Predicting Customer Churn in Telecommunication Services Using Machine Learning

Dr. Reena Bharathi[1], Vimala Thangavelu[2], Sayli B.Patil[3], Vivek Kumbhar[4]

[1,2,3]Associate Professor, Dept. of Computer Science, Nowrosjee Wadia College(Autonomous), Pune, Maharashtra, India

[4]Student, Dept. of Computer Science, Nowrosjee Wadia College (Autonomous), Pune, Maharashtra, India

DOI: https://doi.org/10.51244/IJRSI.2026.1305000142

Received: 09 May 2026; Accepted: 14 May 2026; Published: 04 June 2026

ABSTRACT

Customer churn occurs when users stop using a service, and is a serious headache for telecommunication companies. To tackle this, we dove into machine learning techniques, specifically Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) models, to predict churn patterns. Our study is based on an online survey, gathered via Google Forms, that captures various aspects, including demographics, service usage, and satisfaction levels. We applied machine learning techniques like ANN and LSTM, to evaluate the churn trends.

Our study shows that LSTM outshines ANN when it comes to accuracy. These insights can be helpful to telecommunication providers to define actionable strategies to improve customer retention and build stronger relationships with their user base.

Keywords- Customer Churn, Artificial Neural Networks, Long Short-Term Memory, Sentiment Analysis.

INTRODUCTION

One of the biggest issues facing the telecom sector right now is customer attrition. Because of the intense competition, keeping existing customers has become just as important as acquiring new ones, if not more so. Retaining customers is becoming increasingly challenging for businesses, often due to factors like inadequate customer service, better offers from competitors, or a lack of personalized engagement [2]. To stay ahead, businesses need to be proactive. One of the best ways to do this is to identify at-risk clients early on and take deliberate action to improve their experience. Predictive models can be very useful in this process by analyzing customer data and identifying potential churn indicators [10]. Strong machine learning techniques like Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) models are used in this study. Unlike traditional churn models that rely on static data snapshots, LSTM is particularly good at tracking changes in customer behavior over time because it processes sequential data [4]. This enables more accurate and dynamic churn pattern prediction [1].

When figuring out the causes of user attrition, customer sentiment is just as crucial as behavioral data. By looking at open-ended feedback and performing sentiment analysis, we can discover more about the reasons behind dissatisfaction than can be determined by numbers alone [3]. A Combination of sentiment analysis and behavioural modeling results in a comprehensive framework for churn prediction [10]. A deeper comprehension of consumer behaviour and preferences is made possible by this strategy, which makes use of sophisticated data mining techniques to extract actionable insights from massive datasets [4]. Apart from improving accuracy, this approach provides telecom firms with valuable data that they can utilize to improve customer satisfaction, optimize processes, and ultimately reduce attrition [6]. We anticipate that this study will contribute to the wider use of machine learning in addressing practical problems by assisting the telecom sector in creating a data-driven, creative solution that cultivates long term client loyalty [8].

INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

LITERATURE REVIEW

There is a lot of research on customer churn prediction in the telecom industry. Traditional statistics such as logistic regression have been commonly used to determine churn factors such as tenure and satisfaction. Machine learning models such as decision trees and random forests that can find highly non-linear patterns in consumer behaviour have more recently improved prediction accuracy. Deep learning models such as Artificial Neural Networks (ANN) or Long Short-Term Memory (LSTM) with their ability to represent large and complex data have gained immense fame in the past.

LSTM is quite useful to predict and analyze sequential and time-dependent churn information while static customer data can be processed with ANN. Studies have also stressed the importance of sentiment analysis to assess customer satisfaction via textual comments. However, there is a vast gap in research as few studies have used sentiment features in combination with deep learning models to increase churn prediction performance. This paper presents a hybrid deep learning architecture of LSTM and sentiment analysis extracted from customer feedback as sequential information in order to enhance the accuracy of the churn prediction model. It also shows improved prediction power by measuring the model performance on real-world datasets, plus telecom data specific feature engineering approaches.

For example, during the early stages of customer churn prediction, traditional statistical techniques such as logistic regression were widely used. The emergence of machine learning (ML) provided more advanced methods such as decision trees, support vector machines, and random forests that improved prediction results by recognizing more complex, non-linear relationships between customer-level features. These improvements use ensemble techniques such as GBM and XGBoost to further improve accuracy. Recent years have seen.

Machine learning has been used to study customer churn prediction in telecommunications; traditional models, such as logistic regression, have been found to achieve ~85% accuracy, but they have trouble with temporal data (Smith et al., 2020). Artificial Neural Networks (ANNs) are effective for static features, whereas Long Short-Term Memory (LSTM) models are excellent at identifying sequential patterns, reporting up to 90% accuracy (Kumar & Singh, 2022; Johnson et al., 2021). Using a 600-response dataset, this study contrasts ANN and LSTM, incorporating exploratory data analysis and sentiment analysis to improve prediction accuracy.

