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Ai Based Data Analytics for Crm Optimization

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ABSTRACT

Customer Relationship Management (CRM) systems generate large volumes of customer interaction data through calls, campaigns, and lead records. However, most existing CRM platforms rely on static dashboards and basic reports, which limit their ability to extract actionable insights. This paper presents an AI-based data analytics framework for CRM applications that focuses on customer connectivity analysis, agent performance evaluation, and potential lead conversion using legacy calling data. The proposed system uses descriptive analytics, weighted scoring, normalization techniques, and statistical aggregation to analyze agent efficiency, customer engagement, and campaign effectiveness. Customer connectivity is measured using responsiveness and connectivity scores, while lead conversion potential is evaluated using Cold, Warm, and Hot lead classification. The system provides interpretable, scalable, and data-driven insights that enhance CRM decision-making without relying on complex machine learning models.

***Keywords*— CRM Analytics, Customer Connectivity, Lead Conversion, Data Analytics, Business Intelligence**

1. INTRODUCTION

Customer Relationship Management systems play a critical role in managing interactions between organizations and customers. CRM platforms store valuable data related to customer calls, agent activities, appointments, and lead statuses. Despite the availability of large datasets, many organizations fail to utilize this data effectively due to limited analytical capabilities. Legacy calling data often contains hidden patterns related to customer behavior, agent performance, and campaign outcomes. AI-based data analytics enables organizations to process such data systematically and derive meaningful insights. Instead of using complex machine learning models, descriptive analytics and scoring-based techniques can provide interpretable and business-friendly solutions. This paper proposes an AI-based analytics framework for CRM applications that focuses on three major aspects: agent performance analysis, customer connectivity analysis, and lead conversion potential estimation.

2. PROBLEM STATEMENT

Traditional CRM systems face the following challenges:
- Lack of quantitative analysis for customer connectivity
- Inability to measure agent performance using standardized metrics
- No structured approach to predict lead conversion potential
- Overdependence on manual interpretation of reports

These limitations reduce operational efficiency and affect sales outcomes. There is a need for an intelligent analytics layer that processes legacy CRM data to support data-driven decision-making.

3. OBJECTIVES

The objectives of this project are:
- To analyze agent performance using call and appointment data
- To measure customer connectivity and responsiveness
- To classify customers based on engagement levels
- To evaluate campaign effectiveness using lead conversion strength
- To provide a scalable and interpretable CRM analytics framework

4. LITERATURE REVIEW

Call Agent Performance Analysis based on Logs:

The current paper provides an overview of the CRM call log data to analyze the work of the agents based on some operational metrics, including the total number of calls made, duration of the call, connectivity status, and the outcomes of the response. The paper describes how to process and summarize call logs to determine the productivity of the agent, the fluctuations of their performance, and the daily and periodic activities in terms of calling. The analysis of the call records that the paper is majorly structured around are agent-level call records to enable assessment of such data by the managers.

Customer Segmentation Using CRM Interaction Data:

In this paper, the author explains how analytical techniques can be used to segment the customers using the CRM interaction data. It explains how important customer characteristics like engagement behavior, response rate, and history of interaction can be utilized to develop valuable customer segments. The research underlines the importance of learning the customer behavioral patterns in order to aid the targeted communication and better management of relationship with the customer.

Lead Conversion Analysis Using CRM Data:

The given paper is devoted to the analysis of the CRM lead data to comprehend the conversion behavior and define the factors that contribute to the successful lead outcomes. It discusses the process of analyzing historical data of interactions and response to identify converted and non-converted leads. The article identifies the contribution of data analysis to the enhancement of lead prioritization and sales plans. Optimizing Sales Funnel Efficiency: Deep Learning Techniques for Lead Scoring Integrating Artificial Intelligence with Salesforce: A Literature Review The paper presents a systematized literature review of the implementation of the artificial intelligence into Salesforce CRM. It talks about the integration of AI into the Salesforce modules including Sales Cloud, Service Cloud, and Marketing Cloud to make decision-making processes more automated, personalized, and automated. The paper overviews the current trends in research, application and challenges associated with AI-based CRM systems.

