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Original Article

Machine Learning for Suspicious Behaviour Detection and Churn Prediction in Telecom Customer Call Data

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Abstract *- Auto dealerships get tens of thousands of calls every day from people who want to buy, get repairs, sell, or find work. For car dealerships to get the most out of their customer service agents, ensure customer happiness through great experiences, and boost sales and revenue through deeper engagement with customers, it is critical to understand the purpose of all those calls. This paper introduces a framework that utilizes deep learning (DL) to analyze customer call records and identify questionable patterns of behavior, such as customer churn. The approach utilizes a structured machine learning (ML) pipeline to clean the data, handle missing values, eliminate duplicates and outliers, apply Min-Max scaling to normalize numerical features, and use one-hot encoding for categorical variables. 48 elements from three months' worth of call detail records make up the Telecom Customer Churn dataset. Training data makes up 80% of the processed data, whereas testing data is 20% of the total. It developed a Convolutional Neural Network (CNN) architecture to automatically extract hierarchical feature representations and identify intricate patterns in consumer behavior. Conventional ML models such as Logistic Regression (LR), Random Forest (RF), and Decision Tree (DT) are significantly outperformed by the CNN, which achieves 96.5% accuracy, 91.7% precision, 99.8% recall, 95.6% F1-score, and 0.972 ROC-AUC. These outcomes validate the model's exceptional capability in both classification and generalization.*

Keywords *- Artificial Intelligence, Fraud Phone Call Identification, Analysis, Call Center, Deep Learning, Customer Call Intent Prediction.*

1. Introduction

In nations with developed economies, the telecommunications industry is one of the most important sectors, providing essential communication services to both individuals and enterprises [1]. However, problems like customer churn the loss of important clients to competitors are born out of the fierce competition that service providers confront as a result of the increasing number of operators and quick technical improvements [2][3].Telecom service providers lose significant revenues through customer churn, and the issue has become a major challenge posing a threat to long-term profitability [4][5]. Businesses typically respond to this by implementing three primary strategies: increasing customer retention, upselling to current clients, and gaining new clients [6][7][8].

At the same time, there is another urgent problem in the industry of identifying and preventing dubious actions and fraudulent affairs [9][10][11]. The cost of telecommunications fraud has a serious implication on revenue base and the customer confidence which in turn continues to compound due to the evolving nature of the fraudulent activity [12][13][14]. Suspicious activity can be described as actions that can be perceived as leading to an assumption that an individual is involved or on the verge of getting involved in criminal offenses[15][16]. Thus, such cases should be detected on time and correctly. The growth of security equipment like security cameras and sophisticated analytics highlights the significance of providing automated suspicious activity detection systems [17][18][19].

In addition, given the growing incorporation of voice-based channels of communication, they are dealing with auto dealerships that manage a high number of incoming phone calls every day, including sales inquiries and service requests, vendor scheduling and staffing [20][21]. Relating the intent behind the call in such a setting is crucial in enhancing customer experience, effective resource deployment, and overall performance of the business. Nonetheless, it is not that easy to analyze these huge volumes of call transcripts [22][23].

Recently, advancements in AI and ML have made it possible to develop scalable models for churn prediction and suspicious behavior identification in the telecoms business [24]. DL systems configured through massive amounts of labeled data may recognize complicated behavioral trends and aberrations suggestive of churning or fraud [25][26][27]. Also, scalable data labeling algorithms have been presented that label transcript data at the utterance level to increase model training effectiveness[28]. AI-driven systems for predicting client call intents make use of semantic analysis of large-scale call transcripts to improve engagement, detect anomalies, and support decision-making.

1.1. Significance and Contribution

The telecommunications sector faces dual challenges of customer churn and suspicious behavior detection, both of which significantly impact profitability, customer trust, and operational efficiency. Customer churn results in substantial revenue loss and threatens long-term sustainability, while fraudulent activities erode customer confidence and disrupt service quality. As communication channels expand quickly and the number of consumer contacts rises, traditional analytical methods struggle to accurately identify high-risk customers or detect fraudulent behavior in real time. Deep learning offers a promising solution by enabling automated feature extraction and pattern recognition from complex, large-scale datasets. Yet, there remains a gap in integrated frameworks that address both churn prediction and suspicious activity detection within a unified, scalable architecture. Addressing this gap is crucial for telecom service providers to retain valuable customers, mitigate fraud, and enhance decision-making capabilities in highly competitive markets. A synopsis of the research work's contributions is provided below:

- Leveraged a comprehensive, real-world Telecom Customer Churn dataset containing three months of call detail records with 48 attributes, ensuring the practical relevance and robustness of the proposed model.
- Implemented a comprehensive pipeline for pre-processing, It included removing duplicates and outliers and dealing with missing values, doing Quick encoding of categorical features and normalization of processes using the Min-Max algorithm.
- Suggested a new use of CNNs for structured telecom data to identify intricate feature-functional correlations.
- ROC curve analysis, the model's performance was evaluated using a number of measures, such as accuracy, recall, and F1-score, and precision performance to provide a comprehensive and trustworthy evaluation of its performance in every area of prediction.

1.2. Justification and Novelty

The proposed approach is justified by the need for highly accurate churn prediction models that can handle the complexity and scale of modern telecommunications datasets, where traditional ML models often fail to capture intricate feature interactions and temporal behavioral patterns. The novelty of this work lies in employing a CNN to directly learn hierarchical feature representations from pre-processed customer call records, enabling the model to identify trends in consumer behaviour on both local and global scales. Furthermore, the integration of advanced pre-processing steps, balanced evaluation metrics, and comparative performance analysis against established baselines demonstrates the superiority of the CNN architecture, achieving significantly higher accuracy, recall, and generalization capability. This combination of automated feature extraction, deep learning adaptability, and domain-specific in telecommunications and related applications, optimization provides a reliable and scalable approach for churn detection.

2. Literature Review

Extensive research studies on detecting suspicious behavior and predicting customer churn in In order to inform, direct, and reinforce the development of this study, the telecommunications sector has been surveyed and examined.

