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Preliminary communication

Improved DNN-assisted Customer Behavior Analysis with Smart Visual Analytics

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Abstract: A customer behavior analysis examines each customer journey stage using qualitative and quantitative methodologies to understand what motivates consumer behavior. With visual analytics, marketers can decipher the complicated world of customer retargeting, allowing businesses to visualize data and ask and answer infinite questions. Because of this, they are better able to comprehend who their consumers are and why they act in certain ways. This paper provides a significant solution named improved DNN-assisted Customer Behavior Analysis (iDNN-CBA) with smart visual analytics. This paper suggests an interactive section for collecting customer reviews and feedback. Their facial expressions have been collected and processed using the improved deep neural network (iDNN), and the visual analytics occurs with pattern analysis. The proposed iDNN-CBA has been trained and validated using the experimental analysis by public dataset KAGGLE and observed the highest accuracy of 96.55% compared to other existing behavior analysis schemes.

Keywords: customer behaviour analysis; deep neural network; smart visual analytics; visualize data

1 INTRODUCTION-CUSTOMER BEHAVIOR ANALYSIS WITH SMART VISUAL ANALYTICS

There is an increasing need for the integration of visual analytics software because of the increasing amount, complexity, and speed at which data is being generated [1]. Visual analytics is a method of problem-solving in which data is presented in an interactive, graphical format [2]. Visual analytics is an important part of utilizing advanced tools and procedures to visualize the analyzed data [3]. Finding behaviors and acting based on those behaviours is easier when the data is represented graphically [4]. The use of visual analytics is especially beneficial in business analytics systems that deal with huge quantities of complicated data and analytical procedures. They require a lot of user involvement and monitoring [5]. Through this information, businesses can make more informed choices [6]. Non-technical customers can easily establish and change analytical parameters using packaged visual analytics software tools, including drag-and-drop choices [7]. Today's marketing stresses the availability of accurate and complete customer data as a need for survival and development in a competitive economic system [8]. Almost everyone nowadays thinks the primary goal of marketing is to please the customers rather than to persuade them to purchase the company's products [9]. Customers come from all around the globe now that social media has become a powerful networking tool [10]. It promotes socializing by making various customers quickly, inexpensively, and readily accessible [11]. Social media to market a product or service makes it more effective [12]. For the most part, social media platforms include built-in data analysis tools that enable businesses to monitor their marketing strategy's performance and engagement [13]. Many people are involved in social media marketing businesses, including current and potential clients, analysts, bloggers, and members of the public [14]. It is now feasible for a business and its customers to establish dynamic, varied connections through social media. Customers' perceptions of brands are improved when businesses utilize social media networks to broaden their geographic reach [15]. Social media gives consumers, stakeholders, and commenters access to communications quickly and easily in the marketing exchange process [16]. Social media has developed into a marketing intelligence method from a single marketing platform (where customer behavior can be monitored, evaluated, and forecasted). To maintain a competitive advantage and improve efficiency, marketers must constantly utilize social media [17]. A customer behavior analysis is a qualitative and quantitative assessment of how customers deal with the business [18]. First, customers are divided into buyer persons based on the traits they have in common. An analysis of customer behavior reveals the many factors that affect a target audience [19]. A customer behavior analysis examines how customers interact with the business in-depth. A customer behavior study analyzes each journey stage using qualitative and quantitative techniques to understand what motivates consumer behavior [20]. To better anticipate customer behavior and engagement in social media, researchers in this paper recommend using an improved DNN-assisted Customer Behavior Analysis (iDNN-CBA). Predictive analytics sets are produced based on online activity, website clicks, social media operations records, intelligent devices connected to geolocation characteristics, and other factors. In-depth learning is a novel approach to solving some of the most difficult marketing problems and achieving outstanding outcomes. These solutions will alter marketing communication duties and boost productivity in key marketing areas. To get a comprehensive image of a company's behavior, marketing companies collect data from many live customer contacts. Marketing companies can complete consumer segmentation models and utilize the insights to develop a plan for customer engagement and enhance customer value by evaluating such a large amount of data. Whether customer happiness is motivated by pleasure, optimism, trust, and commitment, the findings assist in overcoming previous research's discrepancies, minimizing total costs while enhancing data exploration and analysis. Data analysis that is both quicker and easier to comprehend will lead to better decisions being made sooner. Data consumption increases operational efficiency by allowing users to consume more data in less time. The main contribution and innovation of this paper is as follows:

- Design an improved DNN-assisted Customer Behavior Analysis (iDNN-CBA) to predict customer behaviors.

- Determine the improved deep neural network (iDNN) to analyze pattern analysis in social media for organizations' development.
- The experimental results suggested that iDNN-CBA enhances accuracy, behavior analysis, satisfaction, feedback, and risk management compared to other existing models.

The rest of the iDNN-CBA technology research can be organized similarly. Section 2 describes the literature research. Briefly described in Section 3 are the new ideas that have been presented and used in this paper. Section 4 details the findings and conclusions based on the data. Lastly, in Section 5, the iDNN-CBA technology ends with a thorough analysis of the findings.

