J. Appl. Math. & Informatics Vol. **41**(2023), No. 5, pp. 1129 - 1143
https://doi.org/10.14317/jami.2023.1129

IMPROVING SOCIAL MEDIA DATA QUALITY FOR EFFECTIVE ANALYTICS: AN EMPIRICAL INVESTIGATION BASED ON E-BDMS

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Abstract. Social media platforms have become an integral part of our daily lives, and they generate vast amounts of data that can be analyzed for various purposes. However, the quality of the data obtained from social media is often questionable due to factors such as noise, bias, and incompleteness. Enhancing data quality is crucial to ensure the reliability and validity of the results obtained from such data. This paper proposes an enhanced decision-making framework based on Business Decision Management Systems (BDMS) that addresses these challenges by incorporating a data quality enhancement component. The framework includes a backtracking method to improve plan failures and risk-taking abilities and a steep optimized strategy to enhance training plan and resource management, all of which contribute to improving the quality of the data. We examine the efficacy of the proposed framework through research data, which provides evidence of its ability to increase the level of effectiveness and performance by enhancing data quality. Additionally, we demonstrate the reliability of the proposed framework through simulation analysis, which includes true positive analysis, performance analysis, error analysis, and accuracy analysis. This research contributes to the field of business intelligence by providing a framework that addresses critical data quality challenges faced by organizations in decision-making environments.

AMS Mathematics Subject Classification : 65D30, 65D32.
Key words and phrases : Social media, decision making, data analytics, social network.

1. Introduction

effective business intelligence systems and making better decisions for organizations. However, a review of the Scopus database shows that there has been relatively little research conducted on social media big data analysis. Between

Received February 21, 2023. Revised May 18, 2023. Accepted June 22, 2023. *Corresponding author.

2012 and 2016, the number of publications on this topic ranged from 1 to 99. In the subsequent period from 2017 to 2021, the number of publications on social media big data analysis has increased significantly and reached up to 200 publications. Business Intelligence (BI) is a process of collecting, analyzing, and interpreting business data to support decision-making [1]. BI plays a significant role in optimizing organizational effectiveness by uncovering emerging opportunities, exposing potential risks, and providing insights that can be used to make better business decisions. While BI systems have traditionally relied on centralized and internal business data, there is a growing need to incorporate unstructured and external data sources such as social media, web logs, and other types of big data.

Big data is characterized by its volume, variety, and velocity, and it presents new challenges and opportunities for BI. By leveraging big data analytics, organizations can gain valuable insights into customer behavior, market trends, and real-time performance metrics. Business Analytics, a subset of BI, focuses on using historical data to predict future outcomes and inform business decisions [2].

As technology continues to evolve, the future of data analysis looks promising. Smarter machines and advanced analytical techniques will enable organizations to extract even more value from their data, while new fields such as automotive, space science, medicine, and psychology will benefit from data-driven insights. The key to success in BI is to develop a comprehensive data strategy that incorporates both structured and unstructured data sources, along with the right analytical tools and processes. By doing so, organizations can unlock the full potential of their data and gain a competitive advantage in their industry [3].

As the use of computer and internet technology continues to increase, Business Intelligence (BI) faces new obstacles in collecting vital data from diverse sources. This data can often be complicated, unstructured, and vital to businesses. For example, Wal-Mart generates about 1 million sales every hour, Twitter releases over 600 million tweets per day, and over 786 million users are active on social media platforms daily. Social media channels like Facebook, YouTube, and Weibo have contributed to nearly 87% of the information available today. Big data has become a topic of significant interest in recent times, largely due to its potential for creating market value [4]. A study conducted in 2019 found that 39% of respondent entities had implemented rigorous analyses, while 84% had utilized advanced experiments over the preceding four years.. Consequently, to stay up to date with the current state of the market and constantly evolving systems, including customer behavior, businesses must analyze vast quantities of data. Big data analytics has the potential to tackle a wide range of present-day issues. The analysis of data will lead to the development of smarter machines, as computers are becoming increasingly capable of learning from data [4]. In the years ahead, numerous industries, including automotive, space science, medicine, and psychology, are expected to interpret emotions using data analysis, facilitating greater comprehension and communication. The potential and challenges of big data analytics are currently a focus of research, as it has the ability to provide valuable insights and improve decision-making in various industries. However, there is still a need for more research on the practical implications of using big data in digital marketing and the operational impact of big data analysis on business intelligence. Studies have shown that data obtained from social networks for big data analysis in business intelligence is unique and relatively under-researched. As a result, there is a lack of research on the operational effects of using big data analysis for business intelligence, particularly in the context of social media.