Pravin et al. (2025) telecommunication sector, due to the switchover of the customer to another organization, the service provider face a huge loss. Churn prediction in any type of business helps preserve customers by meeting all their expectations. A framework has been designed for estimating customer exit within the banking industry using ML algorithms. H2O Atom is used to predict churn from the banking data. By leveraging H2O Atom, they employed various ML approaches, such as Stacked Ensemble, Gradient Boosting Machines (GBM), and Deep Learning approaches. Results demonstrate that the suggested framework attained higher predictive accuracy, surpassing the performance of individual models in metrics like RMSE, MAE, and overall accuracy rates. It help the banking sector to retain its customers [29].

Li, Zhang and Jiang (2024) provide Roberta-MHARC, a model for detecting telecom fraud in text messages that integrates RoBERTa with residual connections and a multi-head attention feature. Basic data category samples were chosen from the CCL2023 telecom fraud dataset, the model constructs a five-category dataset that includes public security fraud, loans, impersonation of leadership acquaintances, customer service impersonation, and regular text. To improve its learning efficiency, the model uses residual connections and a method for multi-head concentration during training. Finally, by combining the cross-entropy loss with an inconsistency loss function, the model enhances the accuracy of its multi-class classification. F1 scores on the FBS dataset were 97.65, the own dataset was 98.10, and the news dataset was 93.69, experimental results show the model's effectiveness on several benchmark datasets[30].

Alhakim, Petchhan and Su (2024) employ TabNet. This DL model enhances customer churn prediction using the IBM Telco Dataset by utilizing sequential focus for well-informed tabular data decision-making. They applied various data balancing methods to deal with the problem of unequal class distributions. There were several methods used, such as SMOTE, an oversampling technique, and hybrid approaches, such as SMOTEENN and SMOTE Tomek, which mix oversampling and undersampling. The methodology was tested using a 10-fold cross-validation and achieved better recognition performance than the state-of-the-art. It obtained an accuracy rate of 96.60% and an F1-score of 96.91. Using TabNet to Improve Customer Churn Forecasting in the Telecom Sector [31].

Saha et al. (2024) To enhance performance, the suggested ChurnNet incorporates a spatial attention module, squeeze and excitation blocks, and a residual block into the 1D convolution layer. Utilizing leftover blocks could potentially address the issue of vanishing gradients. The spatial attention module and the squeeze and excitation block allow ChurnNet can comprehend the interdependencies inside and across channels. In the experiment, three publicly available datasets are utilized to measure performance. Because there is Three data balancing algorithms—SMOTEEN, SMOTE Tomek, and SMOTE—are used when there is a notable class imbalance in the datasets. With accuracy of 95.59%, 96.94%, and 97.52% on three benchmark datasets, respectively, ChurnNet superior the state-of-the-art following a comprehensive experiment and 10-fold cross-validation [32].

Aattouri, Mouncif and Rida (2023) proposed sentiment analysis architecture incorporates preprocessing, sentiment analysis, data input/output interfaces, and a module for decision management. For instance, this module may use sentiment analysis results to escalate calls to a human agent. A survey of pertinent sentiment analysis methods is included, along with a detailed description of the preparation procedures for both text and signal analysis. The paper shows through extensive tests that integrating sentiment analysis produces encouraging results. The accuracy ratings of 74% and 72%, respectively, were consistently attained by the SVM and LSTM models in text-based analysis. The MLP model performed better than the others when voice-based analysis using Mel spectrogram features was used, attaining an accuracy of 0.72. In contrast, the RF model performed better when using MFCC features, with an accuracy of 0.78 [33].

Xiong (2022) has developed a Graph Attention Neural Network (GAT) with a Gated Recurrent Unit (GRU) that has learned spatial and temporal patterns. The idea is to use these trends to identify questionable timestamps in past traffic. The real production data provided by Sinch support this objective. When combined with Isolation Forest, a time-independent model, it ought to yield superior outcomes for the call data as well. Lastly, the test outcomes are presented, along with a thorough examination of the methodology. Additionally, they demonstrated notable improvements over baselines and prior work, achieving 42.4% accuracy and 96.1% recall on the test data supplied by Sinch [34].

Liyanage et al. (2022) concentrated on using 21 distinct criteria to analyze data on about 7000 post-paid customers. The data was first entered into ML methods like artificial neural networks (ANN) and k-nearest neighbors (KNN). Several hidden layers have also been considered by deep neural networks (DNN). According to estimates, 2950 of the 7234 post-paid consumers are churners, whereas 4284 are non-churners. Long short-term memory networks (LSTM) in the DNN produce findings that are 82.46% more accurate than those of the previous techniques. The last step was to use the LSTM method to build the prediction model [35].

Table 1 presents a summary of recent studies on analyzing customer calls, highlighting innovative models, datasets used, key insights, and the challenges faced in each approach.

Table 1: Recent Studies on Customer Calls to Identify Suspicious Behavior Using Machine Learning

Author & Year	Study Focus	Dataset	Key Findings	Limitations / Future Work
Pravin et al. (2025)	Forecasting banking customer attrition using H2O AutoML.	Banking industry customer data	Framework using Stacked Ensemble, GBM, and Deep Learning; achieved high accuracy and outperformed individual models on RMSE, MAE, and overall accuracy.	Future work could explore explainable AI techniques to interpret churn predictions.
Li, Zhang & Jiang (2024)	Telecom fraud text detection with RoBERTa-MHARC.	CCL2023 telecom fraud dataset + additional collected data (5 categories)	Integrated multi-head attention & residual connections; achieved F1-scores of 97.65 (FBS), 98.10 (own dataset), 93.69 (news dataset).	Extend to multilingual datasets and test in real-time detection scenarios.
Alhakim, Petchhan & Su (2024)	Data mining for telecom customer attrition prediction using TabNet and class balancing.	IBM Telco dataset	Applied SMOTE, SMOTEENN, SMOTETomek; achieved 96.60% accuracy and 96.91% F1-score.	Investigate interpretability of TabNet outputs and apply to other industries.
Saha et al., (2024)	ChurnNet with residual blocks, squeeze & excitation, and spatial attention.	3 public churn datasets	Achieved 95.59%, 96.94%, and 97.52% accuracy; outperformed state-of-the-art.	Explore performance on real-time streaming data and large-scale deployments.
Aattouri, Mouncif & Rida (2023)	Sentiment analysis for call center customer interactions.	Text & voice call data	SVM (74% accuracy) and LSTM (72%) for text; MLP (0.72) with mel spectrogram and RF (0.78) with MFCC for voice.	Future work could integrate multimodal fusion for improved accuracy.
Xiong (2022)	Fraud detection in telecom using GAT + GRU with Isolation Forest.	Sinch’s real production call traffic data.	Superior results compared to earlier baselines; 42.4% accuracy and 96.1% recall.	Enhance precision while maintaining high recall; adapt model for unseen fraud patterns.

