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Business intelligence using deep learning techniques for social media contents

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Abstract

Satisfaction Detection is one of the most common issues that impact the business world. So, this study aims to suggest an application that detects the Satisfaction tone that leads to customer happiness for Big Data that came out from online businesses on social media, in particular, Facebook and Twitter, by using two famous methods, machine learning and deep learning (DL) techniques.There is a lack of datasets that are involved with this topic. Therefore, we have collected the dataset from social media. We have simplified the concept of Big Data analytics for business on social media using three of the most famous Natural Language Processing tools, stemming, normalization, and stop word removal. To evaluate the performance of the classifiers, we calculated F1-measure, Recall, and Precision measures. The result showed superiority for the Random Forest classifier the highest value of F1-measure with (99.1%). The best result achieved without applying pre-processing techniques, through Support Vector Machine with F1-measure (93.4%). On the other hand, we apply DL techniques, and we apply the feature extraction method, which includes Word Embedding and Bag of Words on the dataset. The results showed superiority for the Deep Neural Networks DNN algorithm.

Keywords Big data · Business data analytics · Machine learning · Deep learning · Social media

1 Introduction

The world is currently experiencing conflicts everywhere, leading to widespread businesses failure. This makes social media a comfortable place for users to express their feelings and opinions. It includes feelings of satisfaction, joy, anger, love, and sadness, etc. Facebook and Twitter are the most popular social media sites used among Arabic users. Recently, social media has become widespread used among people; this makes it a rich source for big data analytics for researchers to use in their research. In our research, we focus on online big data publications from Facebook and Twitter that contain feelings of satisfaction that can lead to customer happiness from online business. It is an act that means purposely causing individuals to help themselves, which leads to fulfilment.

Big Data is an important concept, it is classified according to (3V's) principle and consists of Volume, Variety, and Velocity [1]. The interaction between humans via social media is an important source of big data. In our time, we are witnessing a huge explosion in data. The

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analysis and processing of this data mainly increase the understanding of customer requirements, thus increasing efficiency and productivity and reducing losses for companies [2].

Data analytics that helps the companies and businesses on social media, to improve their work through knowing advantage and disadvantage from customer on social media, that leads the company's smarter business moves, new economical operations, increase profits, and satisfied customers [3]. NLP is a field of artificial intelligence, prepared to assist computers to understand human spoken languages. In this paper, we are applying Natural language processing (NLP) techniques, which include Normalization, Stop Word Removal, Stemming, and Tokenization. Then, we use supervised machine learning (ML) techniques (Classification), by applying the most famous classifiers, which consist of Support Vector Machine (SVM), Naive Bayes (NB), K-Nearest Neighbor (KNN), Random Forest (RF), and Decision Tree (J48). In addition, we used deep learning (DL) techniques, through applying three famous neural network models, convolutional neural network (CNN), recurrent neural network (RNN), and deep neural network (DNN). The proposed method in brief improves the satisfaction of businesses through state of the art ML technologies based on the data set that have been collected smartly from famous social media platforms. The evaluation process has been conducted using the most popular measures in this field of research. The contribution of this work is as follows:

- Satisfaction Detection for Businesses on Big Data Social Media.
- Providing a comprehensive study using various classifiers, various DL algorithms, various NLP
- Creating multiple social media datasets.

The remainder of this paper will be divided into many sections. Literature Review section reviews the most related works. Methodology section shows the dataset collection, text preprocessing, ML, DL, and evaluation. Experimental Results section discuss our results. The conclusion is in the last section.

2 Literature review

Studied sentiment analysis on social media, based on determining the polarity, which includes positive, negative and natural [4]. In addition, to implement the ML steps, they selected three classifiers SVM, NB, and K-NN. Discussed the sentiment analysis on the twitter, they gathered 1800 tweets from twitter by using Twitter API [5]. The best result was achieved by SVM classifier with features TF-IDF, Bigram, and full stemming with score F-measure = 88.27%.

