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Explainable AI-Based Deep Learning System for Predicting Customer Churn in Telecommunication Industry

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Abstract: Customer churn is a major challenge for the telecommunication industry as the loss of customers impacts revenue and business growth. Early identification of customers who are likely to churn allows telecom providers to develop effective customer retention strategies and increase customer satisfaction. Traditional machine learning approaches often fail to capture complex customer behavior patterns and offer limited interpretability in their predictions. To overcome these challenges, this project proposes an Explainable AI-Based Deep Learning System for prediction of customer churn in telecommunication industry. The system uses IBM Telco customer churn dataset and uses exhaustive data preprocessing techniques such as data cleaning, label encoding, feature scaling and class balancing using SMOTEENN. It employs a hybrid deep learning architecture called ChurnNet comprising a 1D Convolutional Neural Network (1D-CNN), Residual Blocks, Channel Attention, and Spatial Attention mechanisms to learn complex customer behavioural patterns and accurately predict churn probability. In order to enhance credibility and clarity, the suggested system incorporates Explainable Artificial Intelligence (XAI) methods like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) to provide transparency. SHAP performs global feature importance analysis, and LIME provides local explanations for each prediction, allowing users to understand the crucial features influencing the churn decision. The experimental results show that the proposed system has high prediction accuracy, reliability and interpretability, and thus it is a valuable decision-support tool for telecom organizations that aim to reduce customer attrition and improve retention strategies.
Keywords: Customer churn prediction, Telecommunication Industry, SMOTEEN, Deep Learning, 1D-CNN, Residual Networks, Explainable AI, SHAP, LIME, Customer Retention.

I. INTRODUCTION

Telecommunication companies globally encounter a significant challenge in the form of customer churn, which stands as a paramount issue. The endeavor to retain existing clientele proves to be more economically advantageous than the acquisition of new customers, underscoring the criticality of early churn prognosis for the sustenance of profitability and customer contentment. Despite the accumulation of substantial customer data by telecommunication entities, the intricate task of pinpointing probable churners persists due to the diverse array of behavioral patterns and service utilization characteristics exhibited by customers.

The emergence of Artificial Intelligence and Deep Learning has facilitated the development of automated churn prediction systems, enabling the scrutiny of customer behavior and the anticipation of potential churn incidents. Deep learning models exhibit adeptness in capturing intricate interrelations within customer data, thus achieving heightened levels of predictive accuracy. Nonetheless, a prevalent issue with extant models lies in their opacity, rendering predictions bereft of transparent explication, thereby impeding trust and practical integration into business decision-making processes.

This study advocates for an effective and elucidatory customer churn prediction system founded on the ChurnNet architecture. This system employs a hybrid deep learning framework incorporating a 1D Convolutional Neural Network (1D-CNN), Residual Blocks, Channel Attention, and Spatial Attention mechanisms to discern substantive customer behavior patterns. Moreover, Explainable Artificial Intelligence (XAI) methodologies, specifically SHAP and LIME, are assimilated to furnish both global and local elucidations for churn forecasts. By amalgamating precision in prediction with interpretability, the proposed system aids telecommunication providers in comprehending churn determinants and implementing efficacious customer retention tactics.

II. RELATED WORK

Deep learning has become an important approach for customer churn prediction, with recent studies demonstrating its ability to learn complex behavioral patterns from telecommunication customer data. Saha et al. proposed a deep learning-based ChurnNet model for customer churn prediction that utilizes convolutional neural networks to automatically extract important customer behavioral patterns [1]. Yang et al. introduced a hybrid CNN-BiLSTM model with a Coordinate Attention mechanism, where CNN was used for feature extraction and BiLSTM was employed to capture broader behavioral relationships within customer data [2]. Similarly, Zhang and Zhang proposed a GWO-Attention-ConvLSTM model that combines Grey Wolf Optimization, attention mechanisms, and ConvLSTM to capture sequential customer interactions and improve churn prediction performance [3]. Liu et al. developed a fused attentional deep learning model for intelligent customer churn prediction, demonstrating the effectiveness of attention mechanisms in identifying important customer characteristics [4]. Although these deep learning and hybrid approaches provide improved predictive capabilities, their increasing architectural complexity can result in higher computational requirements and limited interpretability of the prediction results. These limitations create a need for an efficient deep learning framework that can accurately model customer behavior while also providing understandable predictions.

