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Twitter Emotion Analytics for Business Intelligence: A Comparative Study of Machine Learning Models

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Abstract:

Text-to-emotion detection in social media has become a vital activity in terms of the sentiment and mental health trends of people, as a tool for business intelligence and decision support. This paper reinstates and expands the deep learning-based sentiment classification framework, initially proposed to analyse Twitter (now X) emotion in terms of the number of emotions: anger (0), joy (1), fear (2), love (3), sadness (4), and surprise (5), with the help of a Multi-Layer Perceptron (MLP) classifier on a large-scale dataset with six emotions. After completing the preprocessing pipeline provided in the referenced study (tokenisation, stop-word removal, and POS-aware lemmatisation), the cleaned text is vectorised using TF-IDF with a vocabulary count of 5,000 features. Although the baseline MLP architecture achieved 85.25% test accuracy (better than the original study), a systematic comparative analysis shows that simple classical models outperform neural approaches for this task. Logistic Regression, trained on the same TF-IDF representation, achieved 89.09% accuracy through 5-fold stratified cross-validation, with improved generalisation and better performance on minority classes such as fear and surprise. The Multinomial Naive Bayes model achieved 83.19% mean cross-validated accuracy. These results offer practical advantages for real-time analytics in organisational settings. The findings challenge the assumption that complex deep learning frameworks are inherently superior for short-text emotion classification using lexical features. Logistic Regression demonstrates higher accuracy, interpretability, and computational efficiency on this dataset of over 416,000 instances, supporting managerial decision-making and social media-based business insights.

Keywords:

Emotion Classification; Social Media Analytics; Business Intelligence; Sentiment Analysis; Decision Support Systems

Introduction

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The rapid growth of social media networks has transformed them into emotion thermometers of individuals in real-time. Recent advances in the application of microblogging text in detecting emotions like joy, sadness, anger, fear, love, surprise, and shock and identifying them with high accuracy have resulted in applications in mental health monitoring, crisis response, and brand sentiment analysis. Moreover, the huge scale of access to user-generated content on services like Twitter (since renamed X) has allowed researchers and organisations to study the behavioural patterns and emotional trends on a scale never previously seen. Social media are also emerging as important data sources of business intelligence and analytics that enable organisations to provide actionable information based on unstructured text data (Chen et al., 2012; Kietzmann et al., 2011).

The theory of six universal basic emotions continues to be the mainstream psychological basis of systems of emotion classification. Happiness, Sadness, Anger, Fear, Disgust and Surprise are the primary ones, but Disgust has been replaced with Love in social media datasets since it is more frequent and much more clearly conveyed via informal language. This adaptation is a consequence of the changing character of digital communication, where emotional expression can be informal and context-specific and social interaction patterns can make significant contributions. This capability of identifying such emotional differences can offer useful information on customer behaviour analysis, marketing strategies, and decision-making processes by the organisation (Davenport, 2014; Wamba et al., 2017).

Deep learning architectures have gained more and more popularity in recent works (Abdullah & Shaikh, 2018; Hamdi et al., 2018). Swami et al. (2025) proposed an MLP-based framework that is alleged to be competitive in performance. Their approach is re-examined in the paper and demonstrates that their classical machine learning models (and especially the Logistic Regression with TF-IDF features) are never worse than those of the neural models on the same item. New developments have also presented hybrid and transfer learning models to enhance the performance of the classification, but these methods tend to be computationally intensive and need more complicated tuning (Ameer et al., 2023; Aslam et al., 2022). Conversely, classical machine learning models are still appealing because of their simplicity, efficiency, and interpretability, especially when they are used on structured feature representations like TF-IDF (Go et al., 2009; Pak and Paroubek, 2010). Moreover, interpretable models are becoming more and more desirable in high-stakes decision-making scenarios where it is vital to have transparency and explainability (Rudin, 2019; Molnar, 2020).

