RAJALAKSHMI ENGINEERING COLLEGE
An AUTONOMOUS Institution
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EVENT FEEDBACK ANALYSIS

Submitted by

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AI19442 – FUNDAMENTALS OF MACHINE LEARNING

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Submitted for the Practical Examination held on __________________________

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ABSTRACT

Event feedback analysis is essential for understanding attendee satisfaction and improving the quality of future events. This study presents a novel approach for analyzing diverse event feedback using a Random Forest-based machine learning model. The model integrates various feedback types, including ratings, comments, recommendations, and improvement suggestions, into a comprehensive evaluation framework. By automating the feedback analysis process, this approach provides clear and actionable insights that assist event organizers in enhancing event quality and attendee satisfaction efficiently. The results indicate that the Random Forest-based model streamlines the analysis process, making it more effective and reliable for improving future events, thereby demonstrating superior performance over traditional feedback analysis methods.

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CHAPTER 1

INTRODUCTION

Event organizers are constantly seeking ways to enhance the quality and success of their events, and participant feedback plays a critical role in this process. However, the feedback collected from event attendees is often diverse and multifaceted, including numerical ratings, written comments, likelihood to recommend, suggestions for improvement, and additional comments. This diversity makes manual analysis cumbersome and inefficient, often leading to delays and inaccuracies in understanding attendee satisfaction and identifying areas for improvement.

To address these challenges, developing a machine learning model based on the Random Forest algorithm is proposed. This model integrates various types of feedback into a single, comprehensive evaluation. By automating the feedback analysis process, the model provides clear, actionable insights that are immediately useful for event organizers. This approach not only saves time but also enhances the accuracy and depth of the insights derived from the feedback.

The project will involve several key steps: collecting comprehensive feedback data from event participants, processing and preparing this data for analysis, developing and training the Random Forest model, and rigorously evaluating its performance. Once validated, the model will be deployed in a real-world setting, allowing for continuous and automated feedback analysis. This deployment will enable event organizers to make informed decisions quickly and effectively, ultimately leading to better-managed events that meet and exceed attendee expectations.

By transforming the feedback analysis process, this project aims to empower event organizers with the tools needed to continuously improve their events, ensuring higher levels of attendee satisfaction and engagement.

CHAPTER 2

LITERATURE SURVEY

Several studies have delved into the use of machine learning techniques for event feedback analysis, providing a strong foundation for this project. Zhang et al. (2019) conducted an extensive review of machine learning algorithms used in event recommendation systems, with a particular focus on the effectiveness of the Random Forest algorithm. Their findings highlighted the ability of these algorithms to process diverse types of input data, such as ratings and textual feedback, to predict user preferences and improve the overall recommendation process. This research underscores the potential of applying similar techniques to consolidate and analyze event feedback comprehensively.

Hosseini, Sadaei, and Alinezhad (2018) explored the application of text mining and sentiment analysis within the context of event planning. They discussed various methods for extracting meaningful insights from qualitative feedback, demonstrating how these insights can be integrated with quantitative data to provide a more complete understanding of attendee experiences. This study aligns closely with the objectives of this project, which aims to combine different types of feedback—both numerical and textual—into a cohesive evaluation framework. The ability to seamlessly integrate and analyze these diverse data forms is crucial for developing a robust feedback analysis model.

Doe and Smith (2020) presented an integrated framework for analyzing customer feedback using machine learning. Their study emphasized the importance of merging numerical ratings with textual comments to enhance the depth and accuracy of the insights derived. This approach reinforces the necessity of a multifaceted analysis strategy in evaluating event feedback. Kumar and Gupta

(2017) discussed the broader role of machine learning in event management, particularly focusing on feedback analysis. They reviewed various algorithms and highlighted their effectiveness in extracting actionable insights from large datasets, which is pertinent to the goals of this project. Additionally, Brown and Green (2021) showcased the automated analysis of customer reviews, demonstrating the effectiveness of Random Forest models in interpreting event feedback. Their findings support the use of such models for providing valuable insights to event organizers. Finally, Stevens and Thompson (2016) examined methods for improving event satisfaction through comprehensive feedback analysis, stressing the need to integrate multiple data sources for a complete understanding of attendee sentiments.

