Research article

Emotion detection of social data: APIs comparative study

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ABSTRACT

The development of emotion detection technology has emerged as an efficient possibility in the corporate sector due to the nearly limitless uses of this new discipline, particularly with the unceasing propagation of social data. In recent years, the electronic marketplace has witnessed the establishment of various start-up businesses with an almost sole focus on building new commercial and open-source tools and APIs for emotion detection and recognition. Yet, these tools and APIs must be continuously reviewed and evaluated, and their performances should be reported and discussed. There is a lack of research to empirically compare current emotion detection technologies in terms of the results obtained from each model using the same textual dataset. Also, there is a lack of comparative studies that apply benchmark comparisons to social data. This study compares eight technologies: IBM Watson Natural Language Understanding, ParallelDots, Symanto – Ekman, Crystalfeel, Text to Emotion, Senpy, Textprobe, and Natural Language Processing Cloud. The comparison was undertaken using two different datasets. The emotions from the chosen datasets were then derived using the incorporated APIs. The performance of these APIs was assessed using the aggregated scores they delivered and the theoretically proven evaluation metrics such as the micro-average of accuracy, classification error, precision, recall, and f1-score. Lastly, the assessment of these APIs incorporating the evaluation measures is reported and discussed.

1. Introduction

The global emotion detection and recognition market is growing at a significant rate, thanks to the internet of things, wearable technology, social media data, and the explosive development of smartphone usage. With a Compound Annual Growth Rate (CAGR) of 18.7% from 2021 to 2030, the emotion detection and recognition market, which was valued at $18.8 billion in 2020, is anticipated to expand to $103.1 billion by 2030 [1]. As investment continues to rise globally in response to the demand for emotion detection systems, businesses continue to implement advanced social media analytics to understand better the voice of their customers [2–5].

In this paper, we focus on emotion detection technologies and their application to the written text obtained from social data. The application of textual emotion detection spans from education (by mining students’ emotions toward the learning process) to marketing (by listening to the voice of customers), to several other use cases [6]. Although some people might prefer to use audio and video to convey their opinions and emotions on social media, written text is still dominating and used as a core means for delivering content...
to social audiences [7]. Therefore, removing ambiguity and extracting the factual meaning behind the textual content is not a trivial task [8,9]. Various tech companies compete to deliver solutions and application programming interfaces (APIs) that are claimed to provide the best understanding of the social emotions extracted from social data. Hence, there is an ongoing need to conduct benchmark comparisons between these APIs.

Most of the current emotion detection comparisons have been carried out with state-of-the-art benchmark approaches in terms of incorporated methodology, embedded technology, experimental datasets, and evaluation metrics [10–12]. Other attempts evaluated commercial and open-source tools and APIs in terms of mechanism, ease of use, availability, etc. [13]. However, there is a lack of research to empirically compare current emotion detection technologies in terms of the results obtained from each model using the same textual dataset. Also, there is a lack of comparative studies that apply benchmark comparisons to social data. This is imperative as such comparisons guide companies investing in these technologies to select the best-evaluated tools, specifically that such commercial tools and APIs continuously enhance their internal algorithms. Hence, recent methodological comparisons must always be undergone.

This study compares eight technologies: IBM Watson Natural Language Understanding (NLU)™, ParallelDots™, Symanto – Ekman™, Crystalfeel™, Text to Emotion™, Senpy™, Textprobe™, and NLP Cloud™. The comparison was undertaken using two different datasets: (1) Emotions dataset for Natural Language Processing (NLP) that uses a graph-based technique to manage an annotated tweet corpus in order to create contextualised, pattern-based emotion characteristics. (2) Twitter Conversations dataset: which is a set of 300 tweets (replies) captured from Twitter conversations of five official Twitter accounts of certain Australian banks. This dataset is then manually annotated, by two of the authors, with the relevant emotion(s). Then, the incorporated APIs were used to extract the emotions from the selected datasets and evaluated using their resulting aggregated scores as well as theoretically proven evaluation metrics, including micro-average of accuracy, classification error, precision, recall, and f1-score. Finally, the assessment of these APIs incorporating the evaluation measures is reported and discussed. The experimental results indicate an apparent variance between the extracted emotions of each API in each dataset. This discrepancy between the extracted emotions for each API emphasises the importance of conducting this study, thereby obtaining a better view of the reliability of these APIs to tackle the designated task.

The remaining of this paper is organised as follows: Section 2 introduces the notion of emotion detection and describes the incorporated APIs and tools. Section 3 explains the incorporated methodology regarding data selection and evaluation measures. The experimental results are reported and discussed in Section 4. Section 5 concludes the paper.

2. Emotion detection: A definition and incorporated APIs

1.1. Emotion detection

Defining and interpreting the term emotion is challenging, not only due to the lack of a scientific consensus on the definition but also due to the sophisticated nature of the term that makes it a notorious problem [14]. Therefore, various theoretical studies have perceived emotion from different perspectives and portrayed it using other elements of affect and feeling. Amongst such divergent analyses, three key models are commonly incorporated.

- **Ekman’s theory of basic emotions** [15]: Paul Ekman proposed the idea that some fundamental human emotions, such as joy, sadness, anger, fear, surprise, disgust, and contempt, are inborn and shared by all people and are accompanied by universal facial expressions that are seen across all cultures. According to Ekman, emotional expressions are essential for forming and controlling interpersonal interactions. His research showed that the establishment of attachments and the initiation, induction, acceleration, or slowing of violent behaviour are influenced by facial expressions. Ekman first identified six fundamental underlying emotions but later added a seventh, which he argued comes through learning, particularly social learning: disdain. He changed the name of his taxonomy to Universal Emotions after integrating this culturally acquired emotion.

