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Optimizing Artificial Neural Network for Customer Churn: Advanced Data Balancing and Feature Selection

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Abstract— Customers are valuable assets in the dynamic business world. However, service dissatisfaction often leads them to switch to competitors, a phenomenon known as customer churn. In telecommunication industry, churn poses a significant challenge as it directly impacts revenue and influences other customers within their social networks to do the same. Consequently, predicting churn has become essential, with numerous researchers employing various methods to classify potential churners. This study builds upon prior research that utilized Artificial Neural Networks (ANN) or Deep Learning to predict churn, achieving an accuracy of 88.12%. To improve model performance, this research implements ANN as the primary algorithm, Random Over-Sampling (ROS) and Synthetic Minority Oversampling Technique (SMOTE) for data balancing, and three feature selection methods: Minimum Redundancy Maximum Relevance (mRMR), Lasso Regression, and XGBoost. The results demonstrate a 0.38% increase in accuracy compared to previous studies. The finding suggests opportunities for further exploration. Future studies can consider alternative feature selection techniques, such as Wrapper Methods or Heuristic/Metaheuristic approaches, which may produce more optimal feature combinations. Other data balancing methods, such as Undersampling techniques (e.g., Random Undersampling, Tomek Links) or Hybrid Methods (e.g., SMOTE combined with Tomek Links), could be explored to address imbalance datasets effectively. These approaches are expected to provide better combinations and to improve overall prediction performance, enabling researchers to develop more robust and accurate models for customer churn prediction in subsequent studies.

Keywords— Customer Churn; Classification; ANN; SMOTE; ROS; XGBoost; LassoRegression; mRMR.

I. INTRODUCTION

Customers are essential assets in the dynamic business world and competitive market. They can move to other services quickly, which usually called customer churn [1]–[3]. For a lot of companies, especially in telecommunication sector, customer churn is a big problem since it directly impacts company revenue [4]–[6]. In addition, customer churn also influences other customers in their social network to do the same [7]. One of the most profitable strategic plan is to retain customer to continue subscribing [8].

Maintaining the loyalty of existing customers to continue subscribing is a reasonably affordable strategy compared to getting new customers as getting new customers costs 6 to 10 times more than retaining customers, thereby eliminating many profits [3], [4], [7], [9]–[13]. Maintaining customer loyalty can be more effective if we able to predict which customers are at churn risk; hence it makes challenge to

determine the suitable churn prediction method. One method that has proven to be quite fit is machine learning techniques, which are very effective, especially for creating customer churn prediction models which they can predict information based on previous data [5], [10], [14], [15].

This study aims to develop an optimized customer churn prediction model by using ANN by integrating advanced feature selection and dataset balancing techniques to achieve higher accuracy compared to previous models. Machine learning technique has been widely used in developing customer churn prediction models and has shown effective results. However, with increasing data volumes, there has been a shift towards to use deep learning techniques in recent years due to its ability to manage data on larger scale than conventional machine learning techniques. The term 'deep' in deep learning refers to using complex neural networks.

Deep learning is part of the Artificial Neural Network (ANN), whose characteristics include various layers in data processing [16]. On methodological level, deep learning is an extension of ANN architectures that are well known in forecasting literature since ANNs certain layers that can be stacked on top of each other to create a "deeper" ANN [17]. Several previous studies have widely used Artificial Neural Networks to create customer churn prediction model. For example, the research for creating customer churn prediction models using Artificial Neural Networks, which achieved 79% accuracy [9]. Another study confers customer churn prediction model using deep learning obtained an accuracy of 88.12% with Artificial Neural Network [16].

Apart from Artificial Neural Networks, there is research discussing customer churn prediction models using K-Nearest Neighbour (KNN), which gets accuracy of 83.97%, Support Vector Machine (SVM) with accuracy of 79.63%, Decision Tree (DT) gets 91.98%, Random Forest (RF) obtained accuracy of 95.74% [18]. However, there are problems in developing process of customer churns prediction. Although prior studies have explored various features selection and dataset balancing methods, the research in investigating their combined impact on ANN models for customer churn prediction is limited. This gap further highlights the need of further analysis to identify optimal technique combination for achieving higher accuracy.

The model development process consists of Data Preparation, Data Preprocessing, Model Training, and Model Evaluation. The problem in the model development process is that the accuracy results could be more optimal due to the complex and varied dataset [19]. To overcome this problem, the customer churn prediction model needs to be optimized thus become more accurate in processing complex and varied datasets in the future. Therefore, in this research, several additional processes will be carried out, such as Feature Selection to find out what features affect the prediction results and Dataset Balancing to overcome the problem of dataset inequality and to get maximum results in the process of developing the model, so that the model will be more optimal and has better accuracy compare to the previous one.

One of the studies [10] used the Gravitational Search Algorithm (GSA) for Feature Selection without doing Dataset Balancing, and the accuracy results were quite good, it was around 80-81%. Still, there was no mention for comparison results between with or without using Feature Selection. Another research study [18] used mRMR and Relief-F for Feature Selection and oversampling for Balancing Dataset. The accuracy results increased from 81.65% (without Feature Selection) to 83.97% using mRMR and 82.15% using Relief-F in KNN algorithm.

