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Article

Emoji, Text, and Sentiment Polarity Detection Using Natural Language Processing

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Abstract: Virtual users generate a gigantic volume of unbalanced sentiments over various online crowd-sourcing platforms which consist of text, emojis, or a combination of both. Its accurate analysis brings profits to various industries and their services. The state-of-art detects sentiment polarity using common sense with text only. The research work proposes an emoji-based framework for cognitive–conceptual–affective computing of sentiment polarity based on the linguistic patterns of text and emojis. The proposed emoji and text-based parser articulates sentiments with proposed linguistic features along with a combination of different emojis to generate the part of speech into n-gram patterns. In this paper, the sentiments of 650 world-famous personages consisting of 1,68,548 tweets have been downloaded from across the world. The results illustrate that the proposed natural language processing framework shows that the existence of emojis in sentiments many times seems to change the overall polarity of the sentiment. By extension, the CLDR name of the emoji is utilized to evaluate the accurate polarity of emoji patterns, and a dictionary of sentiments is adopted for evaluating the polarity of text. Eventually, the performances of three ML classifiers (SVM, DT, and Naïve Bayes) are evaluated for proposed distinctive linguistic features. The robust experiments indicate that the proposed approach outperforms the SVM classifier as compared to other ML classifiers. The proposed polarity detection generator has achieved an exceptional perspective of sentiments presented in the sentence by employing the flow of concept established, based on linguistic features, polarity inversion, coordination, and discourse patterns, surpassing the performance of extant state-of-the-art approaches.

Keywords: emojis; pattern; polarity inversion; sentiment polarity; ML classifiers

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1. Introduction

The origination of the world wide web has caused an expanded use of social networking sites, electronic commerce sites, weblogs, forums, etc. The artists, players, layman, professional organizations, etc. utter their sentiments, expressions, attitudes, and know-how by means of a totally new communicating online language [1] consisting of both textual and emoji [2,3]. Sentiment analysis is such a programmed process of analyzing the huge count of views posted on social media about a given subject [4–12]. It facilitates the companies to enhance their product quality aspects, and regulate market strategy and client service from the user-generated content [1,13,14]. Sentiment analysis is an approach that can be done at the sentence level, document level, and aspect level [15–19].

Today, NLP serves as a major medium of communication between people and machines. The research work [20] depicts a reassuring empirical ground for calculating the excellence of NLP-based languages, clubbing the implicit perception of judgment as an add-on criterion. Whereas the research work of [21] depicts an approach based on a corpus to determine the complexity level of MOEPT, it contributes to regulating the complexity and material of MOEPT. The research work [22] marks the open challenges and forthcoming control for contrastive NLP pertaining to image representation.

Textual tweets consist of alphabets, numbers, and special characters whereas emojis are the pictorial representation of a user's emotions and can be used with text or without text. The emoji portrayal can be a picture, an encoded character, or a sequence of encoded characters. Emojis have provided the world with a new language to express their emotions in vibrant, multicolor, attractive, and amusing ways, with the need for few or no words in the message [3,23–25].

In 1997, the concept of the emoji was initially used in Japanese mobile phones and later adopted by companies such as Google, Apple, Twitter, Facebook, etc. Since, 2006, web-based sentiment, such as the expression on Twitter, e-commerce reviews, social media content, etc., has become an extensively popular research area known as sentiment analysis [1,26]. With the growth of emojis and web-based platforms, users have the choice of proclaiming their conscience by employing text in combination with emojis [2,3,24,25].

The brand-new categories of Google emoji are nongender-specific emojis such as , , and , professions such as judge, farmer, etc., gender emojis such as red hair, curly haired, etc. https://blog.emojipedia.org/apple-emoji-turns-10/2020/08; https://blog.emojipedia.org/apple-emoji-turns-10/#fn1; https://www.apple.com/in/newsroom/2019/07/apple-offers-a-look-at-new-emoji-coming-to-iphone-this-fall/; https://blog.emojipedia.org/google-march-2020-pixel-feature-drop-emoji-changelog/). Emoji 14.0 (https://unicode.org/Public/emoji/14.0/emoji-test.txt accessed on 2 February 2023) was released in September 2021, with emojis such as handshake, bubbles, pregnant man, etc.

The concept-based sentiment analysis approaches [27] aim at semantic analysis using semantic networks or web ontologies of text. It provides a combination of conceptual and affective information [28] attached to natural language sentiments. It is intended to empower comparative fine-grained feature-based sentiment analysis in lieu of isolated sentiments or opinions.

The proposed approach helps in determining the correct polarity of the sentences with text only, text and emoji only, emoji only, along with multiple emojis as well. It also determines the correct polarity with a pattern of coordinated discourse and polarity inversion structures of online natural language sentiments. The correct polarity detection of an online sentiment helps in evaluating product analysis [29], market competitor research, mental wellbeing [30], etc. The correct sentiment polarity evaluation of social media posts of individuals can be utilized in determining the historical and present anxiety, stress, and depression levels as well, which in turn can help in reducing suicide cases in society as well.

The paper presents sentiment polarity computing stationed on a text and emoji-based tree generation, parser generator, and pattern formation. Thus, the central objectives of this research article are enumerated as:

1. Introducing a novel cognitive paradigm of sentiment polarity computing framework based on parser generation by deconstructing the natural language concepts of online sentiments into text and emoji;
2. To propose a cognitive sentence level polarity detection using enormous complex pattern rules for employing the linguistic features of the modern online natural language, i.e., emoji in conjunction with text, text with multiple emojis, emoji only, and text only;
3. To familiarize with extensive rules of pattern-based coordinated, discourse, and polarity inversion structures of online natural-language sentiment polarity-detection generator;
4. The evaluation of the introduced approach is based on three distinctive classifiers: Naïve Bayes, support vector machine, and decision tree with three proposed online linguistic features with emojis, in conjunction with text, text with multiple emojis, emoji only, and text only;

5. To determine which, among the three classifiers, works well with our proposed approach;
6. To conduct extensive experiments with complex sentences to implicate the robustness and effectiveness of the suggested text and emoji-based sentiment polarity detection approach.

