Optimizing call center agent efficiency through deep learning-based classifications using SMFCCAE

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Article Info

Article history:

Received Aug 18, 2024
Revised Jan 17, 2025
Accepted Mar 29, 2025

Keywords:

Call centre
Call centre agents
Deep learning
Ensembles
Motivation
XGBoost

ABSTRACT

Call centers are vital to business operations worldwide, acting as the primary interface between companies and their customers. They handle customer inquiries, manage complaints, and facilitate telephonic sales, making them essential to customer service. However, ensuring quality in the call center industry remains challenging, primarily due to the heavy reliance on call center representatives (CSRs) who manage high volumes of calls. Traditional methods of evaluating CSR performance often rely on manual assessments of small call samples, which can be time-consuming and limited in scope. With the advancement of deep learning techniques (DLTs), there is an opportunity to more accurately assess CSR performance. This study introduces the selecting minimal features for call center agents efficiency (SMFCCE) approach, which optimizes feature selection from CSR data to enhance classification accuracy and speed. The proposed method achieves approximately 85% accuracy, offering valuable insights and recommendations for improving overall call center operations.

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1. INTRODUCTION

The primary objective of managing customer markets is to cultivate loyal customers and establish strong relationships [1]. Businesses aim to maintain these relationships by understanding customer needs and responding effectively, ensuring customer loyalty. While fundamental marketing strategies aimed at attracting new customers can be expensive and time-consuming, there has been a growing focus on services and their marketing [2]. This shift has led to the widespread adoption of call centers in large organizations. Call center representatives (CSRs) are central to customer interactions, responsible for recording transactions, handling user cases, and addressing issues. Figure 1 depicts the growing global market for call center outsourcing, reflecting the industry's expanding role in customer service.

The competitive landscape of modern businesses places significant emphasis on maintaining strong customer relationships, which is essential for sustaining customer loyalty and business growth. Call centers have become critical components of this customer engagement strategy, serving as the primary touchpoint between companies and their clients. These centers are responsible for managing customer inquiries, handling complaints, and executing telephonic sales, thereby directly influencing customer satisfaction and retention. However, the call center industry faces several challenges, particularly in ensuring the consistent performance of CSRs. Traditional methods of evaluating CSR performance typically involve manual qualitative assessments, which are often limited by their reliance on small sample sizes and the subjective nature of human judgment. These methods are not only time-consuming but also prone to inconsistencies, making it difficult to achieve a holistic evaluation of CSR efficiency. Existing solutions for enhancing call center operations include automated call recording systems, interactive voice response (IVR) technologies, and customer feedback surveys [3]-[6]. While these tools help streamline certain aspects of call center management, they often fall short in providing a comprehensive assessment of CSR performance. For instance, automated systems can handle basic tasks but may not accurately measure the quality of human interactions, which is crucial for customer satisfaction [7]-[12]. The major constraints in this field include the high volume of calls that must be managed, the pressure on CSRs to perform consistently under demanding conditions, and the need for accurate and timely performance assessments. Moreover, the variability in customer expectations and the dynamic nature of customer interactions add further complexity to evaluating CSR effectiveness. Through our research, we aim to address these challenges by introducing a novel approach named selecting minimal features for call center agents efficiency (SMFCCE). This approach leverages deep learning techniques (DLTs) to optimize the feature selection process from CSR data, resulting in faster and more accurate classification of CSR performance. Our objective is to enhance the overall efficiency of call center operations by providing actionable insights and recommendations that can lead to significant improvements in customer service quality. Specifically, we aim to achieve higher accuracy in performance classification, thereby enabling call centers to make data-driven decisions in managing and training their CSRs. This work proposes SMFCCE schema which effectively classifies CSRs qualities for providing suggestions that can enhance call centre's effectiveness. Following this introductory section, section 2 discusses the literature review. Section 3 discusses the method introduced in the system. Section 4 details on obtained results with discussions while section 5 concludes this paper.

