Employing Advanced TCN Model to Predict the Success of Bank Telemarketing in Long-term Deposit Subscription

MSc Research Project
Data Analytics

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MSc Project Submission Sheet

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Employing Advanced TCN Model to Predict the Success of Bank Telemarketing in Long-term Deposit Subscription

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Abstract

This research focuses on predicting the success of bank telemarketing campaigns in securing subscriptions to long-term deposits, leveraging the power of Temporal Convolutional Networks (TCNs). TCNs are well-suited for sequential data analysis, allowing the capture of temporal patterns in customer interactions, a critical factor in telemarketing. The study addresses challenges such as data imbalance, high dimensionality, and nonlinear relationships that hinder the predictive power of traditional statistical and machine learning methods. The dataset, sourced from the UCI Machine Learning Repository, underwent comprehensive preprocessing, including handling missing values, encoding categorical variables, and addressing class imbalance using SMOTE. A comprehensive TCN model was designed and implemented, with performance evaluated against traditional models like Support Vector Machines (SVM), Decision Trees, Naïve Bayes, and advanced techniques such as Artificial Neural Networks (ANN) and K-nearest neighbors (KNN). Evaluation metrics including accuracy, F1-score, and AUC-ROC highlighted TCN's superior capability, achieving balanced performance in identifying potential subscribers despite the imbalanced nature of the data. The findings underline TCN's effectiveness in telemarketing prediction tasks, offering financial institutions a robust tool for optimizing campaign strategies. The research establishes TCN as a promising approach to improving customer acquisition and retention in the financial sector.

1 Introduction

1.1 Background

The financial sector is always changing with a focus, on attracting and keeping customers to stay out of the competition being crucial. The financial sector has witnessed tremendous growth with regards to the number of banks with the world's bank count having risen by 15 percent since the onset of this decade (Banking Industry Statistics, 2023). This has further escalated the already competition within companies trying to win over and retain customers. Out of the total of long-term deposits that contribute to around 40 percent of the income of a normal bank, it is of major importance (Smith & Brown, 2022). However it has been observed that long-term deposits have declined by about 10% over the last five years (Financial Times, 2023). This trend has made it necessary for the banks to find other methods which they can adopt to market their services to the people. Telemarketing is a method used by all banks and financial firms to market products like savings accounts, loans, term deposits, and insurance through engaging interactions. Although effective telemarketing encounters difficulties, in pinpointing customers who are more inclined to respond positively to marketing endeavors. Poor targeting does not raise costs. Also runs the risk of annoying customers with repetitive or irrelevant messages.

The advantage of machine learning and deep learning has revolutionized the telemarketing field by providing tools to examine customer behavior trends and forecast the results of telemarketing campaigns. Conventional statistical techniques, such as regression, have typically been utilized for predicting the success of telemarketing. Facing challenges in handling the intricate nature of contemporary datasets that encompass high dimensionality and nonlinear relationships along with the class imbalance issues. Machine learning algorithms such as SVM and Decision Tree have demonstrated enhancements in precision using ensemble learning methods. Recently there has been a rise in deep learning designs, such as Temporal Convolutional Networks (TCNs) which offer an effective method for banks to analyze sequential customer interactions by capturing temporal relationships more efficiently.

In this research, we are predicting and understanding the customer's behavior that has become a cornerstone for optimizing telemarketing strategies. By utilizing predictive models, banks can tailor their campaigns to focus on high-value customers, thereby enhancing the overall efficiency and profitability of their marketing efforts. This research developed into the application of advanced predictive models, particularly TCNs, to address the challenges and opportunities in telemarketing campaign optimization.

Analyzing customer responses to telemarketing initiatives is often problematical because of the factors involved in customers’ decision to respond and the skewed nature of many campaigning results. However, the conventional statistical tools, though serve as initial reference points, have their limitations in terms of analyzing large volumes and complex customer data and do not capture the dynamics in the data. While the performance of these models is significantly sounder, there still lies a temporal complexity that does not serve to perform analysis on sequential data well. TCNs give a lot of advantages in terms of temporal patterns and feature interaction, which makes this model more suitable for telemarketing prediction tasks. This research argues that leveraging Temporal Convolutional Networks not only enhances prediction accuracy but also provides actionable insights for improving telemarketing campaign strategies. By integrating advanced predictive techniques, banks can overcome the inefficiencies of traditional approaches, thereby achieving better customer acquisition and retention outcomes.

Customer reactions, in telemarketing campaigns, are very tricky to anticipate because human behavior is complex, and campaign results are unbalanced in nature. While basic statistical techniques offer some understanding they struggle with datasets and cannot fully grasp the nuanced connections, among customer data.

1.2 Research Questions

- How can a Temporal Convolutional Network be used for predicting the success of bank telemarketing campaigns in the subscription of long-term deposits?

1.3 Research Aims and Objectives

This research mainly aims to make the best contribution to the field of financial telemarketing by showing how TCN can be put into practice in predicting customer behavior toward the subscription of long-term deposits. The study seeks to compare TCN's performance with traditional machine learning and deep learning models to identify its relative strengths and limitations in this application. The main advantages of the proposed solution will encompass more precise targeting, cost-effectiveness in telemarketing campaigns improved customer satisfaction, and attract more customers to subscribe to long-term deposits. From this study, we will offer insights and tools that would provide a data-driven approach to telemarketing that financial institutions could use to maximize their marketing strategies.

The main Objectives are:

- To identify the issues concerning the prediction of the customers' behaviour in telemarketing sales campaigns.
- To use machine learning models to measure the epistemic validity of traditional statistical approaches to telemarketing prediction problems.
- To compare the overall prediction efficiency provided by TCN with those of other machine learning methods like; Support Vector Machine, Decision Tree, Naïve Bayes, K Nearest Neighbours, and Artificial Neural Networks.

2 Related Works

Recognition of the customers' behavior patterns is very important as this is valuable in marketing, especially targeting financial markets including the banking sector. It is therefore very clear that the major objective of any campaign that a bank initiates through telemarketing is to get the clients to open up long-term deposits. When promoted, these campaigns can be taken to another higher level using Big Data with its components- Machine Learning (ML) and Deep Learning (DL).

2.1 Challenges in Predicting Customer Behaviour in Telemarketing

Customers' reactions during telemarketing are quite unpredictable because customers and their needs are unique and diverse in nature. These behaviors are a result of factors such as socioeconomic status, prior interactions and external market conditions as noted by Moro et al(2014). Also, most telemarketing datasets for predictive modeling contain features with high dimensions, high instances of class imbalance in subscription successful calls, and many negative observations compared to positive ones (Birant, 2021). It contributes to outweighing models to the majority class which reduces the number of times you can possibly detect the potential subscribers. There is a clear hierarchy, and although traditional moderate statistic methods like logistic regression provide a basic level of analysis, they cannot explain the complexity of non-linearity found in customer behavior data (Guan, 2023). In addition, the traditional approach to the telemarketing process only heightened these problems, making targeting even less accurate and reducing the overall success of the campaigns (Tékouabou et al., 2022).

