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Research Article

Content Based Hotel Recommender Based on Multi-Aspect Sentiment Analysis by Rating Inference from User Reviews

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ABSTRACT

Introduction: In today's era of e-business, the online purchase of goods and services has become an essential and inseparable part of human life. Recommender systems play a crucial role in helping users select products or services that are both relevant and reasonably priced.

Objectives: Current recommender systems generate product or service recommendations by identifying similarly rated items and matching them with other similar users. However, these systems do not consider user preferences for specific product features and rely solely on single ratings given by other users. The objective of this study is to propose a more accurate recommender system that improves recommendation precision by analyzing multiple aspects of user preferences and increases the personal trust.

Methods: The proposed recommender system enhances accuracy by analyzing user behavior and activities toward different products. It mines user opinions for multiple product aspects by utilizing physical ratings provided for each hotel and determining sentiment scores from textual reviews. Additionally, the system infers new scores from sentiment analysis. Various machine learning classification techniques, such as Naïve Bayes, maximum entropy, Support Vector Machine (SVM), Decision Tree, and Random Forest, are employed along with functional units like feature extraction and sentiment analysis to improve recommendation effectiveness.

Results: The final set of recommendations is prepared by considering multiple aspects of the problem domain rather than relying on single ratings. This approach leads to a more personalized and accurate recommendation system. The proposed system has been tested, and its accuracy outperforms existing similar systems by 2% to 9%.

Conclusions: By incorporating multiple aspects of user opinions and preferences through advanced machine learning techniques, the proposed recommender system achieves higher accuracy compared to traditional models. The improvements in accuracy demonstrate the system's effectiveness in providing more precise and user-centric recommendations.

Keywords: Machine learning, Naïve Bayes, Maximum Entropy, Sentiment Analysis, Opinion Mining, Support Vector Machines, Recommendation Systems, Feature Extraction.

INTRODUCTION

This paper analyzes helpful product reviews using a sentiment-based algorithm to aid purchase decisions. Online reviews are vital in the digital age, and recommender systems enhance user satisfaction. Sentiment analysis extracts reviews from various sources, impacting business and society. Companies use it in applications like recommender systems.

Sentiment analysis classifies reviews based on predicted ratings. Techniques include machine learning (supervised and unsupervised) and lexicon-based methods. Supervised learning uses training data, while unsupervised learning doesn't. Lexicon-based methods analyze semantic relationships. Automatic review assessment using machine learning and sentiment analysis addresses the time-consuming nature of traditional review sorting.

This paper explores dynamic lexicons and algorithms like Maximum Entropy, Naive Bayes, and SVM to classify hotel reviews. Machine learning methods (Naive Bayes, Decision Trees, Random Forest, and GCNs) improve accuracy. The paper covers sentiment analysis importance, related research, the proposed system, dataset evaluation, and experimental results, including a comparative analysis.

Theoretical Background of Supervised Machine Learning Algorithms:

- Naive Bayes: A probabilistic algorithm used for text classification, based on Bayes' theorem. It assumes feature independence and has variations like Bernoulli, Gaussian, and Multinomial.
- Support Vector Machine (SVM): A supervised method for regression and classification, maximizing the margin between data points. It's effective for nonlinear problems and compared with GNNs.
- Decision Tree: A model that divides data into subgroups through binary decisions. It's simple but can overfit.
- Random Forest: An ensemble method combining Decision Trees to increase accuracy and reduce overfitting.
- Graph Convolutional Networks (GCNs): Enhance recommendation models by leveraging user-item relationships in graphs. They capture interaction strength and normalize data.

  Graph Construction and Representation in GCN is explained as under:

  - Node Representation: Nodes represent users and items with enriched features.
  - Edge Representation: Edges represent interactions with weights indicating strength.
  - Graph Construction: Links users and items, forming a bipartite structure.
  - Graph Pre-processing: Handles missing data and normalizes weights.
  - Graph Visualization: Reveals patterns in user-item relationships.

(ii) Aspect based Sentiment Analysis and Recommender System:

Aspect-based sentiment analysis (ABSA) determines sentiment polarity of text aspects. Models like LSTM networks, the interactive attention network (IAN), gated Convolutional Neural Networks, and attention-over-attention (AOA) have been used.

Sentiment analysis methods include:

- Lexicon-based Approach: Uses pre-compiled lists of words to analyze sentiment.
- Supervised Learning Approach: Trains models on labeled data to predict sentiment.
- Unsupervised Machine Learning Algorithms: Finds features without labeled data, using techniques like LDA, NMF, and K-Means.

RELATED WORK AND LITERATURE SURVEY

Systems that can automatically collect, assess, and present opinions in a form that is useful and simple for a user to understand are becoming more and more necessary. Determine either

a) The overall polarity (i.e., positive or negative) or

b) The overall sentiment rating of a review (e.g., one-to-five stars) have been the main goals of early methods to this subject [1][2][3].

However, the various possible dimensions on which an entity can be rated are not sufficiently represented by merely taking into account aggregate reviews. The OpenTable.com review below may indicate a sentiment rating of three stars overall.