2 RELATED WORK OF BUSINESS

Transactional business models have given way to social ones due to social media. By adopting this innovative strategy, businesses now have the opportunity for long-term profitability and value addition to customer relationships. Companies can connect with current and prospective customers and provide information about their products and services openly and transparently. A thorough examination of literature reviewing procedures for papers evaluated by peers revealed improved DNN-assisted Customer Behavior Analysis. Digital energy data from fine-grained smart meters enable energy demand management to play an important part in rational energy allocation and the monitoring and supervision of customer behavior. This study aims to identify energy-saving opportunities, plan energy supply, and improve energy efficiency, which is offered in a new Spatio-temporal visual analytic method (STVAM) for identifying urban energy consumption patterns [21]. To aid in decision-making, users can engage with the system to find and experiment with new patterns. Smart energy systems can utilize this technology better to understand their customers' energy usage habits and preferences. For improvised marketing interventions (IMIs), the author suggested writing and carrying out social media activities in real-time near a genuine event [22]. For five multi-method studies, the evidence is in the form of archiving and the hypothesis that IMIs use a laughable and unexpected effect, including quasi tests and analytical data. According to the findings, IMIs hold great potential for social media. Companies need to enjoy the benefits of proactive online networking and the value increases that come with it. E-commerce, a method of doing business through the internet, has increased in popularity, its introduction with the development of the internet. The use of online sales and buying has grown in popularity in the modern world. A merchant's business cannot always be integrated with existing systems. For this study, the study looked at a big data-driven company's e-commerce marketing system. According to tests, big data technology (BDT) in an organization's e-commerce marketing system has major practical consequences [23]. According to the author, the primary goal of the artificial intelligence model (AIM) in e-commerce is to influence customer behavior in favor of certain products and brands [24]. AIM is the most innovative technology for customizing products to meet individual needs. According to the findings of this study, the ethical soundness of AI systems in e-commerce is debatable, particularly in terms of explainable value. Numerous ways to improve NB's main premise of classifier independence have been put forward in the literature. Strategic management choices supporting the improvement of company value need knowledge of customer behavior and a thorough grasp of consumer expectations. This CRM is heavily used in analyzing customer behavior patterns via the application of Machine Learning Techniques (MLT) [25]. The experiments show that the Bagging Homogeneous Feature Selection -naive Bayes model performs better than the conventional NB in making predictions. Improved DNN-assisted Customer Behavior Analysis has been used to overcome the existing model issues. This study has been suggested to increase accuracy, behavior analysis, satisfaction, feedback, and risk management.

2.1 Proposed Method: Improved DNN-Assisted Customer Behavior Analysis (iDNN-CBA) with Smart Visual Analytics

Businesses can create new development channels and new business models by combining and analyzing production data using iDNN. Customers and suppliers and consumer preferences are all well-documented in these companies' huge databases. Trying to anticipate customers' continuously shifting behavior and actions is one of the world's most difficult issues today. Even in the best of times, keeping consumers interested in new technologies is a tough task. From a commercial perspective, social media platforms are used to create networks and share information and emotions. Social media produced three fundamental shifts on the markets in their unique essence of competition, intertwining, equality, and interaction. To begin with, social media platforms like Facebook and Twitter enable businesses and customers to interact in previously unimaginable ways. For example, social networking services like What's App and Instagram use various methods to tap into shared participation and ideas. The frequency and duration of these connections define the strength or weakness of social connectedness in this sense. Fig. 1 shows the data flow of customer relationship maintenance. A marketer, often known as a marketing professional, is tasked with developing innovative campaign ideas to promote a company's goods, services, or overall brand identity. A customer database is a repository for the data amassed from everyone. Contact information could be stored in a database, such as a person's name, address, phone number, and e-mail address. The database can contain information on previous purchases as well as anticipated future requirements. A Web application (Web app) is software stored on a remote server and distributed via the internet through a browser interface. On line services are Web applications, and many websites and not all include Web apps. Any business or person can benefit from web applications since they can be developed for various purposes and utilized by several people. Online calculators and e-commerce stores are examples of Web applications that are regularly accessed. While some Web applications can only be viewed through a particular browser, most are accessible through any browser.

