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AI-Driven Framework for Location-Aware Sentiment Analysis and Topic Classification of Public Social Media Data in West Malaysia

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Abstract

While social media has facilitated communication, it has also amplified collective attitudes, often leading to polarized opinions and negative emotional expressions that can disrupt social harmony. Consequently, monitoring public sentiments on social media, and identifying thematic trends across regions has become crucial for understanding collective emotions and opinions. Despite advancements in sentiment analysis and topic classification, very little research has been done to integrate geospatial analysis with these techniques, limiting their ability to provide location-aware insights into public sentiments and discussion trends. This study develops an AI-driven framework that leverages social media data to analyze public sentiments and classify discussions into relevant topics. Specifically, this research focuses on understanding the emotions and conversations of Peninsular Malaysia citizens using a self-collected dataset of public Facebook posts, analyzed at the state level to provide location-aware insights. Using VADER for sentiment analysis and zero-shot transformer for topic classification, this study categorizes posts into five predefined topics: politics, religion, tragedy, tourism, and food. The proposed architecture achieves a sentiment classification accuracy of 97% and a topic classification accuracy of 89%. Findings reveal that the Peninsular Malaysian population generally maintains a positive online environment, though some states showed a dominant negative sentiment. Patterns of dissatisfaction were largely related to political issues and local incidents, while positive emotions were primarily associated with tourism, religious festivities, and food-related news. This research not only identifies areas with dissatisfied publics but also explores the topics contributing to this sentiment. By emphasizing location-aware sentiment and topic trends, this framework offers insights to help policymakers and sociologists address region-specific issues, potentially reducing dissatisfaction and fostering a more harmonious society.

Keywords: *Social Media, Natural Language Processing, Sentiment Analysis, Topic Classification, Social Media Monitoring.*

1. Introduction

Social media is a place to [1] express emotions, [2],[7] share opinions, and engage in discussions with an audience of [3], [4] diverse backgrounds and geographies. It harvests an environment where users can discuss social issues, and conduct political discussions, thus [5] promoting tolerance and inclusivity. While it [6] increases awareness, and social mobility, social media also amplifies [8], [14], [15] polarized opinions and misinformation, leading to societal discord.

Several historical events demonstrate the potential of social networks to shape public opinion and influence [9] collective attitudes. For instance, recently a [10] Pakistani man, was accused of spreading disinformation on his website that was believed to have fueled antiimmigration riots in the United Kingdom. Then, supporters of Trump stormed Capitol Hill on 6th January 2021, to stop Congress from announcing the win of Joe Biden as President. This massive riot was [11] organized and discussed up to execution on Facebook, Telegram, and [12] Parler. Similarly, social platforms played an undeniable role in fueling panic during the COVID-19 pandemic. Lelisho [13] conducted a study to research the negative impact of social media during the coronavirus. The results showed that 86.73% of the participants claimed to experience unpleasant psychological effects after being exposed to health-related news from social media. All these incidents show how dangerous unregulated social media discussions can be.

According to the 2024 report of [16] MeltWater, 83% of Malaysians are active social media users, with [16] TikTok, Facebook, and Instagram being the most popular platforms among them. Peninsular Malaysia with its diverse population and urbanized landscape offers a favorable setting for studying the regional sentiment and topic trends.

Yet, Peninsular Malaysian social media has received limited attention from NLP researchers. That too in an isolated manner where the interdependence of sentiment analysis and topic classification is not studied. Furthermore, existing research on social media data also remains limited in integrating geospatial analysis with sentiment and topic classification, thus limiting the ability to analyze region- specific sentiment and topic trends.

In this vein, this study develops an AI-driven framework for location-aware sentiment analysis and topic classification of Facebook data discussing Peninsular Malaysia. By combining VADER for sentiment analysis and zero-shot transformers for topic classification, we provide state-wise insights into public sentiments and thematic trends. Our contributions are as follows:

1. Provides an AI-driven framework that integrates sentiment analysis and topic classification with geospatial mapping to provide state-wise topic and sentiment trends across Peninsular Malaysia.
2. Employs advanced Natural Language Processing (NLP) techniques, including VADER for sentiment analysis and zero-shot transformers for topic classification to classify posts from each state into positive or negative sentiment categories, as well as into five predefined thematic topics: religion, politics, tragedy, tourism, and food.
3. The proposed framework achieves state-of-the-art performance with a 97% accuracy in sentiment classification and an 89% accuracy in topic classification.
4. Utilizes a self-collected dataset of public Facebook posts spanning all 12 states of Peninsular Malaysia addressing the scarcity of Malaysian-focused social media research.