The research article is constructed as follows. Section 2 provides the related work in the field of sentiment analysis polarity detection. Section 3 has contemplated the proposed approach addressing tree formation in Section 3.1, the parsing algorithm in Section 3.2, and the pattern formation rules for text and emoji in Section 3.3. Section 3.6 represents the emoji, text, and final polarity score evaluation. Section 4 provides the implementation details, results, and discussion. Finally, Section 5 includes the conclusion and future work.

2. Related Work

The present state-of-art related to commonsense and knowledge-based conceptual and affective sentiment analysis are discussed below in detail along with Table 1:

The framework [31] refined the corpus utilizing Sentic LDA. It developed clusters labeled with an aspect category; these clusters are then manually labeled based on the number of aspect lexicons available in them. The approach of OntoSenticNet [32] provides an explanation of the hierarchy of concepts by establishing the relationship between concepts and sentiment analysis. The research work in [33] employed common sense knowledge to rig an aspect-based sentiment analysis and a targeted sentiment analysis. They utilized LSTM and hierarchical attention to propose Sentic LSTM. This research work [34] is done with text, and not employing the role of emojis/emoticons.

The research work of [35] expanded the rules of linguistics to extract concept-based features. It has employed FCA to determine features and their association between concept and ontologies relations.

The research work of [36] co-LSTM examines big online data ensuring scalability and is also free from domain constraints. It is a hybrid model of CNN and LSTM. CNN performs well for local feature selection, whereas LSTM is for big text sequential analysis. The researchers here also did not consider the role of emojis in data analysis.

The commonsense-based textual-sentiment analysis [37] is equipped with a multiple-polarity attention framework. It evaluates the strength of various relational insights using the knowledge base of ConceptNet. It efficaciously enhances sentence presentation by adopting a bidirectional LSTM approach coupled with multiple-polarity orthogonal attention. The state of the art has also not considered the role of emojis in this work.

The research work [38] applied latent dirichlet allocation (LDA) and probabilistic latent semantic analysis (PLSA) algorithms enhancing the textual aspect-based sentiment analysis utilizing the concepts, lexicon patterns, and negations for concept learning. It is a graph-based approach and calculated the score among distinctive nodes using the SimRank algorithm. This approach also ignores the role of emojis in sentiment analysis.

The research work in [39] named fine-grained aspect-based sentiment (FiGAS) analysis is also a textual data-based sentiment analysis for the financial and economic domains assigning the polarity scores between −1 and +1. This lexicon-based polarity-detection approach caters to enormous semantic rules, but this approach also does not deal with linguistic-feature emojis of the dataset.

The above-stated research gap and the popularity of emojis/emoticons among social media users [3,23] promoted us to design a commonsense-based conceptual sentiment polarity-detection-based framework.

Table 1. Comparative study of state of the art for various sentiment analysis approaches.

Approach	Linguistic Features	Approach Used/ Classifier Used	Dataset	Accuracy
Poria et al. [31]	Text	SenticLDA, dependency trees, bag of words.	235,793 hotel reviews obtained from the hotel's review site tripadvisor.com, Semeval-2014	Precision of 88.25% for Semeval-2014 dataset
Dragoni et al. [32]	Text	SenticConcept, Domain, Polarity Instance, and Resource.	A semantic network of 100,000 concepts	-
Ma et al. [33]	Text	Sentic LSTM	Semeval-2015, Sentihood	88.80% for SentiHood (development set) and 76.47% for Semeval-2015 dataset
Khattak et al. [35]	Text	SVM, MNB, LR, RF, KNN	Amazon phone reviews	87.5% with SVM classifier
Behera et al. [36]	Text	CNN, LSTM	Airline review, US presidential election review, Movie review, and car self-driving review	98.4% for airline dataset
Liao et al. [37]	Text	Bidirectional LSTM model with multipolarity orthogonal attention	SMP2019-ECISA	88.7% for B+MPOA (BERT)
Pradhan et al. [38]	Text	Naïve Bayes	SemEval-14: Laptop and restaurant	86.32% for restaurant and 82.64% for Laptop dataset.
Consoli et al. [39]	Text	-	English sentences in the economic and financial domains from the commercial Dow Jones data, news, and analytics (DNA) platform.	3.26 average algorithm ranks by using the median score of the nine annotators.
Proposed approach	Text + emoji	SVM Naïve Bayes Decision tree	1, 68,548 tweets posted by 650 unique personages	90.78% with but and adversatives and 92.18% with polarity inversion

Some examples of the state of the art related other than commonsense knowledge-sentiment analysis involve:

The research work in [34] provides cohort analysis based on the solution of real-world issues in the research of e-commerce customers. The research work in [40] accompanied discriminative and semantic evaluations applying similarity variance for topic identification of Persian, integrating them with fuzzy similarity as well. Whereas the research work in [41] indicates the in-depth utility of Markov models for processing natural language in machine learning. The research work [9] aims at predicting the selection of an emoji automatically for a text message and categorizing the tone of the message into seven categories using algorithms of machine learning.

As indicated, the above literature review does not incorporate the role of sentiment polarity evaluation incorporating the linguistic patterns of text, emojis, and multiple emojis, along with coordinated structures, discourse structures, and polarity inversion. Thus, this motivated us to propose an approach for the same.