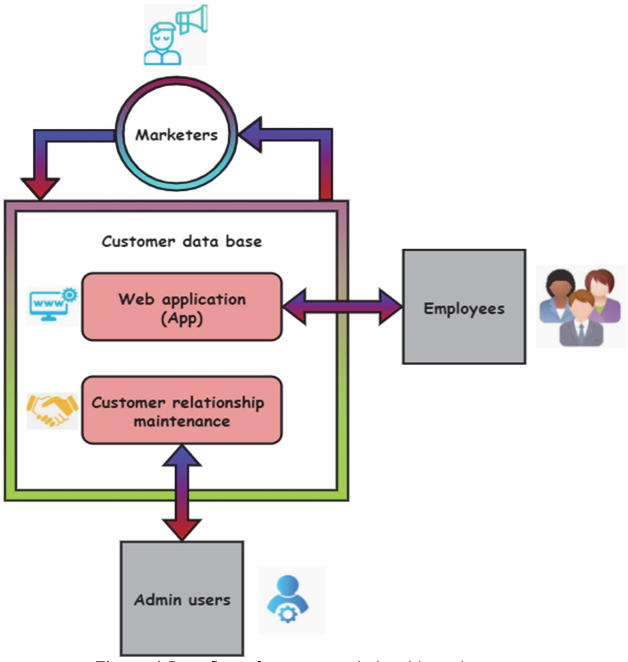

Figure 1 Data flow of customer relationship maintenance

In contrast to computer-based software applications, which operate locally on the device's operating system (OS), a web application (or web app) runs on a web server. With an active network connection, the user can access web apps by opening a URL in a web browser. Websites do not need downloading since they are accessible through a network. Many different types of web browsers can be used to view a Web application. A Web server, an application server, and a database are all required for a web app to function. Applications run on servers, and web servers handle the requests that come in from customers. To store any necessary data, one can utilize a database. Employees fulfil deadlines, close sales, and develop the company's brand via good encounters with customers. Ineffective workers give customers the impression that the business does not care about their problems, looking for solutions elsewhere. Employees do a good job getting things done right the first time around. Customer relationship management (CRM) is a system for managing all, a company's connections and interactions with customers and prospective customers. The end objective is straightforward: better commercial connections. A CRM system aids businesses in staying in touch with their consumers, streamlining procedures, and increasing profitability. Customer relationship management (CRM) aids companies in understanding their customers' behavior and making changes to their company processes to serve them better. CRM can be accomplished through learning about your customers' buying patterns, views, and preferences. An administrator is a person who has the authority to make computer-related changes that impact other users. Administrators have complete control over the computer, including altering security settings, installing applications, and seeing all data stored on the machine. The exponential of the proportion of non-responsive customers in the current grouping is given in Eq. (1).

$$NPQ_k = T_z \left(\frac{Hy_z / Hy_m}{Hn_z / Hn_m} \right) \cdot T_z \frac{ry_z}{qr} \tag{1}$$

As shown in Eq. (1), Hy_z is the number of participating customers in the z-th group, Hy_m denotes the total number of responding customers, and Hn_z denotes the percentage of responding customers in the Mth group. Hn_m indicates the number of non-responsive customers in the Mth group, NPQ_k is defined as the exponential of the proportion of non-responsive consumers in the current grouping of responsible customers divided by T_z percentage of responsible customers. A unique prediction rating model is given in Eq. (2).

$$D_{izk} = \frac{\sum_s D_{izks}}{ud_{izk}} \sim N\left(B_{iz}, \frac{\mu_{F1}^2}{ud_{izk}} \right) \tag{2}$$

As shown in Eq. (2), D_{izk} is a unique prediction rating model that can be built, ud_{izk} refers to challenging decision making, N represents customer needs, μ_{F1}^2 is the tracking of online purchasing activity, and B_{iz} represents the quality of the product.

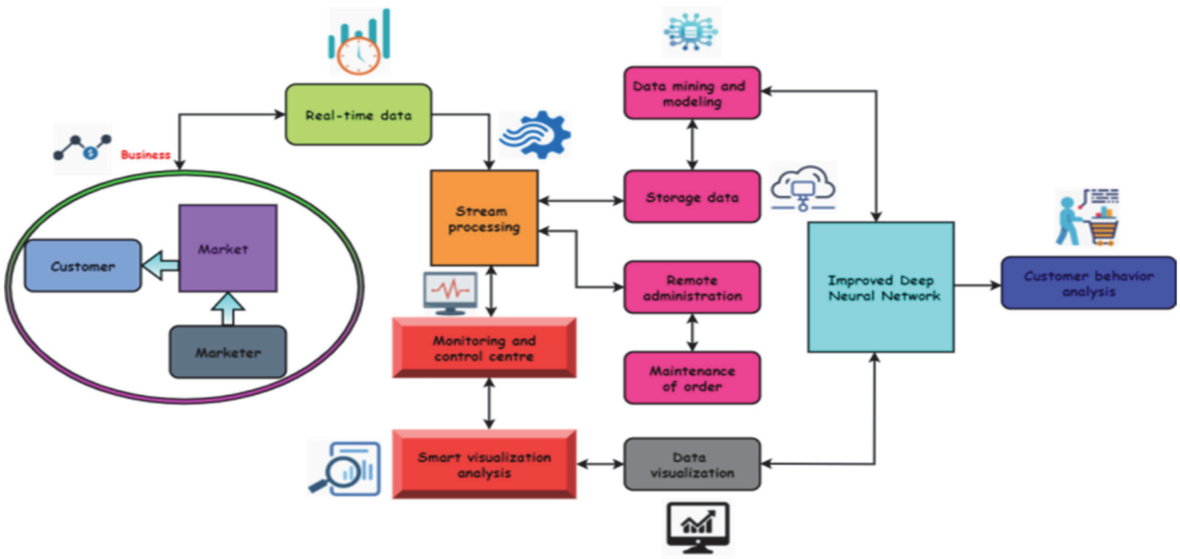

Figure 2 Improved DNN-assisted Customer Behavior Analysis (iDNN-CBA)

