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NLP-Based Sentiment Analysis And User Satisfaction Evaluation of Solar Energy Monitoring Applications

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Abstract: *The increasing adoption of solar energy systems has created a growing demand for digital applications that help users monitor electricity generation, energy consumption, inverter performance and overall system efficiency. However, the usefulness of these applications also depends on user experience and satisfaction. Application-store reviews provide valuable information about user opinions and technical difficulties, but analysing large volumes of unstructured feedback manually is challenging. This study presents an NLP-based framework for analysing user reviews and evaluating satisfaction with solar energy monitoring applications. A dataset containing 1,777 reviews collected from five applications was processed using text preprocessing and Term Frequency–Inverse Document Frequency (TF-IDF) feature extraction. Four machine learning classifiers, namely Multinomial Naive Bayes, Logistic Regression, Support Vector Machine and Random Forest, were evaluated for sentiment classification. Sentiment labels were derived from numerical user ratings, with 1–2 stars classified as negative, 3 stars as neutral and 4–5 stars as positive. The study also applies keyword-based aspect identification to examine eight application features, including interface usability, real-time monitoring, data accuracy, inverter connectivity, notifications, application performance, compatibility and technical support. A provisional AspectLevel Satisfaction Index (ASI) is used to summarize rating-derived feedback associated with these features. Logistic Regression achieved the highest classification accuracy of 75.84%, while Support Vector Machine obtained the highest macro-averaged F1-score of 56.87%. The findings highlight the potential of NLP techniques to identify user concerns and support improvements in solar energy monitoring applications.*

Keywords: Natural Language Processing, Sentiment Analysis, Solar Energy Monitoring Applications, TF-IDF, Machine Learning, Rating-Derived Sentiment, Aspect-Based Analysis

I. INTRODUCTION

Solar energy is an important renewable energy source that contributes to sustainable electricity generation and reduces dependence on conventional energy resources. The increasing installation of photovoltaic systems in residential, commercial, and industrial environments has created a growing need for effective monitoring technologies. Solar energy monitoring applications provide users with information about electricity generation, energy consumption, battery performance, inverter status, and historical energy production. These applications allow users to observe and manage their solar energy systems through mobile devices and web-based dashboards.

Although solar monitoring applications provide several useful facilities, their effectiveness also depends on application quality and user experience. Users may encounter problems such as inaccurate energy readings, delayed data updates,

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unstable inverter connections, application crashes, complicated interfaces, and insufficient technical support. Such difficulties can reduce user confidence and affect the overall usefulness of solar monitoring technology. Understanding these experiences is therefore important for improving the quality and reliability of these applications.

User reviews published on application platforms provide valuable information about customer experiences and opinions. These reviews may include positive feedback about application functionality, negative comments about technical problems, and suggestions for improving existing services. However, reviews are generally written in unstructured natural language and may contain spelling mistakes, abbreviations, technical terminology, and different expressions of opinion. Analysing a large number of reviews manually is time-consuming and may produce inconsistent results.

Natural Language Processing (NLP) provides computational techniques for processing and analysing human language. Sentiment analysis is an important NLP application that is commonly used to categorize opinions into positive, negative, and neutral classes. Machine learning algorithms can identify patterns in textual data and support the automatic classification of user feedback. Techniques such as Term Frequency–Inverse Document Frequency (TF-IDF) convert textual reviews into numerical representations that can be processed by supervised learning algorithms.

Several studies have explored sentiment analysis in renewable-energy applications. Shrestha et al. (2024) examined textual information related to solar-energy policies using artificial intelligence-based techniques. Kim et al. (2025) investigated public attitudes towards solar energy using transformer-based deep learning. Shobil and Al-Hagree (2026) focused on user sentiment in solar energy monitoring application reviews. Jabbar et al. (2026) investigated consumer hesitation towards solar-energy adoption using BERT-based sentiment analysis. These studies demonstrate the growing importance of NLP and machine learning techniques for understanding opinions and attitudes related to solar energy.

However, overall sentiment classification alone may not provide sufficient information about the particular application features associated with user satisfaction or dissatisfaction. For example, users may discuss interface usability, real-time monitoring, data accuracy, inverter connectivity, or technical support in their reviews. Identifying these application-related aspects can help developers understand which features receive frequent feedback and where improvements may be required.