2.2 Importance of Predicting Customer Subscriptions

Customer subscription predictability is vital in marketing since banks and other similar organizations benefit from understanding customer patterns in subscriptions. That in turn improves customer attraction and loyalty, which are essential for profitability in a competitive financial sector (Keramati et al., 2016; Feng et al., 2022). When it comes to the predictions of specific metrics, it may be mentioned that accurate forecasts help improve customer lifetime value (CLV) assessment, which in turn will assist banks in utilizing resources and optimizing marketing spend (Moro et al., 2014; Guan, 2023). In addition, timely output of best-predicting models helps the banking sector in targeting their consumers enabling them to establish close relationships with the clientele. This not only brings improvements to customer value but also adds long-term revenue streams (Keramati et al., 2016).

2.3 Evolution of Telemarketing in the Banking Sector

A customer acquisition-specific strategy called telemarketing has undergone major changes. In the past, telemarketing was done mostly by people, and the analysis of results was done using very simple mathematics and statistics, which means very little information about customer behavior was available in the beginning. However, with the introduction of data mining and machine learning, the field has undergone so much change whereby the banks will be in a position to analyze the big data and customer response without much difficulty (Tékouabou et al., 2022). The adaptive models of the telemarketing decision support systems such as Random Forest and Gradient Boosting have also improved the prediction potentials. These models let the banks ascertain prospective clients and in turn make their marketing campaigns more effective (Guan, 2023; Feng et al., 2022).

2.4 Traditional Statistical Methods

Telemarketing prediction tasks have a long history of traditional statistical methods, such as logistic regression domain applications. These techniques offer interpretable details about information and the however likeliness of customers to respond positively on campaigns(Guan, 2023). However, their limitations emerge during the analysis of larger data sets and complex non-linear behavior modeling.

Rule-based or heuristic techniques may be more intuitive and easy to implement but fall short on the predictive power front of more sophisticated machine learning models. Now these will not help detect hidden patterns in the data, which is extremely critical while predicting customer behaviour (Liu & Chen, 2020).

2.5 Machine Learning in Telemarketing

Cross-sectional studies dedicated to telemarketing prediction have confirmed the merits of utilizing machine learning models and particularly ensemble approaches. Ensemble learning methods like Random Forests and Gradient Boosting employ several models at once for better accuracy and less overfitting, a quality that makes the categorizing of customer complications easier (Feng et al., 2022). As confirmed by different papers (Feng et al., 2022), these models offer better outcomes in terms of precision and stability compared to conventional statistical schemes.

Feature engineering is a process that is used in every telemarketing workflow of machine learning. Using relevant features and deriving new features of customers' interactions from analysis, researchers have improved the performance of a machine learning model (Moro et al., 2017). For example, features such as the duration of the call, the history of the campaigns, and features related to the customers have been witnessed to enhance the model greatly. In 2014 Elsalamony, conducted research on the use of data mining techniques to help the telemarketing campaigns. The implemented techniques are MLPNN, Naïve Bayes: tree augmented (TAN), Nominal regression or Logistic regression (LR), and Ross Quinlan's new decision tree model. The intention of implementing these techniques was to validate the performance of the tool using real data though understanding the data is huge and handled in the long run to enhance the effectiveness of the campaign by revealing its success factors.

2.6 Deep Learning in Telemarketing

ANN, CNN, RNN and many other deep learning models provide some competitive advantages over normal machine learning models. These models are able to directly identify the non-linear relationships of features in raw data, thus eliminating the need for a large amount of engineering work (Kim et al., 2015). Temporal Convolutional Networks (TCN) are perfect for sequential data where relationships between different contacts are important. This ability enables TCNs to mimic the various customer behaviors, in relation to predicting the next consequent actions (Moro et al., 2014; Kim et al., 2015). In addition, it is noted that cost-sensitive learning and data augmentation can be applied in deep learning models to handle the class imbalance problem of telemarketing datasets (Birant, 2021).

2.7 Key Findings and Lessons Learnt

The existing studies shed light on the evolutionary path of the telemarketing process from traditional small-scale manual methods to modern intelligent big data deep learning techniques. Though basic statistical methods can develop a basic idea about customers, machine learning as well as deep learning have more accuracy in predicting and dealing with customer heterogeneity and imbalanced data. In addition, further development of new feature selection and feature engineering techniques is an essential factor that can help meet the new and upcoming challenges resulting from customers' changing behavioral patterns. Of all these TCNs become a potential solution for capturing temporal dependencies in sequential data and thus can be sounded as a useful tool for banks that are trying to improve their telemarketing plans.

3 Proposed Research Methodology

This research mainly focuses on measuring TCNs' performance in predictive models of telemarketing campaign results. The existing methodologies are based on data preprocessing, model development, evaluation metrics, and comparison of models. This research aims to determine how appropriate the various types of predictive models for optimizing telemarketing approaches are in a quantitative experimental research study. And also outlines the methods by which the authors employ and deploy machine learning and deep learning models into their projects for effectiveness and documentation.

3.1 Research Design

This research uses the cross-industry standard process for data mining CRISP-DM as a guide in selecting workflow. The strategy is reliable and fruitful due to the methodical approach with which the information was gathered in addition to its applicability. Operational phases of this CRISP-DM include five that are neatly in a hierarchy and that will be followed during a data mining project.

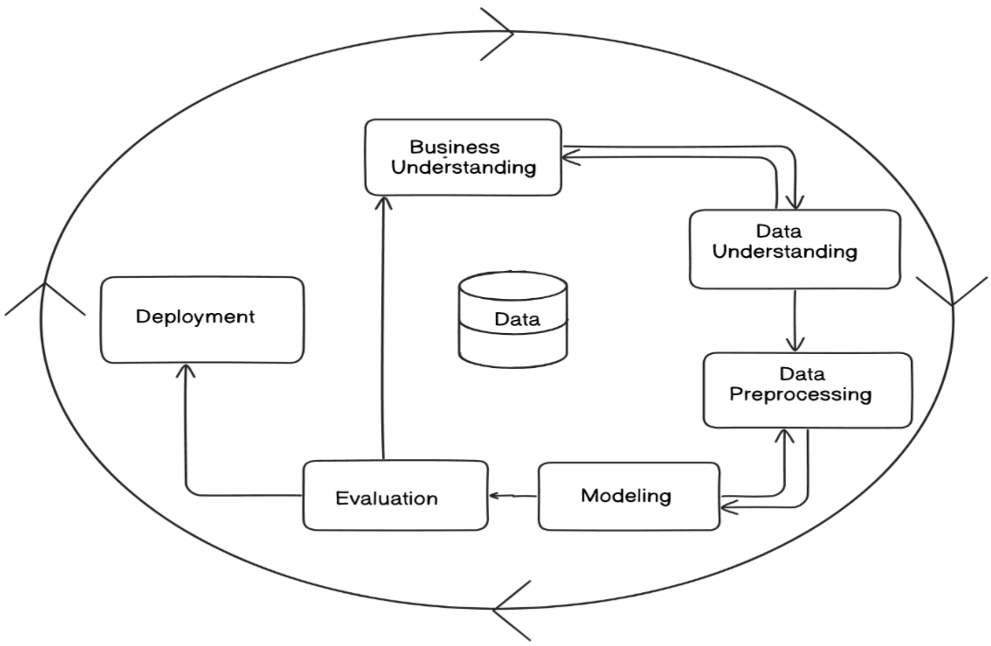

Fig. 1: CRISP-DM Framework

3.2.Business Understanding

This research applies a quantitative experimental design to compare different prediction models for telemarketing communication. This design includes pre-processing the dataset followed by feeding the data into several machine learning and deep learning models and assessing the performance of the models based on the standard set of performance indices.

