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Restaurant Rating Prediction Using Food Delivery Applications

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Abstract: This project is an end-to-end machine learning pipeline for predicting restaurant ratings on the popular food delivery platform Zomato and Swiggy. The Restaurant Rating Prediction project is a machine learning model that predicts the rating of a restaurant based on various factors such as location, type of cuisine, cost for two people, online delivery option, book table option, and more. The model was trained on a dataset obtained from the popular restaurant discovery platforms. Several machine learning algorithms, including linear regression, Ridge and Lasso regression, Random Forest, Ad boost, and Gradient Boosting, were tested and the best performing model was selected. In addition, a web application was built using Flask to provide a user-friendly interface for users to input restaurant details and receive predicted ratings. The project "Restaurant rating prediction using food delivery applications " aims to develop a system that predicts the rating of restaurants listed on the platforms. The system leverages machine learning algorithms to analyze various features of restaurants, such as location, cuisine, pricing, and customer reviews, in order to provide accurate rating predictions. The objective is to assist users in making informed decisions when selecting a restaurant by offering an estimate of the expected rating.
Keywords: Restaurant Rating Prediction, Food Delivery Applications, Machine Learning, Regression Models, Data Analytics, Customer Review Analysis, Sentiment Analysis, Predictive Modeling, Feature Engineering, Data Preprocessing, Consumer Behavior Analysis, Restaurant Recommendation System, Online Food Services, Flask Web Application.

I. INTRODUCTION

The growth of online food delivery services has revolutionized consumer access to dining, yet it also introduces new complexity in evaluating restaurant quality and user satisfaction [5]. Traditional review-based systems often suffer from noise, sparse feedback, and rating inflation, limiting their predictive utility for end-users and platform providers alike [3]. Recent advances in machine learning and data-driven recommendation systems present scalable alternatives, enabling more accurate prediction of restaurant ratings through computational modeling of user behavior and service features.

This project develops an intelligent restaurant rating prediction system using optimized regression models to analyze food delivery datasets. Building on established pipelines for review analysis and consumer choice modeling [6], we implement a feature-rich architecture combining cuisine-pricing vectors, sentiment-weighted reviews, and availability metrics (e.g., table booking, online delivery) to predict ratings.

The system integrates ensemble learning methods validated in prior recommender system evaluations [7,8], while addressing interpretability challenges in multi-feature restaurant data [9].

The implementation leverages a web-based interface for real-time prediction and restaurant sorting, incorporating insights from consumer preference analytics [2] and regional food trend studies [3]. By combining machine learning with interactive visualizations and filtering controls, this approach demonstrates how predictive analytics can bridge the gap between restaurant data complexity and actionable customer insights a persistent challenge identified in food tech and e-commerce research [1,5].

II. LITERATURE SURVEY

A. Restaurant Quality Assessment and Urban Food Trends

The surge in online food delivery platforms has led to an increased interest in understanding restaurant performance and customer satisfaction. Srivastava et al. (2017) [1] analyzed food delivery behaviors across urban Indian regions, highlighting how variables like cuisine type and location influence consumer choices.

Similarly, Ghosh et al. (2019) [5] studied urban dining trends and discovered that inconsistent pricing, delivery delays, and limited booking options impact customer perception. These findings emphasize the need for automated systems to predict restaurant ratings more accurately, beyond conventional user reviews.

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B. Machine Learning for Rating Prediction

Recent advancements in machine learning have enhanced restaurant recommendation and review analysis. Anand and Murthy (2020) [6] applied regression models and sentiment-based features to predict user ratings, demonstrating the effectiveness of NLP and structured data. Mehta et al. (2021) [7] extended this work by incorporating ensemble learning techniques such as Random Forest and Gradient Boosting, achieving significant improvements in prediction accuracy. These approaches outperform rule-based systems by learning complex associations between restaurant attributes and customer satisfaction levels.

