Received: 21 July 2023 | Revised: 16 January 2024 | Accepted: 26 January 2024
DOI: 10.37917/ijeee.21.2.5 Vol. 21 | Issue 2 | December 2025

Open Access

Iraqi Journal for Electrical and Electronic Engineering
Original Article

Understanding the Influence Impact of Social Media on Drug Addiction: A Novel Sentiment Analysis Approach Using Multi-Level User Engagement Data

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Abstract
Drug addiction remains one of the key problems, which troubles each nation nowadays. Though social and economic factors have been contributing to its escalation significantly, recently in recent years a marked rise with drug addiction has witnessed in Iraq. Governments and societies are therefore working hard to find ways of counteracting this trend. Notably, social media networks have become major conduits of the dissemination sensitization about the risks involved in substance abuse addiction as well as consequences that are faced by drug abusers users. On the other hand, there are no studies analyzing user's sentiment regarding drug addiction on social media in Iraq. This paper offers a new approach to fill this gap by presenting an analytical framework for identifying such sentiments of people from posts published on different popular platforms including Facebook and Twitter. In order to achieve this, a new dataset was generated from one of the relevant Facebook pages and comprised three distinct levels of user engagement data. Our goal is to create a direct connection between the research objectives and practical applications which can benefit society. This study's results contribute significantly to the understanding of sentimental movements regarding drug addiction and affect public perceptions on this significant problem. This study makes contributions to such fields are sentiment analysis, social media research and public health by revealing the complex interaction of social media itself, user's feelings towards it or even drug addiction in Iraq. The new approach to analysis of multi-level user engagement data and offers an evidence based solution for dealing with the challenges presented by drug abuse in society. Using a neural network algorithm, the classification model developed has shown excellent performance with an accuracy rate of about 91%.

Keywords
Drug Addiction, Iraq, Neural Network, Sentiment Analysis, Public Perception.

I. Introduction

Drug addiction is the highest challenge to face the Iraqi social background [1]. The social ramifications of drug addiction are highly prevalent, as the effects do not stop with only those who use drugs but permeate through to families and communities in Iraq. This problem not only causes health and psychological problems but also leads to criminal behavior and violence [2]. Various types of drugs spread in Iraq as a result of the geographical location and political and security problems [3]. In recent years, attempts to adopt awareness campaigns targeting the negative effects of drug addiction in Iraq were realized. Organizations like Iraqi National Security Service (INSS) have attempted, by means of public campaigns and general diffusion on the legal side as well as procedures involved in engaging drugs' trafficking or drug addiction. Nevertheless, the availability of drugs and lack powerful structures for regulation treatment and re-socialization have led to ease in accessing illicit substances [4].

Those include the rapid emergence of social networks in Iraq. In Iraq, the number of social media users has increased exponentially and among them is Facebook mainly due to its large population [5, 6]. Capitalizing on the tools of social media, INSS has used these platforms to inform public about dangers associated with drug abuse and provide details regarding legal issues surrounding trafficking by drugs [7].

In this study, we seek to investigate and understand the perceptions of Iraqi social media users regarding drug abuse. Focusing on Facebook, which is very popular in Iraq we will try to get the most out of the many user generated content and comments available.

This approach also offers yet another way of collecting data and analyzing public perceptions, helping in getting much-needed information about the present state-of-mind regarding addiction within society.

User engagement can be understood as both people's presence and activities they use for interacting with digital content, sites or communities [8]. In this study of drug addiction and user sentiment on social media in Iraq, it was crucial to understand the various sentiment people had towards different issues with regards to their active involvement 9. The objective of this study is classifying information on the user's involvement in certain levels which enables to record and interpret different levels of commitment relative with drug addiction attention. Users' engagement analysis offers a deeper investigation, which permits understanding of how diverse groups are ready to state an opinion on drug addiction problems [10]. Measuring user engagement is a critical component in building strategies aimed at developing interventions, communicating successfully and creating policy initiatives which would be based on scientific evidence to deal with the social problem of drug abuse. Considering the multi-level user engagement information, this is a detailed study that leads to more nuanced conclusions regarding public sentiment and its importance for drug addiction surveillance [11].

