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Customer Subscription, Segmentation, and Retention Using Machine Learning Models

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Abstract: In the current era of data-driven marketing, effectively managing customer subscription, segmentation, and retention has become essential for sustaining business growth and enhancing user engagement. This study introduces a unified, explainable framework that concurrently addresses all three dimensions using a blend of machine learning and deep learning methodologies, tailored for practical deployment across diverse domains. For customer subscription prediction, we utilize the Bank Telemarketing dataset, comparing the performance of traditional ensemble learning models with a proposed deep learning model that incorporates data balancing techniques. The proposed model deserves a significant improvement, reaching with 93.00% prediction accuracy. In customer segmentation, we employ a customer purchase-related dataset and evaluate two clustering techniques KMeans and Gaussian Mixture Model (GMM) where GMM demonstrates the most effective separation of customer behavior clusters. Feature scaling is applied on the LRFMSQ (Length, Recency, Frequency, Monetary, Satisfaction, Quantity) attributes to ensure uniformity and improve clustering performance. For customer retention prediction, Telecom data was used, comparing the performance of the proposed method with the existing. The proposed method outperforms the existing. This proposed method consists of a Generative Adversarial Network (GAN) for class imbalance and ConvLSTM with attention mechanism, and Grey Wolf Optimization (GWO).
Keywords: Customer Subscription, Customer Retention, Customer Segmentation, Deep Learning, Machine Learning.

I. INTRODUCTION

Now a days, technology was transforming in a short span, which also changes the customer requirements from a business company. Business company needs to adapt to these changes to survive as a viable contender in the market. Positioning to surpass the competitor is not only sufficient, it also requires analysing the customer behaviour and attract new customers. Analysing customer itself includes, customer retention, where it means customer does not leave the company, and customer segmentation, where categorizing the customer into groups based on their behaviour. Finally, customer subscription denote, extracting new customer who is either completely new to domain or unbiased, or from the competitor company.

By the subscription of customer, it helps to company in improve market position, builds a loyal customer base, and more. In this work, customer subscription prediction was performed in bank sector, where bank performs campaign to promote their products. Challenges includes finding target customer, aversion to commitment, and others. Existing Machine Learning (ML) models relies on manual feature engineering and struggle for complex pattern.

Customer churn indicates that, whether the customer will withdraw the services offered by the company. Retaining the existing customer helps in attract the new customer which is expensive [1], increases the loyalty towards the company, personal referral, and others. For customer retention, research was performed on telecom data, where operating a company was capital intensive due to running of satellite for communication. Proposed method for customer retention includes Generative Adversarial Network (GAN) and Convolutional Long Short Term Memory (ConvLSTM) with general Attention mechanism and Grey Wolf Optimization (GWO).

Customer segmentation is an essential process for grouping customers based on shared behavioral characteristics, enabling more targeted and efficient marketing. Traditional clustering methods like k-medoid often lack the flexibility and accuracy needed for complex datasets. This study introduces a refined approach using Gaussian Mixture Models (GMM), supported by scaled behavioral features such as Length, Recency, Frequency, Monetary, Satisfaction, and Quantity. By applying proper feature preprocessing and advanced clustering techniques, the model delivers more precise customer groupings. These segmented insights allow businesses to improve decision-making, tailor customer experience, and enhance overall operational strategies.

II. RELATED WORKS

Recent research across telecom, banking, and finance sectors has increasingly leveraged machine learning and hybrid models to better understand and predict customer behavior, particularly focusing on churn prediction and retention enhancement. Research [1] introduced an artificial neural network-based decision model tailored to the telecom industry, which effectively categorized customers into three churn-risk levels using dissatisfaction and loyalty factors. This classification enabled service providers to apply differentiated retention strategies.

In the banking domain, [2] employed machine learning algorithms such as XGBoost and Random Forest within a custom-built RShiny visualization app, facilitating real-time churn prediction, segmentation analysis, and interactive dashboards—empowering banks to act swiftly on emerging customer attrition risks. Meanwhile, [3] conducted a comparative study of classical and ensemble models, finding that XGBoost and Random Forest consistently outperformed traditional classifiers in telecom churn forecasting. Their study also emphasized the predictive value of features like customer tenure, contract type, and monthly charges. Research [4] proposed a scalable hybrid system called HCPRs, combining Particle Swarm Optimization (PSO) for feature selection and SMOTE for balancing data classes, demonstrating remarkable accuracy when applied to a large-scale telecom dataset. Extending predictive modeling into financial time series, [5] developed a GAN-LSTM-Attention model for stock price prediction, which successfully captured temporal patterns and delivered robust forecasts for major stocks like Apple and Google. Together, these studies underscore the growing relevance of AI-powered, interpretable, and context-sensitive models in driving data-driven decision-making and strategic planning across industries.

