TELECOM SUBSCRIBER CHURN PREDICTION USING DEEP LEARNING: EXAMINING THE INFLUENCE OF CUSTOMER CHARACTERISTICS AND SERVICE OFFERINGS

PHASE II REPORT

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BONAFIDE CERTIFICATE

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ABSTRACT

Telecom companies are facing a persistent challenge called customer churn, where subscribers terminate their services and switch to competing carriers. This phenomenon directly impacts revenue and long-term sustainability. To address this challenge, telecom companies are increasingly turning to predictive analytics and Deep learning techniques. These techniques involve using vast repositories of historical customer data to develop predictive models that forecast customer churn. By analyzing these models, telecom companies can proactively address churn dynamics and enhance customer retention efforts. To build robust churn prediction models, telecom companies explore a variety of machine learning and Deep Learning algorithms. Traditional approaches like Gradient Boosting and Random Forest remain popular, but there is a growing interest in more advanced methodologies. Models like LightGBM offer promising avenues for enhancing predictive accuracy and performance. Additionally, the integration of Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid architectures like LSTM-CNNs and Wide and Deep Neural Networks present novel opportunities for capturing intricate patterns in customer data and improving churn prediction capabilities. The evaluation and selection of these models entail a rigorous assessment process, where performance metrics such as F1-score, accuracy, recall and precision are meticulously scrutinized. By leveraging historical customer data, including tenure, total charges, monthly charges etc., telecom operators can predict potential churners and take proactive measures to retain at-risk customers, because the cost of acquiring new customers is greater than the cost of retaining the existing customer.

Keywords – Churn; Customer; Deep learning techniques; LightGBM; LSTM-CNNs; Wide and Deep Neural Networks; at-risk customers.

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LIST OF ABBREVIATIONS

LIGHTGBM	-	Light Gradient Boosting Machine
TCN	-	Temporal Convolutional Neural Network
CNN	-	Convolutional Neural Network
WDNN	-	Wide and Deep Neural Network
LSTM	-	Long Short-Term Memory
LR	-	Logistic Regression
NB	-	Naïve Bayes
LGBM	-	Light Gradient Boosting Machine
AUC	-	Area under the ROC Curve
SNA	-	Social Network Analysis
XGBOOST	-	Extreme Gradient Boosting
SVM	-	Support Vector Machine
KNN	-	K-Nearest Neighbors
DEEP-BP-ANN	-	Deep Back Propagation Artificial Neural Network
ROS	-	Robot Operating System
CRM	-	Customer Relationship Management
PRNN	-	Probabilistic Recurrent Neural Network
LSTM	-	Long Short-Term Memory
EDC	-	Electronic Data Dapture
DDOS	-	Distributed denial-of-service

S-RNN	-	Stacked Recurrent Neural Network
ANN	-	Artificial Neural Network
LFNN	-	Locally Feedforward Neural Network
CLARA	-	Clustering Large Applications
BP – BOA	-	Back Propagation - Bayesian Optimization Algorithm
CCP	-	Convolutional Compressive Sensing
PNN1	-	Probabilistic Neural Network 1
PLSTM	-	Probabilistic Long Short-Term Memory
LSTMNN	-	Long Short-Term Memory Neural Network
AUC	-	Area Under The Curve
SOM	-	Self-Organizing Map
PSO	-	Particle Swarm Optimization
RAM	-	Random Access Memory
GPU	-	Graphics Processing Unit
GB	-	Gradient Boosting
I/O	-	Input Output

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Customer churn prediction stands as a crucial instrument for telecom firms in curbing revenue losses and fortifying customer retention. (Maw et al., 2019) By tapping into historical customer data encompassing consumption patterns, billing details, and consumer behavior, telecom operators can forecast potential churners and implement proactive measures to retain vulnerable customers. Machine learning and deep learning algorithms identify indicators of potential churn, facilitating personalized offers and marketing campaigns. Exploratory data analysis reveals insights like gender distribution and demographics ratios, aiding in cost reduction and fostering client relationships in the telecom sector (Sudharsan et al., 2022). In crafting the project solution, a multifaceted approach incorporating Wide and Deep Neural Networks, LightGBM, Temporal Convolutional Neural Networks (CNN), and a fusion of Long Short Term Memory (LSTM) with CNN models will be applied. The Wide and Deep Neural Network combines linear and non-linear relationships, LightGBM excels in handling extensive datasets and feature importance extraction. Temporal CNN captures temporal dependencies, while LSTM-CNN captures long-term dependencies and spatial features. By amalgamating these techniques, the project aims to provide a robust solution for telecom churn prediction, fostering sustainable growth and customer satisfaction.

1.2 OBJECTIVE

The main objective of a customer churn prediction project is to identify customers who are about to churn (stop using the product or service) in the near future.

1. By Utilizing customer data for effective segmentation, tailored retention strategies can be developed, enhancing churn prediction accuracy (Bhatnagar et al., 2019).

2. Ensure cleanliness and compatibility through noise removal and feature selection.

Meticulous preprocessing enhances model reliability for accurate churn prediction.

3. Employ a mix of machine learning and deep learning models. Each model's unique strengths contribute to comprehensive churn analysis and intervention strategies.
4. Rigorously assess model performance using key metrics. This ensures the selection of the most reliable model for proactive retention efforts.
5. Regularly monitor deployed models for consistency. Adaptation to changing customer behavior ensures effective churn risk mitigation over time.

1.3 EXISTING SYSTEM

An emphasized analysis of historical customer data (Bhatnagar et al., 2019). The systematic approach involves a meticulous examination of call logs, usage patterns, and billing information. Employing simple statistical models such as logistic regression or decision trees, the algorithm evaluates specific features to estimate the likelihood of churn. However, inherent limitations hinder its effectiveness. Notably, the manual creation of customer categories using predefined criteria might overlook subtle churn indicators that fall outside these established classifications. Also, the system's reliance on static thresholds to identify at-risk users fails to adapt to the dynamic shifts in customer behavior, potentially resulting in missed opportunities to detect evolving churn patterns. The absence of real-time capabilities further exacerbates these shortcomings, limiting the system's agility to swiftly respond to emerging churn signals. Consequently, the system faces challenges in delivering highly tailored offers or recommendations tailored to individual customer preferences (Gaur et al., 2018), impeding its ability to enhance customer retention strategies.

1.3.1 DRAWBACKS IN EXISITING SYSTEM

1. **Reliance on historical data:** To estimate the chance of churn, the current approach mostly uses past customer data. Nuanced churn indications that result from dynamic changes in customer behavior might not always be captured by this method.

2. **Manually defined customer segments:** Based on preset criteria, customer categories are manually defined. This method might not always be able to identify subtle churn indications that result from sudden changes in consumer behavior.

3. **Static thresholds:** To categorize clients who are at danger, the system often uses static thresholds. This method might overlook dynamic changes in behavior that point to possible churn.

4. **Lack of real-time capabilities:** Due to its lack of real-time capabilities, the current system might find it difficult to react quickly to new churn signals.

5. **Challenges in providing personalized recommendations:** It could be difficult for the current system to provide highly customized offers or recommendations based on each customer's unique tastes.

1.4 PROPOSED SYSTEM

The customer churn prediction system in the telecom industry involves several key steps to ensure accurate and reliable predictions (Hu et al., 2018). First, the raw dataset, which contains various aspects of customer information, undergoes preprocessing to ensure data cleanliness, consistency, and compatibility with the models' requirements. This preprocessing includes noise removal, eliminating inconsistent, missing, or erroneous data points, and feature selection techniques to identify the most relevant features for predicting customer churn. The system employs four primary models, namely LightGBM, Temporal Convolutional Neural Network (TCN), Wide and Deep Neural Network, and a hybrid LSTM-CNN model. The objective is to select the best-performing model that showcases superior accuracy and reliability in predicting customer churn (Ismail et al., 2015). Each model's performance is rigorously evaluated using a suite of appropriate metrics, including accuracy, precision, recall, and F1-score. The best-performing model, LightGBM, is then deployed for real-time customer churn prediction, seamlessly integrated into larger operational systems. Regular monitoring of the deployed model ensures its continued effectiveness and performance consistency over time. The final output of the system categorizes customers into two distinct groups, namely "Happy Customers" and "Customers at High Risk." This segmentation enables telecom companies to take targeted actions to retain their customer base effectively. By achieving these objectives, telecom companies can leverage the strengths of various machine learning and deep learning models to achieve remarkable accuracy and robustness in predicting customer churn, leading to increased revenue, improved customer satisfaction, and long-term success.

1.4.1 ADVANTAGES IN PROPOSED SYSTEM

1. By employing a combination of machine learning and deep learning models such as LightGBM, TCN, Wide and Deep Neural Network, and hybrid LSTM-CNN, the system can achieve higher accuracy in forecasting customer churn compared to traditional methods.
2. Preprocessing techniques play a vital role in refining raw telecom datasets by removing errors, inconsistencies, and outliers. By ensuring data cleanliness and consistency, telecom companies can extract reliable insights essential for informed decision-making.
3. Deployment of the best-performing model, LightGBM, for real-time customer churn prediction allows telecom companies to promptly identify at-risk customers and intervene with targeted retention strategies, minimizing churn rates effectively.
4. The system seamlessly integrates into larger operational systems, facilitating scalability and adaptability to evolving business needs. This ensures that the churn prediction system can grow alongside the company's customer base and operational requirements.
5. Fine-tuning model parameters through iterative optimization improves predictive performance, leading to more accurate churn predictions. This process ensures that models are finely tuned to capture subtle patterns and nuances in customer behavior, enabling proactive intervention strategies.
6. The system employs segmentation algorithms to categorize customers by churn risk, enabling telecom companies to customize retention strategies.

CHAPTER 2

LITERATURE SURVEY

(Agarwal et al., 2022) customer churn, or the progressive drop in repeat business, is a major worry for organizations, particularly in the banking industry. Early switcher detection supports proactive retention initiatives. In order to predict the possibility of customer churn, this article uses machine learning, specifically Logistic Regression (LR) and Naive Bayes (NB), along with information about the client's age, geography, credit history, and balance. NB is revealed to be the best model. The paper promotes enhanced churn prediction methodologies, highlighting the combination of methods, such as LGBM-Classifiers and boosting procedures, for improved accuracy and performance. These developments show promise for future churn computation, offering priceless support for customer retention initiatives.

(Agrawal et al., 2018) In Customer churn, or when a group of customers stop using a company's services, has an effect on a company's profitability and stability, hence it is important to foresee it. Deep Learning stands out because it can find important features in complicated, unstructured datasets like those from the telecom industry. Analyzing the major factors significantly determining churn rates is necessary for understanding and predicting churn. The study uses deep learning to predict churn with an accuracy of 80.03%, showing characteristics that are important for client retention efforts. This study enables businesses to focus on important factors for customer retention, reducing losses to rivals.

(Ahmad et al., 2019) this project presents the essential issue of customer turnover is addressed in this study, particularly in the telecom industry where it has a direct impact on revenues. A churn prediction model is created using machine learning techniques on a big data platform along with cutting-edge feature engineering and selection approaches. The area under the curve (AUC) score for the model is an amazing 93.3%. Notably, adding Social Network Analysis (SNA) elements improves performance even more, increasing AUC from

84% to 93.3%. The model surpasses the XGBOOST method for classification when tested on a sizable dataset from the telecom firm SyriaTel. This study is helpful in guiding profitability and reducing customer churn for telecom firms like SyriaTel.

(Ahmed et al., 2017) the Customer turnover, a crucial component of the telecom industry, frequently results from discontent or better deals from rivals. Churn prediction and prevention are crucial, driving businesses to use various data mining and machine learning techniques. Customized products and effective retention techniques are required due to the intense competition. Hybrid methods are the most accurate, however existing techniques such as meta-heuristics and machine learning show effective churn prediction. This study highlights not just precise churn prediction but also examines churn causes and method shortcomings, laying the groundwork for possible hybrid model development in subsequent studies.

(Amol Chole et al., 2023) In Large businesses, especially those in the telecom sector, face a substantial difficulty as a result of customer turnover, necessitating the development of reliable prediction techniques. By creating a churn prediction model using machine learning and deep learning techniques on a sizable dataset derived from GitHub, this study makes a contribution. The model performed better than expected when tested using algorithms including Random Forest, SVM, KNN, and CNN. The Random Forest approach produced an accuracy of 83.11%. In order to improve churn prediction, future research will concentrate on fine-tuning hyperparameters and investigating various machine learning techniques for feature selection and resampling data.

(Anvita Gupta et al., 2022) predicting customer churn is crucial for banks to proactively engage with at-risk customers and prevent attrition. Early intervention alone can reduce churn by 11%. Utilizing past customer data through machine learning and data science techniques offers a solution. This study compares various churn prediction models used by financial organisations., ultimately advocating for a hybrid approach. Results indicate that this hybrid method outperforms existing models and voting classifiers, showcasing its superior accuracy. This underscores the importance of feature impact assessment and dataset clustering for tailored prediction. Future work may involve further sub-clustering and employing additional classification algorithms for enhanced accuracy and outlier mitigation.

(Bhatnagar et al., 2019) customer churn is a challenge for businesses because of fierce competition and a wide range of telecommunication services. Potential churners must be early identified for retention strategies to succeed and be profitable. Churn categorization encompasses both voluntary and involuntary churn, with an emphasis on anticipating purposeful churn. This forecast, a task for supervised classification, aids companies in retaining customers and lowering customer acquisition expenses. Machine learning classifiers like Logistic Regression, Support Vector Machine and Decision Tree are frequently employed in churn prediction models. This paper evaluates the state-of-the-art in churn prediction research, highlighting issues and suggesting future research directions while providing sage advice for young researchers

(Bhuse et al., 2020) delivers that the customers have many options in today's competitive market, making client turnover a critical concern for banks. In order to retain engagement, this article uses machine learning approaches to forecast client attrition in the banking industry. The study examines consumer behaviour by classifying data using KNN, SVM, Decision Tree, and Random Forest classifiers, as well as feature selection techniques. Following oversampling, experimental results on a Kaggle churn modelling dataset favoured the Random Forest model, displaying improved accuracy. The study stresses the significance of early-stage churn prediction in the banking industry and offers insights for larger-scale applications while using a very small, unbalanced dataset.

