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Research Article

Analysing Public Perception of Solar Energy: An Explainable AI Sentiment Analysis Approach

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Abstract: Addressing the contemporary climate crisis is the need of the hour to protect both people and the planet. As countries embark on green energy revolution, focussing on achieving the United Nations (UN) 2030 agenda for Sustainable Development, guaranteeing universal access to affordable, reliable, and modern energy services stands out as an important goal. As part of the implementation of this goal, solar panel installation scheme has been undertaken by the government of India to encourage widespread adoption of green energy. This research work proposes an effective method to assess the acceptance of this scheme among users and the broader audience. User comments/ feedback from various social networking sites are analysed in this research work using Machine Learning techniques along with Explainable Artificial Intelligence (XAI) to make the machine learning models' predictions more transparent. OpenAI Generative Pre-trained Transformer (GPT) language model is also used to automatically identify key implementation challenges of the scheme by creating a concise summary of the feedback shared by the users. This insight, based on the pain points of the users, can further help in providing recommendations and suggestions to appropriate stakeholders to improve the success rate of this scheme. Five machine learning models- Logistic Regression, Random Forest, Decision Tree, Extreme Gradient Boosting, and Stochastic Gradient Descent- were compared to choose the right technique for sentiment analysis. Among them, Logistic Regression and Stochastic Gradient Descent achieved an accuracy of 93% in predicting the sentiment. Our analysis showed around 63% of user feedback was positive indicating the public acceptance of green energy projects in India despite higher initial investments. The methodology and framework developed during this research work have immense reusability across similar government schemes (where transparency in sentiment analysis and sensitivity of public data are critical) in assessing their effectiveness and identifying areas where improvements are required.

Keywords: ***Explainable Artificial Intelligence; Opinion Mining; Panel Scheme; PM Surya Ghar Muft Bijli Yojana; Rooftop Solar Sentiment Analysis; Sustainable Development Goals***

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1. Introduction

As countries (both developed and developing countries) work towards achieving the United Nations' 17 Sustainable Development Goals (SDGs), goals 7 and 13 emphasise environmental sustainability and climate change, focussing on the transition to greener, cleaner, and renewable energy sources. Solar panel is a good green energy option which harness the power of the sun, contributing to the fight against climate change by generating clean energy and reducing greenhouse gas emission. They also mitigate the intensity of heat waves and conserve water compared to traditional thermal plants, promoting energy efficiency, reducing dependency on fossil fuels, and fostering a cleaner, greener environment for sustainable development and energy security [1]. Understanding this advantage, in February 2024, Indian Government

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launched PM Surya Ghar: Muft Bijli Yojana, a rooftop solar plant scheme[1], to provide solar power solutions to households nationwide, with subsidies and loan options. Investment of over Rs. 75,000 crores is planned as part of this scheme which will cover close to 10 million households with 300 units of free electricity every month. As measuring and tracking the success of this large scheme is very critical for the green energy mission, this research work aims at studying this initiative thoroughly (as a case study) to analyse its impact and effectiveness using various AI techniques.

One of the key requirements for this analysis to produce meaningful insight is to have quality input data. With the rapid expansion of social media, enormous volume of data is generated every second. This data from online platforms such as, review sites, discussion forums, X, blogs, microblogs, comments and messages on social networking sites, is extensively used by individuals and organisations for information gathering and decision making[2]. Hence, mining meaningful insights from such unstructured data is invaluable for critical decision-making. 'Sentiment analysis' or 'Opinion mining' is one such area that helps in identifying and analysing the sentiments, feelings, emotions, opinions, and views expressed about entities such as products, services, individuals, organisations, policies, events, or any other topic [2-3]. Sentiment analysis can be applied in diverse fields like social media monitoring, market research, customer service enhancement, politics, which helps to improve decision making, elevate customer satisfaction, and overall success rate of the system [4]. This research work thus uses social media data and sentiment analysis as the key building blocks of the proposed system.

Effective implementation of Sentiment analysis is the next big challenge. AI is revolutionising the way sentiment analysis is done and improves the efficiency of sentiment analysis significantly [5]. AI helps in automatically detecting sentiments from textual/ visual/ audio data using Natural Language Processing (NLP) and Machine Learning (ML) techniques. Also, it further helps in making right decisions by creating actionable insights. In the recent years, Explainable AI (XAI) has become the latest research topic due to the growing demand for transparency in AI systems. Traditional machine learning models are often like black boxes that do not offer insights into the rationale behind their predictions, making them difficult to understand and interpret their behaviour. In contrast, XAI approaches aim to provide transparent and interpretable machine learning models, ensuring trustworthiness, understandability, and accountability [6]. This makes using XAI in AI based sentiment analysis a great choice as transparency is very critical when pubic sentiments are analysed for making policy changes which will have largescale impact.

In this research, public opinions and comments from various social media platforms about solar panel implementation scheme in India are analysed using AI/ML techniques. A structured approach is used in selecting the appropriate AI/ML algorithm suitable for the implementation. XAI based model interpretations (first of its kind in this context), and OpenAI model based text summarisation are also added to improve the openness, effectiveness and usability of the system. Outcome of this proposed system will provide better insight on the public sentiment/ perception of the solar panel implementation scheme and a comprehensive report which can be used by policy makers to take course correction as required.

Various sections of the paper are outlined as follows: Section 2 reviews prior research on solar panel implementations and XAI. Section 3 elaborates on the research methodology, outlining the various steps involved in this research. Theoretical and visual representation of the research results are depicted and discussed in Section 4. Section 5 concludes the paper by summarising the significant contributions and outcomes of this research and providing recommendations for future research.

2. Literature Review

This section of the paper presents the various researches done in the areas of solar energy and XAI related to sentiment analysis and its model prediction.

[1] Ministry of New and Renewable energy, Government of India, "PM Surya Ghar: Muft Bijli Yojana - National Portal", Available: https://www.pmsuryaghar.gov.in/.

[2] Meltwater and We are Social, "Digital 2024: Global overview report", 2024, Available: https://datareportal.com/reports/digital-2024-global-overview-report.

2.1. Sentiment Analysis on Public Perception of Solar and Other Renewable Energy

The exploration of several research papers on sentiment analysis in solar energy and other renewable energy sources shows varying public perceptions, most of them with positive public sentiments revealing public acceptance of these energy sources. A research work [7] that analysed both editorial publications and social media found that sentiments toward solar power are positive in both cases. Another research work [8] aimed at identifying factors influencing customers' attitudes towards solar energy products in India found that green purchasing behaviour and government initiatives positively influence customers' attitudes. In a research work [9], a RoBERTa-based sentiment classification model was used to analyse public opinion on solar energy across the United States based on tweets extracted in 2020. The results showed more positive sentiment in the Northeast region compared to the South region and also in states that have well-designed and transparent policies for statewide net metering, renewable energy incentives, and solar market maturity.

