An Internship project report entitled

On

Customer Lifetime Value Prediction

In partial fulfillment of the requirements for the award of

BACHELOR OF TECHNOLOGY

In

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Submitted by

Aligeti Sharanya

Under the Esteemed guidance of

Mrs. Chintolla Surekha
(Assistant professor)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

HYDERABAD INSTITUTE OF TECHNOLOGY AND MANAGEMENT

Gowdavelly (Village), Medchal, Hyderabad, Telangana, 501401

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HYDERABAD INSTITUTE OF TECHNOLOGY AND MANAGEMENT

(UGC Autonomous, Hyderabad, Accredited by NAAC (A+), NBA)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
(AI & ML)

CERTIFICATE

This is to certify that the Internship project work entitled "Customer Lifetime Value Prediction" is a bonafide work carried out by **Aligeti Sharanya** bearing **23E51A6605** in partial fulfillment of the requirements for the degree **BACHELOR OF TECHNOLOGY** in **COMPUTER SCIENCE AND ENGINEERING (AI&ML)** by the Jawaharlal Nehru Technological University, Hyderabad, during the academic year 2025-2026. The matter contained in this document has not been submitted to any other University or institute for the award of any degree or diploma.

Internal Supervisor	Program Head
Mrs. Chintolla Surekha	**Dr.Rohit Pachlor**
Assistant Professor	Professor

Head Of The Department

Dr.Padmaja Pulicherla

Professor & HOD

HYDERABAD INSTITUTE OF TECHNOLOGY AND MANAGEMENT

Gowdavelly (Village), Medchal, Hyderabad, Telangana, 501401

Department of Computer Science and Engineering

DECLARATION

I “Aligeti Sharanya” student of ‘Bachelor of Technology in CSM’, session: 2025- 2026, Hyderabad Institute of Technology and Management, Gowdavelly, Hyderabad, Telangana State, hereby declare that the work presented in this project work entitled ‘Customer Lifetime Value Prediction’ is the outcome of our own bonafide work and is correct to the best of our knowledge and this work has been undertaken taking care of engineering ethics. It contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

Aligeti Sharanya (23E51A6605)

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I also want to express our sincere gratitude to all my family members and my friends for their individual care and everlasting moral support.

Aligeti Sharanya (23E51A6605)

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Abstract

Customer Lifetime Value (CLV) is a key metric in business analytics that measures the total revenue a company can expect from a customer throughout their relationship. This project aims to predict CLV using machine learning techniques applied to the Online Retail dataset from the UCI Machine Learning Repository. The data underwent extensive preprocessing, including handling missing values, removing duplicates, and feature engineering to extract valuable insights such as Recency, Frequency, and Monetary (RFM) features for each customer.

Exploratory Data Analysis (EDA) was performed to understand customer purchasing behavior, identify trends in revenue contribution by country, and analyze relationships between key variables. Advanced feature engineering was used to capture unique aspects of customer behavior, such as average order value and purchase frequency patterns. The dataset was then used to train and evaluate multiple regression models — Linear Regression, Random Forest, and XGBoost — to predict customer spending over time.

The model evaluation was done using metrics such as R^2 (coefficient of determination), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Among all the models, Linear Regression achieved the best performance with an R^2 value of 0.81, demonstrating a strong ability to predict customer value. This project highlights how machine learning combined with business analytics can provide data-driven insights to improve customer segmentation, retention strategies, and overall business profitability.

1. INTRODUCTION

1.1 Introduction

Customer Lifetime Value (CLV) prediction is a key concept in data-driven business decision-making. It provides an estimate of the total revenue that a company can expect from a customer throughout the duration of their relationship. Understanding CLV allows businesses to identify their most valuable customers, tailor marketing strategies, and invest resources more efficiently. This project focuses on building a machine learning model to predict CLV using the Online Retail dataset from the UCI Machine Learning Repository, which contains detailed records of customer transactions.

