Predictive Modeling of Social Movement Lifespan through Natural language processing (NLP) and Explainable AI

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***Abstract*—This paper creates an approach using sophisticated sentiment and thematic analysis to determine the lifespan of social media-driven movements. Drawing on data from Facebook, we examine how public responses and sentiment trends define the movement lifespan of movements like #MeToo. We utilize Natural Language Processing (NLP) in tandem with machine learning algorithms to forecast the lifespan of social movements as a function of identification of key themes, changes in sentiment, and other relevant factors. A new metric is developed for measuring legal, cultural, political relevance with respect to public sentiment. It also involves an aspect of SHAP-based explainability, which shall give insight into the impact caused by various factors on movement duration. On our predictive models, we saw a very strong correlation between legal relevance and movement persistence, with a correlation score of 0.72, while neutral sentiment had a correlation of 0.52. Results highlight the great importance of legal context in sustaining social movements. It offers a transparent and interpretable framework for the analysis of social trends using explainable AI.**

***Index Terms*—Sentiment analysis, Social movements, Thematic analysis, Explainable AI, SHAP values**

I. Introduction

Social media has altered the landscape of social activism. They provide an avenue on which people can share their experiences and organize en masse. Movements such as *#MeToo* started off with the intention to allow survivors of sexual harassment to tell their stories. The digital platforms gave voices to those that have been silenced historically. The *#MeToo* Movement, upon the threads of actress Alyssa Milano's tweet in 2017, went viral overnight and spread across all platforms, from Twitter to Facebook, amassing more than 12 million posts and reactions in less than 24 hours [4]. This went viral to show how social media now empowers grassroots campaigns with global reach: one tweet started a global conversation about sexual violence and power.

Its success underlines something very important about the power of social media for social change. Indeed, Twitter and Facebook are new avenues through which the traditional media gatekeepers can be bypassed. A phenomenon like this allows the voicing of marginalized groups to reach wider audiences directly. It has also managed to make the transnational spread of movements, with adaptations into various cultural contexts, easier—an example being *#YoTambien* in Spanish-speaking countries and *#BalanceTonPorc* in France [5]. These local adaptations reflect the universal relevance of issues such as gender-based violence but allow the movement to resonate with specific regional challenges.

While social media-driven movements tend to create somewhat different impacts in different regions, for example, *#MeToo* certainly brought about legislative change and increased consciousness of the issue at hand in the United States. Its reception in other parts of the world has been more complex. In countries such as China, for instance, the movement faced extreme censorship and pushback; it did, however, manage to stir efforts at redefinition when it came to concepts such as sexual harassment [6]. In South Asia, for example, social taboos and deep-rooted cultural norms about sexual violence restrict such discussions from taking place publicly, although the online movement might take root [5]. Differences like these speak to all the ways in which social media and preexisting cultural and legal frameworks intersect to shape grassroots movement trajectories deeply.

Beyond *#MeToo*, movements like *#BlackLivesMatter* have shown how social media can amass the momentum of protest and frame public discourse. These movements have shown how such digital platforms are used not only for organizing and coordinating but also as spaces of public discourse. It is for this reason that digital platforms have become critical sites for the emergence of contemporary social movements. Since an increasing number of social movements are initiated through digital activism, understanding which factors will decide on the success and longevity of which is crucial to activists and policymakers but also to social scientists [4], [6].

But the digital nature of social media activism also brings a number of challenges in another direction, as there is a high probability of online harassment and misinformation. Secondly, the accelerated facility of information to flow through various channels can make movements susceptible to the changing public fancies with alarming speed and might lead to shallow engagements. Such setbacks indeed call for effective use of digital platforms and keen insight into: For instance, legal relevance and cultural context influence the dynamics of social movements. The present paper bridges that gap by attempting to explain how sentiment analysis combined with thematic analysis and machine learning can be used in predicting the survival of a social movement. The current study will analyze movements like *#MeToo* to give explanations

about the indicators that will ensure the continuity of online activism.