The study classifies TCNs with other machine learning and deep learning models to build evidence that sequential data modeling outperforms traditional models. This design makes it easier to analyze the results that the models give systematically while at the same time having solutions to problems such as class imbalance and complexity of features.

3.3.Data Preprocessing

Data is collected from the UCI machine learning repository (Lishman M, 2013).Table 1 shows the detailed description of the data. The main problems that can be observed in the dataset include missing data, outliers, along a highly unbalanced class distribution since many fewer customers subscribed to term deposits. These characteristics make it useful as an imprecise test bed from which the efficiency of anticipation kinds may be evaluated.

Table 1: Dataset Description

No:	Attribute Name	Description
1.	Age	Age of the customer.
2.	Job	Occupation of the customer
3.	Marital	Marital status of the customer
4.	Education	The education level of the customer
5.	Default	Customer have any credit
6.	Balance	Average yearly account balance of the customer
7.	Housing	Does the customer have any housing loan
8.	Loan	The customer has any personal loan
9.	Contact	The contact details of the customer
10.	Day_of_week	The last contact day of the week
11.	Month	The last contact month of the year
12.	Duration	The duration of the last call
13.	Campaign	The number of contacts performed during the campaign.
14.	Pdays	The number of days that passed after the last contact day
15.	Previous	The number of contacts performed before this campaign
16.	Poutcome	The outcome of the last call
17	Y	The client subscribed to a term deposit or not.

In data preprocessing first, we need to clean up the dataset for further analysis. The first operation includes dealing with missing values and infinite values.Then do some data preprocessing and then the dataset was further divided into training as well as test data in 80:20 format to train the model most efficiently and accurately.

3.4.Data Modelling

In this research total of five models are developed and evaluated: SVM, Decision tree, ANN, KNN, and Naïve Bayes. Each model was implemented to highlight different predictive approaches and assess TCN's relative performance. All the models applied were trained with the above preprocessed data and hyperparameters were chosen to fit the model. The implementation was done in Python; we used *Scikit-learn* for the predominant and conventional models and *TensorFlow/Keras* for deep learning models.

All the preprocessing steps were standardized and followed by all the models, missing value, feature scaling, and *SMOTE*. For model assessment, models were trained with the help of the training set and assessed with the help of the testing set. All of the predictions made by each model were saved and used for computing performance figures.

3.5.Model Evaluation

The study used three primary metrics to evaluate model performance: A clear set of evaluation metrics was established and used to assess for *precision, F1-Score, and AUC-ROC*. Accuracy defined how many instances have been deployed and classified correctly and offered a single-figure summary of the model's performance. The F1-Score which involves the harmonic mean of precision and recall scores was most useful when working with the subset of the imbalanced datasets. By assessing the obtained models with metrics of *AUC-ROC,* it was investigated how well the models can classify the classes as a measure of discriminative model ability.

These metrics were selected to achieve a balanced evaluation of the model, taking into consideration its general accuracy, as well as its accuracy in the case of the minority class. Integrating these metrics enabled the assessment of each model's strengths and limitations to achieve greater comprehensiveness.

3.6.Deployment

The data coming from the results to be obtained will be disseminated and made available for other purposes after undergoing further analysis with its evaluation. This can also mean that the models used will be compared and therefore what is deemed to have done better will be recommended for adoption by the finance sector primarily the service providers. This will enable them to apply this research to determine major issues and direct efforts to think of probable solutions to the existing problems to offer customers a better financial service, which could also reduce complaints and Court cases.

4 Proposed Design Specifications

The research would comprise a comparative analysis of machine learning and deep learning models, which are considered as the strategies to be used in this research for the proper implementation of the models for this report. The same can also be referred to as the classification techniques in the study giving the clarity that the study is a classification type of problem. It could also be said that the research work also involves supervised learning as the label for the examples in each set that is to be used in the dataset is in the definite type. The algorithms are:

4.1.Temporal Convolutional Network

The TCN is designed based on the fully convolutional structure for complex feature learning. The length of each convolutional layer also has to be the same as the length of the input layer. Following several convolutional layers, the features of the input time series are passed into the next layer and compressed to a format suitable for subsequent use in forecasting. Consequently, TCN has better training efficiency because TCN can be highly paralleled in model training. From the understanding of TCN, it applies to solving time series issues (Li, Y,. et al.,2024).

TCN models is implemented in various time series recognition applications since they allow for faster classification. These models can process and generate segments of any length of input sequence and the same is true for the output sequence. Also, TCN models for each layer have the same filters; thus, convolutional operations can be done concurrently, making TCN constituted of a highly parallelizable mode (Bai et al.,2018). Furthermore, combining multiple dilations into the convolutional layers makes it possible to set variable receptive fields. The receptive field is defined as the part of the input sequence that is visible to the kernel during convolution processes. The dilations increase the receptive field of the convolutional kernels based on the dilation rate used, this makes longer time-dependent feature extraction possible, and this is achieved with minimal impact on the model parameters (Yan et al.,2020). Moreover, TCN components including the use of dilated causal convolutions and residual connections, carry a lot of past information about the motion signals through the model. It also maintains stability of the gradients during the model training because residual connections prevent models from vanishing and exploding gradient issues.