To accomplish this goal, our strategy is to post on specific Facebook pages that cover issues of drug abuse and other topics also related to narcotics. Data collection and aggregation will be targeted at these pages. The compiled replies by participants will be arranged based on their level of involvement as Low Engagement (LE) to High Engagement (HE). The data will be preprocessed to ensure accuracy and quality. This would be followed by the use of sentiment analysis techniques on sentiments expressed in comments, with several classification algorithms used to develop a predictive model. The distinctive nature of this study relies on the fact that it provides with an opportunity to find out what Iraqi social media users actually think about drug addiction. Utilizing the user-generated comments, we can have a better understanding of public opinion and impressions that goes beyond sample surveys. In addition, through the division of comments into categories depending on levels of engagement we can capture specific types of sentiment and analyze opinions held by various user communities. The study also aims at contributing to the understanding of sentiment analysis within an Iraqi dialectical context.

The literature gap we seek to bridge with our research is in the form of a new angle on drug addiction by analyzing social media sentiment. It is intended for this study to shed light on the problem of drug addiction in Iraq through analysis users' social media opinion and attitude towards by integration user engagement levels with sentiments

analyzing. The use of social media and sentiment analysis allows us to gain valuable information on public opinion, based from which targeted interventions, policies and initiatives can be developed with the aim of dealing effectively with drug addiction within Iraqi society in order to add meaningful insights for existing knowledge.

The organization of this paper is as follows: Section II puts forward an analysis of the present literature and work. Section III describes architecture used. In section IV, gives a clear description of our experimental. In section V analysis and useful information we have obtained from our experimental study. Lastly, Section VII ends the paper by providing a summary of the findings and brainstorming ideas for further research.

II. RELATED WORKS

Drug addiction is a serious and growing problem in societies all over the globe among which Iraq represents one of them. The purpose of this literature review is to examine the contemporary scholarship and knowledge on drug addiction in Iraq upon a set of related studies. This review gives a brief synopsis of each study outlining their relevant outcomes and contributions to the literature.

Motyka, et al. [12] studied the changes within the drug culture in Iraq, emphasizing many factors causing such transformations. These results shed light on the changing dynamics of drug addiction in the country and underscored that interventions and policies must be responsive to these changes. To measure the level of internet addiction and its effects on academic performance among Iraqi medical and paramedical college students, Raouf [13] conducted a study Internet addiction was associated with academic performance through the study The results pinpointed the shortcomings of overuse and that has highlighted the importance to promote health in internet usage among students. Suhail, et al. [14] The study used hierarchical cluster analysis to categorise drug addiction phenomena at various governorates of Iraq. The results showed unique forms of drug addiction throughout the country which enabled an understanding of this issue on a regional level and helped devise region- based interventions. Al-Kubaisy and Mohamed [15] investigated student's awareness of drug addiction phenomenon while in university level. The purpose of their study was to investigate among university students' views, and attitudes about addiction. The results emphasized that students needed better recognition on the risks and consequences of drug addiction as well as educational programs or interventions to address this issue more efficiently.

In some recent study, Kaur, et al. [16] developed the artificial intelligence model for detecting population that are addicted on drugs by using Markov Decision Process. The study suggested a novel method that employed AI methods to detect and group persons affected by drug addiction.

The framework was promising in correctly capturing the population under drug addiction which can be applied to develop focused interventions and systems of support. Knowledge and attitude of substance abuse among the youth in Tikrit, Iraq were examined by Mohammed, et al. [17] Regarding the study, it can be highlighted that patients at risk of drug abuse among young people were researched on levels of knowledge and attitudes. The results brought home the necessity of broad-based training and enlightenment drives that would change a youth's understanding in order to decrease chances for substance use. For example, Obayes, et al. [18] considered sentiment analysis of user opinions on drugs at a more advanced level through Natural Language Processing (NLP) techniques. The results proved the effectiveness of sentiment analysis in discussing end-user attitudes and responses associated with drug administration, which are important elements for making regulations and decisions.

In 'Scenario of Narcotic Types And Addiction In Iraq' by Abdulghani, et al. [19]. The research thus sought to outline the narcotics commonly used in Iraq and their addiction problems. The authors focused on enlightening the wave and trends of drug abuse in Iraq, which show that cases related to addiction are increasing at an alarming rate necessitating effective prevention methodologies or interventions. Motlagh, et al. [20] conducted a study on the consumption trends and social media analysis predicting public opinion on drug legalization. They have instead done a study where they analysed social media data to uncover public opinions on the legalisation of drugs. The results revealed the role social media analysis could play in influencing the perceptions of society on drug addiction and legality.