Discussed the difficulty of emotion detection on Twitter [6]. Consequently, they gathered 134,194 tweet data from Twitter using trending hashtags. They used the WEKA tool, to apply ML, which includes SVM, and Multinomial Naive Bayes (MNB) classifiers. They gathered 3700 tweets from the Twitter ARCHIVIST platform and divided them into three classes, positive, negative, and natural [7]. They used WEKA tool to apply ML classifiers, which include SVM, NB, KNN, and DT classifiers. [8] Analyzed a special type of high-risk natural disasters usually transpiring and causing specifically the "floods". So, they gathered 1434 tweets from Twitter by using Twitter rest API. Then, by using the R language, they applied the classification techniques, which consist of SVM, J48, C5.0, NNET, NB, and k-NN classifiers. [9] Discussed on their search the subject of sports in girls' teaching through Twitter platform. They applied many classifiers by using the RapidMiner tool. Which include NB, SVM, and KNN classifiers. Tried to analyze the tweets, to detect the feeling of the user, to classify the tweet into multiple categories, such as Love, Angry, Joy, Fear, Sadness, etc [10]. Proposed a system, which was called Arabic-Emotion Classification (AR-EMC) model, to categorize the emotion in Arabic tweets. They applied the classification by using WEKA tool, which includes Liblinear SVM, NB, SMO, and J48 classifiers [11].

Many previous rseaches investigted in business intelligence and social media dat extaction, such as in [12, 13]. Investigated the automatic discovery of sentiment analysis on social media [14]. They gathered 1776 tweets from more than 200 users from Twitter. Discussed opinion mining on social media [15]. They collected 151,500 tweets from Twitter, by using Tweepy API, Also, to test their work, they applied ML, which includes, NB, SVM, BNB, Multinomial NB (MNB), Stochastic Gradient Decent, and Logistic Regression (LR) classifiers, by using Python, in particular, Scikit-learn library. Discussed views and feelings on social media, about presidential elections in Egypt 2012 [16]. They gathered 18,278 tweets, which contains the names of candidates for the presidential. They applied classification, by using the WEKA tool, which contains SVM and NB classifiers. Investigated the sentiment analysis on social media, in particular, YouTube [17]. They gathered 30,545 Comment. They used the WEKA tool to apply the classification, which includes SVM, NB, and DT. Discussed a method to extract an opinion target from social media; by certain products of mobile phone brand and express users' opinions about those products, especially on Twitter platform [18]. They used Weka to apply ML, which includes SVM and NB classifiers. Proposed an introductory system, to analysis the emotions on social media [19]. They collected 3200 tweets from Twitter. After that, they applied ML by using Python programming, which includes NB and DT classifiers. Discussed the sentiment analysis on Twitter. They used in their work multiple datasets [20]. Then, they used the WEKA tool, with cross-validation 10, to apply ML, which includes SVM classifier.

Suggested a system to detect Cyber-Bullying and Cyber-Harassment on social media (Facebook and Twitter) Content [21]. They collected around 6000 publications and applied supervised ML techniques which include SVM, NB, KNN, J48, and RF. The best result was achieved by RF. Created the benchmark dataset for sentiment analysis content on social media [22]. They collected 151,548 tweets, by using Tweepy API. They used the NLTK, through the Scikit-learn library to apply the ML, selected many classifiers to implement on this stage. Suggested a new supervised method for discovering issues thoughts in publications on Twitter [23]. They implemented the ML techniques, by applying LR, RF, Gradient Boosting Decision Tree, XGBoost, SVM, Rule-based Classification, and Negation Resolution. Used Twitter as a platform to discuss and analyze sentiment and opinions to detect several harmful actions [24]. They collected 5200 tweets, by using Twitter API. These classifiers were NB, Multinomial NB, Bernoulli NB, LR, SGD, Linear SVM and Nu SVM classifiers. Discussed feeling of user on Twitter [25]. They collected 14,701 tweets related to feeling, by using Twitter API. Then, three psychosocial researchers categorized the tweets. They divided tweets into three sections ‘strongly concerning’, ‘concerning’, and ‘safe to ignore’. Focused on the detection sentiment on social media [26]. They collected 1841 posts from Reddit. They collected 1841 posts, divided into two class’s depression-indicative posts and standard posts. They applied the feature selection with classifiers and ML which includes LR, SVM, RF, Adaptive Boosting, and Multilayer Perceptron Classifiers.

Implemented and evaluated a new method to supervise the mental health of users on Twitter [27]. They selected randomly 120 users of Twitter evenly; divided into two sections. The number of tweets that were gathered 5446 tweets. They divided into four degrees on the danger scale, from 0 to 3 according to what the tweet contains. Suggested an innovative technique for Arabic text categorization [28]. They collected the dataset from the online newspaper articles, this dataset contains 111,728 documents. They applied to CNN. They compared the result with LR and SVM, the result show superiority of the CNN algorithm with an accuracy of 92.94%. Investigated sentiment analysis on twitter, by using DL algorithms [29]. Thus, they used the ASTD dataset, this dataset contains 10,000 tweets. Finally, they applied the DL Algorithms. It includes the Ensemble Model that combines two models, CNN and LSTM models. Investigated the cancer survivors living with Post-Traumatic Stress Disorder (PTSD) on Social Media [30]. They used Twitter to extract the data, by using Twitter API. Therefore, they used the Keras package on python API running on Tensorflow to train DL models. After that, they applied MLP, CNN n-gram, RNN, and CNN. Table 1 shows some comparison between some previous researches.

