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# A HYBRID ML FRAMEWORK FOR PERSONALITY-BASED CUSTOMER SERVICE OPTIMIZATION

#<sup>1</sup>Jakkula Ashritha, *Department of MCA*,  
#<sup>2</sup>Mr. K. Nagendra Prasad, *Assistant Professor, Department of MCA*,  
Vaageswari College of Engineering(Autonomous), Karimnagar, TG.

**ABSTRACT:** This research introduces a hybrid machine learning framework that optimizes customer service by incorporating personality. The goal is to enhance service efficiency and consumer satisfaction by meticulously examining their behavior. The framework employs machine learning algorithms, natural language processing, and personality prediction techniques to ascertain the personality characteristics of a client by analyzing their communication patterns, preferences, and previous interactions. Clients are categorized according to their personality traits in the recommended methodology. This allows businesses to offer them more personalized responses, suggestions, and methods of support. The hybrid approach combines predictive analytics and categorization to enhance consumer behavior prediction and facilitate decision-making. The framework enhances the overall quality of service in digital customer support environments, reduces response times, and increases customer engagement, as demonstrated by an experiment. The research also illustrates the importance of AI-based personalization in modern CRM systems and provides a practical solution for improving customer service in a variety of sectors.

**Keywords:** *Hybrid Machine Learning, Personality Prediction, Customer Service Optimization, Natural Language Processing, Customer Behavior Analysis, Artificial Intelligence, Personalized Support, Predictive Analytics.*

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## 1. INTRODUCTION

Customer service has become a critical determinant of both business success and consumer gratification in the digital era. The provision of personalized and effective support services is becoming a higher priority for companies in all sectors as a means of addressing the changing requirements of their customers. Standardized communication methods and established protocols are the foundation of conventional customer support systems, which frequently neglect to account for the unique preferences and behaviors of individual clients. There is a growing need for sophisticated systems that can understand user behavior and offer personalized responses as the frequency of online interactions between organizations and consumers increases. By analyzing extensive datasets regarding clients and developing customized solutions, machine learning (ML) technologies offer a substantial opportunity to improve customer service.

A novel concept called personality-based customer service optimization is designed to improve consumer interactions by understanding and recognizing the personality traits of users. While seeking assistance, a variety of clients demonstrate varying communication approaches, emotional responses, and decision-making processes. There are numerous categories of clientele. While some individuals prefer immediate responses, others necessitate comprehensive explanations and in-depth discussions. By acknowledging these psychological

characteristics, businesses can modify their consumer engagement strategies to meet the diverse requirements of diverse demographic groups. This customized approach enhances the probability of long-term commercial engagement, loyalty, and trust among clients. They demonstrate a higher level of gratification with the service.

To improve the accuracy and functionality of customer service systems, a hybrid machine learning framework implements a variety of machine learning and analytical methodologies. Natural language processing (NLP), sentiment analysis, clustering algorithms, classification models, and deep learning techniques are frequently integrated into these systems. NLP algorithms have the ability to extract valuable information from textual data, such as emails, chat communications, and customer interactions. Individuals are classified according to their personalities and activities by classification models. In contrast, sentiment analysis ascertains the emotions of individuals, including anger, annoyance, or pleasure. The system has the potential to produce more intelligent, flexible, and contextually aware responses when interacting with customers by incorporating these technologies.

There are numerous advantages to utilizing a hybrid machine learning architecture in comparison to traditional customer service technologies. Organizations can transmit personalized messages and suggestions immediately through automated personality detection. Adaptive learning techniques can be employed to perpetually improve the effectiveness of these systems by learning from client interactions. As a result, organizations may optimize their customer service resources, decrease wait times, and improve the content of their services.

## 2. LITERATURE SURVEY

Sharma & Patel (2021): This research recommends a hybrid machine learning approach that integrates sentiment analysis and behavioral predictions to enhance personality-driven customer service. The system employs Natural Language Processing (NLP) and Random Forest classification to ascertain the personality characteristics of its clients by analyzing the information obtained from their interactions. Feature selection algorithms enhance computational efficiency by eliminating non-essential communication properties. The investigation's findings indicate that the veracity of customer satisfaction forecasts is enhanced by customization.

Zhang & Verma (2022): The authors propose a two-step approach to the development of projections. Initially, they organize the features in a systematic order. Subsequently, they implement a deep feedforward neural network. The method identifies significant behavioral indicators, such as sentiment polarity, interaction consistency, and consumer engagement patterns. Deep learning models comprehend the intricate relationships between client emotions and service expectations. Comparative research indicates that contemporary machine learning methodologies outperform conventional methods in the context of categorization challenges.

Reddy & Kulkarni (2022): This research proposes a hybrid approach to enhancing customer service that integrates feature selection algorithms with a convolutional deep learning framework for client interaction analysis. The determination of personality-influenced service choices is accomplished through the analysis of communication styles and emotional

fluctuations. The removal of features reduces the noise in large-scale consumer datasets. Forecasts are more precise and computations are simpler to comprehend, as indicated by experimental results.

