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Customer Churn Prediction in Telecom: A Deep Learning Approach Using Keras and TensorFlow

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***Abstract* - For telecom companies, customer attrition is a major problem that has a direct impact on retention and revenue. In order to predict churn and take quick retention actions based on customer history, a deep learning model built on Keras and TensorFlow is used for this project. Deep learning enhances the ability to identify intricate data associations when compared to more conventional techniques like logistic regression and decision trees. Data collection, preprocessing, training, and model evaluation are all part of the project. Tenure, charges, and demographics of customers are included in a publicly available data set. Data preprocessing includes feature normalization, categorical variable encoding, and missing value handling. Accuracy and loss criteria are used to train and assess a neural network model with hidden layers. When it comes to identifying risky customers, the deep learning model outperforms the conventional methods due to its high accuracy. The method shows how deep learning can be used in predictive analytics for client retention.**

Keywords: Churn Prediction, Deep Learning, Neural Networks, Keras, TensorFlow, Predictive Analytics, Customer Retention, Feature Normalization, Data Preprocessing, Machine Learning.

I. INTRODUCTION

For telecommunications firms, client churn is a major issue that results in significant revenue loss as customers discontinue their services. Businesses can implement proactive retention strategies and provide individualized solutions to prospective consumers who are about to leave by using churn prediction. The goal of this project is to create a strong churn prediction model based on customer factors including tenure, monthly payments, and service subscriptions using sophisticated deep learning techniques with Keras and Tensor Flow. Businesses may lower attrition rates, boost customer happiness, and optimize marketing campaigns with the help of an accurate churn prediction system.

With data preprocessing, model training, evaluation, and deployment, the project is constructed in an organized manner. To provide high-quality input data, preprocessing procedures include addressing missing values, encoding categorical variables, and scaling features. While even basic algorithms like decision trees and logistic regression can be used for binary classification tasks like churn prediction, they are not very good at spotting intricate, non-linear patterns in data. A multi-layer neural network model that can recognize intricate patterns in consumer behaviour is used to avoid such restrictions.

Recent developments in deep learning have shown that it may be effectively used in predictive analytics, especially when it comes to seeing minute patterns that conventional algorithms miss. This study shows that a deep learning model may perform with high accuracy and generalize well to new data by comparing its performance with more conventional methods. Additionally, data visualization tools are used to provide deep insights into the fundamental causes of client attrition.

This project intends to develop a high-performance, scalable churn prediction system using a neural network-based approach to help telecom operators increase profitability and decrease customer attrition.

II. LITERATURE REVIEW

Utkarsh Kumar et. al This paper explains by handling missing values, encoding categorical variables, and scaling features, the XGBoost model effectively trains on big datasets. Train_test_split is used to split the data, while GridSearchCV and RandomizedSearchCV are used to adjust the hyperparameters. To reduce errors, the fit() function uses gradient boosting. The drawback of this paper is Real-time forecasts are difficult because of their high computing cost, overfitting danger, and poor interpretability. Training is hampered by unbalanced datasets, and accuracy depends on high-quality data. Sensitive client data raises privacy issues and compliance hazards. XGBoost is still a potent predictive analytics method for telecom churn prediction in spite of these difficulties.

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Shams Uz Zaman et. al In his study Machine learning is used in customer churn prediction to examine consumer behavior and pinpoint possible churners. Data collection, preparation (including scaling, encoding, and handling missing values), and feature selection are all steps in the process. Using metrics like accuracy, precision, recall, and F1-score, models such as Logistic Regression, Random Forest, XGBoost, and Neural Networks forecast churn. Predictions are incorporated into customer support systems via deployment as part of proactive retention tactics. The drawback of his study is expensive computation, overfitting risk, feature dependence, and incomprehensibility in intricate models. Despite these obstacles, telecom businesses can improve customer retention and decision-making by using ML-driven churn prediction.