To address this need, this study presents an Aspect-Based Solar Experience and Rating-Aware NLP (ASER-NLP) framework for analysing user reviews of solar energy monitoring applications. The study uses a dataset containing 1,777 reviews collected from five applications. TF-IDF is applied to represent review text, and four machine learning classifiers—Multinomial Naive Bayes, Logistic Regression, Support Vector Machine (SVM), and Random Forest—are evaluated for sentiment classification. Sentiment categories are generated from numerical user ratings, with 1–2 stars classified as negative, 3 stars as neutral, and 4–5 stars as positive. In addition, predefined keywords are used to identify eight application-related aspects. A provisional Aspect-Level Satisfaction Index (ASI) is used to summarize rating-derived feedback associated with these aspects.

The main contributions of this research are:

1. Analysis of 1,777 publicly available user reviews collected from five solar energy monitoring applications.
2. Application of TF-IDF feature extraction for representing review text and evaluating four machine learning classifiers.
3. Comparative evaluation of Multinomial Naive Bayes, Logistic Regression, Support Vector Machine, and Random Forest using standard classification metrics.
4. Identification of eight application-related aspects using predefined keyword matching.
5. Development of a provisional Aspect-Level Satisfaction Index (ASI) based on rating-derived feedback.
6. Identification of frequently discussed application features and potential areas for improving user experience.

The experimental results show that Logistic Regression achieved the highest classification accuracy of 75.84%, while Support Vector Machine obtained the highest macro-averaged F1-score of 56.87%. The findings provide an overview of user feedback and demonstrate how NLP and machine learning techniques can support the analysis of solar energy

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monitoring application reviews. Since sentiment labels were derived from user ratings and aspect identification relied on keyword matching, the results are interpreted within these methodological limitations.

II. METHODOLOGY

The process includes data collection, preprocessing, feature extraction, rating-derived sentiment classification, keyword-based aspect identification, and exploratory satisfaction evaluation.

A. Data Collection

The dataset used in this study contains 1,777 publicly available user reviews collected from five solar energy monitoring applications. The reviews provide information about users' experiences with solar photovoltaic monitoring, inverter performance, energy generation and application functionality.

The dataset contains the following attributes:

1. Application Name: Name of the solar energy monitoring application.
2. Review Text: Written feedback provided by the user.
3. User Rating: Numerical rating ranging from one to five stars.
4. Review Date: Date on which the review was published.

The collected dataset was examined for missing values and duplicate application-review records. No missing values or duplicate records were identified. The dataset covers the period from 15 April 2022 to 28 October 2026. User ratings were retained for generating rating-derived sentiment labels and evaluating user feedback. Personal information was not required for this study.

B. Data Preprocessing

The dataset consisted of 1,777 user reviews collected from five solar energy monitoring applications. Automated language detection identified 1,575 reviews (88.63%) as English, 196 reviews as other languages, and six reviews as unknown.

All 1,777 reviews were retained for analysis without language-based filtering. The dataset was subsequently divided into training and testing subsets for model evaluation. English stop-word removal was applied during TF-IDF vectorization. Therefore, the experiments were conducted on a multilingual dataset using English stopword removal rather than on an English-only dataset.The dataset was also examined for missing values and duplicate application-review records. No missing values or duplicate records were identified. This preprocessing approach maintained the original review collection while preparing the text for TF-IDF feature extraction.No additional preprocessing operations, such as lemmatization, emoji processing, or language-specific translation, were included in the reported experimental pipeline.

C. Feature Extraction

Feature extraction converts textual reviews into numerical representations that can be processed by machine learning algorithms. In this study, Term Frequency–Inverse Document Frequency (TF-IDF) was used to represent the review text.

TF-IDF assigns weights to words based on their frequency within a review and their importance across the complete dataset. It helps identify informative terms while reducing the influence of frequently occurring words.

The TF-IDF representation is calculated as:

$$\text{TF-IDF}(t, d) = \text{TF}(t, d) \times \text{IDF}(t)$$

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Where:

- TF(t, d) represents the frequency of term (t) in document (d).
- IDF(t) represents the inverse document frequency of term (t) across the review collection.

The TF-IDF vectorizer was configured with a maximum of 5,000 features. The resulting numerical representations were used as input for four machine learning classifiers: Naive Bayes, Logistic Regression, Support Vector Machine (SVM), and Random Forest.Contextual transformer-based representations, such as BERT, may be explored in future work to investigate their ability to capture complex meanings and contextual relationships in user reviews.

