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Predicting Human Behavior Using Arabic Sentiment Analysis on Social Media: Approaches and Challenges

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***Abstract*— The rapid growth of social networking and micro-blogging websites has motivated researchers to analyze published content to identify and predict human behavior. With the ongoing growth in data volume, the efficient and effective extraction of valuable information has become crucial. Researchers are tackling this problem using big data analytics. However, most studies have focused on the English language and fewer research efforts have been devoted to the Arabic language. This paper covers the recent Arabic sentiment analysis research, highlighting the most important studies that analyzed content from social media to predict human behavior and the different approaches used. Sentiment analysis studies varied between lexicon-based, traditional machine learning-based, deep learning, and hybrid approaches, in addition to employing swarm intelligence to optimize the performance of text classification algorithms. The reviews showed that Naïve Bayes (NB) and Support Vector Machine (SVM) were the most widely used algorithms among traditional machine learning algorithms. The results also showed that using deep learning approaches achieves better accuracy than other approaches. Also, the use of optimization algorithms based on swarm intelligence had a significant impact on increasing the accuracy of text clustering.**

***Index Terms*— Sentiment Analysis; Human Behavior; Machine Learning; Natural Language Processing; Deep Learning**

I. Introduction

Social media platforms are essential mass communication tools in the modern era. The ever-increasing growth of social networks provides an excellent foundation for analyzing social data, finding patterns among humans, and understanding their behaviors [1], [2]. According to (Smart Insights, 2023)[1], about 59% of the world's population currently uses social media, and the average daily use is estimated at 2 hours and 31 minutes [3]. This massive and steadily increasing number of users generates a vast amount of data in an unstructured format that can include likes, comments, tweets, shares, and views. The extraction of useful information effectively from this huge data became a critical issue, and researchers considered addressing it using big data approaches [4]. Since these data are generated in diverse, high speed, and high volume, big data analytics are the most appropriate choice to identify patterns and predict trends in human behavior. Current approaches to big data analytics for social media mainly rely on machine learning techniques, including classification, clustering, and deep learning [5].

Due to the unrestricted nature of social media, where users can freely share their opinions and perspectives, sentiment analysis plays a significant role in examining this vast amount of unprocessed text data to summarize the overall public sentiment toward a specific topic [6]. Also, analyzing sentiments and opinions about services, products, politics, or any topic people are interested in helps in many applications, such as market analysis, product reviews, sentiment detection, intent analysis, services, and social media monitoring [2].

Sentiment analysis encompasses various machine learning techniques, including linguistic-focused computational classification techniques, Natural Language Processing (NLP), and textual analytics. These techniques identify the opinions and attitudes of individuals toward a particular issue by classifying the polarity of subjects into positive, negative, or neutral. [7]. The importance of analyzing sentiments expressed on social media emerged over the last decade, making it the subject of great interest from researchers in big data analytics [8]. However, most research focused on English and Arabic did not receive the same attention [9]–[11].

This paper reviewed the latest studies investigating Arabic sentiment analysis on social media to determine the latest approaches researchers used to address this issue. The approaches varied between lexicon-based techniques, machine learning-based techniques, whether traditional or based on deep learning, and hybrid approaches that combined methods from the two approaches. The paper also reviewed optimization algorithms based on swarm intelligence to determine their effectiveness in improving the accuracy of sentiment analysis. Finally, the most prominent challenges facing researchers in sentiment analysis in general and those related to the nature of the Arabic language were identified.

The rest of this paper is organized as follows: Section II offers background about the main concepts, including Social Media Data Analytics, Sentiment Analysis, and Predicting Human Behavior. Section III shows the different approaches and algorithms from previous studies, primarily focusing on

[1] http://www.smartinsights.com

studies that dealt with the Arabic language. Section IV discusses this paper's main findings and presents the appropriate guidelines for further research directions. Section V provides the main challenges of sentiment analysis in recent literature. Finally, Section VI summarizes this paper and highlights its contributions and limitations.

II. BACKGROUND

This section will highlight the essential elements discussed in this research paper, including an overview of social media data and the importance of employing big data analytics to extract insights about expected human behavior toward a specific topic. The section also covers the definition of sentiment analysis, its importance, and the typical steps required to perform the sentiment analysis process. The section also will discuss the prediction of human behavior and the role of predictive analytics in transforming data into profitable information.

A. Social Media Data Analytics

The emergence of Web 2.0 contributed to the development of what is known as social media, which relies on creating content through collaboration and participation by users [5], [12]. The increasing volume of data generated by various social media platforms has had a significant impact on the interest in big data analytics to extract insights at the level of texts, images, metadata, or other forms of data [2], [5], [12].

The emergence of big social media data was accompanied by great progress in data analytics methods and tools. This contributed to extracting insights about human behavior, benefiting individuals, companies, and governments. Social media data have been used to discover trends and to implement sentiment analysis [5]. It was clear that organizations and governments are interested in big data analytics to learn about the features of human behavior in various issues, mainly through social media websites like Facebook, Twitter, YouTube, Instagram, and LinkedIn. This interest has encouraged many researchers recently to conduct studies and develop different models and frameworks for analyzing big data generated from social media [12]. However, our focus in the current study will be on studies concerned with sentiment analysis through text analytics of the Arabic language.

B. Sentiment Analysis

Sentiment Analysis is a technique of defining and extracting human emotions through unstructured text and is done through NLP and machine learning [13]. Sentiment Analysis computationally identifies and categorizes opinions of individuals expressed in unstructured text to classify the polarity of their attitude toward a specific topic into positive, negative, or neutral [7], [14].

The monitoring of public sentiment holds significant importance for businesses, organizations, and governments, as they require meaningful insights from user-generated information. Sentiment analysis has found widespread applications across various domains such as healthcare, movies, products, politics, and more. Utilizing sentiment analysis in these diverse areas has become a valuable tool for gaining understanding and insights into public opinions regarding specific topics of interest [4].

The sentiment analysis process has five main steps, as shown in Figure 1. They start with "Data Collection," which could be social media data via APIs. Then the collected text shall be cleaned in the "Pre-processing" step. The cleaning is done through tokenization, stemming, lemmatization, and removing stop words, duplicates, and punctuations. The next step is "Feature Extraction and Selection" the sentiment in the text is identified to determine and analyze the feelings of the individuals. Finally, the feelings are classified in the "Classification Model" step to obtain the outcomes. Usually, sentiment classification can be conducted at three levels: the feature, phrase, and document levels [13].

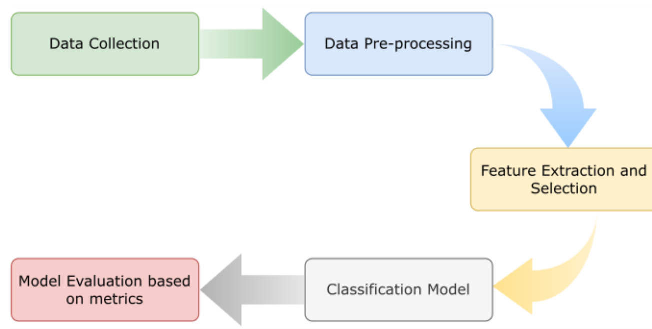

Figure 1: Sentiment Analysis basic workflow [13]

C. Predicting Human Behavior

The nature of human behavior is complicated, and it can be described as "the potential and expressed capacity for physical, mental, and social activity during the phases of human life" [15]. The study of human behavior through unstructured textual data analysis has recently gained significant attention. This surge in interest can be attributed to the abundance of textual data sources [16]. Mining unstructured textual data provides in-depth insights into humans' attitudes, views, sentiments, and emotions toward others and helps predict social behaviors [7]. Human behavior consists of two primary components: personal characteristics and situational demands. However, the connection between these elements and human behavior is complex. In this context, the value of extracting insights from unstructured text data, particularly from social media, becomes apparent as it helps to simplify this complexity and enhance the understanding and evaluation of human behavior as the textual features are closely related to the characteristics of individuals [16]. Textual information in social media posts can reflect people's perspectives, feelings, concerns, and mental health. Because people's activities are closely related to their thinking, information gathered from social media may be helpful for decision-makers in understanding the risk of people's behavior [17]. So, tracking down the sentiment behind social media posts can help relate the context in which people react and progress [18].