3 Methodology

This chapter supplied an explanation of the implemented system. The section describes the overall methodology that must be followed to satisfaction detection for businesses on big data social media by using ML and DL techniques.

3.1 System architecture

In our research, we use both ML and DL techniques to detection satisfaction for businesses on big data social media. Figure 1 displays our system phases.

Toward building our dataset, for training and testing, we have used online publications from social media; Facebook and Twitter. A list of keywords indicating the satisfaction of the person on business social media was created. This list contains keywords mostly related to satisfaction actions. To create a Twitter dataset, we use the TAGS API. It is a free Google sheet that allows you to pull publications through Twitter by searching for a keyword. On the other hand, to extract data (post and comment) from Facebook pages we use the Netvizz v1.6 tool. It is a simple application on Facebook. It allows the researchers to extract the data from Facebook [31]. The total number of datasets is approximately 19,200 tweets and post, before deleting duplicate data, news posts, and deleting publications that have hashtags. After cleaning the datasets, the total number of datasets reached is 8100 tweets and posts. The system has been experimented using Weka ML software tool on a Intel i7 Quad core CPU with Nvidia Geforce GPU. Table 2 shows the details of the datasets. Figure 2 shows the data collection stage.

Then, we chose three Arabic native speakers, to divide the data into two classes positive and negative dataset, based on two questions, is this publication has satisfaction user for businesses? So, if the answer is yes, we will put the publication in the positive class. If the answer no we will put the publication in the negative class.

Table 1 Comparison of previous researches

References	Dataset Info	Data-set source	ML-DL	Best results	F1
[4]	2591 Tweets-comments	Twitter	SVM, NB, K-NN	SVM	75.25
[5]	1800 Tweets	Twitter	SVM, NB	SVM	88.27
[6]	134,194 Tweets	Twitter	SVM, MNB	MNB	75.34
[7]	3700 Tweets	Twitter	SVM, K-NN	SVM	72.2
[8]	1434 Tweets	Twitter	SVM, J48, k-NN	SVM	93.3
[10]	10,000 Tweets	Twitter	CNB, SVM	CNB	68.12
[11]	2025 Tweets	Twitter	SVM, NB, J48	SVM	80.6
[12]	1776 Tweets	Twitter	NB, SMO	SMO	44.1

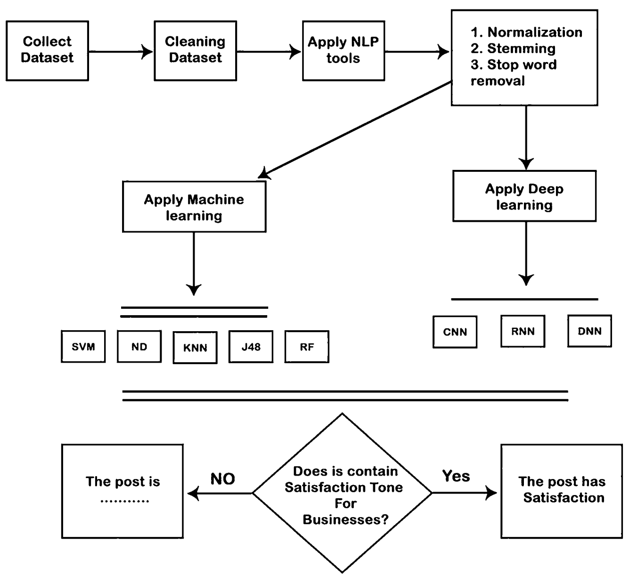

Fig. 1 Proposed system architecture

Table 2 Dataset statistics

Dataset	Positive	Negative	Total
Facebook	1450	2150	3600
Twitter	2674	1826	4500
All data	4124	3976	8100

3.2 Pre-processing tools

3.2.1 Normalization

Normalization is a process of converting the text to a uniform format, it's an important step in our work, in order to help the machine, understand the texts easily. In our work, we create the code in the java language to implement the normalization step. Moreover, the code replaced some letters into a uniform format. Users tend to express their feelings extensively when user, which makes them increase and repeat characters. Therefore, our program removes these duplicates in letters and words in order to facilitate the process of understanding by the machine.