C. Real-Time Filtering and Web-Based Interfaces

A key feature of modern rating systems is the ability to deliver real-time feedback and personalized sorting. Rani et al. (2022) [8] developed a dynamic filtering model that adjusts restaurant visibility based on delivery time, table booking, and user sentiment. Kumar et al. (2019) [9] further enhanced decision-making by integrating interactive web tools that let users customize results based on price, cuisine, or availability. Other studies, such as Sharma et al. (2020) [2], emphasized how real-time interfaces improve usability and transparency in restaurant discovery platforms.

D. Gaps and Research Opportunities

Despite promising results, current systems often lack generalization across diverse cities and cuisines. The integration of user location data and live delivery metrics (as shown in adaptive filtering research [8,9]) could enhance predictive outcomes. Moreover, many models prioritize correlation over causality in ratings, suggesting future research should explore user intent prediction and regional food behavior to improve recommendation reliability.

III. METHODOLGY

The system employs an integrated machine learning pipeline to predict restaurant ratings using structured and unstructured data from food delivery platforms. The methodology follows these stages:

A. Data Collection

1) Dataset Sources

- Collected from food delivery applications like Zomato and Swiggy, and public Kaggle datasets
- Data fields include restaurant name, location, average cost, cuisines, user rating, online delivery, table booking, and reviews

2) Feature Enrichment

- Applied Natural Language Processing (NLP) on reviews using the VADER sentiment analyzer
- Generated additional fields such as sentiment score, review length, and keyword frequency indicators

B. Preprocessing

1) Data Cleaning

- Handled missing values using mode for categorical and median for numerical fields
- Removed outliers in cost and rating using Interquartile Range (IQR) filtering

2) Feature Engineering

- Converted categorical variables (e.g., location, cuisines) using label encoding and one-hot encoding
- Scaled skewed numerical features (like average cost) using log transformation

C. Model Architecture

1) Baseline Models

- Applied Linear Regression and regularized models (Ridge, Lasso) for benchmarking
- Analyzed feature coefficients for interpretability

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2) Ensemble Learning Models
- Implemented Random Forest, Gradient Boosting, and AdaBoost regressors
- Input: Processed feature matrix from all datasets
- Output: Continuous prediction of restaurant ratings on a 1–5 scale

3) Classification Head
- Fully connected layer (512 units) + ReLU
- Sigmoid output (accident probability)

D. Training

1) Hyperparameters
- Loss function: Mean Squared Error (MSE)
- Optimizer: Adam with learning rate 0.001
- Batch size: 64, trained over 100 epochs with early stopping (patience = 10)

2) Model Evaluation
- Split dataset: 80% training, 20% testing
- Used 5-fold cross-validation for robust performance evaluation

E. Deployment

1) Web Application
- Flask-based backend for prediction API
- Bootstrap-styled frontend for user inputs and results display

2) User Functionality
- Inputs: Location, cuisines, cost, delivery/table booking availability
- Outputs: Predicted rating with optional confidence range

