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Analyzing the impact of social networks and social behavior on electronic business during COVID-19 pandemic

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ABSTRACT

The Covid-19 pandemic caused substantial changes, particularly concerning marketing, which led to high digital use. Social networking enables people to communicate easily with others and provides marketers with many ways to interact with consumers. As a consequence of the lock-down, economic activity is declining dramatically. The response of policymakers, the government, and industry to resolving the harm caused by economic factors and how the marketer can react to changing consumer behavior. This study analyzes the impact of social networks and social behavior on electronic business or E-Business during the COVID-19 pandemic using deep learning techniques. This paper introduces the Deep Recurrent Neural Network (DRNN) to predict online shopping behavior for improving E-business performance. The article utilizes clickstream information to forecast online purchase behavior in real-time and target marketing measures. Measures of profit impact with production from classifier metrics demonstrate the feasibility and the usage of deep recurrent learners in campaign targeting via RNN-based clickstream modeling. The numerical results show that the suggested model enhances the profitability ratio of 98.5%, the performance ratio of 97.5%, the accuracy ratio of 96.7%, the prediction ratio of 97.9%, and less error rate of 11.3% other existing methods.

1. Overview of an epidemic and its impact on E-business

A pandemic that crosses international borders and usually affects many people is defined as an outbreak worldwide or across a wide field (Javid, Nazari & Ghaeli, 2019). An epidemic (a sudden outbreak) becomes very normal in a country, continent, or the world of a sensitive population. A pandemic, by definition, causes high mortality (mortality) (Spieth, Schneider, Clauß & Eichenberg, 2019). COVID-19 is the most recently found infectious disease caused by the coronavirus. Before the epidemic in Wuhan, China, in December 2019, the latest virus and disease remained unknown (Kwilinski, Dalevska, Kravchenko, Hroznyi & Kovalenko, 2019; Raj, Manogaran, Srivastava & Wu, 2020). A dedicated WHO social network can find important knowledge about the COVID-19 pandemic (Muñoz & Kimmitt, 2019). In the covid-19 pandemic, Lockdown is intended to defend ourselves and others from the transmission of contamination from one human to another. This ensures that to not leave the house except to purchase food, minimize the number of trips outside, and hopefully, has one stable family member can fly as appropriate (Sparviero, 2019). The most critical problems of citizens post-lock-down were health, climate, unemployment, and job issues. COVID-19 pandemic is feared the prolonged lockout across the country will impede food supply due to labor and access to input for agricultural activities and the shutdown of transport networks (Hsu, Manogaran, Panchatcharam & Vivekanandan, 2018). The crisis COVID-19 as well underlines the complementarities of online and offline channels. While Amazon's sales were up 26% over last year in the first quarter of 2020, its share in global e-commerce in the

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US decreased from 42.1% in January 2020 to 38.5% in June 2020.

The related decline in rural sales is projected to affect food demand and overall economic growth adversely. These causes may have led to an elevated level of anxiety among participants (Ye, Ying, Zhou & Wang, 2019). Apart from social distancing, the pandemic's panic surge has been a difficult mix for many people. Online business or e-business is a business transaction, including sharing data throughout the internet (Galindo-Martín, Castaño-Martínez & Méndez-Picazo, 2019). Commerce is an interchange between groups, companies, and individuals of products and services and can be seen as one of all enterprises' most important activities (Ahvanooey, Li, Zhu, Alazab & Zhang, 2020; Alharbi & de Doncker, 2019). The results of COVID-19 are more seriously concerned with women. It suggests that men will have an impact on their e-business patterns. One-third of men reported pandemics regarding how much they invest in goods than 25 percent of women (Xiao et al., 2020).

In comparison, 36% of males reported affecting their interactions (travel, diner, entertainment, etc.) compared to 28% of females. Social networking will allow e-business to interact with the clients and hear what people think about the brand (Rungsrisawat, Joemsittiprasert & Jermsittiparsert, 2019). Many people living with COVID-19 are not symptomatic and can still spread the virus through droplets that escape their mouths when people talk, sneeze, and cough. Researchers proved that masking even in the long run reduces COVID-19 cases. One of the most striking changes to the lifestyle resulting from the COVID-19 pandemic is the obligatory use of face masks in food stores, restaurants, and other areas. It is essential to slow COVID-19′s spread, especially when wearing a mask near others.

In covid −19, lockdown time improves e-business using social networks and social behavior (Tanwar, Tyagi, Kumar & Obaidat, 2019; Yun, Won, Park, Jeong & Zhao, 2019). The Analysis of social behavior in social Networkshelps to improve e-business based on customer behavior. Social networking can be used for ads, promotional donations, and smartphone apps (Sathishkumar, Agrawal, Park & Cho, 2020). Social networking can support the business: recruit buyers, receive input from consumers, and create customer loyalty. Social trading involves using a vehicle to advertise and distribute goods and services through networking platforms like Facebook, Instagram, and Twitter (BalaAnand, Sankari, Sowmipriya & Sivaranjani, 2015). A Social network-based e-business strategy's effectiveness is measured by how well consumers use retreats, likes, and shares to engage with the company's ads. Social networking plays a critical role in online marketing by developing a stronger social network presence, building leads, and boosting traffic (Kumari et al., 2020). For e-commerce businesses, social media and e-commerce shops are important sales channels. Since the start of the COVID-19 crisis, both channels have experienced greater growth. More than 65% of the COVID-19 crises were linked to a shift in the composition of sales. The survey as well confirms that more customers have searched for essential products online.

During an age of social distance and limited contact, social media has become an important place to interact with others. The purpose of social media platforms is to connect people and help the world stay connected and increase during the pandemic. As many people are being asked to stay, social communication and access to entertainment have maintained relationships. The coronavirus pandemic has pushed many shoppers to shop online because many retail outlets worldwide have either locked down or have limited ability to distance themselves from others. Even at the end of the pandemic, most analysts and e-commerce companies anticipate the growing trend of online shopping. For the improvement of the e-commerce sector, a well-structured social media strategy is necessary (Abdullahi, Sulaiman & Khalaf,). Social media will extract from relationships between individuals, increase investments in productive things, increase customer activity, promote more time, build internet relations and self-esteem by performing a constructive social comparison in the covid-19 pandemic (González, Nieto, Montenegro & López, 2018). The situation is changing quickly; there have been thousands, hundreds, and ten people considered safe to meet in a single location. Many major cities have restaurants, bars, film theatres and gyms shut down. In the meantime, many offices face new challenges in the remote working process. To predict buying conduct online in real-time and plan marketing steps, the paper uses clickstream information. Thus, the measurement of profit impact with classification measurement output shows the viability and use of profound recurrent students in campaigning via RNN-based click stream modeling.