In contrast, several algorithms such as SVM, shown no change in accuracy for those two Feature Selections used. Decision Tree and Random Forest accuracy experienced a decrease for the two Feature Selections used. Meanwhile, the results of the Dataset Balancing process using Oversampling technique after and before Feature Selection decreased the accuracy of all used algorithms. There is also research by [16] using Lasso Regression for Feature

Selection and Random Oversampling for Balancing Datasets on ANN algorithm, with accuracy results of around 86-88%. However, result comparison by using feature selection and those without using feature selection, should be still being mentioned. Therefore, the researcher would conduct an analysis by utilizing and combining several features selection and dataset balancing techniques. It is aimed to determine the accuracy of the best model from several combinations using ANN algorithm and to compare it with the model in previous research. The used feature selection techniques was not only Lasso Regression but also mRMR and XGBoost. The used dataset balancing technique was not only ROS but also uses SMOTE to see which combination of methods was most prudently. Some combinations of methods that were being obtained:

1. Lasso Regression + ROS
2. Lasso Regression + SMOTE
3. mRMR + ROS
4. mRMR + SMOTE
5. XGBoost + ROS
6. XGBoost + SMOTE

This would be combined to different evaluation methods, namely Holdout and 10-Fold Cross-Validation (CV). The following were combinations of evaluation methods:

1. Holdout + Lasso Regression + ROS
2. Holdout + Lasso Regression + SMOTE
3. Holdout + mRMR + ROS
4. Holdout + mRMR + SMOTE
5. Holdout + XGBoost + ROS
6. Holdout + XGBoost + SMOTE
7. 10-Fold CV + Lasso Regression + ROS
8. 10-Fold CV + Lasso Regression + SMOTE
9. 10-Fold CV + mRMR + ROS
10. 10-Fold CV + mRMR + SMOTE
11. 10-Fold CV + XGBoost + ROS
12. 10-Fold CV + XGBoost + SMOTE

In this research, a customer churn model would be created using ANN. In general, ANN could be represented as a system of interconnected neurons since it was inspired by biological neural networks, specifically the human brain [20], [21]. ANN could be used for classification by using features or attributes as input and creating a non-linear function that was being functioned predict the dependent variable [22]. To put it simply, the Artificial Neural Network (ANN) JST Backpropagation process could be divided into training and testing.

Training as mentioned above was learning process of the artificial neural network system, to learn the input values and how to map them to the output until an appropriate model was obtained [23]–[25]. Proper dataset processing was needed to increase model performance and to get high-accuracy results. Therefore, this research used the SMOTE dataset balancing technique to take sample from the minority class and to create new sample synthetically [26], also ROS to reproduce data randomly [16]. Thus, the number of classes between the majority class and the minority class

would be balanced [27].

This research utilized XGBoost, Lasso Regression, and mRMR as feature selection methods. XGBoost was used to identify important features by selecting those with the highest feature importance values. Lasso Regression selected features by identifying those with coefficient values whom not equal to zero on the features [28]. Meanwhile, mRMR was applied to prioritize features with the lowest redundancy and highest relevance values [18], [29]. These methods were employed to improve model accuracy by ensuring that the most significant and relevant features are utilized.

There are two evaluation methods used in this research, the Holdout Method and the 10-fold CV Method, which would be divided into 90% training data and 10% testing data, then using a Confusion Matrix to calculate Accuracy, Precision, Recall, and F-1 Score.

II. MATERIAL AND METHODS

The research methodology was systematically outlined in Fig. 1, detailing the key stages involved in the development of the customer churn prediction model, including Data Preparation, Data Preprocessing, Model Training, and Model Evaluation.

A. Data Preparation

This research used IBM Telco dataset which contains 7043 samples of customer information and 21 attributes, namely: customerID, gender, SeniorCitizen, Partner, Dependents, tenure, PhoneService, MultipleLines, InternetService, OnlineSecurity, OnlineBackup, DeviceProtection, TechSupport, StreamingTV, StreamingMovie, Contact, PaperlessBilling, PaymentMethod, MonthlyCharges, TotalCharges, and Churn (dependent attribute/class). The dataset used was secondary and had been widely used in several previous studies [16]. This dataset was available on Kaggle: <https://www.kaggle.com/code/ahmedshahriarsakib/churn-prediction-eda-statistical-analysis/input>

The dataset was selected for its relevance to the research objectives, as it focuses specifically on customer churn in the telecommunications industry. It provided a comprehensive set of features, including demographic, usage, and payment information, that are critical for building robust churn prediction models. Additionally, the dataset was widely recognized and had been used in prior research, enabling comparative analysis with existing studies. It was publicly available and anonymized nature ensures compliance with ethical standards and allowed for reproducibility of the results. Furthermore, the dataset presented a significant technical challenge due to its imbalanced class distribution, making it an ideal testbed for evaluating data balancing techniques such as SMOTE and ROS. SMOTE and ROS are utilized to address class imbalance since they had demonstrated effectiveness in prior churn prediction research [16], [26]. SMOTE synthesized new minority class samples while maintaining dataset diversity, whereas ROS balanced the dataset by replicating existing minority class samples without introducing noise, ensuring robust model training.

B. Data Preprocessing

IBM Telco dataset contained categorical attributes with two and three unique values. Therefore, five stages of data processing would be performed to create a model that requires numeric attribute values and the process flow. Before processing this 5 stages, we would remove the attribute "customerID" as it did not have a significant impact creating the model. We would also change the data type of "TotalCharges" data type from object to float because this attribute was numeric.

```
def DataPreparation():
    dataset = pd.read_csv('dataset/IBM Telco.csv')
    dataset['customerID']
    dataset['TotalCharges'] = pd.to_numeric(dataset['TotalCharges'],
    errors = 'coerce')
    return dataset
```

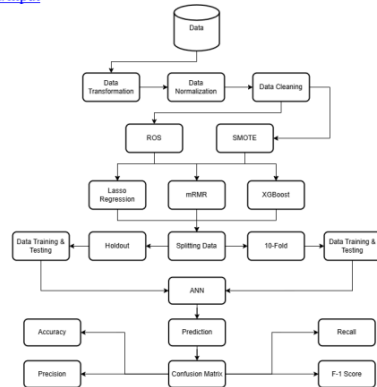


Fig. 1 Research Methodology Framework

1) Data Transformation:

Creating a Customer Churn Prediction model using ANN required a dataset containing numerical values, so that a data transformation process was needed. Two methods would be used in the data transformation process: One-Hot Encoding and label Encoding.

