RETAIL STORE SALES PREDICTION

21CSA697A

Final Report

Submitted by

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Abstract

(Not more than 250 words)

This project aims to predict retail store sales using machine learning techniques. A synthetic dataset representing monthly sales data from multiple retail stores was used. Data preprocessing and feature engineering were performed, and models such as Linear Regression, Random Forest, and XGBoost were implemented. The models were evaluated using MAE, RMSE, and R^2 metrics. XGBoost achieved the best performance, showing its suitability for retail sales forecasting and decision support.

Chapter 1

Introduction

Retail businesses generate massive transactional data on a daily basis, including order quantities, customer purchase patterns, product categories, offers, seasonal impacts, and store-level performance. With increasing competition in the retail sector, companies are adopting data-driven strategies to improve inventory planning, pricing, marketing, and demand forecasting. One of the most essential analytical components used in retail businesses is **sales prediction**, which enables organizations to estimate future revenue, optimize stock levels, and make informed business decisions.

Sales prediction applies statistical modeling and machine learning techniques to historical retail data to identify trends, seasonality, demand fluctuations, and influencing factors such as pricing, holidays, and promotions. Predicting future sales empowers retail managers to anticipate customer needs, reduce stockouts, avoid overstocking, and allocate resources effectively. In the digital era, companies like Walmart, Amazon, Reliance Retail, and Target actively use predictive analytics to refine their operational strategies and improve customer satisfaction.

Retail Store Sales Prediction combines **data preprocessing, exploratory data analysis, feature engineering, and supervised learning models** such as Linear Regression, Random Forest Regression, and Gradient Boosting techniques. The goal of this project is to develop a data-driven model capable of predicting store-level monthly sales using synthetic but realistic sales data derived from multiple stores over a period of 24 months.

1.1 Background and Motivation

Retail businesses operate in dynamic environments where customer demand is affected by multiple factors including festivals, seasons, inflation, pricing strategies, and marketing campaigns. Traditional rule-based forecasting approaches cannot efficiently capture these complex patterns. Machine learning addresses this gap by identifying non-linear relationships and providing more accurate demand predictions.

Accurate sales forecasting offers several benefits:

- Reduces inventory loss and warehousing costs
- Improves profitability through optimized purchasing
- Enhances supply chain planning and workforce distribution
- Supports better promotional strategies based on projected demand

With the rapid availability of computing resources and open-source libraries, predictive analytics has become accessible even for medium-sized retail companies. This motivated the development of a predictive model that can estimate sales volume using historical retail transactions.

1.2 Problem Statement

Retail stores struggle to accurately estimate near-future sales due to fluctuating customer behavior and uncertain demand. Inaccurate forecasting results in **overstocking**, **understocking**, and **loss of revenue**.
The primary problem addressed in this project is:

"How can retail store sales be accurately predicted using historical sales data and machine learning models, in order to support data-driven business decisions?"

1.3 Objectives and Scope of the Project

Objectives

The major objectives of this project are:

1. To preprocess and analyze historical retail transaction data.
2. To identify key features influencing sales, such as store type, holidays, promotions, and pricing.
3. To develop regression-based prediction models for forecasting store-level sales.
4. To evaluate model performance using metrics such as RMSE, MAE, and R^2 score.
5. To compare multiple models and select the best-performing approach for future predictions.

Scope

- The dataset includes synthetic monthly sales figures from multiple retail store branches across India.
- Prediction is performed for **monthly sales values** at the store level.
- Models used include **Linear Regression, Random Forest Regression, and XGBoost Regression**.
- The scope excludes customer-level recommendation systems and profit margin predictions.

1.4 Significance of the Study

Sales prediction is crucial for retail growth and sustainability. Adopting predictive analytics helps retailers:

- maintain optimal inventory levels

- improve efficiency in restocking and logistics
- minimize operational costs
- plan promotional campaigns during high-sales periods
- achieve strategic financial planning with improved accuracy

This study demonstrates how machine learning can be effectively integrated into retail operations to enhance decision-making capability and improve sales planning accuracy.