Liyanage et al. (2022)	Post-paid subscriber churn prediction using ML & DNN (LSTM).	7234 post-paid subscribers data (21 attributes).	LSTM achieved highest accuracy (82.46%)	Improve accuracy via feature engineering and test with other deep architectures.

3. Research Methodology

A structured machine learning pipeline is used in the research technique to forecast customer turnover using the Telecom Customer Turnover Dataset. Before processing began, all outliers, duplicates, and missing values were deleted to guarantee high-quality data. The category features were encoded using the one-hot encoding approach, while the numerical properties were normalized using the Min-Max normalization technique. Next, the data was divided into two parts: 20% for testing and 80% for training. After that, they were separated and stored. A Convolutional Neural Network (CNN) model was finally released to predict churn. Typically, the model's performance was evaluated using metrics including accuracy, precision, recall, and F1-score. ROC curves were utilized to guarantee accurate prediction and classification of customer calls to identify suspicious behaviour. Figure 1 depicts the full process.

Here is a detailed description of each stage depicted in the suggested flowchart for analyzing customer calls to identify suspicious behavior.

3.1. Data Collection

The telecom client churn dataset was utilized in this research. A telecom operator's dataset, which comprises three months' worth of comprehensive client call records, is used in this study. There are 48 attributes in the dataset. Factors such as rate plan, customer loyalty, traffic behaviour, and the type of traffic (incoming/outgoing for voice, SMS, and data) are the most important. Data visualizations such as bar plots and heatmaps were used to examine Suspicious Behavior distribution, feature correlations etc., are given below:

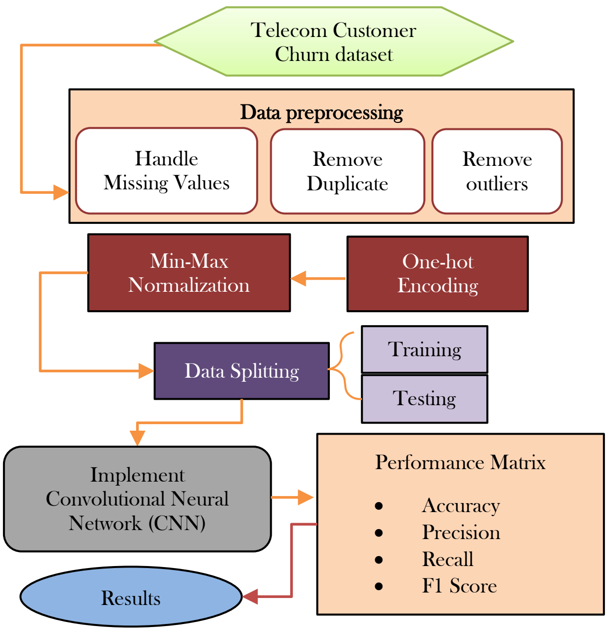

Fig 1: Proposed Flowchart for Analyzing Customer Calls

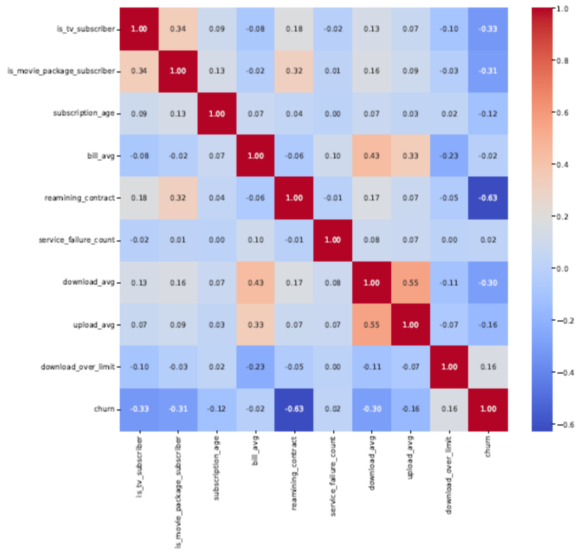

Fig 2: Correlation Matrix for Numeric Features in the Telecom Churn Dataset

A correlation heatmap showing the relationships between churn and several elements of telecom customer behaviour is shown in Figure 2. Red correlation values indicate high positive correlations, while blue correlation values, which can vary from -1 to 1, indicate strong negative correlations. Customers with lengthier remaining contracts are less likely to churn, as seen by the high negative correlation (-0.63) between "remaining_contract" and turnover. Similarly, "download_avg" and "subscription_age" also show moderate negative correlations with churn, indicating that longer-tenured and more actively engaged customers are less prone to leave. Conversely, "is_tv_subscriber" shows a weak positive correlation with churn (+0.33), implying that TV subscribers may be slightly more likely to churn. The matrix provides insights into which features could be important predictors for customer churn modeling using machine learning.

