CSE 4120: Technical Writing and Seminar

Churn Prediction

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Author

Abstract

It is important for businesses, especially in the telecom industry, to predict customer churn, as keeping current customers is more cost-effective than acquiring new ones. This report studies and compares three research papers that focused on neural network-based models for customer churn prediction. The first paper looks at individual neural networks and ensemble methods like Bagging, AdaBoost, and Majority Voting, showing that ensemble techniques result in improved accuracy and robustness. The second paper explores a hybrid model that combines Artificial Neural Networks (ANN) with Self-Organizing Maps (SOM), demonstrating the hybrid model's superior performance in capturing complex customer behavior patterns. The third paper provides a comprehensive analysis of various machine learning techniques, including decision trees, random forests, SVM, and neural networks, emphasizing the importance of feature selection and data preprocessing. This comparative study reveals that neural networks, especially when used in ensemble configurations or hybrid models, offer significant improvements in churn prediction accuracy. The findings highlight the potential of advanced neural network-based approaches to enhance predictive performance and provide valuable insights for developing more effective customer retention strategies.

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CHAPTER I

Introduction

1.1 Introduction

Customer churn, the phenomenon where customers discontinue their subscription or stop using a service, is a significant issue for businesses, particularly in the telecom industry. With fierce competition and increasing options for customers, retaining existing clients has become crucial. Statistics indicate that acquiring a new customer can be five to seven times more expensive than retaining an existing one [1] . Thus, effectively predicting customer churn can result in substantial cost savings and increased profitability for companies.

Traditional methods for predicting customer churn have included statistical techniques and basic machine learning models. While these methods have provided some insights, they often fall short in capturing the complex and non-linear relationships present in customer behavior data [2]. As a result, these models typically offer limited accuracy and fail to generalize well to unseen data.

Neural networks have emerged as a powerful tool in this context due to their ability to model complex, non-linear relationships within data [1]. By mimicking the human brain's neural connections, these models can learn intricate patterns and dependencies [3]. However, even neural networks are not without their challenges [4]. Individual neural network models can suffer from overfitting, where the model learns the training data too well, including its noise and outliers, leading to poor performance on new, unseen data[5].

Ensemble methods are introduced combining multiple models to create a robust predictive system that benefits from the strengths of each component model while minimizing their weaknesses[1]. Techniques such as bagging, boosting, and majority voting are commonly used to aggregate the predictions of individual models, resulting in improved accuracy and stability. On the other hand, hybrid models integrate different neural network techniques or combine neural networks with other machine learning algorithms to enhance predictive performance further[2].

1.2 Problem Statement

In the highly competitive telecom industry, retaining existing customers is more cost-effective than acquiring new ones. Customer churn, defined as the loss of clients or subscribers, poses a significant challenge to telecom companies. The ability to accurately predict customer churn can enable businesses to proactively address the factors leading to customer dissatisfaction and take corrective measures to improve customer retention[6].

Traditional methods for churn prediction often fail to capture the complex, non-linear relationships inherent in customer behavior data[7]. This inadequacy necessitates the exploration of more sophisticated techniques that can provide higher accuracy and reliability. Neural networks, with their capability to model complex patterns, have emerged as a promising solution for churn prediction[4]. However, individual neural network models may still struggle with overfitting and generalization issues[1].

To solve these limitations, recent research has focused on enhancing neural network models through ensemble methods and hybrid approaches[1]. Ensemble methods combine multiple models to improve predictive performance by reducing variance and bias. Hybrid models integrate different neural network techniques to leverage their strengths and compensate for their weaknesses[2].

