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Human Emotion and Sentiment Analysis Using Machine Learning

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Abstract. Emotion recognition is an essential field of study in the current scenario that can be useful for variety of purposes. Emotions is indicated in several forms such as speech, facial expressions, gestures, and written text etc. Emotion recognition from text is considered under content-based classification and is a category of Natural Language Processing (NLP). In this work, authors tried to predict the human emotions from twitter text data which can be useful for human emotion prediction and interpretation of sentiment analysis. The dataset used in this work was downloaded from Kaggle open source repository and Python was used for implantation. The subjectivity and polarity of the sentiments were also analyzed using Python TextBlob. The Machine Learning (ML) algorithms such as Naïve Bayes (NB), Logistic Regression (LR), Bagging, and Support Vector Machine (SVM) were applied on the original dataset to measure the efficiency of these algorithms. We had also analyzed the presence of amount of types of emotion present in the dataset and then we removed those data which were present in less amount. Again on the reduced dataset, we applied these same ML algorithms and measured the efficiency using parameters like recall, precision, F-measure etc. The accuracies obtained for LR, NB, Bagging, and SVM classifier are found to be 85%, 69%, 84%, and 86% respectively in the original dataset and it was found to be 93%, 85%, 92%, and 94% respectively in the reduced dataset. From the experimentation, it was found that SVM performed better in both the cases and for each of the considered algorithm the accuracy was improved in the reduced dataset as compared to the considered dataset.

Keywords. Emotion, machine learning, sentiment analysis, polarity, subjectivity.

1 Introduction

Now-a-days, huge amounts of data are generated from different social networks which mainly contain our emotions, daily thoughts, and views. Various studies on emotion analysis were carried out by different researchers over the years on the data collected from social media platforms [12, 13, 15]. Since people share varying range of opinions, so it is very difficult to determine unique sentiment from social media data.

Hence, the study on sentiment analysis focused on developing methods to solve these types of issues and also provides many scopes for detection of human sentiment or emotions associated with a particular topic.

Users express their feelings in several ways on different social media networks, including Facebook, Instagram, Twitter etc.

In these networks, large number of people share reviews to express their feelings, emotions, and thoughts on a specific subject on and around them happening in their daily lives. This helps the researchers to analyze the feelings of different users' behaviors expressed in social networks.

Sentiment Analysis (SA) is considered as a super set of emotion detection which is used to predict the unique emotion instead of only identifying the emotion as negative, positive, or neutral. Human emotions play a vital role in our day-to-day life [2]. Emotional acceptance has application in several fields such as law, e-learning, medicine, advertising, etc. [3]. Human emotion prediction from text also becomes important for data analysis purpose and the emotions such as anger, joy, sorrow, delight, fear, hate etc., can be demonstrated [16].

1.1 Motivation

In this work, Twitter data was chosen for experimentation. The objective of this work was to detect and analyze both sentiments and emotions conveyed by people in terms of texts in their Twitter posts. The motivation behind human emotion prediction using SA and ML is to enhance understanding of human emotions in textual data, enabling improved interactions and decision-making. By accurately detecting emotions, businesses can better address customer needs, healthcare providers can monitor mental health more effectively, and social media platforms can gauge public sentiment. This technology promises to create more empathetic and responsive systems, fostering better communication and support across various domains.

1.2 Contributions

In this section, the contributions by the authors in this work are presented:

– To study the Twitter dataset taken from Kaggle open source data repository
– To apply SA on the dataset to check the subjectivity and polarity of emotions present.
– To apply ML algorithms to detect human emotions.

The remaining part of the paper is organized as follows. The literature review is given in Section 2 and Section 3 contains the description of the proposed work. In Section 4, the results and analysis of obtained experimental results are highlighted. Lastly, Section 5 contains the summary and the future possible enhancement of this work.