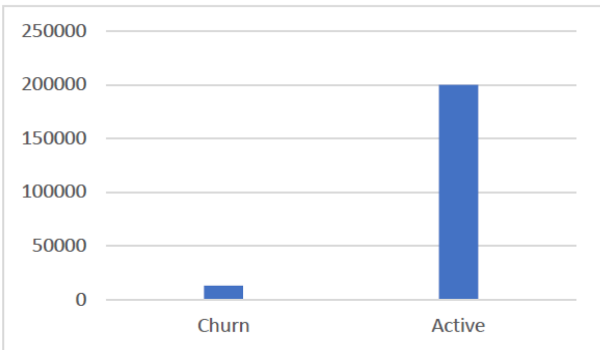

Fig 3: Histogram of the Status Attribute

Figure 3 The customer distribution is depicted in the bar chart in a telecommunication dataset categorized into "Churn" and "Active" users. A vast majority of the customers remain active, with their count nearing 200,000, while a significantly smaller portion fewer than 25,000 have churned. This stark imbalance highlights a typical difficulty with churn forecast issues: class disparity, where the underrepresented churn class is. Such a distribution necessitates the use of appropriate data handling or resampling techniques during model training to ensure accurate churn prediction and prevent bias toward the majority class.

3.2. Data Pre-Processing

The Telecom Customer Churn dataset collection was the first step in preparing the data. This is followed by concatenation and data cleaning to ensure consistency and quality. Among the significant actions, one can list the capacity to handle missing results, eliminate outliers and duplicates, and choose the necessary features for analysis. Data transformation and normalization of the dataset were then carried out. The preprocessing steps are as follows in detail.

- Handling missing values: A dataset's unavailable data must be fairly compensated. Calculating the mean of each attribute and substituting the missing values of each attribute were the steps involved in solving this kind of difficulty.
- Remove Duplicate: Removal of duplicate values is important in the pretreatment of data to preserve its consistency, quality, and correctness. Duplicates may be created due to data entry mistakes, integrating data obtained through two or more sources, or the data gathering.
- Remove Outliers: Removal of outliers during preprocessing of the data to find outliers and either eliminate them or modify them to better represent the data set's overall trend. Because outliers can have an outsized effect on results, this make ML models and statistical computations more accurate and reliable.

3.3. One Hot Encoding

The encoding of data is the process of describing the data in a particular form to enable it to be effectively stored, transmitted or processed. Using one-hot encoding, the ML algorithm can handle data by converting categorical variables into numerical ones.

3.4. Min-Max Normalization

The min-max approach, which restricts the values to a range between 0 and 1, was also used to normalize the data. This was done in an effort to lessen the influence of outliers and simplify the efficacy of the classifiers used. The following mathematical formula served as the basis for normalization Equation 1:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Where X stands for the feature's initial value, X' for its normalised value, X_{min} for its minimum value, and X_{max}Or its maximum value.

3.5. Data Splitting

The technique of separating distinct subsets from a dataset in order to train and assess ML models is known as data splitting. The Telecom dataset was divided into training and test sets, with a 20% allocation to testing and 80% to training.

3.6. Proposed Convolutional Neural Network (CNN)

CNN is a type of feedforward neural network that possesses deep structure and convolutional processing. It is frequently employed in identification and classification tasks across a variety of domains. It possesses the capacity for representation learning, which enables it to learn the most crucial elements of a dataset. CNN's performance has greatly increased since AlexNet, thanks to its hierarchical architecture. Main components of a neural network include the input, convolution, pooling, and full connection layers [36]. These layers map the input $h$in and output $h$out of each layer using nonlinearity and parameter-intensive matrix operations. They can be described in the following way. In Equation 2, the variables W, b, and max() represent weights, bias, and an activation function, respectively.

$$h_{out} = amx(0, h_{in}W + b) \tag{2}$$

The first model has 2 fully connected layers, 1 softmax layer, 6 max pooling layers, and 12 convolutional layers (Figure 4). Before each convolutional layer, there is an activation layer that uses ReLU and a BN layer. The final convolution layer substitutes The average pooling layer of the maximum pooling layer. As the classification layer, Softmax is employed.

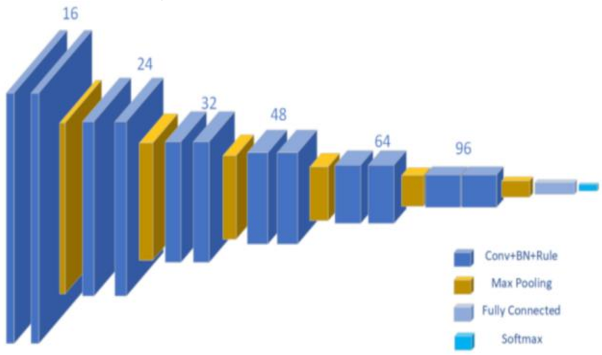

Fig 4: The first CNN Layout

Figure 5 shows that an inception block is a part of the second CNN model. Two issues with CNN classification models are addressed by the Inception model. The first is how to deepen the network while improving the model's classification performance. The second is how to guarantee that the network's accuracy is maintained or enhanced without declining while the model's computational and memory overhead is adequately decreased. Onex1 convolution, which reduces the number of channels, is used to aggregate information. Afterwards, features are retrieved and combined at different sizes to gather data at many scales. Then, the outputs of the features are superimposed onto the subsequent layer. There are three convolution layers and an inception block in the second CNN model.

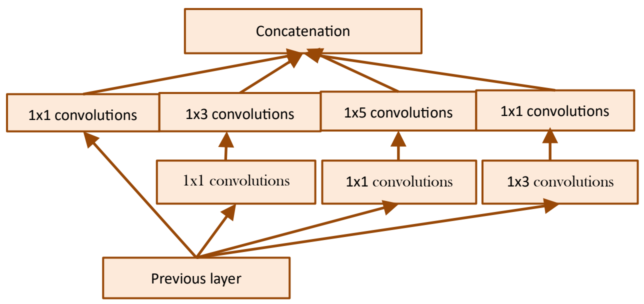

Fig 5: Inception Model

3.7. *Evaluation Metrics*

The CNN model's efficacy was assessed using several performance indicators [37]. The True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) counts were determined by comparing the actual values with the anticipated outcomes from the trained models. From this, the following assessment measures were determined: F1-score, recall, accuracy, and precision:

- True Negative (TN): In this case, the clients are shown to be non-churners, and the model has also identified them as such.
- False Positive (FP): In this case, the model has identified the consumers as churners even though they are observed as non-churners.
- False Negative (FN): Since the clients are categorized as non-churners by the model, they are seen to be churners.
- True Positive (TP): Customers are watched here and labelled as churners.