The first stage, the One-Hot Encoding method from the Python library, used `pd.get_dummies` to convert categorical attributes into numerical value representations. However, in this experiment, the results were in Boolean form. Therefore, changing the numerical form would be made at the next stage. The process flow of the One-Hot Encoding method started from selecting attributes in a condition that the attribute only had more than two unique values and the data type was not the same as `int64` nor `float64` to change the attribute according to the number of unique values and their respective names. The selected attributes were as follows: MultipleLines, InternetService, OnlineSecurity, OnlineBackup, DeviceProtection, TechSupport, StreamingTV, StreamingMovies, Contract, and PaymentMethod. The results of the One-Hot Encoding method process are shown in Table I, and the total attributes are 40 (independent).

TABLE I
ONE-HOT ENCODING PROCESS RESULT

No	Gender	...	PaymentMethod_Mailed check
1	Female	...	False
2	Male	...	True
...	...	...	...
7042	Male	...	True
7043	Male	...	False

In the second stage, the Label Encoding method from the Python library, namely Scikit-learn, was converted non-numeric or Boolean values into numeric ones. In this case, the values were (Male = 1 and Female = 0), (Yes = 1 and No = 0), (True = 1 and False = 0). The process flow of the Label Encoding method started from selecting attributes in a condition that the attribute only has a unique value equal to 2 and the data type was not the same as `int64` nor `float64` to change the attribute value from boolean or categorical to numeric (0 or 1). All attributes were selected except the following 4: SeniorCitizen, tenure, MonthlyCharges, and TotalCharges. The Label Encoding method process results are shown in Table II, which shows all attribute values with boolean and categorical data types being numeric (0 or 1).

TABLE II
LABEL ENCODING PROCESS RESULT

No	Gender	...	PaymentMethod_Mailed check
1	0	...	0
2	1	...	1
...	...	...	...
7042	1	...	1
7043	1	...	0

2) Data Normalization:

Based on information from previous research, the IBM Telco dataset had several attributes with a relatively high-value range. Therefore, Normalization was carried out using the MinMaxScaler method from the Python library, namely Scikit-learn. This method would change attribute values into values in the range [0,1], which was only applied to attributes that have a high-value range.

The process flow of the MinMaxScaler method started from selecting attributes in the condition that the attribute only had more than two unique values and the data type was equal as `int64` and the same as `float64` to changing the attribute value to a value between the range [0, 1]. The selected attributes were tenure, MonthlyCharges, and TotalCharges. Data after processing using the MinMaxScaler method was shown in Table III.

TABLE III
MINMAXSCALER PROCESS RESULT

No	Tenure	MonthlyCharges	TotalCharges
1	0.013889	0.115423	0.001275
2	0.472222	0.385075	0.215867
...	...	...	...
7042	0.055556	0.558706	0.03321
7043	0.916667	0.869652	0.787641

3) Missing Value:

Based on information from previous research, more value were needed for IBM Telco dataset. Therefore, we checked and used the SimpleImputer method from the Python library, namely Scikit-learn, to replace it with the mean value. The SimpleImputer method started by checking missing values and filling in with the average value (mean). The attribute with missing values was TotalCharges with 11 missing values. Data after processing using the SimpleImputer method was presented in Table IV.

TABLE IV
SIMPLEIMPUTER PROCESS RESULT

No	Gender	...	MonthlyCharges	TotalCharges	Churn
488	0	...	0.341294	0.261309	0
753	1	...	0.019900	0.261309	0
936	0	...	0.622886	0.261309	0
1082	1	...	0.074627	0.261309	0
3826	1	...	0.070647	0.261309	0
4380	0	...	0.017413	0.261309	0
5218	1	...	0.014428	0.261309	0
6670	0	...	0.548259	0.261309	0
6754	1	...	0.434328	0.261309	0

4) Balancing Data:

The IBM Telco dataset had a relatively high ratio of positive and negative classes, namely 73.46% (Churn = No) and 26.54% (Churn = Yes). Therefore, data balancing was carried out using the SMOTE method from the Python library, namely Imbalanced-learn, to handle data imbalance

problems by generating synthetic samples for minority classes, thereby avoiding overfitting, which often occurred in simple oversampling methods, and the ROS method from the Python library, namely Imbalanced-learn to handle data imbalance problems by randomly reproducing data in a dataset.

5) Feature Selection:

To reduce data dimensionality, model complexity, and improve overall performance, a feature selection process was implemented using three methods: XGBoost, Lasso Regression, and mRMR. These methods were chosen for their complementary strengths. XGBoost efficiently ranks feature importance while handling high-dimensional datasets [19], Lasso Regression applied regularization to mitigate overfitting [28], and mRMR prioritized features with high relevance and minimal redundancy [29], ensuring the identification of an optimal feature set. All feature selection techniques were implemented using Python libraries, facilitating the selection of features that are most relevant to and influential on the class values within the dataset.

C. Hyperparameter Tuning

After data preprocessing was complete, it was necessary to configure the hyperparameters in the ANN method, the data balancing method, and the feature selection method to produce high-accuracy values.

TABLE V
HYPERPARAMETERS

Method	Hyperparameter	Value
ANN	hidden_layer_sizes	200, 250
	activation	ReLU
	solver	Adam
	max_iter	10000
SMOTE	random_state	42
ROS	sampling_strategy	auto
	random_state	42
Lasso Regression	alpha	0.01
mRMR	K	28
	return_score	TRUE
	show_progress	FALSE
XGBoost		Default

Table V summarized the key hyperparameters used for various machine learning methods in this study. The explanation were as follows:

1) ANN (MLPClassifier):

The ANN architecture was configured with two hidden layers consisting of 200 and 250 neurons, as these configurations were identified through empirical tuning to balance model complexity and training efficiency. The ReLU activation function and Adam optimizer were chosen for their widespread application and proven effectiveness in handling gradient-based optimization challenges in deep learning models [16]. Additionally, the MLPClassifier was set to perform a maximum of 10,000 iterations to ensure convergence and achieve optimal performance through extensive experimentation.

