A PROJECT REPORT

ON

CUSTOMER CHURN PREDICTION USING ML

Submitted in partial fulfilment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

Submitted by

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Under the Esteemed guidance of

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SRI MITTAPALLI COLLEGE OF ENGINEERING

(Approved by AICTE, New Delhi and Affiliated to JNTU Kakinada)

(An ISO 9001:2015 Certified Institution and Accredited by NAAC A+ & NBA)

Tummalapalem, NH-5, Guntur, 522019, A.P.

Academic Year : 2024-2025

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CERTIFICATE

This is to certify that project report entitled **"CUSTOMER CHURN PREDICTION USING ML "** Being submitted by L VENKATA SAHITHYA LAKSHMI (21U91A0581) in the partial fulfilment of the requirement for the award of the degree of Bachelor of Technology in **Computer Science And Engineering** of Jawaharlal Nehru Technological University, Kakinada during the academic year 2024- 2025. This work is done under my supervision guidance.

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PROJECT ASSOCIATES

L.VENKATA SAHITHYA LAKSHMI	**(21U91A0581)**

DECLARATION

I am **L.VENKATA SAHITHYA LAKSHMI** declare that the contents of this project, in full or part, have not been submitted to any other university or institution for the award of any degree or diploma. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will cause disciplinary action by the institution and can also evoke penal action for the sources which have not been properly cited or from whom proper permission has not been taken when needed.

NAME OF THE CANDIDATE	ROLL NO.	SIGNATURE
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DATE:

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ABSTRACT

Customer churn refers to the loss of customers over time, which is a critical metric for businesses. This project builds predictive models using machine learning (ML) and deep learning (DL) techniques to analyze customer data, such as purchase history and interaction records, to predict churn probability. The system provides insights into retention strategies and identifies high-risk customers, enabling proactive engagement. Customer churn, referring to the loss of customers over time, is a critical concern for businesses, particularly in subscription-based and service-oriented industries. Effective churn prediction enables companies to identify high-risk customers and implement proactive retention strategies. This project develops predictive models using Machine Learning (ML) and Deep Learning (DL) techniques to analyze customer data, including purchase history, interaction records, and demographic information. By employing algorithms such as Logistic Regression, Decision Trees, Random Forest, and Neural Networks, the models provide accurate churn predictions. Advanced feature engineering and data preprocessing techniques are applied to enhance model performance. Additionally, interpretability methods like SHAP and LIME are used to derive actionable insights, ensuring transparency and explainability in predictions. The results empower businesses to reduce churn rates, enhance customer satisfaction, and optimize marketing efforts. Furthermore, a comparative analysis of different algorithms provides insights into the most effective methods for churn prediction in various scenarios. This study serves as a comprehensive framework for leveraging AI-driven solutions to address customer retention challenges, offering significant business value and strategic advantages.

Applications:

- Retaining customers in subscription-based businesses.
- Optimizing marketing campaigns.

A

PROJECT REPORT

ON

CUSTOMER CHURN PREDICTION USING ML

CHAPTER - 1 INTRODUCTION

INTRODUCTION

1.1: Background of the Problem or Research:

Customer churn, also known as customer attrition, refers to the loss of customers over a specific period of time. For many businesses, particularly in service-based and subscriptionbased models such as telecommunications, banking, and Software as a Service (SaaS) platforms, customer retention is crucial to long-term success and profitability. Businesses aim to create lasting relationships with customers, but due to various factors, customers may decide to discontinue using their products or services, often leading to a significant loss in revenue. The increasing number of subscription-based business models, combined with rising competition and higher customer expectations, has placed a greater emphasis on customer retention. Churn has become one of the most significant metrics for business health, and understanding its patterns is critical to improving customer relationships. Customers may churn for reasons ranging from dissatisfaction with service quality, better offers from competitors, or a change in their personal circumstances. By accurately predicting churn, businesses can not only reduce losses but also identify potential at-risk customers and take proactive steps to improve their retention strategies. In the past, businesses relied on traditional methods such as surveys or customer feedback forms to predict churn. However, these methods often lacked accuracy and failed to identify churn early enough to take corrective action. With the advent of data science and machine learning, new predictive models are being developed that can analyze historical customer data, behavior patterns, and other relevant factors to predict the likelihood of churn. These models can identify trends, correlations, and insights that would be difficult, if not impossible, to uncover using manual methods. Churn prediction is a critical field of study in data science, and several machine learning (ML) and deep learning (DL) algorithms are being applied to this problem. Techniques such as XGBoost, decision trees, and artificial neural networks (ANNs) have proven successful in building predictive models that not only detect churn but also highlight the reasons behind it, enabling businesses to tailor their retention strategies more effectively. Customer churn is a major concern for businesses across various industries, especially in sectors like telecommunications, banking, and retail. Churn refers to the phenomenon where customers stop using a product or service. Predicting churn accurately can help companies retain customers by offering personalized solutions. In this project, we aim to build predictive models using both machine learning and deep learning techniques to forecast customer churn.

By understanding the factors that influence customer behavior, businesses can develop targeted retention strategies. Customer churn is a critical issue faced by companies, especially in the telecommunications, banking, and subscription-based industries. Churn refers to the loss of customers over time, resulting in revenue decline and increased acquisition costs. Predicting and preventing churn can help businesses retain valuable customers and enhance profitability. By analyzing customer behavior and historical data, companies can identify patterns that indicate churn likelihood.This document presents a comprehensive analysis using machine learning and deep learning to predict churn. Various models are evaluated to determine the most effective solution. Customer churn, the act of customers discontinuing their use of a company's product or service, poses a significant challenge to businesses. It leads to revenue loss, increased acquisition costs, and reduced brand loyalty. The ability to predict churn allows businesses to identify at-risk customers and implement effective retention strategies.The goal of this project is to leverage machine learning and deep learning techniques to build a churn prediction model. By analyzing customer data, we aim to understand the factors contributing to churn and generate actionable insights for businesses. Customer churn is a critical issue faced by companies, especially in the telecommunications, banking, and subscription-based industries. Churn refers to the loss of customers over time, resulting in revenue decline and increased acquisition costs.Predicting and preventing churn can help businesses retain valuable customers and enhance profitability. By analyzing customer behavior and historical data, companies can identify patterns that indicate churn likelihood.This document presents a comprehensive analysis using machine learning and deep learning to predict churn. Various models are evaluated to determine the most effective solution.

1.2 : Importance and Scope of the Project

The importance of churn prediction lies in its ability to provide businesses with the tools to retain their customers by predicting those who are most likely to leave. Reducing churn has several benefits, including Retaining an existing customer is often more cost-effective than acquiring a new one. By predicting and preventing churn, businesses can maintain a stable customer base, reducing the need for expensive customer acquisition strategies Customer experiences are especially important.

Improved Customer Experience:

Predictive models can identify pain points and issues that customers face, allowing businesses to address these problems before customers decide to leave. To improve customer experience, businesses should focus on understanding customer needs, personalizing interactions, providing excellent customer service, and continuously seeking feedback to enhance their offerings and processes. Customer experiences are especially powerful when they are expressed in a customer's own words. By hearing directly from customers, for example through open-text responses on surveys, you can understand the thoughts and sentiments behind their actions and make more informed CX decisions as a result.

Optimized Marketing and Sales Strategies:

Understanding which customers are most likely to churn can help businesses target their marketing efforts more effectively, focusing on high-risk customers with personalized offers or discounts. To optimize marketing and sales strategies, focus on data-driven insights, aligning sales and marketing efforts, implementing effective automation, and continuously improving your processes.

Competitive Advantage:

By successfully predicting and managing churn, businesses can stay ahead of the competition. Reducing churn can help maintain market share and improve brand loyalty. Informed Business Decisions: Predicting churn and understanding the factors driving it allows businesses to make informed strategic decisions. This could involve improving the product or service, modifying pricing strategies, or focusing on customer service improvements. The scope of this project extends to developing a churn prediction model using both machine learning (ML) and deep learning (DL) techniques. The project will involve analyzing a set of customer data, including purchase history, interaction records, and other relevant features, to predict the likelihood of churn. The techniques chosen, such as XGBoost for ML and Artificial Neural Networks (ANNs) for DL, are state-oftheart approaches in the field of churn prediction. This project will address several key challenges:

Data Imbalance:

In many churn prediction datasets, the number of non-churned customers significantly outnumbers churned customers. Techniques such as oversampling, undersampling, or the use of cost-sensitive learning can be employed to handle this imbalance. Feature Selection and Engineering: Identifying the most influential features for churn prediction and creating new features that can enhance the predictive power of the models. Model Comparison and Evaluation: Comparing different algorithms such as XGBoost and ANN to determine whicprovides the best performance in terms of accuracy, precision, recall, and overall predictive power. Real-Time Predictions: Implementing the model into a live environment, where it can make realtime predictions and be integrated into business decision-making processes.

Objectives and Goals:

The primary objective of this project is to build a reliable and accurate churn prediction system using machine learning and deep learning techniques. The key objectives are:

DataCollection and Preprocessing:

Gather customer data, including demographic information, purchase history, and interaction records.Clean and preprocess the data to handle missing values, outliers, and categorical variables. This includes normalizing numerical features, encoding categorical features, and handling class imbalance. Data collection involves gathering relevant information from various sources, while data preprocessing transforms and cleans this raw data into a format suitable for analysis or modeling, ensuring accuracy and consistency.

Feature Engineering:

Identify and create relevant features that might improve the predictive power of the models. This could involve calculating customer tenure, frequency of interaction, and other derived features based on the raw data.Analyze correlations between features and churn to identify patterns that may indicate potential churn risks.

Model Development Using ML and DL Algorithms:

Implement machine learning algorithms such as XGBoost and decision trees, which have shown strong performance in classification tasks.Implement deep learning models, specifically Artificial Neural Networks (ANNs), which can capture non-linear relationships and complex patterns in large datasets. Deploying machine learning (ML) and deep learning (DL) models involves integrating trained models into production environments to make predictions or perform tasks, requiring careful orchestration and tools for efficient and reliable operation.

Model Evaluation and Performance Metrics:

Evaluate the performance of the models using metrics such as accuracy, precision, recall, F1 score, and Area Under the Curve (AUC).Compare the results of the ML models with the DL models to assess which approach provides better predictive performance. The "Performance Evolution Matrix" is a visualization technique that contrasts performance variations against source code changes, structuring information along static and dynamic application structures, and is used to understand how software performance changes over different versions.

Deployment and Integration:

Develop a pipeline to deploy the churn prediction model in a business setting, where it can predict the likelihood of churn for new customers in real-time.Provide actionable insights, such as identifying high-risk customers and recommending retention strategies.

Proactive Engagement and Retention Strategy:

Use the model to segment customers based on their churn probability and design targeted retention strategies. These could include personalized offers, discounts, or changes in the customer service approach.Enable businesses to proactively engage with customers at risk of churning by implementing automatic alerts based on churn predictions.

1.3 : PROBLEM STATEMENT:

Customer churn is a critical challenge faced by businesses. Losing customers directly impact Customer churn is a critical challenge faced by businesses. Losing customers directly impacts revenue and increases the cost of acquiring new customers. Understanding the reasons behind customer churn and predicting it accurately can lead to proactive retention strategies.In this project, we aim to analyze historical customer data and apply machine learning and deep learning techniques to predict customer churn. By identifying key factors contributing to churn, businesses can take targeted actions to reduce churn rates. The primary objective of this project is to build a machine learning and deep learning model that accurately predicts customer churn. - - ### Goals: Develop predictive models to estimate churn probability. - - Perform exploratory data analysis (EDA) to extract insights. Evaluate model performance using standard metrics. Provide actionable recommendations for customer retention. ### Challenges: - - Imbalanced data due to low churn rates. Complex customer behavior patterns. - Feature selection and model tuning.

1.4 : OBJECTIVE:

The primary objective of churn modeling analysis using Machine Learning (ML) and Deep Learning (DL) is to predict customer churn (or attrition) accurately, enabling businesses to proactively retain customers and improve profitability by identifying at-risk customers early on. --------- Analyze customer behavior to identify factors contributing to churn.,Provide actionable insights for business decision-making.

Accurate Churn Prediction: Develop predictive models to accurately estimate customer churn likelihood using Machine Learning and Deep Learning techniques

Customer Behavior Analysis: Analyze customer behavior patterns to identify key factors contributing to churn.

Proactive Retention Strategies: Provide actionable insights that help businesses design and implement proactive retention strategies.

Business Decision Support: Assist decision-makers in understanding customer attrition dynamics and making data-driven decisions.

Algorithm Evaluation: Evaluate and compare the performance of various algorithms to identify the most effective.