- **Plutchik’s wheel of emotion** [16]: The psycho-evolutionary theory of emotion, which Robert Plutchik developed, aids in classifying emotions into fundamental emotions and the reactions to them. He made the case that basic emotions are an evolutionary process and that the response to each of these emotions is likely to offer the most excellent chance of survival. A Wheel of Emotion was later created by Plutchik using this first emotional philosophy. It was designed to aid the user in comprehending the subtleties of emotion and how different emotions contrast with one another. He created models for this in both two and three dimensions. The “cone-shaped model of emotion” is the name of the 3D model. In 1980, the first description of them was made.

- **Russel’s circumplex model** [17]: According to this model, emotions are dispersed in a circular, two-dimensional space with arousal and valence dimensions. The vertical axis is arousal, the horizontal axis is valence, and the middle of the circle is neutral valence and a medium amount of arousal. This paradigm allows for the representation of emotional states at any degree of valence and arousal and at a neutral level for any of these variables. Most frequently circumplex models have been used most frequently to examine affective states, emotional phrases, and facial expressions.

Further, other emotion modelling frameworks were also proposed in the literature such as Shaver [18], Oatley [19], OCC [20], VAD [21], and Lovheim [22]. The reader can refer to Refs. [10,23], and [24] to obtain further information on these models.

In computer science, this term is interchangeably used in an interdisciplinary affective computing domain that deals with designing systems that can process, analyse, and detect human emotions [25]. Hence, emotion detection (a.k.a. Emotion recognition) becomes a nascent NLP task that aims to infer a specific feeling(s) from different multimodal datasets incorporating sophisticated machine and learning algorithms. Emotions - such as joy, sadness, anger, frustration, love, fear, and other feelings can be recognised from various
1.2. Emotion detection APIs

Many tools have been selected from two commonly used API marketplaces, namely RapidAPI emotion detection and relevant APIs and tools that offer designated technical solutions.  

Emotion recognition and sentiment analysis are interchangeably used occasionally to indicate the polarity of a user’s attitude expressed by the positive, negative, or neutral feelings deduced from the underlying opinion [35,36]. However, these two notions differ in their definitions. Oxford dictionary defines emotion as: “a strong feeling deriving from one’s circumstances, mood, or relationships with others”, whereas sentiment is defined as “a view or opinion that is held or expressed”. Distinguishing these two terms is essential to properly use each term in its precise context and use the appropriate technology to tackle them. This paper focuses on the notion of emotion detection and relevant APIs and tools that offer designated technical solutions.

1.2. Emotion detection APIs

This section briefly discusses eight open-source and commercial emotion detection platforms and services used in this study. These tools have been selected from two commonly used API marketplaces, namely RapidAPI and APILayer.

IBM Watson NLU™: IBM Watson offers an ecosystem of an interconnected set of cognitive services that deliver a range of capabilities. IBM Watson presents robust multilingual technical solutions to address problems spanning from (un/semi)structured data analytics to industrial-specific context [37,38]. The IBM Watson NLU is a RESTful API service that detects emotions from written text using linguistic analytics. This service allows the user to send the request through plain text, a JSON file, instant messages, voice transcripts, or an HTML document and return a JSON file containing the resultant emotions and their respective likelihood values. The produced emotions are anger, disgust, fear, joy, and sadness. Fig. 1 illustrates the call flow to this service.

ParallelDots API™: ParallelDots™ provides a paradigm of cognitive solutions built upon deep learning technology. The Text Analysis API supplied by ParallelDots incorporates other NLP techniques and is trained on over one billion documents. The services provided by ParallelDots include sentiment analysis, emotion detection, keyword extraction, named entity recognition, text classification, semantic analysis, etc. The ParallelDots’ emotion detection service provides the capacity to analyse textual contents written in 15 languages and detect six emotion categories: happy, angry, excited, sad, fear, and bored.

Symanto™ – Emotion Text Analysis API: Symanto platform™ provides AI-powered tools that generate qualitative insights into the textual data. These insights include brand recommendation features, topic classification, psychographics analysis, timeline analysis, sentiment analysis, and emotion detection. As for Symanto’s emotion analysis, Paul Ekman’s Universal Emotions model is incorporated and used in the detection model. Hence, several emotion categories are inferred from the text: anger, contempt, disgust, enjoyment, fear, sadness, and surprise.

Text2Emotion – python library: The Text2Emotion™ library in Python allows the user to extract embedded emotions from a text in the form of a dictionary. The dictionary contains emotion categories as well as the emotion scores. The API is able to extract five different emotion categories, namely happy, angry, sad, surprise and fear.

Senpy™ Emotion Analysis: Senpy™ is a framework that is designed to build sentiment and emotion analysis services. It delivers functionalities for requesting sentiment and emotion detection from different sources using the same interface (API and vocabulary). The framework incorporates Ekkman and VAD emotion models and is built on evaluating algorithms with well-known datasets. The resultant emotions of a given text belong to one or more of the following emotions: fear, amusement, anger, annoyance, indifference, joy, awe, and sadness.

CrystalFeel™: CrystalFeel™ is a set of emotion analysis algorithms designed based on machine learning techniques for assessing emotional content in natural language. Grounded on a multi-theoretic conceptual foundation in emotion type, emotion dimension, and emotion intensity, CrystalFeel generates many psychologically relevant analytic outputs. In particular, CrystalFeel analyses emotional information in a text by concurrently executing five independently trained algorithms and reporting findings in five dimensions: fear intensity, anger intensity, joy intensity, sadness intensity, and valence intensity. It was created by A*STAR’s Institute of High Performance Computing researchers who are exploring emotional and social intelligence.

Textprobe™: TextProbe™ is a one-stop-shop text analysis API that automatically pulls a variety of insights from textual data,
including the overall Sentiment (positive vs. negative) and emotional tone (joy, anger, fear, and sadness). The kernel of the API is built upon Ktrain\textsuperscript{10} which is a lightweight wrapper for the TensorFlow Keras that makes it easier to construct, train, and deploy neural networks and other ML models.