3. Proposed Framework

As emojis are used extensively in online sentiments [2,25,42], sentiment polarity detection is accurate in the context of affective cognitive computing by considering both text and emojis. In the proposed model of concept-level sentiment analysis, we have addressed the formation of patterns with the introduction of emojis for commonsense-based sentiment polarity detection. The proposed cognitive–conceptual–affective sentiment polarity detection framework of sentiment sentences (Si), incorporating text and emojis is presented with in Figure 1. The new framework comprises the below segments:

(1) Tree and parsing algorithm generation, a semantic tree, and a parser generator are developed for sentiments consisting of text and emoji;
(2) Pattern formation: it evolves the patterns for the combination of text and emoji-based sentences to determine the accurate polarity of sentiment. It also considered polarity inversion along with a coordinated and discourse structure-based complex patterns for conceptual and context-based sentiment polarity computing;
(3) Polarity evaluation: the polarity of text and emojis are evaluated to evolve the concluding polarity of sentiment sentence considering text and emoji-based patterns of the proposed approach;
(4) The three ML classification techniques are used to train the model proposed;
(5) Final polarity assessment is done based on the above steps two, three, and four. Its generated values are positive, negative, or neutral polarity.

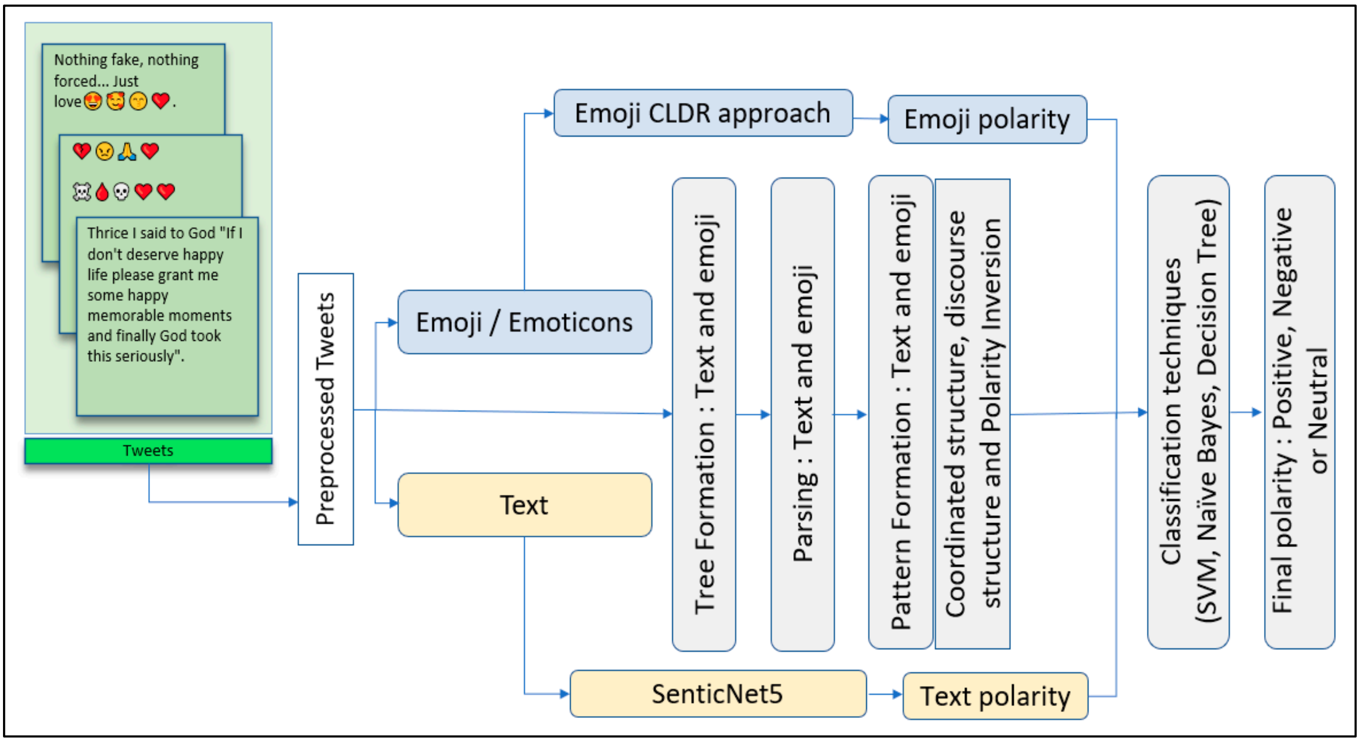

Figure 1. Proposed framework.

3.1. Tree Generation

The purpose of the proposed parser (Figure 2) is to break the online sentiments into a logical form. It interprets online sentiment clauses into concepts to be used in commonsense and affective computing [27,43,44]. The knowledge of the text and emoji linguistic features, along with the conceptual and affective information of their patterns, helps in knowing the emotion, score, and polarity associated with the sentiment more accurately.

