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ClimatePulse: Sentiment and Emotion Analysis of Public Discourse on Climate Change in Social Media using BERT, NER, Multilabel Classification, and Spatio-Temporal Visualization

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Abstract — Climate change poses major global challenges with wide-ranging impacts on ecosystems, health, and policy. Public responses to climate policies are increasingly voiced on social media, producing large volumes of data that require intelligent analysis. This study introduces ClimatePulse, a unified system for analyzing Indonesian public opinion on climate change by integrating sentiment analysis, fine-grained emotion classification, and spatio-temporal visualization. The system leverages a fine-tuned BERT model trained on a balanced dataset of 3,256 tweets. Results demonstrate that the model achieves an accuracy of 75.57% and a Macro F1-Score of 0.7556, outperforming traditional baselines like SVM and Logistic Regression. Specifically, the model excels in detecting negative sentiment with an F1-Score of 0.8151, capturing critical public dissatisfaction. Beyond sentiment, the system identifies dominant emotions (e.g., sadness, joy, fear) and visualizes geographic trends through an interactive map, providing actionable insights for policymakers. While challenges remain in classifying ambiguous neutral texts (F1-Score 0.7035) and detecting sarcasm, ClimatePulse effectively bridges the gap between unstructured social media data and data-driven decision-making, directly supporting SDG 13: Climate Action.

Keywords – BERT, Climate Change, Emotion Classification, Sentiment Analysis, Spatio-Temporal Visualization

I. INTRODUCTION

Climate change is one of the greatest global challenges of this century [1]. It refers to long-term alterations in the Earth’s atmospheric conditions, including temperature and rainfall distribution, which have widespread impacts on various sectors of human life [2]. These physical changes do not occur instantly but develop over extended periods of time [3]. In the context of forests, climate change poses significant threats to both the quality and quantity of forest ecosystems, while deforestation increases greenhouse gas emissions [4]. One of the direct consequences of climate change is the rise of extreme weather, such as prolonged droughts. Severe droughts often lead to forest fires [5], which diminish the forest’s role as the “lungs of the Earth” by reducing oxygen production and weakening its ability to absorb greenhouse gases and carbon dioxide, the primary drivers of global warming [6].

In terms of public health, climate change contributes to the spread of infectious diseases such as malaria, cholera, and dengue fever, which tend to escalate during periods of heavy rainfall [7]. These diseases also proliferate under hot and humid conditions, which are themselves byproducts of changing climatic patterns [8]. Governments and international organizations have introduced various mitigation and adaptation policies, including clean energy transition, carbon emission reduction, and the development of nuclear power plants [9].

However, the success of such policies depends not only on technical and scientific factors but also on public acceptance and response [10]. In the digital era, social media has emerged as a primary channel for the public to express opinions, criticisms, and support regarding environmental issues [11]. Public sentiment toward climate change policies whether positive, negative, or neutral offers valuable insights for policymakers [12], researchers, and environmental activists. Unfortunately, the massive and diverse volume of social media data makes opinion analysis highly challenging [13]. Therefore, there is a need for an intelligent system based on Natural Language

Processing (NLP) that can automatically extract [14] relevant entities (e.g., location names, types of policies, or actors), classify public emotions (such as anger, fear, or hope), and visualize sentiment trends over time.

To address this, the research field has rapidly evolved. Comparative studies confirm that transformer-based models like BERT consistently outperform traditional machine learning for this complex domain [15]. While initial approaches successfully combined BERT-based NER and sentiment analysis recent surveys argue this is insufficient [16]. They highlight the critical need for fine-grained emotion classification (e.g., fear vs. anger) to understand the affective drivers of public opinion [17]. Concurrently, other studies have demonstrated the value of analyzing spatio-temporal trends to map *where* and *when* these discussions occur [18]. However, these advanced analyses multi-label emotion, entity extraction, and spatio-temporal mapping are rarely integrated. A significant research gap persists in developing a single, unified system that combines all three, which this study addresses.

This project is highly relevant to the Sustainable Development Goals (SDGs), particularly SDG 13: Climate Action, which calls for urgent measures to combat climate change and its impacts. By analyzing public sentiment on issues such as forest fires, energy transition, or nuclear power plant development through social media, the system can provide critical insights for governments, environmental organizations, and society to better respond to public opinion. This approach contributes to data-driven decision-making while also raising awareness and encouraging public participation in climate action. This methodology directly answers the call for enhanced data governance to support climate action in Indonesia [19] and demonstrates how NLP can effectively translate unstructured social media data into actionable insights for policymakers [20]. Furthermore, the project aligns with SDG 16: Peace, Justice and Strong Institutions by promoting transparency and inclusivity in climate policies, and with SDG 17: Partnerships for the Goals by fostering collaboration between academics, policymakers, and communities in developing technology-based solutions for environmental sustainability.