Social media emotion analytics is a very important business intelligence system as it allows organisations to track customer feelings, identify emerging problems, and assist in making decisions based on data (Power, 2002; Shim et al., 2002). Such insights can be used by organisations to optimise real-time marketing, strategies to engage customers, and manage risk. Although these developments have taken place, there is still a gap in the knowledge of whether complex deep learning models have a practical benefit over simple, scalable and understandable models in practice in businesses. The majority of the current literature focuses on making models more accurate and pays less attention to the deployment efficiency, model interpretability, and usability in the organisation.

Objectives of the Study

- To recreate and test an MLP-trained emotion classification model on Twitter data
- To compare the deep learning and classical machine learning models performance
- To evaluate the performance of models to deal with class imbalance and high-volume datasets
- To test the relevance of the emotion classification model in business intelligence and decision support systems

The new technologies have led to hybrid and optimised models. The case of a 2024 study implies multi-class sentiment classification on the basis of multi-layer perceptrons in the social network data, as polarisation classes and with high accuracy on the basis of feature selection. In comparison with this, a hybrid framework of 2025 that integrated Twitter-based

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feature selection when used together with MLP to do sentiment classification reported high performance using ensemble techniques. Scalable decision trees on automatic emotion detection in but they claimed that the scalable decision trees lacked the ability to capture semantic nuances as opposed to deep models. The adoption of emojis has also been addressed in which a multi-view deep learning model of fine-grained sentiment classification is based on the assumption that both text and visual (emoji) data are different views which complement each other.

These studies all reflect how the rule-based and superficial ML algorithms are evolving to sophisticated deep learning systems, and their present shortcomings in their ability to cope with multilingualism, sarcasm, and real-time processing. This is further advanced by the existing work, which replicates and extends the work on MLP-based classification, where the comparisons between logistic regression and Naive Bayes show superior accuracies (e.g. 89% when logistic regression is used).

2. Literature Review

2.1 Sentiment & Emotion Analysis in Social Media

Hasan et al. (2021) introduced DeepEmotex, a deep transfer learning model to classify emotion in text messages, which is more effective than traditional MLPs as it uses pre-trained embeddings. In a multi-domain context, Ameer et al. (2023) examined the transfer learning in multi-label emotion classification on social media texts and pointed out the problems of imbalance in classes and the benefits of fine-tuning advanced models. The research on sentiment analysis was earlier developed by Go et al. (2009) and Pak and Paroubek (2010), who laid the foundation of the machine learning methods of user-generated content analysis, which served as a foundation of large-scale emotion detection.

2.2 Machine Learning vs Deep Learning Approaches

A recent work proposes multi-class sentiment classification using multi-layer perceptrons on social network data, which has a very high degree of accuracy as a result of feature selection. On the same note, a hybrid system that entails the application of both feature selection and MLP-based systems has also shown superior results with ensemble methods (Aslam et al., 2022; Uthirapathy and Sandanam, 2023). The use of scalable decision tree models to automatically detect emotions has also been considered (Ranganathan et al., 2018), but they are typically not able to discover semantic nuances as often as deep learning models. Multi-view learning techniques combining textual and emoji-based features to achieve better classification accuracy are also recent developments (Xu et al., 2024).

2.3 Business Intelligence and Social Media Analytics

Social media analytics has emerged as a significant element of business intelligence systems that allow the organisation to draw actionable insights from user-generated content. Emotion-sensitive analysis goes beyond the conventional sentiment polarity and provides greater insights into customer behaviour, brand perception, and engagement patterns. They are becoming popular in marketing strategy, crisis management, and decision support systems (Chen et al., 2012; Wamba et al., 2017).

2.4 Research Gap

All these works underscore the shift in rule-based and shallow machine learning algorithms to more sophisticated deep learning systems, as well as their inabilities to process multilingual data, sarcasm, and in real-time. Although the model accuracy has been improved, prior studies have mainly been based on the deep architectures, and they have not given much attention to efficiency, scalability and interpretability in real-life applications. This is also discussed in the present work, which goes beyond MLP-based classification to compare the results of Logistic Regression and Naive Bayes, which have better performance (e.g. 89% accuracy when applied to Logistic Regression).