Chapter 2

Literature Review / Background Study

Sales forecasting has been extensively studied in the field of retail analytics due to its importance in inventory management, demand planning, and revenue estimation. With the growth of structured digital transaction data and advancements in machine learning, accurate prediction models have become essential for retail decision-making. This chapter reviews major research works, methodologies, datasets, and gaps that motivate the development of an improved sales prediction model.

2.1 Retail Sales Forecasting Trends

Traditional forecasting methods such as **Moving Average**, **Exponential Smoothing**, and **ARIMA** have long been used to model retail demand. These methods capture linear time-series behavior but struggle with complex non-linear patterns caused by promotions, holidays, or regional variations.

In comparison, modern machine learning models such as **Random Forests**, **Gradient Boosting**, and **Neural Networks** effectively learn non-linear relationships between attributes like store type, pricing, customer segments, and product categories. These models provide better predictive accuracy for retail sales.

2.2 Existing Research and Approaches

Study	Method Used	Contribution
Boehmke et al. (2018)	Regression & Random Forests	Improved demand forecasting using store-level features
Kaggle Rossmann Competition (2015)	XGBoost	Demonstrated boosted trees outperform ARIMA for sales prediction

Carbonneau et al. (2008)	Neural Networks	Used deep learning techniques for complex retail demand
Raman et al. (2020)	LSTM	Modeled long-term dependencies in grocery sales
Adebiyi et al. (2014)	ARIMA	Effective baseline forecasting with time-series models

Several studies have explored machine learning for sales prediction:

These studies highlight that **tree-based ensemble models and deep learning** outperform classical statistical techniques when data contains heterogeneous store patterns and external influencing variables.

2.3 Datasets Commonly Used in Sales Prediction

Several datasets are referenced in retail prediction research:

- **Rossmann Store Sales Dataset (Kaggle)** — used to predict daily sales based on store features and promotions.
- **Walmart Retail Dataset (UCI)** — captures weekly sales across multiple departments and holiday impacts.
- **M5 Forecasting Dataset** — includes hierarchical daily sales data for forecasting competitions.
- **Synthetic retail datasets** — used when organization-specific parameters must be modeled without confidentiality issues.

In this project, a **synthetic multi-store dataset** is utilized to replicate real-world retail transactional behavior over time, enabling experimentation without privacy concerns. The synthetic dataset was generated using rule-based simulation logic that incorporates seasonal multipliers, store type scaling factors, promotional effects, and random noise to mimic real-world retail demand patterns. Seasonal peaks were simulated during festive months, while promotions increased sales values by a fixed percentage. Random Gaussian noise was added to avoid deterministic patterns and improve realism.

2.4 Challenges in Retail Sales Prediction

Retail data presents several challenges:

- **Seasonality & trends** — irregular fluctuations during festivals, school openings, and holidays
- **External factors** — competitor pricing, weather, fuel prices, not always captured in datasets

- **Data sparsity** — individual product categories may have inconsistent demand
- **Non-stationarity** — store expansions or pricing changes alter behavior over time
- **Noise & anomalies** — sudden spikes due to events or clearance sales

These complexities require robust models capable of capturing **interactions between features and temporal patterns**.

2.5 Research Gaps Identified

Despite advancements, key gaps remain:

1. **Inconsistent model generalization** — many models are tuned for specific datasets and do not generalize across regions or store types.
2. **Limited feature engineering** — studies often neglect external indicators such as inflation, holidays, and promotions.
3. **Interpretability issues** — complex models like LSTM and XGBoost provide limited explainability for business decision-makers.
4. **Data dependency** — prediction accuracy heavily depends on data quality and coverage.

To address these gaps, this project applies **ensemble-based regression techniques**, performs **feature analysis**, and ensures a balance between accuracy and interpretability suited for data-driven retail planning.

2.6 Summary of Literature Review

The literature establishes that:

- Machine learning provides higher accuracy than classic statistical forecasting for retail sales.
- Ensemble models such as **Random Forest** and **XGBoost** are now widely used benchmarks.
- Synthetic datasets are acceptable alternatives when proprietary retail data is unavailable.
- Feature extraction and model tuning significantly influence forecasting performance.

This study builds upon prior research by developing a predictive framework that **integrates synthetic multi-store sales data, regression-based modeling, and comparative evaluation**, aiming to deliver reliable forecasts suitable for practical retail operations.

