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A DECISION SUPPORT MODEL TO IMPROVE COMPLAINT HANDLING IN E-COMMERCE TO ENHANCE CUSTOMER TRUST

YEHIA HELMY[1], MERNA ASHRAF [2*], AND LAILA ABDELHAMID [3]
[1,2]Department of Business Information Systems, Faculty of Commerce and Business Administration, Helwan University, Cairo, Egypt
[3]Department of Information Systems, Faculty of Computers and AI Helwan University, Cairo, Egypt
Email: [1]ymhelmy@yahoo.com, [2]merna123ashraf@gmail.com, [3] Laila.abdelhamid@fci.helwan.edu.eg

ABSTRACT

In today highly competitive environment, e-commerce businesses confront numerous challenges that threaten their sustainability. Trust is one of these challenges. Customer trust is the key element that ensures customer loyalty. Therefore, businesses striving to maintain a competitive advantage must make their customer the focal point of all operations. Effective complaint handling is one of the key elements for increasing customer trust. The complaint is an invaluable resource for businesses to retain customer trust and loyalty. Given the need to enhance the efficiency of addressing complaints from e-commerce customers, this study aims to revamp the complaint-handling process. This study proposes a new decision support model (E-CDSM) that integrates the automation concept. The model employs a classification approach to classify complaints according to their respective issues, clustering to group similar customers into batches, genetic algorithms to generate a list of suitable solutions for each batch, and a rule-based inference engine to produce instructions that aid staff in making optimal decisions for each complaint. The implementation of the E-CDSM shows a significant reduction in the processing time of complaints, with an increase in the accuracy of solutions provided to customers and the instructions provided to staff to make the best decisions. In turn, improved customer experience which resulted in an enhancement in customer trust and customer loyalty that retains business sustainability in the e-commerce market.

Keywords: *Customer Trust; Complaint Handling; Online Complaints; Text Classification; Decision Support Systems, and Business Sustainability.*

1. INTRODUCTION

The ongoing advancement of digital technology is giving rise to international online marketplaces aka e-commerce. E-commerce affords businesses a plethora of benefits that manifest in various forms, including reduced operating expenses, access to reasonably high markets, facile customer data collection, facile outreach to prospective customers, and ease of scaling up. Even it is still a double-edged weapon because e-commerce businesses face several obstacles [2].

Trust is one of the obstacles that have a significant impact on businesses [2]. Trust is the bond that attaches the customer to the company. The higher the level of trust between businesses and customers. The higher the customer loyalty [3]. Trust is influenced by multiple factors, one of these factors is the company's reputation which is affected by word of mouth [4].

Word of mouth, whether favorable or unfavorable stems from customer experience. If customers' experience doesn't live up to their expectations. Customers might feel dissatisfaction, disappointment, or even complaint [4]. As a result, customers' complaints have a significant influence on a business's trust [5]. Managers thus keep an eye on how complaints are handled. Complaint handling is a technique used for solving customer complaints, and it consists of several phases [5]. Figure 1 summed up the complaint-handling process.

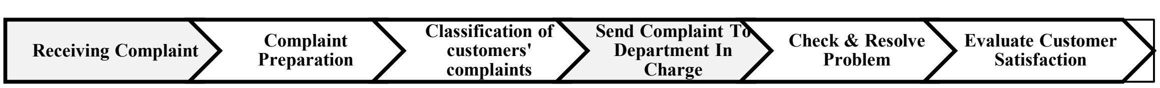

Figure 1. Complaint Handling Phases.

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Most complaint handling systems employ many strategies and tactics to give customers or employees one or more benefits but none of them offers all of them. Therefore, the main goal of this paper is to help e-commerce businesses handle customers' complaints more rapidly and accurately by presenting a decision support model that employs machine learning and a rule-based inference engine to provide quick responses and precise solutions to customers' complaints, and assist staff in many ways to help them make the right decisions in different situations to enhance business trust which is the paper's aim.

The rest of this paper is divided as follows: Section 2 presents the research methodology and related. In Section 3 the proposed model is presented. Section 4 demonstrates the experiments and results. In Section 5, the evaluation is discussed, and Finally, Section 6 presents conclusion and future research.

2. RESEARCH METHODOLOGY AND LITERATURE REVIEW

2.1 Research Methodology

The goal of this paper is to comprehend the complaint-handling process and its various phases to redesign and automate those phases to speed up response times, improve the precision of solutions and assist employees who are overworked or inexperienced in making the best decisions regarding various complaints, all of which will increase customer satisfaction, which will in turn, increase customers trust.

Therefore, the most widely used databases (Science Direct, Springer, and IEEE) were scanned to find articles that were relevant to the paper's goal. For this purpose, Only English-language articles from scholarly journals that were published between 2018 to 2024 have been considered.

The search process was performed based on the primary terms from the paper's goal to ensure that the material employed was pertinent to it and served as a solid foundation for our paper. As a result, the search terms that were utilized were "Customer Trust", "Complaint Handling", "Online Complaints", "Decision Support Systems", and "Business Sustainability". The search yielded 410 articles. Figure 2 illustrates the results of the search process in terms of the year of publication.

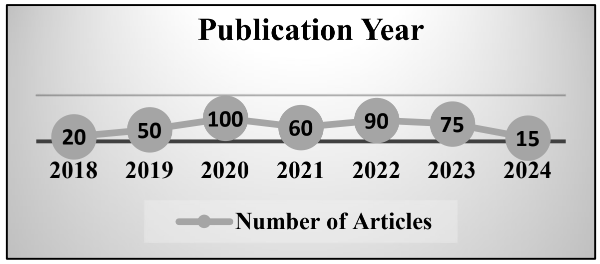

Figure 2. Classification of Articles by Year of Publication.

2.2 Related Work

Effectively addressing complaints has become increasingly important in recent years to strengthen the bond between customers and businesses. For these reasons, many researches were conducted in an attempt to enhance complaint handling in different fields,

[6] Proposed framework to help e-commerce handle customers' complaints concerning trust, transparency, and timeliness. It offers advice on what staff should do when facing these difficulties. The results show that these suggestions assist the complaint-handling department in dealing with complaints effectively.

[7] Developed a Smart Complaint Management System (SCMS) in the educational sector comprising a mobile, chatbot, and web application. According to the findings, the model receives an average score of 4 out of 5 in customer satisfaction.

[8] Proposed a mobile application in the crime sector that would allow people in Riyadh to efficiently file and track complaints. The results show that the system helps the police agency conduct effective criminal investigations.

[9] Proposed an active learning SVM model to automate the processing of customer complaints in the banking sector. The findings demonstrate that, with an accuracy of 86.4%, the proposed model eliminates manual labor and lowers workload.

[10] Proposed a customer complaint management system based on Service Oriented Architecture (SOA) that can raise customer satisfaction in the governmental sector. The outcomes demonstrate that the system' succeeded in fostering citizen loyalty and adaptation.

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[11] Proposed an online illegal event reporting system in the crime sector that is cloud-based. It manages reports of illicit behavior. The results show that the system is compatible with theoretical analysis, case deletion prevention, non-repudiation, authentication, data integrity, and reward systems.

[12] Developed an online system for managing smoking complaints in the health sector to support the World Health Organization's Blue Ribbon Campaign against tobacco use in Malaysia. The results show that the system is effective in tracking duplicate complaints, tracking complaint status, and offering complaint data analysis.

[13] Proposed a Customer Experience Management Platform (CEMP) in the telecommunication sector that encourages customers to engage in regulating the quality of services they receive to lower customer dissatisfaction. The results demonstrate that the system succeeded in providing customer feedback, nearest technician acknowledgment, and user profile maintenance is successful.

[14] Proposed a model based on blockchain in the crime sector to manage complaints for criminal offenses that are both cognizable and not. The results showed that the suggested technique encourages people to come forward and file complaints and offers openness while guaranteeing the confidentiality of stored data.

[15] Proposed an automatic crime reporting system that is based on Raspberry Pi, Microsoft IoT, mobile application, and web application for automated crime reporting and quick reaction. The results demonstrated that the average reporting time to the police control center was reduced to less than 30 seconds.

[16] Proposed a customer complaint management system in the industrial sector that uses artificial neural networks and the Naive Bayesian classifier to swiftly and efficiently answer customers' inquiries. The findings demonstrate that the system successfully lowers costs and effectively manages data while achieving an accuracy of 85%.

[17] Proposed a new complaint platform based on Artificial intelligence in the governmental sector to enhance citizen-government interactions and offer prompt feedback. According to the findings, the proposed model enables face-to-face interaction through chatbots.

[18] Presented a mobile application for reporting bribes in the governmental sector, which has characteristics like decentralized storage that would make data security maintenance less risky, streamline the reporting process, lower the likelihood of erroneous reports, and give direct insight into the report's development.

[19] Proposed a deep learning-based model in the health sector to automatically provide a probable error code for upcoming medical technology complaints. The findings demonstrated that it can correctly identify the problem code in over 75% of instances.

[20] Presented an active learning-based artificial intelligence model in e-commerce that utilizes expert knowledge to generate faster, more dependable complaint processing. The findings demonstrate that the model achieves a 37% increase in accuracy along with a decrease in average complaint processing time.