Recent advances in machine learning (ML) and deep learning (DL) have significantly enhanced predictive modeling for customer behavior, particularly within the telecommunications and banking industries. Research [6] proposed a hybrid model that integrates the Arithmetic Optimization Algorithm (AOA) with a Stacked Bidirectional Long Short-Term Memory (SBLSTM) network to predict customer churn in telecom. Their model, which combines z-score normalization, deep sequential learning, and metaheuristic-based hyperparameter tuning, outperformed traditional classifiers on a benchmark dataset. In the banking sector, [7] addressed class imbalance in telemarketing prediction by using a Multilayer Perceptron (MLP) model with resampling, achieving a 94.27% accuracy and demonstrating the importance of data balancing in model training. Expanding this area, [8] developed an online ensemble learning model incorporating feature selection, SMOTE-based oversampling, and concept drift handling to adaptively predict customer subscription.

Their system achieved 98.6% accuracy on real-world Portuguese bank data. Additionally, [9] evaluated ensemble models such as Random Forest, XGBoost, and Extra Trees to predict customer subscription behavior in bank telemarketing campaigns. Extra Trees achieved the highest accuracy (91.1%), highlighting the effectiveness of ensemble methods. In another study, [10] applied a high-performance ensemble framework to measure the operational efficiency of banks. By using Data Envelopment Analysis (DEA) and predictive models, they demonstrated that ensemble learning can identify critical factors influencing banking performance. Collectively, these studies underscore the importance of advanced ML models, ensemble techniques, and data handling strategies in enhancing the accuracy and adaptability of customer behavior prediction systems across industries.

Recent advancements in customer segmentation and behavior prediction have increasingly leveraged machine learning, statistical modeling, and hybrid approaches to improve marketing precision and consumer insights. Research [11] compared a range of clustering techniques—such as K-Means++, DBSCAN, and GMM—for segmenting online consumers, finding that K-Means++ delivered the most accurate results in predicting Customer Lifetime Value (CLV). Addressing the challenge of high-dimensional data, [12] introduced the Fast Adaptive K-Means (FAKM) algorithm, which integrates feature selection with clustering using an adaptive loss function, avoiding eigenvalue decomposition for improved computational efficiency. Meanwhile, [13] proposed a hybrid framework combining the BTYD statistical model with machine learning classifiers to dynamically predict customer churn by estimating the probability of customer survival (P alive), resulting in high recall scores and better early intervention strategies. To further capture evolving customer behavior, [14] developed the LRFMS model (Length, Recency, Frequency, Monetary, Satisfaction) and applied multivariate time series clustering using distance measures like DTW and SBD, demonstrating higher segmentation accuracy in industrial e-commerce contexts. Finally, [15] combined cluster analysis with logistic regression to forecast online purchase behavior, showing that different behavioral segments respond to unique influencing factors such as bounce rate, product duration, and visitor type, thereby reinforcing the value of segment-specific marketing tactics. Together, these studies reflect a growing emphasis on data-driven, adaptive segmentation strategies that respond to the complexity and dynamism of consumer behavior in digital environments.

III.METHODS AND METHODOLOGY

A. Dataset Description

For subscription the study utilizes the Bank Marketing Dataset sourced from the UCI Machine Learning Repository. The dataset comprises 41,188 instances and 21 attributes, including client socio-demographic details, historical contact records, and campaign-specific information. The target variable is binary, indicating whether a client has subscribed to a term deposit ("yes" or "no"). All categorical values were label-encoded, and the target variable was transformed into a binary integer format, with “yes” represented as 1 and “no” as 0.

For retention, Telecom sector data which was made publicly accessible, and it contains 20 attributes and 2666 instances, out of those 2278 observations belong to class Not Churn and remaining 388 instances belong to Churn. Based on the domain knowledge, few attributes were eliminated and for remaining by using Principal Component Analysis (PCA). Further, dataset was partitioned in the ratio of 8:2 in the random manner for train and test purposes.