Even in one of the older studies conducted in 2017-2018 [10], the analysis of posts collected from the subreddit 'Renewableenergy' showed improved public perceptions of renewable energy resources due to the decrease in the cost of solar panels and the generation of new job opportunities. The analysis of Instagram posts in another work [11] highlighted that solar energy was one of the fastest growing and most preferred renewable energy technologies, widely accepted on a socio-political level. A separate work [12] done on various energy sources using data from Facebook, Instagram, Quora, and Reddit revealed strong positivity towards renewable energy, particularly hydro and solar power. Hydropower was favoured for its minimal environmental impact, and solar energy was favoured due to its contributions to fighting climate change, as well as its accessibility and advancements in technology. Results of another study [13], based on a survey from Swiss respondents, expressed the concern that attitudes towards solar power decrease with infrastructure and large-scale installations.

A study [14] that analysed questions from Naver, one of the largest search engines in the Republic of Korea, between 2008 and 2020 found that the predominantly used words associated with renewable energy were 'solar power', 'power generation', 'energy', and 'wind power' and the predominantly asked questions were connected with the installation of solar power facilities and the power generation methods for different energy resources. Another study [15], conducted by collecting tweets from 2014 to 2016 in Alaska, demonstrated an increased use of keywords such as, 'sun', 'power', and 'nuclear' showing Alaskans' growing positive attitudes towards renewable energy.

Tweets collected over a three-month period from September to November 2020, from Europe, Australia, and the USA, were analysed to understand people's interests and sentiments on GHG (Greenhouse Gas) emissions and their attitudes towards various renewable energy resources [16]. This research analysis predicted that solar and wind energy would emerge as the prominent energy sources in the future. A similar research work [17] which analysed tweets about various energy sources, revealed people's positive attitudes toward renewable energy sources, particularly solar power and wind power, that fetched the highest number of tweets.

A custom survey and a few public social media datasets were used in a research work [18] that demonstrated public acceptance and understanding of various renewable energy sources. When tweets connected with climate change and energy issues from Spain and the U.K. were analysed from January to June 2019 [19], it was found that the messages in the U.K. were not as negative as those in Spain, but renewable energy sources were viewed positively. Another study [20] that used sentiment and correlation analyses of data from Reddit showed that renewable energy and nuclear energy evoke positive emotions in a complementary manner but are perceived as substitutes for negative emotions.

Several research works have conducted bibliometric analysis of various publications on solar energy. A work [21] discussed various types and generations of solar photovoltaic (PV) technologies along with their applications. The analysis of research papers on solar energy published between 2011 and 2021 from the Scopus online database revealed that 72% of the papers were related to SDG7 ('affordable and clean energy'). Another bibliometric study [22], conducted on scientific publications from the Scopus database between 2000 and 2019, showed increase in the number of solar energy articles, indicating its significant growth. In a few studies [23-24], bibliometric analysis conducted using publications from the Web of Science database showed an increase in solar energy publications, with China and the USA as major contributors.

Another literature review [25] conducted between 2009 and 2018 highlighted that fossil fuels continued to contribute much to the worldwide electricity production despite the wide availability of solar energy, which could also be a suitable substitute for fossil fuels. The cause of this discrepancy was a lack of awareness regarding renewable energy technologies, emphasizing the importance of raising awareness about these renewable energy sources.

Review of the above-mentioned research works indicates Solar Energy started gaining public acceptance in the recent years. This trend change is because of various initiatives from the government, reduction in the infrastructure cost, new job opportunities, etc. Except few, most of the research works were done outside India. In this research work, the Indian government's recent initiative – "PM Surya Ghar: Muft Bijli Yojana, a rooftop solar plant scheme" is analysed based on the feedback collected from various social media platforms. Machine Learning models used in this research work also differ from the existing research works reviewed earlier which helps in improving the accuracy of sentiment classification.

2.2. Research Works in XAI

There are various researches that have employed different XAI techniques across multiple domains, along with various machine learning algorithms.

XAI has been applied in only a few research works related to solar energy. The XAI techniques- SHAP (SHapley Additive exPlanations), Anchors, and DiCE (Diverse Counterfactual Explanations) - were used in a research work [26] to interpret a Multi-layer Perceptron (MLP) model for identifying faults in PV systems and SHAP exhibited a high degree of stability and consistency. In another research [27], the features that most impacted the prediction of solar power output was interpreted using SHAP for each machine learning model (LightGBM, XGBoost, Random Forest) employed in the research separately. In a research work [28] that focussed on enhancing the prediction accuracy of Power Conversion Efficiency (PCE) in organic solar cells, XAI techniques- LIME (Local Interpretable Model-agnostic Explanations) and SHAP- were used to find out the key features and their contributions to the models' output, as well as the optimum combination of feature values that produced the highest PCE value. Another research [29] used ELI5 (Explain Like I'm Five) to explain the output of a solar photovoltaic power generation system, identifying each feature's contribution to the final prediction based on their weights.

A few researches in other domains that have utilised these XAI technologies are also mentioned. A study that aimed to detect software defects [30] used LIME and SHAP to offer interpretability of ML model predictions by analysing the impact of various features. In classifying restaurant reviews [31], LIME was employed to interpret the outcome of various ML classifiers and it was found that words were misunderstood and misclassified because the semantic relation between words and their context was not considered. In a work [32] that analysed datasets from Twitter, Facebook, and Reddit, LIME was used to provide in-depth insights into its interpretations. LIME was also applied in another research [33] to an attention-based LSTM model on texts related to LASIK surgery from Arabic tweets. Another study [34] applied LIME to a newsgroup dataset and SHAP to an IMDB dataset to interpret the predictions of several machine learning models.

There are several survey papers on XAI. A paper [35] provided a detailed overview of sentiment analysis techniques and XAI methodologies. The XAI taxonomy, methods, and future research opportunities were discussed in a few other papers [36-37]. There were several other literature review papers [38-42] that presented standard definitions and the need for XAI, different approaches, application domains, challenges, and future directions based on relevant research papers from academic databases covering the period from 2004 and 2022. Another paper [43] presented the applications of XAI methods, along with a manifesto of 27 problems divided into nine groups, with an aim to define and describe the open challenges in XAI research.

There is no direct research using XAI that analyses public perception of solar energy projects or any other projects that aid in decision making by policy makers. And this research is the first of its kind to integrate AI open models to enhance transparency in model behaviour and improve the decision-making process.

3. Methodology

This section thoroughly explains the methodology of the research conducted to achieve the following objectives:

- To analyse the impact of rooftop solar plant scheme in detail, including its pros and cons, for policy-making;
- To improve trust and transparency in machine learning models by gaining deeper insights into their predictions using XAI;
- To enhance the user experience by employing the latest OpenAI GPT language models for report generation.