2) SMOTE:

The Synthetic Minority Sampling Technique (SMOTE) was configured with a random_state of 42 to ensure reproducibility, adhering to best practices in machine learning experiments. This approach had been demonstrated to effectively reduce bias in imbalanced datasets and improve model performance without introducing noise [26].

3) ROS:

Random Over-Sampling (ROS) was selected as a data balancing method due to its ability to replicate minority class samples without altering the original data distribution, ensuring a balanced dataset for training. The method was configured to automatically determine the sampling strategy (sampling_strategy=auto) to balance class proportions, while random_state=42 was set to ensure consistent and reproducible results. The technique had been widely used in predictive modelling tasks, particularly due to its simplicity and effectiveness in handling class imbalance without introducing significant bias [16].

4) Lasso Regression:

Lasso Regression was chosen for feature selection due to its ability to perform both dimensionality reduction and regularization by penalizing less significant features, improving model interpretability and efficiency. The regularization parameter (alpha=0.01) was optimized to balance bias and variance, effectively retaining the most relevant features while reducing overfitting and maintaining model accuracy. This method had been widely adopted in high-dimensional data scenarios for its robust performance [28].

5) mRMR:

The mRMR method employed for feature selection to identify attributes with high relevance to the target variable while minimizing redundancy among selected features. The parameter K=28 was determined experimentally to optimize accuracy, selecting 28 features that contribute significantly to the model. The setting return_scores=True was used to provide insights into feature importance, while show_progress=False suppressed execution progress updates for computational efficiency. This method was particularly effective in datasets with correlated features, ensuring the selection of non-redundant and highly informative attributes [29].

6) XGBoost:

XGBoost was selected for feature selection due to its ability to efficiently rank feature importance while handling high-dimensional datasets. The method leverages its optimized gradient boosting algorithm to enhance predictive accuracy, with the library's default parameters retained to ensure robust and computationally efficient performance. XGBoost's effectiveness and scalability had established it as a standard in feature selection for classification tasks, including churn prediction [19].

D. Evaluation

In this research, a confusion matrix was employed as a model evaluation method because it provided a comprehensive summary of classification prediction results, detailing the number of correct and incorrect predictions

across classes. It included key terms such as True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), which are used to calculate essential metrics like accuracy, precision, recall, and F1-score. To ensure a thorough and balanced assessment of the model's performance, the study used two common evaluation methods: Holdout and 10-Fold Cross-Validation [8]–[11], [16], [28]. The Holdout method, which split the dataset into 90% training and 10% testing, was favoured for its simplicity and computational efficiency, making it suitable for quick benchmarking. However, as Holdout relied on a single dataset split, it might reduce bias and overfitting. To address this limitation, 10-Fold Cross-Validation was employed, iteratively training and testing the model across multiple splits to reduce variance and provide a more generalized performance evaluation. By integrating these two methods, the research balanced computational efficiency with robust validation, by ensuring the proposed ANN-based churn prediction model was rigorously and reliably evaluated for real-world applicability.

1) Accuracy:

A measurement was being done to determine well the model predicts a classification, with equation as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (1)$$

2) Precision:

A measurement was being done to determine well the model made positive predictions in classification, namely how many of all positive predictions are truly positive, with equation as follows:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

3) Recall:

A measurement was being done to determine well the model makes positive predictions on truly positive data, with equation as follows:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

4) F-1 Score:

The harmonic mean of precision and recall, with equation as follows:

$$F-1 \text{ Score} = 2 * \left(\frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \right) \quad (4)$$

III. RESULT AND DISCUSSION

Model evaluation was performed using the Holdout and 10-Fold Cross Validation methods by dividing the dataset into 90% for training data and 10% for testing data. Evaluation was performed in the ANN+SMOTE and ANN+ROS models using each feature selection method. After conducting several model evaluation experiments by

changing the number of features in each feature selection, XGBoost was obtained the best accuracy results from all feature selections with 28 features. Therefore, a comparison would be made between models with the same number of features. Model testing results were shown in Tables VI, VII, VIII and IX.

A. ANN (Without Data Balancing + Feature Selection)

TABLE VI
HOLDOUT AND 10-FOLD CROSS VALIDATION MODEL RESULTS

Evaluation Metric	Data Splitting Method	
	Holdout	10-Fold CV
Accuracy	0.75603	0.75323
Precision	0.56707	0.53501
Recall	0.47938	0.53558
F-1 Score	0.51955	0.53529

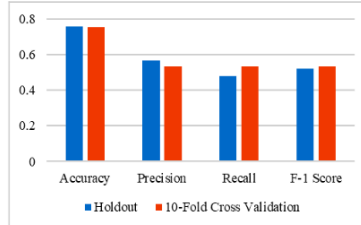


Fig. 2 Comparison of Holdout and 10-Fold Cross Validation Model Results

Table VI and Fig. 2 above presented the baseline performance of ANN model without data balancing or feature selection, showing that the Holdout method achieves slightly higher accuracy (75.60%) compared to 10-Fold Cross-Validation (75.32%), along with marginally better Precision and F1-Score. However, Recall was nearly identical. These results indicated limited generalization capabilities with raw data, reflected in modest performance across metrics.