II. Literature Review

Sentiment analysis is an emergent sub-area within the discipline of Natural Language Processing, very significant for the analysis of social media content. It focuses on categorizing text into one of three: positive, negative, or neutral sentiments. The rise of social media sites has added exponentially to the scope of sentiment analysis, thereby making it possible for researchers to measure public sentiment across various domains such as social movements, politics, and consumer behavior [1].

A. Approaches to Sentiment Analysis

The sentiment analysis landscape can be loosely categorized into three methods, namely: conventional machine learning, deep learning, and ensemble learning methods [1]. Each has its strengths and challenges:

1) **Machine Learning Approaches**: The earlier works on sentiment analysis relied entirely on conventional machine learning algorithms like Naïve Bayes, Support Vector Machines, and logistic regression. Most of the models depend on hand-engineered feature extraction methodology such as Term Frequency Inverse Document Frequency (TF-IDF) and N-grams [1]. These methods are very simple yet considerably effective with small data sizes, especially for binary classification problems.
2) **Deep Learning Techniques**: Deep learning further brought models like RNN, LSTM, and transformer-based models such as BERT. These learn feature representations from text automatically, hence fitting them best to work for understanding nuances in the language of social media [1]. Peng et al. (2023) showed that it was able to do a classification with high accuracy by using BERT for sentiments relevant to social movements like #BlackLivesMatter, highlighting the effectiveness of deep learning in capturing context-specific nuances [3].
3) **Ensemble Learning Methods**: Ensemble learning combines multiple models to enhance general performance. Techniques like Gradient Boosting Machines and Random Forest have been applied to sentiment analysis for better performance and generalization of the model updates [1]. These methods are very effective in scenarios where diverse data sources, such as text and images, are put together for analysis.

B. Datasets and Challenges in Sentiment Analysis

Sentiment analysis depends on multiple data sets, including tweets, reviews, and user-generated data from platforms like Twitter and Facebook. The most frequently used data sets are the Stanford Sentiment Treebank, IMDB reviews, and Twitter data sets on political sentiment analysis [1]. These provide labeled examples that normally find application in training models to find sentiment patterns.

However, in sentiment analysis related to social movements, all things change. For example, in order to understand the nature of sentiments expressed during movements like #MeToo or #BlackLivesMatter involves not only polarity detection but also detecting hidden themes, for example, the legal implications or counter-movements responses [1]. These challenges suggest that there must be an increase in sophistication of the preprocessing techniques, incorporating Named Entity Recognition and topic modeling to capture manifold aspects of social media discussions.

C. Applications to Social Movements

The sentiment analysis studies are increasingly focusing on public opinion related to social movements. Works, such as that of Shamrat et al. [2], presented KNN classifiers for sentiment analysis in COVID-19 vaccine discussions. Other studies analyzed the public reaction to social justice movements using similar methods. For instance, BERT-based models are carried out on big datasets for high accuracy in sentiment classification during movements like #BlackLivesMatter [3].

Another area important to thematic is sentiment analysis. It does this through analysis, whereby it identifies key themes and narratives that shape public discourse. For example, how the use of sentiment analysis together with SHAP-based explainability works in understanding how certain features such as positive sentiment or legal relevance drive movement durability [1]. In fact, such interpretability is vital in order to have insight into the underlying motivators of public intervention into specific movements.

D. Future Directions in Sentiment Analysis

This domain of sentiment analysis keeps evolving with the advent of more advanced models and methods. Recent research seems to indicate a greater awareness and interest in multimodal sentiment analysis, where textual data is merged with images or videos for a more comprehensive opinion of the people about something [1]. Besides, developments in transformer-based systems, like GPT and BERT, make it possible to handle large-scale datasets more efficiently, allowing for new possibilities of real-time sentiment analysis of emerging social movements [1]. Despite these advances, challenges persist, particularly in data quality and the cultural biases of sentiment analysis models themselves. Offsetting these limitations will depend on more robust models that can generalize across a variety of linguistic and cultural contexts, especially in movements that have global ramifications such as #MeToo [6]. Future research should focus on doing method development that integrates the strengths of traditional models with those of deep learning models to provide more accurate and interpretable sentiment analysis.

