Sentimental Analysis (SA) of Employee Job Satisfaction from Twitter Message Using Flair Pytorch (FP) Method

G. Dharani Devi and S. Kamalakannan

Abstract Organizations in the contemporary period face a number of problems as a result of the changing nature of the environment. One of a company's numerous problems is to please its workers in order to manage with an ever-altering and dynamic environment, attain success and stay competitive. The firm must meet the demands of its employees by offering appropriate working circumstances for enhancing efficacy, proficiency, job dedication, and throughput. Twitter is an online social networking site where users may share their thoughts on a wide range of topics, debate current events, criticize and express a wide range of feelings. As a result, Twitter is one of the greatest sources of information for emotion analysis, sentiment analysis, and opinion mining. Owing to a huge volume of opinionated material now created by internet users, Sentiment Analysis (SA) has emerged highly popular in both industry and research. Thus, this paper examines the problem by examining sentiment text as well as emotion symbols such as emoji. Therefore, utilizing the Flair Pytorch (FP) technique, an embedding type Natural Language Programming (NLP) system, and unique strategy for Twitter SA with a focus on emoji is presented. It overtakes state-of-the-art algorithms when it comes to pulling out sentiment aware implanting of emoji and text. Furthermore, 3520 tweets from an organization are accumulated as a dataset, with each tweet containing an emoji. As a result, the recommended FP technique has utilized the "en-sentiment" model for text classification and tokenization to determine the divergence of a sentence established on sentiment words, such as negative or positive, in the sentimental status of tweet, which could be assessed using the respective method's confidence score.

Keywords Twitter · Sentiment analysis (SA) · Job satisfaction · Emoji · Tokenization · Classification

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1 Introduction

One of the most essential aspects of a person's life is their job. Their way of life and social lives are influenced by their employment. As a result, having a pleased staff is critical for each business. In today's India, the private segment performs an important role in boosting the economy. They not only provide excellent services, but they also provide employment chances to a huge number of individuals. Considering the importance of work happiness in improving performance of employee and an influence of private segment to people, the purpose of this study is to learn about employee work satisfaction and the manner it relates to their performance standards. There is a widespread belief that an organization's total throughput and triumph are dependent on workers' operative and proficient performance [1, 2], and that improved performance is dependent on job gratification of workers [3–5]. Employment satisfaction is defined as an employee's good and negative sentiments about his or her job, or the level of enjoyment associated with the job [4]. As a result, one of the most frequently investigated subjects in organizational psychology is work satisfaction [6].

Job satisfaction, as per Locke [7], is the good and joyful sensation that comes from evaluating one's job or work experience. Previous research has shown that when an employee is happy, they are more productive, he will give his all in order to fulfill the organization's goals [8]. Employees that are extremely pleased are more likely to be timely and reliable, as well as more productive, devoted, and fulfilled in their personal life. Employees must be provided prospects in their growth for increasing work satisfaction and therefore enhance performance, i.e., salary pay, employee engagement in policy development, and attempts to enhance corporate obligation. Likewise, the most essential variables for employees' organizational obligation are safety and excellent connections with supervisors and coworkers [9]; the nature of job, supervision style, job stability, gratitude, and promotion are also significant considerations. Similarly, employee involvement in revenue sharing strategies, pension plans, and job security are all positively linked with work happiness, despite the fact that numerous studies have identified professional growth opportunities as the most important driver of job contentment.

The usage of social media in businesses is increasing at an extraordinary rate. Because of the high number of work-based connections and the belief that work is a critical life area, personal social media platforms such as Twitter are increasingly being used for work-related reasons. As a result, a large percentage of publicly viewable tweets are likely to be about work or organizations [10]. Understanding online occupational communication is critical since it is frequently linked to employee happiness and organizational consequences like company reputation. Employees' usage of Twitter may have an impact on their happiness since it allows for horizontal communication and encourages work group sustenance, but it might too make it difficult for employees to disconnect from job beyond working hours.

Employees are honest and reliable communicators of organizational data, thus their tweets can have a beneficial impact on company reputations. However, they can also send tweets that are damaging to business reputation ratings. As a result, employees' usage of social media can be harmful or helpful to both employees and the company. Notwithstanding its relevance for workers and businesses, it is still not known the kind of occupational materials employees post on their Twitter accounts. In order to take a company into the future and ensure continuity, it is critical that the HR responsible for their workers' performance understands the factors that influence their job happiness.