Najm and Khleel [21] studied drug addiction in the setting of paramedical staff attitude to it as well as the practice related issues in Baghdad, Iraq. The researchers set out to realize the paramedical staff's views and their efforts in handling drug addiction problems. The results highlighted the importance of education and empowerment courses for paramedical personnel to serve as active participants in prevention, treatment approaches, and rehabilitation. To conclude, the discussed studies offer insightful information on various aspects of drug addiction in Iraq. Accordingly, the studies presented below contribute to the study of narcotic types, awareness among university students, internet addiction. AI-based identification frameworks and classification methodologies are offered as well as knowledge and attitudes among youths by summarizing them into architectural designs for social networks in public opinion analysis; challenges identified while helping women with addiction perspectives given paramedical staff; sentiment observed interpretation user reviews provided consumer software products Such ... tools can be used in developing viable and effective interventions, policies, and preventative approaches towards the issue of drug addiction within Iraq. Continued studies within this domain need to be conducted so as we grapple with a better understanding and also... Open Read more ≫ This development will influence the results for patients who become addicted by drug use some group in community.

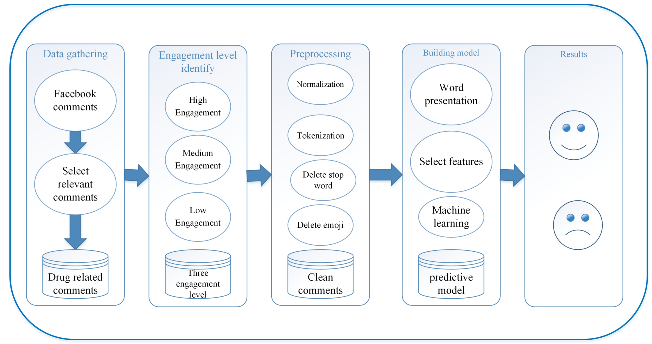

Fig. 1. Proposed Sentiment Analysis Approach

III. Methodology

The proposed methodology contains the five main steps as illustrated in Fig.1 .

1. Data gathering: at this stage, relevant comments are collected. INSS Facebook page is the source of this data. This page was chosen because it is effective in following up and disseminating news related to drug control. All related posts to drug control for the period of August 2021 to March 2022 have been collected. About 5k related posts ware collected.

2. Engagement level identify: to identify EL of each post,

Engagement Rate (ER) for each post should be calculated according to the following equation:-

$$ER = \frac{TPI}{AU} * 100 \quad (1)$$

Where: TPI: represents the number of interaction on the specified post (e.g. reactions, comments, shares) AU: represents the number of active users on the page within a given period of time. The results of the ER calculation for each post calculates the level of engagement. The results are divided into three groups according to the following equation:-

$$n = \frac{Max_E R - Min_E R}{3} \quad (2)$$

$$Low\ engagement\ range = Min_E R ... (Min_E R + n) \quad (3)$$

$$Medium\ engagement\ range = (Min_E R + n) \ldots (Min_E R + 2n) \quad (4)$$

$$High\ engagement\ range = (Min_E R + 2n) \ldots (Max_E R) \quad (5)$$

Where :

Max–ER: the maximum ER appears in the results.

Min–ER: the minimum ER appears in the results.

3. Data prepossessing: At this stage, the collected data is processed to be appropriate and to increase the accuracy of the results. A set of operations will be applied, like delete stop letters and numbers, delete punctuation marks, delete emoji removing misspellings, repeated letters, diacritics, punctuation's, numerals, English words, and elongation. All these contents do not affect the results. To perform the data prepossessing tasks, combination of regular expressions and string manipulation functions in Python are used. After that, a normalization process was applied to particular letters, for example the letters (alif madda, alif hamza↓, alif hamza↑ were converted to (alif).

   Tokenization is the process of dividing a given text into a set of words (tokens) which are separated by spaces. To find the best text representation, this work investigated tow term-weighting schemes, namely, Part-of-Speech tagger (POS tagger) [22] and N-grams [23]. For the experimenting, list of Arabic stop words from [24] were used. At the end of this stage, 25405 tokens are created.

4. Build prediction model: To classify reactions on the topic of drug addiction, an emotion rating model will be built using a previously labeled corpus of the Iraqi dialect, because the users of the page are from Iraq. Sentiment analysis, a crucial component of (NLP), involves the use of machine learning models to determine the emotional tone expressed in textual content. In the context of classifying reactions related to drug addiction, an emotion rating model is trained using a variety of classifiers to identify the most effective approach. The following classifiers were experimented with: Neural Network [25], Logistic Regression [26], Random Forest [27], Naive Bayes [28], Support Vector Machine (SVM) [29], and k-Nearest Neighbors (kNN) [30]. The model training process involves several key steps. Firstly, the labeled corpus of the Iraqi dialect is utilized for training, ensuring cultural and linguistic relevance to the target audience. The dataset is split into training, validation, and test sets to prevent over fitting.