III. Methodology

A. Flowchart of Methodology

Our workflow is shown in Figure 1. Starting from data collection to the development of regression and clustering models, each step addresses specific aspects of the research problem and ensures a thorough analysis of different movements and their duration based on sentiment and thematic features.

TABLE I
PERFORMANCE OF UNOPTIMIZED MODELS

Model	MSE	R^2 Score	RMSE
Linear Regression	202.71	0.3242	14.24
Random Forest	300.22	-0.0009	17.33
Gradient Boosting	439.87	-0.466	20.97
SVR	341.78	-0.1395	18.49
XGBoost	374.35	-0.248	19.35
K-Nearest Neighbors	250.57	0.1646	15.83
Decision Tree	526.67	-0.7558	22.95
AdaBoost	341.37	-0.1381	18.48

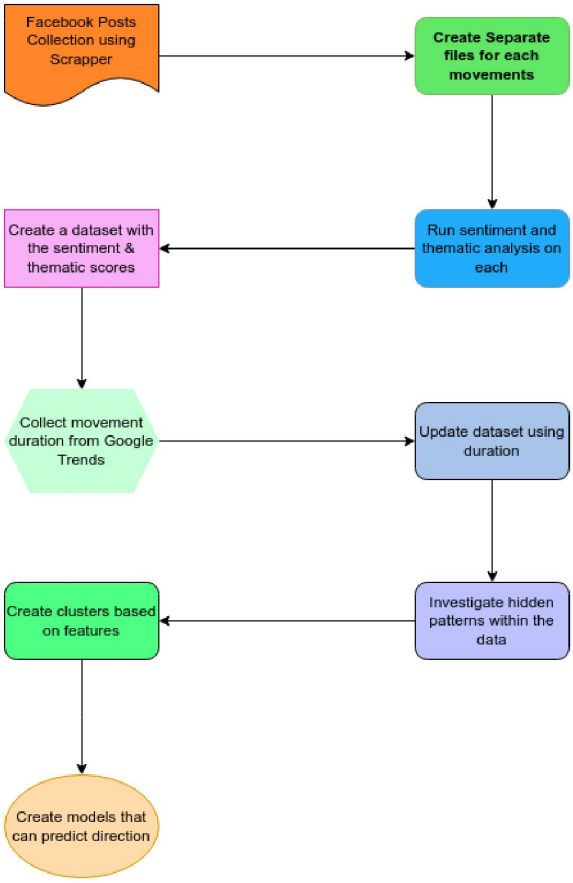

Fig. 1. Workflow of Methodology for Predicting Movement Duration

B. Data Collection and Preprocessing

Data was collected from Facebook posts related to various social media trends, focusing on text content that reflects public reactions to societal issues. The dataset was curated to ensure the inclusion of diverse social movements, ranging from global campaigns like *#MeToo* to regional movements. Preprocessing involved the following steps:

1) **Data Cleaning**: Removal of emojis, special characters, and irrelevant content to retain only meaningful text.
2) **Tokenization**: Splitting text into individual words or tokens for analysis.
3) **Sentiment Labeling**: Applying sentiment analysis tools to classify each post as positive, negative, or neutral.

C. Text Input Analysis Model

A text input analysis model was developed to process new text inputs (e.g., Facebook posts) and calculate sentiment and thematic features dynamically. This model can match new inputs with similar historical movements, enabling real-time assessments of ongoing or emerging social media trends. The model leverages Natural Language Processing (NLP) techniques such as TF-IDF (Term Frequency-Inverse Document Frequency) to extract meaningful information from the text. Additionally, thematic analysis is applied to detect the presence of legal or political relevance, which previous studies have shown to be significant predictors of movement longevity.

D. Model Development

Our approach involves the following models:

1) **Linear Regression for Duration Prediction**: A linear regression model was developed to predict the duration of social movements based on thematic features and sentiment scores. This model quantifies how factors such as sentiment and legal implications influence movement longevity.
2) **Clustering Model**: Developed a clustering model to categorize movements into similar groups based on thematic features, identifying patterns and commonalities among movements. The dendrogram in Figure 2 shows the clustering of movements.