Researchers can gain valuable insights into various aspects of users' behaviors and obtain valuable information by gathering data from Online Social Networks (OSNs) and conducting thorough analyses. The consistent growth of unstructured data has significantly improved behavioral insights and increased the effectiveness of behavioral analysis by enabling the computational extraction of sentiment from expressed personal views [7]. Predicting human behavior can be achieved through predictive analytics, which involves transforming data into valuable, actionable information. This analytical approach utilizes data to anticipate future outcomes of events or assess the likelihood of specific situations occurring. [5], [19]. Accordingly, predictive analytics models are designed to assess historical data, discover patterns, observe trends, and use that information to draw up predictions.

III. Approaches and Algorithms

In the next section, the focus will be on the approaches and algorithms adopted by recent studies to address the topics of sentiment analysis and prediction of human behavior with a primary focus on the Arabic language. This section will also present the studies that employed swarm intelligence algorithms, which proved their effectiveness in analyzing patterns of human social behavior.

A. Sentiment Analysis Approaches

There are three main approaches in which sentiment analysis is implemented. Recent studies have varied among those approaches: Lexicon Based Approach, Machine Learning Based Approach, and Hybrid Approaches. These main approaches and their subdivisions and algorithms based on them are shown in Figure 2.

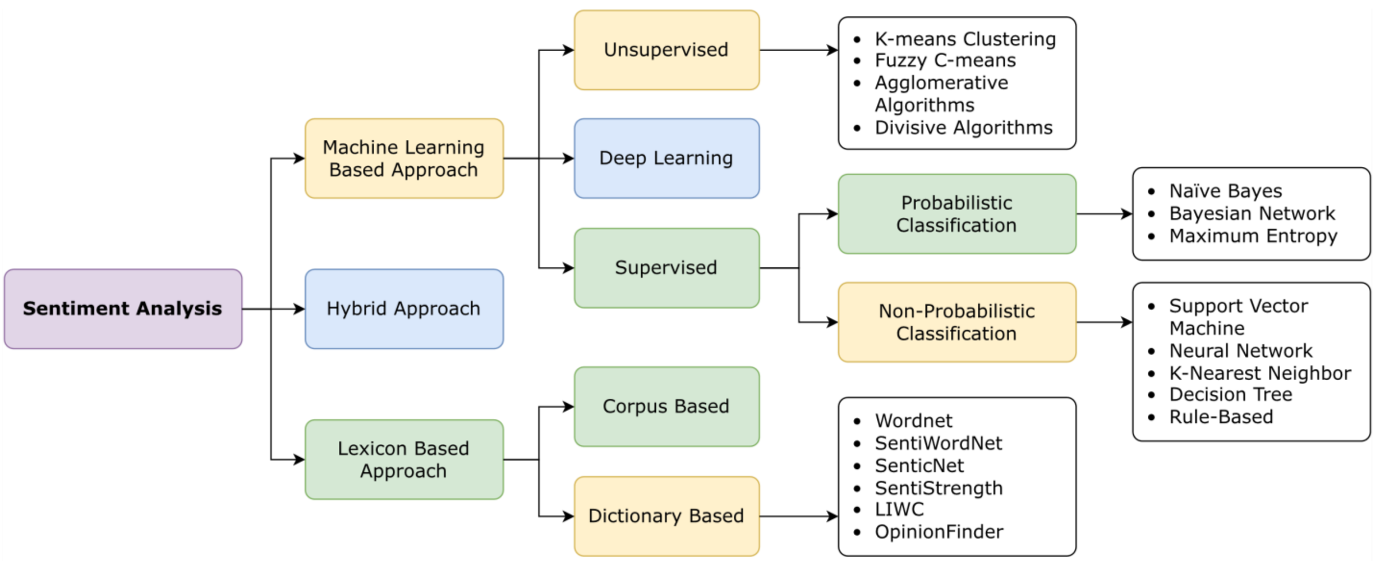

Figure 2: Sentiment Analysis Approaches and Algorithms [10]

1) Lexicon-Based Approaches

The lexicon-based approach depends on a sentiment lexicon and a set of known sentiment terms. Usually, this approach can be categorized into two main approaches: Dictionary-Based and Corpus-Based. In the Dictionary-Based approach, words conveying opinions in the text and their semantic orientation are identified using a dictionary. On the other hand, the Corpus-Based approach identifies the context-specific orientation of words by initially compiling a list of opinion words and subsequently locating other relevant words within a larger corpus. The lexicon-based approach includes a pre-defined word dictionary in which each word is linked with a positive or negative polarity [8], [13].

This approach has attracted the interest of many researchers; Youssef and El-Beltagy (2018) introduced MoArLex, a novel method for automatically expanding an Arabic sentiment lexicon using word embeddings. Through lexicon expansion, a sizable sentiment lexicon was created. The lexicon aims to offer an easily accessible Arabic resource for tasks involving sentiment analysis. MoArLex can incorporate terms frequently used in social media, despite the constructed lexicon having only about 36,775 words, claim the authors. On 1824 tweets, both positive and negative sentiment was analyzed. Accordingly, only 58% of tweets were correctly classified using the technique [20].

Eldefrawi and others (2019) addressed the problem of comparative Arabic opinions through their proposed sentiment analysis technique. The proposed technique uses available resources to obtain the best results. It also reduces human interaction to the initial steps allowing the process to be fully automated. While considering how opinion holders express their opinions, the technique uses the linguistic structure of comparative opinions [21]. Despite the promising results achieved by the proposed technique, the relatively small size of the data used – only 830 comparative opinions - makes it need more tests on larger data sets to confirm its efficiency.

Kaity and Balakrishnan (2019) proposed a language-independent method to overcome difficulties in developing non-English lexicons. Using currently available English lexicons and an unannotated corpus, it automatically creates non-English sentiment lexicons. The proposed approach autonomously detects and extracts novel polarity words using the initial seed lexicons generated by translating three trustworthy English lexicons [22].

Touahri and Mazroui (2021) devised a new lexical resource to evaluate the influence of lexicon expansion and incorporated the concept of lemmas into Arabic sentiment analysis. They developed the lexicon through two distinct techniques: a manual approach that involved extracting sentiment-bearing words from a selected dataset and a semi-automatic method that involved translating an English lexicon into Arabic and conducting a manual verification. Their methodology demonstrated the value of a domain-specific lexicon for classification, including current words in reviews relevant to a specific domain. The outcomes also highlighted how crucial it is to increase the list of negation words to enhance the efficiency of the sentiment analysis system [23].

2) Machine Learning-Based Approaches

This section deals with two machine learning-based approaches; the first is the most common and represents the traditional approach. The second one is based on deep learning, proving its efficiency in various applications such as machine translation, speech perception, computer vision, and natural language processing. When larger data sets are available, deep learning techniques for sentiment analysis have recently outperformed traditional machine learning algorithms.