The block diagram in Figure 1 describes the steps involved in this research work.

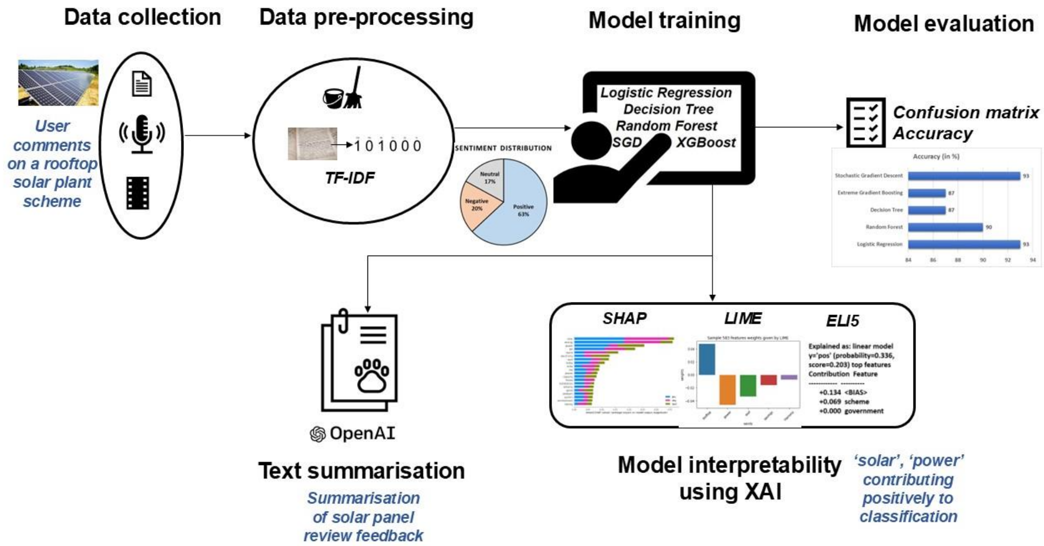

Figure 1. Block diagram showing the steps involved in the research

3.1. Data Collection

Comments and opinions on the rooftop solar plant scheme, 'PM Surya Ghar: Muft Bijli Yojana', are used as the input data for this research work. This was gathered for the period February 2024 to May 2025 from different online sources including X, Reddit, YouTube, Quora, and other discussion forums. Audio from related YouTube videos were converted to text using Google Speech Recognizer and used in this research work. Use of variety of input data (text, audio, video) is an important feature of this research, as it improves the accuracy by diversification. Around 1000 data records collected across different user profiles, different states across India, different formats, etc., were selected carefully for wider representation.

3.2. Data Pre-processing

The gathered data is then pre-processed to make it more meaningful for further analysis and exploration [44] by performing the following steps:

- Removal of duplicate records, hashtags, and URLs;
- Substituting single space for multiple spaces;
- Removal of stop-words like 'he', 'she', 'it', 'the';
- Converting various forms of a word into their root forms through lemmatization (Words like 'launch', 'launches', 'launched', 'launching' were converted to their root form 'launch').

Pre-processed data is then categorised into three sentiment classes: 'Positive', 'Negative', and 'Neutral'. Figure 2 shows the distribution of data records across these three classes. This classification prepares the data for efficient model training.

The TF-IDF ('Term Frequency – Inverse Document Frequency') vectorizer was used to transform the input textual data into a numeric representation [45]. In this vectorizer, the importance of a word is determined by comparing its frequency within the document to the number of documents that contain the word. This numeric vector representation of the data enables efficient application of AI/ ML algorithms in the subsequent steps.

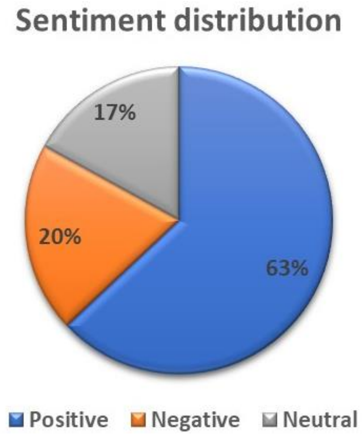

Figure 2. Sentiment distribution of data among three classes

3.3. Training ML Models

Following diverse machine learning models [46-47] were evaluated to understand their performance on the given input dataset. Training various ML models helps to identify the best model that suits the input dataset by comparing their performance:

- Logistic Regression,
- Decision Tree (DT),
- Random Forest (RF),
- Extreme Gradient Boosting (XGBoost) and
- Stochastic Gradient Descent (SGD).

These machine learning models were trained and tested using the input dataset containing user comments on the solar scheme to predict user sentiments.

3.4. Model Evaluation

The metrics employed to assess the performance of machine learning models [48-49] on the input dataset are explained below.

- 'Confusion Matrix' measures the performance of both binary and multi-class classification problems and is depicted as an N x N matrix, where N represents the number of target classes. This matrix describes predicted target values against actual target values. Sample 'confusion matrix' depicting a binary classification problem with 'Positive' and 'Negative' as the two classes is given in Figure 3.

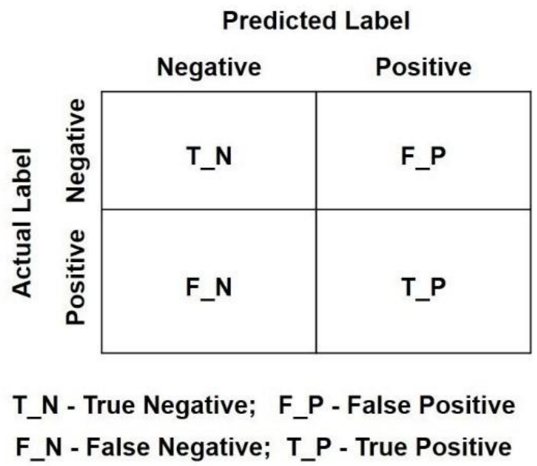

Figure 3. Confusion matrix for binary classification

- The calculation of other metrics from the above confusion matrix is given in Table 1.

Table 1. Performance measure calculation

Metric	Formula
Accuracy	$(T\_N + T\_P)/(T\_N + F\_P + F\_N + T\_P)$
Precision	$(T\_P)/(F\_P + T\_P)$
Recall	$(T\_P)/(T\_P + F\_N)$
F1-Score	2 * (Recall * Precision) / (Recall + Precision)

All the five selected ML models were subjected to these two performance evaluation criteria to identify the suitable model(s) for generating the final result.

3.5. Model Interpretability Using XAI

Traditional machine learning and deep learning approaches function like a black box which means their predictions are not understandable to humans. But Explainable AI (XAI) approaches make those AI models understandable, transparent, and trustworthy by providing explanations for predictions, enabling humans to understand the internal working mechanisms and the factors influencing the outcome of the model. Following three popular XAI Python frameworks [50-52] were chosen to interpret model predictions in this work, considering their diverse features in understanding the inner workings of the models.

