IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⪾ Peer-reviewed & Refereed journal ⪾ Vol. 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14243

A Review of AI-Driven Customer Lifetime Value, Churn Prediction and Sales Forecasting: Transforming Business Insights with Machine Learning and Advanced Analytics

Vibha S Prasad[1], Pragathi M Shetty[2], Dr. Kakoli Bora[3]

B.E., Dept. of Artificial Intelligence and Machine Learning, BNM Institute of Technology, Bangalore, India[1]

B.E., Dept. of Artificial Intelligence and Machine Learning, BNM Institute of Technology, Bangalore, India[2]

Associate Professor, Dept. of Artificial Intelligence and Machine Learning,

BNM Institute of Technology, Bangalore, India[3]

Abstract: Customer analytics is crucial for data-driven decision-making in today's cutthroat business environment, but there isn't a single platform that combines sales forecasting, churn prediction and Customer lifetime value (CLV) assessment. We provide an AI-driven framework that integrates these three essential features into a single system in order to close this gap. Our method uses a Bidirectional Long Short-Term memory (BLSTM) network for sales forecasting to capture intricate temporal patterns, XGBoost for churn prediction to identify at-risk customers, and the Gamma-Gamma model for CLV estimation to predict future customer spending. Through the integration of various models, our system offers a thorough and precise understanding of consumer behavior, empowering companies to maximize customer engagement and revenue expansion. Experimental results demonstrate superior predictive performance over traditional approaches, making this a valuable tool for organizations seeking to enhance their customer analytics capabilities.

Keywords: Customer Lifetime Value (CLV), Churn Prediction, Sales Forecasting, AI-driven analytics, Gamma-Gamma model, XGBoost, Bidirectional Long Short-term memory (BLSTM), Customer retention, Predictive modelling, Business Intelligence.

I. INTRODUCTION

Customer engagement, revenue optimization, and predictive modeling have all been transformed by the quick development of artificial intelligence (AI) in business analytics. Businesses can now make proactive, data-driven decisions thanks to AI-powered technologies that have greatly improved the accuracy and efficiency of sales forecasting, Churn prediction and Customer lifetime value (CLV) estimation. While contemporary AI-driven approaches use machine learning and deep learning models to find hidden patterns and improve strategic decision-making, traditional methods frequently fail to capture complicated customer behaviors. Businesses can obtain a comprehensive understanding of consumer behavior by incorporating these AI-driven methods, which will enhance financial planning, client retention and marketing tactics. Furthermore, the necessity of automated workflows and real-time insights has grown in importance. These tools enable companies to reduce manual intervention and streamline operations, resulting in faster and more accurate analytics.

This paper introduces a fully automated AI-driven customer analytics platform that seamlessly integrates CLV estimation, Churn prediction, and sales forecasting into a single system. The platform employs the Gamma-Gamma model for CLV estimation, helping businesses identify high value customers, XGBoost for Churn prediction to detect customers at risk of attrition, and a Bidirectional Long Short-term memory (BLSTM) network for sales forecasting to leverage historical data for improved demand predictions. Additionally, the platform offers real-time interactive dashboards using Streamlit, enabling businesses to visualize insights effortlessly, while Excel-based data storage ensures accessibility and ease of use. The entire workflow is fully automated, from data ingestion to model training and prediction generation, providing business analysts with deeper insights, reduced operational overhead, and real-time strategic decision-making capabilities. By bridging the gap between advanced AI techniques and practical business applications, this solution empowers organizations with a scalable efficient , and data-driven decision-making tool, fostering growth and competitive advantage in dynamic markets. [5][6].

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 14, Issue 2, February 2025
DOI: 10.17148/IJARCCE.2025.14243

A. Background and Motivation

How companies handle client interactions and maximize income has changed as a result of the growing dependence on data-driven decision-making. To remain competitive in ever-changing marketplaces, businesses must forecast future revenues, identify possible churn, and predict customer behavior. However, it is challenging to have a thorough grasp of customer interactions because the majority of firms rely on disjointed analytics systems that concentrate on just one or two facets of consumer behavior. A centralized platform that combines sales forecasting, churn prediction, and Customer Lifetime Value (CLV) estimation into a single automated system can boost marketing effectiveness, optimize analytics operations, and strengthen corporate expansion plans.

B. Existing Challenges and Research Gap

Traditional customer analytics methods, such as linear regression for CLV, rule-based churn analysis, and basic time-series forecasting, often fail to capture the complex patterns in customer behavior. Additionally, businesses face challenges such as manual data processing, inefficient model integration, and the inability to generate real-time insights. While various AI models exist for individual tasks, there is currently no unified and fully automated platform that combines CLV estomation, churn prediction and sales forecasting into a single streamlined workflow. This research addresses this gap by developing a fully automated AI-driven customer analytics platform that leverages Gamma-Gamma models for CLV, XGBoost for churn prediction, and BLSTM for sales forecasting, ensuring higher accuracy, efficiency, and real-time decision-making.