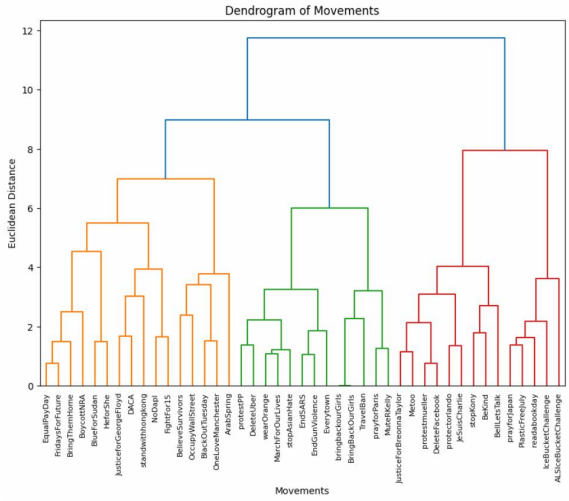

Fig. 2. Dendrogram of Social Movements Clustering

E. Explainability Analysis with SHAP

SHAP (SHapley Additive exPlanations) values were used to assess the impact of each feature on model predictions, providing insights into how each factor contributes to the predicted duration of a movement. The SHAP summary plot in Figure 3 highlights the most influential features, including legal relevance and positive sentiment. The SHAP values help explain which factors contribute the most to a given prediction, ensuring transparency and trust in the model's results.

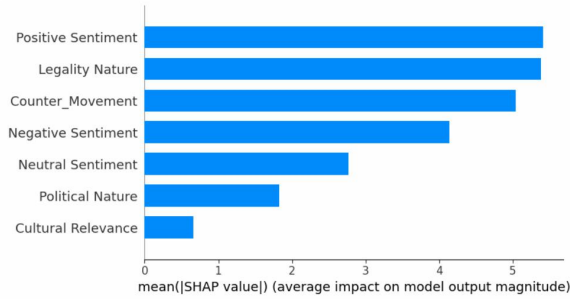

Fig. 3. SHAP Summary Bar Plot

IV. Results

The results of this study highlight the performance of different machine learning models in predicting the duration of social media movements. Both unoptimized and optimized models were assessed, and the comparative results are presented in Tables I and II. The primary evaluation metrics include Mean Squared Error (MSE), R^2 score, and Root Mean Square Error (RMSE).

A. Model Performance

The initial unoptimized models, such as Linear Regression and Support Vector Regression (SVR), demonstrated varying levels of accuracy. For example, Linear Regression achieved an MSE of 202.71 and an R^2 score of 0.3242, indicating that simpler models may be effective when the relationship between features and the target variable is relatively linear. In contrast, more complex models like Gradient Boosting and XGBoost exhibited higher error rates, likely due to overfitting during initial trials [7].

Optimization of hyperparameters led to significant improvements in the performance of these models. For instance, the optimized Gradient Boosting model achieved an MSE of 268.82 and an R^2 score of 0.1038, indicating a better fit to the data after tuning key parameters such as learning rate and maximum tree depth. The Random Forest model, with optimized parameters like max_depth and n_estimators, achieved a more balanced performance, making it suitable for capturing complex interactions among features [9].

B. SHAP Analysis and Model Interpretability

To understand the factors influencing model predictions, SHAP (SHapley Additive exPlanations) analysis was employed. SHAP values provide insights into how each feature contributes to the prediction of movement duration, offering a method to decompose the model's prediction into contributions from each feature, thus ensuring transparency and interpretability [8].

1) SHAP Summary Plot: The SHAP summary plot, shown in Figure 3, highlights the most influential features in predicting movement duration. Key factors such as legal relevance, positive sentiment, and the presence of counter-movements emerged as top predictors. The plot indicates that higher legal relevance and positive sentiment are associated with longer-lasting movements, whereas strong opposition from counter-movements tends to shorten the duration [7], [10]. SHAP values enable a detailed analysis of feature importance, allowing for a deeper understanding of how these thematic and sentiment-based features interact within the model.