Shreyas Rajesh Labhsetwar This paper explains using ML classifiers such as Logistic Regression, Naïve Bayes, AdaBoost, XGBoost, Extra Trees, and SVM, the study predicts telecom customer churn on the BigML Telecom Churn Dataset (3334 instances, 21 attributes). The best performing classifiers were Extra Trees (0.843 AUC), XGBoost (0.787), and SVM (0.735). Data visualization tools found patterns of churn. The drawback is limited dataset size, lack of explicit feature selection, class imbalance, lack of deep learning models, and high computational complexity of SVM and XGBoost. Despite these drawbacks, ML models effectively predict churn, helping telecom companies with retention strategies.

III. ANALYSIS

3.1 Problem Statement

Since customer attrition costs telecom operators a lot of money, it's critical to identify prospective attrition clients. The difficulty lies in developing an efficient system that analyses client information, spots trends, and accurately forecasts attrition. The solution should let businesses take proactive steps to retain consumers, improve customer happiness, and successfully reduce churn rates by utilizing machine learning techniques.

3.2 Existing System

By examining historical data, telecoms have, for many years, understood the reasons why customers left their services. Previously, they used basic rule-based systems and a few simple statistical models such as logistic regression for churn forecasting. Though some insights may be gained from using these, they mostly fail to describe the complex and dynamic nature of ever-changing customer behaviours across the board. The rule-based approach works by putting specific rules—that is, a set of conditions, which may involve, for instance, frequent complaints, late payments, and low levels of service utilization—to make a determination on customers who are deemed to have churn risk. The problem here is that such rules are rigid and not able to model changing customer behavior very well.

Customers change plans, change how they consume services with time, and have different motivators to stay or leave. One-size-fits-all approaches simply do not work. Logistic regression was considered a simple act of assigning some weight on different factors and calculating an overall probability of a customer leaving based on those factors: some of these factors would include the age of the relationship that a customer has with the company, the degree to which they were engaged.

The monthly expenditures are drawn from various factors; however, this method in a real situation assumes that there are direct relations between them. Actually, all sorts of various elements affect customer decisions other than the churn rate itself. And it is this problem of analyzing a variety of interconnected factors which makes such methods difficult to implement.

So it's a huge problem in the telecom industry when it comes to the volumes of data... when you make every call, every message sent, every data session, or every conversation the customer has with a call center or otherwise a considerable amount of data is being generated. There's a wealth of intelligence available. Conventional methodologies struggle to sift through and parse all this data, which usually results in erroneous predictions. Even most of those older platforms lack the capacity to provide such processes in real-time, so companies wouldn't become aware of churn risks

3.3 Proposed System

To tackle the limitations of traditional churn prediction methods, the proposed system will use advanced machine learning (ML) techniques, focusing on data preprocessing, data visualization, feature scaling, and neural networks. These techniques will improve accuracy, capture complex customer behaviours, and provide a more flexible and adaptable approach to predicting churn.

3.4 Data Set Description

The dataset used in this study is a publicly available telecom customer dataset, containing:

- Records: 7,043 customer entries.
- Features: Tenure, Monthly Charges, Total Charges, Internet Service, Contract Type, Payment Method, etc.

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- Target Variable: Churn (Binary classification: Yes/No).

3.5 Data Pre-processing

One of the first steps in building an effective churn prediction model is data preprocessing. This involves handling missing values, removing irrelevant features, and converting categorical data into numerical formats. Data cleaning ensures that the dataset is free from inconsistencies that could negatively impact model performance. Additionally, transforming variables—such as converting text-based features into numerical representations—allows the model to process and analyse data efficiently.

3.6 Data Visualization

In order to offer insights into customer behaviour, the suggested solution would employ data visualization techniques. Through the use of visual representation such as histograms, scatter plots, and correlation matrixes, we will be able to identify patterns and tendencies in customer behaviour. Coloring such factors as tenure, monthly charges, and service usage throughout life provides insight to the business about customer segments that are at a greater risk of churning.