With the rise of e-commerce and digital transactions, large volumes of customer data are generated daily. However, most businesses underutilize this data for long-term profitability analysis. Traditional methods such as historical sales averages fail to capture individual customer behavior. Hence, there is a growing need for analytical systems that can extract patterns, understand customer behavior, and predict future value accurately. This project aims to bridge that gap through the application of machine learning and business analytics.

1.2 Purpose

The purpose of this project is to use machine learning techniques to predict how much value a customer will generate for a business over time. By analyzing historical purchase data, the system identifies behavioral indicators such as purchase frequency, recent activity, and total spending. This helps in developing a model that can forecast future customer worth, allowing organizations to focus their efforts on high-value customers. The prediction model thus serves as a valuable decision-support tool for businesses looking to improve customer retention, marketing effectiveness, and revenue forecasting.

1.3 Problem Definition

Many organizations lack predictive frameworks that help in understanding long-term customer profitability. Transaction data is often raw, inconsistent, and not directly useful for forecasting purposes. Manual estimation techniques are prone to bias and fail to consider dynamic customer patterns. Therefore, this project addresses the problem of automating customer value prediction by applying data cleaning, feature engineering, and regression-based modeling. The challenge is to extract meaningful information from the dataset and build an accurate, interpretable model that can estimate CLV effectively.

1.4 Objective of the Project

The main objective of this project is to design and implement a machine learning model capable of predicting customer lifetime value using structured purchase data. The specific objectives include:

- To preprocess and clean the Online Retail dataset for analysis.
- To extract RFM (Recency, Frequency, Monetary) features that represent customer purchasing behavior.

- To train and compare multiple regression algorithms, including Linear Regression, Random Forest, and XGBoost, to determine which performs best for CLV prediction.
- To evaluate model performance using metrics such as R^2, MAE, and RMSE.
- To visualize customer segments and insights through plots and dashboards, aiding in business decision-making.

  By achieving these objectives, the project aims to demonstrate how predictive analytics can transform raw retail data into actionable insights that improve customer relationship management and profitability forecasting.

2. SYSTEM ANALYSIS

2.1 System Architecture Overview

The proposed Customer Lifetime Value (CLV) Prediction System follows a structured machine learning pipeline designed to process transactional data and generate actionable insights. The architecture begins with data collection from the Online Retail dataset, which contains records of customer purchases, quantities, prices, and timestamps. This data undergoes preprocessing to remove inconsistencies and prepare it for analysis.

The processed data is then passed to the feature engineering stage, where customer-level metrics such as Recency, Frequency, and Monetary (RFM) are calculated. These features form the foundation for model training. Once features are prepared, multiple regression algorithms — including Linear Regression, Random Forest, and XGBoost — are trained to predict the total expected revenue (CLV) per customer.

The trained models are then evaluated using statistical performance metrics such as R^2 (coefficient of determination), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Finally, visual analytics are applied to interpret results, compare models, and identify trends in customer behavior. The modular design of this architecture ensures flexibility, scalability, and easy integration with business dashboards for real-time CLV tracking.

2.2 Key Functional Components

The system consists of several functional components that together perform data transformation, model training, and evaluation:

- **Data Preprocessing Module:**
  This module is responsible for cleaning the dataset by handling missing values, removing duplicate transactions, and excluding invalid or cancelled invoices. It also converts `InvoiceDate` into a standard datetime format for time-based calculations.
- **Feature Engineering Module:**
  This component computes the essential RFM metrics for each customer:
  - *Recency* — number of days since the last purchase,
  - *Frequency* — total number of transactions,
  - *Monetary* — total amount spent.
    Additional derived features such as Average Order Value and Unique Products Purchased are also calculated to enhance predictive accuracy.
- **Model Training Module:**
  The processed features are fed into machine learning algorithms. The project uses Linear Regression, Random Forest, and XGBoost to estimate customer lifetime value. Each model is trained on a training dataset and validated on a separate test set to assess generalization.
- **Evaluation and Visualization Module:**
  After training, models are evaluated using R^2, MAE, and RMSE to determine prediction accuracy. Visualization techniques such as heatmaps, scatterplots, and bar charts are used to interpret

relationships between features and predicted outcomes.