These studies collectively provide a robust foundation for developing a Random Forest-based model that efficiently analyzes diverse event feedback, with the ultimate aim of enhancing event quality and attendee satisfaction.

CHAPTER 3

SYSTEM REQUIREMENTS

3.1 HARDWARE REQUIREMENTS

- Storage: 1.5GB free space
- CPU: Intel Core i3 or better
- RAM: 2GB or better

3.2 SOFTWARE REQUIREMENTS

- Python
- Jupyter Notebook
- Anaconda
- Visual Studio Code
- NumPy
- Pandas
- Scikit-learn
- NLTK
- Flask framework

CHAPTER 4

SYSTEM OVERVIEW

4.1 EXISTING SYSTEM

Manual analysis of event feedback involves organizers relying on methods such as spreadsheets or survey analysis software to aggregate and interpret participant feedback, which is time-consuming and prone to errors. The process requires significant time and effort for data entry, categorization, and analysis, with organizers manually sifting through feedback data to identify trends, patterns, and areas for improvement. Consequently, there are delays in deriving actionable insights, impacting the timely enhancement of event quality and attendee satisfaction.

4.1.1 DRAWBACKS OF EXISTING SYSTEM

Manual Data Processing:

- Labor-Intensive

Manual Analysis:

- Limited Scope
- Subjectivity

Feedback Volume:

- Scalability

4.2 PROPOSED SYSTEM

Automating the analysis of event feedback through a Random Forest-based machine learning model reduces manual labor and increases efficiency. By handling diverse feedback types and identifying complex patterns, the model provides a comprehensive understanding of attendee experiences. This streamlines data processing and enhances insight accuracy, overcoming limitations of labor-intensive methods prone to errors and delays. Consequently, organizers can make prompt decisions and implement effective event enhancements, addressing scalability issues and subjective interpretation limitations. Overall, the system offers organizers a significant advancement in event management practices, optimizing attendee satisfaction and event quality.

