ ਦਾ ਐਲਾਨ ਕੀਤਾ ਹੈ। (Hāṇḍā valōṁ' aikaṭivā iḍī'ā' dī śurū'āta dā ailāna kītā hai)
8. ਸੰਦੀਪ ਸਿੰਘ ਨੇ ਬਾਸਕਟਬਾਲ ਘੁਮਾਉਣ 'ਚ ਨਵਾਂ ਵਿਸ਼ਵ ਕੀਰਤੀਮਾਨ ਬਣਾਇਆ ਹੈ। (Sadīpa sigha nē bāsakaṭabāla ghumā'uṇa' ca navāṁ viśava kīratīmāna baṇā'i'ā hai)
9. ਚੰਡੀਗੜ੍ਹ ਪੋਲੀਟੈਕਨਿਕ ਕਾਲਜ ਵਲੋਂ ਪਲੇਸਮੈਂਟ ਦੇ ਖੇਤਰ 'ਚ ਸ਼ਾਨਦਾਰ ਰਿਕਾਰਡ ਕਾਇਮ ਕੀਤੇ ਗਏ ਹਨ। (Caḍīgaṛha pōlīṭaikanika kālaja valōṁ palēsamaiṇṭa dē khētara'ca śānadāra rikāraḍa kā'ima kītē ga'ē hana)
10. ਬੀ.ਐਸ.ਐਨ.ਐਲ. ਨੇ 6500 ਕਰੋੜ ਰੁਪਏ ਜੁਟਾ ਕੇ ਨਵੀਆਂ ਉਚਾਈਆਂ ਨੂੰ ਛੂਹਿਆ ਹੈ। (Bī. Aisa. Aina. Aila. Nē 6500 karōṛa rupa'ē juṭā kē navī'āṁ ucā'ī'āṁ nū chūhi'ā hai)

Above sentences are chosen carefully from real world data. These sentences are free from abbreviations, emojis, figures and fancy words etc. because we want to develop the realistic system that's why we have used such type of sentences for this evaluation process.

3. Verification of Database

3.1. Subjective Evaluation of Database

Subjective evaluation of data of various classes was held to validate the data that was collected earlier. This subjective evaluation was done by the 150 different readers. 10 sentences of all the classes were given to them for reading and recognizing the particular class of emotion of the sentence. No prior training and feedback were provided to readers. A classification test was held that how many out of them were able to recognize the emotion of the sentence correctly. All the readers are familiar with the Punjabi language very well so that they can provide us the correct results. This process helps us to find out the accuracy of the data in the database so that if any change is required then it could be implemented. The following steps were performed for the subjective evaluation.

1. 150 readers (out of which 75 male and 75 female) has been opted randomly to validate the data of all the classes and they all were of an average age group in between 15 years to 50 years.
2. 10 sentences of all the classes have been opted randomly from the database to check the classification test.

3. Data has been provided to all the readers for reading, understanding and recognizing the type of emotional class represents to that particular sentence. They were allowed to read the sentence again if they could not able to understand the emotional class of the sentence once.
4. Feedback regarding the data collection were also been taken from the readers so that data could be changed if there were any problem in the database.

The main objective behind this subjective evaluation procedure was the development of Punjabi emotional annotated text database which incorporates the specified emotions as well so that it could be able to develop the Punjabi text emotion detection system with great accuracy and also it could work smoothly on all other applications.

3.2 Results of Verification

The step of annotated data collection process followed the next step as subjective evaluation of the collected data. This is the necessary step to check the authenticity of the collected data with specified annotations of emotions in various classes of data. The results of above stated evaluation process are discussed in this section of paper. For this evaluation five metrics are calculated. Firstly recognition rate is calculated to measure the performance of subjective evaluation of data of various classes. Then this database is evaluated by finding the confusions between various classes and the confusion matrix is calculated for various classes. Third metric is precision which is followed by confusion matrix. The next metric is recall for subjective evaluation of database. The last metric is F1 score to evaluate the database. To summarize this results section Macro Average and Weighted Average are also calculated. These performance measures are discussed with their result details as:

1. Recognition Rate
2. Confusion Matrix
3. Precision
4. Recall
5. F1 Score

1. Recognition Rate

Here recognition rate consist total number of correct sentences classified with specified emotions divided by total sentences of that particular class in the given annotated database. The results of recognition rate are shown by the figure 3 below. As shown in the figure 3 recognition rates are good for anger, happiness and disgust as 97.20%, 96.80% and 96.53% respectively. On the other hand recognition rates are 95.33% for fear, 95.13% for sadness and 94.40% for surprise. Although recognition rate for some emotional classes are quite low as compared to others but overall the recognition rate for all the annotated emotional classes are good. The results for this subjective evaluation procedure are satisfactory for the further development of Punjabi emotional text classification system. Recognition rate for all the classes after this evaluation process is given below by figure 3