The paper's principal contribution is

- Designing the DRNN model to predict online shopping behavior to increase the efficiency of e-business.
- Estimating the revenue effects of regular classified metric output reveals the feasibility and use of deep recurring learners for campaign targeting through clickstream modeling using RNN.
- Numerical results have been achieved, which enhance performance, prediction, precision, profitability and lower error rates than other popular methods with the suggested DRNN method.

The rest of the paper is structured as follows: Sections 1 and 2 discussed the Overview of an epidemic on social networks and social behavior. In Section 3, The DRNNhas have been proposed to predict online shopping behavior for improving E-business performance. In Section 4, the simulation results have been executed. Finally, Section 5 concludes the research article.

2. Literature work

Ding-Ding et al. (Ding, Guan, Chan & Liu, 2020) The McKinsey Global Institute's (MGI) Industry Digitalization Framework (MGIIDF) for Google developments to evaluate COVID-19 impacts: Strengthening of the stock market by the modern transformation. This study proposes to analyze the places that have accomplished better, even though the pandemic affects consumer feelings. They find that more mature businesses experience higher competitiveness and profit margins growth during their digital transformation. This is then investigated against the standard price closing sequence with VAR. The sectors are arranged following the MGI Industry Digitalization Framework (MGIIDF). Results and the inventory prices of companies in these sectors are quantified.

Tran, L et al., 2021 Managing the effectiveness of e-commerce platforms in a pandemic. Given the substantial effects on the Covid 19 pandemic market practices, this report provides a systemic structure to determine the effects of the perceived effectiveness of e-commerce platforms(PEEP) on customer economic advantages to forecast sustainable consumption. His-analysis showed that the pandemic fear moderates PEEP ties, economic gain, and sustainable consumption positively. The research explores how the PEEP's economic advantage and the sustainable consumption relationship, accurate on pandemic fear thresholds, mediate.

Junjie Lv1 et al. (Lv, Wang, Wang, Yu & Wang, 2020) Social e-commerce firms or retailers learn to distribute product data to increase buying rates and forecast the revenue trend. This paper extends the social e-commerce customers' purchasing behavior game model SECPG model several different e-commerce social networks, calculates the internal interaction between web and customer exchange, and estimates the buying rate in various social e-commerce networks. To estimate the buying rate. Numerical simulations demonstrate that entities' prestige and cost-to-benefit ratio have particular impacts on the social e-commerce system on the purchasing rate.

Mehmet Kayakuş et al. (Kayakuş & Çevik, 2020) Artificial Neural Networks (ANN) for Estimating the Number of Visitors of E-Commerce Website during Covid19 in Turkey. The COVID-19 mechanism risks public health and even impacts the environment and social life. The quarantine and panic methods, which result from a pandemic, have shaped consumer shopping habits. Changes have been calculated by Artificial Neural Networks (ANN) methodologies in the visitor count of the four e-commerce locations operating in Turkey during the COVID-19 season. As a model built in this report, E-commerce sites should foresee shifts in the number of visitors using COVID-19 statistical evidence. This will help businesses better schedule the number of staff, campaigns, acquisitions, and other costs.

Raza, S. A et al. (Raza, Qazi, Khan & Salam, 2021) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) to investigate and moderate the influence of social isolation on students' behavioral intent and use of the learning management system in students Corona fear. The author's suggestion for future investigators is finally to analyze the expanded model of e-learning acceptance in other countries and territories to examine the influence of the Corona virus.

Saxena, C et al. (Saxena, Baber & Kumar, 2021) invented e-learning quality (ELQ) to understand e-learning quality and student level of satisfaction during this strong shift into e-learning during the COVID-19 pandemic. Of course, the perceived benefits of maintaining social distance have a considerable negative moderating effect, leading to students' satisfaction between empathy and ELQ.

Based on survey methods, there are several problems due to pandemic effects in e-business. In this paper, the DRNN model has been suggested to predict e-business performance online shopping behavior to resolve these problems. The following section, 3, discusses the proposed DRNN method briefly.

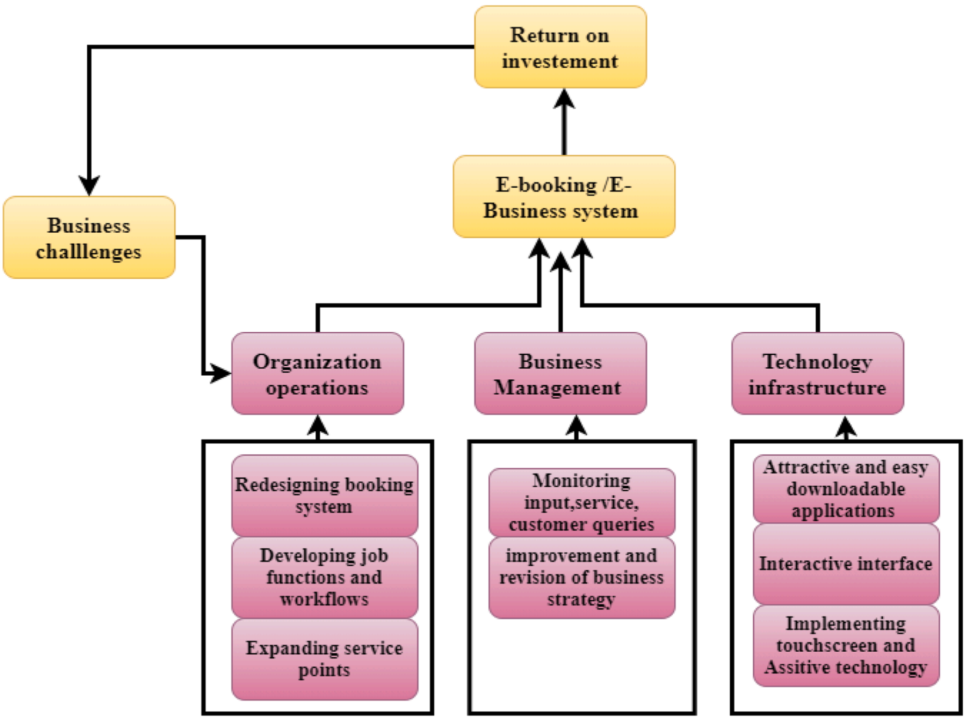

Fig. 1. The fundamentals of the E-Business model.

3. The proposed deep recurrent neural network (DRNN)

This paper discussed the effect on electronic businesses during COVID-19. COVID-19 is the most recent viral coronavirus disease. The pandemic of the COVID-19 is the most important issue for people after lock-in, where health, environment, unemployment, jobs, and e-commerce are concerned. In the pandemic period, e-business promotes the new revolution in social networks for improving the business. Hence, in this paper, DRNN has proposed forecasting online shopping activity using clickstream data in real-time and prioritizing marketing interventions. Revenue effect forecasts using common classification metrics indicate the viability and use of deep recurrent learners in campaigning via RNN click stream modeling.

