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Human Sentiment Analysis on Social Media through Naïve Bayes Classifier

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Abstract: **Deciphering feelings and thoughts from a succession of words is one of the most complex and demanding undertakings. Recognizing sentiments and emotions is one of the most effective ways of expressing feelings and sentiments by writing text. It requires more interest from researchers in advancement than face or voice-based systems. Text based emotion analysis has sparked the attention of many individual researchers to continue their research into distinguishing unique emotions from natural language. The emotion recognition from text field is used in a range of applications, such as recommendation systems, cultural content services that recommend music based on a user's current emotional state, mood tracking, emotion retrieval from suicide notes, capturing emotions in multimedia tagging, detecting objectionable phrases in chats, and so on. In today's information-rich culture, smart sociotechnical systems are gaining traction, with various technologies being employed to gather data from such systems and analyze that data for useful insights into our daily activities. Recent advancements in health monitoring and communications technologies, among other noteworthy achievements, have helped sentiment identification. The trend in artificial intelligence (AI) research in recent years has been to incorporate AI techniques into daily living objects. It is well understood that AI systems will be beneficial to the majority of humans. Emotions are a collection of mental states brought on by a variety of feelings, ideas, and behaviors. People continually communicate emotional cues during the communication process; emotional awareness is vital in human interaction and in many facets of daily life. The seven emotional states (disgust, neutral, happy, sad, angry, astonished, and bored) are extensively described in this study in order to incorporate user text emotions through social media platforms using Correlation based Naive Bayes Classifier and achieve an accuracy rate of 99.99%.**

Index Terms: **Emotion recognition, Sentiment analysis, Naïve Bayes, HCI, Machine Learning.**

I. INTRODUCTION

A feeling is a broad phrase that encompasses a wide range of psychological experiences. Emotions are a collection of mental states brought on by a variety of feelings, ideas, and behaviors. People continually communicate emotional cues during the communication process. Emotion awareness is vital in human interaction and in many facets of daily life. Feelings, which are a crucial component of human sentiments, play a critical part in everyday activities ranging from social connection to judgment and learning. Emotions are diverse mental states with distinct human characteristics, such as individual reality and physiological and emotive responses[1].

Perception Mood Analysis is the technique of evaluating chunks of text to determine whether they are good, neutral, or negative. It provides aid in determining the reviewer's viewpoint on a certain subject. It blends computational linguistics and data analysis methods (IR). The Evaluating Sentiment and Emotion Detection research [2] is motivated by the aggregated user-created information on the Internet. Feelings are sensory receptors in the sensory organ that are linked to thoughts, emotions, social behavior, and satisfaction or displeasure. Humanity exhibits a wide range of emotions on a regular basis when they engage with one another to communicate their sentiments. The demonstrations of emotions can be verbal or non-verbal, with speaking being the most frequent verbal method of expressing emotions, and letters or gestures being the most frequent non-verbal ways.

In today's world, emotions exhibited when discussing thoughts and sentiments are transmitted through ways that may be broadly classified as online and offline. In the offline world, feelings are expressed through letters or spoken encounters.

However, in recent years, the number of people expressing their opinions digitally through online forums such as bloggers, social media applications like Facebook, Twitter, and Instagram,

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etc., and websites has increased drastically all over the world. People are increasingly using social media to share their thoughts, everyday activities, perceptions, moods, and other emotions. As a result, online platforms have grown into massive stores of sentiment data that can be used for assessment. Human-Computer Interaction (HCI) is the crucial interface that allows machines to comprehend and interpret human feelings [3]. Emotion detection plays a significant part in promoting HCI. Emotions have a vital role in interpersonal contact and communication. The informal type of writing challenge for researchers is the communication of emotions via text messaging and personal blog entries[4]. Voice, expression, and writing may all be used to portray emotions.

Emotions, in essence, are perceptual responses that are mostly the result of interactions between several people on various levels. Emotion identification from natural literature is difficult[5] because it is concealed inside the text and necessitates a thorough understanding of the context. Emotions have been extensively researched in psychology as a vital component of human behavior. Sentiment analysis identifies specific moods, which might include a wide spectrum of mental states, including happiness, anger, and fear [6].Its goal is to teach robots to recognize human feelings and raise their level of humanization[7].