In addition, Twitter is a widespread microblogging website that permits users to send, receive, and analyze short, present, and unpretentious communications known as tweets [11]. Consequently, Twitter offers a rich supply of information that may be utilized in the disciplines of opinion mining and SA. Researchers in various disciplines have recently been interested in Twitter data's SA. Many state-of-the-art researches on the other hand, have utilized sentiment analysis to excerpt and categorize data regarding Twitter opinions on a variety of issues including reviews, forecasts, marketing, and elections. This research work focuses on qualitative analysis of a study which utilized one of the employees' social media as twitter account created in the organization. NLP collects and preprocesses employee tweets as well as evaluations from individuals who function as a valuable source for additional analysis and better decision-making.

These evaluations are often unstructured, and data processing, tokenization, and part of speech may be necessary to offer relevant information as a first step in determining the sentiment and semantics of the supplied text contained in the tweet for future applications. The provided text is chunked by NLTK in terms of nouns, verbs, and phrases.

As a result of the outcomes of this work, Twitter data's SA has garnered a lot of consideration as a research subject that can get data regarding an employee's viewpoint by examining Twitter data and traditional SA does not handle special text like intensifiers, emojis, booster words or degree adverbs that influence the sentiment intensity by either increasing or decreasing its word intensity, which has interested academics because of the succinct language utilized in tweets. Emoji usage on the internet has exploded in contemporary years. Smileys and ideograms made it easier for people to convey their feelings in online pages and electronic messages. Emoji like "Face with Tears of Joy" have revolutionized how we interact on social media and microblogging platforms. While it's more challenging to communicate them using words alone, people frequently utilize them.

A single Emoji character may make a text message more expressive. In this paper, we look at the way in which Emoji characters emerge on social media and manner in which they influence SA and text mining. The nature and application of such traits have been investigated via events of good and negative sensations, as well as overall perceptions. As a result, a system is suggested that uses the Flair Pytorch (FP) technique that is an embedding type NLP utilized for taking out attention on emoji and also to extract text embedding in order to determine the divergence of a phrase centered on emotion words namely positive or negative. A Python centered agenda for NLP applications includes classification and sequence tagging. Flair is built around string embeddings, which are a type of contextualized representation. To attain them, sentences from a huge corpus are segmented into character sequences to pre-train a bidirectional language model that "learns" embeddings at the character-level. The model studies to distinguish case-sensitive characters such as proper nouns from related sounding common nouns and various syntactic patterns in real language in this manner, making it extremely useful for responsibilities like part-of-speech and tagging named entity identification.

The organization of the paper is as follows. The literature analysis and state-of-the-art study on employee job contentment utilizing Twitter sentiment information centered on emoji are presented in Sect. 2. The suggested Flair Pytorch (FP) technique is described in Sect. 3 along with an algorithm. The experimental outcomes grounded on confidence score as well as sentimental status of employee tweets regarding job happiness are discussed in Sect. 4. Section 5 comes to end with a conclusion.

2 Literature Review

Dabade et al. [12] propose a study that uses deep learning and machine learning to classify Fine-grain emotions among Tweets of Vaccination (89,974 tweets). Together unlabeled and labeled information are considered in the work. It also uses machine learning libraries such as Genism, Fast text, Flair, spaCy, Vadar, Textblob, and NLTK to recognize emojis in tweets. Employee sentiment analysis, according to Ginting and Alamsyah [13], can give more effective tools for evaluating crucial aspects such as work satisfaction than internal assessments or other traditional techniques. Companies may recognize areas wherein employees are unsatisfied and create methods to boost engagement and, thereby improve retaining employees and enhance output by gaining a deeper picture of employee mood.

According to Inayat and Khan [14], the purpose of this study is to investigate the impact of job contentment on employee performance in Peshawar's (Pakistan) private sector businesses. As a result of the study, it is found that pleased workers performed better than unsatisfied employees, therefore contributing significantly to the elevation of their businesses. Due to the uncertain economic and political situations in Peshawar, it is important for every business to use various strategies and ways to inspire and satisfy its staff in order to achieve high performance.

Wolny [15] investigates this problem by examining symbols known as emotion tokens, which include emotion symbols like emoji ideograms and emoticons. Emotion markers are widely utilized in numerous tweets, as per observations. They are a helpful indicator for SA in multilingual tweets since they immediately communicate one's sentiments regardless of language. The study explains how to use a multi-way emotions classification to expand existing binary sentiment classification techniques.