II. RESEARCH METHOD

The research methodology in this study was designed to develop *ClimatePulse*, a system for analyzing public sentiment and emotions on climate change issues in social media. The method consists of several sequential stages, starting from dataset collection and preprocessing, to feature extraction using BERT, classification of multiple emotion labels, and visualization of spatio-temporal patterns. This structured approach ensures that the model is able to capture not only the textual meaning of public discourse but also the contextual information related to location and time, which are essential for supporting climate-related decision-making in line with SDG 13.

A. Dataset Collection

The dataset for this study comprises 3,256 Indonesian-language tweets scraped from Twitter (X) between January 2023 and December 2024. Focusing on the full_text column, the raw data underwent a comprehensive cleaning process to remove noise, including case folding, tokenization, stopword removal, stemming, lemmatization, normalization, and the elimination of punctuation, numbers, duplicates, and null values. As detailed in Table 1, the final dataset reflects typical online discourse with an average length of 147 characters per tweet.

Following preprocessing, manual annotation was conducted by three independent researchers to label sentiment, emotion, location, and entities. To ensure consistency, a majority-voting mechanism was employed to determine the final sentiment labels where disagreements occurred.

A key strength of this dataset is its balanced distribution across three categories: 1,084 positive (33.29%), 1,087 neutral (33.38%), and 1,084 negative (33.29%) tweets. This structure minimizes class imbalance issues, supporting reliable model training. For development purposes, the dataset was partitioned into an 80% training set (2,604 tweets) and a 20% validation set (651 tweets).

Table 1. Statistical Details of the Dataset

Attribute	Value
Total Tweets	3,256
Collection Period	January 2023 - December 2024
Number of Annotators	3
Positive Tweets	1,084 (33.29%)
Neutral Tweets	1,087 (33.38%)
Negative Tweets	1,084 (33.29%)
Training Set Size	2,604 (80%)
Validation Set Size	651 (20%)
Max Tweet Length	279 characters
Average Tweet Length	147 characters

B. Data Preprocessing

Unlike traditional NLP methods that often require extensive preprocessing [21], this study leverages the capabilities of transformer-based models such as BERT. The preprocessing stage in *ClimatePulse* is minimal, primarily focused on preparing raw text for tokenization and embedding. BERT-based models are designed to process raw text while preserving contextual information that might otherwise be lost through aggressive cleaning techniques such as stopword removal or stemming. However, general cleaning steps were applied to the scraped raw data to ensure consistency and reduce noise before the manual labeling and fine-tuning stages.

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C. *Feature Representation*

Feature representation in *ClimatePulse* is handled automatically through the HuggingFace pipeline integrated with BERT. When a user inputs text, the system directly processes it using the pipeline without requiring explicit manual preprocessing. The AutoTokenizer object from HuggingFace performs subword tokenization (WordPiece algorithm), which splits words into smaller units to handle out-of-vocabulary cases. For example, the word "perubahaniklim" is tokenized into ["perubahan", "##iklim"].

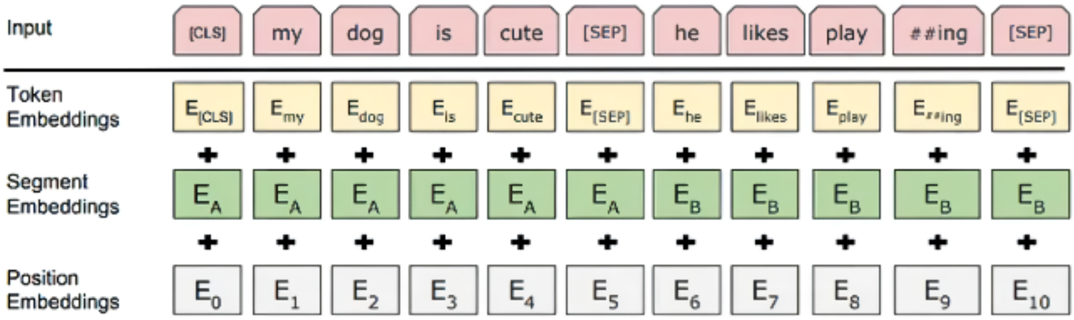

Fig.1. Illustration of BERT embedding layers [22]

Fig.1. illustrates how BERT constructs embeddings by combining three components: Token Embeddings, Segment Embeddings, and Position Embeddings [23]. These embeddings work together to generate contextualized word representations that capture both the meaning of subwords and their order in the sentence [24].