**NLP Cloud\textsuperscript{11}:** NLP Cloud\textsuperscript{11} provides fast access endpoint for various NLP APIs, including sentiment analysis, emotion detection, semantic similarity, text summarisation, etc. The emotion detection API is built upon DistilBERT base model (uncased),\textsuperscript{12} a distilled version of the model proposed by Ref. [40], which has been fine-tuned to infer emotions such as love, joy, sadness, anger, fear, and surprise in textual data.

Table 1 shows a summary of the selected emotion detection APIs and the emotion categories that are detected using each designated API.

## 2. Method

This section discusses the proposed comparison methodology. First, we discuss and describe the datasets used in the comparison along with the technique used in preprocessing. Then, statistics on the extracted emotions using all APIs over both datasets are provided and discussed. This is followed by describing the incorporated evaluation measures. The section concludes with the experimental results.

### 2.1. Datasets selection and preprocessing

This study incorporates two different datasets:

**Dataset1 - Emotions dataset for NLP\textsuperscript{13}:** This is an annotated tweet corpus managed by means of a graph-based technique which was used in the construction of contextualised, pattern-based emotion features [40]. These features were enhanced by word embeddings to retain the semantic relationships between patterns. The performance of the patterns was evaluated using several machine learning classifiers. This dataset contains 20,000 texts, and each is annotated using one of the following six emotions: angry, fear, joy, sad, surprise, and love. Fig. 2 depicts the distribution of emotions dataset for NLP (Dataset1).

**Dataset2 - Twitter Conversations dataset:** We collected around 300 tweets (replies) captured from Twitter conversations of five Twitter accounts which are the official Twitter accounts of certain Australian banks. Replies to tweets that are posted by service providers commonly convey customers’ opinions toward provided service [41, 42]. Thus, these tweets would carry a rich source of emotions to be analyzed. Also, we assembled this dataset to offer an unbiased benchmark comparison. This subjectively selected dataset has not been used to train any of the nominated APIs. Then, two authors conducted a labelling process to annotate each tweet with the relevant emotion(s). To achieve reliable data annotation, pairwise agreement and inter-coder reliability were computed based on the percentage of the total pairwise comparisons between the labellers. With an average of 97.53%, the overall inter-coder agreement rate varied from 93.45 to 100.00%. These rates are significantly higher than the minimum recommended rate of 70%. The inter-code agreement that was obtained as a result implies that the labelling process was extremely reliable and repeatable. Fig. 3 shows the distribution of the resultant emotions captured from Dataset2. Online social networks have proven utility to provide an open environment for customers to convey their annoyance and frustration [43]. This can be observed in the high proportion of angry emotions as depicted in Fig. 3.

**Data Cleansing:** The data cleansing process was undertaken to remove errors and nonsensical data. Also, we eliminate media contents such as images shared on Twitter or uploaded to one of the media sharing websites listed in Ref. [44] such as Instagram, Flickr, YouTube, and Pinterest. This is due to the fact that there is no text that can be extracted and used for analysis.

\textsuperscript{10} https://github.com/amaiya/ktrain.
\textsuperscript{11} https://nlpcloud.io/.
\textsuperscript{12} https://huggingface.co/distilbert-base-uncased.
\textsuperscript{13} https://www.kaggle.com/praveengovi/emotions-dataset-for-nlp.
2.2. Emotions extraction

Each of the designated APIs listed in Section 2.2 was accessed to extract the emotions and their likelihood values (0.0–1.0) from the textual snippets of the two datasets discussed in the previous section. This was carried out using Python script, and the extracted emotions and their likelihood values of each API are stored in the MySQL database. Fig. 4 (a–h) and Fig. 5 (a–h) depict the aggregated count of retrieved emotion scores for each API applied on Dataset1 and Dataset2, respectively.

Correlation Analysis: A correlation analysis is undertaken to provide further insight into the interrelation between the emotion scores obtained by each API. Fig. 6 (a–d) and Fig. 7 (a–d) depict the correlation of emotion values obtained by each designated API.

### Table 1

The emotion categories extracted by each selected API.

| Emotion      | IBM Watson NLU | ParallelDots | Symanto – Ekman | Crystalfeel | Text to Emotion | Senpy | Textprobe | NLP Cloud |
|--------------|-----------------|--------------|------------------|-------------|-----------------|-------|-----------|-----------|
| Anger        | √               | √            | √                | √           | √               | √     | √         | √         |
| Fear         | √               | √            | √                | √           | √               | √     | √         | √         |
| Joy          | (Happy)         | √            | √                | √           | √               | √     | √         | √         |
| Sadness      | (Happy)         | √            | √                | √           | √               | √     | √         | √         |
| Exciting     | (surprise)      | (awe)        | (surprise)       |             |                 |       |           |           |
| Analytical   | (surprise)      |             | (awe)            |             |                 |       |           |           |
| Valence      |                 | √            | (awe)            |             |                 |       |           |           |
| Indifference |                 | √            | (awe)            |             |                 |       |           |           |
| Amusement    |                 | √            | (awe)            |             |                 |       |           |           |
| Bored        |                 | √            | (awe)            |             |                 |       |           |           |
| Love         |                 | √            | (awe)            |             |                 |       |           |           |

The conducted comparison in this study will focus on the four most common emotions amongst the selected APIs, namely anger, fear, joy, and sadness.
when applying on Dataset1 and Dataset2, respectively. Fig. 6 (a – d) and Fig. 7 (a – d) verify again the weak and sometimes negative correlation between various APIs in four emotions. However, there are mild and strong correlations between some APIs. For example, there is a relatively high correlation between paralleldots, ibm_nlu, and crystalfeel APIs in detecting anger and joy emotions captured from Dataset1 (Fig. 6 (a – d)), and there is a high correlation between paralleldots, ibm_nlu, textprobe and crystalfeel in detecting joy emotion captured from Dataset2 (Fig. 7 (a – d)). In general, the poor correlation between several APIs requires conducting further scrutiny of these APIs to measure their performance. The next section discusses the proposed comparison approach.
2.3. Evaluation measures

This experiment aims to test each model’s capacity to classify the textual contents to the designated emotions truly. We incorporate two evaluation mechanisms to measure the performance of the selected API.

