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A Novel Framework to Investigate the Impact of Social Media Advertising Features on Customer Purchase Intention Using Bwo-Dann

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ABSTRACT

Social Media (SM) has turned out to be a platform for marketing and advertising activities. Nevertheless, it is always a challenge for organizations to model SM Advertising (SMA) in a means to effectively attract and also motivate customers into purchasing their brands. This paper proposed a novel framework to scrutinize the SMA features' impact on Customer Purchase Intention (CPI) using the Black Widow Optimization-based Deep Artificial Neural Network (BWO-DANN). Initially, the questionnaires are given to the various customer and the collected answers will be uploaded and are converted into numerical format into the system. The Chicken Swarm Genetic Algorithm-based K-Means (CSGA-KM) is utilized for clustering the questionnaires based on personal information. Then the BWO-DANN is utilized to train the converted questionnaire set. Then, the system is tested by utilizing K-Fold Cross Validation (KFCV). Finally, through the mean model, CPI is found out. The experimentation's outcomes illustrated the system's effectiveness.

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1. INTRODUCTION

SM, to augment consumer brand awareness, has swiftly changed all the traditional marketing approaches by establishing connections betwixt marketers and consumers via generating new possibilities or opportunities [1]. Advertising experts have started utilizing SM appeals in their advertisements to attract consumers' attention as well as address customization of their requirements [2]. Customers are engaged more in major SM platforms say Facebook, Google+, YouTube, Snapchat, along with Twitter [3, 4]. Thus, organizations all through the globe are pondering on the fact that the SM's effect could aid them in attracting and also constructing a CPI for lucrative marketing dealings with the customers [5, 6].

The CPI is a measure for predicting the behavior of customers' decisions on purchasing certain products [7]. If the user is paying attention to a product or service, it means that there is a purchase intention and wishes to obtain it in the longer or shorter term [8]. CPI will happen when customers encompass a positive expression or attitude in the direction of the brand or services [9, 10]. There is a disparate advertising feature that investigates the SM's impact on a CPI, explicitly, the electronics word of mouth (e-WOM), which renders positive or negative comments by means of actual, potential, or past customers concerning a company or product that is available to a mass of people or institutions using the SM [11]. After that, advertisement has turned into a marketing tactic in SM to endorse a product, service, or cause and insisting on the individuals to purchase a product by enhancing the intention rate [12]. Afterward, Customers Relationship Managements (CRM) is the strategy for intending the customers to purchase the product for a long haul by means of just maintaining excellent customer service and also assisting in customer retention as well as driving sales [13, 14]. Furthermore, numerous deep learning models are developed for handling uncertainties and also rendering an automatic response centered on questionnaires or hypothesis SM features on CPI [15].

Numerous researchers analyzed the SM's impact on CPI by utilizing disparate methods say a Back Propagated Neural Networks (BPNN) [16], fuzzy logic [17], Structural Equation Model-centered Neural Network (SEM-NN) [18]. In managing vagueness along with uncertainty in information, the verbal expression imitation and the thinking process to resolve decision-making issues are the tasks of Neural Net works (NN), which will be practical as a well-validated device [19].

Therefore, there is a requisite to perform more examination into such a phenomenon in current years. The prevailing researches have not concentrated on the proposed analysis of the CPI centered on the decision-making on a product. To trounce this challenge, the work has proposed a Framework to examine the SMA features' impact on CPI utilizing BWO-DLNN. The proposed methodology's objective is:

- To Cluster the Questionnaire by means of personal info utilizing Chicken Swarm Genetic Algorithm – KMeans (CSGA-KM)
- To examine the SMA features' impact on CPI utilizing Black Widow Optimization with Deep Artificial Neural Network Algorithm (BWO-DANN).
- To test the questionnaire dataset utilizing K-Fold Cross Validations (KFCV) Testing.
- To find CPI utilizing the Mean Model.

The remaining paper is prearranged as follows: Section 2 reviews the SM's impact on CPI. The proposed framework is briefly elucidated in Section 3. Section 4 renders the experimentation's outcome along with the performance. At last, Section 5 concludes the work in conjunction with future scope.

1.1. Related Works

Alalwan *et al*. [20] intended to identify and also test the key factors associated with SMA that could envisage CPI. The conceptual design was centered on '3' factors as of the extensive unified theory of reception as well as utilization of technology accompanied by interactivity, informativeness, and also perceived relevance. The key outcomes of Structural Equation Modelling (SEM) supported the model's validity along with the significant effect of performance expectancy, hedonics motivation, informativeness, interactivity, along with perceived significance on CPI. The approach hopefully rendered a practical technique on how marketers efficiently planned and implemented their advertisements over SM platforms. However, personality traits weren't deemed.

Wang *et al*. [21] regarded social interaction as a requisite for triumphant Social Commerce (SC). Consumers anticipated an interactive along with social experience whilst buying decisions were made. Centered upon Words of Mouth (WOM) in conjunction with observational learning theories, conceptualized social interactions in SC surroundings were bifurcated into '2' forms: WOM communications were scrutinized on consumers' purchases, and inspected the effect on CPI along with actual purchase behavior. As customers couldn't constantly undergo the true traits of a product purchased by means of the Internet, there was some intricacy for making the proper buying decision.

Ghahtarani *et al*. [22] modeled a theoretical foundation, which incorporated the dimensions of the '2' theories. Furthermore, the information or knowledge shared was regarded as a moderate variable as well as was endeavored for scrutinizing the association betwixt the variables and CPI in the SC context. The statistical sample was 254 individuals brought as of websites. The outcomes illustrated that the dimensions of social capital in addition to social interaction supposition had a vital association with knowledge or information shared. However, there was a feeble positive association betwixt environmental concern and CPI in the directions of products.

Bugshan *et al*. [23] propounded the effect of trust in sharing commerce, Social Commerce Information (SCI) sharing, along with apparent privacy hazard on the forethought to purchase centered on a theoretical design. Data was gathered centered upon online questions that intended towards the consumers as of the markets was analyzed grounded on Partial Least Square-SEM (PLS-SEM). However, the hazard was caused because of the consumer's belief of uncertainty in relation to the possible outcome that would happen in online transactions and also affects the forethought to buy.

Chen *et al*. [24] produced a research design that scrutinized how customers' behavior was learned in conjunction with '3' key SC constituent with affected customers' attitudes in cognitive along with affective dimensions and how such attitude ascertained CPI. Centered upon appraisals, the outcome attained a good purchase intention; however, the vital issue was caused grounded upon the trust, which was regarded to be more vital in SC platforms because of the salient function of peer-generated content.