3. Methodology

The current study has a systematic method to classify feelings, using Twitter text, with the preparation of the data set, preprocessing, feature extraction, model building and evaluation.

Figure 1 shows a word cloud of the processed Twitter text information. This visual representation puts words in different fonts depending on the frequency and significance of

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the words in the dataset. This visualisation will highlight lexical patterns that prevail and will offer an intuitive insight into the textual features that will be relied upon during the classification process.

Figure 1. Word Cloud of Lemmatised Tokens

3.1 Dataset Description

The publicly available dataset is the Emotion Dataset for Emotion Recognition Tasks (Pandey, 2022), which was received on Kaggle. It is derived from CrowdFlower (since acquired by Figure-Eight), and was gathered between 2016 and 2018. The data is 416,809 tweets in English, which have been labelled in six emotional categories. The data is represented in CSV format, and the main attributes include an index, label (type of emotion), and text (content of the tweet), but it does not include extra information, like the time when this was said or the owner of a Twitter account. This data is separated into training (80%), and testing (20%), which includes 333,447 and 83,362 samples, respectively.

Table 1 shows a detailed picture of the distribution of the categories of emotions within training and testing sets, breaking down the number of classes.

Table 1. Distribution of Emotion Classes in the Twitter Dataset

Label	Emotion	Train	Test	Total	%
0	Sadness	96,952	24,238	1,21,190	29.10%
1	Joy	1,12,856	28,214	1,41,070	33.90%
2	Love	27,644	6,911	34,555	8.30%
3	Anger	45,852	11,463	57,315	13.80%
4	Fear	38,168	9,542	47,710	11.50%
5	Surprise	11,976	2,994	14,970	3.60%

Besides the split of the dataset, the general class distribution is also summarised in Table 2, which shows the percentage of each emotion in the dataset.

Table 2. Class Distribution of Emotion Labels

Label	Emotion	Test Set Count	Approximate Full Dataset Count	Percentage
0	Sadness	24,238	~121,190	~29%
1	Joy	28,214	~141,070	~34%
2	Love	6,911	~34,555	~8%
3	Anger	11,463	~57,315	~14%

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4	Fear	9,542	~47,710	~11%
5	Surprise	2,994	~14,970	~4%

The dataset is imbalanced, as it can be seen in Tables 1 and 2, because sadness and joy comprise over 60% of the data, and the least common category is surprise. This imbalance is also a big factor to consider when judging of the performance of the model, especially when the minority classes like love and surprise are involved.

3.2 Data Preprocessing

Raw tweet data is short, informal and noisy text, which may include slang, abbreviations and grammatical inconsistencies. Preprocessing methods are used to clean up the raw text to a structured and analysable format in order to enhance the quality of data. The preprocessing stage starts with the tokenising process of the text, which is divided into single words. This is then followed by the removal of stopwords with NLTK to remove words that occur frequently yet are not very informative. WordNetLemmatizer is then used to perform lemmatisation with part-of-speech tagging to minimise words to their base forms. Moreover, cleaning of texts is also done to eliminate URLs, hashtags, mentions, and emojis. All these measures can be taken to make sure that noise is kept to a minimum and that some meaningful textual information is retained.

3.3 Feature Engineering (TF-IDF)

Upon preprocessing, the textual data is then converted into a numerical format with the help of Term Frequency-Inverse Document Frequency (TF-IDF) vectorisation with a maximum number of features of 5,000. TF-IDF is especially useful with short texts like tweets because it measures the relative importance of words and minimises the weight of common words but less informative words. Such representation improves the performance of models and efficiency in computations.