Fig. 1 shows the fundamentals of the E-Business model. The internet-based e-Booking system is a social network-based software program that can run as Mobile App and Web App, which intelligently covers the business system. The customer needs quick, simple, and hurdle-free access to e-ticketing, which redefined the e-booking business method. The e-Business based e-Booking system meets all the system architecture criteria. It takes response as input from three functions, (1) Business Management, (2) Technology Infrastructure, to operate business smoothly and efficiently,(3) Organization Operations. The system provides an output as Service as well as ROI (Return on Investment). Feedback to review weakness is implemented as Market Challenge, which responds with feedback and analysis to business management, which is corrected or strengthened and becomes the input to the E-Business System. The extensive functionality of each part of this framework is provided. Another great advantage of e-trade offerings for consumers is comparison shopping, which can easily comparisons products, brands and web pages side by side with even potential comparisons. Many shops allow consumers to use discount and price-based methods to compare their products side by side.

Business Management has different roles for smoothly operating an organization. The key feature here is to control the feedback to

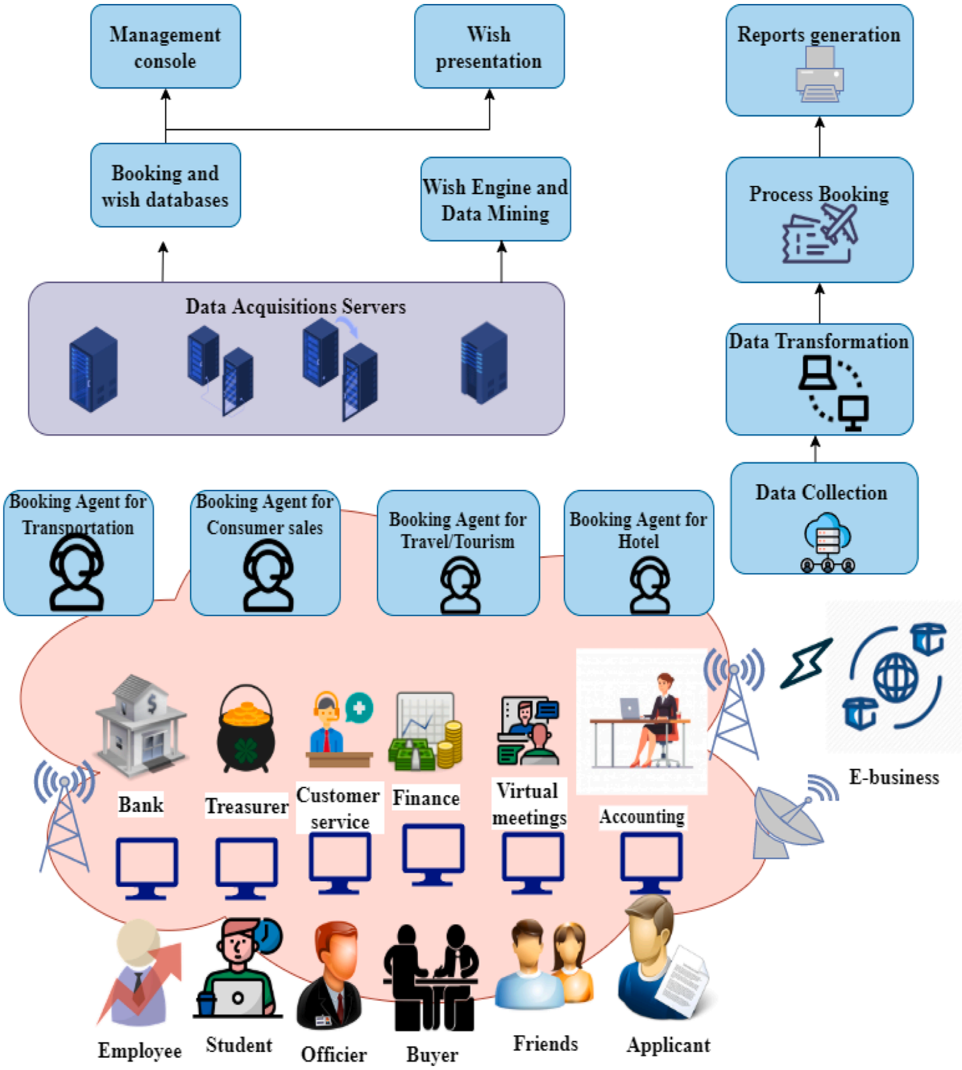

Fig. 2. E-booking System.

the process block, i.e. the e-booking method. It monitors booking forms and variations, customer requests, reaction to services, revising criticism to provide enhanced insight as a policy feature revision. Organization Operations block acts to reshape the booking system's mechanism to maximize the daily service. In addition, it creates job functions and models an enhanced machine workflow. This plan allows the facility to extend the organization to more sales points to satisfy the client. The key role of Technology Infrastructure block is to provide and establish a seamless technology system along with hardware operation and maintenance, installation and acquisition, provision of enticing online downloaded applications, setup of query databases, access to the network without denial of service, and provision of touch screen interactive digital media interfaces and support. This block is known as the E-Booking Engine and is a core part of the entire scheme. E-Business or E-Booking System is a processing feature that takes feedback from the infrastructure of company administration, corporate processes, and technologies—performing with zero market denial of service, promoting the functionality, and offering push technology sales promotions. The Service and Return on the device's investment performance is both a customer or business service and a negligible return on investment ROI. The target of the organization here is a rise in sales with consistent profitability. The feedback plays a crucial role in delivering optimized support, rectifying client, or support criticism optimized by company managers before re-inputting the e-Booking system process feature. Controlling set-up costs and meeting competition from other competitors are the biggest obstacles.

Fig. 2 shows the E-booking system. The social network-based e- booking system is an application that supports the travel, tourism, shipping, hospital, bank, and all forms of service industries with booking service support, e.g., flight bookings, taxi or bus tickets, ships, stadium match tickets, etc. through the cell phone or device or social networks. This allows customers to use these resources online without leaving home. This offers a single point of entry to a worldwide computerized booking and service reservation through the social network, through cell phone to book a ticket, hotel, vehicle, superstore product, pay energy bills, order food, etc., via online mobile service agents. For example, in a hotel, the customer will pick the right hotel in a prime location with new amenities, safe surroundings, and reasonable rates.

In contrast to this, it can be time-consuming or unnecessary, often costly when physically contacting consumers themselves or by direct service agents or brokers. The rise of the internet or the world wide web has revolutionized how customer-customer, business-to-business, and business-to-customer contact is developed or vice versa. Communication and transport, which normally took weeks and months, became a probable matter internationally for a few seconds. With the developments of smartphones, PDAs, and related gadgets known as computers, this technology has evolved dramatically. Social networks gave more meaning to this contact, which is now achieved in the consumers' hands. This encouraged WebApps and MobileApps applications with several aims to make it easier for people to be more successful.

