Explainable AI-Based Mapping of Public Sentiment on the Impact of Environmental Policies: A Cross-Regional Social Media Analysis

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Abstract—**Environmental sustainability policy relies on public attitudes to gauge acceptance and effectiveness, but traditional survey methods fall short in capturing emerging sentiment trends. This study applies machine learning and deep learning techniques, such as Bidirectional Encoder Representations from Transformers (BERT) and Long Short-Term Memory (LSTM), to analyze social media discussions about environmental policies. It turns unstructured data into structured sentiment values and evaluates them using an Extended Policy Analytical Framework. This framework includes region-specific analysis, event-related sentiment trends, emotion profiling, and explainable AI (SHAP-Shapley Additive Explanations) for clarity. BERT outperformed other models, achieving 0.97 accuracy, followed by random forest at 0.94. The results reveal notable sentiment changes around key global policy events, such as COP26 in India (+0.14) and U.S. carbon tax proposals (−0.15), along with emotional trends related to specific issues. A comparative regional analysis showed a performance drop of 5% to 7%, indicating regional differences. Overall, the research demonstrates that explainable AI-driven sentiment analysis can provide useful information to improve policy design and communication.**

***Index Terms*—sentiment analysis, impact on public sentiments, environmental policies, artificial intelligence, explainable AI, deep learning**

I. Introduction

With increasing environmental awareness, sustainability has become a major concern for societies around the globe. The impact of human activity on nature poses a serious problem, often accompanied by potential solutions ranging from technological advancements to legislative changes, business strategies, and educational efforts [1]. Human behavior, while often overlooked, plays a significant role as both a threat and an opportunity for positive change. Understanding human behavior is essential for making sustainability initiatives more effective, helping to tackle some of the toughest challenges facing the environment. Issues like deforestation, industrial pollution, and plastic waste have greatly contributed to climate change, biodiversity loss, and ecosystem damage, creating a need for more effective environmental policies [2].

Public opinion has become an essential input in policymaking on sustainability, with social media sites like X (formerly Twitter), Facebook, and Instagram being rich sources of real-time public discussion. These social media sites offer valuable insights into environmental issue perceptions, allowing quick societal response assessment. As examined by Guber [3], Digital forums in the current hyper-connected era serve as a participatory democracy, enabling citizens to express issues and shape the take-up and effectiveness of sustainability policies worldwide.

Efforts at sustainability, undertaken by organizations in various sectors, are vital responses to environmental concerns. Wang [4] established that 71.2% of sampled cities utilize grant proposals to fund sustainability projects, and 44% plan for these activities. Also, 62.5% of the cities employ information delivery systems aimed at enhancing sustainability. Throughout the world, countries have adopted policies such as carbon taxes, renewable energy, a ban on plastics, and emissions reduction schemes to control environmental destruction [5]. However, each policy calls for the support and cooperation of the public, which can be optimized using the public's perspective to solve problems in advance.

Sentiment analysis can be widely used across a variety of sectors, providing credible information that can inform policies and merit more thoughtful decision-making [6]. For instance, policymakers can utilize these findings to gauge public sentiment regarding proposed environmental policies or regulations, allowing them to engage with stakeholders more effectively. Companies can apply sentiment analysis to understand consumer views on their sustainability efforts [7]. This insight enables them to make informed decisions that enhance corporate social responsibility initiatives and resonate with consumer values. Also, the environmental activist non-profits can get advantage through the more impactful campaigns for cognizance to connect with people's emotions, leading to greater support and participation in their causes. These examples illustrate how sentiment analysis can be practically applied to make better decisions across different sectors and influence environmental policy worldwide.

The proposed study bridges the gap between environmental policymaking and public sentiment through AI-driven opinion analysis [8]. Policymakers often struggle to accurately measure public attitudes toward sustainability projects because traditional polling methods are slow and often inadequate. This research contributes by using advanced machine learning and deep learning techniques to analyze large amounts of social media data, creating a data-efficient and data-driven way to interpret public sentiment around environmental policies [9]. This study also offers a systematic framework for categorizing sentiment as positive, neutral, or negative, aiding policymakers, organizations, and stakeholders to gain deeper insights into societal reactions to various environmental regulations.

The goal of this research is to analyze the public's sentiment and emotional currents regarding environmental sustainability policies in regions and between regions, utilizing complex machine learning and deep learning models. It identifies emerging trends, areas of convergence and divergence, and emotional motivations for public acceptance of such policies [10]. It also assesses the impact of policy framing on shaping region-specific opinions. The integration of AI analytics, environmental science, and social science produces continuous, real-time, evidence-based policy surveillance and decision-making. Sentiment analysis successfully identifies subtle policy-cued language and affective cues within large social media data. With the aid of Shapley additive explanations (SHAPs) for explanation, the paper uncovers keyword-level framing effects. Generally, it makes data-driven findings available to enhance public participation, policy messaging, and sustainable program administration.

II. Literature Survey

AI-based sentiment analysis guides environmental policymaking and sustainability planning through public opinion monitoring in real-time based on large databases. Various approaches, including lexicon-based, Machine Learning (ML), and deep learning methods, have been developed to enhance sentiment classification, enhancing the precision of sustainability-linked policy assessments [11]. More recent advances, including the integration of transformer-based models like Bidirectional Encoder Representations from Transformers (BERT), have further augmented the ability to decipher complex text structures and emotional nuances in social media messages [12].

Several researchers have contributed to furthering sentiment analysis methods for sustainability as well as climate policymaking. In the study, Sham and Mohamed [13] utilized lexicon-based sentiment analysis using ML to examine climate change sentiment, developing a strong framework for interpreting public sentiments regarding climate policies. To enhance communication strategies for sustainability programs, Anderson and Sarkar [14] emphasized the need to capitalize on sentiment knowledge. On the other hand, Loureiro and Alló [15] carried out a cross-country sentiment analysis between the U.K. and Spain. It found regional variations in public attitudes toward energy policies. Toşa *et al*. [16] also analyzed the use of Twitter to facilitate sustainability and green consumption. It presents the role played by social media in influencing environmentally conscious behavior.

The extension of sentiment analysis into multimodal as well as domain-specific applications has further raised its importance in policy-making. In their study, Hasib *et al*. [17] showed the applicability of Deep Learning (DL) models for sentiment analysis of Twitter data to service sectors. It also highlighted the relevance of industry-based sentiment analysis. Their study further utilized sentiment analysis as well as topic modeling on the airline sector. The study highlighted the possibility of AI-based methods for sectoral analysis. In a similar context, Chowdhury *et al*. [18] as well as Miah *et al*. [19] proposed a cross-lingual sentiment analysis model using multimodal methods based on Large Language Models (LLMs), increasing the availability of AI for sentiment understanding across linguistic boundaries. These studies are potential studies for AI-based sentiment analysis in public engagement promotion, influencing targeted sustainability policy, and ensuring environmental regulations are consistent with public concerns and expectations.

Aside from significant advancements in sentiment analysis for environmental policy-making, there are still deficiencies in real-time tracking, cross-lingual sentiment analysis, and multimodal data fusion. Previous studies tended to use small textual samples, ignoring the multifaceted and dynamic nature of worldwide public opinion. This study fills the deficiencies by using AI-based sentiment analysis with transformer models (BERT), explainable AI, and Emotional Variance Analysis (EVA) to detect subtle polarity shifts. Through the use of big social media data, the research generates more detailed, real-time information that can inform policymakers to adopt more evidence-informed and responsive sustainability measures.