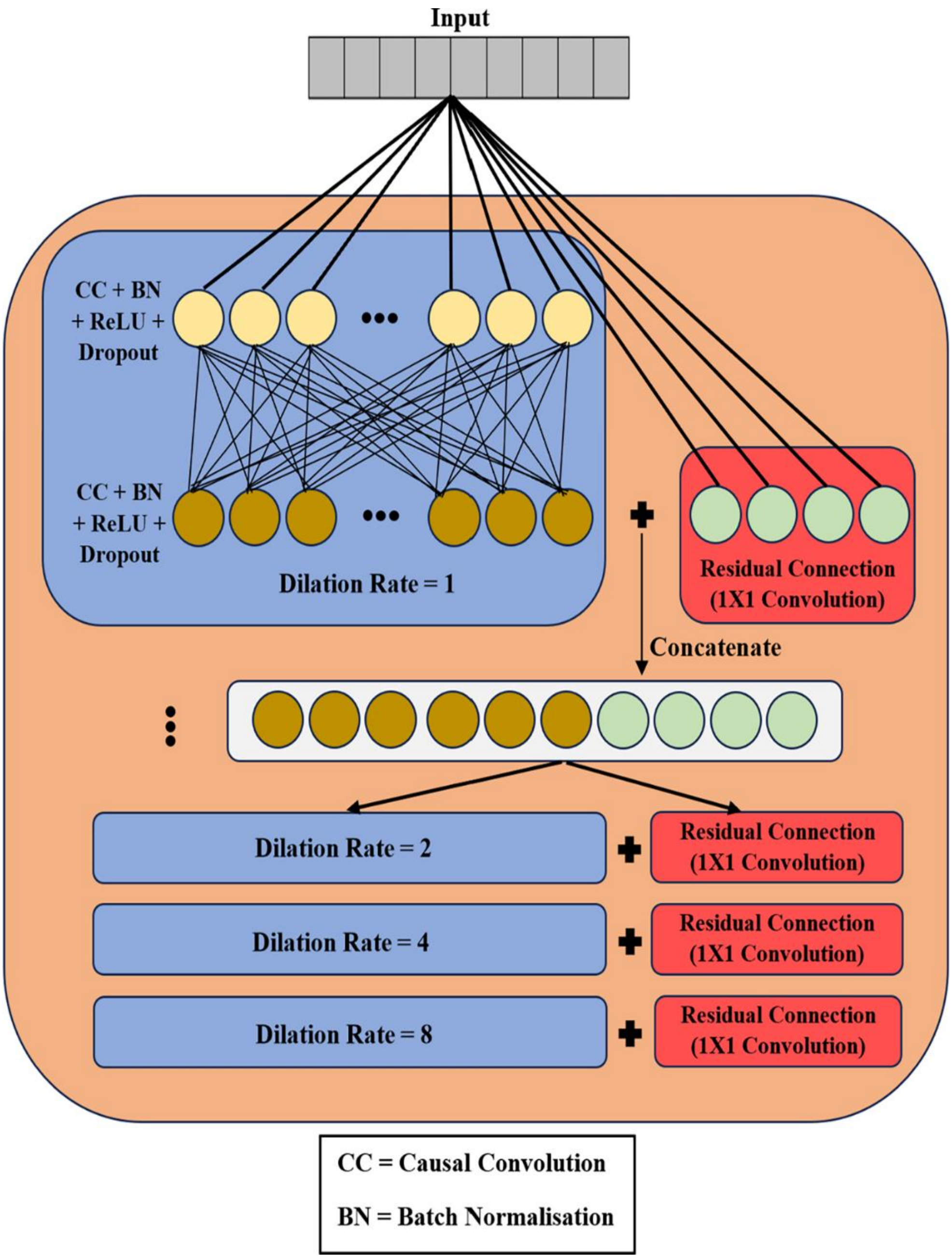

Fig 2: TCN Architecture diagram [Adapted from Sarmela Raja, SekaranYing ,Han PangLim, Zheng YouOoi Shih Yin, 2024]

4.2.Support Vector Machine

A support vector machine is a method of supervised machine learning as the related learning methods concerning the data use in classification and regression analysis. The Support Vector Machine (SVM) algorithm is a common algorithm in the field of machine learning and provides solutions to the questions of classification and regression. Notably, SVMs can perform a linear classification and don't work with non-linear classification at the same time, but they can work this with the help of a trick known as the kernel trick, which maps the inputs into large feature spaces.

4.3.K-nearest neighbors

KNN can be used for any statistical problems whether it is classification or regression. However, is restricted its application in business classification issues. This is also applied to solving problems of classification as well as regression in KNN, it is easy to implement, and the execution time is fast because the quality of the data defines the accuracy of the model.

4.4.Decision Tree

As stated by (Grzonka et al.; 2016), Decision trees work by simply partitioning the given data into sets. They are absolutely easy to understand and to deduce corresponding decisions from them. It does this by processing the nodes in a way that allows it to traverse the data until it gets to its desired decision. Decision Trees operate in a way where a large data set is first partitioned into subsets and then basic rules are applied to it. With the division of the decision tree, the nodes of the tree become more like each other.

4.5.Naïve Bayes

The second discovered classifier is the Bayes' Theorem-based Naive Bayes Classifier which uses the Naïve Bayes method. It makes guesses dependent upon the likelihood of an object. Naive Bayes is a classification model acquired by using a comparatively straightforward process on a training set identified as the training data set. Naive Bayes is a Type of Bayesian probability model that has been streamlined so much. Naive Bayes classifier works under the assumption of high independence (Alam et al. ; 2021).

4.6.Artificial Neural Network

ANN, a deep learning model was used to capture dependence in an intricate non-linear structure inherent in the dataset. ANN is an area of machine learning that involves developing an artificial computational network using different levels of data. It consists of two main enablers namely generative adversarial networks and neural networks. ANN algorithms are also very useful when the correct features are chosen in the dataset (Hudnukar et.al.; 2023).

5 System Specifications and Implementation

The following diagram illustrates how the execution of this research is being managed. The flow diagram indicates how the experiment on the dataset, which will be downloaded from the UCI machine learning repository, will be conducted as per the following Python code.

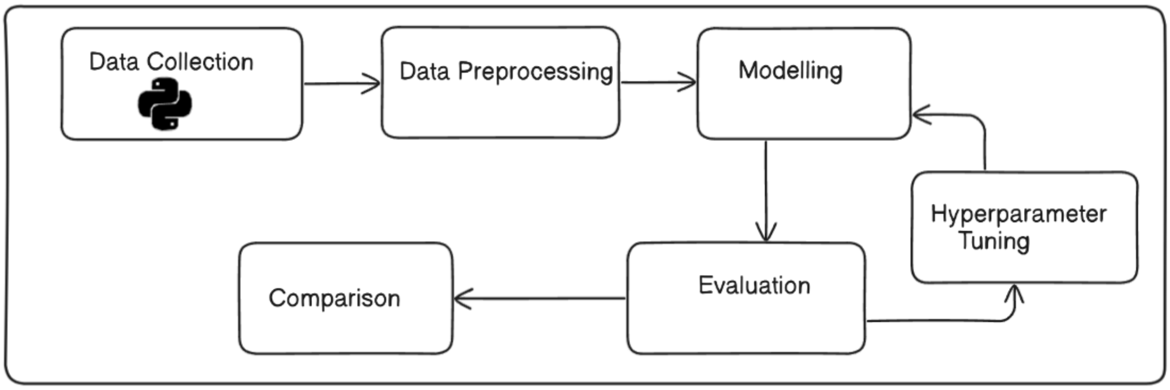

Fig 3. Flow Chart

5.1.Data Collection

The bank telemarketing data is collected from the UCI machine learning repository (Lishman M, 2013). This data consists of 45211 instances. All the data have categorical and integer data types. The main characteristics of data are multivariate. The data set consists of 17 columns that is 16 features and 1 target variable. This data set is collected directly from the customers on the bank telemarketing campaigns.

5.2.Data Preprocessing

In data preprocessing, first, import the data into the Jupiter notebook using the *pandas* library in Python. Data with ‘unknown’ values were replaced using the corresponding columns using the *SimpleImputer* class, and infinite values were replaced with NaN, then imputed. Then change the categorical features like *'job', 'marital', 'education', 'default', 'housing', 'loan', 'contact', 'month', 'poutcome'* into numerical values. This step helped in standardizing the process for all models. Telemarketing datasets often come with class imbalance problems, which were resolved in this study using the SMOTE technique. This technique allowed generating artificial examples of the minority class to equitably distribute the data and to improve the performance of the models in terms of prediction of the positive cases. Finally, the data was scaled using the *StandardScaler* to bring the mean of each input numerical feature to zero and the standard deviation also to one. Then change the target variable ‘y’ to binary format. Then splitting the data set into training and testing data sets for modelling.