- SHAP (SHapley Additive exPlanations)
- LIME (Local Interpretable Model-agnostic Explanations)
- ELI5 (Explain Like I'm Five)

These techniques are integrated into this research to provide insights into model outcomes both globally and locally, aiming to understand the factors influencing sentiment classification of user feedback regarding solar panel implementation. This insight also helps in highlighting the major concerns raised by the users while summarising the feedback.

There are various other XAI frameworks/tools available in the market, such as Shapash (SHAP-based dashboarding), Captum (PyTorch-based), Integrated Gradients, DeepLIFT (Deep Learning Important FeaTures), Grad-CAM (Gradient-weighted Class Activation Mapping), LRP (Layer-wise Relevance Propagation), GraphLIME (Graph LIME), What-If Tool (TensorBoard plugin), AIX360 (AI Explainability 360), OmniXAI (Omni-directional XAI), InterpretML, PFI (Permutation Feature Importance), PDP (Partial Dependence Plot), ALE (Accumulated Local Effects), etc. For this research work, SHAP, LIME and ELI5 are selected over the others for their applicability, simplicity, scalability/reproducibility and novel algorithmic and deeper insight support.

3.6. Text Summarisation Using OpenAI

OpenAI, a leading AI research organisation, provides Python API that allows users to easily access their AI models and integrate them in their applications. This enables them to perform tasks like language recognition, generation, question answering, etc. However, in this research, only the text summarisation facility is used to generate a summary report based on the user feedback and XAI interpretations of sentiment classification. This summary can help in understanding the challenges and difficulties expressed by the users in implementing the solar panel system so that these challenges can be addressed effectively. GPT language model is used for this report generation purpose.

3.7. Tools/ Libraries Used

The following are the important Python libraries used in implementing the various modules involved in this research work:

- nltk - Natural Language Toolkit,
- sklearn - Scikit-learn,
- shap (SHapley Additive exPlanations), lime (Local Interpretable Model-agnostic Explanations), eli5 (Explain Like I'm Five) - XAI Python frameworks for model interpretability and
- openai - GPT Generative Pre-trained Transformer, Large Language Model implementation.

4. Results and Discussion

Based on the model classification of the user feedback/sentiment on Solar panel scheme taken from various social media platforms, it is observed that majority (63%) of the people expressed positive views. This is very encouraging considering the diverse nature of India (cultural, social, economic, and geographical aspects, among others). Though there is scope for improvement based on the negative feedback (constituting 20%), care should also be given to the neutral users (17%) who are still not very impressed by the scheme. This indicates that apart from addressing the challenges faced by the users, policy makers should also spend considerable effort in communicating and clarifying about the significance of green energy and the government's encouragement through subsidy, logistics support, transparency in application process, etc.

Technical findings related to the ML model selection, XAI implementation and sample summary report are detailed in the following sub-sections and presented through charts.

4.1. Comparative Analysis of Model Performance

The performance of the five ML classifiers was evaluated using the input dataset, and their respective accuracies are compared in a graph (Figure 4).

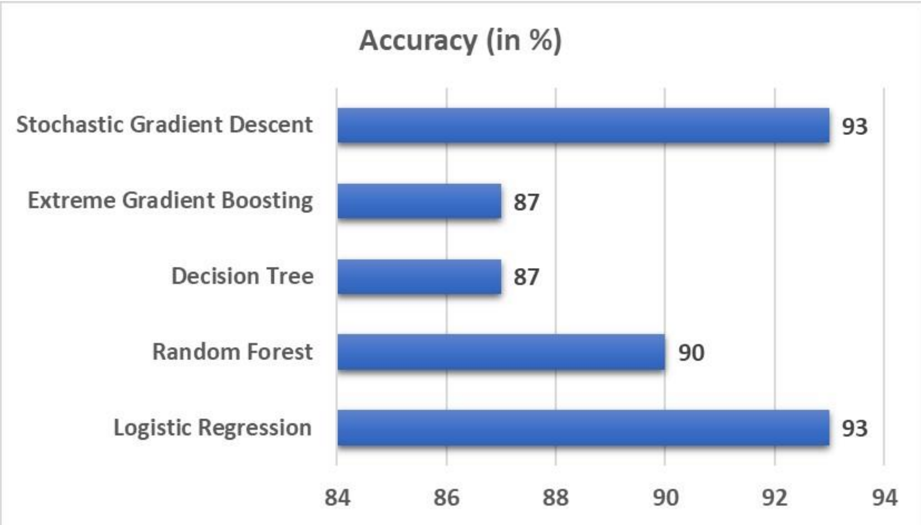

Figure 4. Accuracies of ML classifiers on the input dataset

It is observed from the graph that Stochastic Gradient Descent and Logistic Regression both achieved the highest accuracy of 93%. The other classifiers also attained considerable accuracy percentages.

The values of precision, recall and F1-Score (in percentage) for all the classifiers are shown in Figure 5 and they are also close to Accuracy percentages.

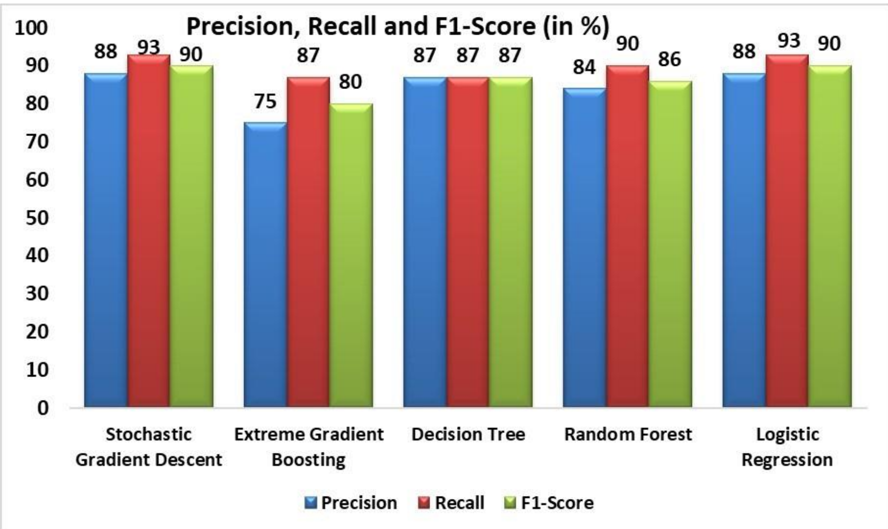

Figure 5. Precision, Recall and F1-Score of ML classifiers on the input dataset

The confusion matrices for all five machine learning classifiers are represented in Figure 6, with the 'actual class' as rows and the 'predicted class' as columns. The diagonal entries show the percentage of correct predictions of the three output classes: Positive, Negative, and Neutral.