Customer churn prediction also requires effective learning of nonlinear relationships and interactions among different customer attributes. Jajam et al. proposed an ensemble deep learning SBLSTM-RNN-IGSA model for customer churn prediction, combining multiple learning and optimization techniques to improve prediction performance [5]. Loukili et al. investigated deep learning together with imbalanced-data techniques to improve customer retention and address the difficulty of correctly identifying churn customers in an imbalanced dataset [6]. Khattak et al. proposed a composite deep learning technique for customer churn prediction, demonstrating the potential of combining deep learning approaches to learn complex customer characteristics [7]. These studies indicate that advanced deep learning architectures can improve the representation of customer behavior; however, the use of multiple learning, optimization, and ensemble components can increase model complexity. Moreover, the black-box nature of deep learning models makes it difficult for organizations to understand the reasons behind individual churn predictions.

Class imbalance and feature representation remain important challenges in customer churn prediction. Amin et al. investigated different oversampling techniques for handling the class imbalance problem in customer churn prediction and demonstrated the importance of improving the representation of minority churn instances [8]. Sana et al. proposed a churn prediction model using data transformation and feature selection methods to identify informative customer characteristics and improve prediction performance [9]. AlShourbaji et al. developed a churn prediction model using Gradient Boosting Machine combined with metaheuristic optimization, demonstrating the effectiveness of optimized ensemble learning for churn prediction [10]. Amin et al. further investigated just-in-time customer churn prediction in the telecommunication sector, emphasizing the importance of identifying potential churners at an appropriate time so that organizations can take proactive retention measures [11]. These studies demonstrate that preprocessing, feature selection, class balancing, and timely prediction play important roles in improving churn prediction. However, conventional feature-based and ensemble approaches may have limitations in automatically learning complex feature relationships, while advanced deep learning models continue to face challenges related to interpretability.

Model interpretability has therefore become an important requirement for practical customer churn prediction systems. Ullah et al. investigated Random Forest and other machine learning techniques for churn prediction and factor identification in the telecommunication sector [12]. Such approaches can provide useful information about important customer factors, but they may not capture complex nonlinear relationships as effectively as specialized deep learning architectures. Explainable Artificial Intelligence techniques can provide an additional mechanism for understanding the decisions generated by complex predictive models. In particular, global explanation techniques can identify the features that generally influence churn predictions, while local explanation techniques can explain the factors responsible for the prediction of an individual customer. Therefore, integrating predictive performance with interpretability is essential for enabling telecom organizations to confidently use churn prediction results for customer retention strategies.

To address these limitations, the proposed ChurnNet framework focuses on combining deep feature learning, attention mechanisms, class-imbalance handling, and Explainable Artificial Intelligence within a unified customer churn prediction system. The proposed architecture incorporates a 1D-CNN, Residual Blocks, Channel Attention, and Spatial Attention to learn complex customer behavioral patterns and identify important feature representations. SMOTEENN is employed to address class imbalance, while SHAP and LIME are integrated to provide global and local explanations of the prediction results. The proposed framework therefore aims not only to improve churn prediction performance but also to provide transparent and understandable insights into the factors influencing customer churn. This combination of accurate prediction and interpretability can support telecom organizations in identifying high-risk customers and developing more effective customer retention strategies.

III. METHODOLOGY

The proposed ChurnNet methodology is designed to predict customer churn in the telecommunication industry while providing interpretable insights into the factors influencing each prediction. The overall process consists of data collection, preprocessing, class balancing, deep learning-based prediction, explainability, performance evaluation, and visualization. The methodology follows a sequential workflow in which the raw customer data is transformed into a balanced and standardized form before being processed by the proposed ChurnNet architecture.