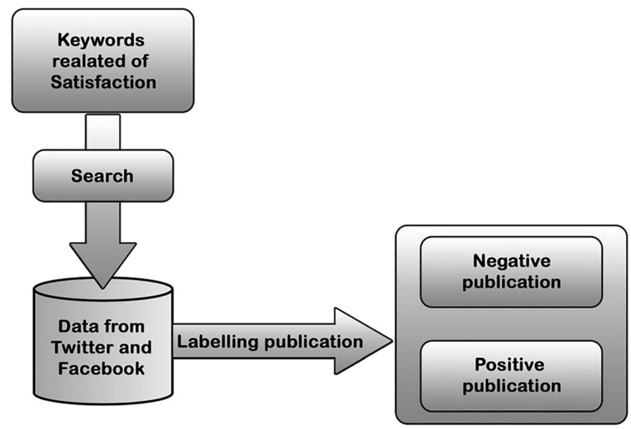

Fig. 2 Data collection stage

3.2.2 Stopword removal

The primary function is to exclude the words that have no value and repeated a lot in the text, which misleads the machine in the process of data analysis. In our work, we apply Stop word removal techniques, which include the Khoja list [32]. We improve the list by adding many words to this list. Thus, we create java code to apply the stop word removal, we put all stop words removal in a single file, and then the code calls the file and applies on the texts of the dataset.

3.2.3 Stemming (P-Stemmer)

The main objective of the stemming process is summarized in removing all affixes of a word to produce the stem, which can help the machine easy to learn because it decreases the number of words that must be learned. In our work, we use the P-Stemmer, it is an Arabic stemmer tool, proposed and developed by Dr. Kanaan and Dr. Fox. P-Stemmer is considered easy to use and clear. Based on previous research on Arabic textual data, P stemmer has provide to achieve the best results compared with many stemmers [33].

3.3 Machine learning

In our research, we apply supervised ML (classification), to detect the online publication that contains a satisfaction for businesses on big data social media, by using WEKA tool. We applied five of the most popular classification algorithms as following (SVM, KNN, RF, NB, and J48). In the following subsections, we provide a theoretical background for each of these classifiers.

3.3.1 Support victor machine (SVM)

SVM is a binary classifier proposed by Vapnik, the main idea of the SVM algorithm is to search the best way to separate the data into two classes, by placing a hyper-plane between them, in order to put similar objects together[34].

3.3.2 Naïve Bayes

The data in the NB algorithm is categorized based on Bayes' theorem, which assumes that there are no relationships between features [33]. Therefore, building the Model with the NB algorithm is easy and useful, particularly with a large dataset. The NB algorithm is a mathematical method, which works by calculating the range between document and all other documents, by the main measure of similarity [35].

3.3.3 K nearest neighbor (KNN)

It is runs based on put the data that are close to each other are similar and those far from each other are not similar. KNN is considered a lazy learning algorithm that depends only on statistics. In addition, the KNN has another limitation represented in choosing the best value of K [36].

3.3.4 Random forest

RF is extremely flexible and has very high accuracy; it also produces effective results with large datasets. The RF classifier is considered complex and takes a long time to implement. Because the RF generates a lot of trees and compared the results [37]. RF algorithm is applied to all datasets; it yields higher accuracy than the SVM algorithm. RF gives higher results with large datasets [38].

3.3.5 Decision trees J48

This algorithm aims to divide the data into smaller sets of data based on some particular attributes. The decision tree model takes the form of a binary tree, and each node in this tree represents one input variable (x) and a split point based on that variable. The DT is fast to learn, is often accurate in solving a wide range of problems, and does not need any special preparation for the data [39, 40].

3.4 Deep learning

The main objective for DL to simulate the structure of the human brain. To make the best decision to solve the problems. In our research, we applied three of the most algorithms popular in DL techniques, which include (DNN, CNN, and RNN). We used the Python programming language to implement DL algorithms. In particular, Keras Libraries. It is an open-source neural network library written in Python. We should turn those tweets into the vector of integers, where each word is a number assigned to the word in the dictionary and the order of the vector creates the sequence of the words. The irrelevant word of a group of words must be distinguished, so we built the word embedding from scratch using a one hot bag-of- word to encode the Arabic tweets, into real vectors, hence, the TF-IDF gives bad results to this data set and was thus ignored. Then, we divided the data as follows: 20% testing to 80% training with fivefold using a cross-validation approach. In our work, we use 4 layers; Input layer, embedding layer, Flatten Layer, and Dense layer.