Thus, the above-stated survey renders a clear illustration of the SM's impact on CPI. Most research did not satisfy the current requirements to render a proper CPI by means of SM. The proposed work develops a framework to scrutinize the SMA features' impact on CPI utilizing BWO-DANN.

2. RESEARCH METHOD: THE IMPACT OF SOCIAL MEDIA ADVERTISING FEATURES ON CUSTOMER PURCHASE INTENTION

In SM, marketing and advertisement activities are being performed. For it, the organizations have depleted time, money, along with resources. SM advertisements, a type of internet ad, are instances of Web 2.0. Customers can have disparate perceptions and also experiences in interacting with SM ads. This is also because of the SM ad's nature, that is, customers are given the chance to engage with the targeted ads more by liking, commenting, posting, re-sharing, and learning. Domestic companies are in the position to confront the digital era and monitor as well as engage their targeted audiences on SM since the values of a brand largely rely on their customers' insight. Therefore, this paper proposed a novel framework intended for investigating the SMA features' impact on CPI. The proposed method's block diagram is shown in Figure 1.

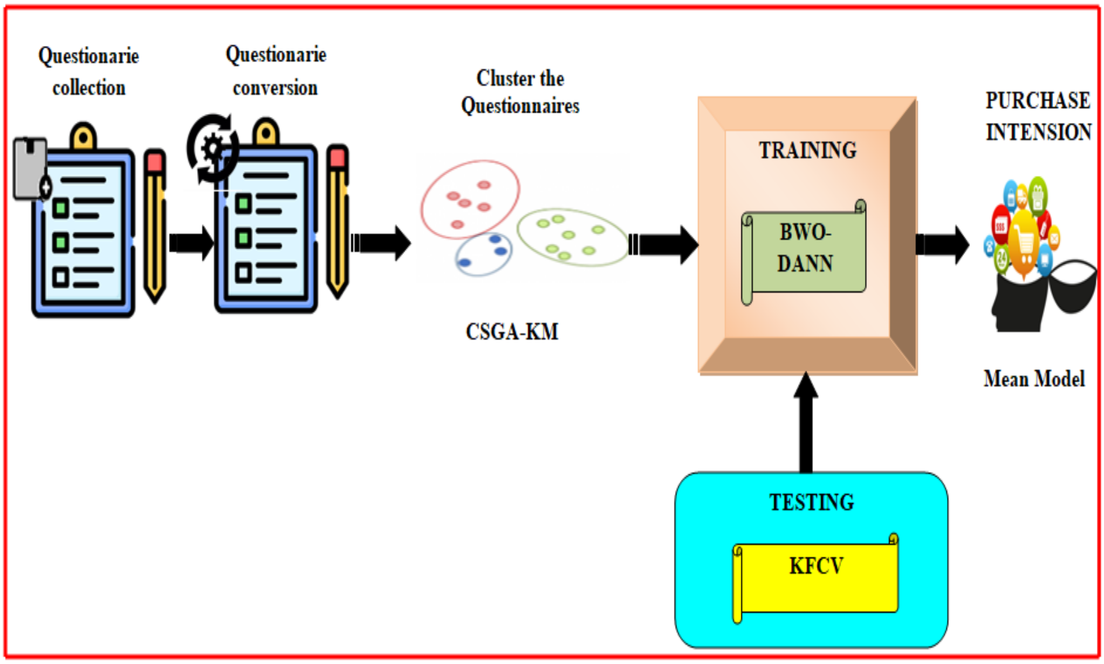

Figure 1. Architecture diagram for the proposed methodology

2.1. Questionnaire Collection

Data gathered as of the respondents is extremely vital to scrutinize the SMA features' impact on CPI. These questionnaires focus on the respondents' views concerning their purchase details, loyalty, awareness, and relationship with the brands, others' influence on the purchase decision, along with views concerning the marketing of brands on the SM say Facebook, Twitter, et cetera. To gather the needed data as of the customers who have already utilized SM, a self-administrative questionnaire was performed. Here, the proposed work utilizes standard questionnaires and gather the respond for the entire questions as of various customers.

The questionnaires encompass 100 questions that are classified into '6' sets of questions. In which, the first set of questions asks about the personal details of customers that comprise customer name, gender, age group, occupation, education, in addition to yearly income. The 2nd questionnaire set is about SM usage by the customer. It includes questions like "how much time on average a customer spent on SM site in a day" and the time during which the customer accesses the SM sites mostly. The 3rd set of questions contain assessments about the comparison of the quantity of time the customer spends on SM in the present year with that of the last year, that is, whether the time has augmented or lessened or the same, in addition, the type of products the customer like to stay connected with the SM, et cetera. The 4th set of questions is about community, connectedness, openness, dependence, along with participation. The trust, perceived value, along with perceived risk is given in the 5th set of questions. The 6th set includes factors, say entertainment, credibility, informativeness, irritation, interactivity, along with purchase intention. The overall depiction of the questionnaire compilation is evinced in the below Figure 2.

Figure 2. Representation of questionnaire collection

The details of the six sets of questionnaire collection are illustrated in Table 1, Table 2, Table 3, Table 4, Table 5, and Table 6.

Table 1. Statistics of customer personal information details

Type of Questions	**Category 1**	**Category 2**	**Category 3**	**Category 4**	**Category 5**
Gender	25% (Male)	75% Female)			
Age group	75% (18-24)	10% (25-34)	14% (35-44)	1% (45-54)	
Occupation	74% (Student)	25% (Salaried people)	1% (Self-employed)		
Education	1% (Diploma)	21% (Post graduation)	56% (Under graduation)	19% (Upto PUC/HSC)	3% (Others)
Yearly income	9% (250000-500000)	91% (less than 250000)			

Table 2. Statistics of usage of social media sites

Type of Questions	**Category 1**	**Category 2**	**Category 3**	**Category 4**	**Category 5**
Since when you have been visiting these social media sites	27% (1-2 years)	10% (3-4 years)	36% (Above 5 years)	27% (Less than a year)	
Social media usage/day	50% (1-3 hours)	1% (24 hours connected)	19% (3-6 hours)	3% (Less than one hour)	27% (Less than an hour)
Time for social media usage /day	14% (12am-6pm)-	2%(12pm-5am	8% (6am-12am)	2% (6am-12pm)	74% (6pm-12pm)