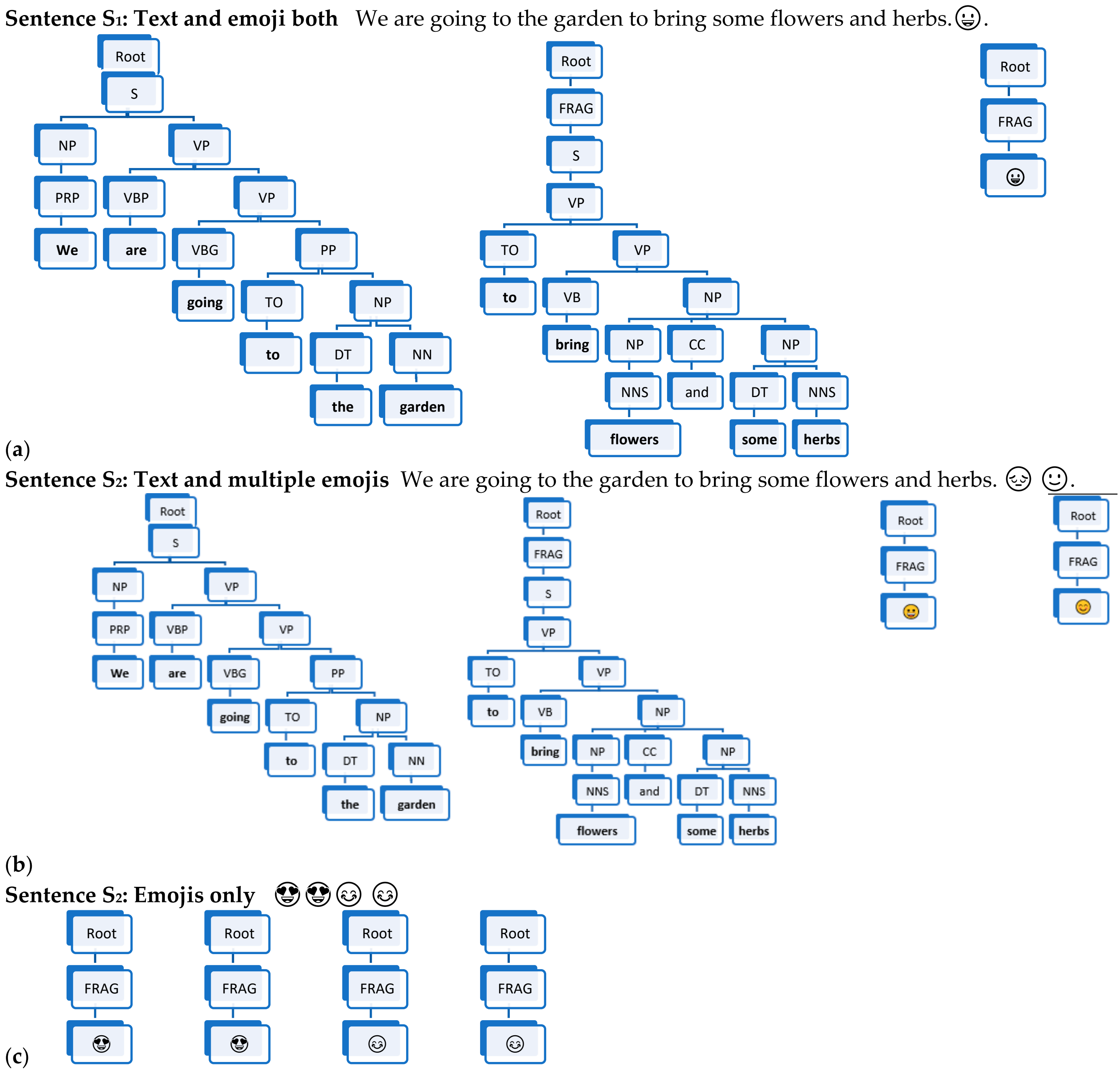

Figure 2. Tree formation for sentiments with (**a**) text and emoji both (**b**) text and multiple emojis (**c**) emojis only.

In POS (part of speech), the object is a noun, pronoun, or noun phrase on which the verb performs an action. The commonsense information can be represented by pairs of objects and emojis. The object-emoji expressions that POS combinations considered are depicted in below Table 2.

Table 2. POS combinations for n-gram based on text and emoji and multiple-emoji combinations.

POS Combinations	Description	Example
	Text + Emoji	
NOUN + EMOJI	Noun and emoji as standalone are added to concept	car 😊, laptop 💻, ice cream 😍.
NOUN + NOUN + EMOJI	Add two nouns as a single concept and emojis as separate.	ice-cream 🌞 🤤, wheelchair 😭, chocolate biscuits 😋.
ADJ + NOUN + EMOJI	Adj + Noun as combinations is added to the objects list. Emoji as isolated are added to the concept.	expensive laptop 😍, beautiful car 🤩.
ADJ + STOPWORD + EMOJI	The adjective and emoji are added to concept.	lovely as ♡ 💧, sparking as 🤩.
NOUN + ADJ + EMOJI	In this pair, adjective, noun, and emoji as standalone are added as a valid concept.	man, big 🌹, flower pink 🌻
STOPWORD + NOUN + EMOJI	The stop word is discarded. The noun and emoji are considered valid.	as man 💪, this flower 🌻 👌.
STOPWORD + ADJ + EMOJI	Emoji and adjective are added as a standalone concept.	as beautiful 🌹 😍 🙂, being happy 😀
	Emoji only	
Emojis	Each emoji is added as a standalone concept.	🌹 😍 🙂
Emojis	Each emoji is added as a standalone concept.	😍 🙂 ✈️ 😒 😒

3.2. Parsing Algorithm Based on Linguistic Feature

The enhanced POS-based n-gram algorithm splits noun phrases along with the emoji into n-grams. (One) First, Algorithm 1 identifies the sentiment as accommodating emoji and text both, emoji only, or text only, (Two) Second, Algorithm 2 In case the sentiment consists of both Text and Emoji, Algorithm 2, will be used for parsing of sentiment. (Three) whereas, if the sentiment contains emojis only then Algorithm 3 is used. Whereas, for tree formation and parsing of sentiment sentence containing text, only then, the research work in [45] is referred.

Algorithm 1: Identify the sentiment as accommodating emoji and text both, emoji only, or text only

---

Input:
Sentiment sentence
Output:
Calling other algorithms based on the content of sentiment sentence.

```
For each sentiment sentence:
    Emoji Unicode Library (sentiment sentence):
       Determine the number of emojis in sentence
      i.e., EmojiCount.
    If (EmojiCount! = 0 && Text also exist)
       # Sentiment contains text and emoji both
       Algorithm 2 is called
    If (EmojiCount! = 0 && Text do not exist)
       # Sentiment contains emoji only
       Algorithm 3 is called
```