This tokenization is implicit but crucial, as it enables BERT to generate contextual embeddings for each token [25]. Unlike traditional NLP approaches, BERT does not require stemming or lemmatization, since it learns word meaning from surrounding context [26]. Similarly, stopword removal is avoided, as common words like "yang", "di", or "dan" may carry structural importance for understanding sentence semantics [27].

Furthermore, pre-trained models are employed to automate labeling tasks, including Named Entity Recognition (NER), sentiment, and emotion classification. This process identifies entities (e.g., "Papua") and affective states without human intervention. These automated outputs provide robust feature representations that serve as critical inputs for the subsequent multilabel classification and spatio-temporal visualization stages.

D. *Multilabel Classification*

Classification is central to the ClimatePulse system for analyzing public opinion. To capture both sentiment polarity and emotional nuances, this study employs a dual-model approach utilizing two distinct BERT-based architectures.

a) Sentiment Classification Model: The first model is a fine-tuned version of mdhugol/indonesia-bert-sentiment-classification, trained to classify text into positive, neutral, and negative categories. To ensure optimal performance for this specific domain, the model was fine-tuned using hyperparameters selected based on transformer best practices. As detailed in Table 2, the training utilized the AdamW optimizer with a learning rate of 2×10^{-5}, a batch size of 16, and specific class weights to maintain stable gradient updates across the balanced dataset. To validate the effectiveness of this fine-tuned BERT model, its performance was benchmarked against traditional machine learning baselines: Support Vector Machine (SVM) and Logistic Regression. As shown in Table 3, the fine-tuned BERT model achieved the highest overall performance with an accuracy of 0.7557 and an F1-Macro score of 0.7556, outperforming both SVM and Logistic Regression. While SVM showed competitive results in the negative class, BERT demonstrated superior capability in distinguishing positive and neutral sentiments, confirming that transformer-based architectures provide a measurable improvement over classical models for Indonesian sentiment analysis.

Table 2. Hyperparameter Configuration for Fine-Tuning

Hyperparameter	**Value**
Pre-trained Model	mdhugol/indonesia-bert-sentiment-classification
Max Sequence Length	128 tokens
Batch Size	16
Learning Rate	2.00×10^{-5}
Epochs	3
Optimizer	AdamW (Weight Decay: 0.01)
Class Weights	Pos: 1.001, Neu: 0.998, Neg: 1.001

b) Emotion Classification Model: The second model, azizp128/prediksi-emosi-indobert, was employed to identify specific emotional tones within the discourse. This model classifies opinions into six granular categories: joy, anger, fear, sadness, disappointment, or neutral. By integrating this emotion detection with the sentiment classifier, the system provides a comprehensive understanding of public perception, moving beyond simple polarity to reveal the specific affective drivers behind climate change discourse.

Table 3. Model Performance Comparison

Model	SVM	Logistic Regression	BERT (Fine-tuned)
Accuracy	0.7358	0.7465	0.7558
F1-Macro	0.7301	0.7420	0.7556
F1-Positive	0.6754	0.6963	0.7481
F1-Neutral	0.6927	0.7123	0.7035
F1-Negative	0.8223	0.8174	0.8151

E. Geolocation and Spatio-Temporal Mapping

This stage aims to map public opinion based on spatial and temporal dimensions [28]. The process begins with the use of a Named Entity Recognition (NER) model, cahya/bert-base-indonesian-NER, to extract key entities from the text, such as location names, organizations, or individuals. If the system does not detect a location through NER, it performs text matching against a predefined list of location keywords, covering provinces, cities, and traditional areas.

Recognized locations are then mapped to geographic coordinates (latitude and longitude) using the geopy geocoding library. This information is used to visualize the distribution of public opinion in map form. At the same time, all analysis results including input text, sentiment labels, emotions, locations, and timestamps are recorded in the file log_tren.csv for trend tracking purposes.

From this historical data, aggregation is carried out to calculate the frequency of mentions of a particular location. The more frequently a location is mentioned, the larger the radius of its marker on the map and the higher its value in the sentiment trend graph. In this way, the system provides a comprehensive visualization of public opinion from both spatial and temporal perspectives, allowing the dynamics of public perceptions on climate change issues to be clearly monitored.