   Each classifier is trained on the training set, and hyperparameters are tuned to optimize performance. The models are then validated on a separate validation set to ensure robustness and prevent over fitting. The final evaluation is conducted on the test set, and performance metrics such as accuracy, precision, recall, and F1 score are employed to assess the effectiveness of each classifier. After testing several approaches to ensure the accuracy of the model, the model with the highest performance is selected.

5. Results: This module provides representation for all the data processing and the analysis performed in the previous module to facilitate comparison as well as interpretation.

IV. EXPERIMENTAL

The experimental stage was divided into two parts. The first part is calculating ER. The purpose of this stage is to divide posts into three groups according to ER. The second part involves preparing a sentiment analysis prediction model. We used Python programming language to all steps at this experimental.

TABLE I.
THE ENGAGEMENT RATES FOR DIFFERENT CATEGORIES

Engagement level	Posts	Sum of interaction	Engagement rate
HE (35%-28.3%)	Post 1	1050	35%
	Post 2	950	31%
	Post 3	945	31%
	Post 4	910	30%
ME (28.3%-21.64%)	Post 5	845	28%
	Post 6	831	27%
	Post 7	764	25%
	Post 8	736	24%
LE (21.64%-15%)	Post 9	615	20%
	Post 10	503	16%
	Post 11	466	15%

1) *Engagement Level Detection*

The data collected contains different EL. A lot of pages have a lot of subscribers, but they are inactive. Therefore, relying on incorrect numbers gives incorrect results. To increase the validity of the ER results, we use the number of active users. The number of active users is calculated to determine the EL. We made a review of the page to follow the number of users and found that the total number of active users are 3k. Table I displays the engagement levels, corresponding posts, the sum of interactions for each post, and the engagement rates for different categories.

Table I. provides an overview of the engagement rates for different categories, specifically focusing on three engagement levels: (HE) with an engagement rate ranging from 35% to 28.3%, Medium Engagement (ME) with a rate of 28.3% to 21.64%, and (LE) ranging from 21.64% to 15%. The table provides the posts in question, totals per interactions for each post and calculated engagement rates. Finally, the statistics demonstrates different user engagement levels for all of the posts higher rates in the HE category and lower engagement observed with respect to ME and LE. This data provides interesting information regarding the level of audience involvement and may contribute to understanding overall trends on engagement within each group.

2) *Sentiment Analysis Model:*

Social networks are a crucial data asset [31]. Following the process of data collection and establishing EL for each set, a dataset will be identified at every level. The selected data is first divided into positive or negative for each level.

In this case, classification process was adapted in accordance with the approach suggested in [7] to decide on polarity of comments. Data annotation was undertaken by three native linguistics experts of Arabic Iraqis. The annotation process employed binary classification, a technique that was found to deliver accurate outcomes. To further analyze the text classification application, they suggested a pattern-based technique. All comments were annotated by the linguistics experts with

TABLE II.
THE ENGAGEMENT LEVELS, CORRESPONDING POSTS

Engagement level	Posts	Number of comments	Number of positive comment	Number of negative comments
HE (35%-28.3%)	Post 1	180	90	90
	Post 2	180	90	90
	Post 3	200	100	100
	Post 4	180	90	90
ME (28.3%-21.64%)	Post 5	180	90	90
	Post 6	180	90	90
	Post 7	180	90	90
	Post 8	180	90	90
LE (21.64%-15%)	Post 9	180	90	90
	Post 10	180	90	90
	Post 11	180	90	90

a value of “1” for positive or 0 for negative sentiment component respectively. Whereas in some cases an expert could not determine with certainty if a clause was positive or negative, such clauses were annotated as “I don’t know—. However, the annotations of these three experts were merged and compared in such a way so that they constituted an well-grounded basis for sentiment analysis. In order to finalize the polarity determination of the comment, we observe used rules from [7]. Table II. provides degree of commitment, related posts, no of comments for each post and the quantity to positive and negative feedbacks.

Table II. has useful data on the engagement rates and accompanying posts. The table focuses on three engagement levels: (HE), (ME), and (LE). Every level of a user’s engagement is connected to particular posts, and the table provides comments number plus positive and negative comment numbers for each post. These data provide a more detailed overview of the overall extent of engagement and sentiment provided by users in each category. It reveals the relationship trends and can be handy in user feedback analysis, engagement review per post type.