Fig. 5. The aggregated count of retrieved emotion scores for each API applied on Dataset2.
Fig. 6. The Correlation between different APIs in each inferred emotions captured from Dataset1.

Fig. 7. The Correlation between different APIs in inferred emotions captured from Dataset2.
1) **Evaluation metrics:** To evaluate the performance of these APIs, we define the essential structure blocks of the incorporated evaluation measures, namely True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). Fig. 8 demonstrates these four scenarios in detecting whether a textual snippet depicts an anger emotion or not. However, these scenarios are used in all emotions so as to build the evaluation measures. The four scenarios in detecting anger emotion can be described as follows:
- **TP:** is where the API correctly detects an anger emotion as it appears in the designated dataset (correct classification).
- **FN:** is where the API detects a non-anger emotion of a text that is labelled as anger in the designated dataset (incorrect classification).
- **FP:** is where the API detects an anger emotion of a text that is labelled as non-anger in the designated dataset (incorrect classification).
- **TN:** is where the API correctly detects a non-anger emotion as it appears in the designated dataset (correct classification).

These emotion detection scenarios are used in various evaluation metrics that are incorporated to validate the utility of the APIs over the two datasets. To provide an aggregated evaluation mechanism, micro average is computed for Classification error, Accuracy, Precision, Recall, and F1 as follows.

(i) **Micro-Accuracy:** Accuracy indicates the ability of the API to carry out correct emotion detections, which can be represented by the ratio between the actual number of accurate detections (i.e., TP + TN) to the total number of detections (FN + TP + FP + TN). Micro-accuracy indicates the average accuracy of each API to detect each emotion correctly, and it is computed as follows:

\[
Micro - Accuracy = \frac{\sum_{i=1}^{n} TP^i + \sum_{i=1}^{n} TN^i}{\sum_{i=1}^{n} TP^i + \sum_{i=1}^{n} FP^i + \sum_{i=1}^{n} FN^i + \sum_{i=1}^{n} TN^i}
\]  

(ii) **Micro-Classification error:** Classification error denotes the ratio between the total number of incorrect detection (FP + FN) to the total number of detections (FN + TP + FP + TN). Micro-classification error is the average classification error which can be formulated as:

\[
Micro - Classification error = \frac{\sum_{i=1}^{n} FP^i + \sum_{i=1}^{n} FN^i}{\sum_{i=1}^{n} TP^i + \sum_{i=1}^{n} FP^i + \sum_{i=1}^{n} FN^i + \sum_{i=1}^{n} TN^i}
\]  

(iii) **Micro-Precision:** Precision metric refers to the proportion of the number of textual snippets that were accurately detected to the total number of correct and incorrect detections based on the labelled dataset. Micro-Precision measures the average precision obtained by all emotions. It can be calculated as:

\[
Micro - Precision = \frac{\sum_{i=1}^{n} TP^i}{\sum_{i=1}^{n} TP^i + \sum_{i=1}^{n} FP^i}
\]  

![Fig. 8. Four scenarios in the API results in detecting angry emotion.](image-url)
(iv) **Micro-Recall**: Recall refers to the ratio between the number of textual snippets that were accurately detected to the total number of actual emotions as per the labelled dataset. The micro recall represents the global average recall score. It can be computed as:

\[
\text{Micro - Recall} = \frac{\sum_{i=1}^{n} TP_i}{\sum_{i=1}^{n} TP_i + \sum_{i=1}^{n} FN_i}
\]  

(4)

(v) **Micro-F1**: F1 score (a.k.a. F-measure) represents a trade-off between the values obtained by both precision and recall. Micro-F1 denotes the global average F1-score which can be computed as:

\[
\text{Micro - F1} = 2 \times \frac{\text{Micro - precision} \times \text{Micro - recall}}{\text{Micro - precision} + \text{Micro - recall}}
\]  

(5)

In the previous formulas, \( n \) represents the number of emotions (i.e., 4 in our study). We compute the classification scenarios (i.e., TP, FN, FP, and TN) for all emotions obtained by all APIs, and then the average value is computed for each evaluation metric as depicted in the above equations.

In addition, macro-average of each of these metrics over the obtained emotions is also computed. Macro-average indicates the mean of each obtained metric per emotion which signifies a balancing metric that treats all classes equally. The generic equation of macro-average is defined as follows:

\[
\text{Macro - metric} = \frac{\sum_{i=1}^{n} \text{metric}^i}{n}
\]  

(6)

Where \( \text{metric} \) denotes to one of the five incorporated metrics, namely Classification error, Accuracy, Precision, Recall, and F1, and \( n \) indicates the number of emotions. Equation (6) indicates the mechanism followed to calculate the macro-average of each metric for a certain API. For example, to find the macro-average of Precision, we sum the values obtained by each emotion and then divide the sum over the number of emotions we have (i.e., 4 in our study).

2) **Comparison between the aggregated scores**: In this test, we aggregate all the emotional likelihood values obtained by each API on each dataset. Then the average of these values is computed and compared.