By utilizing statistical facts, data analytics provides a foundation for managers to make informed decisions about the long-term growth of their companies, including assessing the market and competition[5]. Through data analysis, managers can incorporate all relevant information into their operational decision-making. This article seeks to enhance the understanding of the impact of big data analysis on business intelligence by exploring social media data from Beijing and identifying potential trends. Through this analysis, we hope to shed light on the practical implications of big data for business intelligence, particularly in the context of social media. By identifying trends and patterns in the data, we can gain insights into consumer behavior, market trends, and other factors that can inform business decisions. Ultimately, our goal is to provide a better understanding of how big data can be used to improve business intelligence in the era of social media.

The research questions outlined in the article are:

1. What are the implications of Big Data Analysis for business intelligence, mainly with regards to the data collected from social media?
2. What are some major directions for additional development of market technology through big data analysis?

The article highlights the significance of exploring these questions as they pertain to a field of science that has yet to be extensively studied

The paper contributes to the field in the following ways:

1. It adds to the existing knowledge on the role of big data analysis in business intelligence and helps in understanding the impact of information technology on BI.
2. The findings of the work can enhance the understanding of the industry and aid management and business stakeholders in making better decisions and increasing productivity by developing plans to use big data analysis.
3. The paper highlights the potential of using social media data to improve competitiveness and enhance customer experience in Beijing, thereby providing a useful example of how large social networking information can be leveraged.

The further sections are organized as follows: Section 2 provides an overview of the existing works on big data analytics and business intelligence. The network model for the proposed framework is discussed in section 3. The proposed enhanced BDMS based decision making framework is designed and applied in section 4. Section 5 covers the discussion of the performance evaluations and results. The work concluded in section 6 .

2. Related work

This section discusses the challenges and current solutions in commercial and research portfolio management. It then discusses the main contributions of recent studies on using Business Decision-Making Systems (BDMS) with social media data analytics to develop businesses. Social media data analytics enables organizations to make timely, feasible, and impactful strategic decisions by utilizing the data obtained through social media processing [6]. The author of [7] introduced a consumer segmentation model (CSM) that considers structural and transactional limitations in the analysis of social media data. An improved deep learning algorithm was developed by the researchers to address the challenge posed by the proposed model. They also evaluated its effectiveness against three other optimization algorithms.

In [8], a Big Data Analytic Framework was presented for organizational development based on a new marketing strategy. The framework leverages data generated by the internet, sensing devices, corporate websites, and user-generated content. The work illustrated the methodology and potential of Big Data Analytics (BDA) through three case studies. The four essential components of the BDA message complexity include Big Data application services, system coordination, data sources, and end-users. Furthermore, additional building blocks such as data protection, confidentiality, and administration can enhance information value chains and enable capabilities across the four dimensions of the BDA process.

Feedback from consumers that is genuine and meaningful can be obtained from freely available user-generated content, which is accessible at any time and from any place. However, there is no standardized or organized method for collecting and analyzing this content to inform management decision-making [9]. This approach aims to extract insights on consumer satisfaction from unstructured textual user reviews using big data. A key difference between this research and prior studies is the use of standards to improve communication between decision-makers and big data analytics teams during the decision-making process. These standards provide a clear representation of human preferences, and offer a common notation that both enterprise clients and the research team can easily understand [10].

Authors of [11] introduced a novel interdisciplinary research method called the Information Discovery Model (IDS), which combines, expands, and adapts various approaches for analyzing social media data. The social media analysis process is broken down into four stages: data acquisition, processing, preparation, and evaluation. The paper focused on improving business outcomes, specifically by examining how social media data processing and analysis can be leveraged to enhance marketing and operational practices in order to promote business stability. The proposed IDS method overcomes the limitations of traditional approaches by providing a comprehensive framework that takes into account the various complexities involved in social media data analysis