3.7.1. Accuracy

The proportion of all occurrences in the dataset that the trained model accurately predicted. It's written as Equation 3-

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+Fp+TN+FN}} \tag{3}$$

3.7.2. Precision

The total number of positive cases that a model predicts is its accuracy rate in proportion to precision. Precision indicates, how good the classifier is in predicting the positive classes is expressed as Equation 4-

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \tag{4}$$

3.7.3. Recall

This metric is the proportion of cases that should have turned out positively to those that were correctly predicted to TP. Equation 5 represents it in mathematical form-

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

3.7.4. F1 score

It is a combination that helps to balance accuracy and memory by taking the harmonic mean of the two. Its range is [0, 1]. Mathematically, it is given as Equation 6-

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

3.7.5. Receiver Operating Characteristic Curve (ROC)

The percentage of cases that are successfully labelled as positive vs the percentage that are wrongly classed as positive for numerous decision cut-off points is plotted visually by the ROC. FPR is equivalent to 1-specificity, but TPR is sometimes known as sensitivity or recall.

4. Results and Discussion

The experimental setup displays the outcomes of the CNN model's operation during the training and testing stages. The investigation was conducted on a machine equipped with an Intel Core i7-9850H processor, 32.0 GB of RAM, Intel UHD Graphics 630 and NVIDIA Quadro T2000 graphics, and a 1.0 TB hard drive. The operating systems include Ubuntu 24.04.2 LTS (Kernel 6.11.0-24-generic), X11, GNOME 46, and Python 3.10.16. Following training on the Telecom Customer Churn dataset, the proposed CNN model was evaluated using key performance metrics, including accuracy, precision, recall, and F1-score. As shown in Table 2, the CNN model was able to detect almost all instances of churn with a recall of 99.8%, a precision of 91.7%, and an accuracy of 96.5 %. Additionally, the 95.6% F1-score indicates a performance that strikes a balance between recall and accuracy.

Table 2: Experiment Results of CNN Model for Analyzing Customer Calls on Telecom Customer Churn dataset

Performance Matrix	Convolutional Neural Network (CNN)
Accuracy	96.5
Precision	91.7
Recall	99.8
F1-score	95.6

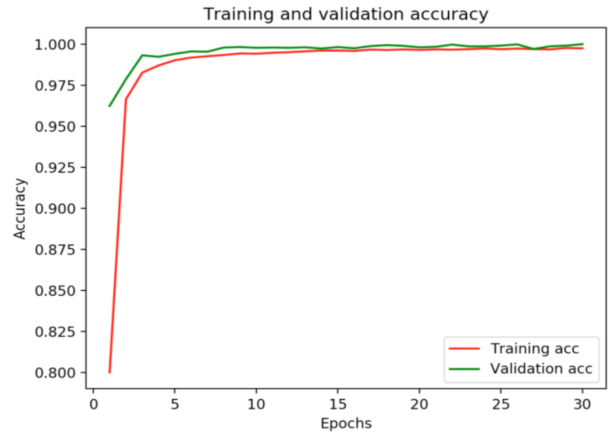

Fig 6: Accuracy Curves for the CNN Model

Figure 6 shows the CNN model's accuracy over 30 epochs, both during training and validation. The fundamental patterns are learnt by the model in the Telecom Customer Churn Dataset quickly, as indicated by the rapid improvement in accuracy within the first few epochs of both curves. In most epochs, the validation accuracy is slightly higher than the training accuracy, and both lines stabilize at high values above 97.5%. The proposed CNN technique for predicting customer calls is reliable and efficient, as shown by the tight correspondence between validation and training results, which implies that the model does not overfit and generalizes successfully.

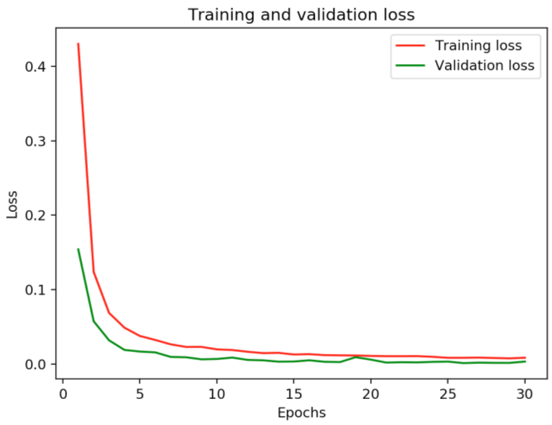

Fig 7: Loss Curves for the CNN Model

Figure 7 displays the training and validation loss of the CNN model during 30 epochs. The validation loss (green line) and training loss (red line) both significantly reduce throughout the early stages of training, suggesting quick learning and successful model convergence. As the epochs go, the losses diminish and eventually reach zero, but the validation loss remains consistently below the training loss. This steady improvement in loss values demonstrates that the model is learning effectively without overfitting, confirming that the proposed CNN model is very resilient and has excellent generalizability on the Telecom Customer Churn Dataset.