B. ANN + Data Balancing

TABLE VII
ANN + DATA BALANCING MODEL RESULTS

Evaluation Metric	Data Splitting Method	Data Balancing Technique	
		SMOTE	ROS
Accuracy	Holdout	0.85411	0.87053
	10-Fold CV	0.83903	0.85844
Precision	Holdout	0.81426	0.83673
	10-Fold CV	0.81672	0.81289
Recall	Holdout	0.92642	0.92830
	10-Fold CV	0.87418	0.93119
F-1 Score	Holdout	0.86673	0.88014
	10-Fold CV	0.84447	0.86803

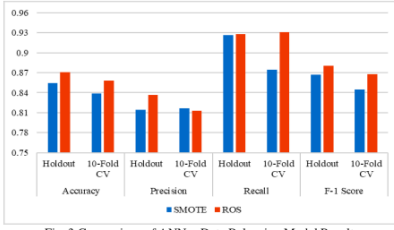


Fig. 3 Comparison of ANN + Data Balancing Model Results

Table VII and Fig. 3 evaluated the impact of data balancing techniques (SMOTE and ROS) on the ANN model, showing significant performance improvements compared to the baseline (Table VI). Accuracy improved to 87.05% with ROS and 85.41% with SMOTE (Holdout). ROS consistently outperformed SMOTE in Recall and F1-Score, highlighting its effectiveness in handling class imbalance.

C. ANN + Feature Selection

Table VIII and Fig. 4 highlight the effects of feature selection methods (Lasso Regression, mRMR, and XGBoost) on the ANN model, showing that XGBoost achieved the highest accuracy (77.73%) under Holdout, surpassing other methods. Similar trends were observed in Precision and F1-Score, but the improvements remained modest compared to Table VII, where data balancing had a more significant impact.

TABLE VIII
ANN + FEATURE SELECTION MODEL RESULTS

Evaluation Metric	Data Splitting Method	Feature Selection Method		
		Lasso Regression	mRMR	XGBoost
Accuracy	Holdout	0.74894	0.76170	0.77730
	10-Fold CV	0.74457	0.75706	0.75408
Precision	Holdout	0.54359	0.57386	0.59686
	10-Fold CV	0.51949	0.54350	0.53816
Recall	Holdout	0.54639	0.52062	0.58763
	10-Fold CV	0.4992	0.52809	0.51685

TABLE IX
ANN + FEATURE SELECTION + DATA BALANCING MODEL RESULTS

Evaluation Metric	Data Splitting Method	Feature Selection Method + Data Balancing Technique					
		Lasso Regression		mRMR		XGBoost	
		SMOTE	ROS	SMOTE	ROS	SMOTE	ROS
Accuracy	Holdout	0.83092	0.84348	0.83961	0.85024	0.86184	0.88502
	10-Fold CV	0.81554	0.82007	0.82985	0.83669	0.84260	0.84550
Precision	Holdout	0.80136	0.80263	0.82500	0.82496	0.83888	0.85128
	10-Fold CV	0.79199	0.77490	0.79829	0.80370	0.81545	0.80613
Recall	Holdout	0.89057	0.92075	0.87170	0.89811	0.90377	0.93962
	10-Fold CV	0.85582	0.90220	0.88268	0.89099	0.88558	0.90974
F-1 Score	Holdout	0.84361	0.85764	0.84771	0.85998	0.87012	0.89327
	10-Fold CV	0.82267	0.83372	0.83837	0.84510	0.84907	0.85481

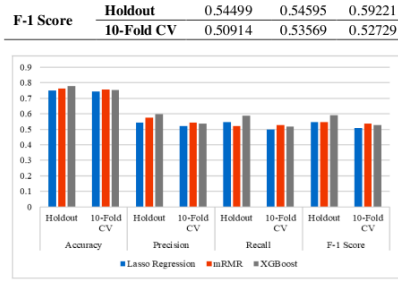


Fig. 4 Comparison of ANN + Feature Selection Model Results

D. ANN + Feature Selection + Data Balancing

Table IX, Fig. 5, and Fig. 6 collectively illustrated the impact of integrating feature selection and data balancing techniques on the performance of ANN model. This analysis highlighted the effectiveness of advanced methodologies, with Fig. 5 providing a detailed breakdown of key metrics—accuracy, precision, recall, and F1-score—across various combinations, and Fig. 6 comparing the outcomes of Holdout and 10-Fold Cross-Validation. Among feature selection methods (Lasso Regression, mRMR, and XGBoost), XGBoost yield the best accuracy (77.73%) under Holdout, outperforming other techniques. However, improvements from feature selection alone remain modest compared to data balancing, as seen in Table VII. Notably, the combination of XGBoost and ROS consistently delivered superior results across all metrics under both validation methods. Based on the results in Tables VI through IX, while Holdout showed higher accuracy, 10-Fold Cross-Validation provided more generalized results, emphasizing the importance of robust evaluation methods to ensure model reliability across varied datasets. These findings underscored that feature selection, while reducing dimensionality and enhancing interpretability, achieved its full potential when combined with data balancing, ensuring robust and generalized model performance. Accordingly, the following points lead further into these findings.

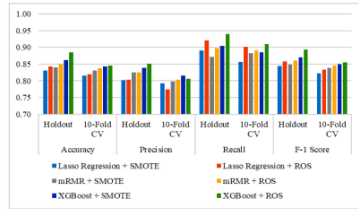


Fig. 5 Comparison of ANN + Feature Selection + Data Balancing Model Results

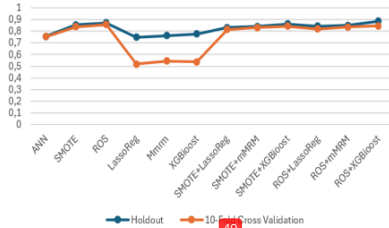


Fig. 6 Comparison Holdout and 10-Fold Cross Validation

1) Data Balancing:

The application of data balancing techniques, such as SMOTE and ROS, significantly enhanced model accuracy by more than 10% for both Holdout and 10-Fold Cross Validation methods compared to models that did not employ data balancing. Among these techniques, ROS (Random Over-Sampling) demonstrated superior performance across all evaluation metrics. It was likely attributed to its capability to effectively address class imbalances while preserving the diversity and distribution of the original dataset.