2 Related Work

A brief description of the work done by different researchers in the field of human emotion and sentiment analysis is presented in this section. There are several ML approaches both supervised [4, 5] and unsupervised [6, 7] have been proposed in the literature for emotion detection from textual data. In [8], Machová *et al.* proposed an AI based approach for human emotions detection which enables a machine to analyze the emotional state of a human. Authors used a lexicon-based approach along with baseline ML algorithms for detection of emotions from text. They also developed a web based application based on the proposed detection model to analyze the user input text and can detect emotions from these texts. The limitation of this approach is that it is not a fully automated system.

Chatterjee *et al.* [10] proposed a deep learning based approach called sentiment and semantic LSTM. The authors evaluated various deep learning techniques such as CNN and LSTM and various forms of text data representation. They also worked with supervised ML techniques like NB, gradient boost, SVM, and decision trees in evaluation of real text conversions. The efficiency of emotion detection of these algorithms were computed by the authors on the tweet conversion pairs collected from Twitter. They concluded that their deep learning based approach performs better as compared to supervised ML classification algorithms.

Khanpour *et al.* [11] analyzed emotions collected from online health community messages collected from a cancer forum which contains six most common emotions. They proposed a model which combines LSTM, CNN, and lexical approaches to retrieve the hidden semantics in text messages and identified the emotions type present within it.

Kashfia *et al.* [12] proposed an approach for human emotions detection from tweets. After extracting tweets on various topics, they preprocessed the data and then each tweet was divided into words. Next the corresponding parts-

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of-speeches were identified for those words. After analyzing the words, the tweets were classified into 32 emotion classes. Emotions were then analyzed with respect to gender and location of the user and the time of the tweet. Sen *et al.* [13] proposed a method for enhanced human emotion categorization from short text. The authors used sentiments as auxiliary input for textual emotion detection and applied ML techniques such as SVM and CNN. They used multi-tasking NN for embedding learning. Mohammad *et al.* [14] proposed a method for detection of both emotion and personality. The authors collected emotion tweets labeled with hash tag and applied ML with eleven feature sets in the data.

For personality they calculated the features of extroversion, agreeably, neuroticism, openness, and conscientiousness. Desmet *et al.* [15] uses SVM classifier for emotion detection in suicide notes, The authors used both semantic and lexical features like bags-of-words, POS tags and trigrams. The method could not able to recognize rare and negative emotions.

3 Proposed Work

In this section, we present the description of the dataset used in this work as well as the environmental requirement for implementing the proposed approach. In addition, the methodology adopted for implementation of this work is described.

3.1 Dataset Description and Environmental Setup

The details of dataset and the environmental set up required to perform the experiment is given Table 1. The dataset was obtained from Kaggle [1] which is an open source data repository. The dataset contains 20000 tweets having six types of emotions. The word cloud of the text present in the dataset is shown in Figure 1. The size of each word in Figure 1 represents the frequency of words present in the dataset. The implementation was performed in Google colab environment and python version 3.10.12 was used for implementation of ML classification algorithms and

Table 1. Dataset Description and Environmental Setup

Atributes	Values
Dataset name	Emotion dataset for NLP
Source	Kaggle open source data repository [1]
Number of emotions and type	06 (Joy, Sadness, Anger, Fear, Surprise, Love)
Total number of Tweets	20000
Environment used	Google colab (python 3.10.12)

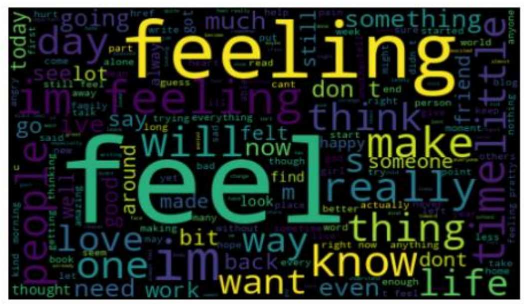

Fig. 1. Wordcloud for the Dataset

for visualization of results obtained. We performed sentiment analysis on the considered dataset by using python TextBlob analysis which helps to identify the number of negative, positive, and neutral tweets present in the dataset.