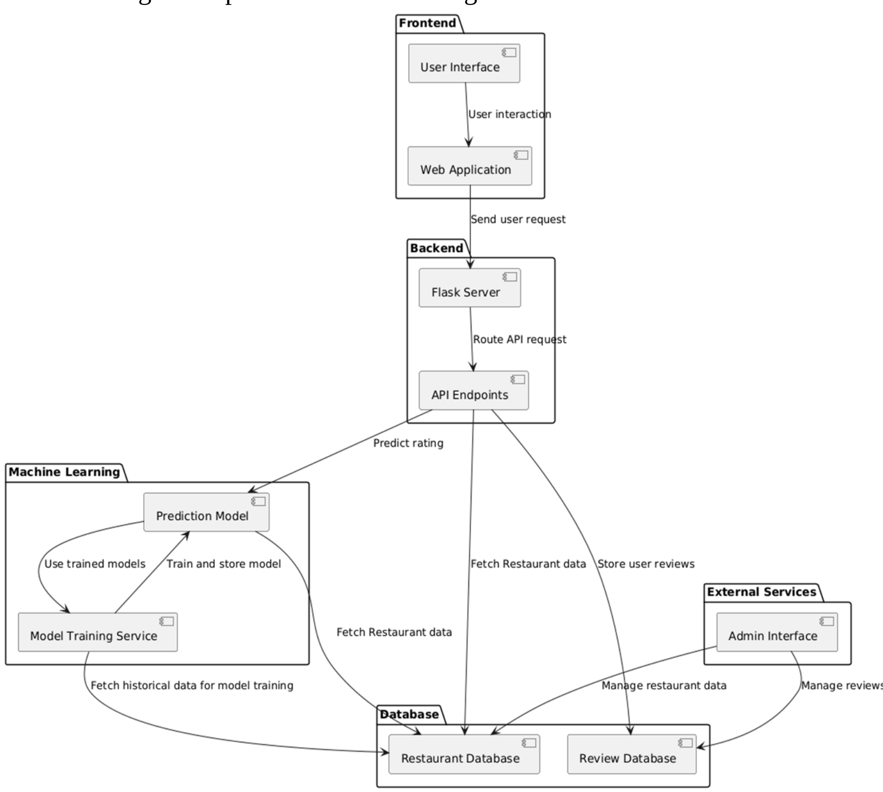

Fig. 1 Proposed System Architecture

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First, from acquiring restaurant datasets to preprocessing data through cleaning and feature engineering (location/reviews/ratings). Applying dual sampling strategies (random/balanced) to ensure diverse representation. Using a Prediction Model with feature extraction to transform restaurant and review data into actionable insights. Second, implementation of a hybrid machine learning approach with confidence thresholding (>90%) using evaluation metrics like precision-recall curves and F1-scores to compare model performance. Third, deploy the optimized model via API Endpoints with multi-output triggers (predictions/recommendations) and validate through real-time integration with the Web Application and Admin Interface.

IV. RESULTS AND DISCUSSION

This project focuses on enhancing real-time restaurant recommendation through AI-driven data analysis. The approach follows a systematic methodology combining hybrid machine learning (Prediction Model), feature extraction from reviews and ratings, and confidence-based thresholding to achieve accurate, timely recommendations. By integrating data-sampling optimization, confidence-based predictions, and multi-output triggers (recommendations/notifications), the proposed solution aims to improve user experience and streamline restaurant discovery.