[21] Proposed the "Anonymo" system in e-commerce as a discreet and efficient way to handle customers' concerns. After analyzing customer concerns, the system gives the end user the proper answers and output. The findings demonstrated that the system achieved an accuracy of 88.26% when classifying complaints using SVM.

[22] Explained the factors that increase the average handling time for e-complaints in e-commerce. And applied classification techniques like k-nearest neighbors and logistic regression on a complaint dataset. The results showed that logistic regression performed better than k-nearest neighbors with an accuracy of 83.9%.

[22] Proposed a water quality complaint management system that is based on water meters and advanced metering infrastructure. This system enables users to report complaints, analyze their water usage in real time, assess how well they are adhering to water advisories, and find leaks that may have occurred after the water meter was installed.

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[23] Proposed a novel method for dividing online complaints into several groups. Twitter complaint "tweets" were collected and classified using a multinomial logistic regression technique. The findings demonstrate that the model was effective in reducing the amount of time needed to handle complaints.

[24] Developed an information system based on React JavaScript technology to improve the handling of customers' complaints about public services. The findings showed that the system expedites connected parties' responses and the customer's complaint-handling procedure.

[25] Developed a customer complaint system in e-commerce based on Extreme Programming that enables customers to contact directly for complaint resolution. The results show that the system is useful and in line with the user's preferences.

[27] Proposed a complaint system in e-commerce that uses text analytics and operational research methods to automatically classify and prioritize complaints. Transformer-based deep learning (DL) approaches are employed for text categorization, while a straightforward weighting approach from the multiple-criteria decision-making (MCDM) is used for the labeling step. According to the findings, it achieves an accuracy (ACCU) of 92.1% and an area under the curve (AUC) of 97%, respectively.

According to the related research, the majority of complaint-handling systems employ a variety of strategies and tactics to give customers or employees (who utilize the system) one or more benefits, like prompt service, precise solutions, or assistance in a variety of ways, but none of them offers all of them, as Table 1 illustrates. Therefore, the main goal of this paper is to provide the three aspects that distinguish the complaint-handling system and help businesses to gain customers trust which are:

- Quick response time.
- Accurate solutions to customers' complaints.
- Accurate instructions that aid employees in making the right decision.

Table 1. An Overview of The Different Facets of Complaint-Handling Systems That The Majority of Research Has Focused On.

Authors	Criteria		
	Responsiveness (Quick Response)	***Reliability (Solutions Accuracy)***	***Capability (Assistance Accuracy)***
[6]	✓	-	✓
[7]	-	✓	-
[8]	✓	-	-
[9]	✓	-	-
[10]	-	✓	✓
[11]	-	-	✓
[12]	-	-	✓
[13]	-	-	✓
[14]	✓	-	✓
[15]	✓	✓	-
[16]	✓	✓	-
[17]	✓	-	-
[18]	-	-	✓
[19]	-	✓	-
[20]	✓	-	✓
[21]	-	✓	-
[26]	✓	-	-
[22]	✓	✓	-
[23]	✓	-	-
[24]	✓	-	-
[25]	✓	✓	-
[27]	✓	-	-
The Proposed Model	✓	✓	✓

3. A DECISION SUPPORT MODEL FOR HANDLING E-COMPLAINTS (E-CDSM)

To meet the tight customer requirements of e-commerce complaints, the complaint handling process must be executed efficiently, especially with e-complaints that increase daily. Therefore, an Electronic Complaints Decision Support Model (E-CDSM) is proposed, for redesigning and automating the handling of e-complaints. The objective of the proposed model is to enable employees in the complaint-handling department to provide customers with appropriate solutions to their complaints in a short response time which increases their satisfaction and enhances their trust in the business, and also provides employees with instructions that help them make the right decision toward a specific complaint and its solution.

The architecture of the proposed model comprises 4 layers. The first layer is the text pre-processing layer; the second layer is the text classification layer; the third layer is the solution generation layer; and the fourth layer is the instructions generation layer. Figure 3 presents the layers of the proposed model.

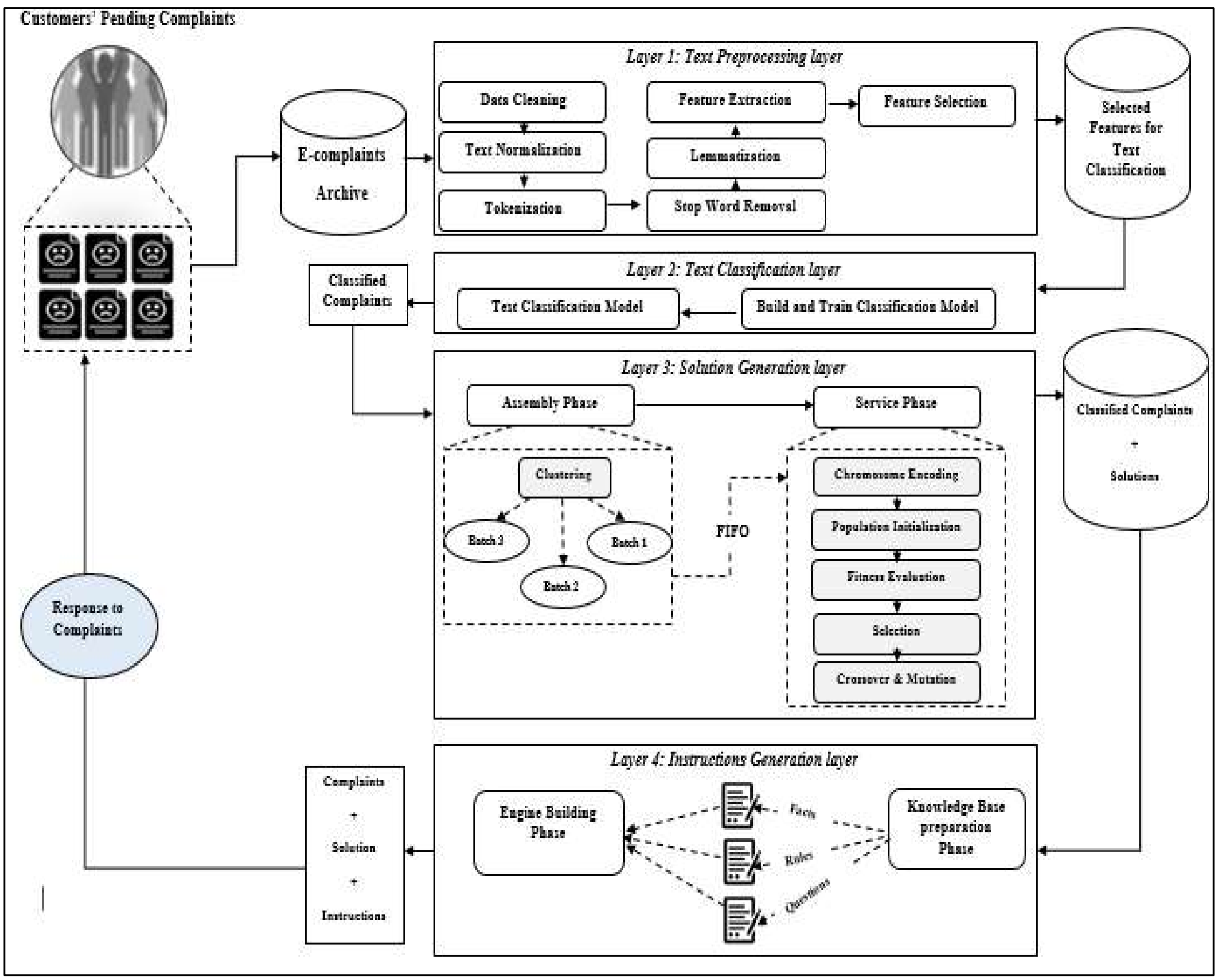

Figure 3. The Proposed (E-CDSM) Model.

3.1 E-complaint Archive

In the e-commerce business, Customers submit their e-complaints through online interfaces or e-mails and these pending complaints wait in the e-complaint archive to be handled by the responsible department.

3.2 Layer 1 (Text Pre-processing Layer)

Text preprocessing is the most crucial and time-consuming layer that prepares e-complaints for further analysis. It is made up of seven important phases which are data cleaning, text normalization, tokenization, stop word removal, lemmatization, feature extraction, and feature selection. Each of these phases has a significant role in preparing e-complaints to be accurately classified in the text classification layer.

3.2.1 Data cleaning phase

This phase is responsible for detecting and fixing any anomalies in data such as missing values, duplicates, outliers, and inconsistencies. Finding empty or Nan values, Finding Records that are identical in all features, the standard deviation and the open refine program are the techniques that are used to detect such anomalies.

After detecting anomalies different fixing methods are used to fix them. To fix missing values, two techniques—imputation and deletion—are applied. When a categorical variable's percentage is larger than 50%, the imputation approach is used to fill it with the dummy variable "missing" and when it is less than 50%, the mode is used to fill it. To remove complaints whose complaint narratives were missing, the deletion approach is applied. Duplicates are fixed by keeping the first record and deleting all others, outliers are fixed by deletion, and inconsistencies are fixed by combining many representations into a single one.