- Traditional Machine Learning

Whether supervised or unsupervised, these methods rely on well-known machine learning algorithms. The model is trained using many labeled documents in the supervised methods. The NB, Maximal Entropy Principle (MEP), and SVM are well-known sentiment analysis and opinion mining techniques. Despite the excellent polarity detection accuracy, the model's performance varies when applied to a different domain [8].

Mostafa (2020) proposed a Traveler Review Sentiment Classifier to analyze the traveler's reviews on Egyptian Hotels and classify each sentiment based on hotel features. The proposed model included text processing, feature selection, and machine learning classification. SVM, NB, and Decision Tree are the three classification methods used by the sentiment model. According to the results, NB has the highest accuracy level. [24].

Mostafa (2021) introduced a sentiment analysis model that employs Word2vec and machine learning methodologies to examine students' sentiments as they engage in remote learning during the pandemic. The word embedding process is used to select the features for the sentiment analysis model, which then employs three machine learning classifiers—Naive Bayes (NB), SVM, and Decision Tree. The Student Sentiment Analysis Model encompasses several stages: text processing, feature selection involving Document Frequency and Word2Vec, and machine learning classification. Additionally, three classifiers, namely NB, SVM, and Decision Tree, were employed in the model. The findings indicated that the NB has the highest classifier accuracy. It should be noted that the sample size must be increased while considering various student majors [25].

Detecting sarcasm in Arabic content on social media is a challenging task that urged Nayel and others (2021) to propose a new model based on SVM, a supervised machine learning algorithm to detect Arabic sarcasm and sentiment on Twitter. SVM as a classifier is known for its effectiveness. Although the model achieves moderate accuracies, they are relatively high, especially regarding Arabic text [26].

Alduailej and Alothaim (2022) used language models trained on a large amount of data before being applied to the final tasks to improve text classification in English. The authors proposed that Arabic could experience similar success to that English sentiment analysis. The researchers used an extensive Arabic dataset to pre-train an XLNet-based language model, which was fine-tuned on diverse Twitter benchmark datasets. Their investigation demonstrated the application of AraXLNet in Arabic sentiment analysis, resulting in improved prediction accuracy for the Arabic language [27].

In their research, Al Sari et al. (2022) examined the sentiment analysis quality of impressions regarding Saudi cruises, focusing on Instagram, Snapchat, and Twitter as the primary data sources. The collected data were categorized into positive or negative classes using machine learning algorithms such as multilayer perceptron (MLP), NB, Random Forest (RF), SVM, and Voting. The findings indicated that RF, SVM, and Voting exhibited superior performance when applied to the Snapchat platform, while RF, SVM, and Voting algorithms performed best for Instagram. On the other hand, NB and MLP demonstrated effective sentiment analysis on the Twitter platform [28].

- Deep learning

Deep learning is the application of Artificial Neural Networks (ANN) to learning tasks using networks of multiple layers. Recently, deep learning has been considered one of the best methods of extracting knowledge from large raw data sets. Deep learning models have shown great potential when applied in the field of NLP. Thus, applying deep learning models to sentiment analysis has also become popular [29].

Unlike the traditional machine learning approaches, where humans design features, feature extraction is a challenging process requiring human intervention. Deep learning addressed this issue using a structure of a deep layered model, so feature learning and extraction are done automatically, achieving better performance and accuracy. Figure 3 presents the differences in sentiment analysis polarity classification between traditional machine learning and deep learning [30], [31].

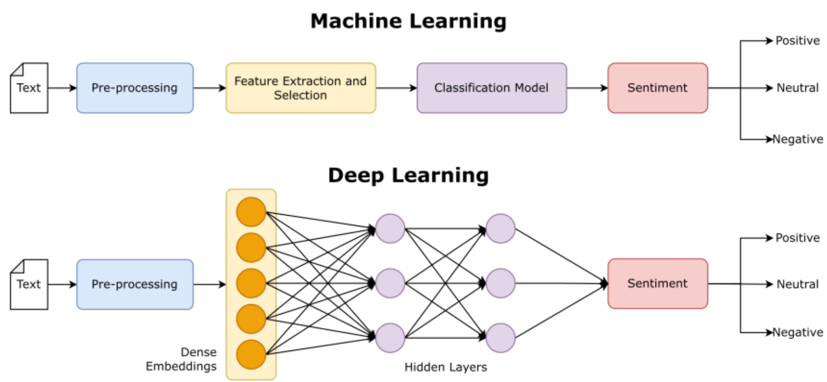

Figure 3: Differences between two classification approaches of sentiment polarity [31]

In their quest to promote deep learning for sentiment analysis in Arabic, Mohammed and Kora (2019) presented a 40k corpus of Arabic tweets discussing various topics, including politics, health, and sarcasm. They also verified the effectiveness of three deep learning models on the suggested corpus. According to their study's findings, Long Short-Term Memory (LSTM) performs better than models using Convolutional Neural Networks (CNN) and Recurrent CNN (RCNN) [32].

Ombabi and others (2020) introduced an innovative deep learning model for sentiment analysis. This novel model incorporates a one-layer CNN architecture to extract local features and two layers of LSTM to capture long-term dependencies. The goal is to overcome the morphological complexity of the Arabic language and the variety of its dialects. Additionally, the researchers employed an SVM classifier for the final classification stage. The FastText word embedding model was utilized to further support their proposed model [33].

To forecast the polarity of opinions and sentiments, Alharbi and others (2021) proposed a sentiment analysis deep learning-based model. Higher-level representations are learned using two different Recurrent Neural Networks (RNN). Three diverse classification algorithms were employed to generate the final output, addressing the challenge of data dependency and enhancing the model's strength [34].

In order to mine Arabic opinions, Al Wazrah and Alhumoud (2021) introduced two neural models, namely the Stacked Gated Recurrent Unit (SGRU) and the Stacked Bidirectional Gated Recurrent Unit (SBi-GRU), to extract Arabic opinions. The study also suggested an innovative technique for eliminating stop words called Automatic Sentiment Refinement (ASR) [35].

To improve sentiment analysis prediction accuracy, Saleh and others (2022) proposed an optimized heterogeneous stacking ensemble model to enhance Arabic sentiment analysis performance. In order to enhance the predictive accuracy of Arabic sentiment analysis, the proposed model employed a fusion of three distinct pre-trained Deep Learning models, including the RNN, LSTM, and Gated Recurrent Unit (GRU), as well as three meta-learners, LR, RF, and SVM. The grid search hyperparameter optimization technique was used to improve the meta-learner models [36].

In a related study, Saleh and others (2022) stated that the Arabic sentiment analysis domain has significantly improved due to deep learning models like CNN and LSTM. Furthermore, incorporating hybrid deep learning models that combine CNN with LSTM or GRU has significantly improved the performance of standalone deep learning models [37].

3) Hybrid Approaches

The hybrid approach combines lexical-based and machine learning-based approaches, using the lexical-based approach to register sentiment. The training data for the approach based on machine learning will then be represented by documents with scores. The hybrid approach is popular because it combines the speed of the lexicon-based approach with the high accuracy of machine learning-based approaches [8], [38].