3.4 Model Development (MLP, Logistic Regression, Naive Bayes)

This research uses three models of classifications, including Multi-Layer Perceptron (MLP), Logistic Regression and Multinomial Naive Bayes. The MLP model is the standard deep learning model, and the Logistic Regression and Naive Bayes are the classical machine learning models. The same TF-IDF feature representation is used to train all models to be consistent and allow fair comparison. This design enables determining the performance differences in terms of accuracy, efficiency and interpretability.

3.5 Evaluation Metrics

Standard classification measures are used to assess model performance, such as accuracy, precision, recall, and F1-score. To keep the classes evenly distributed, a stratified train-test split is implemented, and to guarantee that the model generalisation performance can be estimated reliably, cross-validation is employed. These metrics offer an all-around measure, especially where there is an imbalance of classes. The suggested framework represents a realistic analytics pipeline to be implemented in the business intelligence systems to process massive amounts of social media data.

4. Results

4.1 Model Performance Comparison

In this work, the authors compare the performance of Multi-Layer Perceptron (MLP), Logistic Regression and Multinomial Naive Bayes in terms of the same preprocessed data and TF-IDF feature presentation. The data comprises 416,809 examples and 6 classes of emotions; the training and testing sets have 333,447 and 83,362 samples, respectively.

The performance of the models in comparison shows that the Logistic Regression performs better than the baseline MLP model. Whereas the MLP had a general accuracy of about 85, Logistic Regression had a better accuracy of about 89, indicating that it has a better generalisation. Multinomial Naive Bayes had a relatively lower performance with a mean measure of accuracy of 83.19.

4.2 Accuracy, Precision, Recall

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Table 3 shows the classification performance of the MLP model in various emotion classes with detailed measures such as precision, recall, F1-score and support of each of the classes. The table also shows that the model works well in dominant classes of sadness and joy, but the performance of the model is lower in minority classes.

Table 3. Classification Report of MLP Model

Label	Emotion	Test Set Count	Approximate Full Dataset Count	Percentage
0	Sadness	24,238	~121,190	~29%
1	Joy	28,214	~141,070	~34%
2	Love	6,911	~34,555	~8%
3	Anger	11,463	~57,315	~14%
4	Fear	9,542	~47,710	~11%
5	Surprise	2,994	~14,970	~4%

The precision and recall values of sadness and joy are above 0.89, as depicted in Table 3, meaning that the classes can be well classified. Conversely, other types of classes (love and surprise) have lower F1-scores that are indicative of the difficulties when dealing with unbalanced datasets and subtle differences in emotions.

4.3 Confusion Matrix Analysis

The confusion matrix heatmap gives a visual view of the prediction performance of the model in the form of a heatmap, comparing actual and predicted labels. The distribution of right and wrong classifications is shown in Figure 2, in which darker values in the diagonal are more accurate.