5. SYSTEM OVERVIEW

The proposed system consists of three analytical modules:
Module 1: Customer Connectivity and Agent Performance Analysis
Module 2: Customer Connectivity and Responsiveness Scoring
Module 3: Potential Lead Conversion and Campaign Effectiveness Analysis
Each module operates on CRM datasets and contributes to overall business insights.

6. MODULE 1: AGENT PERFORMANCE AND CUSTOMER CONNECTIVITY ANALYSIS

Module 1 focuses on evaluating agent-level performance using legacy calling data. The dataset includes agent identifiers, call records, appointment details, dialer status, and agent remarks.

Preprocessing steps include:
- Conversion of date fields into standard datetime format
- Mapping of categorical dialer status into numeric values
- Creation of binary indicators for appointment booking and remarks logging

Agent-level aggregation is performed to calculate:
- Total number of calls handled
- Number of appointments bookedRemarks logged by agents
- Average dialer success rate

Key Performance Indicators such as appointment rate and remarks rate are derived to evaluate agent efficiency.

7. MODULE 2: CUSTOMER CONNECTIVITY AND RESPONSIVENESS SCORING

Module 2 focuses on measuring customer connectivity using descriptive analytics and weighted scoring techniques. The customer dataset includes responsiveness scores, connectivity scores, and preferred time slots for contact.

To ensure comparability, responsiveness and connectivity values are normalized using Min-Max scaling. A Customer Connectivity Score is computed using a weighted formula:

Customer Connectivity Score =
$0.4 \times$ Normalized Responsiveness +
$0.6 \times$ Normalized Connectivity

Customers are classified into three categories based on percentile thresholds:
- Highly Connected Customers
- Moderately Connected Customers
- Poorly Connected Customers

Additionally, analysis of the "best time to connect" is performed to identify time slots with higher average connectivity. This helps sales teams optimize calling schedules and improve customer reachability.

8. MODULE 3: POTENTIAL LEAD CONVERSION ANALYSIS

Module 3 analyzes lead conversion potential using campaign-wise lead data. Leads are categorized based on conversion strength as:

Cold Leads: Low conversion probability

Warm Leads: Moderate conversion probability Hot Leads: High conversion probability
Each category is mapped to a numeric score: Cold = 0
Warm = 0.5
Hot = 1
Campaign-level aggregation is performed to compute:
• Total leads generated per campaign
• Average lead effectiveness score
Campaigns are ranked based on these metrics to identify high-performing marketing strategies.

9. METHODOLOGY

The overall methodology follows these steps:
1. Data collection from CRM CSV files
2. Data cleaning and preprocessing
3. Feature engineering and normalization
4. Weighted scoring and aggregation
5. Visualization and ranking of results

The approach emphasizes interpretability and scalability rather than complex predictive models.

10. IMPLEMENTATION

The system is implemented using Python in Jupyter Lab. The following tools are used:
• Pandas for data manipulation
• NumPy for numerical operations
• Scikit-learn for normalization
• Matplotlib for data visualization

Separate analytical pipelines are implemented for each module, and results are exported as CSV files for reporting and dashboard integration.

11. RESULTS AND ANALYSIS

The experimental results demonstrate:
• Clear ranking of agents based on performance scores
• Identification of highly and poorly connected customers
• Optimal time slots for customer engagement
• Detection of campaigns generating high-quality leads

The system provides actionable insights that can improve sales efficiency and customer engagement.
Visual Implementation Results

Fig. 1: Agent Performance Analysis.

Fig. 2: Client Performance Analysis.