(Bin et al., 2007) customer attrition prediction is essential for profitability in the cutthroat Chinese telecom market. Even with insufficient customer data, it's crucial to improve attrition models. The paper recommends decision tree-based experimentation for efficient churn prediction. The churn model's recall rate, precision rate, and F-measure increased as a result of changing the sub-periods of training data, misclassification costs, and sample techniques. With the use of this technique, China Telecom can successfully predict and control customer churn, increasing customer retention in a cutthroat industry. To further improve prediction churn models in related scenarios, future research could investigate alternative data mining techniques.

(Celik et al., 2019) minimizing expenses is essential in today's fiercely competitive environment. Research shows that keeping existing customers costs ten times less than recruiting new ones, highlighting the importance of customer churn monitoring. In the context of customer churn analysis, this paper examines a number of machine learning methods, including ANN, decision tree, SVM, naive bayes, knn, and XG Boost. Machine learning algorithms are considered to be trustworthy substitutes for time-related event estimates, such as customer turnover, even though deep learning approaches exhibit greater performance in complex circumstances. While deep learning approaches excel in complex structures, the Cox regression model efficiently analyses independent variables influencing temporal variables and risk groups. Deep learning techniques are expected to continue to progress and produce even higher success rates over time.

(Fujo et al., 2022) this study addresses the pressing issue of customer churn in the telecom industry by implementing a Deep-BP-ANN model, bolstered by feature selection methods and overfitting prevention techniques. The model outperforms traditional ML techniques like KNN, Logistic Regression, XG Boost, and Naïve Bayes on real datasets (IBM Telco and Cell2cell) with an accuracy exceeding 88%. Lasso regression proves pivotal for feature selection, particularly in datasets with numerous attributes. The ROS technique effectively balances the datasets, and activity regularization aids in mitigating overfitting. Fine-tuning parameters, such as neuron count and epoch number, significantly enhance performance.

(Gaur et al., 2018) says that in Churn research, which makes use of data mining, forecasts client attrition, which is essential in today's cutthroat marketplaces. Predicting customer loss improves marketing, customer loyalty, and communication, which has an effect on profitability. To efficiently retain customers, businesses, particularly telecom providers, concentrate on identifying customer churn factors. Gradient Boosting emerges as the most efficient, followed by Logistic Regression and Random Forest, with SVM performing somewhat less well. These machine learning models include Logistic Regression, SVM, Random Forest, and Gradient Boosted Tree.

(Hu et al., 2018) client churn prediction uses a variety of machine learning classifiers and is essential for client retention and current CRM. Time series customer data analysis is now possible because to recent advancements in data technology, improving accuracy. A pRNN model with LSTM units and product operations has been proposed, and it exhibits great accuracy in predicting churn in the telecom industry. The article covers potential future research topics and emphasizes the importance of recurrent neural networks in processing sequential input. To validate findings and investigate long-term prediction views, additional diversified real-world datasets are required.

(Ismail et al., 2015) the customer management is essential in the telecommunications sector to prevent churn. The large expenses involved with adopting it across the whole customer base can be avoided with targeted retention initiatives for likely churn clients. Utilizing historical churn data and predictive factors, churn management focuses on prediction. While long-term success is assured by keeping existing clients, traditional marketing places greater emphasis on obtaining new ones. With a prediction accuracy of 91.28%, Multilayer Perceptron Artificial Neural Network outperforms conventional statistical models in predicting customer attrition. These information should be used in customer retention initiatives to effectively lower churn rates.

(Karvana et al., 2019) the customer attrition in banking may be accurately predicted by data mining. Recall rates are highly influenced by sample size and inter-class comparisons, favoring a 50:50 data ratio with a 70% recall. Each class has roughly 7,975 samples out of approximately 15,949 data samples. The 50:50 SVM sampling model is the most effective one, which identifies important characteristics like vintage, EDC transaction volume and amount, average balance, and age and generates a large profit of 456 billion. This is consistent with the research, which highlights SVM's accuracy while highlighting Logistic Regression's ability to reduce losses.

(Kumar, P et al., 2023) distributed denial-of-service (DDoS) attacks pose a significant threat to the confidentiality and integrity of computer networks, disrupting web traffic to target servers and impeding authorized user access to services. Detection of DDoS attacks can be challenging, requiring robust mitigation strategies due to the diverse methods used to flood networks or servers. These assaults leverage resource limitations, impacting the functionality of the targeted organization's website infrastructure. Analyzing the most recent datasets is crucial for identifying and understanding the evolving landscape of DDoS attacks, assessing their varied techniques, and evaluating their efficacy. Clients accessing network services are consistently exposed to this pervasive and severe threat, necessitating ongoing vigilance and proactive security measures.

(Kumar, P. et al., 2023) delves into the pressing issue of increasing energy consumption within cloud server farms, highlighting their substantial contribution to environmental pollution resulting from heightened power usage. This study accentuates the complexities associated with mitigating power consumption while upholding agreements concerning service quality. To address this challenge, the paper proposes a solution centered on optimizing resource allocation. This involves a strategic approach that limits the operation of dynamic servers, thereby aiming to curtail energy usage while simultaneously meeting the demands of clients and ensuring efficient task performance. To validate the efficacy of their proposed algorithms, the researchers leverage Cloud Sim, a simulation tool, utilizing real-world data obtained from a significant pool of over 1000 Planet Lab virtual machines. The study underscores the pivotal role played by server farms in this evolving technological landscape, emphasizing the critical need to strike a balance between energy conservation and maintaining high-quality service provision.

(Maw et al., 2019) the companies have a problem from customer churn, which is a result of severe competition and a variety of telecommunication services. For retention initiatives to be successful and profitable, potential churners must be identified quickly. With an emphasis on foreseeing intentional churn, churn categorization includes both voluntary and involuntary churn. This forecast, a supervised categorization task, helps businesses keep clients and cut acquisition costs. In churn prediction models, machine learning classifiers like Support Vector Machine, Logistic Regression, and Decision Trees are widely used. This paper examines current churn prediction research, noting problems and potential areas for future research while offering insightful advice for up-and-coming scientists. The research, though, is time-bound and concentrates on churn that is instigated by the consumer.

(Rahman et al., 2020) the customers have many options in today's competitive market, making client turnover a critical concern for banks. In order to retain engagement, this article uses machine learning approaches to forecast client attrition in the banking industry. The study examines consumer behaviour by classifying data using KNN, SVM, Decision Tree, and Random Forest classifiers, as well as feature selection techniques. Following oversampling, experimental results on a Kaggle churn modelling dataset favoured the Random Forest model, displaying improved accuracy. The study stresses the significance of early-stage churn prediction in the banking industry and offers insights for larger-scale applications while using a very small, unbalanced dataset. The results also show how important oversampling is for resolving data imbalances, especially when applied to SVM classifiers.

(Sudharsan et al., 2022) in the cutthroat and fast-paced telecom sector, client turnover is a significant problem that needs to be addressed. S-RN0N is a unique framework for precise churn prediction. The model divides clients into churners and non-churners, and if churn is anticipated, it prompts further study for retention tactics. Data collection, preprocessing, filtering, grouping, feature engineering, and classification are all included in the suggested methodology. The S-RNN model performs admirably in experimental analysis, attaining outstanding metrics like 98.27% sensitivity, 92.31% specificity, and

95.99% accuracy. The suggested method also performs better in terms of resilience and reliability than current methods.

(Zhang et al., 2022) the telecom companies face a pressing challenge with client churn, impacting profits in a saturated global market. Although attracting new clients is expensive, keeping the ones you already have is more cost-effective. Predicting and preventing customer churn has become a top priority for telecom companies. This study introduces discriminant and logistic regression models using customer segmentation data from major Chinese telecom firms. The findings empower managers to accurately predict customer behaviour, enhance retention strategies, and optimize budgets.

(Zhao et al., 2008) the customer loyalty has a bigger impact on bank profits than things like growth and market share. client churn lowers sales and new client acquisition. Data mining provides for accurate churn prediction and customized marketing tactics. With excellent accuracy and practical considerations, a support vector machine (SVM) model beat other classifiers in predicting bank customer attrition. SVM is a reliable method for churn prediction because of its straightforward classification surface, good generalization, and fitting accuracy.

Table 2.1 Synoptic Overview

Author / Year	**Approach**	**Merits**	**Demerits**
(Agarwal et al., 2022)	It primarily focuses on SVM, Naive Bayes	The study demonstrates the successful implementation of machine learning algorithms in predicting customer churn, with Naive Bayes showing notably high accuracy. The models provide insights to prevent customer attrition and improve business.	However, it could benefit from discussing challenges, limitations, or areas for future improvement in the methodologies applied.

(Agrawal et al., 2018)	It utilizes Artificial Neural Network	The paper demonstrates the effectiveness of Deep Learning techniques, particularly ANNs, in mobile network churn prediction. It highlights the stability of the model across different months and emphasizes the improvement achieved by incorporating location data.	The proposed model may not scale effectively for long-term user interactions and faces challenges in handling textual parameters during data preprocessing, potentially limiting its applicability over extended periods.
(Ahmad et al., 2019)	XGBOOST, Random Forest, GBM, Decision Trees are utilised	The utilization of XGBOOST led to an impressive accomplishment, achieving a notably high AUC value of 93.301%. This outcome notably surpassed the performance of various other algorithms that were put to the test. Notably, the integration of Social Network Analysis (SNA) features played a pivotal role in elevating the accuracy.	Data unavailability to the public due to restrictions by the telecom company, limiting broader research access. The specific journal of publication is not mentioned.
(Ahmed et al., 2017)	It goes through techniques such as SVM, Neural Networks, PSO, Anti Miner+	Hybrid models with SVM, ANN, SOM show high accuracy with lower complexity; rule induction and PSO are effective for churn	Models have limitations like false positives, time complexity for rule-set generation, and issues with

		prediction.	imbalanced data; certain approaches overlook demographic factors and misclassification costs
(Amol Chole et al., 2023)	It involves Random Forest, K - Nearest Neighbours and Support Vector Machine.	The model achieves a notable accuracy in predicting customer churn, which is crucial for revenue retention in the highly competitive telecom industry.	It's essential to consider factors like scalability and real-world implementation challenges in future applications of the model.
(Anvita Gupta et al., 2022)	It utilizes Decision Tree Classifier, Logistic Regression, Stochastic Gradient Descent, Support Vector Machine, K-Nearest Neighbours, Voting Classifier, Random Forest, Naive Bayes.	It emphasizes identifying impactful features and clustering data to apply diverse models for precise predictions. The method showcases potential to extend to multiple sub-clusters for enhanced accuracy.	Limitations could include complexity in determining optimal clusters and potential challenges in scaling the approach for very large datasets without clearly defined clusters.
(Bhatnagar et al., 2019)	It involves KNN, Logistic Regression	The study compares KNN and Logistic Regression for customer churn prediction, favoring KNN with 2.0% higher accuracy.	The study lacks exploration of feature importance and actionable strategies to mitigate customer churn
(Bhuse et al., 2020)	Random Forest, SVM, XG Boost, Ridge classifier, KNN, Deep Neural Network.	The paper provides a comprehensive analysis of different techniques for customer churn prediction in the telecom sector, offering insights into the effectiveness of various	The study does not delve into specific challenges or limitations faced during the implementation of the models. Additionally, the paper does not

		algorithms. The Random Forest model demonstrated the highest accuracy, indicating its potential for real-world applications.	address potential scalability issues that may arise in large-scale telecom operations.
(Bin et al., 2007)	It employs Decision tree	Effective utilization of decision tree for diverse applications in different domains, showcasing its versatility and usefulness in decision-making processes.	Specific limitations or drawbacks of the decision tree method are not detailed in the provided document.
(Celik et al., 2019)	It includes Cox Regression, ANN, KNN, Decision Tree, SVM, Logistic Regression, Naïve Bayes, XG Boost	Accurate prediction of event times for customer churn (Martinsson, 2016) Improved accuracy in predicting customer churn compared to traditional methods	Limitations could include complexity in determining optimal clusters and potential challenges in scaling the approach for very large datasets without clearly defined clusters.
(Fujo et al., 2022)	It is Deep-BP-ANN, CNN, LFNN, Transfer learning, ensemble – classifiers.	Implemented Deep-BP-ANN model outperformed other machine learning techniques, achieving higher accuracy and efficiency.	Improving accuracy in existing models that use deep learning techniquesfor customer churn prediction.
(Gaur et al., 2018)	Logistic Regression, SVM, Gradient Boosting, Random Forest	The study highlights gradient boosting's effectiveness in predicting customer churn for telecom, emphasizing its role in customer retention	The document lacks author names, journal details, and dataset preprocessing.