Table 3. Statistics of assessments of social media sites

Type of Questions	**Category 1**	**Category 2**	**Category 3**	**Category 4**	**Category 5**	**Category 6**	**Category 7**
Purpose of social media network	16% (Based on the product interest)	2% (Celebrities)	29% (Family and relatives)	49% (Friends)	1% (Others)	3% (All the above)	
Comparison of social media site usage last year and present year	Decreased 33%	Increased 39%	Nearly the same 28%				
Comparison of product information search last year and present year	Decreased 22%	Increased 37%	About the same 41%				
Products connected through social media sites	11% (Electronics)	17% (Cosmetics)	17% (Fashion accessories)	10% (Healthcare)	29% (Household products)	4% (Others)	12% (All mentioned)

Table 4. Statistics of interest and participation in social media sites

Type of Questions	Category 1	Category 2	Category 3	Category 4	Category 5
Easy to find the same interest people	Agreed 58%	Disagreed 11%	Neither agreed nor disagreed 14%	Strongly agreed 15%	Strongly disagreed 2%
Develop the intimate relationship with others	Agreed 35%	Disagreed 21%	Neither agreed nor disagreed 26%	Strongly agreed 15%	Strongly disagreed 3%
Easy to share emotions and communicate feelings	Agreed 34%	Disagreed 22%	Neither agreed nor disagreed 8%	Strongly agreed 34%	Strongly disagreed 2%
Easy to be a part of community or interest groups	Agreed 62%	Disagreed 3%	Neither agreed nor disagreed 15%	Strongly agreed 16%	Strongly disagreed 1%
Same login ID for different social media sites	Agreed 38%	Disagreed 28%	Neither agreed nor disagreed 13%	Strongly agreed 17%	Strongly disagreed 4%
Easy to share the same content on different social media sites	Agreed 54%	Disagreed 13%	Neither agreed nor disagreed 5%	Strongly agreed 27%	Strongly disagreed 1%
Requirements of special advanced skills	Agreed 30%	Disagreed 21%	Neither agreed nor disagreed 25%	Strongly agreed 22%	Strongly disagreed 2%
Easy to edit the communicating information	Agreed 45%	Disagreed 5%	Neither agreed nor disagreed 19%	Strongly agreed 30%	Strongly disagreed 1%
Easy to join the social media	Agreed 62%	Disagreed 5%	Neither agreed nor disagreed 5%	Strongly agreed 26%	Strongly disagreed 2%
Easy to join the groups and communities	Agreed 58%	Disagreed 9%	Neither agreed nor disagreed 11%	Strongly agreed 20%	Strongly disagreed 3%
Acquirement of information	Agreed 44%	Disagreed 12%	Neither agreed nor disagreed 14%	Strongly agreed 25%	Strongly disagreed 5%
Publishing posts freely	Agreed 37%	Disagreed 16%	Neither agreed nor disagreed 22%	Strongly agreed 19%	Strongly disagreed 6%
Social media is the first priority to choosing products	Agreed 58%	Disagreed 11%	Neither agreed nor disagreed 19%	Strongly agreed 9%	Strongly disagreed 2%
Easy to search information about products through social media	Agreed 55%	Disagreed 6%	Neither agreed nor disagreed 13%	Strongly agreed 24%	Strongly disagreed 2%
Time to spend on social media is higher than other online websites	Agreed 32%	Disagreed 26%	Neither agreed nor disagreed 28%	Strongly agreed 13%	Strongly disagreed 1%
Making comments about the products through social media `	Agreed 49%	Disagreed 17%	Neither agreed nor disagreed 13%	Strongly agreed 17%	Strongly disagreed 2%
Help friends who have problems regarding the use of social media	Agreed 48%	Disagreed 10%	Neither agreed nor disagreed 24%	Strongly agreed 17%	Strongly disagreed 1%
Participate in a discussion about products introduced by a friend	Agreed 46%	Disagreed 23%	Neither agreed nor disagreed 18%	Strongly agreed 11%	Strongly disagreed 2%
Subscribed a brand or product	Agreed 38%	Disagreed 16%	Neither agreed nor disagreed 32%	Strongly agreed 10%	Strongly disagreed 4%
Searching product information frequently	Agreed 41%	Disagreed 16%	Neither agreed nor disagreed 21%	Strongly agreed 16%	Strongly disagreed 2%

Table 5. Statistics of experience on social media sites

Type of Questions	Category 1	Category 2	Category 3	Category 4	Category 5
Trustworthy of information	Agreed 31%	Disagreed 20%	Neither agreed nor disagreed 32%	Strongly agreed 11%	Strongly disagreed 1%
Sharing experience about buying products or acquiring information	Agreed 42%	Disagreed 17%	Neither agreed nor disagreed 21%	Strongly agreed 17%	Strongly disagreed 3%
Trust the opinion of experts about the products	Agreed 29%	Disagreed 18%	Neither agreed nor disagreed 39%	Strongly agreed 10%	Strongly disagreed 1%
Low probability for getting poor quality products	Agreed 36%	Disagreed 26%	Neither agreed nor disagreed 19%	Strongly agreed 7%	Strongly disagreed 9%
Find products that are apt for personal quality and style	Agreed 54%	Disagreed 6%	Neither agreed nor disagreed 20%	Strongly agreed 18%	Strongly disagreed 2%
Save money for getting information about the product	Agreed 36%	Disagreed 13%	Neither agreed nor disagreed 29%	Strongly agreed 18%	Strongly disagreed 4%
Low probability for leakage of privacy in buying products	Agreed 33%	Disagreed 28%	Neither agreed nor disagreed 20%	Strongly agreed 9%	Strongly disagreed 10%
Find the quality and function through product information	Agreed 39%	Disagreed 14%	Neither agreed nor disagreed 32%	Strongly agreed 11%	Strongly disagreed 4%
Low financial risk	Agreed 41%	Disagreed 20%	Neither agreed nor disagreed 21%	Strongly agreed 16%	Strongly disagreed 2%
Low probability of wasting time on obtaining information about products	Agreed 42%	Disagreed 19%	Neither agreed nor disagreed 34%	Strongly agreed 1%	Strongly disagreed 3%
Low probability of Harming physical health by purchasing products	Agreed 22%	Disagreed 26%	Neither agreed nor disagreed 36%	Strongly agreed 13%	Strongly disagreed 2%
Low probability of getting social pressure in purchasing products	Agreed 25%	Disagreed 23%	Neither agreed nor disagreed 37%	Strongly agreed 12%	Strongly disagreed 3%