F. System Design

Fig.2. Users access the application through a dark-themed interface, enter an opinion or tweet related to environmental issues, and then press the "🔍 ANALYZE" button. The input text is automatically processed through several stages: (1) sentiment classification using the fine-tuned BERT model (positive, neutral, negative), (2) emotion classification with IndoBERT (azizp128/prediksi-emosi-indobert) (joy, fear, sadness, anger, disappointment, neutral), and (3) entity extraction using Named Entity Recognition (NER) with the cahya/bert-base-indonesian-NER model to detect locations, organizations, or individuals. If no location is detected, the system matches the text with a predefined list of location keywords, and then maps the results to geographic coordinates using geopy.

All outputs including input text, sentiment labels, emotions, entities, locations, and timestamps are recorded in the log_tren.csv file for trend tracking. This information is then displayed visually: colors and emojis for sentiment/emotion, a list of detected entities, as well as a public opinion distribution map and sentiment trend graph. The system is built with Streamlit, which integrates data input, model predictions, and result visualizations into a single interactive dashboard.

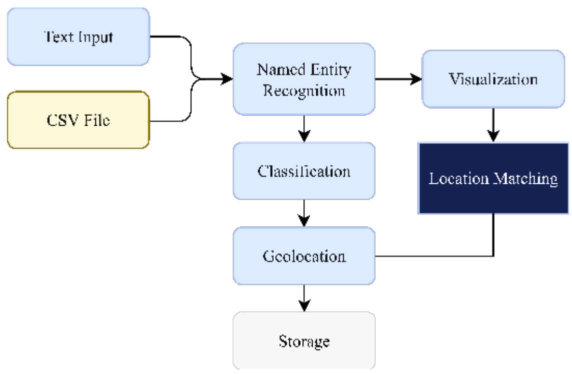

Fig.2. System design of *ClimatePulse*

G. Evaluation Metrics

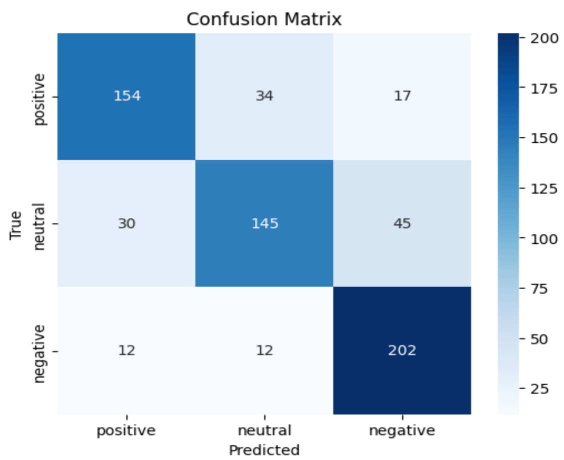

Fig.3. Confusion Matrix

Based on the confusion matrix Fig.3, the fine-tuned model demonstrated strong performance in the positive and negative classes, while the neutral class remained the primary challenge. For the positive class, 163 instances were correctly predicted, although some were misclassified as neutral (32) and negative (10). The neutral class achieved 141 correct predictions but was frequently confused with the positive class (40) and the negative class (39). Meanwhile, the negative class yielded excellent results with 194 correct predictions and only a few errors. Overall, the model was able to distinguish positive and negative sentiments quite well, but improvements are still needed in classifying the neutral sentiment, which tends to be more ambiguous

III. RESULT

The implementation of *ClimatePulse* successfully demonstrates the integration of natural language processing (NLP) models, geospatial analysis, and interactive visualization for the study of public opinion on climate change. The system outputs were evaluated through both individual text testing and batch dataset analysis, producing results that highlight its analytical capabilities across sentiment, emotion, entity extraction, and spatial-temporal mapping. The findings are elaborated in four key aspects: single input performance, visualization effectiveness, batch analysis scalability, and system implications for climate discourse monitoring.

A. Classification Performance

The quantitative assessment of the fine-tuned BERT model is detailed in Table 4, which expands beyond simple accuracy to present Precision, Recall, and F1-Score for each sentiment class. These metrics offer a deeper understanding of how well the classifier distinguishes between positive, neutral, and negative sentiments.

Table 4. Detailed Classification Metrics

Class	Precision	Recall	F1-Score	Support
Positive	0.8152	0.6912	0.7481	217
Neutral	0.6766	0.7327	0.7035	217
Negative	0.7888	0.8433	0.8151	217

The results demonstrate consistent performance across all categories, with a specific strength in detecting negative sentiment. The negative class exhibits the most robust performance, achieving the highest F1-Score (0.8151) and Recall (0.8433), indicating the model is highly effective at capturing public dissatisfaction. The positive class shows strong Precision (0.8152), suggesting that while the model is cautious in predicting positive labels, it is highly accurate when it does so.