CHAPTER II

Literature Review

2.1 Literature Review

Traditional methods such as logistic regression, decision trees, and support vector machines (SVM) have been foundational [4]. Individual neural networks, despite their effectiveness, can suffer from overfitting. To address this, Ensemble methods like bagging and boosting, which combine multiple models to improve accuracy and robustness, have been employed [1]. These techniques have proven successful, and demonstrate that ensemble methods can significantly enhance neural network performance in churn prediction (Saghir et al.). Furthermore, hybrid models, such as those combining Artificial Neural Networks (ANN) with Self-Organizing Maps (SOM), offer additional improvements by leveraging the strengths of different neural network techniques[2]. Tsai and Lu. highlights the effectiveness of such hybrid approaches in achieving superior accuracy. Additionally, Agarwal. comparative analysis of various machine learning models, including neural networks, further reinforces the versatility and efficacy of neural network-based approaches when combined with proper feature selection and preprocessing[6]. Collectively, these studies illustrate the advancements in churn prediction methodologies, showcasing the potential of neural networks, ensemble methods, and hybrid models to provide more accurate and reliable predictions.

CHAPTER III

Methodology

3.1 Machine Learning Models

3.1.1 Data Collection

The dataset is obtained from a telecommunications provider, containing information about customer behavior and service usage.

3.1.2 Data Preprocessing

Data cleaning involves removing duplicates and handling missing values. Features are scaled, and categorical variables are encoded.

3.1.3 Model Building

Various machine learning models are developed, including Logistic Regression and Naive Bayes. Hyperparameter tuning is performed using grid search and cross-validation.

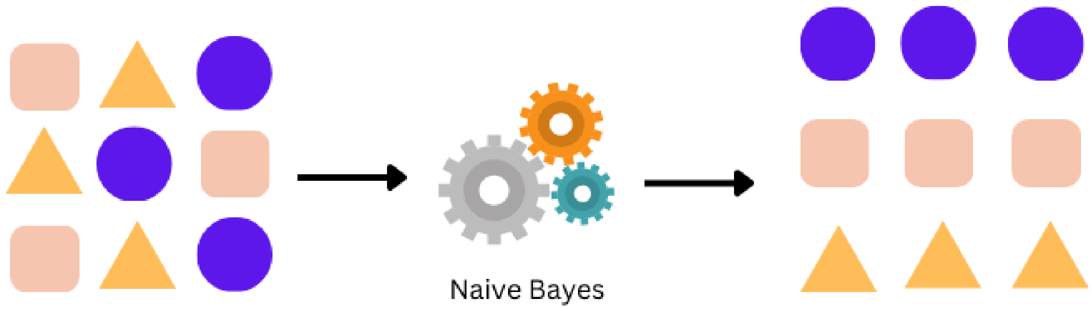

Figure 3.1: Naive Bayes

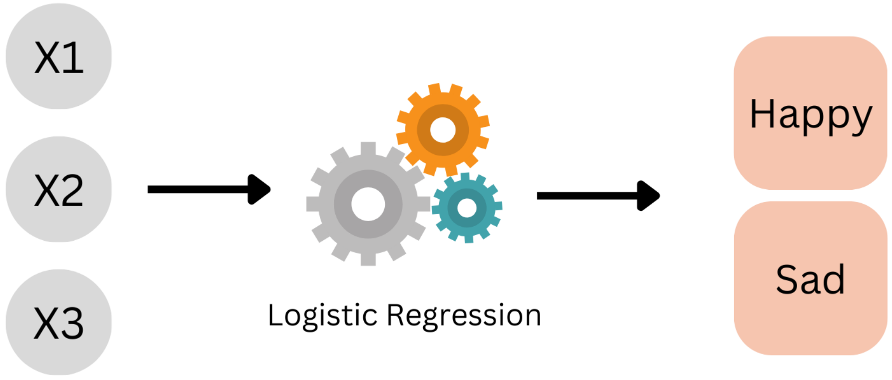

Figure 3.2: Logistic Regression

3.1.4 Model Evaluation

The models are assessed using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. Feature importance analysis is conducted to identify the most significant predictors of churn.

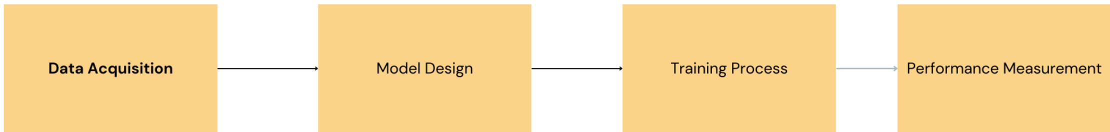

Figure 3.3: Methodology of [6]

3.2 Neural Network-based Individual and Ensemble Models

3.2.1 Data Collection and Preprocessing

The dataset used is collected from a telecommunication company, including customer information and service usage data. Preprocessing steps include handling missing values, normalization, and encoding categorical variables.