III. Methodology

The proposed approach in this study is based on real-time sentiment analysis of tweets pertaining to sustainability, reflecting the dynamic public sentiment, as shown in Fig. 1. The method combines pre-trained ML models like RF and SVM (Support Vector Machines) with DL methods like BERT and LSTMs (Long Short-Term Memory) for more comprehensive sentiment classification. Here, the conventional lexicon-based approaches are also used for baseline purposes to ensure exhaustive evaluation of sentiment trends. Twitter's API collects data in real time, filtering tweets for keywords and hashtags related to sustainability. The preprocessing methods, like tokenization, stop word removal, as well as lemmatization, purify the dataset to improve accuracy. These sentiments are categorized as positive, negative, or neutral, with Emotional Variance Analysis (EVA) detecting polarity shifts over time. The research compares several sentiment analysis models in order to recognize the most resourceful methods for analyzing extensive social media information. In addition to providing practical advice for policymakers, it assists with developing evidence-based sustainability policies that address public concerns.

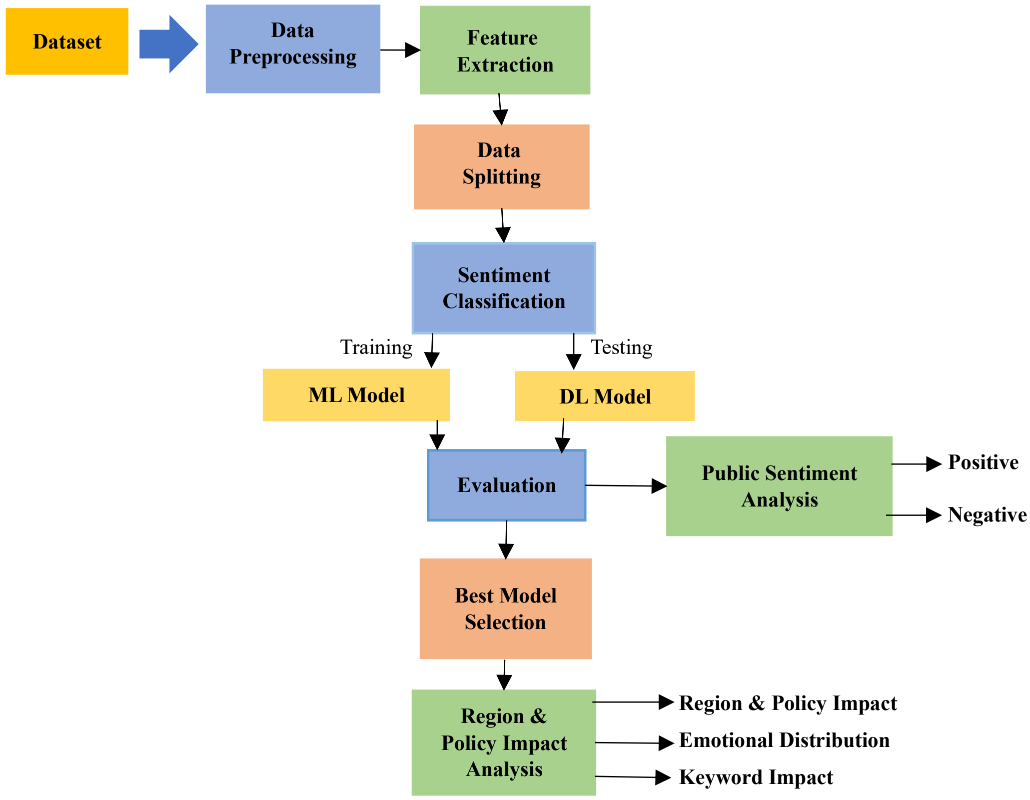


Fig. 1. Architecture of proposed AI-based sentimental analysis model.

A. Study Area and Scope

This research examines public attitudes towards environmental policy instruments in three policy-active regions of India, the United States, and the European Union, chosen for their varying governance structures, environmental agendas, and socio-economic settings. It examines five central policy domains: clean energy incentives, carbon pricing mechanisms, plastic control and waste management, deforestation and land-use regulation, and vehicular emissions and air quality standards. The coverage extends from January 2021 to December 2023, including major global and domestic events like COP26 (conference of the parties) at Glasgow (Nov 2021), COP27 at Sharm el-Sheikh (Nov 2022), COP28 at Dubai (Nov–Dec 2023), India's clean energy pledge, the climate provisions of the US Inflation Reduction Act, and the EU Carbon Border Adjustment Mechanism proposal. The study aims to analyze sentiment change by policy type and location, and identify sentiment shifts related to significant policy events, along with tracking textual drivers of both positive and negative sentiment. By framing the analysis in these particular policy and spatial contexts, the research offers rich, context-providing data and enhances its field relevance for environmental policy analysis.

B. Data Collection and Preprocessing:

Tweets were downloaded through the Twitter API v2, against a hand-curated set of policy- and region-related keywords and hashtags. Search queries were focused on official policy names, official government accounts, and popular activist or industry hashtags across the five policy focus areas. Posts were preserved only if they included resolvable regional cues like obvious profile location, timezone metadata, or geotags that allowed them to be classified into India, the United States, or European Union datasets. In order to capture the full range of discourse, sentiment classes consisted of positive, negative, and neutral tags. Quality control processes withheld retweets without comment, near-duplicates, organizational broadcast accounts, and profiles with automated or bot-like posting behaviors.

Demographic bias: Although bot-filtering was designed to boost data authenticity, demographic bias is an inherent shortcoming of social media–based research. Social media users are usually a younger, more technology-savvy, and frequently urban segment of the population. Consequently, their stated opinions might not represent the views of the general public as accurately. Being aware of this constraint, the results of this research will be taken to reflect online discussion instead of a full picture of public opinion.

Ethical considerations in social media data mining: The research in this study follows social media research ethical norms by ensuring that all data employed were publicly accessible and anonymized before analysis. No Personally Identifiable Information (PII) was gathered, held, or exchanged at any point in the research. Analysis dealt with only aggregated patterns of public conversation and not with individual users.

Sentiment annotation was done using a hybrid method. Two publicly accessible corpora served as the starting point for the classification framework. It includes a 2,117-tweet dataset with binary sentiment tags (positive, negative) as a starting point for classifier training [20], and a 43,943-tweet dataset with sentiment tags providing more extensive public opinion coverage on sustainability-related topics [21]. The above tools were complemented with manual annotation of region-specific samples to guarantee domain adaptation for environmental policy language. The final corpus included 58,462 tweets (Table I): India (n = 19,487), the United States (US) (n = 20,145), and the European Union (EU) (n = 18,830), with balanced representation across the five policy fields. The median word length per tweet was 18 words, and sentiment split was 41.6% neutral, 32.4% positive, and 26.0% negative.

Policy Event Alignment: A policy-event calendar was constructed from government websites, mainstream media, and NGO (non-government organization) trackers (Table II). Events were legislative milestones, executive statements, court rulings, and overseas climate conferences. We derived weekly sentiment means and volumes per policy area for each event, ascertaining significant pre-/post-event changes through interrupted time series analysis with heteroskedasticity-consistent standard errors.