Gives a comprehensive understanding of the emotional health of Malaysians and its underlying causes, thus providing actionable insights for policymakers and sociologists to address region-specific issues and foster social harmony.

The remainder of the paper is divided into the following sections: Section 2 presents a literature review, Section 3 discusses the material and methods, Section 4 discusses the results and discussion, and finally Section 5 presents the conclusion.

2. Literature Review

The ever-growing [31], [32] social media addiction provides an unparalleled opportunity to monitor unfiltered public sentiments and opinions. However, analyzing social media data is trickier than traditional textual datasets due to its noisy, [34] sarcastic, and often [33] ambiguous nature.

Location-aware social media monitoring can help government officials understand the public and aid smooth decision- making. Social media platforms have become the go-to place for citizens to communicate and express themselves on any topic. While government officials also engage on social media, it is difficult to understand the collective views of citizens due to large data volume. Natural Language Processing (NLP) techniques therefore provide an efficient way to analyze this data leading to informed decision making[19] and harmonic online environment.

NLP techniques have often been used to understand the stance of citizens on different social issues. For example,[35] deploys a dictionary-based sentiment analyzer to understand the emotional trends toward migration discourses in European countries. [36] uses VADER to analyze tweets discussing Digital Zakat to understand Muslims's sentient towards this advancement in technology. Furthermore, crucial future research topics in this scope were highlighted using word clouds of each sentiment class [36]. Then, [37] uses Textblob's sentiment analyzer to measure the public's sentiment towards country leaders influenced by the Russo- Ukrainian conflict of 2022. Findings revealed that although the polarity scores of posts from both country's leaders were fairly neutral, Zelenskyy, the Ukrainian President, has a higher positive sentiment than Putin, the Russian President. Nevertheless, sentiment analysis and topic mining of social media data has proven to yield useful insight to public thinking.

Sentiment Analysis is an NLP technique that automates the identification and extraction of emotions and opinions from textual data. It employs different [22],[23] ML and [24], [25] non-ML techniques to comprehend the tone and subjective information in text. [35], deploys three deep neural networks: 1D-CNN, BiLSTM, and a hybrid 1D-CNN + BiLSTM, with and without attention to find out which of these models analyzes public sentiment towards the COVID'19 pandemic most accurately. They used a dataset of Albanian comments from the NIPHK's (National Institute of Public Health of Kosovo) Facebook page and found out that Bi-LSTM with attention had the highest F1-score of 72. Pretrained rule- based sentiment analyzers have also been frequently used for Facebook posts and comments. [36], for example, perform a comparative performance analysis between two pretrained rule-based sentiment analyzers, VADER and Textblob. His results on Facebook posts unveiled that VADER because of its specificity to social media, outperforms Textblob.

Topic classifiers are NLP models that automatically analyze text and categorize it into the most relevant topic(s) from a predefined set. Topic classifiers help in understanding the main themes of large-scale text data, such as [26] social media posts, [27] news articles, or [28] customer reviews, by as- signing labels like "politics," "sports," "technology," "entertainment," etc., based on the content. [39], topic classification was used on Greek Reddit data to categorize posts into 12 topics, including society, politics, technology, education, and more. They applied traditional machine learning models like Gradient Boosting, Stochastic Gradient Descent Classifier, Passive-Aggressive Classifier, and Multi-Layer Perceptron, and transformer-based models like GREEK-BERT and MP- Net. The results showed that the fine-tuned GREEK-BERT model achieved the highest performance, with an F1 score of 79.24% and low Hamming loss, indicating its superiority in classifying posts into appropriate topics compared to other models.

Then in another study, [38] uses zero-shot topic classification to categorize social media posts into 10 hazard classes. The results of their study demonstrated the effectiveness of zero- shot classification in real-world, noisy social media data. It also showed how zero-shot classification is scalable and can accurately perform its task with minimal supervision.

Incorporating location into sentiment and opinion analysis is crucial for capturing the differences in public sentiment across regions. Regional contexts, such as local culture, socioeconomic factors, politics, and recent events, significantly influence people's opinions and emotions. Without accounting for these variations, sentiment and topic analysis may overlook critical insights that are geographically specific and relevant to local decision-making. By integrating location data, researchers can enhance their model [40], [41] performance by identifying patterns and trends that vary by region, such as areas of heightened dissatisfaction or support, and uncover regional issues driving public discourse.