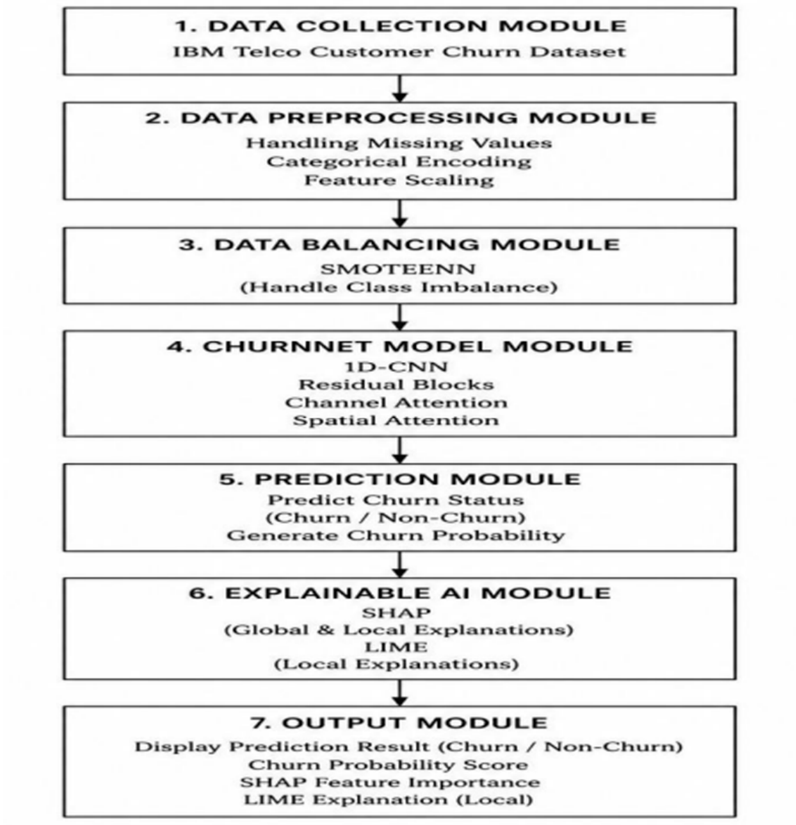

Fig 1: Architectural Representation of the Proposed System

A. Data Collection

The IBM Telco Customer Churn Dataset is used for developing and evaluating the proposed system. The dataset contains 7,043 customer records and 21 variables, including demographic information, subscribed services, account information, billing details, tenure, monthly charges, total charges, and churn status. The churn attribute represents whether a customer has discontinued the service or continues with the service provider.

B. Data Preprocessing

The collected dataset is preprocessed to make it suitable for model training. The preprocessing stage involves handling missing or invalid values, removing irrelevant attributes such as customer ID, converting categorical attributes into numerical representations, and scaling numerical features. These operations ensure that the input data is consistent and suitable for subsequent model processing.

C. Class Balancing Using SMOTEENN

Since churn datasets may contain an unequal distribution between churn and non-churn customers, SMOTEENN is employed to address class imbalance. SMOTE generates synthetic samples for the minority class, while Edited Nearest Neighbors removes inappropriate or noisy samples. This process produces a more balanced dataset and helps the model learn the characteristics of churn customers more effectively.

D. ChurnNet Model Development

The balanced and preprocessed data is provided to the proposed ChurnNet architecture. The model is based on a 1D Convolutional Neural Network (1D-CNN) enhanced with Residual Blocks, Channel Attention, and Spatial Attention mechanisms. The 1D-CNN extracts important feature representations from customer attributes, while Residual Blocks support deeper feature learning. Channel Attention emphasizes important feature channels, and Spatial Attention focuses on significant feature regions. These components work together to capture complex customer behavioral patterns associated with churn.