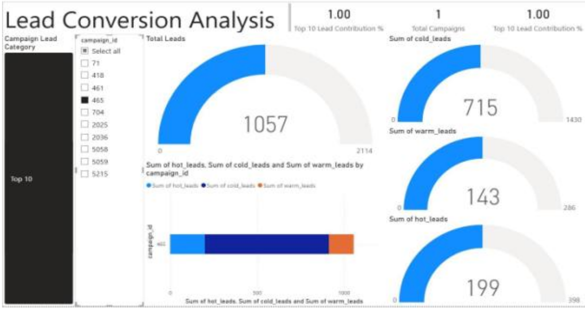

Fig. 3: Lead Conversion Analysis.

analytics framework proves to be interpretable, scalable, and suitable for real-world CRM environments where transparency and business understanding are essential.

12. LIMITATIONS AND FUTURE WORK

Despite its effectiveness, the proposed system has certain limitations. The analysis relies solely on structured CRM data and does not incorporate sentiment analysis or contextual understanding of call remarks. Real-time CRM integration is not implemented, limiting the system to batch-based analysis. Additionally, the approach does not utilize advanced predictive machine learning models.

Future work may include the integration of Natural Language Processing techniques to analyze agent remarks and customer sentiment. Machine learning and deep learning models can be explored for predictive lead conversion analysis. Real-time dashboards, automated alerts, and advanced customer behavior clustering can further enhance the system's analytical capabilities.

13. DISCUSSION

The experimental results demonstrate that descriptive analytics and weighted scoring techniques can effectively extract actionable insights from legacy CRM data. The agent performance analysis clearly differentiates high-performing and underperforming agents based on appointment rates, remarks consistency, and call success indicators. This enables managerial teams to make informed decisions regarding agent training, workload distribution, and performance improvement strategies.Customer connectivity analysis highlights the importance of responsiveness and reachability in CRM operations. The classification of customers into highly connected, moderately connected, and poorly connected categories allows sales teams to prioritize follow-ups and optimize engagement strategies. Additionally, the identification of optimal time slots for customer contact improves call success rates and overall operational efficiency. The lead conversion analysis reveals that campaign effectiveness varies significantly based on lead quality distribution. Campaigns generating a higher proportion of warm and hot leads demonstrate stronger conversion potential. Overall, the proposed

14. REQUIREMENT SPECIFICATION

Hardware RequirementsA system with a minimum of 8 GB RAM, an Intel i5 or equivalent processor, and sufficient storage to handle CRM datasets.

Software Requirements

Python programming environment, Jupyter Lab or Jupyter Notebook, Pandas and NumPy libraries for data processing, Scikit-learn for normalization and analytics, Matplotlib for visualization, and a standard operating system such as Windows or Linux.

15. RELEVANCE OF THE PROJECT

Academic RelevanceThe project enhances understanding of applied data analytics in CRM systems and provides students with practical exposure to real-world business datasets.Industrial Relevance Organizations can utilize the proposed framework to improve sales efficiency, optimize agent performance, and identify high-performing marketing campaigns.Social Relevance Improved customer connectivity and engagement lead to better customer satisfaction and more effective communication strategies.

16. SUSTAINABLE DEVELOPMENT GOALS (SDGS)

The proposed system aligns with the following United Nations Sustainable Development Goals: SDG 8: Decent Work and Economic Growth By improving sales productivity and operational efficiency, the system supports sustainable business growth. SDG 9: Industry, Innovation, and Infrastructure The use of AI-based analytics and data-driven decision-making promotes innovation in CRM and enterprise systems. SDG 12: Responsible Consumption and Production Optimizing customer engagement and lead prioritization reduces unnecessary resource utilization and improves operational sustainability.

17. CONCLUSION

This paper presented an AI-based data analytics framework for CRM applications focused on agent performance evaluation, customer connectivity analysis, and lead conversion prediction using legacy calling data. By applying descriptive analytics and weighted scoring techniques, the system delivers interpretable and scalable insights without relying on complex machine learning models. The proposed approach enhances CRM decision-making, improves customer engagement, and provides a practical solution suitable for real-world business environments.

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