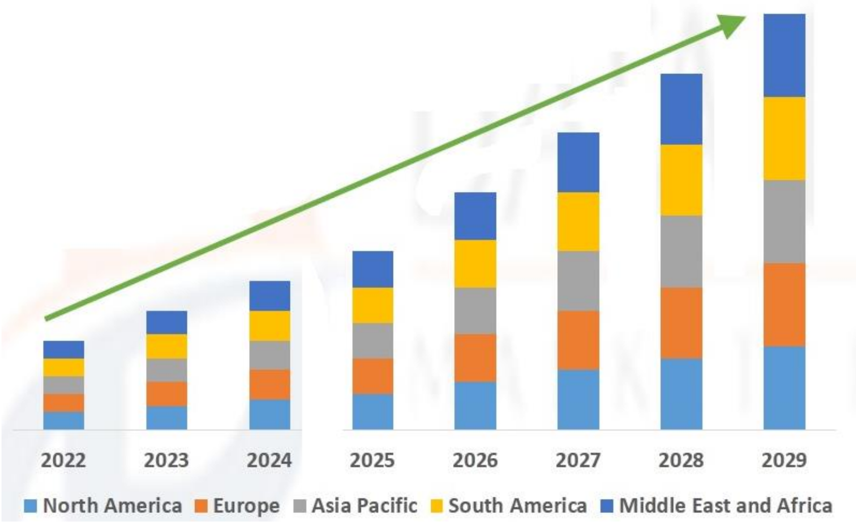

Figure 1. Global call center outsourcing market [13]

Customers often reach out to a company's help desk, which is managed by CSRs at call centers. These interactions, including calls and discussions, are automatically recorded for future reference. CSRs are tasked with immediately assisting customers, who may also interact with automated systems like IVRs that greet them and offer options such as listening to advertisements or promotional offers. Despite these systems, customers frequently experience frustration due to long wait times, inconsistent service, and inadequate solutions. A common complaint is the lack of consistency in the service, as customers cannot predict which CSR will handle their call. Customers have expressed dissatisfaction for various reasons, including difficulty hearing or understanding the CSR, being disconnected during transfers, or receiving poor service due to the use of jargon, extended hold times, or rude behavior. These challenges highlight the need to improve the standards of CSRs operating in call centers. Customers want to know the most important factors that contribute to CSR success to enhance business operations using cold call data. This study aims to provide solutions to improve the quality of CSRs, thereby enhancing the overall efficiency of call centers.

2. LITERATURE REVIEW

Call centres can be categorized as organization based or as independent businesses. Moreover, call centres can be categorized according to their organizational structure including singular centralized call centres or several call centres scattered across several sites. Each form of call centres has their own benefits and drawbacks and hence it becomes imperative to comprehend ideas, procedures, and hazards involved with each form. Organizations that own and run their own call centres benefit in a variety of ways. With only one type of institution as their clients, in-house contact centres have advantages of being able to cater to each caller the attention they need. CSRs receive training to become dependable brand ambassadors and add unique touches to offered client services. The level of customer services may be compromised when contact centres are outsourced where employee devotions may be low. In-house call centres reduce the dangers of disclosing highly protected personal data due to the involvement of third parties. In spite of quality checklists for performance measurements that can ensure consistency of provided services by CSRs, the study in [14] recognised that inability to maintain efficiency and provide consumers with quality services hampered operations. Quality can instill greater confidence to contact with direct representatives. Additionally, internal call centres are more adaptable than call centres that are outsourced as they are directly under the management of organisations, any changes to business procedures could be handled right away [15].