Table 6. Statistics of factors of social media sites

Type of Questions	Category 1	Category 2	Category 3	Category 4	Category 5
Receive advertisements on social media is entertaining	Agreed 51%	Disagreed 9%	Neither agreed nor disagreed 18%	Strongly agreed 15%	Strongly disagreed 7%
Pleasant to recollect about advertisements	Agreed 42%	Disagreed 22%	Neither agreed nor disagreed 22%	Strongly agreed 11%	Strongly disagreed 3%
Advertisement on social media is more enjoyable	Agreed 35%	Disagreed 19%	Neither agreed nor disagreed 23%	Strongly agreed 16%	Strongly disagreed 5%
Advertisements include more excitement and surprises	Agreed 34%	Disagreed 18%	Neither agreed nor disagreed 29%	Strongly agreed 13%	Strongly disagreed 6%

Advertisements include humorous characters	Agreed 23%	Disagreed 25%	Neither agreed nor disagreed 35%	Strongly agreed 11%	Strongly disagreed 6%
Advertisements are a good source of timely information	Agreed 48%	Disagreed 12%	Neither agreed nor disagreed 20%	Strongly agreed 14%	Strongly disagreed 5%
Advertisements are a good source of up to date product information	Agreed 34%	Disagreed 4%	Neither agreed nor disagreed 41%	Strongly agreed 13%	Strongly disagreed 8%
Advertisements make product information immediately accessible	Agreed 46%	Disagreed 11%	Neither agreed nor disagreed 27%	Strongly agreed 11%	Strongly disagreed 15%
Advertisements are convenient sources of product information	Agreed 45%	Disagreed 15%	Neither agreed nor disagreed 28%	Strongly agreed 8%	Strongly disagreed 4%
Advertisements provide complete product information	Agreed 40%	Disagreed 12%	Neither agreed nor disagreed 29%	Strongly agreed 13%	Strongly disagreed 6%
Advertising is realistic	Agreed 36%	Disagreed 15%	Neither agreed nor disagreed 33%	Strongly agreed 11%	Strongly disagreed 5%
Advertising is trustworthy	Agreed 25%	Disagreed 24%	Neither agreed nor disagreed 37%	Strongly agreed 5%	Strongly disagreed 8%
Advertisements are used as reference	Agreed 48%	Disagreed 9%	Neither agreed nor disagreed 26%	Strongly agreed 13%	Strongly disagreed 4%
Advertisements provide appropriate evidence to believe	Agreed 30%	Disagreed 23%	Neither agreed nor disagreed 32%	Strongly agreed 10%	Strongly disagreed 14%
Advertisements sender should be known	Agreed 42%	Disagreed 11%	Neither agreed nor disagreed 28%	Strongly agreed 10%	Strongly disagreed 9%
Advertisements contents are often annoying	Agreed 39%	Disagreed 15%	Neither agreed nor disagreed 21%	Strongly agreed 21%	Strongly disagreed 3%
Advertisements disturb while using a computer or mobile devices	Agreed 49%	Disagreed 15%	Neither agreed nor disagreed 14%	Strongly agreed 21%	Strongly disagreed 1%
Advertisements are excessive and out of control	Agreed 38%	Disagreed 17%	Neither agreed nor disagreed 28%	Strongly agreed 15%	Strongly disagreed 2%
Advertisements in a foreign language are inconvenient	Agreed 30%	Disagreed 31%	Neither agreed nor	Strongly agreed 12%	Strongly disagreed 3%

			disagreed 24%		
Advertisements intrude on the privacy of an individual	Agreed 35%	Disagreed 10%	Neither agreed nor disagreed 34%	Strongly agreed 15%	Strongly disagreed 6%
Preference of ads with a feedback form	Agreed 41%	Disagreed 8%	Neither agreed nor disagreed 30%	Strongly agreed 18%	Strongly disagreed 3%
Preference of ads with chat forums	Agreed 35%	Disagreed 19%	Neither agreed nor disagreed 30%	Strongly agreed 11%	Strongly disagreed 4%
Convenient of ads with more hyperlinks	Agreed 35%	Disagreed 25%	Neither agreed nor disagreed 29%	Strongly agreed 9%	Strongly disagreed 2%
Ads with a high degree of cognitive involvement	Agreed 21%	Disagreed 26%	Neither agreed nor disagreed 33%	Strongly agreed 16%	Strongly disagreed 4%
Advertisements are relevant	Agreed 30%	Disagreed 14%	Neither agreed nor disagreed 33%	Strongly agreed 16%	Strongly disagreed 7%
Try a product recommended on social media	Agreed 40%	Disagreed 17%	Neither agreed nor disagreed 19%	Strongly agreed 17%	Strongly disagreed 6%
Ads are increasing interest to buy the same product	Agreed 41%	Disagreed 19%	Neither agreed nor disagreed 33%	Strongly agreed 4%	Strongly disagreed 3%
Buy products shared by my friends	Agreed 36%	Disagreed 25%	Neither agreed nor disagreed 26%	Strongly agreed 11%	Strongly disagreed 2%
Help to make decisions	Agreed 39%	Disagreed 24%	Neither agreed nor disagreed 22%	Strongly agreed 10%	Strongly disagreed 5%
Influence of purchase choice	Agreed 31%	Disagreed 22%	Neither agreed nor disagreed 30%	Strongly agreed 13%	Strongly disagreed 4%
Advertisements have led me to buy a product that I have never tried before	Agreed 33%	Disagreed 27%	Neither agreed nor disagreed 22%	Strongly agreed 11%	Strongly disagreed 6%

2.2. Questionnaire Conversion

The customers give a proper response to the above-stated questionnaires. These questionnaires are gathered offline in documentary format. Manually investigating customer intention usually takes more time in analyzing the outcomes. Thus, the documentary answers are uploaded and those answers are converted into a numerical format in the system. This converted questionnaire dataset is expressed as:

$$L_q = \{l_1, l_2, l_3, ...l_k\} \tag{1}$$

Wherein L_q implies the converted questionnaire dataset and l_k implies the $k-$ number of customers' information concerning SMA.