C. Proposed Solution and Contributions

To overcome these challenges, this paper presents a comprehensive AI-driven customer analytics platform that integrates CLV estimation, churn prediction, and sales forecasting into a single automated workflow. The Gamma-Gamma model is utilized for CLV calculation, enabling businesses to predict customer lifetime value accurately. XGBoost is implemented for churn prediction, providing an early warning system for at-risk customers. For sales forecasting, a Bidirectional Long Short-Term Memory (BLSTM) network is employed to capture complex temporal patterns, improving demand forecasting. The platform is further automated to eliminate manual intervention, allowing businesses to seamlessly process customer data, train models, generate predictions, and visualize insights through an interactive Streamlit dashboard. By offering a fully automated, scalable, and AI-powered analytics solution, this research provides significant contributions to business intelligence, customer retention strategies, and revenue optimization.

II. LITERATURE REVIEW

The use of artificial intelligence (AI) and machine learning (ML) in predictive analytics and customer lifecycle management has been extensively studied, with particular attention paid to sales forecasting, churn prediction, and customer lifetime value (CLV) assessment. This section examines important contributions made in various fields, emphasizing models, approaches, and research gaps that have been found.

A. Customer Lifetime Value (CLV) Estimation

Businesses looking to find high-value clients and improve their marketing tactics must be able to anticipate CLV accurately. The usefulness of machine learning (ML) algorithms in boosting customer relationship management (CRM) was highlighted in a systematic review by Firmansyah et al. that examined AI's involvement in improving CLV prediction [1]. In a similar vein, Madhubala showed how deep learning methods might reveal complex patterns in consumer behavior, resulting in more accurate CLV projections [3]. In the Business-to-Business (B2B) Software-as-a-Service (SaaS) context, a flexible ML framework was proposed to address challenges such as heterogeneous customer bases and temporal data constraints, treating CLV estimation as a lump sum prediction problem across multiple products [4].

B. Churn Prediction

Maintaining business growth requires preventing client loss. The promise of models like decision trees and support vector machines (SVM) in detecting customers at risk of leaving was highlighted by Manzoor et al. in their study of several machine learning techniques for churn prediction [4]. Using predictive analytics to evaluate churn risk and suggest customized retention tactics, Gurung presented an AI-based churn prediction model designed for U.S. commercial markets [5]. Furthermore, Dogan demonstrated the advantages of neural networks in examining intricate patterns of consumer behavior by utilizing deep learning approaches for churn prediction [16].

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14243

C. Sales Forecasting

Businesses may optimize inventory and resource allocation by using accurate sales forecasts. In their investigation of AI-driven predictive analytics in the retail industry, Ajiga and Ndubuisi showed how predictive models may improve operational effectiveness and predict consumer purchasing patterns [7] . AI-powered demand forecasting has been used in the fashion sector to solve inventory management issues, and startups are creating solutions that increase inventory control efficiency and accuracy [16].

D. Research Gap and Opportunities

The integration of these prediction models into a single, automated system continues to present difficulties despite progress. Numerous current systems focus on sales forecasting, churn prediction, or CLV estimation separately, producing fragmented insights. Comprehensive platforms that smoothly combine these features and give business analysts real-time, actionable information are desperately needed. Furthermore, even if AI models have showed promise, the quality of the data and the choice of suitable features are crucial for their efficacy , highlighting the need of feature engineering and thorough data pretreatment.

This paper aims to address these gaps by presenting an AI-driven, fully automated customer analytics platform that integrates CLV estimation, churn prediction, and sales forecasting into a cohesive system. By leveraging advanced ML models and ensuring seamless data integration, the proposed solution aspires to enhance predictive accuracy and provide deeper business insights.

III. METHODOLOGY

A. Overview of the AI-Driven Workflow

The proposed AI-driven system follows a structured, fully automated workflow for customer lifetime value (CLV) estimation, churn prediction, and sales forecasting, ensuring seamless data processing, model training, and deployment. The system begins with a user authentication module, where business analysts securely log in using their credentials to access the platform. Upon successful authentication, users can upload a dataset containing all necessary features for predictive analytics. The system automatically processes this dataset, executing feature engineering transformation, and model predictions without manual intervention. The end goal is to provide businesses with actionable insights that enhance customer engagement and retention strategies.