E. Model Training and Prediction

The prepared dataset is used to train the ChurnNet model, with stratified cross-validation incorporated during model assessment to provide reliable evaluation while maintaining the distribution of churn and non-churn classes. After training, new customer records are passed through the same preprocessing pipeline and provided to the trained model. The system predicts whether the customer is likely to churn or remain with the service provider and also generates a churn probability score representing the customer's estimated churn risk.

F. Explainable Artificial Intelligence

To improve the transparency of the deep learning model, the proposed system incorporates SHAP and LIME. SHAP is used to determine the contribution of individual features and provide an overall understanding of the factors influencing churn predictions. LIME provides local explanations for individual customer predictions by identifying the factors that influence a particular churn or non-churn decision. These explanations help users understand the reasoning behind the model's predictions.

G. Performance Evaluation

The performance of ChurnNet is evaluated using Accuracy, Precision, Recall, F1-Score, Matthews Correlation Coefficient (MCC), and AUC-ROC. Accuracy measures the overall correctness of predictions, while Precision measures the correctness of predicted churn cases. Recall evaluates the ability to identify actual churn customers, and F1-Score provides a balance between Precision and Recall. MCC evaluates the quality of binary classification, while AUC-ROC measures the ability of the model to distinguish between churn and non-churn customers at different classification thresholds.

IV. EXPERIMENTAL RESULTS

1) *Accuracy:* The overall percentage of correctly classified customer records among all predictions made by the ChurnNet model is represented by accuracy. It indicates how effectively the proposed system correctly identifies both churn and non-churn customers. A higher accuracy value indicates better overall classification performance.

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \qquad (1)$$

2) *Precision:* Precision measures the proportion of correctly predicted churn customers among all customers predicted as churn. Higher precision indicates fewer false positive predictions and demonstrates the reliability of the model in identifying customers predicted to churn.

$$Precision = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad (2)$$

3) *Recall:* Recall measures the ability of the ChurnNet model to correctly identify customers who actually churn. A higher recall value indicates that the model is more effective in detecting potential churners while reducing the number of actual churn customers that are incorrectly classified as non-churn.

$$Recall = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad (3)$$

4) *F1-Score:* F1-Score represents the harmonic mean of precision and recall. It provides a balanced measure of the model's classification performance, particularly when the dataset contains an imbalance between churn and non-churn customers. A higher F1-Score indicates a better balance between correctly identifying churn customers and minimizing false predictions.

$$F1\,Score = 2 * \frac{Precision \text{ X } Recall}{Precision + Recall} \qquad (4)$$

5) *Area Under the Receiver Operating Characteristic Curve (AUC-ROC):* AUC-ROC measures the ability of the ChurnNet model to distinguish between churn and non-churn customers across different classification thresholds. The ROC curve represents the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR). A higher AUC-ROC value indicates better discrimination between churn and non-churn customers, with a value closer to 1 representing stronger classification performance.
6) *Matthews Correlation Coefficient (MCC):* Matthews Correlation Coefficient (MCC) is a balanced performance metric that evaluates the quality of binary classification by considering true positives, true negatives, false positives, and false negatives. It is particularly useful for customer churn prediction because telecommunication datasets can contain imbalanced classes. A higher MCC value indicates that the ChurnNet model performs well in correctly identifying both churn and non-churn customers while minimizing classification errors.

Table.1 Performance Evaluation

DL Model	Accuracy	Macro F1 Score	Recall	Precision	AUC-ROC	MCC
ChurnNet	0.947	0.952	0.952	0.953	0.983	0.893

Table 1 presents the performance of the proposed ChurnNet model, achieving 94.7% accuracy, 95.2% Macro F1-Score, 95.2% recall, and 95.3% precision. The model also achieves an AUC-ROC of 98.3% and MCC of 89.3%, demonstrating strong performance.