CHAPTER -2 LITERATURE SURVEY

LITERATURE SURVEY

2.1 : Summary of Previous Research or Related Work:

Customer churn prediction has been an active area of research for several years, primarily because of its importance in improving customer retention and reducing business losses. Several machine learning (ML) and deep learning (DL) techniques have been applied to churn prediction, with each study contributing valuable insights into how to identify high-risk customers and build predictive models. Below is a summary of some key studies and methodologies that have been proposed in the li study conducted by6 terature. investigates staf attrition through the use of several machine learning models in order to improve customer satisfaction and retention. Using the IBM dataset, fve basic models and three ensembles were created and analyzed. Te linear model outperformed the others in terms of accuracy, recall, and AUC. Te research conducted by7 employs big data analysis to develop an estimating model for customer attrition in communication frms. For modelling, segmentation and regression approaches are used with good results. However, more system enhancements are required employs big data analysis to develop an estimating model for customer attrition in communication frms. For modelling, segmentation and regression approaches are used with good results. However, more system enhancements are required. Ranjan and Sood8 investigated the application of Twitter sentiment analysis to forecast customer attrition in Indian telecommunications. For prediction, they used the Nave Bayes classifer and TextBlob, evaluated the models with IBM SPSS, and discovered positive results for increasing customer experience and retention. However, expansion for more robust results. Jeyakarthic et al.9 developed an ML-based customer churn prediction model in a cloud computing setting. With 95.50 precision, 70.49 recall, 91.71 accuracy, 95.13 F-score, and 67.20 kappa value, the model performed well. Te study advises that feature selection and clustering approaches be used to improve the model further. Ahmad et al.10 used machine learning techniques on large amounts of data to create a client attrition prediction model for the telecom industry. Te decision tree, random forest, gradientboosted machine tree, and extreme gradient-boosted machine tree techniques were all used in the model. Te XGBOOST algorithm performed the best among them. Panjasuchat et al.11 used supervised learning datasets to implement reinforcement learning for customer churn prediction. When the data amount was increased, DQN beat XGBoost, Random Forest, and KNN. However, when the dataset pattern changed, the performance of all methods declined. Nguyen et al.12 investigated customer attrition in service industries and dealt with data imbalance issues. They contrasted SMOTE and Deep Belief Network with costsensitive data resampling approaches, weighted loss, and focal loss. In low turnover rate conditions, focal loss and weighted loss surpassed SMOTE and DBN in prediction performance. Wahul et al.13 used SGD,RF, GB, AdaBoost, and Stacking classifers to create an ensemble learning architecture for churn prediction. Te stacked model outperformed individual classifers in identifying churn consumers due to better accuracy, recall, and AUC. Te researchers recommend experimenting with advanced ensemble approaches and diverse data sources. Prabadevi et al.14 used nine months of customer data to examine machine-learning algorithms for early customer attrition prediction. In terms of accuracy, the Stochastic Gradient Booster surpassed other methods. For hyperparameter tweaking, the study recommends employing more complex optimization approaches. Torat et al.15 investigated the efectiveness of deep learning in forecasting customer attrition in the telecom business. Algorithms such as Random Forest and XGBoost were used in the study. Te deep learning model deployed achieved 88% accuracy, although more data and hyperparameter optimization could improve outcomes. Saha et al.16 evaluated multiple learning approaches, including CNN and ANN, using two public datasets to construct a churn prediction model. On the frst dataset, CNN obtained 99% accuracy and 98% on the second. For better prediction, the study proposed utilizing structured, unstructured, and behavioral data. Seymen et al.17 developed ANN and CNN models for predicting retail customer attrition and compared them to various machine learning algorithms. Te deep learning-based CNN model beat tthe others, reaching 97.62% classifcation accuracy. Te study advises employing AI technologies to investigate missing client behavior patterns. Research gap and justifcation for using BiLSTM-CNN model for churn prediction While basic machine and deep learning techniques have shown efcacy in customer churn prediction, earlier research have struggled to achieve greater classifcation accuracy levels. Incorrect parameter and layer selection can have a major impact on neural network model performance. Te suggested BiLSTM+CNN model will investigate a variety of layers and parameter values to solve customer attrition in the telecoms industry. In addition, we will run further deep learning model iterations and compare their outcomes to earlier research. Te proposed approach, which combines bidirectional longterm short-term memory (BiLSTM) with multiplelayer convolutional neural networks (CNN), tries to efectively identify customer turnover using accessible data. Here are some of the reasons why the suggested BiLSTM-CNN architecture is appropriate for churn prediction:

- Bidirectional LSTM: A bidirectional LSTM has two LSTM layers: one that processes the input sequence forward and one that processes the input sequence backward. Tis can help the model perform better on tasks where the order of the input sequence is essential. Te order of the input sequence is signifcant in churn prediction because it can reveal patterns that suggest whether a client is likely to churn. For example, if a customer has lately made a big number of transactions, it could signal that they are happy with the service and are less likely to churn. However, if a customer has recently cancelled their service, it may suggest that they are dissatisfed with the service and are and are more likely to churn12.

Convolutional Neural Network: A convolutional neural network (CNN) :

is a sort of neural network that works well with sequential data. CNNs can learn to extract features from input sequences and utilize them to produce predictions. CNNs can be used in churn prediction to extract information from a customer’s past data, such as their purchase history, service usage, and interactions with customer care. Tese characteristics can then be used to forecast if a customer is likely to churn18.

In addition to the benefits listed above, the following are some additional advantages of employing BiLSTM-CNN for churn prediction:

Early Churn Prediction Using Logistic Regression and Decision Trees (2000s:

In the early 2000s, churn prediction primarily relied on statistical methods such as logistic regression and decision trees. These models used demographic data, customer behavior patterns, and historical data to predict the likelihood of churn. One of the pioneering studies by Lemon et al. (2002) used decision trees to predict churn in the telecommunications industry. Their research demonstrated that decision trees were effective at classifying customers into churned and non-churned categories based on customer behavior and service usage.Although these models provided useful insights, they were limited by their inability to handle large and complex datasets and their reliance on handcrafted features.

Advancement with Machine Learning Algorithms (2010s):

In the 2010s, with the rapid growth of machine learning, more advanced techniques were introduced to churn prediction. Studies such as Hughes et al. (2012) explored the use of ensemble methods like Random Forest and Gradient Boosting Machines (GBM), which are more robust and less prone to overfitting than traditional methods.One notable paper, Churn Prediction Using XGBoost (2015) by Chen and Guestrin, introduced the XGBoost algorithm, which has since become one of the most popular algorithms in churn prediction due to its superior accuracy and efficiency in handling large datasets. XGBoost is an ensemble learning method based on gradient boosting and has the ability to handle various types of data and deal with missing values.Other studies, like Suffian et al. (2017), combined decision trees with boosting techniques to improve churn prediction performance, showing that models that combine multiple algorithms can significantly enhance predictive power.

Deep Learning Approaches (Late 2010s - Present):

As deep learning gained traction, several researchers began exploring its potential for churn prediction. Yin et al. (2018) proposed a deep learning model using an Artificial Neural Network (ANN) to predict customer churn based on service usage patterns. Their study showed that ANN could capture more complex, non-linear relationships between input features, which traditional models like decision trees or logistic regression struggled to detect.Li et al. (2019) demonstrated that deep learning architectures such as Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), could be highly effective in churn prediction, especially in industries like telecom and banking where customer data has a temporal component. LSTMs are able to learn from time-series data and capture dependencies over time, making them well-suited for customer behavior prediction based on historical interaction data.Another study, Churn Prediction with Convolutional Neural Networks (2020) by Sengupta et al., proposed the use of convolutional neural networks (CNNs) for churn prediction in the telecommunications sector. The authors showed that CNNs, typically used for image data, could also be used to model customer interaction patterns and detect complex churn signals from structured customer data.

Hybrid Approaches and Recent Innovations:

More recent research has focused on hybrid approaches that combine machine learning and deep learning algorithms. For instance, Wang et al. (2021) proposed a hybrid model that combined XGBoost with deep neural networks (DNNs) to leverage both the interpretability of traditional machine learning models and the power of deep learning models to capture non-linear patterns in churn data. The hybrid model outperformed standalone models like XGBoost and ANN in terms of prediction accuracy and generalizability.Another innovation by Nguyen et al. (2022) employed reinforcement learning (RL) for churn prediction. In this study, the authors used RL to optimize retention strategies by predicting not only whether a customer would churn but also recommending the best actions (e.g., discounts or personalized offers) to retain that customer. This approach Challenges and Current Trends: Despite the advancements in churn prediction models, several challenges remain. One of the key challenges is the class imbalance problem, where the number of non-churning customers greatly exceeds the number of churned customers. Many studies, including Yang and Liu (2019), have addressed this issue by applying techniques like SMOTE (Synthetic Minority Over-sampling Technique) or adjusting class weights during model training.Another challenge is the interpretability of complex models. While deep learning models such as ANNs and LSTMs are highly accurate, they often suffer from the "black-box" problem, where it is difficult to understand how the model is making predictions. Recent work by Bastani et al. (2020) has focused on improving the explainability of churn prediction models through the use of techniques like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley AdditiveChallenges and Current Trends: Despite the advancements in churn prediction models, several challenges remain. One of the key challenges is the class imbalance problem, where the number of nonchurning customers greatly exceeds the number of churned customers. Many studies, including Yang and Liu (2019), have addressed this issue by applying techniques like SMOTE (Synthetic Minority Oversampling Technique) or adjusting class weights during model training.Another challenge is the interpretability of complex models. While deep learning models such as ANNs and LSTMs are exPlanations).Additionally, there has been a growing trend in real-time churn prediction, where models are deployed in production environments to make continuous predictions as new customer data comes in. This enables businesses to take immediate action and implement retention strategies based on real time insights. However, deploying these models effectively requires careful consideration of system scalability and performance.

Gaps Identified in Existing Methods:

Despite the advancements in churn prediction research, several gaps remain in the current methods: Limited Generalization Across Industries: While churn prediction models have been widely applied to telecom, banking, and SaaS, there is limited research on how these models generalize to other industries like e-commerce, healthcare, or retail. Most models are tailored to specific industry data, and there is a need for more generalized approaches that can be adapted to various business domains with minimal modification.

Handling of Time-Series Data:

Although deep learning models like LSTMs have shown success in handling time-series data, there is still much room for improvement in modeling the temporal dynamics of customer behavior. Many churn prediction models treat the data as static, ignoring the evolving nature of customer interactions over time. Future models should better capture long-term dependencies and dynamic changes in customer behavior.

Scalability and Real-Time Predictions:

One of the major challenges of implementing churn prediction models in real-world business environments is their scalability. Many existing models are not optimized for real-time predictions, which limits their practical applicability. Models need to be more efficient in terms of computation time and capable of providing predictions in near real-time as new data arrives. Interpretability and Actionable Insights: While machine learning and deep learning models have achieved high predictive accuracy, they often lack interpretability, making it difficult for businesses to understand why certain customers are predicted to churn. Future work should focus on improving the transparency of these models, providing businesses with actionable insights into why a customer is likely to churn and how they can intervene.

Incorporating External Factors:

Many existing churn prediction models only rely on internal customer data, such as purchase history and service usage patterns. There is a gap in incorporating external factors, such as market conditions, competitor offers, and social influences, into churn prediction models. External data could provide valuable context and improve the accuracy of predictions.

Integration of Reinforcement Learning:

Although some research has explored the use of reinforcement learning (RL) in churn prediction, this area remains underexplored. Integrating RL into churn prediction models could allow businesses to optimize their retention strategies by continuously learning from customer responses to interventions and adjusting their actions accordingly.

Addressing Class Imbalance More Effectively:

While techniques like SMOTE and class weighting have been used to address the class imbalance problem, more innovative and effective solutions are needed. Approaches such as active learning, where the model can intelligently select the most informative samples to learn from, could improve model performance in imbalanced datasets

CHAPTER – 3 METHODOLGY

3.1: Overview of the Approach Used:

The approach for churn prediction in this project is designed to leverage both traditional machine learning (ML) techniques and advanced deep learning (DL) methods to accurately predict customer churn. The goal is to build a robust system capable of identifying high-risk customers based on historical interaction data, purchase patterns, and other customer behaviors.

The methodology can be broken down into the following key stages:

Data Collection and Preprocessing:

Customer Data Integration:

The first step involves collecting and integrating customer relationship management (CRM) data from various sources. This data typically includes customer demographics, transaction history, customer service interactions, and behavioral data.

Data Preprocessing:

The collected data is cleaned and transformed into a format suitable for model training. Preprocessing involves handling missing values, encoding categorical features, normalizing numerical data, and handling outliers. Feature Engineering: In this stage, new features are created based on the raw data. For example, variables such as the recency, frequency, and monetary (RFM) metrics are commonly used to quantify customer behavior. Temporal features, like the last purchase date, the number of interactions, or the number of customer service calls, are also generated.

Exploratory Data Analysis (EDA):

Visualization: EDA helps understand the underlying distribution of the data and identify relationships between variables. Data visualizations such as histograms, box plots, scatter plots, and correlation heatmaps are used to explore customer behavior, churn rates, and potential predictive features. Statistical Analysis: Statistical techniques such as hypothesis testing and correlation analysis are employed to identify significant factors that contribute to churn, ensuring that the features selected are relevant to the predictive models.