Each module interacts sequentially, ensuring smooth data flow from preprocessing to visualization, and the results can be further utilized in Power BI or Tableau dashboards for business analysis.

2.3 System Interaction

The CLV prediction system operates through a stepwise interaction among its components:

1. **Data Input:** The system takes the Online Retail dataset as input, which contains transactional data such as InvoiceNo, Quantity, Price, and CustomerID.

2. **Processing Stage:** The preprocessing module cleans and structures this raw data for analysis.

3. **Feature Generation:** The feature engineering component aggregates transaction data by CustomerID to compute Recency, Frequency, and Monetary values.

4. **Model Execution:** The generated features are passed to regression models for training and prediction.

5. **Evaluation and Visualization:** Results from different models are compared and visualized to identify the most accurate prediction method.

This systematic flow ensures that each stage of the process contributes to a more accurate and interpretable CLV prediction pipeline.

2.4 Functional Requirements

Hardware Requirements:

- Processor: Intel Core i5 or higher
- RAM: Minimum 8 GB
- Storage: At least 2 GB of free disk space
- Optional GPU for faster model training

Software Requirements:

- **Operating System:** Windows / macOS / Linux
- **Programming Language:** Python 3.10 or above
- **Libraries Used:** pandas, numpy, scikit-learn, matplotlib, seaborn, xgboost
- **IDE:** Jupyter Notebook / Visual Studio Code
- **Visualization Tools:** Power BI or Tableau for business-level dashboards

These requirements ensure that the system can efficiently handle data preprocessing, model training, and visual analysis without performance bottlenecks.

3. SOFTWARE ENVIRONMENT

3.1 Software Used

The project was developed using Python, which is widely used for data science and machine learning applications because of its simplicity and extensive library support. Python provides efficient tools for data preprocessing, visualization, and predictive modeling.

Key libraries utilized in this project include pandas and numpy for data manipulation, matplotlib and seaborn for visualization, scikit-learn for implementing regression algorithms and evaluation metrics, and xgboost for advanced gradient boosting techniques. These libraries together provide an end-to-end environment for transforming raw transactional data into meaningful business insights.

Additionally, Jupyter Notebook was used as the development interface due to its flexibility in combining code, output, and documentation in one environment. Power BI and Tableau were employed for creating interactive dashboards to visually communicate results and enable business decision-making based on CLV analysis.

3.2 Modules Used in the Project

The system is divided into several key modules, each responsible for a specific stage of the process. These modules work together seamlessly to ensure a structured and efficient workflow.

(a) Data Cleaning Module

This module is responsible for cleaning and preparing the raw dataset. It handles missing CustomerID and Description values, removes duplicate and cancelled invoices, and ensures all transactions are valid. The InvoiceDate field is converted into a proper datetime format to facilitate time-based feature generation.

(b) Feature Engineering Module

In this module, essential behavioral metrics are extracted for each customer. The RFM (Recency, Frequency, Monetary) model is implemented to summarize customer purchasing activity. Additional features, such as Average Order Value and Unique Products Purchased, are computed to enhance the model's predictive strength. This stage transforms transactional data into a structured, customer-level dataset suitable for machine learning.

(c) Model Training Module

This module focuses on applying regression algorithms to predict customer lifetime value. Three models are trained and tested — Linear Regression, Random Forest Regressor, and XGBoost Regressor. Each model is tuned for performance and validated using a test dataset. The models learn the relationships between RFM features and total customer spending.