“The food was very good, but it took over half an hour to be seated, and the service was terrible. The room was very noisy and cold wind blew in from a curtain next to our table. Desserts were very good, but because of the poor service, I’m not sure we’ll ever go back!”

This review demonstrates that an overall rating by itself is unable to convey certain thoughts, as it shows both favourable sentiments regarding a restaurant's food and negative sentiments regarding its ambiance and service. While recommender systems make product recommendations based on user preferences, conventional systems that rely on historical behaviour and straightforward ratings (1–5) provide little information. This is addressed by multi-aspect sentiment analysis, which assesses several facets of user comments to gain a better insight.

Pang et al. [10] pioneered sentiment analysis by employing supervised learning to categorize movie reviews as either positive or negative. Aspect extraction using frequent nouns and noun phrases was first presented by Hu and Liu [11]. However, thorough coverage is difficult due to the requirement for huge labelled datasets for techniques like Conditional Random Fields (CRF) and Hidden Markov Models (HMM).

Several algorithms have been used, such as SVM and Naïve Bayes, with SVM demonstrating superior accuracy in text tasks. By enhancing training methods and context comprehension, recent deep learning models like CNNs, RNNs, BERT [Devlin et al., 2019], and GPT [Radford et al., 2019] have taken sentiment analysis even further.

The below paragraph presents a comparative analysis of various studies on sentiment analysis methodologies, focusing on applications like hotel reviews and aspect-based sentiment analysis (ABSA). **MujthabaGulamMuqeeth, et al. (2024)** evaluated SVM, Random Forest, and Logistic Regression, highlighting gaps in explainability and hybrid methods. **Bin Lu, et al. (2011)** integrated topic modeling for aspect-specific sentiment classification, emphasizing scalability and real-world application challenges. Similarly, **Dilip Singh Sisodia, et al. (2019)** identified SVM’s dominance in hotel review analysis but pointed to gaps in feature engineering.

Several studies explored hybrid methods. For example, **Ganesh N. Jorvekar, et al. (2023)** combined SVM, decision trees, and lexicons for aspect-specific sentiment, while **Reza Nouralizadeh Ganji, et al. (2023)** employed LSTM, CNN, and SMOTE for recommender systems. Advanced methods like **ADNAN ISHAQ, et al.’s (2020)** CNN-GA hybrid and **Ibrahim Nawawi, et al.’s (2024)** zero-shot learning showcase progress in addressing multilingual and domain-specific nuances.

Other works, including **SoumayaOunacer, et al. (2023)** and **Talha Ahmed Khan, et al. (2024)**, emphasized improving feature extraction, scalability, and deep learning integration. Overall, the studies underline SVM’s consistent performance, while calling for advancements in handling imbalances, computational efficiency, and multilingual adaptability.

PROPOSED APPROACH AND IMPLEMENTATION

3.1 Proposed approach of aspect based Sentiment Analysis using Machine Learning Techniques

(i) Loading the dataset: The TripAdvisor benchmark dataset corpuses, which include textual user reviews for various hotels from various users together with their numerical values supplied by the same users, are what we are passing. The total reviews in the training and testing record datasets are then distributed. The reviews will be fed into our suggested framework for sentiment analysis-based process recommendations after being distributed over training and test datasets.

(ii) Pre-processing and preparing model for sentiment analysis: Following sentiment analysis, the dataset must undergo processing procedures. Among the different steps are (1) Pre-processing: a number of tasks include identifying negatives, blind negations, split and stop words, tokenization, POS tagging [15], stemming, word shortening, emoticon detection and removal, and hash tag detection and removal must be carried out in order to pre-process the dataset. (2) Using techniques such as presence/count/Tf-Idf (Term Frequency and Inverse Document frequency), feature-sentiment identification is done using the review corpuses. Here, the feature-sentiment pair's presence could be determined using boolean, count, and Tf-Idf values as integers and float values, respectively.(3) Semantic Transformation and Sentiment Score Calculation: Each feature that is pertinent to the aforementioned user reviews will be given a semantic score. A weighted score is assigned to tagged words in order to determine their sentiment score. Each word has a positive and negative value that is already defined in the lexicon, such as SentiWordNet. Words, sentences, or documents can all have their sentiment scores determined. The total score can then be determined by adding up all of the scores that have already been determined.

Semantic transformation, which involves giving each word aspect a weight, completes the third step outlined in the previous paragraph. The final score, which is used to create a list of recommended hotels, is then determined for each hotel based on the specific aspects listed in list provided.

(iii) Sentiment classification and preparing hotel recommendation list: The supervised machine learning techniques (i) Naïve Bayes (ii) Decision Tree (iii) Support Vector Machine-SVM (iv) Graph Convolutional Network-GCN, are used for sentiment analysis and classification process. Then after we are preparing the hotel recommendation list for the user according to its interested aspect which he or she wants in the hotels recommended. The recommendation list is to be prepared based on newly predicted ratings or scores calculated, in ascending order of these ratings. The new ratings or scores are determined by aggregating actual numerical ratings provided by users for the same hotel and the sentiment scores predicted from analysis of textual user reviews based on individual aspects for the various services for the individual hotels.