		strategies.	
(Hu et al., 2018)	Logistic Regression, Random Forest, PNN1, LSTM, pRNN, pLSTM, LSTMNN	pRNN demonstrates superior performance in customer churn prediction, offering valuable insights for customer relationship management and marketing strategies	The study suggests validating findings with diverse datasets and highlights future research directions such as long-term churn prediction and addressing accuracy-scalability trade-offs.
(Ismail et al., 2015)	Neural Networks, Logistic Regression, SVM, Bayes Network, Rough Set Theory, K-Means, Time Series, Regression Forests, Association Rules	Neural network, specifically the MLP model, demonstrated superior prediction accuracy (91.28%) compared to traditional statistical models like regression analysis.	The high computational complexity and potential overfitting are challenges associated with using neural network models for churn prediction.
(Karvana et al., 2019)	Neural Network, Decision Tree, SVM, Logistic Regression, Naïve Bayes	This project serves as a demonstration of data mining techniques applied specifically to churn prediction, underscoring the crucial significance of sample size in this predictive analysis.	limited data source detail, lack of thorough comparative analysis, insufficient exploration of alternate models, inadequate future research recommendations
(Kumar, P et al., 2023)	The approach analyzes real-time datasets to detect and mitigate DDoS attacks, evaluating various attack vectors for effective defense strategies.	Enhances network resilience by utilizing real-time datasets for accurate DDoS attack analysis. Enables the development of effective defense strategies by evaluating	DDoS attack early detection difficulties could make it more difficult to put mitigation measures in place in a timely manner. Updating defense

		various attack vectors, ensuring uninterrupted service for authorized users.	strategies requires constant adaptation, which makes it difficult to keep defenses in place.
(Kumar, P et al., 2023)	The approach optimizes cloud server farm resource allocation to cut energy consumption, validated using CloudSim with real-world commitment traces from over 1000 virtual machines.	It addresses escalating carbon emissions in cloud computing, striving for efficiency by reducing environmental impact while maintaining service quality.	Challenges may arise in implementing limitations on dynamic servers without compromising performance, and the methodology's effectiveness may vary based on the specific characteristics of the cloud computing environme nt.
(Maw et al., 2019)	CCP, SVM, Random Forest, Neural Network, Decision Tree	Comprehensive analysis of recent literature in churn prediction, revealing emerging research opportunities, and providing insights into the challenges faced in the telecom industry.	Limited to a specific time frame, potential exclusion of important studies, potentially missing broader perspectives.
(Rahman et al., 2020)	It involves SVM, Random Forest, Decision Tree, K - Nearest Neighbours	The SVM model, especially with integrated random sampling, improved predictive accuracy and precision in churn	The SVM model struggled with highly imbalanced data, affecting its predictive capability. The study highlighted challenges

		prediction compared to other models. It addressed data imbalance issues through resampling techniques.	in achieving high accuracy with imbalanced datasets using SVM.
(Sudharsan et al., 2022)	CLARA, BM-BOA, Feature selection, Classification, retention process, Swish RNN.	Achieves high accuracy and sensitivity .Efficient clustering and feature selection methodologies improve performance. Utilizes Swish RNN.	limited discussion on recent data due to the document's age.
(Zhang et al., 2022)	This employs Decision tree, logistic regression, Cluster analysis.	The attainment of a substantial accuracy rate of 93.94% in forecasting customer churn holds significant implications for telecom companies, offering invaluable insights.	Lack of information about the specific journal where the paper was published, and limited discussion on recent data due to the document's age.
(Zhao et al., 2008)	SVM Logistic, Regression Naïve, Bayes ANN	Support Vector Machines (SVM) have demonstrated superior performance over an array of classifiers, showcasing remarkable effectiveness.	SVMs can be sensitive to parameter choice, computationally intensive for large datasets, and less interpretable compared to some other models

From the above Table 2.1 provides a comprehensive overview of various methods proposed by different authors across multiple years. Each approach is described in terms of its methodology, merits, and demerits, covering aspects such as image quality improvement, computational complexity, and applicability to diverse domains.

CHAPTER 3

SYSTEM DESIGN

3.1 INTRODUCTION

A project's design is an important aspect that displays the objective of the model that will be constructed. The process of translating the requirements into a representation of the software is known as software design. The field of design is where excellence is produced. The process of specifically translating customer needs into final products is called design.

3.2 DEVELOPMENT ENVIRONMENT

3.2.1 HARDWARE REQUIREMENTS

The hardware specifications outlined in Table 3.1 serve as the comprehensive system implementation prerequisites, forming the fundamental basis upon which software engineers build their system designs. Rather than delineating the operational procedures, these specifications provide a detailed overview of the system's functionalities and the essential hardware components necessary for its successful deployment. They offer a blueprint guiding engineers in configuring and structuring the system architecture, ensuring compatibility and optimal performance based on the outlined hardware prerequisites.

Table 3.1 Hardware Requirements

COMPONENTS	SPECIFICATION REQUIREMENTS
CPU(Processor)	Inter i5/Ryzen 2000 Series
Clock Speed	525MHz
GPU	Integrated Graphics
STORAGE(HDD/SSD)	2GB
RAM	8GB RAM

3.2.2 SOFTWARE REQUIREMENTS

The system specification is found in the software requirements paper. It ought to have a description and a list of prerequisites. Rather than focusing on how the system should operate, it is a list of what it should perform. The foundation for developing the software requirements specification is provided by the software requirements. It is helpful for tracking the team's progress during the development activity, organizing team activities, carrying out tasks, and predicting costs.

- Python 3.10
- Flask

3.3 ARCHITECTURE DIAGRAM

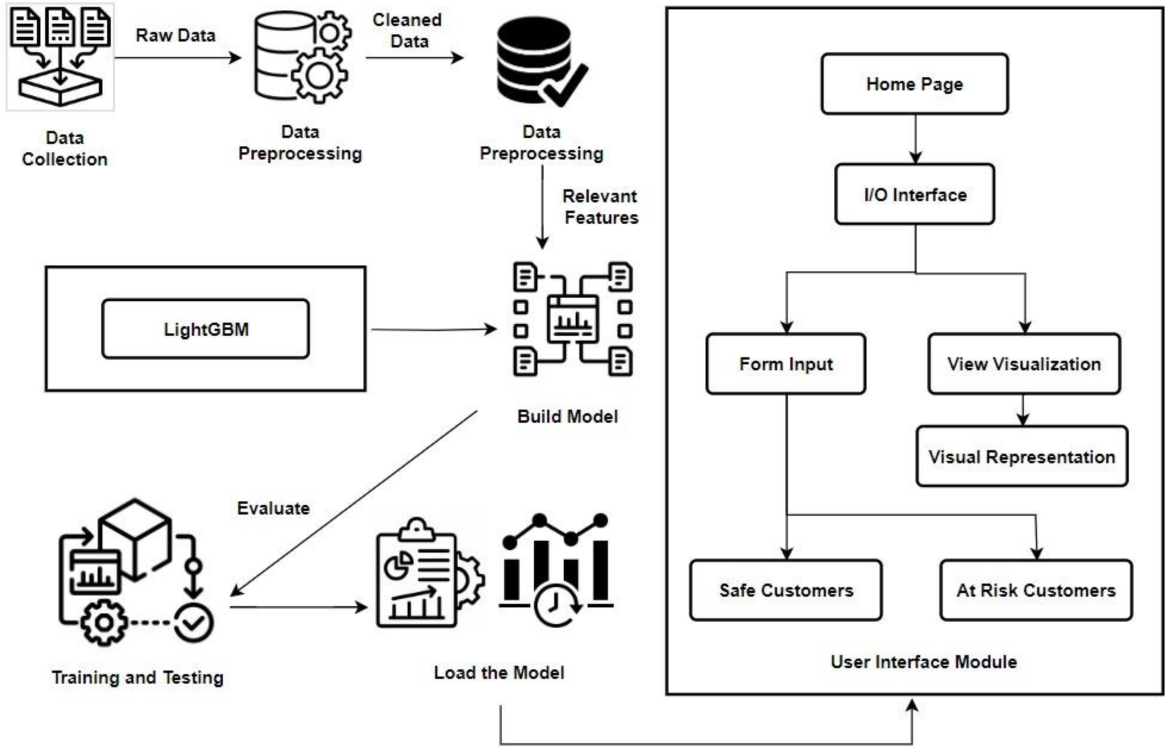

Figure 3.1 Architecture Diagram

In the Fig 3.1, The system begins with the raw dataset, where the customer churn prediction encompasses various aspects of customer information, including demographics, usage patterns, behavioral features, and interaction details. Demographic features such as age, gender, income, education level, and occupation provide insights into the customer's background. Usage patterns, comprising frequency of use, duration, and data consumption, offer an understanding of the customer's engagement with the service. Behavioral features like subscription and payment history, as well as records of customer complaints, shed light on past interactions and experiences.

Prior to inputting the data into machine learning and deep learning models, preprocessing is imperative to ensure data cleanliness, consistency, and compatibility with the models' requirements. This preprocessing involves noise removal, eliminating inconsistent, missing, or erroneous data points, including duplicate records and imputing missing values. Feature selection techniques like correlation analysis, mutual information, or feature importance scores are then employed to identify the most relevant features for predicting customer churn. Subsequently, data preprocessing tasks such as scaling, normalization, and encoding categorical variables are performed to transform the data into a suitable format for the subsequent modeling stages. The system employs four primary models: LightGBM, Temporal Convolutional Neural Network (TCN), Wide and Deep Neural Network, and a hybrid LSTM-CNN model.

LightGBM is a gradient boosting framework that uses tree-based learning algorithms, designed for efficiency in computational resources and memory usage. In customer churn prediction, LightGBM can effectively capture complex patterns and dependencies in the data, enabling accurate identification of customers at risk of churn. Its ability to handle categorical features and imbalance in the churn dataset makes it particularly suitable for this task. LightGBM's fast training speed allows for quick iteration and optimization of churn prediction models in real-time.

TCNs are a type of neural network architecture that excels at processing sequential data, making them particularly suitable for time-series data in customer churn prediction. Dilated causal convolutions, a key component of TCNs, allow for a larger receptive field without increasing the number of parameters.

The Wide and Deep Neural Network combines the benefits of both wide and deep models. Wide models are good at memorizing sparse input features, while deep models learn complex relationships between features. The wide part of the model consists of fully connected layers taking input features, while the deep part has several hidden layers learning complex representations. The output of both wide and deep models is combined using a concatenation layer, allowing the model to leverage the strengths of both types.

The hybrid LSTM-CNN model combines the strengths of both Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs). LSTMs are capable of learning long-term dependencies in sequential data, while CNNs extract local features. The LSTM and CNN components' output is combined using a concatenation layer, allowing the model to leverage the strengths of both types.

Each model's performance in predicting customer churn is rigorously evaluated using a suite of appropriate metrics, including accuracy, precision, recall, and F1-score. Among the models considered, LightGBM emerges as the best-performing one, showcasing superior accuracy and reliability. It is subsequently deployed for real-time customer churn prediction, seamlessly integrated into larger operational systems.

Then it is deployed in the front end where the home page is the entry point of the user interface module. The home page provides an overview of the customer churn prediction and allows users to interact with the system. The I/O interface is responsible for handling the input and output data of the customer churn prediction by entering the form details and analyzing the output. The I/O interface provides an interface for users to enter the details and view the results. The form input is a user interface component that allows users to input data. It considers factors like tenure, online security, backup, device protection, tech support, contract type, paperless billing, monthly and total charges. Tenure, contract type, and service availability significantly impact churn rates. The view visualization is a user interface component that allows users to visualize the results.

By harnessing the strengths of various models, the system achieves remarkable accuracy and robustness, serving as an indispensable tool for predicting customer churn. Ultimately, this predictive capability empowers businesses to retain their customer base effectively, fostering loyalty and driving sustained growth. The final output of the system categorizes customers into two distinct groups: "Happy Customers," predicted to remain loyal, and "Customers at High Risk," identified as likely to churn imminently.

CHAPTER 4

PROJECT DESCRIPTION

4.1 MODULE DESCRIPTION

Customer Churn Prediction is divided into seven modules:

1. Data Collection and Preparation
2. Feature Engineering
3. LightGBM Model
4. Temporal Convolutional Neural Network
5. LSTM – CNN
6. Wide and Deep Neural Network
7. Model Evaluation and Deployment

4.1.1 DATA COLLECTION AND PREPARATION

In the Fig 4.1, Customer churn prediction initiates with a fundamental phase centered on data collection. During this stage, businesses actively source pertinent information from a diverse array of channels such as customer databases, transaction records, user engagements, and feedback surveys. This comprehensive data compilation comprises a spectrum of valuable insights, encompassing demographic particulars, usage patterns, purchasing behaviors, and interactions with customer support services. Subsequently, the amassed data undergoes a critical phase termed data cleaning. This pivotal step involves meticulous handling of various aspects including addressing missing values, identifying and eliminating outliers, and ensuring the overall consistency and accuracy of the data. Through this thorough refinement process, businesses establish a robust and reliable foundation upon which to base more precise churn predictions. This refined dataset serves as a cornerstone for the development of sophisticated models and algorithms, significantly enhancing the accuracy of forecasts regarding customer attrition. Ultimately, the refined data empowers businesses to formulate proactive retention strategies, thereby bolstering customer retention efforts and overall business success.

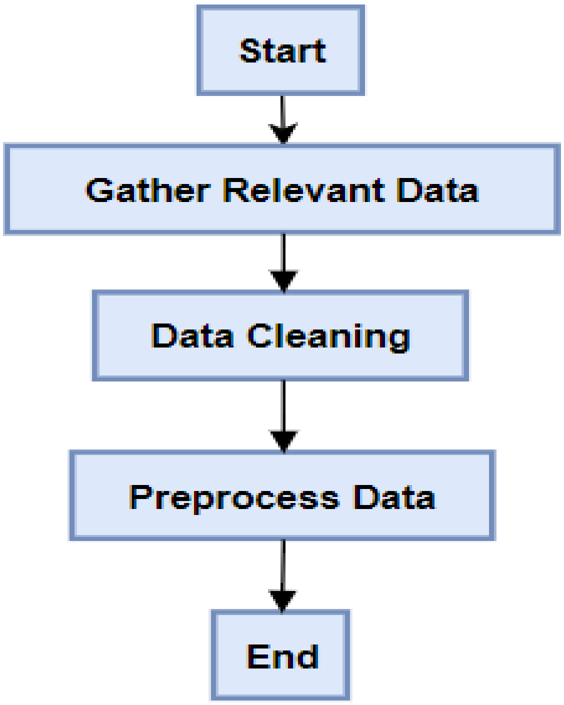

Figure 4.1 Data Collection and Preparation

4.1.2 FEATURE ENGINEERING

In the Fig 4.2, In the process of customer churn prediction, feature engineering plays a pivotal role in refining the predictive model. The initial step involves feature selection, where the most pertinent variables for predicting churn are identified. Following this, feature transformation becomes imperative, necessitating the transformation and preprocessing of selected features. This includes actions such as one-hot encoding categorical variables, scaling numerical features for uniformity, and crafting new features capable of encapsulating customer behaviors or evolving trends. Additionally, for businesses dealing with time-dependent data, a specialized approach is required, often involving time-series analysis. This analysis focuses on understanding patterns within time-related customer activities, enabling the model to account for temporal trends and dependencies. Together, these steps in feature selection, transformation, and time-series analysis contribute significantly to the construction of a robust churn prediction model, ensuring a more comprehensive and nuanced understanding of customer behavior to facilitate informed decision-making for retention strategies.