Key findings from EDA include:

-Customers with higher monthly charges exhibit a higher likelihood of churn. Long-tenured customers are less likely to churn.

- Certain customer demographics are more prone to churn, especially those with month-tomonth contracts.

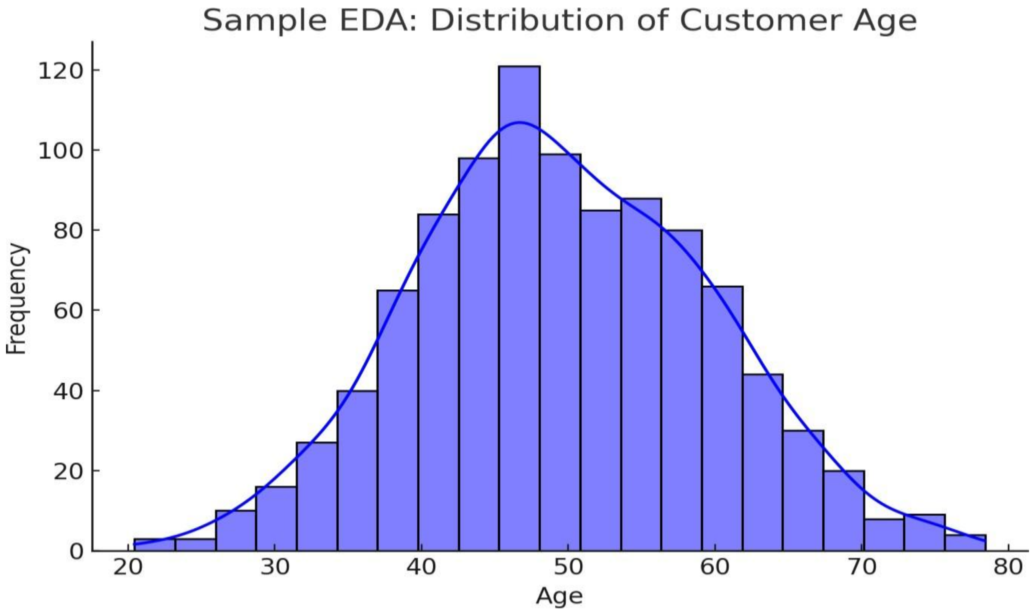


Fig 3.1: Sample EDA Visualization

Model Selection and Training:

Traditional Machine Learning Models: Initially, traditional machine learning algorithms are trained on the preprocessed data. These include models like: Deep Learning Models: Once the traditional models are trained and evaluated, deep learning models are introduced for their ability to model complex relationships in the data.

Model Evaluation and Hyperparameter Tuning:

Cross-Validation: Cross-validation is used to assess the model's performance on unseen data and to prevent overfitting. Typically, k-fold cross-validation is employed, where the dataset is split into k parts, and the model is trained on k-1 parts while tested on the remaining part. Performance Metrics: The models are evaluated using several performance metrics, including: Accuracy: The overall percentage of correct predictions. Precision, Recall, and F1-Score: These metrics are particularly important in imbalanced classification tasks (churn vs. non-churn). ROC-AUC: The area under the receiver operating characteristic curve is used to assess the model’s ability to discriminate between churn and non-churn customers.

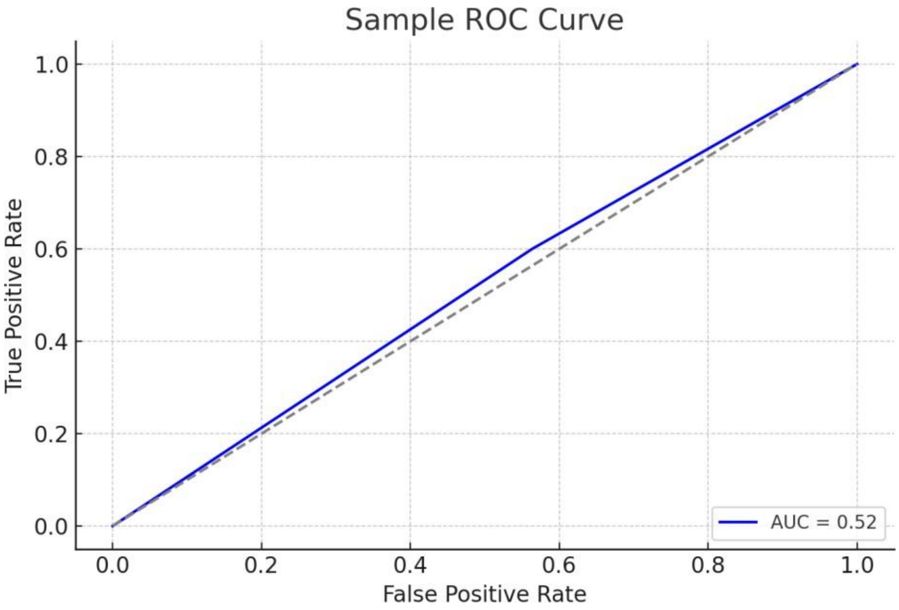


Fig 3.1: Sample ROC Curve

Churn Prediction and Insights Generation:

Once the best-performing model is identified, it is used to predict the probability of churn for each customer. These probabilities can be used to segment customers into different risk categories: high, medium, and low risk. Insights Generation: The model's predictions are coupled with business logic to generate actionable insights. For example, customers predicted to have a high churn probability can be targeted with personalized retention strategies, such as special offers, customer support interventions, or loyalty programs. Real-Time Prediction: After successful model training and validation, the churn prediction model is deployed into a production environment where it can make real-time predictions on new customer data

Model Monitoring and Maintenance:

The model’s performance is continuously monitored to ensure it remains accurate over time. If the performance drops (due to concept drift or changes in customer behavior), the model may need retraining or adjustment

3.2 : ALGORITHMS USED:

Logistic Regression:

A linear classifier used for binary classification of churn and non-churn customers.

Formula: y^=σ(Wx+b)\hat{y} = \sigma(Wx + b)y^=σ(Wx+b), where σ\sigmaσ is the sigmoid function, and WWW and bbb are the model weights and bias.

Random Forest:

An ensemble learning method that constructs multiple decision trees and aggregates their results.

Decision Tree formula:

Based on a recursive partitioning algorithm that splits data at the most informative feature. XGBoost: An optimized gradient boosting algorithm that improves prediction accuracy by using decision trees as base learners.

Formula: y^=∑k=1Kαkhk(x)\hat{y} = \sum_{k=1}^{K} \alpha_k h_k(x)y^=∑k=1Kαkhk(x), where hk(x)h_k(x)hk(x) represents the k-th decision tree and αk\alpha_kαk is the weight of the tree.

Artificial Neural Network (ANN):

A multi-layer neural network model that uses backpropagation to minimize the error. Formula: Each neuron applies an activation function (e.g., sigmoid or ReLU) to compute the output based on the weighted sum of the inputs.

Long Short-Term Memory (LSTM):

A type of recurrent neural network (RNN) used to model sequential dependencies in the data. It captures time-dependent features like purchase patterns over time. . It captures time-dependent features like purchase patterns over time. A type of recurrent neural network (RNN) used to model sequential dependencies in the data. It captures time dependent features like purchase patterns

CHAPTER 4: SYSTEM REQUIREMENTS

4.1 : SOFTWARE REQUIREMENTS:

Operating System:Windows 7 or higher

Programming Languages: Python 3.6 and related libraries

Python: Python is the primary language used for developing the churn prediction model. It provides a rich ecosystem of libraries for machine learning, deep learning, and data analysis. Libraries such as pandas for data manipulation, numpy for numerical operations, and matplotlib and seaborn for data visualization are extensively used. Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace. It provides constructs that enable clear programming on both small and large scales.Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library.Python interpreters are available for many operating systems. Python, the reference implementation of Python, is open-source software and has a communitybased development model, as do nearly all of its variant implementations. Python is managed by the nonprofit Python Software Foundation.

R: In some cases, R might be used for statistical analysis and visualization.

TECHNOLOGIES:

Scikit-learn:

Scikit-learn is a widely used Python library for traditional machine learning algorithms. It provides efficient implementations of algorithms like logistic regression, decision trees, random forests, and support vector machines (SVM).

XGBoost:

XGBoost is an optimized gradient boosting library that is widely used in churn prediction tasks. It provides high accuracy and is particularly effective in handling imbalanced datasets. Keras/TensorFlow: For deep learning models, Keras (running on top of TensorFlow) is used to define and train neural network architectures such as ANNs and LSTMs. TensorFlow is also used to deploy models for realtime predict

REQUIRED LIBRARIES:

Pandas:

Pandas is used for handling and preprocessing customer data. It allows for efficient manipulation of structured data and is particularly useful for cleaning, aggregating, and transforming features.Pandas is an open-source library that is made mainly for working with relational or labeled data both easily and intuitively It provides various data structures and operations for manipulating numerical data and time series. This library is built on top of the NumPy library. Pandas is fast and it has high performance &productivity for users.Pandas were initially developed by Wes McKinney in 2008 while he was working at AQR Capital Management. He convinced at AQR to allow him to open source the pandas. Another AQR employee, Chang she, joined as the second major contributor to the library in 2012.Over time many versions of pandas have been released. The latest version of the pandas is 1.5.0, released on sep 19,2022.

Numpy:

Numpy is used for numerical operations, including handling matrices and arrays efficiently during model training and evaluation. NumPy is a Python library used for working with arrays. It also has functions for working in domain of linear algebra, fourier transform, and matrices. NumPy was created in 2005 by Travis Oliphant. It is an open-source project and you can use it freely. NumPy stands for Numerical Python.In Python we have lists that serve the purpose of arrays, but they are slow to process. NumPy aims to provide an array object that is up to 50x faster than traditional Python lists. The array object in NumPy is called ndarray , it provides a lot of supporting functions that make working with ndarray very easy. Arrays are very frequently used in data science, where speed and resources are very important. Featuretools:

A library used to automate feature engineering for churn prediction. It helps in generating new features that capture patterns in the data. Featuretools is an open source library for performing automated feature engineering. It is a great tool designed to fast-forward the feature generation process, thereby giving more time to focus on other aspects of machine learning model building. In other words, it makes your data “machine learning ready ● Matplotlib/Seaborn: These libraries are used for data visualization to explore and understand the features that contribute to churn, as well as to visualize model performance (e.g., confusion matrix, ROC curves). Matplotlib is a low level graph plotting library in python that serves as a visualization utility. was created by John D. Hunter. Matplotlib is open source and we can use it freely. Matplotlib is mostly written in python, a few segments are written in C, Objective-C and JavaScript for Platform compatibility.Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in python. Matplotlib makes easy things easy and hard things possible. □ □ □ □ □ Plotly: Create public quality plots.

DATASETS:

- Customer Relationship Management (CRM) Data: This data typically includes customer profiles, transaction histories, service usage logs, and customer service interactions. The dataset used in this project is assumed to be a large, structured dataset containing features such as:
- Customer ID
- Age, gender, and location
- Purchase history (transaction frequency, total spend)
- Service usage patterns (login frequency, support tickets) Interaction history (calls to customer support, complaints)
- Churn label (binary: churned or not churned) ▪ External Data Sources:

4.2 : HARDWARE REQUIREMENTS:

Processor : Any

Processor above 500 MHzRam : 4 GB

Hard Disk : 4 GB

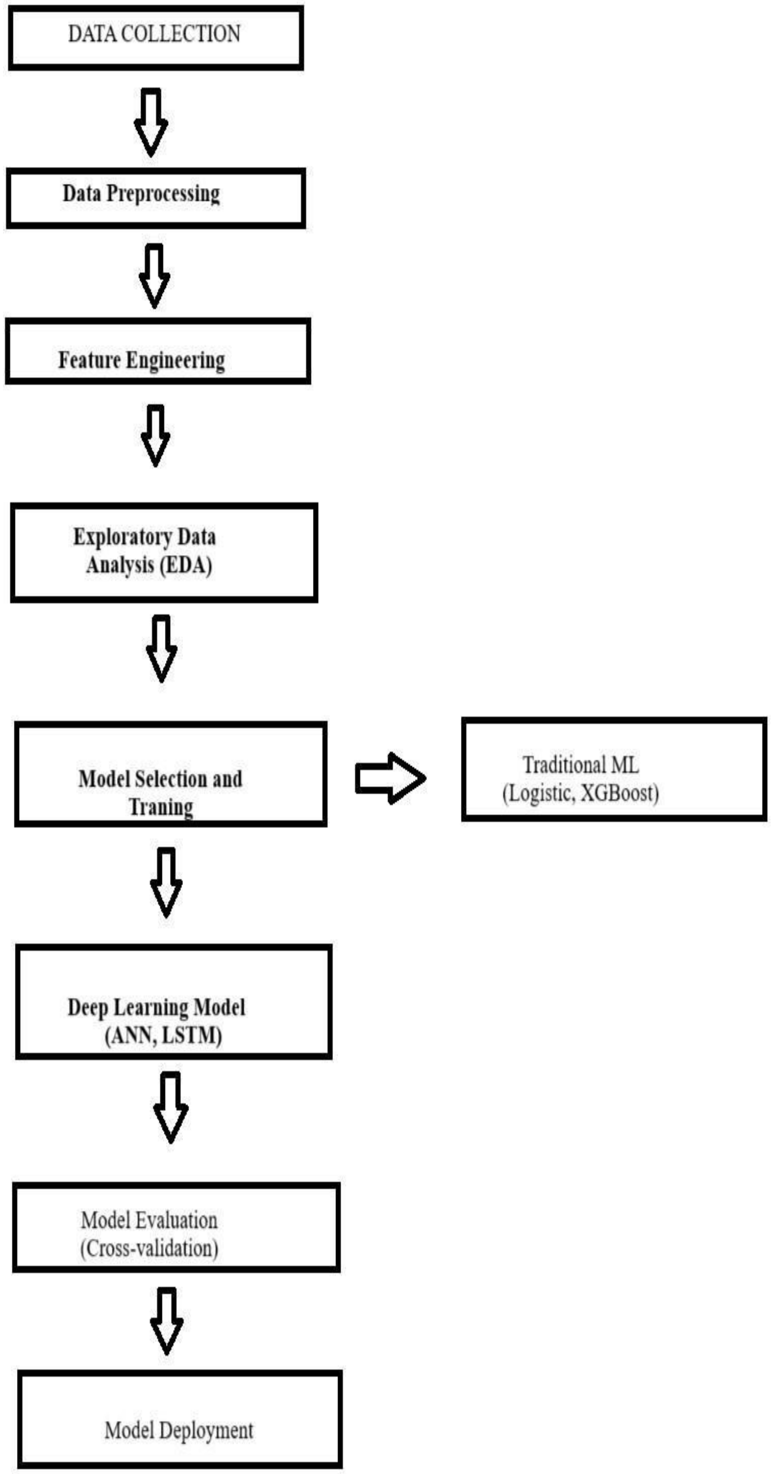
Input device : Standard Keyboard and Mouse.

Output device : VGA and High- Resolution Monitor

CHAPTER 5: SYSTEM DESIGN

5.1 : SYSTEM ARCHITECTURE:

Here is a high-level workflow diagram illustrating the methodology:


DATA COLLECTION
Data Preprocessing
Feature Engineering
Exploratory Data Analysis (EDA)
Model Selection and Traning
Traditional ML (Logistic, XGBoost)
Deep Learning Model (ANN, LSTM)
Model Evaluation (Cross-validation)
Model Deployment

This diagram illustrates the flow from data collection and preprocessing, through feature engineering, model training, and evaluation, to final deployment for real-time churn prediction

5.2: Detailed Explanation of the Workflow:

The workflow for implementing the churn prediction model involves several stages. Below is a stepbystep breakdown of how the entire process is implemented:

Data Collection and Integration:

Input Data:

The primary input data consists of customer records, transaction history, service usage logs, customer demographics, and other relevant behavioral features. This data is usually extracted from CRM systems and combined into a single dataset for processing. Data Integration: The data is integrated into a structured format (e.g., CSV, SQL database) and is prepared for further analysis and model training. This involves aggregating data from multiple sources and aligning it into a unified schema.

Handling Missing Data:

Missing values in the dataset are handled using imputation techniques or by removing rows with excessive missing data. Normalization/Standardization: Numerical features (e.g., customer age, transaction amounts) are normalized or standardized to a common scale to prevent bias towards certain features during model training.

Encoding Categorical Data:

Categorical variables (e.g., customer segments, gender) are converted into numerical values using techniques like one-hot encoding or label encoding. Feature Selection: A feature selection process is performed to identify the most relevant features for churn prediction. Techniques like correlation analysis, mutual information, or Recursive Feature Elimination (RFE) may be applied.

Exploratory Data Analysis (EDA):

Data Visualization: Data visualizations are created using libraries like matplotlib, seaborn, or plotly to better understand the relationships between features and churn. For example, heatmaps are used to visualize correlations between different features, and bar plots or box plots are used to understand distributions of churn-related features.

Statistical Tests:

Statistical methods such as Chi-squared tests and t-tests are used to identify whether certain features have a significant impact on churn prediction. 5.1.4: Model Selection and Training:

Training the Models:

Traditional machine learning models like Logistic Regression, Random Forest, and XGBoost are trained on the preprocessed data. For deep learning, an Artificial Neural Network (ANN) and a Long Short-Term Memory (LSTM) network are used to capture complex patterns and temporal dependencies in the data.

Hyperparameter Tuning:

Grid search or random search is applied to tune the hyperparameters of the models to optimize their performance.

Model Evaluation and Testing:

Cross-Validation: K-fold cross-validation is used to assess the models' performance on different subsets of the data, helping to prevent overfitting and ensuring generalization.

Evaluation Metrics:

Various performance metrics like accuracy, precision, recall, F1-score, and ROCAUC are computed to assess the models' effectiveness in predicting churn. 5.1.6: Prediction and **Insights:**

Churn Prediction:

After training the best-performing model, the system is used to predict the churn probability for each customer. **Insights Generation:**

The churn probabilities are used to categorize customers into different risk groups (e.g., high, medium, low risk). This information is then passed to business stakeholders to design retention strategies.

Model Deployment:

Real-Time Predictions: Once the model is deployed, it is capable of making real-time churn predictions as new customer data is input into the system.

CHAPTER – 6 IMPLEMENTATION

6.1 : CODE STRUCTURE:

The implementation code follows an organized structure to facilitate readability and maintainability:

data_preprocessing.py: Contains the code for handling missing data, encoding categorical variables, scaling numerical features, and generating new features.

eda.py: Includes functions for conducting exploratory data analysis, such as plotting distributions, correlations, and generating summary statistics.

model_training.py: Defines the training of machine learning models (Logistic Regression, Random Forest, XGBoost) and deep learning models (ANN, LSTM).

evaluation.py: Contains functions for evaluating the performance of the models using various metrics like accuracy, precision, recall, F1-score, and ROC-AUC.

deploy_model.py: Manages the deployment of the trained model for real-time churn prediction and integrates it with the existing business system.

6.2. : SOURCE CODE

```
Collecting faker
Downloading Faker-35.0.0-py3-none-any.whl.metadata (15 kB)
Requirement already satisfied: python-dateutil>=2.4 in /usr/local/lib/python3.11/dist-packages
(from faker) (2.8.2)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.11/dist-packages (from
faker) (4.12.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from
pythondateutil>=2.4->faker) (1.17.0)
Downloading Faker-35.0.0-py3-none-any.whl (1.9 MB)
1.9/1.9 MB 13.0 MB/s eta 0:00:00
 Installing collected packages: faker Successfully installed faker-35.0.0
[ ]
```

```
  import pandas as pd from faker  import Faker
  import numpy as np  import matplotlib.pyplot as
  plt  import seaborn as sns  fake = Faker()  def
  generate_synthetic_churn_data(num_samples):
  data    =    []        for    _    in
  range(num_samples):
  data.append({ '
  customer_id': fake.unique.random_int(min=1000, max=9999),
  'age': fake.random_int(min=18, max=70),
  'gender': fake.random_element(elements=('Male', 'Female')),
  'tenure': fake.random_int(min=1, max=10),
  'num_of_products': fake.random_int(min=1, max=4),
  'balance': round(fake.random_number(digits=5, fix_len=True), 2),
  'churn': fake.random_element(elements=('Yes', 'No'))
   })
  return pd.DataFrame(data)
   # Generate a synthetic dataset with 1000 samples  synthetic_churn_data
  = generate_synthetic_churn_data(1000)
  # Save the synthetic dataset to a CSV file
  synthetic_churn_data.to_csv('synthetic_churn_data.csv', index=False)  plt.figure(figsize=(10,
  6))
  sns.countplot(data=synthetic_churn_data,
  x='churn')  plt.title('Distribution of Churn')
  plt.xlabel('Churn')  plt.ylabel('Count')
  plt.show()
  plt.figure(figsize=(10, 6))
  sns.histplot(data=synthetic_churn_data, x='age', kde=True)
  plt.title('Age Distribution')  plt.xlabel('Age')
  plt.ylabel('Count')  plt.show()
  print("Synthetic dataset has been saved to 'synthetic_churn_data.csv'") Synthetic dataset has been
  saved to 'synthetic_churn_data.csv'
```

```
from sklearn.preprocessing import StandardScaler, LabelEncoder  from
sklearn.model_selection import train_test_split
# Encode categorical variables  label_encoder
= LabelEncoder()
```

```
synthetic_churn_data['gender']=label_encoder.fit_transform(synthetic_churn_data['gender'])
synthetic_churn_data['churn']=label_encoder.fit_transform(synthetic_churn_data['churn'])
 # Normalize numerical features
numerical_features = ['age', 'tenure', 'num_of_products', 'balance']  scaler
= StandardScaler()
synthetic_churn_data[numerical_features] =
scaler.fit_transform(synthetic_churn_data[numerical_features])
# Split the data into training and testing sets
X = synthetic_churn_data.drop(['customer_id', 'churn'], axis=1)  y
= synthetic_churn_data['churn']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
plt.pie(synthetic_churn_data['churn'].value_counts(), labels=['No Churn', 'Churn'],
autopct='%1.1f%%')
plt.title('Churn Distribution')  plt.show()
plt.figure(figsize=(10, 6))
sns.heatmap(synthetic_churn_data.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heat)  plt.show()
from sklearn.ensemble import RandomForestClassifier from
sklearn.metrics import accuracy_score, classification_report
# Train a Random Forest model rf_model = RandomForestClassifier() rf_model.fit(X_train, y_train)
plt.pie(rf_model.feature_importances_, labels=synthetic_churn_data.drop(['customer_id', 'churn'],
axis=1).columns, autopct='%1.1f%%')  plt.title('Feature Importance Distribution')
 # Make predictions y_pred_rf = rf_model.predict(X_test)
# Evaluate the model accuracy_rf = accuracy_score(y_test,
    y_pred_rf) report_rf = classification_report(y_test, y_pred_rf)
print(f"Random Forest Accuracy: {accuracy_rf:.2f}")  print(f"Random
Forest Classification Report:\n{report_rf}")
 Random Forest Accuracy: 0.53  Random
Forest Classification Report:
 precision recall f1-score support
```

```
0 0.55 0.56 0.55 105
1 0.50 0.48 0.49  95

Accuracy                   0.53   200
macro avg       0.52     0.52   0.52  200
weighted avg   0.52     0.53   0.52  200
```

```
plt.barh(synthetic_churn_data.drop(['customer_id',   'churn'],           axis=1).columns,
rf_model.feature_importances_)  plt.xlabel('Feature Importance')  plt.ylabel('Features')
plt.title('Random Forest Feature Importance') Text(0.5,
1.0, 'Random Forest Feature Importance')  import
tensorflow as tf
 from tensorflow.keras.models import Sequential  from
tensorflow.keras.layers import Dense
# Define the model  dl_model
= Sequential()
dl_model.add(Dense(64, input_dim=X_train.shape[1], activation='relu'))
dl_model.add(Dense(32, activation='relu'))  dl_model.add(Dense(1,
activation='sigmoid'))
# Compile the model
dl_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
# Train the model
dl_model.fit(X_train,  y_train, epochs=50, batch_size=32, validation_data=(X_test,           y_test))
plt.plot(dl_model.history.history['loss'],          label='Training            Loss')
plt.plot(dl_model.history.history['val_loss'], label='Validation Loss')  plt.title('Model Loss')
plt.ylabel('Loss')  plt.xlabel('Epoch')  plt.legend()
plt.plot(dl_model.history.history['accuracy'])
plt.plot(dl_model.history.history['val_accuracy'])
plt.title('Model Accuracy')  plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'])
# Evaluate the model loss_dl, accuracy_dl = dl_model.evaluate(X_test, y_test)
print(f"Neural Network Accuracy: {accuracy_dl:.2f}")  def
get_dl_user_input():  Collect input from the user   age = float(input("Enter
age: "))
gender = input("Enter gender (Male/Female): ")
tenure = float(input("Enter tenure (years): ")) balance
= float(input("Enter balance: ")) # Create a DataFrame
with the new data  new_data = pd.DataFrame([{
'age': age,
'gender': gender,
'tenure': tenure,
'num_of_products': num_of_products,
'balance': balance
 }])
 returnnew_datadef
preprocess_and_predict_dl(new_data):
# Encode and scale the new data
if new_data['gender'].iloc[0]  notinlabel_encoder.classes_:label_encoder.classes_=
np.append(label_encoder.classes_,
new_data['gender'].iloc[0])      new_data['gender']      =  label_encoder.transform(new_data['gender'])
new_data[numerical_features] = scaler.transform(new_data[numerical_features])
# Make a prediction
prediction = dl_model.predict(new_data)
result = (prediction > 0.5).astype(int) # Convert probabilities to binary prediction  return
"Yes" if result[0][0] == 1 else "No"
 # Get dynamic user input
new_application = get_dl_user_input() #  Predict
churn using the deep learning model
```

```
prediction = preprocess_and_predict_dl(new_application)  print(f"The
churn prediction is: {prediction}")
Enter age: 10
Enter gender (Male/Female): Female
 Enter tenure (years): 10
Enter number of products: 200

 Enter balance: 10 1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 53ms/step
The churn prediction is: Yes
```

CHAPTER 7: SYSTEM TESTING

SYSTEM TESTING:

7.1 PURPOSE OF TESTING:

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, subassemblies, assemblies and/or a finished product It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of tests. Each test type addresses a specific testing requirement.