Emotions are utilized to communicate and execute relationships amongst people. It is a non-verbal type of communication that, like body language, may add interest to a discussion. Happiness, Surprise, Neutral, Anger, Sadness, Disgust, and Fear are the seven universal feelings recognized by diverse civilizations [8]. The increasing rise of the Internet has enabled more on-line conversations, blog posts, and written material on websites, opening up new pathways for detecting emotions from text mining. As a result, a vast volume of content on the internet rich in user opinions, feelings, and sentiments has been generated [4].

The Web 2.0 has produced a useful platform as well as a plethora of new methods for people to engage. Users can share their sentiments, ideas, and perspectives regarding a variety of subjects, events, movies, and individuals on social networks. Human emotions are reflected in these ideas, viewpoints, and attitudes. The analysis of the emotions expressed in these social media writings has yielded a wealth of useful information for both the government and businesses [9].

II. Related Works

The study of social media messages, particularly the detection of user emotions, is a difficult undertaking. Text is one of the most prevalent ways for people to express themselves, especially on social networking sites. Because emotions are so important in human connection, the ability to identify them through text analysis has a variety of applications in human-computer interface[3]. People may now openly communicate their thoughts, ideas, and attitudes through numerous channels, such as text, voice, and video, thanks to the rapid growth of social media platforms. Human emotions are reflected in these thoughts, ideas, and attitudes[9]. When it comes to guaranteeing the unified security of amenities, the human aspect is crucial. In order to avoid the danger of attention and focus loss, it is vital to monitor the state of the automated process. The difficulties of boosting the efficiency of the psychological state are discussed in the article [10]. To identify normalized speech based on speech emotion information, the "genetic algorithms as a feature selection method" (GAFS) algorithm was utilized. To recognize the six target emotions, [1] employed a support vector machine (SVM) method and found an appropriate kernel. [11] Utilizing the Bitalino EEG sensor to collect EEG values at different stages of concentration. To extract significant characteristics from the EEG signal[12,13], statistical coefficients and statistical wavelet transform (SWT) are applied. To create the feature vector, two multi-scale wavelet packet stats and wavelet packet energy stats were used by the author. The model using CNN and LSTM was trained using this feature vector. This technique was nearly 89 percent accurate.

The gyroscope signals of body motion acquired by body-mounted cell phones are used by the author [14] to discern emotions. They created a set of manually constructed characteristics using human gyroscope gait data that may be used to train and accurately predict human feelings.SVM and Random Forest are two supervised learning predictors that calculate features. The categorization accuracy for binary emotions was 95%, and for all six kinds of emotions, it was 86%.The technique for managing children's emotions through EEG data is presented in [15].

3D hand gesture data is given as feature parameters extracted from the Leap Motion sensor[16]. For the assessment of all of these key metrics, the popular KNN technique is used as a gesture data extractor. BCIs (brain computer interfaces) are devices that can circumvent traditional communications networks and provide direct connection and control between the human mind and physical objects by converting various types of brain activity into instructions in real time. These instructions are often used to operate mobile robots [17,18].

To improve the performance of the provided classification problem, [19] introduces a unique deep learning approach for extracting the conjunctive information that represents the interaction between signals in multi-sensor devices.[20] Describes an automated processing pipeline for recognizing emotion and anxiety states based on their psycho physiological features.

The accelerator and angle rotational values generated by hand gestures were measured using an IMU sensor [21]. A microcontroller is linked to all of these sensors. On the microchip, these values are aggregated and delivered to the computer via Bluetooth. The computer application saves the data and displays it on separate channels at the same time. Wearing a multi-sensor glove, data was collected during standing, walking, climbing, and jumping exercises.

In [22], the author proposed a self-attention improved spatial temporal graph convolution layer for skeleton-based emotion identification using a pose assessment approach to extract 3D skeleton positions for the IEMOCAP dataset. The key to discovering approaches for enhancing animal wellbeing [23] is to comprehend animal feelings. There are currently no ‘benchmarks' or empirical evaluations for evaluating and quantifying farm animals' emotional reactions. In modern farming, using sensors to capture biometric data as a way of monitoring animal feelings is a topic of considerable interest[24].

[25] Describes a physiologically based fear identification system for females. Three physiological sensors are used in the suggested architecture, as well as lightweight binary classification and the combination of linear and non-linear characteristics. As a consequence, the state-of-the-art in fear recognition has been achieved, with up to 96.33 percent recognition rate.