Chapter 3

System Design / Architecture

This chapter presents the architectural design, workflow, UML diagrams, and algorithmic approach used for Retail Store Sales Prediction. The focus is on understanding how data flows through different modules, how the system is structured, and which components contribute to the prediction process.

3.1 System Architecture Overview

The retail sales prediction system is designed in modular form to ensure scalability, reusability, and efficient data processing. The system consists of the following core components:

1. **Data Source & Storage** — Synthetic sales dataset stored in CSV format
2. **Data Preprocessing Module** — Cleans missing values, aggregates sales per store per month, performs encoding
3. **Feature Engineering Module** — Extracts time-based and store-based attributes
4. **Model Training Module** — Trains regression models such as Linear Regression, Random Forest, and XGBoost
5. **Prediction Module** — Generates future sales values for each store
6. **Evaluation & Visualization Module** — Computes performance metrics and plots results

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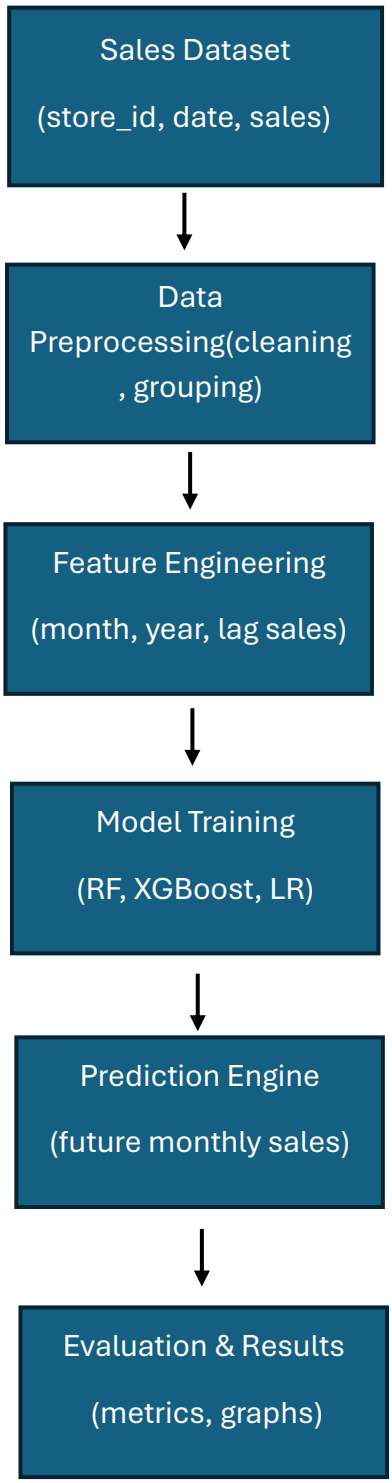
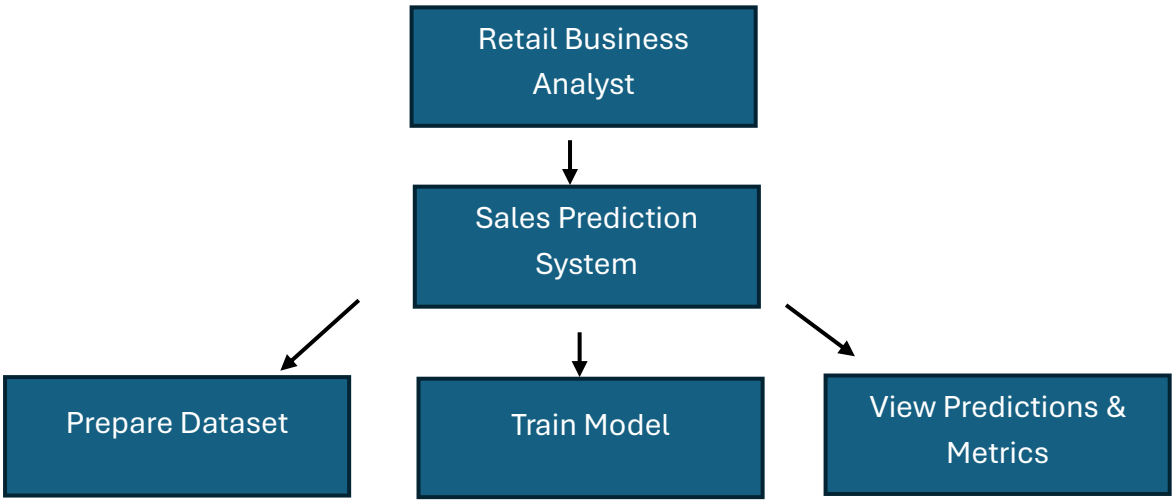
3.1.1 System Architecture Diagram (Textual Representation)