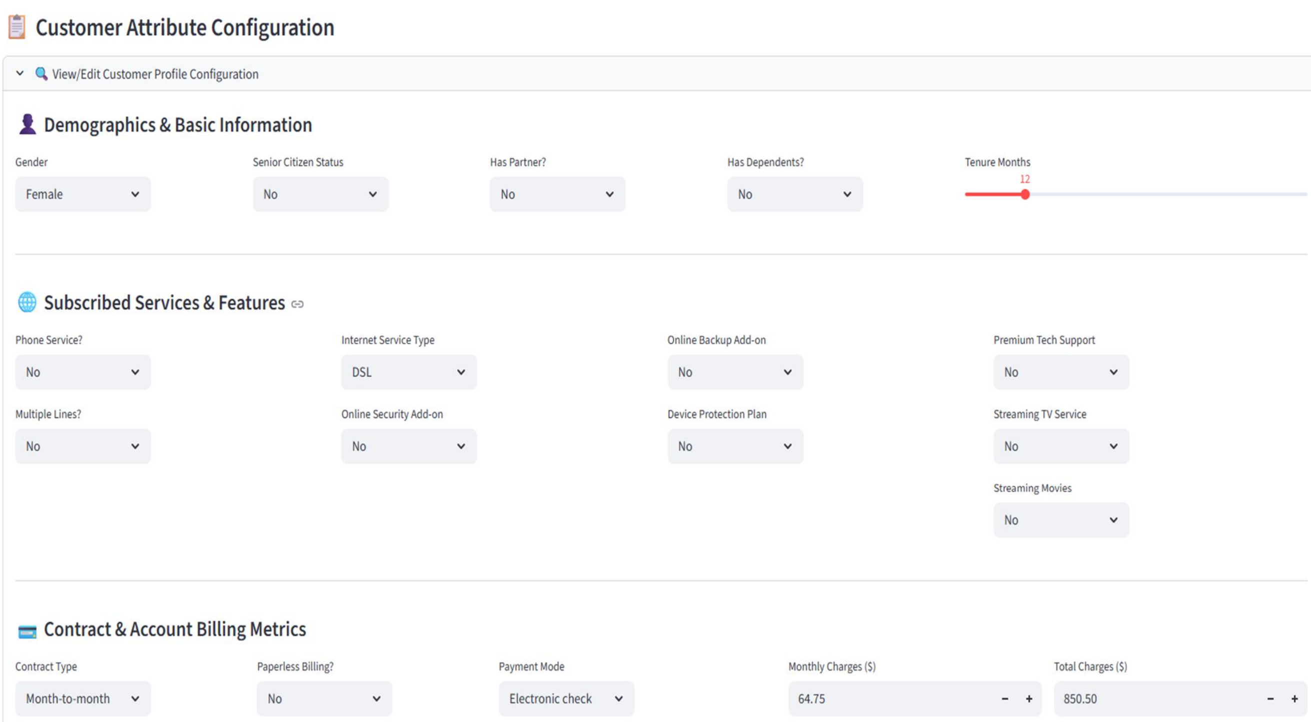

Fig.2 Webpage of Customer Churn Predicton

Displayed is a snapshot of the suggested Customer Churn Prediction System's user interface. It features a well-organized dashboard for input, allowing users to input customer details like demographics, services subscribed to, and billing information through interactive fields. The system analyzes this data using the ChurnNet model to forecast the likelihood of churn. This interface acts as the main gateway for customer analysis, empowering users to set up customer profiles effortlessly to obtain churn forecasts and explainable AI outcomes.

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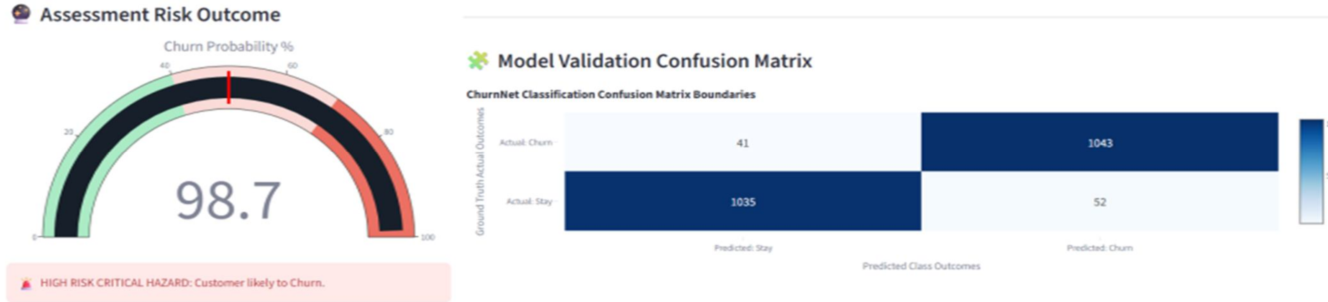