(d) Evaluation and Visualization Module

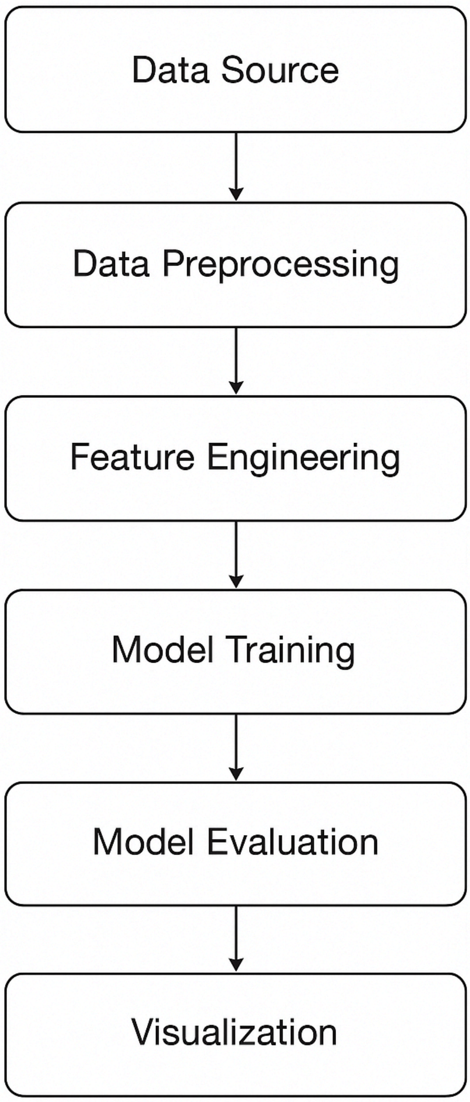
This module evaluates model performance using statistical metrics such as R^2, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). It also generates visualizations such as scatter plots, correlation heatmaps, histograms, and bar charts to interpret model results and customer behavior patterns.

Through these modules, the project provides a complete framework — from data cleaning to actionable business insight — ensuring accuracy, scalability, and interpretability.

4. SYSTEM DESIGN

Block Diagram:

Data Collection → Data Preprocessing → Feature Engineering → Model Training → Evaluation → Visualization



5. IMPLEMENTATION

Sample Code

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
snapshot_date = df['InvoiceDate'].max() + pd.Timedelta(days=1) # for recency calculation
frequency = df.groupby('CustomerID')['InvoiceDate'].count()
recency= df.groupby('CustomerID')['InvoiceDate'].max()
recency= (snapshot_date-recency).dt.days #recent purchase
monetary= df.groupby('CustomerID')['TotalPrice'].sum() #total spend per customer
customer=pd.DataFrame({ 'Recency':recency,
                'Frequency':frequency,
                'Monetary':monetary})
customer['AvgOrderValue']=customer['Monetary']/customer['Frequency']
order_std = df.groupby('CustomerID')['TotalPrice'].std().fillna(0)
customer['OrderAmountStd'] = order_std
unique_products= df.groupby('CustomerID')['StockCode'].nunique()
customer['UniqueProducts']= unique_products
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])
df1 = df.sort_values(['CustomerID', 'InvoiceDate'])
df1['PrevPurchaseDate'] = df1.groupby('CustomerID')['InvoiceDate'].shift(1)
df1['DaysBetween'] = (df1['InvoiceDate'] - df1['PrevPurchaseDate']).dt.days
days_stats = df1.groupby('CustomerID')['DaysBetween'].agg(['mean', 'std']).fillna(0)
days_stats.columns = ['MeanDaysBetween', 'StdDaysBetween']
customer = customer.merge(days_stats, on='CustomerID', how='left')
customer['CLV'] = customer['Monetary']   # short-term CLV

features = ['Recency','Frequency','AvgOrderValue',
        'OrderAmountStd','UniqueProducts',
        'MeanDaysBetween','StdDaysBetween']
X = customer[features]
y = customer['CLV']

from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2, random_state=42)

from sklearn.preprocessing import StandardScaler
scaler= StandardScaler()
X_train_scaled= scaler.fit_transform(X_train)
X_test_scaled= scaler.transform(X_test)

from sklearn.linear_model import LinearRegression
```

```
lr = LinearRegression()
lr.fit(X_train_scaled, y_train)
y_pred_lr = lr.predict(X_test_scaled)
lr.predict([[50,30,50,60,20,0.2,3]])

from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
print("LR R2:", r2_score(y_test, y_pred_lr))
print("LR MAE:", mean_absolute_error(y_test, y_pred_lr))
print("LR RMSE:", mean_squared_error(y_test, y_pred_lr, squared=False))