A broad range of experiments were undertaken to scrutinize the impact of data selection and sentiment analysis relationship with engagement. In addition to features study. The data set comprised 2000 references, in which 1000 was that of positive comments and another including negative ones. Experiments were performed using six classifiers, Neural Network, Logistic Regression, Random Forest, Naive Bayes, SVM and kNN. The experiments include two stages, the first stage in which sentiment analysis was studied for each level of engagement. Second, conducting experiments using two types of word embedding to represent texts Term Frequency-Inverse Document Frequency (TF-IDF) [32] and word2vec [33].

V. EVALUATION

In order to validate performance, we employed the N-fold cross validation. We used 10-fold cross validation to evaluate the performances of logistic Regression, Random Forest, Naive Bayes, SVM and KNN. We used 10-epoch for Neural Network. Confusion matrix used to measure the performance of classification algorithms. It is useful for measuring Accu-

TABLE III.
CONFUSION MATRIX

		Actual value	
		Positive	Negative
Predicted value	Positive	TP	FP
	Negative	FN	TN

racy, Precision, Recall and F-measure.

Where, TP are data that classified as positive and actually attributed to the positive. TN are data that classified as negative and actually attributed to the negative. FP are data that classified as positive and actually attributed to the negative. FN are data that classified as negative and actually attributed to the positive. The following Equations show how to calculate the chosen matrices.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

$$Recall = \frac{TP}{TP+FN} \tag{8}$$

$$F-measure = \frac{2*Precision*Recall}{Precision+Recall} \tag{9}$$

VI. RESULTS

We will evaluate the experimental outcomes and the classification performance for each chosen scenario. Our aim is to conduct a thorough comparison of the results, validate the efficacy of various word representation structures, and assess their performance in conjunction with classifiers.

The word cloud generated from the comments values provides a visual representation of the prominent words or terms that frequently appear in the collected comments. The size and prominence of each word in the cloud are typically proportional to its frequency or significance in the datasets. By analyzing the word cloud, we can gain insights into the sentiments, themes, or topics expressed in the comments. The size of words in the word cloud is directly proportional to their frequency, and some important themes or sentiments related with interest topic are represented by these sizes. The results of this operation are shown in Fig. 2, 3 and 4.

Fig. 2 compares positive and negative words in the type sets. It demonstrates the number or frequency of the positive and negative words, which helps to understand how much sentiment is presented in all dataset. This number allows us to evaluate the discrepancy between the positive and negative attitudes as well as comprehend their effect on data's general mood. Fig. 3. shows the results of tokenization applied to positive words. In classifying the positive words, tokenization was done as a result of which inclusion and grouping took place. This visual helps us see how common and widespread positive words are in the entire dataset.

Fig. 2. Word cloud of comments values

Fig. 4. presents the tokenizing outcomes for detecting negative words. Like in Fig. 2, the terms found into data groups were tokenized and grouped as well. This view provides insight into the occurrence and onset of negativity words all over the dataset. These numbers visually depict the course of action in tokenization and its results. They provide a neat and brief account of the positive and negative word counts that have been distinguished in data collections. These numbers

Fig. 3. Word cloud of positive value.

Fig. 4. Word cloud of negative value.

TABLE IV. Classification Algorithms Performance Cross HL Dataset.

Model	Accuracy	Precision	Recall	F1
Neural Network	0.91	0.91	0.91	0.91
Logistic Regression	0.90	0.90	0.90	0.90
Random Forest	0.84	0.85	0.84	0.84
Naive Bayes	0.75	0.82	0.75	0.73
SVM	0.72	0.76	0.72	0.72
kNN	0.66	0.71	0.66	0.64

can be used by researchers to deduce the sentiment composition, reveal some important patterns or trends and additionally analyze how positive and negative words affected results of overall analysis of classification task. However, these figures just give a snapshot of tokenisation and may further be analyzed or interpreted in other sections as the paper unfolds. Other sentiment analysis algorithms implemented as discussed were Neural Network, Logistic Regression, Random Forests, Naive Bayes SVM and kNN- where every one of them has been reported in the fooling tables based on TF-IDF and word2vec representation method utilized.

Table IV. shows the results of accuracy, precision, recall and F1-score for sentiment analysis with the various models

TABLE V. Classification Algorithms Performance Cross ME Dataset.