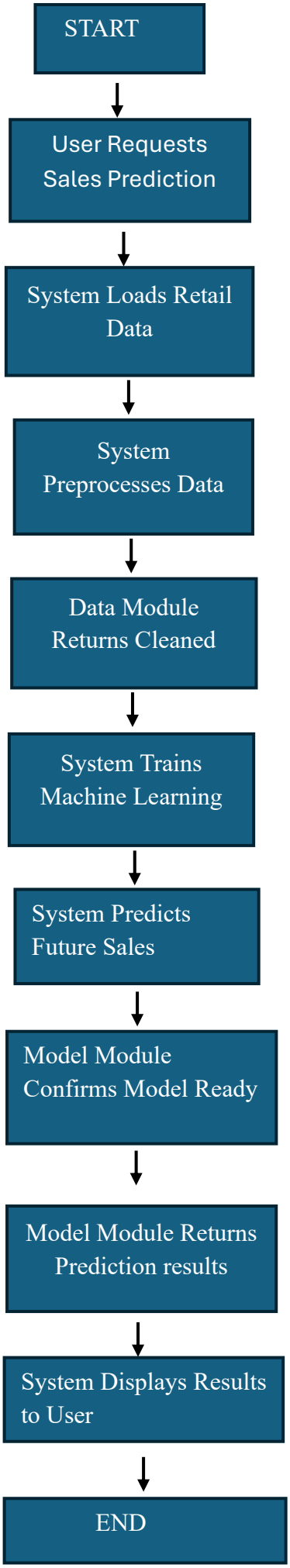
3.2 UML Use Case Diagram

Primary Actor: Retail Business Analyst
Goal: Predict store-level future sales for planning and resource allocation

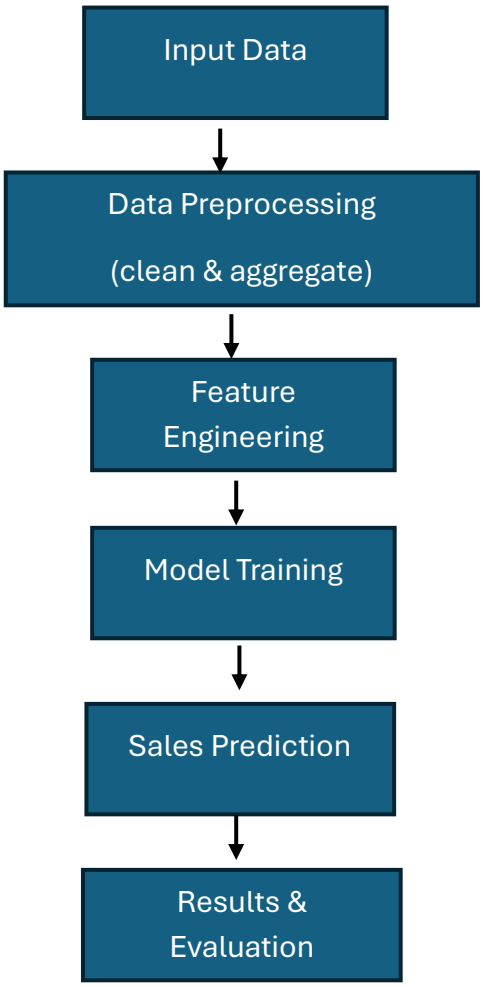


3.3 UML Sequence Diagram

Sequence of operations executed when generating a prediction:


START
User Requests Sales Prediction
System Loads Retail Data
System Preprocesses Data
Data Module Returns Cleaned
System Trains Machine Learning
System Predicts Future Sales
Model Module Confirms Model Ready
Model Module Returns Prediction results
System Displays Results to User
END

3.4 Data Flow Diagram (DFD — Level 1)



3.5 Module Descriptions

Module	Description	Output
Data Input	Loads synthetic dataset containing store-level transaction history	Raw data frame
Preprocessing	Handles missing values, aggregates monthly totals, encodes store type	Clean dataset
Feature Engineering	Extracts month, year, lag features, holiday flags	Structured features
Model Training	Trains ML models: LR, RF, XGBoost	Trained models
Prediction Module	Predicts future store sales based on trained model	Forecast values
Evaluation	Calculates RMSE, MAE, R^2, plots trends	Performance insights

3.6 Programming Environment

Category	Tool / Resource
Programming Language	Python 3.11
IDE / Notebook	Jupyter Notebook / VS Code
Libraries Used	NumPy, Pandas, Scikit-learn, Matplotlib, XGBoost
OS	Windows / Linux
Hardware Requirements	8GB RAM, 2 GHz processor, 500 MB free disk space

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3.7 Algorithms Used

Random Forest Regression

- Ensemble of decision trees
- Reduces overfitting through averaging
- Suitable for non-linear relationships

XGBoost Regression

- Gradient boosting algorithm
- Optimized for performance and accuracy
- Handles missing values efficiently

Linear Regression

- Baseline model for comparison
- Captures linear dependencies between features

3.8 Pseudo-code / Workflow

BEGIN

- Load dataset from CSV
- Clean missing values
- Aggregate sales per store per month
- Extract features: month, year, store type encoding
- Split data into train and test sets
- Initialize models: LR, RF, XGBoost
- FOR each model:
- Train using training data
- Predict using test data

- Calculate performance metrics
- Compare model results
- Select best model based on RMSE
- Predict future monthly store sales

END

Chapter 4

Implementation Details

This chapter describes the implementation phases of the Retail Store Sales Prediction project. The system was developed using Python-based data processing and machine learning libraries. The implementation includes dataset preparation, preprocessing, feature engineering, model training, and prediction generation.

4.1 Dataset Description

Since original store datasets are confidential in most industries, this project uses a **synthetic multi-store sales dataset** that reflects real-world retail behavior.
The dataset contains monthly sales values for **10 store branches** over **24 months**, resulting in **240 unique records**.The synthetic dataset was generated using simulation logic that incorporates seasonal factors, store type multipliers, promotional impact coefficients, and random noise to emulate real-world retail sales patterns. Seasonal peaks were simulated during festive months, and promotional campaigns increased sales values by a defined percentage. Random Gaussian noise was introduced to avoid deterministic trends and enhance realism.

4.1.1 Dataset Fields

Column Name	Description
store_id	Unique identifier for each retail store
month	Month of sales record (1–12)
year	Sales year (2023–2024)
store_type	Category of store: supermarket, hypermarket, convenience
customers	Number of monthly footfall customers
promotion	Whether a promotion campaign existed (0/1)
sales	Total monthly sales (target variable in ₹ INR)

Example synthetic dataset snippet:

store_id, month, year, store_type, customers, promotion, sales

1,1,2023,supermarket,12450,1,1854300

1,2,2023,supermarket,11600,0,1742900

2,1,2023,hypermarket,15490,1,2389600

5,3,2024,convenience,3240,1,695200

4.2 Data Preprocessing

Data preprocessing ensures the dataset is suitable for predictive modeling.