Although internal contact centres could be more dependable, secure, and adaptable than outsourced call centres. Many organizations are turning towards outsourced contact centres as they are more cost-effective options than in-house call centres, since they require lesser maintenances than in-house call centres. Outsourced call centers also eliminate organizational needs for investing in training of CSRs and when call volumes increase, scalability of call center sizes get easily be adjusted to meet customers’ requirements. Call centres serve as complete information networks and have the advantages of requiring singular communication platforms, singular customer relationship management systems, and singular real estate expenditures. Call centres may be given autonomy, with each site processing just certain kinds of calls. For example, technical assistance may fall under the purview of one site, while billing, may fall under the purview of another site. Route particular calls to one location, then use other locations when there is an overflow or when it is beyond business hours as another option for decentralized call centre models. Each location may also be treated equally, similar to centralized locations, routing calls to the next available CSR [16]. The optimal approach will depend on the needs of each healthcare institution, although both centralized and decentralized contact centres can be either in-house or outsourced. A healthcare organization is impacted in numerous ways by the implementation of a call centre strategy. The impact that call centre methods have on healthcare firms' overall customer service standards may be the most evident effect. As customer service quality rises, so do outcomes, customer accessibility to services, and organisational expenses. A newly deployed call centre strategy's organisational implications on an unidentified information delivery system were assessed in the study in [17].

According to the study, company models that prioritise cost-cutting over customer satisfaction and service quality are more successful than those that do not. Furthermore, it discovered that loyal consumers are those that receive outstanding customer service. The adoption of automated call distribution technologies improved contact centres' levels of customer service, such as the general happiness of patients in healthcare systems, while simultaneously increasing their cost-effectiveness. In this instance, the average call response time was 30 seconds, and the number of callers who hung up was under 5%. These metrics were used to show how the quality of the client services given had improved. Another example of a business leveraging its call centre services to enhance quality was the impact of redesigning a network's contact centre on a particular urology clinic within the network. By implementing LEAN methodology to reorganise staff according to call volume, create a backup call coverage system during downtime, move off-site call centre agents to a central location, hire a registered nurse to implement a triage line, and set new performance standards, the call center's efficiency was significantly increased. Applying LEAN and 6 Sigma methodologies to enhance contact centre performance led to greater patient satisfaction and enhanced patient care [18].

Customers may have more access to their required services when call centres are used effectively. Call centre scheduling techniques also play important roles in improving access to timely service. The demand for unsuitable services gets reduced while access to appropriate services during proper time and location are improved with the integration of information technology applications within call centres. As a result, businesses are better equipped to balance the needs of both customers and providers. Many findings from experiments and observations suggest that careful monitoring practises are crucial measures to generating good performances [19]. Performance monitoring, which enables emphasis on agents' work behaviour, includes call listening and observation [20]. According to Richardson and Belt (2001), monitoring is done to make sure the task is being done at the proper rate. Also, from the client's perspective, performance monitoring is seen as one of the primary managerial abilities [21]. Measurement of every aspect of customer service representatives' (CSRs') interactions with clients while providing services is vital for contact centre managers and supervisors [22]. In order to sustain and enhance client loyalty and retention. It is crucial that contact centres practise quality assurance and monitoring on a daily and hourly basis. Feedback from monitoring must also be sent to call centre agents during an offline session. The research Audrey in [23] came to the conclusion that contact centre management should take a more active role by collaborating more closely with their call centre agents. As a result, managers or supervisors would be able to determine the precise coaching and training needed for each agent and receive aid in enhancing the abilities of their personnel. According to databridge market research (2024), the global call center outsourcing market is experiencing significant growth, driven by increased demand for customer service solutions [24].

3. METHOD

A call center is an essential component of customer service operations, where CSRs manage incoming and outgoing calls, addressing inquiries about products or services, resolving complaints, and providing support. The effectiveness of CSRs directly impacts customer experience, making it crucial for them to be knowledgeable, empathetic, and responsive. This study introduces the SMFCCE schema, a framework designed to evaluate the quality and productivity of CSRs using DLTs. The SMFCCE methodology includes several stages, such as exploratory data analysis (EDA), data cleaning, feature extraction, train/test splitting, and classification using ensemble methods. Figure 2 illustrates the overall methodology followed by the SMFCCE schema.