Hasan et al. [16] use Twitter data to examine public perceptions of a product. To begin, we created a pre-processed data architecture based on NLP to filter tweets. Subsequently for the purpose of assessing sentiment, the Bag of Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF) models are utilized. This is a project that combines BoW and TF-IDF to accurately categorize negative and positive tweets. It is discovered that by utilizing TF-IDF vectorizer, SA accuracy can be significantly increased and simulation results demonstrate the effectiveness of our suggested method. Using a NLP approach, we are able to obtain an accuracy of 85.25% in SA.

According to Rosenthal et al. [17], supervised learning is grounded on label datasets which are taught to deliver meaningful results. Apply the maximum entropy, Naive Bayes algorithm, and support vector machine to oversee the learning technique in SA that aids to accomplish excellent success. Stemming, lemmatization, named entity recognition, data extraction, tokenization, parts of speech tagging, create a data frame, text modeling, stopwords removal, and a classifier model are all used in Hasan's SA and each of these processes has its own algorithm and packages to be managed.

According to Shiha and Ayvaz [19], using Emoji characters in SA leads in higher sentiment ratings. Moreover, we discovered that the use of Emoji characters in SA tended to have a greater influence on total good emotions than negative sentiments. In this work, data mining, machine learning, and data science approaches are applied to data gathered on Twitter by Gupta et al. [20]. An overall quantity of 142,656 tweets is sent with 142,656 of them being worked on. The Gradient Boosted Tree has the maximum success rate of functional algorithms, and it can properly categorize on a roughly bipolar and stable dataset having a success rate of above 99%. The goal of Davidescu et al. [21] is to examine the impact of numerous types of flexibility like contractual, functional, working time, and workspace flexibility in order to recognize the importance of flexibility in meeting an employee's specific requirements, which is a crucial factor for long-term HRM.

3 Methodology

The proposed research work has to examine for generating the most successful trends in predicting job satisfaction among the employee in the organization. The target variable present in the dataset is "job satisfaction". Data has been collected from an organization as dataset with different job functions. Moreover, 3520 tweets are collected from an organization based on job satisfaction from the professionals which contain attributes namely, tweet ID and tweet is involved with emoji are used for the analysis in Fig. 1. This research work focuses to identify the exact employee who is not satisfied with his/her job in the organization using twitter conversation tweets. In order to facilitate the identification of sentimental recommended words by NLP wherein it is a SA technique established on embedding that is especially tailored to sentiments communicated on social media.

There are 300 samples considered along with tweet IDs. The work flow of the proposed methodology is illustrated in Fig. 2. Hence, the proposed FP method has utilized "en-sentiment" model for tokenization and text classification to identify the polarity of sentence based on the sentiment words namely positive or negative in the

	Tweet_id	Text
0	1.956967e+09	honestly same
1	1.956968e+09	@r0yaltantrum @shovelwill bruh moment
2	1.956968e+09	My vpn issue is now resolved but I wanna read this chapter but it's a 30 minute read and I need to work https://t.co/tUZwPPTenU
3	1.956968e+09	Before Korea nukes us, does anybody want to fight?
4	1.956968e+09	hi @dannycastillo We want to trade with someone who has Houston tickets, but no one will.
5	1.956968e+09	@charviray Charlene my love. I miss you
6	1.956968e+09	cant fall asleep due to bad appraisal
7	1.956969e+09	Choked on her office works
8	1.956969e+09	Got the news that this year increment is too good
9	1.956969e+09	The storm is here and the electricity is gone
10	1.956969e+09	I ate Something in office canteen, I don't know what it is... Why do I keep Telling things about our office canteen food
11	1.956970e+09	So sleepy again and it's not even that late. I fail once again.
12	1.956970e+09	Screw you @davidbrusseel I only have 3 weeks for project release
13	1.956970e+09	I need skott right now
14	1.956971e+09	has project meeting this afternoon
15	1.956971e+09	why am i so ?
16	1.956971e+09	claire @breakfastnt love the show, got into the office @ 5am and no radio
17	1.956971e+09	I'm at work
18	1.956972e+09	Work today

Fig. 1 Sample Input data of employee tweets

sentimental status of the tweet and it can be evaluated through the confidence score of the respective method.