Facial emotion recognition technologies are useful for detecting driver moods [26]. Many aspects protect drivers from showing their moods on their faces while driving. Therefore, [27] suggests a driver's true emotion classifier based on deep learning. This technique correctly recognizes the driver's generated mood in a driving condition with an accuracy of 86.8%.

A growing number of people are experiencing bad mental states and mental problems as a result of the current global COVID-19 pandemic.[28] Create a naturalistic psychosocial dataset and a long-term global comprehensible emotional computing model based on previous knowledge and multimodal embedded systems.

In today's information-rich culture, smart sociotechnical systems are gaining traction, with various technologies being employed to gather data from such devices and mine that data for helpful insights into our daily actions. Motorist systems, clinical monitoring systems, emotion-aware intelligent systems, and complicated interactive robotic devices are all examples of these technologies [29].

In personal communication, emotion and mood identification are crucial, particularly in the context of socially supportive robots. The authors present a deep learning strategy for mood detection based on a publicly accessible dataset that comprises gyroscope, accelerometer, and heart rate data[30].

Using various types of characteristics and ML (machine learning) and DL (deep learning) pre-trained models, [5] strive to extract emotion connections from emotion detection via natural text.

For contextual emotion detection, a conceptual framework with label inclusion is suggested in[6]. A hierarchical model, in particular, is used to learn the affective perception of a statement depending on its context. Multi-modal emotion recognition based on text and pictures is a solution to the problem of imprecise emotion identification and inadequate model resilience in a single modality such as text, picture, or voice [7].

[8] proposed a Real-Time Facial Expression Identification method based on the HAAR cascading classifier for computer vision and Convolution Neural Networks for expression classification. This model takes advantage of the device's webcam to dynamically show the mood as text with an accuracy of 58% on test data.

Text Mining is a predictive analytics activity that extracts data from a variety of text sources, like blogs and comments, and categorizes it as positive, negative, or neutral.[4] used machine learning to classify Hindi text content into different classes.[31] Propose the Cross Attention Network, a unique speech emotion identification model that employs aligned audio and text data as inputs.

III. Experimental Methodology

In this section, we discuss the key components of the suggested technique for emotion categorization, which includes proposed methodology, experimental environment, data set, data pre-processing and training.

A. *Proposed Method*

In simple terms, a Naive Bayes classifier [32,33] assumes that the presence of one feature in a cluster is unrelated to the presence of any other feature. It is dependent on the Bayes' Principle and the prediction autonomously assumption. The Naive Bayes classifier is easy to build and works well with large amounts of data. Because of its easiness, Naive Bayes is known to outperform even the most powerful classification techniques.

Using P (x), P (c), and P (x|c), the Bayes method can compute the posterior probability P (c|x). Consider the following mathematical equation:

$$P(c \mid x) = \frac{P(c)P(x \mid c)}{P(x)}$$

Where,

$P(x)$ = prior probability of predictor

$P(c)$ = prior probability of class

$P(x \mid c)$ = likelihood (probability of predictor given class)

$P(c \mid x)$ = posterior probability of class (c is a target and x is attribute)

Table 1: **a)** Basic table and then find the possibility in the form of yes and no in **b)** frequency table, and finally, from the frequency table, implement **c)** likelihood table along with probability value for the prediction.

Emotion	State	Emotion	State
Happy	Yes	Neutral	No
Disgust	No	Fear	No
Neutral	Yes	Sad	Yes
Surprise	Yes	Anger	Yes
Fear	No	Happy	No
Sad	No	Disgust	Yes
Anger	Yes	Neutral	Yes
Neutral	No	Surprise	Yes
Surprise	Yes	Fear	Yes
Disgust	Yes	Sad	No

(a) Basic Table

Frequency Table		
Emotion	**Yes**	**No**
Happy	1	1
Disgust	2	1
Neutral	2	2
Surprise	3	0
Fear	1	2
Sad	1	2
Anger	2	
Total	12	8

(b) Frequency Table

Frequency Table				
Emotion	**Yes**	**No**		
Happy	1	1	=2/20	0.1
Disgust	2	1	=3/20	0.15
Neutral	2	2	=4/20	0.4
Surprise	3		=3/20	0.15
Fear	1	2	=3/20	0.15
Sad	1	2	=3/20	0.15
Anger	2		=2/20	0.1
Total	12	8		
	=12/20	=8/20		
	0.6	0.4		

(c) Likelihood table

1) Process for Predicting Emotion

Step 1: Create a frequency table from the set of data.