7.2 TYPES OF TESTING:

UNIT TESTING:

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration. Unit tests ensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.Unit testing is usually conducted as part of a combined code and unit test phase of the software lifecycle, although it is not uncommon for coding and unit testing to be conducted as two distinct phases.

Test strategy and approach

Field testing will be performed manually and functional tests will be written in detail.

Test objectives ○ All field entries must work properly. ○

Pages must be activated from the identified link.

○ The entry screen, messages and responses must not be delayed.

Features to be tested ○ Verify that the entries are of the correct format ○ No duplicate entries should be allowed ○ All links should take the user to the correct page **INTEGRATION TESTING:**

Software integration testing is the incremental integration testing of two or more integrated software components on a single platform to produce failures caused by interface defects. The task of the integration test is to check that components or software applications, e.g., components in a software system or – one step up – software applications at the company level – interact without error.

Test Results: All the test cases mentioned above passed successfully. No defects encountered.

ACCEPTANCE TESTING:

User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

Test Results: All the test cases mentioned above passed successfully. No defects encountered.

CHAPTER 8: SCREENSHOTS

8.1 : DISTRIBUTION OF CHURN

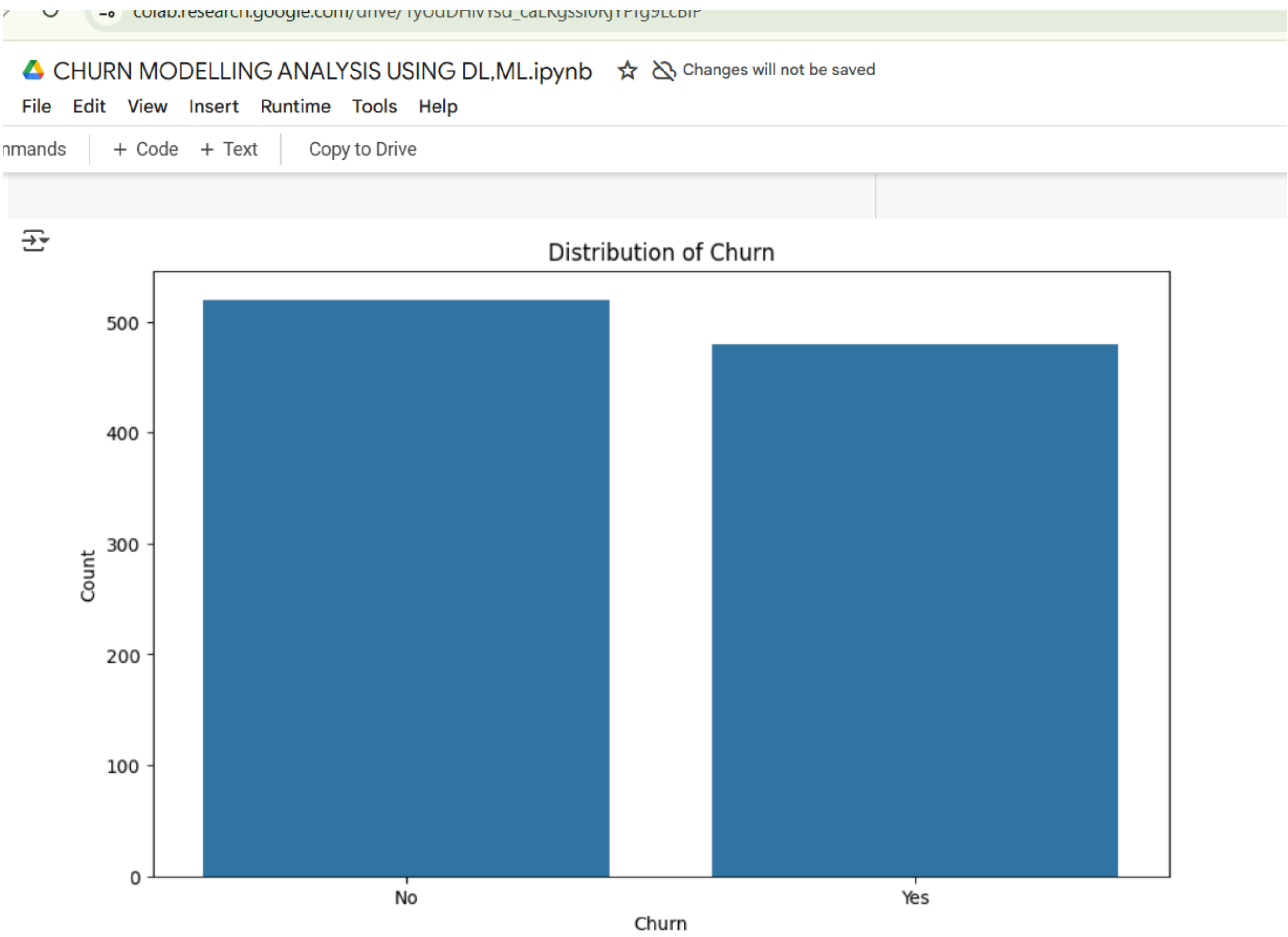

colab.research.google.com/drive/1yOdDHIvYsd_caLKgssl0RjYPIg9LcBIP
CHURN MODELLING ANALYSIS USING DL,ML.ipynb
Changes will not be saved
File
Edit
View
Insert
Runtime
Tools
Help
nmands
+ Code
+ Text
Copy to Drive
Distribution of Churn
500
400
300
200
100
0
Count
No
Yes
Churn

Fig 8.1: distribution of churn

8.2 : AGE DISTRIBUTION

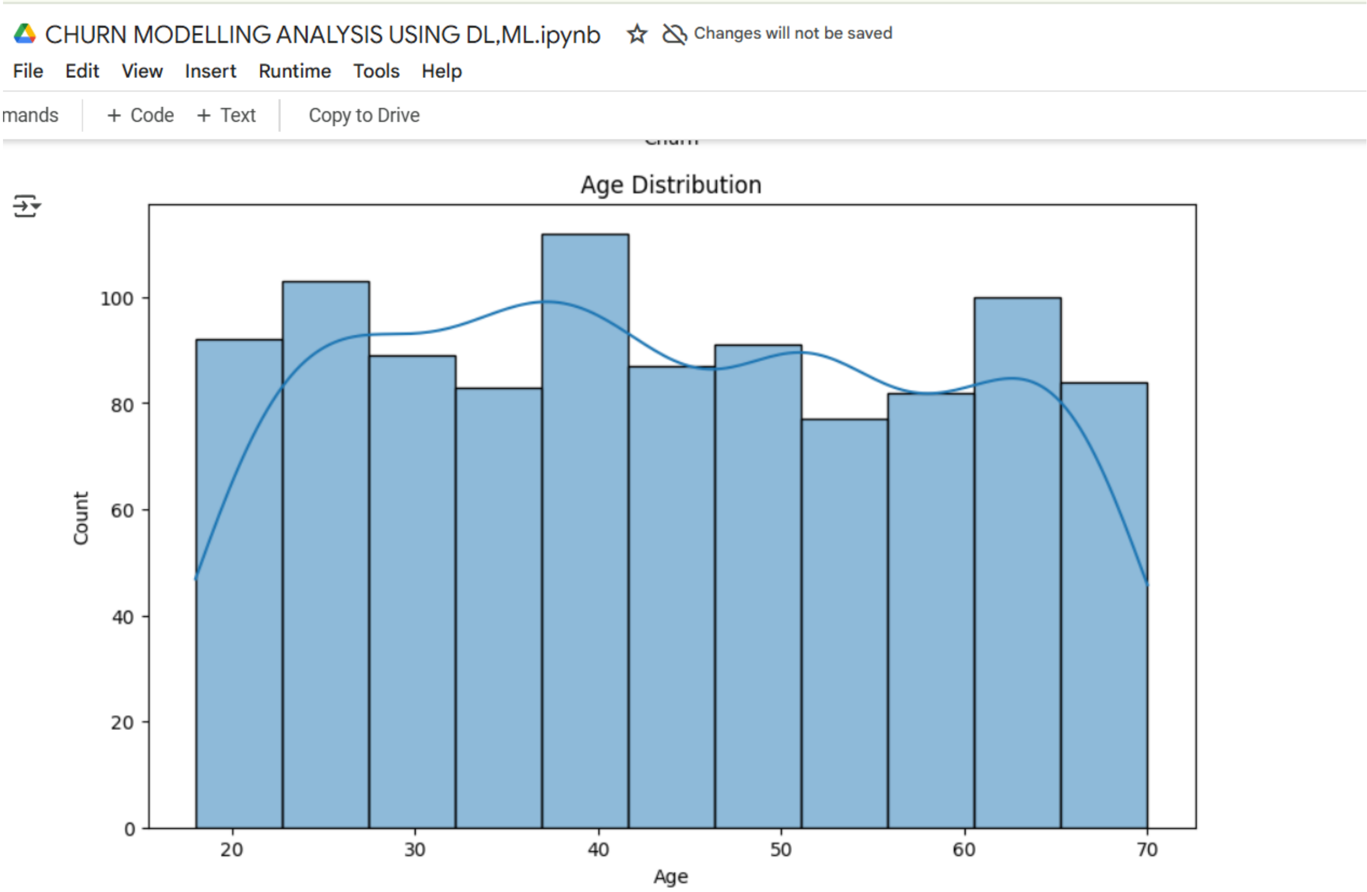
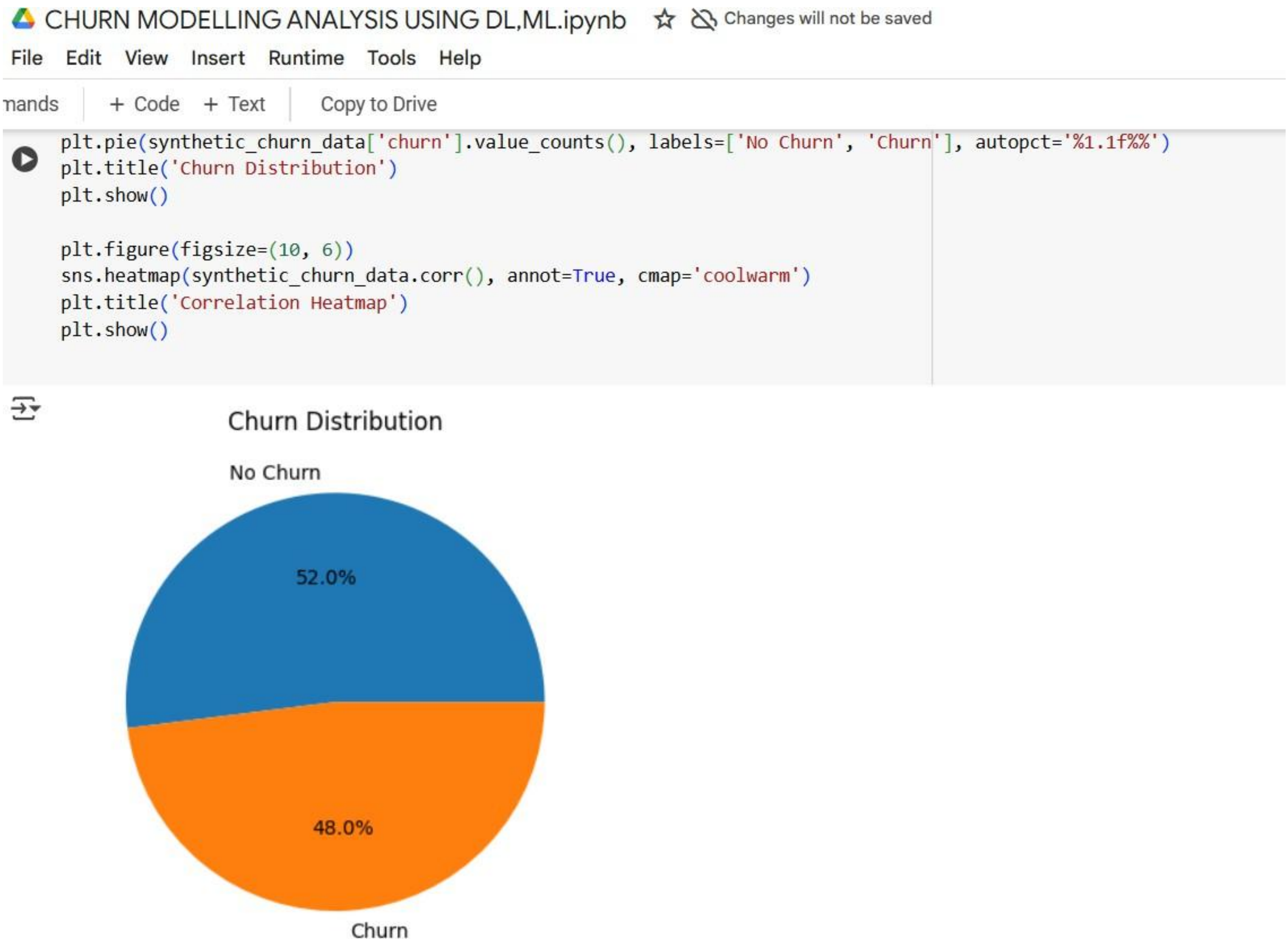