Model	Accuracy	Precision	Recall	F1
Neural Network	0.91	0.91	0.91	0.91
Logistic Regression	0.90	0.90	0.90	0.90
Random Forest	0.84	0.85	0.84	0.84
Naive Bayes	0.75	0.82	0.75	0.73
SVM	0.72	0.76	0.72	0.72
kNN	0.66	0.71	0.66	0.64

TABLE VI. Classification Algorithms Performance Cross LE Dataset.

Model	Accuracy	Precision	Recall	F1
Neural Network	0.91	0.91	0.91	0.91
Logistic Regression	0.90	0.90	0.90	0.90
Random Forest	0.84	0.85	0.84	0.84
Naive Bayes	0.75	0.82	0.75	0.73
SVM	0.72	0.76	0.72	0.72
kNN	0.66	0.71	0.66	0.64

implemented on HE dataset. All those models will be assessed on their capacities to classify instances into either a set of positive sentiments or negative ones. The accuracy measures the global correctness of the model's predictions. Initially, precision shows the fraction of correctly identified positive instances from all positive-instance predictions and recall measures how many correct positives are taken out among true positives. The third metric we have pursued is the F1-score which takes a harmonic value of precision and recall to provide an accuracy value whilst considering both. The following results represent how each of the models performed over our sentiment analysis tasks. With the highest accuracy, precision, recall and F1-score results by rthe Neural Network implies its efficiency when introducing sentiment. Logistic Regression also gives good result where the Random Forest model is coming after that. In terms of accuracy, precision, recall and F1-score Naive Bayes, SVMs and kNN result in relatively low coefficients.

Table V. report the performance measures for specific classification such as classification algorithms used on ME data. The reported measures include the accuracy, precision-recall and F1-score which are standard ways of assessing classification models' effectiveness. The results presented denote the capability of each algorithm in categorizing instances accurately based on engagement levels. The others led to lower accuracy, precision, recall and F1-score compared with the neural network which indicates that this model was strong enough for classifying instances correctly. The Logistic Regression model performs very close to the Random Forest one. Also, Naive Bayes, SVM and kNN demonstrate relatively lower results in terms of crossword accuracy performance metrics such as Accuracy, Precision, Recall and F1 score.

Table VI. shows the performance indicators of various classification algorithms imposed on LE dataset, aimed to measure user engagement rates. The metrics studied comprise accuracy, precision, recall and f1-score which are commonly used for evaluation of the performance of classification models. Results show the performance of each algorithm in classification in enlisting instances to appropriate engagement tiers. Neural Network outperforms this with respect to the

TABLE VII. CLASSIFICATION ALGORITHMS PERFORMANCE CROSS HE DATASET USING TF-IDF.

Model	Accuracy	Precision	Recall	F1
Neural Network	0.91	0.91	0.91	0.91
Logistic Regression	0.90	0.90	0.90	0.90
Random Forest	0.84	0.85	0.84	0.84
Naive Bayes	0.75	0.82	0.75	0.73
SVM	0.72	0.76	0.72	0.72
kNN	0.66	0.71	0.66	0.64

TABLE VIII. CLASSIFICATION ALGORITHMS PERFORMANCE CROSS ME DATASET USING TF-IDF.

Model	Accuracy	Precision	Recall	F1
Neural Network	0.91	0.91	0.91	0.91
Logistic Regression	0.90	0.90	0.90	0.90
Random Forest	0.84	0.85	0.84	0.84
Naive Bayes	0.75	0.82	0.75	0.73
SVM	0.72	0.76	0.72	0.72
kNN	0.66	0.71	0.66	0.64

metrics of accuracy, precision, recall and F1-score thereby indicating its performance in correctly classifying cases. Logistic Regression also performs well followed closely by the Random Forest model. However, Naïve Bayes method might get low scores as compared to SVM and kNN in terms of accuracy score. On the other hand, Naive Bayes, SVM, and kNN achieve relatively lower scores across accuracy, precision, recall, and F1-score metrics.

Results in Table VII. show that in all metrics the Neural Network should have a maximum score with 0.92 for accuracy, precision, recall and F1-score. Logistic Regression is also good scoring model of 0.90 in accuracy, precision and recall with the F1-score homogeneously distributed at that score value below it ranging from SVM to Random Forest. This is followed by Random Forest with the accuracy of 0.85 having relatively same precision, recall and F1-score as SVM's score . In terms of accuracy, precision, recall and F1 score the performance based on this measures for naïve bayes, SVM and KNN is low. Table VIII. show how we performed in

TABLE IX. CLASSIFICATION ALGORITHMS PERFORMANCE CROSS LE DATASET USING TF-IDF.