3.7 Scaling Features

In order to develop serious machine learning models, in particular neural networks, we need to take scaling into consideration. Hence, we would be applying such techniques as standardization (Standard Scaler) or normalization to get the same scale with respect to numerical variables such as total charges and monthly expenses. This avoids any single feature from ascribing to some extent targets. Stability and effectiveness were guaranteed to the extent of the training, streaming job. Correlation analysis was used to select key features that affect churn, features with a high impact include tenure, monthly charges, and contract type. Features with little impact: gender and customer ID. To enhance model performance, Min-Max Scaling was used to standardize features.

3.8 Building a Neural Network

3.8.1 Dataset Split: 20% for testing and 80% for training. The core of the proposed system is a deep learning model based on artificial neural networks (ANNs). This model will consist of multiple layers:

3.8.2 Input Layer: Accepts customer data as input features.

3.8.3 Hidden Layers: Uses activation functions like RELU (Rectified Linear Unit) to capture complex relationships in customer behaviour.

3.8.4 Output Layer: Applies a sigmoid activation function to predict churn probability.

The neural network will be trained using back propagation and optimized using the Adam optimizer to minimize binary cross-entropy loss. This enables the model to learn from patterns in customer behaviour and make highly accurate churn predictions.

3.9 Real-Time Data Processing

The mentioned proposed system will not use old-age churn models to analyse historical data, but it will take customer interactions in real time. By continuous monitoring of the customer activity which includes churn risk identification in a quick way through changes in service usage, support interactions, and payment history, this allows the telecom companies to offer personalized discounts to a customer or improve service quality before the customer actually leaves.

3.10 Model explainability

Incorporating explainability tool like SHAP (Shapley Additive explanations) in the system makes sure that such a system is transparent and usable. It empowers businesses to understand why a set of customers has a high likelihood of churning, motivating them to act based on more targeted and data-driven insights.

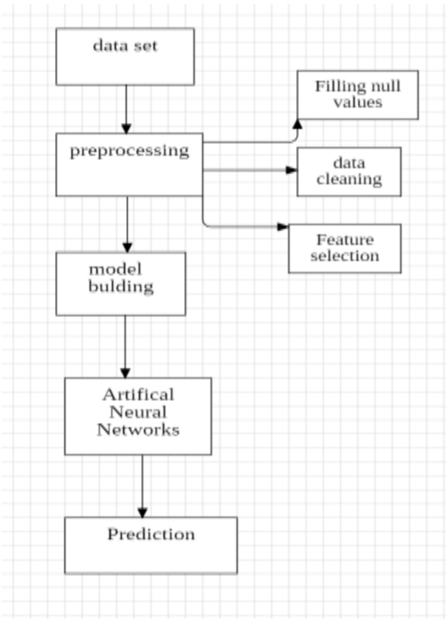

Fig 1: System Architecture

1. Data Set: The unprocessed data used to train the model.

2. Processing: Involves choosing pertinent features, cleansing data, and dealing with missing values.

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- Filling Null data: Uses methods such as mean, median, or mode imputation to replace missing or null data.
- Data cleaning eliminates inaccurate data points, duplicate entries, and discrepancies.
- Feature Selection, To enhance model performance and lower complexity, the most pertinent features are chosen.

3. Model Construction: Specifies activation functions, layers, neurons, and additional hyperparameters.

4. The fundamental computational: model that extracts patterns from data is Artificial Neural Networks (ANN). To maximize performance, several layers and weight modifications are used.

3.11 Prediction

- In this last stage, the trained ANN model uses fresh input data to produce predictions.
- Offers information like probability scores, regression results, or classification.

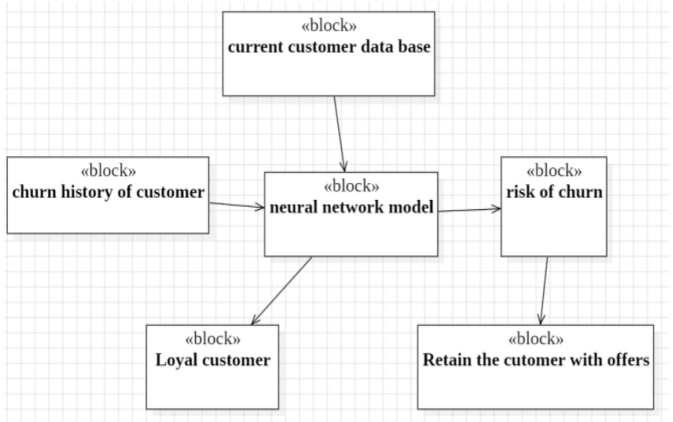

Fig 2: Block diagram of proposed model

Current Client Information:

- Saves data on current clients, such as their demographics, usage trends, and past interactions.
- The neural network model for churn prediction uses this data as input.