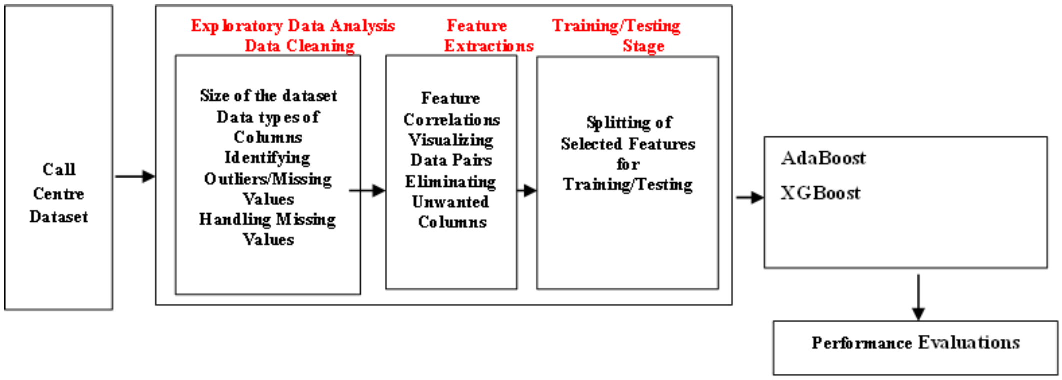

Figure 2. SMFCCE schema's methodology

3.1. Exploratory data analysis and data cleaning

EDA is a vital data analysis technique that often employs visual tools to thoroughly examine datasets. This step helps identify significant patterns, relationships between variables, and potential anomalies that could affect the accuracy of machine learning models. Data cleaning is crucial in this phase, as it involves removing incorrect variables, handling missing values, and eliminating outliers that could distort the results. For instance, columns with more than 15% missing data are typically excluded from the analysis.

3.2. Descriptive statistics

To summarize the central tendency of the observed data, the arithmetic mean (average) is employed, which represents the sum of all individual observations divided by the total number of samples. It is mathematically expressed as:

$$\text{Mean (average): } \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

Where $\bar{x}$ is the mean, x_i are the data points, and nnn is the number of data points.
Median: the middle value when data points are arranged in ascending order.
Mode: the most frequently occurring value in the dataset.

$$\text{Standard deviation } (\sigma)\text{: } \sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i) - \bar{x})^2}$$

Where σ measures the amount of variation or dispersion of a set of values.
Detecting outliers:

Z-score: $z = \frac{x-\mu}{\sigma}$

Where x is a data point, μ is the mean, and σ is the standard deviation. A Z-score greater than 3 or less than-3 is typically considered an outlier.
Interquartile range (IQR): IQR=Q3−Q1
Outliers are often defined as values below Q1−1.5×IQR or above Q3+1.5×IQR.
Handling missing values:
Imputation with mean/median: replace missing values with the mean or median of the column.
If x_i is missing, replace x_i with x̄ or the median.
Dropping rows/columns: remove rows or columns with missing values beyond a certain threshold (e.g., more than 15% missing data).
Normalization:

min-max scaling: $x' = \frac{x-\min(x)}{\max(x)-\min(x)}$

Where x′ is the normalized value.

– Z-score normalization: $x' = \frac{x-\mu}{\sigma}$

Feature extractions: feature extraction reduces the dimensionality of the dataset by summarizing the original features into a more compact set. Techniques such as principal component analysis (PCA) and linear discriminant analysis (LDA) are employed to achieve this:
- PCA: involves calculating the covariance matrix, solving for eigenvalues and eigenvectors, and selecting principal components.
- LDA: focuses on maximizing the ratio of between-class variance to within-class variance for improved separability.

Regularization techniques, including L1 (Lasso) and L2 (Ridge) regularization, are used to prevent overfitting by adding penalties to the loss function. Feature selection further refines the dataset by prioritizing significant features while eliminating irrelevant ones.
PCA:

- Covariance matrix: $\Sigma = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2)\ (x_i - \bar{x})^T)$

Where Σ is the covariance matrix, x_i are the data points, and x is the mean vector.
- Eigenvalues and eigenvectors: solve for λ and v in $\Sigma v = \lambda v$

The eigenvectors corresponding to the largest eigenvalues are used as the principal components.