from xgboost import XGBRegressor
xgb = XGBRegressor(n_estimators=200, learning_rate=0.1, max_depth=6, random_state=42)
xgb.fit(X_train_scaled, y_train)
y_pred_xgb = xgb.predict(X_test_scaled)

from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
print("XGB R2:", r2_score(y_test, y_pred_xgb))
print("XGB MAE:", mean_absolute_error(y_test, y_pred_xgb))
print("XGB RMSE:", mean_squared_error(y_test, y_pred_xgb, squared=False))

y_pred = best_xgb.predict(X_test_scaled) if 'best_xgb' in globals() else y_pred_xgb

plt.figure(figsize=(7,6))
sns.scatterplot(x=y_test, y=y_pred, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel('Actual CLV')
plt.ylabel('Predicted CLV')
plt.title('Actual vs Predicted CLV')
plt.show()
```

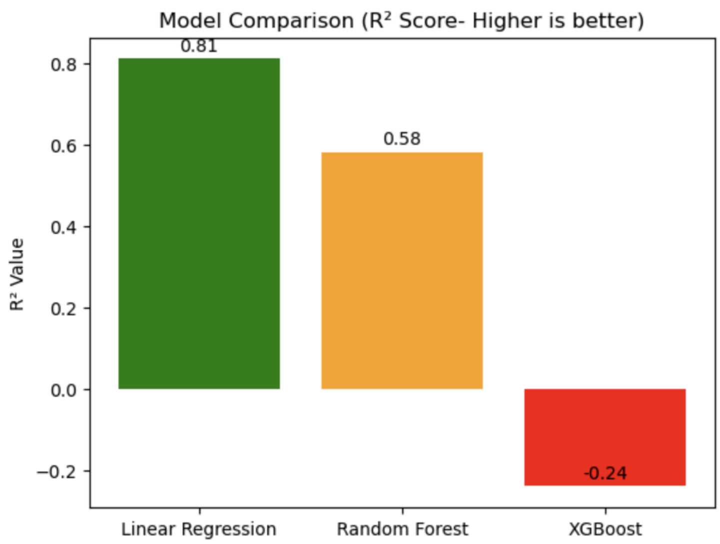
6. TESTING

The testing phase aimed to evaluate the accuracy and reliability of the Customer Lifetime Value (CLV) Prediction System. The dataset was divided into training (80%) and testing (20%) sets to ensure unbiased model assessment. Three regression algorithms — Linear Regression, Random Forest, and XGBoost — were tested and compared using standard evaluation metrics.

The models were evaluated based on R^2 (Coefficient of Determination), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The results are as follows:

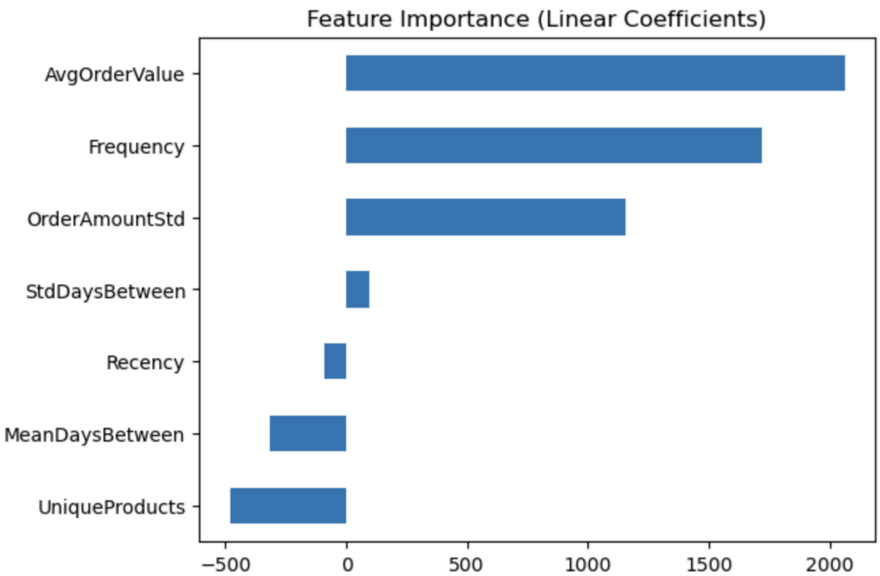
Model	R2	MAE	RMSE
Linear Regression	0.81	409.00	736.67
Random Forest	0.58	166.05	1092.88
XGBoost	-0.24	834.58	1887.53

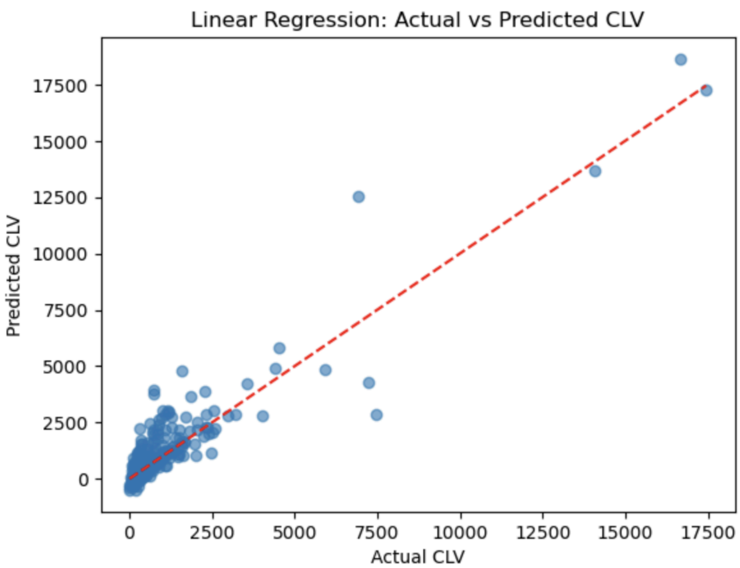
Among the three models, Linear Regression achieved the best performance with an R^2 of 0.81, indicating that it explains 81% of the variance in customer spending. It also maintained the lowest error values (MAE and RMSE), confirming its predictive accuracy. Random Forest performed moderately well, while XGBoost showed poor results, likely due to overfitting on the small dataset.

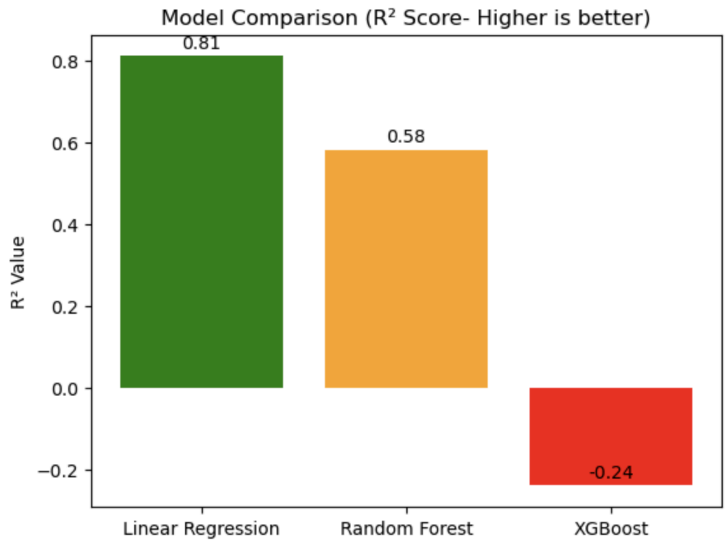


7. OUTPUT SCREENS