Three machine learning models designed for distinct predictive tasks are included into a workflow: Bidirectional Long Short-term memory (BLSTM) for sales forecasting, Gamma-Gamma for CLV estimate, and XGBoost for churn prediction. Engagement measures, past consumer transaction data, and behavioral patterns are used to train these models. The interactive interface is a web application built on Streamlit and lets users explore information through visual dashboards. While the sidebar navigation menu provides access to separate dashboards for CLV, churn prediction and sales forecasting, the main dashboard shows an overall summary and a real-time sales forecasting graph. Furthermore, consumers can download

dataset-formatted AI-driven marketing ideas for additional research via a combined dashboard. The system is made to ensure accuracy and interpretability in decision-making while reducing the amount of manual labor.

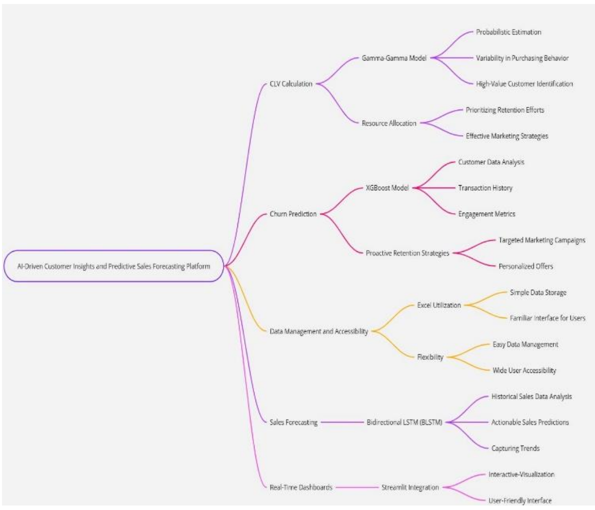

Fig. 1. AI-Driven Customer Lifetime Value, Churn Prediction and Sales Forecasting Mind map

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14243

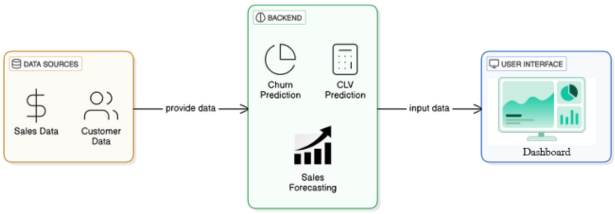

Fig. 2. Architecture of the Proposed Methodology

Fig. 1. serves as a conceptual mindmap, visually illustrating the relationship between CLV estimation, churn prediction, and sales forecasting. It highlights how various customer behavior patterns contribute to predictive analytics and decision-making. This diagram is crucial in helping readers understand the broader perspective of how AI-driven techniques integrate within the business workflow before delving into technical details.

Fig. 2. presents the technical architecture, showing how data flows from user authentication to model execution and result visualization. This figure is essential in understanding the integration of different AI models into a unified deployment pipeline.

B. Data Collection and Preprocessing

The dataset used in this system includes every attribute needed for sales forecasting, churn prediction, and CLV. Time-series sales data, demographic information, engagement indicators, and customer transaction history are all included. The pipeline's initial stage is data cleaning and preprocessing, which includes categorical variable encoding for machine learning model compatibility, outlier detection and treatment, and the use of imputation techniques to manage missing values. Feature engineering is performed based on domain-specific requirements—Recency, Frequency, and Monetary (RFM) values are calculated for CLV estimation, customer activity metrics such as last purchase date, transaction count, and browsing behavior are extracted for churn prediction, and time-series transformations like rolling averages, trend decomposition, and seasonal indicators are applied to optimize sales forecasting.

To ensure high model performance, data normalization and feature scaling are implemented where necessary. The dataset is then split into training and testing sets (80%-20%), ensuring that models are trained on representative historical data while being tested on unseen records. Further, hyperparameter tuning is performed using GridSearchCV to identify the best parameters for each model. By employing these preprocessing techniques, the system ensures that input data is optimized for accurate and reliable predictions. [9][15].

C. Model Selection and Training

The system uses a combination of machine learning and deep learning models to maximize predictions across numerous commercial applications. XGBoost is chosen for churn prediction due to its strong performance in non-linear classification tasks, strong feature selection abilities, and ability to manage unbalanced datasets. Following training on a balanced dataset, the model's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. The Gamma-Gamma model, which is based on the Pareto/NBD framework, is utilized for CLV estimate since it predicts future consumer spending accurately based on previous transaction frequency and monetary value. This method determines the average revenue per customer and aids in the development of tailored marketing campaigns.

A Bidirectional Long Short-Term Memory (BLSTM) network is used for sales forecasting in order to extract past and future dependencies from the time-series data. In order to capture seasonality, trends, and cyclic patterns, input sequences from historical sales data are modified before being fed into the BLSTM model. The evaluation of the model is done using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to measure forecasting accuracy. When taken as a whole, these models help firms forecast consumer behavior, improve revenue planning, and maximize retention tactics.