Consistent with the visual patterns observed in the Confusion Matrix (Fig. 3), the neutral class presents the primary challenge, recording the lowest Precision (0.6766) and F1-Score (0.7035). This reflects the inherent linguistic ambiguity of neutral tweets, which often share lexical characteristics with both positive and negative expressions. Overall, the model achieves a Macro F1-Score of 0.7556, demonstrating a balanced and reliable capability suitable for analyzing diverse public discourse.

B. Single Input Performance

To evaluate the system's capability in processing individual textual inputs, specific test cases were conducted. In a representative instance, the input statement "*PLTN akan dibangun di Papua, saya sangat kecewa*" was processed. The system automatically generated a structured analysis comprising include:

a) a sentiment classification of negative,
b) a dominant emotion detection of anger,
c) the extraction of Papua as a geolocation,
d) the recognition of named entities including PLTN and Papua.

These results validate the system's capability to process textual data in real time, generating outputs that are both semantically rich and affectively interpretable by integrating sentiment, emotion, entity, and location dimensions. The dual-layered classification of sentiment polarity and emotional tone provides a more granular lens for understanding public attitudes, allowing distinctions not only between positive and negative orientations but also between subtle affective drivers for instance, differentiating negative opinions rooted in fear from those stemming from disappointment. Such layered analysis enhances the explanatory depth of public discourse monitoring and strengthens its relevance for policy-oriented decision-making.

C. Spatio-Temporal and Emotion Visualization

The second major output of the system is its visualization layer, which translates raw classification data into interpretative spatial and temporal insights. include:

a) Geospatial Analysis: As shown in Fig.4, the public opinion map aggregates identified locations and plots them based on latitude and longitude coordinates retrieved via geocoding.

This spatial representation allows users to assess how climate-related discourse varies geographically across Indonesia. For instance, the visualization highlights significant clusters of discourse in regions like Kalimantan and Papua. Recurring mentions of these locations in negative contexts provide policymakers with critical, localized insights regarding specific environmental concerns, such as deforestation or industrial development impacts.

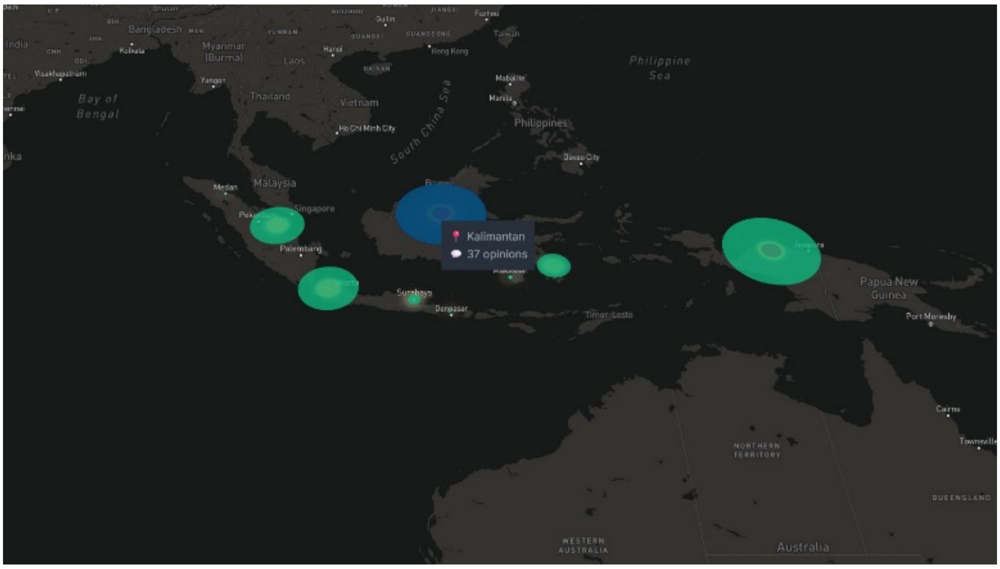

Fig.4. Map of Indonesia showing clusters

b) Emotion Distribution Analysis: Complementing the spatial analysis, the system breaks down public opinion into specific emotional categories. As illustrated in Fig.5, the analysis reveals a complex emotional landscape. "Sadness" (*Sedih*) appears as the dominant emotion, followed by "Joy" (*Senang*) and "Fear" (*Takut*). This distribution suggests that while there is significant concern and grief regarding environmental degradation, there remains a segment of the population expressing hope or positive feedback towards specific mitigation efforts. This granular emotion detection goes beyond simple polarity, offering a deeper understanding of the public's psychological state regarding climate issues.