3. The Network Model

Social media networks provide a platform for users to share images, articles, photos, drawings, scripts, feelings, observations, moods, viewpoints, rumors, and news online. These platforms can be used for information sharing, entertainment, and obtaining feedback on products or issues. Popular social media networks include Facebook, Instagram, LinkedIn, Twitter, WhatsApp, and Igloo [12]. By analyzing consumer behavior, social media networks can improve worker performance, business education, and innovation. Understanding customer needs can help organizations streamline workflows and determine whether to prioritize external or internal customers. Customers who purchase items or services are considered external customers. Customers typically identify their needs, research available options, make a purchase decision, and evaluate their purchase

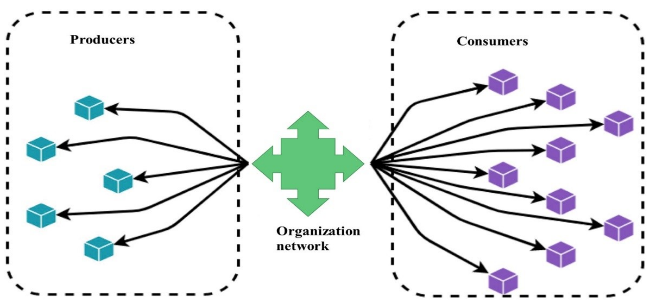

Figure 1. Traditional Business Model

Corporate success can be enhanced by utilizing social networking to foster collaboration both within and outside of an organization. Social networking initiatives (SNI) can improve overall organizational efficiency and contribute to innovative business strategies. Social Networking Initiatives refer to the use of social media platforms to create a network of employees or other stakeholders in an organization. Through SNI, employees can connect with each other, share ideas, and collaborate on projects, regardless of their location or job function. SNI explores the connections between organizations, consumers, and vendors that can be combined to create networks [13-15]. These networks are made up of nodes that represent individual organizations, consumers, and vendors, as well as connecting lines that indicate the strength of their relationships. The study of social networks focuses on the connections between people, such as friendships, family relationships, or financial ties, and involves both nodes and relationships.

These networks can determine an individual's or group's social capital. In a social network diagram, nodes represent actors or individuals, and ties or links represent the connections between them. These nodes and links form the building blocks of a social network, where nodes are the points or actors and edges represent the relationships or links between them. These graphs can represent a single type of relationship (simple) or multiple types of relationships (multiplex). Figure 1 shows the network of consumers and producers and their relationship. Independent consumers and producers are kept in same clusters based on the similarities. Distributors refer to individuals or businesses that purchase and store products to sell through a distribution channel. Acting as intermediaries between manufacturers and retailers or end-users, they work for a company and not on their own behalf. The distribution channel is responsible for making a product or service available to the end-user. In indirect marketing, the producer or service provider sells their product or service through distributors or intermediaries. For the overall distribution channel to be successful, the end-user must receive value [16]. Currently, there is a lack of open platforms that facilitate information sharing and idea exchange between consumers and distributors. However, with the aid of IT systems, it is possible for a single entity to make informed decisions based on a comprehensive overview of activities carried out by different parties. Improved interactions between manufacturers and customers can help manufacturers better manage their tasks and improve efficiency at the customer level.[17-20]. Establishing an open forum for information sharing and exchange among consumers and distributors poses several challenges. These challenges include issues of trust and confidentiality of information, misaligned incentives among various partners, significant investments, and technological difficulties. These challenges need to be addressed to establish a successful information-sharing platform. Figure 2 shows the relationship between consumers and producers over social media. The distinction between a thin line and a thick line represents the soft connection via social media between independent consumers and distributors versus the conventional relationship chain. Developing social networks among consumers and distributors can be beneficial for organizations because it makes it easier to connect and share information about the product and its features, which aligns with social networking initiatives. This research work involves data mining, data processing, data storage, and business decision-making stages. To obtain significant outcomes, surveys and literature studies were used. Social media analytics tools were utilized to convert content into effective business and marketing campaigns. The project aims to be more strategic in business decisions, improve brand awareness, and enhance customer experience. The work conducted a two-phase literature search to gather information. The first phase involved a keyword search and analysis to understand the evolution of the literature in social media. The second phase of the literature search involved manually searching journals for specific information systems to gain a deeper understanding of the evolving perspectives on information systems. Surveys were carried out to investigate issues related to social media data and to identify potential areas for business development improvement. The work focuses on the information exchange between a retailer and its supplier to better understand the process. This methodology allows researchers to investigate and answer questions related to the "why," "what," and "how" of a particular phenomenon or situation. Saunders et al. (2012) state that the case study strategy is useful in generating potential explanations for specific relationships between variables, rather than providing novel insights into the research topic. The paper achieved the objectives by utilizing a case study strategy.