D. Sentiment Classification

Sentiment classification was performed to categorize user reviews into positive, negative and neutral classes. In this study, sentiment labels were generated from numerical user ratings because manually annotated sentiment labels were not available.

The rating-based classification was defined as follows:

1. Negative: Reviews with ratings of 1 or 2 stars.
2. Neutral: Reviews with a rating of 3 stars.
3. Positive: Reviews with ratings of 4 or 5 stars.

Four supervised machine learning algorithms were evaluated using TF-IDF features:

1. Multinomial Naive Bayes: A probabilistic classifier commonly used for text classification.
2. Logistic Regression: A supervised algorithm that estimates the probability of a review belonging to a sentiment category.
3. Support Vector Machine (SVM): A classification technique that identifies decision boundaries between sentiment categories.
4. Random Forest: An ensemble learning algorithm that combines multiple decision trees to generate predictions.

The models were evaluated using accuracy, macro-averaged precision, macro-averaged recall and macroaveraged F1-score. Since the labels were derived from user ratings, the evaluation measures agreement with rating-based proxy labels rather than independently human-annotated textual sentiment.

E. Aspect-Based Sentiment Analysis

Aspect-based analysis was used to identify the main features of solar energy monitoring applications discussed in user reviews. In this study, predefined keywords were used to identify eight aspects: Interface Usability, RealTime Monitoring, Data Accuracy, Inverter Connectivity, Notifications, Application Performance, Technical Support, and Compatibility.

Each review was matched with one or more aspects based on the presence of relevant keywords. The sentiment category associated with each matched aspect was determined using the review's overall star rating: 1–2 stars were classified as negative, 3 stars as neutral, and 4–5 stars as positive.

A single review could be associated with multiple aspects. Therefore, the total number of aspect mentions may exceed the total number of reviews. This approach provides an overview of user feedback across different application features. However, it does not independently determine the sentiment expressed specifically toward each aspect.

F. Rating-Based Sentiment Analysis

In this study, user ratings were used as proxy labels to classify the sentiment of solar application reviews. The ratings were divided into three categories: 1–2 stars as negative sentiment, 3 stars as neutral sentiment, and 4– 5 stars as positive sentiment.

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This rating-based classification provided the sentiment labels required for training and evaluating the machine learning models. The approach enabled a consistent classification process across the collected reviews.

It is important to note that sentiment labels were derived from user ratings rather than independent manual annotation or a separate text-based sentiment analysis model. Therefore, the classification results represent the models' ability to predict rating-derived sentiment categories. A separate comparison between textual sentiment and user ratings was not conducted in this study.

G. User Satisfaction Evaluation

This study uses a provisional Aspect-Level Satisfaction Index (ASI) to summarize rating-derived user feedback associated with individual application features.

The index is calculated as:

$$\mathrm{ASI}(a) = 100 \times [\alpha N(a) + (1-\alpha)R(a)]$$

Where:

- ASI(a) = Satisfaction index for application aspect a.
- N(a) = Average normalized rating-derived sentiment score for aspect a.
- R(a) = Average normalized user rating for aspect a. □ α = Weighting parameter, set to 0.5 in this study.

The normalized rating is calculated as:

$$R_i = \frac{r_i - 1}{4}$$

Where:

- R_i represents the normalized rating score of review i.
- r_i represents the original user rating on a scale of 1 to 5.

The rating-derived sentiment score is assigned as follows:

- Negative (1–2 stars) = 0
- Neutral (3 stars) = 0.5
- Positive (4–5 stars) = 1

The average sentiment score and normalized rating are calculated separately for the reviews associated with each aspect. The resulting ASI ranges from 0 to 100. A higher value indicates comparatively more favourable rating-derived feedback, whereas a lower value indicates a potential area for improvement.

Limitation: Both components of the ASI are derived from the same user ratings. Therefore, the index combines two representations of rating information and should be considered exploratory rather than an independently validated measure of user satisfaction. Further validation using human-annotated sentiment and independent user-satisfaction assessments is required.

III. MODELING AND ANALYSIS

A. Typical Existing Approach

A typical NLP-based sentiment analysis approach processes user reviews collected from online platforms and converts textual information into numerical features using techniques such as Term Frequency–Inverse Document Frequency (TF-IDF) or Bag of Words. Machine-learning algorithms, including Naive Bayes, Support Vector Machine, and Logistic Regression, can then classify reviews into positive, negative, and neutral categories. Such approaches

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generally focus on overall sentiment classification. The present study extends this general approach by adding keyword-based identification of application features and an exploratory evaluation of ratingderived feedback.