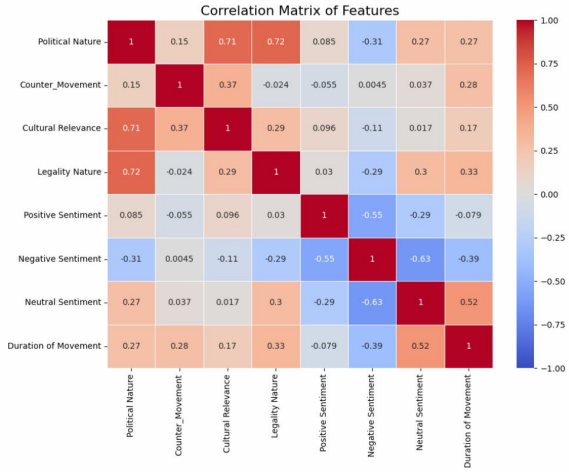

Fig. 4. Correlation Matrix

2) SHAP Dependence and Beeswarm Plots: SHAP dependence plots were used to examine interactions between key features, such as legal relevance and counter-movement intensity. The beeswarm plot revealed that features with wider spreads of SHAP values, such as legal relevance and counter-movement, have greater variability in their impact on predictions. This suggests a nuanced relationship between these factors and movement duration [9].

The beeswarm plot in Figure 5 also indicates that features like legal relevance have a predominantly positive impact, while negative sentiment often leads to a shorter movement lifespan. This detailed view is crucial for identifying which features consistently influence the predictions and understanding the context behind these influences.

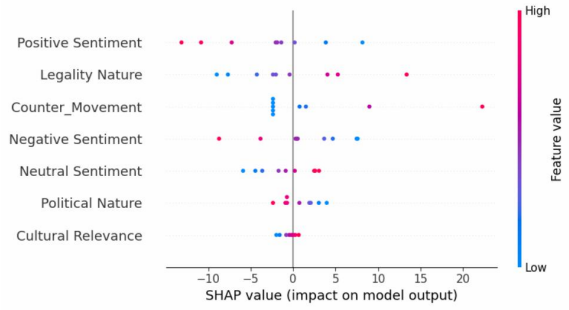

Fig. 5. SHAP Beeswarm Plot of Feature Contributions

C. Model Comparison and Feature Analysis

A comparative analysis of different models reveals the trade-offs between interpretability and predictive power. While

TABLE II
PERFORMANCE OF OPTIMIZED MODELS WITH HYPERPARAMETERS

Model	Optimized Hyperparameters	MSE	R^2 Score	RMSE
Random Forest	max_depth=20, n_estimators=500	279.38	0.0686	16.71
Gradient Boosting	learning_rate=0.01, max_depth=3, n_estimators=200	268.82	0.1038	16.40
SVR	C=10, gamma='scale', kernel='rbf'	280.32	0.0654	16.74
XGBoost	learning_rate=0.01, max_depth=4, n_estimators=150	274.53	0.0848	16.57

models like Random Forest and Gradient Boosting can capture complex feature interactions, their predictions are often more difficult to interpret without tools like SHAP. In contrast, linear models, although less powerful, provide more direct interpretability, making them suitable for understanding how specific factors like sentiment influence outcomes [8].

The decision plot, shown in Figure 6, further illustrates the cumulative impact of features on individual predictions. This type of analysis is valuable for identifying outlier cases where specific features significantly deviate from their typical influence, aiding in both model debugging and refinement [10].