Customer Churn History:

- Has historical records of clients who have withdrawn from the service.
- By comparing previous activities, it assists the model in learning patterns linked to customer attrition.

Neural Network Model:

- Predicts the possibility of a client departing by analysing customer data and churn history.
- Customers are categorized as either loyal or at risk of leaving.

Churn Risk:

- Based on the neural network's predictions, it determines which consumers are most likely to depart.
- Assists companies in taking preventative measures to lower employee turnover.

Retain the Customer with Offers:

- If a customer is in danger, retention tactics like better services, tailored offers, or discounts are used to entice them to stay.

Faithful Client

- Clients who are anticipated to stick with the service.-Companies can keep them engaged over time by rewarding them with loyalty programs.

3.12 Neural Networks Algorithm

1. First, pre-process the data by fetching it:
import pandas as pd df =pd.read_csv("customer_churn.csv")
-Managing values that are missing: df.drop('customerID', axis='columns', inplace=True) df1 =df[df.TotalCharges!="] (df1.TotalCharges) =pd.to_numeric(df1.TotalCharges)

2. Data Visualization:
-Tenure-based customer churn histogram:
import matplotlib.pyplot as plt tenure_churn_no = df1[df1.Churn == 'No'].tenure
df1[df1.Churn == 'Yes'] = tenure_churn_yes.
Plt.hist([tenure_churn_yes, tenure_churn_no], rwidth=0.95, color=['red', 'green'])
#contains the tenure information.

3. To encode categorical data:
-Using pd.get_dummies()
df2 = pd.get_dummies(df1, drop_first=True)

4. Split data:
-Using train_test_split():
import train_test_split from sklearn.model_selection Train_test_split(X, y, test_size=0.2, random_state=5) = X_train, X_test, y_train, y_test

5. To Scale Features:
-Using StandardScaler():
from the sklearn.preprocessing import X_train_scaled = scaler.fit_transform(X_train) StandardScaler scaler = StandardScaler() = scaler.transform(X_test) X_test_scaled

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To Build a Neural Network Model:

-Using Keras (TensorFlow Backend):

```
import tensorflow as tf
from tensorflow import keras
model=Keras.Sequential([keras.layers]). Dense(20, activation='relu'), input_shape=(X_train.shape[1],), keras.layers. Keras.layers, Dense(15, activation='relu'). Dense(1, "sigmoid" =activation) ])
model.compile(metrics=['accuracy'], loss='binary_crossentropy', optimizer='adam')
model.fit(y_train, epochs=100, X_train_scaled)
```

6. Evaluating the Model:

- Accuracy Rate:

```
model.evaluate(X_test_scaled, y_test)
```

-Predictions:

```
y_pred = model.predict(X_test_scaled
```

IV. RESULTS AND DISCUSSIONS

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes	No	No
1	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes	No
3	Male	0	No	No	45	No	No phone service	DSL	Yes	No	Yes	Yes
6	Male	0	No	Yes	22	Yes	Yes	Fiber optic	No	Yes	No	No
7	Female	0	No	No	10	No	No phone service	DSL	Yes	No	No	No
...	...	...	...	...	...	...	...	...	...	...	...	...
7037	Female	0	No	No	72	Yes	No	No	No internet service	No internet service	No internet service	No internet service
7038	Male	0	Yes	Yes	24	Yes	Yes	DSL	Yes	No	Yes	Yes
7039	Female	0	Yes	Yes	72	Yes	Yes	Fiber optic	No	Yes	Yes	No