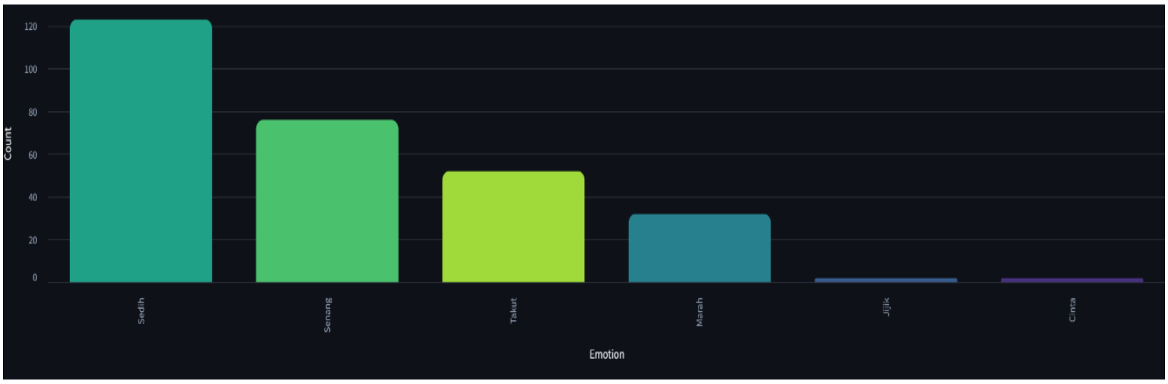

Fig.5. Bar chart of Emotion Count

c) Temporal Sentiment Trends: In parallel, the sentiment trend graph (Fig.6) displays temporal shifts in public opinion. By tracking the frequency of positive, neutral, and negative sentiments over time, the system reveals how reactions evolve in response to climate policies or environmental events. The trend visualization is particularly relevant for crisis monitoring; sudden spikes in negative sentiment (represented by the red line) can signal immediate public dissatisfaction following specific incidents. Conversely, the stability of neutral sentiment indicates sustained, objective discussions within the community.

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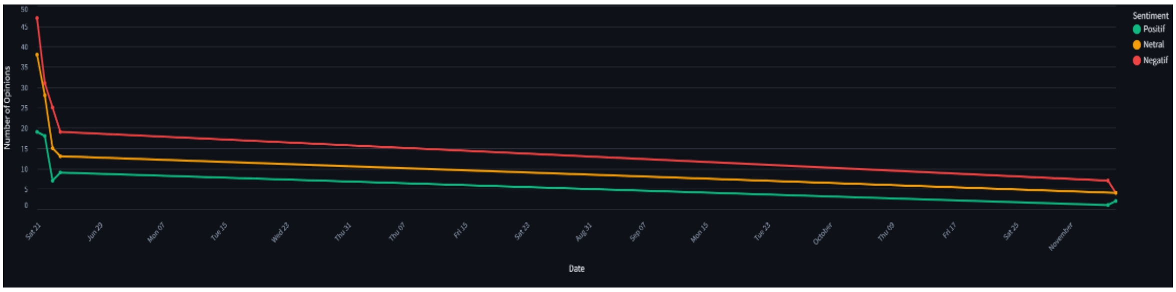

Fig.6. Line chart of Sentiment over time

D. *Batch Analysis Scalability*

Another critical advantage of ClimatePulse lies in its scalability through bulk dataset processing, which significantly enhances its applicability for large-scale research, monitoring, and policy analysis. The system incorporates a batch processing mechanism designed to ingest vast collections of heterogeneous and unstructured textual data. These datasets are automatically parsed, normalized, and enriched through a multi-stage pipeline that integrates sentiment polarity, emotional tone, and named entity recognition, thereby producing rich semantic layers of information. The raw input is systematically transformed into structured outputs, facilitating flexible export functionality for offline exploration, advanced statistical modeling, longitudinal studies, or integration into external analytical workflows. This design ensures not only efficiency in handling massive datasets but also robustness in delivering high-quality insights for diverse research and decision-making contexts.

This feature enables researchers and practitioners to analyze thousands of opinions simultaneously, rather than being limited to single inputs. Such scalability is essential for capturing large-scale public discourse trends, such as reactions to international climate summits, nationwide policy shifts, or environmental disasters. By providing both micro-level (individual text) and macro-level (bulk dataset) perspectives, the system ensures methodological flexibility.