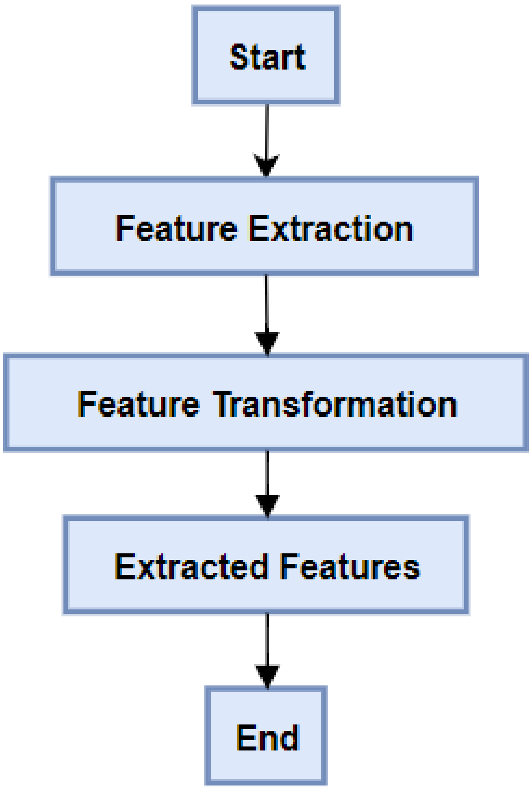

Figure 4.2 Feature Engineering

4.1.3 LIGHTGBM

In the process of customer churn prediction using LightGBM in the Fig 4.3, several key steps guide the construction of an effective predictive model. Initially, the model is initialized with parameters such as the number of estimators, which determines the number of boosting rounds, and the objective function, typically binary classification for churn prediction. Evaluation metrics, such as AUC ROC or accuracy, are then chosen to assess model performance. Further, parameters like the number of leaves, maximum depth of trees, and maximum data in leaf are set to control tree complexity and prevent overfitting. The learning rate governs the step size during optimization, influencing the model's convergence speed. Verbosity controls the amount of information printed during training. Subsequently, the model undergoes training on the dataset, where it iteratively builds decision trees to minimize the specified objective function. After training, the model's performance is evaluated on a separate test dataset using the chosen evaluation metric. Iterative parameter tuning may be conducted to optimize model performance further. Once satisfied with performance, the trained model is deployed for real-time churn prediction, aiding in informed decision-making for retention strategies. Overall, meticulous parameter selection and training contribute to the development of a robust LightGBM churn prediction model, enhancing understanding of customer behavior and facilitating proactive retention efforts.

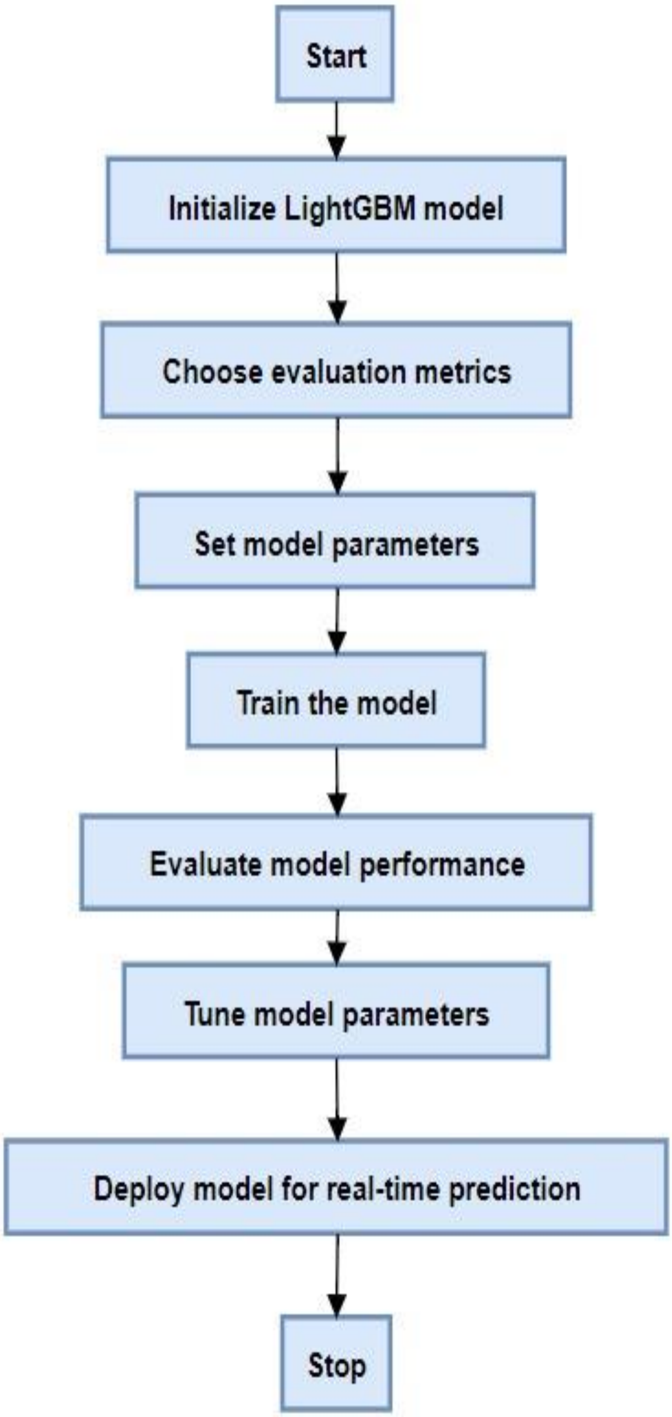

Figure 4.3 LightGBM

4.1.4 TEMPORAL CONVOLUTIONAL NEURAL NETWORK

In the Fig 4.4, The utilization of a Temporal Convolutional Neural Network (TCN) represents a sophisticated and systematic approach to model construction, as described in the provided code snippet. Initially, the architecture of the TCN is meticulously crafted, featuring convolutional layers designed to extract nuanced temporal patterns inherent within sequential data. These convolutional layers serve as the backbone of the model, adeptly discerning intricate dependencies that evolve over time, thereby enabling a profound understanding of the underlying dynamics driving customer behavior. Moreover, the strategic incorporation of max-pooling layers further enhances the efficacy of the TCN by facilitating the downsampling of extracted features, ensuring computational efficiency while retaining essential information crucial for accurate churn prediction. Subsequently, a pivotal Flatten layer is introduced, tasked with reshaping the output from the convolutional layers into a streamlined, one-dimensional vector. This transformation lays the groundwork for seamless integration into densely connected layers, fostering the synthesis of extracted features and the emergence of higher-level abstractions essential for discerning patterns indicative of churn behavior. Within the densely connected layers, the TCN model orchestrates a symphony of computational prowess, meticulously integrating the diverse array of extracted features. Through iterative training on historical data, the model navigates a landscape of parameter adjustments, fine-tuning its internal configurations to minimize prediction errors. The evaluation phase serves as a litmus test for the model's mettle, rigorously scrutinizing its capacity for generalization on a separate test dataset. This critical appraisal not only validates the model's performance but also illuminates areas warranting further refinement, guiding iterative fine-tuning of hyperparameters and architecture to attain peak predictive performance. As the Telecom Churn Network (TCN) attains a desirable level of accuracy and reliability, it becomes primed for implementation in practical business settings. In real-world scenarios, TCN's predictive capabilities offer valuable insights that enable businesses to anticipate and address customer churn proactively. By leveraging TCN's predictive prowess, companies can develop tailored retention strategies aimed at retaining valuable customers.

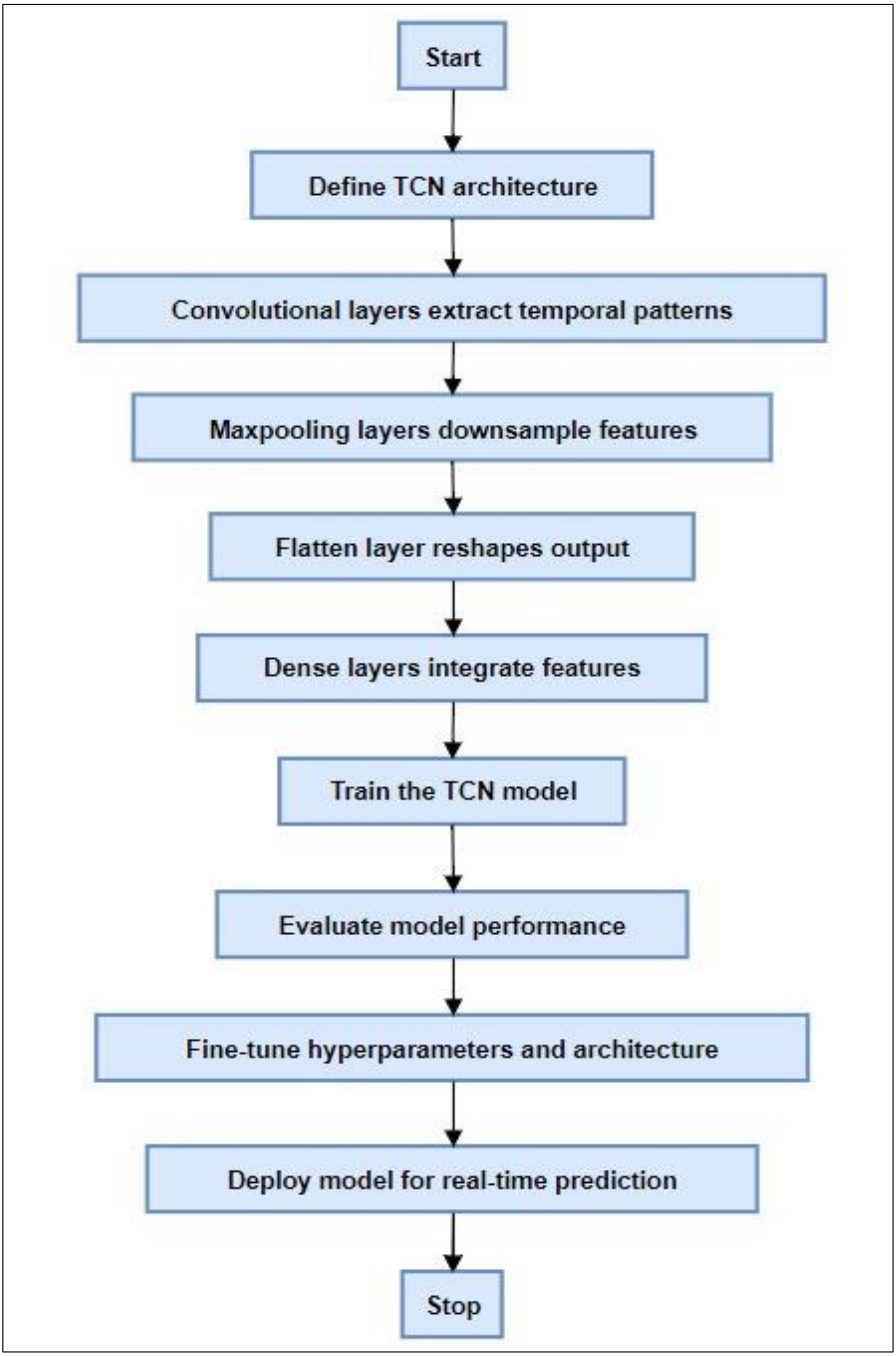

Figure 4.4 Temporal Convolutional Neural Network

4.1.5 LSTM – CNN

In the Fig 4.5, The advent of a Hybrid LSTM-CNN model heralds a new era of predictive analytics, seamlessly amalgamating the formidable capabilities of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architectures. The orchestrated synergy between these components transcends conventional methodologies, enabling the comprehensive capture of both intricate temporal and spatial patterns inherent within the data. As elucidated in the provided code snippet, the LSTM component assumes the mantle of processing sequential data, leveraging its inherent ability to retain memory of past states. This cognitive prowess allows the LSTM to discern temporal dependencies crucial for the accurate prediction of churn behavior, thus laying the foundation for informed decision-making. Simultaneously, the CNN component operates on spatial data, harnessing the power of convolutional layers to extract salient features representative of underlying patterns. Through a meticulously orchestrated sequence of operations, including batch normalization and activation layers, the CNN enhances the representation of features, thereby enriching the model's predictive capabilities. The outputs stemming from these distinct yet complementary components are seamlessly integrated through concatenation, thereby fostering a holistic representation that encapsulates both temporal and spatial dimensions of the data. Subsequent integration into densely connected layers facilitates the synthesis of the fused features, culminating in the emergence of higher-level abstractions essential for effective churn prediction. Throughout the iterative training process, the model undergoes a transformative journey, honing its ability to discern significant temporal and spatial patterns indicative of churn behavior. Hyperparameters and architecture are meticulously fine-tuned, ensuring the optimization of predictive accuracy and the maximization of model performance. The validation phase, conducted on a separate test dataset, serves as a crucible wherein the model's mettle is tested against real-world scenarios. This rigorous evaluation not only validates the model's capacity for generalization but also provides invaluable insights into its strengths and areas requiring further refinement. Upon achieving a satisfactory level of performance, the hybrid LSTM-CNN model stands poised for deployment in real-time churn prediction scenarios.