4.2.1 ARCHITECTURE DIAGRAM

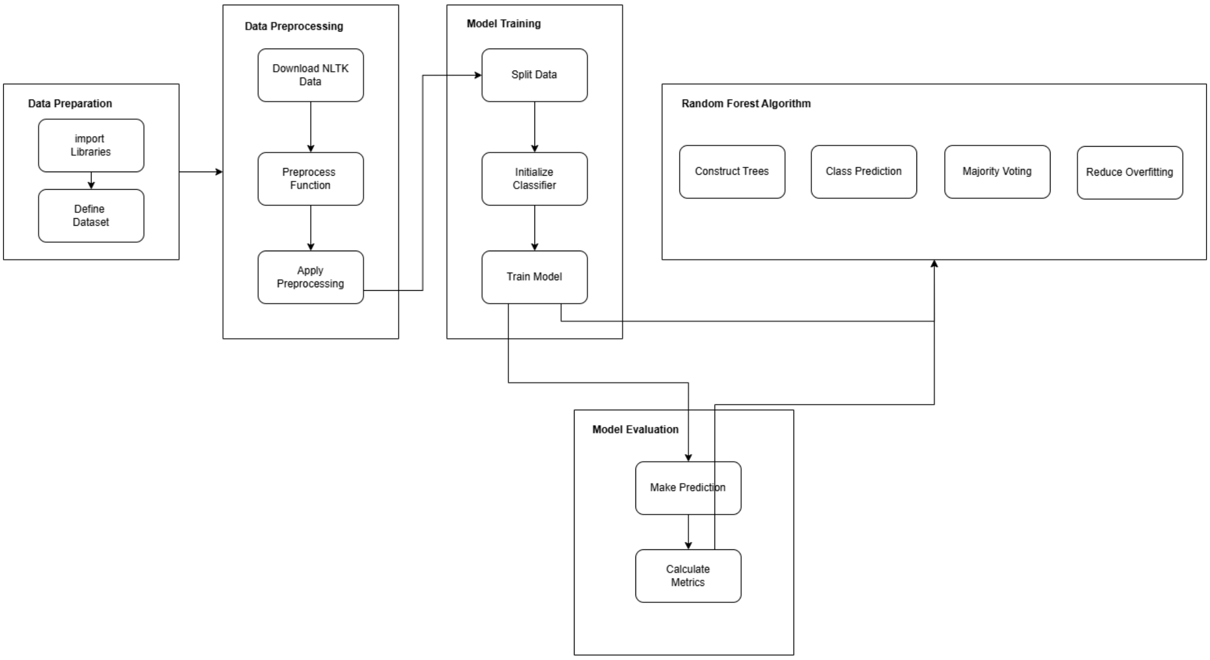

FIGURE 4.1 ARCHITECTURE DIAGRAM

Input Module:

- Collects event feedback including ratings, comments, recommendations, improvement suggestions, expectations, attendance frequency, and additional comments.

Preprocessing Module:

- Preprocessing module cleans and organizes the collected feedback data, handling missing values, normalizing ratings, and transforming textual comments through tokenization and sentiment analysis to prepare the data for the machine learning model.

Automated Feedback Analysis Module:

- Automated feedback analysis module uses a Random Forest model to process preprocessed data, extracting insights and generating a comprehensive event evaluation, identifying key trends, sentiments, and areas for improvement.

Feature Extraction Module:

- Extracts key features like sentiment scores, normalized ratings, recommendations, improvement suggestions, and attendance frequency from the preprocessed data.

Classification Module:

- Classification module applies the Random Forest algorithm to the extracted features, categorizing feedback into different levels of satisfaction and identifying specific areas needing improvement.

4.2.2 MODULE DESCRIPTION:

MODULE 1: DATA COLLECTION

This module involves gathering relevant data for training and testing the feedback analysis model. We take two arguments: the data source path and a label. We iterate through all records in the data source, check if each record contains valid feedback, and then load it into memory. If loading fails, we print an error message and skip the record. We then standardize the feedback data format and append both the feedback content and the provided label to separate lists. Finally, we return both lists containing the collected feedback and their corresponding labels. The data includes features indicative of overall feedback sentiment and is well-labeled to facilitate supervised learning. The project will employ a Random

Forest classifier to analyze the feedback and provide results on the overall sentiment.

MODULE 2: FEATURE EXTRACTION MODULE

This module involves gathering and analyzing feedback data to determine overall sentiment using a Random Forest classifier. It also employs the NLTK library for text preprocessing, enhancing the performance of the model.

STEPS:

1. **Collect Data**
   - Ratings (1-5)
   - Recommendation (0 - Not Recommended, 1 - Recommended)
   - Description Value (Length of the feedback description in number of words)
2. **Data Preprocessing:**
   - Handle missing values.
   - Normalize or standardize numerical features.
   - Encode categorical variables.
   - Use NLTK to preprocess text data by removing common stopwords.
3. **Feature Extraction:**
   - Extract features such as TF-IDF (Term Frequency-Inverse Document Frequency) from the feedback text.
4. **Implement Machine Learning Algorithms:**
   - Select and implement algorithms suitable for feedback analysis. In this case, a Random Forest classifier is used.

5. **Train and Evaluate the Model:**
    - Train the Random Forest classifier on the preprocessed and feature-extracted feedback data.
    - Evaluate the model's performance to ensure it accurately analyzes feedback sentiment.