3.2.2 Text normalization phase

This phase is responsible for normalizing text to be free from any URLs, mentions, hashtags, contractions, emojis, abbreviations, elongated characters, punctuations, and digits.It includes the following methods:

1. Remove URLs, Mentions, and Hashtags.
2. Expand Contractions.
3. Replace emoticons and emojis.
4. Replace abbreviations and slang.
5. Replace elongated characters.
6. Fold to lowercase.
7. Remove punctuation.
8. Remove digits.

3.2.3 Tokenization phase

This phase separates normalized complaints into tokens. The word Tokenization method is used in this phase to break down the text into individual words by using white spaces as delimiters.

3.2.4 Stop word removal phase

This phase eliminates all the stop words that represent low-level information to make the focus only on the important information. The deletion approach is used in this phase to eliminate all the stop words.

3.2.5 Lemmatization phase

In this phase, the wordnet lemmatizer database which provides semantic relationships between its words is used to return words to their root words to be used in the feature extraction phase.

3.2.6 Feature extraction phase

This phase is responsible for converting the normalized text into machine-understandable numerical values. Two feature extraction methods are applied in this phase. The labeling encoding technique in Equation 1 [28] turns each distinct issue into a numerical value and TF-IDF in Equation 2 [29] turns lemmatized words into a matrix of features that will be used in the text classification layer.

$$X(m) \Rightarrow N(m) \qquad (1)$$

Where
X represents the categorical value of feature m.
N represents the numerical value of feature m.

$$\text{TF-IDF}(t,d,D) = TF(t,d) * \log\left(\frac{D}{df_t}\right) \qquad (2)$$

Where
t represents the terms;
d represents each document;
D represents the collection of documents;
df_t represents the sum of documents with the term t in it.

3.2.7 Feature selection phase

This phase is responsible for choosing particular features to be used in the text classification layer. The suitable features for the Text classification layer are chosen using the chi-square method in Equation 3[30]

$$\text{Chi-square } (X^2) = \sum \frac{(O-E)^2}{E} \qquad (3)$$

Where
O represents observed frequencies.
E represents expected frequencies

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3.3 Layer 2 (Text Classification Layer)

This layer classifies pending complaints that were prepared in the text preprocessing layer to their pertinent issues so that they can be sent to the appropriate department for resolution. This layer is composed of the build and train phase ,and the test phase.

3.3.1 Build and train phase

In this phase, the classifier is constructed using the decision tree in Equation 4 [31], which demonstrates its effectiveness in multi-class classification. And 80% of the complaint data are used to train it to produce accurate results.

$$\text{GainRatio}(S, a) = \frac{\text{Gain}(S,a)}{\text{Entropy}(a)} \qquad (4)$$

Where
S represents train dataset S $[(x_1,y_1),(x_2,y_2),..,(x_m,y_m)]$.
a represent an attribute from Attribute set A $=\{a_1,a_2,\ldots,a_d\}$.

3.3.2Test phase

In this phase, 20% of the complaint data are used to measure the classifier performance in terms of its effectiveness (precision, recall, and f1) as well as speed.

At the end of this layer, The pending complaints were finally classified into their relevant issues and made ready for resolution by the accountable department.

3.4 Layer 3 (Solution Generation Layer)

This layer is responsible for providing solutions for customers' complaints. The input for this layer is the classified complaints that are prepared by the text classification layer. The assembly phase and the service phase are the two phases that make up this layer.

3.4.1 Assembly phase

This phase is responsible for clustering pending complaints that stand in a queue waiting for their turn to be resolved into batches based on the issue and method utilized. When the queue fills up to its K limit, batches start to form. Each of the generated batches contains x number of complaints but is treated as a target customer that needs a solution because all the complaints that exist in each batch are very similar. In this phase, the k-means in Equation 5 [32] is used to create batches and the batches begin to move to the servers to be resolved using the First In First Out (FIFO) principle.

$$J(V) = \sum_{i=1}^{c}\sum_{j=1}^{c_i}\left(\left\|x_i - v_j\right\|\right)^2 \qquad (5)$$

Where
J(V) represents the objective function.
$\|x_i - v_j\|$ *is* the Euclidean distance between x_i and v_j.
c_i *represents* the number of data points in i^{th} cluster.
c represents the number of cluster centers.
[4]

3.4.2 Service phase

This phase provides solutions for the batches which are produced in the assembly phase using the genetic algorithm.

A customer-solution matrix, denoted by C_S(c,s) is created and used in this phase, where c stands for the customer and s for the solution. C_S(c,s) can have a value of 0 or 1, with 0 denoting that the customer c didn't provide the solution s a rating.

- **Criterion 1:** Each individual stands for a group of potential solutions.
- **Criterion 2:** The batch for which the solutions are generated is the target customer.
- **Criterion 3:** The similarity is a customer-based similarity value that determines the degree of connection between the target customer and the customers who rated at least one solution within an individual. This value can range between -1 and 1.
- **Criterion 4:** The best list of solutions is a set of solutions with the highest degree of similarity between the target customer and the customers who rated at least one solution belonging to this set and possible favorite solutions of high prediction rates to the target customer.

Following the analysis of the customer-solution matrix C_S(c,s), the initial population of M individuals is chosen randomly. The individual within the initial population contains random solutions. Following that, a loop with a maximum number of iterations (maximumG) is started. The current generation is used to create the following generation. The similarity value of each individual is calculated within the loop. The top candidates are then selected based on the similarity value. The parents are selected to produce children by applying the single-point crossover and single-point mutation. After that, the prediction value of each of the generated individuals is calculated. At the end, the target customer is given the best list of solutions, which is comprised of the solutions provided by the individual with the greatest similarity and prediction scores.

- **Genetic representation**

In the service phase, Every individual is represented by a 1-dimensional array that serves as a possible list of recommendations for the target customer. Each gene in an individual is a potential solution. Therefore, there are M possible alternative sets of solutions to the target customer with M individuals (population size). Each one should include the solution that has been rated by the target customer as well as other options that have not yet received a rating from the target customer. Therefore, N solutions that can be offered to the target customer are contained in every individual.

- **Fitness function**

In the service phase, The Truncation selection procedure is applied where the fitness value is used as a filtering threshold. To give the target customer a more precise and high-quality solution, this value is derived using two distinct norms: similarity in Equation 6 [33] and prediction in Equation 10 [33]. Each individual's fitness displays its goodness. The best individual is therefore the one with the highest fitness value. The most effective individual z offers the target customer a single set of solutions with high similarity and high prediction scores.

The filtering level in this phase is established under the presumption that people who share comparable interests are likely to have similar attitudes about other interests. In other words, during this phase, a list of solutions that have been rated by the target customer's neighbors is searched. The total similarity values, Sim(x, c), between the target customer and all the customers who rated at least one solution within (z) are equal to the similarity value of the individual (z) in Equation 6. As a similarity metric, the Pearson correlation metric is employed, the Pearson correlation metric in Equation 8 [33] yields results in the range of -1 to 1. To solve the issue of having a high similarity value for a small number of solutions as opposed to a somewhat lower similarity value for a large number of solutions, the Jaccard metric in Equation 9 [33] is employed.

$$\text{Similarity}(z)= \sum_{c\in C} \text{Sim}(\text{targetCustomer}, c) \tag{6}$$

$$\text{Sim}(\text{targetCustomer},c) = \text{Psim}(\text{targetCustomer}, c) * \text{Jaccard}(\text{targetCustomer}, c) \tag{7}$$

$$\text{Psim}(\text{targetCustomer},c) = \frac{\sum_{i\in S}(r_{\text{targetCustomer},s}-\bar{r}_{\text{targetCustomer}})(r_{c,s}-\bar{r}_c)}{\sqrt{\sum_{i\in S}(r_{\text{targetCustomer},s}-\bar{r}_{\text{targetCustomer}})^2}\sqrt{\sum_{i\in S}(r_{c,s})-\bar{r}_c)^2}} \tag{8}$$

$$\text{Jaccard}(\text{targetCustomer},c) = \frac{|C_{\text{targetCustomer}} \cap C_C|}{|C_{\text{targetCustomer}} \cup C_C|} \tag{9}$$

Where

C represents the set of all customers who rated at least one solution in z.The similarity between the customers targetCustomer and c, Sim(targetCustomer, c).

Psim(targetCustomer, y) is the Pearson correlation metric in Equation 8.

Jaccard(targetCustomer,y) is the Jaccard metric in Equation 9.

S is the group of solutions that both customers targetCustomer and c have rated. Each customer in C rated at least one solution of z.

$r_{(targetCustomer,s)}$ is the rate of customer targetCustomer on solution s.

$\bar{r}_{(targetCustomer)}$ is the mean rating value of customer targetCustomer.

$|C_{targetCustomer} \cap C_C|$ represents the number of solutions that both customers targetCustomer and c rated.

$|C_{targetCustomer} \cup C_C|$ represents the number of either targetCustomer or c rated solutions.

- **Selecting the best solutions**

The final generation, which comes after the GA is finished running, includes a number of the best individuals. Each individual represents a list of solutions and those solutions are rated by the neighbors of the target customer. At this point, One of the individuals should be selected and provide its solutions to the target customer. Therefore, the prediction rate of each individual z for the target customer in Equation 10 is computed. This is equal to the sum of the prediction rates for the target Customer, and every solution s ∈ z. The modified weighted sum yields predicted rates for each of the individual's

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solutions, and the best individual is the one with the highest prediction rate.