To perform segmentation, we use a Customer Shopping Dataset containing 10,000 records, each uniquely identified by a Customer ID. The dataset was collected from the automotive industry, specifically focusing on customer purchases of various vehicle spare parts. It captures essential behavioral and transactional details such as Recency, Frequency, Monetary Value, Purchase Satisfaction, and Visit Length. These attributes provide a comprehensive understanding of customer shopping patterns, helping businesses analyze engagement, spending habits, and satisfaction levels to support decision-making in marketing and personalization.

B. Data Preprocessing

To implement subscription to ensure consistent feature scaling and facilitate neural network convergence, all numerical features were standardized using Z-score normalization. Categorical attributes were encoded using label encoding to convert them into numerical representations compatible with the model input format. One of the primary challenges identified in the dataset was class imbalance, wherein the number of non-subscribing customers significantly outweighed those who subscribed. To mitigate this imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied. SMOTE generates synthetic instances of the minority class, thereby improving the model’s generalization capabilities and reducing prediction bias.

For retention data, a clear class imbalance was observed. To solve this, Generative Adversarial Network (GAN) was used. GAN consists of generator and discriminator, the aim of generator was to generate fake data, so that it fools the discriminator as it was real, and aim of discriminator was to classify, the generated fake data as real or fake. If the classification was done in the favor of generator, weights of discriminator gets updated, and vice-versa. Initially, discriminator was trained using real data and generator was trained using the pattern observed by the discriminator. This process will continue until the required number of fake samples were generated.

An effective segmentation started with organizing the customer data through standard preprocessing methods such as handling missing values, removing duplicates, applying Min-Max normalization, and treating outliers in key numeric fields. An effective segmentation started with organizing the customer data through standard preprocessing methods such as handling missing values, removing duplicates, applying Min-Max normalization, and treating outliers in key numeric fields. A behavioral model named LRFMS was then developed using five key features: Length, Recency, Frequency, Monetary, and Satisfaction, which together offer a complete view of customer behavior. These features provided a strong foundation for clustering, enabling the identification of meaningful patterns in customer segments.

C. Model Architecture

The classification problem was addressed using a Deep Neural Network (DNN) in the subscription built with the TensorFlow Keras Sequential API. The model architecture consists of five fully connected layers, structured as follows represented in Fig. 1.

- Input Layer: Accepts standardized feature vectors based on the number of features.
- Hidden Layers:
- First Hidden Layer: 256 neurons with LeakyReLU (α=0.1), followed by Batch Normalization and Dropout (rate = 0.4).
- Second Hidden Layer: 128 neurons with LeakyReLU (α=0.1), followed by Batch Normalization and Dropout (rate = 0.3).
- Third Hidden Layer: 64 neurons with LeakyReLU (α=0.1), followed by Batch Normalization and Dropout (rate = 0.2).
- Fourth Hidden Layer: 32 neurons with LeakyReLU (α=0.1), followed by Batch Normalization.
- Output Layer: A single neuron with sigmoid activation for binary classification.