Algorithm 2: Sentiment containing both Text and Emoji

```
Input:
Sentiment sentence containing text and emoji both.
Output:
Parsing of sentiment sentence.
Segregate the NounPhrase, emoji and bigram.

Determine NounPhrases and Emojis in Sentence
For ∀ NounPhrase with adjacent Emoji:
  Separate the NounPhrase into bigrams and emojis
  Concept = ∅;
  For ∀ NounPhrase:
    For ∀ bigram with adjacent emoji in the phrase of Noun:
        Tag the bigram with POS
        If NOUN + EMOJI:
          append noun and emoji to Concept
        else if NOUN + NOUN + EMOJI:
          append noun + noun and emoji to Concepts
        else if ADJECTIVE + NOUN + EMOJI:
          append noun, adjective + noun, emoji to Concepts
        else if ADJECTIVE + STOPWORD + EMOJI:
          append adjective and emoji to Concepts
        else if NOUN + ADJECTIVE + EMOJI:
          append noun, adjective and emoji to Concepts
        elseif STOPWORD + NOUN + EMOJI:
          append noun and emoji to Concepts
        else if STOPWORD + ADJECTIVE + EMOJI:
          append emoji and adjective to Concepts
        else
          append to Concepts: entire bigram and different
          concepts of remaining Emojis as isolated.
    end
  end
end
```

Algorithm 3: The sentiment containing emojis only.

```
Input:
Sentiment sentence containing emoji.
Output:
Parsing of sentiment sentence.
Segregate the different emojis.
Determine Emojis in Sentence
For each Emoji:
  Split different emojis
  For each emoji:
    Tag polarity category
    Initialize concept to Null;
    Append to Concepts: Different concepts of all Emojis.
  end
end
```

3.2.1. Algorithm 1

Algorithm 1, stated below, takes the input as sentiment. Then, on the basis of its content, further algorithms are called that use the n-gram approach for POS.

3.2.2. Proposed Algorithm 2: Text with Emoji, POS-Based n-Gram Algorithm

The proposed algorithm 2 shows the steps of processing the parsing of sentiment containing text and emoji both. As depicted in Figure 2a, it segregates the bigrams, noun phrase, and emojis from the POS. As an example, shown in Figure 2a,b, the algorithm generates different concepts from bigrams $\wedge$ emoji. This will help in identifying the commonsense patterns of text with emoji, which is essential for accurate and complete knowledge of sentiment or feelings expressed in online sentiments.

3.2.3. Proposed Algorithm 3: Emoji Only, POS-Based n-Gram Algorithm

Proposed Algorithm 3 shows the steps of processing the parsing of sentiment containing emojis only. As depicted in Figure 2c it segregates the various combinations of emojis.

3.3. Pattern Formation

The proposed pattern formation are linguistic rules utilized for the acquirement of the sentiment's polarity based on common sense and affective information consisting of text and emoji both, text with multiple emojis, emoji only, or text only. The dependency relation of the proposed pattern provides the flow of sentiments running concept using text and emojis. With the usage of emojis, the emotional and informational content communicated by the online user in its sentiment becomes completely different.

Sentence S_4:

(a) It is an excellent approach.

(b) It is an excellent approach 😏.

(c) It is an excellent approach 😊.

For example, S_4(a) is a positive sentiment, S_4(b) is a positive sentence considering text only i.e., "It is an excellent approach" and neutral if analyzed with complete sentiment with emoji, i.e., "It is an excellent approach 😏". Whereas in S_4 (a) and S_4(c), the sentiment with text only and text and emoji is positive in both cases.

These examples clearly show the significance of the emoji in sentiment polarity computing. Most of the studies of sentiment polarity computing [6,43,45,46] do not consider the emotional and information content of emoji, without which the affective and commonsense knowledge-based sentiment polarity detection [47] cannot be acquired completely. Thus, in sentiment analysis, concept and context play an important role [32].

An example of a sentiment sentence (S_5) reflects three different psychologies and moods of wishing 'Happy Birthday'. S_5(a) shows general birthday wishes. S_5(b) reflects the feeling and mood of wishing happy birthday along with party mood. S_5(c) is a multiword and emoji expression intending to wish and attend birthday party.

Sentence S_5:

(a) Happy birthday!!!

(b) Happy birthday!!! Party 🎂 🕯️ 🎉 😮‍💨

(c) Happy birthday!!! Party 🎂 🕯️ 🎉 🏃😩⌚

Example S_5(b) and S_5(c) are the same as S_5(a) if the sentiment analysis is done with text only. In actuality, the semantics and psychology of the three sentiments of example S_5 are completely different because of the usage of different type, category, and counts of emojis.

3.4. Polarity Inversion Pattern Rules

The polarity of an emoji also acts as an essential polarity-switching operator in online sentiment expressions, as discussed in examples S_4 and S_5. The polarity inversion pattern rules are mentioned below, and their examples are depicted in Table 3:

i. Text and Emoji

- Polarity of both text and emoji is positive, then the overall online sentiment polarity is also positive;
- In case text and emoji polarity is negative, then the overall online sentiment polarity is also negative;
- In case text and emoji are having opposite polarity, then the overall online sentiment polarity is neutral.

ii. Emoji only

- The sentiment polarity is positive if all emoji's polarity in sentiment is positive;
- The sentiment polarity is negative if all emoji's polarity in sentiment is negative;
- The sentiment polarity is negative in case the count of emoji with negative polarity is greater than the count of emoji with positive polarity, or vice versa;
- The polarity of sentiment is neutral if the count of emojis having a positive polarity is equal to the count of emojis having a negative polarity.

iii. In case of multiple emojis in a sentence,

- Firstly, the semantic pattern of text and the immediate emoji are formed and their polarity is evaluated as per rule i;
- Secondly, the polarity of the remaining emojis is determined, in case the positive emojis are more than the negative emojis, then the polarity of the remaining emoji will be taken as positive or vice versa. In case the count of positive and negative emojis used are equal, then the polarity of the remaining emojis will be considered neutral;
- The final polarity of the sentence will be determined based on the commonsense concept and context generated from patterns of text and multiple emojis. Examples are given in Table 4.

Table 3. Polarity inversion pattern sample.