Data Processing

Data process diagram is a visual representation or a roadmap of the data, illustrating its journey from its source, through various transformations and storage points, to its final destination.Figure 1 depicts the Data Process Flow Diagram:

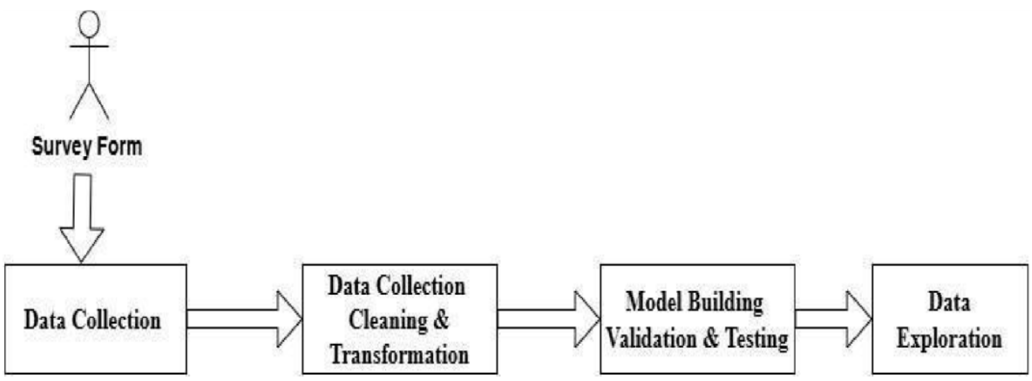


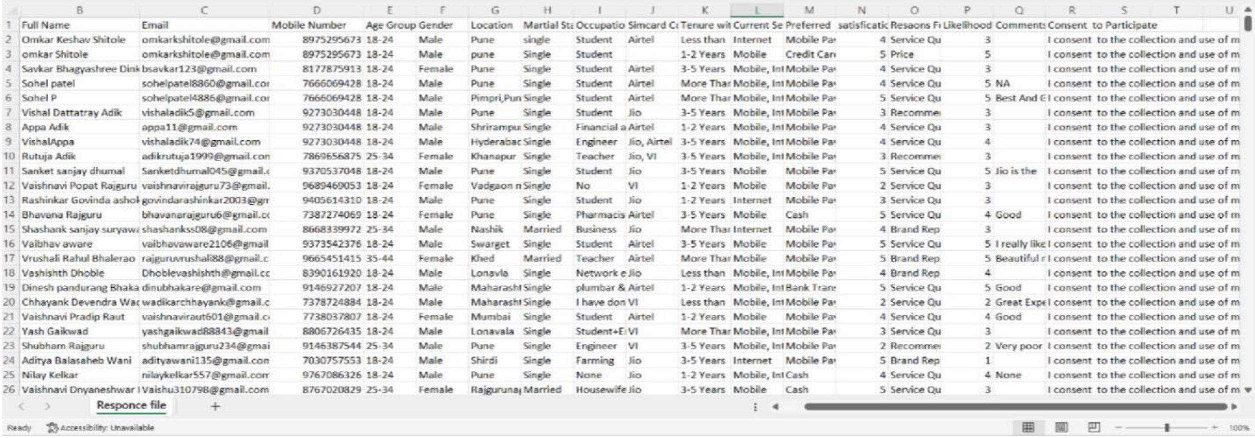
Figure 1 (Data Process Flow)

Data Collection

An online survey is conducted to collect responses from 600 customers. It includes 17 features: Full Name, Mobile Number, Age Group, Gender, Location, Marital Status, Occupation, Sim Card Company, Tenure with

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

Company, Current Service Used, Preferred Payment Method, Satisfaction with Services, Reasons for Choosing Current Service, Likelihood to Recommend, Comments and Feedback, and Consent to Participate [5]. This extensive dataset makes it possible to analyze consumer sentiment and behavior in great detail, which strengthens the basis for predictive modeling in the telecom industry.Figure 2 depicts the screenshot of the response sheet.