2.3. Clustering the Questionnaire by Personal Information

Here, the questionnaire is regarded centered upon personal information. The procedure of grouping abstract objects into clusters of similar ones is termed Clustering. Centered upon data similarity, it separates the data into groups, and after that, assigns the labels to every group. Here, the CSGA-KM is utilized to cluster the questionnaires. In the K-Means, the centroids point is picked arbitrarily. The random updating procedure didn't render better clustering outcomes. Thus, the proposed system utilizes Chicken Swarms Optimization (CSO) to choose the optimal centroids points. The CSO is fundamentally a stochastic optimizations algorithm, which mimics the chicken swarm's hierarchical order along with the behaviors. Here, the genetics algorithm (GA) is utilized in the updating process to enhance the outcomes. The algorithmic strategy for the CSGA-KM is elucidated below:

At first, implies the number of clusters M and arbitrarily allocates every data point D_P as of the questionnaire dataset as initial centroids. However, arbitrarily allotting the D_P will not render a better clustering outcome. Thus, the CSO is utilized to get optimum cluster centroids. The complete chicken swarm is split into subgroups, i.e., each sub-group has '1' rooster, a few hens, together with several chicks. All chickens search for food as per their disparate movement principles. A hierarchy exists within every subgroup, and there is a rivalry amongst disparate subgroups as well. In CSO, first, initialize the population of P_c chickens and assign the number of the roosters, the hens, the chicks, along with the mother hens, correspondingly, as N_r, H_s, C_s, and H_m. The best N_r chickens are presumed to be roosters, whilst the bad C_s ones are deemed as chicks. And the rest are considered as hens. All P_c virtual chickens signified via their positions as:

$$Z_{u,v}^{t} \left(u \in [1,........P_c], v \in [1,.........X]\right) \tag{2}$$

At time step t, foods are searched on a $X-$ dimensional space. The optimization issues are minimal ones. Therefore, the best N_r chickens regard to the ones with N_r minimum fitness values. After updating their positions, to ameliorate the optimization accuracy level, the system proposed a GA for updating their new positions. Here, the '2'-point crossover is employed and is mathematically written as,

$$O_1 = \frac{|Z_{u,v}^{t}|}{3} \tag{3}$$

$$O_2 = O_1 + \frac{|Z_{u,v}^{t}|}{2} \tag{4}$$

This brings about effectual optimization. Here q_1 and q_2 are the '2' crossover points. The mutation is executed by swapping the genes as of every chromosome with the arbitrary new genes. These new genes are formed with no repetition in the chromosome. Now, the new optimal position attained after cross-over and mutation are signified as $Z_{u,v}^{new}$. Then, the rooster's motion is written as,

$$Z_{u,v}^{t+1} = Z_{u,v}^{new+t} * \left(1 + Rand\left(0, \sigma^2\right)\right) \tag{5}$$

$$\sigma^2 = \begin{cases} 1, & if \ f_u \le f_k \\ \exp\left(\frac{f_k - f_u}{|f_u| + \varepsilon} \right), & otherwise \end{cases} \quad (6)$$

Here, $k \in [1, P_c], k \ne u$, $Rand(0, \sigma^2)$ signifies a Gaussian distribution, where "0" indicates mean value and "σ^2" symbolizes the standard deviation. ε indicates the smallest constant in the computer and is utilized to avert zero-division error, k signifies a rooster's index, and f specifies the fitness value equivalent to Z. Now, the solution of a hen is updated. The hens could follow their group-mate roosters while searching for food, which is denoted as,

$$Z_{u,v}^{t+1} = Z_{u,v}^{new+t} + Q_1 * Rand * \left(Z_{y_1,v}^{new+t} - Z_{u,v}^{new+t}\right) + Q_2 * Rand * \left(Z_{y_2,v}^{new+t} - Z_{u,v}^{new+t}\right) \quad (7)$$

$$Q_1 = \exp\left(\left(f_u - f_{y_1}\right) / \left(f_u + \varepsilon\right)\right) \quad (8)$$

$$Q_2 = \exp\left(f_{y_2} - f_u\right) \quad (9)$$

Where, $Rand$ signifies a uniform arbitrary number over [0, 1], $y_1 \in [1, ...P_c]$, indicates the index of a rooster (the hen u 's group-mate), whilst $y_2 \in [1, ...P_c]$ signifies the index of a randomly picked chicken (either hen or rooster) as of the swarm. Here, $y_1 \ne y_2$. At last, the chicks trail their mother while foraging for food, which is written as:

$$Z_{u,v}^{t+1} = Z_{u,v}^{new+t} + B * \left(Z_{m,v}^{new+t} - Z_{u,v}^{new+t}\right) \quad (10)$$

Where, $Z_{m,v}^{new+t}$ signifies the new position of the u^{th} chick's mother ($m \in [1, P_c]$), B parameter indicates that a chick would trail mother whilst foraging for its food. These updates render the optimal centroid "D_p^o", which could be deployed in further processing stages.

Afterward, generate a cluster with all the D_P's similar (closest) to centroids. Now, the distance (E_D) betwixt D_P's and optimal centroids is calculated, which is mathematically written as:

$$E_D = \sum_{i=1}^{n} |(D_p)_i - (D_p^o)_i| \quad (11)$$

Next, the D_P is allotted to the cluster center (optimum centroids), whose distance as of the cluster center is a minimum of the entire cluster centers. At last, the centroids are computed for the clusters via evaluating the average of all D_P's in each cluster, which is written as:

$$Mean = \frac{S_{D_p}}{N_{D_p}} \quad (12)$$

Where,

S_{D_p} - Sum of each D_P's,

N_{D_p} - Number of D_P's

Grounded on these steps, the questionnaire is clustered centered on the customers' personal information.

2.4. Training Using BWO-DANN Algorithm

Training a model means learning better values for the bias and the weights as of the labeled examples. This step is chiefly utilized to train the converted questionnaire dataset for designing the framework that investigates the impacts of SMA features on CPI. The converted questionnaire dataset would be trained with the utilization of the BWO-DANN algorithm. Artificial neural network (ANN) that stands as the machine learning approach is most widely utilized to investigate the impacts of CPI. Particularly, NNs are utilized for predicting CPI. As many hidden layers (HL) are utilized in this ANN, it is termed as a deep learning framework [25] [26]. The weight value in this ANN is optimized by utilizing the Black Widow Optimization (BWO) algorithm [27] for lessening the back-propagation problem. The DANN has 3 layers, which are the input layer (IL), HL, and output layer, which are explicated below,

Step 1: Input Layer

It receives the values of the explanatory attributes as input for every observation. In general, the number of input nodes in an IL is equivalent to that of the explanatory variables. The IL proffers the patterns to the network, which interacts with a minimum of one HL. The converted questionnaires dataset is assigned to train the system, and their equivalent weight is determined as follows:

$$L_q = \{l_1, l_2, l_3, ...l_k\} \tag{13}$$

$$W_q = \{w_1, w_2, w_3, ...w_k\} \tag{14}$$

Here, the random weight values are inefficient in accurately predicting the CPI. On this account, they are optimized utilizing the BWO algorithm. The BWO algorithm follows the distinctive mating conduct of black widow spiders and it embraces an exclusive cannibalism stage. On account of cannibalism, species with unsuitable fitness are eradicated as of the circle, thereby resulting in early convergence. BWO is assessed on 51 disparate benchmark functions and 3 real-world engineering optimization problems for verifying its efficiency in acquiring the optimum solutions for the problems.