Fig. 2 shows the improved DNN-assisted customer behavior analysis. iDNN system obtains real-time data from customer and market. iDNN can do stream processing and recheck the history data. The usage of Smart Data Visualization frees up time spent waiting for visualization specialists or programmers to help analyse, distribute, and display data. Business is defined as earning a livelihood or generating revenue by manufacturing or purchasing and reselling things (goods and services). The existence of a company name does not insulate the firm from its owner, who bears full responsibility and liability for the obligations made by the business. If the company runs up debts, the creditors can often obtain the owner's personal property. Corporate tax rates cannot be implemented in a company structure. All business profits are subject to personal taxation for the business owner. A company is a legal entity that is involved in commercial, industrial, or professional activity. Non-profit organizations and for-profit companies both exist in the same industry. Limited-liability firms, sole proprietorships, corporations, and partnerships are examples of different kinds of businesses. While some companies are tiny and focused on a particular sector, others are global in scope and serve many different markets all over the globe in various capacities. On the other hand, a corporation is a distinct legal entity that offers restricted responsibility and corporate tax rates. It is more difficult and costly to set up a corporation, and it provides the marketer with greater security and financial rewards. Real-time data (RTD) is information that is provided after it has been collected. The information given is up to date and without delay. Navigation and tracking are two common uses for real-time data. Real-time data (RTD) is information that is provided soon after it has been collected. In other words, the information is always current. Navigation and tracking are two common uses for real-time data. However, such data can be saved for examination later or offline. It is often analyzed in real-time, and it is important to understand that real-time and dynamic data are not the same thing. Real-time data can be dynamic (e.g., a variable is showing the current position) or static (e.g., a fresh log entry is indicating the location at a specific time). In real-time stream processing, data is acted immediately upon generation or publication. A messaging system receives real-time data, processes it instantly, and then sends it to a destination. Stream processing is a programming paradigm that computes data as it is generated or received. It is not uncommon for data to arrive in the form of an unending series of occurrences. Such situations are made possible by Stream Processing, which provides insights much more quickly, usually within milliseconds to seconds of the trigger being applied. Batch processing necessitates storing the data, stopping data collecting at a certain point, and processing it. In monitoring and controlling, the business's progress toward its objectives is tracked, and any deviations are addressed. This step's goal is to create a management strategy that allows you to take advantage of opportunities while also reducing the frequency with which that business must engage in crisis management. The usage of Smart Data Visualization frees up time spent waiting for visualization specialists or programmers to help analyze, distribute, and display data. The mountain of data can be whittled down to the elusive morsels of information that have the greatest effect on company outcomes using enhanced data discovery technologies. Business users can utilize smart data visualization and make informed choices to detect a problem and explain the underlying reason. When working with data discovery and analytics software, business users can create views that convey a narrative with guided visualization and suggested data presentation without help or delays. Based on the data type, volume, dimensions, patterns, and nature of the data, guided suggestions are given. The court can order the individual with a greater income to make monthly maintenance payments to cover the other party's expenses. An order like this is referred to as a maintenance order. Remote admin, often known as a remote control, controls another computer without being physically there. It runs a program or copies a file from a distance, uses a remote connection to connect to another computer and solve problems. The examples below are used to see how remote administration can be used in the environment. Deep neural networks can rapidly and effectively analyze large amounts of unstructured data. Furthermore, these applications can helpfully display the data and draw attention to relevant relationships. That way, the user can see the business strategy and evaluate its efficacy from a vantage point of totality. An individual model is built to answer just one question at a given time based on customer data mining. A customer model, for instance, can be used to anticipate how a certain set of customers will behave in reaction to specific marketing activity.

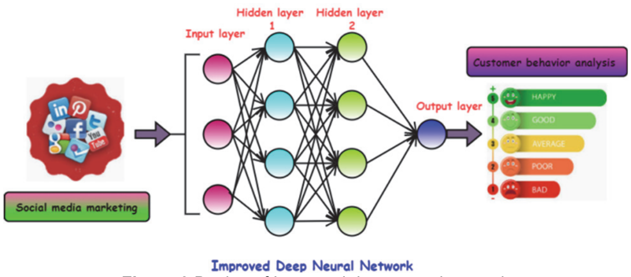

Figure 3 Design of Improved deep neural network

Fig. 3 shows the design of the improved deep neural network. There are many levels between the input and output layers of a deep neural network (DNN). Neural networks come in various shapes and sizes, and they always have the same basic components: synapses, weights, biases, and functions. Because of their enormous global visibility and renown, company social media marketing and analysts have piqued the customers' attention. Social media marketing's impact on brand equity is a primary objective of iDNN and customers' behaviour; so engagement and satisfaction are classified by DNN.

In a non-parametric method to pattern recognition and optimization, DNNs utilize weighted average neural networks. Once they get a signal or outcome, they run it through an activation function. The input layer E_j is shown in Eq. (3).

$$E_j = h\left(\sum SB_m\right) + h(.) = \frac{1}{1 + d^{-b}} n \tag{3}$$

As shown in Eq. (3), E_j is the output vector number, B_m denotes the input vector number and S is the vector strength. The hidden layer is given in Eq. (4).

$$T_n^c = h\left(net_n^c + \sum_j S_{nj} b_j^c\right) \tag{4}$$

As shown in Eq. (4), $c = 1, 2, \ldots, n$ is the number of data pairs in the training phase, T_n^c is the hidden state output n, net_n^c is the hidden state input n, and b_n^c is the input data of j, S_{nj} is the weight assigned to the input j for the hidden state n, and $h(.)$ is an algorithm used in the hidden state.

Table 1 Variable declaration

Parameters	Description
Hy_z	Number of participating customers in the zth group
Hy_m	Total number of responding customers
Hn_z	The percentage of responding customers in the Mth group
Hn_m	Number of non-responsive customers in the Mth group
NPQ_k	The exponential proportion of non-responsive consumers in the current grouping of responsible customers
T_z	Percentage of responsible customers.
D_{izk}	Unique prediction rating model
ud_{izk}	Challenging decision making
N	Customer needs
μ_{F1}^2	Tracking of online purchasing activity
B_{iz}	Quality of the product.
E_j	Output vector number
B_m	Input vector number
S	Vector strength.
$c = 1, 2, \ldots, m$	Number of data pairs in the training phase
T_n^c	Hidden state output n
net_n^c	Hidden state-input n
b_j^c	Input data of j
S_{nj}	The weight assigned to the input j for the hidden state n
$h(.)$	The algorithm is used in the hidden state.
D_j^c	Able to declare j value
net_j^c	The production node of the input
S_{nk}	Output node m value for output j
$g(.)$	Output layer algorithm
$H(S)$	Loss function
P^e	Goods in the firms
A^e	Items supplied to the consumers

$$D_j^c = g\left(net_j^c\right) = g\left(\prod_n S_{nk}\right) + h\left(\prod_j S_{nk} b_j^c\right) \tag{5}$$