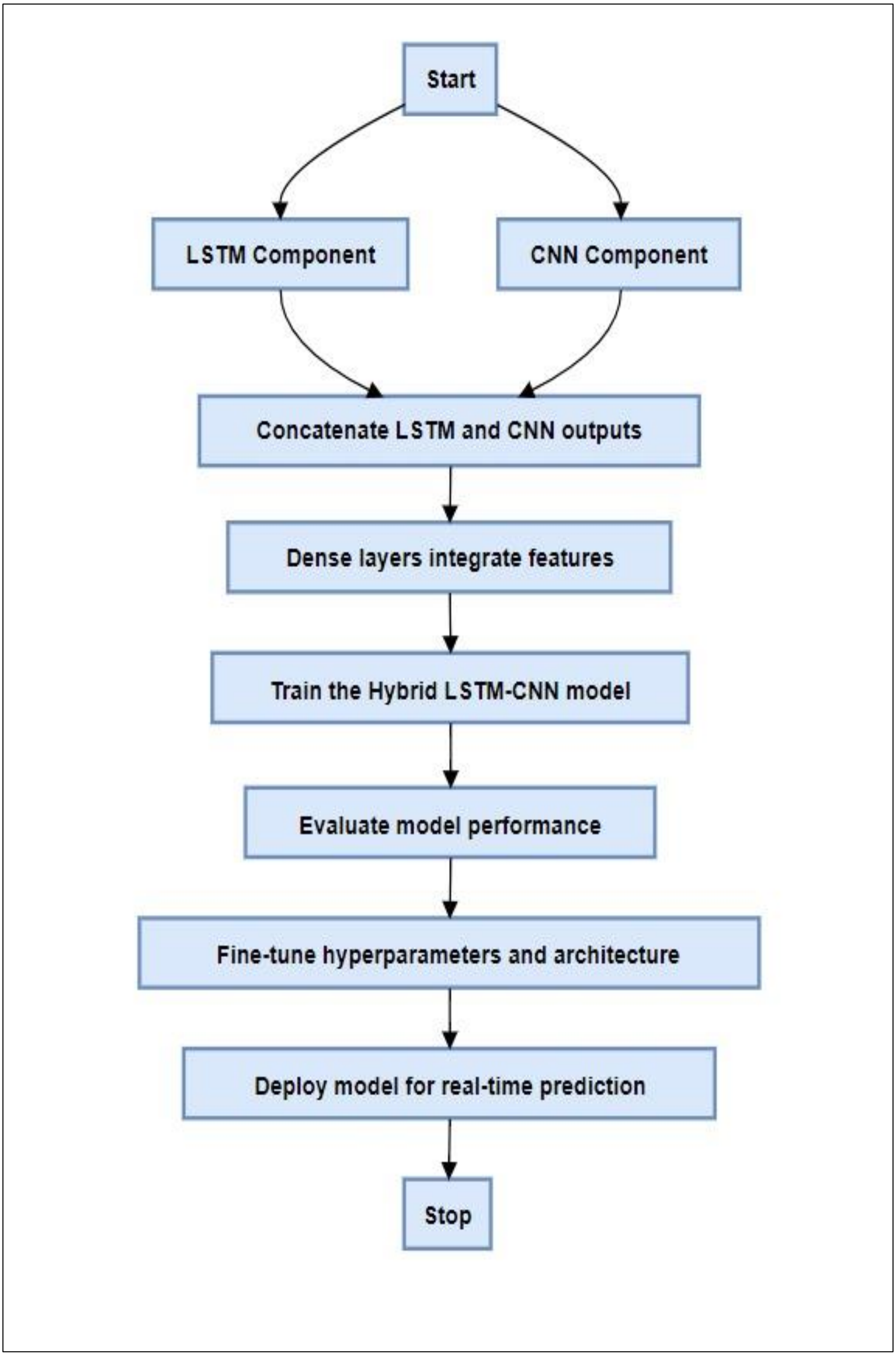

Figure 4.5 LSTM – CNN

4.1.6 WIDE AND DEEP NEURAL NETWORK

In the Fig 4.6, In the realm of customer churn prediction, the advent of a Wide and Deep Neural Network model heralds a transformative approach, orchestrating a strategic fusion of wide and deep components to unlock unparalleled predictive insights. As delineated in the accompanying code snippet, the wide component serves as the vanguard, encompassing a broad spectrum of sparse features that encapsulate diverse customer attributes and interactions. In stark contrast, the deep component delves into the depths of feature representations, traversing multiple layers to unravel complex patterns and interactions latent within the data. The harmonious convergence of these disparate yet complementary components is epitomized by the concatenation of their outputs, thereby merging the expansive coverage of the wide component with the nuanced insights gleaned from the deep component. This symbiotic integration lays the groundwork for the subsequent integration into dense layers, where the fused features undergo a transformative metamorphosis, enabling the emergence of higher-level abstractions essential for accurate churn prediction. Throughout the iterative training process, the model embarks on a journey of refinement, meticulously adjusting its parameters to minimize prediction errors and enhance predictive accuracy. The crucible of evaluation, conducted on a separate test dataset, serves as a litmus test for the model's mettle, scrutinizing its ability to generalize and perform effectively in real-world scenarios. Upon validation, the Wide and Deep Neural Network emerges as a formidable tool, poised for deployment in real-time churn prediction endeavors. Armed with actionable insights derived from the amalgamation of wide-ranging attributes and intricate feature representations, businesses are empowered to proactively devise retention strategies that mitigate churn and foster customer loyalty. Ultimately, the Wide and Deep Neural Network epitomizes a paradigm shift in customer churn prediction, harnessing the complementary strengths of both wide and deep components to offer a comprehensive and nuanced approach. In the intricate realm of customer dynamics, this pioneering model illuminates the path to unparalleled efficiency and effectiveness. Its transformative capabilities serve as a guiding light for businesses, leading them through the labyrinth of challenges towards a future characterized by resilience, adaptability, and enduring growth.

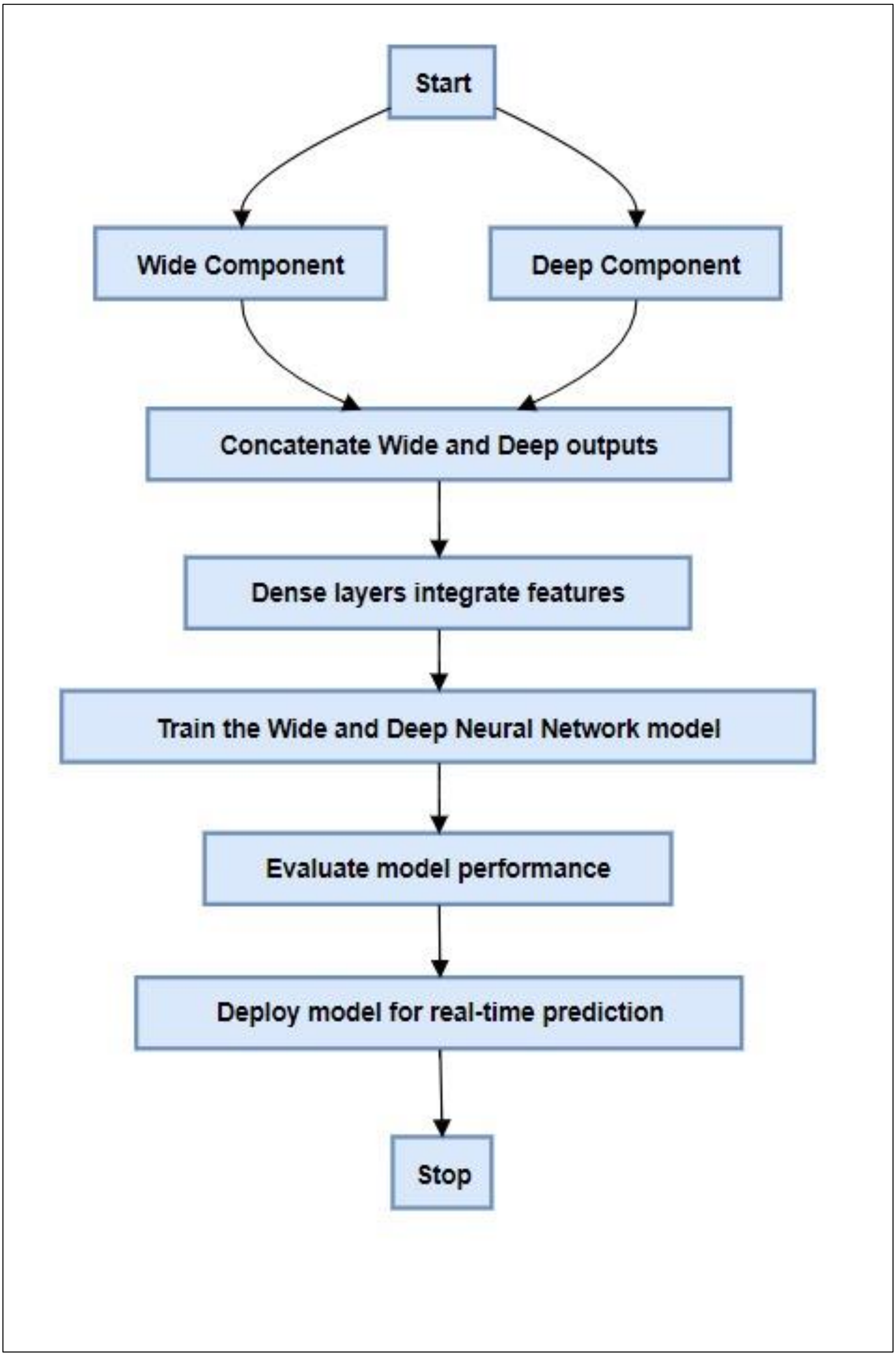

Figure 4.6 Wide and Deep Neural Network

4.1.7 MODEL EVALUATION AND DEPLOYMENT

In the Fig 4.7, The culmination of churn prediction involves meticulous evaluation of model performance using a spectrum of metrics aligned with business objectives, such as recall, accuracy, precision, and F1 score. These metrics provide critical insights into the model's effectiveness in predicting churn, ensuring relevance and significance in decision-making. Once the optimal model, like LightGBM, is identified, it undergoes deployment into a production environment for real-time predictions, enabling proactive customer retention strategies. Continuous monitoring becomes paramount to ensure sustained performance, while periodic retraining with new data facilitates adaptation to evolving trends, thereby enhancing the system's efficacy over time. This iterative process forms a dynamic and resilient churn prediction system, empowering businesses to address customer attrition effectively and bolster their retention efforts.

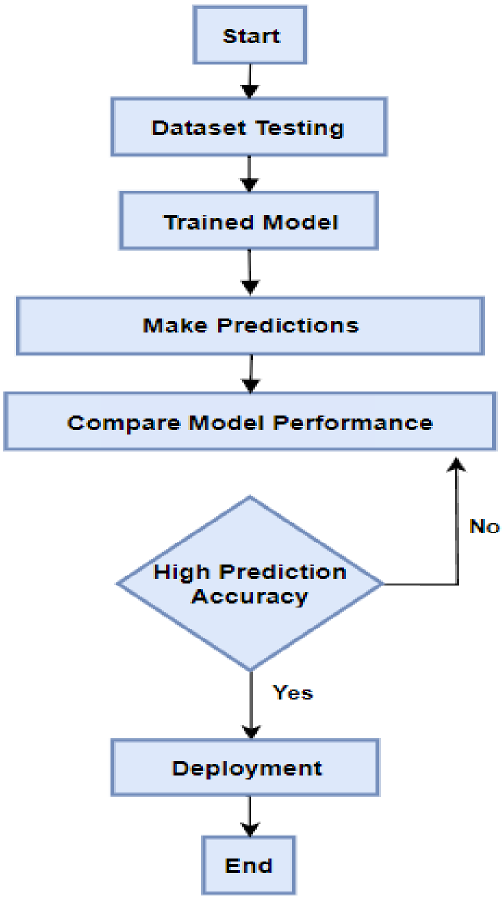

Figure 4.7 Model Evaluation and Deployment

CHAPTER 5
IMPLEMENTATION AND RESULT

5.1 IMPLEMENTATION

The customer churn prediction system represents a sophisticated integration of various machine learning and deep learning models strategically designed to achieve precise churn prediction. Its inception begins with the ingestion of raw data encompassing customer information, ranging from demographic details to usage patterns and behavioral features. The comprehensive system harnesses the capabilities of four primary models: LightGBM, TCN (Temporal Convolutional Network), Wide and Deep Neural Network, and a hybrid LSTM-CNN model. LightGBM, renowned for its utilization of tree-based learning algorithms and innovative techniques like Gradient-based One-Side Sampling (GOSS) and Histogram-based Gradient Boosting (HGB), stands out for its efficiency and accuracy in churn prediction. TCN specializes in processing sequential data, while the Wide and Deep Neural Network amalgamates sparse feature memorization with intricate relationship learning. The hybrid LSTM-CNN model leverages the long-term dependency learning prowess of LSTM networks and the local feature extraction capabilities of CNNs The evaluation of model performance is conducted meticulously, employing accuracy, precision, recall, and F1-score. Through this rigorous assessment, LightGBM emerges as the most effective model, showcasing its superiority in churn prediction tasks. Subsequently, it seamlessly transitions into deployment for real-time churn prediction, seamlessly integrated into operational systems and subjected to continual monitoring to ensure sustained effectiveness over time. The final output, categorizing customers into distinct segments such as "Happy Customers" and "Customers at High Risk," facilitates the implementation of personalized retention initiatives tailored to individual customer needs.

5.2 RESULTS

In the Fig 5.1 and Fig 5.2, The evaluation of test outcomes in predicting customer attrition surfaces unique performance patterns among the different models used in this research. Especially recognizable is the superior performance of the LightGBM model, which manages to attain an admirable accuracy level of 96%. This remarkable singular precision plays a significant role in attaining a total accuracy of 96%. Conversely, the Temporal Convolutional Neural Network (TCNN) manifests a resilient performance, achieving a 92% accuracy rate that trails closely behind the LightGBM model. Demonstrating its capability to decipher temporal and spatial patterns within the customer's data, the LSTM - CNN combined model delivers a respectable accuracy of 90%. In comparison, the Wide and Deep Neural Network attains a relatively lower accuracy rate of just 68%. These results underscore the variability in model performance, with LightGBM leading in predictive accuracy and the Wide and Deep Neural Network exhibiting a lower accuracy rate.