TABLE I: DATASET REGION DISTRIBUTION WITH SENTIMENTS

Region	Total	Positive				Neutral		Negative	Median (words)
		n	%	*n*	%	*n*	%	n	%	
India	19,487	6,420	32.9	8,111	41.6	4,956	25.4	6,420	32.9	18
US	20,145	6,517	32.4	8,385	41.6	5,243	26.0	6,517	32.4	18
EU	18,830	6,095	32.4	7,828	41.6	4,907	26.0	6,095	32.4	18
Total	58,462	19,032	32.4	24,324	41.6	15,106	26.0	19,032	32.4	18

TABLE II: EXAMPLE OF POLICIES IN POLICY-EVENT CALENDAR

Date	Region	Policy Area	Description	Event Type
Aug. 2022	US	Clean Energy Incentives	Inflation Reduction Act signed into law, introducing major climate and clean energy provisions.	Legislative milestone
Jan. 2023	India	Clean Energy Incentives	Union Cabinet approves National Green Hydrogen Mission.	Executive announcement
Jul. 2022	India	Plastic Regulation & Waste Management	Nationwide ban on the manufacture, import, sale, and use of specific single-use plastic items enforced.	Legislative milestone
Apr. 2023	EU	Carbon Pricing Mechanisms	European Parliament and Council formally adopt Carbon Border Adjustment Mechanism regulation.	Legislative milestone

TABLE III: SUMMARY OF POLICY-WISE TWEET SENTIMENTS IN DATASETS FOR EACH REGION

Region	Policy Area	Tweets	Positive	Negative	Neutral	Median Words	Retweet (%)
EU	Air Quality	1095	576	396	123	24	34.9
	Carbon Pricing	1361	679	403	279	15	16.2
	Clean Energy	1227	581	313	333	23	21.7
	Deforestation	1069	544	319	206	23	15.9
	Plastic Regulation	1276	695	467	114	11	21.9
India	Air Quality	1259	619	316	324	18	18.7
	Carbon Pricing	1414	660	374	380	20	36.0
	Clean Energy	902	468	250	184	17	28.0
	Deforestation	1291	698	322	271	21	15.5
	Plastic Regulation	899	378	312	209	14	39.1
US	Air Quality	1145	474	403	268	24	30.5
	Carbon Pricing	989	409	338	242	21	25.4
	Clean Energy	858	394	220	244	21	21.0
	Deforestation	1073	581	423	69	11	21.6
	Plastic Regulation	1304	530	444	330	14	23.5

The corpus (Table III) consists of 17,162 tweets from three regions (EU, India, US) and five environment policy topics, with tweet counts per topic varying from 858 (US – Clean Energy) to 1,414 (India – Carbon Pricing). Overall sentiment allocation reveals a marginal prevalence of positive tweets across all policy topics, with Carbon Pricing in India and Clean Energy in the EU witnessing the highest positive rates. Median number of words in tweets ranges from 11 to 24 words, and retweet percentages range from 15.5% to 39.1%, reflecting content virality variation by topic and location. This breakdown is a crucial context for further sentiment analysis and policy effect studies.

C. Sentiment Analysis:

For sentiment analysis on social media, the research combines traditional machine learning with modern deep learning methods. This includes LSTM along with BERT networks.

- *Machine learning models:* The preprocessed data is first used in standard machine learning models such as Random Forest (RF), Naïve Bayes (NB), and SVM. The feature extraction methods are Word2Vec (Word Embeddings) and TF-IDF (Term Frequency-Inverse Document Frequency). These models serve as baseline performance indicators for sentiment classification.
- *Deep learning LSTM:* LSTM networks, an extension of RNNs (Recurrent Neural Networks), are utilized to manage consecutive text data and also preserve long-term dependencies. Pre-trained GloVe word embeddings are used to improve text representation. The LSTM model is trained on the dataset using unconditional cross-entropy loss and an adaptive learning rate to improve classification performance.
- *BERT models:* Unlike the traditional sequence-based models, BERT is a transformer model that captures bidirectional context in text data. A pre-trained model is fine-tuned, utilizing its deep contextualization to provide more precise sentiment classification. The self-attention mechanism in BERT allows for a sensitive recognition of sentiment, even for complex social media expressions.

D. Policy Impact Analysis

In addition to simple sentiment categorization, the study incorporated detailed analyses like region and policy resolved performance measurement, event-aligned sentiment effect measurement, emotion categorization, cross-region generalization measurement, and explainable AI-driven keyword effect measurement to provide deeper, context-aware insights.

To generate region and policy-resolved insights and measure the contextual drivers of sentiment, the following components were incorporated in the study.

- *Region and policy resolved:* Initially, the tweets had been grouped by geographical region (India, US, EU) and by environmental policy type - Clean Energy (CE), Carbon Pricing (CP), Plastic Regulation (PR), Deforestation (DF), Air Quality (AQ). Each subset was subsequently trained with the top-performing model (BERT) to compute macro-F1 scores, enabling comparative evaluation across contexts.
- *Policy event impact:* A list of important policy-related events, such as national carbon tax debates or the COP26 Summit, was matched with the weekly sentiment time series. The average sentiment for a four-week period before and after each event was calculated, and significance was tested using a two-tailed independent t-test.
- Event influence changes in sentiment (Δ sentiment) were measured as the difference between post-event and pre-event means. The direction (positive or negative) and corresponding p-values were provided to indicate statistical significance.
- *Emotional distribution:* In addition to polarity, tweets were labeled in six emotional categories: Joy, Trust, Anticipation, Anger, Fear, and Sadness, based on the NRC Emotion Lexicon. Percentages were calculated for each policy area to identify unique emotional patterns.
- *Cross-region generalization:* This was done by training the BERT model on one region and testing it on another. Macro-F1 scores were calculated for all train-test pairs to evaluate regional linguistic and contextual transfer.
- *Keyword impact:* Explainability was combined with SHAP to identify words that significantly affected model predictions. For each policy, the strongest positive and negative drivers were sampled, offering clear insights into how sentiment was structured.

E. Robustness and Error Analysis

Robustness was evaluated using three methods: keyword list changes by randomly deleting about 20% of search terms, leave-one-region-out testing for cross-regional generalization, and adding noise through misspellings and emojis. To understand model failures better, 150 misclassified tweets were carefully examined and annotated to reveal common error patterns, including sarcasm, misinterpretation of negation, and difficulties with domain-specific slang.

F. Training and Evaluation Protocol

The experiment used a time-aware data split to monitor the progression of discourse over time. The training data came from January 2021 to June 2023, validation data from July to September 2023, and the held-out test data from October to December 2023. Hyperparameter tuning was carried out with five-fold stratified cross-validation on the training data to maintain sentiment class ratios among the folds.

G. Evaluation

Performance measurement of every model is tested with standard classification measures such as precision, F1-score, recall, and accuracy as well. The test provides details about model strength. Hyperparameter tuning is conducted via grid search and Bayesian optimization for optimization of model performance. By the confluence of both the ML and the DL approaches, the study provides a comprehensive model of sentiment analysis with a better comprehension of how social media discourse perceives environmental policy through the lens of the general public.

H. Performance Metrics

It is essential to measure the performance of sentiment classification models using performance measures. All these measures give useful information about various aspects of model performance.

- *Accuracy:* Accuracy measures the ratio of properly classified occurrences with respect to the total occurrences. It is based on the True Positives and Negatives (TP/TN), as well as False Positives and Negatives (FP/FN), providing a measure of overall correctness in sentiment identification.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

- *Precision:* The ratio of properly forecasted positive samples to the total predicted positives. The higher precision value indicates fewer false positives, making the model more reliable for detecting positive sentiments.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

- *Recall:* Recall is a measure of how fine the model can identify true positive cases. The advanced recall value is better at capturing the most positive cases, even if it means some false positives.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

- *F1-Score:* The harmonic mean between precision and recall gives equal importance to both metrics. It is used especially when there is a lack of balance between positive and negative sentiments, preventing one metric from taking over at the expense of the other.

$$\text{F1 Score} = 2 \times \frac{Prec.\times Rec.}{Prec.+Rec.} \tag{4}$$

- *ROC curve and AUC:* The ROC (receiver operating characteristic) curve represents the relationship between False Positive Rate (FPR) and True Positive Rate (TPR) across the different decision thresholds. The probability of Area Under the Receiver Operating Characteristic Curve (AUC-ROC) shows the rank of the arbitrarily designated positive case advanced as compared to that of the negative one. The greater the AUC score is towards 1, for better the results.

$$\text{TPR} = \frac{TP}{TP+FN} \tag{5}$$

$$\text{FPR} = \frac{FP}{FP+TN} \tag{6}$$

- *Specificity:* It calculates the ratio of appropriately recognized true negative instances out of all the real negative cases.