[17] propose a real-time sentiment analysis framework de- signed to monitor evolving public opinion, with a case study focused on climate change. They specifically analyzed tweets by Greta Thunberg and her followers. The framework used bi-directional Long Short-Term Memory (LSTM), a deep learning model, to classify both sentiments and emotions. Sentiment categories included support, strong support, opposition, and strong opposition, while emotions were classified as joy, inspiration, anger, and discrimination. The model yielded classification accuracies ranging from 87% to 89% across the different sentiment and emotion categories. While [17]'s study didn't provide a location-aware analysis of the tweets, their study indicated that geographic location plays an essential role in shaping public opinions.

[18] present a deep learning-based framework for topic-level sentiment analysis on social media data. The model detects topics in real time and analyzes the associated sentiments. For topic detection, the authors used online latent semantic indexing constrained by regularization, allowing them to identify topics at the sentence level. The sentiment analysis was performed using an attention-based LSTM network, which links the sentiment to the detected topics in each sentence. The model was trained on the SemEval-2017 Task 4 Subtask B dataset and tested on both the SemEval dataset and additional datasets collected from Twitter under the hashtags #Ethereum, #Bitcoin, and #Facebook. The results demonstrated that the model performed well, achieving an average recall above 0.79 for all datasets.

[42] introduces TClustVID, a clustering-based classification and topic extraction model designed to analyze public tweets related to COVID-19. Using datasets from IEEE Dataport, TClustVID extracted key topics from clustered tweets, categorizing them into positive, neutral, and negative sentiments. It then identified frequent topics in these tweets, providing insights into public opinions and attitudes about COVID- 19, infection prevention, and misinformation. In the same domain, [43] leverages NLP techniques to analyze COVID-19 discussions from social media. Using topic modeling, they discovered key public issues related to the pandemic. [43] applied an LSTM recurrent neural network for sentiment classification of COVID-19-related comments, achieving an accuracy of 81.15%.

[44] proposes a social media mining approach combining topic modeling and sentiment analysis to analyze Samsung Galaxy Note 5 reviews on Reddit. Using Latent Dirichlet Allocation (LDA) and a sentiment-driven opportunity algorithm, the approach evaluates the importance and satisfaction levels of product topics, prioritizing them for development. Table 1 compares the above-discussed studies with the pro- posed approach. It can be observed that most existing studies are based on a specific event (such as [42], [43] COVID-19), theme (such as [17] climate change or [18] fintech), or objective (such as [44- 48] customer review analysis), thus lacking a generalized social media analysis. Additionally, location-specific social media analysis is scarce[49-50]. Moreover, most of these studies apply topic modeling in their research, which is unsupervised and lacks the precision of supervised topic classification, leading to less actionable results.

3. Methods

This section overviews the study area, dataset details, data cleaning and preprocessing steps, and the techniques used for sentiment analysis and topic classification. Figure 1 presents the overall architecture of the methodology pipeline.

3.1. Study Area

Peninsular Malaysia, comprising [45]11 States (Figure 2) is a diverse and dynamic region with significant economic,

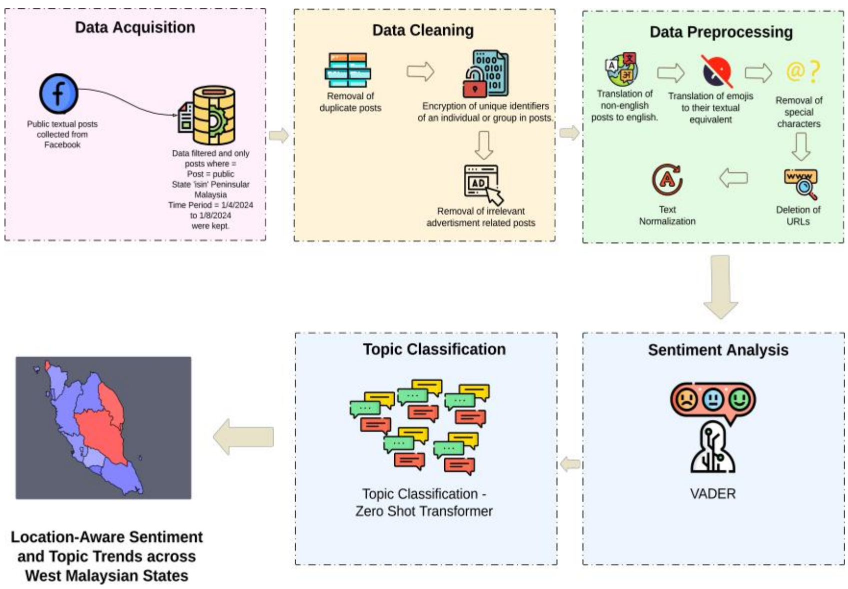

Fig. 1. Proposed methodology pipeline.