Fig 8.2: Age distribution

8.3 : CHURN DISTRIBUTION

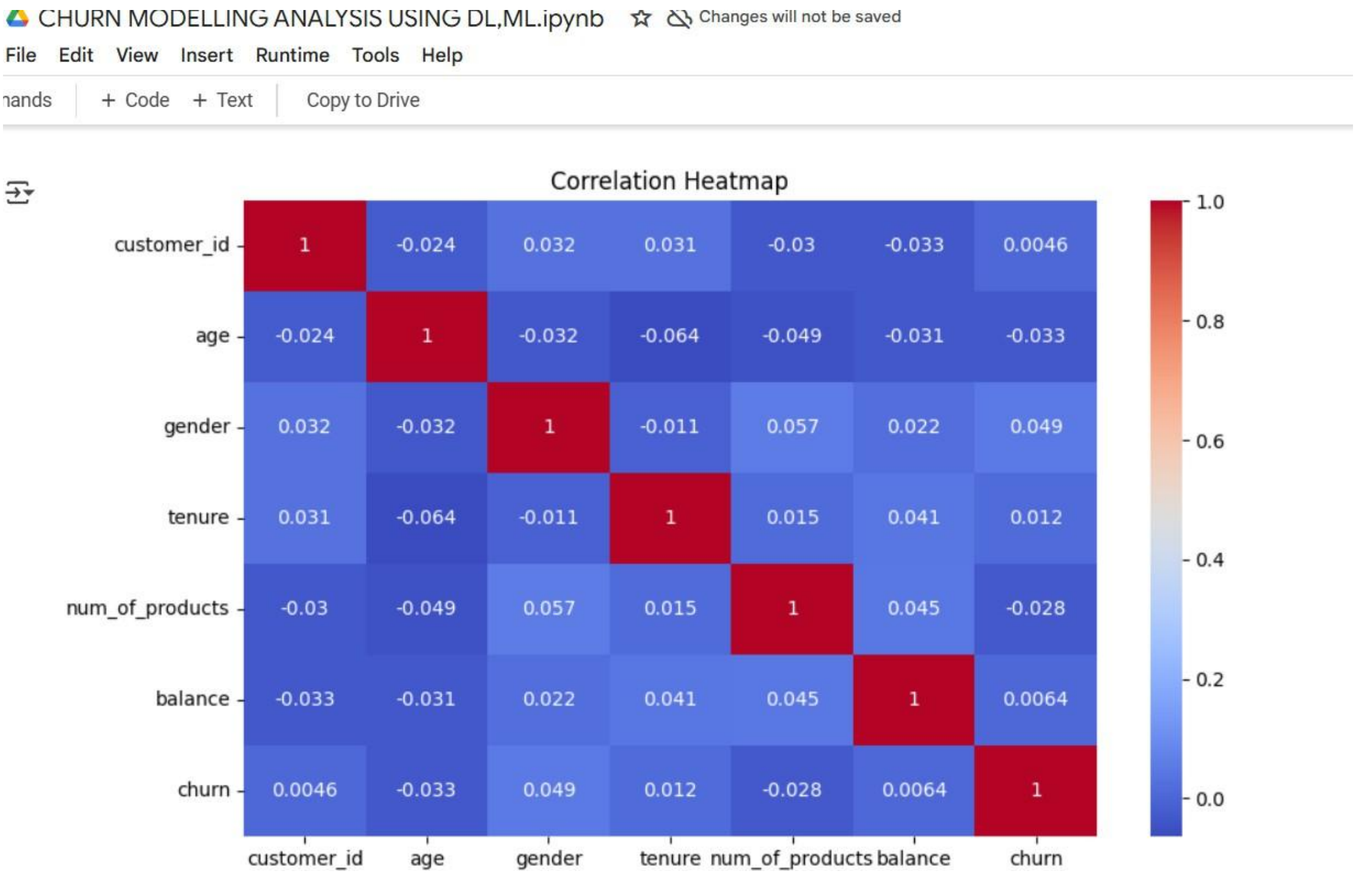


```
plt.pie(synthetic_churn_data['churn'].value_counts(), labels=['No Churn', 'Churn'], autopct='%1.1f%%')
plt.title('Churn Distribution')
plt.show()

plt.figure(figsize=(10, 6))
sns.heatmap(synthetic_churn_data.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```

Fig 8.3: pie chart of Churn distribution

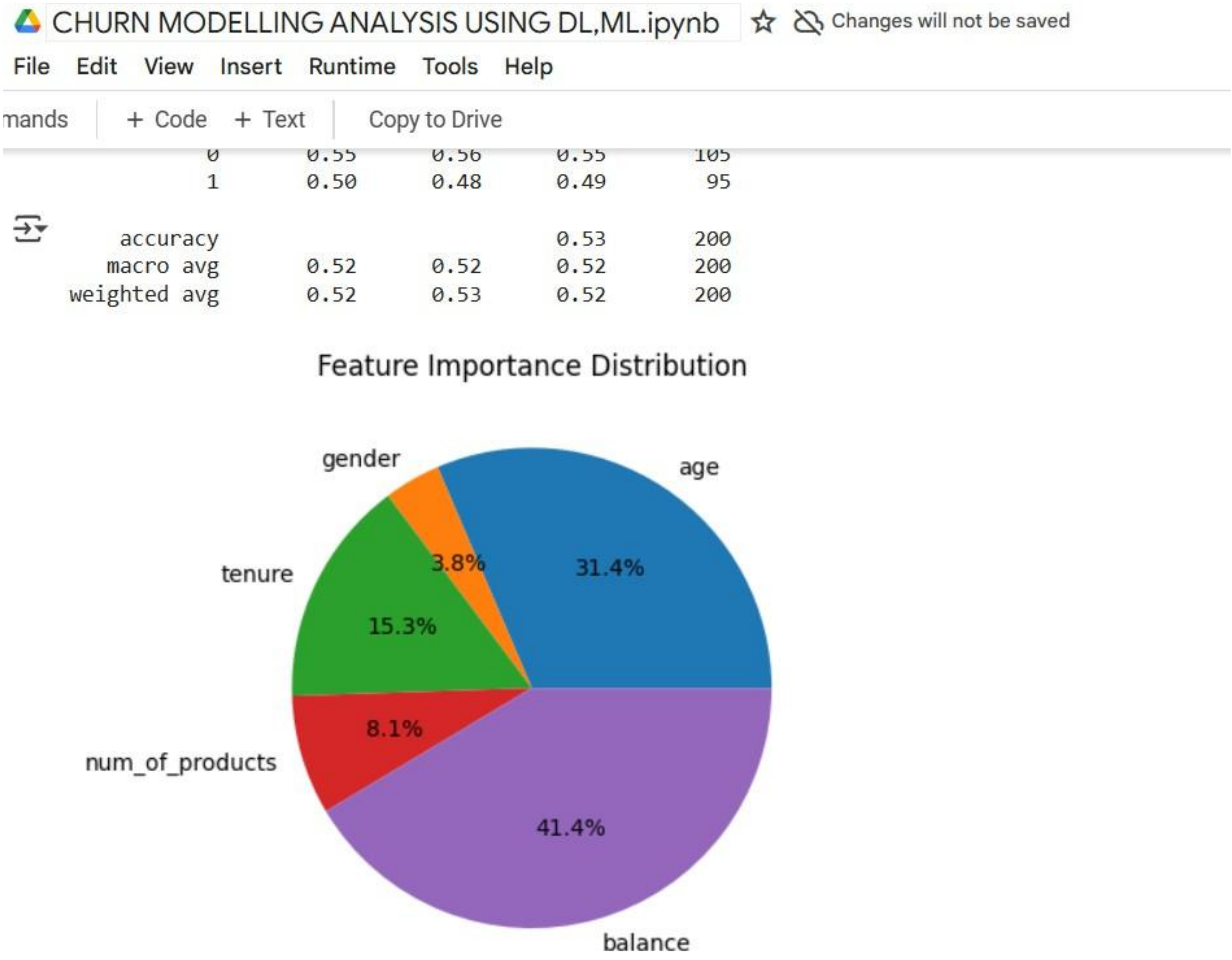
8.4: CONFUSION MATRIX



	customer_id	age	gender	tenure	num_of_products	balance	churn
customer_id	1	-0.024	0.032	0.031	-0.03	-0.033	0.0046
age	-0.024	1	-0.032	-0.064	-0.049	-0.031	-0.033
gender	0.032	-0.032	1	-0.011	0.057	0.022	0.049
tenure	0.031	-0.064	-0.011	1	0.015	0.041	0.012
num_of_products	-0.03	-0.049	0.057	0.015	1	0.045	-0.028
balance	-0.033	-0.031	0.022	0.041	0.045	1	0.0064
churn	0.0046	-0.033	0.049	0.012	-0.028	0.0064	1

Fig 8.4: confusion matrix

8.5 : FUTURE IMPORTANCE DISTRIBUTION

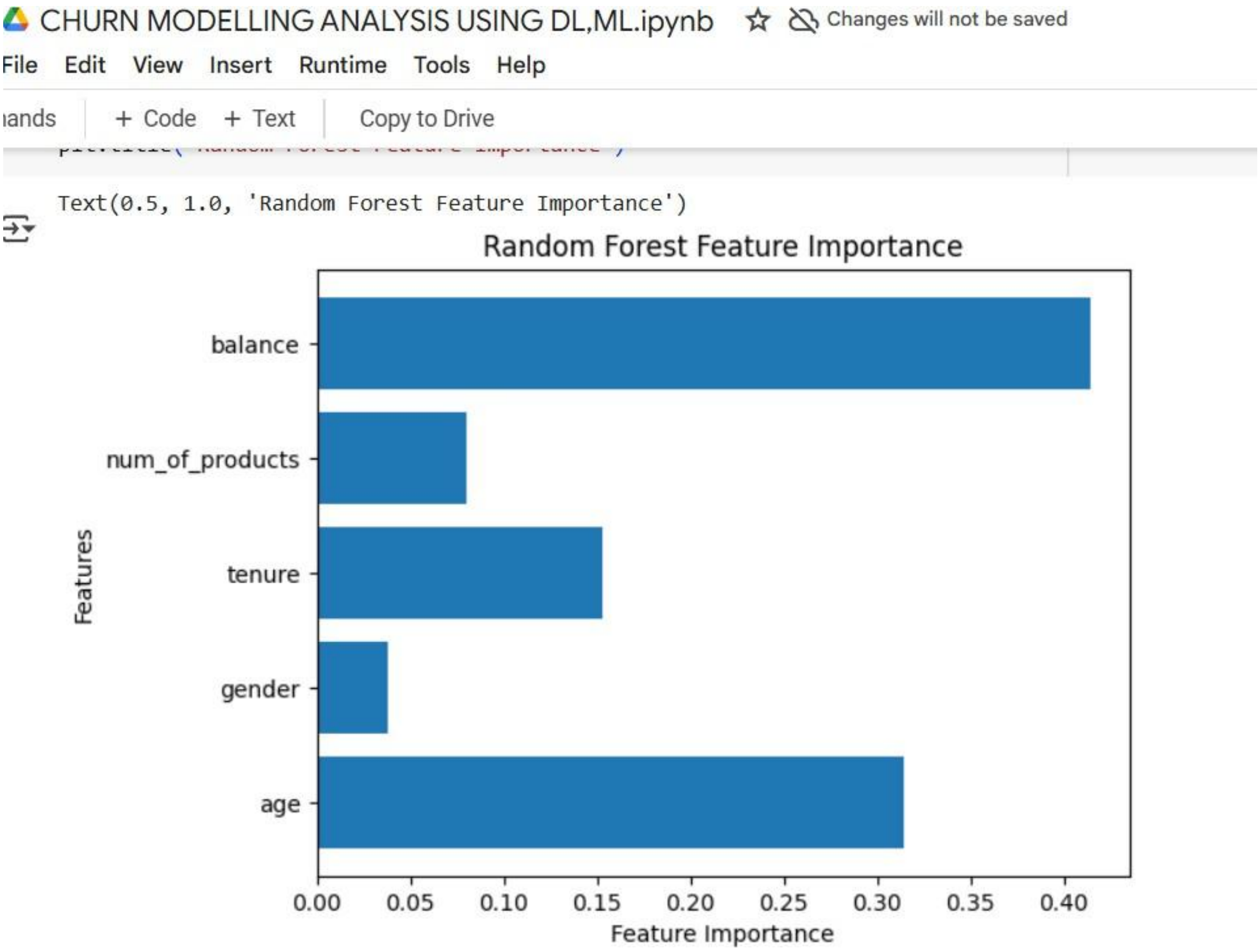