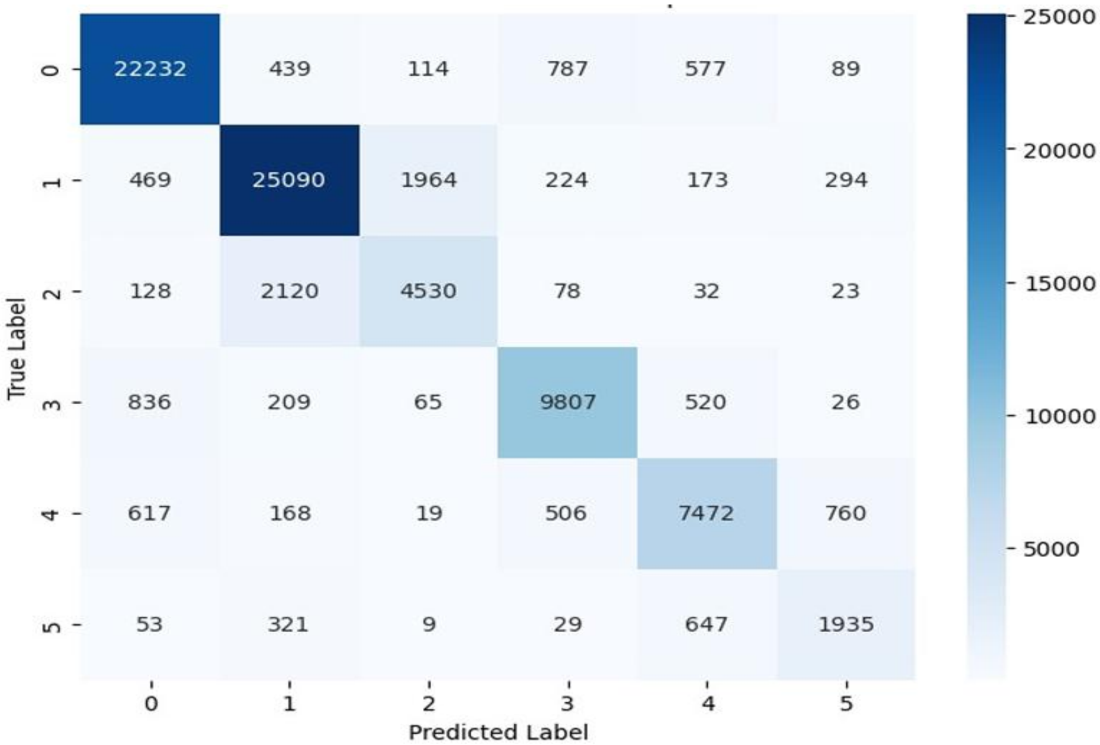

Figure 2. Confusion Heat Matrix

The model, as shown in Figure 2, has a good classification performance in sadness and joy as shown by high diagonal values. Nonetheless, misclassification tendencies can also be

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observed, especially with similar emotions in terms of meaning. As an example, love can often be mistaken for joy, whereas fear can be mistaken with anger or surprise.

This confusion matrix of Logistic Regression, as shown in Figure 3, also shows that the model had a better classification accuracy as compared to the MLP model.