Model	Accuracy	Precision	Recall	F1
Neural Network	0.92	0.93	0.93	0.92
Logistic Regression	0.90	0.90	0.90	0.90
Random Forest	0.85	0.85	0.84	0.84
Naive Bayes	0.74	0.82	0.75	0.73
SVM	0.72	0.72	0.72	0.72
kNN	0.68	0.71	0.66	0.64

TABLE X. CLASSIFICATION ALGORITHMS PERFORMANCE CROSS HE DATASET USING WORD2VEC.

Model	Accuracy	Precision	Recall	F1
Neural Network	0.92	0.92	0.92	0.92
Logistic Regression	0.90	0.90	0.90	0.90
Random Forest	0.85	0.85	0.84	0.84
Naive Bayes	0.74	0.82	0.75	0.73
SVM	0.72	0.72	0.72	0.72
kNN	0.68	0.71	0.66	0.64

TABLE XI. CLASSIFICATION ALGORITHMS PERFORMANCE CROSS ME DATASET USING WORD2VEC.

Model	Accuracy	Precision	Recall	F1
Neural Network	0.92	0.92	0.92	0.92
Logistic Regression	0.90	0.90	0.90	0.90
Random Forest	0.85	0.85	0.84	0.84
Naive Bayes	0.74	0.82	0.75	0.73
SVM	0.72	0.72	0.72	0.72
kNN	0.68	0.71	0.66	0.64

terms of the classification algorithms on the available ME dataset through TF-IDF features. The Neural Network model has the greatest results in all measures, 0.92 accuracy, precision recall and F1-Score Logistic Regression also has a good performance where it generates an accuracy, precision recall and F1-score of 0. In second place is Random Forest which gives an accuracy of 0.85 and slightly stable precision, recall as well as F1-score. Naive Bayes, SVM and kNN perform more poorly on review classification task than the remaining models. Using the performance metrics provided in Table IX, these results demonstrate how the classification algorithms performed on LE dataset as provided using TF-IDF features. Both the neural network and logistic regression models perform best on all metrics, with an accuracy of 0.92 for not pregnant women only predictions subset and of 0.90 respectively. The Neural Network just performs better in dull figures scores results with it has precision and recall of 0.93 which are slightly higher than the other classifier's measure values. In close range, Random Forest follows closely with accuracy of 0.85 and somewhat stable precision, recall and F1-score performances across the datasets tables as for Naive Bayes, SVM and kNN, the most significant disadvantage is lower performance compared to other models. It is worth mentioning that these findings are instance of the provided data set as well as TF-IDF feature representation. The algorithms' performance can also range based on the characteristics of the dataset, feature engineering or other conditions.

The results from Table X. show by what means the classification models worked out on this LE dataset given with Word2Vec embedding. The Neural Network and Logistic

TABLE XII. CLASSIFICATION ALGORITHMS PERFORMANCE CROSS LE DATASET USING WORD2VEC.

Model	Accuracy	Precision	Recall	F1
Neural Network	0.92	0.93	0.93	0.92
Logistic Regression	0.90	0.90	0.90	0.90
Random Forest	0.85	0.85	0.84	0.84
Naive Bayes	0.74	0.82	0.75	0.73
SVM	0.72	0.72	0.72	0.72
kNN	0.68	0.71	0.66	0.64

Regression models demonstrated the best results on all performance metrics. With F-measure being 0.92, the accuracy value received from this Neural Network was also equal to 0.92 while precision and recall slightly exceeded these values with scores of up to 0.94 for both rates (Neural Network). Close behind was the Logistic Regression model which achieved an accuracy of 0.90, demonstrating uniformity across precision, recall and F1-score. The resulting accuracy for the Random Forest model was 0.85 with relatively stable precision, recall, and F1-score values. Conversely, Naive Bayes; SVM and kNN demonstrated relatively worse performance when compared to the rest of models.

Table XI shows the performance metrics of various classification algorithms on ME dataset with word2vec embedding. These results shed light on how accurate, precise and recall outperformed each algorithm alongside the F1 score. The Neural Network scored the highest accuracy of 0.92, with a very close score being Logistic Regression at 0.90 The accuracy for Random Forest was 0.85, while that of Naive Bayes generated an accuracy level of 0.74 . It was followed by SVM, as well kNN classifiers had lower accuracies of 0.72 and 0.68 respectively.