Following diagram in Figuure 1 shows our proposed framework for a content based recommender system based on multi aspect sentiment analysis. We have implemented the said approach on a benchmark dataset which is provided by TripAdvisor as training data.

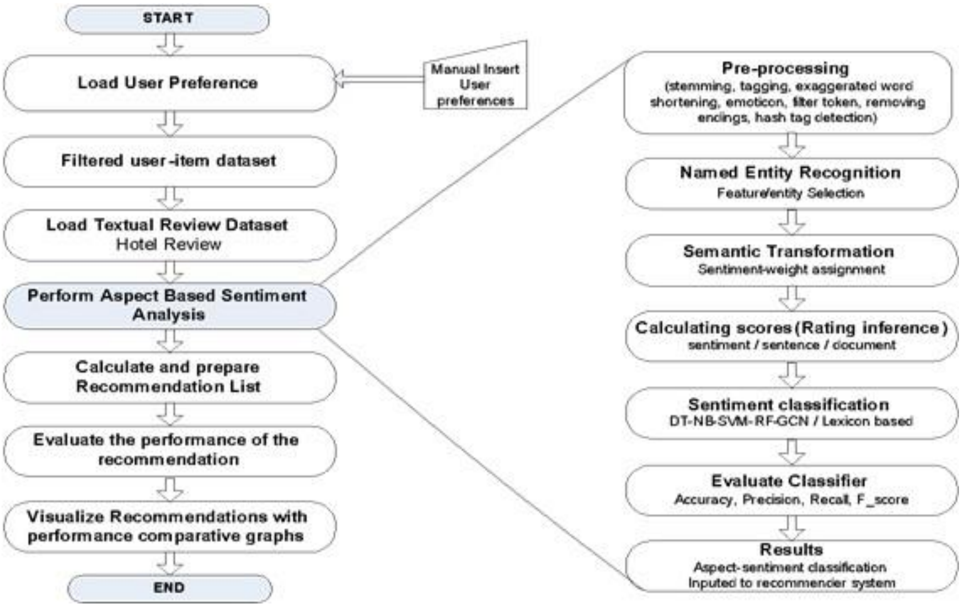


Figure 1. Recommender System using supervised

3.2 Dataset and Evaluation Criteria

(i) Dataset:

As discussed earlier we are applying our proposed method on Parsed reviews are included in the TripAdvisor Gold Standard Dataset, which is used as training data. Value, room, location, cleanliness, check-in, food, and service are the seven aspects that the TripAdvisor dataset includes. It also includes textual user reviews for various hotels from various users, along with numerical ratings ranging from 0 to 5 stars. A rating of -1 indicates that this aspect rating is absent from the original reviews. Here, we are testing the suggested approach by confirming the different criteria mentioned in the article's preceding part. We are contrasting the suggested method's sentiment analysis base performance with that of other unsupervised sentiment analysis techniques. Following paragraph contains the details of the used dataset on which we are applying the proposed approach.

TripAdvisor Hotel Review Dataset: is a gold standard dataset which has reviews for different 1759 hotels spread all over the world consisting of 238,860 user reviews provided by millions of users spread across the world.

It is only the attraction to use this dataset just because each one hotel review entry contains multi-aspect numerical ratings provided along with not only the overall rating for that hotel but also the textual opinions from various past customers for that hotel. So we can have a different list of hotels recommended which can satisfy the user according to the individual aspects.

(ii) Evaluation Parameters:

We are assessing the effectiveness of the suggested method for a subset of hotels in the dataset. The performance of the method is assessed here for the aforementioned datasets by validating the outcomes under the various assessment metrics (1) Accuracy (2) Precision (3) Recall (4) F-score. Using the aforementioned settings, we will assess each of the three supervised machine learning algorithms' performance on the given dataset.

3.3 Proposed Algorithms and Procedures

Algorithm: sentiment rating calculation based on user aspect

Initialize:

RatingSummary = {}

For each entry in FeedbackData:

Extract:

positive_score, negative_score = entry.sentiment_metrics

feedback_text = entry.content

#Split the feedback_text into keywords

For each keyword in keywords:

    If keyw is in AspectKeywords and not in AspectDetails:

        Add keyw to AspectDetails

    Identify emotion_words from feedback_text related to keyword

    #Compute the count of emotion_words:

    emotion_count = len(emotion_words)

    Add emotion_count ->AspectDetails[keyw]["emotion_count"]

#Determine the polarity of emotion_words: sentiment_type

If sentiment_type == "positive":

    positive_score_combined=emotion_count+positive_score+ negative_score

    Add positive_score_combined->AspectDetails[keyw]["positive_total"]

Else if sentiment_type == "negative":

    negative_score_combined = emotion_count + positive_score + negative_score

    Add negative_score_combined->AspectDetails[keyw]["negative_total"]

For each aspect in AspectDetails:

    sentiment_strength=(aspect["positive_total"]- aspect["negative_total"]) / aspect["emotion_count"]

    Add sentiment_strength ->AspectDetails[aspect]["sentiment_score"]

Return AspectDetails

The different term used in this procedure is explained below

RatingSummary: A data structure (e.g., dictionary) initialized to store the results of the analysis. It will eventually contain the aggregated details for all the aspects found in the feedback data.