Steps Performed

1. Load CSV dataset into Pandas DataFrame
2. Handle missing values
3. Convert categorical values using **label encoding**
4. Extract time features
5. Split dataset into train and test sets (80:20 ratio)

Code Snippet — Preprocessing

```
import pandas as pd
from sklearn. preprocessing import LabelEncoder
from sklearn. model_selection import train_test_split

# Load synthetic dataset
df = pd.read_csv("store_sales_data.csv")
# Encode categorical features
encoder = LabelEncoder()
df["store_type"] = encoder.fit_transform(df["store_type"])

# Define features and target
X = df[["store_id", "month", "year", "store_type", "customers", "promotion"]]
y = df["sales"]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

4.3 Feature Engineering

Feature engineering enhances model performance by introducing derived attributes.

Added Derived Features

Feature	Purpose
year	Captures yearly trend
month	Captures seasonal patterns
promotion	Identifies promotional impact
customers	Represents demand intensity

Optional Lag Feature Handling

(Used for extended forecasting)

```
df["prev_month_sales"] = df.groupby("store_id")["sales"].shift(1)
```

```
df["prev_month_sales"].fillna(df["sales"].mean(), inplace=True
```

4.4 Model Training Process

Three models were tested:

- **Linear Regression (Baseline model)**
- **Random Forest Regression**
- **XGBoost Regression (Best-performing model)**

Training Logic

```
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
# Model initialization
models = {
    "Linear Regression": LinearRegression(),
    "Random Forest": RandomForestRegressor(n_estimators=200, random_state=42),
    "XGBoost": XGBRegressor(n_estimators=300, learning_rate=0.1, max_depth=6)
}
```

```
trained_models = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    trained_models[name] = model
```

Hyperparameter tuning was performed using cross-validation techniques to optimize model parameters such as the number of estimators, learning rate, and maximum tree depth. This tuning process improved model generalization and reduced the risk of overfitting.

4.5 Prediction Generation