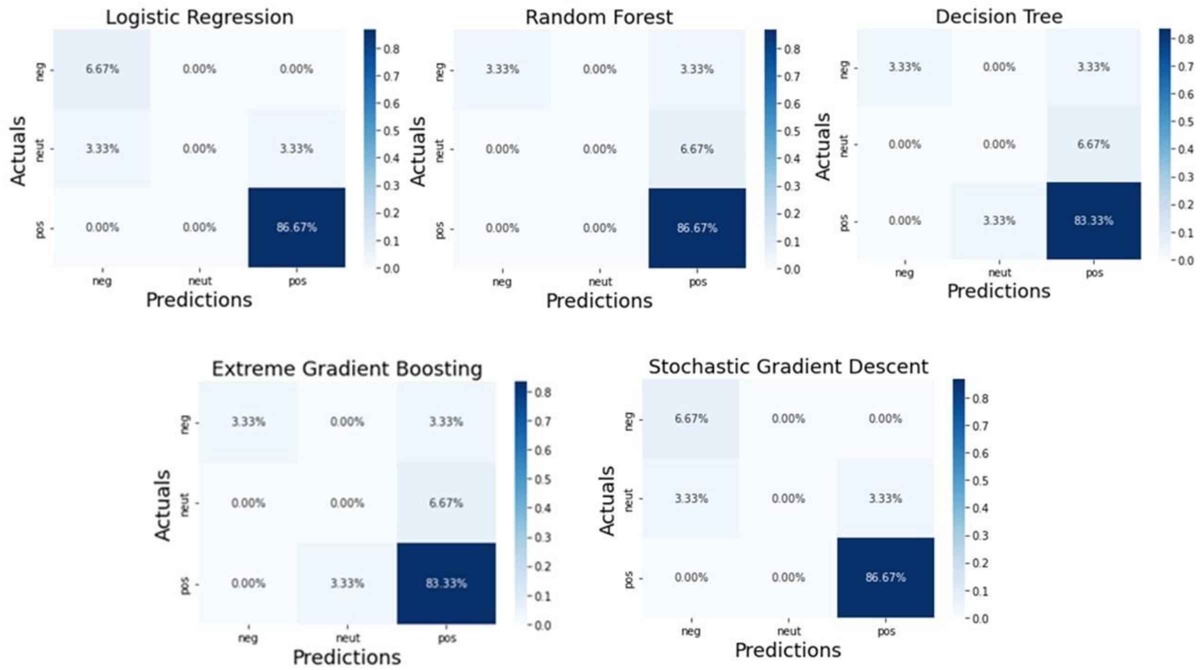

Figure 6. Confusion matrices of ML classifiers

The test results above, considering performance and accuracy values, demonstrate that Stochastic Gradient Descent and Logistic Regression models make more accurate predictions and are therefore the preferred models for the input dataset used in this research.

Since real-time dataset of user comments on solar panel scheme is used in this research and no other research work has used the same, direct comparison of system performance is not possible. Thus, the performance of various ML classifiers was compared to identify the right classifier for the input dataset.

4.2. Interpretability Insights

This section explains how XAI is used in understanding the reason behind the workings of ML algorithm. For this research work, three Python libraries- SHAP, LIME, and ELI5 are selected for ML algorithm interpretation. The following user feedback is used as sample in the subsequent sections while explaining how these libraries work in interpreting the ML algorithm prediction and different ways each library presents the interpretations.

Text used for explanation:

- Positive feedback - *"Turn your roof into a savings account! Harness the power with rooftop solar."*
- Negative feedback - *"There is confusion in availing subsidy by consumers. May be supplier is exploiting loop holes."*
- Neutral feedback - *"Can house owners install panels of their choice or they have to buy govt solar panels. What about AMC & service requirements."*

4.2.1. SHAP

SHAP is used to provide both local and global explanations of ML model predictions. Local explanations help to understand individual predictions whereas global explanations provide an overview of feature importance across the dataset.

Variable Importance Plot: Global Interpretation:

The Variable Importance Plot in SHAP provides global interpretation to help us understand the importance of each feature in the model prediction. The impact of a feature on the three classes- Positive ('pos'), Negative ('neg'), and Neutral ('neut')- is stacked to create the feature importance plot given in Figure

7. The features are ranked by their average Shapley values, with the most important features at the top and the least important ones at the bottom.

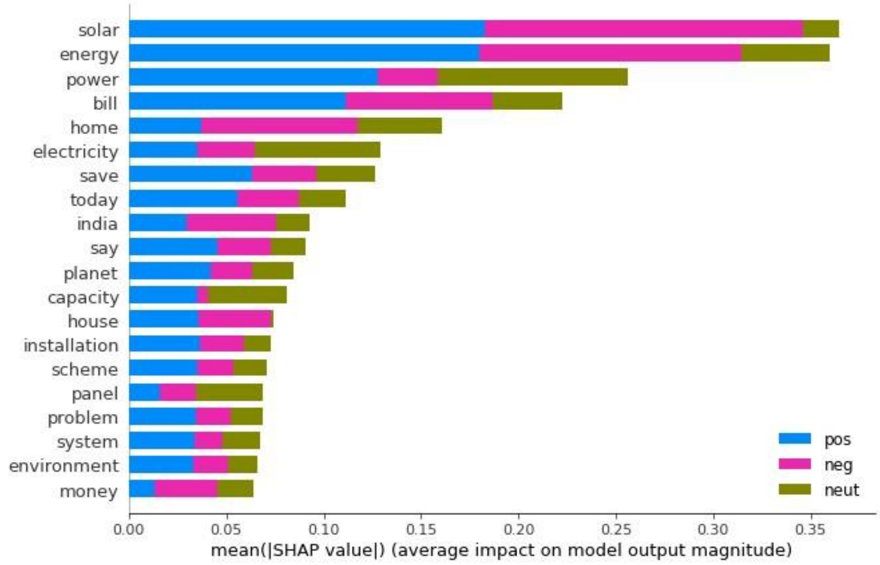

Figure 7. Variable importance plot

It is evident from Figure 7 that words like 'money' and 'panel' are hardly classified as Positive ('pos'). However, words like 'solar', 'energy', and 'power' are significantly contributing to the 'pos' classification. This may indicate "money" may be an important factor which negatively impacts the scheme's success.

Force_plot:

This plot helps in understanding the ML model behaviour for a specific data instance. Here, we will explain how the user feedback - *"Turn your roof into a savings account! Harness the power with rooftop solar."* is classified and how each feature in this feedback contributes to the overall sentiment of the sentence (in Figure 8).