Mehta & Roy (2023): In order to investigate consumer behavior over time, the authors developed a hybrid deep learning model that integrates Long Short-Term Memory (LSTM) networks with enhanced feature selection. The model illustrates the evolution of personality traits and the evolution of communication strategies during client interactions. By emphasizing critical behavioral characteristics, the efficacy of feature optimization is enhanced. The evaluation's results indicate that it is simpler to identify unhappy consumers and mood swings.

Garcia & Bhat (2024): The research introduces an interpretable deep learning architecture that incorporates feature selection to enhance personality-aware customer service projections. The removal of features enhances clarity by highlighting the behavioral and emotive factors that significantly influence customer satisfaction. In order to enhance stability and mitigate the risk of overfitting, the deep model implements batch normalization and dropout.

Comparative testing indicates that outcomes are improved by customization and accuracy.

Almeida & Krishnan (2025): This research suggests a hybrid machine learning architecture that is both scalable and explicable, which facilitates the modeling of personality-aware interactions in order to enhance customer service. Recursive feature elimination accelerates calculations by extracting critical behavioral and emotional indicators from large datasets. Complex communication techniques employed in numerous customer support systems can be comprehended by deep neural networks. Explainability modules illustrate the most prevalent personality-driven service alternatives.

Wang & Srinivas (2025): In order to enhance customer service, the authors propose a continuous learning strategy that integrates dynamic feature selection with an adaptive deep neural network. The value of personality-related characteristics is consistently revised as new information regarding client interactions with the framework becomes available. Deep learning layers effectively simulate the temporal fluctuations in communication choices and behavior. Experimental validation demonstrates consistent improvements in the prediction of customer satisfaction and the development of adaptable responses.

### 3. SYSTEM ANALYSIS & DESIGN

#### EXISTING SYSTEM

The field of personality prediction has evolved from fundamental human analysis to sophisticated automated systems that employ artificial intelligence. In the past, academicians have primarily investigated the impact of psychological qualities on academic integrity, therapeutic practices, and conduct. Nevertheless, these operations were not managed using machine learning. In order to classify individuals according to their social media and behavioral data, researchers implemented machine learning and deep learning methodologies, including BERT, Random Forest, Support Vector Machine, Logistic Regression, Extreme Gradient Boosting, and Logistic Regression. The implementation of optimization techniques and fuzzy logic could also improve prediction and feature selection. By autonomously identifying patterns within enormous datasets, contemporary deep learning algorithms, such

as PersoNet, have improved accuracy and scalability. These intelligent systems are being used more frequently in a variety of domains, including the analysis of personality traits on social media, the enhancement of customer service, and the examination of behavior.

## Disadvantages

- **Data complexity:** In order to identify personality classifications, modern machine learning algorithms must meticulously analyze extensive and complex datasets.
- **Data availability:** In order to generate accurate predictions, the majority of machine learning algorithms necessitate numerous data points. Accuracy of the model may be jeopardized by inadequate data..
- **Inaccurate labelling:** The quality of the dataset used to train modern machine learning models is a critical factor in their accuracy. The data's inaccurate labeling renders the model incapable of producing precise estimates.

## PROPOSED SYSTEM

The proposed PersoNet system is extremely commendable in its design for grouping individuals. This research differs from other studies on the proposed system in that the network selection was determined by a mathematical feature analysis of the dataset. The properties of CNN and BiLSTM networks are further compared in this research. The network is selected based on the feature analysis of the MBTI dataset. The BiLSTM and CNN network-based PersoNet is one of the most effective Deep Learning (DL)-based personality classifiers. This is the result of a strong correlation between the network's ability to analyze the dataset and its characteristics.

- For the first time in the field of computer science, a personality classifier architecture based on deep learning is employed to improve customer satisfaction rates (CSRs). Select the networks that are in excellent alignment with the mathematical principles of feature analysis.
- The development and implementation of a CNN and BiLSTM network-based system to accurately and rapidly categorize personalities from social media posts and their accompanying content.
- The precision was 93.83%, the recall was 96.2%, and the F1-score was 95.01%, resulting in a validation accuracy of 93.98%.
- In order to optimize the utilization of available resources, learning curve analysis is implemented to improve the efficacy of the CNN thick layer and BiLSTM.