The model returns the individual for whom the similarity value is the highest if several individuals have the highest prediction value, which is quite improbable. And If more than one individual has the same highest prediction and greatest similarity values, the model returns the one with the highest prediction and highest similarity values.

$$\text{Predict}(z,\text{targetCustomer}) = \sum_{s\in z} P_{\text{targetCustomer},s} \quad (10)$$

$$P_{(\text{targetCustomer},s)} = \bar{r}_{\text{targetCustomer}} + \frac{\sum_{c\in C}(r_{\text{targetCustomer},s} - \bar{r}_{\text{targetCustomer}}) * \text{Psim}(\text{targetCustomer},c)}{\sum_{c\in C} \text{Psim}(\text{targetCustomer},c)} \quad (11)$$

At the end of this layer, many pending complaints are resolved at once and are provided with a list of appropriate solutions which may help in reducing response time and increasing customer satisfaction which are key factors in customer trust.

3.5 Layer 4 (Instructions Generation Layer)

This layer is responsible for creating instructions for the employees in the complaint handling department on how to reach the solutions provided in the solution generation layer to overcome the mistakes that some employees make. These mistakes could be the result of insufficient staff experience or work overload at a particular period. As a result, these instructions are viewed as a support to make the right decision that can satisfy customers in a variety of scenarios and issues. A rule-based inference engine is thus created in this layer through the preparation of the knowledge base and the creation of the engine.

3.5.1 Knowledge base preparation phase

In this phase, three files are created by using a prolog which are the fact file containing all the facts, the rule file containing all the if-then rules, and the question file containing all the questions that relate to the facts and rules. These files are used as input for the inference engine to feed it with the required knowledge.

3.5.2 The engine building phase

In this phase, the inference engine is built by [11] Pyke. This inference engine uses a backward chaining approach which takes the required knowledge which is the issue, the sub-issue, and the generated solution, and begins to provide the employees with instructions on how the customer can reach the generated solutions. So the employee can make the right decision and put the customer in the right direction even if there is a workload or he/she has low experience in certain situations.

At the end of this layer, The e-commerce e-complaints handling process has been modified by completing the proposed model layers.

4. EXPERIMENTS AND RESULTS

The main purpose of the experiment is to validate the effectiveness of the proposed models' layers in enhancing the complaint handling process. To achieve the paper's goal of enhancing customer trust to help businesses maintain sustainability in the highly competitive market.

4.1 Data Acquisition

This paper evaluates the proposed model on a customer complaint dataset [38] that includes 670,598 records of customers' complaints. These data were labeled completely and are available for open research. Table 2 illustrates a sample of the dataset.

Table 2. A Sample of Customers' Complaints.

Date received	Product	Sub-product	Issue	Sub-issue	Consumer complaint narrative	Company public response	Company	Tags	Consumer consent provided?	Date sent to company	Company response to consumer	Timely response	Complaint ID
07/29/2013	Credit card	Other	servicing, payments, escrow account	auto	They keep calling me, made phone contact at least XXXX times.	NRA Group	Wells Fargo & Company		N/A	07/30/2013	Closed with explanation	Yes	469035

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07/29/2013	Mortgage	phone	delivery	Incorrect information	They said the wrong persons name to me both agreed it was not me.	JPMorgan Chase	Bank of America		N/A	07/30/2013	Closed with non-monetary relief	Yes	469037
07/29/2013		Other	Loan servicing, payments, escrow account			JPMorgan Chase	JPMorgan Chase & Co.		N/A	07/30/2013	Closed with explanation	Yes	469284

4.2 Text Pre-processing Layer (Layer 1)

The goal of this layer is to get the input data from Table 2 ready for the following analysis. In this layer, the following phases were applied:

4.2.1 Data cleaning

This phase is responsible for finding and fixing anomalies.

4.2.1.1 Detecting and handling missing values

The percentage of missing values in each field is shown in Table 3.

Table3. Missing Values And Their Percentage.

Field Name	**Percentage of Missing Values**
Date received	0%
Product	0%
Sub-product	29%
Issue	0%
Sub-issue	59%
Consumer complaint narrative	82%
Company public response	78%
Company	0%
State	0.79%
Zip code	0.79%
Tags	85%
Consumer consent provided	68%
Submitted via	0%
Date sent to company	0%
Company response to consumer	0%
Timely response	0%
Consumer disputed	6%
Complaint ID	0%

As shown in Table 3, some fields have missing values. To fix these missing values, Imputation and deletion techniques were used.

- **Imputation**

Two types of imputation methods were applied: the mode and the dummy variable. For categorical features whose percentage is greater than 50% a dummy variable named "missing" was utilized and for those less than 50% the mode (most frequent class) was utilized.

- **Deletion**

The deletion was applied to the records that "consumer complaint narrative" field which contains the complaints of customers was empty. Table 4 shows the dataset after handling missing values.

Table 4. Customers' Complaints Without Missing Values.

Date received	**Product**	**Sub-product**	**Issue**	**Sub-issue**	**Consumer complaint narrative**	**Company**	**Tags**	**Consumer consent provided?**	**Submitted via**	**Date sent to company**	**Company response to consumer**	**Timely response?**	**Consumer disputed?**	**Complaint ID**
03/24/2015	Credit card	Other mortgage	Other	Missing	Received Capital charge card offer XXXX. A :(	Capital One	Missing	Consent provided	Web	03/30/2015	Closed with explanation	Yes	No	1297939
03/23/2015	Debt collection	Other (i.e. phone, health club, etc.)	Improper contact or sharing of info	Contacted me after I asked not to	I don't know how they got my cell number. I t...	CCS Financial Services, Inc.	Missing	Consent provided	E-mail	03/23/2015	Closed with explanation	Yes	No	1296593

4.2.1.2 Detecting and handling duplicates

Duplicates refer to records that contain identical data [34]. And as shown in Table 5, there are no duplicates exist in the data.

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Table 5. Duplicate Values in Each Record.

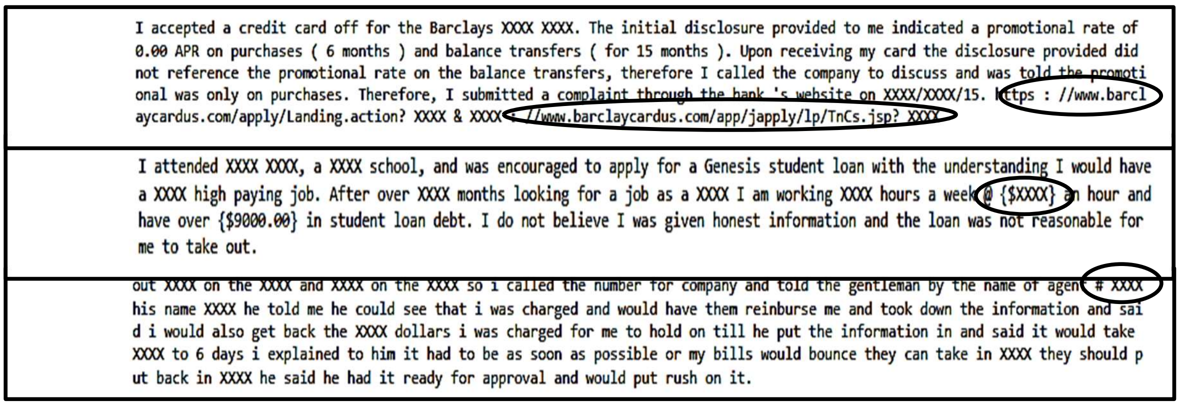
Record Number	Duplicates
0	False
1	False
…	…
114699	False
114700	False
114701	False
114702	False

4.2.2 Text normalization

This phase applied to the "Consumer complain t narrative" field which comprises customers' co mplaints. To achieve the phase's goal the follow ing steps were applied:

4.2.2.1 Remove urls, mentions, and hashtags

In this step, The URLs, Mentions, and Hashtags were removed. Figure 4 depicts a sample of three complaints. The first one has links, the second one has mentions, and the third one uses hashtags. This unnecessary noise that didn't offer any information to the machine was eliminated.



I accepted a credit card off for the Barclays XXXX XXXX. The initial disclosure provided to me indicated a promotional rate of 0.00 APR on purchases (6 months) and balance transfers (for 15 months). Upon receiving my card the disclosure provided did not reference the promotional rate on the balance transfers, therefore I called the company to discuss and was told the promoti onal was only on purchases. Therefore, I submitted a complaint through the bank 's website on XXXX/XXXX/15. https : //www.barcl aycardus.com/apply/Landing.action? XXXX & XXXX : //www.barclaycardus.com/app/japply/lp/TnCs.jsp? XXXX

I attended XXXX XXXX, a XXXX school, and was encouraged to apply for a Genesis student loan with the understanding I would have a XXXX high paying job. After over XXXX months looking for a job as a XXXX I am working XXXX hours a week @ {$XXXX} an hour and have over {$9000.00} in student loan debt. I do not believe I was given honest information and the loan was not reasonable for me to take out.

out XXXX on the XXXX and XXXX on the XXXX so i called the number for company and told the gentleman by the name of agent # XXXX his name XXXX he told me he could see that i was charged and would have them reinburse me and took down the information and sai d i would also get back the XXXX dollars i was charged for me to hold on till he put the information in and said it would take XXXX to 6 days i explained to him it had to be as soon as possible or my bills would bounce they can take in XXXX they should p ut back in XXXX he said he had it ready for approval and would put rush on it.