Limitations of Typical Existing Approaches

1. Limited feature-level analysis of application reviews.
2. Difficulty capturing complex opinions and contextual meaning in user feedback.
3. Limited integration of rating-derived feedback with application feature-level analysis.
4. Limited evaluation of individual application features and their associated user feedback.

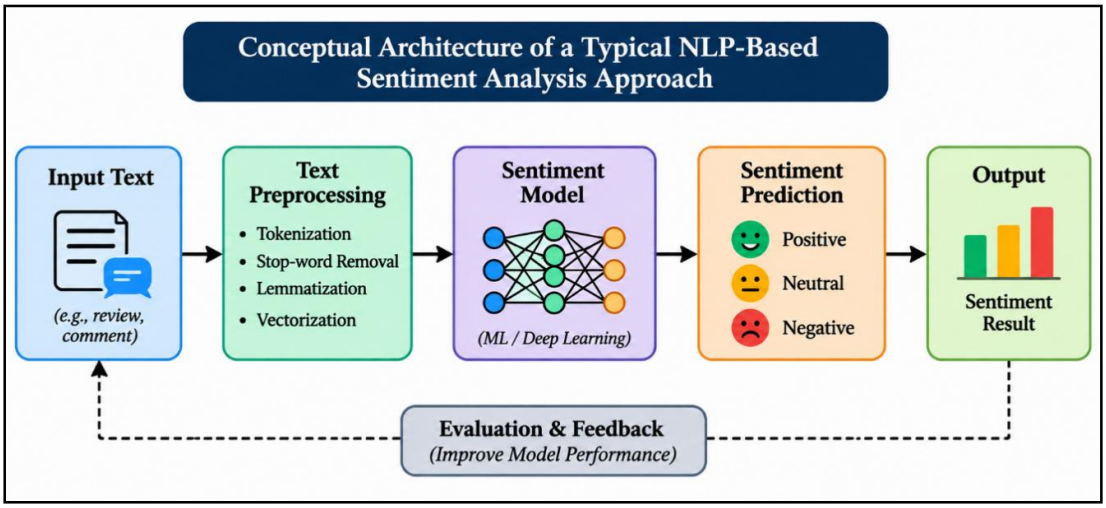


Figure 1: Conceptual Architecture of a Typical NLP-Based Sentiment Analysis Approach

B. **Proposed System Architecture**

The proposed ASER-NLP framework is designed to analyse user reviews and evaluate rating-derived feedback for solar energy monitoring applications. It consists of interconnected modules that transform raw reviews into meaningful classification and aspect-level satisfaction information.

The main components are:

1. Review Collection Module.
2. Data Preprocessing Module.
3. TF-IDF Feature Extraction Module.
4. Machine Learning-Based Sentiment Classification Module.
5. Keyword-Based Aspect Identification Module.
6. Rating-Based Sentiment Labelling Module.
7. Aspect-Level Satisfaction Evaluation Module.
8. Result Visualization Module.

The framework begins with the collection of publicly available application reviews. The preprocessing module prepares the review text for analysis, while the TF-IDF module converts textual information into numerical feature vectors. Four machine learning classifiers are then trained and evaluated to predict rating-derived sentiment categories.The keyword-based aspect identification module matches reviews with predefined application features, such as interface usability, real-time monitoring, data accuracy, and inverter connectivity. The sentiment category associated with each identified aspect is obtained from the overall user rating. Finally, the satisfaction evaluation module calculates a provisional Aspect-Level Satisfaction Index (ASI), and the visualization module presents the classification and aspect-level results.The framework provides an organized approach to understanding user feedback.

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However, it does not independently identify aspect-specific textual sentiment or perform a separate comparison between text-predicted sentiment and numerical ratings.