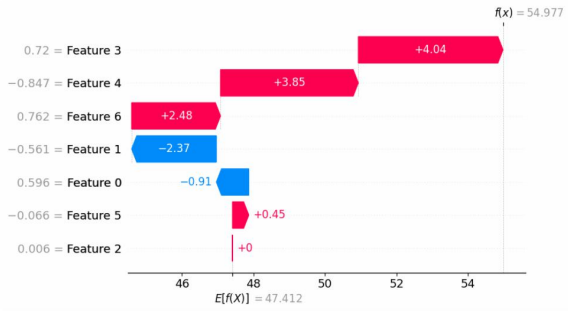

Fig. 6. Decision Plot Highlighting Feature Contributions to Predictions

D. Conclusion of Results

The results demonstrate the value of combining SHAP-based explainability with traditional performance metrics. This combination provides a more comprehensive understanding of model behavior, ensuring that stakeholders can trust the predictions while gaining insights into the underlying factors driving movement duration. The study's use of SHAP values to elucidate feature impacts represents a significant advancement in the interpretability of machine learning models for social trend analysis [7], [10].

V. DISCUSSION

The findings emphasize the importance of explainable AI in understanding complex machine learning models, particularly in the context of predicting social media movement duration. Integrating SHAP (SHapley Additive exPlanations) values has proven to be crucial for transparency, offering clear insights into how different features contribute to model predictions [11]. This is especially valuable in scenarios where interpretability is as critical as predictive accuracy, such as analyzing social movements and public sentiment.

A. Importance of Explainability in Social Trend Analysis

Explainability is essential for building trust in AI models, especially when these models are used to make predictions that impact social or policy-related decisions. For example, SHAP values allow data scientists to decompose model predictions into contributions from individual features, making it easier to understand why certain factors like legal relevance or sentiment have a stronger influence on the duration of movements [12], [13]. This transparency helps stakeholders, including policymakers and activists, gain confidence in the model's decisions and use the insights for actionable strategies.

B. Challenges in Interpreting Complex Models

One of the primary challenges in using SHAP and other interpretability methods is the difficulty in managing large feature spaces, especially with high-dimensional datasets. For instance, when analyzing a wide array of thematic and sentiment features, the SHAP framework may produce complex visualizations that require careful interpretation to identify significant patterns [11]. Additionally, SHAP's reliance on computational resources can be a limitation for real-time analysis in large-scale applications, as calculating SHAP values for deep learning models may become resource-intensive [13].

Another challenge is the risk of misinterpreting feature importance due to potential spurious correlations. As noted in studies on sentiment analysis, features that appear significant according to SHAP values might not always reflect meaningful relationships in the real world [13]. For example, a feature like the presence of a specific word in social media posts might have a high SHAP value but could be the result of a coincidental pattern rather than a true indicator of movement longevity. Addressing such spurious correlations requires careful validation and, in some cases, augmenting the training data with more diverse examples to ensure robustness.

C. Comparing Interpretability Techniques

In addition to SHAP, other interpretability techniques like LIME (Local Interpretable Model-agnostic Explanations) are often used to explain model predictions. While LIME offers simplicity and is effective for providing local explanations, SHAP is generally preferred for its ability to provide consistent and globally interpretable explanations across a dataset [12]. This makes SHAP more suitable for understanding the overall behavior of models used in social trend analysis, where it is crucial to assess how different factors impact predictions across a wide range of cases.

The use of SHAP values also complements traditional performance metrics like MSE and R^2 scores, allowing re-

searchers to balance accuracy with interpretability. For instance, while a model may achieve high accuracy in predicting movement duration, the use of SHAP enables the identification of which specific factors (e.g., positive sentiment or legal relevance) are driving these accurate predictions [11].

D. Implications for Future Research

The insights derived from SHAP analysis can inform future work in social media analysis and AI model development. By understanding the key drivers of model predictions, researchers can design more targeted interventions to enhance the longevity of social movements. Additionally, the emphasis on interpretability in this study highlights the need for developing more efficient algorithms for SHAP calculations, enabling the application of these methods in real-time and large-scale social media analytics [13].

Moreover, as AI models become increasingly integrated into decision-making processes, the focus on fairness and transparency will continue to grow. Future research should explore the combination of SHAP with fairness-aware AI techniques, ensuring that predictions do not inadvertently favor or disadvantage specific groups [12]. This is particularly relevant in social movements where the interests of marginalized communities are often at stake.