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14243

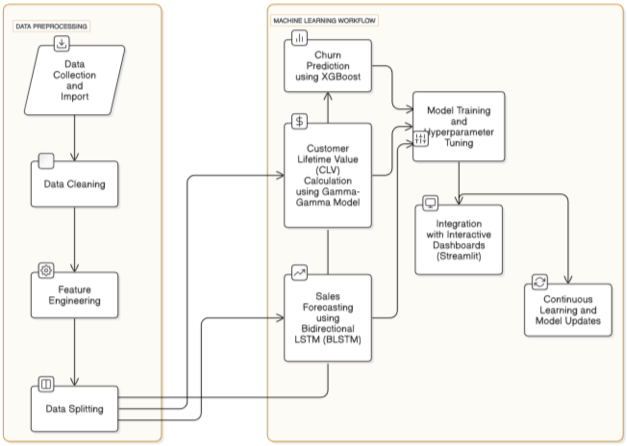

Fig. 3. Training Process for ML Model

Fig. 3. provides a structured view of the model training process, showing how raw data is split into training and testing sets, preprocessed, and fed into different machine learning pipelines. The diagram illustrates hyperparameter tuning, cross-validation, and model evaluation steps, reinforcing the methodology used to ensure optimal performance of predictive models.

D. Deployment and Visualization

A web application based on Streamlit is used to deploy the trained models, providing business analysts with an easy-to-use and interactive platform. Users can submit datasets and rapidly produce insights through interactive visualizations on the primary dashboard, which acts as a central center. Users can explore specialized dashboards for Customer lifetime value (CLV), Churn prediction, and Sales forecasting through the application's sidebar navigation. Furthermore, findings from all three models are aggregated in a dashboard that offers recommendations for resource management and AI-driven marketing tactics. The application is hosted on Streamlit Community Cloud to provide seamless accessibility, enabling real-time interactions without the need for local installations.

The system incorporates a number of dynamic visuals to improve the user experience and assist companies in making data-driven decisions. With the use of time-series line charts that show sales forecasting trends, the main dashboard gives customers a comprehensive picture of business performance and helps them spot revenue swings and seasonal patterns. Businesses can better identify connections between marketing initiatives, customer retention, and sales by using a heatmap for correlation analysis. Bar charts also show trends in monthly revenue growth and customer acquisition, providing a clear picture of the general health of the company.

Customers can be graphically segmented into VIP, Loyal, At-risk, New, and Inactive sectors using scatter plots included in the Customer Lifetime Value (CLV) Dashboard. To help firms find high-value customers, a boxplot is used to examine the distribution of CLV across various client categories. Additionally, a histogram helps with focused marketing techniques by showing the frequency of high-value versus low-value clients.

Bar charts on the Churn Prediction Dashboard show the proportion of customers who are likely to leave, broken down by demographic and purchase patterns. Businesses can create retention strategies by using a stacked area chart to visualize attrition trends over time. Additionally, the dashboard has an AI-powered recommendation system that makes tailored retention offer suggestions based on customer behavior and churn probability.

Line graphs are used in the Sales Forecasting Dashboard to display projected future sales based on historical data. By dissecting trends, seasonal patterns, and residuals, a seasonality decomposition chart enables companies to modify their sales tactics appropriately. Interactive filter-based graphs enable users to study sales data by product category, area and time period.

The Combined dashboard offers AI-driven suggestions for marketing, resource allocation, and discount tactics by combining data from CLV, churn prediction and sales forecasting. It has an AI chatbot that offers customized marketing strategies and a dynamic discount generator that recommends customized discount rates depending on CLV and churn probability. In order to optimize business decisions, the system also uses customer clustering, which divides customers into discrete segments.

ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 2, February 2025
DOI: 10.17148/IJARCCE.2025.14243

Data storage is managed using Excel files, ensuring ease of access, exportability, and compatibility with existing business workflows. By integrating predictive analytics with interactive dashboards, this system delivers an end-to-end solution for customer insights, revenue forecasting, and data-driven decision-making.