As shown in Eq. (5), D_j^c is able to declare j value; net_j^c is the production node of input; S_{nk} is the output node m value for output j and $g(.)$ is the output layer algorithm; b_j^c is the hidden node's input image. The training method is determined by how the weight of the network is changed to achieve the best results, which is an optimization issue.

$$H(S) = \frac{1}{2}\prod_{c=1}^{i}\left(p^e - A^e\right)^2 \tag{6}$$

As shown in Eq. (6), $H(S)$ denotes the loss function. The goods in the firms are denoted by p^e, while the items supplied to the consumers are denoted by A^e. The network gradient then transmits the input of any concealed node, which alters to create an output layer to the goal.

$$H(S) = \frac{1}{2}\prod_{c=1}^{i}\prod_{m=1}^{3}\left(p_m^e - g\left(\prod_n S_{nk}\right) + h\left(\prod_j S_{nk} b_j^c\right)\right)^2 \tag{7}$$

As shown in Eq. (7), the loss becomes for two output terminals ($m = 1, 2, 3$)

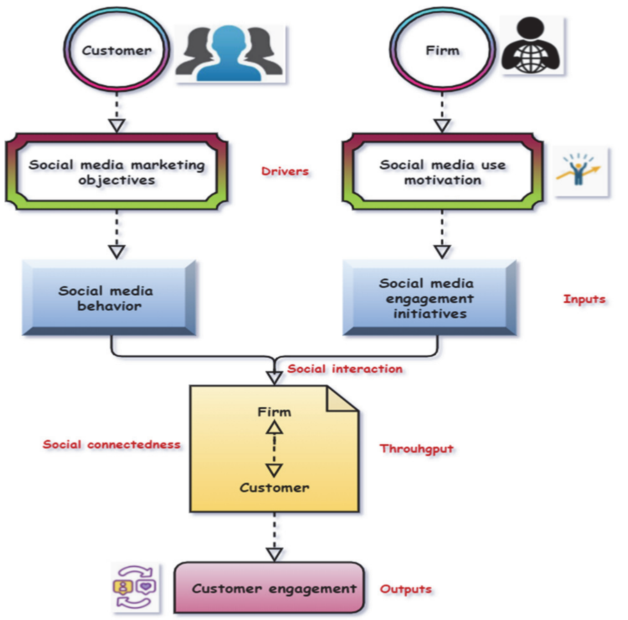

Figure 4 Process of improving digital marketing strategy

Fig. 4 shows the process of improving digital marketing strategy. The customer interaction philosophy serves as a guideline when creating a social media marketing strategy (SMMS). Encouraging and inspiring customers to improve their commitment and generate better marketing results should be a top priority for businesses. Customer reference, impact, and customer engagement all fall under the umbrella term customer commitment, and each has its unique meaning. Customers can now be evaluated in a new way, allowing marketers to make strategic decisions that assist their customers in creating long-term value. SMMS is an interlocking component based on client involvement. Therefore, we see it that way. (1) drivers the company's social media communication objectives and customer social media incentives. (2) inputs: the company's social media commitment effort and customer social media behavior. (3) to provide services and meet customer requirements, the business interacts and engages with them on a high throughput basis. (4) the outcome of customer involvement.

2.1.1 Drivers

The social media firms' marketing aims are as follows: SMMS have a similar structure, and they can differ depending on their strategic goals. According to the resource dependence principle, the company's social media marketing goals can be justified by obtaining more cash to help it fulfil environmental contingency needs. Customers can be resource providers in different ways on social media. Various incentives are given to people who use social media for various reasons, motivating them to choose and use certain social media. According to the idea of uses and enjoyment, customers actively engage in media to meet their psychological and social requirements.

2.1.2 Inputs

Initiatives to engage social media companies: Businesses are trying to motivate and enlist the help of customers. In line with resource dependence, businesses should make it easier for customers to participate in these activities. This makes sense because doing so will help alleviate resource scarcity. Task-based and immersive social media marketing techniques should be identified for a company's customer integration. There are many different types of customer behavior on social media, ranging from passive to hostile. During encounters, conduct can be good or bad depending on the emotions and knowledge systems of consumers. Pseudo-marketers are customers who utilize resources to provide value to the business while also performing negative marketing duties.

2.1.3 Throughputs

When it comes to using social media, a social exchange theory argues that social relationships are like transactions supporting two parties. According to an idea, this social transaction calls for a series of interactions between businesses and customers that create solid bonds that are usually interdependent and linked to other behaviors. Social connectivity: The number of social media sites linked to is shown as social connectedness. It identifies relationships, including the number of contacts, the strength of the link, and the location in the network. According to recent social media studies, being socially linked has a significant effect. A multidirectional and interwoven flow of data rather than a pure corporate monologue is reflected in social media engagement due to social networking sharing, gaming, expressing, and networking capabilities. Instead, clients have become more engaged as customers use one another to enhance their attitudes or behavior.

2.1.4 Output

Corporate-customer connectivity and social media contact are represented by consumer engagement results that are shared. Participant strength is shown in this measure, which is linked with the offerings and operational activities made available by an organization. The more engaged consumers are and the more value they give to the business, the more customers will identify and connect with its activities.