El-Beltagy and colleagues (2018) introduced a model that integrates a machine learning approach with features derived from an Arabic sentiment lexicon and the textual content, to conduct Arabic sentiment analysis. They focused on analyzing Arabic sentiment analysis. With publicly accessible datasets, their developed model outperformed all other Arabic sentiment analysis systems. However, they identified shortcomings in their modal, particularly concerning handling negation [39]. Despite the results achieved by this model, there is still room for improvement in terms of accuracy. This is because machine learning models sometimes struggle to capture implicit features or aspects of the text [40].

Moussa and others (2019) introduced a hybrid framework, combining both lexicon-based and machine learning-based techniques for sentiment analysis. The framework utilizes the Sum-of-Votes approach from the lexicon-based technique and the Bag-of-Words technique to detect the polarity of sentences and reviews accurately. The outputs were fed as features to Machine Learning Classifiers. The goal of the novel framework was to offer solutions for the drawbacks of the lexicon-based technique, such as scalability, domain dependency, and unreliability [14].

Elshakankery and Ahmed (2019) developed a learning system for sentiment analysis with a semi-automatic approach that can adapt the lexicon to reflect linguistic changes. HILATSA is a hybrid approach that combines lexicon-based and machine learning techniques to determine the sentiment polarities of the tweets. The suggested method has been evaluated using a variety of datasets. The system's ability to learn new words is impacted by automatic lexicon updating. Nonetheless, the learning process must be limited, or the system may learn incorrectly. Although time-consuming, manual annotation of the tweets the system uses to extract and learn new words has proven beneficial when combined with the automatic part [41].

B. *Predicting Human Behavior Approaches*

Recent studies attempt to develop more accurate models for predicting human behavior by analyzing unstructured textual data. In a recent systematic review, Davalli et al. (2020) investigated 87 articles to discover the primary methods employed to identify and predict human behavior were examined. A key discovery from their review was the strong correlation between textual characteristics and the behaviors and traits exhibited by individuals. The review revealed significant differences among approaches, including dissimilarities in feature selection and extraction and variations in the classification method employed, with accuracy ranging from 58.0% to 82.8% for social media characteristics [16]. According to their review, the authors divided the studies that developed techniques to predict human behavior into two main categories.

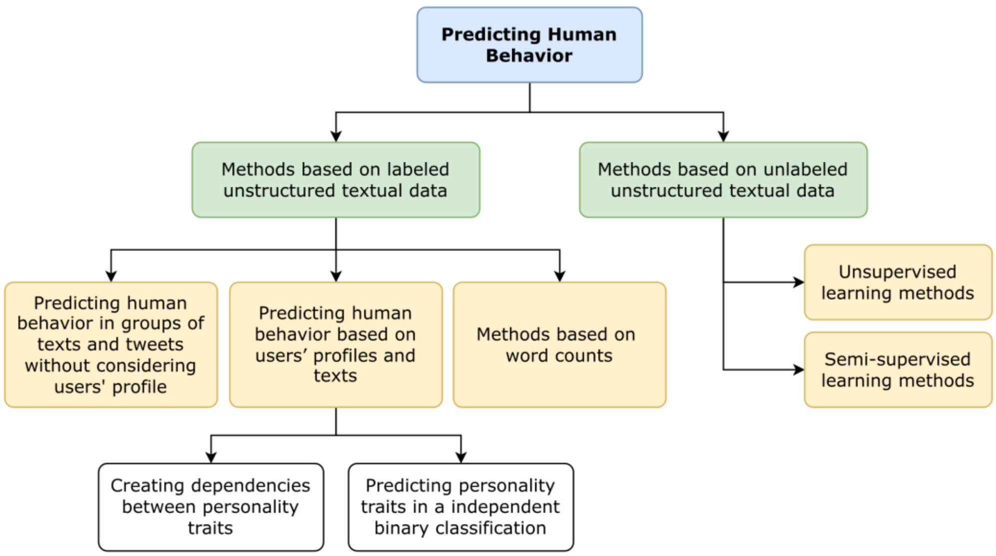

Figure 4: Predicting Human Behavior Data-Based Approaches [16]

As shown in Figure 4, diverse data-driven methods are employed to predict human behavior in unstructured textual data. The methods based on labelled unstructured textual data fall under the first of two main categories that can be used to categorize these approaches. In this category, human behavior can be predicted using information gleaned from user profiles as well as information gleaned from collections of texts and tweets. Moreover, the second category encompasses approaches that rely on unlabeled unstructured textual data. These methods can also be divided into semi-supervised and unsupervised learning methods [16].

A few studies addressed human behavior prediction in Arabic. For example, the project presented by Zaghouani (2018) aimed to build a corpus for addressing psychological problems, including depression and self-harm. The project tried to achieve this by observing social media across Arab countries. The author suggested creating a labeled corpus with sentiment analysis to study young people's behavior through their social media posts [42].

S. Aljameel and others (2020) proposed a sentiment analysis approach to gather and prepare a dataset to make predictions about individuals' awareness of the precautionary procedures to prevent COVID-19 outbreaks in five regions of Saudi Arabia. According to the results, the highest accuracy was produced by bigram TF-IDF with SVM of 85%. Prediction of each region's population awareness was made using the proposed model [43]. The accuracy of their model can still be enhanced by building machine learning models while using feature selection and parameter tuning.

C. *Optimization Techniques*

Optimization is one of the essential components of machine learning, as most machine learning algorithms seek to build an optimized model. Since we are experiencing massive data availability, the efficiency and effectiveness of numerical optimization algorithms mainly depend on applying machine learning models [44]. Recently it has become common to use various optimization techniques in sentiment analysis, mainly optimizing feature extraction.

In a recently published study, Priyanka and Walia (2023) present a detailed survey of the literature to determine the popularity of optimization techniques used during sentiment analysis [45]. The study noted that algorithms based on Swarm Intelligence possess the main proportion among the different optimization techniques related to sentiment analysis [45].

In analyzing social behavior patterns, the Swarm Intelligence technique has emerged as a recent application [5]. Swarm Intelligence is an effective problem-solving technique in artificial intelligence. It is part of Nature-Inspired Algorithms (NIA), which draws inspiration from various organisms such as ants, bees, and wasps. It incorporates intelligence derived from a structured collection of interacting organisms or agents. Swarm intelligence optimization algorithms have many advantages: speed, parallelism, fault tolerance, modularity, autonomy, adaptation, and scalability [46]. The success of swarm intelligence algorithms in solving machine learning issues, particularly text clustering, has led to their recognition as promising techniques [47]. The most common Swarm Intelligence algorithms are shown in Figure 5.

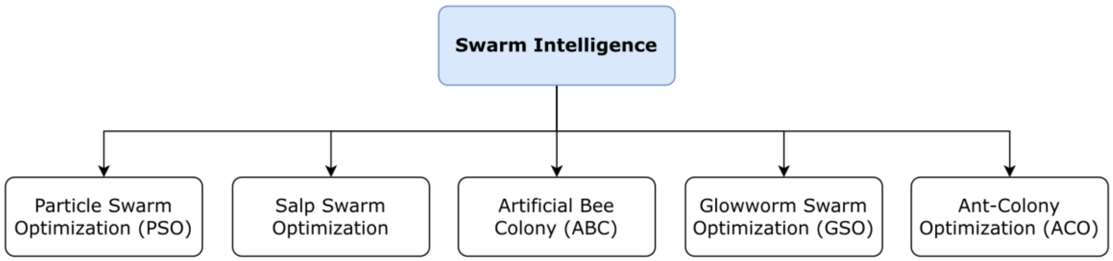

Figure 5: Classification of common Swarm Intelligence algorithms [48]

Tubishat and others (2019) introduced a hybrid model for Arabic Sentiment Analysis. The model aims to overcome its limitations by incorporating techniques such as filter feature reduction and optimization algorithms. Additionally, utilizing the Elite Opposition-Based Learning (EOBL) method improves the standard Whale Optimization Algorithm (WOA) regarding population diversity and quality. Additionally, WOA is being improved using Differential Evolution (DE) evolutionary to prevent the model from being trapped in local optima [9].