3.3. Linear discriminant analysis

To quantify the dispersion of class-wise mean vectors relative to the overall data mean, the between-class scatter matrix is computed, capturing the separability among different classes. It is defined as:

Between-class scatter matrix (S_B): $S_B \sum_{i=1}^{C} n_i\ (\mu_i - \bar{\mu})\ (x_i - \bar{x})^T)$

Where c is the number of classes, n_i is the number of samples in class i, μ_i is the mean vector of class i, and μ is the overall mean vector.

Within-class scatter matrix (S_W): $S_B \sum_{i=1}^{C} \sum_{x_k\, \varepsilon C_i} n_i\ (x_k - \bar{\mu})\ (\mu_i - \bar{x})^T)$

Where x_k are the samples in class i.
Regularization techniques:
- L1 regularization (Lasso): adds a penalty equal to the absolute value of the magnitude of coefficients.

Loss function: $L = \sum_{i=1}^{n}(y_i - \bar{\bar{y}}_i)^2 + \lambda \sum_{j=1}^{p}|\beta_j|$

- L2 regularization (Ridge): adds a penalty equal to the square of the magnitude of coefficients.

Loss function: $L = \sum_{i=1}^{n}(y_i - \bar{\bar{y_i}})^2 + \lambda \sum_{j=1}^{p} \beta_j^2$

Feature selection is another often employed method for minimising the amount of features in a dataset. In contrast to feature extraction, the objective of feature selection is to prioritise the significance of the dataset's current features and remove any that are unimportant (no new features are added).

3.4. Test/train splits

A method for assessing a machine learning system's performance is the train-test split. Problems involving classification, regression, or any other supervised learning technique may be resolved using it. The dataset needs to be split into two categories first. The training dataset serves as the initial subset for model fitting. Instead of training the model on the second subset, the dataset's input components are given to it, and its predictions are then created and compared to predicted values. The second in question is the test dataset. The train-test split technique is a rapid and simple procedure, and the results offer assessments of the efficacy of machine learning algorithms for certain predictive modelling problems. The goal is to assess the machine learning model's performance using fresh data that weren't used to train the model. If target values or projected outcomes are absent, test/train fit on existing data with known inputs and outputs is used to generate predictions on fresh examples in the future. When a large enough dataset is available, the train-test technique is appropriate. Machine learning models for classification or regression may be evaluated using a train-test split. Test dataset stands in contrast to the train dataset, which is used to assess how well the machine learning model fits the data.

3.5. Classifications

In statistics and machine learning, classification is a supervised learning technique in which computer programmes make new observations or categorise existing data depending on what they have learned. Incoming data is mapped to predefined categories using classifier algorithms. Classification models use the training data as input to forecast classes or categories or to draw conclusions. Binary, multiple-class, or multiple-label categorizations can all be used in classifications. Binary classifications are classification kinds that have two possible results (true or false). Samples are assigned to target classes in multi-class classifications if there are more than two classes. In multi-label classifications, many labels or goals are applied to the same sample. Lazy or enthusiastic learners can be characterised in classification learning. Learners save data which is divided into categories based on the most important information. When compared to enthusiastic pupils, they have more time for prediction. as in k-nearest neighbours (KNNs). Before receiving data for predictions, eager learners build a classification model using the training data that is already available. It must be able to follow a single theory that applies to the whole field. They spend less time making predictions since they practise a much. Examples include artificial neural networks (ANNs), decision trees, and naive bayes. Boosting is an ensemble modelling technique designed to turn a large number of poor classifiers into a few powerful ones. Weak models are used sequentially to construct models in order to achieve this. This work uses booting (XGBoost) for classifications and evaluations of selected features by the proposed SMFCCE schema. The sequential tree construction method is approached by XGBoost using a parallelized implementation. This is made possible by the interchangeability of the two inner loops that compute the features and the outer loop that counts the leaf nodes of a tree when creating base learners. This stacking of loops prevents parallelization since the outer loop, which is the more computationally expensive of the two, cannot be begun until the inner loop, which is the more expensive of the two, has been finished. The loops are reconfigured using initialization, a global scan of all instances, and sorting with parallel threads to save runtime. This decision improves algorithmic efficiency by balancing any parallelization overheads in computation. Below is a list of the XGBoost algorithm.