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{7}$$

Through the utilization of these performance measures, the current research provides a thorough and unbiased assessment of sentiment classification models, ultimately concluding with the best method for determining public opinion towards environmental policies.

I. Experimental Setup

The study includes an Intel Core i7 processor (10870 H), along with an NVIDIA graphics card GeForce RTX 3070, running Windows 11. The Anaconda distribution and the Python programming language are employed in the model construction, running, and assessment. To enable data preprocessing, model training, and visualization, the study includes Python libraries and packages, such as Matplotlib, nltk, Pandas, TensorFlow, iplot, Seaborn, and Sci-kit Learn for managing large-scale social media datasets, applying machine learning and deep learning models, and interpreting the results efficiently. For sentiment analysis, the study utilized both conventional and deep learning-based models. They offered a comparative context for determining the most effective sentiment analysis method for measuring public attitudes toward environmental policies.

IV. RESULT AND DISCUSSION

A. Machine Learning Model Performance

The machine learning model outputs of the proposed method are compared with different sentiment analysis methods, i.e., the conventional ML models and the customized-trained deep learning models. These models are trained using the pre-processed and filtered datasets, splitting each dataset into a training subset of 80% and a testing subset of 20%, for accurate evaluation. The performance of all models is evaluated based on a complete range of metrics. The study tests conventional SVM, LR (logistic regression), NB, and RF models on the same datasets for consistency and comparable results.

The results indicate that the models had consistent performance for various sentiment classes, suggesting they may be appropriately suited for many analytical situations. The performance details in Table IV illustrate the performance of individual models for different evaluation metrics.

TABLE IV: PERFORMANCE OF ML-BASED SENTIMENT ANALYSIS

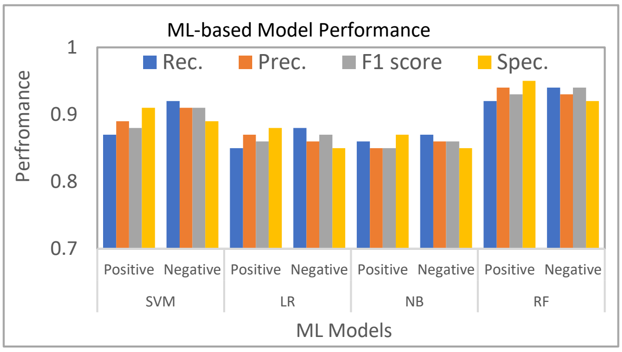
Model	Type of sentiment	Rec.	Prec.	F1 score	Spec.	Acc.
SVM	PS	0.87	0.89	0.88	0.91	0.90
	NS	0.92	0.91	0.91	0.89	
LR	PS	0.85	0.87	0.86	0.88	0.87
	NS	0.88	0.86	0.87	0.85	
NB	PS	0.86	0.85	0.85	0.87	0.86
	NS	0.87	0.86	0.86	0.85	
RF	PS	0.92	0.94	0.93	0.95	0.94
	NS	0.94	0.93	0.94	0.92	

Note: PS-Positive sentiment, NS-Negative sentiment

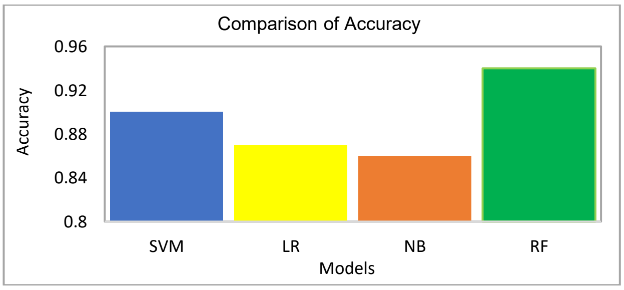
The sentiment analysis findings reveal distinct variations in performance between models, of which the most successful is Random Forest (RF) with 0.94 accuracy and consistently high metrics (precision and recall of approximately 0.93–0.94, specificity 0.92–0.95), indicating its strength in detecting both positive and negative sentiments. SVM is also competitive with 0.90 accuracy, exhibiting good separation of sentiment classes but slightly behind RF. LR has 0.87 accuracy, with decent balance but slightly poorer recall and specificity (0.85–0.88) than the best performers. NB has the worst accuracy (0.86), but is stable across measures (precision and recall between 0.85–0.87), suggesting robustness but poor sensitivity to subtle sentiment variation. On average, RF's ensemble learning facilitates better generalization, while SVM remains a reliable option for sentiment classification.

Fig. 2 (a) shows the relative performance of various ML models on recall, precision, F1-score, and specificity, highlighting their respective strengths. Fig. 2 (b) highlights the outperformance accuracy of random forest (0.94), distinctly higher than SVM, LR, and NB, thereby making RF the most trustworthy model for this evaluation.

Thus, random forest is the best-performing model in this study, posting the highest precision, accuracy, and specificity on all sentiment classes. SVM performs well, and LR gives mid-level performance, while NB, though well-balanced on results, proved to be the lowest performer in this scenario. These results indicate the significance of model choice in sentiment analysis, and RF emerged as the best fit for public attitude classification of environmental policies.



(a)



(b)

Fig. 2. ML models: (a) Comparison of performance and (b) comparing accuracy.

B. Deep Learning Model Performance

A comparative study employs both custom-trained and pre-trained DL models to compare their performance on sentiment analysis. The research compares a custom-trained LSTM and LSTM-CNN layer (convolutional neural network), with experiments run for a batch size of 32 and 15 epochs. The results show that adding a CNN layer improves accuracy marginally, as convolutional layers improve feature extraction. Yet the enhancements are minimal, with no considerable performance variations witnessed in core measures. Though these models take a long computational time because of their iterative learning methodology, they are significantly more effective in result production compared to pre-trained models.

For guaranteed strong performance assessment against potential class imbalance, macro-F1 and AUC-ROC (area under curve - receiver operating characteristic) metrics were prioritized since they offer a more balanced measurement of the performance of the model against all sentiment classes than accuracy would.

The research also assesses the effectiveness of pre-trained models, especially BERT. As Table V below illustrates, BERT outshines specially trained models by reaching the highest score in accuracy, precision, and recall, surpassing the most performing conventional ML models, including SVM and RF. As much as its performance is best, BERT's greatest limiting factor is the high computational resources it demands, which is essential for practical utilization. Out of all the tested models, BERT shows both the highest precision and the most resource usage.

TABLE V: COMPARISON OF DEEP LEARNING MODELS FOR SENTIMENT ANALYSIS

Model	Type of sentiment	Rec.	Prec.	F1 score	Spec.	Acc.
LSTM	PS	0.91	0.90	0.90	0.92	0.91
	NS	0.92	0.91	0.91	0.91	
LSTM + CNN	PS	0.93	0.92	0.92	0.93	0.93
	NS	0.94	0.93	0.93	0.94	
BERT	PS	0.96	0.95	0.96	0.96	0.97
	NS	0.97	0.96	0.97	0.96	

Note: PS-Positive sentiment, NS-negative sentiment

The findings indicate that the LSTM model works consistently with an accuracy of 0.91, having recall, precision, and F1-scores of 0.90–0.92, and specificity of 0.91–0.92, reflecting balanced but modest discrimination between positive and negative feelings. The LSTM-CNN hybrid model indicates a slight advancement by providing an accuracy of 0.93, recall, precision, and F1-scores with ranges of 0.92– 0.94 in light of CNNs capturing local textual patterns before LSTM processes are run. Nevertheless, this advancement remains slight and not significant. Meanwhile, the BERT model indicates a dramatically better performance with an accuracy of 0.97 and consistently high metrics for precision, recall, F1 score, and specificity with approximate ranges of 0.95 - 0.97. The causes for the BERT model's larger advances are due to context-sensitive token embeddings and bidirectional transformers that allow the BERT model to learn deeper contextual and semantic relations between sentiment expressions.