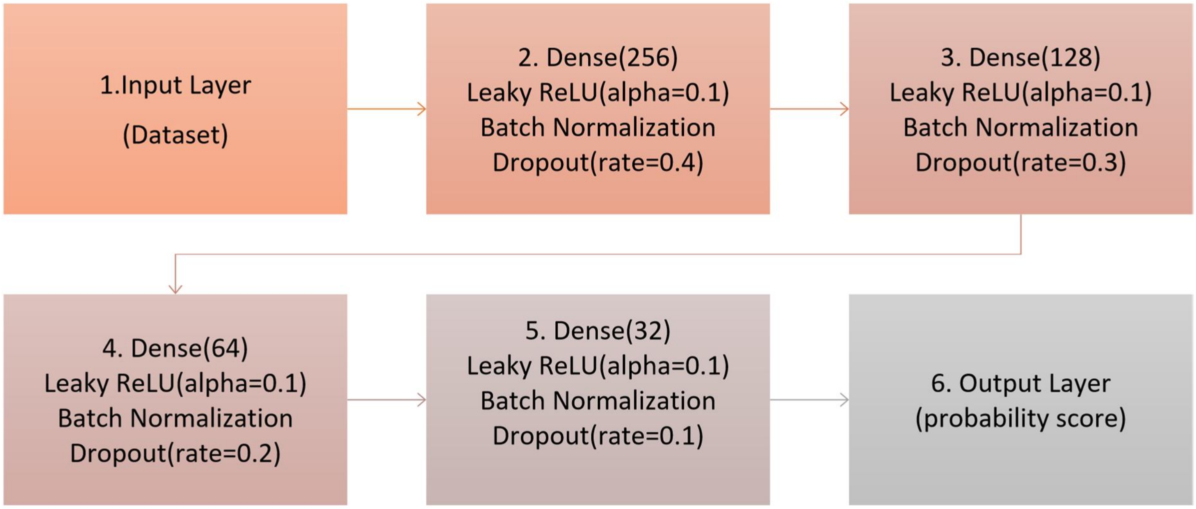

Fig 1: Detailed architecture of multi-layer perceptron for customer subscription

The architectural choices were made to effectively capture non-linear feature interactions and reduce overfitting. Leaky ReLU activation functions were employed to address the vanishing gradient problem, while Batch Normalization improved training stability. Dropout layers were integrated to introduce regularization by randomly deactivating neurons during training.

To solve the retention problem, model was developed using the Convolutional Long Short Term Memory (ConvLSTM) and few other layers. The architecture of ConvLSTM was represented in Fig. 2, where it consists, input gate, forget gate and output gate. Initially, forget gate, will discard the any unnecessary pattern observed, input gate will capture the new data pattern, and finally, output gate will provides the output pattern. The terms t and t-1 represents the time steps and c and h represents the cell state and hidden state, which hold the long term memory and short term memory, respectively. Finally, σ and tanh were the activation functions, and * and + represent the matrix multiplication and addition operations.

In the model, after the ConvLSTM layer, other layers were BatchNormalization, Dropout, Flatten, two pairs of Dense and Dropout with LeakyReLu activation function and a Dense with sigmoid activation function. In addition to this, model was developed with the inclusion of an Attention mechanism and Grey Wolf Optimization (GWO) technique.

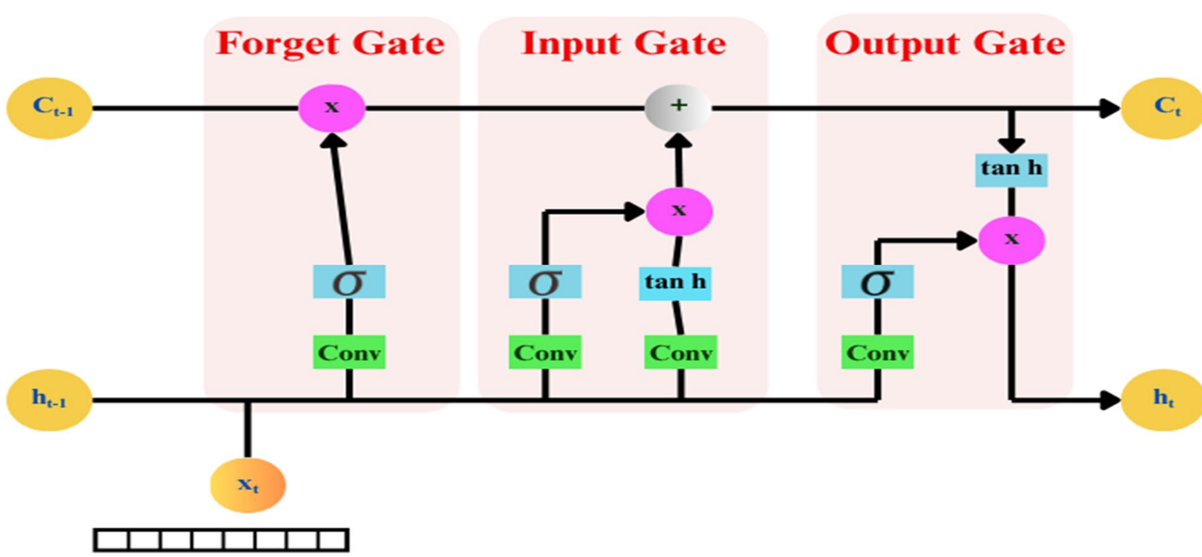

Fig. 2 Detailed architecture of ConvLSTM with all three gates and working of each gate at time t for customer retention

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In general, attention mechanism was used to particularly focus on specific part of the input which contributes more to the target output, in this work general attention mechanism was used. GWO is strategy developed using the hunting technique of Wolves. It consists, α which is the leader of the pack, β was the member who helps the leader and have capability to hunt instead of α, δ was the member who guides the pack and follow the α and β, and finally, ω was the remaining pack. In this optimization technique, α, β and δ were the first, second and third best solutions respectively.