Example	Text Polarity [45]	Emoji Polarity [23]	Proposed Approach Polarity
I like it 😃.	Pos.	Pos.	Pos.
I like it 😒.	Pos.	Neg.	**Neutral**
I do not like it	Neg.	NA	Neg.
I do not like it 😃.	Neg.	Pos.	**Neutral**
I did not appreciate it 😒.	Neg.	Neg.	Neg.
I do not hate it 😃.	Pos.	Pos.	Pos.
I do not dislike it 😒.	Pos.	Neg.	**Neutral**

Table 4. The polarity of sentences based on the commonsense concept and context generated from patterns of text and multiple emojis used in a sentence.

Sentences	Text and Immediate Emoji Polarity Based on Proposed Approach	Remaining Emoji Polarity [23]	Proposed Approach Polarity
The guest house is not good to stay 🙂.	Neutral	-	Neutral + − = Neutral
The guest house is not good to stay 🙂 🙂 🙂.	Neutral	Pos.	**Neutral + Pos. = Pos.**
The guest house is not good to stay 😏 😏.	Neg.	Neg.	Neg. + Neg. = Neg.
The guest house is not good to stay 😏 🙂.	Neg.	Pos.	**Neg. + Pos. = Neutral**

3.5. Coordinated and Discourse Pattern Rules

The proposed patterns illustrate the articulation of the different members of coordinated and discourse sentiment in a combination of emojis. The adversatives connect two sentiments of opposite polarity such as but, still, however, otherwise, etc., similar to what is shown in this particular section. Its examples have been depicted in Table 5.

Table 5. But and adversatives pattern.

Example	Left Conjunct [45]	Right Conjunct [45]	Emoji Polarity [23]	Text Polarity [45]	Proposed Approach
The jewel is lovely but costly 😂.	Pos.	Neg.	Pos.	Neg.	**Neutral**
The jewel is lovely but costly 😭.	Pos.	Neg.	Neg.	Neg.	Neg.
The jewel is lovely but not costly 😃.	Pos.	Pos.	Pos.	Pos.	Pos.
The jewel is lovely but not costly 😢.	Pos.	Pos.	Neg.	Pos.	**Neutral**
The jewel is lovely but <cough cough cough> 😃.	Pos.	undefined	Pos.	Neg.	**Neutral**
The jewel is lovely but <cough cough cough> 😭.	Pos.	undefined	Neg.	Neg.	Neg.
The jewel is not lovely but <cough cough cough> 😃.	Neg.	undefined	Pos.	Pos.	Pos.
The jewel is not lovely but <cough cough cough> 😭.	Neg.	undefined	Neg.	Pos.	**Neutral**
<cough cough cough> but the bike is sporty 😭.	undefined	Pos.	Neg.	Pos.	**Neutral**
<cough cough cough> but the bike is sporty 😃.	undefined	Pos.	Pos.	Pos.	Pos.
<cough cough cough> but the bike is costly 😭.	undefined	Neg.	Neg.	Neg.	Neg.
<cough cough cough> but the bike is costly 😃.	undefined	Neg.	Pos.	Neg.	**Neutral**

The but and adversatives: in adversative sentiments, the second part of the sentence dominates the sentiment of the first part of the sentence using "But". The various possibilities of the commonsense-based pattern for "but" are depicted in Table 5. The overall polarity of the pattern is dependent on the second part of the adversative and the emoji. Some of the selective rules are enumerated below:

i. The polarity of both the adversative right member and the emoji is positive, then the overall polarity will be positive, same is vice versa with negative polarity;
ii. The polarity of the adversative right member and emoji are opposite, then the overall polarity will be neutral;
iii. The polarity of the adversative right member is undefined, then the polarity of the left member is inverted, then in this case:
    - The inverted polarity of the left member and emoji polarity are negative, then polarity will be negative;
    - The inverted polarity of the left member and emoji polarity are opposite, then the pattern polarity will be neutral.
iv. The polarity of the adversative left member is undefined, then in this case:
    - The polarity of both the right member and the emoji are positive, then the pattern polarity will be positive;
    - The polarity of both the right member and the emoji are negative, then text and emoji pattern polarity will be negative;
    - The polarity of the right member and the emoji are opposite, then the text and emoji pattern polarity will be neutral.
v. In case, of multiple emojis in a sentence:

- Firstly, the sentic pattern of text and the immediate emoji are formed, and their polarity is evaluated as per rules from i–iv;
- Secondly, the polarity of the remaining emojis is determined. In case the positive emojis are more than negative emojis, then the polarity of the remaining emoji will be taken as positive or vice versa;
- In case the count of opposite polarity emojis used are equivalent, then the polarity of the remaining emojis will be considered neutral.
- The final polarity of the sentence will be determined based on the commonsense concept and context generated from the suggested patterns of text and multiple emojis. Examples are depicted in Table 6;

Table 6. The polarity of sentence based on the commonsense concept and context generated from proposed patterns of multiple emojis used in sentence.

Sentences	Text and Immediate Emoji Polarity Based on Proposed Approach	Remaining Emoji Polarity [23]	Proposed Approach Polarity
The guest house is good to stay but the room size is small 🙂 🙂 🙂.	Neutral	Pos.	**Neutral + Pos. = Pos.**
I wish you very Happy Anniversary but without party 😟 😟??	Neg.	Neg.	Neg. + Neg. = Neg.
She dances very beautifully but her dress was also awesome 😜 😜.	Neutral	Neg.	**Neutral + Neg. = Neg.**
She dances very beautifully but 😜 😜.	Neg.	Neg.	Neg. + Neg. = Neg.

3.6. Emoji, Text, and Final Polarity Evaluation

The preprocessed tweets are divided into text and emoji parts. The common sense-based polarity of text is evaluated using the existing SenticNet [45] approach. The polarity of the emojis used in tweets are evaluated by using a CLDR-based emoji score and polarity-determining approach [23].