Dataset	Model	Accuracy	Precision	Recall	F1-Score
Telco-Customer-Churn.csv	LightGBM	95	96	96	96
	Temporal Convolutional Neural Network	93	95	95	95
	LSTM - CNN	89	86	99	92
	Wide and Deep Neural Network	67	66	82	80
telecom_customer_churn.csv	LightGBM	93	93	96	94
	Temporal Convolutional Neural Network	91	89	92	91
	LSTM - CNN	88	87	90	88
	Wide and Deep Neural Network	66	64	69	66
WA_Fn-UseC_-Telco-Customer-Churn.csv	LightGBM	92	90	90	91
	Temporal Convolutional Neural Network	90	89	88	88
	LSTM - CNN	87	86	87	86
	Wide and Deep Neural Network	64	65	65	65

Table 5.1 Comparison of Models

PRECISION:

$$\boldsymbol{Precision} = \frac{\boldsymbol{True\ Positive}}{\boldsymbol{True\ Positive} + \boldsymbol{False\ Positive}}$$

RECALL:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

F1 - SCORE:

$$F1 - Score = 2\ x\ \frac{Precision * Recall}{Precision + Recall}$$

Figure 5.1 Confusion Matrix

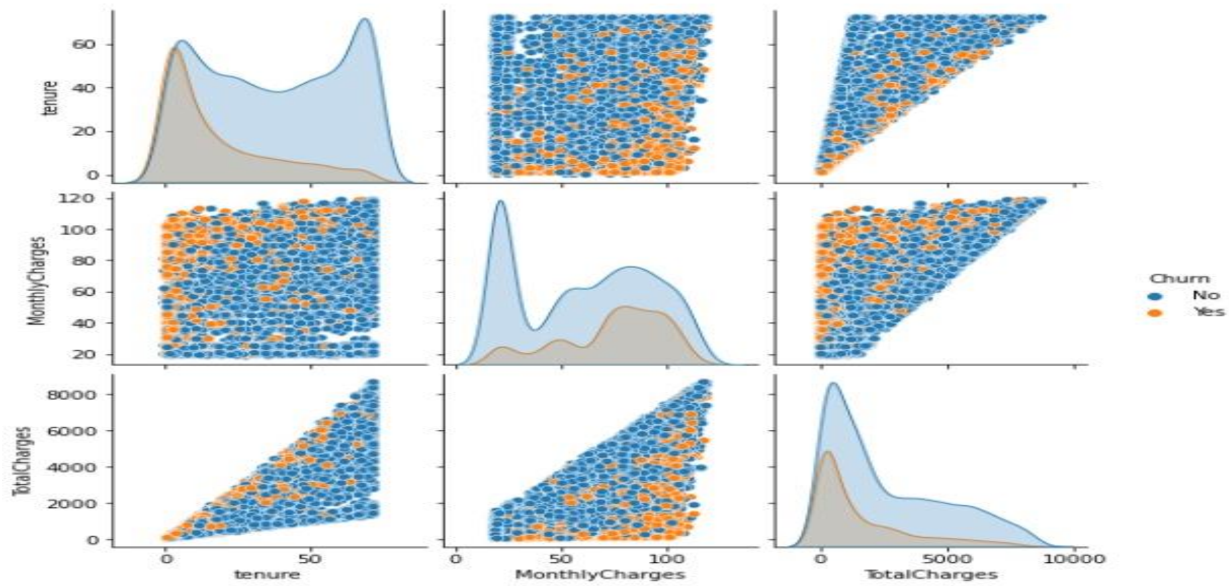

Figure 5.2 Scatter Plot

5.2.1 OUTPUT SCREENSHOTS

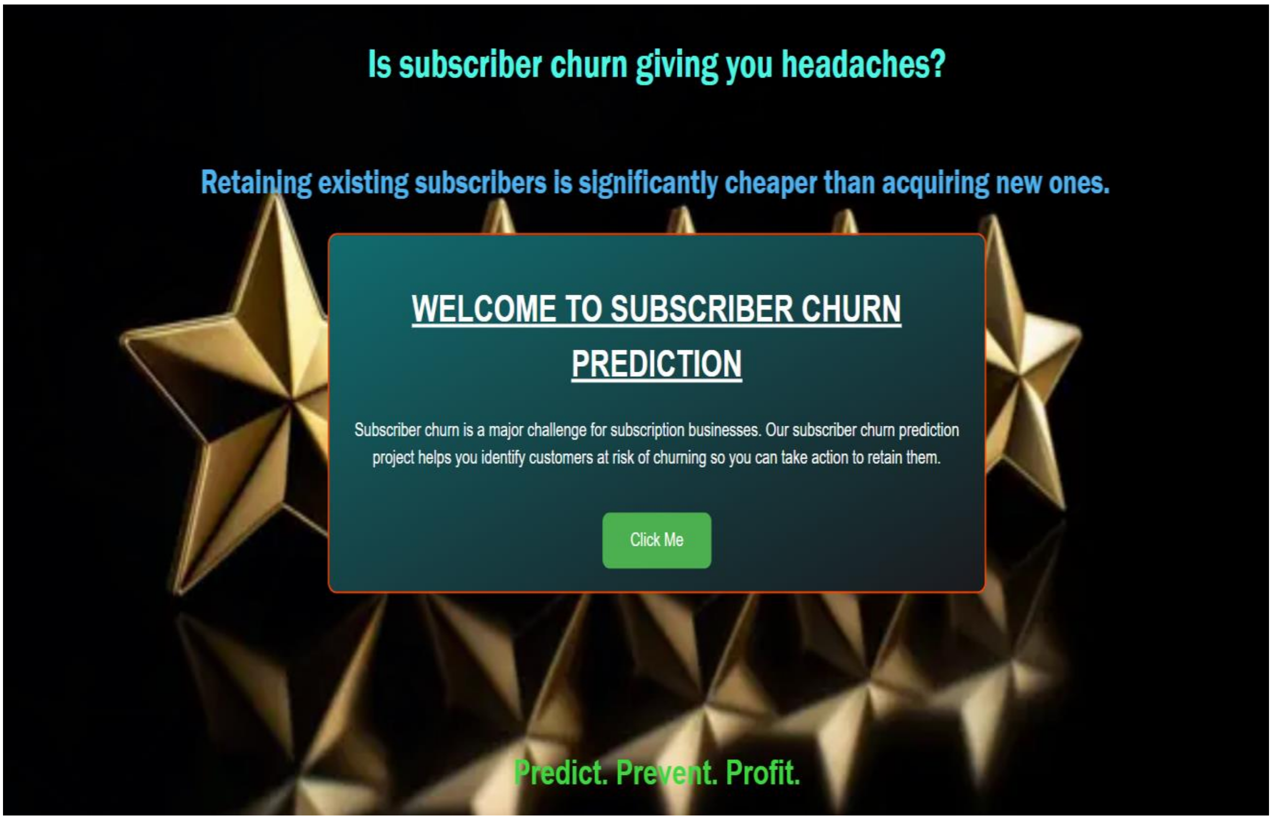

Figure 5.2.1.1 Home Page

The Fig 5.2.1.1, Home page for Subscriber churn prediction project tailored for telecommunications companies, helps telecom companies navigate customer loyalty with foresight. Our mission is clear to assist telecommunication enterprises in reducing customer churn and amplifying revenue streams. Harnessing the power of advanced analytics and machine learning algorithms, our predictive tool is designed to identify subscribers who are at risk of canceling their subscriptions. Businesses can effectively retain their valuable customers by deploying proactive measures based on these predictions Our cutting-edge solution not only predicts churn but also empowers companies to prevent it, ultimately leading to enhanced customer satisfaction reduced operational costs, and heightened profitability. With our project, telecommunication companies can stay ahead of the curve, ensuring long-term success in today's dynamic market landscape. subscriber churn prediction is the crystal ball revealing opportunities for customer retention and growth. The Click Me button takes the user to the prediction page where the result for the inputs is shown.

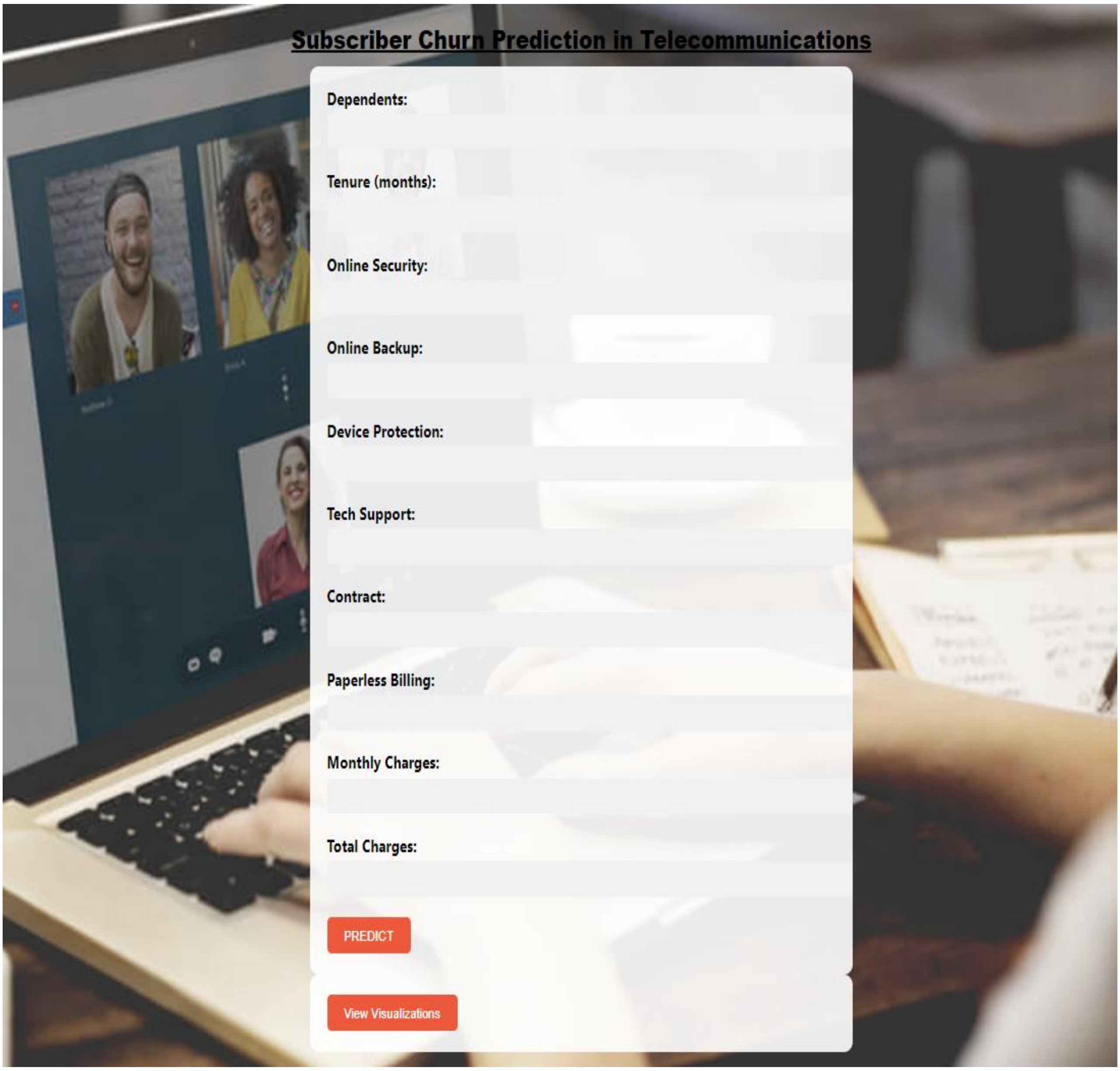

Figure 5.2.1.2 User Interface

The Fig 5.2.1.2, is the user interface for subscriber churn prediction. The image depicts a subscriber churn prediction model crucial for telecom companies. It considers factors like tenure, online security, backup, device protection, tech support, contract type, paperless billing, monthly and total charges. Tenure, contract type, and service availability significantly impact churn rates. Longer tenure, comprehensive services, and favorable contract terms correlate with lower churn. Utilizing this model, telecom providers can proactively identify at-risk subscribers and implement targeted retention strategies, thereby maintaining a stable customer base and minimizing churn.