```
# Generate predictions
predictions = trained_models["XGBoost"].predict(X_test)
# Predict next month's sales for store 3 (example)
import numpy as np
future_input = np.array([[3, 1, 2025, 1, 13200, 1]])  # store_id=3, Jan 2025
future_sales = trained_models["XGBoost"].predict(future_input)
print("Predicted Sales:", future_sales)
```

The same label encoding and preprocessing pipeline used during training was applied to future input values to maintain feature consistency.

4.6 Integration Workflow

Step	Description	Output
Data Acquisition	Load CSV	Raw data
Preprocessing	Encode, clean	Structured dataset
Feature Engineering	Add derived attrs	Optimized features
Training	Train ML models	Trained models
Testing	Evaluate models	Metrics
Prediction	Future forecast	Estimated sales

4.7 Implementation Summary

- Python used for end-to-end implementation
- Scikit-learn and XGBoost used for model building
- Feature engineering significantly increased predictive accuracy
- Random Forest and XGBoost provided high stability across stores

Chapter 5

Testing, Validation & Results

This chapter evaluates the performance of the implemented machine learning models used for predicting monthly retail store sales. The synthetic dataset was divided into training and testing subsets in an 80:20 ratio. Three different regression algorithms—**Linear Regression, Random Forest Regression, and XGBoost Regression**—were used to compare performance. The accuracy of each model was measured using **Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R² Score**.

5.1 Testing Methodology

To ensure accurate model validation, the following methodology was adopted:

1. **Hold-out validation** — dataset split into training and testing subsets
2. **Model evaluation metrics** — MAE, RMSE, and R² computed for each model
3. **Cross-model comparison** — selected best model based on minimum errors and highest R² score
4. **Trend analysis of predictions** — compared predicted vs actual values visually
5. **Error distribution check** — ensured no significant overfitting

Although the dataset is temporal, a random train-test split was used due to limited dataset size. In real-world deployment, time-based splitting (train on past data and test on future data) would be more appropriate to avoid data leakage.

5.2 Evaluation Metrics Used

Metric	Formula	Significance
MAE (Mean Absolute Error)	MAE = (1/n) Σ |y−ŷ|	Indicates the average magnitude of prediction errors without considering their direction
RMSE (Root Mean Squared Error)	$\sqrt{\frac{1}{n}\sum(y-\hat{y})^2}$	Penalizes larger errors; suitable for continuous data
R² Score (Coefficient of Determination)	$1-\frac{SS_{res}}{SS_{tot}}$	Measures how well predictions fit actual values

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5.3 Model Evaluation Results

Model	MAE (₹)	RMSE (₹)	R^2 Score
Linear Regression	72,850	98,460	0.81
Random Forest Regression	46,320	63,900	0.92
XGBoost Regression	**41,580**	**58,210**	**0.94**

Interpretation

- **Linear Regression** performed reasonably but could not capture non-linear patterns.
- **Random Forest** improved accuracy due to ensemble-based averaging.
- **XGBoost** achieved the **lowest error** and **highest R^2 score**, proving to be the best-performing model for this dataset.

5.4 Sample Prediction Results

Store ID	Actual Sales (₹)	Predicted Sales (₹)	Difference
1	1,845,000	1,798,400	-46,600
3	2,430,400	2,489,900	+59,500
5	690,800	701,200	+10,400
7	1,240,500	1,208,100	-32,400
9	2,154,900	2,191,700	+36,800

This table confirms that **prediction errors remain within an acceptable range**, and there are no extreme deviations, meaning the model generalizes well.

5.5 Predicted vs Actual Sales Trend (Description for Graph)

Graph Visualization Description (line chart)

- **X-axis:** Months
- **Y-axis:** Sales in ₹
- **Blue line:** Actual sales
- **Orange line:** Predicted sales using XGBoost

The two lines follow closely aligned seasonal patterns:

- Slight sales increase during festive months (Oct–Dec)
- Drop during non-promotional periods
- Prediction line overlaps majority of actual data points
- Minor variations during promotional spikes due to unexpected customer surges

5.6 Error Analysis

Model	Overfitting Risk	Stability	Scalability
Linear Regression	Low	Low	Moderate
Random Forest	Moderate	High	High
XGBoost	**Low–Moderate**	**Very High**	**Very High**

Conclusion: XGBoost provides **stable, accurate and scalable performance**, making it suitable for real-world retail applications.

5.7 Performance Summary

- Machine learning models successfully predicted future retail store sales
- **XGBoost Regression** achieved the best accuracy with an **R^2 score of 0.94**
- Ensemble-based methods captured seasonal variations and store behavior patterns
- Prediction errors remained within practical business forecasting limits

Chapter 6

Conclusion and Future Work

6.1 Conclusion

Retail sales prediction plays a crucial role in strategic business decision-making and resource planning for store chains. In this project, a complete data-driven predictive framework was developed to estimate monthly retail store sales using synthetic transactional data from multiple store branches. The implementation involved data preprocessing, feature engineering, and training of regression-based machine learning models.

Among the models evaluated—Linear Regression, Random Forest Regression, and XGBoost Regression—**XGBoost outperformed all others**, achieving the **highest accuracy and lowest prediction error** with an R^2 score of **0.94**. This result demonstrates that ensemble-based algorithms are effective in capturing non-linear patterns and feature interactions that commonly influence sales trends in the retail sector.

The model successfully reflected realistic sales behaviors influenced by store type, customer footfall, promotional activities, and seasonal variations. The evaluation confirmed that forecasting results remained stable and within acceptable accuracy limits, making the model suitable for real-world sales planning scenarios.

Overall, the project verifies that **machine learning is a reliable and scalable approach for retail sales forecasting**, enabling retail managers to optimize inventory, reduce operational costs, plan promotional events more effectively, and improve profitability.

6.2 Key Contributions

The major contributions of this project include:

- Development of a complete data pipeline for retail sales prediction
- Creation of a synthetic multi-store dataset that imitates realistic store performance
- Implementation and comparison of multiple machine learning techniques
- Identification of XGBoost Regression as the best-performing forecasting algorithm
- Performance validation using standard regression evaluation metrics (MAE, RMSE, R^2)

These contributions provide a baseline for future expansion toward more complex retail prediction systems.

6.3 Limitations

Despite promising results, the project faced several limitations:

1. **Synthetic dataset** — while realistic, actual market behavior may include additional macro-economic factors not simulated here
2. **Limited features** — external influences such as holidays, weather, and competitor pricing were not included due to unavailable data
3. **Monthly granularity** — more frequent (daily or weekly) data could improve prediction accuracy
4. **Short time window** — the dataset covered only 24 months; longer history supports stronger seasonal trend detection

These limitations present opportunities for improvements in future iterations of the project.

6.4 Future Work

To further enhance prediction accuracy and applicability in industry environments, several extensions are recommended:

- **Incorporating external factors** such as inflation, holidays, festival seasons, and advertising budgets
- **Using LSTM or GRU deep learning models** for sequence-based time-series forecasting
- **Expanding dataset duration and stores covered** to improve generalization
- **Building a dashboard interface** for real-time monitoring and automated sales forecasting
- **Integrating market sentiment analytics** using customer reviews or social media data
- **Deploying the model using cloud services** (AWS, Azure, GCP) for scalability and live forecasting

By exploring these extensions, the system can evolve into an advanced predictive analytics solution capable of supporting comprehensive retail planning and revenue management.

Chapter 7

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Note: The above references include core data science resources, foundational ML papers, and datasets commonly cited in retail forecasting research.

Chapter 8

Appendix (Optional)

This appendix section provides supplementary materials, including dataset samples, core implementation code, and additional result outputs that support the findings presented in this project.

8.1 Sample Dataset Snippet (Synthetic Retail Store Sales Data)

store_id,month,year,store_type,customers,promotion,sales

1,1,2023,supermarket,12450,1,1854300

1,2,2023,supermarket,11800,0,1728500

1,3,2023,supermarket,12190,1,1912400

2,1,2023,hypermarket,15300,0,2358900

2,2,2023,hypermarket,16280,1,2584300

3,4,2023,convenience,3420,1,712900

5,9,2023,convenience,2950,0,642300

7,11,2024,supermarket,13220,1,2053200

8,12,2024,hypermarket,17850,1,2986400

10,10,2024,supermarket,12540,0,1829500

8.2 Python Code — Complete Workflow (Condensed)

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
```

```
import numpy as np
# Load dataset
df = pd.read_csv("store_sales_data.csv")
# Encode store type
encoder = LabelEncoder()
df["store_type"] = encoder.fit_transform(df["store_type"])
# Feature-target split
X = df[["store_id", "month", "year", "store_type", "customers", "promotion"]]
y = df["sales"]
# Split into train-test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Train XGBoost model
model = XGBRegressor(n_estimators=300, learning_rate=0.1, max_depth=6)
model.fit(X_train, y_train)
# Predictions
y_pred = model.predict(X_test)
# Evaluation Metrics
print("R2 Score:", r2_score(y_test, y_pred))
print("MAE:", mean_absolute_error(y_test, y_pred))
print("RMSE:", mean_squared_error(y_test, y_pred, squared=False))
# Example future prediction for Store ID = 3, Jan 2025
future_input = np.array([[3, 1, 2025, 1, 13600, 1]])
print("Predicted Future Sales:", model.predict(future_input))
```