FeedbackData: The dataset containing user reviews or feedback entries. Each entry includes textual feedback and associated sentiment metrics.

positive_score, negative_score: Sentiment metrics extracted from the feedback entry. These represent numerical values indicating the intensity of positive and negative sentiments in the feedback.

feedback_text: The textual content of a single feedback entry, which will be analyzed to extract aspects and sentiments.

keyw: Words or phrases obtained by splitting (tokenizing) the feedback text. These will be evaluated to determine if they are related to predefined aspects.

AspectKeywords: A predefined set of terms representing the aspects of interest (e.g., "delivery," "quality") that the algorithm is designed to analyze.

AspectDetails: A dictionary where details for each aspect are stored. Each key is an aspect, and the value contains information such as counts of emotion-related words, total sentiment scores, and computed sentiment strength.

emotion_words: Words in the feedback text that express emotion or sentiment related to a particular aspect (e.g., "good," "bad," "excellent"). These are identified based on their association with a specific keyword.

emotion_count: The number of emotion-related words found for a specific aspect. This count provides a measure of the feedback's emotional content.

sentiment_type: The polarity (positive or negative) of the identified emotion words. It is used to classify whether the sentiment is favorable or unfavorable.

positive_score_combined: A combined metric for positive sentiment, calculated as the sum of the number of emotion words, the positive sentiment score, and the negative sentiment score.

negative_score_combined: A combined metric for negative sentiment, similar to the positive score but used for negative sentiment calculations.

AspectDetails[keyword]["positive_total"]: The cumulative positive sentiment score for a specific aspect. It aggregates all positive contributions found in the feedback.

AspectDetails[keyword]["negative_total"]: The cumulative negative sentiment score for a specific aspect. It aggregates all negative contributions found in the feedback.

sentiment_strength: A normalized score for an aspect, calculated as the difference between the total positive and negative scores divided by the count of emotion-related words. It reflects the overall sentiment strength or polarity for the aspect.

AspectDetails[aspect]["sentiment_score"]: The final computed sentiment score for each aspect, representing its overall sentiment strength.

AspectDetails: The algorithm outputs the AspectDetails dictionary, which contains comprehensive sentiment analysis for all identified aspects. This includes counts, total scores, and normalized sentiment strength.

Algorithm: create Suggestions List

For each object in object_set:

Initialize: object_similarity_data = []

For each profile in user_profiles:

If profile has not evaluated object:

similarity_score = compute_hotel_suggestions(user, item)

Append similarity_score -> object_similarity_data

procedure: compute_hotel_suggestions (user, item):

Initialize:

total_score = 0

total_weights = 0

For each evaluated_object in profile's previously evaluated items:

similarity_factor = determine_similarity(item, evaluated_items)

total_score += similarity_factor × evaluated_object_rating

total_weights += similarity_factor

Return total_score / total_weights

procedure: find_similar(item1, item2)

If (item1, item2) exists in object_similarity_data:

Return object_similarity_data[(item1, item2)]

Else:

shared_attributes=Count of attributes common to both item1 and item2

total_attributes=Total number of attributes in item1 and item2

similarity_metric = shared_attributes / total_attributes

Store similarity_metric in object_similarity_data[(item1, item2)]

Return similarity_metric

RESULTS, EVALUATION, AND ANALYSIS

4.1 Performance Evaluation and Analysis of Existing approaches (Accuracy): Sentiment analysis techniques [20]

Table 1. Machine Learning:

Author	Dataset	Accuracy (%)
Dave et al.	Amazon, CNET	SVM(85.8-87.2) NB(81.39-87.0)
Abbasi et al.	US and Middle Eastern Web forum postings	SVM(95.55)

Table 2. Lexicon Based:

Author	Dataset	Accuracy (%)
Hu and Liu	Amazon, CNET	84.00
A. Khan et al.	IMDB, Skytrax, Tripadvisor	86.60
Zhang et al.	Luce, Yoka	82.62

Table 3. HybridApproach:

Author	Dataset	Accuracy (%)
Fang et al.	Multi-domain sentiment dataset	66.80

Zhang et al.	Twitter	85.40
Mudinas et al.	CNET, IMDB	82.30

4.2 Performance evaluation of Base Machine Learning Algorithms

Data sets: used off-line benchmark datasets

(1) Movie Review Dataset : 1000 positive and 1000 negative pre-processed, grouped, Movie opinion reviews, Available as polarity dataset v2.0, provided by nltk corpus in Python.

(2)Positive-Negative dataset : contains 500 positive and 500 negative anonymous opinion user reviews.

(3) TripAdvisor benchmark Hotel Review dataset : contains 238000+ reviews for more than 1700 hotels collected from various users across the world.