Initially, tweets of the employees are collected based on the tweet IDs. Twitter users tweet regarding almost any topic, which is another benefit of the service. Employees express their ideas and thoughts about both negative and positive situations. Together emoji and text messages are included in the tweet's context. Emoji usage on the internet has exploded in contemporary years. Smileys and ideograms made it easier for people to convey their feelings in online pages as well as electronic messages. Emoji like "Face with Tears of Joy" have revolutionized how we interact on microblogging platforms and social media. Employees frequently utilize them when describing their expressions with words is challenging.

A single Emoji character may make a text message more expressive. When a city's name is displayed alone, it has no sentimental meaning. If the user combined this name with an Emoji, the text might comprise an emotion value. A happy face Emoji character for instance, might convey someone's good attitude about the city. Conversely, by utilizing the angry face Emoji "😫" with a brand name may indicate unfavorable sentiments against the brand. The nature and application of such traits have been investigated via events of good and negative sensations, as well as complete perceptions. To examine the impact and utilization of Emoji characters on social network feelings, we studied employee sentiments regarding job satisfaction levels. The extraction of emoji contained in a tweet using NLP is deployed used to recognize the emoji included in the message. Later define extract emoji and "emoji.demojize" to convert emoji to text information. The URL and "_" amid the transformed emoji

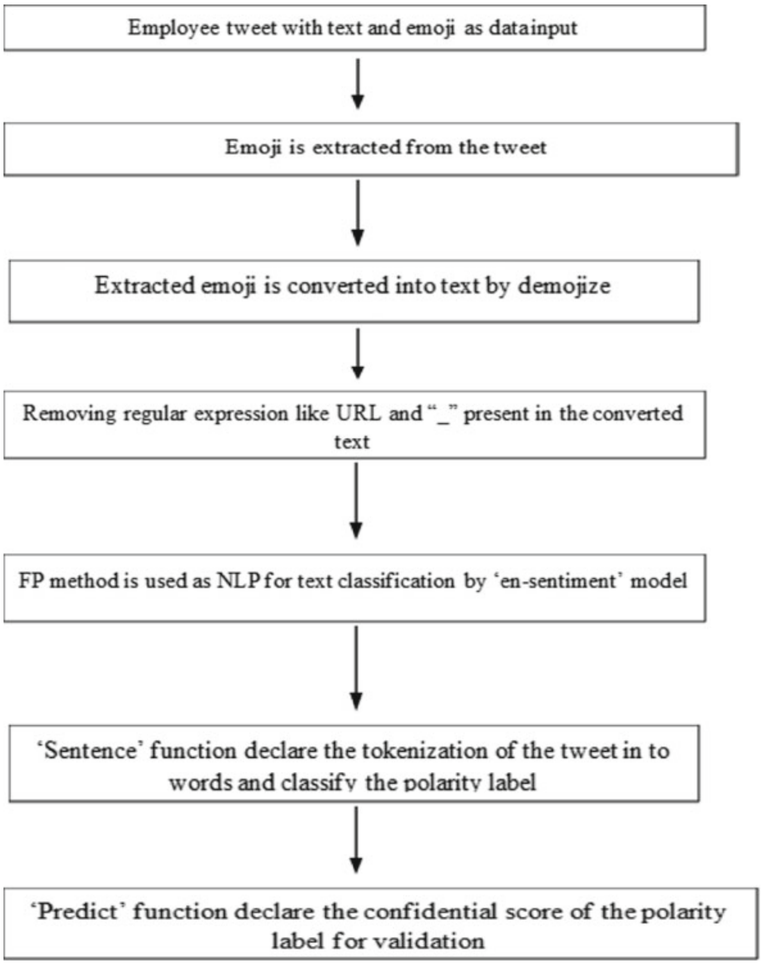

Fig. 2 Proposed FP method as SA to analyze employee job satisfaction

text are then deleted from the tweet utilizing systematic expression. The text classification procedure begins with NLP and the embedding FP technique, which includes extraction and data processing utilizing the 'en-sentiment' model.

