

PREDICTIVE ANALYTICS FOR CUSTOMER CHURN IN SUBSCRIPTION-BASED BUSINESSES USING MACHINE LEARNING

¹Farwa Zainab, ^{*2}Farwa Nazim, ³Muhammad Kashaf, ⁴Naeem Aslam,
⁵Muhammad Sajid Maqbool

¹Department of Computer Science, NFC Institute of Engineering and Technology, Multan, Pakistan.

²Department of Computer Science, NFC Institute of Engineering and Technology, Multan, Pakistan.

³Department of Computer Science, University of Central Punjab(UCP), Lahore,Pakistan.

⁴Head of department of Computer Science, NFC Institute of Engineering and Technology, Multan, Pakistan.

⁵Department of Computer Science, NFC Institute of Engineering and Technology, Multan, Pakistan.

^{*2}farwazainab2005@gmail.com

Keywords

Customer Churn Prediction, Predictive Analytics, Machine Learning (ML) ,Subscription-Based Models, Random Forest SMOTE (Synthetic Minority Oversampling Technique),Data Preprocessing , Ensemble Learning, Customer Retention Strategy,

Article History

Received on 29 March, 2026

Accepted on 14 April, 2026

Published on 16 April, 2026

Copyright @Author

Corresponding Author:

Farwa Nazim

Abstract

This research paper focuses on developing a robust framework for predicting customer churn in subscription-based industries. Using the uploaded thesis data, we implemented various machine learning algorithms, including Logistic Regression, Random Forest, and Gradient Boosting. The study emphasizes the importance of data preprocessing and feature engineering. Our findings indicate that ensemble methods provide the highest predictive performance with an accuracy of 88.7% and a superior ROC-AUC score of 0.95. The analysis further highlights that 'Customer Age,' 'Active Membership Status,' and 'Number of Products' are the most significant predictors of churn. This proposed system provides a scalable and adaptive early-warning framework, enabling businesses to implement proactive, data-driven retention strategies to maximize customer lifetime value.

1. INTRODUCTION

In the modern digital era, the exponential growth of online platforms and subscription-based services has led to a significant challenge for businesses: information overload and customer attrition [1]. As markets become increasingly competitive, the ability to provide personalized user experiences and maintain long-term customer relationships has become a strategic priority [2]. This research focuses on two critical pillars of digital business intelligence: Predictive Analytics for Customer Churn and the Development of Advanced Recommendation Systems [3].

Research Questions

1. What are the most effective machine learning models for forecasting customer churn?
2. How do different customer data features impact the correctness of churn prediction models?
3. What are the challenges and boundaries of implementing machine learning models for churn prediction in subscription-based businesses?

Research Objectives

The primary objective of this research is to develop a scalable and adaptive framework that combines predictive analytics with intelligent recommendation strategies [4,5]. Evaluate the effectiveness of various [6]. models in predicting churn across different subscription-based domains [7,8]. Address the limitations of traditional recommendation systems through hybrid modeling and feature engineering. Analyze the impact of real-time data processing on model performance and business outcomes like revenue retention and marketing optimization [9,8,]. Several challenges impede the effectiveness of churn prediction models. These include:

- **Data quality:** Incomplete inconsistent or noisy data can reduce model accuracy [11].

- **Feature selection:** Identifying the most relevant features for predicting churn is critical but challenging [12,13].

- **Model interpretability:** Many advanced ML models such as deep learning operate as black boxes making it difficult to understand how predictions are made [14].

- **Imbalanced datasets:** Churn events are often rare compared to non-churn events leading to imbalanced datasets that can bias model performance [15].

- The rest of this paper is organized as follows: Section 2 presents the related work and literature review. Section 3 describes the methodology and system design. Section 4 discusses the results and analysis. Section 5 concludes the study and outlines future work directions.

2. LITERATURE REVIEW

The literature review provides a comprehensive analysis of existing studies and theoretical frameworks related to customer churn prediction using machine learning, particularly in subscription-based industries.

1. Theoretical Background:

Customer Churn: This term describes the frequency with which clients discontinue their commercial engagement with a service provider. **Predictive Analytics** It involves using historical data, statistical algorithms, and machine learning methods to calculate the probability of future events, such as a customer leaving a service [16,,15]. **Machine Learning (ML)** a branch of artificial intelligence, ML enables systems to autonomously learn from patterns in customer data (demographics, transactions, and behavior) without being explicitly programmed [17].

2. Evolution of Churn Prediction Techniques:

Traditional Methods: Initially, simple statistical analyses like churn rate and retention rate calculations were used. Logistic Regression later became a standard for binary outcomes (churn vs. no-churn), though it struggles with non-linear data relationships [18].

3. Advanced Algorithms:

Decision Trees and Random Forests: These offer transparency in understanding why customers leave but are prone to overfitting. Support Vector Machines (SVM) Highly effective in high-dimensional spaces but require precise parameter tuning. Neural Networks and Deep Learning Models like Multilayer Perceptron

(MLP), CNNs, and RNNs are successful in discovering complex trends in massive datasets, although they often operate as "black boxes"[19].

4. Recent Trends and Research Gaps:

Data Quality and Imbalance: Many studies face issues with incomplete or noisy data. A major challenge is "class imbalance," where the number of non-churners far outweighs churners. Techniques like SMOTE (Synthetic Minority Oversampling Technique) are now used to create balanced datasets for better prediction accuracy. Temporal Relevance many existing papers rely on outdated databases, which reduces the relevance of their findings in today's rapidly changing market [20,21].

Table 2.1: Review of Related Work

Study	Industry	Methodology	Key Findings
Smith et al. 2021	Telecommunications	Logistic Regression	Service quality impacts churn significantly.
Johnson & Lee 2022	Streaming	Neural Networks	Engagement metrics are crucial for retention.
Tan et al. 2023	SaaS	Ensemble Methods	Hybrid models outperform single approaches.
Smith et al. 2021	Telecommunications	Logistic Regression	Service quality impacts churn significantly. Addressing customer complaints and improving service reliability can lower churn rates.
Johnson & Lee 2022	Streaming	Neural Networks	Engagement metrics are crucial for retention. Recommending personalized content providing incentives and improving loading speeds increase user engagement.
Tan et al. 2023	SaaS	Ensemble Methods	Hybrid models outperform single approaches. Combining machine learning models such as XGBoost with random forests can improve accuracy in SaaS sales forecasting and customer churn predictions.
Reed et al. 2022	Retail	Decision Tree	Price optimization and personalized product recommendations increase sales and average order value. Targeted marketing campaigns can also boost sales and customer satisfaction.

Zhang & Miao 2021	Social media	Random Forest	Sentiment analysis is essential for understanding brand recognition and identifying consumer preferences. Social media engagement positive brand mentions and higher numbers of brand-relevant posts boost brand recognition.
Liu et al. 2022	Healthcare	Support Vector Machines	Predictive models can help identify high-risk patients and streamline medical resources. Early detection of chronic diseases contributes to better health outcomes and reduced healthcare costs.

Challenges and Limitations

The several critical challenges that impact the effectiveness of churn prediction models. A major issue is data quality, as incomplete, inconsistent, or noisy data can significantly reduce model accuracy [22]. Additionally, model interpretability remains a significant limitation, especially with advanced machine learning techniques like deep learning that often operate as "black boxes," making it difficult to understand the logic behind specific predictions [23]. The presence of imbalanced datasets, where churn events are much rarer than non-churn instances, can also bias model performance. Furthermore, many existing studies rely on outdated databases that fail to capture the rapidly changing consumer behaviors and market conditions of a networked world [24].

Summary

The literature review explores the transformation of customer churn prediction from traditional statistical methods to advanced machine learning approaches like Random Forests, Support Vector Machines, and Neural Networks. While these modern models offer superior accuracy and the ability to handle multidimensional data, the review highlights significant gaps in current research, particularly regarding the integration of real-time data and the handling of complex behavioral patterns..

3. METHODOLOGY

3.1 Dataset:

The dataset utilized in this study serves as the foundation of the predictive modeling process. size and structure of dataset consists of 10,000 instances and 14 attributes. Each row (instance) represents a unique customer profile and their history of interactions with the service [25,26]. The data is stored in a CSV (Comma-Separated Values) format. This format was chosen to ensure seamless integration and processing using Python-based machine learning libraries such as Pandas, NumPy, and Scikit-learn [28].