Algorithms tested: Maximum Entropy, Naïve Bayes, SVM

- **Table 4.** The evaluation measures for **Movie Review (Single fold)** Dataset, are as under by(Word features and with stopwords removed)

	ME	Naïve Bayes	SVM
Accuracy	0.7220	0.7280	0.8640
Precision	0.8060	0.8056	0.8651
Recall	0.7220	0.7280	0.8640
F-Measure	0.7015	0.7096	0.8639

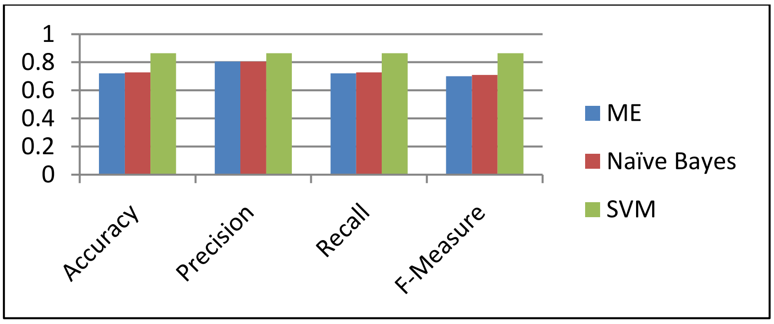


Figure 2. ML algorithms performance for Movie Review Dataset

- **Table 5.** The evaluation results measures for **Positive-Negative Review (Single fold)** Dataset are as under, Train on 750 instances, Test on 250 instances (Word features and with stopwords removed)

	ME	Naïve Bayes	SVM
Accuracy	0.7520	0.7800	0.8760
Precision	0.8153	0.8414	0.8766
Recall	0.7520	0.7800	0.8760
F-Measure	0.7389	0.7696	0.8760

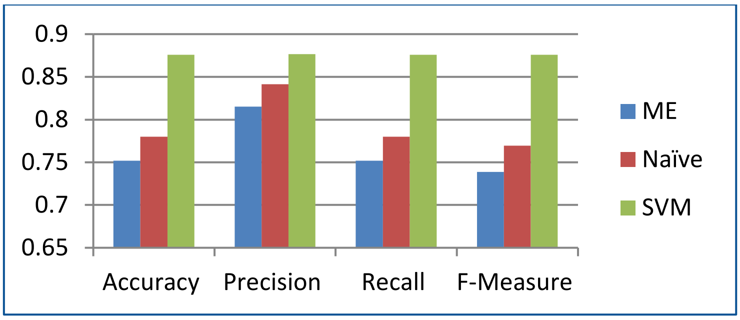


Figure 3. ML algorithms performance for Positive-Negative Dataset

- **Table 6.** The evaluation results measures for **TripAdviser**Datasetcontains 238000+ reviews of more than 1700 hotels are as under,(Word features and with stopwords removed)

	ME	**Naïve Bayes**	**SVM**
Accuracy	0.7520	0.7800	0.8760
Precision	0.8153	0.8414	0.8766
Recall	0.7520	0.7800	0.8760
F-Measure	0.7389	0.7696	0.8760

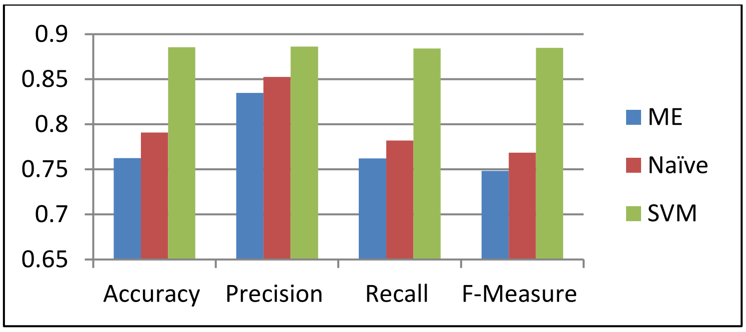


Figure 4. ML algorithms performance for TripAdviser Dataset

4.3 Performance Evaluation and Analysis of Proposed approach

Using machine learning methods and classification on the aforementioned dataset, we are implementing sentiment analysis in this model. The assessment parameters Accuracy, Precision, Recall, and F-score are then used to assess the sentiment analysis procedure in the suggested recommender system. As described in the preceding section, the performance of different machine learning-based algorithms is assessed for each specific hotel characteristic or aspect using sentiment analysis on the Trip Advisor hotel review dataset:

1. Aspect: Room

Table 7: Evaluation of Machine Learning algorithms for Room Aspect

Algorithm	Accuracy	Precision	Recall	F-Score
Decision Tree	0.86	0.86	0.86	0.86
Naïve Bayes	0.89	0.89	0.88	0.88
Linear SVM	0.9	0.91	0.9	0.9
Random Forest	0.88	0.89	0.89	0.89
Nov-GCN	0.91	0.92	0.91	0.91

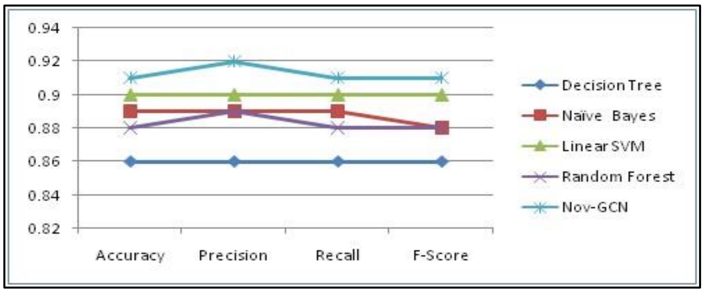


Figure 5. Machine Learning algorithms for Room aspect

2. Aspect: Location

Table 8: Evaluation of Machine Learning algorithms for Location Aspect

Algorithm	Accuracy	Precision	Recall	F-Score
Decision Tree	0.87	0.87	0.87	0.87
Naïve Bayes	0.89	0.89	0.89	0.88
Linear SVM	0.90	0.90	0.90	0.90
Random Forest	0.89	0.89	0.89	0.89
Nov-GCN	0.90	0.90	0.90	0.89