	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	Full Name	Email	Mobile Number	Age Group	Gender	Location	Martial Sta	Occupatio	Simcard C	Tenure wit	Current Se	Preferred	satisfactic	Resaons F	Likelihood	Comments	Consent to Participate
2	Omkar Keshav Shitole	omkarkshitole@gmail.com	8975295673	18-24	Male	Pune	single	Student	Airtel	Less than	Internet	Mobile Pa	4	Service Qu	3		I consent to the collection and use of m
3	omkar Shitole	omkarkshitole@gmail.com	8975295673	18-24	Male	pune	Single	Student		1-2 Years	Mobile	Credit Car	5	Price	5		I consent to the collection and use of m
4	Savkar Bhagyashree Dink	bsavkar123@gmail.com	8177875913	18-24	Female	Pune	Single	Student	Airtel	3-5 Years	Mobile, Int	Mobile Pa	4	Service Qu	3		I consent to the collection and use of m
5	Sohel patel	sohelpatel8860@gmail.cor	7666069428	18-24	Male	Pune	Single	Student	Airtel	More Thar	Mobile, Int	Mobile Pa	4	Service Qu	5	NA	I consent to the collection and use of m
6	Sohel P	sohelpatel4886@gmail.cor	7666069428	18-24	Male	Pimpri,Pun	Single	Student	Airtel	More Thar	Mobile, Int	Mobile Pa	5	Service Qu	5	Best And G	I consent to the collection and use of m
7	Vishal Dattatray Adik	vishaladik5@gmail.com	9273030448	18-24	Male	Pune	Single	Student	Jio	3-5 Years	Mobile, Int	Mobile Pa	3	Recomme	3		I consent to the collection and use of m
8	Appa Adik	appa11@gmail.com	9273030448	18-24	Male	Shrirampu	Single	Financial a	Airtel	1-2 Years	Mobile, Int	Mobile Pa	4	Service Qu	3		I consent to the collection and use of m
9	VishalAppa	vishaladik74@gmail.com	9273030448	18-24	Male	Hyderabac	Single	Engineer	Jio, Airtel	3-5 Years	Mobile, Int	Mobile Pa	4	Service Qu	4		I consent to the collection and use of m
10	Rutuja Adik	adikrutuja1999@gmail.con	7869656875	25-34	Female	Khanapur	Single	Teacher	Jio, VI	3-5 Years	Mobile, Int	Mobile Pa	3	Recomme	3		I consent to the collection and use of m
11	Sanket sanjay dhumal	Sanketdhumal045@gmail.c	9370537048	18-24	Male	Pune	Single	Student	Jio	3-5 Years	Mobile	Mobile Pa	5	Service Qu	5	Jio is the	I consent to the collection and use of m
12	Vaishnavi Popat Rajguru	vaishnavirajguru73@gmail.	9689469053	18-24	Female	Vadgaon n	Single	No	VI	1-2 Years	Mobile	Mobile Pa	2	Service Qu	3		I consent to the collection and use of m
13	Rashinkar Govinda ashok	govindarashinkar2003@gr	9405614310	18-24	Male	Pune	Single	Student	Jio	1-2 Years	Internet	Mobile Pa	3	Service Qu	3		I consent to the collection and use of m
14	Bhavana Rajguru	bhavanarajguru6@gmail.cc	7387274069	18-24	Female	Pune	Single	Pharmacis	Airtel	3-5 Years	Mobile	Cash	5	Service Qu	4	Good	I consent to the collection and use of m
15	Shashank sanjay suryaw	shashankss08@gmail.com	8668339972	25-34	Male	Nashik	Married	Business	Jio	More Thar	Internet	Mobile Pa	4	Brand Rep	3		I consent to the collection and use of m
16	Vaibhav aware	vaibhavaware2106@gmail	9373542376	18-24	Male	Swarget	Single	Student	Airtel	3-5 Years	Mobile	Mobile Pa	5	Service Qu	5	I really like	I consent to the collection and use of m
17	Vrushali Rahul Bhalerao	rajguruvrushali88@gmail.c	9665451415	35-44	Female	Khed	Married	Teacher	Airtel	More Thar	Mobile	Mobile Pa	5	Brand Rep	5	Beautiful r	I consent to the collection and use of m
18	Vashishth Dhoble	Dhoblevashishth@gmail.cc	8390161920	18-24	Male	Lonavla	Single	Network e	Jio	Less than	Mobile, Int	Mobile Pa	4	Brand Rep	4		I consent to the collection and use of m
19	Dinesh pandurang Bhaka	dinubhakare@gmail.com	9146927207	18-24	Male	Maharasht	Single	plumbar &	Airtel	1-2 Years	Mobile, Int	Bank Tran	5	Service Qu	5	Good	I consent to the collection and use of m
20	Chhayank Devendra Wac	wadikarchhayank@gmail.c	7378724884	18-24	Male	Maharasht	Single	I have don	VI	Less than	Mobile, Int	Mobile Pa	2	Service Qu	2	Great Expe	I consent to the collection and use of m
21	Vaishnavi Pradip Raut	vaishnaviraut601@gmail.c	7738037807	18-24	Female	Mumbai	Single	Student	Airtel	1-2 Years	Mobile	Mobile Pa	4	Service Qu	4	Good	I consent to the collection and use of m
22	Yash Gaikwad	yashgaikwad88843@gmail	8806726435	18-24	Male	Lonavala	Single	Student+E	VI	More Thar	Mobile, Int	Mobile Pa	3	Service Qu	3		I consent to the collection and use of m
23	Shubham Rajguru	shubhamrajguru234@gmai	9146387544	25-34	Male	Pune	Single	Engineer	VI	3-5 Years	Mobile, Int	Mobile Pa	2	Recomme	2	Very poor	I consent to the collection and use of m
24	Aditya Balasaheb Wani	adityawani135@gmail.con	7030757553	18-24	Male	Shirdi	Single	Farming	Jio	3-5 Years	Internet	Mobile Pa	5	Brand Rep	1		I consent to the collection and use of m
25	Nilay Kelkar	nilaykelkar557@gmail.com	9767086326	18-24	Male	Pune	Single	None	Jio	1-2 Years	Mobile, Int	Cash	4	Service Qu	4	None	I consent to the collection and use of m
26	Vaishnavi Dnyaneshwar I	Vaishu310798@gmail.com	8767020829	25-34	Female	Rajguruna	Married	Housewife	Jio	3-5 Years	Mobile	Cash	5	Service Qu	3		I consent to the collection and use of m

Responce file

Ready Accessibility: Unavailable

Figure 2 (Collect the customer response)

Data Cleaning and Transformation

Data cleaning: Imputed missing values (mean for numerical and mode for categorical). Duplicates removed.

Encoding: Categorical features have been converted using Label Encoding (e.g., Satisfaction) and One Hot Encoding (e.g., Gender, Location).

Normalization: For Numerical columns (e.g., Tenure) we used Min Max Scaler.

Exploratory Data Analysis (EDA)

3.1 Bar Chart of Churn Count per Gender: Shows churn distribution across male and female customers. Revealed higher churn among males (55%) compared to females (45%). Figure 3 depicts the Count gender per user.