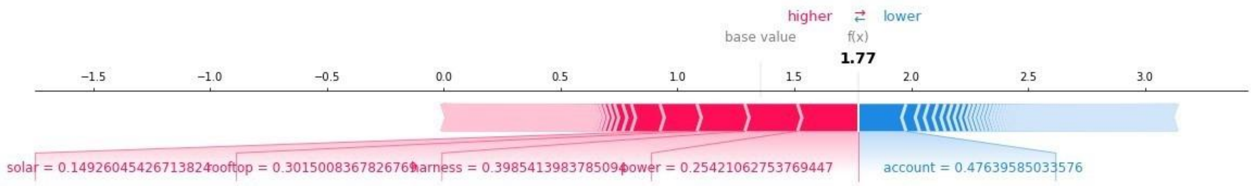

Figure 8. Force_plot for an instance (positive feedback)

In this plot, the model's predicted probability (predict_prob) is 1.77. Features that increased the model score are shown in red colour, whereas those that decreased the score are shown in blue colour. The larger the arrow, the greater the impact of the feature on the output.

This interpretation explains clearly how each feature is contributing to the overall sentiment classification and will help us to identify any potential issues with the ML algorithm performance, establish trust in the Model prediction and fix any biases based on the features importance assigned to each word.

4.2.2. LIME

There are many visualisation functions available in LIME to generate local explanations for predictions. The prediction for the above text with positive user feedback is explained below. The actual class of the text, along with the predicted class from the black box model and the prediction probabilities for the three output classes, are shown in Table 2.

Table 2. Predicted and actual classes for the sample (positive feedback)

Text: 'Turn your roof into a savings account! Harness the power with rooftop solar.'
Probability (Negative) = 0.11394541736915417 Probability (Neutral) = 0.09830979659398749 Probability (Positive) = 0.7877447860368584
Predicted Class = pos
True Class = pos

The explanation for various classes as a list of weighted features is given in Table 3. Only the first five most important features, that contribute the most to the class label, were chosen.

Table 3. Features contributing to each class along with their weights

List of weighted features related to class 0, 'neg'	List of weighted features related to class 1, 'neut'	List of weighted features related to class 2, 'pos'
'roof', 0.08272750746800571	'rooftop', 0.0477044791415446	'power', 0.07421802475415275
'solar', -0.06790598009987386	'power', -0.04629326026447198	'solar', 0.0670418570722956
'rooftop', -0.059696391948005086	'roof', -0.03353139021932733	'roof', -0.048072729040244594
'power', -0.029735832899963503	'savings', -0.015827983653484437	'savings', 0.04143601545083258
'Harness', -0.025572412668199245	'Harness', -0.00710446957896334	'Harness', 0.03199007277297808

It is important to note that the words which are positive towards one class may be negative towards another class. For example, 'power' is positive towards classification of 'pos' but negative towards the other two classes, 'neg' and 'neut'.

Local Interpretability Prediction:

Another visualisation for the same instance (positive feedback) is shown in Figure 9. The graph on the left shows the prediction probabilities for sample 13 from the input dataset as 11% negative, 10% neutral, and 79% positive. The next three pictures show the feature importance scores for this specific sample. In relation to 'pos' classification, 'power' and 'solar' have 7% feature importance score, followed by 'savings' with 4%. For each class, words on the right side of the line are positively contributing to the classification of that particular class, and words on the left are negatively contributing to its classification.

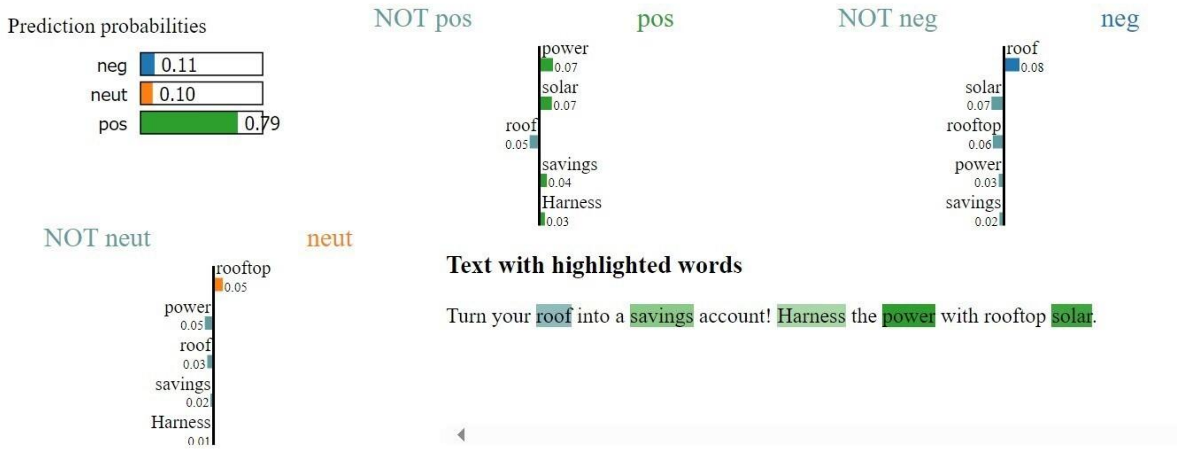

Figure 9. Local interpretability prediction of the positive sample

Interpretation of a NEGATIVE user feedback:

Sample data instance which is classified as Negative by the ML algorithm is interpreted using LIME as below (Table 4). Text sample used for analysis is "There is confusion in availing subsidy by consumers. May be supplier is exploiting loop holes."

Table 4. Predicted and actual classes for a negative sample

Text: 'There is confusion in availing subsidy by consumers. May be supplier is exploiting loop holes'
Probability (Negative) = 0.7466698623543641 Probability (Neutral) = 0.08943578593877935 Probability (Positive) = 0.16389435170685662
Predicted Class = neg
True Class = neg

First graph in the below picture (Figure 10) shows the prediction probabilities for the given sample data. It is classified as 75% Negative, 9% Neutral and 16% Positive, indicating the overall sentiment is Negative.

Subsequent graphs further explain the overall classification and help in understanding how the feature importance score of each word influences the classification. As explained earlier, words on the right side of a classification line have positive impact while the left side words have negative impact for the given classification. In the sample data, word "consumers" contributes to the negative classification with impact in "negative" and "not positive" categories. Similarly, the word "subsidy" also adds to the negative influence. This makes the overall Prediction Class of the given test as Negative considering the feature importance score of each word and their impact as inferenced by LIME.