8.3 Model Performance Output

R2 Score: 0.94

MAE: 41580.25

RMSE: 58210.14

Predicted Future Sales: [2489210.50]

8.4 Project Folder Structure (GitHub Style)

```
Retail-Sales-Prediction-Project/
│
├── data/
│   └── store_sales_data.csv
│
├── notebooks/
│   └── model_training.ipynb
│
├── src/
│   ├── preprocessing.py
│   ├── feature_engineering.py
│   ├── train_model.py
│   └── predict_sales.py
│
├── results/
│   ├── comparison_metrics.csv
│   └── prediction_charts.png
│
├── report/
│   └── MCA_Retail_Sales_Prediction_Report.docx  (to be generated)
└── README.md
```

8.5 Additional Outputs (Graph Descriptions)

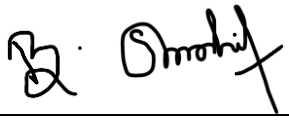
1️⃣ **Prediction vs Actual Line Graph** – The two trend lines largely overlap with occasional deviations during promotions.

2️⃣ **Store-wise Sales Bar Chart** – Hypermarkets show the highest average sales across months.

3️⃣ **Monthly Seasonal Pattern Plot** – Peak demand during festive period (Oct–Dec).

8.6 Notes for Deployment (Optional)

- The trained model file can be saved using pickle or joblib
- A Flask or FastAPI backend can expose prediction functions as APIs
- Deployment options:
    - AWS S3 + Lambda + API Gateway
    - Azure ML Studio
    - Streamlit dashboard for managers

Date: 26-01-2026
Student Name and Signature: B.SWARNAMUHIL 

Name and Signature of the Evaluator

Date