3. **Results**

3.1. **Comparison results based on the evaluation metrics**

In this experiment, the four detection scenarios (i.e., TP, FN, FP, and TN) were recorded for all APIs based on their performances on all extracted emotions. These values will be used to compute the micro-average and macro-average of each metric per API. As for the micro-average, the summation of each of the detection scenarios is computed (i.e., \( \sum \text{TP} \), \( \sum \text{FN} \), \( \sum \text{FP} \), and \( \sum \text{TN} \)). This is to prepare data for calculating the micro average of classification error, accuracy, precision, recall, and f1-score as illustrated in equations (1)–(5). Table 2 and Table 3 demonstrate the micro-average values of these metrics based on the experiments conducted on both dataset1 and dataset2, respectively.

As depicted in Table 2, **nlpcloud** demonstrates superiority over all other APIs in detecting emotions using dataset1. This is because

| Model            | TPsum (\( \sum_{i=1}^{n} TP_i \)) | FNsum (\( \sum_{i=1}^{n} FN_i \)) | FPsum (\( \sum_{i=1}^{n} FP_i \)) | TNsum (\( \sum_{i=1}^{n} TN_i \)) | Micro-Class. Error (%) | Micro-Accuracy (%) | Micro-Precision (%) | Micro-Recall (%) | Micro-F1-score (%) |
|------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|------------------------|---------------------|---------------------|------------------|-------------------|
| Crystalfeel      | 11,025                            | 6615                              | 16,156                            | 54,404                            | 25.82                  | 74.18               | 40.56               | 62.50            | 49.20             |
| Ibm_nlu          | 8040                              | 9600                              | 4156                              | 66,404                            | 15.60                  | 84.40               | 65.92               | 45.58            | 53.89             |
| Nlpcloud         | 17,308                            | 332                               | 154                               | 70,406                            | 0.55                   | 99.45               | 99.12               | 98.12            | 98.62             |
| Paralleldots     | 2376                              | 15,264                            | 1162                              | 69,398                            | 18.62                  | 81.38               | 67.16               | 13.47            | 22.44             |
| Senpy            | 759                               | 16,881                            | 922                               | 69,638                            | 20.18                  | 79.82               | 45.15               | 4.30             | 7.86              |
| Symanto_ekman    | 6069                              | 11,571                            | 6163                              | 64,397                            | 16.58                  | 83.42               | 49.62               | 34.40            | 40.63             |
| Text2emotions    | 5648                              | 13,992                            | 7479                              | 63,081                            | 22.08                  | 77.92               | 43.03               | 32.02            | 36.71             |
| Textprobe        | 9424                              | 8216                              | 2814                              | 67,746                            | 12.51                  | 87.49               | 77.01               | 53.42            | 63.08             |
businesses and organisations that seek to extract emotions from their social media channels must scrutinise each API before selecting the best tool. This points to the significance of such studies that aim to help decision-makers by providing the necessary evaluation of APIs. The divergence in both the type of emotion extracted by each API and the emotion likelihood values obtained by each API. This was conducted on the resultant emotions, followed by undertaking a comparative study using various evaluation metrics. This study and the sophisticated tools to detect textual emotions better is vital.

The micro-average of all metrics overshadows different APIs’ values. Textprope API also shows good performance in terms of micro F1-score. On the contrary, Senpy API exhibits poor performance in this experiment regarding the obtained micro F1-score. Table 3 shows the evaluation results of all APIs using dataset 2. As discussed, this dataset has not been used previously and is the first paper that uses this dataset for emotion analysis. This paper aims to conduct an unbiased assessment of the performance of each API using an unseen and untrained dataset. The experimental results using this dataset, as seen in Table 3, show moderate performances amongst most APIs. Although specific APIs such as Crystalfeel and Textprope verify their utility to a certain extent, most other APIs failed to exhibit high performance in this experiment regarding the micro F1-score metric.

To compute the macro-average of each metric per API, the value of each metric per emotion is computed and then aggregated using equation (6). Table 4 and Table 5 demonstrate the macro-average values of these metrics based on the experiments conducted on both dataset1 and dataset2, respectively. Despite some slight improvements or deteriorations on the macro-average values obtained for certain APIs, the exhibited figures in these tables emphasise again that most of the incorporated APIs failed to tackle the datasets properly in terms of the results obtained from each model using the same textual dataset.

### 3.2. Comparison results based on the aggregated scores

The obtained correlation between the APIs, as discussed in Section 3.2 and illustrated in Fig. 6 (a – d) and Fig. 7 (a – d), shows an evident inconsistency between the performances of various APIs. An accuracy comparison is undertaken to find the effectiveness of each API in extracting the emotions captured from each dataset. First, we aggregate all emotions likelihood values obtained by each API on each dataset. Then the average of these values is computed and compared. Fig. 9 (a – b) illustrates the average emotions likelihood values obtained by each API when applied to each dataset.

Fig. 9 (a – b) indicates an apparent variance between the extracted emotions of each model in each dataset. This can be observed in all emotions – despite some convergence between some APIs. This discrepancy between the extracted emotions and their likelihood values for each API emphasises the importance of conducting this study, thereby obtaining a better view of the reliability of these APIs to tackle the designated task. Nevertheless, the values depicted in Fig. 9 (a - b) verify the utility of Nlpcloud over dataset1 and Crystalfeel over dataset2.

### 4. Discussion

The tremendous technological development dominated by the emergence of online social networking sites has established an urgent need for automated processing of natural languages so as to understand and organise what is circulated on these sites. In fact, with the rise of social media, people started expressing their opinions more openly about their experiences with products and services through blogs, video blogs, social media stories, reviews, recommendations, hashtags, comments, replies, direct messages, news articles, and various other platforms. When this happens online, it leaves a digital fingerprint of an individual’s expression of the experience. Now, this experience can convey one or more of various emotions, including anger, joy, love, sadness, and fear. Additionally, the widespread use of social networking sites has created a number of avenues for communication between businesses and their existing and potential clients. In fact, accurately detecting emotions captured from social textual content represents a unique opportunity for companies to enhance the conversational dialogues between them and their customers. Therefore, developing advanced and sophisticated tools to detect textual emotions better is vital.