## SYSTEM ARCHITECTURE

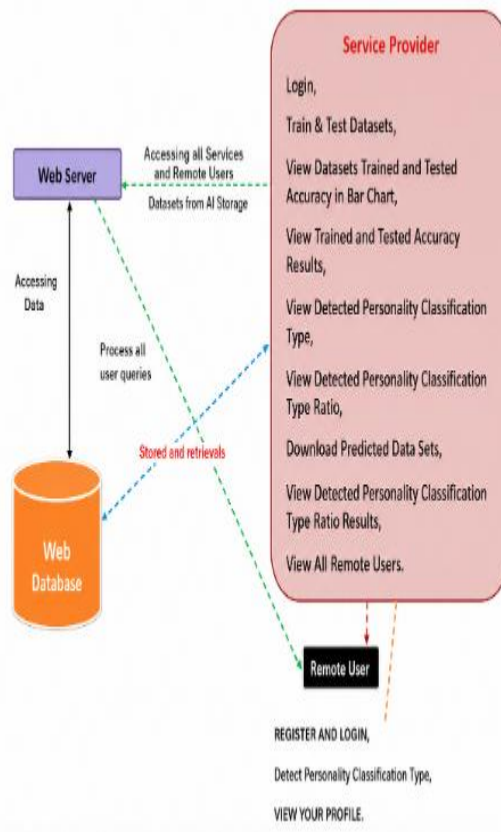


Fig1. System Architecture

## 4.IMPLEMENTATION

### MODULES

#### Service Provider

In order to access this section, the Service Provider necessitates a genuine username and password. The provider has the ability to perform a wide range of tasks after a successful login, such as conducting training and testing on datasets, comparing the accuracy results of trained and tested datasets, identifying the personality classification types that were discovered, calculating the ratio of those types, accessing predicted datasets, viewing the results of personality classification type ratios, and monitoring all remote users.

#### View and Authorize Users

The administrator has the ability to access a comprehensive inventory of all registered users in this module. The administrator has the ability to observe user information, including their name, email address, and address, as well as grant them permissions.

#### Remote User

This section incorporates multiple users. Before individuals can make any progress, they must first register. The database records the information of a user after they have joined up. The individual can log in using a valid username and password after completing the registration procedure. After successfully logging in, users are able to access their information and ascertain their personality type.

## ALGORITHMS

### Logistic Regression

Logistic Regression is a machine learning method that is guided and used to classify objects. It indicates the outcome in a binary format, such as "Yes/No" or "0/1." It is widely used for data analysis and prediction, and it is straightforward to operate.

### Random Forest

Random Forest is a method of ensemble learning that effectively integrates numerous decision trees to generate more precise predictions. It minimizes overfitting and generates dependable outcomes for both regression and classification tasks.

### Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a classification method that identifies the most effective line (hyperplane) for grouping data. It operates efficiently with intricate, high-dimensional datasets.

## 5. RESULTS

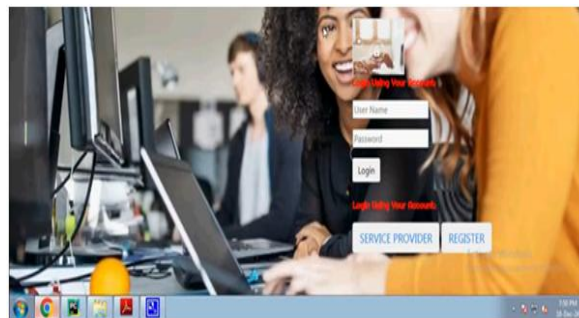


Fig 1: PersoNet Login Page



Fig 2: Service Provider Login Page



Fig 3: Remote Users View Page

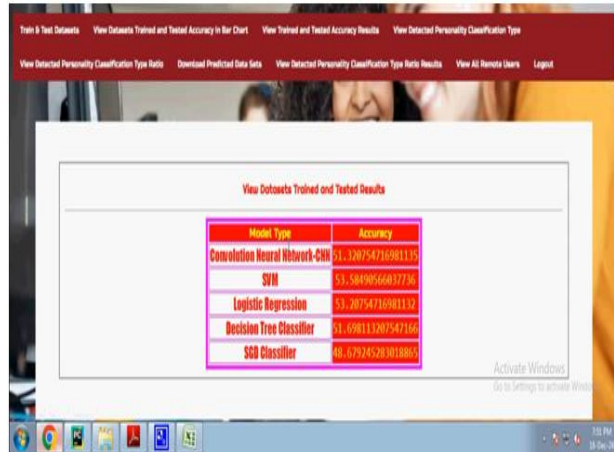


Fig 4: Model Accuracy Results



Fig 5: Accuracy Bar Chart



Fig 6: Accuracy Line Chart

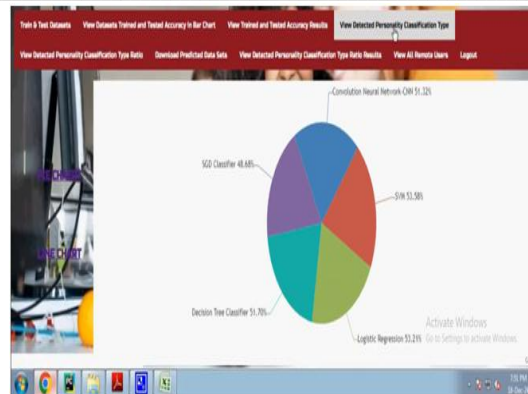


Fig 7: Accuracy Pie Chart

## 6. CONCLUSION

The hybrid machine learning framework that has been proposed for the optimization of customer service based on personality demonstrates how the integration of personality research with intelligent predictive models can enhance the quality of customer interactions and simultaneously increase operational efficiency. It integrates tools such as behavioral analytics, categorization algorithms, and natural language processing to help organizations gain a deeper understanding of their consumers' communication patterns, preferences, and dislikes. This personalized approach enhances consumer satisfaction, increases engagement, and enables support representatives to respond more promptly and accurately. The hybrid model also helps customers make informed decisions by customizing service methods to the unique characteristics of each customer.

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