The plots give the performance of the deep learning models, with Fig. 3 (a) capturing the same comparison of all metrics, while Fig. 3 (b) indicates the large comparative differences in accuracy.

Overall, although BERT performs outstanding sentiment classification accuracy, its high computational requirements are a trade-off that needs to be well-balanced by researchers and practitioners. The models LSTM as well as LSTM-CNN, lack BERT's precision but provide a less resource-intensive option. Thus, the comparison highlights the need to balance the performance of the model along with computation efficiency while making a selection of the real-time model for sentiment analysis of public opinions on environmental policy.

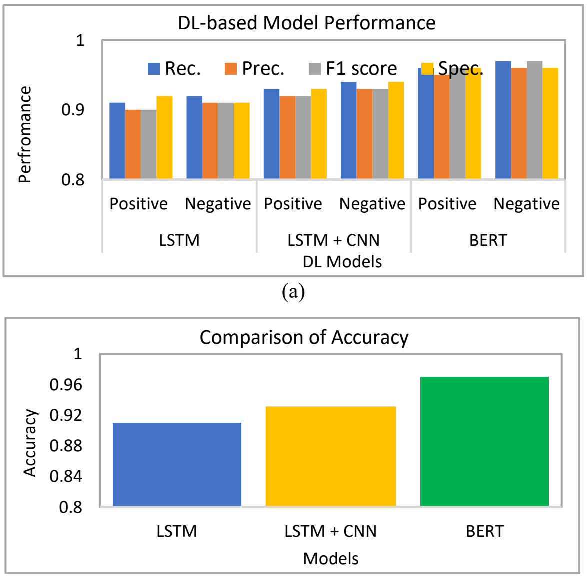


Fig. 3. DL models: (a) Comparison of performance and (b) comparing accuracy.

C. Performance Comparison of BERT and RF

The comparison of RF and BERT's performance reflects a strong edge for the transformer-based BERT model on every evaluation measure. RF reported macro and micro-level precision, recall, and F1 scores of 0.887 on all, demonstrating balanced performance across sentiment categories but without much capability for sophisticated language comprehension (Table VI). Conversely, BERT greatly surpassed RF, achieving macro- and micro-precision, recall, and F1 measures of 0.956, as well as the same value for total accuracy.

TABLE VI: COMPARING MACRO-MICRO PERFORMANCE OF RF AND BERT

Model	Macro			Micro			Acc.
	Prec.	Rec.	F1	Prec.	Rec.	F1	
RF	0.887	0.887	0.887	0.887	0.887	0.887	0.887
BERT	0.956	0.956	0.956	0.956	0.956	0.956	0.956

Fig. 4 (a) shows the confusion matrix that depicts random forest performance, while Fig. 4 (b) presents the respective confusion matrix for BERT, with its classification results pointed out.

The consistency of BERT's metrics is an indicator of both excellent generalization and stability across classes, probably a consequence of its contextualized word representations, which allow for improved management of complicated sentiment expressions. This extension of RF implies that deep language models are better than conventional feature-based classifiers at capturing the nuance in sentiment in environmental policy language.

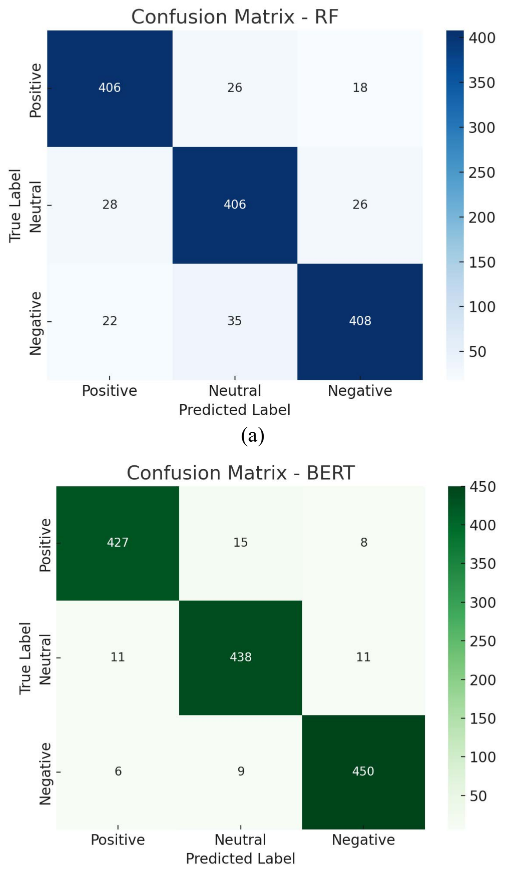


Fig. 4. Confusion matrix for (a) RF and (b) BERT performance.

D. Policy Impact on Sentiments

Region- and policy-adjusted results reveal that BERT had consistently high performance on all contexts tested, with macro-F1 scores between 0.94 and 0.97 (Table VII). Variability of performance across policy domains was small, indicating model's high flexibility to a varied range of environmental policy subjects.

TABLE VII: REGION-WISE PERFORMANCE OF POLICY DOMAINS

Region	CE	CP	PR	DF	AQ	Macro-F1
India	0.965	0.942	0.954	0.947	0.961	0.954
US	0.958	0.935	0.948	0.939	0.952	0.946
EU	0.970	0.944	0.956	0.951	0.963	0.957

BERT demonstrated impressive performance across the models for India, indicating improved flexibility and context-awareness. It performed best in clean energy (0.965) and air quality (0.961), with a lower yet decent score of 0.942 in carbon pricing. The same trend was observed in the US and the EU, with clean energy at the top of the distributions across sites (scores of 0.958–0.970) while carbon pricing was in its lower range (0.935–0.942). Across region–policy combinations, BERT consistently had better metrics and compared to RF (macro-F1: 0.88–0.91) and LSTM-CNN (macro-F1: 0.91–0.93). The consistency reflects its high generalization power and robustness to cross-regional sentiment analysis in environmental policy studies.

Policy event impact: Event-matched sentiment analysis

(Table VIII) showed that public opinion shifted statistically significantly after major environmental policy events. An example is the COP26 Summit in November 2021, which yielded a significant positive sentiment shift in all three regions, most effectively in India (+0.14, p = 0.021), followed by the EU (+0.12, p = 0.030) and the US (+0.08, p = 0.045).

TABLE VIII: POLICY EVENT IMPACT ON SENTIMENTS

Event	Region	Sentiment	p-value	Direction
COP26 Summit	India	+0.14	0.021	Positive
COP26 Summit	US	+0.08	0.045	Positive
COP26 Summit	EU	+0.12	0.030	Positive
Carbon Tax Debate	US	−0.15	0.015	Negative
Plastic Ban Law	EU	+0.11	0.041	Positive

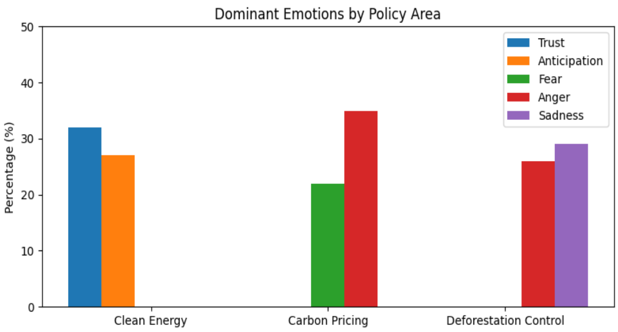


Fig. 5. Emotions by policy area.