Figure 4. A Sample of Complaints with (URLs, Mentions, and Hashtags).

4.2.2.2 Expanding contraction

In this step, all the contractions were expanded out of customers' complaints. The input of this step is the "customer complaints narrative" field and the output is the "no_ contractions" field as shown in Table 6.

Table 6. A Sample of Customers' Complaints without Contractions.

Consumer complaint narrative	no_contractions
Received Capital charge card offer XXXX. A :(	Received Capital charge card offer XXXX. A... :(
I don't know how they got my cell number. I t...	I do not know how they got my cell number. I t...
I 'm a longtime member of Charter Bank/...	I am a longtime member of Charter Bank/……..

As illustrated in Table 6 at records two and three, "don't" was expanded to "do not" and " 'm" was expanded to "am".

4.2.2.3 Replacing emoticons and emojis

In this step, any emoji was replaced with a word that corresponds to it. The input of this step is the "no_contractions" field and the output is the "no_ emoji" field as shown in Table 7.

Table 7. A Sample of Customers' Complaints without Emojis.

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Consumer complaint narrative	no_contractions	no_emoji
Received Capital charge card offer XXXX. A :(	Received Capital charge card offer XXXX. A... :(	Received Capital charge card offer XXXX. A…sad
I don't know how they got my cell number. I t...	I do not know how they got my cell number. I t...	I do not know how they got my cell number. I t...
I 'm a longtime member of Charter Bank/...	I am a longtime member of Charter Bank/……..	I am a longtime member of Charter Bank/...

As illustrated in Table 7 at the first record, the ":(" emoji was replaced with the word "sad".

4.2.2.4 Replacing abbreviations and slang

In this step, any slang or abbreviation was replaced with its true word. The input of this step is the "no_emoji'" field and the output is the "no_ abbreviation" field as shown in Table 8.

Table 8. A Sample of Customers' Complaints without Abbreviations &Slangs.

Consumer complaint narrative	no_contractions	no_emoji	no_abbreviations
After looooooooooking at my credit report, I saw a col...	After looooooooooking at my credit report, I saw a col...	After looooooooooking at my credit report, I saw a col...	After looooooooooking at my credit report, I saw a col...
I received a gr8 call from a XXXX XXXX about 10.	I received a gr8 call from a XXXX XXXX about 10.	I received a gr8 call from a XXXX XXXX about 10….	I received a great call from a XXXX XXXX about 10…..

As illustrated in Table 8 at the two record, the "gr8" abbreviation was replaced with the word "great".

4.2.2.5 Replacing elongated characters

In this step, any elongated word was replaced with its actual word. The input of this step is the "no_ abbreviation" field and the output is the "no_elongated" field as shown in Table 9.

Table 9.A Sample of Customers' Complaints without Elongated Words.

Consumer complaint narrative	no_contractions	no_emoji	no_abbreviations	no_elongated
After looooooooooking at my credit report, I saw a col...	After looooooooooking at my credit report, I saw a col...	After looooooooooking at my credit report, I saw a col...	After looooooooooking at my credit report, I saw a col...	After looking at my credit report, I saw a col...
I received a gr8 call from a XXXX XXXX about 10.	I received a gr8 call from a XXXX XXXX about 10.	I received a gr8 call from a XXXX XXXX about 10….	I received a great call from a XXXX XXXX about 10…..	I received a great call from a XXXX XXXX about 10….

As illustrated in Table 9 at the first record, the elongated word "looooking" was replaced with "looking".

4.2.2.6 Folding to lowercase

In this step, all the text was changed to lowercase. The input of this step is the "no_elongated" field and the output is the "lower_case" field as shown in Table 10.

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Table 10. A Sample of Customers' Complaints in a Lower-Case Format.

Consumer complaint narrative	no_contractions	no_emoji	no_abbreviations	no_elongated	lower_case
After loooooooooooking at my credit report, I saw a col...	After loooooooooooking at my credit report, I saw a col...	After loooooooooooking at my credit report, I saw a col...	After loooooooooooking at my credit report, I saw a col...	After looking at my credit report, I saw a col...	after looking at my credit report, i saw a col...
I received a gr8 call from a XXXX XXXX about 10.	I received a gr8 call from a XXXX XXXX about 10.	I received a gr8 call from a XXXX XXXX about 10….	I received a great call from a XXXX XXXX about 10…..	I received a great call from a XXXX XXXX about 10….	i received a great call from a xxxx xxxx about 10...

4.2.2.7 Removing punctuation

In this step, all the punctuations in customers' complaints were removed. The input of this step is the "lower_case" field and the output is the "no_punctuations" field. As shown in Table 11.

Table 11. A Sample of Customers' Complaints without Punctuation.

Consumer complaint narrative	no_contractions	no_emoji	no_abbreviations	no_elongated	lower_case	no_punctuations
I 'm a longtime member of Charter Bank/...	I am a longtime member of Charter Bank/……..	I am a longtime member of Charter Bank/...	I am a longtime member of Charter Bank/...	I am a longtime member of Charter Bank/.	i am a longtime member of charter bank/...	i am a longtime member of charter bank...
After loooooooooooking at my credit report, I saw a col...	After loooooooooooking at my credit report, I saw a col...	After loooooooooooking at my credit report, I saw a col...	After loooooooooooking at my credit report, I saw a col...	After looking at my credit report, I saw a col...	after looking at my credit report, i saw a col...	after looking at my credit report i saw a col...

As illustrated in Table 11 , "/" and "," were eliminated.

4.2.2.8 Removing digits

In this step, any digits that were combined with words in the text were eliminated. The input of this step is the "no_punctuations" field and the output is the "no_number" field as illustrated in Table 12.

Table 12. A Sample of Customers' Complaints without Digits.

Consumer complaint narrative	no_contractions	no_emoji	no_abbreviations	no_elongated	lower_case	no_punctuations	no_number
After loooooooooooking at my credit report, I saw a col...	After loooooooooooking at my credit report, I saw a col...	After looooooooooooking at my credit report, I saw a col...	After loooooooooooking at my credit report, I saw a col...	After looking at my credit report, I saw a col...	after looking at my credit report, i saw a col...	after looking at my credit report i saw a col...	after looking at my credit report i saw a col...
I received a gr8 call from a XXXX XXXX about 10.	I received a gr8 call from a XXXX XXXX about 10.	I received a gr8 call from a XXXX XXXX about 10….	I received a great call from a XXXX XXXX about 10…..	I received a great call from a XXXX XXXX about 10….	i received a great call from a xxxx xxxx about 10...	i received a great call from a xxxx xxxx about 10...	i received a great call from a xxxx xxxx about ...

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As illustrated in Table 12 at the second record,the digit "10" was eliminated.

At the end of this phase, the data were completely cleaned and normalized to be used as input for the tokenization phase.

4.2.3 Tokenization

This phase is responsible for separating a piece of text into smaller units called tokens. The field "no_number" that was generated in the previous phase was used as input for this phase. Table 13 illustrates a sample of tokenized words.

Table 13. A Sample of Tokenized Complaints.

Consumer complaint narrative	no_contractions	no_emoji	no_abbreviations	no_elongated	lower_case	no_punctuations	no_number	tokenized complaints
After looooooooooking at my credit report, I saw a col...	After looooooooooking at my credit report, I saw a col...	After looooooo oooking at my credit report, I saw a col...	After looooooooooking at my credit report, I saw a col...	After looking at my credit report, I saw a col...	after looking at my credit report, i saw a col...	after looking at my credit report i saw a col...	after looking at my credit report i saw a col...	[after, looking, at, my, credit, report, i, sa...
I received a gr8 call from a XXXX XXXX about 10.	I received a gr8 call from a XXXX XXXX about 10.	I received a gr8 call from a XXXX XXXX about 10….	I received a great call from a XXXX XXXX about 10…..	I received a great call from a XXXX XXXX about 10….	i received a great call from a xxxx xxxx about 10...	i received a great call from a xxxx xxxx about 10...	i received a great call from a xxxx xxxx about ...	[i, received, a,great, call, from, a, xxxx, xxxx, about,...

4.2.4 Stop-words removal

The purpose of this phase is to eliminate stop words. By omitting stop words, the low-level information was eliminated from the text to focus on the important information. The field "tokenized complaints" that was generated in the previous phase was used as input for this phase. Table 14 illustrates a sample of customers' complaints without stop-words.

Table 14. A Sample of Customers' Complaints without Stop-Words.