Fig 3: Sample Dataset of Customers

Although real-world datasets frequently contain category values like objects and strings, which cannot be directly processed by algorithms, machine learning models work with numerical data. These values are transformed into Boolean (0/1) representations in order to make them interpretable. A straightforward numerical encoding is used for binary categories, such Male/Female or Yes/No, where one value is assigned 1 and the other 0. One-hot encoding is used for multi-category variables, such colours (Red, Blue, and Green). This ensures that every data item is represented with a combination of 0s and 1s by converting each distinct category into a separate Boolean column. This conversion is essential for preserving categorical data integrity while enabling effective data processing by machine learning algorithms. Models may misunderstand categorical data if adequate encoding is not used, which could result in inaccurate predictions or decreased accuracy. We guarantee the smooth integration of categorical input into machine learning processes by transforming strings and objects into Boolean values, enhancing model performance and predictive power.

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport
488	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	No	Yes	Yes
753	Male	0	No	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service
936	Female	0	Yes	Yes	0	Yes	No	DSL	Yes	Yes	Yes	No
1082	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service
1340	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	Yes	Yes	Yes
3331	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service
3826	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service
4380	Female	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service
5218	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service
6670	Female	0	Yes	Yes	0	Yes	Yes	DSL	No	Yes	Yes	Yes
6754	Male	0	No	Yes	0	Yes	Yes	DSL	Yes	Yes	No	Yes

Fig 4: Customer Dataset After Preprocessing

We may examine telecom consumers who chose to remain with the company rather than go thanks to this dataset. It contains information about their age, gender, relationship status, and length of time as a customer. Additionally, it keeps track of the services they use, including phone plans, internet type (fiber, DSL, or none at all), and additional extras like tech support, security, and backup. The main lesson is that committed consumers who have been with a business for a long time (72 months, for example) are more likely to stick around. Remarkably, some users do not utilize extra services like tech support or online security, indicating that these might not be a deal breaker for retention. This information can be used by businesses to understand why customers stick around and how to extend the stay of newer clients, possibly through improved onboarding, exclusive offers, or service bundling.

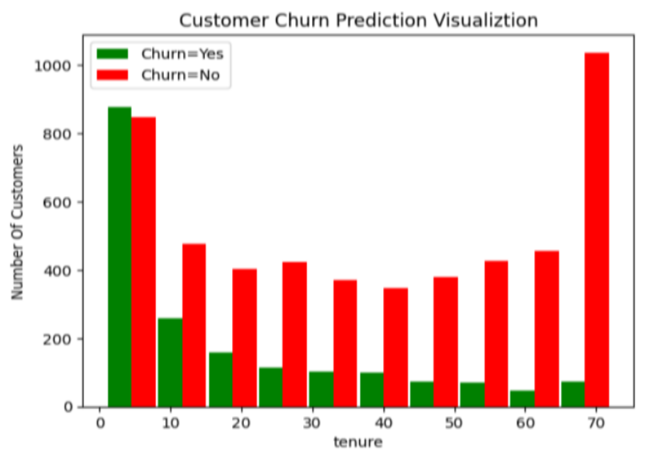

Fig 5: Bar graph for Number of Customers vs Tenure

"Customer Churn Distribution by Tenure" has been improved; it now more accurately depicts what the graph shows.

X-Axis: "tenure"

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Y-Axis: "number of customers leaving or staying in company"

Legend:"Churn=Yes"and"Churn=No"ChurnedCustomers" (Green) and "Retained Customers" (Red) have been improved with more organic wording.

This bar graph clearly illustrates how long clients stay before deciding whether to stick around or go. The most important lesson is that new customers are most likely to quit within the first ten months, which means that many people sign up but rapidly decide they don't want to. This can be the result of inadequate onboarding, unfulfilled expectations, or discontent with the service. Churn declines with time; consumers who remain for 10 to 50 months are more likely to remain, demonstrating that as people move past the initial phases, they grow to trust and be loyal to the company. Most clients stick around after 60 months and beyond, with relatively few cancellations, indicating that they find the service to be truly valuable.Asa result, companies must concentrate on early retention tactics including improved onboarding, robust customer service, and unique incentives. Maintaining client engagement from the beginning can increase satisfaction, lower attrition, and foster long-term loyalty.