The final sentiment polarity is evaluated by combining the role of proposed patterns of text and emoji, text and multiple emojis, emoji only, and text only, generated using the rules and techniques elaborated in Sections 3.1–3.3 with the calculated text and emoji polarity depicted above in Section 3.6.

The detailed calculation of sentiment polarity using the proposed approach and using state of the art are represented in Tables 3–6.

4. Experiment, Results, and Discussion

The dataset of tweets (sentences, Si) downloaded using Twitter (https://pypi.python.org/pypi/tweepy/2020/09 accessed on 2 February 2023) API (application programming interface) consists of approximately 168,548 tweets posted by the 650 different top most followed multitudinal personages across the world [3,24,25].

The downloaded user-generated dataset is preprocessed to eliminate the special characters, pictures, slang, etc. The emojis and their Unicode are referenced through the emojipedia (https://emojipedia.org/emoji-14.0/2021/11), whereas libraries of sentic net (https://pypi.org/project/senticnet/2021/07) and VADER (https://pypi.org/project/vaderSentiment/2021/02 accessed on 2 February 2023) [48] are also used. From the downloaded dataset, 30% is used as a training dataset and 70% is taken as a testing dataset. The training dataset is manually annotated for evaluating the performance.

We have considered a dataset of 4158 emojis [23] and 1281 emoticons (https://pc.net/emoticons/browse/a/2021/01 accessed on 2 February 2023) in the research work.

Tables 3–7 also reflect the consistency of the proposed framework, irrespective of domain.

Table 7. Proposed work results for various ensemble of the linguistic features available in sentiment sentences.

Sentences	Text Polarity [45]	Proposed Approach	Accurate Polarity
The guest house is good to stay but the room size is small 🙂 🙂 🙂.	**Neg.**	**Pos.**	**Pos.**
I wish you very Happy Anniversary!!! Party 😟 😟??	**Pos.**	**Neg.**	**Neg.**
She dances very beautifully 😈 😈 😈.	**Pos.**	**Neg.**	**Neg.**
The idea was not good 🤪	**Neg.**	**Neutral**	**Neutral**

Consider an example in Table 3; *I like it* 😒. When analyzed for text only, it gives positive sentiment polarity [49], whereas, on analyzing the emoji only it gives negative polarity. However, according to the proposed approach to analyzing both the text and emoji part of the sentence, the sentiment polarity acquired is neutral, which is the more accurate polarity of the sentence.

As mentioned in Table 4, the accurate polarity of the sentence, *The guest house is not good to stay* 😏 🙂, is neutral. Whereas the polarity of text and emoji, *The guest house is not good to stay* 😏, in combination as per rule of the patterns of polarity inversion of text and emoji gives polarity negative and 🙂, *emoji only*, is of polarity positive.

Consider the example of <*cough cough cough*> *but the bike is sporty* 😭, mentioned in Table 5. The left part of but is undefined, whereas, then the polarity of text, *the bike is sporty*, i.e., the right conjunct is of positive polarity and the polarity of 😭 is negative. Thus, the polarity of the sentence, as per the proposed approach, is neutral, which is also the correct polarity of the sentence.

Table 7 declares the correct polarity evaluation by the proposed approach following the polarity inversion, coordinated and discourse structures, and distinctive proposed patterns with multiple emojis.

The performance of our proposed model is evaluated based on four evaluation parameters [25,50–52].

Accuracy: the ratio of correctly-predicted samples to the total observations.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

Precision: it is the ratio of truly-positive samples to the complete true predicted cases.

$$Precision = \frac{TP}{TP + FP}$$

Recall: it refers to the ratio of correctly-predicted positive samples to the actual positives.

$$recall = \frac{TP}{TP + FP}$$

The F1 score is the evaluation of the harmonic mean between precision and recall.

$$F1\ score = \frac{2 * precision * recall}{precision + recall}$$

Table 8 depicts the machine learning classifiers [53–60] relative to the performance of the proposed approach by using accuracy, recall, and F score. A sequence of experiments is performed with each of the proposed linguistic features to analyze the importance of the respective feature in improving the performance of the classifier. The SVM classifier has shown the highest accuracy of 82.8 among the three classifiers with all three linguistic features.

Table 8. The experiment results of various ML classifiers for different combinations of linguistic features.

ML Classifier	Linguistic Features	Recall	F-Score	Accuracy
SVM	Text only, emoji only, and combination of text with emoji (Proposed approach: All features)	75.5	79.8	**82.8**
	Text only	74.9	77.4	80.4
	Emoji only	64.3	68.6	69.3
Naïve Bayes	Text only, emoji only and combination of text with emoji (Proposed approach: All features)	69.9	72.4	75.4
	Text only	67.7	70.4	71.4
	Emoji only	60.3	67.5	69.2
Decision Tree	Text only, emoji only and combination of text with emoji (Proposed approach: All features)	73	76.6	79.3
	Text only	71.3	74.9	79.3
	Emoji only	69.5	70.6	70.8

Figure 3 depicts the performance comparison of the three classifiers using the proposed approach. Figures 4–6 depict the values of the F-score, recall, and accuracy for the linguistic patterns of text and emoji, text and multiple emoji, emoji only, and text only using ML classifiers SVM, Naïve Bayes, and decision tree, respectively.

Table 9 declares the accuracy of the proposed research work above the present approach based on sentiment sentences equipped with 'but' adversatives and polarity inversion sentiment sentences with different combinations of emojis using the SVM classifier. Along with text and multiple emojis, the proposed approach shows a 90.78% accuracy for but and adversatives, whereas an accuracy of 92.12% for polarity inversion using the SVM classifier.