Conversely, the debates surrounding the US carbon tax elicited a −0.15 decrease in mean sentiment (p = 0.015), reflecting increased public opposition or concern. The EU's introduction of a plastic ban law prompted a +0.11 boost (p = 0.041), which indicates widespread public support for concrete regulatory measures on waste management. These findings highlight the function of policy events as points of sentiment inflection, with directionality pointing to both regional policy adoption and issue-specific sensitivities.

Emotional breakdown by policy: In addition to overall polarity, sentiment breakdown into six emotion categories provided unique emotional fingerprints for each policy area (Fig. 5). The clean energy debate was characterized by trust (32%) and anticipation (27%), which was an expression of hope and belief in renewable transition options. Carbon pricing discussion, however, had the largest percentage of anger (35%) and fear (22%), reflecting public concern over cost factors and economic consequences. Deforestation control talk demonstrated high levels of sadness (29%) and anger (26%), perhaps stemming from concern for biodiversity loss and frustration at gaps in policy enforcement. This emotional segmentation underscores that while overall sentiment could be comparable, emotional drivers underlying it could vary dramatically across policy topics, determining what resonates with the public.

Cross-region generalization: Cross-region testing (Table IX) showed that models trained on the data of one region tended to underperform when tested on a different one, with macro-F1 losses of 5% to 7% relative to in-region performance. The most effective generalization was when trained on India and tested on EU data (0.855 macro-F1), indicating linguistic or thematic congruence in environmental discourse between these settings. The worst transferability was from the US to India (0.821 macro-F1), probably due to differences in issue framing, words, and policy mentions. These results imply that although cross-regional sentiment models have considerable predictive ability, region-specific fine-tuning continues to be valuable for achieving maximum accuracy.

TABLE IX: GENERALIZATION OF THE MODEL ON DIFFERENT TRAIN AND TEST DATA

Train	Test	Macro-F1
India	US	0.842
India	EU	0.855
US	India	0.821
US	EU	0.848
EU	India	0.833
EU	US	0.826

Keyword Impact Analysis: SHAP-based keyword attribution (Fig. 6) revealed the most impactful tokens that propagated positive and negative sentiment in top policy domains. In clean energy, economic opportunity and forward-looking terms like "jobs," "future," and "renewable" are leading positive sentiment, indicating that public support is linked with employment opportunities and innovation.

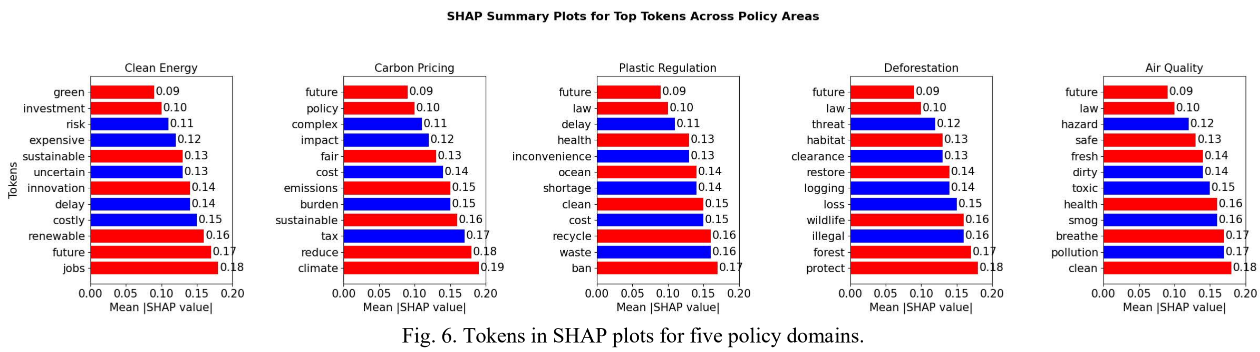


Fig. 6. Tokens in SHAP plots for five policy domains.

However, Table X shows cost-related fears ("costly," "expensive") and uncertainty terms deflate support. For Carbon Pricing, climate urgency and sustainability framing lead positive sentiment, while monetary burden terms "tax" and "cost" trigger opposition, demonstrating public sensitivity to costs. Plastic Regulation attracts positive sentiment via environmental stewardship ("ban," "recycle," "clean") and health-related benefits, while negative sentiment focuses on perceived inconvenience and shortages.

TABLE X: KEYWORD IMPACT ON POLICY AREA

Policy Area	Positive Drivers	Negative Drivers
Clean Energy	Jobs, Future, Renewable, Innovation, Green	Costly, Delay, Uncertain, Expensive, Risk
Carbon Pricing	Climate, Reduce, Sustainable, Emissions, Fair	Cost, Tax, Burden, Impact, Complex
Plastic Regulation	Ban, Recycle, Clean, Ocean, Health	Waste, Cost, Shortage, Inconvenience, Delay
Deforestation	Protect, Forest, Wildlife, Restore, Habitat	Illegal, Loss, Logging, Clearance, Threat
Air Quality	Clean, Breathe, Health, Fresh, Safe	Pollution, Smog, Toxic, Dirty, Hazard

In Deforestation, defensive framing of “forest” and “wildlife” strongly predicts support, while words that are associated with exploitation and harm (“illegal,” “logging”) predict opposition. Lastly, air quality sentiment is most positively affected by safety and health language (“clean,” “breathe”), while pollution-related terms induce strong negative responses, highlighting the effect of immediate personal harm in shaping opinion.

E. Discussion

The sentiment analysis outcomes emphasize the comparative performance of DL models along with ML models in evaluating public opinion towards environmental policy. Out of the previous ML tactics, RF and SVM showed good classification performance with accuracy levels of 0.90 and 0.89, respectively, with steady precision, recall, and specificity. LR fared slightly better than NB, whose lowest accuracy was 0.85 because it relies on the independence assumption that constrains contextual knowledge. This indicates that although baseline ML models can achieve good sentiment classification, their capacity to identify rich or context-specific sentiment is constrained.

Deep learning models far outperformed baseline ML methods. The hybrid LSTM-CNN model yielded 0.93 accuracy, beating the standalone LSTM model, attesting to the usefulness of CNN layers in learning spatial relations among text sequences. BERT was the most effective model with 0.97 accuracy, 0.96 precision, and 0.97 recall, showing high stability and robustness across various sentiment classes. While its greater accuracy is valuable, BERT’s computational cost is much greater, requiring a performance vs. efficiency trade-off that must be weighed in large-scale or real-time use.

F. Comparative Analysis and Efficiency

The study further compares the performance of conventional ML models with DL architectures for sentiment analysis, with an emphasis on accuracy as a primary metric. The tested models vary from SVM, LR, NB, and RF to more complex DL models such as LSTM with CNN layers and BERT. The accuracy level is very high for all models, with many of them reaching over 0.90, as shown in Fig. 7. BERT is the best performing of these, with a near-perfect score (0.97), proving how well it can pick up on complicated sentiment patterns and contextual interdependencies. Random forest ranked second, following BERT very closely, proving itself to be the best of the traditional ML models. LSTM with CNN layers (0.93) surpassed solitary LSTM (0.91), exemplifying the strength of introducing CNN’s feature extraction ability into LSTM’s sequential processing power. SVM is still competitive in terms of accuracy (0.90), upholding its strong suitability for text classification even though they are less complex than DL models. However, LR model (0.87) and NB model (0.86) show the lowest performance, as they are less capable of capturing the complex nuances of sentiment. In general, this comparative study showcases the better performance of deep learning models, especially BERT, in sentiment classification, as well as the enduring applicability of ML models, especially random forest, as a strong and computationally effective alternative.