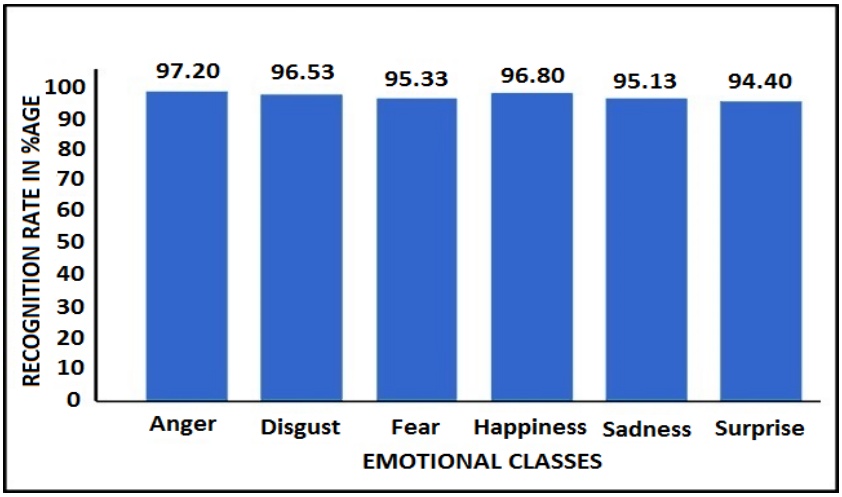

Figure 3: Recognition rates for all classes

2. Confusion Matrix

Another performance metric is a Confusion Matrix. Basically it is a graphical representation of the results of above said procedure. This is a matrix with equal row count and column count, in confusion matrix N represents count of target classes. Accuracy of any procedure alone can be mislead if we have not an equal number of observations in each class or if more than two classes exist in our dataset so, confusion matrix helps us to find what type of error are in our procedure because the another name of confusion matrix is error matrix. Each row in a confusion matrix gives an actual class on the other hand each column shows a predicted class. The basic proposal behind this matrix is to find that how many times the instances of a class are misclassified or in the other words we can say that how many times a classification model was confused the target class with predicted classes. Confusion matrix for the above discussed evaluation process for database is exposed by figure 4 below.

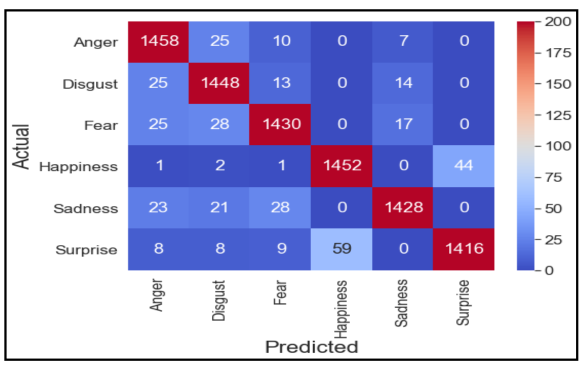

Figure 4: Confusion matrix for all classes

From this confusion matrix it can be noticed that anger emotion is most distinguishable and occurred less confusions with other emotional classes. Disgust and happiness classes have sometimes confused. Fear, sadness and surprise were also confused but very less extent. So, overall the results of this evaluation process are satisfactory. To wrap up confusion matrix is much healthier approach for evaluation of the correctness of classification method. Before taking into light on next performance measure we have to clear up four terms. The first one is True Positive, second is true Negative, thirds is False Positive and last is False Negative. These are discussed in next section.

3. Precision

This is very important and popular measure in classification process. It represents the division of total true positives count and total predicted positives count or we can say that it provides the value of division of positives predictions is really treated positive by evaluation process. It can be calculated by the following formula.

$$P = TP / (TP + FP)$$

Where P, TP, FP stands for precision, true positive and false positive respectively. True Positive states the total amount of terms correctly predicted as actual class. In the above example from the confusion matrix it can be seen that 1458 is the true positive value for anger class, 1448, 1430, 1452, 1428 and 1416 are for disgust, fear, happiness, sadness and for surprise respectively. False Positive states total amount of terms that incorrectly predicted as actual class. Results of Precision for anger is 0.95, for disgust is also 0.95 and 0.96, 0.96, 0.97 and 0.97 are for fear, happiness, sadness and for surprise respectively. The overall results for precision are quite satisfactory.

4. Recall

This is also very important and popular measure in classification process. It gives the total correct positive predicted classes from all positive classes from database. Recall provides information about those positive predictions that are missed. In other words recall states the division of true positive by addition of true positive with false negative. It can be described by the help of following formula.

$$R = TP/ (TP + FN)$$

Where R, TP and FN stands for recall, true positive and false negative respectively. False negative gives the total terms those are incorrectly predicted as negative class but actually these terms is positive. Results of recall for anger is 0.97, for disgust is also 0.97 and 0.95, 0.97, 0.95 and 0.94 are for fear, happiness, sadness and for surprise respectively. The overall result for recall is also quite satisfactory.