E. *System Evaluation and Implications*

Across all testing scenarios, *ClimatePulse* demonstrated consistent performance in sentiment classification and emotion recognition, while entity and location extraction proved robust in detecting Indonesian-specific references. The integration of visualizations enhanced interpretability, making complex analytical results accessible to non-technical stakeholders such as policymakers, NGOs, and the general public.

However, certain limitations were also observed. For instance, while the system effectively identifies explicit location mentions (e.g., "*Papua*"), implicit references or abbreviations may still pose challenges. Similarly, sarcasm and figurative language can occasionally lead to misclassification of emotions. These challenges point to potential areas for refinement in future development, such as incorporating sarcasm detection or expanding the location keyword dictionary.

Despite these limitations, the system offers substantial contributions to the monitoring of climate-related public opinion. By combining advanced NLP models with geospatial and temporal analytics, *ClimatePulse* serves as a practical tool for identifying patterns in societal responses to climate change. Its outputs can inform evidence-based decision-making, facilitate early detection of emerging environmental concerns, and support public engagement strategies in line with sustainable development goals.

IV. DISCUSSION

The results of this study demonstrate that *ClimatePulse* is capable of providing a comprehensive analysis of public opinion related to climate change, both through single text inputs and large-scale CSV-based analysis. The system not only generates sentiment classification (positive, neutral, negative), but also detects dominant emotions (happiness, fear, anger, sadness, disappointment), while extracting location entities to be visualized in spatial maps and temporal trend graphs. This indicates that *ClimatePulse* captures both the affective and semantic dimensions of public opinion, offering richer insights compared to traditional sentiment analysis methods.

Compared to prior research that commonly relied on classical approaches such as TF-IDF and SVM, this system demonstrates advantages by leveraging transformer-based BERT models capable of contextual word understanding. This approach eliminates the need for extensive manual preprocessing (e.g., stemming, stop word removal, or lemmatization), making the analysis pipeline more efficient. Moreover, the inclusion of spatio-temporal visualizations makes *ClimatePulse* more informative than studies that only present numerical classification results. Several strengths of this system can be highlighted:

a) Automated and real-time processing through the HuggingFace pipeline.
b) High scalability, supporting both single input and large datasets in CSV format.
c) Interactive visualizations, including public opinion maps and sentiment trend graphs for easier interpretation.

d) Integrated multi-label analysis, covering sentiment, emotion, entities, and locations in a single workflow.

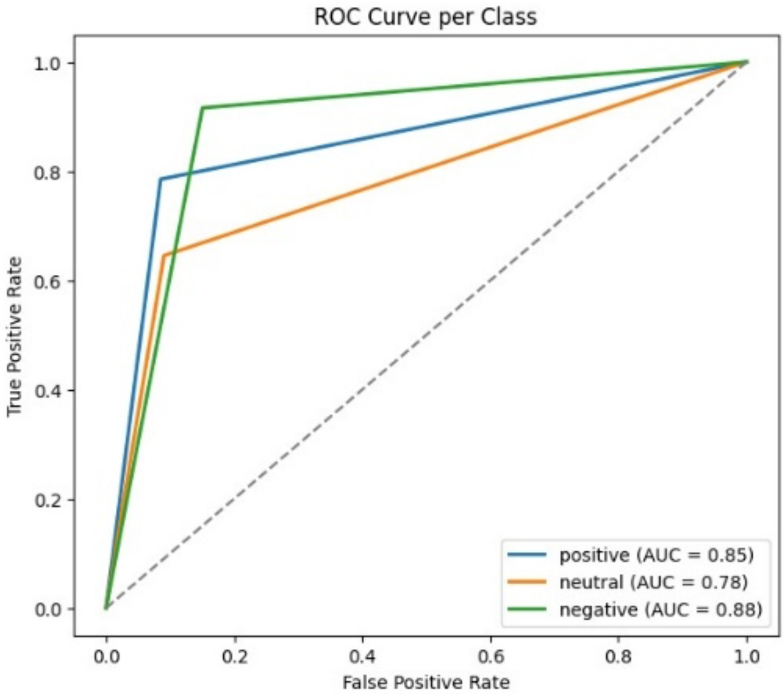

Fig. 7 ROC Curve of the Fine-Tuned Sentiment Classification Model

In addition to these strengths, the performance of the sentiment classification model was further evaluated using the ROC curve in Fig.7. The ROC curve illustrates the classification performance of the model across the three sentiment classes: positive, neutral, and negative. The Area Under the Curve (AUC) values indicate the discriminative ability of the model for each class. Specifically, the positive class achieved an AUC of 0.85, demonstrating a strong ability to distinguish positive texts from the others. The neutral class obtained the lowest AUC score of 0.78, suggesting that the model faces challenges in accurately identifying neutral texts, which are often more ambiguous. Meanwhile, the negative class achieved the highest AUC score of 0.88, reflecting the model's strong capability in recognizing negative sentiment. Overall, the results indicate that the model performs well, with all AUC values exceeding 0.75, though improvements are still needed for the neutral class.