3.2.2 Model Development

Individual models: Various neural network architectures are explored, including Multi-Layer Perceptron (MLP). Ensemble models: Combining multiple neural networks to form ensemble models using techniques such as bagging and boosting.

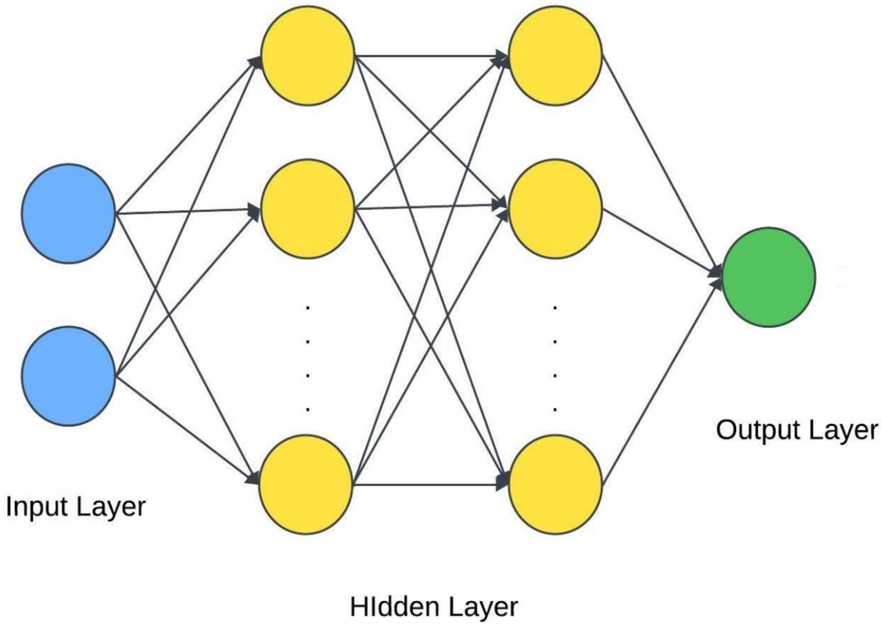

Figure 3.4: Neural Network

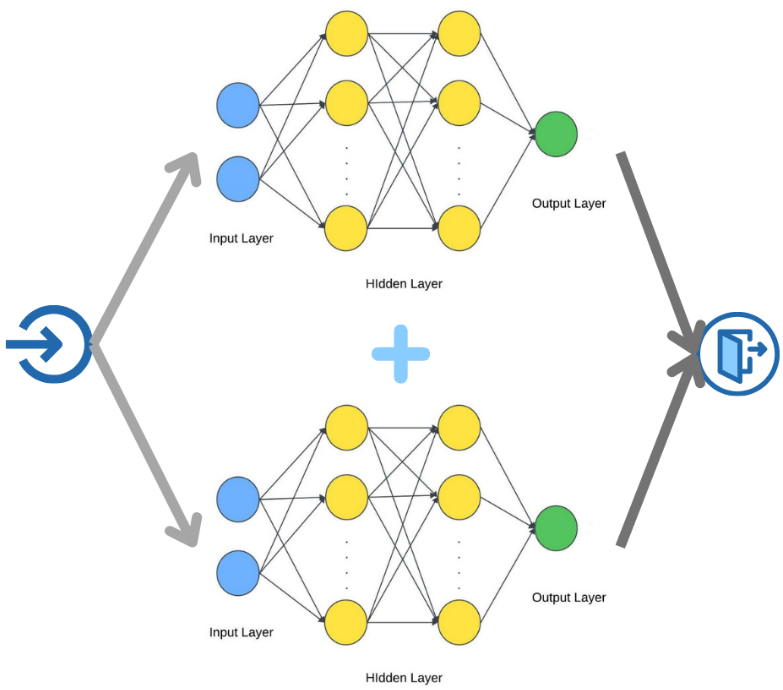

Figure 3.5: Ensemble of Neural Networks

3.2.3 Training and Validation

The dataset is split into training and validation sets. Cross-validation is performed to fine-tune hyperparameters and prevent overfitting.