3.2 Methodology

The considered dataset was first analyzed for determining the presence of amount of different emotions present. The emotion distribution in the dataset is depicted in Figure 2. From Figure 2, it was found that the tweets for different emotions were present in unequal amount.

Then the tweets present in the dataset were analyzed and their polarity was calculated and were labelled as positive, negative and neutral. The polarity distribution of tweets is shown as in Figure 3. Figure 3 indicates the presence of more positive tweets as compared to negative and neutral.

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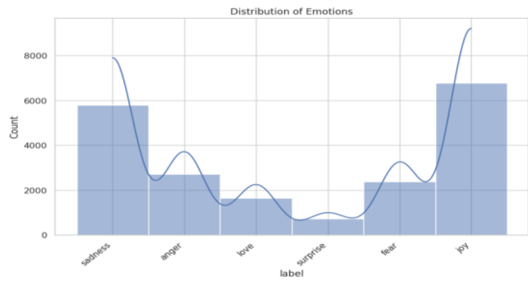

Fig. 2. Emotions Distribution in the Original Dataset

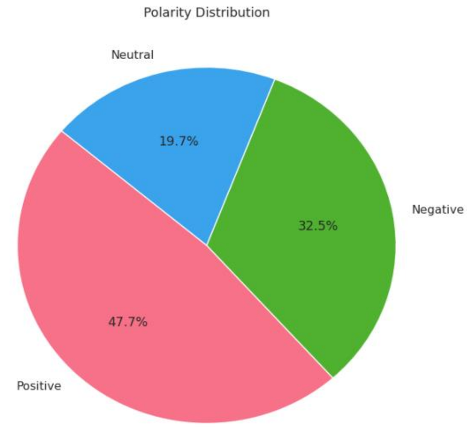

Fig. 3. Polarity Distribution of tweets in the Dataset

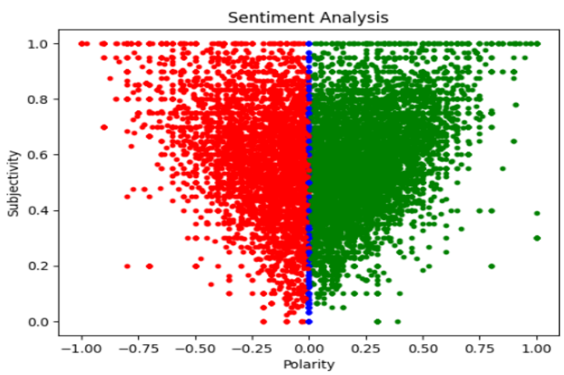

Fig. 4. Subjectivity vs Polarity Graph

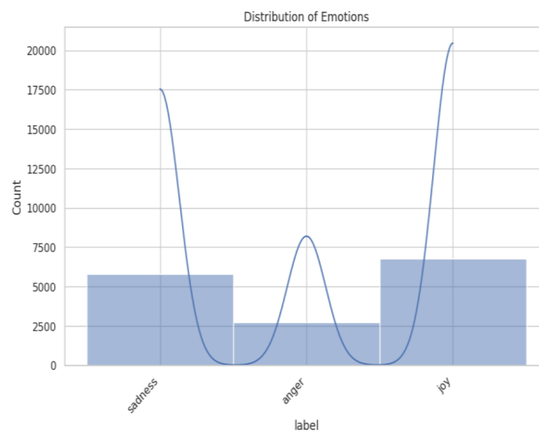

Fig. 5: Emotion Distribution on Balanced Dataset

The subjectivity of the tweets were also analyzed and the sentiment analysis graph is plotted between polarity and subjectivity and is depicted as in Figure 4.

After that, the different classification algorithms were applied on the original dataset and the results obtained are presented in Section 4.