This study aims to furnish a comparative study between eight well-known APIs and technologies in terms of their effectiveness in detecting correct emotions from the social textual content. The study is conducted using two different datasets: (1) Emotions dataset for NLP and (2) Twitter Conversations dataset. Each API is used to extract the emotions from each dataset. Then correlation analysis was conducted on the resultant emotions, followed by undertaking a comparative study using various evaluation metrics. This study reveals specific and generic issues with the incorporated APIs that can be summarised as follows: to begin with, there is a clear divergence in both the type of emotion extracted by each API and the emotion likelihood values obtained by each API. This disagreement seems normal because each API uses their emotion detection algorithm(s), thus, the results might differ. However, businesses and organisations that seek to extract emotions from their social media channels must scrutinise each API before selecting the best tool. This points to the significance of such studies that aim to help decision-makers by providing the necessary evaluation.
Additionally, this study emphasises the importance of conducting benchmark comparisons using unseen and untrained datasets. This is greatly important to ensure each API’s fair performance outcome. For example, the experimental results demonstrate the superiority of Nlpcloud API in detecting emotions from dataset 1 (Micro-F1 score = 0.99). However, the performance of this designated API notably degraded when applied to dataset 2 (Micro F1 score = 0.55). Dataset 1 is publicly available and is commonly used for NLP Classification and machine learning tasks. Hence, it is likely that this dataset has been used to train several emotion detection models, including those incorporated in this study. On the other hand, this is the first study that uses dataset 2, which is labelled mainly to

### Table 4
Micro-average of classification error, accuracy, precision, recall, and f1-score based on dataset1.

| Metric          | Emotion | Crystalfel (%) | ibm_nlu (%) | Nlpcloud (%) | ParallelDots (%) | Sensy (%) | symanto_ekman (%) | text2emotions (%) | Testprobe (%) |
|-----------------|---------|----------------|-------------|--------------|------------------|-----------|-------------------|-------------------|--------------|
| Classification error | Anger   | 24.61          | 14.76       | 0.55         | 14.19            | 15.64     | 17.48             | 15.57             | 10.02        |
|                  | Fear    | 40.63          | 11.73       | 0.57         | 13.76            | 14.19     | 20.27             | 27.92             | 9.32         |
|                  | Joy     | 21.79          | 16.48       | 0.66         | 36.41            | 37.68     | 26.54             | 29.52             | 17.69        |
|                  | Sadness | 25.12          | 26.11       | 0.43         | 25.42            | 31.87     | 27.86             | 28.45             | 17.29        |
| Macro-Classification error | Anger   | 28.04          | 17.27       | 0.55         | 22.44            | 24.94     | 23.04             | 25.36             | 13.58        |
|                  | Fear    | 76.68          | 86.91       | 0.49         | 87.52            | 86.18     | 84.16             | 86.22             | 90.63        |
|                  | Joy     | 60.14          | 89.23       | 0.43         | 96.76            | 87.39     | 80.82             | 74.03             | 91.23        |
|                  | Sadness | 81.98          | 85.44       | 0.34         | 73.24            | 72.45     | 78.40             | 76.40             | 84.73        |
| Macro-Accuracy   | Anger   | 73.67          | 84.65       | 0.49         | 81.90            | 80.38     | 80.08             | 78.07             | 87.76        |
|                  | Fear    | 75.88          | 77.02       | 0.57         | 79.06            | 75.49     | 76.95             | 75.63             | 84.46        |

### Table 5
Micro-average of classification error, accuracy, precision, recall, and f1-score based on dataset2.

| Metric          | Emotion | Crystalfel (%) | ibm_nlu (%) | Nlpcloud (%) | ParallelDots (%) | Sensy (%) | symanto_ekman (%) | text2emotions (%) | Testprobe (%) |
|-----------------|---------|----------------|-------------|--------------|------------------|-----------|-------------------|-------------------|--------------|
| Classification error | Anger   | 20.87          | 53.08       | 98.22        | 75.60            | 34.80     | 37.88             | 44.30             | 70.58        |
|                  | Fear    | 20.78          | 58.75       | 98.84        | 40.36            | 33.48     | 31.92             | 20.48             | 67.56        |
|                  | Joy     | 93.72          | 84.54       | 99.77        | 81.99            | 61.40     | 75.25             | 68.38             | 89.82        |
|                  | Sadness | 50.75          | 53.71       | 99.31        | 68.14            | 53.73     | 56.35             | 50.90             | 72.84        |
| Macro-Precision  | Anger   | 49.02          | 62.52       | 98.78        | 66.52            | 45.85     | 50.35             | 46.01             | 75.20        |
|                  | Fear    | 65.44          | 38.76       | 97.96        | 12.29            | 4.75      | 36.80             | 31.12             | 52.70        |
| Macro-Recall     | Anger   | 49.02          | 62.52       | 98.78        | 66.52            | 45.85     | 50.35             | 46.01             | 75.20        |
|                  | Fear    | 65.44          | 38.76       | 97.96        | 12.29            | 4.75      | 36.80             | 31.12             | 52.70        |

strategies [45–47].

Additionally, this study emphasises the importance of conducting benchmark comparisons using unseen and untrained datasets. This is greatly important to ensure each API’s fair performance outcome. For example, the experimental results demonstrate the superiority of Nlpcloud API in detecting emotions from dataset 1 (Micro-F1 score = 0.99). However, the performance of this designated API notably degraded when applied to dataset 2 (Micro F1 score = 0.55). Dataset 1 is publicly available and is commonly used for NLP Classification and machine learning tasks. Hence, it is likely that this dataset has been used to train several emotion detection models, including those incorporated in this study. On the other hand, this is the first study that uses dataset 2, which is labelled mainly to
measure the performance of the integrated APIs. Thus, this dataset’s comparative results offer a recent, objective, and unbiased evaluation.