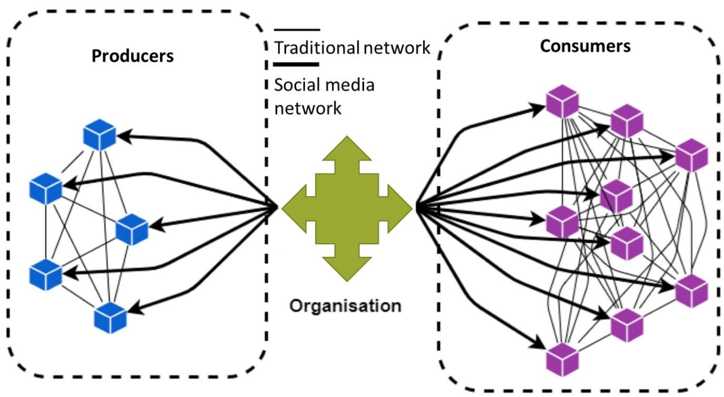

Figure 2. Social media network based model

Management of decision execution is a methodical approach to monitoring, communicating, and evaluating decision-making. Since decision-making is fundamental to leadership, decision-making is to leaders what customer relationship management is to salespeople. Generally, managers are responsible for overseeing the progress and productivity of their subordinates within the organization. In addition to fundamental managerial skills such as decision-making, problem-solving, delegation, and meeting management, management also encompasses team building, identification of new job roles, recruitment and training of new employees, and managing employee performance. Managers typically have a good understanding of the activities within their team, such as how to create a new product. Various management techniques such as consumer segmentation model (CSM), information discovery model (IDS), big data analytics (BDA) tools, sentiment analysis (SA), and business decision management systems (BDMS) are used to analyze the impact of social media networks on an organization's business development. Customer segmentation involves dividing a company's customers into groups based on their similarities, which is necessary to maximize the value of each customer to the business. The Design, Build, Run, and Analyze steps are iteratively repeated until the desired outcome is achieved. The below figure 3 shows the big data assisted social media business model:

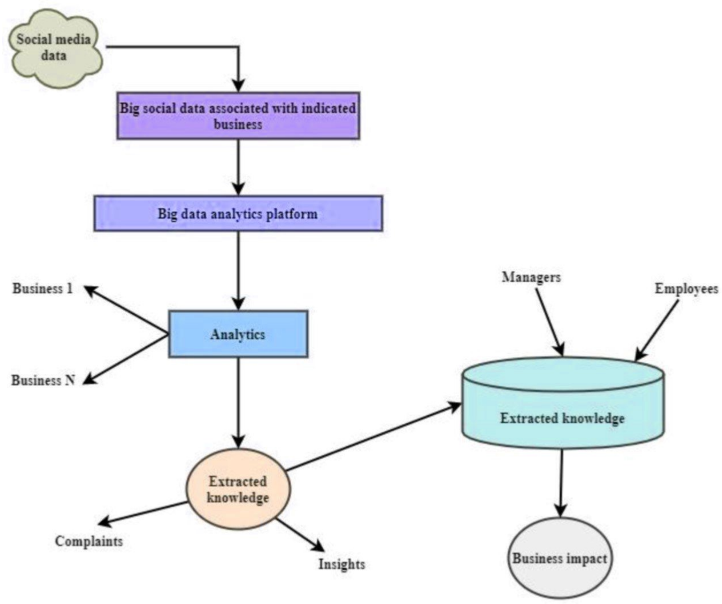

FIGURE 3. Big data assisted social media business model

The model analyzes data from social media platforms and provides insights into the impact on businesses based on the analysis. It recommends an organizational learning framework to help companies effectively use big data analytics to compare social media data against competitors and uncover valuable insights. However, there is currently no established framework within the knowledge management (KM) industry to guide businesses in leveraging vast amounts of social media data for informed decision-making. The proposed framework incorporates big data technologies as a solution to address the issue. The objective of the work was to examine a significant volume of social media data regarding organizations and their competitors, and to present and evaluate competition assessments across different domains, such as activities, products, issues, and other aspects that could affect operational effectiveness. Organizations can utilize various big data systems such as IBM, Sybase, MySQL, to collect, organize, and analyze information gathered from different Facebook pages. Analyzing large quantities of data and information gathered from popular social media platforms allows for more efficient and effective analysis. Storing the collected data in a knowledge base and sharing it with top management through the organization's existing management information system is a viable option. This approach is especially suitable for client service-oriented industries like e-commerce, finance and health care.