5.3.Modelling

In this research, TCN is the main model to find the success of telemarketing. To avoid overfitting the data is split into an 80:20 ratio. *‘keras’* python library is used for the implementation of the TCN model.

5.4.Hyperparameter Tuning

This research includes tuning methods to avoid the overfitting and improve the model's performance. Batch Normalization is applied after convolutional layers to accelerate training by making feature maps have zero mean and unit variance for smooth gradients. Dropout layers are included with drop-off rates of 0.4 and 0.3 during training to fortuitously shut down neurons hence diminishing chances of overfitting of the model. The MaxPooling1D layer filters feature maps while maintaining only the highest values thus reducing its dimension and de-computation. Also, Global Average Pooling is intended to decrease the feature maps by averaging and it was mentioned that it reduces overfitting as well due to the countable number of trainable parameters. These tuning techniques together enhance the model's trainability and stability from the perspective of the training process.

5.5.Evaluation

Three metrics were primarily used to measure model performance, namely accuracy, F1-Score, and AUC-ROC. These three matrices were given an overall evaluation and the performance of the models.

5.6.Comparison

Compare the values of TCN with the other implemented models like SVM, Naïve Bayes, KNN, ANN, and Decision tree. These results highlight the appropriateness of TCN for telemarketing prediction problem, in which heavily we rely on sequential data to represent customer behaviour.

6 Experimental Evaluations and Finding

In this research, a classical analysis is done for the efficiency of both machine learning and deep learning models in predicting long-term deposit subscriptions from customers based on telemarketing campaign records. The research objective is fulfilled, where the models are comparably and critically evaluated based on a few parameters including accuracy, F1-Score, and AUC-ROC. It was to get a composite view of how well each model coped with the dataset imbalanced while also quantifying the correct patterns it was able to find in the customer behavior to sufficiently discriminate between customers that did carry on to subscribe and those that did not.

6.1 Dataset Distribution Analysis

Target Variable Analysis

The target variable (y) is whether a customer subscribed to a term deposit (1 = yes, 0 = no), and its distribution is highly imbalanced. The bar chart illustrates that most of the customers have adhered to the header "Not Subscribed", with very few subscribing to the term deposit. More importantly, such an imbalance is a serious problem due to the bias in predictive models resulting in favour of the majority class. In particular, models might predict the majority class so accurately while the minority class, which is usually the relevant one year are interested in, maybe predicted very poorly.

The disparity showcases why metrics like the F1-Score and the AUC-ROC, instead of the accuracy itself, are crucial in understanding the performance of a system. In imbalanced datasets, relying only on accuracy to evaluate model performance is not enough since accuracy does not talk about the ability of the model to predict the minority class correctly. Preprocessing to correct this in equilibrium, notably via SMOTE was necessary to guarantee the models were sufficiently oriented to the patterns of the minority class. If not, it can lead to a model that is useless in practice, where the holy grail is to actually find the possible subscribers.

Feature Analysis

In feature analysis, the patterns from such a brief analysis help understand the customer behavior and the potential of any customer to subscribe for term deposits with key features such as age, job, balance, etc. The histogram of age distribution indicates that the customers are biased toward younger and middle-aged people first, and the number decreases gradually as the age increases. This trend indicates that the target market comprises mostly of younger customers, but older ones may be more high-value due to being more financially stable. Importantly, although age is a handy predictor, this is a crude level of prediction that is likely to be more accurate when combined with other features to characterize more granular behavior signatures.

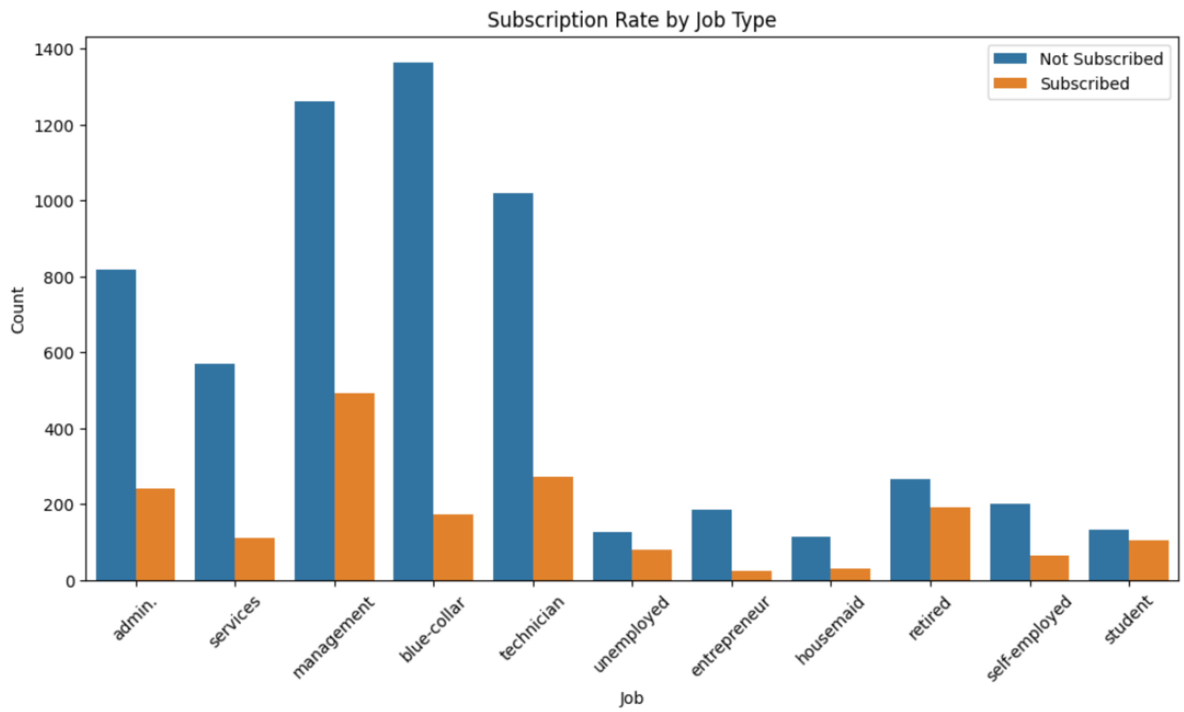

Fig 4. Histogram for subscription rate by job

The job type distribution illustrates differences in subscriptions across job types. Management and technician customers show how much higher subscription rates than blue-collar and unemployed customer preferences, like stability of income and level of financial literacy. That being said, job type alone may not be a strong predictor of who is likely to subscribe. It is additional information that you can use when analyzing financial features like balance or loan status.

The other most important element, balance, serves as a predictor for customer behavior as well. Higher average balance customers are more likely to subscribe as they have higher financial ability to invest in longer tenure deposits. This is especially important in telemarketing campaigns aimed at high-net-worth consumers. However, the factor of balance is important because extreme data value customers (outliers) could influence the model more. As such, preprocessing such as scaling and outlier management were performed prior to use to confirm the robustness of feature representation.