To identify distinct customer segments based on shopping behavior, two clustering algorithms were applied to the LRFMS feature set:

- KMeans Clustering: This algorithm partitions the data into a predefined number of clusters by minimizing the variance within each group. It is efficient and works well when clusters are spherical and evenly distributed. In this context, KMeans helped in forming clear and compact customer groups based on behavioral similarity.
- Gaussian Mixture Model (GMM): Unlike KMeans, GMM is a probabilistic approach that assumes each cluster follows a Gaussian distribution. It is more flexible in modeling clusters with different shapes, sizes, and overlaps. GMM was particularly useful for capturing nuanced patterns in customer behavior that might not be well-separated in space.

The overall process followed for segmentation is shown in Fig. 3, which outlines the key steps: data collection and preprocessing, LRFMS feature engineering, application of clustering models (GMM and KMeans), evaluation using classification metrics, and model comparison based on both metrics.

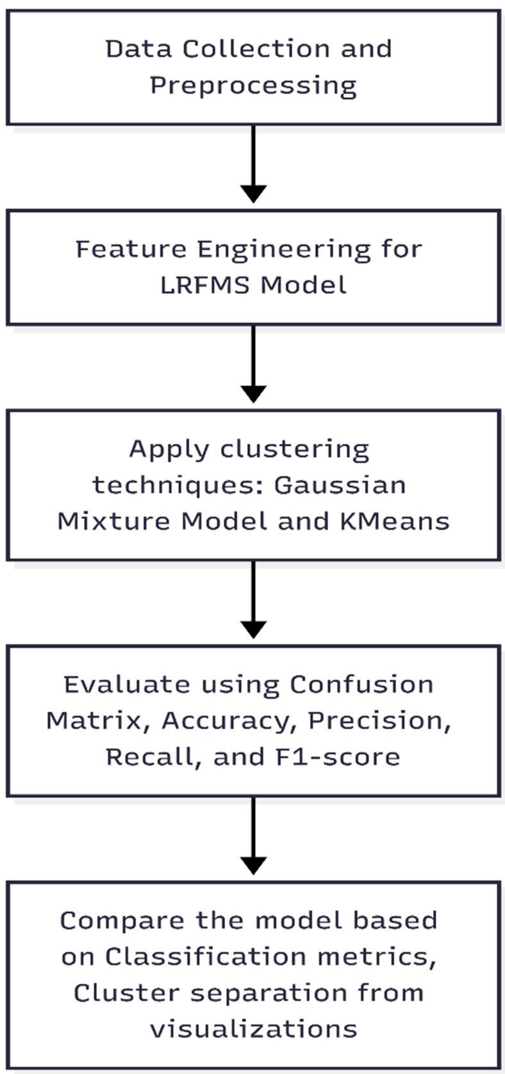

Fig. 3 Workflow diagram representing the stages of customer segmentation using the LRFMS model and clustering evaluation.

D. Training Strategy

In approach subscription after balancing the dataset, the data was split into training (80%) and testing (20%) subsets. The model was compiled using the Adam optimizer with a learning rate of 0.001 and trained using the binary cross-entropy loss function. Training was performed for up to 50 epochs with a batch size of 16. To enhance convergence and prevent overfitting, the training process included the following callback mechanisms:

1) ReduceLROnPlateau: Dynamically reduces the learning rate upon stagnation in validation loss.
2) EarlyStopping: Stops training if the validation loss does not improve over five consecutive epochs and restores the best weights.

These mechanisms helped optimize learning efficiency and improve model generalization.

Similarly, in the case of retention, the partitioned train data was used for train the model. For, model training, adam optimizer was used along with the loss function which was focal loss. Model training was performed in 20 epochs with the batch size of 128. To prevent overfitting, early stopping criteria was applied and it was not satisfied as the loss of model was not high from epoch to epoch.

To evaluate the quality of clustering, the dataset was split into 80% for training and 20% for testing. Cluster labels generated by KMeans and GMM were treated as pseudo-targets for training classification models on the training set. These models were validated on the test set to examine how well the clusters generalized to unseen data. This approach ensures that the segments formed are not only statistically valid but also consistent in classification performance.