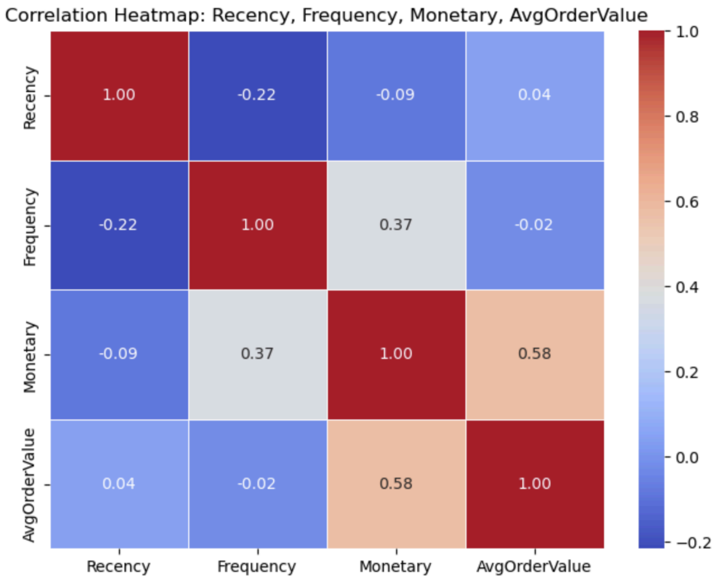
The output screens represent the visual and analytical results generated during the implementation and testing phases of the Customer Lifetime Value (CLV) Prediction System. Visualization plays a key role in understanding customer behavior patterns, relationships among variables, and model performance. All visual outputs were generated using Python libraries such as matplotlib and seaborn







Model Comparison (R² Score- Higher is better)
R² Value
0.81
0.58
-0.24
0.8
0.6
0.4
0.2
0.0
−0.2
Linear Regression
Random Forest
XGBoost



Correlation Heatmap: Recency, Frequency, Monetary, AvgOrderValue
Recency
Frequency
Monetary
AvgOrderValue
1.00
-0.22
-0.09
0.04
-0.22
1.00
0.37
-0.02
-0.09
0.37
1.00
0.58
0.04
-0.02
0.58
1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

8. CONCLUSION AND FUTURE SCOPE

8.1 Conclusion

The Customer Lifetime Value (CLV) Prediction System successfully demonstrates how data analytics and machine learning can be applied to understand customer behavior and forecast long-term revenue potential.
By analyzing transaction data from the Online Retail Dataset (UCI Repository), the project extracted key behavioral metrics — Recency, Frequency, and Monetary (RFM) — to model customer value.

Through the implementation of regression-based algorithms such as Linear Regression, Random Forest, and XGBoost, the system aimed to estimate how much revenue a customer would generate over time.
After testing and evaluation, the Linear Regression model was identified as the best performer, achieving an R^2 score of 0.81, which indicates a strong predictive relationship between customer activity and monetary value.

This project not only highlights the importance of feature engineering and data preprocessing in predictive modeling but also demonstrates how simple yet powerful models can outperform complex ones when applied to well-prepared datasets.