A digital tourism agency allows customers to book travel from any location and with their range of better choices in the shortest

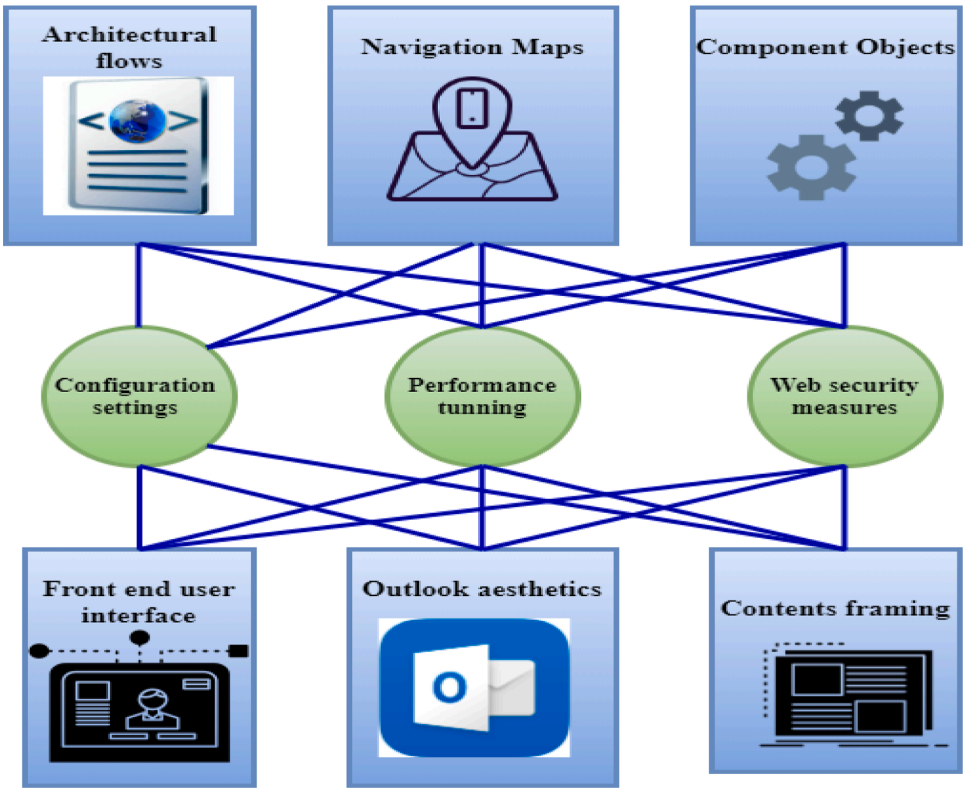

Fig. 3. social network-based e-business platform.

possible time. The workflow model of the e-Booking method involves stages of data collection, sorting and categorization, descriptive review, and communication of reports. The collected data is typically unstructured, varying from company to consumer presentation of desire. The data filtering is added to categorize and divide into categories, bearing in attention the analytical and subjective data interpretation. The mechanics of informative graphs to satisfy group or client needs have now become easy to comprehend. The analysis of natural language, voice recognition information, and advanced artificial intelligence techniques are used on customer service pages. The graphic views of these details have conclusions to encourage sales and services.

Fig. 3 shows the social network-based e-business platform. The social network involves connectivity with certain network technology to objects, where the software application's user access interface is currently required. Typically, technological applications from WebApp or MobileApp are used. These methods are structured to take web science methodology into account with the definition bearing on sociology, computer science, economics, and mathematics formulation, etc. Because social network formulates analysis from different disciplines, constituting Sociology, Computer Science, Economics, mathematics, etc. In the proposed architecture, all such components are pursued. In terms of performance, accessibility, usability, maintainability, protection, and time-to-release metrics, the consistency of a WebApp / MobileApp should be considered. The major considerations are ease, continuity, robustness, visual appeal, identity, and navigability, which should be based on keeping social problems in mind. Nine different areas are mainly focused while designing of WebApp or MobileApp of E-Booking App. These are 1) Front-end User Interface,2) Content framing, 3) Outlook Aesthetics, 4) Navigation.5) Architectural Flows, and (6) Components, 7)Performance tuning, and (8) Security, (9) Configuring web/mobile setup. The highest and most comprehensive Web / Mobile App interface strategy, i.e., the approach of Object-Oriented Hyper Media Design (OOHMD), is followed. To design an abstract GUI, conceptual vision, navigational chart, and deployment graphics, OOHMD recommends a systematic method. The architecture paradigm for WebApps and MobileApps for IBE is explained in Fig. 3. The User Interface (UI) front-end architecture includes the UI entity's framework with screen layout, interaction mode information, and certain navigation system information. The outlook or graphic design, i.e., "Aesthetics," is better defined as "look and feel"; it is known to include object color schemes, colors, contrast, brightness, geometric views, text size, and color, font type, and their placement with image images. Any WebApp / MobileApp content is deemed particularly vulnerable, and carelessness causes a lot of misunderstanding. Therefore, the frame layout, composition, the outline of material objects, links, and relationships with the primitive navigation basis of browsing are considered when designing material. A hypermedia structure is constructed in all or hybrid linear, hierarchical, network, and grid systems when constructing web architecture. The social network infrastructure is then connected to the correctly designed content layout structure, bearing in attention the ease of navigation to accomplish the Web / MobileApp objective. All those ideals are integrated. To achieve the primary purpose of the Web / MobileApp, the navigation design emphasis is set on navigation and surfing flow between all content objects. Semantic navigation units are built with characteristic object knowledge describing various navigation modes connected with links and nodes. To follow the site mechanism as part of the semantics, a navigation syntax is developed. The comprehensive logic processing architecture is considered an integral part of the component to be built such that the component can be calibrated and completely usable according to health.