To tackle the challenge of Arabic sentiment analysis, Alzaqebah and others (2020) suggested an enhancement to the Salp Swarm Algorithm (SSA), a bio-inspired optimizer designed for feature selection. The algorithm runs through two stages. In the initial phase, a filtering technique utilizing the Information Gain (IG) metric is employed to reduce the feature set. Using a wrapper technique, the second phase combines the basic SSA optimizer with four distinct S-shaped transfer function variants. The Particle Swarms Optimizer (PSO) and the Grey Wolf Optimizer (GWO) were outperformed by the proposed SSA's reported results when combined with S-shaped transfer functions regarding classification precision [49].

Marie-Sainte and Alalyani (2020) proposed a new Firefly Algorithm-based Feature Selection (FAFS) method for Arabic Text Classification. The results confirm the efficacy of the proposed feature selection method in improving the accuracy of Arabic Text Classification. However, It should be noted that only one Arabic documents corpus was tested due to the inaccessibility of the other corpus mentioned in the literature [50].

Alhaj and others (2022) introduced a novel text classification model named Optimal Configuration Determination for Arabic Text Classification (OCATC) to enhance the performance of Arabic text classification using machine learning techniques. The Particle Swarm Optimization (PSO) algorithm is employed to classify Arabic text to find the optimal combination of three components: feature selection techniques, machine learning classifiers, and a set of features [51].

IV. Discussion

This paper aims to review the most important approaches to Arab sentiment analysis on social media that can help predict human behavior. The reviews of research papers in this regard have shown the critical role big data analytics techniques play in analyzing sentiments and opinions across social media. These techniques included algorithms ranging from Machine Learning classifiers to NLP techniques, lexical-based techniques, and finally, Swarm Intelligence Algorithms.

The results of the reviewed studies show that neither lexicon-based approaches nor traditional machine learning methods adequately address the sentiment analysis problem. Even those approaches that tried to combine the two approaches did not reach an accuracy of 84%. While the results were very encouraging in the approach based on deep learning, with an average accuracy of up to 90%, the percentages were close to reaching 98% for the ASTC dataset while using deep learning models such as RNN, GRU, LSTM along with meta-learner LR. Also, the use of optimization algorithms based on swarm intelligence had a significant impact on improving the results of text classification and reaching an average of 90% accuracy.

As shown in Table 1, the most used classifiers for Arabic Sentiment Analysis are Naïve Bayes (NB) and Support Vector Machines (SVM). Typically, these classifiers rely on manually designed features derived from statistical computations and lexicons [39].

TABLE 1: SUMMARY OF ARABIC SENTIMENT ANALYSIS APPROACHES

Study	**Main idea**	**Approach Type**	**Method/Algorithm**	**Datasets**	**Evaluation**
Youssef and El-Beltagy [20]	Expanding an Arabic sentiment lexicon automatically by leveraging word embeddings, namely MoArLex.	Lexicon-based	Word embedding	Twitter	**Accuracy:** 58%
Eldefrawi and others [21]	A sentiment analysis technique of comparative Arabic opinions using the linguistic structure.	Lexicon-based	Comparative relation	Dataset [52], Facebook, Twitter, and public blogs	***f-measure***: 96.5%
Kaity and Balakrishnan [22]	A technique that automatically creates non-English sentiment lexicons.	Lexicon-based	Corpus-based	Facebook	**Accuracy:** 78%
Touahri and Mazroui [23]	A novel lexical resource to assess the impact of lexicon growth.	Lexicon-based	Unigrams + bigrams + Information Gain + SVM	Multi-domain datasets	**Accuracy:** HTL 94% PROD 87% MOV 84% RES 84%
Lamiaa Mostafa [24]	The Traveller Review Sentiment Classifier is utilized to examine reviews from travelers regarding hotels and categorize the sentiment expressed in each review.	Machine Learning-Based	NB, SVM, Decision Tree	Reviews: TripAdvisor, Booking, Expedia, Trivago	**Accuracy:** NB 85% SVM 79% Decision Tree 71%
Lamiaa Mostafa [25]	Using Word2vec and Machine Learning techniques, they analyze students' sentiments during the pandemic.	Machine Learning-Based	NB, SVM, Decision Tree	1000 Students sentiment	**DF Accuracy:** NB 87% SVM 79% Decision Tree 76%
Nayel and others [26]	A model based on SVM to detect Arabic sarcasm and sentiment on Twitter.	Machine Learning-Based	SVM	Twitter	**Accuracy:** SVM 74%
Alduailej and Alothaim [27]	AraXLNet is the first Arabic XLNet-based language model that improves text classification accuracy.	Machine Learning-Based	XLNet Language Model	Multiple Datasets	**Accuracy:** AraXLNet, with Farasa 95%, 93%, 85%
Al Sari and others [28]	Analyzing the effectiveness of sentiment analysis in evaluating impressions concerning cruises in Saudi Arabia.	Machine Learning-Based	MLP, NB, RF, SVM, Voting	Instagram, Snapchat, Twitter	**Accuracy:** **Instagram:** SVM 98% **Snapchat:** SVM, MLP, RF, Voting 100% **Twitter:** MLP, NB 90%
Mohammed and Kora [32]	Arabic sentiment analysis uses three deep learning models: CNN, LSTM, and RCNN.	Deep Learning	CNN, LSTM, RCNN	Twitter	**Accuracy:** 81%
Ombabi and others [33]	A one-layer CNN architecture-based deep learning model for local feature extraction in Arabic.	Deep Learning	CNN, LSTM, SVM, FastText, Word Embedding	Multi-domain corpus	**Accuracy:** 91%
Alharbi and others [34]	A deep learning-based model for sentiment analysis that predicts the polarity of opinions and sentiments.	Deep Learning	GRU, LSTM	Reviews, Twitter	**Accuracies:** 94%, 90%