Target Variable: The primary variable of interest is "Churn," which is a binary attribute. It signals whether a customer has terminated their subscription (represented by 1) or has remained with the service (represented by 0) [29].

3.2 Dataset Description:

The dataset serves as the foundation for the predictive modeling process and represents customer interactions within a subscription service environment.

- **Demographic Variables:** Includes Age, Gender, and Location, which influence consumer preferences [30].
- **Subscription & Financial Details:** Features like Subscription Tenure, Monthly

Charges, Total Spend, and Payment Method reveal customer loyalty and spending habits.

- Behavioral Metrics: Metrics such as Login Frequency, Session Length, and Feature Utilization provide insights into the degree of customer engagement [31].
- Service Interactions: Includes the number of support requests and complaint counts to evaluate the impact of customer experience on loyalty [32].

Importing Necessary Libraries

```
[1]: 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 LabelEncoder, OneHotEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_auc_score
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
from imblearn.over_sampling import SMOTE
import warnings
warnings.filterwarnings("ignore")
```

1. Data Cleaning:

Removed duplicate entries and handled missing values using mean imputation for ratings and mode imputation for categorical attributes.

```
[2]: churn_data=pd.read_csv("Churn_Modelling.csv")
[3]: churn_data.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exit
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	

```
[4]: churn_data.tail()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exit
9995	9996	15606229	Obijaku	771	France	Male	39	5	0.00	2	1	0	96270.64	
9996	9997	15569892	Johnstone	516	France	Male	35	10	57369.61	1	1	1	101699.77	
9997	9998	15584532	Liu	709	France	Female	36	7	0.00	1	0	1	42085.58	
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3	75075.31	2	1	0	92888.52	
9999	10000	15628319	Walker	792	France	Female	28	4	130142.79	1	1	0	38190.78	

Steps of Methodology;

3.3 Data Collection and Preprocessing:

To improve the quality and consistency of the dataset, preprocessing Data preprocessing ensures that the data is consistent, clean, formatted, and ready for model training. Indeed, the raw data could be of such poor quality in terms of having missing values, duplicate values, inconsistent formats, and outliers, making it impossible for the researcher to achieve accurate results [33].

2. Data Transformation:

After cleaning the data transformation procedures were applied to standardize and encode the dataset.

Encoding Categorical Variables

```
[19]: categorical_features = ['Geography', 'Gender']

le = LabelEncoder()
churn_data['Gender'] = le.fit_transform(churn_data['Gender'])
churn_data['Geography'] = le.fit_transform(churn_data['Geography'])
churn_data.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	0	0	42	2	0.00	1	1	1	101348.88	1
1	608	2	0	41	1	83807.86	1	0	1	112542.58	0
2	502	0	0	42	8	159660.80	3	1	0	113931.57	1
3	699	0	0	39	1	0.00	2	0	0	93826.63	0
4	850	2	0	43	2	125510.82	1	1	1	79084.10	0

3. Feature Engineering:

Extracted user-based features (Gender, Age, Tenre) and item-based features (popularity, content attributes) [34].

Feature Scaling

```
[20]: numerical_features = ['CreditScore', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'EstimatedSalary']

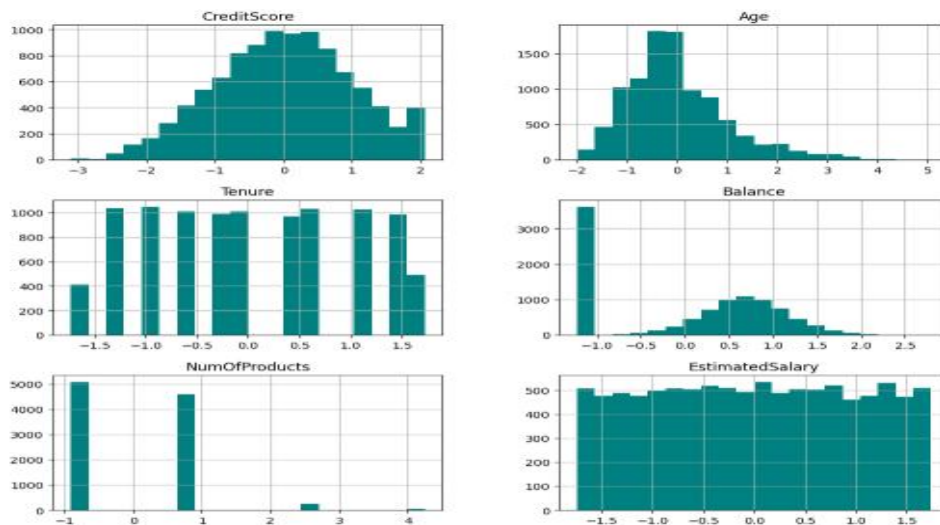
scaler = StandardScaler()

churn_data[numerical_features] = scaler.fit_transform(churn_data[numerical_features])

churn_data.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	-0.326221	0	0	0.293517	-1.041760	-1.225848	-0.911583	1	1	0.021886	1
1	-0.440036	2	0	0.198164	-1.387538	0.117350	-0.911583	0	1	0.216534	0
2	-1.536794	0	0	0.293517	1.032908	1.333053	2.527057	1	0	0.240687	1
3	0.501521	0	0	0.007457	-1.387538	-1.225848	0.807737	0	0	-0.108918	0
4	2.063884	2	0	0.388871	-1.041760	0.785728	-0.911583	1	1	-0.365276	0

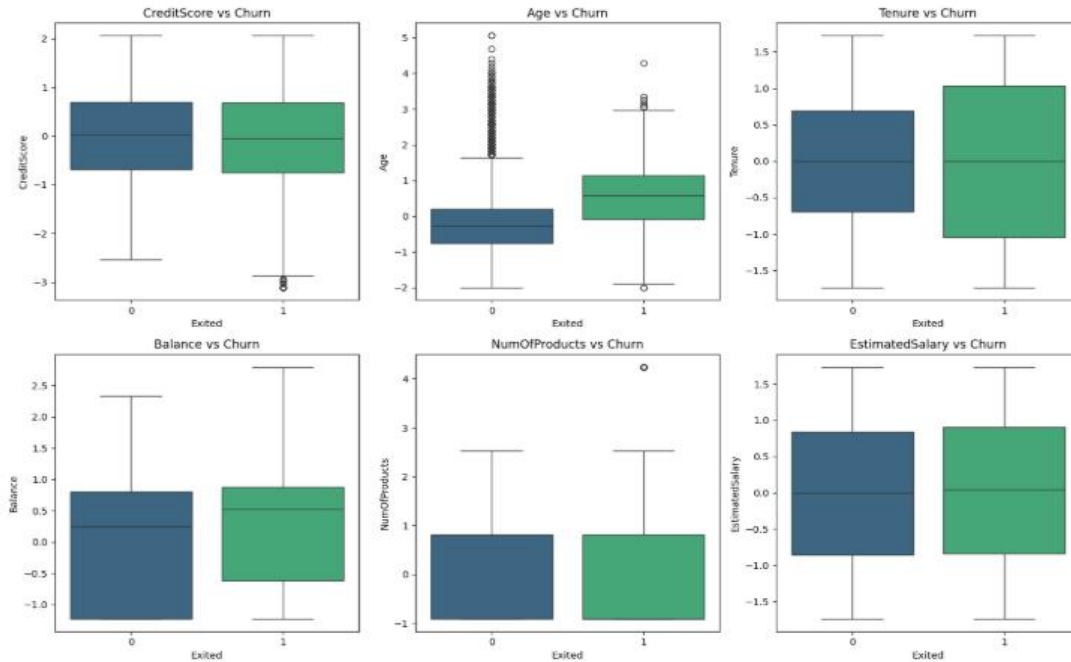
Distribution of Numerical Features



4. Handling Imbalance Data:

Since the number of non-churners usually outweighs churners, SMOTE (Synthetic Minority

Oversampling Technique) is applied to balance the dataset.