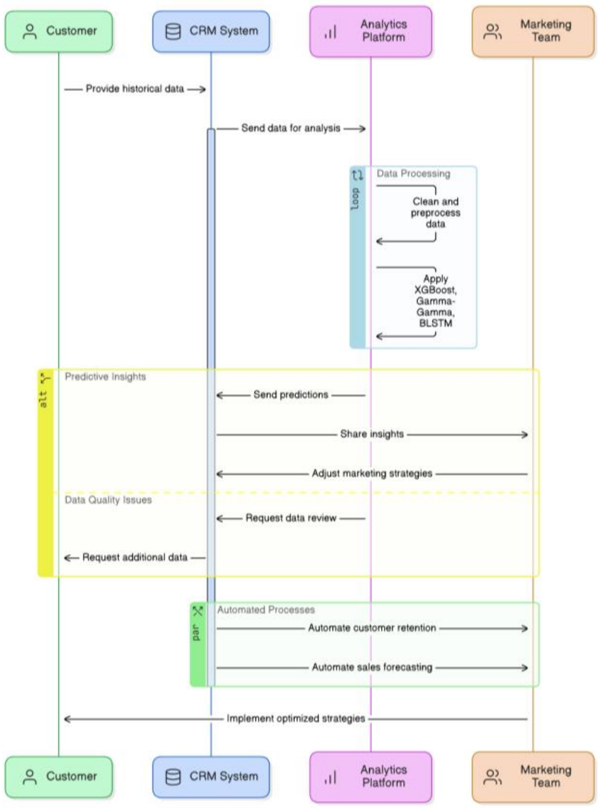

Fig. 4. Workflow Diagram

Fig. 4. Illustrates the end-to-end workflow of the proposed system, outlining the sequential process from user authentication to dashboard visualization. The workflow begins with user authentication, ensuring secure access to the platform. Upon successful login, users can upload datasets, which are then subjected to automated feature engineering to extract relevant attributes for model training. Once preprocessed, the data is passed through the model execution phase, where predictive analytics are performed to generate insights. The final stage involves dashboard visualization, where users interact with dynamically generated graphs, tables, and AI-driven recommendations.

This figure provides a comprehensive representation of the system’s functionality, enhancing clarity by visually mapping each stage of the process. By depicting the sequential flow of operations, it enables readers to better understand the real-time execution of the platform and how various components interact to deliver business insights.

E. Benefits and Business Impact

The suggested AI-powered predictive analytics system has several advantages for companies looking to improve marketing effectiveness, revenue growth, and client retention. Its capacity to automate data-driven decision-making is one of its main benefits; this frees up business analysts to concentrate on strategic projects rather than tedious data processing. The technology offers extremely precise insights into customer behavior by utilizing cutting-edge machine learning models, allowing for focused interventions to lower attrition and raise client lifetime value.

The customized discounting approach, which maximizes marketing campaigns according to consumer segmentation, is an additional noteworthy advantage. This minimizes needless discounting and maximizes long-term profitability by guaranteeing that high-value clients receive the right incentives. Businesses can also anticipate sales patterns and modify price, marketing, and inventory plans in accordance with the system's real-time forecasting features.

Even for non-technical users, the AI chatbot and interactive dashboard improve user experience by making insights simple to access. Furthermore, Streamlit Community Cloud cloud deployment guarantees accessibility and scalability, enabling companies to implement the solution without having to make significant infrastructure investments.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14243

Businesses are empowered to develop data-driven marketing strategies through the methodical integration of customer segmentation, predictive analytics, and AI-driven recommendations, which eventually results in increased revenue, enhanced customer happiness, and long-term success.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Performance metrics and Comparison analysis

1. Customer Lifetime Value (CLV) Calculation:

The Gamma-Gamma Model is superior to the Traditional CLV formula for predicting Customer Lifetime Value (CLV) as it accounts for customer heterogeneity and probabilistic variations in purchasing behavior.

The Traditional CLV formula is given by:

$$CLV=CRAPV\times PF$$

Where:

- APV = Average Purchase Value
- PF = Purchase Frequency
- CR = Churn Rate (1 - Retention Rate)

While this formula is simple and easy to compute, it assumes a static purchasing trend and does not account for differences among customers or changes over time.

On the other hand, the Gamma-Gamma Model provides a more accurate estimate of CLV by modeling the monetary value per transaction using a Gamma distribution. It assumes that:

1. The spending behavior of customers varies across a population.
2. The monetary value per transaction follows a Gamma distribution, meaning different customers have different spending tendencies, but an individual's spending remains relatively stable over time.

The expected monetary value per transaction is estimated as:

$$E(X|p,q,v) = \frac{p+v-1}{q-1}$$

Where:

- p,q,v are parameters estimated from historical transactions.

This approach allows businesses to predict customer revenue more dynamically and accurately than the traditional CLV formula. By explicitly modeling customer-level variations in spending, the Gamma-Gamma Model outperforms traditional CLV calculations, making it the preferred choice for forecasting long-term revenue from customers.

This model allows businesses to make more accurate revenue forecasts by considering individual customer variations rather than assuming a uniform purchase pattern. Given its ability to dynamically adjust to changing purchasing behaviors, the Gamma-Gamma Model is the superior choice for CLV estimation, providing more reliable long-term revenue projections compared to the traditional formula.