- Initially, evaluation of fitness function E_f at a widow is done by calculating the fitness of widow as,

$$Fitness = E_f\ (widow) \tag{15}$$

- In BWO, the best individuals are chosen as parents WP_1, WP_2 as per the procreating rate for every generation. Every pair of children is evaluated as:

$$WC_1 = \alpha \times WP_1 + (1-\alpha) \times WP_2 \tag{16}$$

$$WC_2 = \alpha \times WP_2 + (1-\alpha) \times WP_1 \tag{17}$$

Where, $\alpha \sim U(0,1)$,

WC_1 and WC_2 - children.

The mother and children are put to an array and sorted grounded on their fitness value. Then the populace size is restored via competition or cannibalism.

- At last, it updates the weight values by utilizing the below equation,

$$W_q^o = \frac{1}{2} * \frac{Pop_1 + Pop_2}{T_{pop}} \tag{18}$$

Where,

T_{pop} - Total number of population,

Pop_1 and Pop_2 - the 1st and 2nd population of the spiders

Then, the summation of product values of the input converted questionnaire data and the arbitrarily selected optimal weight value is evaluated, which is stated as:

$$I_q = \sum_{q=1}^{n} L_q . W_q^o \tag{19}$$

Where,

I_q - Assigned value

L_q - Converted questionnaire dataset

W_q^o - Optimal weight value

Then, the activation function "A_q" of the network is evaluated as:

$$A_q = f\left(\sum_{q=1}^{n} L_q . W_q^o\right) \tag{20}$$

Then, A_q is sent as input to the HL.

Step 2: Hidden Layer

The layer separated as of the external world is concerned as HL. The HL takes inputs as of the IL and performs its job of calculating and transforming the outcome to output nodes. An HL is made of a pack of hidden nodes. Here, the network multiplies the output of A_q with the weight values and then sums it with the bias value, which is mathematically expressed as:

$$H_q = B_q + \sum_{q=1}^{n} A_q . W_q^o \tag{21}$$

Where,

H_q - HL's output, B_q - Bias value.

Step 3: Output Layer

It receives connections as of the HLs or the IL. It returns an output value corresponding to the predictions of the response variable and it takes the output layer's output. It is stated as:

$$O_q = B_q + \sum_{q=1}^{n} H_q . W_q^o \tag{22}$$

Lastly, the loss function "$Loss_q$" is evaluated with the below equation,

$$Loss_q = [T_q + O_q] \tag{23}$$

Where, T_q - Target output of NN

For $Loss_q$, set the minimum value as the threshold. When the initialized threshold met this fitness, the output is concerned as the final output. Contrarily, the position of the weight is renewed and the weight is optimized by utilizing the same BWO algorithm. Again, the output unit is determined centered on this BWO-DANN algorithm, and the output data is trained for the retrieval process. The BWO-DANN algorithm has the below pseudocode (Figure 3).

Input: Converted questionnaire dataset (L_q)
Output: updated weight (i.e. adjusted weight)

Begin
  Initialize H_q be hidden layer's output, W_q^o be the optimized weight value, and B_q
  Calculate the number of training samples
    $Numquestinnaires = Q$
  If (Q=0)
    Error (Q is not an integer)
  End if
  While ($k < iter$) do
    Update the optimized weight value using BWO
      Determine the fitness value of the function
      Compute each pair of children by using
        $WC_1 = \alpha \times WP_1 + (1-\alpha) \times WP_2$
        $WC_2 = \alpha \times WP_2 + (1-\alpha) \times WP_1$
    For H_q do
      Estimate activation function by using
        $A_q = f\left(\sum_{q=1}^{n} L_q . W_q^o\right)$
      Calculate hidden layer output using $H_q = B_q + \sum_{q=1}^{n} A_q . W_q^o$
      Calculate output layer output using $O_q = B_q + \sum_{q=1}^{n} H_q . W_q^o$
      Update the targeted output of the neural network
    End for
  End while
End

Figure 3. Pseudocode for the BWO-DANN algorithm

2.5. TESTING USING KFCV

After the training of the converted questionnaire dataset, the model is tested centered on the KFCV in respect of accuracy and precision. For assessing the performance, test data is utilized. KFCV is a procedure utilized for estimating the skill of the model on new data and its procedures are explicated below,

Step 1: Initially, the original testing dataset (that is, L_q) is partitioned to "a" equal subsets. Every subset is named a fold and is written as $k_1, k_2, k_3, ...k_a$. In this research, 5 folds are applied for testing.

Step 2: for $i = 1$ to $i = a$

- Consider the fold k_i , as a validation set, whereas, the other $a-1$ folds as the cross-validation testing set
- Test the system utilizing the cross-validation testing set and assess the model's accuracy (evaluation score) by validating the predicted results against the validation set as follows:

$$Accuracy = \frac{C''_{pc}}{T''_{tc}} \times 100\% \tag{24}$$

Where, C''_{pc} - Correctly predicted class, T''_{tc} - Total testing class.

Step 3: At last, the performance of the complete testing set centered on the evaluation score is summarized.

2.6. Purchase Intention Using Mean Model

A notable step in investigating the impacts of SMA features on CPI is Purchase intention. It is an imperative indicator for assessing customer behavior since it could gauge the likelihood of a customer to purchase a product. When the purchase intention is higher, the customer's readiness to purchase a product will be higher. This work examines the CPI utilizing the mean model. It takes the average between the total customers who commented on the questionnaires and the customers who commented about the SM sites centered on gender and age. It is expressed as:

$$Mean = \frac{S_{cpi}^{"}}{T_{cpi}^{"}} \quad (25)$$

Where,

$S_{cpi}^{"}$ - Sum of the customers who have commented on the questionnaires about SMA

$T_{cpi}^{"}$ - The total number of customers commented on the questionnaires.

In this research, male gender and above 25 years are filtered from the term $S_{cpi}^{"}$. These evaluations effectively predict CPI.

3. RESULTS AND DISCUSSION

Here, the performance of the proposed novel framework for investigating the impacts of SMA features on CPI is analyzed. For validating the performance gains of the BWO-DANN algorithm, it is contrasted to the existing classifiers. This work regards the collected questionnaire dataset. The performances are analyzed as explicated in the below sections. Here, the proposed BWO-DANN algorithm is analogized to the conventional ANN, Support Vector Machine (SVM), Adaptive Neuro-Fuzzy Inference System (ANFIS), and also K-Nearest Neighbour (KNN) algorithms. Furthermore, the proposed BWO-DNN model is compared with existing works such as AHP+fuzzy based GA [28], and SEM [20] methods.