Table 1. Comparison of Existing Literature with the Proposed Method

Paper	Sentiment Analysis	Topic classification/ Modeling	Generalized	Location-aware
[17]	✓			
[18]	✓	✓		
[42]	✓	✓		
[43]	✓	✓		
[44]	✓	✓		
Proposed Model	✓	✓	✓	✓

Political and cultural influence. It carries a diverse population of three major ethnicities: Malays, Chinese, and Indians, who form a blend of urban and rural communities. Malays, who are primarily Muslims, are essential to the political and cultural identity of the nation. The Chinese community, largely Buddhist, Taoist, or Christian, has been influential in business and commerce, while the Indians, mainly Hindu or Muslim, have substantially contributed to Malaysia's culture and education. This diverse ethnic fabric contributes to Malaysia's dynamic cultural, linguistic, and religious landscape by reflecting the country's history of colonization, migration, and trade. Although Bahasa Malaysia is the official language, many people speak English, Mandarin, and Tamil, reflecting society's multilingualism. In addition to influencing Malaysia's social structure, this diversity offers a distinctive framework for examining local sentiments and opinions.

Fig 2. The state boundaries of our study area: Peninsular Malaysia

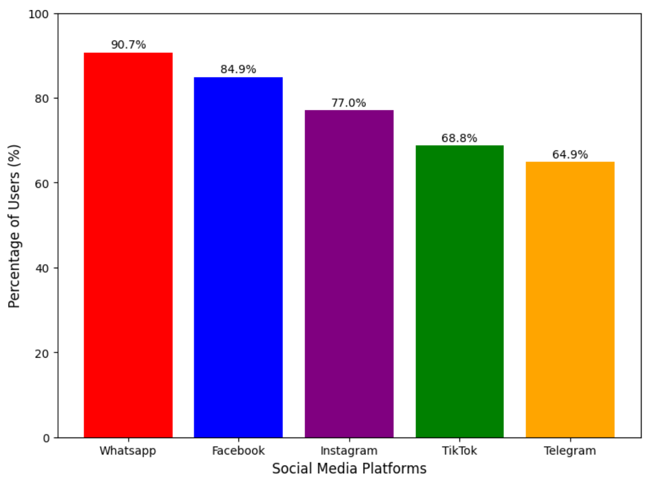

Fig 3. Top 5 Most-Used Social Media Platforms in Malaysia (2024)

Because of West Malaysia's sizable and engaged online population, social media is useful for gauging popular sentiment. The bar chart in Figure 3 presents the [16] most popular social platforms in Malaysia as of 2024. WhatsApp, because of its ease of communication and privacy protection is used by 90.7% of Malaysian social media users for personal and professional messaging. Up next, 84.9% of the active population use Facebook, for its multifunctional platform, offering features like public groups, events, and news sharing. Hence, the fundamental reason to choose Facebook for data collection was its large audience, availability of public forums (groups and pages), and news-sharing nature. Then, 77.0% of online Malaysians preferred Instagram for its visually appealing content, influencer marketing, and photo/video sharing among younger demographics. At 68.8%, TikTok gained traction for short-form video content and creativity. Lastly, Telegram with 64.9% of online Malaysians is popular for its large group capacity, and secure file-sharing capabilities.

3.2. Data Acquisition

Public posts discussing Peninsular Malaysia were collected from Facebook between 1st April 2024 and 1st August 2024. This four-month period was chosen to ensure the dataset remained relevant to recent discussions while providing a substantial volume of data for analysis. Only textual posts were taken; in cases where posts included images and text, only the text portion was retained for analysis. A word profile was developed for data collection, containing approximately 70 geographic keywords from Peninsular Malaysia. These keywords included 'Selangor','George Town', 'Perlis', 'Penang', 'Batu Arang', 'Pahang', 'Rantau Panjang', 'Langkawi', 'Kota Bharu', 'Mersing', 'Kuala Lumpur', 'Terengganu', 'Subang Jaya', 'Kelantan', and 'Johor Bahru' among others. Approximately 1,000 public Facebook posts were gathered, adhering to Facebook's ethical guidelines. Since these keywords were geographic in nature, the data collected could be easily organized according to states, allowing for more structured and state-specific analysis.

The data utilized in this research was collected following Facebook's ethical guidelines and platform policies. Only publicly available posts were analyzed, ensuring individual privacy and rights were fully respected. All personal identifiers, such as names, were carefully removed or encrypted to further safeguard user anonymity. Additionally, efforts were made to ensure that the content analyzed did not compromise the identity of individuals or communities mentioned in the posts.