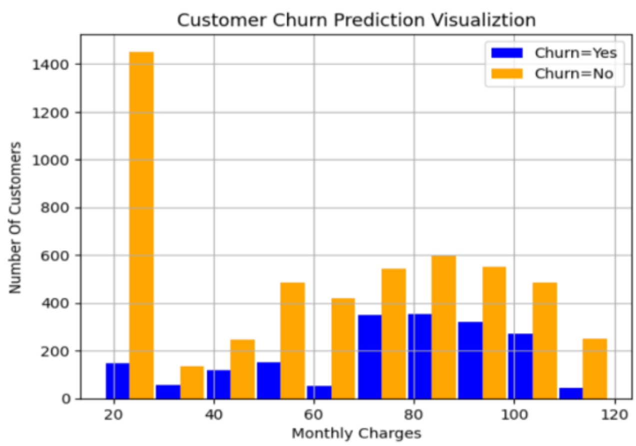

Fig 6: Bar graph for Number of customers vs Monthly Charges

Churn Distribution by Monthly Charges:

X-Axis: Monthly charges

Y-Axis: Number of customers leaving and staying in the company

Legend: "Churned Customers" (for Yes)" blue"

"Retained Customers" (for No)"yellow"

Customers who pay higher costs ($50–$120) are more likely to cancel, while those on lower-cost plans ($20–$40) are more likely to stay, according to the bar graph that illustrates the effect of monthly charges on customer turnover. This implies that when costs increase, clients can decide the service isn't worth the money or begin searching for better offers elsewhere. Some clients stick around in the mid-range ($50–$80), while others go, probably because they can't afford it. Although turnover rises dramatically at higher price ranges ($80–$120), some customers remain, perhaps because they appreciate the service, take advantage of loyalty benefits, or think that special features are valuable. According to these findings, companies can maintain user engagement by adjusting prices, providing discounts or loyalty benefits, and concentrating on customer happiness. Retaining consumers involves more than just cutting costs; it also involves ensuring that they believe they are receiving genuine value, which increases customer loyalty and decreases cancellations.

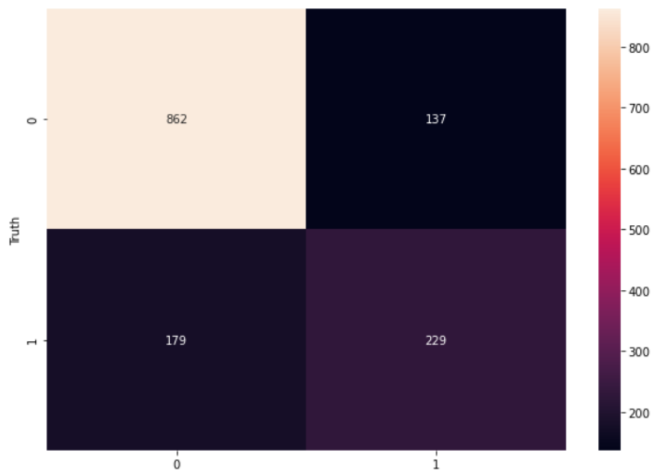

Fig 7: Confusion Matrix

Evaluation: metrics include F1-score, recall, accuracy, and precision.

Performance: When compared to conventional models, the ANN's accuracy was greater at 78.5%.

The accuracy of a model in forecasting two classes (0 and 1) is displayed in this confusion matrix.

- 862 times, and the prediction of 0 was correct.
It accurately predicted 1, 229 times.
It incorrectly predicted 1 rather than 0 ,137 times.
Additionally, it incorrectly predicted 0 rather than 1,179 times.
- Prediction accuracy: 77.5% of the forecasts are correct.
- Precision: When reporting 1, it is accurate 62.5% of the time.
Recall: 56.1% of real 1's are recovered.