3.1. Evaluation Metrics

The proposed model performance is contrasted regarding some qualitative metrics, say, accuracy, recall, sensitivity, f-measure, specificity, precision, training time, and testing time. The basic parameters that are assessed are 'true positive' (y_p), 'true negative' (y_n), 'false positive' (x_p), and 'false negative' (x_n) values. The confusion matrix for this research work is shown in Figure 4.

	Predicted CPI		
		Positive	Negative
Actual CPI	Positive	True Positive (TP) (47.6)	False Negative (FN) (1.34)
	Negative	False Positive (FP) (1.56)	True Negative (TN) (49.5)

Figure 4. Confusion matrix of CPI prediction

These mathematical denotations of the performance metrics are explicated below.

a) Accuracy

It implies the probability that a CPI is accurately identified, that is, the customers' intention on SM sites. It is evaluated as:

$$Accuracy = \frac{y_p + y_n}{y_p + y_n + x_p + x_n} \quad (26)$$

b) Sensitivity

It is the ability of a screening test for detecting a true positive, which reflects the test's ability to properly predict the CPI, or, if 100%, predict all CPI by those customers testing positive on the test. It is expressed mathematically as:

$$Sensitivity = \frac{y_p}{y_p + x_n} \quad (27)$$

c) Specificity

It implies the ratio between the accurate prediction of CPI and the total classified result and is evaluated as:

$$Specificity = \frac{y_n}{y_n + x_p} \quad (28)$$

d) Precision

It indicates the number of exactly predicted CPI over all the predicted information for a specified class and is stated as,

$$\Pr ecision = \frac{y_p}{y_p + x_p} \tag{29}$$

e) Recall

It is the number of precisely predicted purchase intentions over all the records available for a specific class in the dataset and is written as,

$$\operatorname{Re} call = \frac{y_p}{y_p + x_n} \tag{30}$$

f) F-measure

It utilizes the precision value and recall value to find their harmonic mean for the holistic evaluation of a system and is written as:

$$F - measure = \frac{2 \, . \Pr ecision \, . \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \tag{31}$$

g) Training time

It is gauged by taking the difference betwixt the training starting time "$start\ (t)$" and training ending time "$End\ (t)$". It implies the time taken to train the dataset and is mathematically written as:

$$T_{time}(t) = End\ (t) - Start\ (t) \tag{32}$$

3.2. Comparative Analysis

The comparative section explicates the comparison graph of the statistical measure results. Here, the comparison is done between the proposed BWO-DANN and the existing ANN, SVM, KNN, ANFIS, AHP+fuzzy based GA, and SEM methods regarding metrics, say, sensitivity, accuracy, specificity, f-measure, recall, precision, together with training time. This comparison could be graphically explicated using the below Figures 5-8.

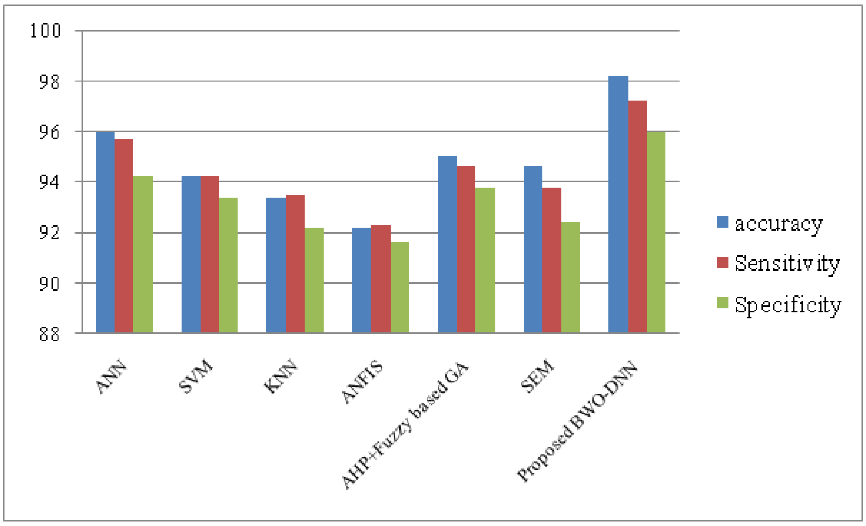

Figure 5.Accuracy, sensitivity, and specificity graph for the proposed model with the existent classifiers

Discussion: Figure 5 analogizes the proposed BWO-DANN with the existing ANN, SVM, KNN, ANFIS, AHP+fuzzy based GA, and SEM methods centered on their performance in respect of the sensitivity, accuracy, together with specificity. The sensitivity, accuracy, together with specificity metrics are proportions and are necessary for investigating the CPI. Here, the proposed BWO-DANN classifier attains 98.35 % accuracy, but the existing ANN, SVM, KNN, ANFIS, AHP+fuzzy based GA, and SEM methods attain an accuracy level of 96%, 94.2%, 93.4%, 92.2%, 95%, and 94.6% which is smaller when analogized to the proposed BWO-DANN classifier. Likewise, the proposed BWO-DANN offers 97.33% sensitivity and 96.36% specificity, but the existing classifiers proffer low sensitivity along with low specificity. From this discussion, the classifier that shows the topmost performance is the proposed BWO-DANN.

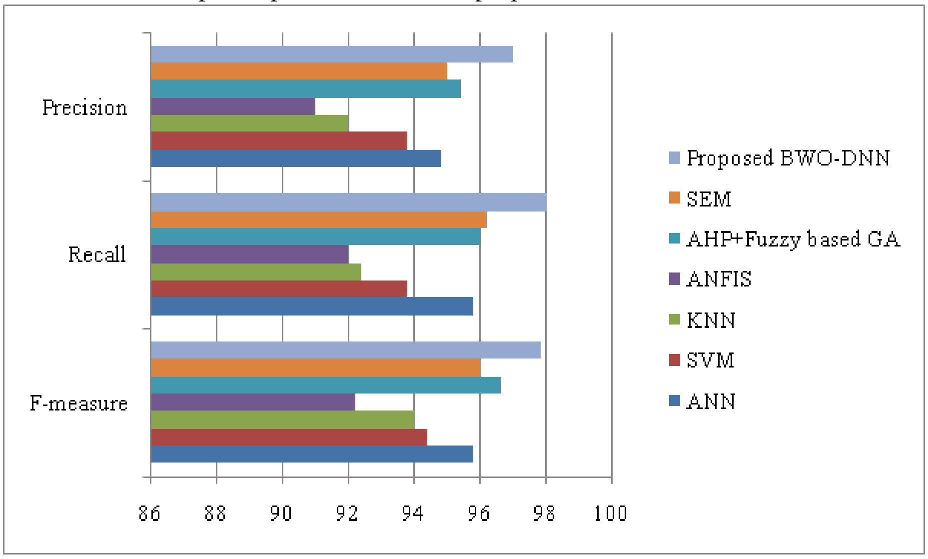

Figure 6. Comparative analysis of the proposed model with the conventional classifiers