4. RESULTS AND DISCUSSION

This section presents the experimental findings from the proposed SMFCCE scheme, which was implemented on an advanced micro devices (AMD) Athlon CPU with 4 GB of RAM using Python 3.9. The dataset used for the experiments, known as the car insurance cold calls report, was obtained from Kaggle. This dataset was sourced from a US bank that offers auto insurance alongside its standard services. The bank regularly conducts marketing campaigns to attract new customers by contacting potential clients to promote various vehicle insurance options. The dataset includes general client information (such as age and employment status) and specific details about ongoing and past insurance sales campaigns (such as communication type, last contact date, and the number of previous attempts).

Dataset overview: the dataset's features are as follows:

– Id: unique ID number.
– Age: age of the client.
– Job: client's job.
– Marital: marital status of the client.
– Education: client's education level.
– Default: whether the client is a defaulter.
– Balance: average yearly balance.
– HHInsurance: whether the household is insured.
– CarLoan: whether the client has a car loan.
– Communication: type of communication.
– LastContactMonth: month of the last contact.
– LastContactDay: day of the last contact.
– CallStart: start time of the last call (HH:MM).
– CallEnd: end time of the last call (HH:MM).
– NoOfContacts: number of contacts during this campaign for this client.
– DaysPassed: number of days since the last contact from a previous campaign.
– PrevAttempts: number of contacts performed before this campaign.
– Outcome: outcome of the previous marketing campaign.
– CarInsurance: whether the client subscribed to car insurance.

4.1. Selecting minimal features for call center agents efficiency schema’s exploratory data analysis

EDA plays a crucial role in uncovering new insights and developing a deeper understanding of the data. The initial step involved examining the shape of the dataset and its columns, datatypes, and basic statistics. The numerical columns—*Default*, *HHInsurance*, *CarLoan*, and *CarInsurance*—contained binary values (0 s and 1 s). Categorical features were also assessed.

SMFCCE data cleaning: handling missing values is a significant challenge in data analysis, as missing data can impede calculations and visualizations. In our dataset, the *result* and *communication* fields were prone to missing values, with numerous missing entries in the *job* and *education* categories. The data cleaning process involved imputing missing values for the *job* and *education* fields using Python’s backfill/frontfill methods. For fields with extensive missing data, such as *result* and *communication*, the missing values were replaced with "None."

SMFCCE feature extractions: feature engineering is vital for enhancing the performance of machine learning algorithms. Continuous variables like *Age* and *Balance* were binned into five buckets using the quartile cut method. The *CallStart* and *CallEnd* times, initially stored as object variables, were converted into datetime format to calculate the actual *CallTime*. This calculated *CallTime* was then binned, and the original columns were removed. Categorical variables were encoded as dummy variables to be included in the model-building process, and correlations between variables were examined using a heatmap. Notably, a positive correlation was observed between *DaysPassed* and *PrevAttempts*. Figure 3 illustrates the correlations between variables.

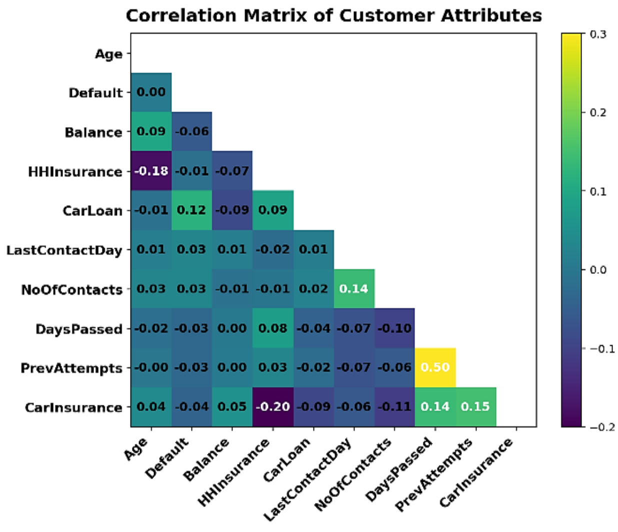

Figure 3. Correlations between variables

SMFCCE test/train splits: to ensure sufficient data for model training and evaluation, the train-test split method was employed. The k-fold cross-validation technique was also used as a model assessment alternative, particularly beneficial when data is limited or when models are computationally expensive to train. The train-test split was configured with standard sizes to evaluate model performance accurately.