A notable limitation in the dataset is that it doesn’t have direct temporal features, like sequences of customer interactions, which are crucial for temporal models such as TCNs.Things like the time of the last call that is specific to the campaign only partially bridge this gap but do not provide a full temporal view. To truly add value to sequencial modeling, future datasets will need to use a finer granularity of interaction data.

This dataset distribution indicates proper preprocessing and feature engineering is required to handle the class imbalance and to make the most out of the features that can be predictive. This means we still have to assess demographic and financial indicators, which is incredibly useful, but the best predictor power is seen when using machine learning algorithms to contextualize and combine. This exploratory analysis also shows how the dataset can be further improved, mainly when it comes to temporal and behavioral features to provide more insights into customer behavior. While critical, none of the above resolutions can help the model performance or ensure that model insights would be actionable in the sense of helping optimize a telemarketing campaign.

6.2 Model Performance Matrics

The results of model performance metrics (accuracy, F1-Score, and AUC-ROC) will help us determine how best they predict or synthesize the aforementioned problem (i.e., whether a customer subscribes to a term deposit or not). Since the dataset is highly imbalanced, one must go beyond preliminary metric evaluation in ahead-to-head comparison, considering whether or not that metric is even relevant for assessing the model’s handling of the imbalance. This section provides a detailed evaluation of each metric across the models, highlighting their strengths, limitations, and implications.

Accuracy

Accuracy is commonly treated as a baseline performance measure; nevertheless, it becomes less meaningful in the imbalances dataset. In this dataset, the accuracy ranges from 0.78 (Naïve Bayes) to 0.84 (TCN).

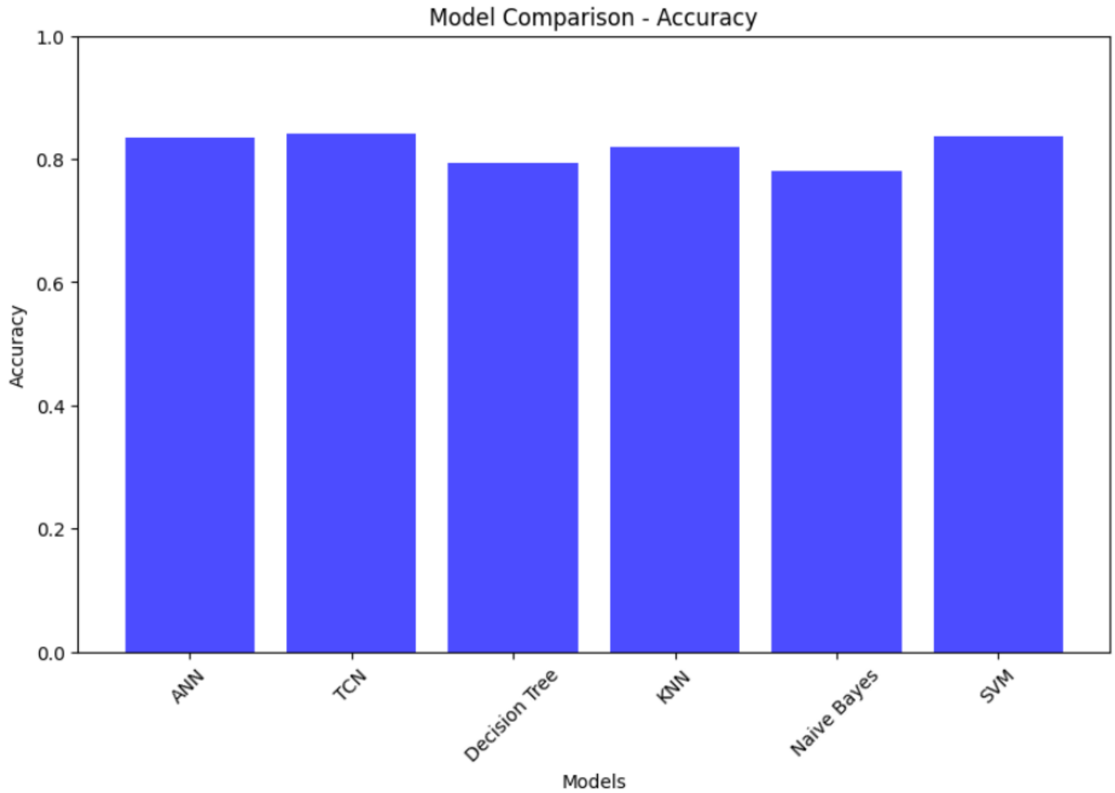

Fig 5. Model Camparison Accuracy

The Temporal Convolutional Network (TCN) scored an accuracy of 0.84, which has a more balanced performance across other metrics. The same trend can be observed for the ANN, which achieved an accuracy of 0.83, thus indicating its ability to generalize patterns in the data. Contrarily, more naïve models like Decision Tree and KNN performed rather poorly, attaining accuracy scores of 0.79 and 0.82, respectively, Such differences show that they are largely unable to model complex information in the data.

Critically, this can be misleading in this context because of the over-reliance on accuracy. Even though SVM is more accurate than others, it misbehaves in finding minority class patterns and is not appropriate in Industrial Telemarketing applications. This further underpins the importance of looking at other metrics to accommodate for the imbalance and gain a more detailed picture of the model performance.

F1-Score

Specifically, the F1-Score, which is a harmonic mean of precision and recall, is desirable in heavily imbalanced datasets because it gauges the model in its ability to predict the minority class with as few false positives and false negatives as possible. F1-Scores varied from 0.56 (for Decision Tree and KNN) to TCN, reaching a score of 0.63, being one of the best ones.