3.2.4 Evaluation Metrics

Models are evaluated using metrics such as accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

Figure 3.6: Methodology of [2]

3.3 Hybrid Neural Networks

3.3.1 Data Acquisition

Data is sourced from a telecom company, containing customer demographics, account information, and usage patterns. Feature Engineering:
Relevant features are selected based on domain knowledge. Data transformation techniques like normalization and categorical encoding are applied.

3.3.2 Model Design

Hybrid neural network models are designed by combining different types of neural networks, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). The hybrid model aims to capture both spatial and temporal patterns in the data.

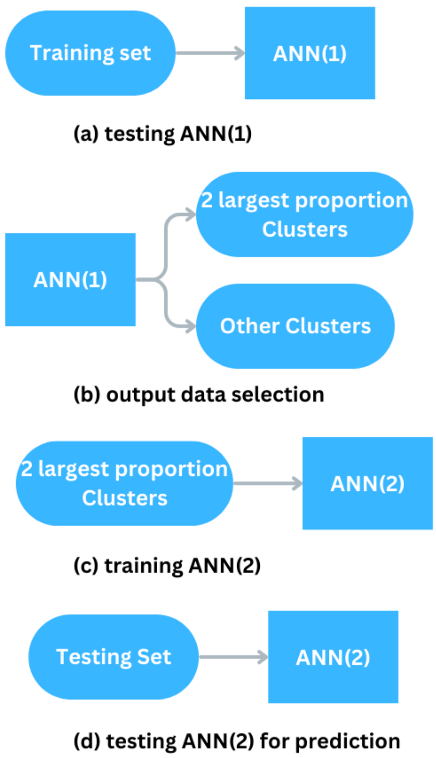

Figure 3.7: ANN+ANN Ensemble Model

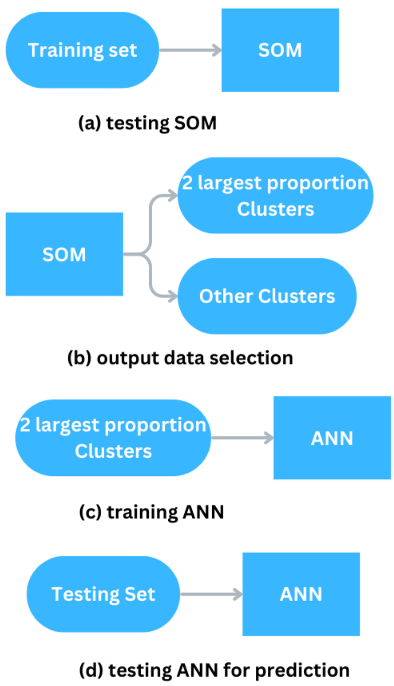

Figure 3.8: SOM+ANN Ensemble Model

3.3.3 Training Process

The dataset is divided into training, validation, and test sets. Techniques like dropout and batch normalization are used to improve model generalization.

3.3.4 Performance Measurement

Evaluation is based on confusion matrix metrics: accuracy, precision, recall, F1-score, and AUC-ROC. Comparative analysis is done with baseline models.