Fig.3 Evaluation of ChurnNet Model with Churn Probability and Confusion Matrix Analysis.

Fig.3 shows the forecast outcomes of the new Customer Churn Prediction System. The churn probability meter reveals a 98.7% chance of churn, labeling the customer as probable to leave. By juxtaposing real and forecasted customer results, the confusion matrix showcases how well the ChurnNet model recognizes churn and non-churn clients, proving its efficacy in this task.

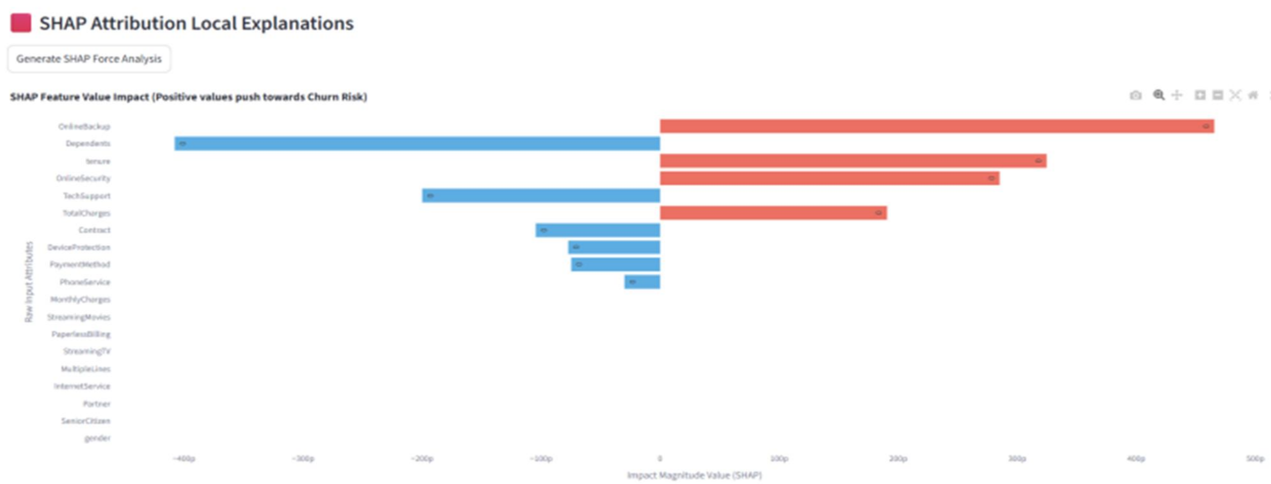

Fig.4 Analyzing Customer Churn Prediction with SHAP-Based Feature Importance

Fig.4 illustrates a SHAP local explanation for predicting customer churn. It displays how each customer attribute impacts the likelihood of churn: positive values raise the risk, while negative values reduce it. This visual tool highlights the key factors influencing the prediction, enhancing understanding and clarity of the model's decision-making process.