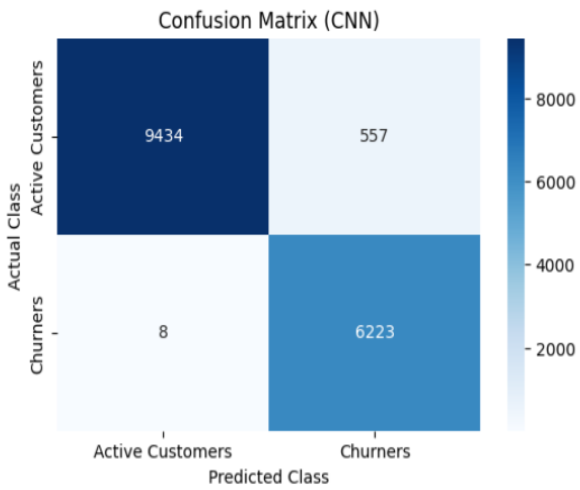

Fig 8: Confusion Matrix for CNN

Figure 8 shows the confusion matrix for customer attrition prediction using the CNN model. It shows the distribution of correctly and mistakenly classified occurrences across two classes Churners and Active Customers. Out of the actual active customers, 9,434 were correctly identified, while 557 were misclassified as churners. Conversely, among actual churners, 6,223 were accurately predicted, with only 8 misclassified as active customers. The diagonal values are high, which means the model performs very well in predicting and has very few misclassifications. Hence, the CNN model distinguishes between two classes with remarkable accuracy and resilience.

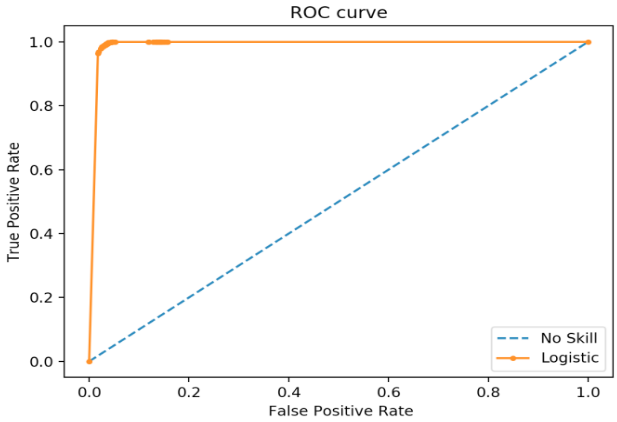

Fig 9: ROC Curve for CNN Model

Figure. 9 shows the ROC curve of the CNN model used to predict customer churn, which demonstrates its discriminative performance for the active and churner customers. According to the curve, the increase is sharp as it moves up to the upper-left corner, A low False Positive Rate (FPR) and a high True Positive Rate (TPR) are displayed. The model performs exceptionally well when identifying patients, surpassing the no-skill baseline, as seen by its AUC value of 0.972. Such a high AUC indicates the strength and efficiency of CNN's approach to precisely detect churners and reduce false alerts, which makes this model a good choice to be used on churn detection tasks.

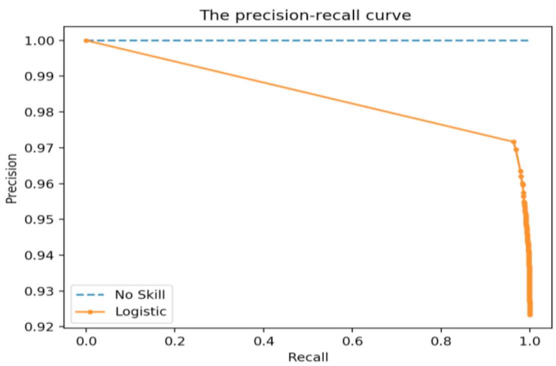

Fig 10: Precision-Recall Analysis of the CNN Model

Figure. 10 shows the CNN model's Precision-Recall (PR) curve in customer churn predictions, showing how precision and recall values trade off at different classification thresholds. At any level of recall, which in this case is maximum, the curve retains a high precision of greater than 0.92. Thus, it shows that the model can detect churners with a low number of false positives. Whereas the horizontal dashed line denotes the no-skill classifier baseline, the CNN model is superior across the range.

4.1. Comparative Analysis

Table 3 gives the accuracy comparison of diverse predictive models used to predict customer calls by using the Telecom Customer Churn Data. Out of the usual ML models, LR produced 78.70% accuracy and Random Forest (RF) a slight increase of 80.81%. Both were considerably outperformed by the DT model, which achieved an accuracy of 94% meaning that it was able to capture decision boundaries in the dataset. It is important to note that CNN recorded the greatest accuracy of 96.5% indicating that deep learning models are much better at learning complex patterns and feature representation using the telecom churn data. Such findings indicate that the traditional models yield satisfactory performance, but the DL modeling methods have better predictive accuracy in this task.

Table 3: Accuracy Comparison of Different Predictive Models of Customer Calls Prediction Using the Telecom Customer Churn Dataset

Models	Accuracy
LR[38]	78.70
RF[39]	80.81
DT[40]	94
CNN	96.5

Predicting customer calls using a CNN architecture that uses complicated pattern capture and automatic feature extraction is done using the Telecom Customer Churn dataset. Because hierarchical feature representations are learned directly in the input, the CNN has a high predictability of 96.5% and displays high generalization to novel data. It is a very effective method to process large-scale telecom datasets, can scale up to real-time prediction making, and can be applied to various telecommunication analytics like churn prediction, fraud detection and call intent classification, thus enabling better decision making, and operating more efficiently.

4.2. Limitations and Future Work

Despite the high accuracy and robust generalization ability that is exhibited by the proposed CNN-based churn prediction framework, there exist some limitations. In real-world situations, the model's performance may not yield the expected outcomes since it is sensitive to the quality of the data, especially when partial datasets are present. Also, the imbalance of the classes in churn datasets may be because preprocessing partially solved the issue; however, it can still influence the classification of minority classes in significantly skewed distributions. The existing model also pays much attention to stationary historical data of calls and fails to involve time dynamics or streaming data that are widely used in working telecom conditions. Additional future research will examine more hybrid models like CNN-LSTM and attention-based models to capture the sequential patterns in behaviour. Additionally, it will investigate new approaches to addressing imbalances, such cost-sensitive learning, and generate synthetic data to embed with explainable AI, making it easier for business stakeholders to interpret. Streaming analytics and multi-task learning extensions to simultaneously perform churn prediction, fraud detection, and assessment of service quality in real-time will also increase the applicability of the proposed framework in large-scale telecommunications operations.