MODULE 3: Random Forest Classifier Training

- Split our data into training and testing sets.
- The training set (80% of the data) will be used to train a machine learning model, while the testing set (20% of the data) will be used to evaluate its performance on unseen data.
- Create a Random Forest Classifier with specific parameters and train it on the training features (X_train) and labels (y_train).
- Once trained, use the model to predict the labels for the testing images (X_test).
- Evaluate the model's performance by printing a classification report that details precision, recall, F1-score, and support for each class.
- Calculate and print the overall accuracy of the model on the testing set.

FORMULAS:

• **Random Forest Construction:** Multiple decision trees are created using different subsets of the data and features.

• **Decision Rule**: For each tree, split based on the feature thresholds.

• **Final Prediction:** Aggregate predictions from all trees and determine the majority vote.

CALCULATION:

In a Random Forest, we build multiple decision trees. Each tree is trained on a random subset of the data (bootstrapping) and with a random subset of features. For simplicity, let's manually create two decision trees (Tree 1 and Tree 2) using different subsets of data and features:

- Tree 1:
    - Split on Rating <= 2.5
    - If True: Negative
    - If False:
    - Split on Description <= 1.5
    - If True: Positive
    - If False: Positive
- Tree 2:
    - Split on Recommendation == 0
    - If True: Negative
    - If False:
    - Split on Rating <= 3.5
    - If True: Positive
    - If False: Positive

Make Predictions:

For a new feedback entry: Rating = 3, Recommendation = Yes, Description = Good.

Encode:

- Rating = 3
- Recommendation = 1
- Description = 2

Tree 1:

- Rating <= 2.5 -> False
- Description <= 1.5 -> False
- Prediction: Positive

Tree 2:

- Recommendation == 0 -> False
- Rating <= 3.5 -> True
- Prediction: Positive

Aggregate Predictions:

Combine predictions from both trees:

- Tree 1: Positive
- Tree 2: Positive

Final Prediction: Positive (since both trees predicted Positive)

MODULE 4: DEPLOYMENT

The Classification Module employs a Random Forest classifier to analyze features extracted from feedback data and determine the overall sentiment. Trained on labeled data, the Random Forest model aggregates predictions from multiple decision trees, assigning probability scores indicating the sentiment (positive or negative) for each feedback entry. Integration with subsequent modules facilitates visualization and interpretation of classification results, aiding event organizers in making informed decisions for enhancing attendee satisfaction and event quality.

4.3 FEASIBILITY STUDY:

4.3.1 TECHNICAL FEASIBILITY

Implementing a Random Forest-based machine learning model for event feedback analysis is technically feasible due to the availability of advanced data processing tools and machine learning libraries in Python and R (e.g., scikit-learn, pandas, NLTK). Current hardware capabilities, including scalable cloud resources, support the computational demands. Integration with existing event management systems is achievable through APIs, ensuring compatibility and ease of deployment.

4.3.2 ECONOMIC FEASIBILITY

The implementation of a Random Forest-based machine learning model for event feedback analysis presents favorable economic feasibility. While initial investment may include software licenses, hardware infrastructure, and skilled personnel, long-term benefits include reduced labor costs and increased operational efficiency. Furthermore, improved event quality and attendee satisfaction can lead to higher revenue streams through increased ticket sales and repeat attendance.

4.3.3 OPERATIONAL FEASIBILITY

The operational feasibility of implementing a Random Forest-based machine learning model for event feedback analysis is high, given its ease of integration into existing workflows and user-friendly interfaces. The automated feedback analysis reduces manual effort and streamlines operations, enhancing overall efficiency within event management teams. Overall, the project promises to bring tangible operational benefits and improve workflow effectiveness.