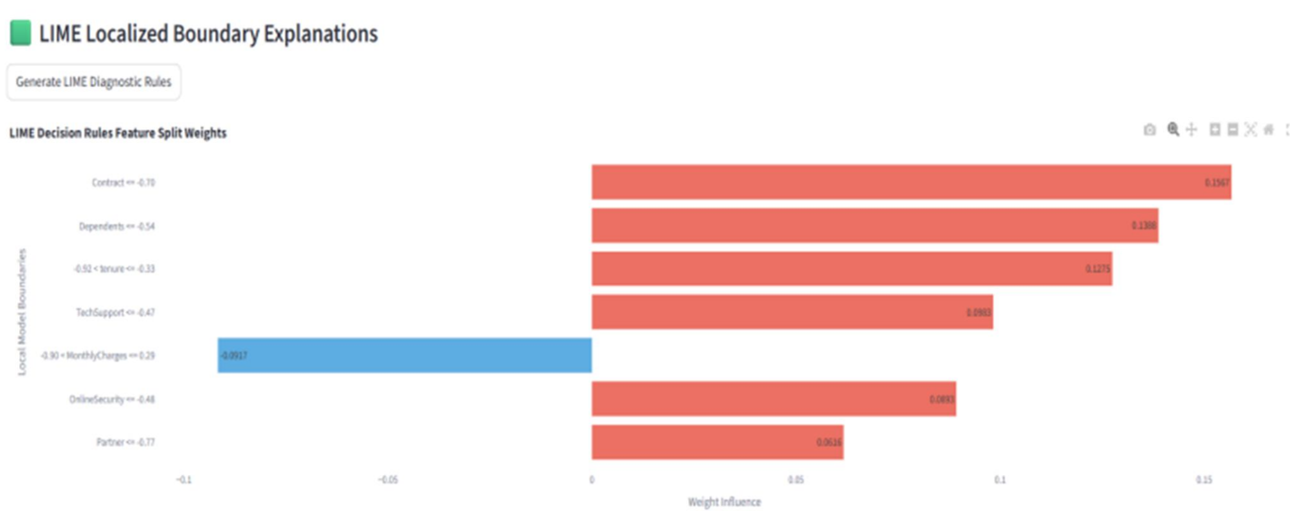

Fig.5 LIME-Based Local Explanation for Customer Churn Prediction

Fig.5 shows the LIME local explanation for customer churn prediction in a clear and detailed manner. It shows the decision rules and feature weights impacting the model's forecast, emphasizing which customer characteristics impact churn risk positively or negatively. This visual aid enhances the ChurnNet model's transparency by offering a straightforward breakdown of specific predictions.

V. CONCLUSION

The proposed system for Customer Churn Prediction, based on Explainable AI, effectively showcases the fusion of deep learning and explainable artificial intelligence for predicting churn in the telecommunications sector. The ChurnNet model, incorporating 1D-CNN, Residual Blocks, and Attention Mechanisms, adeptly captures intricate customer behavior patterns to deliver precise churn forecasts. Mitigating class imbalance through SMOTEENN and ensuring robust model assessment via 10-Fold Cross Validation are integral components of this system.

The incorporation of SHAP and LIME bolsters model transparency by elucidating the variables influencing churn predictions, thereby fostering comprehension and trust in the system. Moreover, the user-friendly Streamlit-based interface facilitates interactive customer analysis and prediction visualization. Empirical findings underscore the system's robust performance, evidenced by elevated Accuracy, Precision, Recall, F1- Score, MCC, and AUC-ROC metrics.

In summary, this system offers a precise, dependable, and interpretable solution for customer churn prediction, empowering telecom providers to pinpoint high-risk customers and deploy effective retention strategies. Prospective refinements could encompass leveraging larger datasets, advanced deep learning frameworks, and realtime deployment to enhance predictive efficacy.

VI. FUTURE SCOPE

Future enhancements can focus on developing a real-time churn monitoring system that continuously analyzes customer activities such as usage changes, recharge behaviour, and service interactions to identify sudden increases in churn risk. The system can also incorporate causal analysis and Graph Neural Networks to better understand relationships between customers, services, and churn behaviour. Concept-drift detection can further help identify changes in customer behaviour over time and maintain reliable predictions. Further research can explore real-time alert generation and reinforcement learning based retention strategies, where high-risk customers are immediately identified and suitable retention actions are recommended. Integration with live telecom databases and streaming platforms can make the system more responsive, while privacy-preserving synthetic data generation and evaluation on larger real-world datasets can improve its practical applicability and scalability.