Step 2: Make a table of likelihoods by calculating the probabilities like Surprise probability = 0.15 and probability of state of emotion is 0.6.

Step 3: Compute the posterior probability for each class using the Naive Bayesian method. The conclusion of the prediction is the class with the maximum posterior probability.

Person is Surprised?

P (Yes | Surprised) = P (Surprised | Yes) * P (Yes)/P (Surprised)

Here we have P (Surprised |Yes) = 3/12 = 0.25, P (Surprised) = 3/20 = 0.15, P (Yes) = 12/20 = 0.6

Now, P (Yes | Surprised) = 0.25 * 0.6 / 0.15 = 1.0, which has a higher probability.

i.e. the person is **100%** surprised.

Naive Bayes uses a similar approach to forecast the likelihood of various classes based on different attributes. This approach is typically used for text classification and issues with several classes.

B. Dataset

Humans have the ability to convey their emotions in a multitude of ways, including through facial expressions, body movements, movement, conversation, and so on. Furthermore, people are capable of expressing a wide range of emotions. Andbrain[34] is a dataset taken from the Kaggle website and utilized in this experiment. Sentences, comments, blogs, and Twitter are used to create datasets.

C. Experimental Environment

Google spent years developing TensorFlow, AI architecture, and Colaboratory, a development platform. Google Colab, or simply Colab, is the new name for the Colaboratory. The Colaboratory, or "Colab" for short, is a browser-based platform that allows anybody to develop and run any Python code. It is particularly well suited for computer vision, data analysis, and teaching. Colab is a cloud-based notebook platform that is free to use. The utilization of GPU is another appealing feature that Google provides to developers. Colab is a free application that supports GPU. It's secure, at least as secure as your Google Doc. No one else has access to your personal Colab notebooks.

IV. Experimental Result and Discussion

In the present study, a novel model using Nave Bayes methods was devised for human attention state recognition. The whole data pre-processing and feature extraction was done on Google Colab and tested on a Kaggle dataset. The developed model acquired an astounding accuracy of 100%, which can differentiate between Neutral, Attentive, Happy or Sad. The model, during our calculation, takes about.0125 seconds for its learning period. The deficiency in accuracy has occurred due to under saturation of data as our data-set is not adequate enough to train the complex model we built.