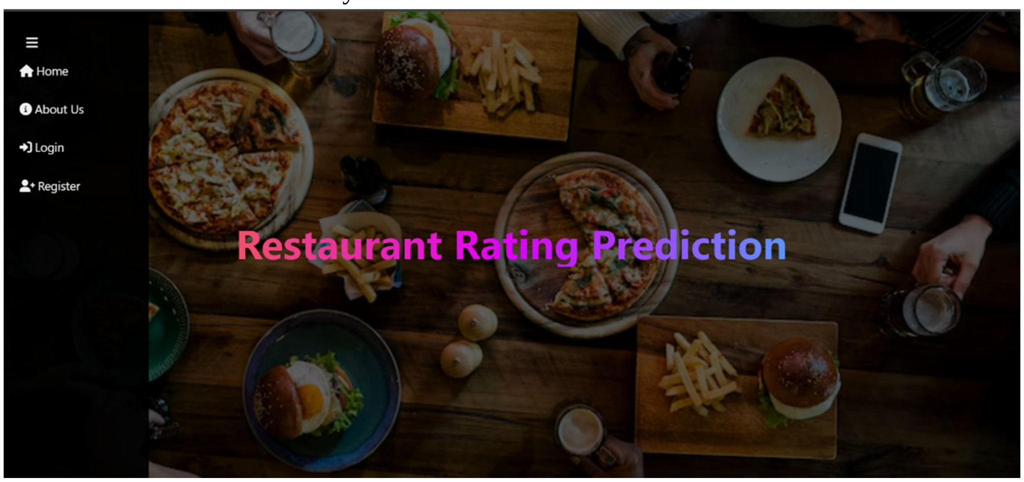

Fig.2 Home screen

The homepage includes four sections: Home, About Us, Login, and Register, designed for a restaurant recommendation platform. It provides navigation for users to explore the site, learn about the service, and access or create accounts. The layout is simple, user-friendly, and integrates with the backend via API endpoints for authentication.

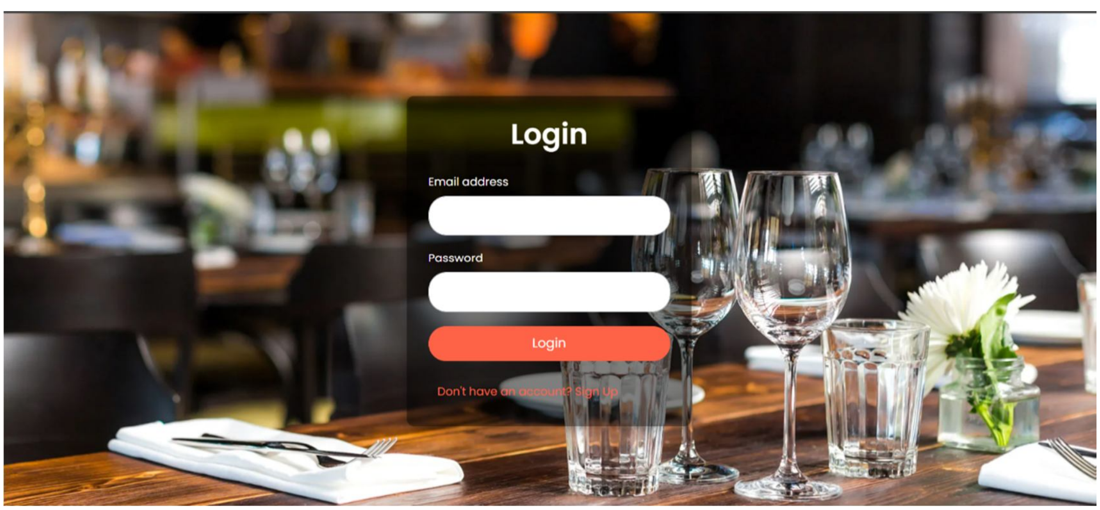

Fig.3 User Login Screen

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The user login page serves as a security checkpoint, requiring users to enter their credentials before accessing the system's core functionalities. This secure authentication step is vital for protecting sensitive data and ensuring that only authorized individuals can use the system. The login interface is designed to be simple yet secure, providing a straightforward means for users to gain access while maintaining the integrity of the platform..