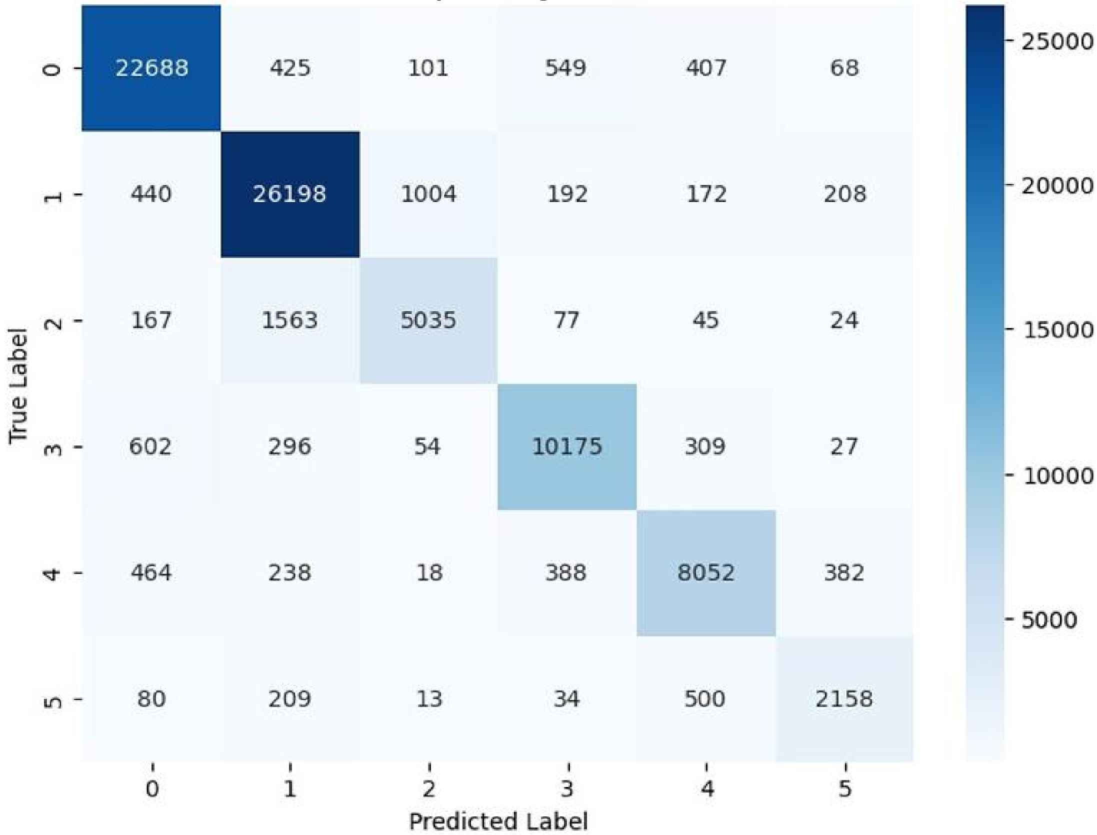

Figure 3. Confusion Heat Map for Logistic Regression

The stronger diagonal dominance is observed in Figure 3, which demonstrates better prediction performance, but there is still some confusion between the minority classes.

4.4 Cross-Validation Results

The models are tested by means of cross-validation. Table 4 is a summary of the cross-validation results of Logistic Regression, which shows the average accuracy of the results of several folds.

Table 4 shows that, on average, Logistic Regression has a cross-validation accuracy of around 89.09 and is able to perform well on the various subsets of the dataset. Multinomial Naive Bayes, in its turn, has a lower average accuracy of about 83.19, which means that it performs rather poorly with generalisation.

Table 4. Cross-Validation Performance of Models

Class	Precision	Recall	F1-Score	Support
0	0.91	0.92	0.92	24238
1	0.89	0.89	0.89	28214
2	0.68	0.66	0.67	6911
3	0.86	0.86	0.86	11463
4	0.79	0.78	0.79	9542
5	0.62	0.65	0.63	2994
Accuracy	-	-	0.85	83362
Macro Avg	0.79	0.79	0.79	83362
Weighted	0.85	0.85	0.85	83362

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Avg				

The results show that simpler models like Logistic Regression have efficient and scalable solutions and hence can be applied in real-time business analytics.

5. Discussion

This paper shows that conventional machine learning models are at least useful in identifying emotions in Twitter text, especially with a large, preprocessed dataset (over 416,000 labelled samples). The Multi-Layer Perceptron (MLP) classifier had a reported accuracy of 85.25 as compared to 82% in the reference study (Swami et al., 2025). This is due to the better preprocessing methods and application of TF-IDF vectorisation with a controlled feature space that is better in representing discriminative terms (Go et al., 2009; Pak and Paroubek, 2010). The findings also indicate the influence of the nature of datasets, especially the imbalance of the classes. Classes like sadness and joy make up a large percentage of the dataset and this helps to classify these classes with a higher degree of accuracy. Nonetheless, minority classes like love and surprise are characterised by relatively worse performance, which means that the predictions of the model are dependent on the distribution of data (Ameer et al., 2023).

The comparative analysis indicates that the Logistic Regression is better than the MLP and Naive Bayes since it has a better cross-validation accuracy of 89.09% and a better generalisation ability. This observation upholds the assertion that basic linear models can prove to be very effective in short text classification in conjunction with powerful feature engineering models like TF-IDF (Liu, 2012; Pang and Lee, 2008). In comparison with Naive Bayes, which relies on the assumption of feature independence, the interaction between the features in Logistic Regression can be better modelled, with improved classification performance. Deep learning models, like MLP, on the other hand, demand more computational resources and cannot necessarily capture meaningful patterns with sparse representations. It has been demonstrated recently that more sophisticated models, including CNNs, RNNs, and hybrid ones, can enhance performance, yet they may demand a lot of tuning and computation (Abdullah and Shaikh, 2018; Aslam et al., 2022).