4.2. Classifier evaluations

Once a classifier is developed, evaluating its accuracy and efficiency is critical. Various methods were employed to assess the classifiers, including accuracy scores, cross-validation scores, classification reports (precision, recall, F1-score, support), ROC curves, and confusion matrices. The models were trained using the AdaBoost (with parameters n_estimators=400, learning_rate=0.1) and XGBoost (with parameters n_estimators=1000, learning_rate=0.01) classifiers. The results showed the classification accuracy achieved by the classifiers on the outputs of the proposed scheme, as depicted in Figure 4.

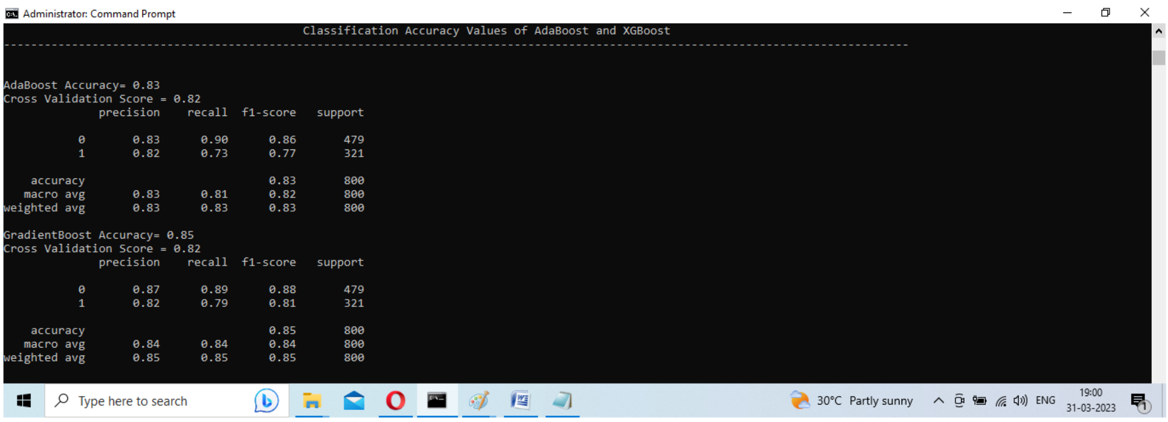

Figure 4. Obtained classifications accuracies by classifiers on the outputs of the proposed scheme

The true positive rate and true negative rate were also calculated, with F1-scores representing the weighted averages of precision and recall. The confusion matrix, shown in Figure 5, provided a comprehensive performance statistic for the machine learning classification scenarios. The amount of accurate forecasts that the occurrence is positive is known as the true positive rate. The real negative is defined as the outcomes that were accurately expected to be negative. F1-scores are weighted averages of precision and recall, where recall (TP/(TP+FN)) is the percentage of pertinent instances that have been found among all of the instances, and precision (TP/(TP+FP)) is the proportion of pertinent instances found among the retrieved instances. They are essentially used as a relevance assessment, with the intended result being negative but being false. For machine learning classification scenarios where the output may be two or more classes, the confusion matrix is a performance statistic.

