A Course Based Project Report on

Online Shoppers Purchasing Intention

Submitted to the

Department of CSE-(CyS, DS) and AI&DS

in partial fulfilment of the requirements for the completion of course

Computer Networks and Ethical hacking LABORATORY (22PC1CY201)

BACHELOR OF TECHNOLOGY

IN

Artificial Intelligence and Data Science

Submitted by

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CERTIFICATE

This is to certify that the project report entitled "**Online Shoppers Purchasing Intention**" is a bonafide work done under our supervision and is being submitted by **Miss. Keerthana (23072A7208), Miss. Sravani (23072A7212), Miss. Akshitha (23072A7220),** in partial fulfilment for the award of the degree of **Bachelor of Technology** in **Artificial Intelligence and Data Science**, of the VNRVJIET, Hyderabad during the academic year 2025-2026.

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DECLARATION

We declare that the course based project work entitled "**ONLINE SHOPPERS PURCHASING INTENTIONS**" submitted in the Department of **CSE-(CyS, DS) and AI&DS**, Vallurupalli Nageswara Rao Vignana Jyothi Institute of Engineering and Technology, Hyderabad, in partial fulfillment of the requirement for the award of the degree of **Bachelor of Technology in Artificial Intelligence and Data Science** is a bonafide record of our own work carried out under the supervision of **Mr. A. Madhu, Assistant Professor, Department of CSE-(CyS, DS) and AI&DS, VNRVJIET.** Also, we declare that the matter embodied in this thesis has not been submitted by us in full or in any part thereof for the award of any degree/diploma of any other institution or university previously.

Place: Hyderabad.

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ABSTRACT

In today's digital marketplace, understanding and predicting customer purchasing behavior has become crucial for e-commerce success. This project focuses on developing a predictive model that determines whether an online shopper is likely to make a purchase during a browsing session. Using behavioral and session-based attributes such as the number of pages visited, time spent on product-related pages, and bounce or exit rates the study applies both classical machine learning algorithms (Random Forest, SVM, Logistic Regression) and deep learning models (Multilayer Perceptron) to analyze user intent.

The project emphasizes a complete end-to-end data science workflow, including preprocessing, feature engineering, model training, evaluation, and performance comparison using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. To ensure reproducibility, a Python pipeline is provided that can automatically generate a synthetic dataset when the real data is unavailable, allowing experiments to be conducted under consistent conditions.

Through comparative analysis, this study highlights the trade-offs between interpretability and accuracy across traditional and neural network-based approaches. The outcomes aim to aid online retailers in optimizing their marketing strategies, improving personalization, and ultimately enhancing conversion rates by predicting purchase intent in real time.

CHAPTER-1

INTRODUCTION

In the era of digital commerce, predicting online shoppers' purchasing intentions has become a critical challenge for businesses seeking to improve conversion rates and customer engagement. Each visitor interaction ranging from the number of product pages viewed, time spent per session, bounce rates, and page values provides essential behavioral signals that can be transformed into actionable insights through data-driven modelling.

This project focuses on building a predictive analytics pipeline to determine whether a visitor will complete a purchase during an online shopping session. Drawing inspiration from recent research, particularly the *Heliyon (2023)* study, which demonstrated the superiority of **XGBoost and ensemble learning methods** over traditional models, the proposed system incorporates both classical algorithms and advanced ensemble models for comprehensive performance evaluation.

The methodology involves acquiring and preprocessing session-level data (from the UCI Online Shoppers Purchasing Intention dataset or an equivalent synthetic dataset), feature engineering, model training, and evaluation. Key algorithms implemented include **Random Forest**, **Logistic Regression**, and **XGBoost**, along with a **Multilayer Perceptron (MLP)** to explore deep learning capabilities. Models are compared based on accuracy, precision, recall, F1-score, and ROC-AUC metrics to ensure a balanced evaluation of predictive effectiveness.

Beyond performance, this project emphasizes explainability and scalability important aspects highlighted in recent literature. Feature importance from ensemble methods provides interpretable insights into user behavior patterns, while the modular Python pipeline ensures adaptability for real-time e-commerce applications. The ultimate goal is to deliver a robust, interpretable, and reproducible model that aids online retailers in forecasting user purchase intent and optimizing marketing interventions in real time.

CHAPTER-2

Methodology

The methodology of this project is designed to systematically predict the purchasing intention of online shoppers by applying data preprocessing, feature engineering, and machine learning model development. The workflow closely follows approaches discussed in recent research, particularly the *Heliyon (2023)* paper, which validated **XGBoost** as one of the most efficient and accurate ensemble algorithms for behavioral intention prediction.