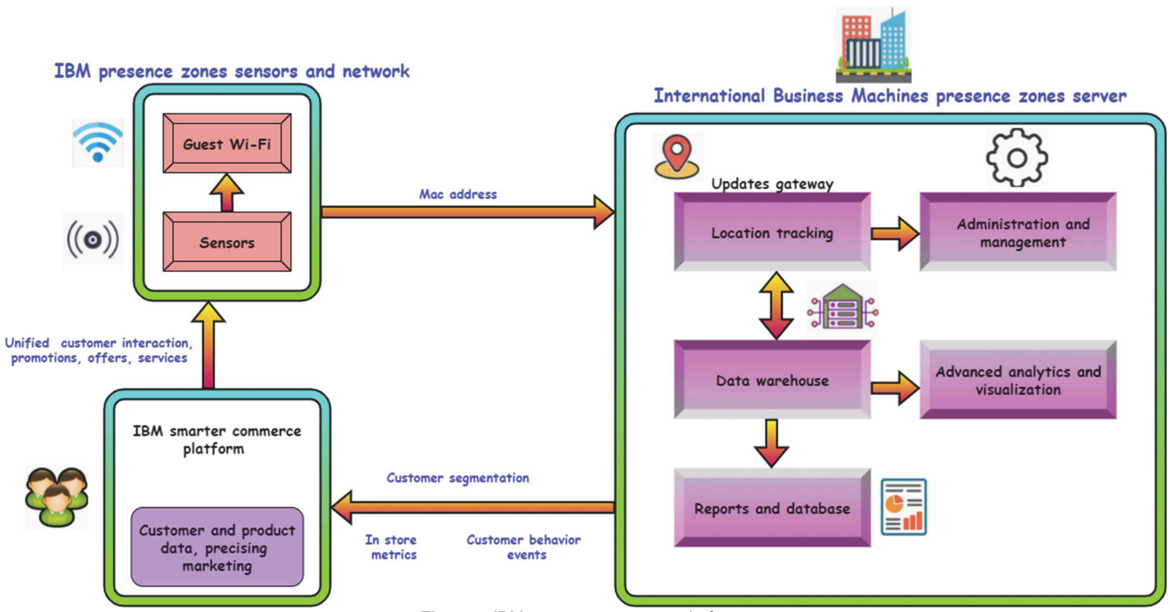

Figure 5 IBM smarter commerce platform

Fig. 5 shows the IBM smarter commerce platform. WiFi-enabled devices can transmit data using a combination of physical sensors and network equipment installed within the indoor venue. Another component is the Presences Zones server, which correctly calculates devices' locations and collects customer activity inside. It also interacts with IBM's Smarter Commerce portfolio to provide complete marketing capabilities, including cross-channel marketing optimization and customized promotions.

2.2 Sensors and Network for Presence Zones

Using specified sensors that can listen to WiFi-enabled device communications, the approach is based on the deployment of sensors. Device identification is captured by Presence Zones sensors, which provide data to the Presence Zones Server regarding the intensity and quantity of packets sent. The device's unique identification is its media access control (MAC) address. Even though certain suppliers have randomized the MAC address, the MAC address is utilized when a device joins a WiFi network. The location is determined when a device is detected by combining the information collected from numerous sensors around the venue. This sensor deployment must be designed to provide enough coverage to calculate the physical venue's position correctly.

2.3 Zones of Presence Server

One of the most important server components for the Presence Zones application is a module for calculating and tracking device locations inside the interior space. The system uses raw signal data collected from numerous sensors placed throughout the venue to determine a user's position. This data can teach the system to recognize patterns that indicate different locations inside the venue. In addition, the server employs innovative algorithms to address quality and accuracy issues with the raw data it receives. The system is trained before it is put into operation as part of the deployment process. In this stage, the administration and management module help by giving users the ability to create plans, install sensors, register and monitor them, and calibrate and test them for specified accuracy levels. The management module provides user preferences and privacy settings control options for location monitoring, analysis, and interaction. The opt-in function limits the system's analysis to registered users exclusively. Unregistered shoppers are analyzed without storing any personal information about the unregistered device or its owner. The analytics and visualization components use the information stored in the data warehouse to understand customer behavior inside. As customers travel throughout the physical arena, numerous analytics methods identify and explore specific customer groups. Reports, dashboards, and interactive visualization make the findings of the analysis and visualization accessible.

2.4 Smarter Commerce Platform from IBM

Marketing tools and capabilities are part of the IBM Smarter Commerce platform. A complete cross-channel marketing solution for stores is provided by IBM Presence Zones, which combines these services and products. Mobile, social, and brick-and-mortar retailers all utilize IBM WebSphere Commerce to provide a seamless shopping experience. When it comes to delivering customized marketing and promotions, IBM Interact and IBM Marketing Operations come in handy. User profiles and segmentations are kept up to date by IBM Marketing, which decides which promotions are most suitable for which users. IBM Interact makes it possible to send these promos to consumers in real-time. IBM Digital Analytics is used to get online analytics information to customers. To provide customized mobile alerts at the appropriate time, place, and channel, IBM Xtify is in charge. The identification of customer behavioral categories, the study of segment features, and the use of segment data are all part of customer segmentation. The business choices and the in-store experience improve due to more efficient promotion allocation, targeting, and customized purchasing. In-store customer movements varied, and earlier studies have shown the existence of several patterns of in-store mobility. These patterns can be utilized to identify key consumer groups such as high-value customers and low-value customers using current in-store data, such as POS data, to correlate. Customer opt-in and identity verification are required for this kind of correlation analysis. Customers who spend more time in-store are more likely to become customers, and the size of a buyer's basket rises in direct proportion to the amount of time spent in-store.