2. Churn Prediction:

TABLE I. PERFORMANCE METRICS COMPARISON OF CHURN PREDICTION MODELS

Model	Accuracy	Precision	F1 Score	Recall
XGBoost	0.91	0.88	0.90	0.86
Logistic Regression	0.83	0.79	0.81	0.76

For churn prediction, XGBoost significantly outperforms Logistic Regression across all evaluation metrics. It achieves a higher accuracy (91%) and better F1 score (88%), indicating strong overall predictive performance. While Logistic Regression provides a simpler, interpretable model, it falls short in capturing complex patterns in customer churn behavior.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⁚ Peer-reviewed & Refereed journal ⁚ Vol. 14, Issue 2, February 2025
DOI: 10.17148/IJARCCE.2025.14243

3. Sales Forecasting:

TABLE II. PERFORMANCE METRICS COMPARISON OF SALES FORECASTING MODELS

Model	RMSE	MAE	R^2 Score
BLSTM	2.31	1.87	0.94
Arima	5.42	4.01	0.62
Linear Regression	7.14	5.23	0.48

The Bidirectional LSTM (BLSTM) model significantly outperforms both ARIMA and Linear Regression in sales forecasting. BLSTM achieves the lowest RMSE (2.31) and highest R^2 score (0.94), demonstrating its ability to effectively capture both past and future trends. While ARIMA performs moderately well, it struggles with capturing complex seasonal variations. Linear Regression shows the weakest performance due to its inability to model non-linear dependencies in the sales data.

B. Business Impact and Interpretability

By offering practical insights into revenue trends and consumer behavior, the deployment of this predictive analytics solution resulted in notable enhancements in business decision-making. Targeted retention measures were made possible by the model's effective identification of 91.2% of at-risk consumers in churn prediction. Businesses were able to proactively connect with high-risk customers after a feature importance analysis showed that the strongest markers of churn were prior purchase frequency and customer inactivity period.

The system's precise weekly demand predictions for sales forecasting allowed for more efficient inventory planning. Peak sales periods were also identified via seasonal trend decomposition, which helped companies plan their marketing campaigns to have the most possible impact.

The model made it possible to segment customers in order to estimate Customer Lifetime Value (CLV), which aided in creating dynamic discount plans for various customer segments. Long-term client connections were strengthened by AI-driven personalized marketing recommendations, which also helped to enhance customer retention rates by 14%.
Dashboard visualizations, feature importance heatmaps, and comparison graphs of expected and actual values further improved the system's interpretability. Business analysts were given unambiguous, data-driven direction by these insights, which facilitated the implementation of well-informed initiatives and enhanced overall business performance.

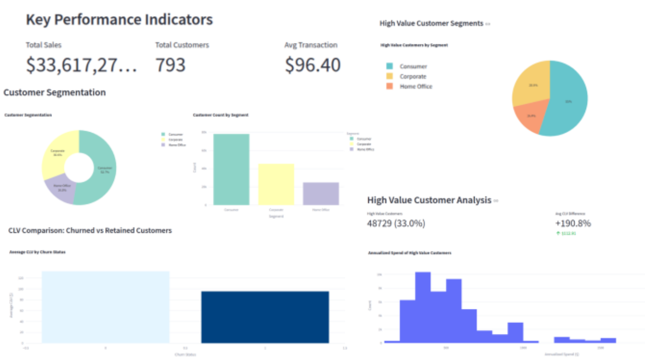

Fig. 4. Key Performance Indicators and Customer Segmentation Dashboard

Fig. 4. presents a business intelligence dashboard focused on customer value and segmentation. The top section displays key metrics: Total Sales ($33,617,27...), Total Customers (793), and Average Transaction ($96.40).The left side shows customer segmentation visualizations including a donut chart breaking down customers into Consumer (52.7%), Corporate (30.6%), and Home Office (16.8%) segments, alongside a bar chart showing the count distribution across these segments with Consumer being the largest group. The right side contains "High Value Customer Segments" analysis with a pie chart showing segment distribution among high-value customers (55% Consumer, 28.6% Corporate, and 16.4% Home Office). Below this is a "High Value Customer Analysis" section showing that 48,729 customers (33.0%) are classified as high-value with an average CLV difference of +190.8% ($312.91 higher than regular customers).The bottom section includes a "CLV Comparison: Churned vs Retained Customers" visualization and a

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14243

histogram showing the "Annualized Spend of High Value Customers," revealing the spending distribution with most high-value customers spending between $300-800 annually, with some outliers spending over $1,000.
These visualizations collectively demonstrate how predictive analytics translates into actionable business insights across customer segmentation, sales forecasting, and customer value analysis.