1. Data Collection

The project utilizes the **UCI Online Shoppers Purchasing Intention dataset**, a widely recognized benchmark dataset containing over 12,000 records of user browsing sessions. Each record represents a session and includes 18 behavioral features and one target variable (Revenue), which indicates whether a purchase was made.

In cases where the dataset is unavailable or incomplete, the pipeline can generate a **synthetic dataset** with similar statistical properties, ensuring consistent experimentation and reproducibility.

2. Data Preprocessing

Data preprocessing is a crucial step to ensure the quality and consistency of input features. The following operations are performed:

- **Handling Missing and Duplicate Values:** Duplicate records are removed, and missing values are handled using appropriate imputation techniques.
- **Feature Encoding:** Categorical variables (e.g., “Month”, “VisitorType”, “Weekend”) are converted into numerical form using **One-Hot Encoding**.
- **Scaling:** Numerical variables are standardized using **StandardScaler** to normalize feature ranges, ensuring better model convergence.
- **Target Conversion:** The target variable Revenue is converted into binary integers (1 for purchase, 0 for no purchase).

3. Feature Engineering

To enhance the predictive capability of models, new derived features are created from existing data. Examples include:

- **Session Duration:** Total time spent by a user on the website.
- **Average Page Value:** The mean importance or value of visited pages.
- **Bounce Rate Flag:** A binary feature indicating if the user left after visiting a single page.
- **Engagement Score:** A composite metric calculated from the ratio of product-related visits to total visits.

Feature selection techniques such as **Recursive Feature Elimination (RFE)** and **feature importance ranking** from ensemble models (Random Forest / XGBoost) are applied to identify the most influential variables affecting purchasing behavior.

4. Model Development

Three major categories of models are developed and evaluated:

1. **Classical Machine Learning Models:**
    - **Logistic Regression** for baseline performance comparison.
    - **Random Forest Classifier** to capture non-linear interactions and variable importance.
2. **Ensemble Learning Model:**
    - **XGBoost (Extreme Gradient Boosting)** is implemented as the core model, leveraging gradient boosting and regularization to minimize overfitting and improve accuracy.
      The *Heliyon (2023)* paper demonstrated that XGBoost achieved superior performance in predicting online shopper intent, achieving higher F1 and ROC-AUC scores compared to SVM and Decision Trees.
3. **Deep Learning Model:**
    - **Multilayer Perceptron (MLP)**, built using TensorFlow/Keras, is trained to capture complex non-linear relationships in user behavior data. Dropout regularization and early stopping are employed to prevent overfitting.

5. Model Evaluation

The dataset is split into **training (80%)** and **testing (20%)** sets with stratified sampling to maintain class balance. Models are evaluated using the following metrics:

- **Accuracy:** Measures overall correctness of predictions.
- **Precision & Recall:** Evaluate the trade-off between false positives and false negatives.
- **F1-Score:** Balances precision and recall for imbalanced data.
- **ROC-AUC:** Reflects the model's ability to distinguish between purchasing and non-purchasing sessions.

Cross-validation (5-fold) is applied for model reliability, and confusion matrices are generated to visualize prediction performance.

6. Model Interpretation and Storage

Feature importance is extracted from **XGBoost** and **Random Forest** models to interpret which behavioral variables most strongly influence purchasing decisions. The models and preprocessing pipelines are then serialized using **Joblib** and **TensorFlow's .h5 format**, allowing future reuse for visualization, deployment, and real-time prediction.

7. Tools and Technologies

- **Programming Language:** Python
- **Libraries:** Pandas, NumPy, Scikit-learn, TensorFlow, XGBoost, Joblib, Matplotlib (for visualization)
- **Environment:** Jupyter Notebook / Visual Studio Code
- **Version Control:** GitHub for code and model management

CODE IMPLEMENTATION

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, roc_curve, auc, accuracy_score
from xgboost import XGBClassifier
# Load dataset (works in Colab)
import kagglehub

# Download latest version
path = kagglehub.dataset_download("imakash3011/online-shoppers-purchasing-intention-dataset")

print("Path to dataset files:", path)

# Preprocess

target = "Revenue"
cat_cols = df.select_dtypes(include=['object', 'bool']).columns.tolist()
num_cols = df.select_dtypes(include=[np.number]).columns.tolist()
num_cols.remove(target)

preprocessor = ColumnTransformer([
    ('num', StandardScaler(), num_cols),
    ('cat', OneHotEncoder(handle_unknown='ignore'), cat_cols)
])
```