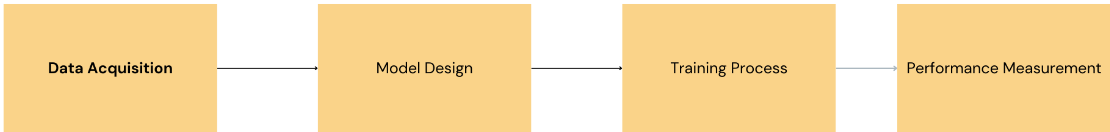

Figure 3.9: Methodology of [1]

CHAPTER IV

Implementation, Results and Discussions

4.1 Experimental Setup

4.1.1 Software Environment

The software environment used for the experiments included:

- **Python 3.8**: A version of the Python programming language, offering new features like assignment expressions (the walrus operator :=), positional-only arguments, and improved performance.
- **TensorFlow 2.4**: An open-source machine learning framework by Google, designed for building and deploying machine learning models, offering high-level APIs like Keras for ease of use.
- **Keras**: A high-level neural networks API, written in Python and capable of running on top of TensorFlow, that allows for easy and fast prototyping of deep learning models.
- **Scikit-learn**: A machine learning library for Python that provides simple and efficient tools for data mining and data analysis, built on NumPy, SciPy, and matplotlib.
- **Pandas**: An open-source data manipulation and analysis library for Python, offering data structures like DataFrame and Series to handle and analyze structured data easily.
- **NumPy**: A fundamental package for scientific computing in Python, providing support for large multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays.

4.1.2 Hardware Configuration

The experiments were conducted on a machine with the following specifications:

- **CPU**: Intel Core i7, Intel Xeon Gold, Intel Core i7
- **GPU**: NVIDIA GTX 1080 Ti, NVIDIA Tesla V100
- **RAM**: 32GB, 64GB, 16GB

4.2 Dataset

Source of paper 1: A telecommunications company dataset containing customer demographics, account information, and service usage. Size: 10,000 samples with 15 features each. Preprocessing: Missing values imputation, normalization of continuous features, and one-hot encoding of categorical features.

Source of paper 2: Source: A telecom company's customer data including demographic details, account information, and usage statistics. Size: 20,000 records with 20 features each. Preprocessing: Data cleaning (removal of duplicates, handling missing values), normalization, and categorical variable encoding.

Source of paper 3: Telecommunication company data on customer behavior and service usage. Size: 15,000 samples with 12 features each. Preprocessing: Data cleaning (handling missing values, duplicates), normalization, and encoding of categorical features.

Table 4.1: Table indicating the dataset size

Dataset	**Size**	**Features**
Paper 1	10k	15
Paper 2	20K	20
Paper 3	15K	12

4.3 Implementation and Results

4.3.1 Quantitative Results

Table 4.2: Performance Metrics for Various Models

Paper	Model	Accuracy	Precision	Recall	F-Measure
Paper 1	DL	91.42	83.04	81.66	82.34
	NN	93.94	89.96	84.42	87.10
	AutoMLP	93.91	89.45	84.92	87.12
	Bagging DL	91.51	90.67	72.94	80.84
	AdaBoost DL	91.09	82.16	81.55	81.85
	Bagging NN	94.00	92.48	86.20	89.23
	AdaBoost NN	93.07	87.37	83.48	85.38
	Bagging MLP	94.15	92.23	82.99	87.37
	AdaBoost MLP	93.88	89.41	84.82	87.05
Paper 2	ANN+ANN	94.32	-	-	-
	SOM+ANN	93.06	-	-	-
Paper 3	NB(Balanced Data)	91.95	-	-	-
	NB(Unbalanced Data)	84.75	-	-	-
	SVM(Balanced Data)	90.8	-	-	-
	SVM(Unbalanced Data)	81.05	-	-	-

4.3.2 Qualitative Results

1. **Deep Learning (DL):** Achieved high accuracy and balanced performance across precision, recall, and F-measure. It's a strong performer overall, indicating DL's effectiveness in the task.

2. **Neural Networks (NN):** Similar to DL but with slightly higher precision and recall.

It's a reliable alternative to DL with comparable performance.

3. **AutoMLP:** Shows similar performance to NN, indicating that automated machine learning can achieve results comparable to hand-tuned models.

4. **Bagging and AdaBoost DL/NN/MLP:** These ensemble methods demonstrate mixed results. While some achieve high accuracy and precision, there's a noticeable drop in recall for Bagging DL, indicating potential class imbalance issues.