Consumer complaint narrative	no_contractions	no_emoji	no_abbreviations	no_elongated	lower_case	no_punctuations	no_number	tokenized complaints	no_stop_words_complaints
I don't know how they got my cell number. I t...	I do not know how they got my cell number. I t...	I do not know how they got my cell number. I t...	I do not know how they got my cell number. I t...	I do not know how they got my cell number. I t...	i do not know how they got my cell number . i t...	i do not know how they got my cell number. i t...	i do not know how they got my cell number. i t...	[i, do, not, know, how, they, got, my, cell, n...	[know, got, cell, number, told, de...
I 'm a longtime member of Charter Bank/...	I am a longtime member of Charter Bank/……..	I am a longtime member of Charter Bank/...	I am a longtime member of Charter Bank/...	I am a longtime member of Charter Bank/.	i am a longtime member of charter bank/...	i am a longtime member of charter bank...	i am a longtime member of charter bank...	[i, am, a, longtime, member, of, charter,...	[longtime, member, charter, bank, citi..

As illustrated in Table 14 at records one,and two, stop words like "i" and "am" were eliminated.

4.2.5 Lemmatization

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During this phase, words were returned to their root words or lemma by comparing words to a linguistic dictionary. The field "'no_stop_words_complaints'" is the input field and the output is the “complaintss” field. Table 15 illustrates a sample of the lemmatization output.

Table 15. A Sample of Customers' Complaints after Lemmatization.

Consumer complaint narrative	no_contractions	no_emoji	no_abbreviations	no_elongated	lower_case	no_punctuations	no_number	tokenized complaints	no_stop_words_complaints	complaintss
I don't know how they got my cell number. I t...	I do not know how they got my cell number. I	I do not know how they got my cell number. I	I do not know how they got my cell number. I t...	I do not know how they got my cell number. I t...	i do not know how they got my cell number. i	i do not know how they got my cell number. i.	i do not know how they got my cell number. i	[i, do, not, know, how, they, got, my, cell, n...	[know, got, cell, number, told, de...	[know, get, cell, number, tell, de...
I 'm a longtime member of Charter Bank/...	I am a longtime member of Charter Bank/…	I am a longtime member of Charter Bank/...	I am a longtime member of Charter Bank/...	I am a longtime member of Charter Bank/.	i am a longtime member of charter bank/...	i am a longtime member of charter bank...	i am a longtime member of charter bank...	[i, am, a, longtime, member, of, charter,...	[longtime, member, charter, bank, citi..	[longtime, member, charter, bank, citi..

2.2.6 Feature extraction

This phase is responsible for turning preprocessed data into numerical data that machines can comprehend. In this phase, the Label encoding technique was applied to the "issue" field, and the TF-IDF technique was applied to the “complaints” field.

Table 16. Results of Label Encoding.

Issues	complaintss	Issues_id
missing information	[receive, capital, charge, card, offer, sad, ...	0
improper contact	[know, get, cell, number, tell, de...	1
rewards	[longtime, member, charter, bank, citi..	2
incorrect information	[look, credit, report, see, collection, acc...	3

2.2.6.1 Label encoding

In this step, each unique issue is assigned an integer value. As illustrated in Table 16.

2.2.6.2 Vectorization

In this step, the TF-IDF method was applied to convert the "complaintss" field to a matrix of TF-IDF features that will be used in the text classification layer. Table 17 illustrates the results.

Table 17. The TF-IDF Matrix.

sign	signal	signature	significant	silent	similar	simple	simulate	sink	site
0	0.0626196	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0.0632336	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0.0549813	0	0	0	0	0	0	0.0549813
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0.0549813	0	0	0.079761	0	0

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2.2.7 Feature selection

After obtaining the feature extraction results, the data in Table 17 were used to perform the chi-square test to reduce the feature space to a manageable size. Different experiments with different numbers of features were conducted to determine the appropriate number of features that could be used in the next layer, which resulted in 4,000 features.

At the end of this layer and after feature selection the complaints became ready to be classified in the text classification layer. An overview of the text preprocessing layer's phases is shown in Figure 5.

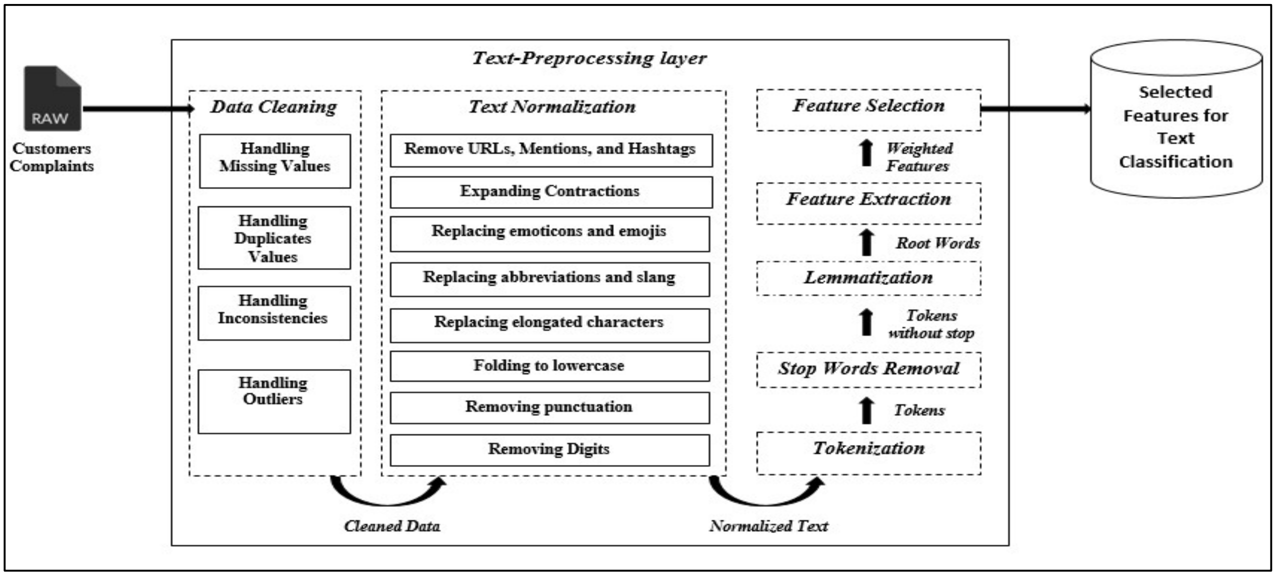

Figure 5. Summarization of Text Preprocessing Layer.

4.3 Text Classification Layer (Layer 2)

This layer is responsible for classifying customers' complaints to the relevant issue to send them to the department in charge. In this layer, the following phases were applied:

4.3.1 Data splitting

In this phase, an "80:20" spitting ratio with stratified sampling was set for the classification model.

4.3.2 Build and train the model

In this phase, the Decision Tree [DT] algorithm was used and was trained with 80% training data.

4.3.3 Test the model

In this phase, the classification model under the "80:20" splitting ratio with a stratified sampling was tested. The results are shown in Table 18.

Table 18. Results of the Classification Model.

Algorithms	Data Splitting (80:20)				
	Accuracy (%)	*Precision*	*Recall*	*F1-Score*	*Time [min]*
DT	99%	0.998	0.998	0.998	1

According to the results, it demonstrated that DT can classify customers' complaints with an accuracy of 99%, F1-measure of 99%, and runtime of 1 minute.

At the end of this layer, unresolved customers' complaints were classified into their related issues, and sub-issues and were prepared to be forwarded to the responsible department for resolution. Table 19 displays a sample of pending complaints that were utilized as input in the next layer.

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Table 19. A Sample of Pending Customers' Complaints.

Date received	Complaint ID	Consumer complaint narrative	Issue
2015-10-04	1591880	I have reported this XXXX times now it keeps getting added back to my credit reports. I live aboard from XXXX to XXXX returned to XXXX XXXX, XXXX and XXXX reporting debts……………..	login, addresses [addresses]
2015-05-01	1356504	What happened to me is almost verbatim what is described in XXXX v. XXXX XXXX XXXX filed in Florida XXXX District Court. I switched from a reliable internet provider...	[login security]

4.4 Solution Generation layer (Layer 3)

The role of this layer is to come up with solutions for each group of customers who are highly similar and potentially require the same solution. For this purpose, the k-means and genetic algorithms were applied.

4.4.1 Assembly phase

In this phase, the pending complaints in Table 19 that were received on the same day were categorized into batches with k-means. Each of these batches has similar complaints that require the same solutions. To determine the optimum number of clusters, the elbow method was utilized. The elbow method compares the percentage of clusters that will form an elbow at a point to determine the best number of clusters [35]. Figure 6 shows the results of the elbow method.

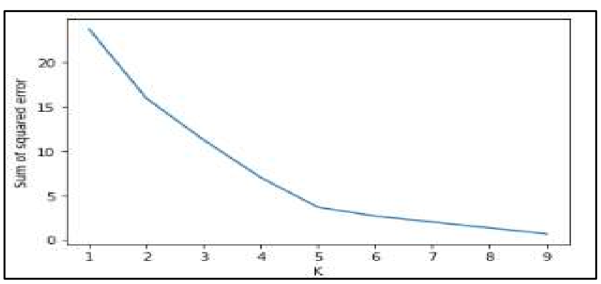

Figure 6. Results of the Elbow Method.