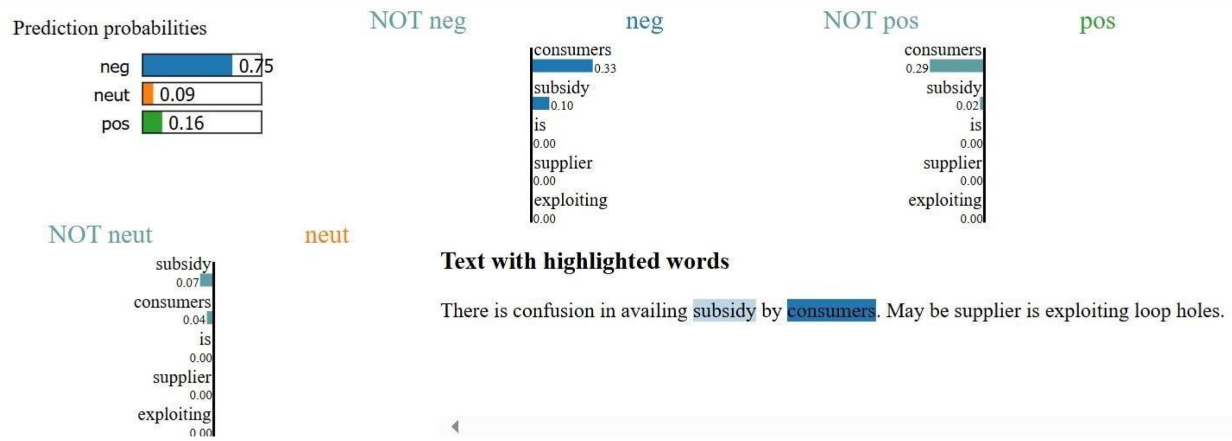

Figure 10. Local interpretability prediction of the negative sample

Interpretation of a NEUTRAL user feedback:

Similar to the inference of sample Positive and Negative classifications, Neutral classification is analysed using the below data instance (Table 5). The sample text is "Can house owners install panels of their choice or they have to buy govt solar panels. What about AMC & service requirements."

Table 5. Predicted and actual classes for a neutral sample

Text: 'Can house owners install panels of their choice or they have to buy govt solar panels. What about AMC & service requirements.'
Probability (Negative) = 0.23232590456980706 Probability (Neutral) = 0.40604354324311 Probability (Positive) = 0.36163055218708295
Predicted Class = neut
True Class = neut

Below Figure (Figure 11) which shows the graphs from LIME helps in understanding how this sample data instance is classified as Neutral by the ML algorithm. First graph in the below figure shows the prediction probabilities for each of the classification, which indicates 41% probability for Neutral, 36% probability for Positive and 23% probability for Negative classification. This gives the overall classification as Neutral with the next option as Positive.

To help in understanding this classification further, subsequent graphs show feature importance score of each word and how it influences the overall classification. Graph which shows the Neutral classification has words – buy, panel, choice as major contributors along with other words with smaller contribution making the overall probability as Neutral. It is noted that, this sample instance indicates lack of awareness of the user which if addressed properly can turn into a positive case. This reasoning is further reinforced by the fact that the positive classification probability score is very close to the Neutral score. This inference helps in identifying Neutral cases (with high positive influence) as issues which can be easily addressed (compared to the negative cases) as they are mainly because of lack of awareness or indecision.

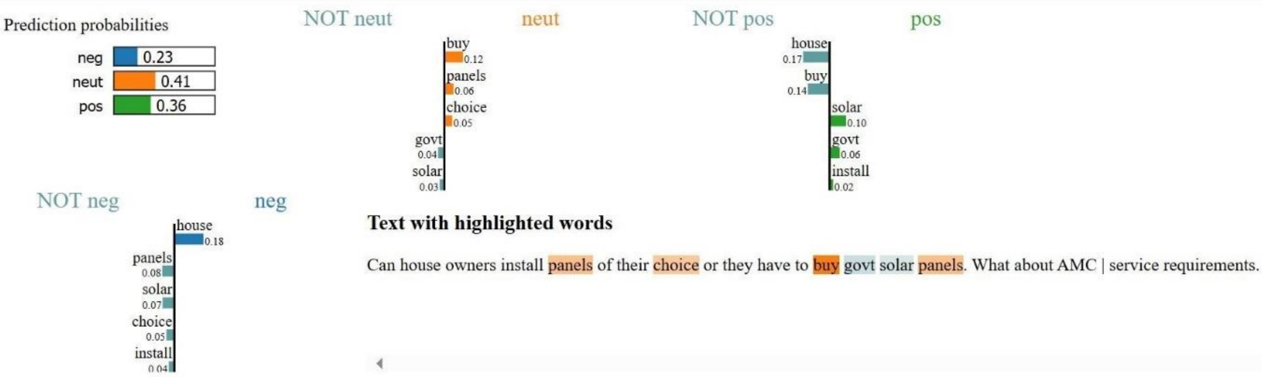

Figure 11. Local interpretability prediction of the neutral sample

4.2.3. ELI5

Global Explanation:

The global explanations on how the model predicts the test data for each class is given in Table 6, specifying the words that are predictive for each class.

Table 6. Global explanation on the model's prediction

y='pos' top features		y='neg' top features		y='neut' top features	
Weight	**Feature**	**Weight**	**Feature**	**Weight**	**Feature**
+0.169	india	+0.062	solar panels	+0.612	energy
+0.134	<BIAS>	+0.042	panels	+0.610	solar
+0.071	scheme	+0.035	people	+0.436	<BIAS>
+0.001	government	-0.144	electricity	+0.399	people
-0.023	electricity	-0.175	government	+0.367	panels
-0.199	solar	-0.300	scheme	+0.318	solar panels
-0.265	energy	-0.309	india	+0.229	scheme
-0.380	solar panels	-0.346	energy	+0.174	government
-0.409	panels	-0.411	solar	+0.167	electricity
-0.435	people	-0.571	<BIAS>	+0.140	india

Individual Predictions:

The model's prediction for the positive sample is given in Table 7, highlighting the features that contributed to individual predictions along with the probabilities associated with each class. This demonstrates which words had the greatest impact on the prediction and whether each word contributed positively or negatively to it. The label <BIAS> denotes the model's underlying bias towards or against a particular class.

Table 7. Prediction of the instance with positive feedback

Explained as: linear model					
y='neg' (probability=0.114, score=-2.065) top features		y='neut' (probability= 0.098, score=-2.230) top features		y='pos' (probability=0.788, score=1.253) top features	
Contribution	**Feature**	**Contribution**	**Feature**	**Contribution**	**Feature**
+0.406	roof	+0.200	rooftop solar	+0.385	power
-0.153	power	+0.114	rooftop	+0.359	savings
-0.193	harness	-0.146	harness	+0.314	solar
-0.197	savings	-0.151	solar	+0.308	harness
-0.241	rooftop solar	-0.208	savings	+0.116	rooftop
-0.254	solar	-0.333	roof	-0.010	rooftop solar
-0.288	rooftop	-0.341	power	-0.107	roof
-1.147	<BIAS>	-1.363	<BIAS>	-0.113	<BIAS>

Based on the above XAI model interpretations, it is understood that certain keywords are more influential in deciding the prediction outcome. For example, "money" is one of the keywords which influences the model to provide "negative" prediction. Such XAI interpretations can be used effectively in preparing the report on user feedback and improvement plan.