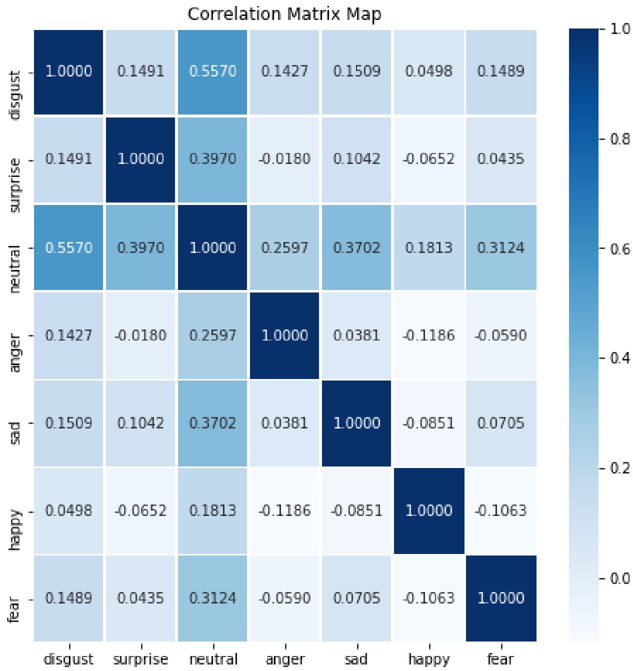

Fig. 1: Correlation Matrix Map using Naïve Bayes Classifier

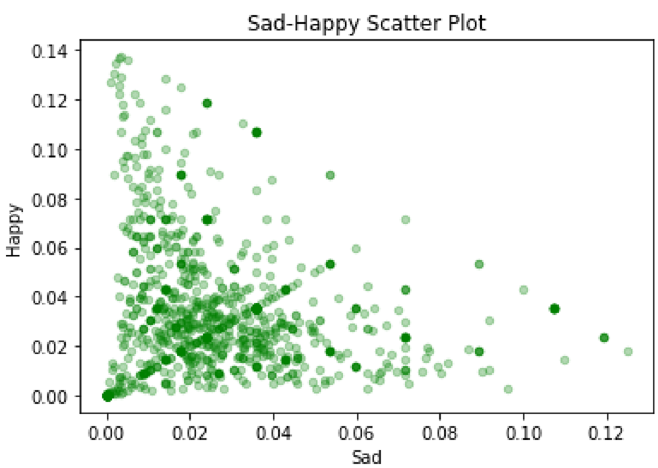

Fig. 2: Scatter Plot of Sad-Happy Emotion

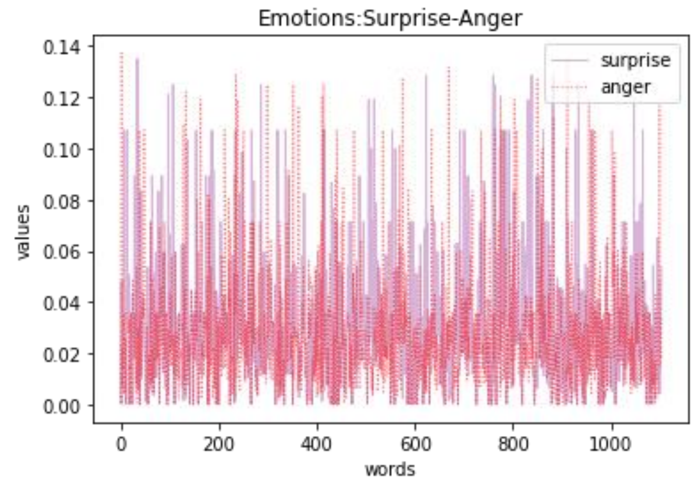

Fig. 3: Emotions: Surprise-Anger

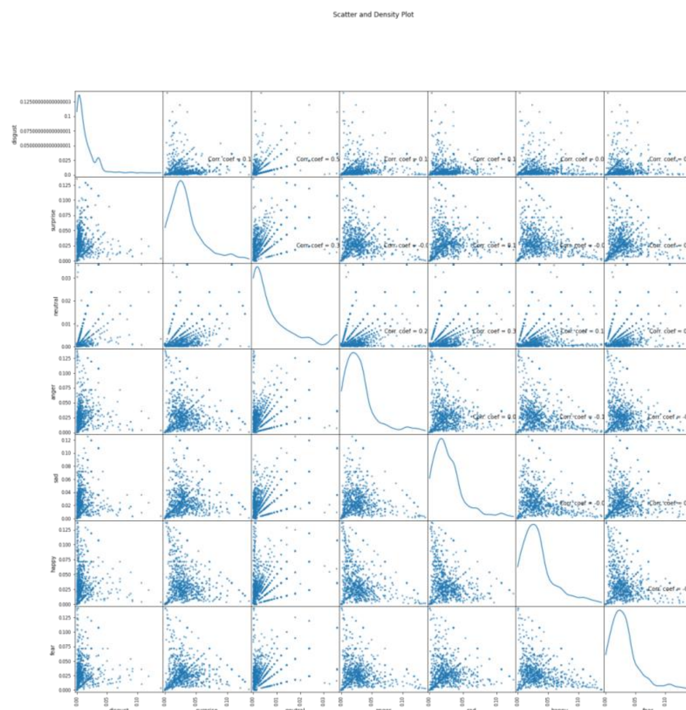

Fig. 4: Emotions: Scatter Matrix of all emotions

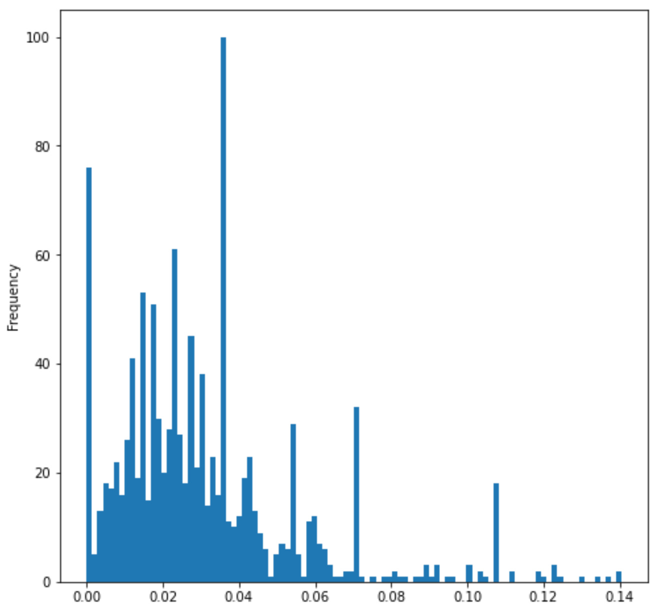

Fig. 5: Histogram of Fear Data

Figure 1 illustrates correlation matrix of all the seven emotions, through which we can easily understand the coefficients of correlation between emotions. The correlation between two emotions is shown in each cell of the table. A correlation matrix can be used to summarize data, as an input to a more sophisticated study, or as a diagnostic tool for further studies. Fig. 2 shows the graphical view of happy and sad emotions from the dataset using scatter plots. Scatter plots show how two emotions in a data collection relate to one another. The X-axis represents the sad emotion i.e. independent emotion, while the Y-axis represents the dependent emotion i.e. happy, whereas fig.3 visualizes the surprise and anger emotions. Scatter Matrix Plot of all the correlation coefficient values of all emotions in fig. 4. The scatter plot matrix plots all the pair wise scatter between distinct emotions in the form of a matrix in a dataset for 7 set of emotions. The scatter plot matrix has 7 rows and 7 columns for each of the 7 emotions in the dataset.

The distribution of numerical data is represented by a histogram, which is an approximate representation. Karl Pearson was the first to bring it up. To make a histogram, split the full range of values into a series of intervals and count how many values fall into each interval. Bins are often defined as non-overlapping, sequential periods of a variable. The bins (intervals) must be next to each other and are usually (but not always) of the same size. Fig.5 is a graphical observation of fear data using a histogram.