3.4.1 Convolutional neural networks (CNN)

The structure of CNN is inspired by the neurons of brains' human and animals. CNN has three main advantages, namely, parameter sharing, sparse interactions, and equivalent representations. To fully utilize the two-dimensional structure of an input data, local connections, and shared weights in the network are used, as an alternative of traditional fully connected networks. This results in very fewer parameters, which presents the network faster and easier to train. These cells are sensitive to small sections of a scene rather than the whole scene. In other words, the cells operate as local filters over the input and extract spatially local correlation existing in the data [41].

3.4.2 Recurrent neural networks (RNN)

RNN uses sequential information in the network. This attribute is vital in many applications where the embedded structure in the data sequence carries beneficial knowledge. RNN is a type of DL network that contains loops

(Recurrent) within networks, that can estimate the next value by using the Previous information. Also, these networks are very important to identify the subsequent sequence of certain data, by retaining important features, as well as predicting future data [42].

3.4.3 Deep neural networks (DNN)

The DNN finds the correct mathematical manipulation to turn the input into the output, whether it is a linear relationship or a non-linear relationship. The network is moving through the layers calculating the probability of each output. Each mathematical manipulation as such is considered a layer, and complex DNN has many layers, hence the name "deep" networks. The goal is that eventually, the network will be trained to decompose an image into features, identify trends that exist across all samples, and classify new images by their similarities without requiring human input [43].

4 Experimental work

In this section, we present the results of the proposed work to detect the feeling of satisfaction for businesses on big data social media, based on the content of social media, in particular, Facebook and Twitter. This will be detected by applying ML (classification) and DL techniques. The scale (Recall, Precision, and F1-Measure) measures the accuracy of the results of datasets. In this work, we will use five types of classifiers, including KNN, SVM, NB, Random Forest, and J48. On the other hand, we will use three types of deep learning techniques, including CNN, RNN, and DNN. In addition, we applied three preprocessing tools, including Stop-Word Removal, Normalization, and Stemming. We have trained the classifiers on datasets collected from Arabic social media, having been divided by human experiences into positive and negative. In this research, we used WEKA 3.8 toolkit [44]. This toolkit was developed by the University of Waikato in New Zealand. This toolkit is written in Java. Also, we used Tenfold cross-validation since it gives high efficiency of the outcomes compared with other folds. We conducted many experiments during this study, initially, we applied ML techniques (SVM, NB, KNN, J48, and RF) on all datasets. Then we applied ML techniques after separating the data set into two categories, Facebook and Twitter. In the first experiment, we used preprocessing, including Stop-Word Removal, Normalization, and Stemming. In the other experiment, we apply ML techniques without using preprocessing tools. Also, all previous steps have also been applied to the dataset of Facebook and Twitter. Finally, we applied DL techniques (CNN, RNN, and DNN) on all datasets. Then we separating the dataset into two categories, Facebook and Twitter.

4.1 Evaluation measurements

In our study, to evaluate our classifiers, we use three popular measures used in data mining techniques, which include precision, recall, and F-measure. Precision: Determined the possibility that if a random publication should be classified as positive, and then this is the right decision. See Eq. 1

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FN})},\ \text{if TP} + \text{FN} > 0 \tag{1}$$

Recall: Determined the possibility that if a random publication should be classified as positive, and then this is the taken decision. See Eq. 2

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FP})},\ \text{if TP} + \text{FP} \ > 0 \tag{2}$$

F1-measure: It is a measure that merges precision and recall is the harmonic average of precision and recall. See Eq. 3

$$\text{F1 - Measure} = \frac{(2 \times \text{Recall} \times \text{Precision})}{(\text{Recall} + \text{Precision})} \tag{3}$$

4.2 Experimental results

4.2.1 Apply classification with preprocessing tools on all dataset

In this experiment we apply the five classifiers (NB, SVM, KNN, J48, and RF) on all dataset, with preprocessing tools, which includes Normalization, Stop-Word Removal, and Stemming. Table 3 shows the Precision. The results show achievement of (97.3%) for NB, (98.8%) for SVM, (86%) for KNN, (95.6 %) for J48 and (99.1 %) for RF.

Table 4 shows the Recall. The results show achievement of (97.2%) for NB, (98.8%) for SVM, (82%) for KNN, (95.6%)for J48 and (99.1%) for RF.

Table 5 and Fig. 3 shows the F1-measure. The results show achievement of (97.2%) for NB,(98.8%) for SVM, (82%) for KNN, (95.6%) for J48 and (99.1%) for RF.