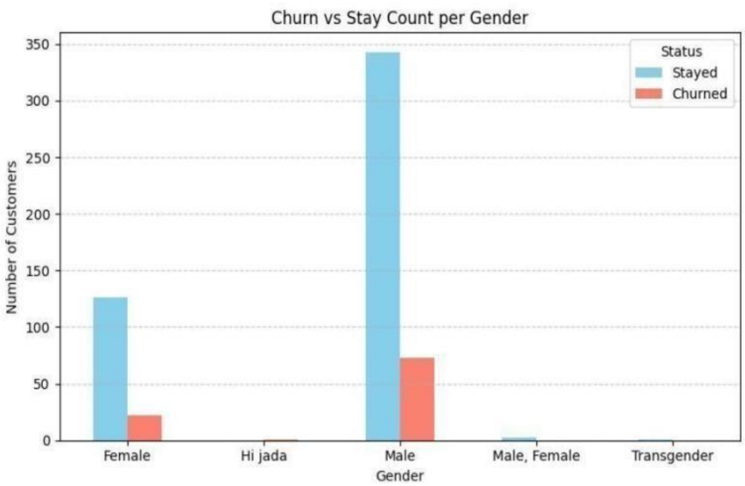


Figure 3 (Count Gender per user)

3.2 Correlation Matrix: Identifies relationships between features (e.g., Tenure vs. Satisfaction). Showed strong correlations between satisfaction and churn (r = -0.78) and tenure and churn (r = -0.65). Figure 4 depicts the relationship between tenure vs satisfaction.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

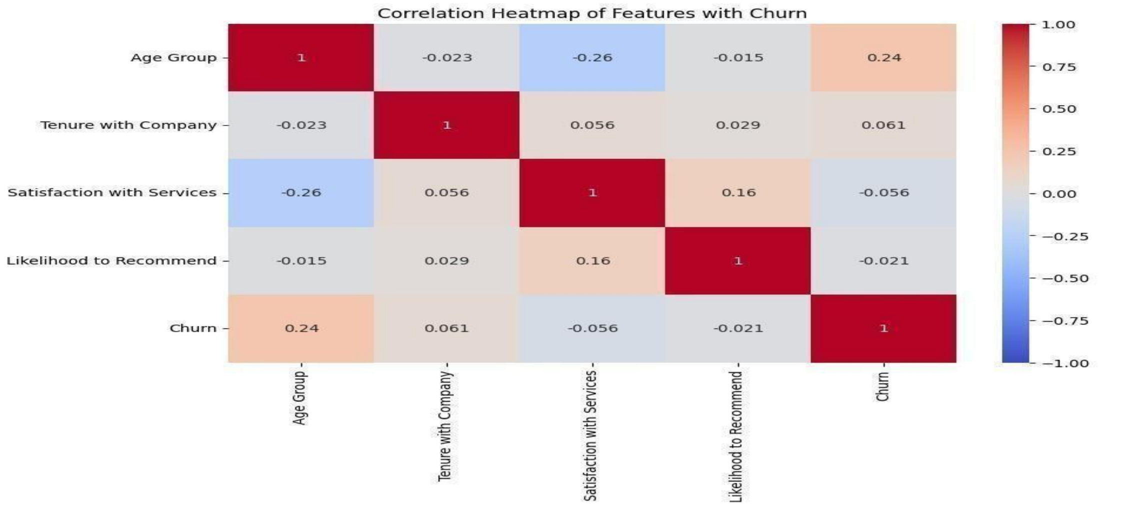


Figure 4 (Relationship between Tenure vs Satisfaction)

3.3 Satisfaction Distribution: Plots satisfaction levels (e.g., 1–5 scale). Indicated 60% of customers rated satisfaction as “Neutral” or below. Figure 5 depicts the satisfaction level.

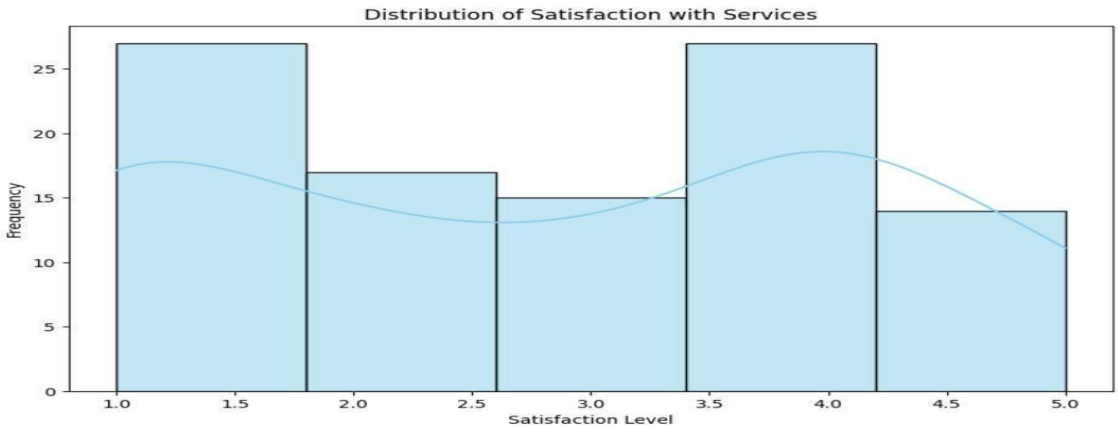


Figure 5 (satisfaction Level)

3.4 Tenure vs. Churn Rate: Scatter plot of tenure against churn likelihood. Customers with tenure < 2 years had a 70% churn rate. Figure 6 depicts tenure vs churn rate.