Table 2. Accuracy comparison with other models

Authors	**Classifier**	**No. of Emotions (Tested)**	**Accuracy**
Krishnan et al. [33]	Naïve Bayes classifier	3	99%
Sneha et al. [32]	Cauchy Naive Bayes Classifier	7	80%
Despande et al. [3]	Random Forest Classifier	12	88.39%
Lakshmi et al. [8]	CNN	7	58%
Li et al. [7]	LSTM	5	80%
Proposed Method	**Naïve Bayes classifier**	**7**	**99.99%**

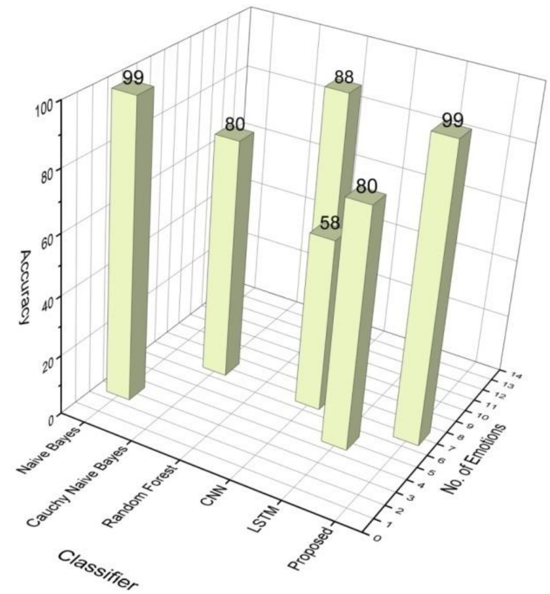

Fig. 6: Classifiers Comparison with Accuracy and number of emotions

Conclusion

With relation to this developed model, we will be focusing on two main future targets. First, we believe our data-set contains average numbers of data that needs to be increased to a larger data-set. In this way, we aim to secure higher accuracy for our model with an increased number of features. On average, a lot of the work done on the subject of AI mostly focuses on detecting the conditions rather than diving deeper into the fundamental explanation behind such feelings. Because of poor emotion correlation, the original approaches to emotion detection had a lot of failures. Using a Naive Bayes classifier, we attempt to extract several forms of emotion from genuine text in this suggested study. We aim to extract the seven basic emotions from natural language by applying a classifier to the sample dataset, such as sorrow, disgust, fear, anger, guilt, shame, and joy. When compared to the other classifier we used in this application for emotion recognition from text, our comparison findings clearly show that the Naive Bayes classifier is more accurate and efficient.

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