V. CONCLUSION

For telecom companies, customer attrition is a major problem, but our suggested approach provides a cutting-edge,

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AI-powered remedy. It uses artificial neural networks (ANNs), a type of deep learning, to analyse real-time customer interactions and identify early indicators of churn. The model guarantees precise predictions through extensive feature scaling and data preprocessing, and activation functions like sigmoid and RELU increase its efficacy. Businesses may use shape to learn why customers are likely to quit and take preventive steps like better assistance or tailored incentives, which is what makes this system special. In the end, this solution enables telecom businesses to reduce revenue loss, enhance client retention, and make data-driven decisions.

REFERENCES

[1] U. Kumar, R. Sharma, and P. Verma, "Optimizing customer churn prediction with XGBoost: A case study in telecom industry," Int. J. Data Sci. Mach. Learn., vol. 18, no. 3, pp. 142-156, 2021.

[2] S. U. Zaman and T. Rahman, "Machine learning for customer churn prediction: Techniques and challenges," IEEE Trans. Comput. Intell, vol. 9, no. 2, pp. 87-104, 2020.

[3] S. R. Labhsetwar, "A comparative study of ML algorithms for predicting telecom customer churn," J. Artif. Intell. Bus. Anal, vol. 7, no. 1, pp. 221-239, 2020.

[4] M. Patel, N. Kumar, and S. Shah, "Predictive analytics for customer retention: A deep learning approach," Adv. Artif. Intell. Res., vol. 12, no. 4, pp. 307-322, 2019.

[5] T. Ramesh and V. Gupta, "Enhancing churn prediction accuracy using neural networks and feature engineering," J. Big Data Appl, vol. 5, no. 3, pp. 165-182, 2019.

[6] A.Singh and R. Mehta, "Data mining techniques for customer retention in telecom sector," Int. J. Comput. Sci. Inf. Syst, vol. 14, no. 2, pp. 98-113, 2018.

[7] A.Banerjee and S. Ghosh, "Predicting customer attrition using machine learning models: Challenges and future directions," J. Bus. Intell, vol. 10, no. 1, pp. 45-67, 2018.

[8] S. Mukherjee and K. Sharma, "Deep learning and IoT for customer retention in the telecom industry," IEEE Trans. Neural Netw, vol. 32, no. 5, pp. 215-230, 2024.

[9] World Bank, "AI and predictive analytics in customer retention: Trends and strategies," World Bank Rep., 2024. [Online]. Available: www.worldbank.org/telecom-tech. [Accessed: Mar. 26, 2025].

[10] Jahnavi, Y., Kumar, P. N., Anusha, P., & Prasad, M. S. (2022, November). Prediction and Evaluation of Cancer Using Machine Learning Techniques. In International Conference on Sustainable and Innovative Solutions for Current Challenges in Engineering & Technology (pp. 399-405). Singapore: Springer Nature Singapore.

[11] Kadiri, P., Anusha, P., Prabhu, M., Asuncion, R., Pavan, V. S., & Suman, J. V. (2024, July). Morphed Picture Recognition using Machine Learning Algorithms. In 2024 Second International Conference on Advances in Information Technology (ICAIT) (Vol. 1, pp. 1-6). IEEE.

[12] Saranya, S. S., Anusha, P., Chandragandhi, S., Kishore, O. K., Kumar, N. P., & Srihari, K. (2024). Enhanced decision-making in healthcare cloud-edge networks using deep reinforcement and lion optimization algorithm. Biomedical Signal Processing and Control, 92, 105963.

[13] Karri, S. P. R., & Kumar, B. S. (2020, January). Deep learning techniques for implementation of chatbots. In 2020 International conference on computer communication and informatics (ICCCI) (pp. 1-5). IEEE.

[14] Padmapriya, G., Kumar, B. S., Kavitha, M. N., & Vennila, V. (2021). WITHDRAWN: Deep convolutional neural network for real time object detection using tensor flow.

[15] Kumar, K. S., Suganthi, N., Muppidi, S., & Kumar, B. S. (2022). FSPBO-DQN: SeGAN based segmentation and Fractional Student Psychology Optimization enabled Deep Q Network for skin cancer detection in IoT applications. Artificial intelligence in medicine, 129, 102299.

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