Neural Network scored 0.92 for each metric, which consists of precision, recall and F1 score; therefore it performed well given all measures are balanced with the same values. Logistic Regression, Random Forest, and Naive Bayes had similar precision scores of between 0.84 to 0.90, and their recall rankings were in the same range level following F1 Scores as shown below SVM and kNN had negligible differences for these metrics, as the SVM classification algorithm achieved a precision of 0.72 recall value that stood at and F1 score 0.72 while kNN obtaining values of 0.71, 0.66, and 0.64, respectively. Generally, performance across all the metrics was best by Neural Network and Logistic Regression algorithms with Neural Network slightly having an upper hand.

Table XII. shows how different classification algorithms perform in the LE dataset with word2vec embedding. In terms of precision, recall, and F1 score, the Neural Network demonstrated consistent values of 0.93 for precision and recall, along with an F1 score of 0.92. This indicates a balanced performance across all metrics. Logistic Regression, Random Forest, and Naive Bayes exhibited similar precision, recall, and F1 scores, ranging from 0.84 to 0.90. SVM and kNN had slightly lower values in these metrics, with SVM achieving precision, recall, and F1 scores of 0.72, and kNN obtaining values of 0.71, 0.66, and 0.64, respectively.

Regarding precision, recall and F1 score got the Neural Network achieved 0.93 for both capabilities while obtained an F1 score of 92 This signals an equally sound performance on all fronts. Logistic Regression, Random Forest, and Naive Bayes achieved close precision, recall, F1 score of between 0.84- 0.90 SVM and kNN managed to record somewhat lower scores in these metrics with SVM achieving a precision, recall, F1 of 0.72 while the values were recorded at 0.71 so also for kNN . In general, the Neural Network and Logistic Regression algorithms performed best on all metrics, with a slight advantage of the former over accuracy and F1 score.

Overall, the best performing in term of all other measures due to classification is Neural Network. The two other best performing methods are Logistic Regression and Random Forest, which almost parallel Neural Network. However, naive Bayes, SVM and kNN tend to produce inferior accuracy scores when judged against the precision score or F1-score ratings.

Nevertheless, the noted findings are valid only with regard to suggested presented statistics and selected features representations (TF-IDF and Word2Vec embeddings), as algorithm quality sensitivity might change because of multiple factors. The Neural Network and Logistic Regression algorithms remain consistent leaders in accordance with all evaluated metrics while it is possible to note that the first outperforms a little when considering accuracy and F1-score

VII. CONCLUSION

The significance of sentiment analysis on social media in the study, on drug addiction dynamics and user engagement is clear. The conclusions draw attention to the urgent social issue of drug addiction and its growing incidence in Iraq due to a range of socioeconomic factors. Another contribution is the recognition of social media platforms as powerful tools for creating a buzz about drug addiction and its consequences. This study has filled a major gap in research by introducing new methods for sentiment analysis on social media,developed using data related to drug addiction and Iraq. Yet, the accumulation and processing of a unique dataset from a relevant Facebook page split into three particular levels interrelating with user engagement have offered great hopefulness for showing sentiment patterns concerning drug addiction in America. The created classifying model based on the neural network algorithm has demonstrated high-level performance, which is about 91% in accuracy. The research findings enhance under-

standing of the way in which society perceives drug addiction problem and attitudes it finds acceptable or unacceptable, specific for Iraq region, allowing policy makers as well as health providers and community organizations to plan intervention beyond generic strategies.
The research bears much importance in terms of its contribution to evidence-based decision-making on the issue of fighting drug intervention. Using sentiment analysis and multilevel user engagement social media data, stakeholders may develop more efficient prevention that will provide tools for implementing successful rehabilitation programs. Additionally, the research indicates this issue's relevance and necessity of further studying social media platforms with regards to changing patterns in terms drug addiction may bring to societies.
However, this cross-section brisk study generated invaluable insight regarding the nature of drug addiction and user participation in Iraq through sentiment analysis on social media; alteration's limitations should be recognized. The first limitation refers to the generalizability of our findings due to the lack of variety in terms of data set, collected from a single Facebook page. The opinions that are found on this platform may not be the authentic representation of a wide range depending on all social media channels or even among wider population. Furthermore, the three separate levels of user participation identified in our study might be an over simplification of the intricate range of users' interactions on social media.
The study contributes to the better understanding of interconnections between social media, user sentiment and drug addiction in Iraq. It lays a foundation for future research as well as interventions targeted at controlling the negative impacts of drug use, in an effort to enhance individual and community health and resilience against drug use.

CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

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