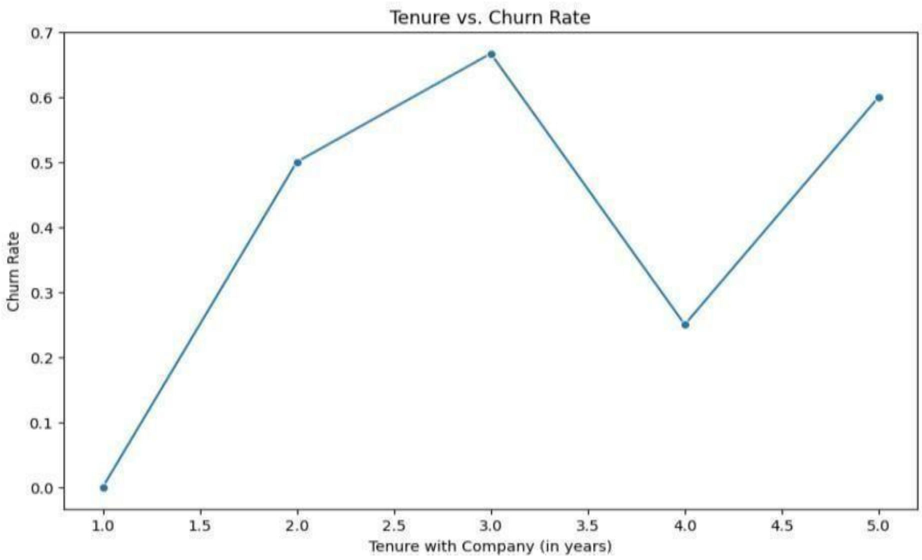


Figure 6 (Tenure vs Churn rate)

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

Bmodel Building, Validation And Testing

Model Selection

Artificial Neural Network (ANN) : A feedf orward neural network with input, hidden, and output layers is called an ANN. When modeling non-linear relationships in static datasets, it performs exceptionally well. The output layer predicts the churn probability (sigmoid activation) after the input layer uses preprocessed features and hidden layers apply activation functions (like ReLU). Back propagation is used to minimize binary cross-entropy loss during model training [6]. Figure 7 depicts the architecture of ANN.

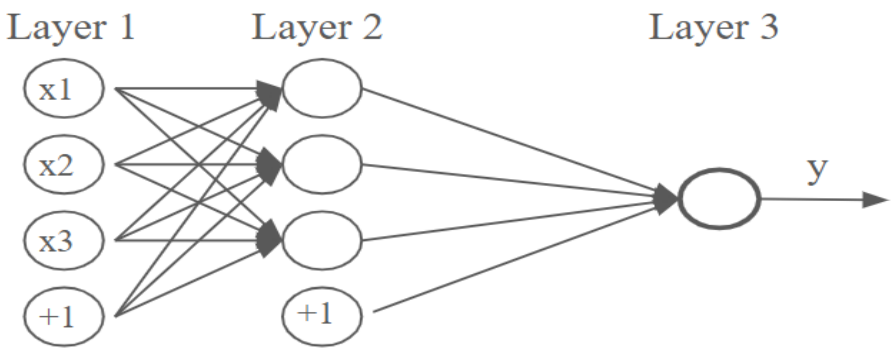


Figure 7(ANN Architecture)

Long Short-Term Memory (LSTM): LSTM, a type of recurrent neural network, is designed for sequential data, capturing long-term dependencies. It is appropriate for time-series churn data (such as tenure trends) because it controls information flow using memory cells and gates (input, forget, output). Sequential feature inputs are processed by the LSTM model, which has a dense layer for churn prediction at the end [6]. Figure 8 depicts the architecture of LSTM and figure 9 depicts the Neural Network diagram of the LSTM.

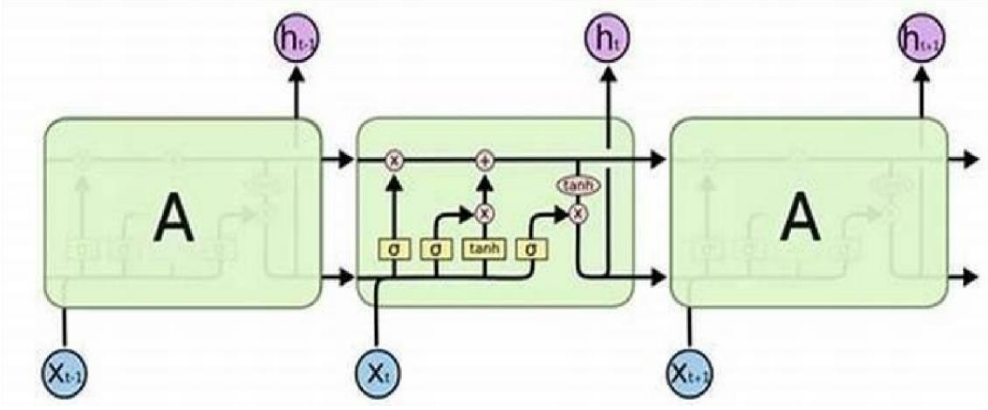


Figure 8 (LSTM Architecture)