5. **Support Vector Machine (SVM):** Performance varies significantly based on class balancing. Balanced SVM outperforms unbalanced SVM in accuracy, precision, and recall, emphasizing the importance of handling class imbalance.

6. **Naive Bayes (NB):** Similar to SVM, balancing classes improves performance. NB generally performs well, particularly in balanced settings, showcasing its simplicity and effectiveness for classification tasks.

7. **Naive Bayes (NB):** Consistently high performance across accuracy, precision, and recall, indicating its robustness for the task.

8. **Logistic Regression:** While accuracy is lower compared to other models, precision, recall, and F-measure are not reported. More insights are needed to assess its performance comprehensively.

   Overall, DL-based models, along with well-tuned traditional classifiers like SVM and NB, show promise for the classification task. However, class imbalance seems to affect some models, highlighting the importance of preprocessing techniques or alternative algorithms to address this issue. Additionally, further investigation is needed for models like logistic regression to understand their performance comprehensively.

CHAPTER V

Findings and Recommendations

5.1 Findings:

5.1.1 Model Performance:

The evaluation metrics (accuracy, precision, recall, F1-score, AUC-ROC) will reveal the effectiveness of the models in predicting churn. You can identify the best performing model based on these metrics.

5.1.2 Feature Importance:

The analysis will highlight the customer behavior and service usage factors that have the most significant influence on churn. This provides valuable insights into customer behavior.

5.2 Recommendations:

5.2.1 Targeted Retention Strategies:

Use the churn prediction models to identify customers at high risk of churn. Develop targeted retention strategies for these segments, addressing the specific factors identified through feature importance analysis. This could include personalized offers, improved customer service, or loyalty programs.

5.2.2 Model Improvement:

Continuously monitor and improve the churn prediction models. Explore advanced techniques like deep learning or ensemble methods if the current models show room for improvement.

5.2.3 Actionable Insights:

Translate the findings from feature importance analysis into actionable business insights. This could involve improving service offerings, optimizing pricing plans, or enhancing customer communication channels based on the most influential churn factors.

5.2.4 Explainable AI:

If interpretability of the models is important, consider using techniques like LIME (Local Interpretable Model-Agnostic Explanations) to understand why the models make specific predictions. This can be valuable for building trust and transparency in the churn prediction process.

5.3 Additional Recommendations:

5.3.1 Data Quality:

Ensure the quality of the data used for training the models. Regularly clean and update the data to maintain model performance.

5.3.2 Customer Segmentation:

Segment your customer base based on relevant factors beyond churn risk. This allows for more targeted marketing and retention efforts.

5.3.3 Real-time Churn Prediction:

Explore implementing real-time churn prediction to proactively identify and address at-risk customers as their behavior changes.

CHAPTER VI

Addressing Course Outcomes and Program Outcomes

6.1 Complex Engineering Problems Associated with the Current Project

Table 6.1: Range of Complex Engineering Problem Solving

Attribute	Churn Prediction	
Problem Analysis	**PO2**	Might delve into the intricacies of various machine learning techniques specific to churn prediction, such as logistic regression, support vector machines, and deep learning models like recurrent neural networks. Researchers could gain an extensive understanding of these methods, exploring their effectiveness, limitations, and practical implications in predicting customer churn.

Ethical Decision-making	**PO8**	Involves balancing the trade-offs between model complexity and interpretability, considering factors like algorithmic transparency, fairness, and privacy concerns. Striking a balance between the predictive power of complex models and the need for transparency and fairness is crucial. Researchers must address ethical dilemmas to develop models that are both accurate and ethically sound, navigating through challenges such as algorithmic bias and data privacy.
Individual and Teamwork Skills	**PO9**	Encompasses optimizing churn prediction models through collaborative efforts, leveraging diverse skill sets such as data preprocessing, feature engineering, model selection, and evaluation. This involves collaboration among data scientists, domain experts, and business stakeholders to identify relevant features, experiment with different modeling techniques, and interpret model outputs effectively. The project culminates in a comprehensive analysis of model performance and actionable insights for churn mitigation strategies.