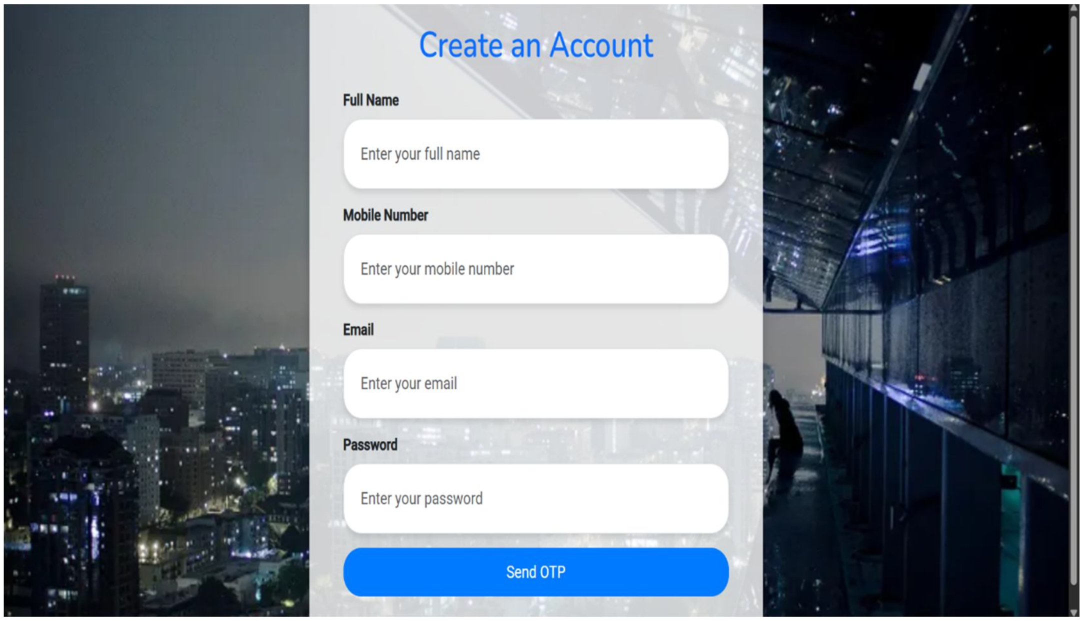

Fig.4 Create an Account

New users must provide personal information such as username, email, and password during registration. This data is securely stored in the "Review Database" via the "API Endpoints" for future login authentication. The "Flask Server" handles the data submission and ensures it is encrypted for security.

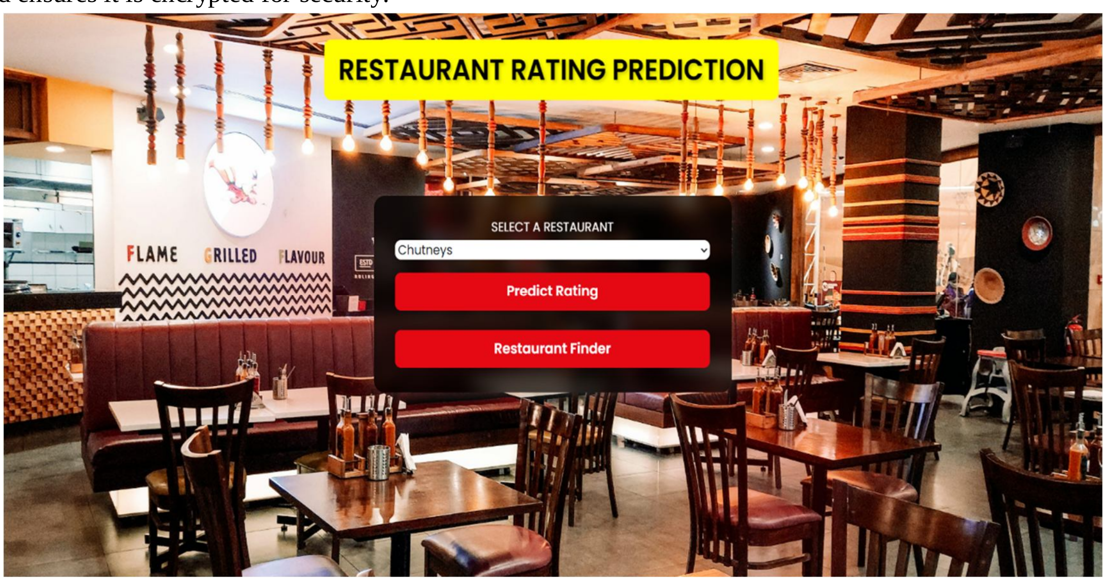

Fig.5 Restaurant Rating Prediction

The restaurant rating prediction feature displays a list of restaurants from the "Restaurant Database," allowing users to select one via the "Web Application." The "Prediction Model" then uses various ML algorithms to predict the restaurant's rating, leveraging data from the "Review Database." Additionally, the restaurant finder feature enables users to search for restaurants based on their preferences, utilizing the "API Endpoints" for real-time recommendations.