5. Conclusion

In the telecommunications industry, the current growth has been unprecedented, with technical advances and growing demand for connectivity. One of the most pressing issues that a telecom service provider has to address, however, is the high level of client turnover. The issue of customer turnover influences the growth potential of telecom companies, besides leading to losses in terms of revenue. This study uses the Telecom Customer turnover dataset to provide a DL model that might be utilized to forecast client attrition in the telecom industry. A well-organized ML pipeline was introduced, and quite extensive pre-processing was performed involving missing values filling, removing duplicates and outliers, one-hot encoding, and Min-Max normalization. A CNN architecture has been written to exploit its hierarchical feature learning abilities and the ability to recognize complex patterns. The test outcomes showed an elevated accuracy of 96.5% with excellent precision, recall, and F1-score values, which suggest good classification efficiency and the capability to generalize towards non-observed data. The robustness of the proposed method was also demonstrated by the ROC-AUC value of 0.972 and high, but stable, precision-recall profile. Further research may explore advanced models like CNN-LSTM or attention mechanisms to better capture temporal associations in call sequences. Feature selection and dimensionality reduction could reduce complexity and costs, while resampling or cost-sensitive learning may improve minority class detection.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest concerning the publishing of this paper.

References

[1] D. Patel, “Enhancing Banking Security: A Blockchain and Machine Learning- Based Fraud Prevention Model,” *Int. J. Curr. Eng. Technol.*, vol. 13, no. 06, Dec. 2023, doi: 10.14741/ijcet/v.13.6.10.

[2] V. Kavitha, G. H. Kumar, S. V. M. Kumar, and M. Harish, “Churn Prediction of Customer in Telecom Industry using Machine Learning Algorithms,” *Int. J. Eng. Res.*, vol. V9, no. 05, pp. 181–184, May 2020, doi: 10.17577/IJERTV9IS050022.

[3] H. Kali, “Optimizing Credit Card Fraud Transactions Identification And Classification In Banking Industry Using Machine Learning Algorithms,” *Int. J. Recent Technol. Sci. Manag.*, vol. 9, no. 11, pp. 1–12, 2024.

[4] Y. Kim, “Convolutional neural networks for sentence classification,” in *EMNLP 2014 - 2014 Conference on Empirical Methods in Natural Language Processing, Proceedings of the Conference*, 2014. doi: 10.3115/v1/d14-1181.

[5] V. Prajapati, “Enhancing Threat Intelligence and Cyber Defense through Big Data Analytics : A Review Study,” *J. Glob. Res. Math. Arch.*, vol. 12, no. 4, pp. 1–6, 2025.

[6] D. Patel, “Leveraging Blockchain and AI Framework for Enhancing Intrusion Prevention and Detection in Cybersecurity,” *TIJER – Int. Res. J.*, vol. 10, no. 6, 2023.