4. Data Processing

Data collection is achieved through social media network data set and data recovery is achieved through information retrieved from the social network. Data processing or extraction involves grouping or categorizing data based on specific characteristics or criteria outlined in a report. In the context of data mining, data extraction refers to the analysis of a pre-classified dataset to identify patterns and group them into known categories. With the vast amounts of data being collected from social media platforms, the next step in the data extraction process is processing the data which was collected in the earlier step. Different techniques have been utilized for data processing, including consumer segmentation modeling (CSM), Information discovery systems (IDS), big data analytics (BDA), sentiment analysis (SA), and big data management systems (BDMS).. Prior to the data extraction algorithm, the data is subjected to pre-processing, which typically involves procedures such as case folding, verification, filtering, and cleaning to ensure data quality.

4.1. An Enhanced BDMS approach.

The use of social media platforms, including social networks, surveys, review panels, and evaluations, is rapidly increasing. Companies are required to automatically filter and identify new business opportunities. However, the vast amount of data on social media makes it challenging to detect consumer sentiments in real-time. This difficulty is compounded by the fact that different fields use varying terminologies, resulting in multidimensional data that are unique to each field. In image analysis, domain adaptation can play a critical role. Most consumers nowadays prefer to buy fabrics and apparel through e-commerce platforms, which are often linked to social media networks. To cater to this trend, a specialized BDMS framework has been developed to recommend more efficient and competitive online fashion options. The framework categorizes clothing items into various groups such as men's, women's, tops, jackets, dresses, etc. It then matches fabric photos preferred by consumers with those in the dataset. The BDMS can quickly learn to recognize clothing images' heterogeneity by identifying the various attributes. Compared to conventional methods, the BDMS search delivers an instant recovery response. Social media network analysis based on BDMS consumer data can be used to process data from time intervals and integrate it with social media networks. To start the analysis, we first need to look at the social media network data for multiple time periods, as represented by Equation (1)

$$\theta = \frac{1}{on} \sum_{op} [(wk + rc) \cdot (tj + cj) + (v' + (wk \cdot iz)) \cdot rc \cdot \left(\frac{ud}{ep}\right)] \tag{1}$$

The data obtained from various social media networks is analyzed using a mathematical equation denoted as θ. This analysis helps in making management decisions, denoted as rc, based on the standard and nonstandard state of the product. The quantity of data is denoted as 'on', and the quantified information is denoted as 'op'. Multi-social media network data is represented as 'wk', and feedback signals, such as alerts or identification signals, are sent based on the mined data about the organization's business. The extracted data related to the organization's business operations have been transmitted along with a feedback signal that functions as an alert or identification signal. The BDMS model incorporates economic parameters and growth factors for significant data extraction purposes. It then implements the cost element. The business economic model includes the median square error, weight declining shape, and gradient approximation to detail the variance between the identified data and the forecasted data.

$$L(W, d, v, w) = \frac{1}{2} \left\| h(w, d(vj)) - (wk) \right\|^2 \tag{2}$$

The function L takes four arguments: W, d, v, and w. The expression inside the function is a mathematical formula for the objective function, which typically measures the quality of the model or the solution found by an optimization algorithm. The expression starts with a constant factor of 12, which is often used to simplify the computation of derivatives in optimization. The expression involves some variables and operations that are not defined in the given equation. Here are the assumptions I made: h(w, d(vj)) represents the output of a neural network or some other kind of model, given the input w and the transformed input d(vj). wk represents the true (or expected) output for the input w, which is typically provided as part of the training data. The expression $\|\ldots\|_2^2$ represents the squared L2 norm or Euclidean distance between two vectors or matrices, which is often used as a loss function in machine learning. The goal of an optimization algorithm would be to find the values of the parameters W, d, v, and w that minimize the value of the objective function L. This would typically involve computing the derivatives of L with respect to each parameter and adjusting the values accordingly.

In this research, a comparative analysis is used to determine if δ_m is closer to δ. The sparse violation, $\sum_{j=1}^{NM}(\delta_m - \delta)$, is compared based on comparative analysis and it is given in Eq. (3), where $\delta \ln \delta$ and $\delta_m \ln(1-\delta)$ indicate the logarithmic computation of sparse violation factor and logarithmic deviation of the subsequent iterations, respectively.