Without data visualisation, it would be difficult to readily arrive at a conclusion in data science. Even if the outcome is established by tables, it might be difficult to analyse each figure and draw conclusions. Even a non-technical individual may complete those duties with ease by using charts and graphs. Executives and managers enjoy looking at reports that have visualisations because it makes it easier for them to make complicated choices [25], [26]. The pairplot that pairs and plots fields of interest is shown below. The heatmap is used to choose the factors for the Pairplot that influence the result. The dimensionality reduction technique of feature extraction reduces initial sets of raw data to levels suitable for processing [27]. The large number of variables in these enormous data sets makes them difficult to process computationally. "Feature extraction" refers to methods for selecting and/or combining variables into features, which greatly decreases the amount of data that must be processed while accurately and completely describing initial data set. When less processing power is required without losing crucial or pertinent data, the feature extraction strategy is advantageous. Reduced duplicate data might help an analysis by using feature extraction. The data reduction and computer-generated attempts to combine variables into features speed up the learning and generalisation stages of the machine learning process. The most significant characteristics identified in this investigation were call times, last contacted day, balances payable, contacts count, successes of outcomes, ages, insurances, non-communications, days passed after call, and no net outcomes. Figure 6 illustrates the cumulative gain chart as applied to the SMFCCAE schema, showcasing the gains achieved by leveraging this predictive model.

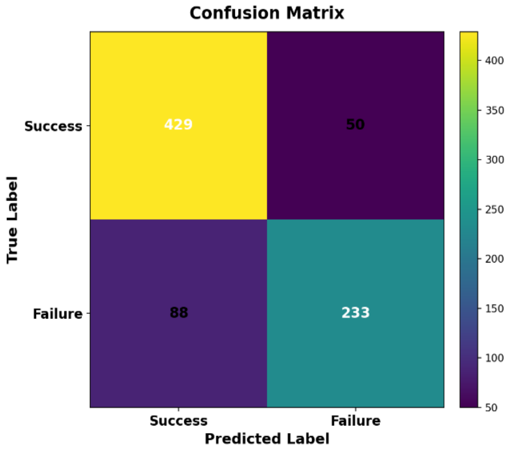

Figure 5. Confusion matrix of the SMFCCAE schema

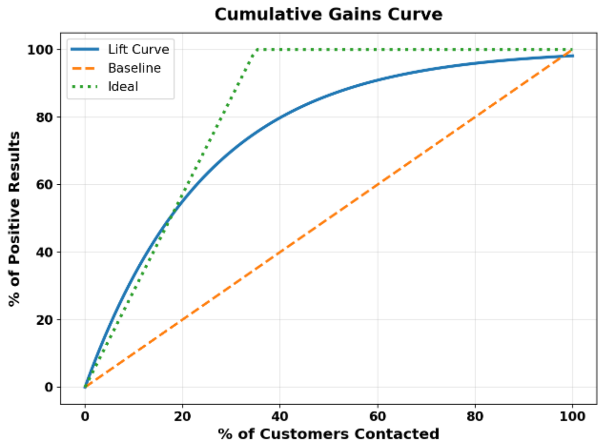

Figure 6. Chart of cumulative gains obtained by SMFCCAE schema

The following steps can be taken to improve the skills of CSRs: i) provide call centre employees with people skills training so that they can be friendlier and more engaging with customers during calls; ii) keep a tracker that reminds of follow-ups so that the representative can speak with the customer again and try to persuade them to buy car insurance; iii) choose customers with good credit scores and account balances so that the time invested in them is useful; and iv) focus on older people with a higher income.

5. CONCLUSION

This study significantly advances our understanding of evaluating CSRs in call centers through the application of DLTs. By introducing the SMFCCE framework, we have demonstrated that it is possible to achieve an impressive classification accuracy of 85% using a minimal set of features, highlighting the efficiency of DLTs in improving call center performance. The findings indicate that the SMFCCE framework enhances assessment accuracy and operational efficiency, providing actionable insights into CSR productivity. This approach offers practical benefits for businesses, leading to better customer satisfaction and retention while addressing critical human resource challenges such as stress and turnover. The study's implications extend to the research field by showcasing the potential of advanced analytics in operational management and suggesting further exploration of its applications in various industries. For the community, implementing the SMFCCE framework can lead to significant improvements in service quality and workforce management. Future research could explore broader applications of the framework, integration with emerging technologies, and long-term effects on CSR performance and call center operations. Overall, this research underscores the transformative potential of DLTs and emphasizes the importance of addressing human resource factors to enhance call center operations.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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