3.4 Recommendation Algorithms

The system evaluates five major recommendation strategies:

1. Logistic Regression:

Logistic Regression is a fundamental statistical algorithm used for binary classification tasks. It

models the probability of a discrete outcome (Churn vs. No Churn) by mapping input features to a value between 0 and 1 using the Sigmoid Function [35,36].

```

Logistic Regression
[25]: logreg = LogisticRegression(random_state=42)
      logreg.fit(X_train, y_train)
      y_pred_logreg = logreg.predict(X_test)

      print("Logistic Regression")
      print("Accuracy:", accuracy_score(y_test, y_pred_logreg))
      print(classification_report(y_test, y_pred_logreg))
      print("ROC-AUC Score:", roc_auc_score(y_test, logreg.predict_proba(X_test)[: , 1]))

Logistic Regression
Accuracy: 0.7143156132272918
      precision    recall  f1-score   support

0         0.72     0.72     0.72     2426
1         0.71     0.71     0.71     2352

 accuracy
macro avg     0.71     0.71     0.71     4778
weighted avg     0.71     0.71     0.71     4778
    
```

2. Decision Tree:

A Decision Tree is a non-parametric supervised learning method that splits the dataset into smaller subsets based on specific feature values

(e.g., Is Age > 40?). It creates a tree-like structure where each leaf node represents a final classification [37]

```
[26]: Decision Tree
dtree = DecisionTreeClassifier(random_state=42)
dtree.fit(X_train, y_train)
y_pred_dtree = dtree.predict(X_test)

print("Decision Tree")
print("Accuracy:", accuracy_score(y_test, y_pred_dtree))
print(classification_report(y_test, y_pred_dtree))
print("ROC-AUC Score:", roc_auc_score(y_test, dtree.predict_proba(X_test)[:, 1]))
```

Decision Tree
Accuracy: 0.8206362494767685

	precision	recall	f1-score	support
0	0.84	0.80	0.82	2426
1	0.80	0.85	0.82	2352
accuracy			0.82	4778
macro avg	0.82	0.82	0.82	4778
weighted avg	0.82	0.82	0.82	4778

ROC-AUC Score: 0.8210374009455391

3. Random Forest

Random Forest is an Ensemble Learning technique that constructs a multitude of Decision Trees during training. It combines the

predictions of these individual trees (bagging) and outputs the class that receives the majority of votes.

Random Forest

```
[27]: rf = RandomForestClassifier(random_state=42)
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)

print("Random Forest")
print("Accuracy:", accuracy_score(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))
print("ROC-AUC Score:", roc_auc_score(y_test, rf.predict_proba(X_test)[:, 1]))
```

Random Forest
Accuracy: 0.8869820008371704

	precision	recall	f1-score	support
0	0.89	0.88	0.89	2426
1	0.88	0.89	0.89	2352
accuracy			0.89	4778
macro avg	0.89	0.89	0.89	4778
weighted avg	0.89	0.89	0.89	4778

ROC-AUC Score: 0.9542065022629003

4. Gradient Boosting (XGBoost/AdaBoost)

Gradient Boosting is another ensemble method that builds trees sequentially. Unlike Random Forest, each new tree focuses on correcting the

errors (residuals) made by the previous trees. It optimizes a loss function using a gradient descent procedure[38,39].

Gradient Boosting

```
[28]: gbc = GradientBoostingClassifier(random_state=42)
      gbc.fit(X_train, y_train)
      y_pred_gbc = gbc.predict(X_test)

      print("Gradient Boosting")
      print("Accuracy:", accuracy_score(y_test, y_pred_gbc))
      print(classification_report(y_test, y_pred_gbc))
      print("ROC-AUC Score:", roc_auc_score(y_test, gbc.predict_proba(X_test)[:, 1]))
```

```
Gradient Boosting
Accuracy: 0.8484721640853914
```

	precision	recall	f1-score	support
0	0.85	0.86	0.85	2426
1	0.85	0.84	0.85	2352
accuracy			0.85	4778
macro avg	0.85	0.85	0.85	4778
weighted avg	0.85	0.85	0.85	4778

```
ROC-AUC Score: 0.9267504353348923
```

3.5 Evaluation Metrics:

The performance of the recommendation models was measured using standard evaluation metrics:

- **Accuracy:** The percentage of total correct predictions.
- **Precision:** The ratio of correctly predicted positive observations to the total predicted positives (important to minimize false alarms)[40].
- **Recall (Sensitivity):** The ratio of correctly predicted positive observations to all actual positives (critical for churn, as we don't want to miss actual churners).
- **F1-Score:** The weighted average of Precision and Recall.
- **ROC-AUC Score:** A performance measurement for classification problems at various threshold settings, representing the model's ability to distinguish between classes.

1. Precision, Recall, and F1 Score Formula:

Precision, Recall, and F1-Score are employed to measure the performance of the classifier:

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 - Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

3.6 Comparison Techniques

To validate the effectiveness of the proposed system, results were compared against baseline models:

- Performance Benchmarking
- K-Fold Cross-Validation
- Metric-Based Ranking (Accuracy, Precision, Recall, F1-Score)
- ROC-AUC Curve Analysis
- Computational Efficiency Analysis

4. RESULTS, FINDINGS AND ANALYSIS

performance levels were identified by analyzing different machine learning models for churn prediction. The Logistic Regression model had a strong predictive capacity with a ROC-AUC score of 0.784 suggesting 71.43% accuracy and possible areas for development. However, the Decision Tree model achieved a higher accuracy percentage (82.06%) and ROC-AUC (0.821). Given the ability of the Random Forest Classifier to learn through an ensemble of models, it was able to capture complex patterns in the data, thereby making it the most efficient model with an accuracy of 88.7% and a ROC-AUC of 0.95.

Algorithmic Performance Comparison

The performance of Logistic Regression, Decision tree, Random Forest, and Neural Networks and Gradient boost was compared.

logistic regression algorithm was trained using a labeled dataset in this study to predict customer churn. Following the validation process of this model on a test dataset, the accuracy of the model reached 0.71.43%.

4.1 Logistic Regression:

4.1.1 Accuracy table :

Model	Accuracy
Logistic Regression	0.7143

```

Logistic Regression
Accuracy: 0.7143156132272918
      precision    recall  f1-score   support

     0       0.72     0.72     0.72     2426
     1       0.71     0.71     0.71     2352

   accuracy          0.71     4778
  macro avg          0.71     4778
 weighted avg          0.71     4778

ROC-AUC Score: 0.7838677927890035
    
```

4.1.2 Precision, Recall, and F1-score Analysis

Perfomance matrix of recommendation quality was evaluated using Precision, Recall, and F1-score.