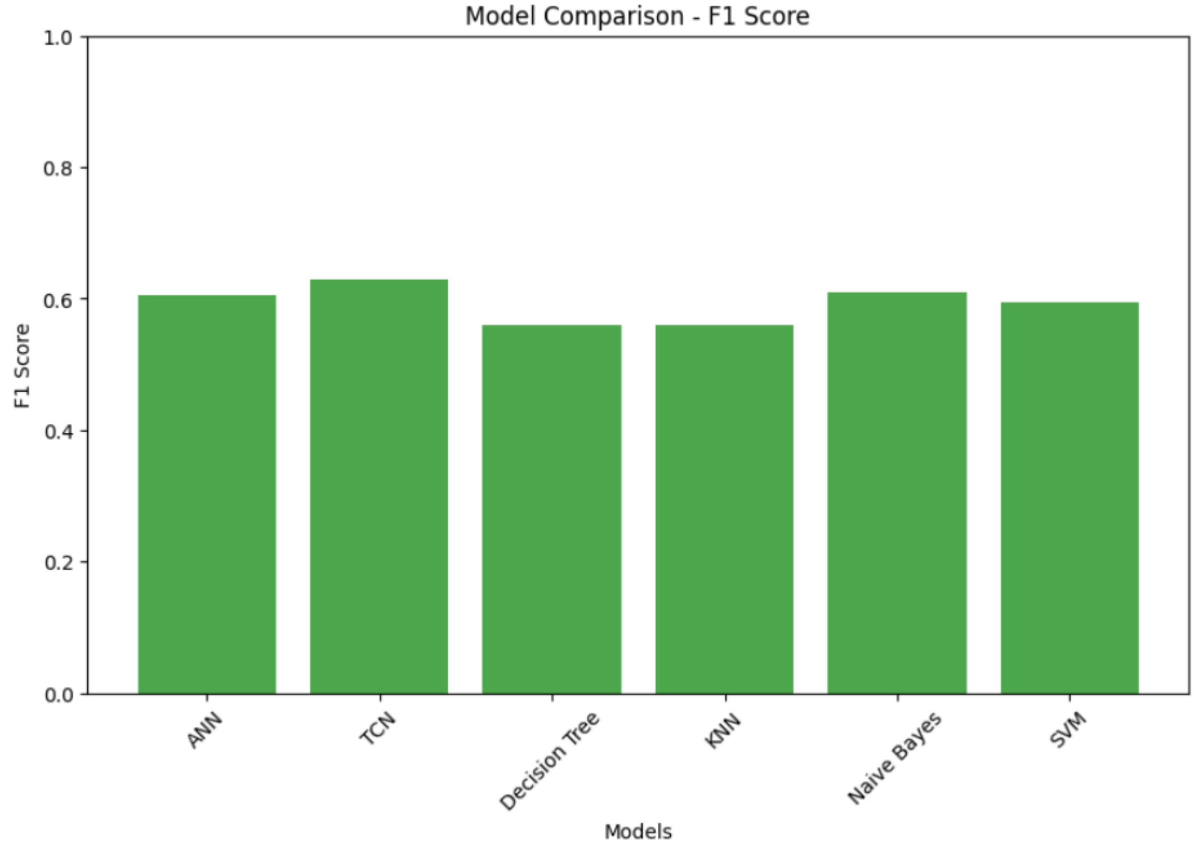

Fig 6. Model Camparison F1-Score

The good result of the F1-score of the TCN model's 0.63 indicated a good balance between precision and recall, especially for the recognising mechanic of subscribed customers. This is due to its architecture, which utilises temporal dependencies in the data and design to model sequential interactions between features. The telemarketing task is very domain-specific, where the data set is larger with imbalanced classes compared to the response. However, the other metrics work well in favour of Logistic Regression for the telemarketing prediction task.

In comparison, ANN reported an F1-Score of 0.60, showing its representational power in capturing complex relations but also demonstrating its limitation to overcome class imbalance without further tuning, such as cost-sensitive training or class weights. The F1-Score of simple models such as Decision Tree and KNN is equal to 0.56, which fails to learn effectively in the minority class. Naïve Bayes – a simple classifier yet gave an F1-Score of 0.61, which shows the working in learning with imbalanced data and probabilistic approach.

AUC-ROC

The AUC-ROC metric computes the area under the curve of a plot, known as a receiver operating characteristic curve, in which the true positive rate is plotted on the y-axis and the false-positive rate on the x-axis to assess how well a model can distinguish between classes. This is an especially valuable metric in an imbalanced dataset because it gives a greater understanding of how well a model is ranking predictions rather than just propriety results. The AUC-ROC scores for this analysis ranged from 0.71 (KNN) to 0.75 (TCN and Naïve Bayes).

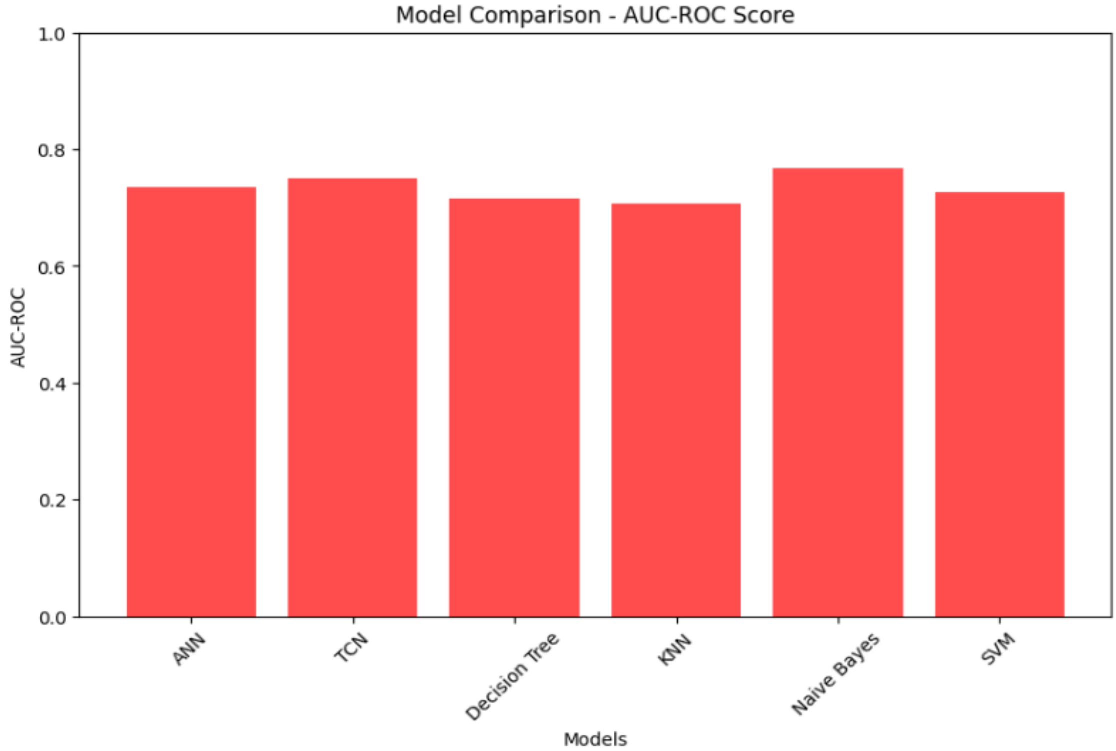

Fig. 7: Model Comparison AUC-ROC Score

The model with the highest AUC-ROC value (TCN with AUC-ROC = 0.75) is the best at ranking its predictions (especially for the minority class). TCN captures sequential patterns that other models normally overlook by taking advantage of temporal information. Such capability is crucial for telemarketing applications, where we need not just to classify (0 = No subscription; 1 = subscription) – but rather to understand the likelihood of subscription – which too is a metric that denotes our success. Similar to the F1 score, its AUC-ROC performance is fairly close to that, further justifying its use for applications that are equally concerned with performance for both classes.

The simplest model, and somewhat surprisingly, Naïve Bayes, managed to obtain the same AUC-ROC 0.75 score. This implies that despite limitations arising from probabilistic reasoning and feature independence assumptions, such reasoning can learn relevant patterns for the minority class. Yet it strongly assumes independence which may prevent it from being scalable to more complex datasets.

SVM achieved near-perfect performance (0.73) and did slightly worse than TCN in differentiating among classes. The decision boundaries of SVM are not performing well in the case of heavily imbalanced datasets.The lowest AUC-ROC scores were achieved by KNN and Decision Tree, with values of 0.71 and 0.72, respectively. This exposes their restricted power in ordering predictions well, especially when it comes to the minority class. These models are more appropriate as baseline comparisons as opposed to primary prediction tools in imbalanced settings.