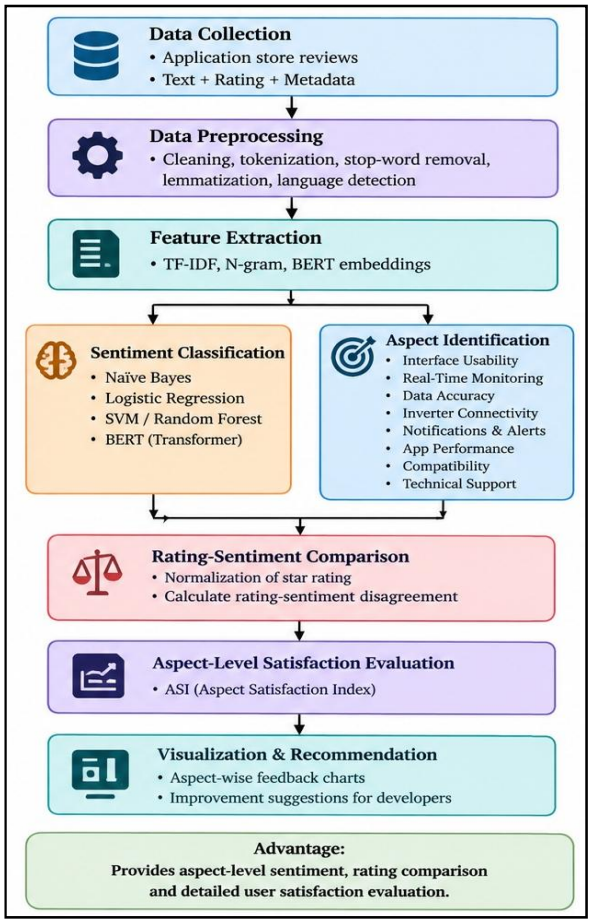


Figure 2: Proposed Architecture of the ASER-NLP Framework for User Satisfaction Evaluation of Solar Energy Monitoring Applications.

The rating-based sentiment labelling module assigns sentiment categories using the overall star ratings provided with the reviews. Ratings of 1–2 stars are labelled negative, 3-star ratings are labelled neutral, and 4–5-star ratings are labelled positive. These labels are used as proxy sentiment classes for training and evaluating the machine-learning models. They are not based on independent manual annotation of the review text.

C. Mathematical Modeling

The proposed study uses TF-IDF-based text representation and supervised machine learning algorithms to classify user reviews into rating-derived sentiment categories.

Let the collected review dataset be represented as:

$$D = \{(x_i, y_i)\}_{i=1}^{n}$$

Where:

- D represents the dataset.

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- x_i represents the input feature vector of the i-th review.
- y_i represents the corresponding sentiment label. □ n represents the total number of reviews.

where (x_i) represents the textual content of review (i), and (y_i) represents its sentiment label derived from the user rating.

1. Sentiment Label Defination

$$y_i = \begin{cases} \text{Negative}, & \text{if rating is 1 or 2} \\ \text{Neutral}, & \text{if rating is 3} \\ \text{Positive}, & \text{if rating is 4 or 5} \end{cases}$$

2. TF-IDF Feature Representation

$$X_i = \text{TFIDF}(x_i)$$

Where:

- y_i represents the rating-derived sentiment label of review i.
- X_i represents the numerical feature vector of review i.
- x_i represents the original text of review i.
- TFIDF (x_i) converts the review text into a numerical feature vector using TF-IDF.

The resulting feature vectors are used to train and evaluate four machine learning classifiers: Naive Bayes, Logistic Regression, Support Vector Machine, and Random Forest.

For aspect-level analysis, predefined keywords are used to match reviews with relevant application features. The sentiment category of each matched review is taken from its overall star rating. A review may be associated with multiple aspects.

This mathematical formulation describes the implemented rating-based classification and keyword-based aspect analysis. It does not represent an independently trained aspect-specific sentiment detection model.

D. Model Training and Testing

The dataset was divided into training and testing subsets using a stratified 80:20 split, with a random state of 42 to ensure reproducibility. The training subset was used to train the machine learning classifiers, while the testing subset was used to evaluate their performance on unseen data.

Stratification helped maintain the original sentiment-class distribution across both subsets. Accuracy, macro-averaged precision, macro-averaged recall, and macro-averaged F1-score were used as evaluation metrics.

E. Tools and Technologies

The proposed system was implemented using Python in the Google Colab environment. The following tools and libraries supported data processing, feature extraction, machine-learning model development, and result visualization:

1. Python: Used as the primary programming language for implementing the analysis.
2. Google Colab: Provided the cloud-based notebook environment for executing the experiments.
3. Pandas and NumPy: Used for dataset handling, data manipulation, and numerical operations.
4. Scikit-learn: Used for TF-IDF feature extraction, stratified train-test splitting, machine-learning classification, and performance evaluation.
5. Matplotlib and Seaborn: Used for visualizing sentiment distribution, model performance, and aspectlevel results.