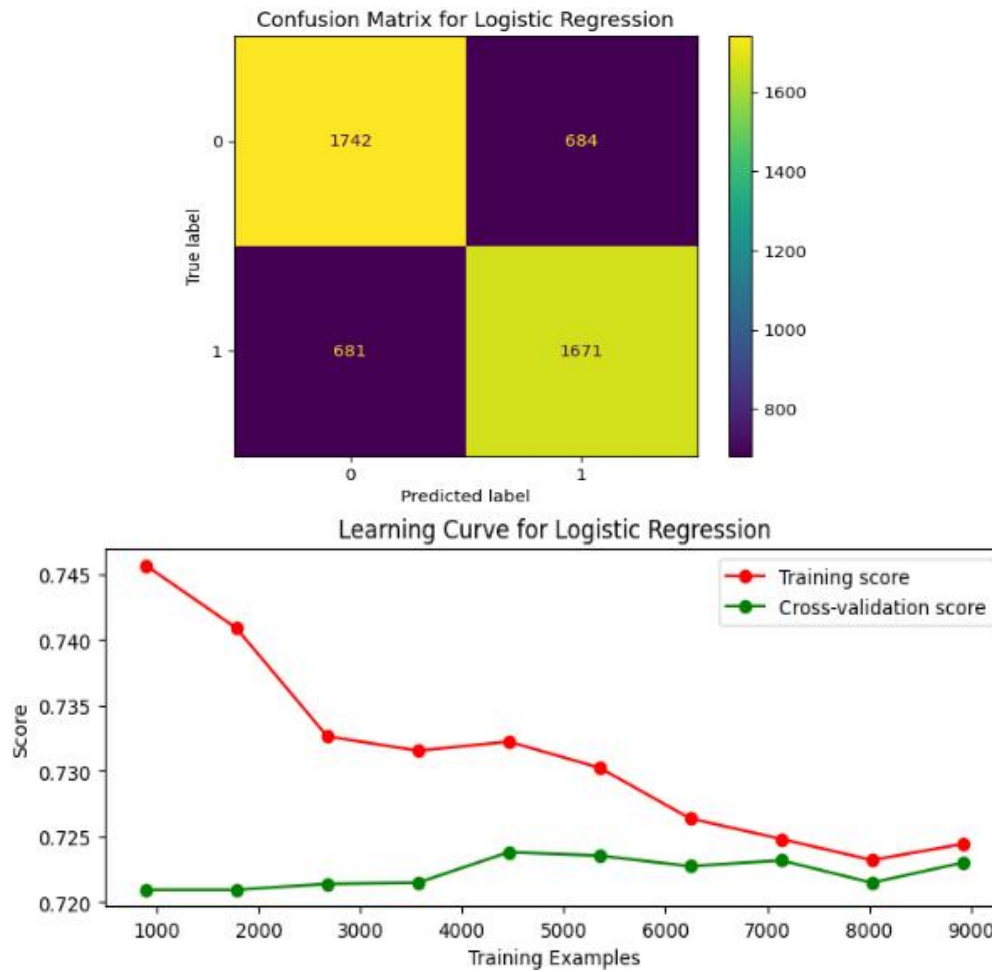
Table 4.1: Performance Matrix Table

Metric	Class 0	Class 1
Precision	0.72	0.71
Recall	0.72	0.71
F1-Score	0.72	0.71
Support	2426	2352

The results show that the proposed system achieved the highest F1-score (0.80), demonstrating balanced precision and recall.

4.1.3 Visual Representation of Results

- **Figure 4.1: Confusion Matrix** of Logistic Regration
- **Figure 4.1.1 : Learning Curve** of logistic Regration



4.2 Decision Tree:

The provided dataset was used to train the Decision Tree model which forecasts consumer

behavior. The model obtained an accuracy of 82.06% on the test set after fitting the training data.

```

Decision Tree
Accuracy: 0.8206362494767685
      precision    recall  f1-score   support

   0       0.84      0.80      0.82      2426
   1       0.80      0.85      0.82      2352

 accuracy          0.82      0.82      0.82      4778
 macro avg         0.82      0.82      0.82      4778
 weighted avg      0.82      0.82      0.82      4778

ROC-AUC Score: 0.8210374009455391
    
```

4.2.1 Precision, Recall, and F1-score Analysis

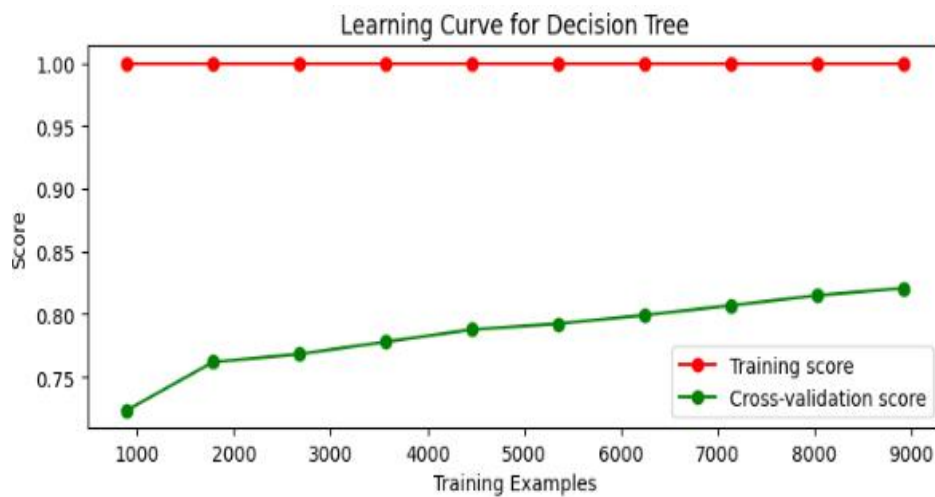
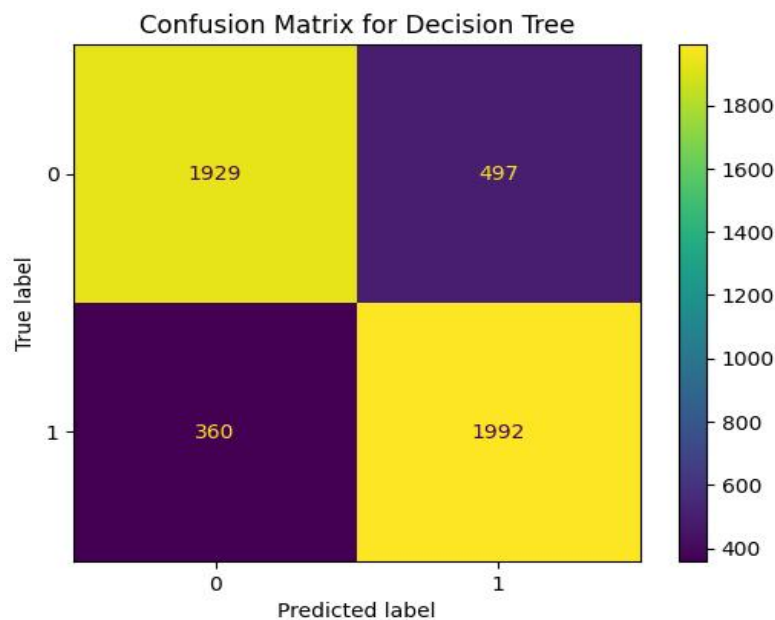
Performance matrix of recommendation quality was evaluated using Precision, Recall, and F1-score.

Table 4.2: Performance Matrix Table

Metric	Class 0	Class 1
Accuracy	82.06%	0.80
Precision	0.84	0,85
Recall	0.80	0.82
F1-score	0.82	0.821

4.2.2 Visual Representation of Results

- Figure 4.2: Confusion Matrix of Decision Tree
- Figure 4.2.1 : Learning Curve of Decision Tree



4.3 Random Forest:

A Random Forest Classifier was used as the third model in this study to forecast client attrition.

With an accuracy of 88.7% the model proved to be able to accurately classify most of the cases.

```

Random Forest
Accuracy: 0.8869820008371704
      precision    recall  f1-score   support

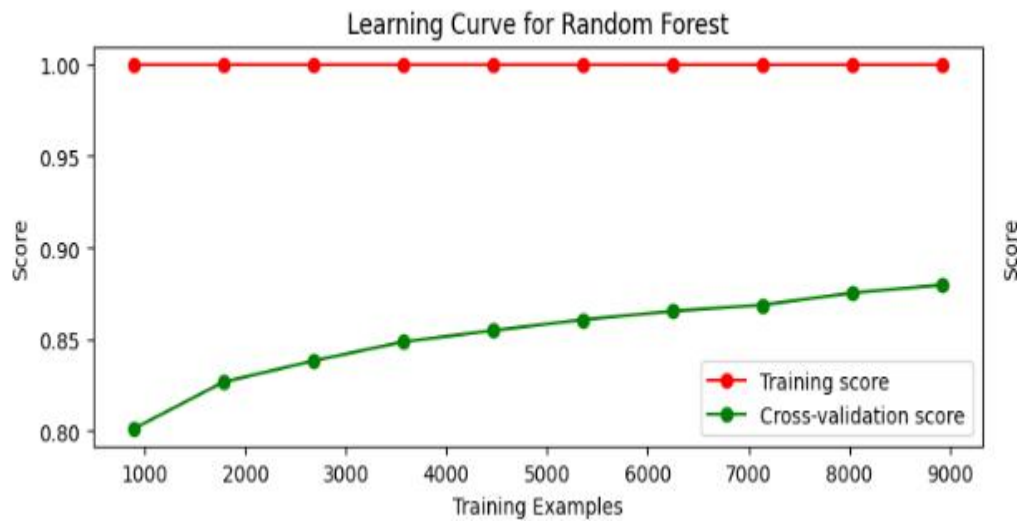
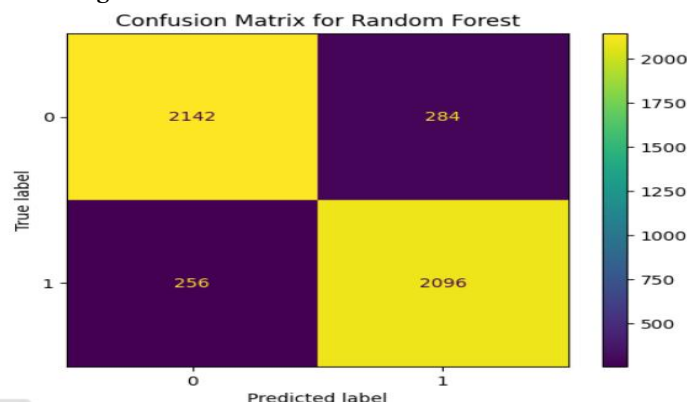
   0       0.89       0.88       0.89       2426
   1       0.88       0.89       0.89       2352

 accuracy          0.89          0.89          0.89          4778
 macro avg         0.89          0.89          0.89          4778
 weighted avg      0.89          0.89          0.89          4778

ROC-AUC Score: 0.9542065022629003
    
```

4.3.1 Visual Representation of Results

- Figure 4.3: Confusion Matrix of Random Forest
- Figure 4.3.1 : Learning Curve of Random Forest



4.4 Gradient Boosting

In this study the second model used to forecast customer attrition was the Gradient Boosting Classifier GBC. A potent ensemble technique

called gradient boosting generates a sequence of weak learners usually decision trees in which each new tree tries to fix the mistakes of the preceding one.