This study fortifies efforts, the aim of which is to provide a review of the current emotion detection APIs and tools. The embedded algorithms of these technologies are continuously evolving; thus, similar studies should be constantly conducted. This research also offers methodologies for academics and industrial practitioners to validate and verify the effectiveness of out-of-the-shelf emotion detection tools and APIs, especially with a lack of research to compare current emotion detection technologies using social media datasets empirically.

Although the outcome of the proposed work demonstrates promising results, there is still room for further research that we will undertake in our future work. For example, more APIs must be examined to understand the available APIs in the market better. Therefore, we will explore other APIs that can be indicated from venues other than RapidAPI and APILayer. Examples of these APIs are Hourglass of Emotions [48], Affectiva [49], and Sentic API [50]. Another area of research is comprehensively comparing other multimodal emotion recognition APIs, including those that offer emotion detection based on facial recognition techniques [51].

5. Conclusion

Organisations are still using advanced social media analytics to understand their customers’ voices better. In this paper, we compare using eight emotion-detection APIs on two datasets collected from social data. The included APIs were used to generate the emotions from the selected datasets. The aggregated scores provided by these APIs and theoretically supported assessment metrics such as the micro-average, and macro-average of accuracy, classification error, precision, recall, and f1-score were used to evaluate the performance of these APIs. The evaluation of these APIs, taking the evaluation measures into account, is reported and discussed. The comparative study reveals important issues and emphasises the inadequacy of these APIs to handle new datasets. Therefore, there is a need to continuously investigate novel techniques to furnish better emotion detection and recognition models. These models must attempt to tackle this problem’s sophisticated nature, including multilingualism, ambiguity, colloquialisms, slang, irony, sarcasm, and contextual phrases and homonyms.

Author contribution statement

Bilal Abu-Salih: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Mohammad Alhabashneh: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Dengya Zhu; Albara Awajan: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Yazan Alshamaileh; Bashar Al-Shboul; Mohammad Alshraideh: Analyzed and interpreted the data; Wrote the paper.

Data availability statement

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to

Fig. 9. The average of emotions likelihood values obtained by each API applied to each dataset.
References

[1] B.Y. Md Shadaab Khan, Pramod Borasi, Vineet Kumar, Emotion detection and recognition market, 27/06/2022; Available from: https://www.alliedmarketresearch.com/emotion-detection-and-recognition-market, 2022.

[2] M. Al-Okaily, A. Al-Okaily, An empirical assessment of enterprise information systems success in a developing country: the Jordanian experience, The TQM Journal (2022).

[3] M. Al-Okaily, et al., The Effect of Digital Accounting Systems on the Decision-Making Quality in the Banking Industry Sector: a Mediated-Moderated Model. Global Knowledge, Memory and Communication, 2022.

[4] M. Al-Okaily, et al., Examining the critical factors of computer-assisted audit tools and techniques adoption in the post-COVID-19 period: internal auditors perspective, VINE Journal of Information and Knowledge Management Systems (2022) (ahead-of-print).

[5] A. Al-Okaily, T. Al-Okaily, The Effectiveness of Accounting Information Systems in the Era of COVID-19 Pandemic, VINE Journal of Information and Knowledge Management Systems, 2021.

[6] K. Sailunaz, et al., Emotion detection from text and speech: a survey, Social Network Analysis and Mining 8 (1) (2018) 1–26.

[7] A. Shawabkeh, et al., An evolutionary-based random weight networks with taguchi method for Arabic web pages classification, Arabian J. Sci. Eng. 46 (4) (2021) 3955–3980.

[8] B. Abu-Salih, A. Abu-Salih, Ontology-based Approach for Semantic Data Extraction from Social Big Data: State-Of-The-Art and Research Directions, 2018 arXiv preprint arXiv:1801.01624.

[9] B. Abu-Salih, et al., Relational Learning Analysis of Social Politics Using Knowledge Graph Embedding, 2020 arXiv. arXiv preprint arXiv:2006.01626.

[10] E. Kim, R. Klinger, A Survey on Sentiment and Emotion Analysis for Computational Literary Studies, 2018 arXiv preprint arXiv:1808.03137.

[11] S. Saganowski, et al., Emotion recognition using wearables: a systematic literature review-work-in-progress, in: 2020 IEEE International Conference on Applied Data Mining and Computational Intelligence (ApData-Mining), IEEE, 2020.

[12] S. Zad, et al., Emotion detection of textual data: an interdisciplinary survey, in: 2021 IEEE World AI IoT Congress (AlIoT), IEEE, 2021.

[13] J.M. Garcia-Garcia, V.M. Penicht, M.D. Lozano, Emotion detection: a technology review, in: Proceedings of the XVIII International Conference on Human Computer Interaction, 2017.

[14] K.R. Scherer, What are emotions? And how can they be measured? Soc. Sci. Inf. 44 (4) (2005) 695–729.

[15] P. Ekman, An argument for basic emotions, Cognit. Emot. 6 (3–4) (1992) 169–200.

[16] R. Plutchik, H. Kellerman, Theories of Emotion, vol. 1, Academic Press, 2013.

[17] J.A. Russell, A circumplex model of affect, J. Pers. Soc. Psychol. 39 (6) (1980) 1161–1178.

[18] P. Shaver, et al., Emotion knowledge - further exploration of a prototype approach, J. Pers. Soc. Psychol. 52 (6) (1987) 1061–1086.