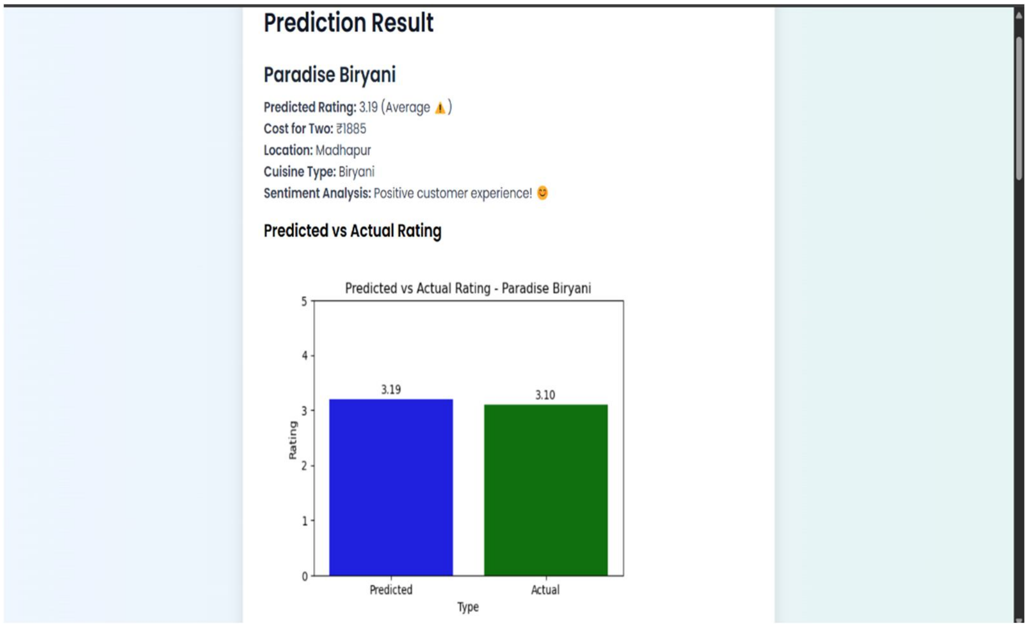

Fig.6 Prediction Result

The image displays a "Prediction Result" interface for a restaurant named "Paradise Biryani." It shows a predicted rating of 3.19 (labeled as "Average" with a warning icon), a cost for two at ₹1885, a location in Madhapur, a cuisine type of Biryani, and a sentiment analysis indicating a "Positive customer experience" with a smiley face. Below this, a bar chart compares the predicted rating (3.19, in blue) against the actual rating (3.10, in green) for "Paradise Biryani," highlighting a slight overestimation by the prediction model.