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RESULTS AND DISCUSSION

The experimental results show that Logistic Regression achieved the highest accuracy of 75.84% among the four evaluated classifiers. It also obtained the highest macro-averaged precision of 79.05%. Support Vector Machine achieved the highest macro-averaged recall of 55.34% and F1-score of 56.87%.

These results indicate that no single classifier performed best across all evaluation metrics. Naive Bayes and Random Forest recorded comparatively lower macro-averaged F1-scores. The results also suggest that class imbalance may have influenced model performance, particularly in identifying neutral and positive reviews.

A. Dataset Analysis

The collected dataset consisted of 1,777 user reviews from five solar energy monitoring applications. The reviews were analyzed to understand the distribution of user feedback and the overall sentiment patterns. The dataset contained 1,133 negative reviews, 206 neutral reviews, and 438 positive reviews, based on rating-derived sentiment labels. This analysis provided an overview of user satisfaction and the feedback patterns present in the collected reviews.

Table 1. Dataset Characteristics

Sr. No.	Parameter	Result
1	Number of applications	5
2	Total reviews collected	1,777
3	Reviews after preprocessing	1,777
4	Missing records	0
5	Duplicate application-review records	0
6	Manually annotated reviews	0
7	Language distribution	1,575 English (88.63%); 196 detected as other languages; 6 unknown
8	Data collection period	15 April 2022 – 28 October 2026

The dataset contained 1,777 user reviews collected from five solar energy monitoring applications. The sentiment distribution was imbalanced, with 1,133 negative reviews, 438 positive reviews, and 206 neutral reviews. Negative reviews formed the largest category, while neutral reviews represented the smallest category. A stratified 80:20 train-test split was used to preserve the class distribution in both subsets. No class-weighting or resampling technique was applied in the reported experiments.

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B. **Sentiment Classification Analysis**

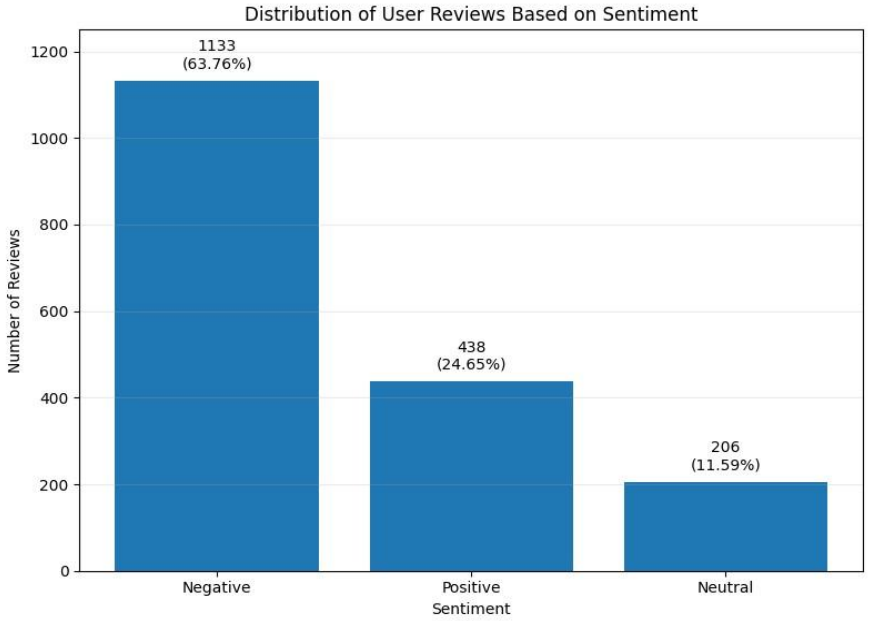


Figure 3: Sentiment Distribution Graph

Figure 3 illustrates the distribution of sentiment categories among the collected reviews. Based on rating-derived labels, 1,133 reviews were classified as Negative, 206 as Neutral, and 438 as Positive.

Table 2. Comparative Evaluation of Sentiment Classification Models

Sr. No.	Model	Accuracy	Precision	Recall	F1-Score
1	Naive Bayes	71.35%	53.36%	44.02%	43.33%
2	Logistic Regression	75.84%	79.05%	53.45%	55.66%
3	SVM	73.88%	62.19%	55.34%	56.87%
4	Random Forest	73.03%	56.60%	50.44%	49.87%

The sentiment labels used in this study were derived from user ratings rather than manual human annotation.