IV. RESULTS

This section reports the experimental results derived from evaluating the proposed deep learning model for predicting customer subscription outcomes in a bank marketing context. The evaluation was conducted on the test subset obtained after class rebalancing through SMOTE, ensuring a fair assessment of the model's generalization capability. The chosen performance metrics include Accuracy, Precision, Recall, and F1 Score, which collectively offer a comprehensive view of the model's effectiveness in a binary classification setting.

The model under investigation is a Multilayer Perceptron (MLP), trained with carefully designed architecture and optimized hyperparameters. Table I presents the quantitative performance of the model.

Table I
Performance of Multi-Layer Perceptron for Customer Subscription

S.No.	Task	Model	Accuracy	Precision	Recall	F1 Score
1	Customer Subscription	MLP	0.9417	0.8958	0.9790	0.9356
2	Customer Retention	ConvLSTM with Attention and GWO	0.9028	0.9308	0.9145	0.9226
3	Customer Segmentation	KMeans-based Classification	0.954	0.953	0.954	0.954
4		GMM-based Classification	0.982	0.982	0.980	0.981

As illustrated in Table I, the Multilayer Perceptron demonstrated robust classification performance, achieving an accuracy of 94.17%, signifying its strong overall capability in correctly identifying both subscribing and non-subscribing clients. The model attained a precision of 89.58%, indicating that most of the clients predicted as potential subscribers were indeed actual subscribers. Notably, the recall value of 97.90% highlights the model’s exceptional sensitivity in capturing nearly all true positive instances, which is vital in the banking sector where missing a genuine subscriber can impact campaign effectiveness. The resulting F1 Score of 93.56% confirms the balanced nature of the classifier, reflecting a favorable trade-off between precision and recall.

Overall, the results affirm that the proposed deep learning framework effectively learns complex patterns in the customer data and generalizes well to unseen instances. This performance makes it a viable candidate for real-world deployment in targeted marketing applications, where accurate customer profiling and prediction are essential.

Customer retention results were presented in Table I, our method delivered strong performance across all key evaluation metrics. It achieved a precision of 93.08%, meaning most of the positive predictions it made were correct. With a recall of 91.45%, the model was also able to successfully identify the majority of actual positive cases. The balance between these two metrics is reflected in the F1-Score of 92.26%, showing the model performs reliably across different types of data. Overall, it reached an accuracy of 90.28%, indicating that the predictions were correct in most cases. These results suggest that the model is both accurate and consistent, making it a reliable choice for practical applications.

For customer segmentation, the clustering results were evaluated to determine how well each model grouped customers based on their behavioral patterns. Two algorithms, KMeans and GMM, were used to generate cluster labels, which were then assessed using classification metrics. The Table I below summarizes their performance.

The GMM-based model achieved higher performance across all metrics, showing its strength in modeling complex and overlapping customer behaviors. KMeans also performed well and remains a practical option when simplicity and speed are preferred.

Overall, these results highlight the effectiveness of GMM in handling overlapping or non-spherical clusters within customer shopping behavior data, while reaffirming the baseline strength of KMeans in practical clustering applications.

V. CONCLUSION AND FUTURE DIRECTION

This study on customer subscription approach proposed a deep learning-based Multilayer Perceptron (MLP) model to predict customer subscription behavior in bank marketing campaigns, achieving a high accuracy of 94.17% along with strong precision, recall, and F1-score values. The model effectively identified key predictors such as call duration, previous campaign outcomes, and past contact status, offering meaningful insights to improve marketing strategies. For future work, integrating explainable AI tools like SHapely Additive exPlanaitons (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) can enhance transparency and trust, especially among business users. Additionally, incorporating advanced models such as BERT and LSTM could further improve prediction accuracy by capturing context from customer messages or sequential behavior data. These enhancements would be especially useful in real-time decision-support environments like CRM systems, where the model could adapt dynamically to evolving customer patterns. Expanding the model to handle multi-class outputs and time-series trends can also provide more granular and forward-looking insights. Overall, the current work establishes a strong foundation for intelligent marketing systems and opens promising directions for future development in predictive analytics.