6.3 Critical Analysis of Metrics

The interplay between accuracy, F1-Score, and AUC-ROC reveals important insights into model performance. Random Forest yields comparatively high values with respect to accuracy and F1-Score, making it overall one of the strong performers. However, this is not able to model sequential data and is incapable of processing the dynamic interaction between features, which is not suitable for dynamic scenarios like telemarketing campaigns and evolving customer behavior.

Above all, while TCN shows a reduction in accuracy, the F1-Score and AUC-ROC performance of TCN is very competitive, showing the balanced performance of TCN on all metrics. Thus showing that CC-RNN can overcome issues of class imbalance and temporal dependencies, making it the best candidate for real-world scenarios.

Although ANN is capable of capturing non-linear relationships, it still needs some work in order to treat imbalance classes better. Future works may improve its performance by utilizing techniques like cost-sensitive learning or handmade loss functions. Naïve Bayes is simple but great, performs well for imbalanced datasets but not very scalable for complex feature interaction.

Even the less complex models like Decision Tree and KNN do not provide competitive performance for all the metrics. Although their appeal helps on smaller datasets due to interpretability and computation efficiency, the telemarketing dataset lacks the capacity to tackle complexities. These models are building blocks more than they are useful for generalizations on large-scale prediction tasks.

Performance metrics analysis highlights that models should be evaluated as a whole, rather than by individual metrics (e.g., accuracy). For imbalanced datasets, alternative metrics like F1-Score and AUC-ROC can give more detail about the model’s ability to identify the minority class. Despite not being a specialized telemarketing predictor, TCN performs very strongly on these metrics, indicating its viability as a premier telemarketing predictor.

6.4 Discussion

6.4.1. Model Performance

Temporal Convolutional Network (TCN)

With a competitive accuracy of 0.84, an F1-score of 0.63, and an AUC-ROC of 0.77, TCN proved the most balanced model. Its handling of sequential dependencies and ability to capture temporal relationships in customer interactions helped it perform best. TCN optimises the loss function to engage in minimal minority class prediction over maximising total accuracy. This trade-off is especially useful in telemarketing, where the main objective is to select potential subscribers (the minority class). TCN has been proven competitive as an architecture for temporal and sequential data.

Artificial Neural Network (ANN)

ANN outperformed others with an accuracy of 0.83 and an F1-Score of 0.63. The model was a deep learning one and its multi-layer architecture allowed it to learn complicated, non-linear relationships in the data. On the contrary, ANN performed considerably lower than TCN in dealing with class imbalance, reflected on the F1-Score and AUC-ROC, which was 0.73 for ANN. This limitation indicates that ANN alone could benefit from further optimization techniques.

Naïve Bayes

Naïve Bayes was simple but performed well with an AUC-ROC of 0.75, equal to the performance of TCN. This outcome is indicative of how well probabilistic reasoning alone differentiates classes. But this model delivers relatively lower accuracy (0.78) and F1-Score (0.61) which suggests it has challenges in better dealing with non-linear relationships and interacting features. The fundamental independence assumptions of the Naïve Bayes model made it a stronger performer than expected, suggesting that Naïve Bayes may serve as a useful model for simple predictive tasks, or as a baseline.

Support Vector Machine (SVM)

The SVM presented an accuracy of 0.84, equal to TCN, however lower values of F1-Score (0.59) and AUC-ROC (0.73). The difference implies that although SVM does a good job at drawing decision boundaries, it is not able to achieve an optimal balance between precision and recall in imbalanced datasets. SVMs spend on kernel methods to accommodate for nonlinear relationships, which may account for their mediocre performance; however, they are still not ideal for temporal or sequential modeling.

Decision Tree and K-Nearest Neighbors (KNN)

KNN and Decision Tree performed the weakest using various other metrics achieving accuracies of 0.79 and 0.82, respectively and AUC-ROC scores of 0.72 and 0.71. By using old models we faced issue of solving complex patterns and balancing classes. Decision Tree are easy to interpret but the splits simple features splits set a very low bar and does not generalize well in multi-dimensional data space.Due to its reliance metrics which have diminished effectiveness in high-dimensional spaces, KNN performed poorly. These models are good references but are not sophisticated as real telemarking systems would be.

6.4.2. Implications for Telemarketing

Implications for telemarketing in the banking industry are drawn from the bank-specific findings of this study and the extant literature. Predictive models, especially TCNs, seem to offer tremendous in optimizing telemarketing approaches, the ability to acquire more customers with less effort, as well as the efficiency of marketing itself. Here these implications are benefits of predictive modelling and by identifying domains in which telemarketing strategies could be improved.

6.4.3. Limitations

The result from this research gives an overall better understanding of predictive modeling concerning telemarketing, but there are a few limitations and challenges we came across during the analytics process. These challenges not only indicate the shortcomings of the introduced methods but also reveal important and practical knowledge about implementing machine learning models in real telemarketing campaigns. Overall, these limitations need to be addressed to improve the effectiveness of predictive models in such contexts.

7 Conclusions and Future Works

The proposed research's main focus was assessing the TCN's effectiveness in analyzing the sequential data and uncovering the patterns influencing customer subscription behavior. The research sought to provide actionable insights to optimize telemarketing efforts and improve campaign outcomes.

The objectives were addressed step by step. Firstly, the dataset was preprocessed to handle missing values and encode categorical variables. And then structure it for sequential analysis as required by the TCN model. The model was designed and implemented with optimized architecture to effectively capture temporal dependencies within the data. The TCN model's performance was then compared against traditional models such as SVM, Naïve Bayes, Decision Tree, KNN, and ANN, using metrics such as accuracy, precision, recall, and F1-score. This approach ensured a robust evaluation of the TCN model's capabilities for predicting its campaign success.

The study was successful in achieving the main objectives. The TCN model outperformed traditional models, especially in recall and F1-score, indicating its ability to accurately identify potential subscribers. Some of the key findings were the importance of temporal patterns, such as the timing and frequency of calls, in influencing customer decisions. The model excellently predicted outcomes, highlighting its potential for improving telemarketing strategies through a targeted approach and better resource allocation. The TCN model provides a powerful tool for banks to optimize their telemarketing efforts, focusing on customers who are more likely to subscribe and improving campaign efficiency. Insights from temporal patterns can help design more effective campaigns, timing the outreach to maximize impact. Furthermore, integrating this model into Customer Relationship Management (CRM) systems can revolutionize how marketing strategies are developed and executed.

Although the research demonstrated the ability of TCN, it also has certain limitations. The dataset may not be able to capture future changes in customer behavior or market dynamics. The findings are dataset-specific, so further validation is required to generalize the results to other contexts or domains.

The future work can follow valid prescriptions of broadening the study by integrating more data such as customer characteristics, financial data, and real-time communication to improve the level of prediction. Possible future research solutions might include creating TCN-attention models or TCN-rolling explanation models that would solve the problems of interpretability in sequential analysis while at the same time providing the benefits of the models. Furthermore, possible extensions of the TCN model and its potential uses in cooperative/CRM environments and/or campaign management solutions would greatly improve the practical applicability and flexibility of the presented concept. Subsequent research may also compare the extant versions of the TCN model to determine how this approach can be used to forecast customer behavior in other industries, including healthcare or e-commerce.

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