Reviews with 1–2 stars were classified as Negative, 3-star reviews as Neutral, and 4–5-star reviews as Positive. Therefore, the reported results measure the ability of the machine learning models to predict rating-derived sentiment categories.

Among the evaluated models, Logistic Regression achieved the highest accuracy of 75.84% and the highest macro-averaged precision of 79.05%. SVM achieved the highest macro-averaged recall of 55.34% and F1-score of 56.87%. These results indicate that different classifiers performed differently across the evaluation metrics. The findings should be interpreted in the context of rating-derived proxy labels.

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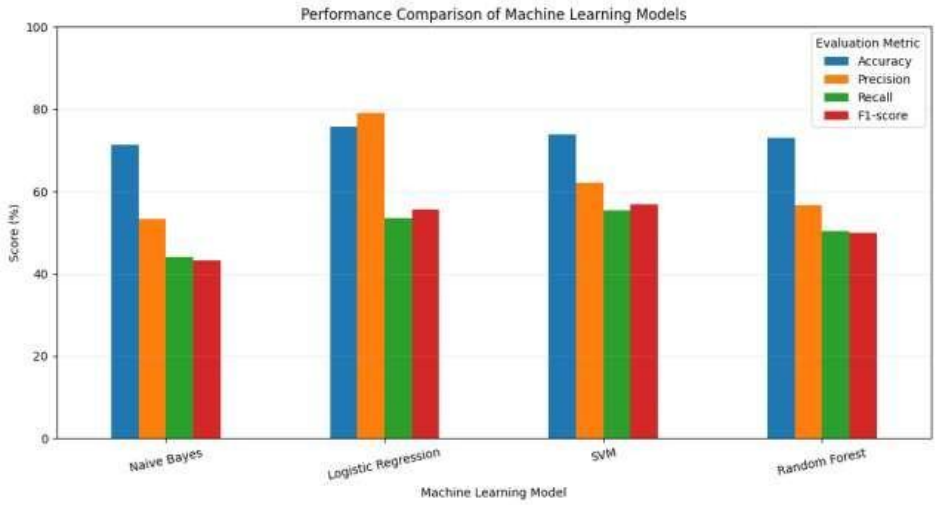


Figure 4: Model Performance Comparison Graph

C. Aspect-Level Satisfaction Analysis

Table 3. Keyword-Matched Aspect Mentions and Rating-Derived Sentiment Counts

Sr. No.	Aspect	Reviews	Positive	Negative	Neutral
1	Interface Usability	80	29	41	10
2	Real-Time Monitoring	437	83	290	64
3	Data Accuracy	62	15	38	9
4	Inverter Connectivity	253	37	192	24
5	Notifications	50	8	34	8
6	Application Performance	250	32	177	41
7	Technical Support	185	29	141	15
8	Compatibility	151	19	112	20

Aspect mentions were identified using predefined keywords, and sentiment categories were assigned based on the overall user ratings. A single review could be associated with multiple aspects; therefore, the total aspect mentions may exceed the number of collected reviews.

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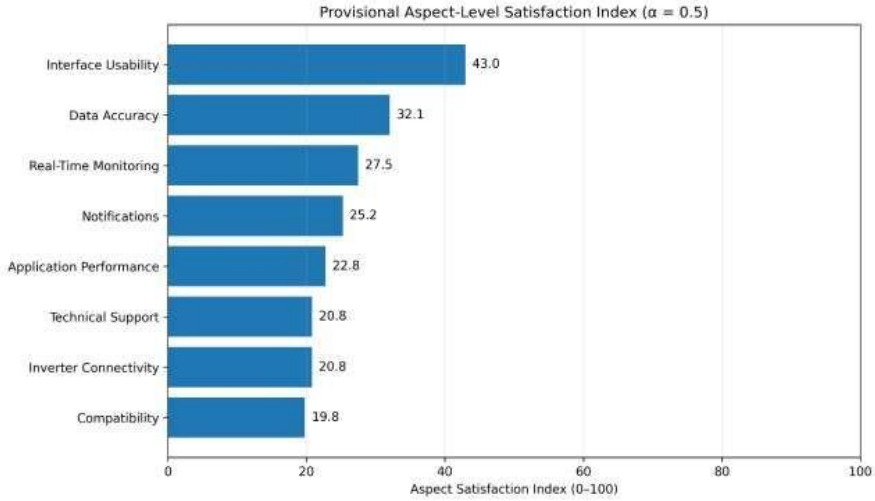