As shown in Figure 6, the best number of clusters for pending complaints on a certain day and time is five clusters. So the number of clusters was set to five. The results of the k-means algorithm are shown in Table 20.

Table 20. A Sample of Customers' Complaints Clusters.

User ID	Cluster
0	1
1	3
3	4
4	1
8	2
9	0
11	0
15	4

As shown in Table 20, five batches were generated with two complaints in each of the first, second, and fifth batches while each of the third and fourth batches only had one complaint. So by the end of this phase, the batches became ready to be solved in the service phase.

4.4.2 Service phase

At this phase, a list of solutions for each batch (the target customer) was produced using the GA. Before implementation, the GA parameters had been defined. Specifically, the rates of mutation and crossover. An optimum crossover and mutation rate that best suits the GA mechanism development was found through a process of trial and error. The parameter values utilized in this phase are displayed in Table 21.

Table 21. The parameters of the GA.

Parameter	Settings
Crossover Rate	0.8
Mutation Rate	0.2
Maxiumum Generation	100
Population size	2000
Number of genes	5

To evaluate the performance of the GA, the recall, precision, F1, and time taken to provide the solution list were calculated. Table 22 shows the results.

Table 22. The Performance Evaluation of the GA.

Criteria	Precision	Recall	F1	Time [min]
Result	75%	100%	85%	5

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The results demonstrated that GA can provide the appropriate solution with an F1 of 85% and within 5 minutes.

At the end of this layer, each batch received a list of solutions to their issue.

4.5 Instructions Generation Layer (Layer 4)

This layer is responsible for developing instructions for the employees in the complaints handling department on how to reach the solution generated in the previous layer. Therefore, a rule-based inference engine was built through the use of PyKE.

4.5.1 Knowledge base preparation

The inference engine and the knowledge base are the two main parts of a rule-based inference engine. As a result, Three files were prepared to create a knowledge base using prolog language:

1. *Knowledge Fact Base* (KFB) files for **fact bases**.
2. *Knowledge Rule Base* (KRB) files for **rule bases**.
3. *Knowledge Question Base* (KQB) files for **question bases**.

Figures 7, 8, and 9 depict the files created to be used by the inference engine.

```
#facts

payment_charges_giftcard(True)
login,addresses,security&privacy(True)
membership,subscription or communication(True)
payment,charges or gift card(True)
prime(True)
product issues(True)
Customs(True)
Currency Settings(True)
Login Security(True)
Data Privacy(True)
Manage Subscription(True)
Check Messages(True)
Update Payment (True)
```

Figure 7. A Sample of Fact (KFB) File.

```
# bc_simple_rules.krb

what_to_do_international_shopping1
    use what_to_do(happy)
    when
        questions.any_problem($ans)
        check $ans in (1,)
        questions.any_international_shopping($ans)
        check $ans in (1,)

what_to_do_shopping1
    use what_to_do(hi)
    when
        questions.any_problem($ans)
        check $ans in (1,)
        questions.any_international_shopping($ans)
        check $ans in (2,)

what_to_do_login1
    use what_to_do(cute)
    when
        questions.any_problem($ans)
        check $ans in (2,)
        questions.any_login($ans)
        check $ans in (2,)
```

Figure 8. A Sample of Rule (KRB) File.

```
# questions.kqb

any_problem($ans)
        what is the problem?
        ---
        $ans = select_1
                1: international shopping
                2: login,addresses,security&privacy
                3: membership,subscription or communication
                4: payment,charges or gift card
                5: prime
                6: product issues

any_international_shopping($ans)
        what is the subproblem?
        ---
        $ans = select_1
                1: Customs
                2: Currency Settings

any_login($ans)
        what is the subproblem?
        ---
        $ans = select_1
                2: Login Security
                3: Data Privacy
```

Figure 9. A Sample of Question (KQB) File.

4.5.2 Engine building phase

These files were used by the Pyke inference engine to apply rules to facts and find instructions related to the solution that was generated for customers in the previous layer. Figure 10 shows a simulation of how the employees can know how exactly the solution can be reached with a little information.