One of the major beneficial and most commonly used NLP applications is text classification which includes the grouping or identifying the text in term of particular categories or class. There are various techniques available to accomplish this process but this research has utilized "en-sentiment" functions for training the ML model for classifying the text as either "Positive" or "Negative". In addition, word embeddings are solid real-number vectors used in one for each word in this respective dictionary. In NLP, the distinguishing characteristics are nearly usually words! However, how should a word be represented in a computer? You can save the ASCII character exemplification of the word, nevertheless it simply informs you what the word denotes and very little regarding what it signifies you could figure out its part of speech or characteristics from its capitalization and nothing more than that. What's more, how do you think you'd be able to mix these images? We typically expect dense amount produced from neural networks with $|V|$ dimensional inputs, wherein V denotes dictionary, yet the results are generally only a few dimensions (For example—if we're just forecasting a few labels). What is the best way to get from a big dimensional space to a minor dimensional one?

Why don't we utilize a one-hot encoding as a substitute of ASCII representations? Specifically, we use an Eq. 1 to represent the term www.

$$\overbrace{[0, 0, \ldots 1, \ldots 0, 0}^{|V|\text{ elements}} \tag{1}$$

where 1 denotes that is placed in a location exclusive to www. Every other word will have a 1 in one place and a 0 in every other place. In this study, "en-sentiment" model is used to augment NLP library by tokenizing the sentence with "flair.data.sentence". The tweet's phrase is tokenized into words and counted. Pytorch framework for NLP applications includes classification and sequence tagging based on the Flair programming language. Since it enabled mixing multiple sorts of word embeddings accumulated together to offer the model even more contextual consciousness, Flair rapidly emerged as a widespread framework for the purpose of classification problems also. A contextualized representation known as string embeddings lies at a core of Flair. To acquire them, sentences from a huge corpus are fragmented into character sequences to pre-train a bidirectional language model that "learns" embeddings at the character-level. The model learns to distinguish case-sensitive characters (for instance, proper nouns from identical sounding common nouns) and various syntactic configurations in real language in this manner, making it extremely useful for responsibilities such as part-of-speech tagging and named entity identification.

Flair's capability to "stack" word embeddings like Embeddings from Language Model (ELMo) or Bidirectional Encoder Representations from Transformers (BERT) with "Flair" (i.e., string) embeddings. The instance mentioned below illustrates the manner to use Flair embeddings to create a layered embedding of BERT (base, cased) or ELMo (original) embeddings. The stacking representation is transformed into a document embedding, which is a single embedding for a whole text sample. This permits us to reduce a complicated, arbitrary length depiction to a fixed-size tensor that could be stored in GPU memory for the purpose of training. The power of stacking embeddings (either ELMo or BERT) in this manner stems from the point that character-level string embeddings obtain latent syntactic-semantic information without the use of concept of a word, whereas stacked word embeddings from a peripheral pre-trained neural network model provide additional word-level context.

This improves the model's capacity to recognize an extensive array of syntactic characteristics in the provided text, permitting it to outperform traditional word embedding models. The sentiment words that have previously been learned in the library are then computed using "data.labels".

3.1 Sentiment Scoring

The "model.predict" is assigned to label the polarity value of respective tweet as positive or negative. Pandas' current framework is used to create the scoring system. However, the text is transformed to a sentence object before the learned model is loaded (Every sentence in a sample is represented by a tokenized depiction). Therefore, the clear bias over predicting the extreme value for sentiments is done through FP model whereas the count of tweets increases may produce noisy which is considered using En-sentiment function. Thus, the Flair models predict method is utilized to predict a class label based on the SoftMax output layer's maximum index which is later retrieved as an integer and sample-wise saved in a Pandas Data Frame. Moreover, the label values are represented as sentiment label as negative or positive and the data labels.score is utilized to determine the confidential secret score of a corresponding tweet.

Algorithm of FP method for SA

Input: the Flair models predict method is used,

Output: Sentiment status and Confidence score

Step 1: Read the tweet text as input file from the employee tweet with twitter ID and extracting the emoji by extract_emojis in a separate column as emoji unicode.

Step 2: Converting the extracted emoji unicode into respective text by emoji.deemojize and defining delimiters = "," .

Step 3: Removing of special text like "_" and URL as data preprocessing to make it as a complete text file and placed in the separate column as a dataset of employee tweet.

Step 4: Flair package is imported and embedding of words and text is done by flair.embedding.

Step 5: Initially model of flair pytorch is loaded with dataset of employee tweet by flair.models.TextClassifier.load("en-sentiment"). The model gets trained into flair and stored in the file of "sentiment-en-mix-distillbert_4.pt".

Step 6: The extracted text is made tokenized using flair.data.Sentence() which carry out the list file into respective output as word token count.