Case 1: To predict the social network based e-business consumer buying behavior

Solution 1: This study describes conversion-less error classification to predict when a social user carries out such social behavior to a market. It considers a transitional e-commerce social network to buy without a lack of generality and embrace everyday actions in the covid-19 pandemic. The basic notion of social behavior is conversion is not empirical with the clickstream classification. The social network outlines the following clickstream classification issue. Let the training set be made up of the user session array$Y = y_1, \ldots y_M$ and the binary results or marks $y = y_1$, their known results $X = x_1, \ldots x_M$ A label x_j mark is 0 if a conversion is done in the j session and 1 otherwise. In addition, let $\breve{Y} = \breve{Y}_1, \ldots \breve{Y}_{\breve{M}}$Denotes the labels of which, new incoming sessions. $\breve{X} = \breve{x}_1, \ldots \breve{x}_{\breve{M}}$ are unknown. Multiple page views are used in every $Y \& \breve{Y}$ session. In particular,$Y_j = (Y_j^{(1)}, \ldots, Y_j^{(S_j)})$known as a session$j$ where $Y_j^{(s)} \in Q^d$is the session S -th page view and has numerous features that define the page vision. Remember that the number of page visions, that is, the duration of the session S_jDiffers throughout periods. Accordingly, Y_j can be denoted by a $Y_j \times c$ matrix, where the first dimension's size is arbitrary. Assumed this setup, the clickstream classification objective is to identify features that could appropriately forecast unsure labels for new live sessions in Eq. (1).

$$e : y \to x, e\left(\breve{y}_j\right) = \breve{X}_j \tag{1}$$

As inferred in Eq. (1) shows the new live clickstream classification. This classification improves e-business profitably. The incoming sessions should hold for many of the $\breve{M}$ for most algorithms, the result of $e$is, not a mark an approximation of the likelihood showing the result $\breve{X}_j = 1$. They define a likelihood threshold β to achieve a discrete class prediction. If the result of the chance is greater than β, the predicted mark is 1 and 0. Compared to standard binary classification, the particular arrangement of input data makes a big difference. Recall that a matrix of dynamic first dimension for a session y_j is represented. Therefore, the y and $\breve{y}$A matrix cannot depict it for further additional assumptions. A fixed dimension matrix as input is needed for DRNN, such as logistic regression. A summary of strategies to resolve this problem is offered in the next discussion—a flexible and commonly available simulation such as a multi-layer perceptron (MLPs).

Nonetheless, MLPs cannot accumulate sequential dependencies in successive data, being limited to forward relations. RNNs have been more properly implemented in sequential model data. To this end, RNNs provide repetitive layers extending feed-forward layers, including forwarding relations to all the units and cycles of the subsequent layer that feed the unit's output into that unit.

Recurring or cyclical relations, like ordering in the network, promote with clickstream data. A recurrent layer helps record navigation patterns during the session at various times. Session j navigation patterns are encoded with the page view vector values$Y_j^{(1)},\ldots,$ $Y_j^{(S_j)}$. E-Business need to predict the outcomes of a session live in a scenario $s \ < S_j$. The recurrent layer's hidden state time step can be determined as in Eq. (2):

$$g^{(s)} = h\left(Z^{gy}y_j^{(s)} + Z^{gg}g^{(s-1)} + a_g\right) \tag{2}$$

Fig. 4 and shown in Eq. (2) hidden state recurrent layer time step, where Z^{gy} and Z^{gg} are the matrices that, in the next step, contain the weights of the relation from the input into the hidden level and to the hidden layer,a_g is the hidden layer's bias vector. In addition, $h$is a non-linear function called activation.

A hidden state recurrent layer is a neural network that is dedicated to dispensation an order of data x(t)= x(1), . . ., x(τ) with the time step index t ranging from 1 to τ. For tasks that involve consecutive inputs, such as talking and verbal, it is often better to use a hidden recurrent layer.

A*tang* is a mutual option. $\mathrm{h(w)} = \frac{\exp(\mathrm{w})-\exp(-w)}{\exp(\mathrm{w})+\exp(-w)}$i.e.) $h(w) = \max(0, W)$in obtaining desired RNN properties for sequences, hidden states are important. First, it adds information to the network from every phase, thus shaping time dependencies. Second, all sessions and time stages include parameters of the hidden state. Inputs from different shapes can be taught from this sharing of a parameter; sessions in our environment have different page views with $\mathrm{g}^{(s)}$, the network will provide forecasts. This exchange of parameters helps e-business to learn inputs in multiple types. This means sessions with different pages in our settings. Due to $\mathrm{g}^{(s)}$, the network output predictions are expressed in Eq. (3):

$$\breve{x}_j^{(s)} = \delta(Z^{xg}g^{(s)} + a_x) \tag{3}$$

Fig. 5 and Eq. (3) show the hidden state recurrent layer time step output prediction. The result of high accuracy to hidden state recurrent layer time step output calculated.

Gradient concerning output $\boldsymbol{a_x}$ is calculated pretentious the $\boldsymbol{a_x}$ are used as the quarrel to the softmax function to obtain the vector of chances over the output.

The$\mathrm{a_x}$output layer biases are the $\mathrm{Z^{xg}}$ is related to the hidden weight matrix to the output layer. The net result is transferred over a sigmoid function to ensure that the output varies from 0 to 1. A binary classification issue is the converter classification,$\delta(\mathrm{w}) = \frac{1}{1} +$ $\exp(-W)$theory indicates that RNN's can model contextual addictions for a continuous period. In reality, long-term dependencies of trouble learning occurred, as gradient values sometimes fall short or erupt over several years. This occurrence, which is called the extinguishing gradient issue, describes the next two architectures.

The proposed long-short term memory model(LSTM) is the solution for the issue of absence gradients. The long-short term memory layer nodes are described by the memory cells shown in Fig. 6 instead of ordinary recurrent units. 1. A four-part memory cell is an input

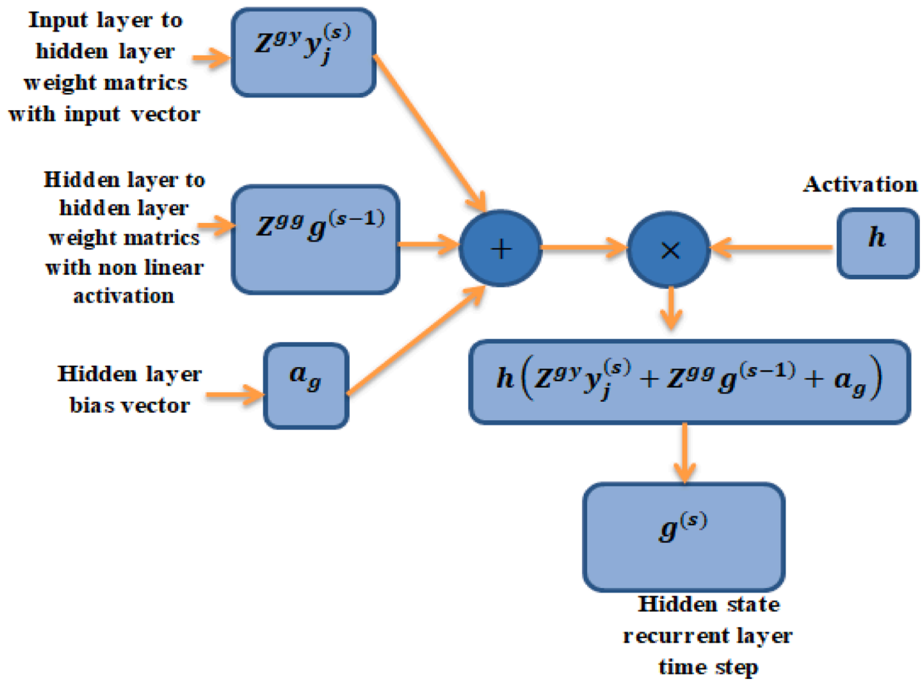

Fig. 4. Hidden State Recurrent Layer Time Step.