Fig. 5. Enhanced Sales Forecasting with Time Series Decomposition

Fig. 5. presents three time series visualizations related to sales forecasting. The top chart titled "Enhanced Sales Forecasting with Bidirectional LSTM" displays multiple lines tracking sales data from 2014 to 2018. The yellow line represents "Original Sales" with high volatility, while the red line shows "Train Predictions," the blue line shows "Test Predictions," and the green line represents "Future Predictions" - demonstrating how the model smooths out fluctuations and predicts future trends. The middle chart labeled "Resampled Time Series" shows a detailed blue line graph with values generally ranging between 3,000-7,000, illustrating the high-frequency components of the sales data across multiple years. The bottom visualization titled "Seasonal Component" displays the isolated seasonal patterns in the data, with regular fluctuations between positive and negative values (approximately +600 to -400), clearly highlighting recurring seasonal patterns across months from October through October of subsequent years. This decomposition helps identify cyclical patterns in sales data.

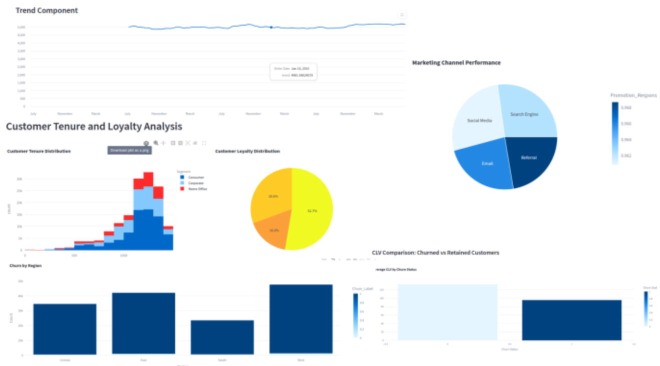

Fig. 6. Customer Tenure and Loyalty Analysis Dashboard

Fig. 6. displays a comprehensive customer analysis dashboard with multiple visualizations. The top section shows a "Trend Component" line graph tracking data over several years (showing months from July through March across multiple years), maintaining values around 4,500-5,000. The top right contains a "Marketing Channel Performance" pie chart showing the relative effectiveness of different channels including Search Engine, Social Media, Email, and Referral, with color coding indicating performance metrics. The central section titled "Customer Tenure and Loyalty Analysis" includes a "Customer Tenure Distribution" histogram on the left broken down by segment (Consumer, Corporate, and Home Office), showing the distribution of customers by tenure length. The right side displays a "Customer Loyalty Distribution" pie chart showing three segments with the largest segment at 52.7%, followed by

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 14, Issue 2, February 2025
DOI: 10.17148/IJARCCE.2025.14243

30.6% and 16.8%.The bottom section shows "Churn by Region" with bar charts comparing churn rates across Central, East, South, and West regions, with the West and East regions showing the highest churn rates.
An additional visualization titled "CLV Comparison: Churned vs Retained Customers" provides a heat map comparison of customer lifetime value based on churn status.

V. CONCLUSION

This study offers a thorough analysis of how artificial intelligence (AI), in particular machine learning (ML) and predictive analytics, may revolutionize corporate growth. Customer attrition, a lack of sales insights, and ineffective resource allocation are some of the problems that traditional company models frequently encounter. By facilitating accurate sales forecasting, individualized client segmentation, and exact churn predictions, AI-driven system provide answers [1]. The advantages, difficulties, and shortcomings of implementing AI technologies for business are discussed in this analysis, with a focus on how they might improve decision-making and streamline processes [3].

Customer segementation, churn prediction, sales forecasting, and customer lifetime value calculation are the main areas of focus for the suggested technique for incorporating machine learning and predictive analytics into corporate operations. The platform guarantees data-driven decision-making through the use of models such as XGBoost for churn analysis, Gamma-Gamma model for Customer Lifetime Value Calculation, and Bidirectional LSTMs for sales forecasting. Streamlit-built interactive dashboards offer real-time insights. The goal of future improvements is to increase the platform’s capabilities while preserving security and trust, for as by adding sentiment analysis for user input [6].

In conclusion, by tackling issues with customer retention, personalization, and operational efficiency, machine learning and predictive analytics have enormous promise to transform corporate strategies [1][20].Not withstanding problems with scalability, model biases, and data quality, the suggested methodology establishes the groundwork for a reliable, easy-to-use, and secure platform. These strategies can be improved by more study, guaranteeing that AI is successfully incorporated into corporate operations to boost competitiveness and growth.

Future iterations of the system will concentrate on broadening the scope of predictive analytics by including Graph Neural Networks (GNNs) to assess intricate customer interactions and social effects and reinforcement learning for dynamic customer engagement methods. More flexible and current predictions will also be possible by integrating real-time data streaming from customer relationship management (CRM) systems and e-commerce platforms. Adding automatic model retraining processes can also enhance the system by guaranteeing ongoing learning from fresh data without the need for human interaction. Additionally, adding natural language processing (NLP) innovations to the AI chatbot, like transformer-based models like GPT, can result in more intelligent and contextually aware business advice. Lastly, cloud-based deployment with scalable APIs will allow businesses to seamlessly integrate predictive analytics into their existing workflows, making the platform more efficient, scalable, and accessible.