Al Wazrah and Alhumoud [35]	Using word embedding, SGRU and SBi-GRU, two neural models are employed to extract opinions in Arabic.	Deep Learning	GRU, SGRU, SBi-GRU	Arabic sentiment analysis (ASA)	**Accuracy:** 91%
Saleh and others [36]	Improved performance of Arabic sentiment analysis using a heterogeneous stacking ensemble model.	Deep Learning	RNN, LSTM, GRU, LR, RF, SVM, DT, KNN	Arabic Sentiment Twitter Corpus (ASTC), ArTwitter, (AJGT)	**Accuracy:94** **ASTC:** 98% **ArTwitter:**92% **AJGT:** 93%
Saleh and others [37]	The ideal ensemble staking model consists of three pre-trained models: deep layers of CNN, hybrid CNN-LSTM, and hybrid CNN-GRU.	Deep Learning	CNN, CNN-LSTM, CNN-GRU	Main-AHS, Sub-AHS, ASTD	**Accuracy:90** **Main-AHS:** 92% **Sub-AHS:**96% **ASTD:** 81%
El-Beltagy and others [39]	A model for implementing Arabic sentiment analysis incorporates features from an Arabic sentiment lexicon into the ML approach.	Hybrid Approach	MNBU, SVM, Complement Naïve Bayes (CNB)	Multiple Datasets from Twitter	**Accuracy:** **MD:** 81% **RR2:** 85% **BBN:** 71% **SYR:** 81% **SR:** 83%
Moussa and others [14]	A hybrid framework that accurately determines the polarity of sentences by combining the results of the lexicon-based Sum-of-Votes and Bag-of-Words techniques.	Hybrid Approach	Sum-of-Votes + Bag-of-Words + SVM	Four reviews datasets	**Accuracy:** 91%
Elshakankery and Ahmed [41]	Combining lexicon-based and machine learning-based approaches to deal with the rapid change in word usage and structure.	Hybrid Approach	SVM, LR, RNN	Twitter	**Accuracy:** **3-class classification:** 74% **2-class classification:** 84%
Aljameel and others [43]	Predicting the level of individuals' awareness of preventive measures against COVID-19 outbreaks in Saudi Arabia.	Hybrid Approach	TF-IDF, SVM	Twitter	**Accuracy:** 85%
Tubishat and others [9]	Two improvements for Whale Optimization Algorithm (WOA)	Swarm Intelligence	WOA, EOBL, IG, SVM	OCA, Arabic Twitter, Political, Software	**Accuracy:** **OCA:** 96%, **Arabic Twitter:** 88%, **Political:** 88%, **Software:** 92%
Alzaqebah and others [49]	An enhancement of the Salp Swarm Algorithm (SSA) designed for feature selection to solve the problem of Arabic sentiment analysis	Swarm Intelligence	SSA, IG, S-shaped transfer functions	Arabic tweets dataset [53]	**Accuracy:** **(T1):** 80% **(T2):** 74% **(T3):** 67 %
Marie-Sainte and Alalyani [50]	A new Firefly Algorithm-based Feature Selection method to deal with Arabic Text Classification.	Swarm Intelligence	FAFS, SVM	BBC and CNN Arabic websites	**Precision:** 99.4%
Alhaj and others [51]	Using machine learning techniques to enhance the performance of Arabic text classification.	Swarm Intelligence	PSO, LR, RF, KNN, DT SVC, LSVC, SGD NN	CNN, BBC, Alj-News SANAD (Arabiya) Abuaiadah	**Accuracy:** **DS A:** 97.5% **DS B:** 93.6% **DS C:** 97.2% **DS D:** 96.7% **DS E:** 97.5%

By examining the comparison table between the different research used in sentiment analysis, Figure 6 shows that the lexicon-based approaches achieved the least accuracy among the reviewed studies, with an average of 80%. In comparison, both the machine learning and the hybrid approaches obtained very close averages of 84% and 83.8%, respectively. These results indicate that approaches that used Deep Learning techniques and those that employed Swarm Intelligence algorithms were superior to others, with an average accuracy of 90% and 90.1%, respectively.

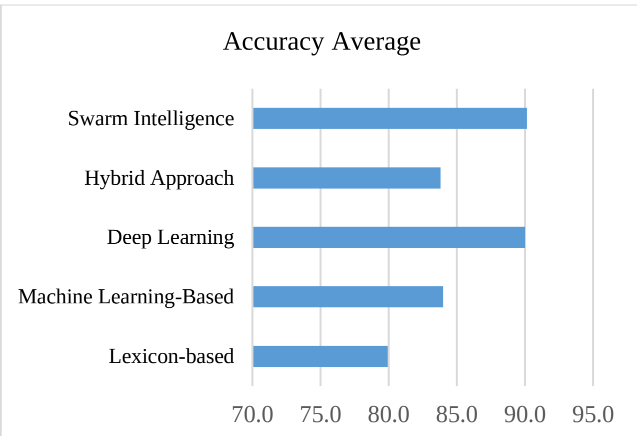

Figure 6: Accuracy average of reviewed sentiment analysis approaches

V. CHALLENGES

Recent surveys and literature reviews on the topic of sentiment analysis have revealed many challenges that researchers are trying to address with the many available methods and algorithms [2], [13], [40]. In their extensive survey, Abkenar and others (2021) thoroughly examined big data analytic methods applied to social networks, encompassing studies published from 2013 to August 2020. Their comprehensive review highlighted the significant unresolved issues in utilizing natural language, particularly concerning opinion and sentiment analysis. The review defined nine unsolved challenges from the sentiment analysis aspect where researchers failed to achieve high accuracy [2]. Another recent review by Nandwani and Verma (2021) concluded the challenges in sentiment analysis and emotion detection by six unsolved challenges [40], while Jindal and Aron (2021) listed five challenges that still exist for sentiment analysis, where more research is needed [13]. Wankhade and others (2022) surveyed to address the sentiment analysis methods, applications, and challenges. Their survey revealed that those challenges create barriers to accurately defining sentiments and determining their appropriate polarity [54].

TABLE 2: SUMMARY OF SENTIMENT ANALYSIS CHALLENGES

Abkenar and others [2]	**Nandwani and Verma** [40]	**Jindal and Aron** [13]
Domain dependency	Comparative Sentences	Domain-Specific
The low-resource languages	Lake of Resources	
Sarcasm Detection	Sarcasm and Irony Sentences	Sarcasm detection
Detecting slang	Web Slang	
Heterogeneous nature of data	Multiple Aspects	Multiple opinions in a sentence
Unreliable and incomplete data	Implicit Aspects	Negation handling
Semantic relationships across multiple sources of data.		
Subjectivity detection		Subjectivity detection
Spam detection		

Referring to previous studies, the most critical challenges of sentiment analysis are:

A. *Domain dependency*

As sentiment analysis is contextual and dependent on the domain, the polarity of words and phrases can differ across different domains. Therefore, a classifier trained specifically for one domain may produce unreliable outcomes if applied to other domains. Also, the meaning of words can change significantly according to the context in which they are used [2], [13].

B. *Lake of Resources*

Most of the available resources for sentiment analysis are mainly built for the English language. One obstacle hindering sentiment analysis's effectiveness is the absence of pre-established dictionaries and tools available for various languages. An example of this challenge is that some algorithms require a large dataset with annotations. However, collecting data is not challenging; manual tagging is more time-consuming and less reliable [2], [40].

C. *Detecting Sarcasm*

Sentiment analysis categorizes texts as positive, negative, or neutral. Hence, one of the major challenges in sentiment analysis is to identify irony, where sentences convey negative meanings despite incorporating words with positive connotations, which means that the text is intended to have another meaning. Because people often express their feelings of anger and resentment in sarcastic sentences, an in-depth analysis should be conducted to identify sarcasm [2], [13], [40].

D. *Detecting Slang*

Slang is the most widely used language among people to express their feelings. Detecting slang is a considerable challenge because slang often contains extreme emotions. With the growing use of social media, what is known as Web slang, is usually used by young people and can include unfamiliar terms and acronyms [2], [40].

E. Detecting Subjectivity

Revealing subjectivity is vital in sentiment analysis. Sometimes the text is neutral in one person's opinion but not so for the other, which means the sentence has a different interpretation. Detecting subjectivity is performed to separate factual information from opinions that will need further processing [2], [13].

In addition to those common challenges, conducting sentiment analysis for the Arabic language added more challenges, some related to the nature of the Arabic language and others to the scarcity of resources in this field [55]. Mulki and others (2017) conducted a survey to compare and evaluate Arabic sentiment analysis research performances. The survey highlighted the major challenging issues encountered while conducting Arabic sentiment analysis as follows [55]:

A. Complex morphology

In Arabic, a word can be expressed in multiple grammatical categories while maintaining its core meaning, a phenomenon referred to as inflectional morphology. The complexity of Arabic morphology stems from its utilization of a root and pattern system, where a single set of consonants, known as the "root," combines with different vowels (أ، و، ي) as well as diacritics and more consonants [55].