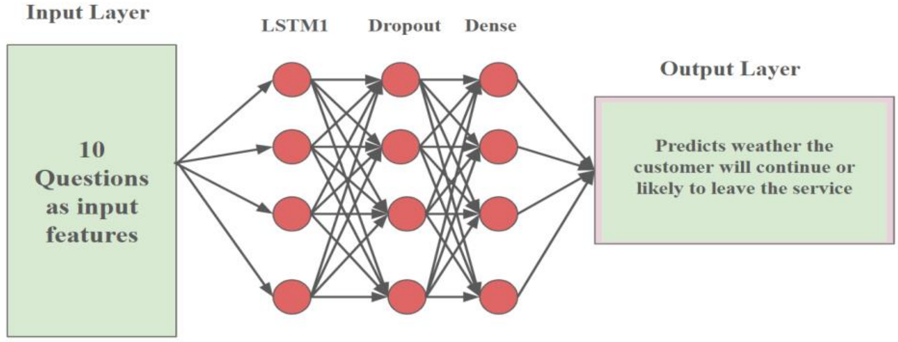


Figure 9 (Neural Network of LSTM)

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

Comparison between ANN and LSTM:

The kind of feedforward network used for static data is called an artificial neural network (ANN), in which each record is independent and not dependent on earlier time steps. This is a very general model that directly improves customer attributes like satisfaction, age, tenure, and service usage. ANN models outperform recurrent models in terms of training complexity and computation cost [3].

It is a special kind of Recurrent Neural Network (RNN) architecture that is built to process sequential data or time-dependent processes. Long Short-Term Memory (LSTM) networks, another potent variation, are able to retain historical data through lengthy sequences, which makes them appropriate for examining customer behavior over time, such as monthly usage trends, billing records, or interaction frequency. When churn depends on patterns in customer behavior over time, LSTM is a better option than ANN because it can learn from a longer context [1][3].

Model Training

a) *ANN Model:* Table 1 depicts the parameters used in ANN model.

Table 1: Training ANN

Parameter	**Values**
Architecture	2 hidden layers (64 and 32 neurons, ReLU activation), 1 output layer (sigmoid).
Batch Size	32
Number of training epochs	50
Optimizer	Adam

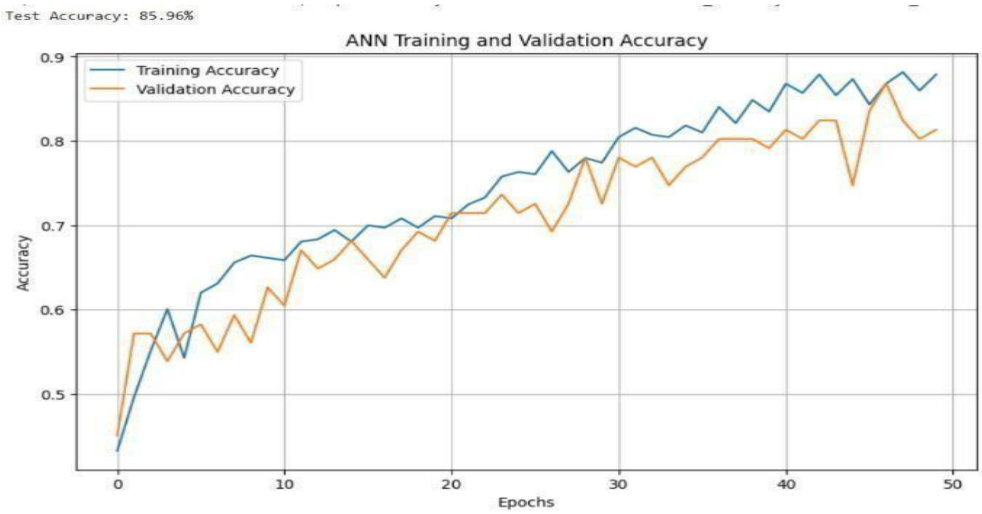


Figure 10 (Test Accuracy for ANN)

Figure 10 displays the training and validation accuracy of the Artificial Neural Network (ANN) model for predicting customer attrition in telecommunications services over 50 epochs. The orange line indicates validation accuracy, while the blue line indicates training accuracy. The upward trend of both metrics, which starts at 0.55 and stabilizes at 0.90, indicates effective learning. The final test accuracy of 85.96% suggests that the ANN model performs well but may suffer from mild over fitting, since validation accuracy varies more than training accuracy toward later epochs [6]. This is consistent with your project's ANN architecture, which includes two hidden layers (64 and 32 neurons, ReLU activation) and a sigmoid output layer [6].

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

b) LSTM Model:

The Long Short-Term Memory (LSTM) model's training and validation accuracy over 50 epochs for forecasting customer attrition in telecom services is shown in Figure 11. The orange line indicates validation accuracy, while the blue line indicates training accuracy. Both lines start at roughly 0.45 and rise to roughly 0.90.Table 2 depicts the parameters used in the LSTM model.