Table 3 Precision for all classifiers with preprocessing tools on all dataset

Classifiers	Precision
NB	0.973
SVM	0.988
KNN	0.860
J48	0.956
RF	0.991

Table 4 Recall for all classifiers with preprocessing tools on all dataset

Classifiers	Recall
NB	0.972
SVM	0.988
KNN	0.820
J48	0.956
RF	0.991

Table 5 F1-measure for all classifiers with preprocessing tools on all dataset

Classifiers	F1-measure
NB	0.972
SVM	0.988
KNN	0.820
J48	0.956
RF	0.991

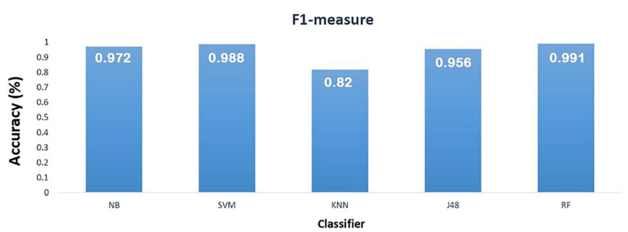

Fig. 3 The F1-measure for all classifiers with preprocessing tools on all datasets

4.2.2 Apply classification without preprocessing tools on all dataset

In this experiment we apply the five classifiers (NB, SVM, KNN, J48, and RF) on all dataset, without preprocessing tools. Table 6 shows the Precision. The results show achievement of (84.4%) for NB, (93.4 %) for SVM, (74.5 %) for KNN, (87.2 %) for J48 and (93 %) for RF.

Table 7 shows the Recall. The results show achievement of (84.3 %) for NB, (93.4 %) for SVM, (69.5 %) for KNN, (87.1 %) for J48 and (93 %) for RF.

Table 6 Precision for all classifiers without preprocessing tools on all dataset

Classifiers	Precision
NB	0.844
SVM	0.934
KNN	0.745
J48	0.872
RF	0.930

Table 7 Recall for all classifiers without preprocessing tools on all dataset

Classifiers	Recall
NB	0.843
SVM	0.934
KNN	0.695
J48	0.871
RF	0.930

Table 8 F1-measure for all classifiers without preprocessing on all dataset

Classifiers	Recall
NB	0.842
SVM	0.934
KNN	0.679
J48	0.871
RF	0.930

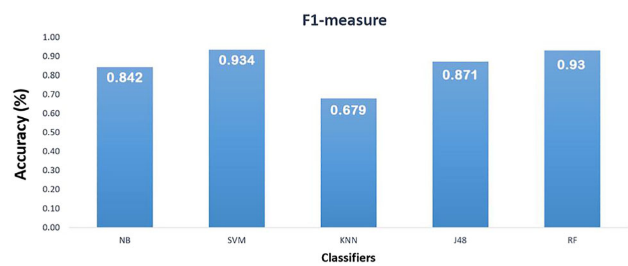

Fig. 4 The F1-measure for all classifiers without preprocessing tools on all datasets

Table 8 and Fig. 4 shows the F1-measure. The results show achievement of (84.2 %) for NB, (93.4%) for SVM, (67.9 %) for KNN, (87.1 %) for J48 and (93 %) for RF.

Table 9 and Fig. 5 display the comparison of the F1-measure results of all classifiers with preprocessing that, and F1-measure results without apply preprocessing tools.

4.2.3 Apply classification with preprocessing tools on facebook dataset

Table 10 and Fig. 6 shows the result of Precision, Recall, and F1-measure for all classifiers with preprocessing tools on Facebook dataset. The results show that the RF, SVM, NB, and J48 classifications achieved the highest value respectively compared with the KNN classifier.

Table 10 Precision, Recall and F1-measure for all classifiers with Preprocessing on Facebook Dataset.

Table 9 F1-measure for all classifiers with preprocessing and without preprocessing for all dataset

Classifiers	F-measure with preprocessing	F-measure without preprocessing
NB	0.972	0.842
SVM	0.988	0.934
KNN	0.820	0.679
J48	0.956	0.871
RF	0.991	0.930

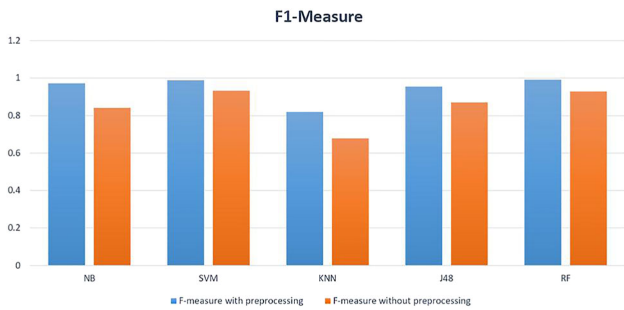

Fig. 5 The F1-measure for all classifiers with and without preprocessing tools for all datasets