E. Conclusion of Discussion

Overall, the use of SHAP for model interpretability in this study has provided valuable insights into the dynamics of social media trends. The ability to explain complex model behaviors ensures that stakeholders can trust the outcomes and leverage the findings to support impactful social change. Addressing the computational challenges of SHAP and exploring complementary methods like LIME can further strengthen the robustness and applicability of explainable AI in future studies.

VI. Limitations

While this study has demonstrated the potential of SHAP (SHapley Additive exPlanations) values in enhancing model interpretability, several limitations remain that could impact its applicability in real-world settings.

A. Computational Complexity

A key challenge associated with SHAP is its computational complexity. The calculation of SHAP values is rooted in Shapley values from game theory, which requires considering all possible combinations of feature inputs to assess their contributions to the model's prediction. This results in exponential time complexity, making SHAP computationally intensive, especially for models with a large number of features [17]. To mitigate this, approximation methods like the TreeExplainer have been developed, which optimize computations for tree-based models. However, for non-tree models such as k-nearest neighbors or deep learning models, the computational burden remains significant, often requiring simplifications or approximations that may compromise accuracy [14].

B. Dependency on Visual Interpretations

Another limitation of SHAP values is their dependency on visualizations for effective interpretation. While SHAP provides quantitative contributions of each feature, understanding these contributions often requires summary plots, force plots, or dependency plots [13]. These visual tools are invaluable for interpreting SHAP values but can be challenging to produce and analyze when dealing with high-cardinality categorical variables or datasets with a large number of features. Moreover, the effectiveness of these visualizations can be reduced if users are not well-versed in interpreting such complex graphical representations.

C. Limitations in Capturing Feature Interactions

Although SHAP values are known for capturing interactions between features, they may not always fully account for non-linear interactions in more complex models like neural networks or deep learning architectures. While SHAP can approximate feature contributions, subtle interactions may still be overlooked in models with intricate, multi-layered dependencies [16]. This can result in less accurate explanations, potentially leading stakeholders to draw incomplete conclusions about model behavior.

D. Applicability to Different Models

The flexibility of SHAP as a model-agnostic tool is advantageous, but it does have varying effectiveness across different types of models. SHAP works particularly well with tree-based models such as gradient boosting and random forests, where the TreeExplainer offers significant performance improvements. However, for other model types like support vector machines or neural networks, the KernelExplainer, which is often used, can be slower and less efficient [15]. This makes SHAP less suitable for real-time applications where quick model explanations are required.

E. Interpretation Challenges and User Expertise

The interpretability of SHAP values is highly dependent on the expertise of the user analyzing the model. While SHAP aims to provide clear insights into model behavior, the raw SHAP values are often not meaningful without context. Users must understand how to interpret these values within the context of their specific problem domain [17]. This can pose a challenge in cases where decision-makers or stakeholders lack a strong background in data science or machine learning, potentially leading to misinterpretation of model explanations.

F. Impact on Real-Time Decision-Making

The computational demands and complexity of SHAP analysis can also hinder its application in real-time decision-making environments. For instance, in scenarios where rapid model updates are necessary—such as fraud detection or dynamic content recommendation—calculating SHAP values can introduce latency, making the approach less practical for immediate analysis needs [14]. As machine learning models continue to be deployed in time-sensitive applications, balancing the need for interpretability with the requirement for speed remains a critical challenge.

G. Conclusion of Limitations

Despite these limitations, SHAP remains a powerful tool for model explainability, offering valuable insights into how features influence predictions. Addressing these challenges, such as improving computational efficiency and making visual interpretations more accessible, could further enhance the utility of SHAP in various machine learning applications.

VII. Future Work

Future research in the area of explainable AI (XAI) for sentiment analysis and social media trend analysis offers several promising directions. One important area is the further refinement of SHAP (SHapley Additive exPlanations) values for real-time applications. Although SHAP provides robust interpretability for complex models, its computational demands make it less suitable for dynamic environments like real-time social media monitoring. Research into more efficient approximation methods, such as those that optimize calculations for deep learning models, could significantly reduce latency and enable broader adoption in time-sensitive applications [19], [20].