Moreover, the misclassification patterns in the confusion matrix show that the similarities between the semantically close emotions are hard to differentiate, e.g. love and joy. This drawback aligns with the previous studies, as they note the difficulty of classifying emotions in informal text and the importance of understanding the context (Xu et al., 2024; Hasan et al., 2021). Social media analytics is an important aspect of contemporary business settings as it helps organisations to derive meaningful information that can be applied in their operations based on user-generated content (Chen et al., 2012; Kietzmann et al., 2011). The findings of this paper have shown that explainable machine learning models can be used to efficiently solve large-scale sentiment analysis without the need for complicated infrastructure. Emotion classification can provide more information than conventional sentiment analysis as it can identify finer emotional states, which can be utilised to improve customer experience, refine marketing behaviours, and track brand perception (He et al., 2013; Hennig-Thurau et al., 2013). The insights are especially useful in areas like crisis detection, engaging customers and competitive analysis.

These findings indicate that social media analytics can be effective in organizations through interpretable models like Logistic Regression without the need to have a complicated infrastructure. The classification of emotions helps companies determine customer dissatisfaction, possible crises, and enhance their engagement strategy. These data can be used especially well in marketing decision-making and real-time tracking of the mood of the population. The results of this research are in line with the increased significance of Business Intelligence (BI) and Decision Support Systems (DSS) in data-intensive organisations. BI systems may be equipped with social media analytics to facilitate the real-time decision-making process and strategic planning (Sharda et al., 2018; Davenport, 2014). Handling big volumes of unstructured data and providing actionable insights is one of the essential elements of modern analytics systems (Gandomi and Haider, 2015; McAfee et al., 2012).

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Moreover, the interpretable models are especially useful in the case of DSS, where transparency and explainability are required in managerial decision-making (Power, 2002; Shim et al., 2002). Practically, organisations can utilise analytics solutions at a reduced cost, which is computed by using efficient and scalable models like Logistic Regression, without compromising performance by doing so. This advocates the application of emotion analytics in the real world of business and the responsiveness of an organisation to market dynamics (Wamba et al., 2017; Molnar, 2020).

6. Conclusion

This paper shows how machine learning methods are useful to identify emotions in Twitter text using a big dataset. The reproduction and expansion of the deep learning-based sentiment classification model proves that both the neural and classical models can perform highly. Multi-Layer Perceptron (MLP) offered an accuracy of 85.25, whereas Logistic Regression had a better performance in all models with an accuracy of about 89, which means that it has a better generalisation ability. Such findings indicate that preprocessing methods like tokenisation, stopword removal, lemmatisation, and TF-IDF feature representation can be useful in enhancing performance with regard to classification. The results of the present study have major implications for the field of business intelligence and analytics because they prove that simple, interpretable models are capable of offering high-performance without the need to engage complicated computation tools. Logistic Regression is an effective and efficient tool to work with large volumes of social media analytics, which makes it convenient to use in real-time to monitor sentiments and customer feedback, study, and manage crises. Although the study has good outcomes, it suffers from a number of limitations. The dataset is skewed in terms of classes, and it negatively impacts minority classes like love and surprise. Also, TF-IDF representation does not reflect the contextual semantics, which can restrict the possibility to differentiate between the closely related emotions. Further studies can consider the development of more advanced methods to overcome these shortcomings. Possible lines of inquiry are the application of oversampling techniques like SMOTE to deal with the imbalance of the classes, the inclusion of contextual language models like BERT, and an extension of the analysis to multilingual samples to enhance generalizability. Moreover, the deployment of emotion classification systems in real-time can be used to improve social media analytics, personalisation in user experiences, and decision support systems. As a business, the study points out the significance of choosing models that are accurate, interpretable and computationally efficient to be used in decision support systems.

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