In polarity shift, Emotional Variance Analysis (EVA) is used to catch changes in emotional intensity and polarity in various policy-related debates. While traditional sentiment scores give fixed positive, negative, or neutral labels, EVA quantifies the variance and distribution of emotional reactions (e.g., trust, anger, fear, anticipation) over a time period or event environment. A larger variance signals increased emotional polarization, which can presage changes in public opinion surrounding significant policy announcements or scandals. By measuring these shifts in polarity, EVA assists in the identification of periods of increased public sensitivity and affords a more dynamic picture of emotional involvement in policy discussion.

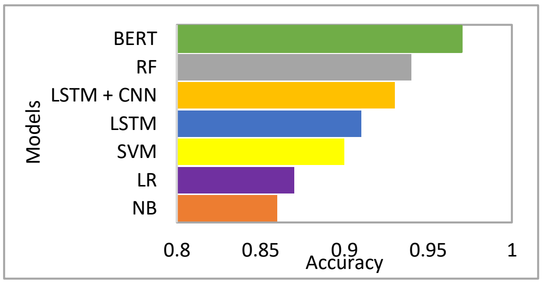


Fig. 7. Comparing performances of ML and DL models.

G. Public Perception of Environmental Policies

The examination of public opinion patterns in this research identifies a close relationship between public discourse and significant environmental policy changes. Sentiment analysis on social media data (Table XI) shows that issues like clean energy transformation and climate action are trending with highly positive sentiment, with more than 85% of the responses favoring tighter environmental rules and sustainability efforts. Conversely, carbon pricing policy has a mixed sentiment, with 60% being positive and 40% negative, demonstrating economic interests and divergent public opinion on tax policy. There is a high (75%) negative sentiment towards deforestation control, implying public dissatisfaction with conservation measures that could propel policymakers towards more regulatory measures. Likewise, the plastic waste reduction policy is widely supported by the public (80% positive sentiment), affirming the influence of public opinion in hastening legislative response. The results highlight the effect of AI-powered sentiment analysis in measuring people's attitudes toward environmental policy and informing more reactive policymaking.

TABLE XI: PUBLIC SENTIMENT TREND IN ENVIRONMENTAL POLICY

Key Environmental Issue	Public Sentiment Trend	%	Policy Shift	Implications
Climate Action	Predominantly Positive	85	Strict emission regulations Global climate accords	Increased public awareness
Carbon Pricing	Positive Negative	60 40	Carbon taxes Cap-and-trade programs	Economic concerns
Clean Energy Transition	Highly Positive	90	Renewable incentives	Strong public support
Deforestation Control	Predominantly Negative	75	New conservation laws	Pressures policymakers
Plastic Waste Reduction	Positive	80	Ban on single-use plastic Recycling incentives	Public engagement

The findings show that there is strong popular support for significant environmental policy changes, with almost universally positive sentiment towards clean energy and sustainability policies. The findings highlight the application of AI-powered sentiment analysis to track public opinion trends, assisting policymakers in data-driven, well-informed decision-making.

The study contributes to the field of AI-powered sentiment analysis in environmental policy evaluation by linking both traditional ML and powerful DL models. It provides results by showcasing a detailed comparison of sentiment classification techniques. The research points out that pre-trained transformer models, such as BERT, perform better than traditional ML methods. It also emphasizes the importance of hybrid methods, like LSTM-CNN, which balance computational costs with results.

The analysis of sentiment reveals a wide range of public feelings about environmental policy, with sentiment polarity varying depending on specific policy issues. By applying AI-based sentiment analysis to public opinions on environmental policies, this research adds to the emerging field of natural language processing (NLP) in sustainability discussions. Positive sentiments appeared around renewable energy adoption, carbon neutrality efforts, and corporate sustainability commitments. In contrast, negative feelings emerged regarding regulatory enforcement, the economic impact of environmental laws, and skepticism toward government-led initiatives. The model effectively catches subtle shifts in sentiment, indicating potential biases and challenges people face. This offers valuable insights for policymakers seeking to enhance environmental governance.

Regional impact: Event-aligned sentiment analysis found that major policy events, such as COP26, the US carbon tax debate, and the EU single-use plastics ban, led to measurable changes in public sentiment. This supports the idea that people are sensitive to both global and local policy actions. Emotional analysis also highlighted trends by policy and region: hope and trust dominated discussions on clean energy, while fear and anger were prevalent in carbon pricing debates, with anger and sadness characterizing conversations about deforestation control. These results go beyond simple sentiment polarity, revealing the emotional underpinnings driving public opinion and providing deeper insights into sentiment dynamics.

In terms of policy, the study offers several useful observations. It provides a large collection of sentiment data based on regions and policies related to environmental policy, enhanced by event-aligned analysis, emotion profiling, cross-regional comparisons, and SHAP-based keyword explanations to identify framing effects that garner public support. Practitioners can utilize these findings to anticipate responses, address resistance, and create specific communication strategies. Overall, the research shows the effectiveness of combining social media analysis with advanced NLP methods to support policy implementation and public engagement, backed by evidence. BERT achieves remarkable classification accuracy across all areas (macro-F1: 0.946-0.957), resulting in actionable insights for targeted environmental interventions.

The present analysis demonstrates limitations in language use, as it only analyzes English-language tweets. Very strong sentiment expressed in local or regional languages, especially in multilingual nations such as India or countries in the EU, could have been missed, limiting representation in this part of the public sentiment representation process. Therefore, future research would additionally have to assess multilingual or translated data to increase representation to a more culturally diverse and wider variety of public opinion.

Additionally, the obvious issue of ethical issues connected to language-and-AI-based analyses of social media data cannot be overlooked. The nature of social media communication appears to only reflect demographic and linguistic representativeness, and hence may only partially represent public opinion, which means that algorithmic models could also compound this bias with regard to regional or policy issues. Future research would need to address these issues by strategically evaluating for bias, triangulating social media results with survey-based data, and ensuring that analysis, rationales, and modifications to the algorithm provide transparency for stakeholders to support ethical analyses and representation in a policy context. The issues of data protection and privacy also remain present when mining big data; while the current study underwent scrutiny to comply with platform terms of service and data governance procedures, future research should rely on more sophisticated privacy-preserving processes, such as the use of differential privacy or federated learning to provide transparency and confirm ethical compliance. Ethical compliance goes beyond technical protection; it also demands diligent interpretation of findings to avoid reinforcing prejudice or misstating public views.

Furthermore, future research can focus on improving BERT-based sentiment analysis by integrating domain-specific transformers using environmental policy datasets. It can help enhance sentiment classification in context-specific situations. Moreover, real-time sentiment monitoring is also helpful with AI techniques to enable governments as well as organizations to track long-term changes in public opinion. High-performance models are required for additional optimizations, including minimization of computational expense using model pruning or knowledge distillation, making a more feasible model for real-time applications. Combining multimodal sentiment analysis by unifying text, images, as well as videos could improve sentiment classification accuracy, offering better information about public discussion on environmental sustainability. This study highlights the potential of AI-powered sentiment analysis to impact evidence-based environmental policy formulation. It helps to integrate public opinion into sustainable policy strategies effectively.