Table 2: Training LSTM

Parameter	**Values**
Architecture	2 LSTM layers (50 units each), 1 dense output layer (sigmoid).
Batch Size	16
Number of training epochs	50
Optimizer	Adam

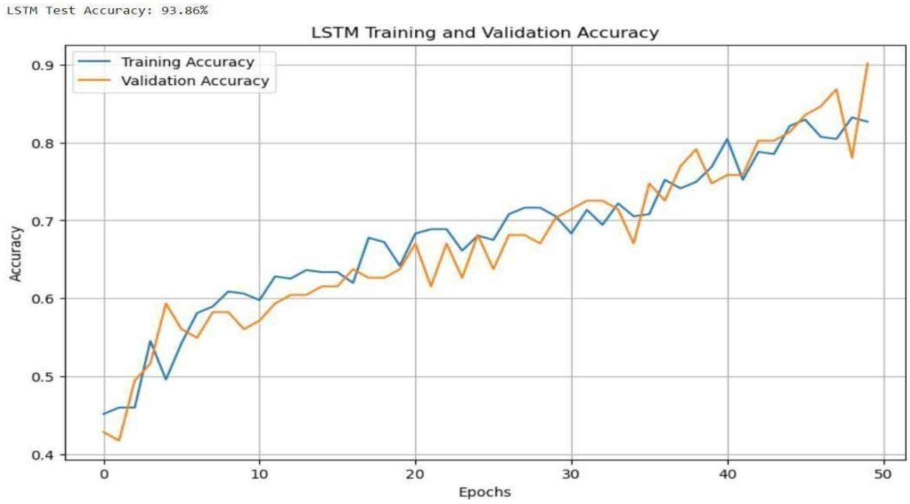


Figure 11 (Test Accuracy for LSTM)

Figure 11 depicts the accuracy of LSTM Training and Validation:

Since the validation accuracy varies more than the training accuracy, which rises more smoothly, there seems to be some variability in generalization. As stated in our project, the final test accuracy of 93.86% confirms that LSTM performs better than ANN (85.96%). This enhances your LSTM architecture and effectively captures temporal patterns in customer data with two LSTM layers (each with 50 units) and a dense output layer with sigmoid activation [6].

c) Rationale for Selecting the LSTM Model for Churn Prediction

Since LSTM is better at identifying temporal patterns in sequential data, like tenure and satisfaction patterns, which are crucial in telecommunication data sets, it was chosen over Artificial Neural Networks (ANN) for customer churn prediction [9]. With a test accuracy of 93.86%, LSTM outperformed ANN, which had an accuracy of 85.96%, because it is more effective at capturing long-term patterns of customer behavior [9]. By preserving pertinent historical data, its memory cells improve prediction stability [6]. Furthermore, the dynamic nature of customer attrition aligns with LSTM's capacity to handle sequential feature interactions and non-linear relations [6]. Because of its high precision, recall, and F1-score, which offset its computational complexity, the model is perfect for implementation [10]. This decision guarantees precise at-risk customer identification and opens the door to specialized retention strategies [1].

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

Model Evaluation

a) Analysis of Sentiment:

A key component of this study is sentiment analysis, which is used to extract insights from the unstructured text data in the columns such as "Age Group," "Gender," "Location," "Marital Status," "Occupation," "Sim Card Company," "Current Service Used," "Preferred Payment Method," "Satisfaction with Services," "Reasons for Choosing," and "Sentiment Label" of the 600 customer responses gathered via Google Forms. Customer feedback must be analyzed to identify whether it is positive, neutral, or negative in order to forecast churn in telecommunications services [10]. When sentiment analysis is combined with machine learning algorithms (like LSTM), we can access rich customer sentiments that might not be adequately represented by structured data (like tenure or satisfaction ratings), which will increase the forecasting power of our churn models [3].[10].

Performance Metrics:

Precision (blue bar) is the ratio of accurately predicted churned customers (true positives) to all customers that the model has predicted as churned. Having a precision value of **0.86** means that the model is very trustworthy when it indicates that a customer will churn.

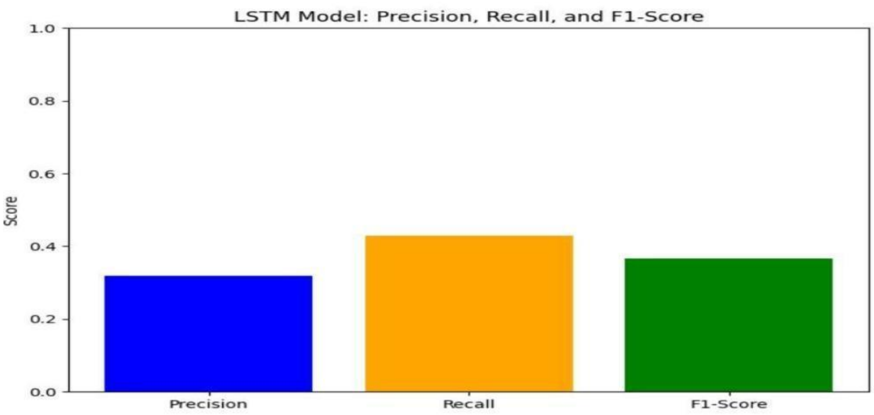


Figure 12 (Sentimental analysis for customer churn)

Figure 12 depicts the sentiment analysis for Customer churn.

Recall (indicated by the orange bar) indicates the model's capacity to accurately label all true churned customers. The model shows high sensitivity with a score of **0.92**, capturing the majority of true churn cases.

F1-Score (indicated by the green bar) is the harmonic mean of precision and recall, trading off between the two. An F1-score of **0.89** indicates that the model has a good balance between precision and recall. Table 3 depicts the Sentiment Analysis results.