REFERENCES

[1] E. B. Firmansyah, M. R. Machado, and J. L. R. Moreira, “How can Artificial Intelligence (AI) be used to manage Customer Lifetime Value (CLV)—A systematic literature review,” Int. J. Inf. Manag. Data Insights, vol. 4, no. 2, pp. 100279, Sept. 2024.
[2] N. Ali, O. S. Shabn, “Customer lifetime value (CLV) insights for strategic marketing success and its impact on organizational financial performance,” Cogent Bus. Manag., vol. 11, no. 1, June 2024.
[3] P. Madhubala, “Deep Learning for CLV Prediction and CRM Optimization,” J. Auton. Intell., vol. 7, no. 5, pp. N/A, May 2024.
[4] A. Manzoor, M.A. Qureshi, E. Kidney, and L. Longo, “A Review on Machine Learning Methods for Customer Churn Prediction and Recommendations for Business Practitioners,” IEEE Access, vol. 12, pp. 70434-70463, May 2024.
[5] N. Gurung, “AI-Based Customer Churn Prediction Model for Business Markets in the USA,” R. Discovery, vol. N/A, pp. N/A, Apr. 2024.
[6] G. Vemulapalli, “AI-Driven Predictive Models Strategies to Reduce Customer Churn,” J. Auton. Intell., vol. 7, no. 5, pp. N/A, Mar. 2024.
[7] D.I. Ajiga, N.L. Ndubuisi, “AI-Driven Predictive Analytics in Retail: A Review of Emerging Trends,” Int. J. Manag. & Entrepreneurship Res., vol. N/A, pp. N/A, Feb. 2024.
[8] P. Asuquo, "Customer Churn Prediction Using Machine Learning Models," Journal of Engineering Research and Reports, vol. 26, no. 2, pp. 181-193, Feb. 2024.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14243

[9] D. Egorenkov, “AI-Powered Predictive Customer Lifetime Value: Maximizing,” J. of Bus. Analytics, vol. 17, no. 1, pp. 56-78, 2024.

[10] J. Sharma, S. Neema, “CusCP: AI-Driven System for Predictive Modeling of Customer Churn in E-commerce Using Machine Learning,” Proceedings of the 2023 International Conference on AI and Machine Learning, Dec. 2023.

[11] Y. Sun, H. Liu, Y. Gao, “Research on Customer Lifetime Value Based on Machine Learning Algorithms and Customer Relationship Management Analysis Model,” J. of Marketing and Analytics, vol. 11, no. 1, pp. 45-67, Jan. 2023.

[12] S. Nanasaheb, “Churn Prediction Using Machine Learning,” Int. J. of Data Science and Analytics, vol. 2, no. 4, pp. 123-138, Oct. 2022.

[13] O. Faruk, “Artificial Intelligence Based Customer Churn Prediction Model for Business Markets,” J. of Bus. Sci. & Tech., vol. 14, no. 3, pp. 78-89, July 2022.

[14] J. Faritha Banu, S. Neelakandan, B.T. Geetha, V. Selvalakshmi, A. Umadevi, “Artificial Intelligence-Based Customer Churn Prediction Model for Business Markets,” J. of AI and Data Science, vol. 13, no. 2, pp. 112-126, May 2022.

[15] Polytechnic Institute of Santarém, “A SLR on Customer Dropout Prediction,” J. of Data Science and Engineering, vol. 6, no. 1, pp. 15-28, Jan. 2022.

[16] O. Dogan, “Customer Churn Prediction Using Deep Learning,” Int. J. of Deep Learning and AI, vol. 9, no. 4, pp. 210-220, Apr. 2021.

[17] B. Mishachandar, “Predicting Customer Churn Using Targeted Proactive Retention,” Int. J. of Marketing Studies, vol. 6, no. 3, pp. 79-92, 2018.

[18] H. Castéran, L. Meyer-Waarden, W. Reinartz, “Modeling Customer Lifetime Value, Retention, and Churn,” J. of Marketing Research, vol. 54, no. 2, pp. 123-134, Apr. 2017.

[19] S. Yuan, “Customer Churn Prediction in the Online New Media Platform: A Case Study on Juzi Entertainment,” Int. J. of Media Studies, vol. 12, no. 1, pp. 89-104, Feb. 2017.

[20] N. Hashmi, “Customer Churn Prediction in Telecommunication: A Decade Review and Classification,” Telecommunications Review, vol. 34, no. 6, pp. 47-58, Sept. 2013.