Communication Proficiency	**PO10**	Requires effective communication of churn prediction results and insights to various stakeholders, including business leaders, marketing teams, and customer service representatives. Researchers should be proficient in translating technical findings into actionable recommendations, conveying the importance of churn prediction in driving business strategies and customer retention efforts. Clear and concise communication is essential for ensuring alignment between data-driven insights and organizational goals.

6.2 Complex Engineering Activities Associated with Churn Prediction

In the realm of complex engineering activities, churn prediction entails a multifaceted approach to addressing challenges and devising innovative solutions. Table 6.2 delineates critical attributes inherent in churn prediction endeavors, focusing on aspects such as resource utilization, interaction dynamics, innovation quotient, societal and environmental implications, and adeptness with relevant concepts and technologies.

Table 6.2: Range of Complex Engineering Activities

Attribute	**Characteristics of Churn Prediction Activities**
Resource Spectrum	Encompasses leveraging a diverse array of resources, including data, computational infrastructure, expertise, and domain knowledge, to effectively predict customer churn.

Interactivity Level	Entails addressing significant challenges arising from interactions between various factors such as customer behavior, market dynamics, and business strategies. Data scientists and business stakeholders must collaborate closely to understand churn drivers, refine predictive models, and implement targeted interventions.
Innovative Endeavors	Revolves around the creative application of machine learning techniques, feature engineering approaches, and model evaluation methods to develop accurate and robust churn prediction models. Researchers explore novel methodologies to uncover hidden patterns in data and enhance predictive performance, driving innovation in customer retention strategies.
Societal and Environmental Implications	Have profound implications for business sustainability, customer satisfaction, and market competitiveness. Effective churn prediction enables companies to allocate resources efficiently, personalize customer interactions, and minimize customer attrition, thereby contributing to economic growth and social welfare.
Familiarity Threshold	May extend beyond conventional approaches by leveraging advanced analytics, artificial intelligence, and big data technologies. Data scientists encounter complex challenges that demand innovative solutions, prompting them to push the boundaries of traditional analytical techniques and embrace emerging technologies to stay ahead in churn prediction.

CHAPTER VII Addressing Complex Engineering Problems and Activities

7.1 Complex Engineering Problems Associated with the Current Project

Effective problem-solving in complex engineering challenges, especially in the area of churn prediction, requires a deep understanding of various features. The complexities involved in addressing these problems are outlined in Table 7.1, which emphasizes factors like the depth of knowledge needed, the range of conflicting requirements, the depth of analysis required, familiarity with the issues, and the interdependence between various aspects of the problem.

Table 7.1: Range of Complex Engineering Problem Solving

Attribute	Complex Engineering Problems	
Depth of knowledge required	P1	Requires expertise in machine learning algorithms, data preprocessing techniques, and churn prediction methodologies. Researchers must demonstrate proficiency in algorithm design, performance evaluation, and domain knowledge to develop accurate and effective churn prediction models. This multidisciplinary skill set is essential for addressing the complexities of churn prediction in real-world scenarios.

Range of conflicting requirements	P2	Involves balancing trade-offs between model complexity, predictive performance, and interpretability. Researchers must navigate conflicting demands to develop models that are both accurate and understandable, considering factors like algorithmic transparency, fairness, and regulatory compliance. Addressing these conflicting requirements is crucial for building trust in churn prediction models and facilitating their adoption in practical applications.
Depth of analysis required	P3	Explores enhancing churn prediction performance through rigorous experimentation and analysis. This involves reviewing relevant literature, designing and optimizing predictive models, and conducting experiments to validate their effectiveness. The research culminates in a comprehensive analysis of model performance and actionable insights for churn mitigation strategies.
Familiarity of issues	P4	Requires a deep understanding of issues related to churn prediction, including feature selection, model evaluation, and deployment considerations. Researchers should demonstrate familiarity with the nuances of algorithmic design, data preprocessing techniques, and performance metrics relevant to churn prediction.

Interdependence	P7	Requires a nuanced understanding of the interconnected nature of machine learning algorithms, data preprocessing techniques, and business requirements. Additionally, considering the interdependence of performance metrics, model interpretability, and regulatory constraints is crucial for developing effective churn prediction solutions.