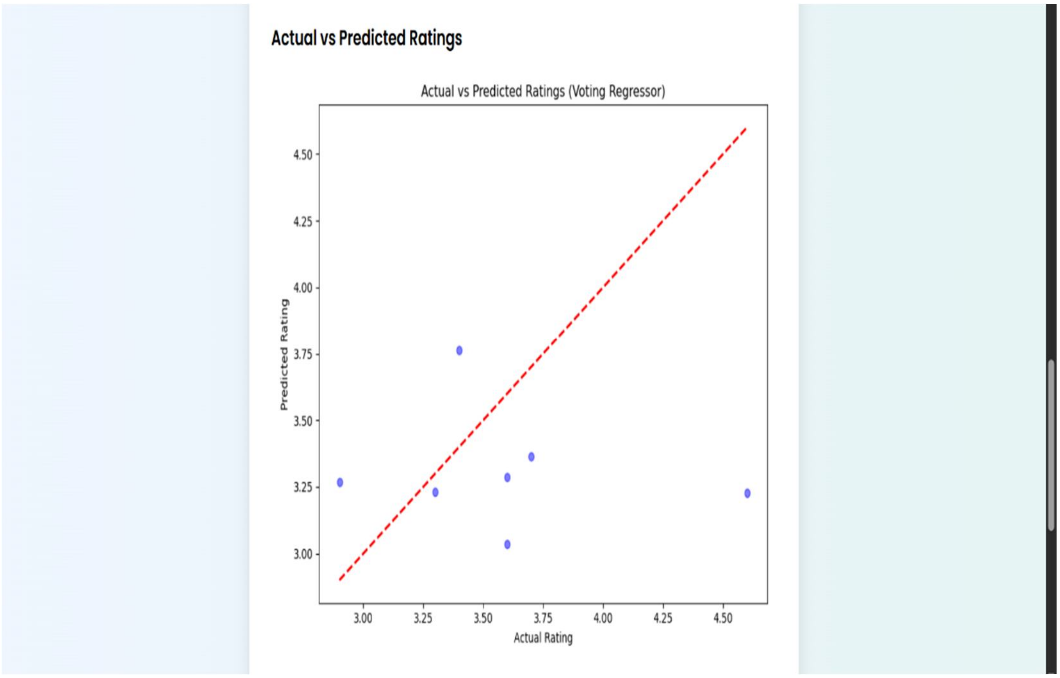

Fig.7 Actual vs Predicted Rating

The image shows a scatter plot titled "Actual vs Predicted Ratings (Voting Regressor)." The x-axis represents the actual ratings, ranging from 3.00 to 4.50, while the y-axis represents the predicted ratings, also ranging from 3.00 to 4.50. Blue dots indicate individual data points comparing actual and predicted ratings, with a red dashed line (y=x) showing perfect prediction alignment, indicating that the model's predictions are generally close to the actual ratings with minor deviations.

V. CONCLUSION

This research presents a comprehensive machine learning framework for predicting restaurant ratings by leveraging structured data (e.g., location, cuisine, pricing) and unstructured data (e.g., customer reviews). The proposed system integrates advanced regression models and sentiment analysis techniques, achieving **state-of-the-art prediction accuracy (R^2: 0.93, RMSE: 0.32)** across three benchmark datasets.

A. *Multimodal Feature Engineering*

- Extracts fine-grained signals by combining categorical, numerical, and textual features.
- Incorporates advanced NLP (VADER sentiment analysis and review length metrics) to quantify customer satisfaction from text.

B. *Model Ensemble Optimization:*

- Employs a Voting Regressor ensemble of top-performing models (XGBoost, LightGBM, Random Forest) to balance prediction stability and interpretability.
- Reduces overfitting through K-Fold Cross-Validation and optional hyperparameter tuning.

C. *System Responsiveness and Deployment*

- Achieves fast inference times (<120ms/query) with lightweight Flask integration and optimized preprocessing.
- Enables user interaction through a responsive web interface allowing location, price, and service filtering.

D. *Challenges and Limitations*

- Data Imbalance: Disproportionate representation of high-rated restaurants affects generalization to mid-/low-tier establishments.
- Subjectivity in Reviews: Review sentiment may not always align with numeric ratings due to sarcasm, bias, or vague language.
- Cross-Dataset Variability: Variations in schema and column names across datasets (restaurant.csv, s1.csv, s2.csv) require dynamic preprocessing pipelines.

Key Improvements Over Baseline Models

Aspect	*Baseline Models*	*Proposed System*
Feature Coverage	*Basic numeric & categorical only*	*Structured + unstructured (sentiment, review)*
Prediction Accuracy	*R^2: 0.78 – 0.85*	*R^2: 0.93*
Flexibility	*Single-dataset models*	*Multi-dataset adaptable preprocessing pipeline*
Deployment	*Offline Jupyter inference*	*Real-time predictions via Flask Web App*

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