4.3. Text Summarisation

This step involves generating a text summary based on the challenges and concerns expressed by the users regarding solar panel implementation. Review comments from users along with XAI interpretations of sentiment classification were used in creating this feedback summary. Python API of OpenAI's GPT was used to generate this summary report and the output of the same is provided in Figure 12. This summary will help the concerned decision makers to understand the pain points of the users and take appropriate corrective actions as needed.

4.3.1. Technical and Ethical Considerations in GPT-Based Summarisation

Limitations of GPT Summarisation and Mitigations Strategies:

This research work uses GPT 4 from OpenAI for abstractive text summarisation. GPT uses transformer architecture which is a form of Neural Network, aimed at performing Natural Language Processing tasks like summarisation. Though this model is pre-trained with a massive amount of data for a high-quality output, inherently there are some limitations which need to be taken care while using this approach.

Hallucination: Summary may contain information which is not present in the original text as GPT may try to fill in gaps as required. This condition is avoided through strict prompts like "Summarise without adding any new facts".

Context Loss: This happens when the size of the input text is very large and it exceeds the limit of the GPT model - how much it can retain at once. In this research work, this problem is avoided by limiting the input text token size and also setting appropriate context in the prompt to make sure the tokens are parsed with the right context.

General Overview

Feedback on the scheme shows strong support for its environmental and economic potential, especially in reducing electricity costs and promoting energy independence. However, implementation concerns persist, particularly regarding subsidy clarity, vendor practices, and DISCOM cooperation. Neutral voices emphasized the need for better awareness and phased investments.

Key Negative Insights

- Policy Gaps: Lack of clarity on subsidy process and past scheme learnings.
- Vendor/Discom Issues: Exploitative pricing and delays in net metering.
- Cost & Infrastructure: High setup costs, battery maintenance, grid limitations.
- Access Concerns: Low-income/kuccha home exclusion; state-level political bias.
- Import Dependency: Limited local manufacturing affects sustainability
- Tech Challenges: No incentives for >3KW systems; poor energy-use matching.
- Public Trust: Skepticism around political motives and fairness

Action Plan

- Launch transparent, digital subsidy & net metering systems.
- Regulate vendors and incentivize DISCOM support.
- Promote inclusive policies for low-income homes.
- Invest in local solar supply chains.
- Enable hybrid smart systems with battery storage.
- Conduct nationwide awareness and technician training drives.

Figure 12. Summary of concerns from solar panel review feedback

Misrepresentation: When the GPT model is not clear on the intent of the request or tone required to generate the summary, the summary generated may contain misrepresented information. This may also happen in case of very specialized domains for which GPT may not have enough training data. This condition is avoided in this research work by strict prompts like – "Maintain professional tone which is suitable for senior decision makers/ government authorities".

Inconsistency: As GPT outputs are probabilistic, summary generated using the same content can vary if repeated. Also, the format of the output may not be consistent if it is not strictly dictated in the prompt. This condition is avoided by controlling the parameters of the prompt strictly regarding the expected output and the format.

As there are no standard evaluation metrics to compare the quality of the output and GPT model outputs are probabilistic, we have given at most importance to the above-mentioned mitigations to get the best and consistent results for the summary generation task. Prompt defined based on the above conditions is given below.

Generate a comprehensive summary report based on the following user feedback for the Solar Panel Implementation Scheme. The feedback has been classified into three categories: Positive, Negative, and Neutral. Also included the XAI model interpretation which highlights the top keywords influencing the classification.
The summary should include the following sections:

1. *General Feedback Summary:*

- *Provide a brief, overall summary of the general feedback, incorporating user sentiments from all three categories (positive, negative, and neutral).*

2. *Negative Feedback Summary:*
   - *List 5-7 key points outlining the negative feedback received from the users. Highlight the main issues and concerns expressed.*
3. *Improvement Plan and Suggested Action Items:*
   - *Conclude with a few lines discussing potential improvement plans and suggested actions that could be implemented based on the negative feedback.*

Please Summarise without adding any new facts. Maintain professional tone which is suitable for senior decision makers/government authorities.

Ethical Handling of User Data:

This research work adheres to the ethical, legal and social media platform specific requirements around privacy, consent and responsible use of user data by implementing the following measures.

User Privacy: This work does not store any identifiable details like name, profile data, profile picture, etc., while collecting and storing the user comments from various social media platforms. There is no direct quote of the user feedback, instead abstractive text summarization makes sure that the user feedback is paraphrased without any reference to the original text.

Consent and Platform Policies: Terms of Service (ToS) of each platform is adhered while collecting research data. This research work avoids publishing raw user data, attempting to re-identify users, use of user meta data, etc., to make sure data from platforms like X and Reddit are handled with care according to their set guidelines.

Bias and Representation: ML models can aggravate the representation bias based on how the sampling is done. It may be possible that the user feedback data may not accurately represent a diverse population. XAI techniques are used to examine the ML output and make sure the results are not skewed or biased based on vocal minorities.

5. Conclusion and Future Scope

In an era where the world recognises the urgency to create a more sustainable environment, integration of the renewable energy sources becomes highly essential. As we strive to combat climate change and prevent environmental degradation, understanding the public sentiments towards these technologies becomes invaluable for their promotion and implementation.

To facilitate this endeavour, this research work analyses user feedback data from various online sources like X, YouTube, and discussion forums related to the rooftop solar plant scheme. Collection and analysis of various types of input data (text, audio, video) from different sources is an unique aspect of this research. It was observed from the input data that 63% of people had positive views toward this scheme, while 20% with negative views, and the remaining 17% were neutral in their views.

When five ML classifiers (Logistic Regression, Decision Tree, Random Forest, Extreme Gradient Boost and Stochastic Gradient Descent) were evaluated on the input data, both Logistic Regression and Stochastic Gradient Descent achieved an accuracy of 93% in predicting the user sentiment. To get a deeper understanding of model predictions, three XAI techniques, SHAP, LIME, and ELI5, were employed. This research has thoroughly analysed how various features contributed to the classification of input data into three categories: Positive, Negative, and Neutral. It delved deep into both local and global interpretability, providing suitable examples to illustrate them. With the objective of understanding the concerns and challenges expressed by people regarding solar panel implementation scheme, user feedback with sentiment classification was summarised using OpenAI's Text Summariser tool. This is intended to help policy makers in understanding the issues that need to be addressed and the potential corrective actions that should be considered when new schemes are launched or existing schemes are revised.

In the future, user comments and feedback on various energy sources (solar, wind, etc.) can be combined with geospatial data to provide recommendations for choosing the right approach by considering various factors like geographical location, weather, cost, demand, and resource availability.

CRediT Author Contribution Statement

Japhne Anbarasan: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft and Writing – review & editing; Murugeswari Rathinam: Project administration, Resources, Supervision and Validation.

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