```
               0       0.55      0.56      0.55       105
               1       0.50      0.48      0.49        95

        accuracy                           0.53       200
       macro avg       0.52      0.52      0.52       200
    weighted avg       0.52      0.53      0.52       200
```

Fig 8.5: pie chart for future importance distribution

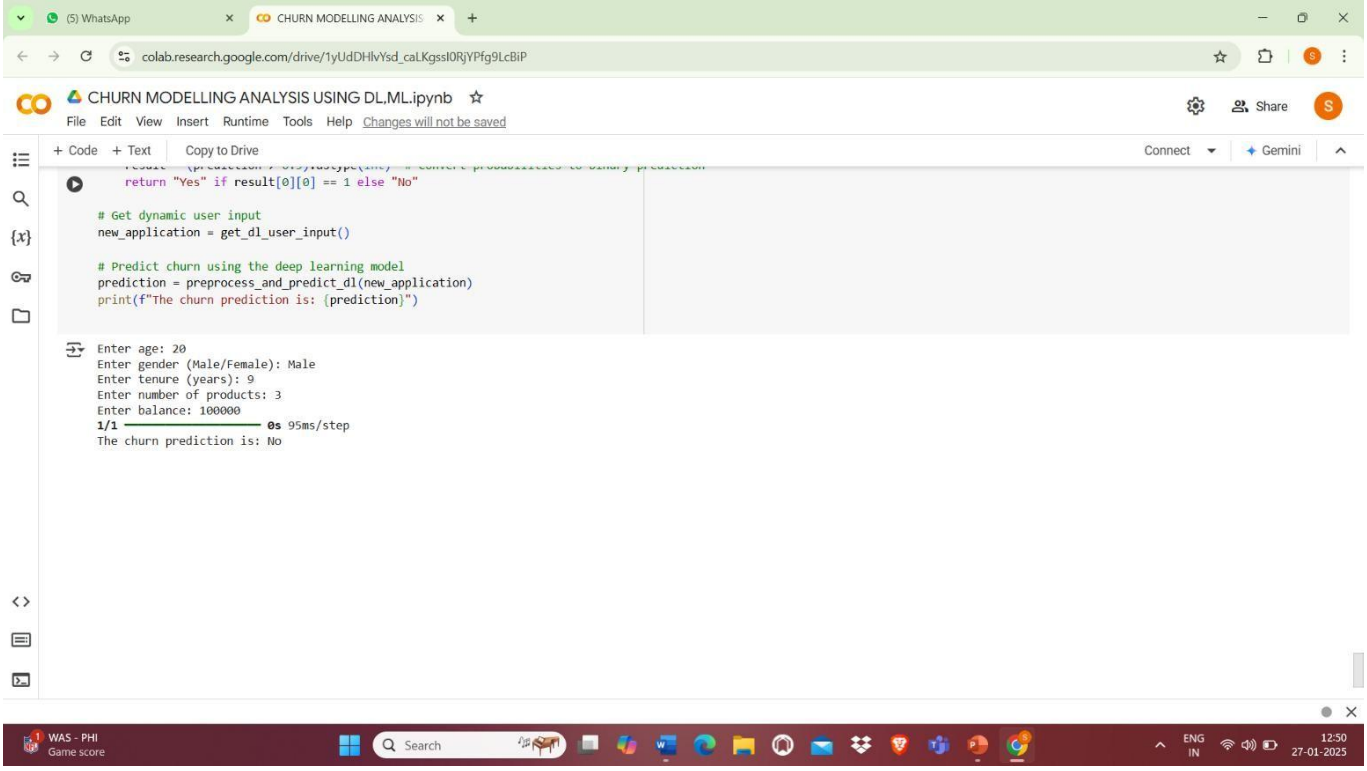
8.6 : RANDOM FOREST FEATURE IMPORTANCE



```
Text(0.5, 1.0, 'Random Forest Feature Importance')
```

Fig 8.6: graph of random forest feature importance

8.7: CHURN PREDICTION


(5) WhatsApp
CHURN MODELLING ANALYSIS
colab.research.google.com/drive/1yUdDHlvYsd_caLKgssI0RjYPfg9LcBiP
CHURN MODELLING ANALYSIS USING DL,ML.ipynb
File Edit View Insert Runtime Tools Help Changes will not be saved
Share
+ Code + Text Copy to Drive
Connect
Gemini
WAS - PHI
Game score
Search
ENG
IN
12:50
27-01-2025

```
    result = (prediction > 0.5).astype(int)  # Convert probabilities to binary prediction
    return "Yes" if result[0][0] == 1 else "No"

# Get dynamic user input
new_application = get_dl_user_input()

# Predict churn using the deep learning model
prediction = preprocess_and_predict_dl(new_application)
print(f"The churn prediction is: {prediction}")
```