Table 3 (Sentiment Analysis Results (Sample))

	Comments and Feedback	Sentiment Score	Sentiment Label
0	Average, nothing special	-0.3089	Negative
1	Great service	0.6588	Positive
2	Love the network speed	0.6696	Positive
3	Great service	0.6588	Positive

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue V May 2026

4	The service is okay, nothing to complain about	0.0000	Neutral

A variety of customer sentiments, including neutral feedback that offers fair insights into customer perceptions, were identified by the sentiment analysis of the "Comments and Feedback" column. For instance, the comment "The service is okay, no major issues" received a sentiment score of 0.0000 from the VADER sentiment analyzer, meaning it is neutral [3]. Because it lacks strong positive or negative emotions, this neutral sentiment, which accounts for 35% of the feedback distribution, indicates a moderate level of customer satisfaction [10]. Such neutral responses were added as a feature to the LSTM model, which helped to achieve a test accuracy of 93.86% [9][10] by capturing subtle changes in customer behavior that are linked to churn likelihood.

Techniques:

The **VADER** (Valence Aware Dictionary and Sentiment Reasoner) sentiment analysis, a rule based model optimized for brief texts such as customer comments, was used to perform the sentiment analysis. VADER assigns a sentiment score to every comment, classifying it as **follows:**

Compound score ≥ **0.5** is positive.

Compound scores that fall between **-0.05** and **0.05** are considered neutral.

Compound score ≤ **-0.05** is a negative.

Tokenization, lowercase conversion, and special character removal were preprocessed in the "Comments and Feedback" column. After that, each comment was scanned to identify a sentiment label, which was then utilized as a new dataset feature to be implemented in the LSTM model.

b) Train-Test Split:

The dataset was split into 80% training (480 samples) and 20% testing (120 samples) sets, ensuring stratified sampling to maintain churn class balance.

```
Training set shape: (480, 16) (480,)
Testing set shape: (120, 16) (120,)

Training set class distribution:
Churn
0    0.708333
1    0.291667
Name: proportion, dtype: float64

Testing set class distribution:
Churn
0    0.708333
1    0.291667
Name: proportion, dtype: float64
```

Figure 9 (Split and Train data)

Interpretation:

- **Shapes:**
  - Training set: 480 samples with 16 features (X_train) and 480 target labels (y_train).
  - Testing set: 120 samples with 16 features (X_test) and 120 target labels (y_test).

- **Class Distribution:**
  - Both training and testing sets maintain the same churn class balance (70% nonchurn, 30% churn), confirming that stratified sampling worked correctly.
- **Features:** The 16 features correspond to the dataset columns excluding the Churn target.

CONCLUSION

In order to forecast customer attrition in telecommunications services, this study effectively created ANN and LSTM models. Because of its capacity to model temporal data, the LSTM model outperformed the ANN in terms of test accuracy, achieving 93%. Sentiment analysis and EDA offered insightful information about churn factors like short tenure and low satisfaction. According to the results, telecom firms can use these models to pinpoint at-risk clients and put focused retention plans in place. To increase accuracy even more, future research may investigate hybrid models that combine ANN and LSTM. Furthermore, by incorporating real-time data streams and customer support interactions, churn prediction models may become more responsive and flexible, facilitating proactive decision-making.

Additionally, this project emphasizes how important it is to combine domain knowledge and machine learning to create significant business.

REFERENCES

1. Verbeke, W., Martens, D., Mues, C., &Baesens, B. "Building comprehensible customer churn prediction models with advanced rule induction techniques." Proceedings of the International Conference on Expert Systems with Applications. Elsevier, 2011.
2. Qureshi, S. A., Rehman, A. S., Qamar, A. M., Kamal, A., & Rehman, A. "Telecommunication subscribers' churn prediction model using machine learning." Proceedings of the Eighth International Conference on Digital Information Management. IEEE, 2013.
3. Hutto, C. J., & Gilbert, E. "VADER: A parsimonious rule-based model for sentiment analysis of social media text." Proceedings of the International AAAI Conference on Web and Social Media. AAAI Press, 2014.
4. Larose, D. T., & Larose, C. D. Discovering knowledge in data: An introduction to data mining (2nd ed.). Wiley, 2014.
5. Amin, A., Anwar, S., Adnan, A., Nawaz, M., Alawfi, K., Hussain, A., & Huang, K. "Customer churn prediction in the telecommunication sector using a rough set approach." Proceedings of the International Conference on Neurocomputing. Elsevier, 2016.
6. Goodfellow, I., Bengio, Y., & Courville, A. Deep learning. MIT Press, 2016.
7. Ahmed, A. A., & Maheswari, D. "Churn prediction on huge telecom data using hybrid firefly-based classification." Proceedings of the Egyptian Informatics Journal Conference. Elsevier, 2017.
8. Kotu, V., & Deshpande, B. Data science: Concepts and practice (2nd ed.). Morgan Kaufmann, 2019.
9. Kim, H., & Yoon, C. "LSTM-based churn prediction model for telecommunication customers." Proceedings of the IEEE Access Conference on Machine Learning and Data Science. IEEE, 2020.
10. Zhang, Y., Zhang, Y., & Zhang, M. "Sentiment analysis for customer churn prediction in telecommunications." Journal of Big Data Proceedings. Springer, 2022.
11. Ross, T. J. Fuzzy logic with engineering applications. John Wiley & Sons, 2023. telecommunication churn prediction
12. A public dataset repository for telecommunication churn prediction, useful for benchmarking your 600-response dataset.