Figure 5. Provisional Aspect-Level Satisfaction Index of Solar Energy Monitoring Application Features

The aspect-based analysis identified the major features discussed in user reviews, including Interface Usability, Real-Time Monitoring, Data Accuracy, Inverter Connectivity, Notifications, Application Performance, Technical Support, and Compatibility. The results provide an overview of user feedback across these application features based on keyword matching and rating-derived sentiment categories. Figure 5 presents the provisional satisfaction scores of eight major features of solar energy monitoring applications. Interface Usability achieved the highest ASI score of 42.97, indicating comparatively more favourable rating-derived feedback for this aspect. Compatibility recorded the lowest ASI score of 19.78, suggesting a potential area for improvement. Inverter Connectivity and Technical Support also showed relatively low scores.

These findings highlight application features that may require further attention. However, the ASI is exploratory because both its sentiment and rating components are derived from the same user ratings. Therefore, it should not be interpreted as an independently validated measure of user satisfaction.

D. Rating and Sentiment Comparison

The relationship between numerical user ratings and textual sentiment is an important aspect of user satisfaction evaluation. In this study, numerical ratings were used to generate the sentiment labels for model training and testing. Therefore, an independent comparison between rating values and text-predicted sentiment was not performed. Further experiments using independently annotated textual sentiment are required to evaluate disagreements between numerical ratings and written user opinions reliably.

E. Discussion

The experimental results demonstrate that traditional machine learning algorithms can be used to classify sentiment categories in solar energy monitoring application reviews using TF-IDF features. Among the four evaluated classifiers, Logistic Regression achieved the highest accuracy of 75.84%, while SVM obtained the highest macro-averaged F1-score of 56.87%.

The findings also highlight differences in model performance across evaluation metrics. Although Logistic Regression achieved higher accuracy and macro-averaged precision, SVM obtained the highest macro-averaged F1-score, indicating the strongest combined precision and recall performance among the evaluated classifiers.

The aspect-level analysis identified Real-Time Monitoring, Inverter Connectivity, and Application Performance as frequently discussed features. The results provide useful insights into the areas that receive user feedback. However,

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aspect identification was based on predefined keywords, and sentiment categories were derived from overall star ratings rather than independently detected aspect-specific opinions.

The proposed ASER-NLP framework combines rating-based sentiment classification, machine learning evaluation, and keyword-based aspect analysis to organize user feedback. Its findings should be interpreted with consideration of the dataset size, rating-derived labels, and keyword-matching approach. Future research can improve the framework through manual sentiment annotation, contextual language models, and independent aspect-level sentiment analysis.

IV. CONCLUSION

This study presented an NLP-based approach for analysing user reviews and evaluating satisfaction with solar energy monitoring applications. A dataset of 1,777 reviews from five applications was examined using TF-IDF feature extraction and four machine-learning classifiers: Naive Bayes, Logistic Regression, Support Vector Machine, and Random Forest.

Among the evaluated models, Logistic Regression achieved the highest accuracy of 75.84%, while Support Vector Machine obtained the highest macro-averaged F1-score of 56.87%. These results indicate that different evaluation metrics can highlight different aspects of classifier performance. The analysis also identified eight application-related aspects, including real-time monitoring, inverter connectivity, application performance, and technical support. The aspect-level findings showed recurring user concerns, particularly in real-time monitoring and inverter connectivity.

The proposed Aspect-Level Satisfaction Index (ASI) provided an exploratory way to summarise aspect-related satisfaction. However, because both sentiment labels and rating information were derived from the same star ratings, the index should be interpreted as provisional rather than as an independent measure of satisfaction.

The study has limitations. Sentiment labels were generated from user ratings rather than manual human annotation, and aspect categories were identified through keyword matching. Furthermore, language-specific processing was not applied to non-English reviews. Future work can use manually annotated multilingual datasets, more advanced aspect-based sentiment methods, and contextual models such as BERT to examine whether classification quality and aspect-level interpretation can be improved.

Overall, this study demonstrates how review-based NLP and traditional machine-learning techniques can help identify user feedback patterns and potential improvement areas in solar energy monitoring applications.

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