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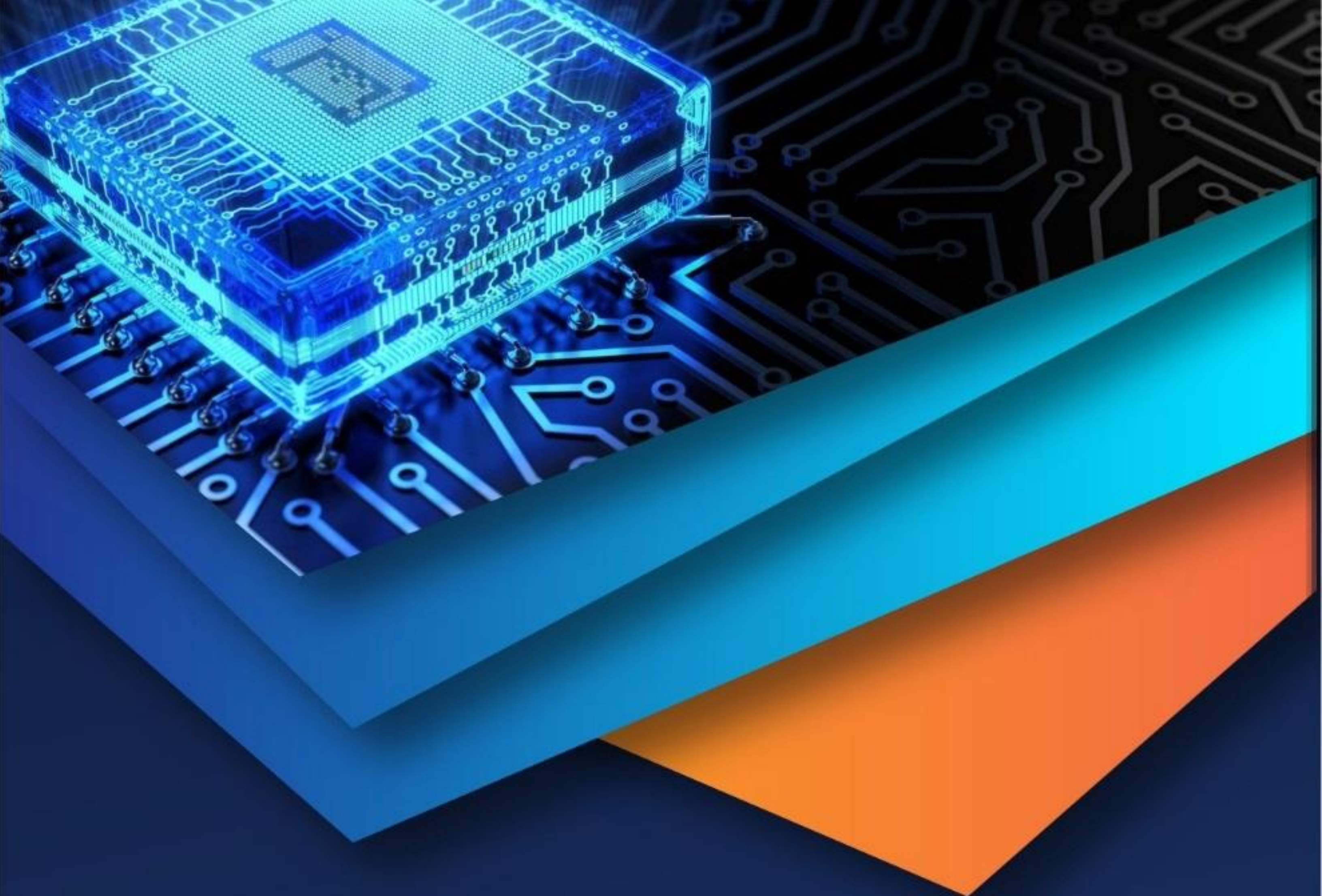

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