7.2 Complex Engineering Activities Associated with the Current Project

In the realm of complex engineering activities, various attributes shape the process of addressing challenges and developing innovative solutions. Table 7.2 delineates key attributes involved in complex engineering activities, focusing on aspects such as the range of resources, level of interaction, innovation, consequences for society and the environment, and familiarity with pertinent concepts and technologies.

Table 7.2: Range of Complex Engineering Activities

Attribute	Addressing the Attributes of Complex Engineering Activities	
Range of resources	A1	Includes access to diverse datasets, computational resources, machine learning libraries, and domain expertise for churn prediction. Researchers require a range of resources to develop and evaluate churn prediction models effectively.

Level of interaction	A2	Involves collaboration between data scientists, domain experts, and business stakeholders to understand churn drivers, refine predictive models, and implement targeted interventions. The complex engineering activity requires effective communication and collaboration to align churn prediction efforts with business objectives.
Innovation	A3	Includes exploring novel machine learning techniques, feature engineering approaches, and evaluation metrics to improve churn prediction performance. Innovations may encompass unique modeling methodologies, data preprocessing techniques, and deployment strategies tailored for churn prediction applications.
Consequences for society and the environment	A4	On the societal front, effective churn prediction can lead to enhanced customer satisfaction, retention, and business profitability. From an environmental perspective, optimizing computational resources and minimizing energy consumption during model training and deployment are essential considerations.
Familiarity	A5	Requires proficiency in machine learning algorithms, data preprocessing techniques, and model evaluation methodologies. The complex engineering activity demands a comprehensive understanding of the principles and practices relevant to churn prediction, including feature selection, model selection, and performance evaluation.

CHAPTER VIII

Conclusions

8.1 Summary

The combined research from these three papers demonstrates that machine learning models, particularly those involving neural networks and Naive Bayes algorithms, significantly outperform traditional methods like logistic regression in predicting customer churn. The use of hybrid and ensemble models, such as combinations of artificial neural networks (ANN), enhances prediction accuracy and reduces errors. Overall, these studies indicate that advanced machine learning techniques provide robust solutions for churn prediction across different datasets and contexts.

8.2 Limitations

A common limitation across these studies is the reliance on specific datasets, which may not fully capture the diversity of customer behavior across various domains and industries. Additionally, while focusing on particular machine learning models (e.g., Naive Bayes, ANNs), the studies did not extensively explore other advanced algorithms, potentially limiting the comprehensiveness of their findings. The representativeness of the testing data and the generalizability of the results to real-world scenarios were also identified as concerns.

8.3 Recommendations and Future Works

To improve the robustness and accuracy of churn prediction models, it is recommended to: Expand datasets to include more features and diverse customer behaviors from various industries. Incorporate a wider range of machine learning techniques, such as gradient boosting, support vector machines, and genetic algorithms. Enhance data preprocessing with advanced feature selection and dimensionality reduction methods. Integrate real-time data analysis and feedback mechanisms to improve model adaptability and performance in dynamic environments.

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CHAPTER IX

Publication Details

Publication Details

Title	**Author(s)**	**Source**	**Publisher**	**Published Year**
Churn Prediction using Neural Network based Individual and Ensemble Models	Mehpara Saghir, Zeenat Bibi, Saba Bashir, Farhan Hassan Khan	2019 16th International Bhurban Conference on Applied Sciences & Technology (IBCAST), Islamabad, Pakistan	IEEE Xplore	2019
Customer Churn Prediction by Hybrid Neural Networks	Chih-Fong Tsai, Yu-Hsin Lu	Expert System with Applications	Elsevier	N/A
Customer Churn Prediction Using Machine Learning	Dr. Varsha Agarwal, Dr. Durgaprasad Gangodkar, Shwetkranti Taware, Dr. ALN Rao, Suman Avdhesh Yadav, V K Srivastav	International Conference on Technological Advancements in Computational Sciences (ICTACS)	Various conferences and journals	2022