For telecom retention prediction, ConvLSTM method with GAN, Attention mechanism, and GWO yields 90%. By the improvement of performance of GAN, better results might get achieved which was the limitation of this work. The customer segmentation strategy implemented in this analysis successfully categorized consumers based on behavioral attributes using the LRFMS model. Clustering techniques such as GMM and KMeans were used to uncover actionable insights, allowing businesses to identify high-value, loyal, and at-risk customer groups. Although the dataset was sourced from the automotive spare parts sector, this methodology is highly adaptable and can be applied to customer data across various industries, including retail, e-commerce, and services. These insights can be leveraged to design targeted marketing strategies, improve customer retention, and drive overall business growth. Looking ahead, integrating time-based clustering approaches like TimeSeriesKMeans may enable a better understanding of changing customer behavior and support timely business decisions.

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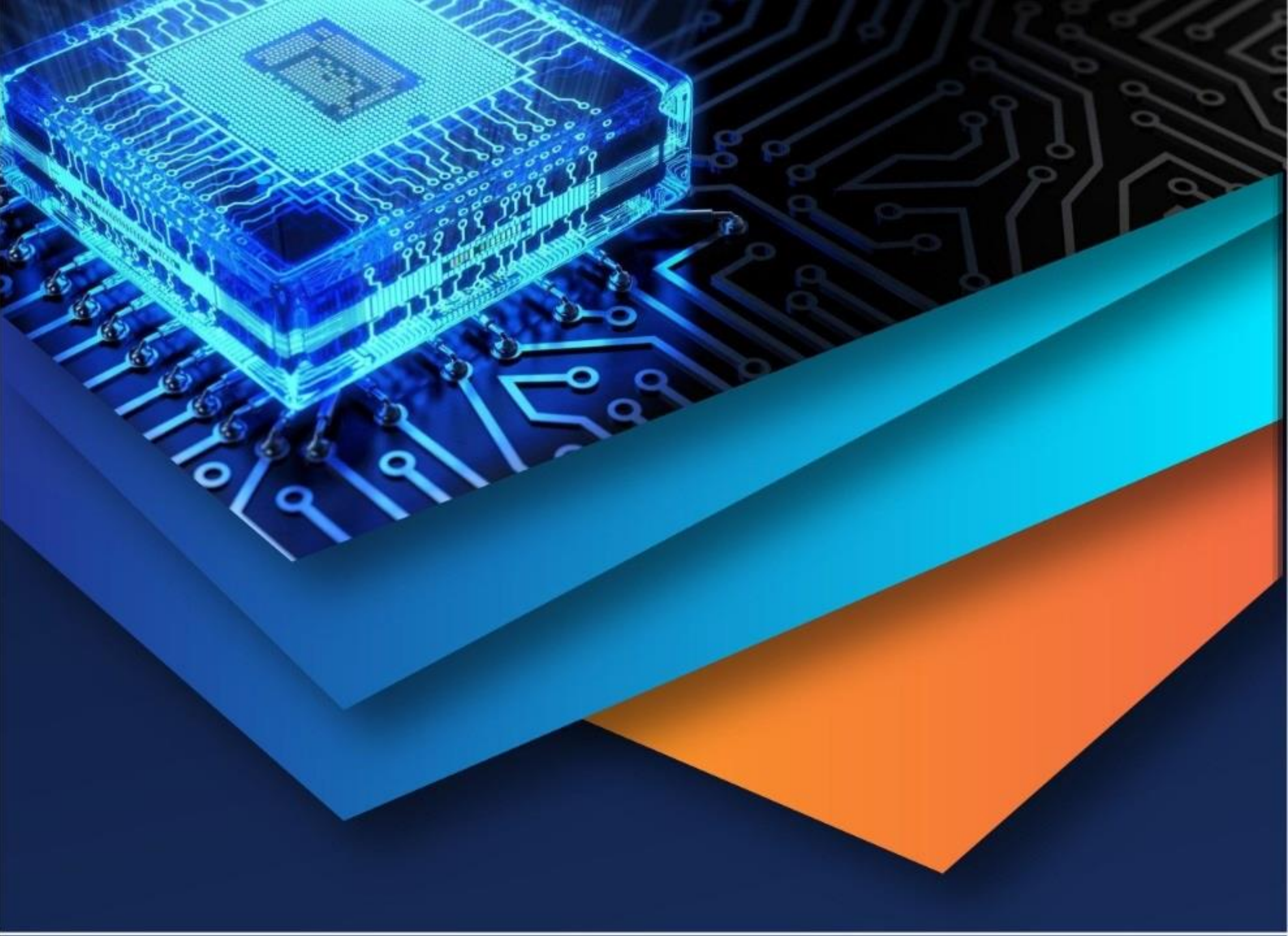

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