3.3. Data Cleaning and Preprocessing

The data collected underwent thorough cleaning, as shown in Figure 1, to ensure relevance and privacy. Duplicate posts were identified and removed to prevent repetition. Posts that were purely advertisement-based, such as property sales or rentals, job postings, and tuition ads, were filtered out, leaving the dataset with 600 posts. Additionally, any personal identifiers, such as names of individuals or groups, were encrypted or removed (depending on the nature of the post) to safeguard privacy and ensure that no one was targeted in the analysis. It must be kept in mind that user identities were anonymized, and no data targeted specific individuals or groups, thus the cleaning process ensured a refined and ethically compliant dataset for further processing.

Non-English posts were then translated into English because many advanced NLP models are trained predominantly on English language and thus perform exceptionally well on English text. Next, emojis were converted into their textual descriptions using Python's "emoji" library to preserve the post's emotional context. This was done because emojis often carry nuances of emotion not easily expressed in plain text and removing them would result in the loss of essential sentimental insights. After this, special characters and URLs were removed to reduce noise in the data. Lastly, text normalization was applied to convert all texts to lowercase.

3.4. Sentiment Analysis

After preprocessing, sentiment analysis was performed using VADER (Valence Aware Dictionary and sEntiment Reasoner). VADER is a rule-based model designed to detect sentiment in social media posts, accounting for common social media elements like informal language, slang, and phonetic spellings. Its lexicon assigns positive or negative values to words and computes sentiment intensity scores. Each post in the dataset was evaluated using the "compound¯polarity" function of VADER, which provides a polarity score between -1 and 1. Posts with a score between -1 and 0 were classified as negative, while those between 0 and 1 were classified as positive. VADER was chosen due to its high accuracy with informal, short texts that are common on platforms like Facebook.

VADER's ability to process and quantify emotional cues made it an ideal fit for this study, where understanding sentiment across various topics was essential. Additionally, its pre-trained model on large corpora ensures accurate sentiment detection without custom training, which would otherwise be resource intensive.

3.5. Topic Classification

The processed posts were classified into five main topics: food, tourism, politics, religion, and tragedy. This categorization was chosen based on observations during the data screening process, where it became evident that most discussions revolved around these themes. These topics cover various interests and societal issues, reflecting the diverse nature of public discourse in Peninsular Malaysia. A zero-shot classification transformer model was employed for topic classification. Zero-shot transformers use Facebook's BART, a pre-trained transformer model, to predict the topic for a given text. When provided with a list of candidate labels (in this case, food, tourism, politics, religion, tragedy), the model generates predictions for how likely the input text belongs to each label. By encoding both the input text and the labels into a shared vector space, it calculates similarity and assigns the most appropriate category. This method bypasses the need for large, topic-specific training datasets, making it suitable for this exploratory research.

4. Results and Discussion

This section presents the exploratory data analysis of our dataset, the insights obtained from sentiment analysis, and finally the insights obtained from topic classification.

4.1. Exploratory Data Analysis

Exploratory Data Analysis (EDA) of the dataset revealed some interesting patterns across the states of Peninsular Malaysia. Figure 4 presents the percentage (%) of the volume of posts contributed by each state. The distribution is notably skewed, with certain states contributing a larger percentage of posts than others

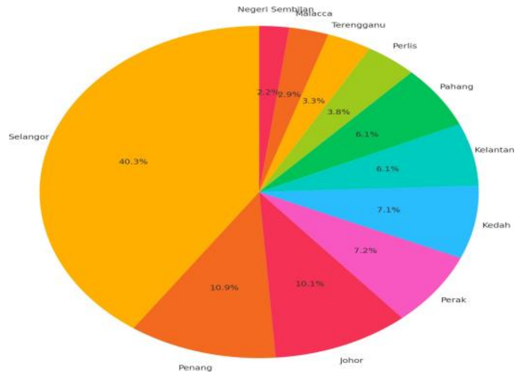

Fig 4. Percentage (%) volume of posts contributed by each state.

Selangor is the most active state in terms of social media posts, accounting for approximately 40.3% of the total data collected. This can be attributed to Selangor's large population and role as a central urban and economic hub. Johor and Penang follow behind, contributing 10.1% and 10.9% of the total posts, respectively. These states also serve as key economic and industrial regions. Other states like Perak (7.2%), Kedah (7.1%), Kelantan (6.1%), and Pahang (6.1%) contributed moderately to the dataset, while states such as Terengganu, Perlis, Negeri Sembilan, and Malacca account for smaller portions, each contributing less than 4% of the total posts. Hence, the state-wise post density highlights the concentration of online activity in a few key states, which may correlate with population density, economic activity, and internet accessibility.