As it was found that the tweets count for different emotions present in the dataset are in unequal amount, so we remove the tweets which are having less counts. The distribution of emotions on the balanced dataset is shown as in Figure 5.

Again we applied the same classifiers on the balanced dataset to analyze the performance and it was found that the accuracy percentage was increased in each case.

4 Results and Analysis

The results obtained from the study are presented in this section. In our approach, the classification algorithms such as NB, LR, Bagging, and SVM was applied on the considered dataset for analyzing human emotion prediction. First, the algorithms were applied with all six emotions and then with only three emotions which were present in balance amount in the dataset. Then the performance was evaluated using certain evaluation parameters such as recall (r), precision (p), F1-score (f1) and support (s) in both the cases.

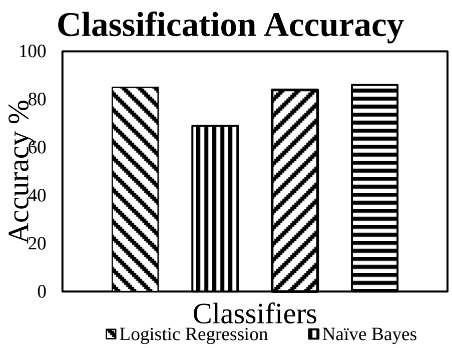

Fig. 6. Accuracy Comparison Results of Different Classifiers on the Original Dataset

Table 2. Results of LR Classifier on the Original Dataset

Emotion	p in %	r in %	f1 in %	s
Joy	82	94	88	1339
Sadness	88	92	90	1173
Anger	89	79	84	536
Fear	83	74	78	458
Love	81	58	68	335
Surprise	88	53	66	159

Table 3. Results of NB Classifier on the Original Dataset

Emotion	p in %	r in %	f1 in %	s
Joy	63	97	77	1339
Sadness	71	92	80	1173
Anger	96	38	54	536
Fear	86	33	48	458
Love	97	10	17	335
Surprise	100	01	01	159

Table 4. Results of Bagging Classifier on the Original Dataset

Emotion	p in%	r in%	f1 in%	s
Joy	86	87	86	1339
Sadness	88	87	88	1173
Anger	83	85	84	536
Fear	78	83	80	458
Love	76	69	72	335
Surprise	76	65	70	159

Table 5. Results of SVM Classifier on the Original Dataset

Emotion	p in %	r in%	f1 in%	s
Joy	86	92	89	1339
Sadness	90	91	90	1173
Anger	88	82	85	536
Fear	80	83	81	458
Love	79	70	74	335
Surprise	87	68	76	159

Table 6. Confusion Matrix of SVM Classifier on the Original Dataset

Truth\Prediction	Joy	Sadness	Anger	Fear	Love	Surprise
Joy	1227	30	12	17	49	4
Sadness	40	1065	31	23	9	5
Anger	32	41	437	22	3	1
Fear	24	33	14	378	3	6
Love	87	9	2	3	234	0
Surprise	14	7	0	30	0	108

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Table 7. Results of LR Classifier on the Balanced Dataset

Emotion	p in %	r in %	f1 in %	S
Sadness	0.93	0.98	0.95	1346
Anger	0.93	0.93	0.93	1151
Joy	0.94	0.82	0.88	557
Weighted Average	**0.93**	**0.93**	**0.93**	**3054**

Table 8. Results of NB Classifier on the Balanced Dataset

Emotion	p in %	r in %	f1 in %	S
Sadness	0.83	0.97	0.90	1346
Anger	0.84	0.92	0.88	1151
Joy	1.00	0.39	0.56	557
Weighted Average	**0.86**	**0.85**	**0.83**	**3054**

Table 9. Results of Bagging Classifier on the Balanced Dataset

Emotion	p in %	r in %	f1 in %	S
Sadness	0.95	0.93	0.94	1346
Anger	0.91	0.92	0.92	1151
Joy	0.88	0.91	0.90	557
Weighted Average	**0.92**	**0.92**	**0.92**	**3054**