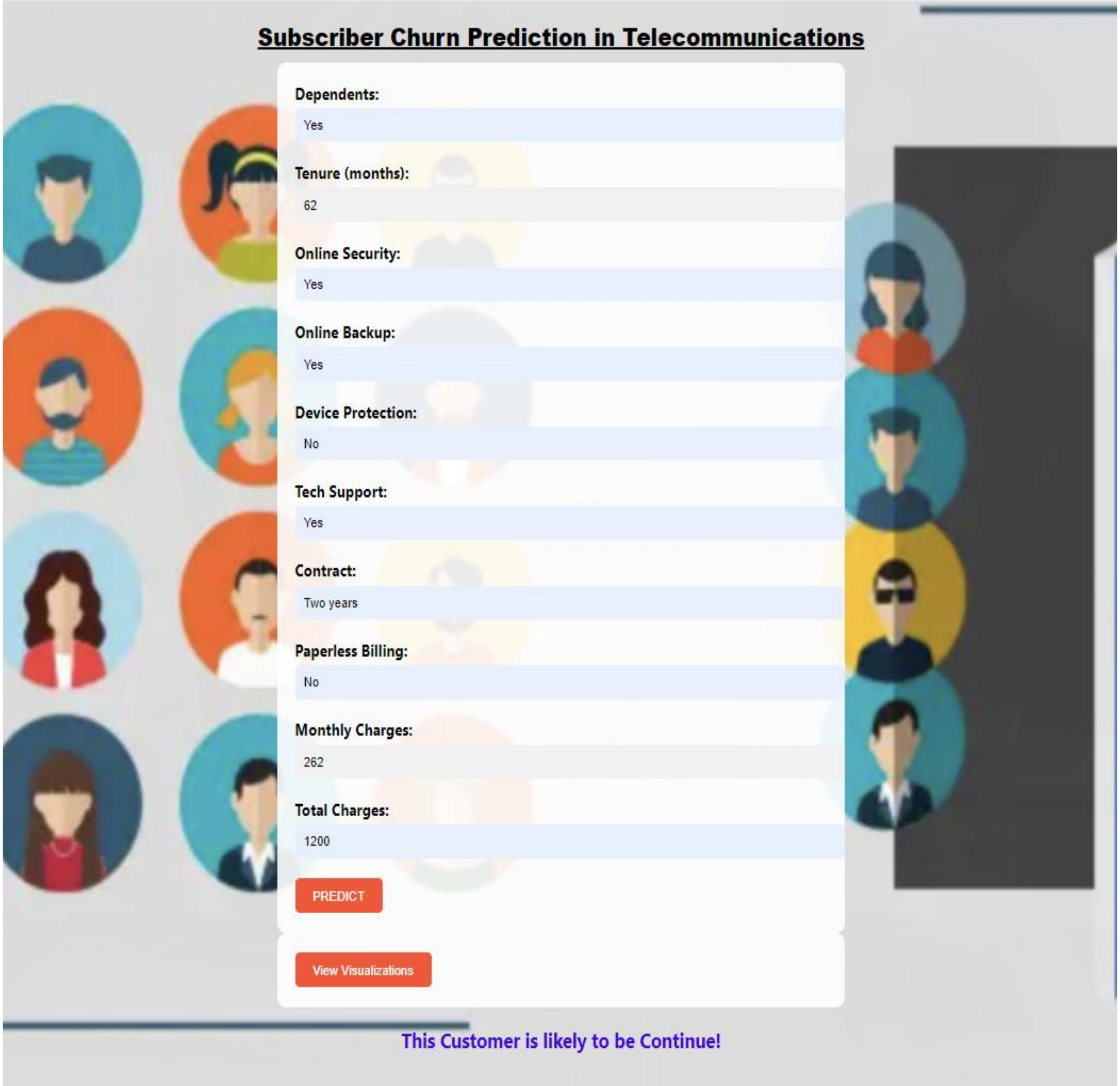

Figure 5.2.1.3 Customer Likely to be Continued

In the Fig 5.2.1.3, The analysis of a telecommunications customer's subscription details suggests that they are likely to continue their service. This inference is drawn from various factors, including their tenure of 62 months, subscription to online security, online backup, and tech support services, absence of device protection, and a two-year contract. Additionally, their choice of not opting for paperless billing and the consistent payment of 262 units monthly, totaling 1200 units, further supports this prediction. This assessment is part of a broader effort to anticipate and mitigate subscriber churn, a critical concern in the telecommunications industry.

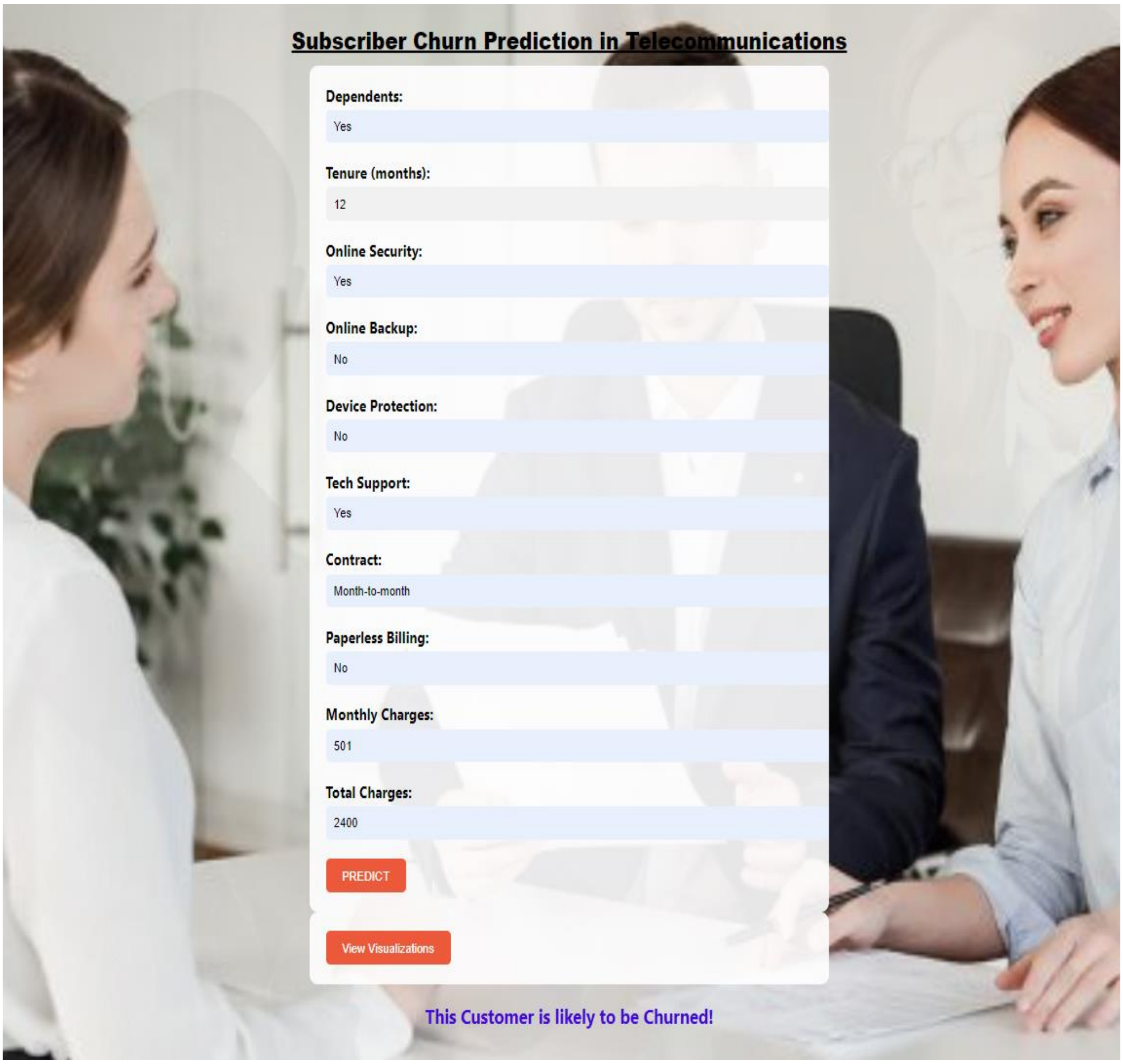

Figure 5.2.1.4 Customer Likely to be Churned

In the Fig 5.2.1.4, The Subscriber Churn Prediction process in Telecommunications entails analyzing various factors to anticipate customer discontinuation. Initially, customer data is collected, encompassing tenure, service usage, contract type, and billing preferences. For instance, a customer with a 12-month tenure, subscribed to Online Security but not Online Backup or Device Protection, used Tech Support, and has a Month-to-month contract without Paperless Billing, with Monthly Charges of $501 and Total Charges of $2400. Utilizing deep learning algorithms, the prediction model assesses these factors to gauge churn likelihood.

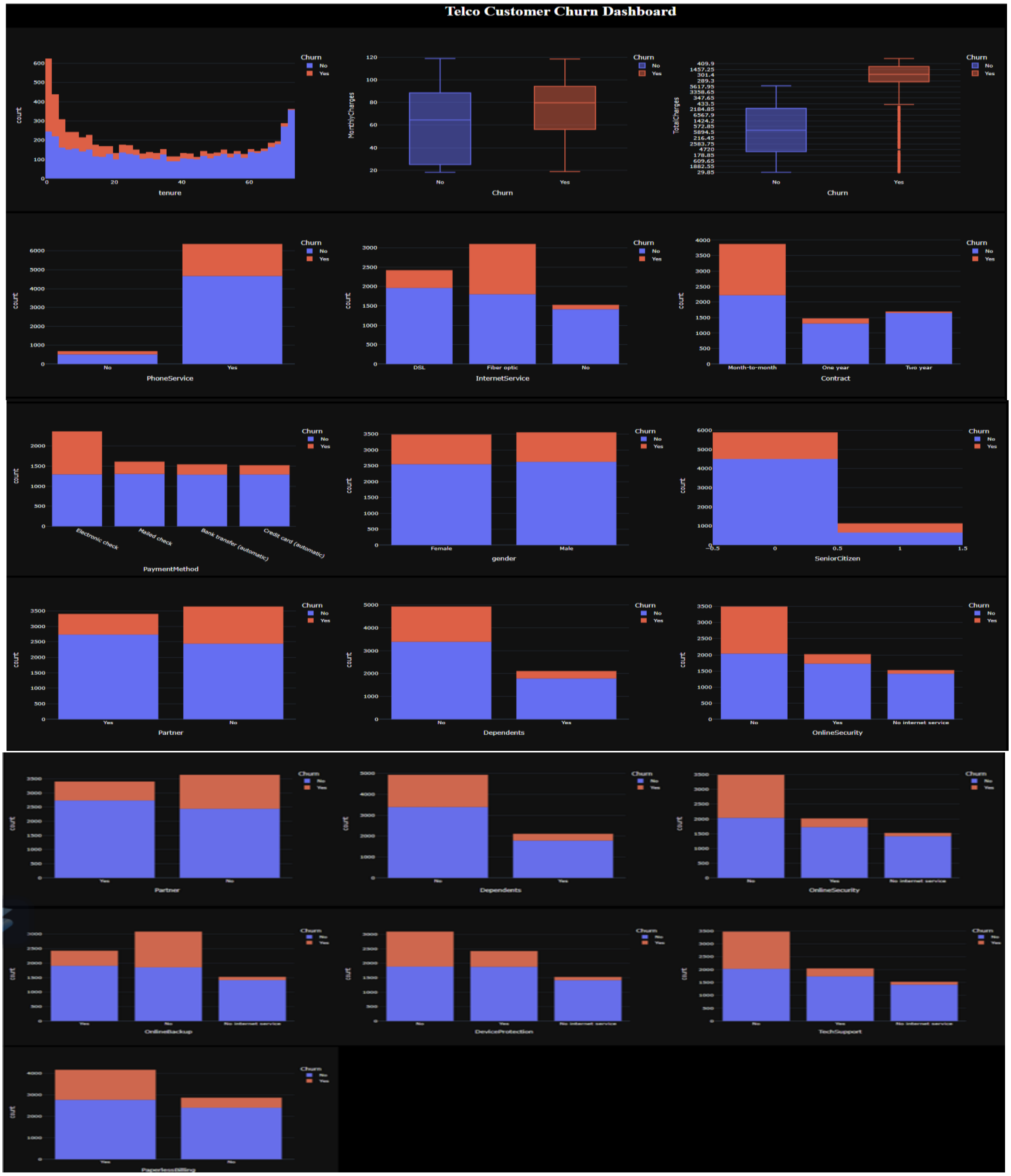

Figure 5.2.1.5 View Visualizations

In the Fig 5.2.1.5, The Dashboard is designed to display real-time or near-real-time insights into model performance. These dashboards provide stakeholders with intuitive visualizations and alerts to identify performance issues and trends quickly.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

In summary, a range of deep learning and machine learning models have been effectively utilized in this study. LightGBM emerges as the top performer in predicting customer attrition within the telecom industry. Employing advanced models like LightGBM, Temporal Convolutional Neural Network, LSTM-CNN, Wide and Deep Neural Networks, among others, has enabled a comprehensive understanding and prediction of customer churn dynamics. These models have displayed varying levels of success in capturing diverse aspects of customer behavior and temporal relationships present in the input data by thoroughly analyzing historical customer data. Notably, the implementation of LightGBM has yielded remarkable results, showcasing its proficiency in handling large datasets and accurately identifying patterns indicative of potential churn. The research underscores the importance of feature engineering, meticulous model evaluation, and hyperparameter tuning to optimize predictive performance across different models. Telecom companies can leverage the actionable insights provided by the forecasts, including feature importance analysis and visualizations, to formulate targeted client retention strategies.

6.2 FUTURE WORK

In Phase I of the project, the initial step is to meticulously identify and scrutinize the diverse inputs required for various models. This involves a thorough examination of numerous papers and e-journals to derive essential insights and propose goals for the project. As the project transitions into Phase II, the focus shifts towards the practical execution of the proposed work. This involves the actual implementation of the suggested strategies and methodologies, followed by a detailed analysis of the obtained results. To further enhance the precision and effectiveness of forecasting, the project will advance into real-time execution, harnessing the power of cutting-edge deep learning and machine learning models. This strategic integration aims to leverage the capabilities of these advanced technologies for more accurate predictions and insights.