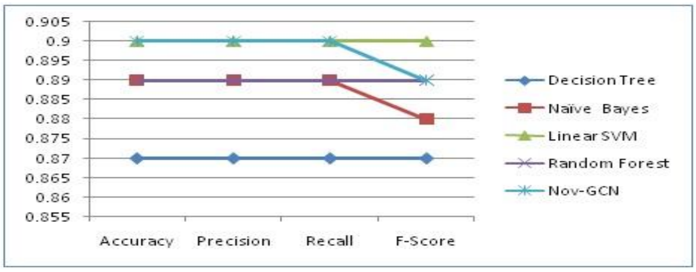
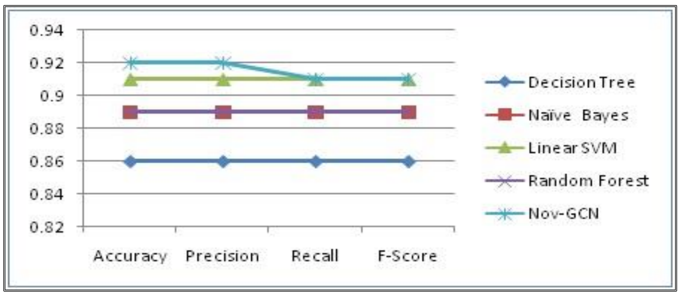


Figure 6. Machine Learning algorithms for Location aspect

3. Aspect: Services

Table 9. Evaluation of Machine Learning algorithms for Services Aspect

Algorithm	Accuracy	Precision	Recall	F-Score
Decision Tree	0.86	0.86	0.86	0.86
Naïve Bayes	0.89	0.89	0.89	0.89
Linear SVM	0.91	0.91	0.91	0.91
Random Forest	0.89	0.89	0.89	0.89
Nov-GCN	0.92	0.92	0.91	0.91



Figuure 7. Machine Learning algorithm for Service aspect

4. **Aspect: Cleanliness**

Table 10. Evaluation of Machine Learning algorithms for Cleanliness Aspect

Algorithm	Accuracy	Precision	Recall	F-Score
Decision Tree	0.87	0.87	0.87	0.87
Naïve Bayes	0.88	0.88	0.88	0.88
Linear SVM	0.90	0.90	0.90	0.90
Random Forest	0.89	0.89	0.89	0.88
Nov-GCN	0.90	0.91	0.90	0.90

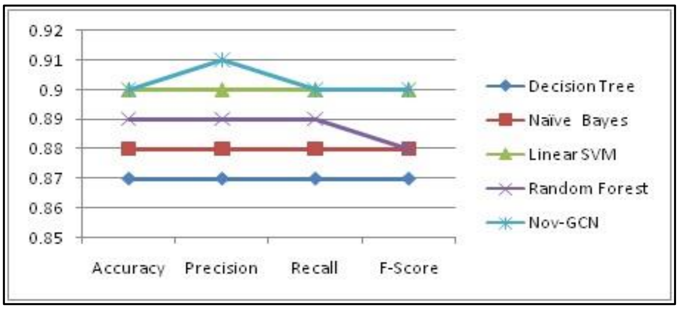


Figure 8. Machine Learning algorithms for Check In aspect

(6) Aspect: Front-Desk

Table 11. Evaluation of Machine Learning algorithms for **Front-Desk** Aspect

Algorithm	Accuracy	Precision	Recall	F-Score
Decision Tree	0.87	0.87	0.87	0.87
Naïve Bayes	0.89	0.89	0.89	0.89
Linear SVM	0.90	0.90	0.90	0.90
Random Forest	0.89	0.89	0.89	0.89
Nov-GCN	0.89	0.91	0.91	0.90

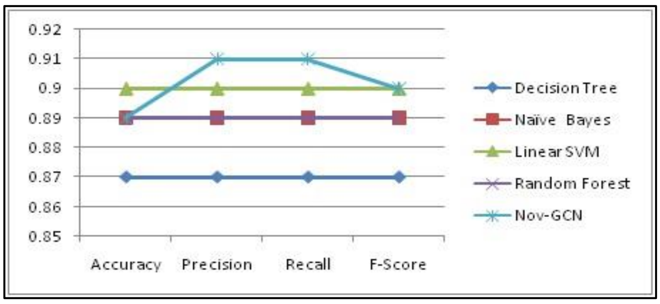


Figure 9. Machine Learning algorithms for Front Desk In aspect

4.4 Comparison of evaluation: Base line approaches using Supervised Machine Learning methods tested by various authors and our proposed approach