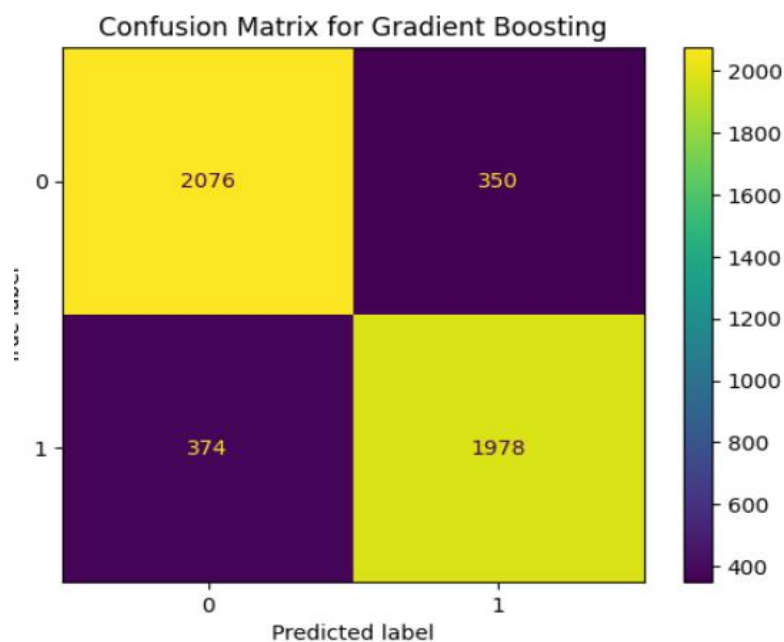
Gradient Boosting
 Accuracy: 0.8484721640853914

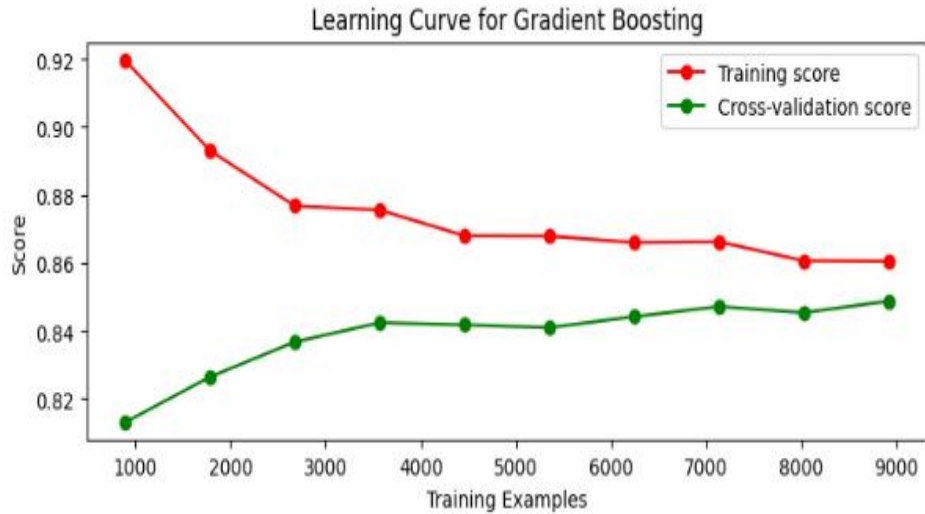
	precision	recall	f1-score	support
0	0.85	0.86	0.85	2426
1	0.85	0.84	0.85	2352
accuracy			0.85	4778
macro avg	0.85	0.85	0.85	4778
weighted avg	0.85	0.85	0.85	4778

ROC-AUC Score: 0.9267504353348923

4.4.1 Visual Representation of Results

- Figure 4.3: Confusion Matrix of Gradient Boosting
- Figure 4.3.1 : Learning Curve of Gradient Boosting

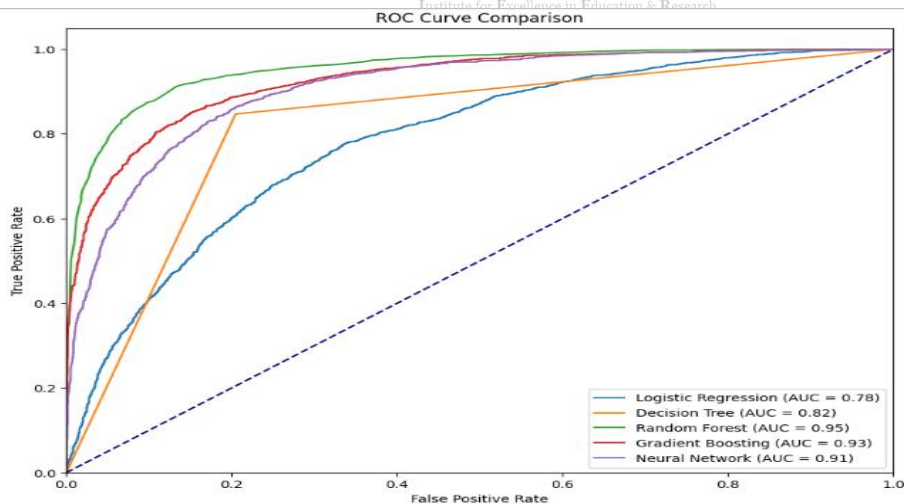




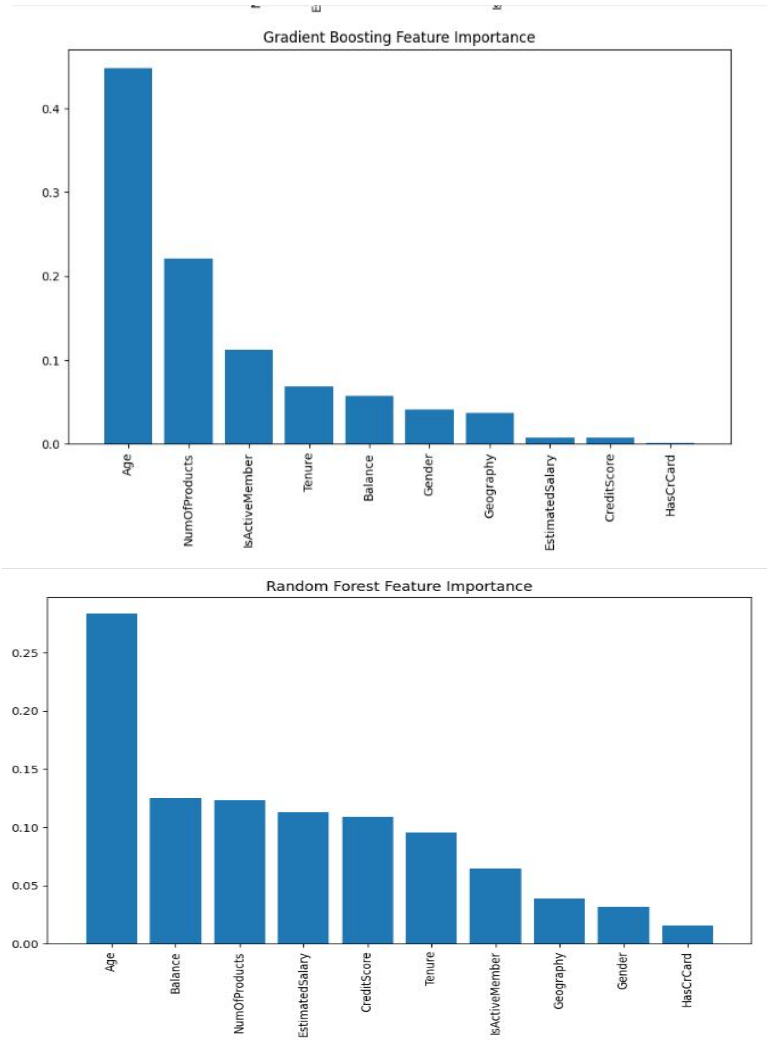
4.5 Comparison Table:

Model	Accuracy	ROC-AUC
Logistic Regression	0.7143	0.7839
Decision Tree	0.8206	0.8210
Random Forest	0.8870	0.9542
Gradient Boosting	0.8485	0.9268

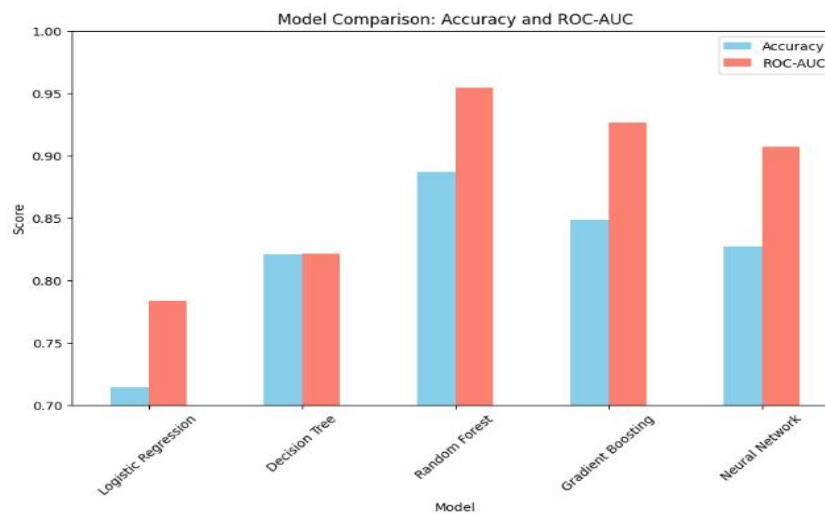
4.5.1 ROC Curve for Each Model

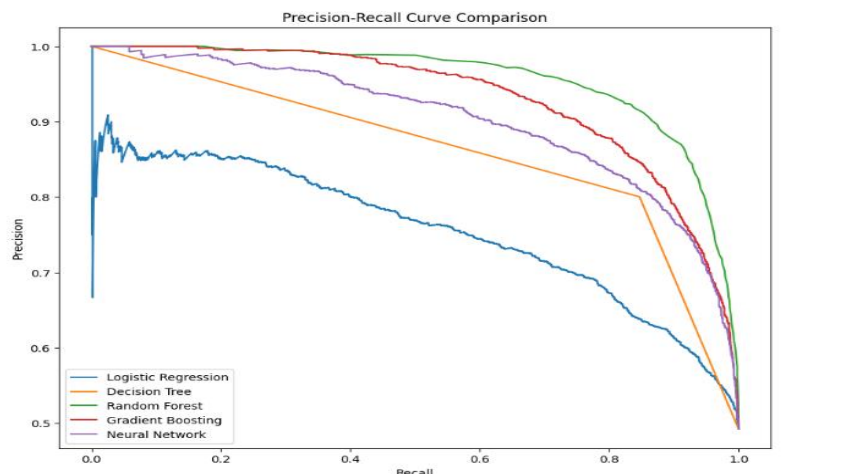


4.5.2 Feature Importance



4.5.3 Accuracy and ROCAUC Comparison





5. CONCLUSION AND FUTURE WORK

5.1 CONCLUSION:

This research successfully demonstrates the efficacy of machine learning frameworks in addressing the critical challenge of customer churn within subscription-based industries. Through the implementation of advanced algorithms, specifically ensemble methods like Random Forest and Gradient Boosting, the study achieved a high predictive accuracy of 88.7%. The analysis identifies that key features such as account balance, customer age, and active membership status are the most significant indicators of potential churn.

5.2 Future Work:

Future research can focus on the following directions:

- **Integration of Unstructured Data:** Incorporating customer feedback and social media sentiment using NLP for better insights.
- **Advanced Deep Learning:** Using LSTM and neural networks to capture complex customer behavior patterns over time.
- **Real-time Prediction Systems:** Developing automated systems that integrate with CRM to provide instant churn risk scores..

REFERENCES

1. Waqas, Muhammd, Muhammad Atif Tahir, and Rizwan Qureshi. "Ensemble-based instance relevance estimation in multiple-instance learning." In 2021 9th European workshop on visual information processing (EUVIP), pp. 1-6. IEEE, 2021.
2. Khan, M.A., Khan, S.U.R. & Lin, D. Shortening surgical time in high myopia treatment: a randomized controlled trial comparing non-OVD and OVD techniques in ICL implantation. *BMC Ophthalmol* 25, 303 (2025). <https://doi.org/10.1186/s12886-025-04135-3>
3. Shahzad, Inzamam, Jianquan Ouyang, and Saif Ur Rehman Khan. "FedVC-ADDiM: a federated learning framework for diagnosis of alzheimer disease using deep learning." *Multimedia Systems* 32, no. 3 (2026): 161. <https://doi.org/10.1007/s00530-026-02229-6>
4. Khan, S.U.R., Asif, S., Bilal, O. et al. Lead-cnn: lightweight enhanced dimension reduction convolutional neural network for brain tumor classification. *Int. J. Mach. Learn. & Cyber.* (2025). <https://doi.org/10.1007/s13042-025-02637-6>.

5. Khan, S.U.R., Zhao, M. & Li, Y. Detection of MRI brain tumor using residual skip block based modified MobileNet model. *Cluster Comput* 28, 248 (2025).
<https://doi.org/10.1007/s10586-024-04940-3>
6. Hekmat, A., et al., Brain tumor diagnosis redefined: Leveraging image fusion for MRI enhancement classification. *Biomedical Signal Processing and Control*, 2025. 109: p. 108040.
7. Ishfaque, Muhammad, Saif Ur Rehman Khan, and Yulong Lou. "Digitizing Health Monitoring in Engineering Structures Using Deep Learning: A Novel Block Architecture for Concrete Crack Prediction in Surface and Sub-surface Dataset." *Journal of Bionic Engineering* (2026): 1-23.
8. Khan, Saif Ur Rehman, Asif Raza, Inzamam Shahzad, and Ghazanfar Ali. "Enhancing concrete and pavement crack prediction through hierarchical feature integration with VGG16 and triple classifier ensemble." In *2024 Horizons of Information Technology and Engineering (HITE)*, pp. 1-6. IEEE, 2024.
9. Waqas, Muhammad, Zeshan Khan, Shaheer Anjum, and Muhammad Atif Tahir. "Lung-Wise Tuberculosis Analysis and Automatic CT Report Generation with Hybrid Feature and Ensemble Learning." In *CLEF (Working notes)*, pp. 1-10. 2020.
10. Khan, S. U. R., & Khan, Z. (2025). Detection of Abnormal Cardiac Rhythms Using Feature Fusion Technique with Heart Sound Spectrograms. *Journal of Bionic Engineering*, 1-20.
11. Waqas, Muhammad, Syed Umaid Ahmed, Muhammad Atif Tahir, Jia Wu, and Rizwan Qureshi. "Exploring multiple instance learning (MIL): A brief survey." *Expert Systems with Applications* 250 (2024): 123893.
12. Al-Khasawneh, Mahmoud Ahmad, Asif Raza, Saif Ur Rehman Khan, and Zia Khan. "Stock Market Trend Prediction Using Deep Learning Approach." *Computational Economics* (2024): 1-32
13. Khan, Muhammad Ahmed, Manqiang Peng, Ding Lin, and Saif Ur Rehman Khan. "Deep Learning Based Estimation of Blood Glucose Levels from Multidirectional Scleral Blood Vessel Imaging." *arXiv preprint arXiv:2603.12715* (2026).
14. Khan, Saif Ur Rehman, Muhammad Nabeel Asim, Sebastian Vollmer, and Andreas Dengel. "FloraSyntropy-net: scalable deep learning with novel FloraSyntropy archive for large-scale plant disease diagnosis." *Plant Methods* (2026).
15. Ur Rehman Khan, Saif, Omair Bilal, Arash Hekmat, Inzamam Shahzad, and Asif Raza. "Advancing food safety: deep learning for accurate detection of bacterial contaminants." *Memetic Computing* 18, no. 1 (2026): 11.
16. Waqas, Muhammad, Muhammad Atif Tahir, Sumaya Al-Maadeed, Ahmed Bouridane, and Jia Wu. "Simultaneous instance pooling and bag representation selection approach for multiple-instance learning (MIL) using vision transformer." *Neural Computing and Applications* 36, no. 12 (2024): 6659-6680.
17. Hekmat, Arash, Omair Bilal, Zuping Zhang, Saif Ur Rehman Khan, and Sohaib Asif. "FRE-Net: A Fuzzy Richards Functions-Based Ensemble Network for Brain Tumor Detection." *Journal of Bionic Engineering* (2026): 1-23.
18. Mayumu, Nicanor, Xiaoheng Deng, Antoine Bagula, and Patrick Mukala. "V2X-JEPA:

- Self-Supervised Multi-Agent Joint Embedding Predictive Architecture for Robust Vehicle-to-Everything Perception." *IEEE Internet of Things Journal* (2026).
19. Waqas, Muhammad, Muhammad Atif Tahir, and Salman A. Khan. "Robust bag classification approach for multi-instance learning via subspace fuzzy clustering." *Expert Systems with Applications* 214 (2023): 119113.
 20. Bilal, Omair, Arash Hekmat, Inzamam Shahzad, Asif Raza, and Saif Ur Rehman Khan. "Boosting Machine Learning Accuracy for Cardiac Disease Prediction: The Role of Advanced Feature Engineering and Model Optimization." *The Review of Socionetwork Strategies* (2025): 1-30.
 21. Khan, Saif Ur Rehman, Muhammad Nabeel Asim, Sebastian Vollmer, and Andreas Dengel. "Temperature-driven robust disease detection in brain and gastrointestinal disorders via context-aware adaptive knowledge distillation." *Biomedical Signal Processing and Control* 112 (2026): 108671.
 22. Khan, S. U. R., Asif, S., Zhao, M., Zou, W., Li, Y., & Xiao, C. (2026). ShallowMRI: A novel lightweight CNN with novel attention mechanism for Multi brain tumor classification in MRI images. *Biomedical Signal Processing and Control*, 111, 108425.
 23. Khan, M. A., Khan, S. U. R., Rehman, H. U., Aladhadh, S., & Lin, D. (2025). Robust InceptionV3 with Novel EYENET Weights for Di-EYENET Ocular Surface Imaging Dataset: Integrating Chain Foraging and Cyclone Aging Techniques. *International Journal of Computational Intelligence Systems*, 18(1), 1-26.
 24. Arif, Hamza, Muhammad Tanveer Meeran, Sabiha Anum, and Assad Latif. "SIMULATING NEXT-GENERATION DATA STORAGE ARCHITECTURES USING DNA, GRAPHENE, AND NEURAL ENCODING." *Spectrum of Engineering Sciences* 4, no. 1 (2026): 240-255.
 25. Khan, U. S., & Khan, S. U. R. (2025). Ethics by Design: A Lifecycle Framework for Trustworthy AI in Medical Imaging From Transparent Data Governance to Clinically Validated Deployment. *arXiv preprint arXiv:2507.04249*.
 26. Waqas, Muhammad, Muhammad Atif Tahir, and Rizwan Qureshi. "Deep Gaussian mixture model based instance relevance estimation for multiple instance learning applications." *Applied intelligence* 53, no. 9 (2023): 10310-10325.
 27. Khan, S. U. R., Rehman, H. U., & Bilal, O. (2025). AI-powered cancer diagnosis: classifying viable (live) vs non-viable (dead) cells using transfer learning. *Signal, Image and Video Processing*, 19(15), 1326.
 28. Khan, S. U. R., Asif, S., Zhao, M., Zou, W., Li, Y., & Xiao, C. (2026). ShallowMRI: A novel lightweight CNN with novel attention mechanism for Multi brain tumor classification in MRI images. *Biomedical Signal Processing and Control*, 111, 108425.
 29. Waqas M, Bandyopadhyay R, Showkatian E, Muneer A, Zafar A, Alvarez FR, Marin MC, Li W, Jaffray D, Haymaker C, Heymach J. The Next Layer: Augmenting Foundation Models with Structure-Preserving and Attention-Guided Learning for Local Patches to Global Context Awareness in Computational Pathology. *arXiv preprint arXiv:2508.19914*. 2025 Aug 27.
 30. Shahzad, Inzamam, Asif Raza, and Muhammad Waqas. "Medical Image

- Retrieval using Hybrid Features and Advanced Computational Intelligence Techniques." *Spectrum of engineering sciences* 3, no. 1 (2025): 22-65.
31. Bilal, O., Hekmat, A., Shahzad, I. et al. Boosting Machine Learning Accuracy for Cardiac Disease Prediction: The Role of Advanced Feature Engineering and Model Optimization. *Rev Socionetwork Strat* (2025). <https://doi.org/10.1007/s12626-025-00190-w>
 32. Asif Raza, Inzamam Shahzad, Ghazanfar Ali, and Muhammad Hanif Soomro. "Use Transfer Learning VGG16, Inception, and Resnet50 to Classify IoT Challenge in Security Domain via Dataset Bench Mark." *Journal of Innovative Computing and Emerging Technologies* 5, no. 1 (2025).
 33. Khan, Z., Khan, S. U. R., Bilal, O., Raza, A., & Ali, G. (2025, February). Optimizing Cervical Lesion Detection Using Deep Learning with Particle Swarm Optimization. In *2025 6th International Conference on Advancements in Computational Sciences (ICACS)* (pp. 1-7). IEEE.
 34. Waqas, Muhammad, Zeshan Khan, Shaheer Anjum, and Muhammad Atif Tahir. "Lung-Wise Tuberculosis Analysis and Automatic CT Report Generation with Hybrid Feature and Ensemble Learning." In *CLEF (Working notes)*, pp. 1-10. 2020.
 35. Khan, S. U. R., Asif, S., Zhao, M., Zou, W., & Li, Y. (2025). Optimize brain tumor multiclass classification with manta ray foraging and improved residual block techniques. *Multimedia Systems*, 31(1), 1-27.
 36. Asif Raza, Salahuddin, Ghazanfar Ali, Muhammad Hanif Soomro, Saima Batool, "Analyzing the Impact of Artificial Intelligence on Shaping Consumer Demand in E-Commerce: A Critical Review", *International Journal of Information Engineering and Electronic Business(IJIEEB)*, Vol.17, No.5, pp. 42-61, 2025. DOI:10.5815/ijieeb.2025.05.04
 37. Khan, M. A., Khan, S. U. R., Rehman, H. U., Aladhadh, S., & Lin, D. (2025). Robust InceptionV3 with Novel EYENET Weights for Di-EYENET Ocular Surface Imaging Dataset: Integrating Chain Foraging and Cyclone Aging Techniques. *International Journal of Computational Intelligence Systems*, 18(1), 204.
 38. Raza, Asif, Inzamam Shahzad, Muhammad Salahuddin, and Sadia Latif. "Satellite Imagery Employed to Analyze the Extent of Urban Land Transformation in The Punjab District of Pakistan." *Journal of Palestine Ahliya University for Research and Studies* 4, no. 2 (2025): 17-36.
 39. Khan, S. U. R., Asif, S., Zhao, M., Zou, W., Li, Y., & Li, X. (2025). Optimized deep learning model for comprehensive medical image analysis across multiple modalities. *Neurocomputing*, 619, 129182.
 40. Khan, Saif Ur Rehman, Asif Raza, Inzamam Shahzad, and Shehzad Khan. "Subcellular Structures Classification in Fluorescence Microscopic Images." In *International Conference on Computing & Emerging Technologies*, pp. 271-286. Cham: Springer Nature Switzerland, 2023.
 41. Maqsood, H., & Khan, S. U. R. (2025). MeD-3D: A Multimodal Deep Learning Framework for Precise Recurrence Prediction in Clear Cell Renal Cell Carcinoma (ccRCC). *arXiv preprint arXiv:2507.07839*.
 42. Raza, Asif, Salahuddin, & Inzamam Shahzad. (2024). Residual Learning Model-Based