5. F1 Score

F1 score represents the Harmonic Mean of both measures. Those measures are recall and precision. It provides stability factor for the results of precision and recall in one number. It is one of the common measure to find out how successful a classification process is carried out? In order to calculate this firstly precision and recall have to calculate. It can be shown by the help of following formula:

$$\text{F1 Score} = 2\times [(P\times R) / (P+R)]$$

Results of F1 Score for anger is 0.96, for disgust is also 0.96 and 0.96, 0.96, 0.96 and 0.96 are for fear, happiness, sadness and for surprise respectively. From above results it can be observed that this performance measure provides same value for all the class labels which helps to know us about the success rate of the evaluation process without any confusion. The overall result for F1 Score is also quite satisfactory. Above are the various metrics to find out the performance of this subjective evaluation process. The results of these metrics can be summarized by the table 2.

Table 2: Results of precision, recall and f1 score

Metrics / Classes	Precision	Recall	F1 Score
Anger	0.95	0.97	0.96
Disgust	0.95	0.97	0.96
Fear	0.96	0.95	0.96
Happiness	0.96	0.97	0.96
Sadness	0.97	0.95	0.96
Surprise	0.97	0.94	0.96

From the above table it can be observed that the values of Precision and Recall provide a complete picture about the success rate of this evaluation process. F1 score also provides one value against all the labels of emotional classes. If the requirement of one single value is for precision and recall then we can be calculated other averaging methods. This average can also find out for F1 Score. Macro Average is one of the averaging methods. Another is Weighted Average. These averages are calculated as below.

i) Macro Average

This is nothing but it is the arithmetic mean of the precision of given classes. It returns a single value for all the classes which represents average precision value of this evaluation process. It can be find out by the following formula:

$$\text{Macro Average for Precision} = (0.95+0.95+0.96+0.96+0.97+0.97) / 6 = 0.96$$

In the same way Macro Average for Recall and F1 Score can be calculated as below by the following formula:

$$\text{Macro Average for Recall} = (0.97+0.97+0.95+0.97+0.95+0.94) / 6 = 0.96$$

$$\text{Macro Average for F1 Score} = (0.96+0.96+0.96+0.96+0.96+0.96) / 6 = 0.96$$

ii) Weighted Average

Weighted Average can be find out as the multiplication of the sum of the total data count by the precision of particular class divided by the data count for all classes in a database. In this database total numbers of data count is 1721. So to find out the weighted average for precision we can apply the following formula:

$$\text{Weighted Average for Precision} = (340\times0.95+293\times0.95+258\times0.96+280\times0.96+280\times0.97+270\times0.97) / 1721 = 0.96$$

In the same way Weighted Average for Recall and F1 Score can be calculated as below by the following formula:

Weighted Average for Recall = (340×0.97+293×0.97+258×0.95+280×0.97+280×0.95+270×0.94) / 6 = 0.96

Weighted Average for F1 Score = (340×0.96+293×0.96+258×0.96+280×0.96+280×0.96+270×0.96) / 6 = 0.96

Both the above averaging methods provide a single value with the help of which we can find out the success rate of the evaluation process. Any classification model can be evaluated with the help of these above discussed performance measures. The overall results of these metrics are satisfactory. Results of macro and weighted average are presented in table 3.

Table 3: Macro and weighted average of metrics for all the Classes

	Macro Average	Weighted Average
Precision	0.96	0.96
Recall	0.96	0.96
F1 Score	0.96	0.96

4. Applicability of Developed Database

This annotated Punjabi emotional database would further used for the development of emotion detection system from Punjabi text that also has immense potential for application areas in various fields such as in field of psychology to predict human's mind by deducing emotions from text provided by various people and helping psychologist to get away people from their depression and stress. Another major application of emotion detection from text is to provide the emotion tagged text as an input to text-to-speech synthesis system. Emotions can also be detected from social media, like from social media human's mood can be detected. Emotion detection from text also plays great role in monitoring behaviour control system, computational linguistics as opinion mining, affective computing and natural language interface and text based communication environments such as blogs and e-mails etc. and detecting personality traits. So, a wide range of applications are based on automated emotion detection system to mark emotion tags for Punjabi text.

5. Conclusion

In nutshell, we can say that the main goal behind creation of this annotated database is to find the realistic emotions from text of Punjabi language. Various standard steps were followed for collection, annotations, designing and verification of this database. Many challenges were came while making this process a real source

of emotions finder out of which one major obstacle was to find out those people who possessed reading and understanding capability of Punjabi language. Another major challenge was to selection of sentences so that it could represent the realistic emotions. Readers were also allowed to read again and again if they could not able to get the emotional class of given sentence once. Another major challenge was to selection of sentences so that it could represent the realistic emotions. This annotated emotional text database produced for Punjabi language would be further used for the development of Emotion Detection System for Punjabi Language.

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