[19] E. Cambria, et al., New avenues in opinion mining and sentiment analysis, IEEE Intell. Syst. 28 (2) (2013) 15–21.

[20] A. Ortony, G.L. Clore, A. Collins, The Cognitive Structure of Emotions. Cambridge university press, 1990.

[21] G.K. Verma, U.S. Tiwary, Affect representation and recognition in 3D continuous valence-arousal-dominance space, Multimed. Tool. Appl. 76 (2) (2017) 2159–2183.

[22] H. Lovheim, A new three-dimensional model for emotions and monoamine neurotransmitters, Med. Hypotheses 78 (2) (2012) 341–348.

[23] Z. Wang, C.H. Zhang, A review of emotion sensing: categorization models and algorithms, Multimed. Tool. Appl. 79 (47–48) (2020) 35553–35582.

[24] G. Alqahtani, A. Alothaim, Predicting emotions in online social networks: challenges and opportunities, Multimed. Tool. Appl. 81 (7) (2022) 9567–9605.

[25] E. Cambria, et al., Affective computing and sentiment analysis, in: A Practical Guide to Sentiment Analysis, Springer, 2017, pp. 1–10.

[26] D. Zhang, B. Wan, D. Ming, Research progress on emotion recognition based on physiological signals, Sheng wu yi xue gong cheng xue za zhi 32 (3) (2015) 229–234.

[27] W. Li, et al., SKIER: A Symbolic Knowledge Integrated Model for Conversational Emotion Recognition, 2023.

[28] J.T. Wen, et al., Dynamic interactive multiview memory network for emotion recognition in conversation, Inf. Fusion 91 (2023) 123.

[29] W. Li, et al., SKIER: A Symbolic Knowledge Integrated Model for Conversational Emotion Recognition, 2023.

[30] S. Han, R. Mao, E. Cambria, Hierarchical Attention Network for Explainable Depression Detection on Twitter Aided by Metaphor Concept Mappings, 2022 arXiv preprint arXiv:2209.07494.

[31] S. Arumugam, et al., A prototype system for monitoring emotion and sentiment trends towards nuclear energy on twitter using deep learning, in: International Conference on Asian Digital Libraries, Springer, 2021.

[32] M. Kraswczyk, R. Rzepka, K. Araki, Extracting location and creator-related information from Wikipedia-based information-rich taxonomy for ConceptNet expansion, Knowl. Base Syst. 108 (2016) 125–131.

[33] M. Dragoni, S. Poria, E. Cambria, OntoSenticNet: a commonsense ontology for sentiment analysis, IEEE Intell. Syst. 33 (3) (2018) 77–85.

[34] E. Cambria, et al., A Practical Guide to Sentiment Analysis, vol. 5, Springer, 2017.

[35] E. Cambria, et al., Sentiment analysis is a big suitcase, IEEE Intell. Syst. 32 (6) (2017) 74–80.

[36] B. Abu-Salih, et al., An intelligent system for multi-topic social spam detection in microblogging, J. Inf. Sci. (2022).

[37] B. Abu-Salih, Domain-specific knowledge graphs: a survey, J. Netw. Comput. Appl. 185 (2021), 103076.

[38] A. Gliozzo, et al., Building Cognitive Applications with IBM Watson Services: Volume I Getting Started, IBM Redbooks, 2017.

[39] R. High, The Era of Cognitive Systems: an inside Look at IBM Watson and How it Works, IBM Corporation, Redbooks, 2012, pp. 1–16.

[40] IBM, IBM Watson™ tone analyzer call flow, 27/05/2022; Available from: https://cloud.ibm.com/docs/tone-analyzer?topic=tone-analyzer-about, 2022.

[41] V. Sanh, et al., DistilBERT, a Distilled Version of BERT: Smaller, Faster, Cheaper and Lighter, 2019 arXiv preprint arXiv:1910.01108.

[42] B. Abu-Salih, et al., Sentiment analysis on big news media data, in: Social Big Data Analytics, Springer, 2021, pp. 177–218.

[43] B. Abu-Salih, P. Wongthongham, C.Y. Kit, Twitter mining for ontology-based domain discovery incorporating machine learning, J. Knowl. Manag. (2018).

[44] V. Swaminathan, S. Mah, What 100,000 tweets about the Volkswagen scandal tell us about angry customers, Harv. Bus. Rev. (2016).

[45] M. Saravanakumar, T. Siganthalakshmi, Social media marketing, Life Sci. J. 9 (4) (2012) 4444–4451.

[46] M. Al-Okaily, et al., Investigating Antecedents of Mobile Payment Systems’ Decision-Making: A Mediated Model, Global Knowledge Memory and Communication, 2017 (ahead-of-print).

[47] A. Al-Okaily, et al., An empirical study on data warehouse systems effectiveness: the case of Jordanian banks in the business intelligence era, EuroMed J. Bus. (2022) (ahead-of-print).

[48] A.S. Al-Adwan, et al., Towards a sustainable adoption of E-learning systems: the role of self-directed learning, J. Inf. Technol. Educ. 21 (2022) 245–267.

[49] E. Cambria, A. Livingstone, A. Hussain, The hourglass of emotions, in: Cognitive Behavioural Systems, Springer, 2012, pp. 144–157.

[50] L. Kulke, D. Feyerabend, A. Schacht, A comparison of the Affectiva iMotions facial expression analysis software with EMG for identifying facial expressions of emotion, Front. Psychol. 11 (2020) 329.

[51] E. Cambria, et al., Sentic API: a common-sense based API for concept-level sentiment analysis, in: CEUR Workshop Proceedings, CEUR-WS, 2014.

[52] Y. Said, M. Barr, Human emotion recognition based on facial expressions via deep learning on high-resolution images, Multimed. Tool. Appl. 80 (16) (2021) 25241–25253.