B. Lack of resources

The general lack of resources has previously been mentioned as a challenge to sentiment analysis in languages other than English; however, despite the abundance of Arabic content, there is a lack of Arabic sentiment datasets and dictionaries. Even with attempts to create some Modern Standard Arabic (MSA) standard datasets, few are publicly available [55].

C. Negation

Negation is one of the challenges of sentiment analysis in Arabic, which must be discovered and addressed because it can reverse the sentence's meaning, giving an opposite polarity. This task is more difficult when dealing with different Arabic dialects, as the negation tools differ from those used in formal MSA [55].

D. Arabizi usage

One of the common challenges when analyzing Arabic sentiment is the use of Arabizi – also known as "Franco Arabic." It is a newly emerging variant in which Arabic numerals and Roman letters express feeling mainly through social media. This makes classifying sentiments complex and requires appropriate tools to convert Arabizi into MSA that is easy to deal with and categorize [55].

E. Dialects variances

Many Arabic dialects have different geographical locations, each with vocabulary and expressions. However, there may be common vocabulary between them, and the challenge is that the shared vocabulary between dialects may differ in the feelings they express. Since most of the Arabic content used on social media has been disseminated using these different dialects, addressing this challenge will constitute an essential step toward analyzing Arabic sentiment [55].

VI. CONCLUSION

This paper investigated a critical topic related to predicting human behavior through Arabic sentiment analysis on social media and reviewed the most significant challenges facing researchers. Previous studies utilized big data analytics technologies to analyze sentiments, identify patterns and predict trends in human behavior. The paper shows that deep learning techniques have improved sentiment analysis tasks. The results of the comparisons made in this paper indicate the efficacy of combining various methods to improve sentiment analysis accuracy. Additionally, using optimization methods based on swarm intelligence algorithms significantly increased accuracy. The paper also highlighted the most common challenges for sentiment analysis. The promising results of deep learning techniques and optimization by swarm intelligence algorithms can motivate further studies.

REFERENCES

[1] Y. Tyshchuk and W. A. Wallace, “Modeling Human Behavior on Social Media in Response to Significant Events,” IEEE Trans. Comput. Soc. Syst., vol. 5, no. 2, pp. 444–457, Jun. 2018.

[2] S. Bazzaz Abkenar, M. Haghi Kashani, E. Mahdipour, and S. M. Jameii, “Big data analytics meets social media: A systematic review of techniques, open issues, and future directions,” Telemat. Informatics, vol. 57, no. January, p. 101517, Mar. 2021.

[3] D. Chaffey, “Global social media statistics research summary 2023,” Smart Insights, 2023. [Online]. Available: http://www.smartinsights.com/social-media-marketing/social-media-strategy/new-global-social-media-research/. [Accessed: 10-Mar-2023].

[4] Q. A. Xu, V. Chang, and C. Jayne, “A systematic review of social media-based sentiment analysis: Emerging trends and challenges,” Decis. Anal. J., vol. 3, no. May, p. 100073, 2022.

[5] N. A. Ghani, S. Hamid, I. A. Targio Hashem, and E. Ahmed, “Social media big data analytics: A survey,” Comput. Human Behav., vol. 101, no. August, pp. 417–428, Dec. 2019.

[6] M. Al-Ayyoub, A. A. Khamaiseh, Y. Jararweh, and M. N. Al-Kabi, “A comprehensive survey of arabic sentiment analysis,” Inf. Process. Manag., vol. 56, no. 2, pp. 320–342, 2019.

[7] E. Gutierrez, W. Karwowski, K. Fiok, M. R. Davahli, T. Liciaga, and T. Ahram, “Analysis of human behavior by mining textual data: Current research topics and analytical techniques,” Symmetry (Basel)., vol. 13, no. 7, p. 1276, Jul. 2021.

[8] I. El Alaoui, Y. Gahi, R. Messoussi, Y. Chaabi, A. Todoskoff, and A. Kobi, “A novel adaptable approach for sentiment analysis on big social data,” J. Big Data, vol. 5, no. 1, p. 12, Dec. 2018.

[9] M. Tubishat, M. A. M. Abushariah, N. Idris, and I. Aljarah, “Improved whale optimization algorithm for feature selection in Arabic sentiment analysis,” Appl. Intell., vol. 49, no. 5, pp. 1688–1707, May 2019.

[10] M. Kaity and V. Balakrishnan, “Sentiment lexicons and non-English languages: a survey,” Knowl. Inf. Syst., vol. 62, no. 12, pp. 4445–4480, 2020.

[11] D. Gamal, M. Alfonse, E.-S. M. El-Horbaty, and A.-B. M. Salem, “Implementation of Machine Learning Algorithms in Arabic Sentiment Analysis Using N-Gram Features,” Procedia Comput. Sci., vol. 154, pp. 332–340, 2019.

[12] M. S. Rahman and H. Reza, “A Systematic Review Towards Big Data Analytics in Social Media,” Big Data Min. Anal., vol. 5, no. 3, pp. 228–244, Sep. 2022.

[13] K. Jindal and R. Aron, “A systematic study of sentiment analysis for social media data,” Mater. Today Proc., no. xxxx, Feb. 2021.

[14] M. E. Moussa, E. H. Mohamed, and M. H. Haggag, “Opinion mining : a hybrid framework based on lexicon and machine learning,” 2019.

[15] R. M. Lerner, M. H. Bornstein, and J. Kagan, “human behaviour,” Encyclopedia Britannica. [Online]. Available: https://www.britannica.com/topic/human-behavior. [Accessed: 04-