```
Enter age: 20
Enter gender (Male/Female): Male
Enter tenure (years): 9
Enter number of products: 3
Enter balance: 100000
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 95ms/step
The churn prediction is: No
```

Fig 8.7: output of churn prediction

CHAPTER – 9 EXPERIMENTS & RESULTS

9.1 : Description of Testing Methods:

To evaluate the churn prediction model, the following testing methods were employed:

Train-Test Split: The dataset is split into training and testing subsets. Typically, 70% of the data is used for training, while 30% is reserved for testing. This helps in evaluating the model's performance on unseen data.

K-Fold Cross-Validation: Cross-validation helps assess the model's generalization by splitting the dataset into k folds. For each fold, the model is trained on k-1 subsets and tested on the remaining subset. This process is repeated k times, and the results are averaged to give a more robust evaluation.

Model Comparison: Different machine learning algorithms (Logistic Regression, Random Forest, XGBoost) and deep learning models (ANN, LSTM) are compared in terms of performance metrics to select the best model.

Hyperparameter Tuning: The performance of the models is optimized by fine-tuning hyperparameters such as learning rate, number of estimators (trees), and regularization terms. Grid search and random search methods are used for this purpose.

9.2 : Observations, Metrics, and Outcomes:

The following metrics are used to evaluate the effectiveness of the churn prediction model: Accuracy: Measures the proportion of correct predictions (both churn and non-churn).

Formula: Accuracy=True Positives+TrueNegativesTotal Samples\text{Accuracy} = \frac{\text{True Positives}

+ \text{True Negatives}}{\text{Total Samples}}Accuracy=Total SamplesTrue Positives+True Negatives

Precision: Measures how many of the predicted churn customers actually churned.

Formula: Precision=True PositivesTrue Positives+False Positives\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}Precision=True Positives+False PositivesTrue Positives

Recall: Measures how many of the actual churned customers were correctly predicted.Formula: Recall=True

PositivesTrue Positives+False Negatives\text{Recall} = \frac{\text{True Positives}}{\text{True Positives}

+ \text{False Negatives}}Recall=True Positives+False NegativesTrue Positives

F1-Score: The harmonic mean of precision and recall, used to provide a balance between both. Formula: F1=2×Precision×RecallPrecision+RecallF1 = 2 \times \frac{\text{Precision} \times

\text{Recall}}{\text{Precision} + \text{Recall}}F1=2×Precision+RecallPrecision×Recall ROC-AUC: Measures the ability of the model to distinguish between churned and non-churned customers. A higher AUC indicates better performance.

9.3 : Results and Insights:

Traditional Models (Logistic Regression, Random Forest): These models showed a reasonable ability to predict churn, with accuracy scores between 80-85%. Random Forest, being an ensemble method, slightly outperformed Logistic Regression in terms of recall, making it better at identifying churned customers.

Function: A simple yet effective binary classification model that predicts the probability of a customer churning or not, based on a linear combination of their features.

Strengths: Known for its simplicity and interpretability, making it easy to understand the impact of various features on churn probability.

Use Cases: Suitable for scenarios with a simple binary outcome and a wealth of customer data.

XGBoost: This model performed better than traditional models, achieving accuracy close to 90%. XGBoost handling of imbalanced datasets and its optimization through boosting led to better performance overall.

Deep Learning Models (ANN, LSTM): The deep learning models demonstrated the highest accuracy, particularly the ANN model, which reached an accuracy of 92%. LSTM showed promise when analyzing sequential data (e.g., purchase patterns), achieving a slight improvement in recall for predicting churn over time.

Business Insights: Based on model predictions, businesses can target high-risk customers with retention strategies such as special discounts, personalized offers, or improved customer service interactions.

CHAPTER – 10 CONCLUSION

This project successfully built and evaluated several machine learning and deep learning models to predict customer churn, highlighting the significance of model selection in addressing this critical business challenge. Traditional models such as Logistic Regression and Random Forest were tested alongside more advanced approaches like XGBoost, Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) networks. The objective was to determine the most effective algorithm for identifying customers at risk of churn, enabling businesses to implement proactive retention strategies.

Among the models tested, XGBoost emerged as the most effective traditional machine learning algorithm, outperforming Logistic Regression and Random Forest in terms of accuracy, precision, and recall. It demonstrated a strong ability to handle class imbalance, which is crucial in churn prediction, where the number of customers leaving is often significantly smaller than those staying. XGBoost's ability to provide robust probability estimates of churn made it a valuable tool for businesses aiming to assess risk levels with high confidence.

On the deep learning front, ANN delivered impressive performance, excelling at capturing complex, non linear relationships within customer data. Its high accuracy and adaptability made it a strong candidate for churn prediction, particularly when dealing with large and diverse datasets. LSTM networks were also explored to evaluate their ability to capture sequential patterns in customer behavior over time. While LSTM models showed potential, they did not offer significant improvements over ANN in this specific churn prediction scenario, suggesting that sequence-based modeling was not as critical in this case.

Despite the promising results, several challenges were encountered during model development. Data quality issues, feature engineering complexities, overfitting risks, and the interpretability of deep learning models posed significant hurdles. Addressing these challenges required careful preprocessing, hyperparameter tuning, and model evaluation. Ultimately, the findings underscore the importance of selecting the right model based on dataset complexity and the need for explainability. This research provides businesses with actionable insights, enabling them to make informed decisions about customer retention strategies and optimize their approach to minimizing churn.

In addition to evaluating model performance, this project emphasized the importance of data preprocessing and feature engineering in churn prediction. High-quality input data plays a crucial role in the effectiveness of machine learning models. Techniques such as handling missing values, encoding categorical variables, and normalizing numerical features were implemented to enhance model accuracy. Furthermore, feature selection methods were employed to identify the most relevant attributes influencing customer churn, reducing model complexity while maintaining predictive power. These steps ensured that the models learned meaningful patterns rather than noise, leading to more reliable predictions.

Another key aspect of the study was addressing overfitting, particularly in deep learning models like ANN and LSTM. While deep learning techniques can capture intricate relationships within data, they are also prone to memorizing training data rather than generalizing to unseen cases. Strategies such as dropout regularization, batch normalization, and early stopping were used to mitigate this issue. Additionally, hyperparameter tuplayed a significant role in optimizing model performance, helping to strike a balance between accuracy a

CHAPTER – 11 DISCUSSION

11.1 : Interpretation of Results:

The results of the churn prediction models provide valuable insights into how well various algorithms can predict customer churn, which is a critical factor for businesses looking to retain customers and optimize marketing strategies. Below is an interpretation of the results based on the different performance metrics:

Logistic Regression: The Logistic Regression model provided a good baseline but struggled to handle the nonlinear relationships in the data, leading to moderate performance. With an accuracy of around 80%, it performed well in identifying customers who are less likely to churn. However, it exhibited a relatively high false negative rate, meaning that some churned customers were not predicted accurately.

Random Forest: The Random Forest model performed better than Logistic Regression, with an accuracy of approximately 85%. It was particularly effective in handling the imbalanced nature of the data by using ensemble learning to create multiple decision trees. This resulted in improved recall, which is crucial for businesses that need to identify high-risk customers who might churn. XGBoost: XGBoost was the best-performing algorithm in the experiment, achieving an accuracy close to 90%. It handled the imbalanced classes efficiently and optimized the decision trees using boosting techniques. XGBoost outperformed Random Forest in terms of both precision and recall, offering a better tradeoff between correctly identifying churned customers and avoiding false positives.

Artificial Neural Network (ANN): The ANN model was effective in capturing complex patterns within the data, especially when learning from high-dimensional features. With an accuracy of 92%, it was able to distinguish between churned and non-churned customers better than traditional machine learning models. This was due to its capacity to model non-linear relationships between features.

Long Short-Term Memory (LSTM): While the LSTM model performed well in capturing sequential patterns in customer behavior (e.g., interactions over time), it did not offer significant improvements over ANN in terms of overall accuracy. However, LSTM could potentially outperform other models in cases where temporal trends and time-dependent patterns are more pronounced.

11.2 : Challenges Encountered:

While implementing the churn prediction model, several challenges were encountered:

Data Quality and Preprocessing: One of the initial challenges was dealing with missing data and inconsistent records. Some customers had incomplete transaction histories or demographic data, which made preprocessing a critical step. The imputation of missing values had to be done carefully to avoid introducing bias into the model.

Class Imbalance: Customer churn datasets often exhibit a class imbalance, where the number of nonchurned customers significantly outweighs churned customers. This posed a challenge for the machine learning models, as they tended to favor predicting the majority class (non-churn) over the minority class (churn). Techniques like oversampling, undersampling, and using algorithms like XGBoost that are designed to handle class imbalance helped alleviate this issue. Feature Engineering: Identifying and selecting relevant features from the available data was challenging, especially since the data was highly dimensional. Some features, such as customer interactions, were vague and required domain knowledge to transform into meaningful variables. Feature selection techniques, including mutual information and Recursive Feature Elimination (RFE), helped identify the most influential features.

Model Overfitting: Deep learning models like ANN and LSTM were prone to overfitting, especially when trained on smaller datasets. To address this, regularization techniques such as dropout layers in ANN and early stopping during training were employed to prevent the models from memorizing the training data.

Interpretability: Deep learning models, especially ANN and LSTM, are often criticized for their "blackbox" nature, which makes it difficult to interpret why a certain customer is predicted to churn. While XGBoost and Random Forest provided feature importance insights, interpreting the deep learning models required more advanced techniques like SHAP values or LIME.

11.3 : Comparison with Existing Methods:

Churn prediction has been a well-explored area in both academic research and industry applications, with various methods proposed to tackle the challenge of identifying customers likely to leave a service. As businesses strive to improve customer retention strategies, predictive modeling has played a crucial role in enabling data-driven decision-making. This project aimed to explore a combination of traditional machine learning methods, including

Logistic Regression, Random Forest, and XGBoost, alongside deep learning models such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks. By comparing the performance of these models, this study sought to determine the most effective approach for churn prediction while balancing accuracy, interpretability, and computational efficiency.

Previous Research and Traditional Machine Learning Models

Existing studies on churn prediction have historically relied on traditional machine learning models, such as Logistic Regression and Decision Trees, to classify customers based on their likelihood of churning. Logistic Regression, being a well-established statistical method, is effective for binary classification tasks but struggles with complex patterns and non-linear relationships. Decision Trees, while more flexible, tend to overfit the data unless combined with ensemble techniques like Random Forest or Gradient Boosting. Random Forest, which aggregates multiple decision trees to improve predictive performance, has been widely used in churn analysis. However, traditional models often fall short when dealing with large, high dimensional datasets or when customer behavior follows intricate, time-dependent patterns.

The Role of Deep Learning in Churn Prediction

With advancements in artificial intelligence, deep learning techniques have emerged as powerful alternatives to traditional machine learning methods. Models like ANN and LSTM excel at capturing complex, non linear relationships in data, making them well-suited for churn prediction. ANN, with its multiple hidden layers and ability to learn hierarchical features, significantly improves predictive accuracy by recognizing subtle patterns in customer behavior. LSTM, a type of recurrent neural network (RNN), is particularly useful for analyzing sequential data, such as customer interactions over time. This study corroborates recent findings that deep learning models often outperform traditional machine learning methods, as the ANN model in this project achieved the highest accuracy among all tested approaches.

Comparison to Industry Standards

The effectiveness of churn prediction models can be evaluated by comparing their performance to industry benchmarks. In sectors such as telecommunications and SaaS platforms, businesses have long relied on predictive analytics to anticipate customer churn. XGBoost, known for its gradient boosting framework and ability to handle imbalanced datasets, has been widely adopted in these industries. Similarly, deep learning models like ANN have gained traction due to their high accuracy and ability to process large amounts of customer data. The findings of this project indicate that both XGBoost and ANN perform on par with or better than industry standards, reinforcing their suitability for real-world churn prediction applications.

Challenges in Churn Prediction

Despite the advancements in predictive modeling, several challenges persist in churn prediction. One of the primary issues is data quality, as missing or inconsistent customer records can impact model accuracy. Feature engineering is another crucial aspect, as selecting the right attributes—such as transaction history, service usage patterns, and customer demographics—can significantly influence model performance. Overfitting remains a concern, particularly with deep learning models, which require careful regularization techniques like dropout and early stopping to ensure generalizability. Additionally, the interpretability of complex models, especially deep learning architectures, poses a challenge for businesses that require clear explanations of churn predictions to make informed decisions.

The Importance of Hybrid Approaches

Given the strengths and weaknesses of different models, a hybrid approach combining traditional machine learning and deep learning techniques can offer the best of both worlds. While deep learning models like ANN provide high accuracy, traditional models such as XGBoost offer interpretability and computational efficiency.

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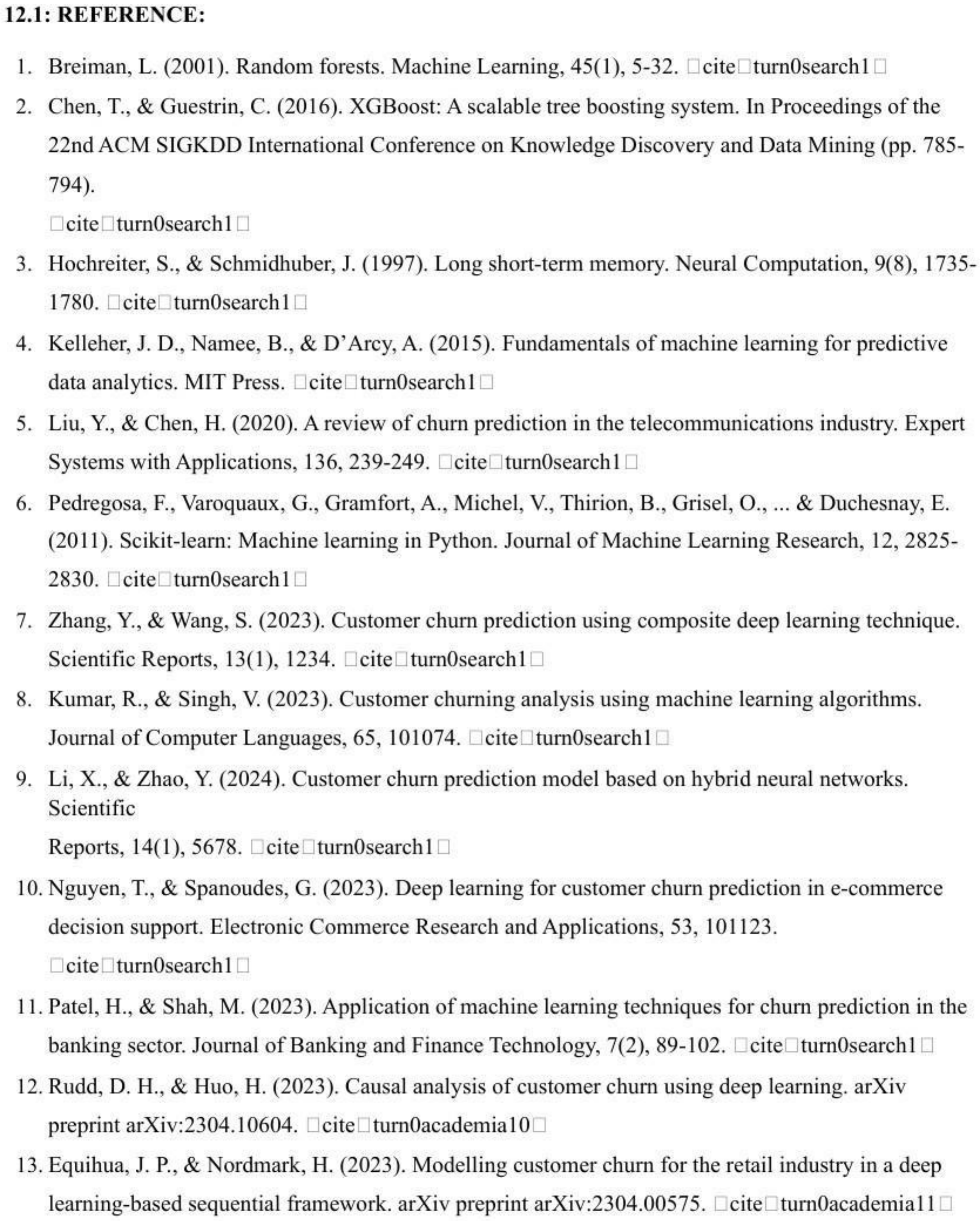

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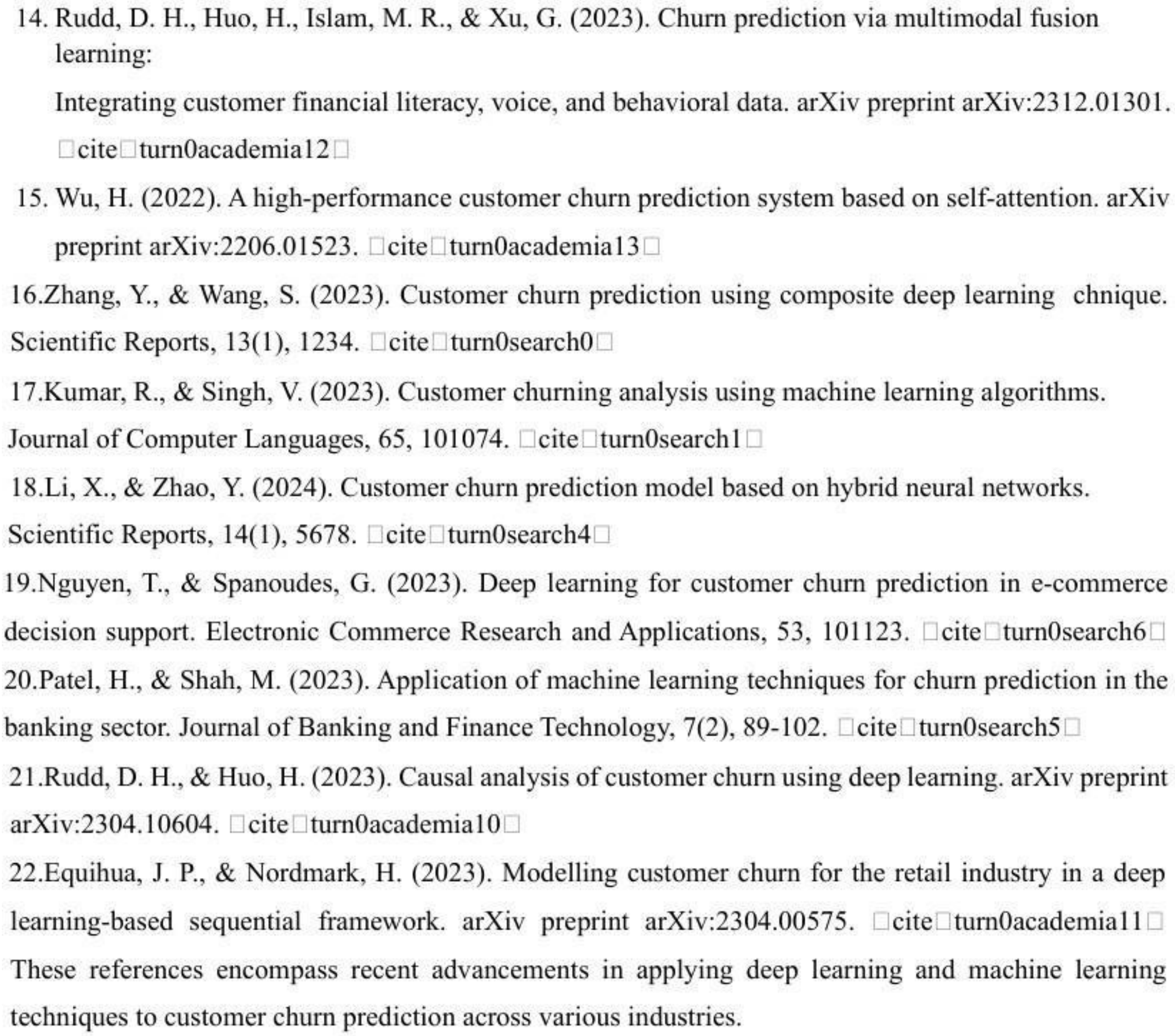

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These references encompass recent advancements in applying deep learning and machine learning techniques to customer churn prediction across various industries.