Step 7: The function "from flair.models import TextClassifier" and filename.predict() has determined the sentence label output as sentiment status and confidence score.

Step 8: The label.value represent the sentiment status as well as label.score represent the confidence score and returns.

4 Result and Discussion

In the flair library, there is a predefined tokenizer using the *segtok* (https://pypi.org/project/segtok/) library of python. To use the tokenization just the "use_tokenizer" flag value is true. If tokenization is not necessary for respective phrase or sentence set flag value as false. It can be also defined as a label of each sentence and its related topic using the function add_tag. In Pandas, a scoring method is executed using the current framework just as it is done previously. The text is transformed to a Sentence object when the learned model is loaded (Every sentence in a sample is represented by a tokenized depiction.). The Flair models predict system is used to envisage a class label utilizing softmax output layer's maximum index, which is later retrieved as an integer and sample-wise saved in a Pandas DataFrame. Alternatively, the Flair models require a long time to train that may be a major bottleneck in actual universe. However, they do demonstrate the superiority of contextual embeddings over traditional word embeddings for fine-grained categorization.

Contextual string embeddings that attain latent syntactic-semantic information and this goes above and beyond traditional word embedding. The major differences are.

- Without any clear notion of vocabulary, they are educated and thus essentially model words as character sequences.
- they are contextualized by words around them, denoting that depending on their contextual use, the same word will have distinct embeddings.

While working on NLP projects, context is crucial. Sequence modeling is focused on learning to anticipate next character established on preceding characters. Contextual String Embeddings are a new form of word embedding that incorporates the interior states of a trained *character language* model into an "en-sentiment" model. In basic terms, it employs some underlying principles of a trained character model, such as the fact that words in various phrases might have different meanings. Figure 3 displays one of the instances from employee tweet that is taken into account for an distinct clarification of tokenization. A sentence is about learning to tokenize sentences into words, and the total number of words in sentence is 27.

```
In [93]: from flair.models import TextClassifier
         SA_model.predict(SA)
         SA

Out[93]: Sentence: "My vpn issue is now resolved but I wanna read this chapter but it 's a 30 minute read and I need to work loudly cryi
         ng face"   [- Tokens: 27  - Sentence-Labels: {'label': [NEGATIVE (0.9755)]}]
```

Fig. 3 Tokenization of sentence from employee tweet

```
In [95]: SA.labels[0].value
Out[95]: 'NEGATIVE'

In [96]: SA.labels[0].score
Out[96]: 0.9754629731178284
```

Fig. 4 Polarity value and score from employee tweet tokenized words

The predict function has assist in learning the next character prediction based on the earlier characters that form the basic sequence modeling. Figure 4 illustrates the classified label of polarity present in the employee tweet sentence is "NEGATIVE" as the value. Simultaneously, the confidence level of classified polarity label in the sentence is represented 0.9755 as score.

However, the instance is applied to all the records of the employee tweets and the sentences are tokenized with the leverage of contextual string embedding and text classification is done through predict with the text polarity label. Hence the value of the classified polarity label is represented in the attribute "Sentimental Status" and the score of the classified polarity label are represented in the attribute "Confidence Score" are shown in Fig. 5. The tweet author of employee is identified by their twitter id which helps the employer to identify the emotions and sentiments of the employees working in their organization.

Moreover, the proposed FP method has identified the sentiments present in the tweet as simple as possible without reading there each tweets. Therefore, the proposed FP method is made to evaluate with existing TextBlob technique is shown in Fig. 6.

Figure 6 illustrates that polarity of TextBlob describes in term of sign "−" represents negative SA and default represents the positive SA. Moreover, the confidence score represents the subjectivity of the respective tweet. When comparing the confidence level, FP technique shows better confidence score of the sentiment status than TextBlob method. Thus, the FP technique can segregate the positive and negative sentiment status employees and can provide mentors or training to improve the

Out[98]:

	Tweet_id	Text	Emoji_from_text	mod_text	Sentiment Status	Confidence Score
0	1.956967e+09	honestly same 😭	[😭]	honestly same loudly crying face	NEGATIVE	0.999687
1	1.956968e+09	@r0yaltantrum @shovelwill bruh moment 😭	[😭]	@r0yaltantrum @shovelwill bruh moment loudly crying face	NEGATIVE	0.999897
2	1.956968e+09	My vpn issue is now resolved but I wanna read this chapter but it's a 30 minute read and I need to work 😭 https://t.co/tUZwPPTenU	[😭]	My vpn issue is now resolved but I wanna read this chapter but it's a 30 minute read and I need to work loudly crying face	NEGATIVE	0.975463
3	1.956968e+09	Before Korea nukes us, does anybody want to fight? 😭	[😭]	Before Korea nukes us, does anybody want to fight? loudly crying face	NEGATIVE	0.999933
4	1.956968e+09	hi @dannycastillo We want to trade with someone who has Houston tickets, but no one will. 😕	[😕]	hi @dannycastillo We want to trade with someone who has Houston tickets, but no one will. confused face	NEGATIVE	0.999974
...	...	...	...	...	...	...