Aug-2022].
[16] M. R. Davahli et al., "Identification and prediction of human behavior through mining of unstructured textual data," Symmetry (Basel)., vol. 12, no. 11, pp. 1–23, 2020.
[17] L. Li, Z. Ma, H. Lee, and S. Lee, "Can social media data be used to evaluate the risk of human interactions during the COVID-19 pandemic?," Int. J. Disaster Risk Reduct., vol. 56, no. February, p. 102142, Apr. 2021.
[18] K. Chakraborty, S. Bhattacharyya, and R. Bag, "A Survey of Sentiment Analysis from Social Media Data," IEEE Trans. Comput. Soc. Syst., vol. 7, no. 2, pp. 450–464, Apr. 2020.
[19] C. S. R. Prabhu, A. S. Chivukula, A. Mogadala, R. Ghosh, and L. M. Jenila Livingston, Big data analytics: Systems, algorithms, applications. 2019.
[20] M. Youssef and S. R. El-Beltagy, "MoArLex: An Arabic Sentiment Lexicon Built Through Automatic Lexicon Expansion," Procedia Comput. Sci., vol. 142, pp. 94–103, 2018.
[21] M. M. Eldefrawi, D. S. Elzanfaly, M. S. Farhan, and A. S. Eldin, "Sentiment analysis of Arabic comparative opinions," SN Appl. Sci., vol. 1, no. 5, pp. 1–11, 2019.
[22] M. Kaity and V. Balakrishnan, "An automatic non-English sentiment lexicon builder using unannotated corpus," J. Supercomput., vol. 75, no. 4, pp. 2243–2268, Apr. 2019.
[23] I. Touahri and A. Mazroui, "Deep analysis of an Arabic sentiment classification system based on lexical resource expansion and custom approaches building," Int. J. Speech Technol., vol. 24, no. 1, pp. 109–126, Mar. 2021.
[24] L. Mostafa, "Machine Learning-Based Sentiment Analysis for Analyzing the Travelers Reviews on Egyptian Hotels," in Advances in Intelligent Systems and Computing, vol. 1153 AISC, no. April, Springer International Publishing, 2020, pp. 405–413.
[25] L. Mostafa, "Egyptian Student Sentiment Analysis Using Word2vec During the Coronavirus (Covid-19) Pandemic," Springer International Publishing, 2021, pp. 195–203.
[26] H. Nayel, E. Amer, A. Allam, and H. Abdallah, "Machine Learning-Based Model for Sentiment and Sarcasm Detection," Proc. Sixth Arab. Nat. Lang. Process. Work., no. Ml, pp. 386–389, 2021.
[27] A. Alduailej and A. Alothaim, "AraXLNet: pre-trained language model for sentiment analysis of Arabic," Journal of Big Data, vol. 9, no. 1. 2022.
[28] B. Al sari et al., "Sentiment analysis for cruises in Saudi Arabia on social media platforms using machine learning algorithms," J. Big Data, vol. 9, no. 1, 2022.
[29] L. Zhang, S. Wang, and B. Liu, "Deep Learning for Sentiment Analysis : A Survey," WIREs Data Min. Knowl. Discov., vol. 8, no. 4, pp. 1–25, Jan. 2018.
[30] A. B. Nassif, A. Elnagar, I. Shahin, and S. Henno, "Deep learning for Arabic subjective sentiment analysis: Challenges and research opportunities," Appl. Soft Comput., vol. 98, p. 106836, 2021.
[31] N. C. Dang, M. N. Moreno-García, and F. De la Prieta, "Sentiment Analysis Based on Deep Learning: A Comparative Study," Electronics, vol. 9, no. 3, p. 483, Mar. 2020.
[32] A. Mohammed and R. Kora, "Deep learning approaches for Arabic sentiment analysis," Soc. Netw. Anal. Min., vol. 9, no. 1, pp. 1–12, 2019.
[33] A. H. Ombabi, W. Ouarda, and A. M. Alimi, "Deep learning CNN–LSTM framework for Arabic sentiment analysis using textual information shared in social networks," Soc. Netw. Anal. Min., vol. 10, no. 1, pp. 1–13, 2020.
[34] A. Alharbi, M. Kalkatawi, and M. Taileb, "Arabic Sentiment Analysis Using Deep Learning and Ensemble Methods," Arab. J. Sci. Eng., vol. 46, no. 9, pp. 8913–8923, 2021.
[35] A. Al Wazrah and S. Alhumoud, "Sentiment Analysis Using Stacked Gated Recurrent Unit for Arabic Tweets," IEEE Access, vol. 9, pp. 137176–137187, 2021.
[36] H. Saleh, S. Mostafa, A. Alharbi, S. El-Sappagh, and T. Alkhalifah, "Heterogeneous Ensemble Deep Learning Model for Enhanced Arabic Sentiment Analysis," Sensors, vol. 22, no. 10, pp. 1–28, 2022.
[37] H. Saleh, S. Mostafa, L. A. Gabralla, A. O. Aseeri, and S. El-Sappagh, "Enhanced Arabic Sentiment Analysis Using a Novel Stacking Ensemble of Hybrid and Deep Learning Models," Appl. Sci., vol. 12, no. 18, pp. 1–25, 2022.
[38] M. M. Ali, "Arabic sentiment analysis about online learning to mitigate covid-19," J. Intell. Syst., vol. 30, no. 1, pp. 524–540, 2021.
[39] S. R. El-Beltagy, T. Khalil, A. Halaby, and M. Hammad, Combining lexical features and a supervised learning approach for arabic sentiment analysis, vol. 9624 LNCS. Springer International Publishing, 2018.
[40] P. Nandwani and R. Verma, "A review on sentiment analysis and emotion detection from text," Soc. Netw. Anal. Min., vol. 11, no. 1, 2021.
[41] K. Elshakankery and M. F. Ahmed, "HILATSA: A hybrid Incremental learning approach for Arabic tweets sentiment analysis," Egypt. Informatics J., vol. 20, no. 3, pp. 163–171, Nov. 2019.
[42] W. Zaghouani, "A Large-Scale Social Media Corpus for the Detection of Youth Depression (Project Note)," Procedia Comput. Sci., vol. 142, pp. 347–351, 2018.
[43] S. S. Aljameel et al., "A sentiment analysis approach to predict an individual's awareness of the precautionary procedures to prevent covid-19 outbreaks in Saudi Arabia," Int. J. Environ. Res. Public Health, vol. 18, no. 1, pp. 1–12, Dec. 2021.
[44] S. Sun, Z. Cao, H. Zhu, and J. Zhao, "A Survey of Optimization Methods From a Machine Learning Perspective," IEEE Trans. Cybern., vol. 50, no. 8, pp. 3668–3681, Aug. 2020.
[45] Priyanka and K. Walia, "Popularity of Optimization Techniques in Sentiment Analysis," pp. 523–534, 2023.
[46] C. Baydogan and B. Alatas, "Sentiment analysis in social networks using social spider optimization algorithm," Teh. Vjesn., vol. 28, no. 6, pp. 1943–1951, Dec. 2021.
[47] L. Abualigah et al., "Advances in meta-heuristic optimization algorithms in big data text clustering," Electron., vol. 10, no. 2, pp. 1–29, 2021.
[48] S. Dhawan, R. Gupta, A. Rana, and S. Sharma, "Various Swarm Optimization Algorithms: Review, Challenges, and Opportunities," Springer Singapore, 2021, pp. 291–301.
[49] A. Alzaqebah, B. Smadi, and B. H. Hammo, "Arabic Sentiment Analysis Based on Salp Swarm Algorithm with S-shaped Transfer Functions," 2020 11th Int. Conf. Inf. Commun. Syst. ICICS 2020, pp. 179–184, 2020.
[50] S. Larabi Marie-Sainte and N. Alalyani, "Firefly Algorithm based Feature Selection for Arabic Text Classification," J. King Saud Univ. - Comput. Inf. Sci., vol. 32, no. 3, pp. 320–328, Mar. 2020.
[51] Y. A. Alhaj, A. Dahou, M. A. A. Al-qaness, and L. Abualigah, "A Novel Text Classification Technique Using Improved Particle Swarm Optimization : A Case Study of Arabic Language," pp. 1–18, 2022.
[52] H. ElSahar and S. R. El-Beltagy, "Building Large Arabic Multi-domain Resources for Sentiment Analysis," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 9042, A. Gelbukh, Ed. Cham: Springer International Publishing, 2015, pp. 23–34.
[53] N. A. Abdulla, N. A. Ahmed, M. A. Shehab, and M. Al-Ayyoub, "Arabic sentiment analysis: Lexicon-based and corpus-based," 2013 IEEE Jordan Conf. Appl. Electr. Eng. Comput. Technol. AEECT 2013, 2013.
[54] M. Wankhade, A. C. S. Rao, and C. Kulkarni, A survey on sentiment analysis methods, applications, and challenges, vol. 55, no. 7. Springer Netherlands, 2022.
[55] H. Mulki, H. Haddad, and I. Babao, "Modern Trends in Arabic Sentiment Analysis: A Survey," TAL Trait. Autom. des Langues, vol. 58, pp. 15–39, 2017.