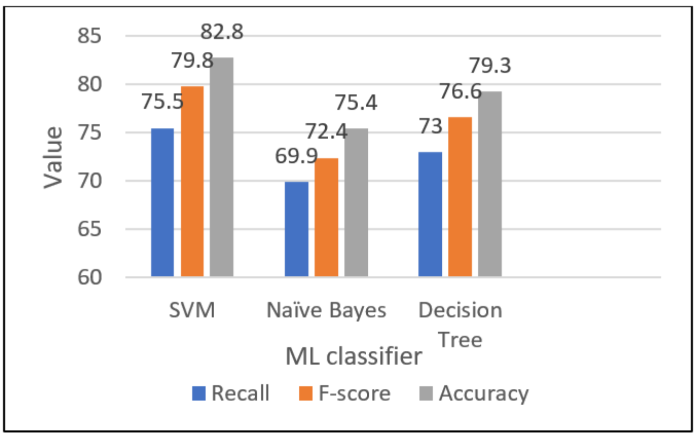

Figure 3. Classifiers relative performance for the proposed approach.

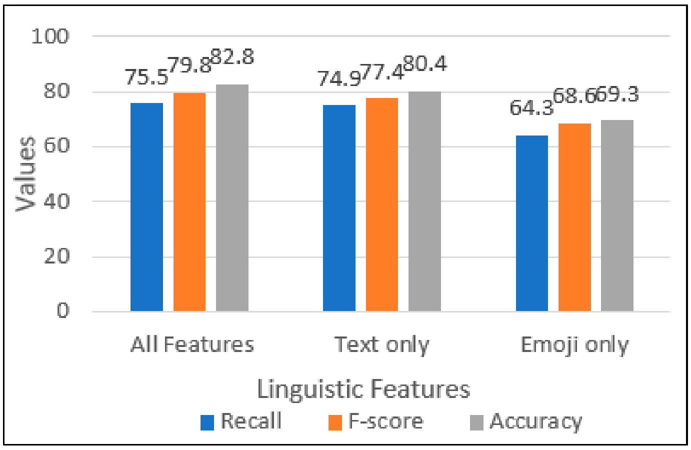

Figure 4. Different linguistic features relative performance for SVM classifier.

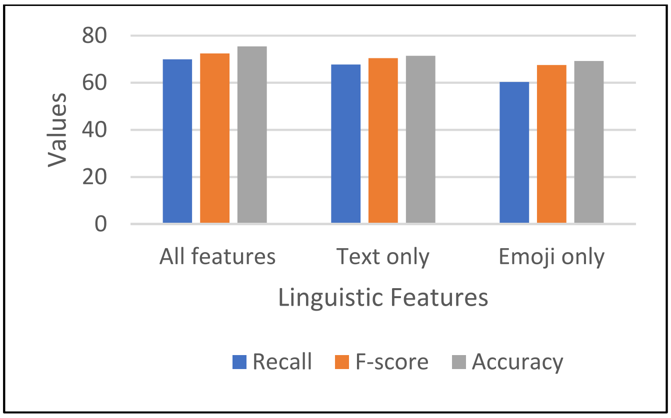

Figure 5. Relative performance of different linguistic features for Naïve Bayes classifier.

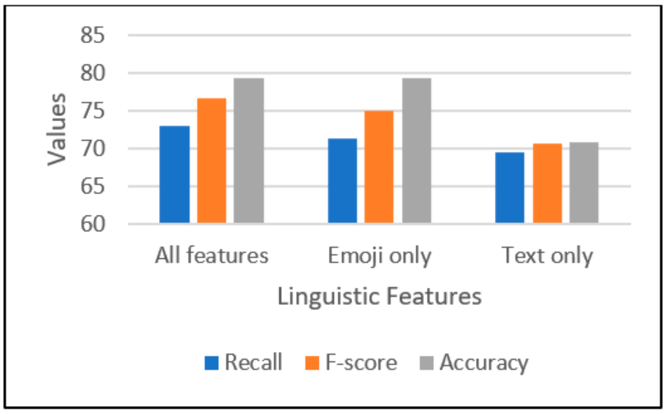

Figure 6. Different linguistic feature's relative performance for decision tree classifier.

Table 9. The state-of-the-art comparison with the proposed approach of text and multiple emoji patterns of 'but' and polarity inversion sentiment sentences using the SVM classifier.

Approach	But and Adversatives Accuracy	Polarity Inversion Accuracy
Poria et al. [45]	87.9%	88.6%
Socher et al. [7]	56.6%	64.4%
Proposed approach	90.78%	92.12%

Thus, the proposed approach helps in determining the correct polarity of the sentences with text only, text and emoji only, emoji only, and multiple emoji. It also determines the correct polarity with the pattern of coordinated, discourse, and polarity inversion structures of online natural-language sentiments. The correct polarity detection of an online sentiment helps in evaluating product analysis, market competitor research, mental wellbeing, etc.

5. Conclusions and Future Scope

The proposed sentiment polarity computing is an approach that provides a conceptual and affective level of NLP while incorporating the role of emojis. It conglomerates commonsense computing with a contextual perception of concept flow within a sentence aggregating the role of its linguistic features.

As is clear from the examples given in Tables 3–7 usage of one or multiple emojis with or without text plays a very crucial role in sentiment prediction. The results clearly indicate that the sentiment polarity evaluation, along with text and emoji, can invert the polarity results predicted with the text only. Thus, the proposed approach plays a crucial role in generating a correct and accurate sentiment knowledge of the expressions. Table 9 clearly indicates the significance of the proposed approach over the existing approaches with the use of the proposed linguistic pattern-rule-based approach coupled with complex 'but' and 'polarity inversion' rules significantly improved the performance of approaches.

The limitations of the proposed approach lie in that efforts can be built to do the same kind of analysis utilizing more distinctive and complex sentences and online content such as photos, graphic interchange format (GIF), video recordings, etc. The current research work provides further recommendation to do a detailed generation of dependency rules using perceptive, cognitive, and other computing models as well. In addition, the future direction aims to incorporate the available domain knowledge to better interpret the linguistic patterns of text.

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