Discussion: Figure 6 is analyzed for finding the performance level of the existing ANN, SVM, KNN, ANFIS, AHP+fuzzy based GA, and SEM methods and the proposed BWO-DANN in respect of precision, f-measure along with recall metrics. If precision is higher, then it indicates that an algorithm substantially returns more pertinent results than irrelevant ones. And, an algorithm returns maximum relevant results only for higher recall value. Here, the existing ANFIS classifier acquires 90.79 % precision, 91.87 % recall, and 92.12 % f-measure. In addition, the existing SEM method acquires 95% precision, 96.2% recall, and 96% F-measure. The proposed BWO-DANN classifier offers 96.32 % precision, 97.69 % recall, and 97.37 % f-measure, which is greater when analogized to all existing classifiers. From these results, the proposed BWO-DANN classifier acquires an encouraging efficiency on considering the existing classifiers.

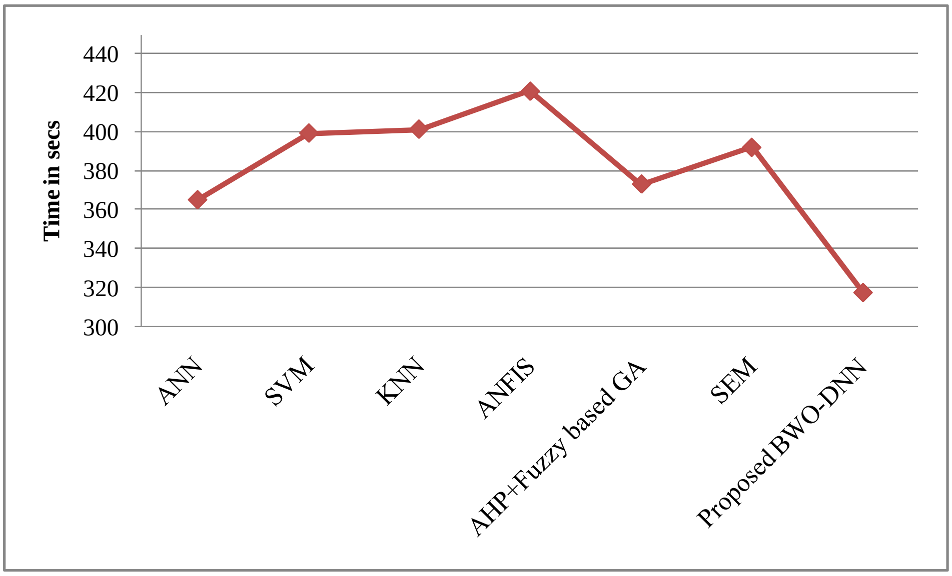

Figure 7. Training time graph for the proposed model with the existing models

Discussion: Figure 7 contrasts the proposed BWO-DANN classifier and the existing classifiers centered on their respective performance regarding training time. Training time is as well concerned as an imperative measure for predicting CPI. Here, the existing ANFIS, ANN, SVM, KNN, AHP+fuzzy based GA, and SEM methods take 421s, 365s, 399s, 401s, 373s, and 392s training time. But the proposed one takes just 317s training time, which is lower when analogized to all existing classifiers. From these results, the proposed BWO-DANN is confirmed to show the topmost performance.

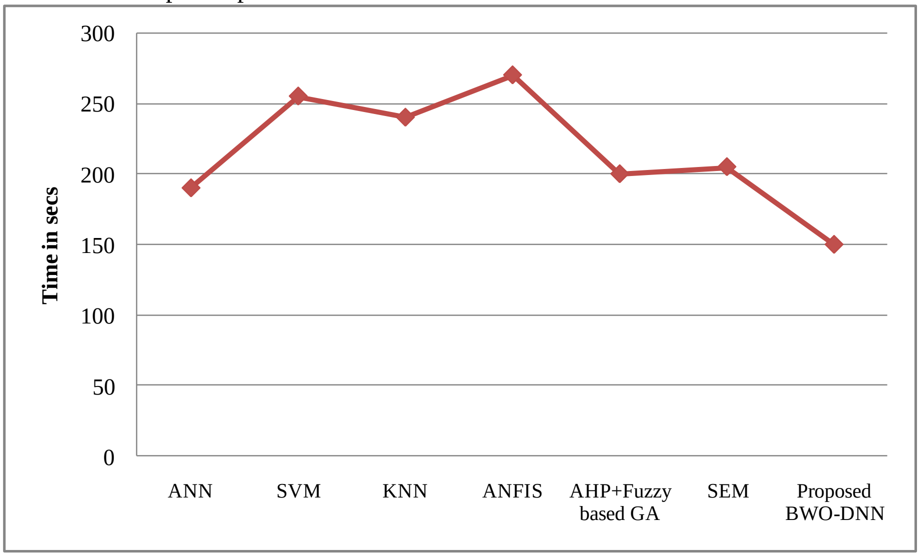

Figure 8. Testing time graph for the proposed model with the existing models

Discussion: Figure 8 shows the testing time graph for the proposed and existing models. The proposed model takes 150s and it is 21.05%, 41.18%, 37.50%, 44.44%, 25%, and 26.83% better than existing ANN, SVM, KNN, ANFIS, AHP+fuzzy based GA, and SEM methods respectively. Thus, the outcomes reveal that the proposed model is well suited for CPI prediction.

4. CONCLUSION

The attention of practitioners and researchers has been increasing on the issues of SMA over the marketing area. On this account, this work proposed a framework for investigating the impacts of SMA features on CPI utilizing the BWO-DANN algorithm. The data for the current investigations were gathered as of the converted questionnaire dataset. During the performance analysis, the proposed BWO-DANN and existing ANN, SVM, KNN, and ANFIS classifiers are analogized centered on their performance regarding some qualitative metrics. The system's performance was noticed to have a notable impact on the CPI via some metrics, like accuracy, sensitivity, precision, f-measure, specificity, training time, and recall. Here, the proposed framework acquires 98.35% accuracy with less training time. From the empirical outcomes, the proposed one effectively predicted the CPI. In the future, more questionnaires can be gathered from online, and advanced machine learning algorithms can be used to predict the CPI.

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