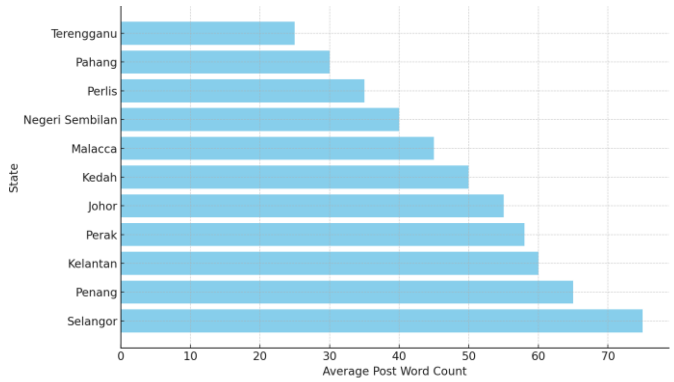

Fig 5. Average post length per state.

Figure 5 illustrates a bar chart showing the average post length per state. The post length here refers to the number of words in the content of posts. As observed, Selangor has the longest average post length, approaching approximately 74 words on average. This could indicate that users here tend to provide more detailed or elaborate content compared to other states. Penang, Kelantan, and Perak also exhibit relatively long posts, each with an average post length exceeding 60 words. These regions may have users engaging in more detailed discussions or reports. Johor and Kedah show moderate post lengths, ranging between 55 and 60 words which suggest concise conversations in these states. Finally, Negeri Sembilan, Malacca, Perlis, Pahang, and Terengganu have shorter average post lengths, particularly Terengganu, where average post length is just over 17 words. This could reflect a trend of brevity. The variation in post length across states may reflect different user behavior, regional communication patterns, or even linguistic tendencies (e.g., more formal versus casual speech).

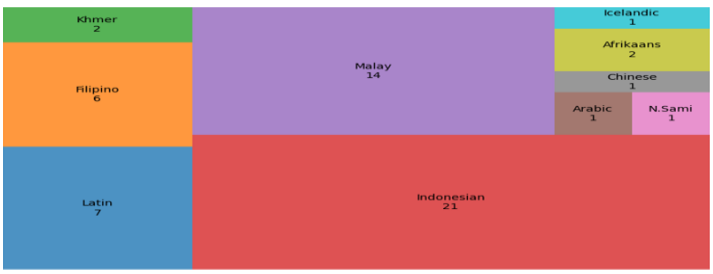

Fig. 6. Distribution of non-English posts in the dataset.

Figure 6 shows a treemap representing the distribution of non-English posts in the dataset. Each rectangle represents a specific language, with the size of the rectangle corresponding to the number of posts detected in that language. Indonesian (id) language has the largest share, with 21 posts, followed by Malay (ms) language with 14 posts. However, since the Malay language is derived from the Indonesian language, translator libraries are prone to inter-labeling them. Hence, it can be said that Indonesian and Malay combined contributed to 35 posts. Next, Latin (la) and Filipino (tl) account for 7 and 6 posts, respectively, showing moderate representation. While Khmer (km), Afrikaans (af), Chinese (zh), Arabic (ar), Icelandic (is), and Northern Sami (se), also appear but have 1-2 posts each.

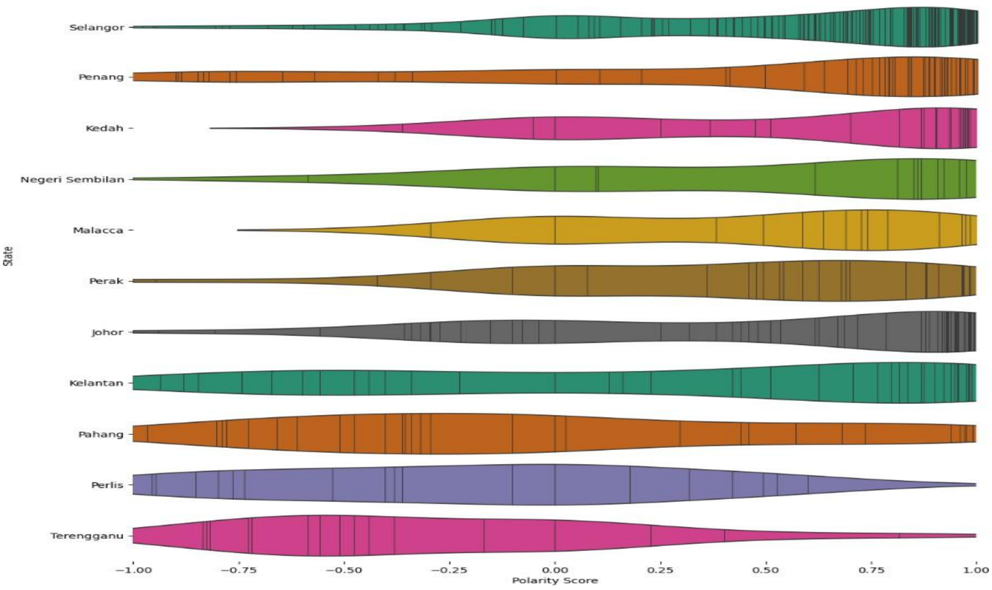

Fig 7. State-wise polarity score distribution.

