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# Machine Learning Internship Report

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## Task 1: Predict Restaurant Ratings

### Objective

Build a machine learning model to predict the aggregate rating of a restaurant based on features like cuisine type, pricing, services, and more.

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### Data Overview

- Total Records: 9,551
  - Total Features: 21
  - Missing Values: 9 (in '**Cuisines**' column)
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### Data Preprocessing

- Filled missing 'Cuisines' with '**Unknown**'
  - Created new feature: Cuisine\_Count
  - One-hot encoded popular cuisines: *Italian, Indian, Chinese, etc.*
  - Converted table booking and online delivery into numeric (binary) format
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### Exploratory Data Analysis

#### Visualizations:

- Histogram of rating distribution

- Average rating by price range
- Average rating by cuisine
- Correlation matrix

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### Model Performance

| Model             | RMSE   | MAE    | R <sup>2</sup> |
|-------------------|--------|--------|----------------|
| Linear Regression | 1.2905 | 1.0733 | 0.2684         |
| Random Forest     | 1.2438 | 0.9835 | 0.3203         |
| Gradient Boosting | 1.2080 | 0.9694 | 0.3589         |

 Best Model: Gradient Boosting Regressor

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### Feature Importance

| Feature              | Importance |
|----------------------|------------|
| Price range          | 0.5393     |
| Average cost for two | 0.2378     |
| Has_Online_delivery  | 0.1352     |
| Cuisine_Count        | 0.0427     |
| Has_Indian           | 0.0206     |
| Table booking        | 0.0045     |
| Has_Chinese          | 0.0185     |
| Has_Japanese         | 0.0092     |

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### Insights

- Price and cost are the strongest predictors
  - Online delivery positively impacts ratings
  - Cuisine diversity influences rating
  - Table booking has minimal effect
  - Indian and Chinese cuisines contribute more than Japanese
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## Limitations & Improvements

- $R^2 \approx 0.36 \rightarrow$  indicates limited predictive power
  - Suggested enhancements:
    - Add location data (e.g., proximity to landmarks)
    - Incorporate review text sentiment
    - Include operating hours
    - Explore hybrid and deep learning models
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## Task 2: Recommendation System

### Goal

Build a content-based recommender system to suggest restaurants based on user preferences.

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### Example 1: High-End Italian Restaurant Lover

| Restaurant                   | City      | Cost  | Rating |
|------------------------------|-----------|-------|--------|
| Ristorante Prego             | Noida     | ₹1200 | 3.1    |
| San Gimignano - The Imperial | New Delhi | ₹5000 | 3.7    |

|                    |           |       |     |
|--------------------|-----------|-------|-----|
| The Krib           | New Delhi | ₹2500 | 3.2 |
| Prego - The Westin | Gurgaon   | ₹3000 | 3.8 |
| Bella Cucina       | Gurgaon   | ₹4000 | 4.1 |

#### Diversity Metrics:

- Cities: 3
- Cuisine Entropy: 0.000
- Price Range Entropy: 0.7219

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#### Example 2: Budget Asian Food Lover

| Restaurant | City      | Cost  | Rating |
|------------|-----------|-------|--------|
| Red        | Gurgaon   | ₹1200 | 3.0    |
| Soi Thai   | New Delhi | ₹1500 | 3.6    |
| Noshi      | New Delhi | ₹1000 | 4.2    |
| China Bowl | New Delhi | ₹800  | 3.9    |
| Shagun     | New Delhi | ₹800  | 3.9    |

#### Diversity Metrics:

- Cities: 2
- Cuisine Entropy: 1.5774
- Price Range Entropy: 0.9710

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#### Example 3: Food Quality Enthusiast

| Restaurant | City      | Cost | Rating |
|------------|-----------|------|--------|
| Keventers  | New Delhi | ₹400 | 3.9    |
| RollsKing  | Noida     | ₹300 | 3.8    |

|                   |           |      |     |
|-------------------|-----------|------|-----|
| Tonico Cafe       | Kochi     | ₹400 | 4.0 |
| Atul Chaat Corner | New Delhi | ₹100 | 3.8 |
| Novelty Dairy     | New Delhi | ₹200 | 4.1 |

#### Diversity Metrics:

- Cities: 3
  - Cuisine Entropy: 0.0000
  - Price Range Entropy: 0.0000
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#### Implementation Highlights

- Preprocessing: filled missing values, binary cuisine indicators
  - Feature engineering: extracted key cuisines
  - Similarity metric: Cosine similarity
  - Evaluation: Entropy and uniqueness of results
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#### Future Improvements

- Add location-based filtering
  - Implement hybrid recommender systems
  - Consider restaurant operating hours
  - Integrate user feedback loops
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## Task 3: Rating Classification

### Goal

Classify restaurant ratings into categories:

- Low, Medium, High, Excellent

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## Model Results

| Model               | Accuracy | Macro F1-score |
|---------------------|----------|----------------|
| Logistic Regression | 0.5568   | 0.42           |
| Random Forest       | 0.5835   | 0.48           |
| SVM                 | 0.5667   | 0.43           |
| Gradient Boosting   | 0.6112   | 0.47           |

✅ Best Classifier: Gradient Boosting Classifier

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## Task 4: Geographic Analysis

### Dataset Stats

- Unique cities: 141
- Unique localities: 1,208
- Unique countries: 15
- Final Dataset Size: (9,551, 24)

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### Geographic Range

- Latitude: -41.330 to 55.976
- Longitude: -157.948 to 174.832
- Map File: [global\\_restaurant\\_distribution.html](#)

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## Top 10 Cities by Restaurant Count

1. New Delhi — 5473
2. Gurgaon — 1118
3. Noida — 1080
4. Faridabad — 251
5. Ghaziabad — 25
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## Top Cities by Average Rating

1. Inner City — 4.90
2. Quezon City — 4.80
3. Makati City — 4.65
4. Pasig City — 4.63
5. Mandaluyong — 4.63

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## Top Cities by Cuisine Type (Example: New Delhi)

- North Indian: 2425
  - Chinese: 1638
  - South Indian: 411
  - Fast Food: 1304
  - Italian: 376
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# Conclusion

**This project successfully addressed key machine learning challenges in the restaurant domain:**

- **Pricing and delivery options are critical for predicting ratings**
  - **Content-based recommendation aligns well with user profiles**
  - **Gradient Boosting models achieved best regression & classification performance**
  - **Geographic visualizations reveal cuisine preferences and restaurant clustering**
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