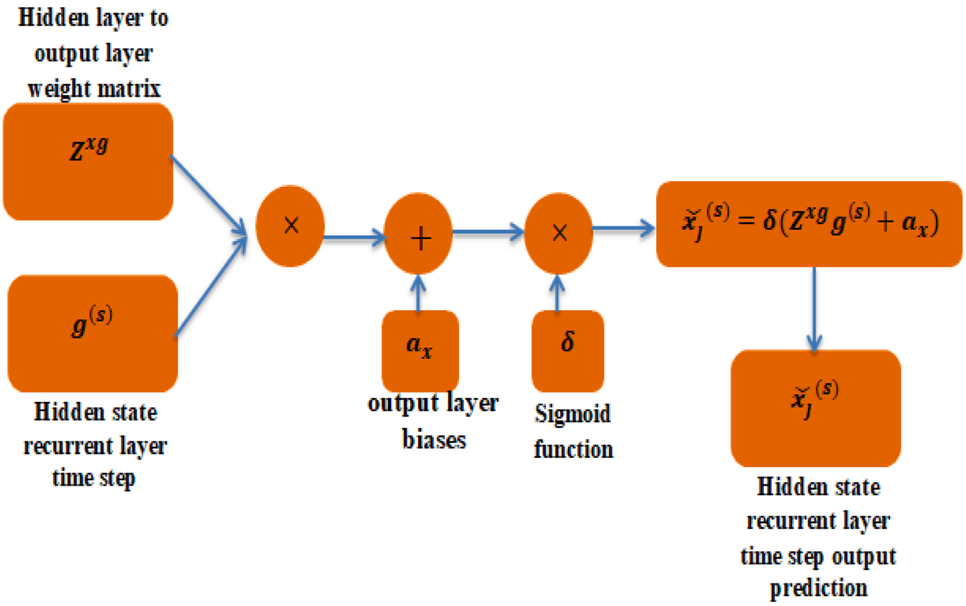

Fig. 5. Hidden State Recurrent Layer Time Step Output Prediction.

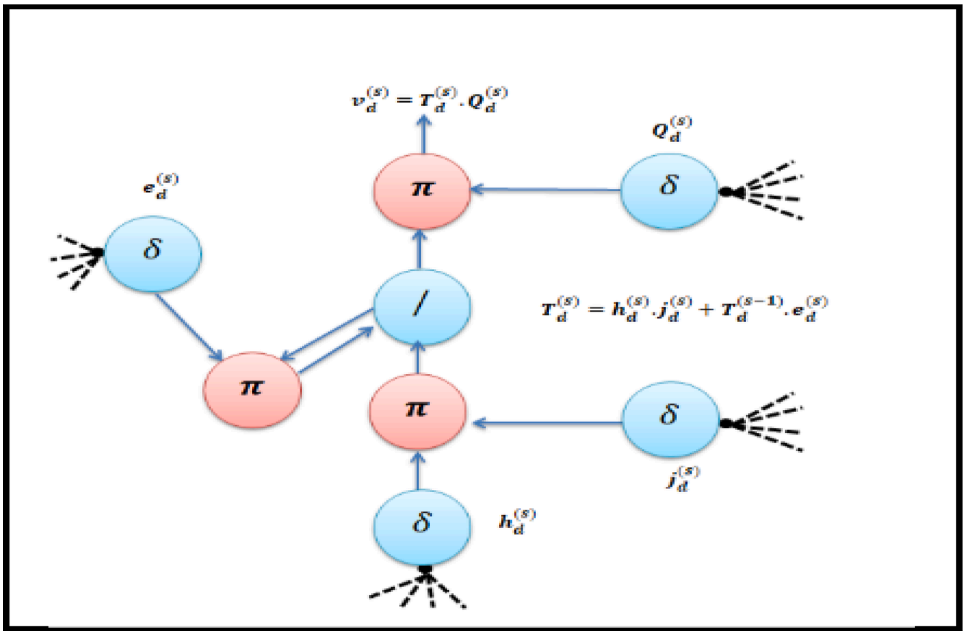

Fig. 6. LSTM memory cell.

gate$j_d^{(s)}$, an input unit with a self-recurrent cycle $h_d^{(s)}$, a forgotten gate $e_d^{(s)}$ and an output gate $Q_d^{(s)}$. In the same direction as in the equation. Input vectors $y_j^{(s)}$are treated by each variable and hidden state in the prior layer $g^{(s-1)}$are converted into linear combinations transformed in a non-linear activation (3),

In Eq. (4) are given the values for the input unit, and the input gate for every memory cells in long-short term memory as follows:

$$\left.\begin{aligned} j^{(s)} &= \left(Z^{jy} y_j^{(s)} + Z^{jg} g^{(s-1)} + a_j\right) \\ h^{(s)} &= tang\left(Z^{hy} y_j^{(s)} + Z^{hg} h^{(s-1)} + a_h\right) \end{aligned}\right\} \tag{4}$$

In Eq. (4), the input unit and the input gate are represented. Note that for the relation of weight matrices, DRNN uses the to-from notation. $Z^{jy}$is the matrix of the relation weight of input values, Z^{jg} the connection weight matrix of the hidden state,$j^{(s)}$ and $h^{(s)}$Determine which new existing input information is to be used to change the state of the cell. The condition of the cell, in Fig. 6, represented the middle node acts as long-term memory, preserving time signals from all previous processes. All previous time steps store signals, and it acts as long-term memory. To eliminate obsolete data from the cell state, introduced a forget gate in Eq. (5):

$$e^{(s)} = \delta\left(Z^{ey}y_j^{(s)} + Z^{jy}h^{(s-1)} + a_h\right) \tag{5}$$

Fig. 6 shows the LSTM memory cell, and Eq. (5) shows the forgot gate. It is possible to determine cell state values for these three sections of the memory cell. Let's indicate element-wise reproduction. Then cell state is stated as (6)

$$T^{(s)} = g^{(s)} \odot i^{(s)} + T^{(s-1)} \odot e^{(s)} \tag{6}$$

As derived in Eq. (6) shows the cell state. As the cell state involves signals from current and previous times, not every signal will lead to the actual cell output. Nevertheless, all obsolete details may be worth remembering, for some may again become important for forecasting results later. For example, consider when a consumer has to browse two separate items, like shoes and t-shirts. Assume that in recent pages, the customer has watched at the shoes.