To address over-reduction challenges in the SMN model, the integration of weight domain products is done. This involves minimizing the weight range to eliminate irrelevant data, while still maintaining the social media network's overall structure. By reducing the weight length, the model can effectively filter out unnecessary information and ensure that only relevant data is included.

Equation (3) is given as follows:

$$\sum_{j=1}^{NM} (\delta_m \| \delta) = \sum_{j=1}^{NM} \delta_m \ln\left(\frac{\delta_m}{\delta}\right) + (1-\delta)\ln\left(\frac{1-\delta}{1-\delta_m}\right) \tag{3}$$

The weight reduction process is a critical factor in the SMN model, and it is determined by the weight reduction factor (γ). The magnitude of the fluctuating utility can be explained in the economic function, where the weight reduction time can impact the economic process if the weight decline is too minimal. Conversely, a too-large γ value could lead to underfitting. In this paper, a smaller value of γ is assumed, and the parameter is adjusted according to the source data of the investigational data ($(W_{mjk})^2$).

Eq. (4) provides the weight weakening procedure, and the resulting utility communication is observed when all the elements in the economic function $L(W, d)$ are expressed in Eq. (8).

$$L(W, d) = \frac{\gamma}{2} \sum_{j=0}^{o} \sum_{k=0}^{o} \sum_{m=0}^{o} (W_{mjk})^2 \tag{4}$$

The ascent parameter holds great importance in network optimization and modification when it comes to social media data analytics. The process of comparative analysis computation is commonly utilized to identify the deviation of each successive economic gradient. This method involves comparing the predicted value of a variable to its actual value in real-time and using this comparison to modify the SMN variables. It is a useful technique for controlling data extraction and ensuring accuracy in SMN analysis. Eqs. (5) and (6) detail the gradient computation.

$$\frac{\partial L_{\text{sparse}}(W, d)}{\partial W_{mjk}} = \frac{1}{j} \sum_{j=0}^{o} \frac{\partial L(W, d, v_j, w_k)}{\partial W_{mjk}} + \alpha W_{mjk} \tag{5}$$

$$\frac{\partial L_{\text{sparse}}(W, d)}{\partial d_{mjk}} = \frac{1}{j} \sum_{j=0}^{o} \frac{\partial L(W, d, v_j, w_k)}{\partial d_{mjk}} \tag{6}$$

Eqs. (5) and (6) describe the computation of the gradient in terms of data extraction error parameters (W) and (d), respectively, with $\frac{\partial L_{\text{sparse}}(W,d)}{\partial W_{mjk}}$ and $\frac{\partial L_{\text{sparse}}(W,d)}{\partial d_{mjk}}$ representing the source data for experimentation. The constant α is used in the comparative analysis, and the investigation samples are based on data extraction error variables. By using the comparative analysis technique, the deviation can be eliminated during the processing phase of social media data analytics. The resulting deviation can be obtained by evaluating Eq. (7).

$L_{\text{sparse}}(W, d)$

$$= \frac{1}{j}\sum_{m=0}^{o}\frac{1}{2}\|h(w,d(v_j)) - w_j\|^2 + \alpha\sum_{N=1}^{M}(\delta_m - \delta) + \frac{\gamma}{2}\sum_{j=0}^{o}\sum_{k=0}^{o}\sum_{m=0}^{o}(W_{mjk})^2 \quad (7)$$

The final computed deviation ρ_{nmj} can identify the deviation of the final computed layer in the forward transmission phase $z - h(w, d(v))$ utilizing the extracted data (e_{nmj}). The deviation for the initial layer is expressed in Eq. (8).

$$\rho_{mj} = \left(\sum_{j=0}^{o} W_{m,jk}\rho_{m+1,j} + \alpha\left(\left(\frac{1-\delta}{\delta_m}\right) + \left(\frac{1-\delta}{1-\delta_m}\right)\right)\right) f'(e_m) \quad (8)$$

where:

ρ_{mj} : This is the deviation for the initial layer.

$\sum_{j=0}^{o}$: This is the summation over all the output units of the subsequent layer $(m+1)$.

W_{mjk} : This is the weight between the jth input unit of the current layer (m) and the kth output unit of the subsequent layer $(m+1)$.