Table 10 Precision, recall and F1-measure for all classifiers with preprocessing on facebook dataset

Classifiers	Precision	Recall	F1-measure
NB	0.922	0.920	0.919
SVM	0.940	0.941	0.940
KNN	0.809	0.758	0.721
J48	0.878	0.879	0.879
RF	0.959	0.959	0.959

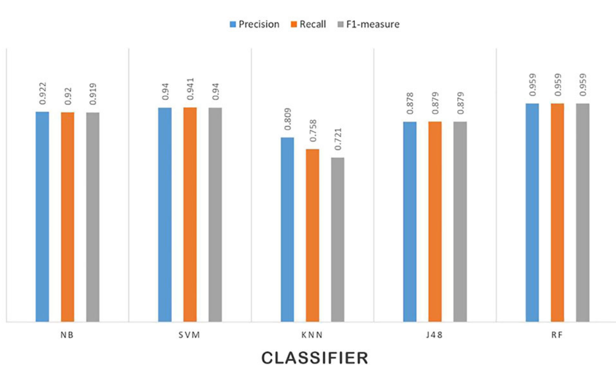

Fig. 6 Shows the result for all classifier with preprocessing tools for facebook dataset

Table 11 Precision, recall and F1-measure for all classifiers with preprocessing on twitter dataset

Classifiers	Precision	Recall	F1-measure
NB	0.981	0.981	0.981
SVM	0.991	0.991	0.991
KNN	0.862	0.841	0.830
J48	0.961	0.959	0.959
RF	0.993	0.993	0.993

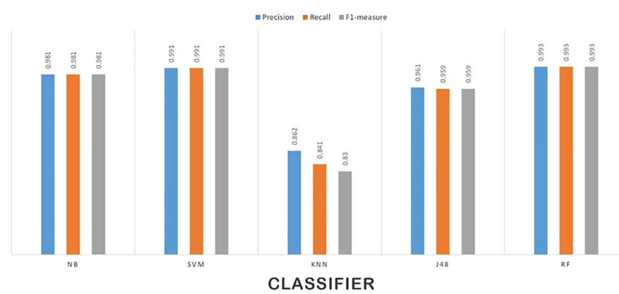

Fig. 7 Precision, recall and F1-measure for all classifiers with preprocessing tools on twitter dataset

Table 12 Precision, recall and F1-measure for all classifiers with preprocessing on all datasets

Algorithm	Precision	Recall	F1-measure
DNN	0.96	0.96	0.96
CNN	0.94	0.94	0.94
RNN	0.76	0.53	0.62

4.2.4 Apply classification with preprocessing tools on twitter dataset

Table 11 and Fig. 7 shows Precision, Recall and F1-measure for all classifiers with preprocessing tools on Twitter dataset. The results showed that the RF, SVM, NB, and J48 classifications achieved the highest Recalls respectively compared with KNN classifier.

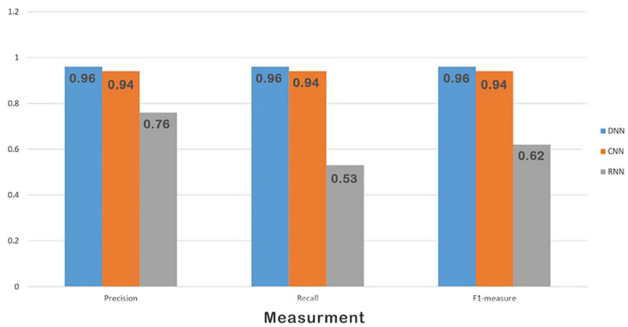

Fig. 8 Precision, recall and F1-measure for all classifiers with preprocessing on all datasets

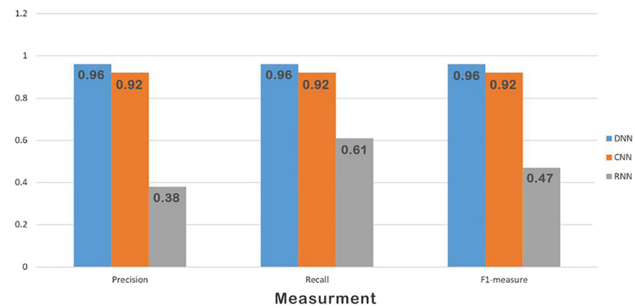

Fig. 9 Precision, recall and F1-measure for all classifiers with preprocessing on facebook datasets

4.2.5 Apply deep learning techniques with preprocessing tools on all dataset

Table 12 and Fig. 8 shows Precision, Recall, and F1-measure for all algorithms with preprocessing tools (Stop Word Removal and Tokenization) on all datasets. The results showed that the DNN and CNN algorithms achieved the highest value respectively compared with the RNN algorithm.