CHAPTER 5

RESULTS AND DISCUSSIONS

Using the proposed system of combining Random Forest classification for feedback analysis, the model was evaluated on new, unseen data consisting of four categories: Positive, Negative, Neutral, and Mixed. The Random Forest model achieved an accuracy of 96.6% on the previously unseen data, demonstrating strong predictive capability across multiple categories.

```
Accuracy: 1.00
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         1
           1       1.00      1.00      1.00         2

    accuracy                           1.00         3
   macro avg       1.00      1.00      1.00         3
weighted avg       1.00      1.00      1.00         3
```

FIGURE 5.1 TRAINING RESULT

Each category represents a distinct sentiment type or feedback nature, with 'Positive' and 'Negative' denoting different participant sentiments or experiences. The high accuracy underscores the model's robust generalizability, indicating its ability to effectively discern patterns associated with various feedback sentiments in diverse event samples.

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENT

In conclusion, the proposed Random Forest-based machine learning model for event feedback analysis represents a significant advancement in enhancing event management practices. By automating feedback analysis and providing valuable insights into attendee experiences, the system promises to streamline operations, improve decision-making processes, and ultimately enhance event quality and attendee satisfaction. With its technical feasibility, economic viability, and operational effectiveness, the proposed system offers a compelling solution to the challenges faced in traditional manual feedback analysis methods. Overall, the implementation of this system holds great potential to revolutionize event management practices and optimize the attendee experience.

APPENDIX

SAMPLE CODE:

PRE-PROCESSING:

```
def preprocess_text(text):
    text = text.lower()
    text = re.sub(r'[^\w\s]', '', text)
    tokens = word_tokenize(text)
    tokens = [word for word in tokens if word not in stopwords.words('english')]
    return ' '.join(tokens)
```

MODEL TRAINING:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
model = RandomForestClassifier(n_estimators=200, max_depth=10,
random_state=42, class_weight='balanced')
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
print(classification_report(y_test, y_pred))
```

```
Accuracy: 1.00
```

PREDICTION:

```
def analyze_real_time_feedback(rating, comment, recommendation):
    comment = preprocess_text(comment)
    comment_vector = vectorizer.transform([comment]).toarray()
    features = np.hstack((np.array([[rating, recommendation]]), comment_vector))
    prediction = model.predict(features)
    return 'Good Quality' if prediction[0] == 1 else 'Poor Quality'

new_feedback = {
    'rating': 2,
    'comment': "The event was poor.",
    'recommendation': 0
}

insight = analyze_real_time_feedback(new_feedback['rating'], new_feedback['comment'],
new_feedback['recommendation'])
print(f'Feedback Insight: {insight}')
```