Fig. 5 Sentimental status and confidence score of employee tweet about job satisfaction

	Text	Sentiment	Emoji_from_text	mod_text	TextBlob Polarity	TextBlob Confidence score	FP Sentiment Status	FP Confidence Score
0	honestly same 😭	0	[😭]	honestly same loudly crying face	-0.100000	0.362500	NEGATIVE	0.999687
1	@r0yaltantrum @shovelwill bruh moment 😭	0	[😭]	@r0yaltantrum @shovelwill bruh moment loudly crying face	-0.200000	0.600000	NEGATIVE	0.999897
2	My vpn issue is now resolved but I wanna read this chapter but it's a 30 minute read and I need to work 😭 https://t.co/tUZwPPTenU	1	[😭]	My vpn issue is now resolved but I wanna read this chapter but it's a 30 minute read and I need to work loudly crying face	-0.200000	0.600000	NEGATIVE	0.975463
3	I thought Wendy's injuries were just bearable but heck she's badly hurt. Broken pelvis, wrist, and what else!? SBS… https://t.co/lzKEx80MM9	0	[]	I thought Wendy's injuries were just bearable but heck she's badly hurt. Broken pelvis, wrist, and what else!? SBS…	-0.600000	0.533333	NEGATIVE	0.999937
4	Before Korea nukes us, does anybody want to fight? 😭	0	[😭]	Before Korea nukes us, does anybody want to fight? loudly crying face	-0.200000	0.600000	NEGATIVE	0.999933
5	We talked for most of the evening earlier but still dinduu 😭	0	[😭]	We talked for most of the evening earlier but still dinduu loudly crying face	0.100000	0.533333	NEGATIVE	0.999969
6	@queennaija Zangggggg I need to go get mines retouched ASAP 😭	0	[😭]	@queennaija Zangggggg I need to go get mines retouched ASAP loudly crying face	-0.200000	0.600000	NEGATIVE	0.999182
7	@FutbolStxve @LFC @JamesMilner @andrewrobertso5 You really had this ready incase they posted and pasted it 😭	0	[😭]	@FutbolStxve @LFC @JamesMilner @andrewrobertso5 You really had this ready incase they posted and pasted it loudly crying face	0.066667	0.433333	NEGATIVE	0.999604

Fig. 6 Sentimental status and confidence score comparison of FP technique with TextBlob in job satisfaction tweet

employee skills. This proposed SA can identify the negative polarity employees and spent enough time in providing space to the employees for the reasonable requirements to retain them for their organization.

5 Conclusion

In such fields, maximum of text-based systems of examination might not necessarily be effective for sentiment analysis. To create an important progress in this field, we as academics still require fresh concepts. The usage of emoji characters in symbol analysis can improve the precision of identifying a wide range of emotions. The emoji is transformed into the appropriate Unicode words before being treated as text, and the FP technique is used as NLP to improve text classification outcomes. Integration of NLP techniques with symbol analysis will most likely be the most effective algorithms. In this paper, SA is involved with FP method as NLP to achieve the state-of-the-art performance. However, there is rule-based NLP method like VADER and text blob has been involved for text classification but this research introduced the embedding based on contextual string. Therefore, it conglomerates a further strong and fine-grained trained character language which is effectively represented the compound sentiment and semantic data with "en-sentiment" centered model. This study created a model for SA that permits instantaneous analysis of Twitter API streaming feeds and classification of divergence to give useful insight about the users and industry. In Pytorch, the built-in classifier of "en-sentiment" may be used as data analysis tools which classify the text polarity label with value as well as the confidence score. This confidence score will evaluate the polarity label value as the accuracy. This assist in identifying the employee with the negative polarity by the employer. Later the employer can provide training or counseling to retain such employee within the organization.

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