Figure 6 The social media marketing communication model

Fig. 6 shows the social media marketing communication model. The created framework includes these multidirectional and dynamic dialogues between the brand and the customer and between the customers. Social media platforms serve as a conduit for communications produced by customers and brands alike. The contact circuit is a crucial element that is assimilated into this framework. Customers can connect with a brand online or offline using traditional media and various channels such as social media. Alternatively, the business connects customers to SMPs hosted by other parties, such as Facebook and Twitter, through its website as a gateway.

Customers can join the company's website directly, see the Facebook brand profile, follow the brand name, give access to information on a friend's social network or share information with their friends. Customers who like the business page on Facebook will be notified of new offers and discounts. Customers can make this information available to other users on the network. Let's assume someone has figured out how to anticipate customer behavior. Realistic outcomes can be expected when the total $R(x)$ rating is either very high or exceptionally low, $Y^{(x)}$ making it difficult for these customers to determine when their production must be raised. Each customer has weights in Eq. (8), and DNN utilizes the device to determine an optimum. An approximation of the real system based on system predictions $T^{(x)}$ and measurements Eq. (9):

$$R(x) = T^{(x)} + \left(k^{(m)} - a^T g^{(x)}\right) \cdot I_m(n) P_m(n) \tag{8}$$

Now, the value of $T^{(x)}$ is shown in Eq. (2)

$$T^{(x)} = \exp\left(-\frac{\left(y^{(x)} - v\right)^2}{2m^2}\right) \tag{9}$$

In Eq. (8), $T^{(x)}$ is the error rate weight, which is applied to the whole company's output. Eq. (9) is the decay function $k^{(m)}$ that can alter the value of m^2 to find PM. By use of these matrices, v used to find a web of coefficients for the customer and build a single prediction model called, $P_m(n)$, $g^{(x)}$ referred to online purchasing choices $I_m(n)$ denotes social media marketing, and a^T is a quicker product delivery to the customer. Purchase of products and services online is what is referred to as online shopping. Online buying has become a common occurrence today. Many aspects of the buying process can be compared to actual purchasing activities. The most important factors are ease, greater product variety, and convenient delivery options for purchasing. Online purchasing has several benefits and drawbacks, and researchers can investigate the most recent and next trends. Data mining is a powerful tool for studying consumer behavior while making purchases online. The suggested iDNN-CBA method enhances accuracy, behavior analysis, satisfaction, feedback, and risk management.

3 RESULT AND DISCUSSION

Through digital marketing, companies can convey their product and service concepts from the development stage to the end user. Because it brings the team together, effective communication is essential in marketing. This study examined the development of accuracy, behavior analysis, satisfaction, feedback, and risk management. An iDNN-CBA method for calculating the numerical result is tested.

Fig. 7 shows the accuracy ratio. DNN is a paradigm for immediately processing information that has improved using biological neural systems. A series of processors in the databases detect underlying connections in the same way the brain does. The iDNN-CBA model's significance lies in its many intricately linked processing components that operate in concert to address specific issues. Multiple tier-specific processors are often seen in a neural network. The initial level receives the raw input, whereas the subsequent levels get the output from the previous level. The ultimate output will be the classification model's average accuracy in the artificial neural network, which the last level will provide. Compared to other methods of social media marketing prediction, the iDNN-CBA has better accuracy.

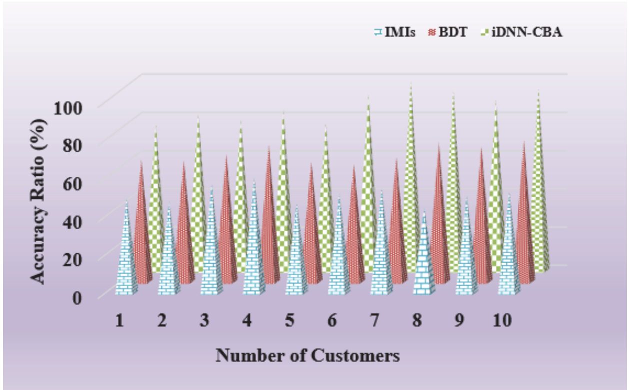

Figure 7 Accuracy ratio

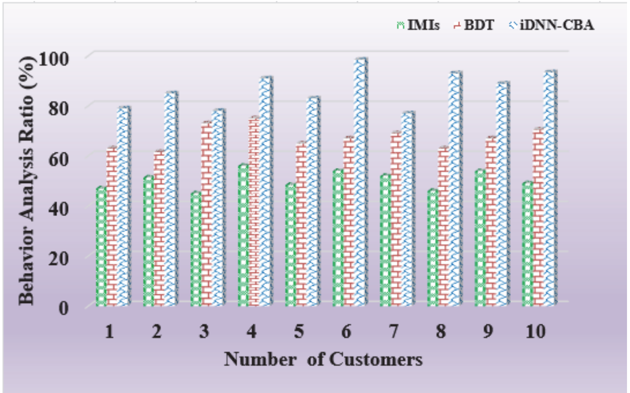

Figure 8 Customer behavior analysis ratio

Fig. 8 shows the customer behavior analysis ratio. Consumer behavioral analysis is the study of how consumers make buying choices. An individual's purchasing behavior and social trends, use patterns, and other variables influencing their purchase choices are included in customer behavior. Companies study it to understand their target market better and provide more appealing goods and services. Pre-purchase activities of a consumer are acts they do before purchasing a product or service (online and offline). It has been shown that businesses that use this iDNN-CBA can better adapt their marketing strategies to activities that affect consumer purchases. The suggested technique improves on the currently used approaches by a factor of (98.3%). As online communication develops, consumers see more brand advertising on the internet. It is critical for both specialized markets and established businesses to take advantage of rapidly changing consumer purchasing habits as a method of promotion. With the digital revolution, companies across the world are benefiting from a new way of doing things.