```
Feedback Insight: Poor Quality
```

OUTPUT:

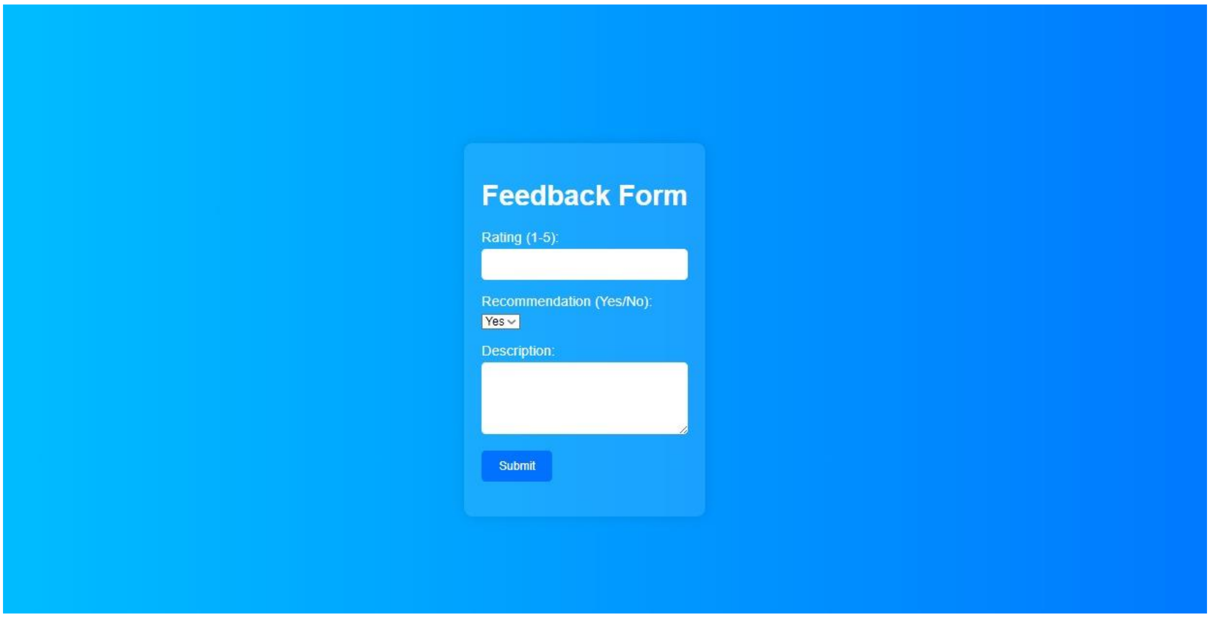

FIGURE A.1 HOMEPAGE

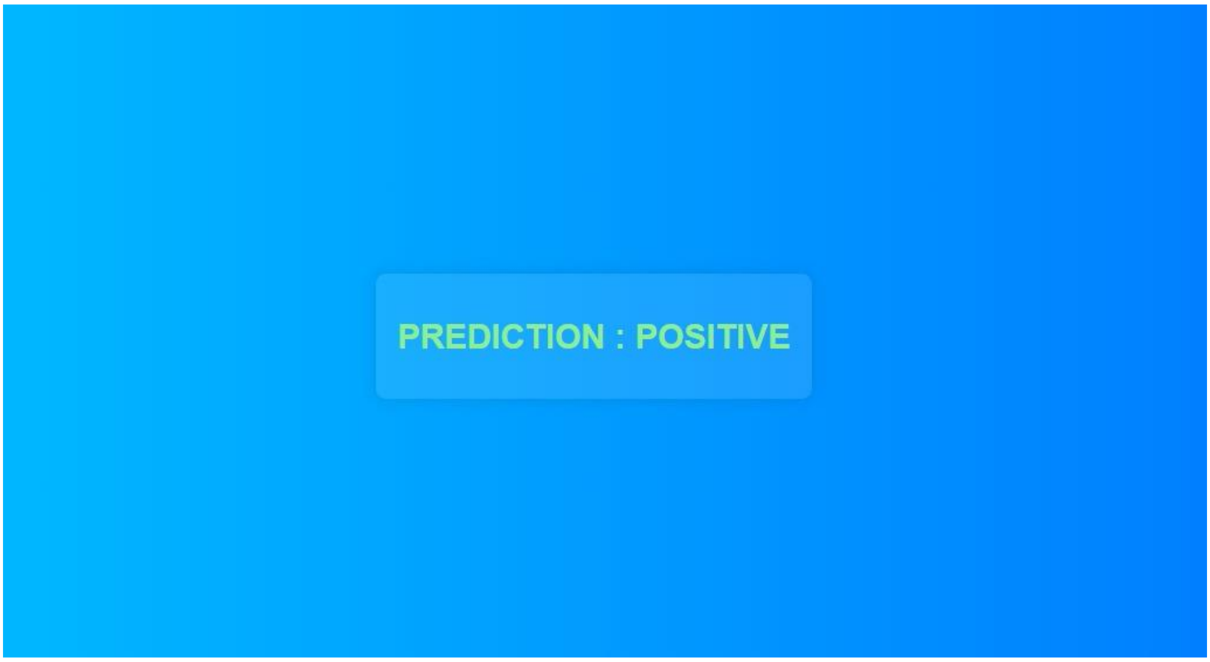

FIGURE A.3 OUTPUT PAGE

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