The integration of visual analytics using matplotlib, seaborn, and Power BI/Tableau further enhanced interpretability, allowing business stakeholders to gain actionable insights from the results.

Overall, the project provides a practical and effective framework for customer segmentation, value prediction, and decision-making — making it highly relevant in the field of data-driven marketing and business intelligence.

8.2 Future Scope

Although the developed system achieved promising results, there are several directions for future improvement and expansion:

1. **Long-Term Data Integration:**
The current model used only three months of transactional data. Incorporating a longer time frame could improve prediction accuracy and capture seasonality or changing customer behavior trends.
2. **Advanced Modeling Techniques:**
Future versions can explore Deep Learning or Time-Series Forecasting approaches such as LSTM networks to predict CLV dynamically over time.
3. **Customer Segmentation Enhancement:**
Applying **K-Means** or **Hierarchical Clustering** on RFM metrics can create distinct customer groups (e.g., loyal, new, at-risk customers), enabling targeted marketing strategies.
4. **Real-Time CLV Tracking:**
Integrating the model with business dashboards or CRM systems would allow organizations to update CLV predictions automatically as new data becomes available.

9. ACKNOWLEDGEMENT

We express our sincere gratitude to all those who have contributed directly or indirectly to the successful completion of this project titled **“Customer Lifetime Value (CLV) Prediction.”**

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10. REFERENCES

10.1 Websites

During the development of this project, I referred to various online resources and official documentation to gain a deeper understanding of machine learning concepts, data preprocessing techniques, and visualization methods.
The following websites were particularly helpful:

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