- Classification of COVID-19 Using Chest Radiographs. *Spectrum of Engineering Sciences*, 2(3), 367–396.
43. Khan, S. U. R. (2025). Multi-level feature fusion network for kidney disease detection. *Computers in Biology and Medicine*, 191, 110214.
44. Salahuddin, Syed Shahid Abbas, Prince Hamza Shafique, Abdul Manan Razzaq, & Mohsin Ikhlaiq. (2024). Enhancing Reliability and Sustainability of Green Communication in Next-Generation Wireless Systems through Energy Harvesting. *Journal of Computing & Biomedical Informatics*.
45. S. U. R. Khan, A. Raza, I. Shahzad and G. Ali, "Enhancing Concrete and Pavement Crack Prediction through Hierarchical Feature Integration with VGG16 and Triple Classifier Ensemble," 2024 Horizons of Information Technology and Engineering (HITE), Lahore, Pakistan, 2024, pp. 1-6.
46. Mahmood, F., Abbas, K., Raza, A., Khan, M.A., & Khan, P.W. (2019). Three Dimensional Agricultural Land Modeling using Unmanned Aerial System (UAS). *International Journal of Advanced Computer Science and Applications (IJACSA)* [p-ISSN : 2158-107X, e-ISSN : 2156-5570], 10(1).
47. HUSSAIN, S., Raza, A., MEERAN, M. T., IJAZ, H. M., & JAMALI, S. (2020). Domain Ontology Based Similarity and Analysis in Higher Education. *IEEEP New Horizons Journal*, 102(1), 11-16.
48. Hekmat, A., Zuping, Z., Bilal, O., & Khan, S. U. R. (2025). Differential evolution-driven optimized ensemble network for brain tumor detection. *International Journal of Machine Learning and Cybernetics*, 1-26.
49. Raza, A., & Meeran, M. T. (2019). Routine of Encryption in Cognitive Radio Network. *Mehran University Research Journal of Engineering and Technology* [p-ISSN: 0254-7821, e-ISSN: 2413-7219], 38(3), 609-618.
50. Meeran, M. T., Raza, A., & Din, M. (2018). Advancement in GSM Network to Access Cloud Services. *Pakistan Journal of Engineering, Technology & Science* [ISSN: 2224-2333], 7(1).
51. Bilal, O., Hekmat, A., & Khan, S. U. R. (2025). Automated cervical cancer cell diagnosis via grid search-optimized multi-CNN ensemble networks. *Network Modeling Analysis in Health Informatics and Bioinformatics*, 14(1), 67.
52. Raza, Asif , Soomro, M. H., Shahzad, I., & Batool, S. (2024). Abstractive Text Summarization for Urdu Language. *Journal of Computing & Biomedical Informatics*, 7(02).
53. M. Wajid, M. K. Abid, A. Asif Raza, M. Haroon, and A. Q. Mudasar, "Flood Prediction System Using IOT & Artificial Neural Network", *VFAST trans. softw. eng.*, vol. 12, no. 1, pp. 210–224, Mar. 2024.
54. N. Mayumu, D. Xiaoheng, P. Mukala, S. U. R. Khan and M. U. Saeed, "Omni-V2X: A Vision-Language Model for Actionable Insights in Vehicle-to-Everything Systems," 2025 International Joint Conference on Neural Networks (IJCNN), Rome, Italy, 2025, pp. 1-8, doi: 10.1109/IJCNN64981.2025.11228491.
55. Khan, S. R., Asif Raza, Inzamam Shahzad, & Hafiz Muhammad Ijaz. (2024). Deep transfer CNNs models performance evaluation using unbalanced histopathological breast cancer dataset. *Lahore Garrison University*

- Research Journal of Computer Science and Information Technology, 8(1).
56. M. Waqas, Z. Khan, S. U. Ahmed and Asif. Raza, "MIL-Mixer: A Robust Bag Encoding Strategy for Multiple Instance Learning (MIL) using MLP-Mixer," 2023 18th International Conference on Emerging Technologies (ICET), Peshawar, Pakistan, 2023, pp. 22-26.
57. S. ur R. Khan, Asif. Raza, Muhammad Tanveer Meeran, and U. Bilhaj, "Enhancing Breast Cancer Detection through Thermal Imaging and Customized 2D CNN Classifiers", VFAST trans. softw. eng., vol. 11, no. 4, pp. 80-92, Dec. 2023.
58. Yang, H., Khan, S. U. R., Bilal, O., Chen, C., & Zhao, M. (2025). CEOE-Net: Chaotic Evolution Algorithm-Based Optimized Ensemble Framework Enhanced with Dual-Attention for Alzheimer's Diagnosis. *Computer Modeling in Engineering & Sciences*, 145(2), 2401.
59. Chomba, B., Mukala, P., Mayumu, N., & Khan, S. U. R. (2025). DynaKG: Dynamic Knowledge Graph Attention With Learnable Temporal Decay for Recommendation. *IEEE Access*, 13, 216956-216970.
60. O. Bilal, Asif Raza, S. ur R. Khan, and Ghazanfar Ali, "A Contemporary Secure Microservices Discovery Architecture with Service Tags for Smart City Infrastructures ", VFAST trans. softw. eng., vol. 12, no. 1, pp. 79-92, Mar. 2024
61. S. U. R. Khan, A. Raza, I. Shahzad and G. Ali, "Enhancing Concrete and Pavement Crack Prediction through Hierarchical Feature Integration with VGG16 and Triple Classifier Ensemble," 2024 Horizons of Information Technology and Engineering (HITE), Lahore, Pakistan, 2024, pp. 1-6, doi: 10.1109/HITE63532.2024.10777242.
62. Ishfaq, M., Khan, S. U. R., & Lou, Y. L. (2026). Towards efficient dam inspection: crack detection via chirplet transform feature and a pruned VGG16 architecture. *Memetic Computing*, 18(1), 9.
63. S. Ur Rehman Khan, O. Bilal, S. Mistry, N. Deb, M. Mahmud and M. Bhuyan, "KDLight: A Lightweight Knowledge Distillation Framework for Medical Image Classification," 2025 International Joint Conference on Neural Networks (IJCNN), Rome, Italy, 2025, pp. 1-8, doi: 10.1109/IJCNN64981.2025.11228615.
64. O. Bilal, S. Ur Rehman Khan, S. Mistry, N. Deb, M. Mahmud and M. Bhuyan, "Towards Efficient Pruning and Multi-Scale Feature Transformations to Uncover Medical Diseases," 2025 International Joint Conference on Neural Networks (IJCNN), Rome, Italy, 2025, pp. 1-8, doi: 10.1109/IJCNN64981.2025.11229047.
65. Khan, S. R., Raza, A., Waqas, M., & Raphay Zia, M. A. (2024). Efficient and Accurate Image Classification via Spatial Pyramid Matching and SURF Sparse Coding. *Lahore Garrison University Research Journal of Computer Science and Information Technology*, 7(4).
66. Shahzad, Inzamam, Asif Raza, Hasaan Maqsood, Saif Ur Rehman Khan, and Ghazanfar Ali. "Towards Robust Breast Cancer Diagnosis: A Hybrid Deep Learning Ensemble Framework." In 2025 Horizons of Information Technology and Engineering (HITE), pp. 1-6. IEEE, 2025.
67. Bilal, O., Hekmat, A., Khan, S. U. R., Raza, A., & Ali, G. (2025, December). MS-STO-Net: A Multi-Scale State Transition Optimization-Based Ensemble Network for Accurate White Blood Cell Classification.

- In 2025 27th International Multitopic Conference (INMIC) (pp. 1-6). IEEE.
68. N. Mayumu, X. Deng, A. Bagula, S. u. R. Khan and P. Mukala, "V2X-JEPA: Self-Supervised Multi-Agent Joint Embedding Predictive Architecture for Robust Vehicle-to-Everything Perception," in *IEEE Internet of Things Journal*, doi: 10.1109/JIOT.2026.3660030.