APPENDIX

CODE

app.py

```
import numpy as np

import pandas as pd

from sklearn.preprocessing import LabelEncoder

import pickle

from flask import Flask, request, render_template, redirect, url_for

import dash

from dash import dcc, html

import plotly.graph_objects as go

import plotly.express as px

# Load Telco Customer Churn dataset

telco_data = pd.read_csv('Telco-Customer-Churn.csv')

# Initialize Flask app

app = Flask(__name__)

# Initialize Dash app within Flask app

dash_app = dash.Dash(__name__, server=app, url_base_pathname='/dashboard/')

# Define layout for Dash app

dash_app.layout = html.Div(style={'backgroundColor': 'black', 'color': 'white'}, children=[

    html.H1("Telco Customer Churn Dashboard", style={'textAlign': 'center'}),

    html.Div([

        dcc.Graph(id='tenure-histogram', figure=px.histogram(telco_data, x='tenure', nbins=50,
color='Churn’, template='plotly_dark')),], style={'width': '30%', 'display': 'inline-block'}),
```

```
html.Div([
    dcc.Graph(id='monthlycharges-boxplot', figure=px.box(telco_data, x='Churn', y='MonthlyCharges', color='Churn',template='plotly_dark')), style={'width': '30%', 'display': 'inline-block'}),
html.Div([
    dcc.Graph(id='totalcharges-boxplot', figure=px.box(telco_data, x='Churn', y='TotalCharges', color='Churn', template='plotly_dark')),], style={'width': '30%', 'display': 'inline-block'}),
html.Div([
    dcc.Graph(id='phoneservice-countplot', figure=px.histogram(telco_data, x='PhoneService', color='Churn', template='plotly_dark')), ], style={'width': '30%', 'display': 'inline-block'}),
html.Div([
    dcc.Graph(id='internetservice-countplot', figure=px.histogram(telco_data, x='InternetService', color='Churn', template='plotly_dark')), ], style={'width': '30%', 'display': 'inline-block'}),
html.Div([
    dcc.Graph(id='contract-countplot', figure=px.histogram(telco_data, x='Contract', color='Churn', template='plotly_dark')), ], style={'width': '30%', 'display': 'inline-block'}),
html.Div([
    dcc.Graph(id='paymentmethod-countplot', figure=px.histogram(telco_data, x='PaymentMethod', color='Churn', template='plotly_dark')), ], style={'width': '30%', 'display': 'inline-block'}),
html.Div([
    dcc.Graph(id='gender-countplot', figure=px.histogram(telco_data, x='gender', color='Churn',template='plotly_dark')), ], style={'width': '30%', 'display': 'inline-block'}),
```

```
html.Div([
    dcc.Graph(id='seniorcitizen-countplot', figure=px.histogram(telco_data, x='SeniorCitizen', color='Churn', template='plotly_dark')), ], style={'width': '30%', 'display': 'inline-block'}),
html.Div([
    dcc.Graph(id='partner-countplot', figure=px.histogram(telco_data, x='Partner', color='Churn', template='plotly_dark')), ], style={'width': '30%', 'display': 'inline-block'}),
html.Div([
    dcc.Graph(id='dependents-countplot', figure=px.histogram(telco_data, x='Dependents', color='Churn', template='plotly_dark')), ], style={'width': '30%', 'display': 'inline-block'}),
html.Div([
    dcc.Graph(id='onlinesecurity-countplot', figure=px.histogram(telco_data, x='OnlineSecurity', color='Churn', template='plotly_dark')),], style={'width': '30%', 'display': 'inline-block'}),
html.Div([
    dcc.Graph(id='onlinebackup-countplot', figure=px.histogram(telco_data, x='OnlineBackup', color='Churn', template='plotly_dark')),], style={'width': '30%', 'display': 'inline-block'}),
html.Div([
    dcc.Graph(id='deviceprotection-countplot', figure=px.histogram(telco_data, x='DeviceProtection', color='Churn', template='plotly_dark')),], style={'width': '30%', 'display': 'inline-block'}),
html.Div([
    dcc.Graph(id='techsupport-countplot', figure=px.histogram(telco_data, x='TechSupport', color='Churn', template='plotly_dark')),], style={'width': '30%', 'display':
```

```
'inline-block'}),
    html.Div([
        dcc.Graph(id='paperlessbilling-countplot', figure=px.histogram(telco_data,
x='PaperlessBilling', color='Churn', template='plotly_dark')),], style={'width': '30%',
'display': 'inline-block'}),
])


# Route for home page
@app.route("/", methods=['GET', 'POST'])
def index():
    if request.method == 'POST':
        return redirect(url_for('home'))
    return render_template('index.html')
# Route for home page
@app.route("/home", methods=['GET', 'POST'])
def home():
    if request.method == 'POST':
        return redirect(url_for('predict'))
    return render_template('home.html')
# Route for dashboard page
@app.route("/dashboard")
def dashboard():
    return dash_app.index()
```

```
# Route for prediction
@app.route("/predict", methods=['GET', 'POST'])
def predict():
    if request.method == 'POST':
        Dependents = request.form['Dependents']
        tenure = float(request.form['tenure'])
        OnlineSecurity = request.form['OnlineSecurity']
        OnlineBackup = request.form['OnlineBackup']
        DeviceProtection = request.form['DeviceProtection']
        TechSupport = request.form['TechSupport']
        Contract = request.form['Contract']
        PaperlessBilling = request.form['PaperlessBilling']
        MonthlyCharges = float(request.form['MonthlyCharges'])
        TotalCharges = float(request.form['TotalCharges'])
        model = pickle.load(open('Model.sav', 'rb'))
        data = [[Dependents, tenure, OnlineSecurity, OnlineBackup, DeviceProtection,
TechSupport, Contract, PaperlessBilling, MonthlyCharges, TotalCharges]]
        df = pd.DataFrame(data, columns=['Dependents', 'tenure', 'OnlineSecurity',
            'OnlineBackup', 'DeviceProtection', 'TechSupport', 'Contract',
            'PaperlessBilling', 'MonthlyCharges', 'TotalCharges'])
        categorical_feature = {feature for feature in df.columns if df[feature].dtypes == 'O'}
        encoder = LabelEncoder()
        for feature in categorical_feature:
            df[feature] = encoder.fit_transform(df[feature])
```

```
        single = model.predict(df)

        probability = model.predict_proba(df)[:, 1]

        probability = probability*100

        if single == 1:

            op1 = "This Customer is likely to be Churned!"

        else:

            op1 = "This Customer is likely to be Continue!"

        return render_template("home.html", op1=op1,

                               Dependents=request.form['Dependents'],

                               tenure=request.form['tenure'],

                               OnlineSecurity=request.form['OnlineSecurity'],

                               OnlineBackup=request.form['OnlineBackup'],

                               DeviceProtection=request.form['DeviceProtection'],

                               TechSupport=request.form['TechSupport'],

                               Contract=request.form['Contract'],

                               PaperlessBilling=request.form['PaperlessBilling'],

                               MonthlyCharges=request.form['MonthlyCharges'],

                               TotalCharges=request.form['TotalCharges'])

    else:

        return redirect(url_for('home'))


if __name__ == '__main__':

    app.run(debug=True)
```

REFERENCES

1. Agarwal, V., Taware, S., Yadav, S. A., Gangodkar, D., Rao, A. L. N., & Srivastav, V. K. (2022, October). Customer-Churn Prediction Using Machine Learning. In 2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS) (pp. 893-899). IEEE.
2. Agrawal, S., Das, A., Gaikwad, A., & Dhage, S. (2018, July). Customer churn prediction modelling based on behavioural patterns analysis using deep learning. In 2018 International conference on smart computing and electronic enterprise (ICSCEE) (pp. 1-6). IEEE.
3. Ahmad, A. K., Jafar, A., & Aljoumaa, K. (2019). Customer churn prediction in telecom using machine learning in big data platform. Journal of Big Data, 6(1), 1-24.
4. Ahmed, Ammar & Maheswari, D. (2017). A review and analysis of churn prediction methods for customer retention in telecom industries. 1-7.
5. Amol Chole, Rushikesh Chavan, Shradha Mandan & Trupti Mate. (2023). Customers Churn Prediction using Machine Learning and Deep Learning. In 2023 Journal of Emerging Technologies and Innovative Research, ISSN-2349-5162.
6. Anvita Gupta, Komanduri Srikar, Sreenitya Mandav. (2022) 'Customer Churn Prediction in Banking Sector - A Hybrid Approach', International Journal for Research in Applied Science & Engineering Technology (IJRASET), pp. 1-6.
7. Bhatnagar, A., & Srivastava, S. (2019, December). A robust model for churn prediction using supervised machine learning. In 2019 IEEE 9th international conference on advanced computing (IACC) (pp. 45-49). IEEE.
8. Bhuse, P., Gandhi, A., Meswani, P., Muni, R., & Katre, N. (2020, December). Machine learning based telecom-customer churn prediction. In 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS) (pp. 1297-1301). IEEE.
9. Bin, Luo & Peiji, Shao & Juan, Liu. (2007). Customer Churn Prediction Based on the Decision Tree in Personal Handyphone System Service. Proceedings - ICSSSM'07: 2007 International Conference on Service Systems and Service Management. 1 - 5.
10. Çelik, O., & Osmanoglu, U. O. (2019). Comparing to techniques used in customer churn analysis. Journal of Multidisciplinary Developments, 4(1), 30-38.

11. Fujo, S. W., Subramanian, S., & Khder, M. A. (2022). Customer churn prediction in telecommunication industry using deep learning. Information Sciences Letters, 11(1), 24.
12. Gaur, A., & Dubey, R. (2018, December). Predicting customer churn prediction in telecom sector using various machine learning techniques. In 2018 International Conference on Advanced Computation and Telecommunication (ICACAT) (pp. 1-5). Ieee.
13. Hu, J., Zhuang, Y., Yang, J., Lei, L., Huang, M., Zhu, R., & Dong, S. (2018, December). pRNN: A recurrent neural network based approach for customer churn prediction in telecommunication sector. In 2018 IEEE International Conference on Big Data (Big Data) (pp. 4081-4085). IEEE.
14. Ismail, M. R., Awang, M. K., Rahman, M. N. A., & Makhtar, M. (2015). A multi-layer perceptron approach for customer churn prediction. International Journal of Multimedia and Ubiquitous Engineering, 10(7), 213-222.
15. Karvana, K. G. M., Yazid, S., Syalim, A., & Mursanto, P. (2019, October). Customer churn analysis and prediction using data mining models in banking industry. In 2019 international workshop on big data and information security (IWBIS) (pp. 33-38). IEEE.
16. Kumar, P., & Kumar, S.V. (2023). DDoS Attack Prediction System Using Machine Learning Algorithms. In: Tuba, M., Akashe, S., Joshi, A. (eds) ICT Systems and Sustainability. ICT4SD 2023. Lecture Notes in Networks and Systems, vol 765. Springer, Singapore.
17. Kumar, P., Vinodh Kumar, S., & Priya, L. (2023). An Approach for Energy-Efficient Resource Allocation Through Early Planning of Virtual Machines to Servers in Cloud Server Farms. In: Doriya, R., Soni, B., Shukla, A., Gao, XZ. (eds) Machine Learning, Image Processing, Network Security and Data Sciences. Lecture Notes in Electrical Engineering, vol 946. Springer, Singapore.
18. Maw, M., Haw, S. C., & Ho, C. K. (2019, November). Customer Churn Prediction in Telecommunication: An Analysis on Issues, Techniques and Future Trends. In 2019 IEEE Conference on Sustainable Utilization and Development in Engineering and Technologies (CSUDET) (pp. 148-153). IEEE.
19. Rahman, M., & Kumar, V. (2020, November). Machine learning based customer churn prediction in banking. In 2020 4th international conference on electronics, communication and aerospace technology (ICECA) (pp. 1196-1201). IEEE.

20. Sudharsan, R., & Ganesh, E. N. (2022). A Swish RNN based customer churn prediction for the telecom industry with a novel feature selection strategy. Connection Science, 34(1), 1855-1876.
21. Zhang, T., Moro, S., & Ramos, R. F. (2022). A data-driven approach to improve customer churn prediction based on telecom customer segmentation. Future Internet, 14(3), 94.
22. Zhao, J., & Dang, X. H. (2008, October). Bank customer churn prediction based on support vector machine: Taking a commercial bank's VIP customer churn as the example. In 2008 4th International Conference on Wireless Communications, Networking and Mobile Computing (pp. 1-4). IEEE.

PUBLICATION STATUS I

Anandhi S, Ilakia S R, Shruthi K. (2023, October). Customer Churn Prediction using Deep Learning Scopus-Journal.

TITLE	**:**	Customer Churn Prediction using Deep Learning
AUTHOR	**:**	Anandhi S, Ilakia S R, Shruthi K
CONFERENCE NAME	**:**	International Conference on Intelligent Computing and Smart Communication Systems
JOURNAL	**:**	Scopus Indexed -Journal
MODE OF PUBLICATION	**:**	Online
STATUS	**:**	Accepted

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PUBLICATION STATUS II

Anandhi S, Ilakia S R, Shruthi K. Telecom Subscriber Churn Prediction Using Deep Learning: Examining the Influence of Customer Characteristics and Service Offerings. Scopus-Journal.

TITLE	**:**	Telecom Subscriber Churn Prediction using Deep Learning: Examining the Influence of Customer Characteristics and Service Offerings
AUTHOR	**:**	Anandhi S, Ilakia S R, Shruthi K
CONFERENCE NAME	**:**	International Conference for Intelligent technologies
JOURNAL	**:**	Scopus Indexed -Journal
MODE OF PUBLICATION	**:**	Online
STATUS	**:**	Submitted

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237 - SHRUTHI K <200701237@rajalakshmi.edu.in>

International Conference for Intelligent technologies : Submission (2837) has been created.

1 message

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Track Name: CONIT2024

Paper ID: 2837

Paper Title: Telecom Subscriber Churn Prediction using Deep Learning: Examining the Influence of Customer Characteristics and Service Offerings

Abstract:
Predicting customer churn is essential for telecom companies. They utilize historical customer data to create predictive models employing Deep learning algorithms. While traditional methods like Gradient Boosting and Random Forest are common, more advanced techniques such as LightGBM, Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks are gaining traction due to their enhanced accuracy. Thorough evaluation using metrics like F1-score and ROC-AUC helps in selecting the most suitable model. Telecoms strive to retain customers by actively addressing churn patterns and customizing retention strategies. The objective is to pinpoint customers at risk and tailor retention tactics to their specific preferences, thereby empowering providers with actionable insights to strengthen their competitive edge amid market fluctuations.

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Secondary Subject Areas: Not Entered
Submission Files: Telecom Subscriber Churn Prediction using Deep Learning Examining the Influence of Customer Characteristics and Service Offerings.docx (1 Mb, Wed, 01 May 2024 15:55:01 GMT)

Submission Questions Response: Not Entered

Thanks,
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