4.2.6 Apply deep learning techniques with preprocessing tools on facebook dataset

Table 13 and Fig. 9 shows Precision, Recall, and F1-measure for all algorithms with preprocessing tools (Stop Word Removal and Tokenization) on Facebook datasets. The results showed that the DNN and CNN algorithms achieved the highest value respectively compared with the RNN algorithm.

4.2.7 Apply deep learning techniques with preprocessing tools on Twitter dataset

Table 14 and Fig. 10 shows Precision, Recall, and F1-measure for all algorithms with preprocessing tools (Stop Word Removal and Tokenization) on Twitter datasets. The results showed that the DNN and CNN algorithms achieved the highest value respectively compared with the RNN algorithm.

Table 13 Precision, recall and F1-measure for all classifiers with preprocessing on facebook datasets

Algorithm	Precision	Recall	F1-measure
DNN	0.96	0.96	0.96
CNN	0.92	0.92	0.92
RNN	0.38	0.61	0.47

Table 14 Precision, recall and F1-measure for all classifiers with preprocessing on twitter datasets

Algorithm	Precision	Recall	F1-measure
DNN	0.96	0.96	0.96
CNN	0.92	0.92	0.92
RNN	0.46	0.38	0.55

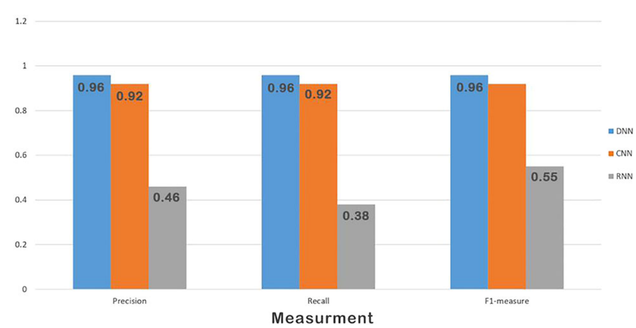

Fig. 10 Precision, recall and F1-measure for all classifiers with preprocessing on twitter datasets

4.3 Conclusions

In our research work, we proposed a system that works to detect the Satisfaction tone that leads to customer happiness for Big Data that came out from online businesses on social media, in particular, Facebook and Twitter. We focused on collecting data that contain sadness, depression, and suicide thoughts. Thus, we have collected 8100 online publications from Facebook (Posts and comments) and Twitter. In addition, we used three techniques of NLP, which include Normalization, Stop Word Removal, and Stemming. After that, we use the ML techniques, to applied five classifiers on the dataset, which include NB, SVM, KNN, J48, and RF. We used F1-Measure, Precision, and Recall measurement to calculate the accuracy of the classifiers. The result showed superiority for RF classifier the highest value of F1-measure. On the other hand, the best result achieved with all datasets without applying preprocessing techniques through SVM. On the other hand, we apply DL techniques, which include CNN, DNN, and RNN. The result showed superiority for the DNN Algorithm with the highest value of F1-measure, followed by CNN and RNN with respectively with all datasets and by applying Stop Word Removal and Tokenization.

Author Contributions All Authors worked in an equivalent load at all stages to produce this research

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Data availability The data set used in the work will be available upon request

Declarations

Conflict of interest The authors have not disclosed any competing interests.

Informed consent I have read and I understand the journal information and have agreed to all mentioned terms and conditions.

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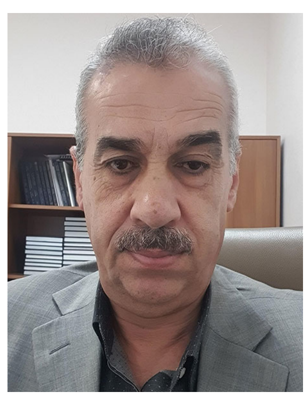

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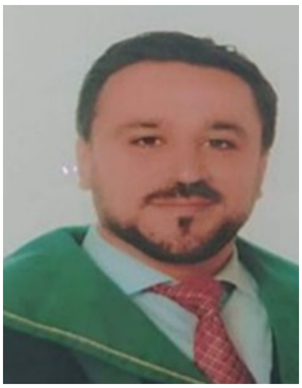

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