ρ_{m+1j} : This is the deviation for the kth output unit of the subsequent layer $(m+1)$.

α : This is the competitive analysis constant.

δ : This is the deviation factor computed by the logarithmic computation of the sparse violation factor $\delta \ln \delta$.

δ_m : This is the deviation factor for the current layer (m).

e_m : This is the extracted data for the current layer (m).

$f'(e_m)$: This is the derivative of the activation function used for the extracted data e_m.

5. Experimental Evaluation

The simulation was conducted using the operating system Ubuntu 16 (64 bits), 8GB RAM, eight-core processor, the presentation control used was Data stack Operations Center Inventiveness, and Windows stage belongs to DatastaxDeviceCenter2.5.0 using Cassandra framework. The proposed e-BDMS based decision making framework is developed and deployed. The performance parameters considered are precision, efficiency, delay, a genuine positive rate, error rate and results. In the simulation analysis, the purchasing histories and interests of 10 customers were examined to predict their next purchases. The predicted values were then compared to the actual values to determine the accuracy of the predictions. The figure3 below show the actual positive values that were obtained. The analysis showed that the proposed BDMS framework had the greatest positive impact among the tested approaches.

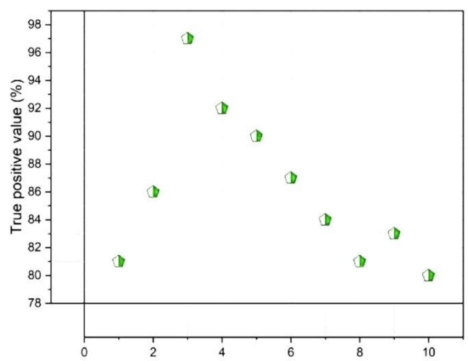

FIGURE 4. True positive rate of the proposed work.

Table 1 present the results of the investigation of a developed system called E-BDMS for managing consumer feedback and control periods. In both cases, E-BDMS outperformed various conventional management techniques, including CSM, IDS, BDA, and SA, in terms of accuracy, system reliability, F-1 measure, and deviation rate. For example, compared to the conventional management techniques, E-BDMS improved accuracy, reliability, and F-1 measure by 29.52%, 16.98%, and 31.01%, respectively, for managing consumer feedback. Similarly, for control periods, E-BDMS showed a significant improvement in accuracy, system reliability, F-1 measure, and deviation rate by 85.5%, 93.7%, 86.8%, and 7.0%, respectively, compared to the conventional CSM management approach. The improvement in accuracy, reliability, and F-1 measure was 27.51%, 39.16%, and 31.22%, respectively, for control periods. Meanwhile, the deviation rate was minimized by 65.83% and 52.71% for managing consumer feedback and control periods, respectively

TABLE 1. Consumer Feedback Analysis

Metrics	IDS (%)	CSM (%)	SA (%)	BDA (%)	E-BDMS (%)
Accuracy	70.2	65.2	81.2	78.2	90.3
Reliability	72.5	70.2	71.3	69.8	79.3
F1-measure	61.8	60.3	70.2	73.4	89.9
Deviation rate	13.4	14.6	13.6	15.6	4.2

This work proposes and analyzes the E-BDMS based decision making model, which utilizes big data to assist with social media analytics for businesses. The model examines various simulation parameters, including social media mentions, social media index, and brand purchases. The results show that the E-BDMS decision making model provides a highly accurate analysis of social media, which can help the organization improve their efficiencies.

6. Conclusion

Business intelligence has been a vital area that employs data analysis to produce key information for business decision-making. Companies and research institutions have a significant interest in analyzing user-generated data to gain knowledge. This article proposes a E-BDMS based decision making system that uses social media data analytics to develop businesses. E-BDMS framework provides an in-depth understanding of key principles, issues, and functionalities of big social data developments. By using social data analytics, companies can obtain decision-making support and investment opportunities, as evidenced by current use scenarios. The experimental outcomes exhibit that e-BDMS attains remarkably competitive outcomes. We aim to include deep neural networks in social media data analytics in the future. Social media analysis facilitates the collection and identification of meanings from data gathered on social channels to support business decisions and monitor activity performance accordingly. .

Conflicts of interest : The authors declare no conflict of interest.

Data availability : Not applicable

Acknowledgments : We gratefully acknowledge Department of Computer Science, Alagappa University for providing the resources and support.

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