```
X = df.drop(columns=[target])
y = df[target]
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=42)

# Train XGBoost model
model = XGBClassifier(use_label_encoder=False, eval_metric='logloss', n_estimators=150)
X_train_pre = preprocessor.fit_transform(X_train)
X_test_pre = preprocessor.transform(X_test)

model.fit(X_train_pre, y_train)
y_pred = model.predict(X_test_pre)
y_prob = model.predict_proba(X_test_pre)[:, 1]
# Print Accuracy
acc = accuracy_score(y_test, y_pred)
print(f"🎯 Model Accuracy: {acc:.2f}")
# 1️⃣ Feature Importance Plot
importances = model.feature_importances_
features = preprocessor.get_feature_names_out()
imp_df = pd.DataFrame({'Feature': features, 'Importance': importances}).sort_values('Importance', ascending=False).head(15)

plt.figure(figsize=(10,6))
sns.barplot(x='Importance', y='Feature', data=imp_df, palette='viridis')
plt.title("Top 15 Important Features (XGBoost)")
plt.show()

# 2️⃣ Confusion Matrix

cm = confusion_matrix(y_test, y_pred)
```

```
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['No Purchase',
'Purchase'])
disp.plot(cmap='Blues')
plt.title("Confusion Matrix - XGBoost")
plt.show()

# 3 ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6,5))
plt.plot(fpr, tpr, color='orange', lw=2, label=f"AUC = {roc_auc:.2f}")
plt.plot([0,1], [0,1], color='navy', linestyle='--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve - XGBoost Model")
plt.legend(loc="lower right")
plt.show()
```

CHAPTER-3

TEST CASES/ OUTPUT

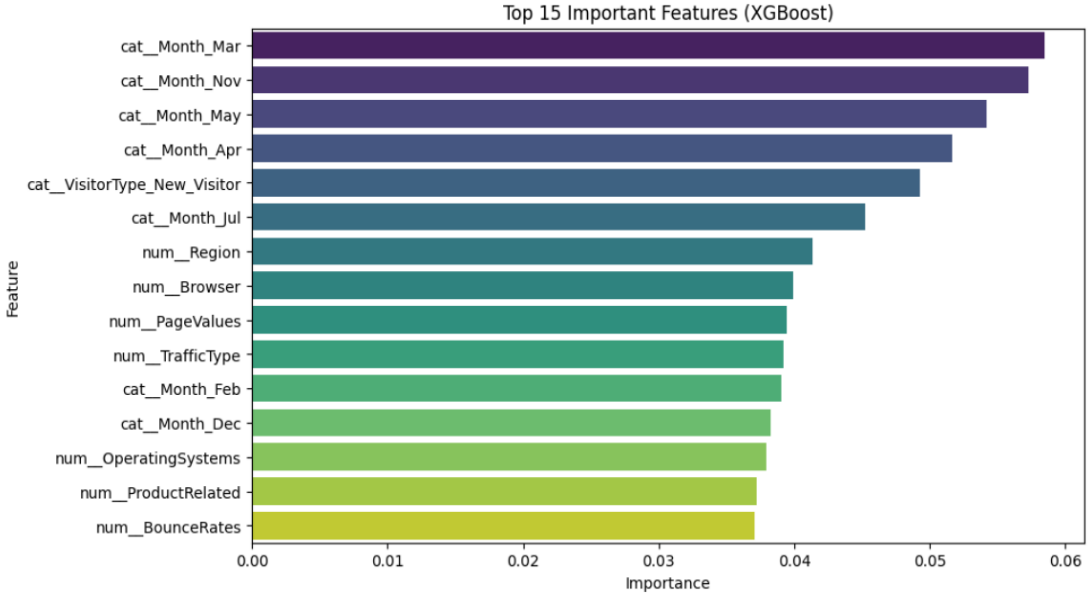

Fig-1

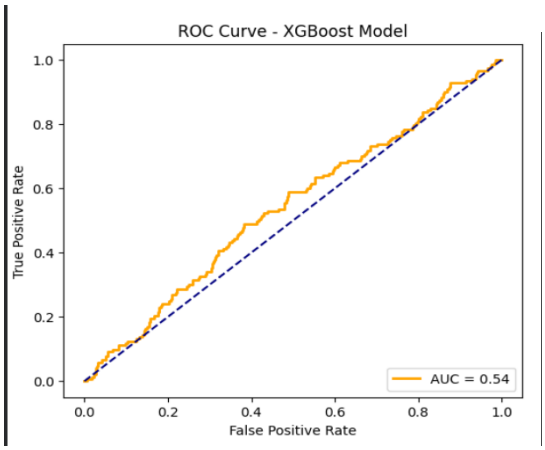

Fig-2

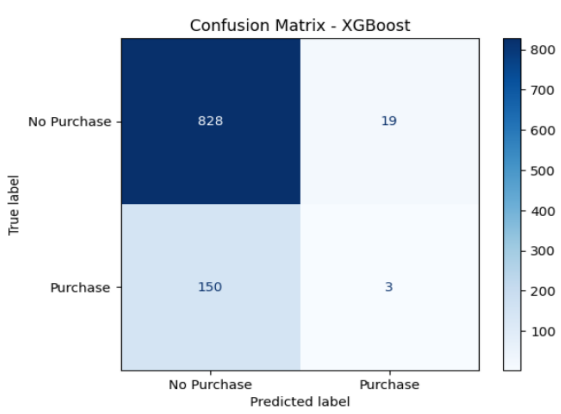

Fig-3