2) Feature Selection:

Feature selection led modest performance enhancements, with approximately 2% increase in accuracy for the Holdout method and 0.2% improvement for the 10-Fold Cross Validation method. Among the evaluated feature selection techniques, XGBoost achieved the highest improvement, which attributed to its ability to rank features by importance and minimize redundancy effectively. In comparison, Lasso Regression and mRMR delivered consistent but slightly lower enhancements in model performance.

3) Data Balancing + Feature Selection:

The combination of data balancing and feature selection produced highest overall performance, with an improvement of approximately 12% in Holdout accuracy and 9% in 10-Fold Cross Validation accuracy compared to models that do not employ these techniques. Among the combinations tested, XGBoost with ROS achieved the best results across all evaluation metrics, particularly excelling in Recall and F-1 Score. As illustrated in Fig. 6, the ROS + XGBoost

combination consistently delivered superior results, by emphasizing its effectiveness for applications requiring high recall, such as customer churn prediction.

4) Implications

The choice between the Holdout and 10-Fold Cross Validation (CV) methods had important implications for model performance and applicability. While the Holdout method often achieve higher accuracy, it was prone to overfitting due to its dependency on a single data split, which might only partially represent the diversity of the dataset. In contrast, the 10-Fold CV method provided more robust and consistent performance across varying datasets, making it the preferred choice for real-world scenarios that involve diverse or evolving data. For business-critical applications, such as customer churn prediction, the combination of ROS and XGBoost offers an optimal balance of high performance, interpretability, and computational efficiency. Moreover, models validated through 10-Fold CV were recommended for production deployment, as this approach ensures greater generalizability and reliability when applied to unseen datasets.

E. Comparison of Studies

In previous research [16], there were several results of previous research and comparisons with this research on the IBM Telco dataset.

TABLE X
RESULTS OF PREVIOUS RESEARCH

No	Authors	Dataset	Classifiers	Evaluation Model	Accuracy (%)
1	Agrawal et al. [30]	IBM Telco	Multi-layered ANN	Holdout 80% for training and 20% for testing	80.03%
2	Mohammad et al. [31]	IBM Telco	ANN	Holdout 70% for training and 30% for testing	85.55%
3	Momin et al. [32]	IBM Telco	ANN	Holdout 90% for training and 10% for testing	82.83%
4	Fujo et al. [16]	IBM Telco	ANN	Holdout 90% for training and 10% for testing	88.12%

Table X compared the results of ANN models that were created previously with different evaluation methods and models on the IBM Telco dataset. Based on the results from Table 9, the research obtained the best results compared to other studies and provides recommendations for using feature importance techniques such as XGBoost, dataset balancing techniques such as ROS, and implemented into web applications using Flask. Therefore, this research could contribute on the optimization of ANN model that was created previously by using different feature selection and balancing dataset techniques and following the recommendations that have been given. A comparison of model evaluation results would be shown in Table XI.

TABLE XI
COMPARISON OF MODEL EVALUATION RESULTS

No	Authors	Holdout	10-Fold CV
1	Agrawal et al. [30]	80.03%	Not Applied
2	Mohammad et al. [31]	85.55%	Not Applied
3	Momin et al. [32]	82.83%	Not Applied
4	Fujo et al. [16]	88.12%	86.57%
5	Proposed Method	88.50%	84.54%

F. Data Privacy and Compliance

Data privacy was a top priority in this research. All data used had undergone anonymization, where personally identifiable information had been removed or encrypted to prevent unauthorized disclosure. Furthermore, this research complied with applicable data privacy regulations, as the data had already been anonymized.

G. Responsible Implementation and Risk Management

By considering the technical aspect, this research also emphasized the importance of responsible application of the model in real-world environments. Before implementing, a risk assessment would be conducted to identify and mitigate potential negative impacts, such as prediction errors that could affect business decisions or customer experiences. Long-term impact monitoring would also be implemented to ensure the model continues being functioned as intended without causing unintended side effects. As part of these efforts, internal controls would be introduced to prevent model misuse, including transparency policies, regular audits, and oversight mechanisms to ensure the model is used fairly and ethically.

H. External Validation and Research Limitations

External validation was an important step that needs to be carried out to convince the generalization of the proposed model. Although internal validation resulted using Holdout and 10-Fold CV had shown good model performance, testing this model on different datasets was essential to assess its robustness and generalization. Plans included testing the model on other telecom datasets available in public repositories such as Kaggle and UCI Machine Learning Repository. Additionally, we would apply the model in real-world scenarios in collaboration with local telecommunications companies to evaluate the model performance in natural operational environments. This implementation would involve integrating the model into existing Customer Relationship Management (CRM) systems to identify high-risk customers in real-time and facilitate proactive retention strategies, such as offering personalized service plans or discounts. The model ability to handle diverse datasets with varying levels of imbalance would also be evaluated using scalable techniques like ROS and XGBoost to ensure consistent performance in practical settings. This pilot would include analysis of fewer and more diverse customer data, allowed us to assess the model's ability to handle a wider variety of data.

Although this research has showed promising results in optimizing Artificial Neural Network (ANN) models for

customer churn prediction, several limitations must be noted. First, the dataset used in this research came from a single source, IBM Telco, which might only partially represent the variety of customer data and behaviours in the broader telecommunications industry. Thus, the findings of this study might lack generalizability to telecommunication companies with different customer demographics, services, or geographic markets. Second, this research did not consider changes in customer behaviour over time, which could affect the model accuracy in the long term. Incorporating temporal and behavioural trends into the model could further enhance its predictive capabilities, particularly in dynamic customer environments. Third, although data balancing methods such as SMOTE and ROS were used to overcome class imbalance, they could also introduce bias.