Firstly, if the user continues searching for this product type, it will be necessary to retain the details of the T-shirt page views. Therefore the information from the cell state should not be removed. However, these signals can be trivial if forecast the session's outcomes in the current page view when trends seen in previous shoe views are more important. That is why the LSTM does not cross the cells' state and uses an output gate in Eq. (7):

$$Q^{(s)} = \delta\left(Z^{Qy}y_j^{(s)} + Z^{Qg}g^{(s-1)} + a_o\right) \tag{7}$$

As shown in Eq. (7), the cell state filter has been denoted. Ensures that appropriate current and past information is created when moving the whole-cell state to the subsequent layer. A cell state variant filtered by $Q^{(s)}$ is then used as the network output, i.e.

$$g^{(s)} = tang(T^{(s)}) \odot Q^{(s)} \tag{8}$$

As inferred in Eq. (2) shows the output layer. The final network prediction is focused on the propagation$g^{(s)}$ to an output layer given in Eq. (2).

The LSTM cell reveals that studying long-term dependency entails the expense of some other model parameters. The simplification of LSTM will be easier if fewer model parameters have been required without losing their core advantages. The promise to launch the Gated Recurrent Unit (GRU). In this relation, a GRU Cell includes an update gate and a reset gate identified by in Eq. (9):

$$\left.\begin{aligned} P^{(s)} &= \delta\left(Z^{Py}y_j^{(s)} + Z^{Pg}g^{(s-1)} + a_P\right) \\ V^{(s)} &= \delta\left(Z^{Vy}y_j^{(s)} + Z^{Vg}g^{(s-1)} + a_V\right) \\ \breve{g}^{(s)} &= tang\left(Z^{\breve{g}y}y_j^{(s)} + P^{(s)} \odot Z^{Pg}g^{(s-1)} + a_{\breve{g}}\right) \end{aligned}\right\} \tag{9}$$

As shown in Eq. (9), the update gate has been represented. This incorporates the input gate and the forget LSTM gate characteristics into one gate. The final cell output is evaluated using the values from the updated door for the GRU layer $V_d^{(s)}$as weights linear interpolation among the previous layer output and the output in the equation created by the candidate (10):

$$g_d^{(s)} = V_d^{(s)}\breve{g}_d^{(s)} + \left(1 - V_d^{(s)}\right)g_d^{(s)} \tag{10}$$

As found in Eq. (10), the final cell output has been calculated. Hence the enhanced performance to calculate the final cell output. This update gate then monitors the amount of memory content that must be forgotten and the new memory content. More periodic calculations are needed to update one unit as there are fewer gates in the GRU than the LSTM. Since both methods have several properties, it is not necessarily possible to select beforehand one to use for a particular problem.

Assume thatp_j marketing of merchandise to consumers j an issued e-coupon lowers all bought goods by a fraction of the initial price. E-Business would evaluate$\zeta = 0.1$, just 90% of the total price of the goods purchased must be paid by a customer who gets the voucher. Moreover, $r$may denote the likelihood that the coupon's price discount would turn a consumer who did not intend a purchase into a buyer. Social behavior will be denoted as$r$ the probability of redemption. On the other hand, if the consumer is targeted or has already arranged, an e-coupon is expected to be used without modifying the original schedule. In both cases, direct income adjustments are not feasible. However, remember that fake buying sessions include chances not to reach legitimate consumers who do not shop. Given this situation, an e-coupon campaign will gain in revenue is expressed (11):

$$\Delta\pi = \sum_{j=1}^{M_{sr}} r \times p_j \times (1 - \zeta) - \sum_{j=1}^{M_{er}} P_j \times \zeta \tag{11}$$

As derived in Eq. (11) shows the e-coupon campaign gains revenue.$M_{sr}$is the true positive number, and M_{er} is known as the false positive number of sessions.The proposed DRNN analysis clickstream data to calculate the method enhances performance, prediction, accuracy, profitability, and lower error rate in social network-based e-business.

4. Numerical results and discussion

The proposed DRNN and social network can be used in e-business during the COVID-19 pandemic, and results have been performed based on performance, prediction, accuracy, profitability, and error rate. The proposed systems consider 100 customers for behavior analysis

i **Profitability Ratio Evaluation**

E-business brings many benefits to a business, like growing the demand for the product and productivity that will automatically improve their business profitability; well, development in the e-business may lead a business to success. Suppose companies react reliably and suitably during this pandemic crisis. In that case, it will eventually benefit the business in the long run, and the organization will come out profitably from the potential economic downturn. Strategies such as trust & e-loyalty, value creation, and knowledge management in E-business are part of a company's development to increase productivity and profitability. The deep learning method predicts customer buying behavior and will increase the profitability ratio in the E-business platform. Fig. 7 shows the profitability ratio when compared to other existing methods.

i **Performance Ratio Analysis**

The latest coronavirus disease pandemic has brought huge global difficulties for corporations, impacting most companies. For example, financial problems arise because of the coronavirus pandemic's effects, the epicenter's declining business sectors. In most governments, rapid regulation is enforced, such as closure and lockdown of non-essential companies, and social distance amongst citizens is strongly encouraged. The provisions are intended to safeguard improved opportunities to eliminate the virus outbreak. Digital applications such as E-business will act as an important way, even after the epidemic, to increase operational volatility and improve the survival rate. However, confidence in consumers may impact e-business's overall performance. In this study, the proposed improvements include physician visits and effort, time and information strategies such as ratings, a large shopping, and electronic notifications. These variables are considered to improve the performances of e-business in the ordering of distance products in new norms after the Coronavirus pandemic, even applicable for other industries and situations. Fig. 8 shows the performance ratio using the proposed deep learning model (DRNN).

i **Accuracy Ratio Determination**

Artificial Intelligence and Deep Learning can offer individualized customer experiences by predicting how customer behavior will impact present business models and support change marketing operations. Market segmentation involves recognizing similar characteristics of consumers' homogeneous groups to improve marketing activities by improving resource allocation and developing customized strategies. If target groups are known before, the challenge becomes a grouping task in a controlled learning process. Increased interest in identifying new liquidity sources compels financial firms to consider new ways of detecting extremely likely people and saving money. The proposed DRNN method accurately predicts customer behavior in the E-business platform when compared to other existing methods. Fig. 9 shows the accuracy ratio.

i **Prediction Ratio**

The study uses clickstream data to predict in real-time the behavior of online purchasing and marketing. Clickstream data is

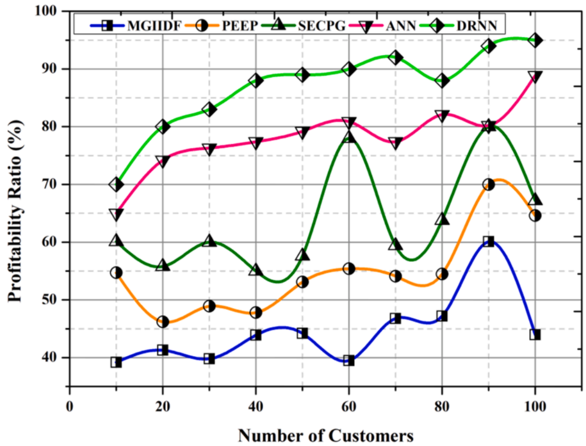

Fig. 7. Profitability Ratio Evaluation.