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```
what is the problem?
  1. international shopping
  2. login,addresses,security&privacy
  3. membership,subscription or communication
  4. payment,charges or gift card
  5. prime
  6. product issues
? [1-6] 2
---------------------------------------------------------------
what is the subproblem?
  1. Login Security
  2. Data Privacy
? [1-2] 1
---------------------------------------------------------------
 which of the following is the selected solution?
   1. Remove Cookies
   2. Clear History
 ? [1-2] 1
 Action:A corrupt cookies file may be included in your browser.
        Click the menu button.
        Click Help and select More Troubleshooting Information.
        Under the Application Basics section next to Profile Folder.
        Click Open Your profile.
```

Figure 10. Simulation to The Rule-Based Engine.

As illustrated in Figure 10. If the problem that the employee encountered is 'login, address, security, and privacy' and the subproblem is login security. Additionally, the solution suggested in the solution generation layer is to remove cookies. As a result, the engine will automatically give the employee information about the problem and the procedures that must be followed to reach the solution. Consequently, whether the employee is overworked or unaware of the problem at hand. The instructions that the engine provides to the employee help him to make the right decision and avoid mistakes or long wait times in searching for a solution.

To evaluate the performance of the engine, the recall, precision, F1, and time taken to provide the instructions were used. Table 23, shows the results.

Table 23. The Performance Evaluation of the Inference Engine.

Criteria	Precision	Recall	F1	Time [min]
Result	83%	90%	86%	1

At the end of this layer, the problem of lack of knowledge or modernity that many employees may face will be reduced because everything appears in front of them.

After completing the proposed model's layers, The paper''s goal of solving frequently discrete customers' complaints in batches and providing them with a better solution and instructions on how to implement this solution in less time was met, which enhanced customer satisfaction and customer trust which is the main goal of the paper.

5. EVALUATION

To demonstrate that the proposed model (E-CDSM) outperforms the other models used in the handling of e-complaints, various experiments were conducted that emphasized the model's effectiveness in three areas: a reduction in total handling time, an improvement in the accuracy of solutions, and the effectiveness of instructions provided to employees to increase customer satisfaction.

5.1 Experimental Data

Three datasets were used in the different experiments to test the effectiveness of the proposed model:

- **Amazon Review data,** this dataset includes reviews (ratings, text, helpfulness votes), product metadata (asin, descriptions, category information, price, brand, and image features), and links (also viewed/also bought graphs) [36].
- **Complaint data from the fuman kaitori center**, these data serve as a platform for consumer complaints. It has users who post their complaints in Japanese. Each complaint includes a User ID, Complaint, Category, subcategory, and product information (asin). These data were translated into English for use in the analysis [37].
- **Consumer Complaint data**, this dataset contains different complaints that customers have made about multiple products (data received, date finished, product, issue, complaint, date closed) [38].

5.2 The Experiments Methodology

The evaluation process depended on three different experiments. The first experiment tests the model's ability to generate highly accurate solutions to customer complaints. The second experiment tests the model's performance in retrieving appropriate instructions related to customer complaints and solutions. And The third experiment tests the model's ability to reduce complaint-handling time.

5.3 Results

5.3.1 Experiment 1: (evaluate the effectiveness of the solutions)

In this experiment, two different datasets were used:complaint data [37] and amazon review data [36].

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To test the model against [39] model, the complaints data was used to represent pending complaints that needed to be resolved, and the Amazon review data was used to represent customers (neighbors) who rated the same product that had the issue as well as other products. To implement the test the GA parameter was defined, specifically a crossover rate and mutation rate. In this experiment, a crossover rate of 80% and a mutation rate of 20%, were selected for testing under a population size of 2000.

The evaluation process compares the effectiveness of The E-CDSM in providing the right solutions which in this experiment are the recommended items related to solving customers' complaints. The E-CDSM 's effectiveness and accuracy were measured in terms of Similarity in Equation 12 [33], precision in Equation 13[40], recall in Equation 14 [40], and F measure in Equation 15 [40]. Table 24 shows the results of Experiment 1.

- **Similarity**

Similarity scores are determined by comparing two data objects, attribute by attribute, and computing the results by summing the squares of the magnitude differences between each attribute. Using Pearson's correlation, a score between -1 and +1 is generated. A high score (near + 1) indicates that two objects are very similar. The Pearson coefficient for two unrelated objects would be close to zero [41].

Similarity=

$$\frac{\sum_{i\in I}(r_{targetuser,i}-\bar{r}_{target\ user})(r_{u,i}-\bar{r}_u)}{\sqrt{\sum_{i\in I}(r_{targetuser,i}-\bar{r}_{target\ user})^2}\sqrt{\sum_{i\in I}(r_{u,i}-\bar{r}_u)^2}} \quad (12)$$

Where

U is the set of all users who rated at least one item in the list.

I is the group of items that both users target user and u have rated. Each user in U rated at least one item in the list.

$r_{target\ user,\ i}$ is the rate of user(target user)on item i.

$\bar{r}_{target\ user}$ is the mean rating value of user(target user).

- **Precision**

Precision is the ratio of accurately positive samples to the total number of positive predicted samples [40].

$$\textbf{Precision} = \frac{\text{Correct recommended solutions}}{\text{All recommended solutions}} \quad (13)$$

- **Recall**

Recall shows the proportion of positively identified positive samples to all positive samples [40].

$$\textbf{Recall} = \frac{\text{Correct recommended solutions}}{\text{Relevent Solutions}} \quad (14)$$

- **F1-Score**

F1- score also known as the F-measure. It denotes the harmonic mean of recall and precision [40].

$$\textbf{F1-Score} = 2 * \frac{\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}} \quad (15)$$

Table 24. Experiment 1 Results.

Model	*Performance Measures*			
	Similarity	*Recall*	*Precision*	*F1*
The E-CDSM	0.64	1	0.78	0.88

As shown in Table 24, testing the models illustrated that the E-CDSM based on the Genetic algorithm achieved substantial effectiveness with a similarity of 64% and an F-measure of 88%. Figure 11 compares the E-CDSM results with the [39] model in terms of similarity.

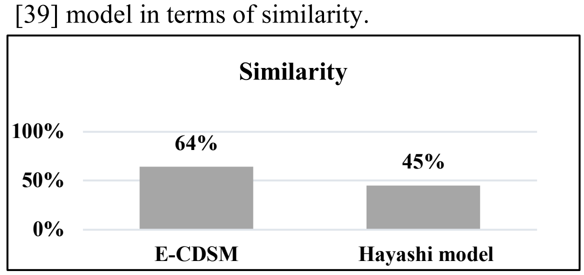

Figure 11. The difference in similarity between the E-CDSM & Hayashi model.

As shown in Figure 11, the E-CDSM outperformed the Hayashi model with a 19% increase in terms of similarity. This is because, whilst Hayashi offers items based entirely on similarity, the E-CDSM model offers solutions based on both similarity and prediction rate.

5.3.2 Experiment 2: (evaluate the effectiveness of the instructions)

To evaluate the performance of the E-CDSM in retrieving the appropriate instructions relating to

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the customer's complaints and solutions. The meta-data from Amazon reviews [36] and complaint data [37] were used. It was converted into rules to assess the model's ability to provide the correct outcome. Figure 12 provides a simulation of the shape of the rules used in the paper and those used in the Experiment.

Rules in the E-CDSM model.	Rules to test the model.
IF Problem is X, and Sub-problem is Y, and Solution is Z THEN Instructions is W.	IF Problem is A, and Sub-problem is B, and Solution is E THEN Description is D.

Figure 12. The difference between the rules used (in paper & in testing).

The left side of Figure 12 shows that if the pending complaints are classified as related to problem X and sub-problem Y, and the generated solution is Z, then the instructions for reaching this solution are W. Similarly, the right side shows that if the problem is A, the sub-problem is B, and the solution is E, then the Description must be D.

After converting Amazon product meta-data and complaint data to IF-THEN rules, a sample of 2000 and 11,000 rules were randomly selected for the experiment. To begin the evaluation, the rules were written in prolog language to be used in Pyke's knowledge base. The E-CDSM's ability to retrieve the correct consequent part of the rule was measured using an Accuracy in Equation 16 [40].

- **Accuracy**

Accuracy is one of the most widely used metrics for measuring the performance which is calculated as the ratio of samples that are correctly predicted to all samples [40].

$$\text{Accuracy} = \frac{\textbf{Number of correct predictions}}{\textbf{Total number of predictions}} \qquad (16)$$

To test the ability of the model to retrieve the correct instructions under different circumstances, each sample contains the following types of rules:

- **Correct rules:** To assess the model's ability to retrieve the right result when the knowledge base is strong.
- **Missing rules:** To assess the model's ability to retrieve the right result when the knowledge base is incomplete.
- **Duplicate rules:** To assess the model's ability to retrieve the right result when the knowledge base contains duplicate values.
- **Closed loop rules:** To assess the model's ability to retrieve the right result when the knowledge base rules are written incorrectly. Table 25 displays the accuracy results and time taken for each sample.

Table 25. The model's accuracy results.

Samples	Accuracy	Time (min)
Sample 1 (2000)	95%	1
Sample2 (11,000)	93.2%	5

As demonstrated in Table 25, the E-CDSM has a high ability to retrieve the right results if the input matches the rules in the knowledge base, and it is unaffected by the number of rules or whether there are duplicate rules or not. However, if the input does not match any rule's antecedent, or if there are closed rules, the engine returns nothing. This means that numerous factors have a negative impact on the model's results such as,

- Insufficient knowledge.
- The wrong rule pattern.

This shows that both inference engines and humans have drawbacks. If the input knowledge, rules, and facts are insufficient or have syntax problems. It will result in ambiguous results. For humans, if a human has no experience with a particular problem, he or she cannot solve it correctly and will waste time. However, if he has the experience, he can solve it. But if there is a workload, time is also consumed, in contrast to the inference engines.

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5.3.3 Experiment 3: (evaluate reduction in complaint handling time)

To prove that E-CDSM outperforms the other models in terms of complaint handling time. A consumer complaint data [38] was used in this experiment. In the E-CDSM, the complaint handling time (service time) includes the following: 1. Time of classifying complaints. 2. Time of assembling similar complaints into batches. 3. Time of providing the solution, and 4. Time of providing instructions.

This experiment tests whether the usage of the batching concept along with automatic text classification, automated solution generation, and automated instruction provided can reduce complaint handling time or not. To experiment, two tests were performed. The first one is processed without the batching concept. The second one is processed with the batching concept.

To illustrate the experiment, we consider an identical server case in which there are c identical servers in parallel and there is just one waiting line. Table 26 illustrates the different parameters used in this Experiment.

Table 26. The parameters of Experiment 3

Parameters	Description
λ	The arrival rate and equal 1/E[Interarrival time].
μ	The service rate and equal 1/E[service time].
c	The number of servers.
ρ	the utilization of the server.
p_n	Is the probability that there are n customers in the system.
L	Mean number of customers in the system.
L_q	Mean number of customers in the queue.
W_q	Mean waiting time in the queue.
W	Mean waiting time in the system.

To implement the experiment, A sample of 2000 complaint was used, the number of servers used were 3, the interarrival time was exponentially distributed with a mean of 10 mins, the service time was exponentially distributed with a mean of 8 mins, and the maximum size of the batch was 4. The results of the two tests were compared based on the mean wait time in the system in Equation 21 [42] which is derived from the little theorem by calculating the utilization of the server in Equation 17 [42] and the number of customers in the queue in Equation 18 [42], and the mean wait time in the queue in Equation 20 [42],as shown in Table 27.

$$\rho = \frac{\lambda}{c\mu} \qquad (17)$$

$$L_q = \frac{p0(\frac{\lambda}{\mu})^c \rho}{c!(1-\rho)^2} \qquad (18)$$

Where
P0 is the probability that there are 0 customers in the system.

$$P0 = 1/[\sum_{m=0}^{c-1} \frac{(c\rho)^m}{m!} + \frac{(c\rho)^c}{c!(1-\rho)}] \qquad (19)$$

$$Wq = \frac{Lq}{\lambda} \qquad (20)$$

$$W = Wq + \frac{1}{\mu} \qquad (21)$$

Table 27. Complaint handling time before and after Batching.

Criteria	Before Batching	After Batching	Difference
W	8.17 min	2 min	6.17 min

As illustrated in Table 27, The time that pending complaints wait in the system decreased from 8.17 minutes to 2 minutes with the deployment of the E-CDSM. This means that the E-CDSM succeeded in reducing waiting time (response time) which will lead to an increase in customer satisfaction.

Based on the outcomes of the three experiments. It has [17] ven that the E-CDSM succeeded in meeti per's goals, involving giving customers appropriate responses to their complaints, giving employees clear instructions that help them avoid making mistakes or lacking experience, and assisting them in managing their workload. Additionally, it decreases the response time for complaints which boosts customer satisfaction and customer trust toward business.

5. CONCLUSION AND FUTURE WORK

This paper provided a decision support model that can handle many discrete, frequent complaints that could face any e-commerce company. The E-CDSM utilizes a rule-based inference engine with classification, clustering, and genetic algorithms to efficiently handle complaints and promptly deliver the appropriate result to decision-makers. The results showed that E-CDSM outperformed other models in reducing

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response times by 6.17 minutes, raising the accuracy of solutions given to customers by 19%, and reducing the percentage of mistakes that may exist in staff decisions. Therefore it achieves the paper's objectives in enhancing customer trust to retain business sustainability in the highly competitive market, clarifying the role of various machine learning techniques in improving the way complaints are handled, demonstrating the role of a rule-based inference engine in mitigating the negative impact of staff members' inexperience or work overload. There are many avenues to extend the research. Some of these directions are mentioned below:

- Our proposed model can be extendable for overcoming customer churn by using sentiment analysis. Sentiment analysis is the process of analyzing digital text to determine if the emotional tone of the message is positive, negative, or neutral. It helps identify positive, negative, and neutral sentiments within complaints that can help businesses detect whether this customer has an intention to leave or not. And to make the right decision regarding him. The previous studies ignored sentiment analysis despite its advantages. As a result, our future work was to integrate sentiment analysis into our model to help managers make the right decision towards customers who send complaints and have a strong intention to leave whether this complaint is resolved or not.
- Constructing a tool that can speed up the processing of data in the text preprocessing phase.

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