Nevertheless, this research made a unique contribution by integrating advanced feature selection techniques, such as XGBoost, with data balancing methods like ROS, significantly improving model performance across accuracy, precision, recall, and F1-score. The proposed model offered practical value for the telecommunications industry by enabling real-time identification of high-risk customers through integration into existing CRM systems, facilitating proactive retention strategies. Additionally, testing the model on external datasets from different geographic regions and market segments would provide insights into its scalability and robustness, ensuring its practical applicability in diverse telecommunication settings. Its scalability and robustness across diverse customer segments ensured that the model remains a valuable tool for long-term churn management despite these limitations.

IV. CONCLUSION

This research had successfully optimized Artificial Neural Network (ANN) models for customer churn prediction, achieving superior accuracy of 88.50% using the Holdout method. Although the 10-Fold Cross Validation method showed slightly lower accuracy at 84.54%, the findings highlighted the critical role of feature selection techniques, dataset balancing, and data preprocessing in enhancing model performance. The integration of advanced techniques such as XGBoost for feature selection and ROS for data balancing significantly improved prediction accuracy, providing a scalable and adaptable framework for application in the telecommunications industry.

Future research could enhance this model by incorporating temporal dynamics and customer behaviour trends to improve long-term adaptability and accuracy. Validating the model on datasets from diverse geographic regions and market segments would also be essential to ensure generalizability and robustness. By addressing these areas and exploring additional feature engineering and data balancing methods, this research laid the foundation for developing even more effective and scalable churn prediction solutions in dynamic, real-world scenarios.