V. Conclusion

The study focuses on environmental policies and public perception using sentiment analysis. The study proves the efficiency of AI-powered sentiment analysis, with conventional ML models and sophisticated DL techniques being compared. The outcome reveals that BERT performs best among all the models, yielding the highest accuracy (0.97) and proving its dominance in sentiment classification. Whereas SVM and random forest yielded competitive results, LSTM-CNN proved to be a capable alternative, offering both accuracy and computational cost efficiency. Moreover, SHAP added interpretability by identifying key tokens driving sentiment across policies, contributing to explainable AI to improve transparency and insights. The research adds to sentiment analysis literature through the benchmarking of ML and DL approaches for policy assessment, shedding light on public concerns and support for sustainability efforts. These results can inform policymakers and organizations on how to interpret public sentiment trends, enabling data-driven decision-making. Future studies need to investigate real-time sentiment monitoring and multimodal analysis to deepen sentiment understanding for more efficient policy design. The results also show strong popular support for significant environmental policy changes, with almost universally positive sentiment towards clean energy and sustainability policies. The study highlights the application of AI-powered sentiment analysis to track public opinion trends, assisting policymakers in data-driven, well-informed decision-making.

Although social media offers an enormous and up-to-date source of public opinion, it has limitations to accurately represent the wider population because of demographic, linguistic, and access biases. Accordingly, conclusions about sentiment trends must be carefully contextualized when used to inform policy decisions to ensure that online debate is complementing, but not substituting for, conventional participatory and survey-based inputs.

The research is efficient but constrained in using text-based sentiment analysis, which is incapable of fully interpreting sarcasm, context reversals, or multimodal messages. The high computational cost of deep models such as BERT makes real-time scaling difficult. The research is based on English tweets, and it might overlook non-English opinions, as well as on social media data biased toward very active people. Future studies must incorporate multimodal analysis, take up multilingual datasets, and mix social media with ordinary surveys or news outlets. Utilizing explainable AI will enhance transparency, and scalable transformer models can boost scalability. Widening to longitudinal and cross-platform analyses would offer richer findings on changing public sentiment for more responsive environmental policies.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

All authors contributed to this work. H. E. Khodke and V. Srinadh carried out the research; Priti S. Lahane and Shivaji R. Lahane performed data analysis; Priti S. Lahane and V. Srinadh prepared the manuscript; R. Juliana and Vishal Naranje contributed to methodology development and reviewed the final draft. All authors approved the final version.

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References

[1] W. Ge, L. Deng, F. Wang, and J. Han, "Quantifying the contributions of human activities and climate change to vegetation net primary productivity dynamics in China from 2001 to 2016," *Sci. Total Environ.*, vol. 773, 145648, Jun. 2021.

[2] J. Awewomom, F. Dzeble, Y. Takyi *et al.*, "Addressing global environmental pollution using environmental control techniques: A focus on environmental policy and preventive environmental management," *Discov. Environ.*, vol. 2, no. 1, 8, Feb. 2024.

[3] D. L. Guber, "Research synthesis: public opinion and the classical tradition: redux in the digital age," *Public Opin. Q.*, vol. 85, no. 4, pp. 1103–1127, Jan. 2022.

[4] S. Gore, S. Padmalal, I. Dayanand, G. Rao, "Enhancing sentiment analysis in social media texts using transformer-based NLP models," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 11, no. 8, pp. 208–216, 2024.

[5] M. Yadav, A. Pandey, and X.-H. Nghiem, "Policy and regulatory approaches to mitigating micro- and nano plastic pollution," *Global Impacts of Micro- and Nano-Plastic Pollution*, 2024, pp. 309–330. doi: 10.4018/979-8-3693-3447-8.ch013

[6] D. Amangeldi, A. Usmanova, and P. Shamoi, "Understanding environmental posts: Sentiment and emotion analysis of social media data," *IEEE Access*, vol. 12, pp. 33504–33523, 2024.

[7] L. Wang, L. Chen, and C. Li, "Research on strategies for improving green product consumption sentiment from the perspective of big data," *J. Retail. Consum. Serv.*, vol. 79, 103802, Jul. 2024.

[8] S. Gore, D. Jadhav, M. Ingale, S. Gore, and U. Nanavare, "Leveraging BERT for next-generation spoken language

understanding with joint intent classification and slot filling," in *Proc. 2023 International Conference on Advanced Computing Technologies and Applications (ICACTA) IEEE*, 2023. doi: 10.1109/ICACTA58201.2023.10393437

[9] R. Sharma, B. Singh, and A. Khamparia, "Machine learning and generative AI techniques for sentiment analysis with applications," in *Generative Artificial Intelligence for Biomedical and Smart Health Informatics*, Wiley, 2025, pp. 183–208. doi: 10.1002/9781394280735.ch10

[10] W.-T. Hong, J. Whyte, and J. Xue, "A natural language processing–driven framework for policymaking in infrastructure development," *J. Constr. Eng. Manag.*, vol. 151, no. 5, May 2025. doi: 10.1061/JCEMD4.COENG-15954

[11] E. Medeiros and B. Valente, "Assessing impacts of public policies towards environmental sustainability in an EU region: North of Portugal," *Eur. Plan. Stud.*, vol. 32, no. 2, pp. 410–429, Feb. 2024.

[12] A. Bello, S.-C. Ng, and M.-F. Leung, "A BERT framework to sentiment analysis of tweets," *Sensors*, vol. 23, no. 1, 506, Jan. 2023.

[13] N. Mohamad Sham and A. Mohamed, "Climate change sentiment analysis using lexicon, machine learning and hybrid approaches," *Sustainability*, vol. 14, no. 8, 4723, Apr. 2022.

[14] T. Anderson and S. Sarkar, "From words to action: Sentiment analysis on sustainability initiatives," in *Proc. SoutheastCon*, Mar. 2024. doi: 10.1109/SoutheastCon52093.2024.10500089

[15] M. L. Loureiro and M. Alló, "Feeling the heat? Analyzing climate change sentiment in Spain using twitter data," *Resour. Energy Econ.*, vol. 77, 101437, Apr. 2024.

[16] C. Toşa and A. K. M. Tarigan, "Beneath the hashtag: multifaceted insights into sustainable consumption and production from historical Twitter data," *Sustain. Sci. Pract. Policy*, vol. 21, no. 1, Dec. 2025. doi: 10.1080/15487733.2024.2440952

[17] K. M. Hasib, M. Iqbal, F. Shah, J. Mahmud, M. Popel, M. Showrov, S. Ahmed, and O. Rahman, "A survey of methods for managing the classification and solution of data imbalance problem," *J. Comput. Sci.*, vol. 16, no. 11, pp. 1546–1557, Nov. 2020.

[18] A. K. Chowdhury, S. Sujon, M. Shafi *et al.*, "Harnessing large language models over transformer models for detecting Bengali depressive social media text: A comprehensive study," *Nat. Lang. Process. J.*, vol. 7, 100075, Jun. 2024.

[19] M. S. U. Miah, M. M. Kabir, T. Bin Sarwar, M. Safran, S. Alfarhood, and M. F. Mridha, "A multimodal approach to cross-lingual sentiment analysis with ensemble of transformer and LLM," *Sci. Rep.*, vol. 14, no. 1, 9603, Apr. 2024.

[20] D. Stammbach, N. Webersinke, J. A. Bingler, M. Kraus, and M. Leippold, "A dataset for detecting real-world environmental claims," arXiv, arXiv:2209.00507, 2022.

[21] E. Guzman. Climate sentiment in twitter. (2020). [Online]. Available: https://www.kaggle.com/datasets/joseguzman/climate-sentiment-in-twitter

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