Another promising direction is the integration of multimodal data into sentiment analysis frameworks. While this study focused primarily on text data from platforms like Facebook, future work could extend the analysis by incorporating images, videos, and even audio clips from social media. This multimodal approach could offer a more comprehensive understanding of public sentiment and engagement, especially for visually-driven movements like *#BlackLivesMatter* or *#ClimateStrike* [18]. Techniques such as transformer-based models have shown potential in handling multimodal inputs and could be adapted for this purpose.

The exploration of other explainability methods like LIME (Local Interpretable Model-agnostic Explanations) alongside SHAP is another avenue for enhancing model transparency. LIME's local explanations provide a different perspective on feature importance, particularly in cases where SHAP may struggle with computational efficiency or when fine-tuning explanations at the instance level [19]. Combining SHAP's global interpretability with LIME's localized insights could offer a more holistic understanding of how different factors influence social movement dynamics.

Additionally, expanding the dataset to include platforms such as Twitter, Instagram, and emerging social media sites could provide a more diverse range of data points. Different platforms have unique user demographics and modes of engagement, which could reveal variations in sentiment trends and movement longevity. Incorporating data from these platforms would enhance the generalizability of models and provide richer insights into how social movements evolve across various online communities [18].

Another area worth exploring is the application of advanced models like Long Short-Term Memory (LSTM) networks, Transformers, and Graph Neural Networks (GNNs). These models excel at capturing temporal dependencies and relationships between data points, making them well-suited for analyzing the evolution of sentiment and thematic trends over time [20]. For instance, LSTM and Transformers could help model the sequential nature of social media posts, providing deeper insights into how sentiments shift as a movement gains traction or faces opposition.

Lastly, ethical considerations in using AI for social movement analysis are critical. As models become more capable of influencing public perception, there is a need for frameworks that ensure transparency, fairness, and unbiased outcomes. Research into fairness-aware AI techniques, combined with explainability tools like SHAP, can help address biases in sentiment analysis models and ensure that they are equitable across different demographic groups [20].

By addressing these areas, future research can enhance the effectiveness and scope of predictive models for social media trends, providing stakeholders with actionable insights that are both accurate and interpretable.

VIII. Conclusion

This study has highlighted the potential of combining sentiment analysis, thematic analysis, and SHAP-based explainability to predict the duration of social media movements. By employing advanced models alongside interpretability tools like SHAP, this research contributes to a deeper understanding of how public sentiment and thematic elements influence the trajectory of digital activism. The integration of SHAP values provides transparency in model predictions, offering a clear view into the factors that contribute to the longevity of movements, such as legal relevance and positive sentiment.

One of the key takeaways from this study is the importance of explainable AI (XAI) in enhancing stakeholder trust in predictive models. XAI methods, including SHAP, offer a way to demystify complex models, ensuring that both data scientists and decision-makers can understand the rationale behind predictions. This transparency is particularly critical in fields like social movement analysis, where the stakes include public perception and policy implications [21], [22].

Moreover, this study underscores the ongoing challenge of balancing model complexity with interpretability. While models like LSTM and transformers provide sophisticated tools for analyzing sequential data, their complexity often makes them difficult to interpret without advanced methods like SHAP. Future research should continue to explore ways to make these models more transparent, ensuring that the insights derived from them can be practically applied [22].

The findings of this research also open avenues for future work in incorporating multimodal data sources, such as images and videos, into sentiment analysis frameworks. This could enable a richer analysis of social media trends, capturing the visual and textual elements that contribute to the public's engagement with movements [21]. Additionally, as AI models become more integrated into decision-making processes, ensuring fairness and mitigating bias will be crucial. Combining SHAP with fairness-aware AI approaches can help address potential disparities in predictions, fostering a more equitable understanding of social trends [22].

In conclusion, this study demonstrates the significant role of XAI in making complex models interpretable, thereby

providing actionable insights into the dynamics of social media-driven movements. By expanding the scope of analysis to include diverse data sources and refining explainability techniques, future research can further enhance the predictive capabilities and societal impact of AI in understanding digital activism.

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