Table 12: Evaluation of Baseline methods using Supervised Machine Learning Methods (Paper-1) [54]

Aspect	**Room**			**Location**			**Cleanliness**			**Check-In**			**Service**		
Algorithm	**SVM**	**RF**	**NB**	**SVM**	**RF**	**NB**	**SVM**	**RF**	**NB**	**SVM**	**RF**	**NB**	**SVM**	**RF**	**NB**
Precision	0.75	0.81	0.77	0.73	0.79	0.7	0.81	0.79	0.83	0.65	0.74	0.72	0.72	0.84	0.76
Recall	0.78	0.72	0.79	0.73	0.72	0.69	0.81	0.72	0.8	0.66	0.59	0.74	0.71	0.6	0.74

F1-Score	0.76	0.75	0.78	0.73	0.74	0.69	0.81	0.74	0.81	0.66	0.6	0.73	0.71	0.61	0.75
Accuracy	0.83	0.85	0.84	0.81	0.8	0.8	0.84	0.8	0.85	0.76	0.8	0.8	0.81	0.82	0.83

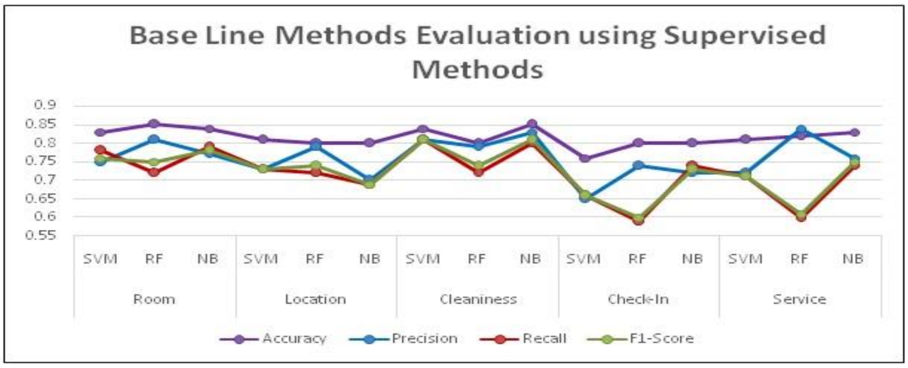


Figure 10. ML algorithms Aspect Evaluation of Baseline methods suggested in (Paper-1)[54]

Table 13: Evaluation of Proposed Method Supervised Machine Learning Methods

Aspect	Room				Location				Service			
Algorithm	**SVM**	**NB**	**RF**	**Nov-GCN**	**SVM**	**NB**	**RF**	**Nov-GCN**	**SVM**	**NB**	**RF**	**Nov-GCN**
Accuracy	0.9	0.89	0.88	0.91	0.89	0.88	0.88	0.9	0.91	0.89	0.88	0.92
Precision	0.91	0.89	0.89	0.92	0.91	0.89	0.91	0.9	0.91	0.9	0.91	0.92
Recall	0.9	0.88	0.89	0.91	0.89	0.89	0.88	0.9	0.9	0.89	0.89	0.91
F1-Score	0.90	0.88	0.89	0.91	0.90	0.89	0.89	0.89	0.90	0.89	0.90	0.91

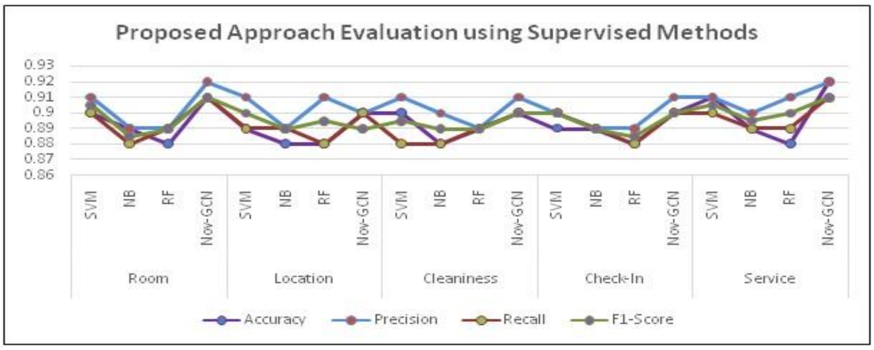


Figure 11. ML algorithms Aspect Based Evaluation of My Proposed Approach

Table 14: Evaluation of Base line methods using Supervised Machine Learning Methods (Paper-2) [55]

Metrics/Classifiers	LR	RF	NB	DT	KNN	SVM
Accuracy	87.37	89	82.87	74.44	75.87	87.63
Recall	60.73	66.19	53.17	43.57	50.25	62.39
Precision	83.84	84.51	57	56.2	80	82.41
F1-Score	64.04	70.55	54.02	43.53	54.16	66.54