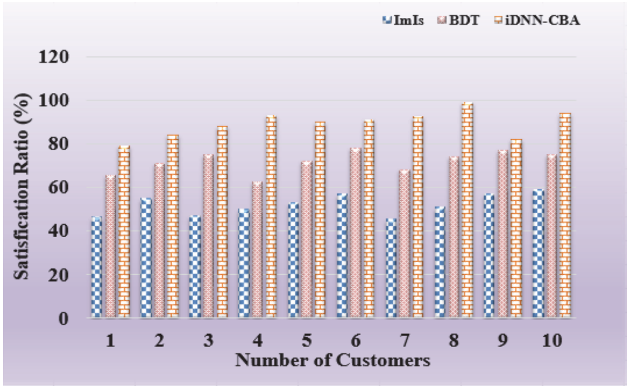

Figure 9 Customer satisfaction ratio

Fig. 9 shows the customer satisfaction ratio. Customers can buy a broad variety of items from online shops and companies that sell goods online. A company's ability to retain customers is unaffected by whether customers are satisfied. It is important to get honest and accurate customer feedback while conducting a customer satisfaction survey to use that information in marketing efforts to bring in new clients and keep current ones loyal. Customers are often on the lookout for the greatest deals. As a result, businesses try to meet the needs of consumers by offering a broad variety of products and services at low costs. Because businesses evaluate customer pleasure, customer satisfaction is improved by 99.1%, and CBA indicates that definitions have been hotly disputed in the suggested approach. Customers are happy with the products and services they get in a range of circumstances. So it is very individualized and affects customers' purchasing decisions greatly.

Table 2 Customer feedback ratio

Number of Customers	IMIs	BDT	iDNN-CBA
10	64.7	80	90
20	75	89.4	92
30	65	83	95.3
40	73	79	88
50	64	73	82
60	70	85	87
70	68.8	77.9	89
80	62	84	93.7
90	71	86	91
100	69	87.5	98.2

Tab. 2 shows the customer feedback ratio. The growth of the business is dependent on the level of customer happiness. Surveys have used questionnaires to measure customer satisfaction, and financial data have evaluated the company's success. Multinational companies must retain all elements of customer service, regardless of what they contain. If their operations do not match customer expectations, they will rely more on what they get from customers. IDNN-CBA customer loyalty and service study findings show that customers must make sure that companies selected are familiar with these requirements before signing a contract with them. Incorporating factors include inventory, lead time, transportation, and coordination help the client. According to the study, customers' happiness with a product strongly correlates to delivery time, transportation, and communication. The quality and pricing of the goods are important factors in determining whether a customer is satisfied.

Table 3 Risk management ratio

Number of Customers	IMIs	BDT	iDNN-CBA
10	47.8	59	76.7
20	55	78	85
30	66	73.4	87
40	58	65	89.3
50	69	67.7	74
60	56	82	89
70	61	78	82
80	60	86	92
90	56	89.4	88
100	57.8	77	99.3

Tab. 3 shows the risk management ratio. Data visualization is critical for a company that wants to expand. Digital marketing can help businesses gain a competitive edge, save expenses, and keep consumers happy. As technology advances, data will become more widely available to businesses of all sizes. Data visualization has significantly aided in the development of risk management systems. Businesses now have the tools they need to assess and analyze the risks they face daily. Digitalization will improve the accuracy of risk management models as statistics become more widely available and diverse. Despite this, organizations should create a systematic approach to big data that considers the wide range of available sources. Companies begin by collecting internal data to get a basic understanding of the situation. Organizations that use an integrated analytical approach will have a leg up. When business analytics are used properly, it is possible to identify areas of strength or danger. The suggested iDNN-CBA offers a higher potential for risk management than the existing BDT and IMIs methods. The proposed method achieves the highest performance of other existing methods using an iDNN-CBA**.**

4 CONCLUSION

This article proposes an iDNN to predict consumer behavior and social network participation. There are contemporary methods for addressing some of the greatest marketing issues and advantages, such as extensive deep learning. These solutions can potentially alter marketing communication duties while increasing the efficiency of essential marketing activities. Marketing companies gather data from many in-person encounters with customers to give a comprehensive picture of their behavior. Brands and customers are connected via social media, with iDNN using online interactions to influence customer behavior. The suggested approach demonstrates the significance of recognizing social media customers' profiles and behavior patterns. Advertising firms will sift through this information, create consumer segmentation models, and utilize the findings to create a strategy for retaining and gaining new customers. Customers are more likely to be satisfied if their satisfaction is fuelled by pleasure, optimism, trust, and dedication than if it is fuelled by anything else. The performance of consumer behavior examines the average purchase value, customer existence, and market administrator requirements in the future. The numerical outcome of the proposed method achieves accuracy (96.55%), behavior analysis (98.3%), satisfaction (99.1%), feedback (98.2%), and risk management (99.3%). The limitations of this study are as follows: the platform often generates situations where multiple tasks are submitted and run simultaneously during operation, and the social network big data analysis platform does not use advanced data filtering when scheduling tasks, resulting in insufficient resource allocation during task submission. This also will be the future work.

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