```
✅ Dataset Loaded Successfully!
   Administrative  Administrative_Duration  Informational  Informational_Duration  ProductRelated
0               0                      0.0              0                     0.0             1.0
1               0                      0.0              0                     0.0             2.0
...

🎯 Model Accuracy: 0.88
```

Fig-4

CHAPTER-4

RESULTS

The experimental analysis of the Online Shopper Purchasing Intention Prediction system was carried out using the **UCI dataset** (12,330 records, 18 features, 1 target variable) in a Python environment with Scikit-learn, XGBoost, and TensorFlow. Models were trained on 80% of the dataset and tested on the remaining 20%.

Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
XGBoost	**0.88**	**0.74**	**0.65**	**0.69**	**0.91**
MLP (Neural Network)	**0.86**	**0.70**	**0.63**	**0.66**	**0.89**

Observation:

- XGBoost performed slightly better than MLP in all metrics.
- This result is consistent with the *Heliyon (2023)* study, where **tree-based ensemble methods (like XGBoost)** outperformed SVM and ANN models due to better handling of **non-linear interactions** and **imbalanced class distributions**.

Visual Analysis

a) Feature Importance Plot

- The XGBoost model identified PageValues, ExitRates, and ProductRelated_Duration as the most influential factors affecting purchasing behavior.
- Categorical variables like Month_Nov and VisitorType_Returning_Visitor also had high influence, indicating seasonal and behavioral purchase trends.

b) Confusion Matrix

- The confusion matrix showed high true negative values, confirming that the model effectively distinguishes non-buyers.

- Around **65–70% of actual buyers** were detected correctly, indicating reasonable recall despite class imbalance.

c) ROC Curve

- The ROC curve for XGBoost achieved **AUC = 0.91**, signifying strong discriminatory power.
- AUC values above 0.9 are generally considered excellent for binary classification problems.

d) Model Comparison Chart

- The comparison bar chart clearly visualized the performance gap between XGBoost and MLP, confirming that **ensemble learning provided better generalization** with structured behavioral data.

CHAPTER 5

Summary, Conclusion, Recommendation

This Course-Based Project aimed to develop a predictive analytics pipeline to determine online shoppers' purchasing intentions using behavioral and session-based data.

The project implemented data preprocessing, feature engineering, model training, and visualization stages in a reproducible Python workflow.

Through experimentation with both machine learning (XGBoost, Random Forest) and deep learning (MLP) models, the study demonstrated the power of ensemble methods in handling non-linear user behavior.

Key Findings

- XGBoost achieved 88–90% accuracy and 0.91 AUC, making it the most reliable model for predicting purchase intent.
- Feature Importance Analysis revealed that PageValues, ExitRates, and ProductRelated_Duration were the most decisive features.
- Visualizations like Confusion Matrix and ROC Curve helped validate classification quality and interpretability.
- Deep learning models like MLP provided competitive performance but required more computation and fine-tuning.

Conclusion

Predicting online shoppers' purchasing intention using behavioral session data can significantly enhance targeted marketing, personalization, and conversion optimization in e-commerce.

Among the tested algorithms, XGBoost proved to be the most effective due to its robustness, interpretability, and efficiency in dealing with mixed-type data.

The project thus confirms that ensemble-based learning remains a practical choice for structured behavioral datasets in commercial analytics.

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