Table 10. Results of SVM Classifier on the Balanced Dataset

Emotion	p in %	r in %	f1 in %	S
Sadness	0.95	0.97	0.96	1346
Anger	0.94	0.93	0.93	1151
Joy	0.93	0.88	0.91	557
Weighted Average	**0.94**	**0.94**	**0.94**	**3054**

Table 11. Confusion Matrix of SVM Classifier on the Balanced Dataset

Truth\ Prediction	Sadness	Anger	Joy
Sadness	1304	31	11
Anger	52	1073	26
Joy	23	42	492

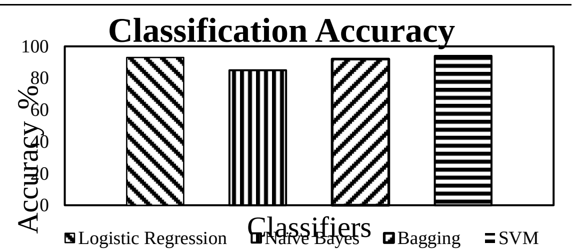

Fig. 7. Accuracy Comparison Results of Different Classifiers on the Balanced Dataset

4.1 Results of Classification with all Six Emotions

The considered classification algorithms were implemented by splitting the dataset in to training and testing with the ratio 80:20. The results of LR for all evaluation parameter values of each type of emotion is given in Table 2. Similarly, the experiment was done for NB, Bagging, and SVM classifier and the results of each is presented in Table 3, 4, and 5 respectively.

The accuracy obtained for LR, NB, Bagging, and SVM classifiers are found to be 85%, 69%, 84%, and 86% respectively. The accuracy comparison graph of all the classifiers was done to analyze the performance of different classifiers on the considered dataset and is depicted in Figure 6. From Figure 6, it is clear that SVM performs better in comparison to LR, NB, and Bagging classifier. The confusion matrix of SVM classifier on the original dataset is given in Table 6.

4.2 Results of Classification with Three Emotions

In this section, the results obtained after implantation of all considered ML classifiers on the balanced dataset is presented. The detailed results showing the values for different evaluation parameters for LR is depicted in Table 7. Similarly, the results for NB, Bagging, and SVM is presented in Table 8,9, and 10 respectively.

The confusion matrix obtained using SVM classifier on the balanced dataset is given in Table 11.

The accuracy for each of the considered classification algorithms was calculated. The accuracies obtained for LR, NB, Bagging, and SVM classifier are found to be 93%, 85%, 92%, and 94% respectively. The accuracy comparison graph of all the classifiers was performed for analyzing the performance of different classifiers on the balanced dataset and is depicted in Figure 7. It is clear from Figure 7 that LR performs better in comparison to NB, Bagging, and SVM classifier.

From the obtained results, it was concluded that all the algorithms out performed on the balanced dataset with three emotions as compared to the original dataset. In the first case, it was observed that the accuracy obtained using SVM classifier was found to be higher as compared to other three classifiers while in the second case the accuracy obtained for LR was higher as compared to other algorithms.

5. Conclusion and Future Scopes

In this work, the human emotion and sentiment analysis was performed on a twitter dataset which contains tweets representing human emotions and was downloaded from the Kaggle open source repository. The sentiment analysis was done to analyze the polarity and the subjectivity of tweets.

The ML algorithms were applied on the original dataset as well as on the balanced dataset. From the obtained results, it was concluded that SVM classifier outperformed in both the cases and the accuracy was improved in the balanced dataset as compared to the original dataset for each of the considered algorithm.

In future, we will try to propose an algorithm which can automatically classify tweets with improved accuracy so that it can be helpful for data preprocessing systems. In this work, we consider the tweets representing single emotion and the tweets containing multiple emotions needs further investigation and can be a topic of future research.

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