4.2. Sentiment Analysis Insights

Each post was evaluated via VADER to determine its polarity score and classify it as positive or negative. Figure 7 shows a violin plot capturing the sentiment polarity scores across Peninsular Malaysian states. It visualizes the distribution of positive and negative sentiments within each state. Selangor, Penang, Kedah, Negeri Sembilan, Malacca, Perak, and Johor have a high volume of positive sentiment posts, which can be observed by the increased width of the violin at the positive end of the scale. Kelantan has an almost equal distribution of positive and negative posts, while Pahang, Perlis, and Terengganu show a stronger tendency towards negative sentiment, with a very low volume of positive polarity posts. The results of VADER achieved an accuracy of 97% against the manual annotations of the dataset.

4.3. Topic Classification Insights

Zero-shot topic classification uncovered patterns and key discussion points across the dataset. Figure 8 presents a heat map showing the distribution of topics in different states. The intensity of the color in each cell indicates the number of posts for each topic within a state. Selangor stands out as the state with the highest number of posts across all topics, although the categories of ”travel” (124 posts), ”food” (60 posts), and ”tragedy” (41 posts) have the highest numbers. This suggests that Selangor is a central hub for diverse discussions, likely due to its metropolitan nature and larger population. States like Penang (38 travel posts, 10 food posts) and Johor (36 travel posts, 10 food posts) also make major contributions to the common themes of ”travel” and ”food” that are found in many states. These patterns may reflect these states’ cultural and tourism-related importance. Overall post

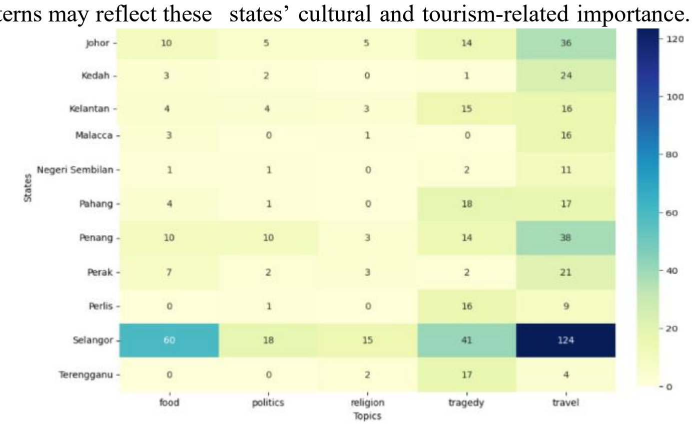

Fig 8. State and topic-wise post distribution.

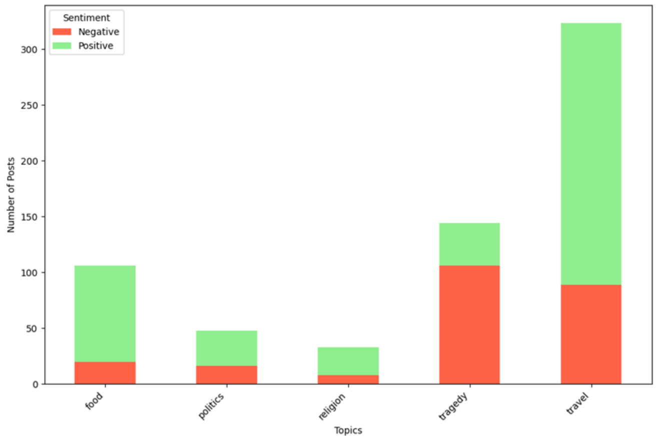

Fig 9. Distribution of sentiment across topics.

Counts are lower in states like Perlis, Negeri Sembilan, and Terengganu, which may be a sign that fewer people are participating in the online discussion or that these areas are contributing less to the dataset. States like Kelantan (15 posts), Johor (14 posts), and Selangor (41 posts) appear to have a lot of ”tragedy” discussions. This can be a reflection of certain instances or occurrences in these states. With no sharp increases in any one area, subjects like ”politics” and ”religion” are more evenly spread among the states. States like Penang and Kelantan, on the other hand, exhibit comparatively more interest in political subjects, although posts about religion are marginally more prevalent in Kelantan and Selangor. The zero-shot classifier achieved an accuracy of 89% in categorizing posts in the predefined topics, against the manually annotated dataset.