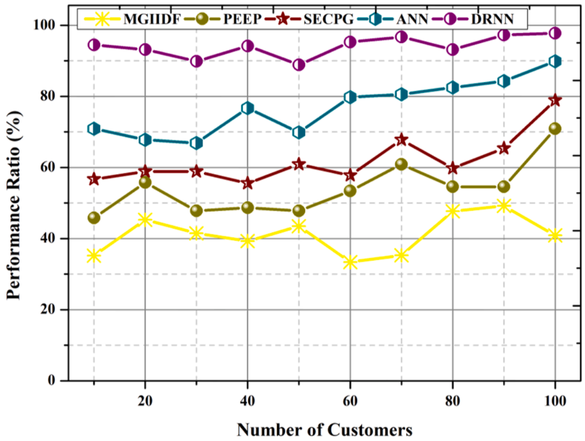

Fig. 8. Performance Ratio Analysis.

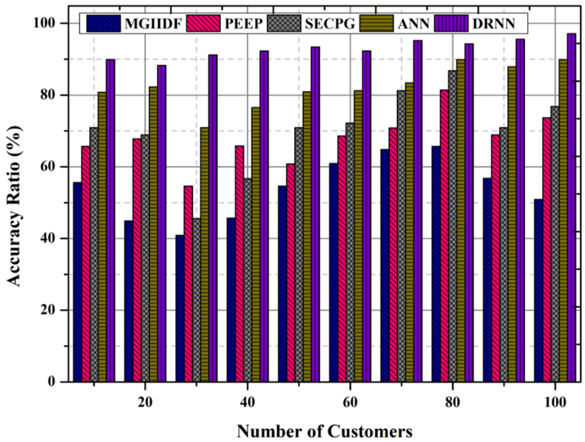

Fig. 9. Accuracy Ratio Determination.

generated sequentially, whereas standard supervised machine learning algorithms use tabular data. It is not evident if the clickstream data can be used for consumer behavior. The proposed method used in earlier work is called clipping by any click, trains, and predicts on a page view level. Using supervised machine learning algorithms as a single instance allows each page view to break the user clickstream's sequential structure. The text follows a different direction and addresses consumer behavior's predictive task as a series classification issue. The study indicates that DRNNs are ideal for sequential data collection and resolving several methodological shortcomings of earlier attempts to produce customer behavior predictions from click-stream information utilized by supervised machine learning algorithms. Fig. 9 shows the prediction ratio using the proposed DRNN method.

i **Error rate**

This study considers the LSTM and GRU architectures for the classification problem with the last sigmoid layer and changes the loss function. It builds a naive baseline interpretation to verify whether any suggested linear regression result is rational, predicting every transactions' median order range in the training collection. Analytical performance of orders with normal regression parameters for absolute mean error (MAE) and squared root average error (RMSE) and R^2 is forecast. The DRNN model is ideal as variances in error estimates marginalize non-buying future command values. In comparison with other existing systems, the proposed model has a lower error rate. The error rate of the proposed DRNN model can be seen in Fig. 10.

The proposed DRNN uses a clickstream analysis to predict e-business behavior in E-business. The proposed DRNN method improves performance, prediction, precision, profitability and error rates, and Prediction when compared to McKinsey Global Institute's Industry Digitalization Framework (MGIIDF), the effectiveness of e-commerce platforms, and social e-commerce customers' purchasing behavior game model, Artificial Neural Networks(ANN) methods, (Fig. 11)

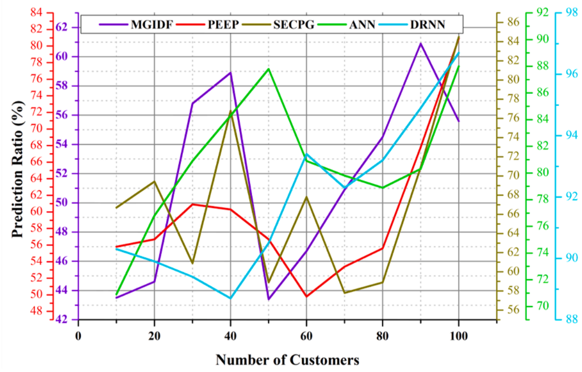

Fig. 10. Prediction Ratio.

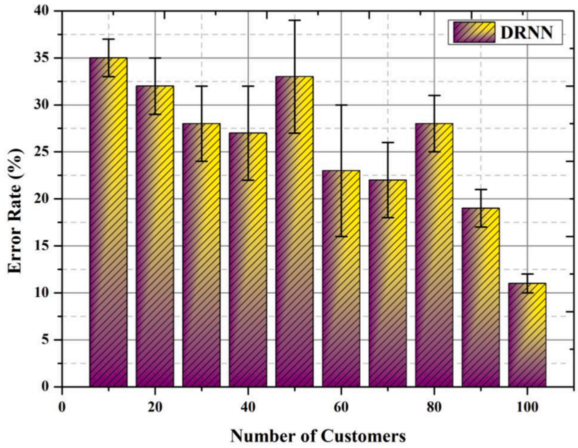

Fig. 11. Error rate.

5. Conclusion

This study offered certain initial thoughts on how the ongoing Covid-19 epidemic impacts E-business, marketing philosophy, and consumer ethics. This pandemic bids excessive opportunities for businesses to actively involve in different marketing initiatives during the crisis and potentially catalyze a modern era of business growth in the long run. The customer decision's ethical dimension has become noticeable during the pandemic, changing customers towards more prosocial and responsible consumption. E-business is a new revolution for a business to create a competitive advantage and increase overall revenue and productivity over other competitors. Improved customer trust, such as improving safety systems and privacy, rewarding customers based on the amount they purchase or their consistent purchases of the products each month, and offering customers a discount or promotion to purchase large quantities of their products. By creating value and building stronger trust between customers and companies. E-business is a good approach to business for customers who spend a lot of time on the Internet. EBusiness has a positive impact on the environment instead of traditional companies that spend extensively on building and scheduling their business. The proposed DRNN method effectively predicts customer behavior in the E-business platform. Numerical results show that the method proposed improves the return ratio of 98.5%, the performance ratio of 97.5%, the prediction ratio of 96.7%, and the failed error of 11.3% of other existing methods.

Author statement

Conception and design of study: Cheng Luo
Acquisition of data: Cheng Luo
Analysis and/or interpretation of data: Cheng Luo

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