The evaluation results indicate that the neutral class exhibits the lowest performance, with an F1-Score of 0.7035, compared to the positive and negative classes. This suggests that the model encounters difficulties in identifying neutral expressions, which often overlap lexically and semantically with both positive and negative sentiments. Several strategies may help address this weakness. First, refining the annotation guidelines and improving annotator alignment could reduce inconsistencies, as the lower precision in the neutral class indicates frequent misclassification. Enhancing the dataset with additional linguistic cues commonly found in neutral statements such as hedging phrases, objective descriptions, or the absence of emotional markers may also improve the model's ability to differentiate neutrality. Although the dataset is balanced in terms of class counts, increasing the linguistic diversity of neutral examples through paraphrasing or contextual data augmentation may further enhance generalization. Additionally, alternative loss functions such as focal loss can help the model place greater emphasis on hard-to-classify neutral samples, complementing the existing class weighting approach. Conducting detailed error analysis, including confusion trends between neutral and other classes, would also provide insights for refining preprocessing or model configuration. Collectively, these strategies could strengthen the classifier's capability to more accurately detect neutral sentiment and close the performance gap observed across classes.

Nevertheless, some limitations were identified. First, the system still struggles with detecting implicit or abbreviated references to locations. For instance, the phrase *"Tanah Cendrawasih"* referring to Papua is often not recognized. Second, sarcastic or figurative language tends to cause misclassifications for example, the sentence *"Hutan habis, saya senang sekali!"* may be read as positive sentiment, while its intended meaning is negative. Third, mixed language use (Indonesian-English) or informal slang commonly found on social media remains challenging for the current models.

The implications of this research are significant, particularly in the context of supporting SDG 13 (Climate Action). With *ClimatePulse*, stakeholders such as governments, NGOs, and academics can monitor public perception of environmental issues more systematically. This information can serve as a decision support tool in policy formulation, public communication strategies, and conflict mitigation efforts regarding climate-related policies.Future work may focus on several improvements:

a) Integrating a sarcasm detection module to enhance classification accuracy.
b) Expanding the location and entity dictionaries to capture implicit references or slang.
c) Fine-tuning BERT with a domain-specific climate dataset to increase result relevance.
d) Incorporating data from other platforms, such as Instagram, TikTok, or online news, to broaden the scope of public opinion monitoring.

In conclusion, *ClimatePulse* not only serves as a prototype for sentiment analysis but also shows potential to evolve into a more comprehensive and adaptive platform for monitoring public discourse on climate change, thereby supporting sustainable environmental development in Indonesia.

V. CONCLUSSION

This study successfully developed *ClimatePulse*, a public opinion analysis system on climate change issues that leverages a fine-tuned BERT algorithm combined with Named Entity Recognition, multi-label classification, and spatio-temporal visualization. The system is capable of analyzing both real-time inputs and large-scale CSV datasets, producing sentiment classification, emotion detection, entity extraction, as well as public opinion maps and sentiment trend graphs.

The results show that *ClimatePulse* effectively captures both the affective and semantic dimensions of public discourse. The integration of spatio-temporal visualization makes the system more informative compared to traditional methods, while also providing practical support for monitoring environmental issues. These findings have direct implications for advancing SDG 13 (Climate Action) by offering data-driven insights to inform policy development.

Nevertheless, several limitations remain, such as difficulties in detecting implicit or abbreviated location mentions, limited handling of sarcastic language, and challenges with slang or mixed-language text. Future research directions may include:

a) Integrating a sarcasm detection module to improve classification accuracy.
b) Expanding the location and entity dictionaries to better adapt to linguistic variations.
c) Incorporating data from other social media platforms (Instagram, TikTok, online news) to broaden the scope of public opinion monitoring.

In conclusion, *ClimatePulse* is not only a functional prototype for sentiment analysis but also demonstrates strong potential to evolve into a comprehensive platform for public opinion monitoring, contributing to sustainable environmental development in Indonesia.

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