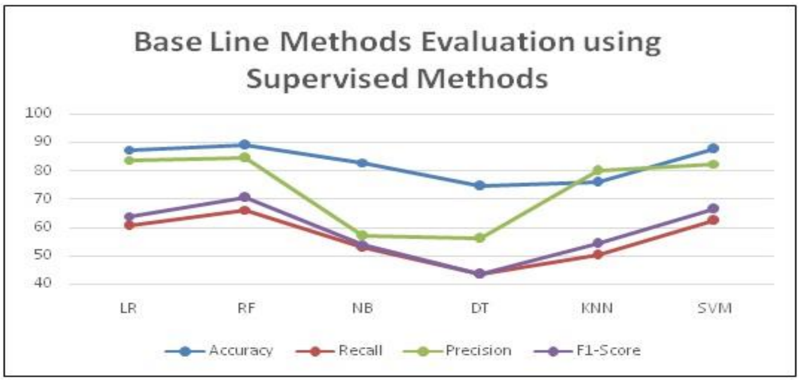


Figure 12. ML algorithms overall Evaluation of Baseline methods suggested in (Paper-2)[55]

Table 15: Evaluation of Proposed Method Supervised Machine Learning Methods:

Classifiers	**SVM**	**NB**	**RF**	**Nov-GCN**
Accuracy	0.898	0.886	0.882	0.906
Recall	0.908	0.894	0.898	0.912
Precision	0.894	0.886	0.886	0.904
F1-Score	0.901	0.890	0.892	0.902

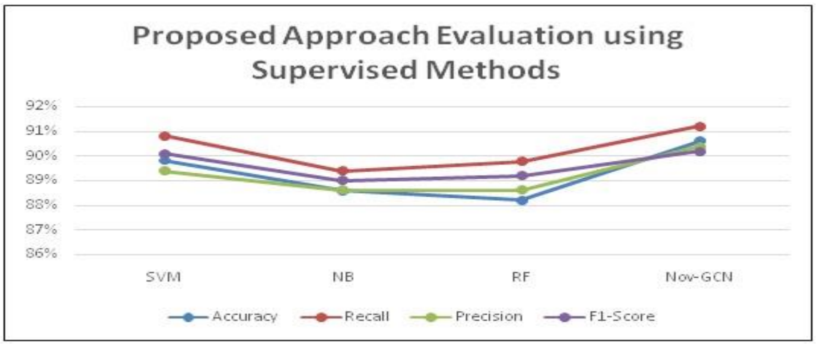


Figure 13. ML algorithms overall Evaluation of My Proposed Approach

CONCLUSION

The performance evaluation shows that supervised methods excel in accuracy, especially in classifying specific categories, allowing precise boundary distinctions. However, these models require additional knowledge for learning and involve complex, computationally intensive training and labelling processes, which can slow down classification compared to other models. Key findings from the research contribute to improving product recommendation systems by extracting relevant aspects from online reviews and utilising user purchasing preferences. The enhancements include: (1) Aspect Extraction Approach, which combines dependency relations with rule-based frequent noun methods to identify meaningful product aspects, though the rule-based method may struggle with large datasets; (2) Product Ranking Algorithm, introducing an aspect-weighted sentiment scoring method that ranks products based on user preferences, outperforming baseline methods; (3) Feature Selection Techniques, suggesting that supervised methods work better for balanced datasets and recommending further research on user ratings as class labels; and (4) Recommendation List Creation, which generates lists based on review analyses, incorporating detailed data like hotel names, locations, prices, and user ratings for specific aspects.

Statistical Analysis:

Based on evaluation shown in previous chapter my proposed method “content based recommender system based on sentiment analysis utilizing rating inference from user review” out performs the baseline methods suggested by two researchers in the article[54][55] in terms of accuracy for Hotel Review offline dataset provided by TripAdvisor.

The accuracy of my proposed model is superior than the baseline method suggested by I Putu Ananda Miarta Utama; et al. in [54] by (1) 7% using SVM, 4% using Random Forest and Naive Bayes methods for Room aspect. (2) For Location aspect it out performs by 10% using SVM, 9% and 8% using Random Forest and Naive Bayes methods respectively. (3) For Service aspect my method out performs the baseline method by 8% using SVM, 7% and 5% using Random Forest and Naive Bayes methods respectively. For the remaining two aspects cleanliness, and check-in also my proposed method have quite higher accuracy then the base line stated methods.

Similarly, if we compare my proposed approach with the baseline method suggested by Soumaya Ounacer; et al. in [55], my suggested methods shows higher overall accuracy of sentiment analysis and classification by 2.17% using SVM, -0.8% and 5.73% using Random Forest and Naive Bayes methods respectively.

FUTURE ENHANCEMENT

The study demonstrates that gcn-based classifiers perform well on suggested datasets. Future work could explore other domains, calculate sentiment scores based on specific aspects and customer ratings, and refine the classifier accordingly. Current aspect extraction methods, which rely on linking nouns to sentiment words, may not suit domains like medical insurance claims, where aspects are more descriptive. Refining heuristics for such domains is necessary.

Additionally, incorporating emotional features has been shown to improve sentiment classification, raising the question of its potential impact on recommendation systems. Future research could focus on creating user profiles based on reviews and integrating booking data with user preferences, while addressing privacy concerns. Temporal aspect importance could also enhance recommendations by adapting aspect weights over time. Finally, an alternative method involves modeling product relationships and deducing optimal aspect weights through computational graphs and backpropagation.

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