Figure 9 displays a bar chart that compares the distribution of positive and negative sentiments across five key topics: food, politics, religion, tragedy, and travel. Tourism emerges as the most discussed topic, with over 300 posts being primarily positive. Food has just about 100 posts, also with a mostly positive sentiment. A similar pattern is observed with politics, and religion, both of which have less than 50 posts but are mostly positive. Tragedy, however, sees a higher proportion of negative sentiment, where out of approximately 145 posts, 105 are negative. This suggests that tourism and food evoke more positive reactions, while tragedy understandably carries more negative sentiment.

4.4. Discussion

The findings highlight significant variation in topic engagement and sentiment distribution across Malaysian states, influenced by factors like population density, cultural significance, and regional events. Selangor’s dominance in post volume aligns with its urban and demographic prominence, while the sentiment analysis confirms predictable emotional responses, such as negativity in tragedy-related posts. These insights underscore the utility of social media analytics in understanding localized public discourse, but also reveal limitations in data coverage and classification accuracy.

4.4.1. Challenges

Several challenges were met during the development of the proposed framework. Firstly, ethical considerations arise when utilizing social media platforms for data collection. Obtaining ethical approval and ensuring the privacy and consent of users can be challenging, as these platforms often do not provide comprehensive guidelines for the research use of data[50-51]. Moreover, the increasing prevalence of paywalls on various social platforms, like X, makes data collection expensive.

Secondly, gathering location-specific data is difficult because most social media posts lack geo-tags. One way can be to find location-specific discussion threads such as state- or city-focused subreddits or Facebook groups, but the likelihood of consistently finding such forums for every region is limited. Another option is to create word profiles using city or state names as keywords (as used in this study) to collect location-specific data. However, this method only captures a small portion of posts, as not all users explicitly mention geographic locations in their content.

4.4.2. Limitation and Future Work

Despite the promising capabilities of this study, several limitations must be acknowledged. The study only uses public English-language Facebook posts, thus providing a limited representation of the Peninsular Malaysian population. Older adults or rural populations may be underrepresented, leading to a potential sampling bias. Additionally, Facebook’s algorithmic filtering may influence which posts are visible and collected. Moreover, while VADER is effective for English sentiment analysis, it may struggle with code-mixed text (e.g., posts combining Malay and English). This could lead to inaccuracies in sentiment classification for such posts. Similarly, zero-shot transformers are powerful but face challenges in accurately classifying topics for ambiguous or context-dependent posts. For example, distinguishing between politics and tragedy in posts discussing a political crisis could be problematic. Looking ahead, several avenues for future work can be undertaken. One improvement can be to feed real-time data to the framework to develop a dashboard for up-to-date sentiment and topic monitoring across different states of a country. This would enable a more dynamic understanding of public emotions as they evolve. Moreover, multimedia data, such as images and videos, can be integrated, as many users now prefer visual content. This could yield richer insights into public sentiments, as visual elements often carry the emotional weight that text alone may not convey. Lastly, stronger or fine-tuned models than VADER and zero-shot transformers can be used to further enhance the sentiment and topic classification reliability of the framework.

5. Conclusion

With the widespread use of social media, monitoring online activity has become crucial for understanding public sentiment and addressing potential socio-political challenges. Social media platforms serve as spaces for communication and reflect public opinion, making monitoring social media sentiments and trending topics essential for governance, public emotional health, and security. However, a location- aware analysis of sentiment and topic trends on social media is important to understand how specific issues or topics are perceived in different regions, enabling targeted decision-making. This paper offers a state-by-state landscape of public sentiment and opinion, offering an intuitive tool for understanding regional moods. The study uses a self- collected dataset of public posts from Facebook, discussing Peninsular Malaysia, and leverages advanced NLP models to classify posts into positive or negative sentiment and the topics of religion, politics, tragedy, tourism, and food. It uses VADER for sentiment analysis and a zero-shot transformer model for topic classification. The accuracy of sentiment analysis and topic classification was calculated against the manual annotation of the dataset, achieving an impressive 97% accuracy in sentiment classification and 89% in topic classification. Thus, by offering location-aware insights into public sentiment and the key topics driving discussions, this research can help these stakeholders understand public opinion, anticipate regional tensions, and respond proactively to emerging issues.

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