[7] H. P. Kapadia, "Voice and Conversational Interfaces in Banking Web Apps," *J. Emerg. Technol. Innov. Res.*, vol. 8, no. 6, pp. g817–g823, 2021.
[8] B. Patel, H. Mallisetty, and K. M. Rao, "Artificial Intelligence Helper Application for Delivering Effective Presentations," 2024.
[9] A. K, M. Jayan, and L. Jacob, "Categorizing Disaster Tweets Using Learning Based Models for Emergency Crisis Management," in *2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS)*, IEEE, Mar. 2023, pp. 1133–1138. doi: 10.1109/ICACCS57279.2023.10113105.
[10] R. Patel, "Security Challenges in Industrial Communication Networks: A Survey on Ethernet/IP, Controlnet, and Devicenet," *Int. J. Recent Technol. Sci. Manag.*, vol. 7, no. 8, pp. 54–63, 2022.
[11] J. Mishra, B. B. Biswal, and N. Padhy, "Machine Learning for Fraud Detection in Banking Cyber security Performance Evaluation of Classifiers and Their Real-Time Scalability," in *2025 International Conference on Emerging Systems and Intelligent Computing (ESIC)*, IEEE, Feb. 2025, pp. 431–436. doi: 10.1109/ESIC64052.2025.10962752.
[12] K. T. S, L. R. K. J, N. Manasa, N. V Sannu, and R. Firdaus, "Suspicious Activity Detection Using Convolution Neural Network and Visual Geometry Group-19," vol. 11, no. 4, pp. 501–508, 2024, doi: 10.17148/IARJSET.2024.11471.
[13] V. Verma, "Deep Learning-Based Fraud Detection in Financial Transactions: A Case Study Using Real-Time Data Streams," *ESP J. Eng. Technol. Adv.*, vol. 3, no. 4, pp. 149–157, 2023, doi: 10.56472/25832646/JETA-V3I8P117.
[14] R. Q. Majumder, "A Review of Anomaly Identification in Finance Frauds Using Machine Learning Systems," *Int. J. Adv. Res. Sci. Commun. Technol.*, pp. 101–110, Apr. 2025, doi: 10.48175/IJARSCT-25619.
[15] D. D. Rao, D. Dhabliya, A. Dhore, M. Sharma, S. S. Mahat, and A. S. Shah, "Content Delivery Models for Distributed and Cooperative Media Algorithms in Mobile Networks," in *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, IEEE, Jun. 2024, pp. 1–6. doi: 10.1109/ICCCNT61001.2024.10724905.
[16] H. P. Kapadia, "Generative AI for Real Time Conversational Agents," *Int. J. Curr. Sci.*, vol. 13, no. 3, pp. 201–208, 2023.
[17] M. Arafat, A. Qusef, and G. Sammour, "Detection of Wangiri Telecommunication Fraud Using Ensemble Learning," in *2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology, JEEIT 2019 - Proceedings*, 2019. doi: 10.1109/JEEIT.2019.8717528.
[18] M. Liu, J. Liao, J. Wang, and Q. Qi, "AGRM: Attention-Based Graph Representation Model for Telecom Fraud Detection," in *IEEE International Conference on Communications*, 2019. doi: 10.1109/ICC.2019.8761665.
[19] G. Mantha, "Transforming the Insurance Industry with Salesforce: Enhancing Customer Engagement and Operational Efficiency," *North Am. J. Eng. Res.*, vol. 5, no. 3, 2024.
[20] M. Gridach, H. Haddad, and H. Mulki, "Churn Identification in Microblogs using Convolutional Neural Networks with Structured Logical Knowledge," in *3rd Workshop on Noisy User-Generated Text, W-NUT 2017 - Proceedings of the Workshop*, 2017. doi: 10.18653/v1/w17-4403.
[21] R. Patel, "Automated Threat Detection and Risk Mitigation for ICS (Industrial Control Systems) Employing Deep Learning in Cybersecurity Defence," *Int. J. Curr. Eng. Technol.*, vol. 13, no. 6, 2023.
[22] V. Shah, "Scalable data center networking : Evaluating virtual extensible local area network-Ethernet virtual private network as a next-generation overlay solution," *Asian J. Comput. Sci. Eng.*, vol. 8, no. 3, pp. 1–7, 2023.
[23] K. Mallikarjuna Rao Bhavikkumar Patel, "Suspicious Call Detection and Mitigation Using Conversational AI," *Defensive Publ. Ser.*, 2023.
[24] D. Rao, "Strategizing IoT Network Layer Security Through Advanced Intrusion Detection Systems and AI-Driven Threat Analysis," *J. Intell. Syst. Internet Things*, vol. 12, no. 2, pp. 195–207, 2024.
[25] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," *1st Int. Conf. Learn. Represent. ICLR 2013 - Work. Track Proc.*, pp. 1–12, 2013.
[26] J. Zhong and W. Li, "Predicting Customer Call Intent by Analyzing Phone Call Transcripts Based on CNN for Multi-Class Classification," 2019. doi: 10.5121/csit.2019.90702.
[27] D. D. Rao, S. Madasu, S. R. Gunturu, C. D'britto, and J. Lopes, "Cybersecurity Threat Detection Using Machine Learning in Cloud-Based Environments: A Comprehensive Study," *Int. J. Recent Innov. Trends Comput. Commun.*, vol. 12, no. 1, 2024.
[28] N. K. Prajapati, "Federated Learning for Privacy-Preserving Cybersecurity: A Review on Secure Threat Detection," *Int. J. Adv. Res. Sci. Commun. Technol.*, pp. 520–528, Apr. 2025, doi: 10.48175/IJARSCT-25168.
[29] A. Pravin, B. L. S. Bizotto, M. Sathiyanarayanan, and T. P. Jacob, "Enhanced Framework to Predict Customer Churn Using Machine Learning," in *2025 International Conference on Inventive Computation Technologies (ICICT)*, 2025, pp. 8–12. doi: 10.1109/ICICT64420.2025.11005219.
[30] J. Li, C. Zhang, and L. Jiang, "Innovative Telecom Fraud Detection: A New Dataset and an Advanced Model with RoBERTa and Dual Loss Functions," *Appl. Sci.*, vol. 14, no. 24, p. 11628, Dec. 2024, doi: 10.3390/app142411628.
[31] M. F. Alhakim, J. Petchhan, and S.-F. Su, "Leveraging TabNet for Enhanced Customer Churn Prediction in the Telecommunication Industry," in *2024 International Conference on Consumer Electronics - Taiwan (ICCE-Taiwan)*, 2024, pp. 717–718. doi: 10.1109/ICCE-Taiwan62264.2024.10674508.
[32] S. Saha, C. Saha, M. M. Haque, M. G. R. Alam, and A. Talukder, "ChurnNet: Deep Learning Enhanced

Customer Churn Prediction in Telecommunication Industry," *IEEE Access*, vol. 12, pp. 4471–4484, 2024, doi: 10.1109/ACCESS.2024.3349950.

[33] I. Aattouri, H. Mouncif, and M. Rida, "Call Center Customer Sentiment Analysis Using ML and NLP," in *Proceedings - SITA 2023: 2023 14th International Conference on Intelligent Systems: Theories and Applications*, 2023. doi: 10.1109/SITA60746.2023.10373715.

[34] C. Xiong, "Telecom Fraud Detection Using Machine Learning KTH Thesis Report," *Degree Proj. Comput. Sci. Eng.*, 2022.

[35] R. P. H. Liyanage, B. T. G. S. Kumara, B. Kuhaneswaran, and S. Prasanth, "Deep learning approach for detecting customer churn in telecommunication industry," in *Social Customer Relationship Management (Social-CRM) in the Era of Web 4.0*, 2022. doi: 10.4018/978-1-7998-9553-4.ch009.

[36] H. Li, Y. Wei, and C. Zhu, "Convolutional Neural Network Analysis for Modulation Classification of Wireless Communication Signal," *Adv. Transdiscipl. Eng.*, vol. 30, pp. 827–833, 2022, doi: 10.3233/ATDE221103.

[37] V. Chang, K. Hall, Q. A. Xu, F. O. Amao, M. A. Ganatra, and V. Benson, "Prediction of Customer Churn Behavior in the Telecommunication Industry Using Machine Learning Models," *Algorithms*, vol. 17, no. 6, 2024, doi: 10.3390/a17060231.

[38] N. M. AbdelAziz, M. Bekheet, A. Salah, N. El-Saber, and W. T. AbdelMoneim, "A Comprehensive Evaluation of Machine Learning and Deep Learning Models for Churn Prediction," *Inf.*, vol. 16, no. 7, pp. 1–29, 2025, doi: 10.3390/info16070537.

[39] Y. Wei, "Telco Customer Churn Prediction," *Highlights Sci. Eng. Technol.*, vol. 92, pp. 218–226, 2024, doi: 10.54097/84bmrd32.

[40] M. K. Mittal, "Customer Churn Analysis in Telecom Using Machine Learning Techniques," Dublin, National College of Ireland, 2022.