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REFERENCES

- [1] A. Amin, F. Al-Obeidat, B. Shah, A. Adnan, J. Loo, and S. Anwar, "Customer churn prediction in telecommunication industry using data certainty," *J. Bus. Res.*, vol. 94, pp. 290–301, Jan. 2019, doi: 10.1016/j.jbusres.2018.03.003.
- [2] Q. Bi, "Cultivating loyal customers through online customer communities: A psychological contract perspective," *J. Bus. Res.*, vol. 103, pp. 34–44, 2019.
- [3] X. Xiahou and Y. Harada, "B2C E-Commerce Customer Churn Prediction Based on K-Means and SVM," *J. Theor. Appl. Electron. Commer. Res.*, vol. 17, no. 2, pp. 458–475, Jun. 2022, doi: 10.3390/jtaer17020024.
- [4] S. O. Abdulsalam, M. O. Arowolo, Y. K. Saheed, and J. O. Afolayan, "Customer Churn Prediction in Telecommunication Industry Using Classification and Regression Trees and Artificial Neural Network Algorithms," *Indones. J. Electr. Eng. Informatics*, vol. 10, no. 2, pp. 431–440, Jun. 2022, doi: 10.52549/ijeeci.v10i2.2985.
- [5] S. M. Sina Mirabdolbaghi and B. Amiri, "Model Optimization Analysis of Customer Churn Prediction Using Machine Learning Algorithms with Focus on Feature Reductions," *Discret. Dyn. Nat. Soc.*, vol. 2022, 2022, doi: 10.1155/2022/5134356.
- [6] M. Vaudevan, R. S. Narayanan, S. F. Nakeeb, and Abhishek, "Customer churn analysis using XGBoosted decision trees," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 25, no. 1, pp. 488–495, Jan. 2022, doi: 10.11591/ijeecs.v25i1.pp488-495.
- [7] A. De Caigny, K. Coussement, and K. W. De Bock, "A new hybrid classification algorithm for customer churn prediction based on logistic regression and decision trees," *Eur. J. Oper. Res.*, vol. 269, no. 2, pp. 760–772, 2018, doi: 10.1016/j.ejor.2018.02.009.
- [8] A. K. Ahmad, A. Jafar, and K. Aljoumaa, "Customer churn prediction in telecom using machine learning in big data platform," *J. Big Data*, vol. 6, no. 1, Dec. 2019, doi: 10.1186/s40537-019-0191-6.
- [9] Y. Khan, S. Shafiq, A. Naeem, S. Ahmed, N. Safwan, and S. Hussain, "Customers Churn Prediction using Artificial Neural Networks (ANN) in Telecom Industry," *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 9, 2019, doi: 10.14569/IJACSA.2019.0100918.
- [10] P. Lalwani, M. K. Mishra, J. S. Chadha, and P. Sethi, "Customer churn prediction system: a machine learning approach," *Computing*, vol. 104, no. 2, pp. 271–294, Feb. 2022, doi: 10.1007/s00607-021-00908-y.
- [11] S. Wu, W. C. Yau, T. S. Ong, and S. C. Chong, "Integrated Churn Prediction and Customer Segmentation Framework for Telco Business," *IEEE Access*, vol. 9, pp. 62118–62136, 2021, doi: 10.1109/ACCESS.2021.3073776.
- [12] S. Kumar and M. Kumar, "Predicting Customer Churn Using Artificial Neural Network," in *Communications in Computer and Information Science*, vol. 1000, Springer International Publishing, 2019, pp. 299–306, doi: 10.1007/978-3-030-20257-6_25.
- [13] G. Torzkadeh, J. C. J. Chang, and G. W. Hansen, "Identifying issues in customer relationship management at Merck-Medco," *Decis. Support Syst.*, vol. 42, no. 2, pp. 1116–1130, 2006, doi: 10.1016/j.dss.2005.10.003.
- [14] A. Amin *et al.*, "Just-in-time customer churn prediction in the telecommunication sector," *J. Supercomput.*, vol. 76, no. 6, pp. 3924–3948, Jun. 2020, doi: 10.1007/s11227-017-2149-9.
- [15] C. Wang, D. Han, W. Fan, and Q. Liu, "Customer churn prediction with feature embedded convolutional neural network: An empirical study in the internet funds industry," *Int. J. Comput. Intell. Appl.*, vol. 18, no. 01, p. 1950003, 2019.
- [16] S. W. Fujo, S. Subramanian, and M. A. Khder, "Customer Churn Prediction in Telecommunication Industry Using Deep Learning," *Inf. Sci. Lett.*, vol. 11, no. 1, pp. 185–198, Jan. 2022, doi: 10.18576/isl/110120.
- [17] A. De Caigny, K. Coussement, K. W. De Bock, and S. Lessmann, "Incorporating textual information in customer churn prediction models based on a convolutional neural network," *Int. J. Forecast.*, vol. 36, no. 4, pp. 1563–1578, 2020, doi: 10.1016/j.ijforecast.2019.03.029.
- [18] M. Rahman and V. Kumar, "Machine Learning Based Customer Churn Prediction in Banking," in *Proceedings of the 4th International Conference on Electronics, Communication and Aerospace Technology, ICECA 2020*, Institute of Electrical and Electronics Engineers Inc., Nov. 2020, pp. 1196–1201, doi: 10.1109/ICECA49313.2020.9297529.
- [19] P. Swetha and R. B. Dayananda, "Improved XgBoost Machine learning Algorithm for Customer Churn Prediction," *EAI Endorsed Trans. Energy Web*, vol. 7, no. 30, pp. 1–7, 2020, doi: 10.4108/eai.13-7-2018.164854.
- [20] Y. Chen, L. Song, Y. Liu, L. Yang, and D. Li, "A review of the artificial neural network models for water quality prediction," *Appl. Sci.*, vol. 10, no. 17, 2020, doi: 10.3390/app10175776.
- [21] R. Dastres, M. Soori, A. Neuml, N. Systems, and I. Journal, "Artificial Neural Network Systems," *Int. J. Imaging Robot.*, vol. 21, no. 2, pp. 13–25, 2021.
- [22] A. A. Hussin Adam Khatir and M. Bee, "Machine Learning Models and Data-Balancing Techniques for Credit Scoring: What Is the Best Combination?," *Risks*, vol. 10, no. 9, p. 169, Aug. 2022, doi: 10.3390/risks10090169.
- [23] Y. Antonisfia, R. Susanti, - Elendi, S. Anderson, and F. Anisa, "Design and Development of a Coffe Blending Device with Carbon Monoxide (CO) Level Identification Based on Artificial Neural Networks," *Int. J. Adv. Sci. Comput. Eng.*, vol. 5, no. 3, pp. 239–246, 2023, doi: 10.62527/ijasece.5.3.171.
- [24] R. Susanti, R. Nofendra, Z. Zaini, M. S. A. bin Suhaimi, and M. I. Rusydi, "The Use of Artificial Neural Networks in Agricultural Plants," *Andalus J. Electr. Electron. Eng. Technol.*, vol. 2, no. 2 SE-Articles, pp. 62–68, Jan. 2023, doi: 10.25077/ajeet.v2i2.32.
- [25] R. Susanti, Z. R. Aidha, M. Yuliza, Suryadi, and S. Yondri, "Artificial neural network application for aroma monitoring on the coffe beans blending process," *Int. J. Informatics Vis.*, vol. 2, no. 3, pp. 147–152, 2018, doi: 10.30630/ijov.2.3.86.
- [26] H. Zhang, L. Huang, C. Q. Wu, and Z. Li, "An effective convolutional neural network based on SMOTE and Gaussian mixture model for intrusion detection in imbalanced dataset," *Comput. Networks*, vol. 177, no. May, p. 107315, Aug. 2020, doi: 10.1016/j.comnet.2020.107315.
- [27] F. Zulfikri, D. Tryanda, A. Syarif, and H. Patria, "Predicting Peer to Peer Lending Loan Risk Using Classification Approach," *Int. J. Adv. Sci. Comput. Eng.*, vol. 3, no. 2, pp. 94–100, 2021, doi: 10.62527/ijasece.3.2.57.
- [28] S. Shafiee, L. M. Lied, I. Burud, J. A. Dieseth, M. Alsheikh, and M. Lillemo, "Sequential forward selection and support vector regression in comparison to LASSO regression for spring wheat yield prediction based on UAV imagery," *Comput. Electron. Agric.*, vol. 183, no. 1432, p. 106036, 2021, doi: 10.1016/j.compag.2021.106036.
- [29] M. Billah and S. Waheed, "Minimum redundancy maximum relevance (mRMR) based feature selection from endoscopic images for automatic gastrointestinal polyp detection," *Multimed. Tools Appl.*, vol. 79, no. 33–34, pp. 23633–23643, 2020, doi: 10.1007/s11042-020-09151-7.
- [30] S. Agrawal, A. Das, A. Gaikwad, and S. Dhage, "Customer Churn Prediction Modelling Based on Behavioural Patterns Analysis using Deep Learning," in *2018 International Conference on Smart Computing and Electronic Enterprise (ICSCEE)*, 2018, pp. 1–6, doi: 10.1109/ICSCEE.2018.8538420.
- [31] N. Muhammad, S. A. Ismail, M. Kama, O. Mohd Yusop, and A. Azmi, *Customer Churn Prediction In Telecommunication Industry Using Machine Learning Classifiers*. 2019, doi: 10.1145/3387168.3387219.
- [32] S. Momin, T. Bohra, and P. Raut, "Prediction of Customer Churn Using Machine Learning BT - EAI International Conference on Big Data Innovation for Sustainable Cognitive Computing," A. Haldorai, A. Ramu, S. Mohanran, and C. C. Onn, Eds., Cham: Springer International Publishing, 2020, pp. 203–212.

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